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Creating A "First-cut" Species Distribution Map for Large Areas from Forest Inventory Data

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Abstract

Data from the USDA Forest Service's Eastwide forest inventory database (EWDB) can be used to create general maps of several forest variables/attributes, including tree species distribution, stand size classes, and modeled attributes like forest disease susceptibility across a large part of the Eastern United States. This was accomplished using both a simple moving window average and by incorporating geostatistical techniques. A measure of the local variability was calculated to provide some measure of both the spatial and attribute uncertainty contained within that average value. Over such a large area, the full benefit of the geostatistical techniques is not always being used because of the broad-scale averaging of the spatial structure present in the data. However, when severe time constraints are imposed, this study illustrates that an analysis as simple as calculating a moving window average of the FIA inventory data does provide a picture of spatial distribution that is clearer and potentially less misleading than a point map and that is of higher spatial resolution than county summaries. In addition, using indicator kriging provides an estimate of the probability of a condition, which is particularly useful when a specific threshold is of interest, when the variables of interest are recorded in classes, or when the definition of that threshold involves several variables. Using a few geostatistical techniques, we can reduce the disadvantages of both point maps and county summaries, while retaining the opportunity to take advantage of any spatial structural information that is available in the data when sufficient time is available to do so. They are termed "first-cut" maps because they do not contain any of the refinements, such as further utilizing the spatial structure available, that are possible when additional time is available. This report focuses on the analytical procedures that can be used to quickly generate such large area "first cut" maps.

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Introduction

The Forest Inventory and Analysis (FIA) units of the USDA Forest Service are responsible for providing periodic assessments of the nation's forest resources and conducting inventories by state, or groups of states, in cycles that range from 8 to 15 years. These inventories provide information on the amount, status, and character of the forest resources across the country. All states, except Alaska, have been inventoried at least once, and most states east of the Mississippi and some west (for example, CA, OR, WA) have been inventoried at least three times. Tree-level data (species, diameter, height, status, crown ratio, crown class, damage, tree grade, tree class), stand-level data (stand age, stand size, forest type, stand origin, owner group, land use, disturbance, stand structure), and plot-level data (slope, aspect, latitude, longitude) are collected at each location (Hansen et al. 1992; Alerich 1996[1]). These data provide detailed information on the composition and diversity of existing forest vegetation across the United States, attributes that cannot yet be identified effectively from remotely sensed sources. Other sources of ground inventory data do exist, but they usually lack sufficient detail, are based on small samples, combine studies with different sample designs and sampling procedures, or are limited to political boundaries (McWilliams et al. 1993). Thus, the nationwide forest inventory data collected by FIA represents an extensive dataset of numerous forest characteristics across the country that is extremely useful for broad regional- and landscape-level analyses.

In addition to the forest inventory data, there is a need for continuous spatial output of this type of forest information—maps depicting where and how these forest attributes are distributed across the landscape. Forest management and regional planning are largely spatial problems, and research into understanding forest change, mortality, habitat use, or health, usually includes a spatial component. Thus, it is desirable to display the FIA data spatially to present a picture of where within states and regions certain variables predominate (such as tree species) or where certain conditions occur (such as older and larger stands of oak potentially susceptible to oak wilt). This information may be used simply as a focus for discussion; a catalyst for further analysis; or directly as a critical dataset in other analyses, decisions, and models. Because FIA data are only available at sample plot locations, creating such a map requires a model of the resource, so that we can interpolate information between known locations.

FIA data frequently have been summarized by county for a quick look at forest variables across large areas (for example, Beltz et al. 1992). However, for some questions, the spatial resolution of counties is too coarse and can be misleading. It can mask subtle or contrasting distributions simply because the area size or shape crosses into several different local spatial patterns (Monmonier 1991). This is particularly common when administrative boundaries are used to describe ecological features. Also, such averages are typically not provided with a picture of the spatial variability that actually exists in the landscape—local variability, which can be an extremely important factor in both planning decisions and research assumptions. At the other extreme, presenting the values themselves in a point map can result in a map that is difficult to interpret because of the intimate mix of high and low values, and difficult to create effectively because of its sensitivity to the cartographic presentation of point sizes and colors. There is, however, enough spatial information available in the FIA inventory to summarize these data to a finer resolution. There are a sufficient number of plots available, for example, to aggregate the data relatively quickly to spatial units smaller than counties. This is accomplished by taking advantage of the known spatial location of each sample plot and a few spatial analytical techniques such as moving window analyses and geostatistical techniques, or both.

Geostatistics is a branch of statistics that studies phenomena in space. It offers a set of tools and techniques that can be applied when trying to understand the spatial characteristics of a phenomenon, or when trying to estimate it in a spatial context at unsampled locations. Geostatistical techniques include measures or descriptions of spatial dependence, such as the variogram, and methods of interpolation, such as kriging or simulation. Kriging, and the related routines of conditional simulation, offer a way of creating a relatively continuous surface of estimated values that take advantage of the spatial structure inherent in the sample dataset. Kriging estimates are essentially weighted moving averages of the original data values, taking the distance, direction, and redundancy of neighboring points into account using a model defined from the sample variogram. Many useful references exist within the earth sciences where geostatistics have been widely used and developed (Isaaks and Srivastava 1989; Deutsch and Journel 1992; Srivastava 1994; Wackernagel 1995; Goovaerts 1997), and increasingly in ecology and forestry (Samra et al. 1989; Rossi et al. 1992; Fouquet, C. de. and Mandallaz 1993; Liebhold et al. 1993; Mowrer 1994; Riemann Hershey et al. 1997). Geostatistics is a field of

[1]Alerich, D. 1996. Field instructions for the fifth inventories of New Hampshire and Vermont. Unpublishd report on file at U.S. Department of Agriculture, Forest Service, Northeastern Research Station, Forest Inventory and Analysis Unit, Radnor, PA. 90 p.

many different techniques. Each interpolation technique makes different assumptions about the data, contains procedures of many different computational intensities, and generates different kinds of output. Which technique is most appropriate and which parameters are most applicable depends heavily on the phenomena being examined, the sample data being used, the kind(s) of output desired, and the time available to do the analysis. Spatial correlation or autocorrelation is well known to exist in forest ecosystem variables (for example, Legendre and Fortin 1989). And this spatial structure is evident even at the scale of sampling of FIA data (Riemann Hershey et al. 1997). If we are able to utilize the spatial structure present in the sample data, we should be able to improve our estimates of those values (Biondi et al. 1994).

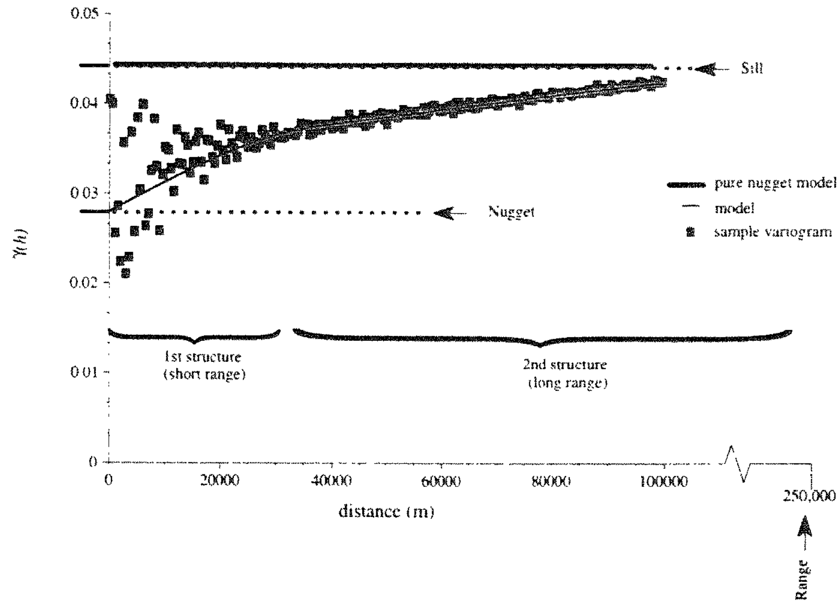


Figure 1.—The components of a sample variogram, and two possible models.

This study illustrates a simple procedure for displaying FIA data spatially over large areas. The procedure takes more advantage of the known plot locations than previous county summaries. This report focuses on the analytical procedures used to generate such large area first-cut maps.[2]

Methods

Data

The sample plot data were from the national FIA inventory. The intensity of sampling varies by region and state, but averages one field plot for every 5,000 acres (individual state averages range from approximately 1,200 to 8,000 acres). For those states included in the study, the distance between forested plots and their nearest neighbor averages 3,300 meters with a range of 1,800 to 5,900 meters. The data are from the most recent inventory collected in each state and are available in the Eastwide Database (EWDB). The actual dates of data collection range from 1980 to 1995.

For tree species occurrence, an importance value of percent basal area/acre (%ba/acre) was used, indicating the proportion of a plot that is occupied by that species in terms of basal area/acre.

A forest/nonforest overlay was used as a mask on all final maps to limit the visual impression of those counties and cells in primarily nonforested areas. The difference is particularly noticeable in central Minnesota and Wisconsin where a few forested plots amidst predominately farmland can have a large effect. This mask is necessary because the FIA inventory data alone are not a sufficiently intense sample to reflect the fine spatial scale at which forest/nonforest occurs as a result of the physical geography and current and historical land use patterns. The ridge and valley area in Pennsylvania, for example, is an area of farmed valleys and forested hilltops not resolvable by the intensity of FIA ground plots. For that purpose, a more detailed dataset such as that derived from satellite imagery or FIA photointerpretation data[3] is required. The dataset used as the forest/nonforest mask in Figures 3 to 6 was derived from 1991 AVHRR (Advanced Very High Resolution Radiometer) data (Zhu 1992).

Assessment of Spatial Dependence

Both a variogram and an indicator variogram were calculated to assess the spatial dependence present in the data. The variogram summarizes spatial continuity, and essentially depicts the variation between sample data values at increasing distances from each other (Isaaks and Srivastava 1989). Spatial dependence is present if the nugget (that is, that variation that remains unexplained by neighboring values) is less than the sill (the global variation calculated for all values in the dataset). The range is that

[2]The methods used in this study are described in detail in Rossi et al. (1993) and Isaaks and Srivastava (1989); the geostatistical analysis was performed using GSLIB routines (Deutsch and Journel 1992) with some additional routines written by R.E. Rossi.

[3]FIA photointerpretation data are collected on a much more intensive grid of approximately one point for every 285 acres. Riemann Hershey, Rachel; Drake, D.A.; Ramirez, M.A. Producing a forest/nonforest map from the FIA photointerpretation data using Indicator Kriging. Unpublished report on file at USDA Forest Service, Northeastern Research Station, Forest Inventory and Analysis Unit, Radnor, PA.

distance at which the variogram reaches the sill. Figure 1 illustrates a sample variogram and its basic components. The amount of spatial dependence present is reflected by how small the nugget is compared to the sill—how much of that spatial variation is explained by neighboring values. If there is recognizable spatial structure in the variogram, a model can be fitted to that structure. It is this model of how values vary (on average) with distance away from any single point that is used to incorporate spatial structure into the kriging routines. A pure nugget model is one where there is no spatial dependence, and the variation at all distances, even those close together, is the same as the sill or global variation (dataset variance).

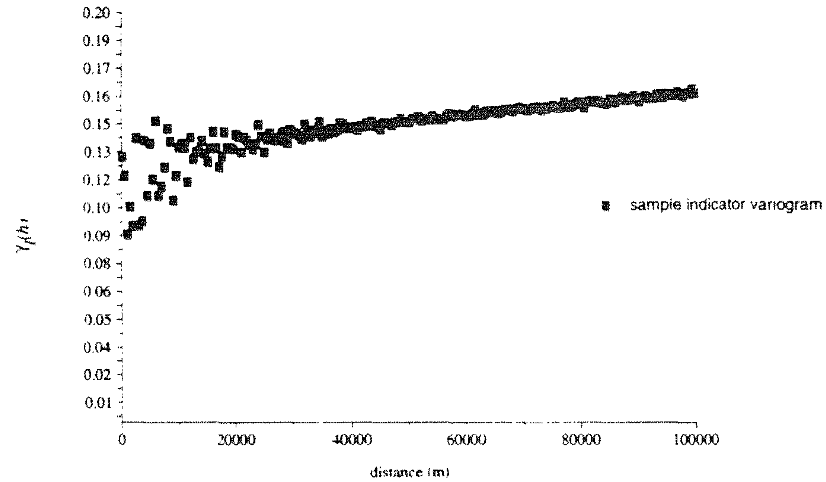


Figure 2.—The indicator variogram calculated for oak occurrence, using a cutoff of .001 percent basal area/acre (essentially 0).

Spatial Estimation

Three spatial estimation techniques were used: ordinary kriging (OK) using a model of the spatial structure present, ordinary kriging with a pure nugget model (= a moving window average), and indicator kriging (IK). In all of the estimation techniques used, the results were calculated to a resolution of 10-km x 10-km grid cells (100 km^2), using a search radius of 10-km (314 km^2). The search radius (and the shape of the search area) defines the maximum distance and direction for points to be included in the estimation. The search radius used here was chosen to be large enough to capture a minimum of five plots in all areas not subject to the nonforest mask, but small enough to minimize the smoothing effect of averaging. The few exceptions to this occur where the search area borders either a large body of water or nonforested land. The sampling intensity varies considerably between the states in the Eastern United States, with New Jersey, Iowa, Illinois, and Alabama limiting how small this averaged area could be. Many of the Lake States and Southern States contain sampling intensities that could support averaging using a search radius much smaller than 5 km. The size of the reporting area (that is, the resolution of the output dataset) is not as critical to the final results as the search radius, but the smaller the reporting cell size is compared to the search radius, the more gradual the transition between cell values and thus the smoother the display of the output. A relationship of 1:3 was used here.

Ordinary kriging was the first technique used to estimate/summarize the EWDB variables. Kriging estimates are essentially weighted moving averages of the original data values—taking the distance, direction, and redundancy of neighboring sample points into account, based on the model defined from the variogram of the sample data. No anisotropy was observed and an omnidirectional variogram was used. Ordinary kriging was run first using a model of the spatial dependence/structure found in the variogram. The model used included two structures in addition to the nugget to describe the short- and long-range structures observed in the variogram (Fig. 1). The parameters of the model were:

Number of Structures	*Nugget effect*	*Function*	*Range (m)*	*Component*
2	.028	spherical	38,000	.0063
		spherical	250,000	.0145

Next, OK was run with a pure nugget model (that is, where the nugget = the sill). Here, the sill was calculated simply as the variance (σ^2) of the entire dataset, or the average squared difference of the observed values (x_i) from their mean (m), where n is the number of points in the entire dataset.

$$\sigma^2 = 1/n \sum_{i=1}^{n} (x_i - m)^2$$

In this situation, OK is the equivalent of a *moving window average*, because no weighting is applied to the sample plots used in the estimation. To do this, the total dataset variance, or the sill, was used as the nugget. This is called a 'pure nugget' model, because the model parameters are now defined very simply as having a nugget of σ^2 and no additional structures (Fig. 1). This represents a slightly faster, easier technique that could be accomplished by many different software packages and could be employed when time constraints for generating a rough map are most severe. The advantage of using OK is that if there is any spatial structure present in the data, it can be incorporated easily into the estimate.

The third geostatistical technique employed was IK. Indicator kriging uses an indicator transform to divide the data into two classes—above and below a designated cutoff value, or based on whatever criteria are chosen. It is thus a particularly useful technique when there is a specific threshold of interest, such as 1) whether a species is present or not (>0 percent basal area/acre), or 2) whether there is a particular category of interest, such as sawtimber stands. For each estimated cell, IK provides an estimate of the probability that it falls above or below that cutoff value. Thus, in the example used here, the output dataset indicates the probability that a tree species occurs at that location. Because of the lack of spatial structure in the indicator variogram (Fig. 2), a pure nugget variogram was also used in the IK. The sill was calculated simply as

$$p * (1 - p)$$

where p = the proportion of the dataset that falls below the cutoff value of interest (Isaaks and Srivastava 1989; Deutsch and Journel 1992; Rossi et al. 1993). As with OK, if there is no spatial structure present and a pure nugget model is used, the result of IK is essentially the same as a moving window average of 0 to 1 data (that is, the data would have to be first converted to 0's and 1's corresponding to below and above the cutoff value).

Spatial Variability and Uncertainty

With any statistical summarization or estimation, high local spatial variability contributes to the uncertainty that at any given point within that cell the estimated value will be true. A map of local statistics, such as the standard deviation of the values encountered within the search radius at each location, can give an effective picture of the magnitude and location of the spatial variability and heterogeneity of that attribute/phenomenon. To provide important uncertainty and variability information along with the summarized maps, the moving window approach was used to calculate the local standard deviation for each grid cell. To provide this information along with the county-level map, standard deviation was also calculated for each county.

Results and Discussion

We know from previous studies that even with the relatively sparse sampling intensity of the FIA inventory data there is considerable spatial dependence among species percent basal area/acre values in local areas (Riemann Hershey et al. 1997; Riemann Hershey, in press). This structure is lost, however, when an area this large is treated as a single unit—effectively averaging the different spatial structures of several different populations. Populations in a geostatistical sense are those groups of sample plots that, when a variogram is calculated separately for them, exhibit a different amount of spatial dependence or variogram shape/type, and thus would require a very different model to describe that dependence. This could be true with oak, for example, whose distribution and abundance patterns across the more mountainous subregions of the central Appalachians is very different spatially from its distribution in the Coastal Plain or the dataset as a whole. A variogram calculated from the entire dataset represents an average of often several distinctly different component variograms. At the scale of examination used in this study—the entire Eastern United States—it is not expected that many of the FIA variables will exhibit much spatial dependence or structure. This is due to the number of substantially different ecoregions included in this area, and the correspondingly different 'populations' of each species that are encountered and averaged together (Riemann Hershey et al. 1997).

In this study, the variograms calculated for the entire area typically had very little spatial structure or dependence, depicted by a noisy variogram at small lag distances and a high nugget—60 to 70 percent of the sill (global variance) in both the sample and indicator variograms for oak (Figs. 1 and 2). In general, where there is any spatial structure at all, using it will improve the estimate. However, at times the amount of information gained by incorporating the spatial information is less than the effort required to incorporate it. Whether it is incorporated depends upon the objectives of the study. In addition, where it is known that the spatial structure is actually an average of substantially different populations in different areas (for example, oak distribution in the coastal provinces vs. oak distribution in the central Appalachians), using a model fitted to an average of that data may not represent the real underlying spatial structure in many local areas (see also Riemann Hershey, in press). In such situations a simple moving window approach can be both the fastest and most appropriate method for estimation at this scale.

The results of a moving window average (here OK with a pure nugget model) are presented in Figures 3 and 3a. In this example, there was little advantage to incorporating a model of that spatial structure into the estimate. When a map was created using a model of that spatial structure that had a spatial dependence of only 30 percent, the results amounted to less than a 0.05 percent change in the final map. This simply illustrates that when there is limited spatial dependence in the sample variogram, there is a limited effect in incorporating that into the estimation.

Compared to the county-level summary (Figs. 4 and 4a), the maps resolved to 10-km grid cells (produced either with OK or moving window average) offer a picture of species distribution at a much higher resolution (~17x finer). Counties in this area of the country average 1,750 km? in size compared to the 100-km^2 grid cells used here. The result is a much more heterogeneous and somewhat more realistic picture of the distribution of oak across the Eastern United States, without being so noisy as to hide the underlying large-scale trends and patterns, which are probably of interest at this scale of examination. The results also illustrate that there is a noticeably lower uncertainty associated with each area when values are averaged over a smaller area (Figs. 3a and 4a). Compared to a point map (Fig. 5), the kriged maps are easier to interpret, and provide tree species cover information for easy overlay with other data sources.

Figure 6 illustrates the results of IK in terms of the probability of oak occurrence (defined as >0.1 percent basal area/acre, capturing effectively anything greater than 0). Depending on the objective, any probability could be used

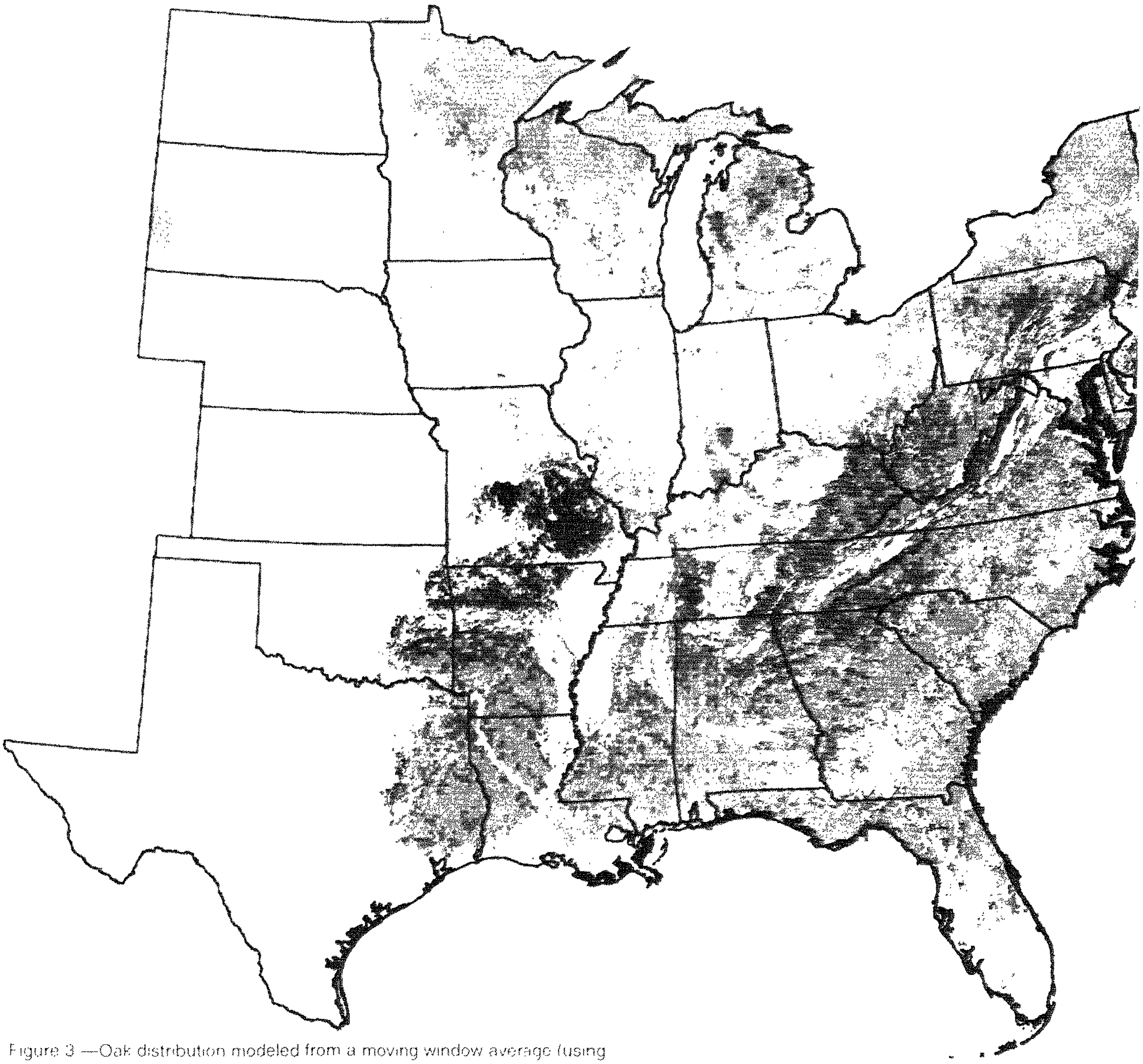


Figure 3 —Oak distribution modeled from a moving window average (using OK with a pure nugget model).

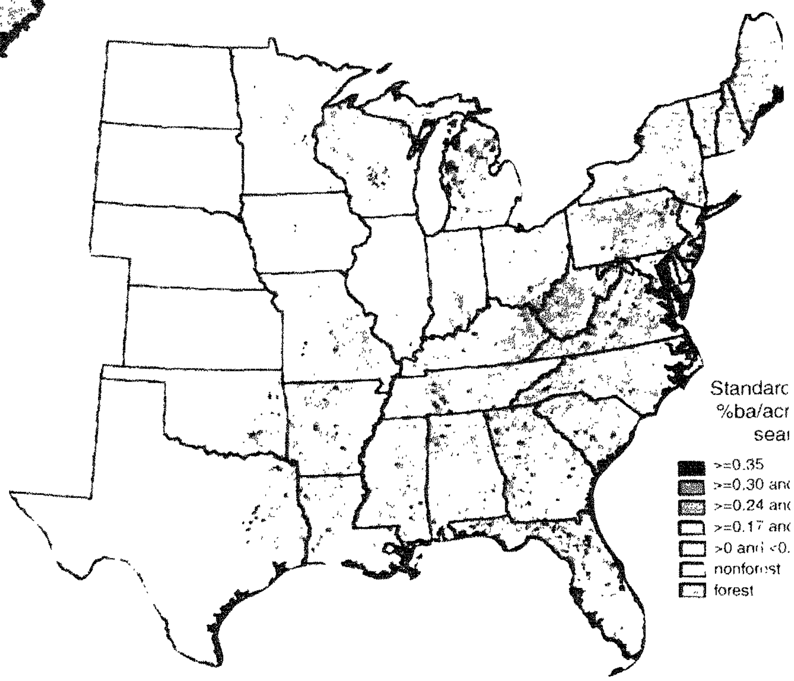
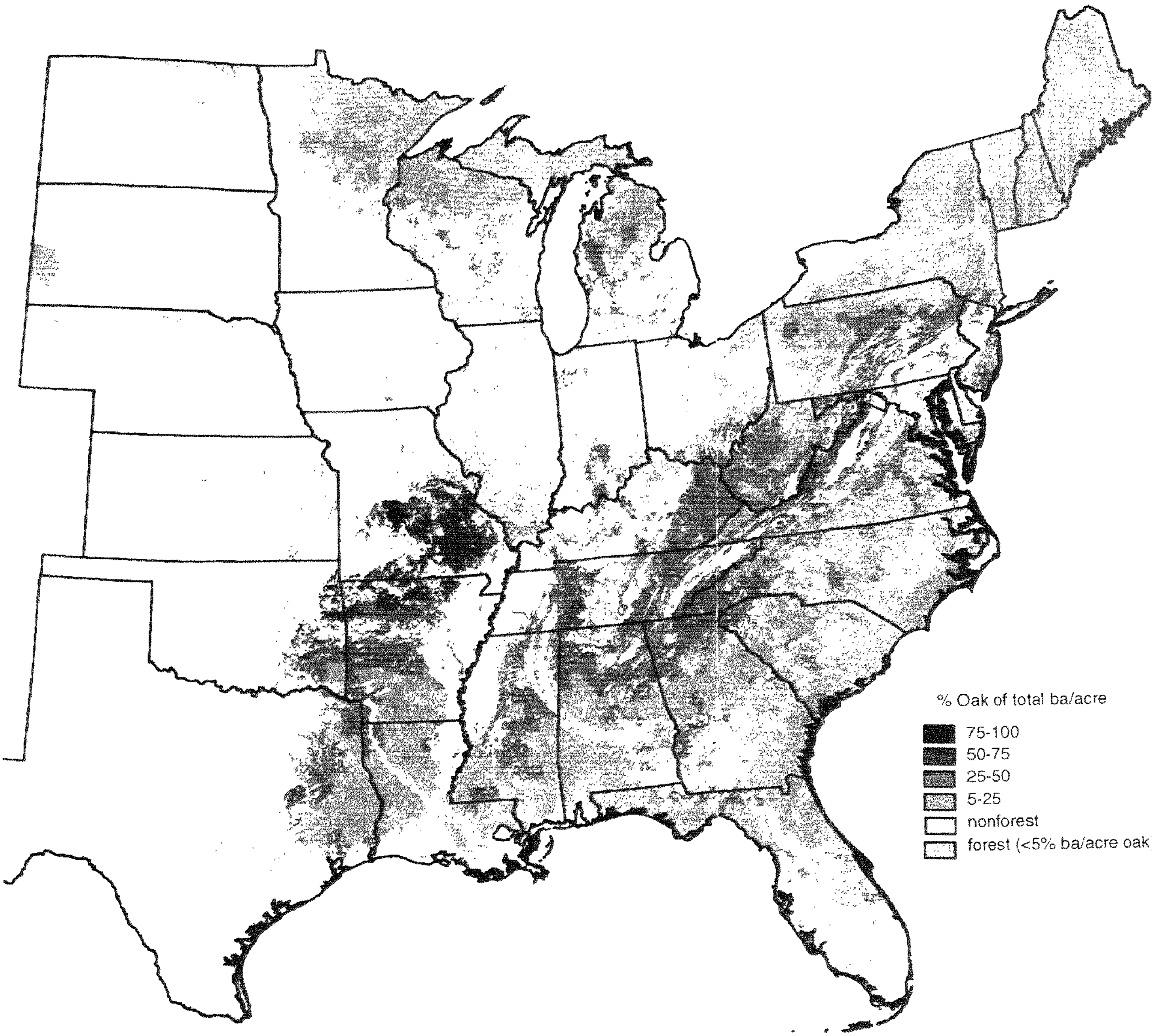


Figure 3a.—The "uncertainty" of the moving window averages, depicted as the standard deviation of percent basal area/acre values within the search area.



—Oak distribution modeled from county-level averages.

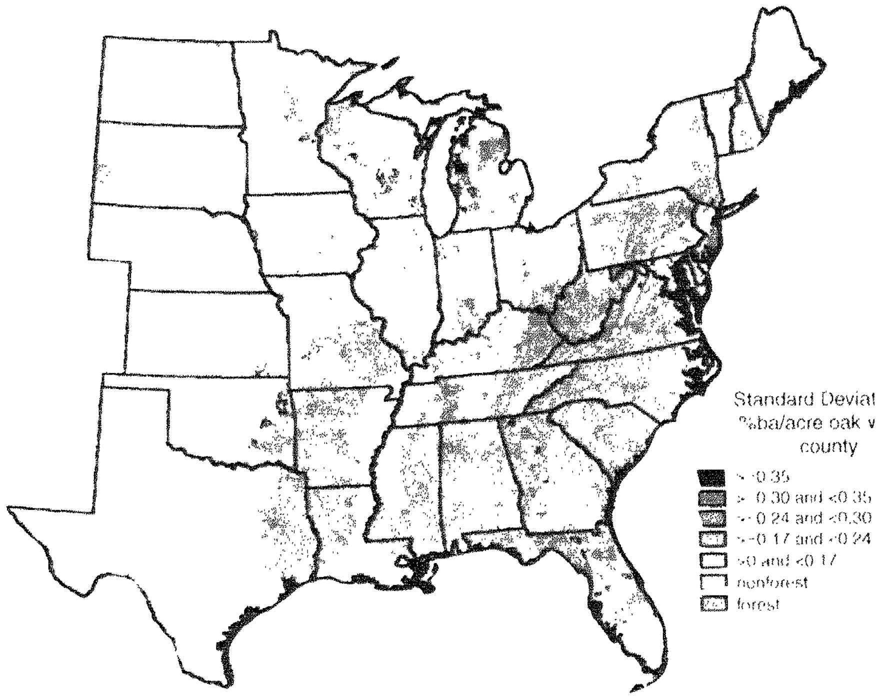


Figure 4a.—The "uncertainty" of the county-level averages, depicted as the standard deviation of percent basal area/acre values within each county

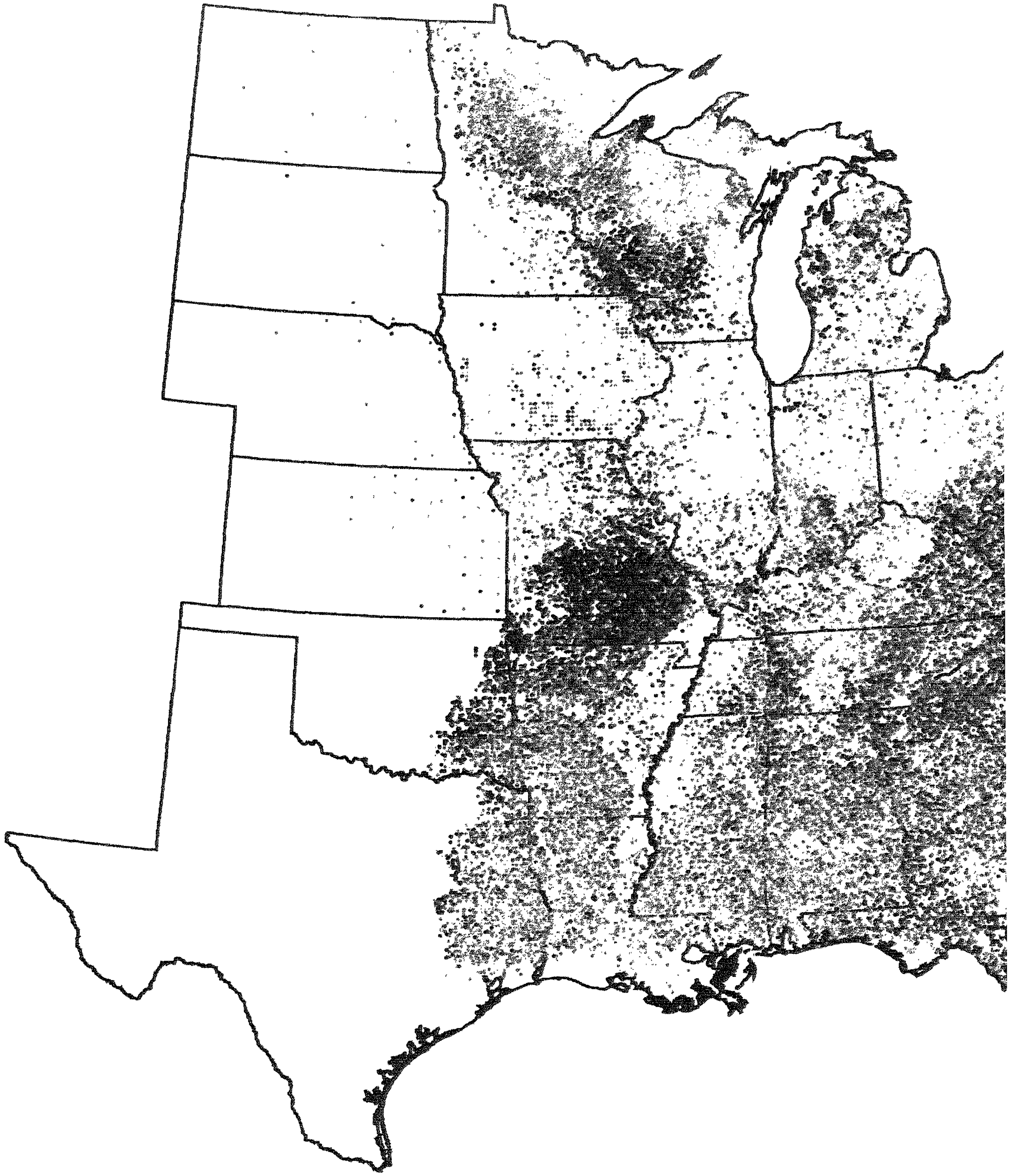
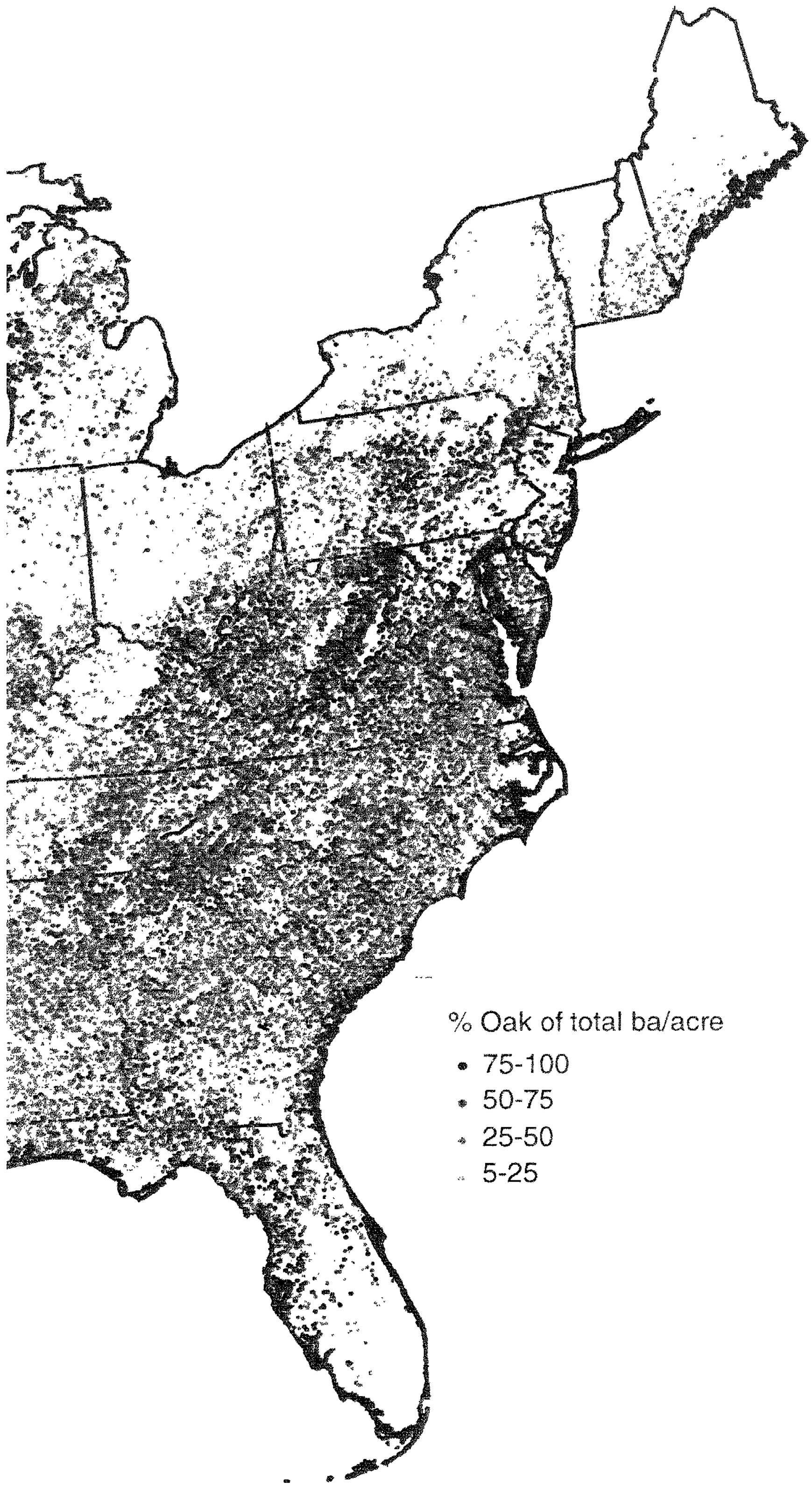
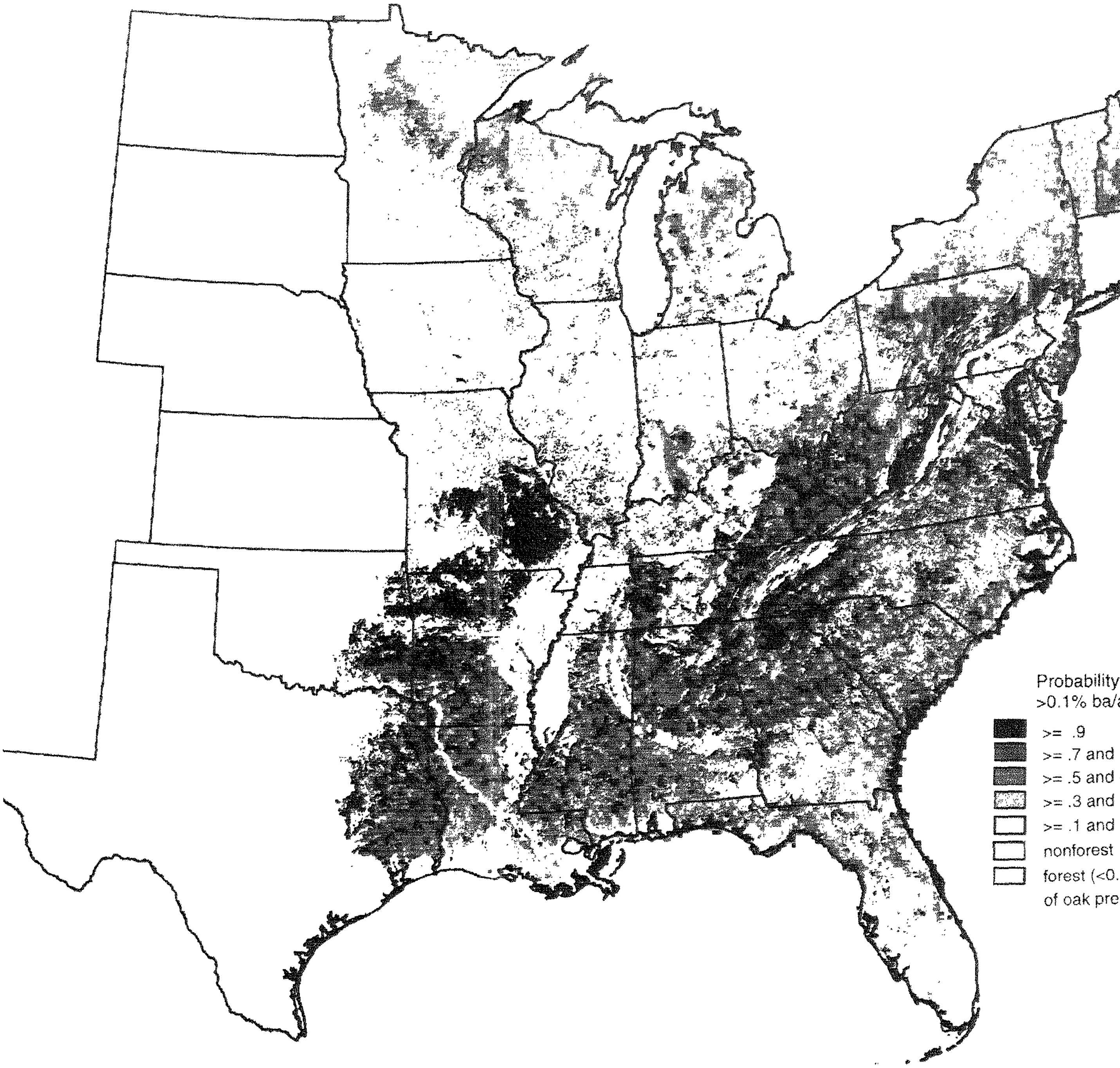
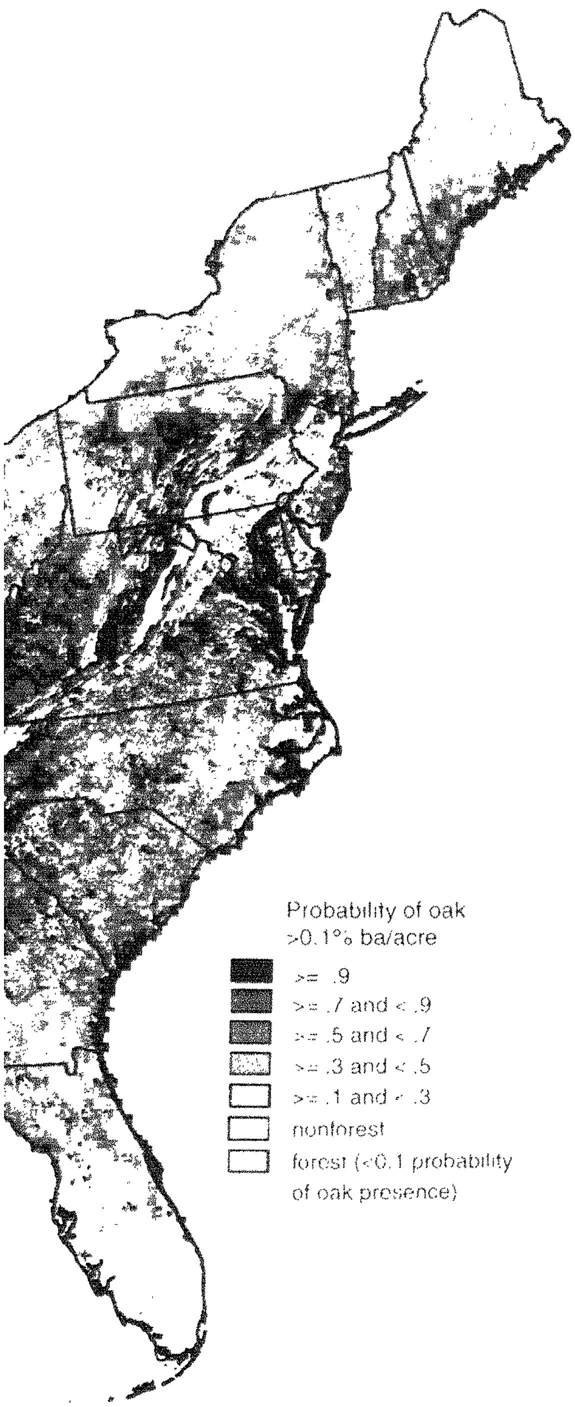


Figure 5.—A point map displaying oak percent basal area/acre values by plot location. Although a very useful analytical tool for examining the original data, its presentation is very sensitive to point size, color, and drawing order, and can be misleading.


% Oak of total ba/acre
75-100
50-75
25-50
5-25



—The results of IK provided a map of the probability of oak occurrence
ıs >0.1percent basal area/acre).


Probability of oak
>0.1% ba/acre
>= .9
>= .7 and < .9
>= .5 and < .7
>= .3 and < .5
>= .1 and < .3
nonforest
forest (<0.1 probability
of oak presence)

as the cutoff value. For example, if a particular insect is known to live in hemlock stands and the objective is to limit the search to only those areas where there is a high probability of finding suitable conditions for the insect (minimizing errors of commission), we might set the cutoff at the probability level of > 0.8. If, however, we are most interested in finding all areas where the insect is likely to occur (minimizing errors of omission), we might choose a probability level for species occurrence much lower, for example, > 0.4 (Riemann Hershey, in press).

There is uncertainty associated with any measurement or estimate. Knowing the uncertainty is critical information and, consequently, an important part of data collection, data management, and data analysis. It affects how much weight is given to different sources of data/information in both subsequent decisions and analyses. And in datasets modeled to broader spatial scales, where the spatial resolution/detail being reported is necessarily a summary of local conditions, the uncertainty provides an indication of the magnitude of that local variation. Therefore, accompanying each distribution map is a map of the local variability present in the data. The maps describing this local uncertainty associated with the average reported appear in the upper right-hand corner of Figures 3 and 4. Each depicts the standard deviation of the values encountered within the search radius at each location in Figure 3 and within each county in Figure 4. High local spatial variability contributes to the uncertainty that at any given point within that cell the estimate being reported will be true. Local standard deviations provide a useful picture of the magnitude and location of the spatial variability and heterogeneity of that attribute/phenomenon. Frequently, the variables measured in the FIA inventory do exhibit high spatial variation at the sampling intensity of the FIA data. This information can be used to determine where the uncertainty is too high to be used in a certain decision, and where additional information or sample data might be used to lower that uncertainty.

Conclusions

These maps provide far more spatial resolution than previous summaries of FIA variables by county. They also provide clearer and potentially less misleading information (depending upon the cartographic presentation) than when the information is displayed as a point map. Investigations into the spatial structure of tree species in individual states and ecoregions reveal that considerable spatial information is available in the data that is not being used in this analysis. However, when severe time constraints are imposed, this study illustrates that an analysis as simple as calculating a moving window average of the national forest inventory data does provide a picture of distribution that is both clearer and potentially less misleading than a point map, and of higher spatial resolution than county summaries.

These maps provide only a broad-scale look at species distribution in this area. They are termed "first-cut" species distribution maps because in working with such a large area, much of the spatial pattern and structure present in individual local areas is lost when the area is examined as a whole, and any model that is fit to that averaged spatial structure usually contains a very high nugget and is relatively non-specific to any particular area. In general, the larger the area incorporated into the calculation of a single variogram, the more chance of averaging together two or more different 'populations' of that tree species (or whatever variable/phenomenon is being examined), each with a different spatial structure. From previous studies of individual states and individual ecoregions in the northeastern United States, it is readily evident that tree species in these smaller areas can exhibit dramatically different spatial structure (Riemann Hershey et al. 1997). Thus, with tree species at least, there is much potential for fine-tuning the models, and correspondingly the final map, if time is available to examine and incorporate the spatial structure in each local area.

However, such a cursory approach can be applied even when there are severe time limitations. And if the limits of the data are respected (here, with a 10-km cellsize and 10-km search radius), the results can provide a broad-scale picture of the distribution of many of the variables available in the EWDB.

With any map, some measure of the uncertainty of the estimate contributes to its usefulness. The uncertainty or local variability maps accompanying each distribution map provide essential information on the heterogeneity of the phenomenon in each local area (as revealed by the current level of sampling) and indicate how much smoothing was essentially applied to create the summarized map.

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