Using Widely Spaced Observations of Land Use, Forest Attributes, and Intrusions to Map Resource Potential and Human Impact Probability

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Abstract.-Scant information exists about the spatial extent of human impact on forest resource supplies, i.e., depreciative and nonforest uses. I used observations of ground-sampled land use and intrusions on forest land to map the probability of resource use and human impact for broad areas. Data came from a seven-state survey region (Alabama, Arkansas, Louisiana, Mississippi, east Oklahoma, Tennessee, and east Texas) containing 32,000 land-use plots, with detailed attribute information for about half of these plots classed as forest land. Forest land attributes included human-associated intrusions (beverage containers, garbage, livestock grazing, timber management activities), proximity to nonforest land, forest fragment size, ownership, and forest type. Tools included geographic information software, a 100 MHz Pentium I processor, and 0.4-ha land-use and forest resource sample plots nominally spaced at 4.8-km intervals. I transferred information from sample plot locations to grid cells sized large enough to minimize computer memory storage and computation requirements, and small enough to conservatively model information from adjacent cells with plot information and include no more than one sample plot per cell. Results used spatially moving averages, with examples, to assess the spatial context of forest resources. Maps displayed regions of high and low probability of altered forest resources, forest attributes, and patterns qualitatively correlated with nonforest land-use neighborhoods. Findings suggested land areas with potential for multiple resource uses and forest land vulnerable to nonforest conversion.

Regional resource inventories (e.g., the USDA Forest Service's Forest Inventory and Analysis [FIA] and the Natural Resources Conservation Service's National Resources Inventory [NRI] program) document the status and change in land use and resource production from widely spaced observations at ground-sampled locations. Limited spatial information exists about the extent and potential for human impact, i.e., depreciative and multiple uses, on resource supplies. These inventory findings traditionally provide tabular statistics and note attribute locations spatially by political subdivision, e.g., by state and county. I conducted a study to (1) document an approach to more uniformly illustrate spatial relationships of inventoried attributes from widely spaced ground observations, and (2) make an initial, coarse-scale evaluation of the extent and probability of regional resource potential from observations of human intrusions. Examples that follow use land-use surveys, forest resource inventories, and ground observations, but the methods of this study could be applied to most other systematically sampled, widely spaced earth surface surveys.

Ground-based regional forest resource inventory sample plots in the United States, which range in size from 0.1 to 8 ha, are generally too small or otherwise an inadequate sample for quantifying resources other than forest vegetation, such as wildlife populations and recreation opportunities. Resources requiring larger samples must be aggregated to larger land divisions. Sample information aggregated by county, for example, yields estimates of black bear habitat and primitive-oriented recreation opportunities (Rudis and Tansey 1995). Although aggregation by county or other administrative division in inventory planning is often straightforward, natural resources and the processes that affect them may not be aligned with those divisions. An intuitively appealing approach is to aggregate information with a uniform-sized, large-area division, or "window," that encompasses several sample plots. Incorporating the context (location, adjacency, and neighborhood) with spatially referenced sample plot locations entails calculating spatially moving averages, i.e., moving the window across the earth surface so that the average at any location always depends on the nearest plot values. "Neighborhoods" are broad regions with similar attributes or values.

Of particular interest are forest resources adjacent to nonforest uses or in nonforest neighborhoods named by their predominant land use. Forest land in urban and built-up land neighborhoods or adjacent to roads may yield lower forest land estimates than estimates that ignore these contexts (Befort *et al.* 1988). Forest land near urban areas has reduced timber harvests (Barlow *et al.* 1998) and primitive-oriented recreation opportunities (Rudis 1987). In regions of high human population

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density, forest plots are associated with smaller forest fragments-which suggests lower logging profitability, fewer forest-interior wildlife species, and diminished primitive forest recreation opportunities (Rudis 1998). Forest land in agriculture-dominated regions may represent a temporarily fallow field or shade for livestock as much as it represents a potential supply of timber products.

In this paper, I focused on questions such as "Where do beverage containers, garbage dumping and livestock grazing occur in forests?' "Why are they located there?' "Where are the most and least fragmented forests?' "Is the concentration of forest plantations in the South widespread, composed only of loblolly pine forests, and exclusively concentrated in forest-industry-held areas of the region?" Answers provided geographic descriptions and fueled generation of hypotheses about regions with affected timber supplies, resource problem areas, and novel multiple-resource production opportunities.

METHODS

Data came from U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis (FIA) surveys conducted between 1988 and 1995 for Alabama, Arkansas, Louisiana, Mississippi, east Oklahoma, Tennessee, and east Texas. FIA sampled land use systematically and estimated approximate latitude and longitude for 32,000 0.4-ha sample plots spaced at 4.8-km intervals. They obtained more detailed attribute information on about 17,000 plots classed as forest land.

Kriging, variography, conditional analysis, and associated geostatistics make up a suite of analytical methods for estimating the spatial dependence of sample plots, spatially averaging plot attributes across different directions of a land surface, selecting weights for distant samples, and assessing the likelihood of patterns obtained (Deutsch and Joumel 1998, Isaaks and Srivastava 1989). Hershey (1996) noted that kriging is "not extremely time-consuming nor difficult to process." However, such approaches are computationally intensive for large data sets and require considerable online memory capacity. Converting sample plot values to cover probabilities and averaging these values uniformly along a land surface is a coarse, but readily straightforward, geostatistical approach for exploratory analysis. This spatially moving average approach is particularly appealing with restricted memory capacity and limited geostatistical software. Attributes are spatially autocorrelated (associated with other samples in close proximity) when predicted from their context. Examination and hypothesis formation follow in three steps: (1) map the data in a land coordinate system, (2) choose the appropriate grain size, and (3) illustrate the mean probability for the attributes of interest and suggest potential causes for patterns obtained. Further assessments would then estimate resource statistics, such as area and volume, by regions having similar attribute probabilities.

For this initial exploratory effort, I first converted FIA sample plot locations to grid cells, calculated spatially moving averages, and then examined patterns. FIA used the intersection of 4.8-km lines aligned on county maps in cardinal directions to establish plots. FIA based plot locations on these lines, in latitude and longitude, yielding accuracy better than ±0.8 km (Dennis Jacobs, personal communication). I transferred sample attribute information to 2.4-km grid cells oriented in cardinal directions to limit computations. At the 2.4-km grid-cell size, the dimension was "small enough to define the most detailed geographic feature" (ESRI 1996b), yet large enough to minimize computer memory storage space and software calculations. The transfer to 2.4-km grid cells nominally assigned one grid cell per south central United States FIA sample plot, even at county borders. The grid-cell dimension-about half the size of the approximate space between sample plots-permitted a conservative interpolation from adjacent grid cells with sample plot attribute information.

Spatially moving averages used here were estimates within a circle of a given radius. The spatially moving averages for land use estimated the probability of forest and nonforest cover for each grid cell with sample plot attribute information. The grain size was the radius of the circle used to calculate spatially moving averages. A grain size of 4.8-km radius (approximately 7,240 ha) encompassed about 13 grid cells--up to 5 of which were FIA sample plots. This yielded an occurrence probability of 0, 1, 2, 3, 4, or 5, out of 5 samples. Only grid cells associated with sample plots contributed to averages.

Because single resource surveys commonly note attributes only on land areas of interest, the likelihood of sampling the attributes varies with land use. Table 1 lists expected values at selected grain sizes for south central FIA data. For small grain sizes, estimates are most reliable in uniform land-use regions. In many cases, a tine grain size limits interpretability, because sample size is low and random patterns obscure broader patterns. A grain size with a 24-km radius represents about 18 1,000 ha, 49 FIA land-use samples, or 25 forest attribute samples (if 50 percent forested). This grain size may be most appropriate for county and regional assessments, but contains fewer of the details needed for township and city planning.

I used location information from sampled plots to model occurrence probability by interpolation. Indicator maps suggested locations with high or low probability of categorical attributes. Interval maps suggested locations with high or low values of a continuous attribute, e.g.,

Table 1.-*Radius, area, and expected number of samples to calculate spatially moving average values, Forest Inventory and Analysis surveys of the south central United States*

Radius (English units)	Land area (English units) represented by the mean	Nominal number of land-use plots	Nominal number of forested plots (if 50 percent forested)
2.4 km (1.5 mi)	1,810 ha (4,470 ac)	0.5	0.3
4.8 km (3.0 mi)	7,240 ha (17,900 ac)	5	3
9.6 km (6.0 mi)	28,900 ha (71,500 ac)	13	7
24.0 km (15.0 mi)	181,000 ha (447,000 ac)	49	25
48.0 km (30.0 mi)	723,000 ha (1,790,000 ac)	109	55

forest fragment size. Interpolation of the means was straightforward, i.e., the technique assumed that the attribute probability (or attribute value) varied continuously and uniformly across the sampled region.

I employed the circular neighborhood mean statistics function within ArcView 3.0a geographic information software with the Spatial Analyst extension (ESRI, Inc. 1996b). Calculation of means provided averages beyond the range of the sampled region-a scenario in classic statistics comparable to drawing a regression line beyond the range of the data. To mask these areas, I created a data layer of grid cells with 20 percent or less forest land probability, based on a 4.8-km radius grain size and averaged from land-use sample plots. For south central FIA surveys of forest attributes, the mask included grid cells with no forests (extensive areas of nonforest land in the Mississippi Alluvial Plain) and extensive areas with no FIA plot samples (nonsurveyed locations and largely nonforested counties in western Oklahoma, western Texas, and extreme south Louisiana).

Estimation occurred in three stages, following a specific protocol: (1) define, record, and import into the software the attributes tied to objectives of interest; (2) generate land-use probability maps; (3) generate forest attribute maps. Due to space limitations, I have illustrated only a few of the attributes in this report. Rudis *(in press)* illustrated others that were likely spatially autocorrelated, such as hunting, restrictive signs (hunting restricted, no trespass, or keep out), timber management (harvest, site preparation, plantation establishment), tree and forest composition, site productivity, damage agents, and nonforest land-use proximity.

Samples were of 0.4-ha earth cover at the intersection of 4.8-km lines in cardinal directions established county by county in the south central states. FIA collected detailed information on forest land—0.4 ha and larger, ≥37 m in width, and not developed for nonforest uses. I selected a few of the many FIA attributes listed in the field manual (FIA Staff 1994) as examples to illustrate spatial relationships. These were: (1) Human-associated litter—presence or absence of beverage containers, or apparent garbage dumps within a 0.4-ha sample area. The purpose was to note prior use and accessible areas for urban recreation opportunities (e.g., picnicking), and degraded recreational values for primitive recreation opportunities (e.g., hunting, wilderness hiking). In forests, if the majority of beverage containers formerly contained alcoholic beverages-as was true along roadsides (Dennis Brezina, Aluminum Anonymous, Chesapeake City, MD, personal communication, 1998)—then they also suggested locations with potential safety hazards. (2) Livestock grazing-presence of cattle, dung, trails, or livestock tracks on the 0.4-ha plot, which suggested recent livestock grazing. The purpose was to note areas without exclusive timber production, With potentially degraded forest resources, or with agroforest (silvopastoral) management. (3) Forest fragment size classæcontiguous forest area class associated with a 0.4-ha sample plot. "Contiguous" forest meant unbroken by water or nonforest cover ≥37 m wide and determined from 158,000 scale high-altitude color aerial photographs. Classes were 0.4 to 4.0 ha (midpoint 2 km), 5 to 20 (12), 21 to 40 (30), 41 to 202 (121), 203 to 1,012 (607), 1,013 to 2,023 (1,518), and >2,023 (set at 3,323 ha). Although one fragment could be large enough to be associated with more than one sample plot, every plot was assumed to be a different fragment. The purpose was to estimate forest land with economic harvest potential, primitive recreation opportunities, and habitats for wildlife in need of seclusion (black bear) or large expanses of forest land (Cerulean warbler). (4) Selected timber management activities: forest plantations, forest industry ownership, and forest type of the 0.4-ha plot, as described in field manuals (FIA Staff 1994).

To generate land-use and forest attribute maps from ground information, I opted to convert FIA plot latitude and longitude estimates (accuracy better than 0.8 km) to Albers equal-area projection. I used ArcView 3.0a with the Spatial Analyst extension (ESRI, Inc. 1996b) on a personal computer with a Microsoft Windows 95 operating system, a 100MHz Pentium I processor, and 144 MB of Random Access Memory (RAM). The added RAM was to help speed the processing of input and output of the large seven-state FIA data set (32,000 records). If using GIS software other than ArcView 3.0a and Spatial Analyst 1.1, note that the order of steps below may vary. If using another data set, adapt the procedures noted in parentheses that are specific to south central U.S. FIA data.

Land-Use Maps

1. Obtain location of plot sample land-use estimates (0.4-ha plots sampled at 4.8-km intervals). 2. Convert plot sample locations to an ArcView grid at one-half the spacing (2.4-km cells). 3. Reclassify ArcView grid cells with land-use estimates as binary (0=nonforest, 1=forest), and estimate the mean value probability by averaging across an area with multiple samples. (A radius that encompassed up to five south central FIA samples used a 4.8-km radius, yielding probabilities of 0, 20, 40, 60, 80, or 100 percent.)

Forest Attributes

1. Obtain location of plot sample attribute estimates within the land use of interest. 2. Convert plot sample locations to an ArcView grid at one-half the spacing (2.4-km cells). 3. Reclassify ArcView grid cells: 3a. If an indicator attribute, reclassify as a binary variable ("0"=forest without attribute, "1"=forest with attribute), and estimate mean probability, in percent. 3b. If an interval attribute (e.g., forest fragment size class), determine whether attribute values are normally distributed, and if so, transform them as needed. (Forest fragment size class is best represented as log[midpoint of forest fragment size class.]) Generally, attribute estimates outside the land use of interest are classed "no data." 4. Estimate the mean (a) percentage or (b) value, by averaging across an area with multiple samples at a grain-cell size appropriate to the objective and sampling density. (For FIA forest attributes, a 9.6-km radius encompassed 7 to 13 samples, and a radius of 24 km encompassed about 25 to 49 samples [see table 1]). 5. Remove or "mask" from the map all land uses not sampled or not of interest. (For forest land attributes, use estimates with an 80 percent probability [from land-use map estimation]that the locations were nonforest).

RESULTS AND DISCUSSION

Illustrated by sample plot location and by forest land probability are forest and nonforest land use (fig. 1). Forest land probability came from forest occurrence averaged over a 7,240-ha area encompassed by a radius of 4.8 km, which incorporated about five land-use plots. The spatially moving average assumed uniform probability of forest land. In the real world, however, forest land is more frequent along the direction of, and close to, water courses, on steep terrain, and associated with particular soils and climate patterns. The simplified ground sample-based averaging procedures used in this report ignored them. More detailed geostatistical analyses by ecoregion or physiography, testing of hypotheses, and relaxation of isotropic forest probability assumptions are needed to quantify uncertainty. Because FIA located the sample plots on a regular grid, I made no extensive examination of alternative grain sizes. In this case, and in others with a random array of sample locations, results were likely indicative, but not definitive, because representations of forest area (and forest attribute data described below) at other grain sizes could lead to other conclusions.

At the 9.6-km radius, depicting averages of attributes collected only on forest land held greater uncertainty. This grain size provided estimates of more heuristic value, because averages included very few sample observations. Figure 2 illustrates both the sample value locations and the averages for beverage container occurrence in forests. Among prominent areas of high probability was a broad area along the very few forests of the Mississippi Delta in eastern Arkansas, the White River and Interstate 40 rest stop between Little Rock, AR, and Memphis, TN.

Resulting patterns varied with changes in grain size. I used a 9.6-km radius as a minimum, a 4%km maximum, an intermediate radius of 24 km, and beverage containers in forested areas as an example (fig. 3). In these three depictions, the universal conclusion from FIA data was that the Mississippi Delta in eastern Arkansas had a larger concentration of forests with beverage containers, on average, than other areas. I settled on the 24-km radius for subsequent analyses, because the 24-km radius grain size yielded lower uncertainty (averages based on about 25 forested plots). The 24-km radius grain size also approximated the size of a county planning area, or portion of a large city, which the larger grain size obscured.

Human Impact: Beverage Containers and Garbage Dumping

Beverage containers did not appear to occur at random within forests at a 24-km grain size (fig. 4a). In addition to the litter problem, if most beverage containers were from alcoholic beverages, then there were likely drinking problem areas as well. Forest land proximity to urban and built-up land explained much of the distribution of forests with beverage containers (fig. 4b). In urban land-use neighborhoods, impact varied with the municipality. Municipalities with widely recognized recycling initiatives, such as Chattanooga, TN, were more effective in

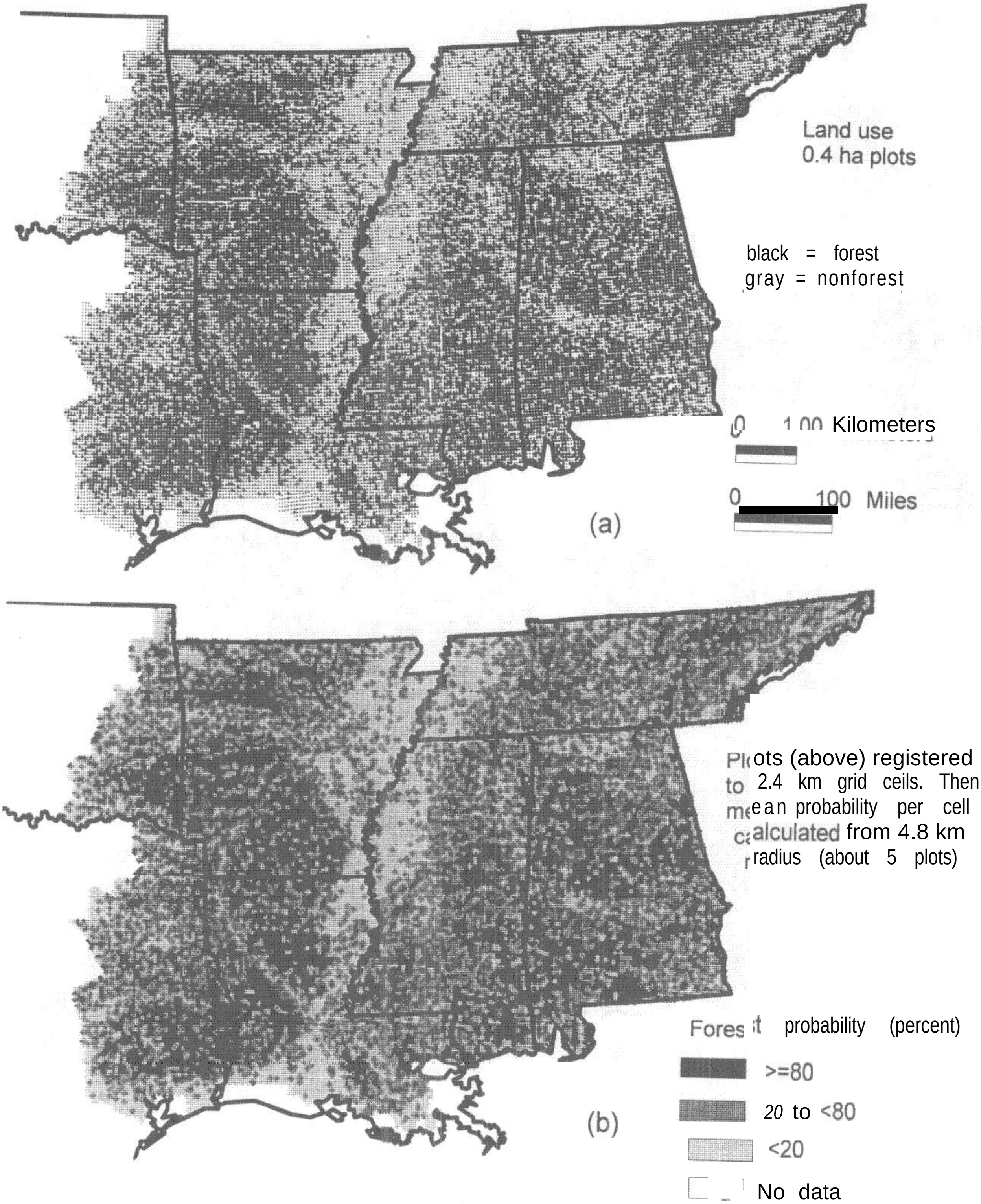

Figure 1.—*USDA Forest Service, Forest Inventory and Analysis (a) sample plots by land use, and (b) forest area probability (4.8-km radius), south central United States, 1988-1995.*

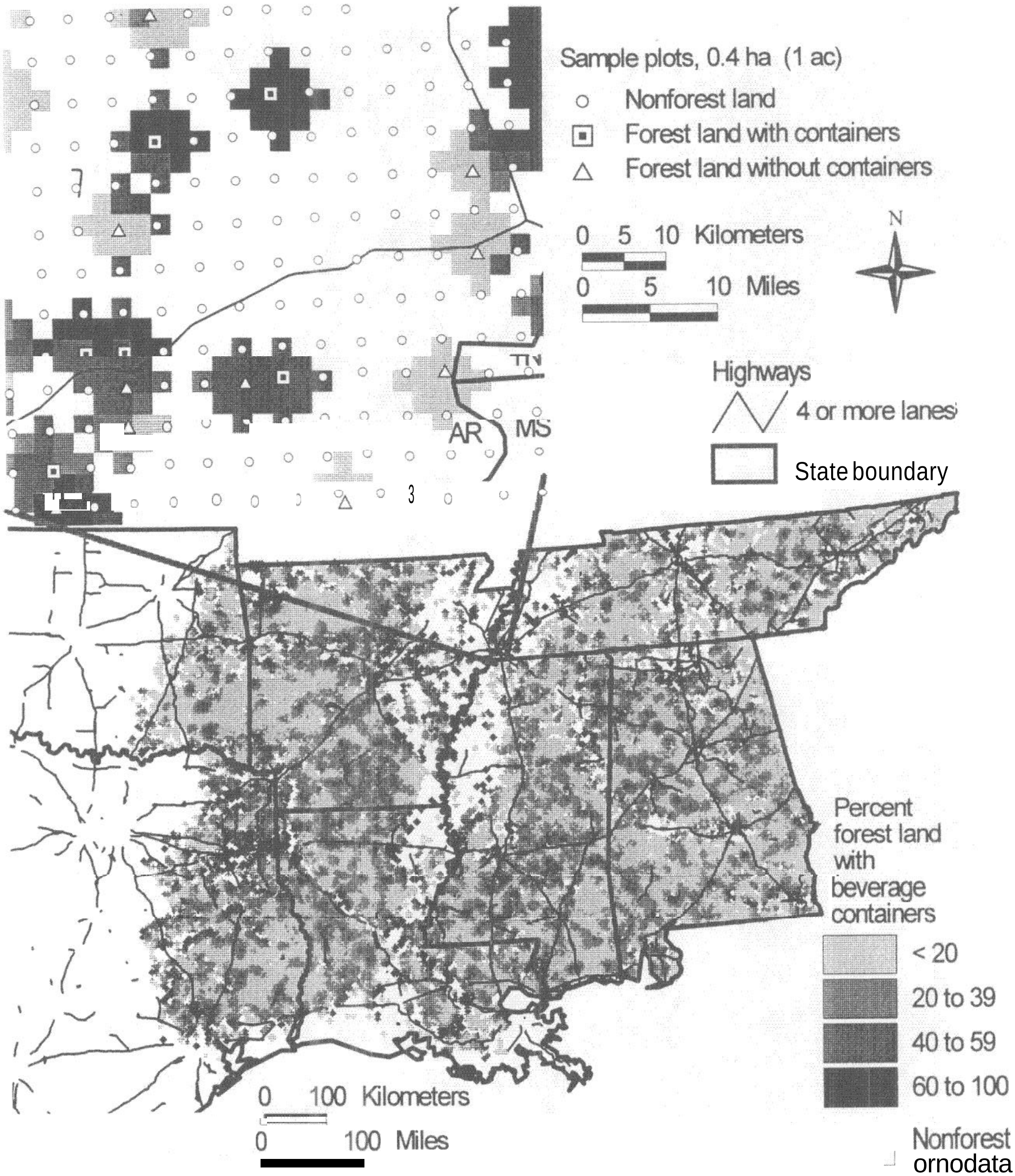

Figure 2.—*Beverage container probability in forests, south central United States, 1988-1995 and highways of four or more lanes (ESRI, Inc. 1996a). Inset: beverage container probability in forests near Memphis, TN. Probability estimates used a 4.8-km radius for forests and a 9.6-km radius for forest attributes. (For these and subsequent figures, nonforest land was defined as ≥80 percent probability of nonforest land use within a 4.8-km radius.)*

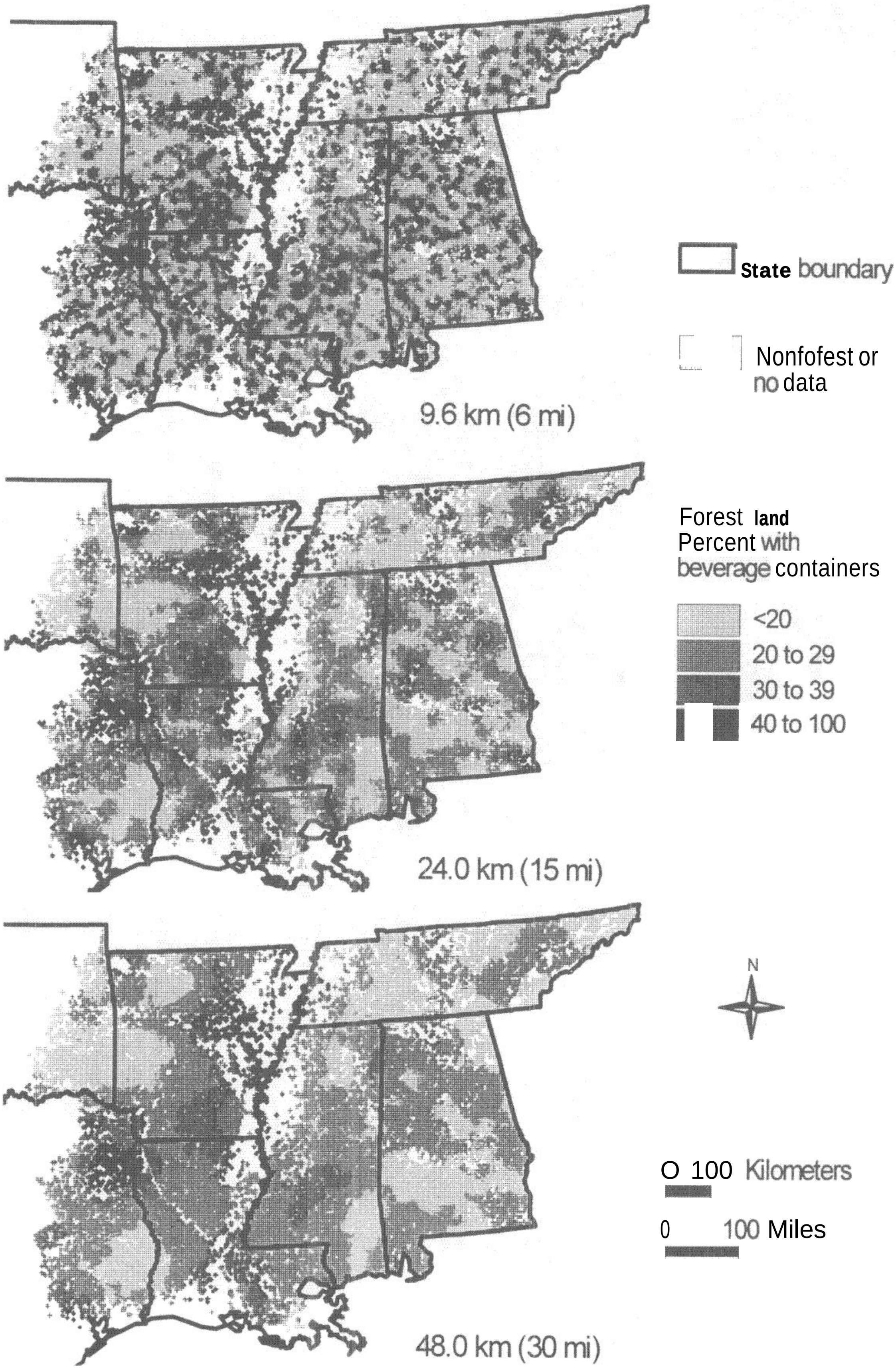

Figure 3.—*Beverage container probability in forests at 9.6-, 24-, and 48-km radius grain sizes, south central United States forests, 1988-1995.*

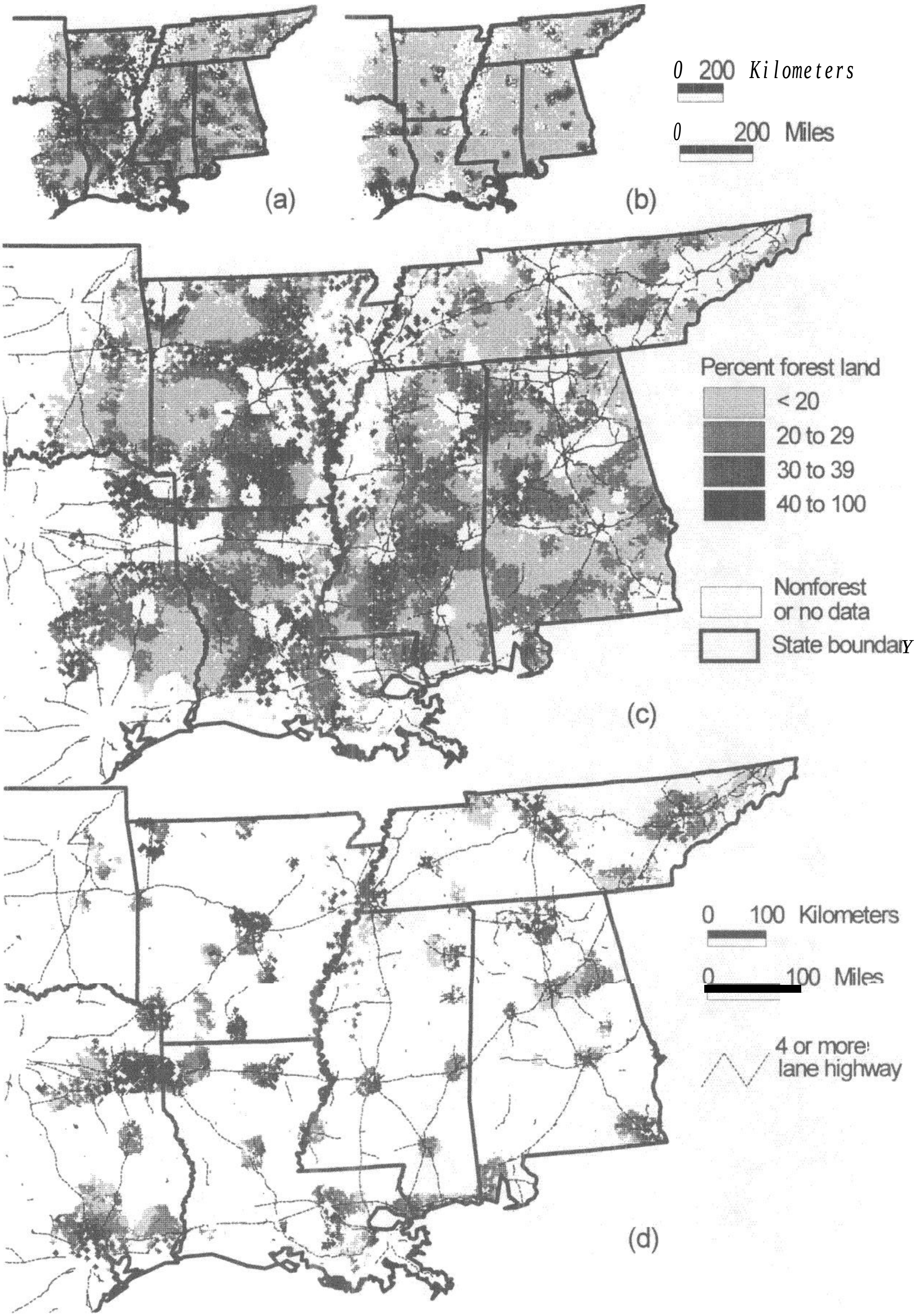

Figure 4.—(a) *Beverage container probability in forests; (b) forest land within 1.6 km of urban and built-up land $\geq$ 4 ha (10 ac); beverage container probability in forests (c) outside and (d) inside 1.6 km of urban and built-up land $\geq$ 4 ha (10 ac), 24-km radius grain size, south central United States, 1988-1995. Figures (c) and (d) include highways of four or more lanes.*

minimizing beverage containers than cities to the west (fig. 4c). In rural landscapes, forests with beverage containers were more commonly downstream of major water bodies, close to urban areas, and sparsely forested landscapes "ear areas of dense population. Potential problem locations in rural areas were "ear Hazen, AR; major roadways south of Jackson, MS: and Mt. Pleasant. TX (fig. 4d).

Garbage dumping in forested areas occurred more frequently near selected urban areas and major highways (fig. 5). Forests with garbage dumping were more prevalent downriver, downwind, and at lower topographic positions than those upriver, upwind, and at higher elevations. Most garbage dumping occurred "ear cities or along specific stretches of highways near populated areas. Other studies (Rudis 1995a, 1995b) found that older forest stands, smaller forest fragments, and those closest to roads were more likely to accumulate beverage containers and other litter.

Neighborhoods: Livestock Grazing in Forests

Livestock grazing in forests was not a random phenomenon. It occurred in selected areas more often than others (fig. 6a). Much was explained by the neighborhood, because most grazing in forests occurred in pasture-dominated landscapes (figs. 6b, 6c). Forests in these areas were vulnerable to periodic grazing, due to the proximity of the forests to livestock. Forests in nonpasture landscapcs were less likely to be vulnerable. Some livestock grazing in forests occurred outside pasture-dominated landscapes (fig. 6d). Several of these locations may represent neighborhoods with active agroforestry operations, because they contained substantial forest industry land holdings or were pine plantations (and the western forest fringe of east Oklahoma and east Texas forest land). Further examination with more precise spatial estimates and correlates of browse potential, e.g., stand age and tree density class, may provide a more complete understanding of spatial relationships.

Interval Attribute: Fragmented Forests

I used forest fragment size class to illustrate one example of an interval attribute. Illustrated are mea" fragment size using untransformed (fig. 7a) and logarithm transformed (fig. 7b) midpoint values. I" this case, nonforest points did not contribute to the estimates. Comparisons with state maps showed that most of the large fragments were either in mountainous areas, such as the Boston Mountains of the Ozark National Forest, or in low-lying areas, such as the Atchafalaya Basin of Louisiana. The most fragmented forests were near major urban areas, the Mississippi Delta, and other cropland- or pasture-dominated land-use areas.

Co-occurring Distribution Patterns: Plantation, Industry, and Type

Perception of widespread occurrence of pine plantations periodically surfaces among those concerned with

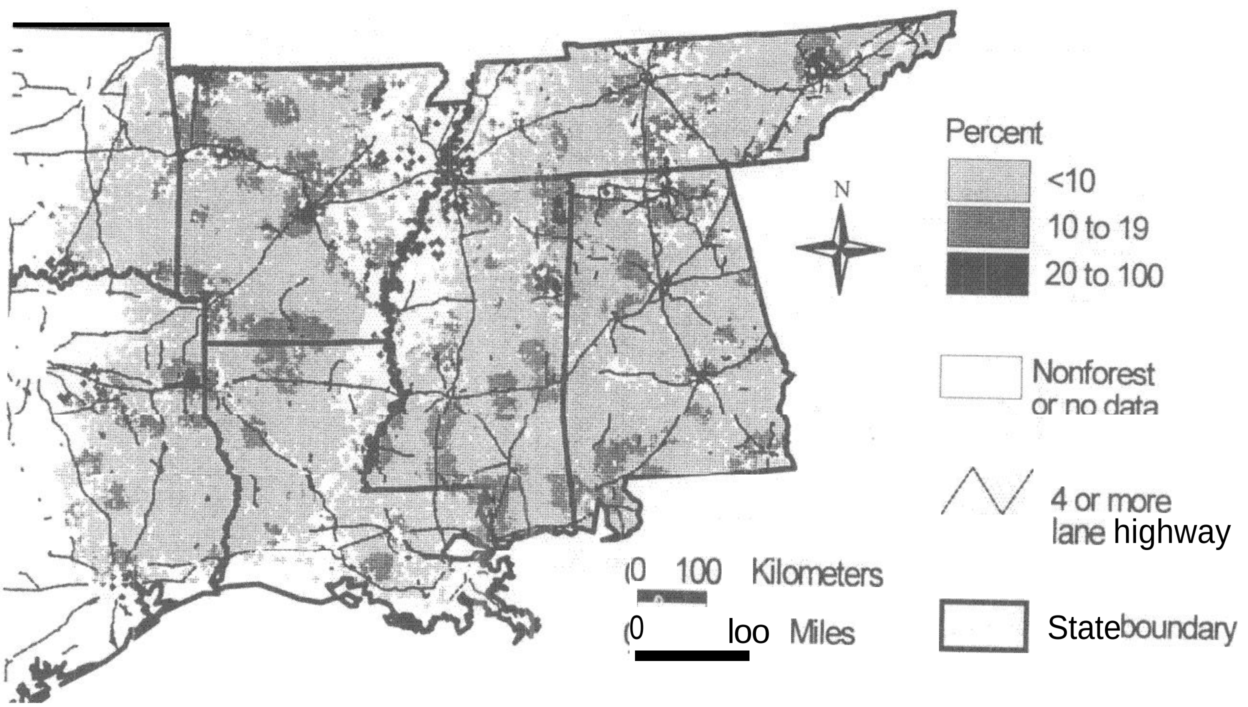

Figure 5.—*Garbage probability in forests, south central United States forests, 1988-1995, and highways of four or more lanes.*

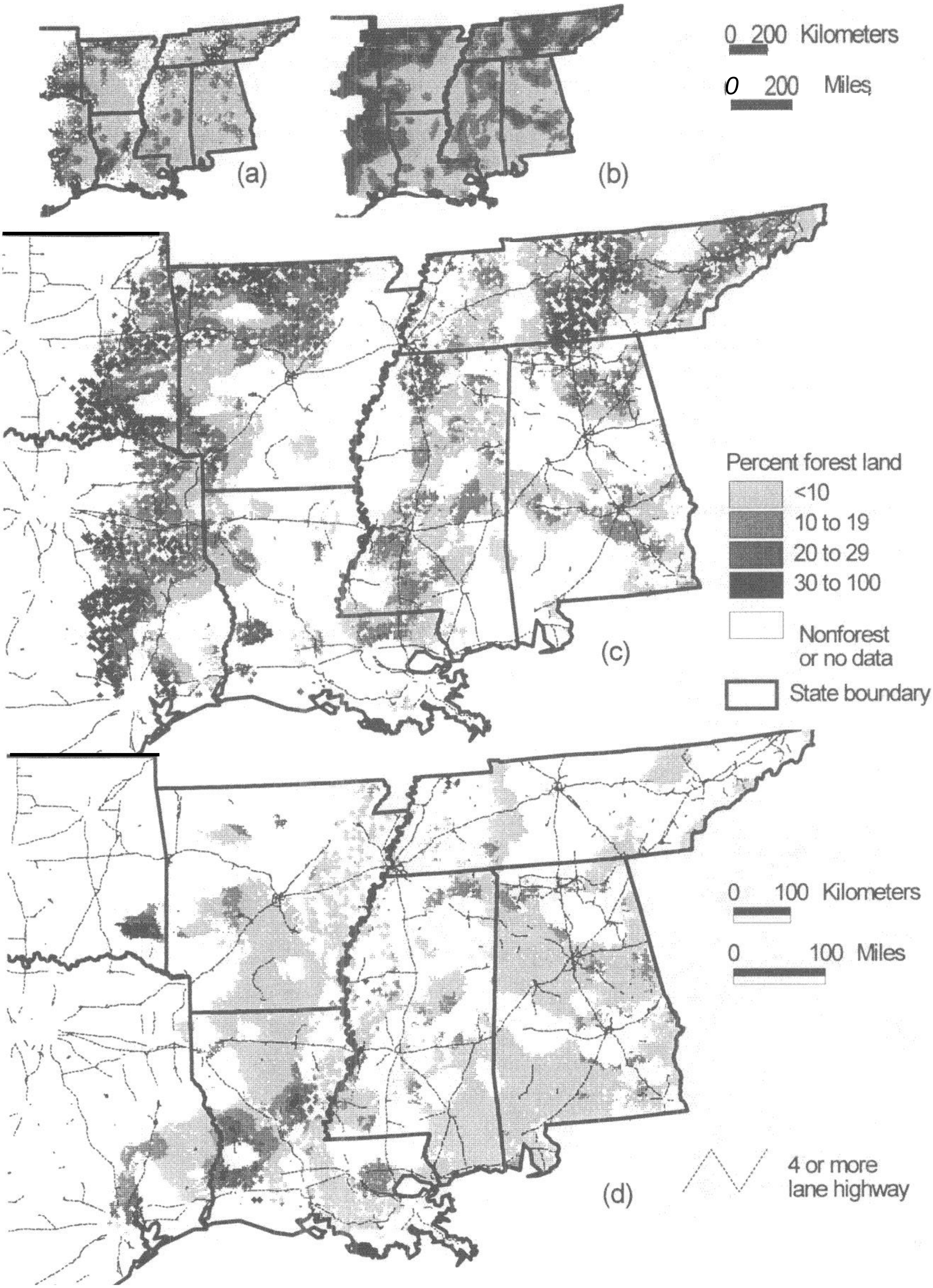

Figure 6.—*Probability of (a) livestock grazing in forests (c) within and (d) outside pasture neighborhoods, and (b) pasture land probability, south central United States forests, 1988-1995. Figures (c) and (d) include highways of four or more lanes.*

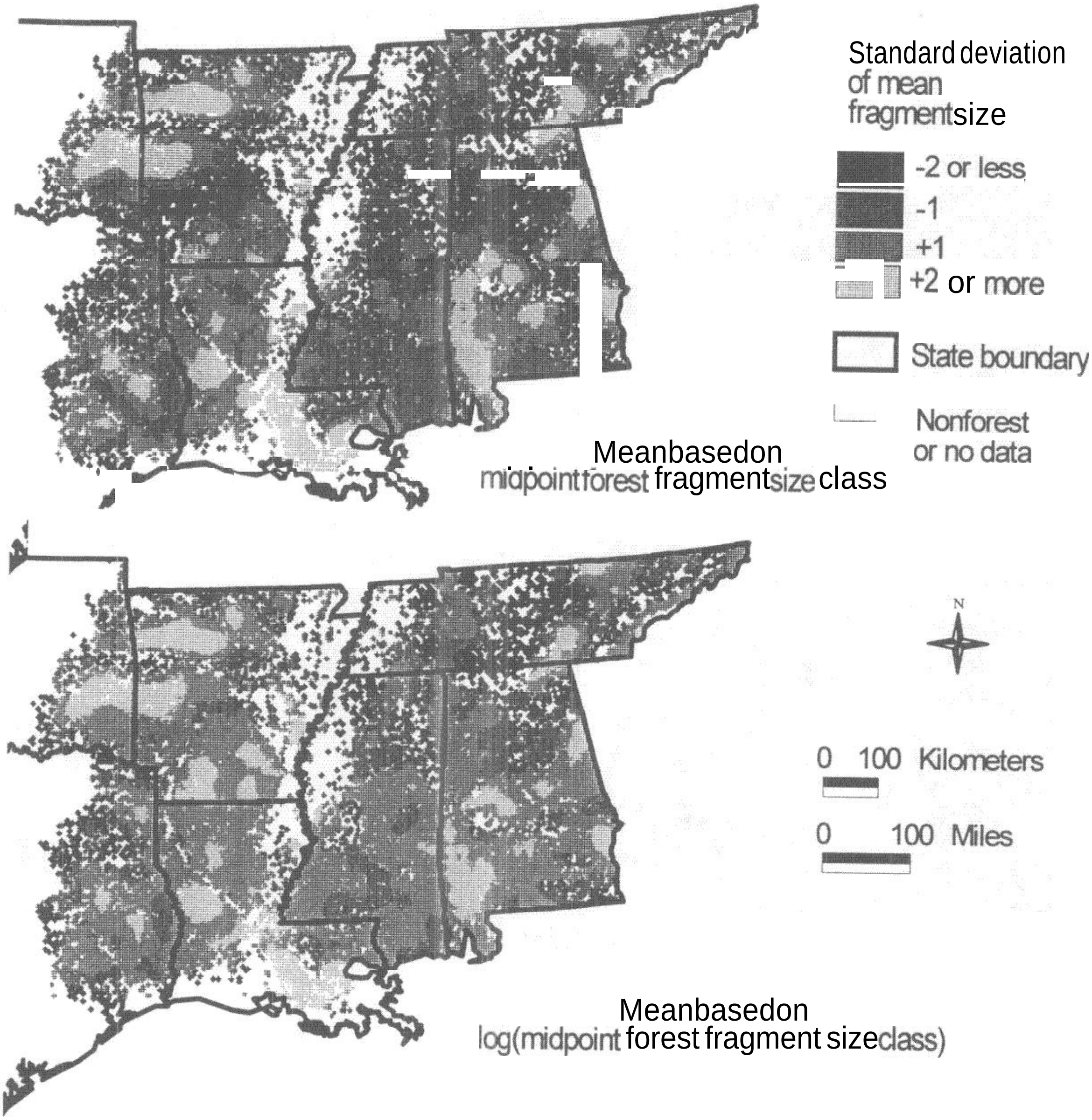

Figure 7.—*Fragmented forest land probability, using (a) untransformed midpoint values (b) logarithm transformed midpoint values, south central United States forests, 1988-1995.*

biological diversity. Other tabular or county-scale information noted that they were widespread, concentrated in selected regions (Boyce and Martin 1993. Rudis 1998). and on the increase (Birdsey and McWilliams 1986, Rudis 1991). At a grain size of 24-km radius, forest plantation distributions were widespread, with very few areas containing plantation probability greater than 40 percent (fig. 8a). While most plantations were of loblolly pine. and many plantations were owned by forest industry, there was not a one-to-one correspondence with forest plantations and forest industry land (tig. 8b), or with the distribution of loblolly pine forest type (fig. Xc). Although not examined here, plantation distribution patterns may be more closely correlated with pulp mill proximity or regionally successful forestry incentive programs.

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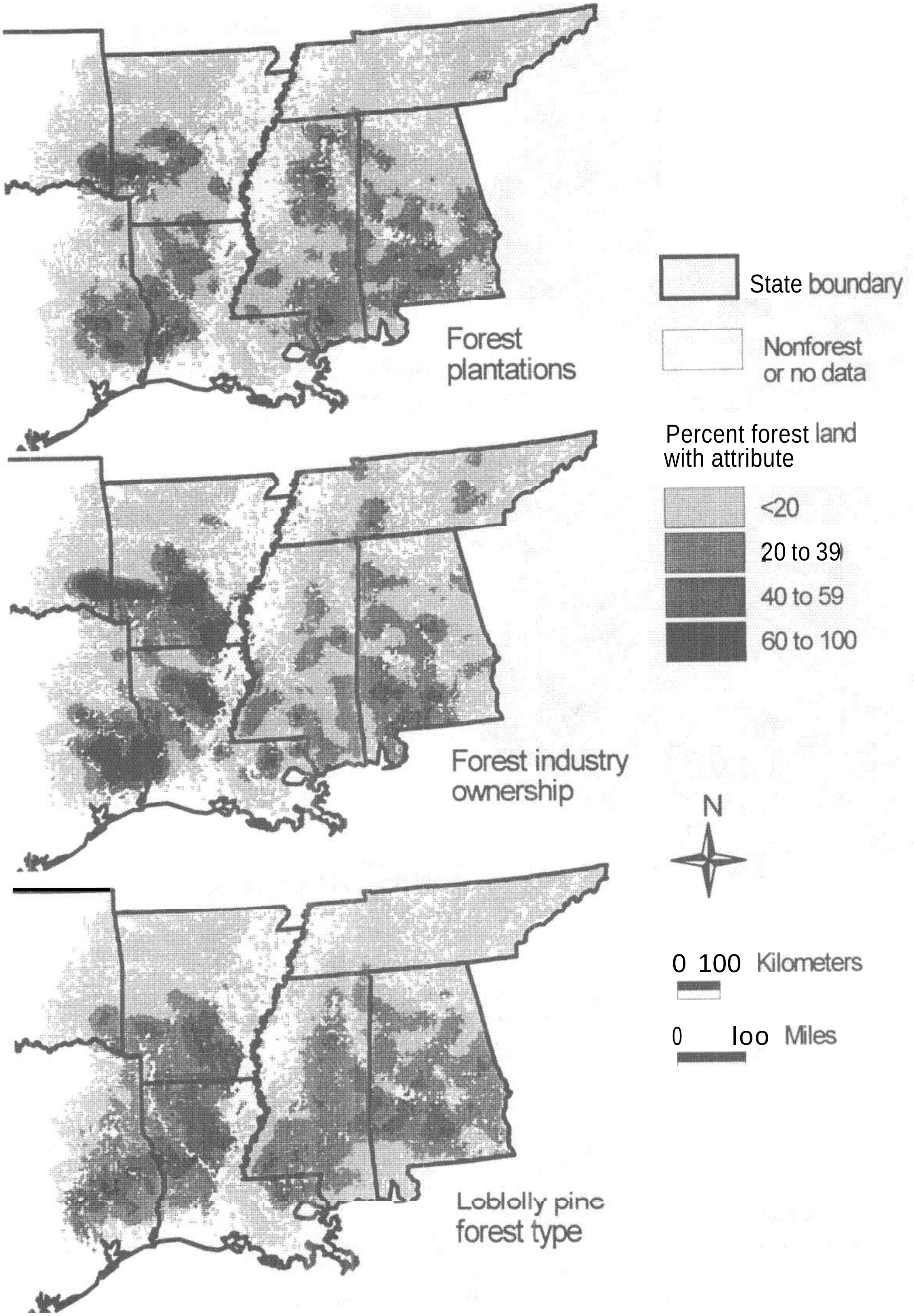

Figure 8.—*Probability of (a) forest plantations, (b) forest industry ownership, and (c) loblolly pine forest type, in south central United States forests, 1988-1995.*

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