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economics

Sawmill Industry in Tennessee: Assessing Location Pattern Changes and Their Effects on Sawlog Procurement Distribution

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Within the southern US forest products industry, the sawmill sector has experience a high rate of mill exits. Between 1999 and 2011, the number of operating sawmills dropped by 77%. However, average mill sawlog consumption increased during the same period. Changes in the number and consumption capacity of sawmills pose questions related to resulting shifts in the spatial distribution of active sawmills in Tennessee for 1999 and 2011. We also investigated the effect of new location patterns on roundwood production across the state. Mill information was obtained from the US Department of Agriculture Forest Service Forest Inventory and Analysis Timber Products Output program survey of primary wood-using mills. The analysis revealed significant changes in the location of active mills and the areas supplying them. Tennessee's sawmill industry shifted from a random distribution of wood demand originating from mills scattered across the state to clear localization patterns.

Keywords: cluster analysis, hardwood sawmills, spatial distribution

The sawmill industry has experienced a steady decline in the number of mills operating across the southern United States (Alabama, Arkansas, Georgia, Florida, Kentucky, Louisiana, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, and Virginia). Net change in active mills varies by state, with decreases in 2011 ranging from close to 30% to more than 70% of a state's 1999 sawmill base (Figure 1). However, new and remaining sawmills are procuring increasing volumes of roundwood, on average, across the region. Average mill receipts increased by more than 15% during this period, from approximately 1,755 thousand cubic feet (mcf; 49,646 m^3) per mill in 1999 to 2,026 mcf (57,370 m^3) per mill in 2011. The sizable change in mill numbers has likely altered the geographical distribution of mills, possibly changing patterns of roundwood demand and procurement. These new location patterns could affect forest management intensity and local economies.

Tennessee has long been characterized as a hardwood lumber state, historically second only to Pennsylvania in total production. Although production has declined since the Great Recession, the state still is among the top five producers of hardwood lumber. As previous research has documented, production has been concentrated historically in central Tennessee. Luppold and Bumgardner (2009) note that this region accounted for 52–63% of the state's annual lumber production between 1979 and 2005. They also determined that most of the production increase in central and western Tennessee between 1979 and 2005 resulted from existing mills expanding capacity, whereas the bulk of increase in East Tennessee during the same period was due to the construction of new, large-capacity mills. However, given the economic downturn in 2008–9, these patterns may have been substantially altered. For example, in an assessment of Appalachian hardwood sawmills between 2008 and 2010, Lin et al. (2011) reported that although the vast majority of mills reported reduced production levels, the declines were larger for newer and smaller mills.

In addition to changes in production levels, Tennessee experienced substantial shifts in the number of mills in all size classes during the past decade. To our knowledge, the spatial distribution of these changes across the state has not been analyzed. The following study addresses this gap by investigating the changes in the spatial distribution of sawmills and observed patterns of wood procurement for Tennessee. However, assessing the factors that likely influenced these changes is beyond the scope of this article. We evaluated location patterns of sawmills in 1999 and 2011, the earliest and latest data years available at the time of this study, to determine if significant differences in spatial location existed. We also explored the change in sawlog procurement across the state and how the two periods differed in terms of procurement distribution.

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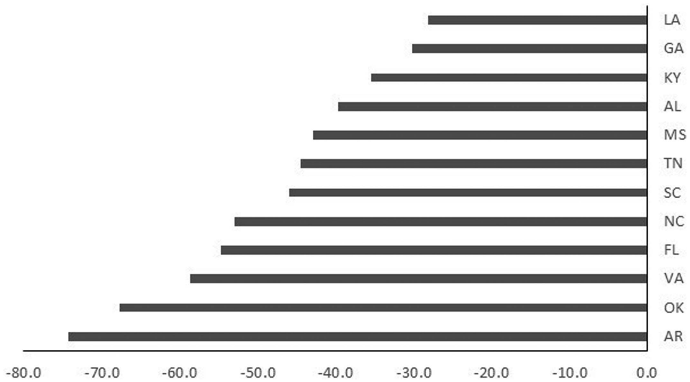

Figure 1. Percentage change in sawmill numbers by state, 1999 to 2011.

Literature Review

The distribution/concentration of industries has long been a popular topic of economic research, but it gained additional interest in the past 20 years. Ellison and Glaeser (1997) developed an initial index (EG index) to test for firm localization that considers industrial concentration and manufacturing agglomeration, variations of which have been extensively used (e.g., Ellison et al. 2010, Wang et al. 2014, Delgado et al. 2016). Duranton and Overman (2005) developed an index that addresses a shortcoming they noted in the Ellison and Glaeser approach. Specifically, they contend that previous attempts simplify computations, but they result in several problems, including restricting the analysis to one spatial scale, spurious correlations, and treating spatial units symmetrically regardless of differences in location (Duranton and Overman 2005, p. 1078–79). As a means of avoiding these problems, they use a point pattern methodology in which the patterns of locations of each facility are compared to that of conditional measure of a randomly distributed pattern. The conditional random pattern considers the natural nonrandom site locations available to industry. Duranton and Overman (2005) contend that this approach is comparable across industries, controls for overall conglomeration and industry concentration, is unbiased with respect to scale and aggregation, and provides a measure of the results' significance. They demonstrate the methodology using a data set for UK manufacturing. Among the results, they note that localization is driven by larger firms for some industries whereas smaller firms are the drivers for others. Sawmilling and planning of wood were identified as being one of the most dispersed industries, with no localization among the six industries in the study.

The point pattern methodology has been used in several studies since the original work by location (Duranton and Overman 2005). For example, Falck et al. (2014) used the methodology to evaluate the influence of incumbent firms on new firm location decisions in Germany. The results reveal that 40% of new firms "coagglomerate" with incumbent firms in West Germany; only 5% do so in East Germany. They note that location decisions are "highly context-specific. . ., significantly shaped by the respective economic and institutional conditions," (Falck et al. 2014, p. 16). Koh and Riedel (2014) evaluated the localization patterns of manufacturing and service industries in Germany and reported that 78% of the firms exhibited some level of localization at the 5% significance level, with the service industry being much more localized. The authors also support some of the arguments that Duranton and Overman (2005) make for their approach. Specifically, Koh and Riedel (2014) note that the EG index is sensitive to aggregation levels, making it difficult to interpret and unsuitable for cross-country comparisons.

Previous works analyzing forest products industry location have measured location using complete spatial randomness as a baseline rather than evaluating location against a relative random pattern. Complete spatial randomness assumes that a mill could locate anywhere within the study area whereas a relative random pattern restricts random location to a set of sites where a mill could possibly locate, therefore excluding sites where zoning restrictions or terrain conditions could prevent location (Duranton and Overman 2005). Under the complete randomness scenario, Aguilar and Vlosky (2006) found primary forest products industries in Louisiana clustering around areas close to the forest resource. From the profit maximizing rationale, a primary wood processing mill will locate closer to the forest resource to reduce the costs of transportation of raw material from forest to mill. The location constraint imposed by transportation leads to mill agglomeration around areas close to the resource (Aguilar 2009). Hagadone and Grala (2012) identified clustering of the Mississippi forest products industry, with higher aggregation observed on the secondary industry compared with the primary industry. Kies et al.'s (2009) clustering study of German forest industries reports sawmill location patterns of smaller sawmills displaying weaker concentration tendencies with disperse clustering. However, their study was based on geographical aggregated units rather than point analysis.

Methods

We investigated two questions based on data observed during 1999 and 2011: Did sawmills in 2011 exhibit a significantly different distribution pattern compared to 1999 locations? Did sawlog consumption patterns change significantly between these two periods? We addressed each item using a different approach. We used a point pattern analysis and matched-pair tests to answer the first question and used matched-pair tests and a hot spot analysis to address the second question.

Mill Distribution Patterns

We investigated the spatial pattern of mill locations using the point pattern methodology developed in Duranton and Overman (2005). In general terms, the method involves estimating the distribution of bilateral distances of observed industry locations and establishing confidence intervals for this distribution based on bilateral distances from simulated sets of random locations (referred to as counterfactuals).

We applied the point pattern analysis to Tennessee's sawmill locations to identify spatial patterns and to determine if changes in distribution had occurred. For each data year, t, we calculated the Euclidian distance between each pair of sawmill locations, resulting in $n_t(n_t - 1)$ distances, used to estimate the kernel smoothed density, or K-density, at a distance d as

$$K_t(d) = \frac{2}{n_t(n_t - 1)/h_t} \sum_{i=1}^{n_{t-1}} \sum_{j=i+1}^{n_t} f\left(\frac{d - d_{ij}}{h_t}\right)$$

where n_t is the number of mills at time t, d_{ij} is the distance between mills i and j, h_t is the bandwidth for time t, and f represents the Epanechnikov kernel function. The Epanechnikov kernel function minimizes the mean integrated squared error, resulting in optimal efficiency. However, research has found that choice of kernel is not as significant as the choice of bandwidth (Silverman 1986). We

Table 1. Mean and median bilateral distances, mill movement, and hardwood consumption as percentage of total volume by mill size category, 1999 and 2011.

Year	Size category	n_t	Bilateral distances Mean (mi)	Bilateral distances Median (mi)	Mill movement Exit (n)	Mill movement Entry (n)	Hardwood consumed (%)
1999	Small	308	140	124			84
	Large	132	135	118			92
	All	440	142	125			90
2011	Small	158	128	104	241	91	97
	Large	86	131	115	70	24	99
	All	244	130	110	311	115	98

Note: n_t represents the number of mills for respective year and size category (small if <10 employees, large if ≥10 employees).

calculated the optimal bandwidth as $h_t = 0.79(IQR)n_t^{-1/5}$, as recommended for skewed and long tailed distributions (Salgado-Ugarte et al. 1995), where IQR is the interquartile range. We estimated the K-density for values of d from 0 to each year's median distance (Table 1 shows median distances used). Given the bounded nature of the data (all positive values), we applied the reflection correction method described in Silverman (1986).

We built the counterfactuals by drawing random samples of n_t points from a pool of conditional locations. Selecting point locations completely at random could result in sites with characteristics that prevent actual mill location, such as areas under zoning restrictions or with natural barriers (Duranton and Overman 2005). Furthermore, we expect some level of deviation from pure random pattern distribution because primary mills would tend to locate close to the forest resource to minimize transportation costs. Therefore, we based our simulations on random points drawn from a set of forest products industry locations (primary and secondary mills), which should more closely approximate potential sawmill locations. We repeated the simulation 1,000 times, calculating the K-density for each simulated set. The density values from the simulated samples were used to estimate global confidence bands (at 95% confidence) as described in Duranton and Overman (2005). Graphical representation of the K-density distribution and confidence bands allows for easy detection of the spatial patterns present. Evidence of dispersion is found when the K-density lies below the low confidence band and never above the upper band. Aggregation is detected when the K-density lies above the upper confidence band. To further understand sawmill location patterns, we examined mill size and conducted the point pattern analysis on a subset of small-size mills (those with <10 employees) and a subset of large mills (mills with 10 or more employees).

We complemented the point distribution analysis with a geographical examination of changes in mill concentration in the 2 years studied. A raster coverage of the state was created, using ArcMap 10.3, dividing the state into a grid of 1-mi^2 cells (2.59 km^2) resulting in 42,149 raster cells. Each raster cell (represented by its center point p) was assigned a value based on the density of mills around it, which was estimated as

$$D_{pt} = \frac{1}{n_t}\sum_{i=1}^{n_t}\left(\frac{1}{d_{pi}}\right)$$

where D_{pt} is the measure of mill concentration around point p at time t and d_{pi} is the Euclidian distance from raster point p to mill i.

Table 2. Summary statistics for matched-pair differences.

Variable	N	Median	Mean	SD	Skewness	Kurtosis
ΔD*	4,215	0.0007	0.0004	0.0029	1.2119	18.8352
ΔP	95	0.0010	0.0014	0.0025	−0.6226	5.3159
ΔV	95	0.0585	0.6031	4.7606	3.1096	18.2995
$\Delta V_{softwood}$	95	0.0165	0.1955	0.2541	−2.0362	8.9549
$\Delta V_{hardwood}$	95	0.0818	0.7986	4.6671	3.2520	19.2225

Note: *Corresponds to 10% of raster points, drawn at random.

Preliminary analysis of the matched-pair differences revealed deviation from normality (Table 2). Therefore, we evaluated the matched pairs using the nonparametric Wilcoxon signed-rank and the sign tests. Under the null hypothesis of a distribution with mean zero, the tests assess equality of matched pairs. Although the Wilcoxon test assumes equal distribution of the paired observations, the sign test makes no assumption on the distributions.

Mill Consumption Patterns

Changes in sawlog consumption patterns were assessed using county production and mill location information to assign a mill influence value to each county. Mill influence was represented in two ways—procurement distance and procured sawlog volume weighted by distance to source.

We estimated county procurement distance, $P_{k,t}$, as

$$P_{k,t} = \frac{1}{n_t}\sum_{i=1}^{n_t}\left(\frac{1}{d_{ik}} \times I_{ik,t}\right)$$

where k represents county ($k = 1$ to 95), d_{ik} is the Euclidean distance between the centroid of county k and mill i, and $I_{ik,t}$ is an indicator variable with a value of 1 if mill i draws timber from county k at time t and 0 otherwise. In a similar manner, county procurement volume ($V_{k,t}$) was estimated as

$$V_{k,t} = \frac{1}{n_t} \times \frac{1}{v_t}\sum_{i=1}^{n_t}\left(\frac{1}{d_{ik}} \times v_{ik,t}\right)$$

where v_t is the volume of sawlogs produced by the state to supply state mills and $v_{ik,t}$ represents the volume of sawlogs procured to mill i by county k at time t. To facilitate estimation, only volumes consumed by local mills and harvested within the state were considered. The volume of sawlogs from other states accounts for less than 2% of the total sawlog volume consumed; therefore, its exclusion should not significantly affect the results. Differences in procurement distances and volumes between the two periods were analyzed with the matched-pair tests described earlier.

Matched-pair tests reveal if significant differences exist across the state (population median) but do not provide information as to geographical distribution of changes or how these differences might vary across the state. We tested for the existence of geographic patterns using the hot-spot analysis available with ArcMap spatial statistics tools with corresponding change values for county k as

$$\Delta P_k = P_{k,2011} - P_{k,1999},$$

$$\Delta V_k = V_{k,2011} - V_{k,1999}.$$

ArcMap's hot-spot analysis calculates the Getis-Ord Gi* statistic, which measures spatial aggregation of weighted points looking at each point, including the one being evaluated, in relation to neighboring features to identify if local observed patterns differ from that

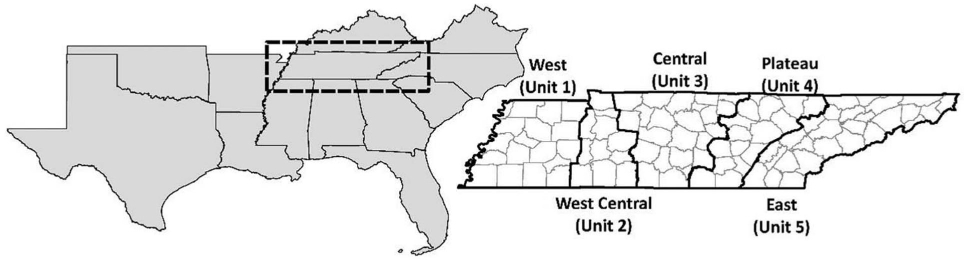

Figure 2. The state of Tennessee with corresponding FIA units.

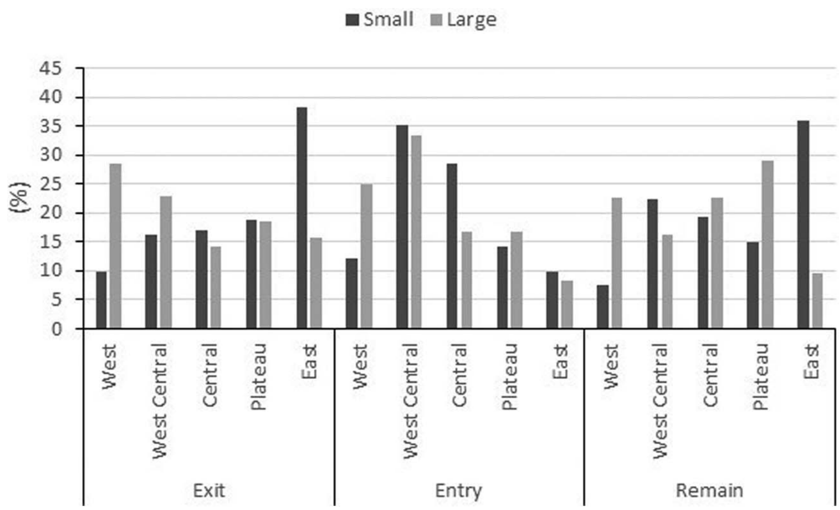

Figure 3. Mill movement by FIA survey unit and mill size category.

of the general observed pattern (Getis and Ord 1992). To further examine county-level sawlog volume patterns, we also conducted hot-spot analysis using volumes disaggregated by species group (softwood and hardwoods).

Data

Information for sawmill log procurement comes from the US Forest Service (FS) Forest Inventory and Analysis (FIA) Timber Products Output (TPO) periodic mill canvass. The TPO program performs periodic surveys of all active primary wood processing mills to estimate volume and flow of wood harvests. Mill survey frequency varies across the FS regional units, with the FS southern region collecting information biennially for all primary mills except pulp mills, which are annually surveyed. Part of the information gathered includes volume of roundwood consumed by tree species and by county of origin. Sawmill location coordinates were obtained from the TPO program, supplemented with information from Google Earth (Google, Inc. 2015) searches using mill addresses as needed. Geographic coordinates for the set of conditional locations used to randomly select our counterfactuals were compiled from the Wood2Energy (2014) and Forest Products Network (Southern Group of State Foresters 2015) databases. The conditional pool of locations, which was used in both years, included 1,061 mill locations.

Study Area

We applied the point pattern analysis to sawmill sites in the state of Tennessee. Figure 2 shows the state with corresponding FIA units (groups of counties that share similar physiographic characteristics), which we used to help describe the distribution of mill changes as well as to disaggregate timberland characteristics.

Between 1999 and 2011, Tennessee experienced a 45% drop in the number of active sawmills. A large portion of the state's sawmill industry is composed of small operations (which we defined as those with <10 employees). However, the share of small mills has declined, a result of mill closures and mill expansions. Although at the beginning of the study period 70% of mills employed fewer than 10 employees, that fraction fell to 65% by 2011. As seen in Table 1, a slight majority of mills operating in 2011 were active in 1999 (53%, or 129 mills of the 244 active mills). Most mill movement (entries and exits) involved small sawmills, with 91 of the 158 mills active in 2011 (or 58% of active small mills) corresponding to mills that started operations after 1999 compared with only 28% (or 24 of 86) of new active large mills operating in 2011. As shown in Figure 3, exits (mills active in 1999 but not in 2011) of small sawmills occurred primarily in the East unit, which experienced close to 40% of all small-mill exits. Large-mill exits were higher in the West and West-Central units, with both units accounting for close to 50% of all large-mill exits. Entries (mills that began operations after 1999 and were open in 2011) were located primarily in the West Central unit for both small and large mills. In contrast, the East unit had the lowest percentage of mill entries. A larger portion (36%) of remaining small mills (those active in 1999 and 2011) were located in the East unit. In contrast, fewer of the remaining large mills (<10%) were located in the East unit.

Total wood consumption from small sawmills was stable during the 2 years studied, representing 21% of all receipts in 1999 and

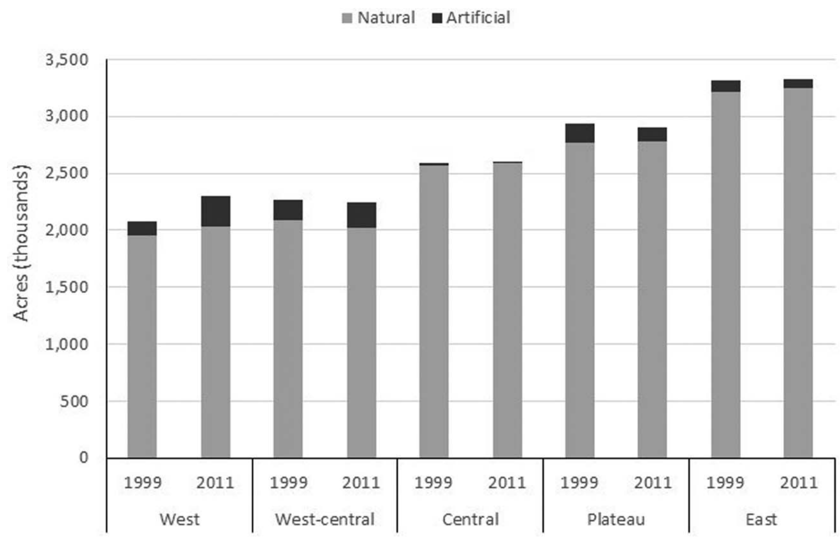

Figure 4. Area of timberland by FIA survey unit and stand origin, 1999 and 2011.

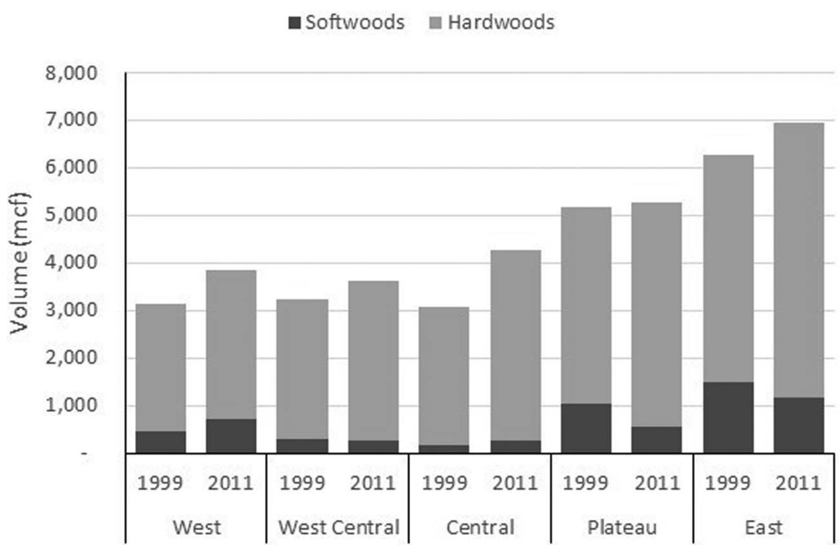

Figure 5. Net volume of growing stock on timberland by FIA survey unit and major species group, 1999 and 2011.

22% in 2011. However, the state's industry experienced a change in species mix consumed, with use of softwood species rapidly declining. Table 1 shows the percentage that hardwoods comprise of the total volume consumed by small and large mills. Both large and small mills consumed less hardwoods in 1999 compared with 2011, although the difference is more significant for small mills, which increased their proportion of hardwoods consumed from 84% to 97% of total volume. Sawmills in 1999 consumed 18 million cubic feet (mmcf) of softwoods (509,770 m^3), which decreased by 88% (to 2 mmcf or 56,640 m^3) by 2011. This drop in softwood consumption reflects, in part, mill response to market changes, specifically the reduced demand for southern pine sawtimber resulting from the 2008–9 economic downturn. Tennessee also experienced an outbreak of southern pine beetle in the 1999–2002 period, which contributed to significant changes in softwood stock on the East and Plateau units (Oswalt et al. 2016).

Tennessee is a hardwood state, with 87% of the state's timberland net volume of growing stock found in hardwood species. More than 80% of the state's hardwood timberland area is classified as the oak-hickory forest type. However, timberland characteristics (such as species composition, volume, and stand origin) vary across the state. As seen in Figure 4, FIA data show most timberland area corresponding to naturally regenerated stands. The West and West Central units contained the largest percentage of timberland area with signs of artificial regeneration, both in 1999 and 2011. Although total timberland area was stable across most units during the 2 years studied, the West unit showed a 10% increase in timberland area. The East and Plateau units displayed the highest net volume of growing-stock trees, as shown in Figure 5. We also observed larger volumes of growing stock in 2011, compared with 1999, across all units except the Plateau, the volume of which was stable during this period. Figure 5 also shows most of this increase in growing-stock volume occurring in hardwood species, with softwoods decreasing significantly in the Plateau and East units and increasing in the West unit. Similar tendencies are observed for net volume of sawlog trees (Figure 6), with the East and Plateau units holding the largest volumes. The West-Central unit contained the lowest net volume of

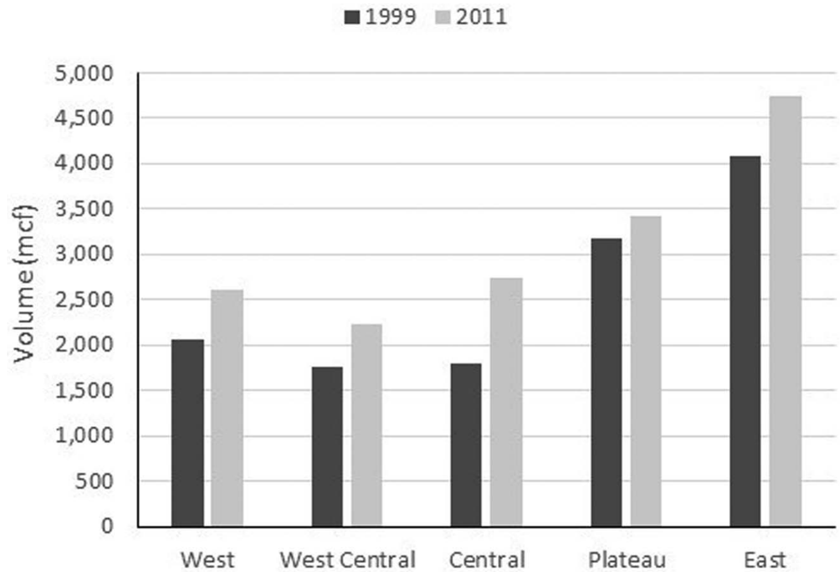

Figure 6. Net volume of sawlog portion of sawtimber trees on timberland by FIA survey unit, 1999 and 2011.

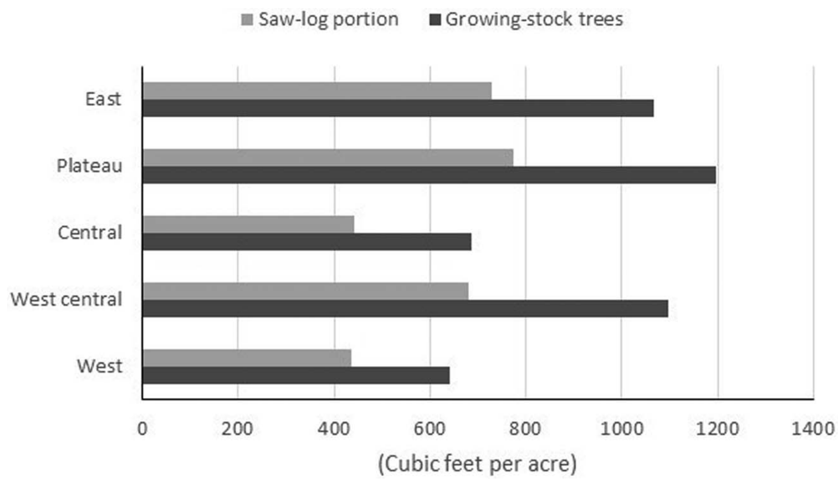

Figure 7. Net volume of growing-stock trees and sawlog portion of sawtimber trees relative to each unit's total land area, Tennessee 2011.

growing-stock trees; however, relative to its size this unit had the second largest volume of growing-stock trees per acre (Figure 7). Likewise, when considering a unit's total area, both the West and Central units rank lowest in terms of growing-stock trees and sawlog volumes per acre. Considering tree grade (i.e., sawtimber-size trees with potential for factory-grade material), we observe a decline in grade across all units (Figure 8), with the sharpest change in the Central unit followed by the Plateau. A larger proportion of high-grade trees was found in the West unit in both years. Oswalt et al. (2012) provide trend information on hardwood tree grade, showing significant decline between the 1999 and 2009 forest inventories with tree grade 1 decreasing 68% over this time period (from 22% to 7% of total sawtimber volume).

Results

The point pattern analysis revealed a clear difference in mill distributions (Figure 9), with 1999 sawmills distributed in a random pattern, whereas 2011 mills exhibited significant localization (as described earlier, a K-density above the upper confidence band indicates localization). Considering patterns by mill size (Figure 10), we observed small sawmills (<10 employees) exhibiting the same pattern as the overall set, with random distribution in 1999 and aggregation in 2011. However, large sawmills displayed no change, with localization evident in both years.

The raster analysis (Figure 11) illustrates that the 1999 mills are more dispersed across the state, with high mill influence spread across the state, whereas 2011 mills displayed a marked concentration around the south side of the West-Central unit and fewer active mills (low mill influence) in Tennessee's East and West units. The matched-pair tests revealed a significant difference ($P < 0.001$) between the two raster sets (Table 3, ΔD variable), corroborating the graphic evidence.

Average mill procurement distances by FIA unit (Figure 12) revealed both small and large mills in the Central unit procuring sawlogs from a smaller area in 2011 than in 1999. Average procurement distance in the Central unit decreased 36% for large mills and 22% in small mills. Large sawmills in the state's East unit exhibited the largest increase in average procurement distance (28%). The average procurement distance of remaining and closed mills was very similar (close to a 1-mile difference). However, this comparison

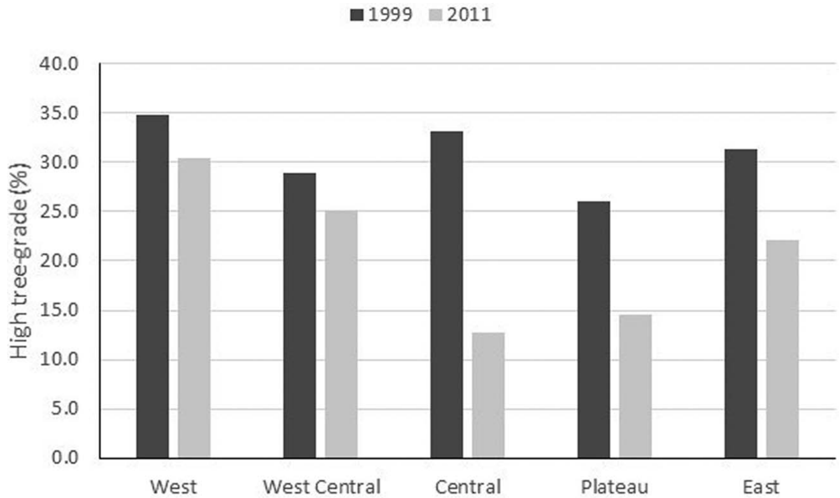

Figure 8. Proportion of high-grade trees from growing-stock volume on timberland by FIA survey unit, 1999 and 2011.

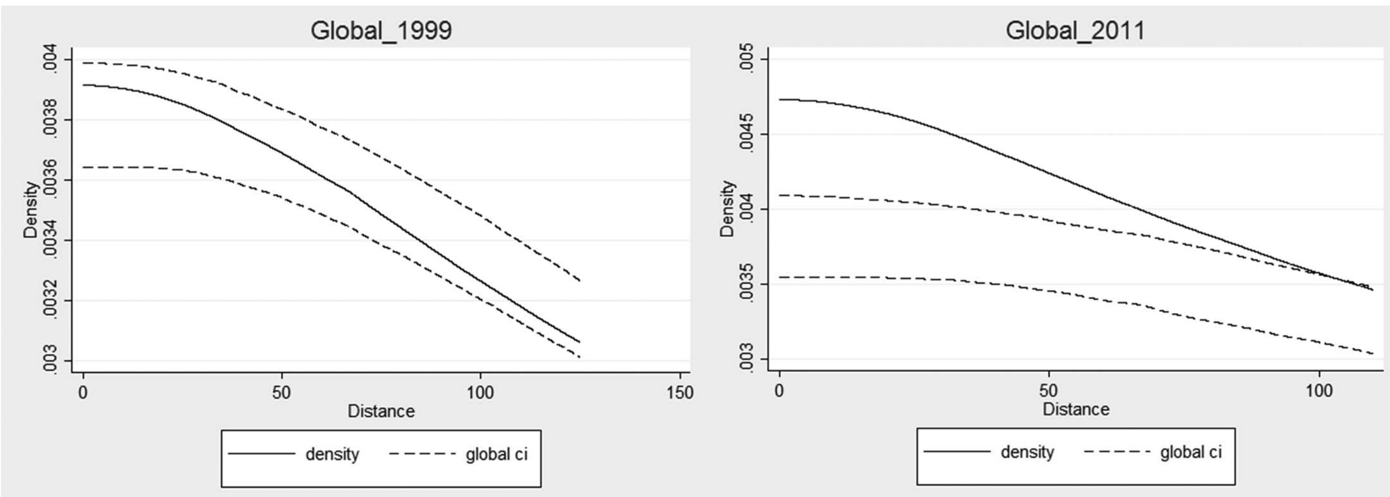

Figure 9. K-density with global confidence interval (ci) bands for all active sawmills, 1999 and 2011.

could underestimate procurement distances of exiting mills because we can only use procurement information available in 1999 rather than procurement distances close to each mill's exit time. However, matched-pair tests of wood consumption patterns revealed that the changes in procurement distances and procured volumes were not statistically significant when considered at the state level (Table 3, variables ΔP and ΔV). Interestingly, hot-spot analysis of matched-pair differences (Figure 13A) revealed a few counties where increases in procurement volume appeared larger relative to neighboring counties. These counties coincide with the areas of mill concentration observed in Figure 11. Differences by species group were also noticeable (Figure 13B), with softwood volumes showing cold-spot counties across the East and Plateau units and one hot spot to the north of the Central unit. Hardwood procurement volumes increased for counties in the southern side of the West-Central unit, matching the hot-spot results for the overall procurement volume.

Discussion and Conclusions

We examined the change in sawmill geographical distribution and wood procurement patterns resulting from the reduced number of active sawmills in the state of Tennessee. To reduce transportation costs, primary forest product mills locate close to the timber resource; therefore, a certain level of mill aggregation is expected (Aguilar 2009). However, we find that although large mills clustered in both years studied, small-mill location exhibited a random pattern in 1999 and clustering in 2011. Interestingly, Duranton and Overman (2005) noted that in their study large firms drove localization in some industries whereas smaller firms were the drivers in others. In our analysis, small mills were the drivers of overall random distribution in 1999; both were "localizing" by 2011. The observed change in the location pattern of small sawmills (<10 employees) indicates possible advantages from clustering, which could include access to logging capacity and/or final product markets among others. Although clustering can be advantageous, it could also affect the level of closures observed at a given time because larger numbers of mills in one geographical area will ultimately result in higher costs for raw materials and labor.

The West-Central unit of the state appears the most heavily affected in terms of mill localization. As expected, this area of the state also exhibited procurement volume hot spots, indicating increases in our measure of procurement volume. According to current FIA forest inventory, this FIA unit houses the second largest volume of growing-stock trees per acre and the second highest proportion of higher-grade trees. Further research is needed to evaluate

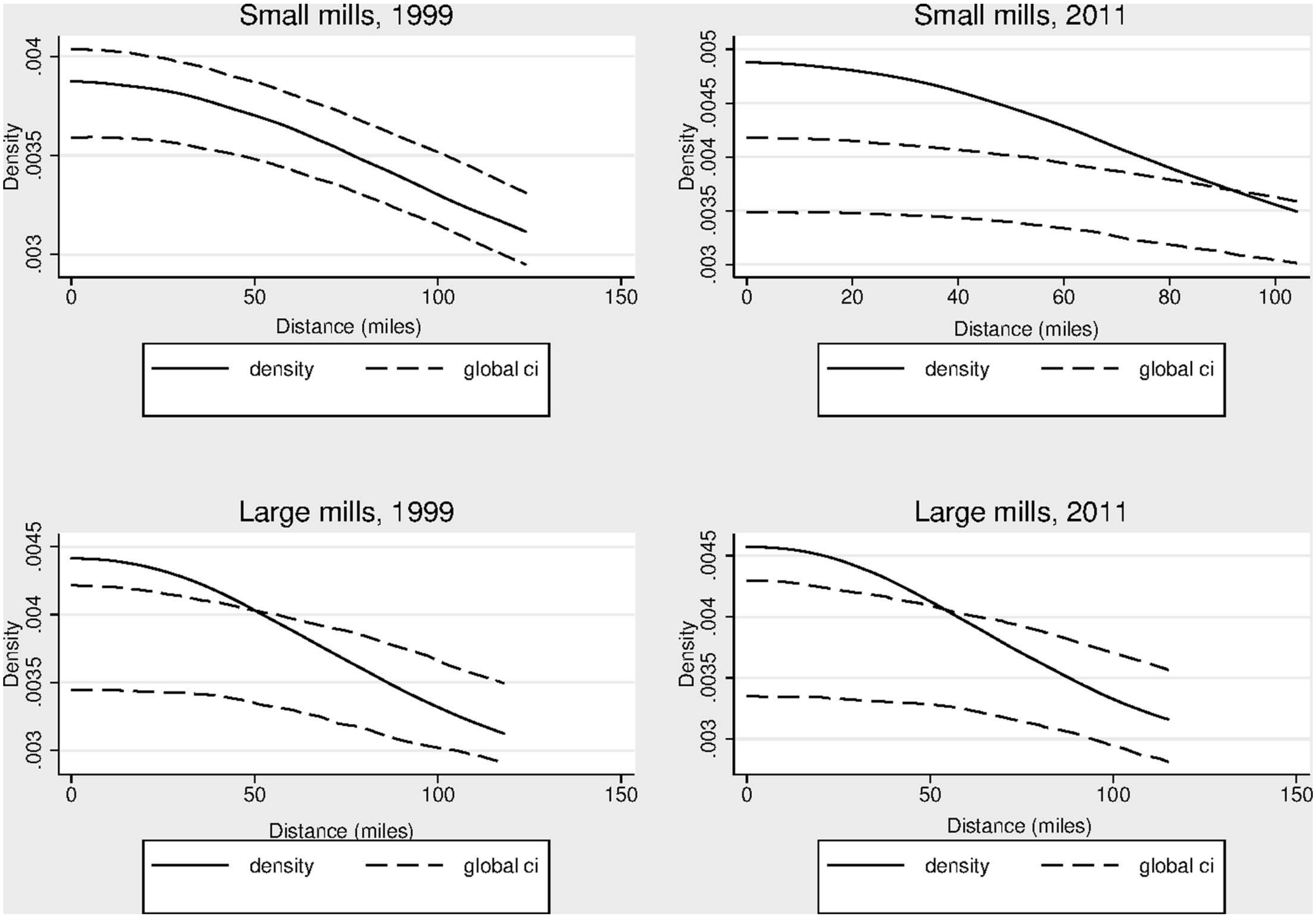

Figure 10. K-density with global confidence interval (ci) bands for all active sawmills by mill size category, 1999 and 2011.

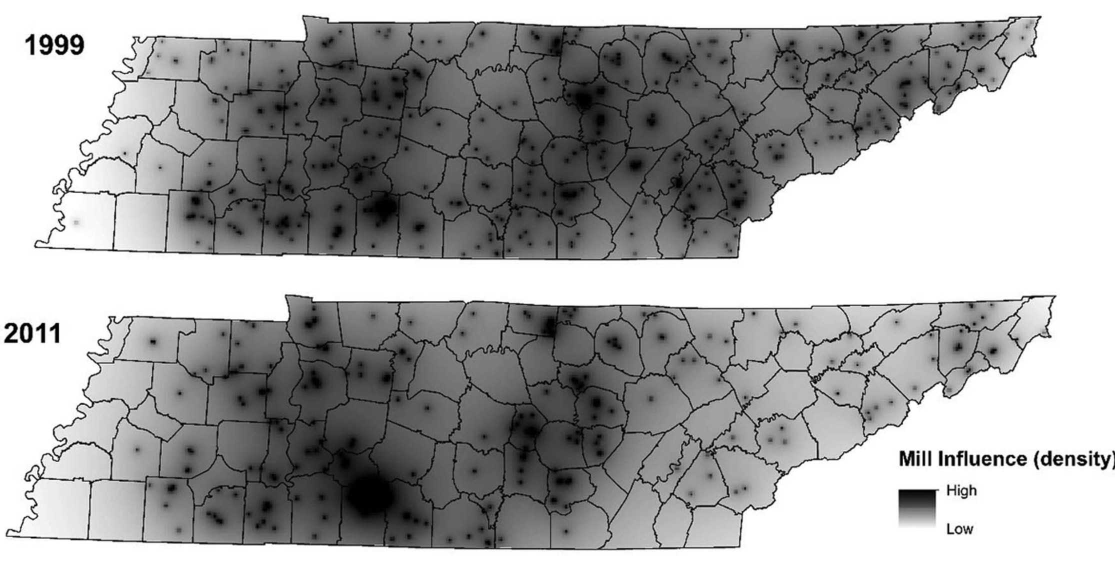

Figure 11. Sawmill concentration (density) in Tennessee, 1999 and 2011.

impact to forest conditions in the West-Central unit compared with the rest of the state. Shifts in mill geographical distribution can have implications for forest management because new patterns can imply a change in market availability to landowners. Fewer market options can discourage landowners from actively managing their lands for timber production or use intermediate harvest to improve the health, structure, and/or composition of their forestlands. Conversely, mill aggregation could lead to more intensive management in response to higher sawlog demand. Although we cannot evaluate if the observed localization is having an effect on management at this

Table 3. Matched-pair test statistics.

Variable	Wilcoxon signed-rank z	Prob > z	Sign test (*P* value)
ΔD*	−8.306	0.000	0.000
ΔP	0.403	0.687	0.606
ΔV	0.004	0.997	0.682
$\Delta V_{softwood}$	−5.189	0.000	0.000
$\Delta V_{hardwood}$	−1.206	0.228	0.305

Note: *Corresponds to 10% of raster points, drawn at random.

time, our results provide justification for further research into the forest management response that these mill concentration changes might motivate.

Under the present study, we cannot evaluate the relationship between forest stock change and mill movement with certainty. However, considering mill movement patterns in relation to FIA-reported changes in resources (declines in softwood volumes and high-grade stock) provides some insights. For example, considering the Central unit, it appears that mill movement and stock grade shared a weak connection. The Central unit had the sharpest decline in tree grade; however, the unit showed one of the lowest rates of mill exits and the second highest mill entry. Considering Tennessee's change in softwood stock volumes, affecting largely the East and Plateau units, a stronger connection with mill movement could be present because both units displayed the largest rates of exits and lowest mill entry. Further research is needed to formally evaluate the effect of clustering on mill closures under changing market and forest resource conditions and to evaluate the effect of mill distribution changes on labor patterns.

However, mill centralization did not significantly affect the state's median procurement volume or procurement distance. This finding counters Luppold and Bumgardner's (2009) inference that mills may reduce procurement zones with increasing fuel prices, which certainly rose during the period examined. This points to other exogenous factors influencing mill procurement areas that likely countered the effect of higher fuel prices, resulting in changes in procurement areas not statistically significant at the state level. Examining the geographical distribution of county procurement, rather than the state median, we observed hot spots indicating increasing procurement volumes from counties in the West-Central unit relative to neighboring areas. This corresponds with the unit's observed mill concentration pattern and highlights the significance of geographical analysis at a disaggregated level to study the effects of mill distribution on wood procurement. Although the analysis does not include formal testing to examine links between location pattern changes and wood consumption changes, results from the spatial

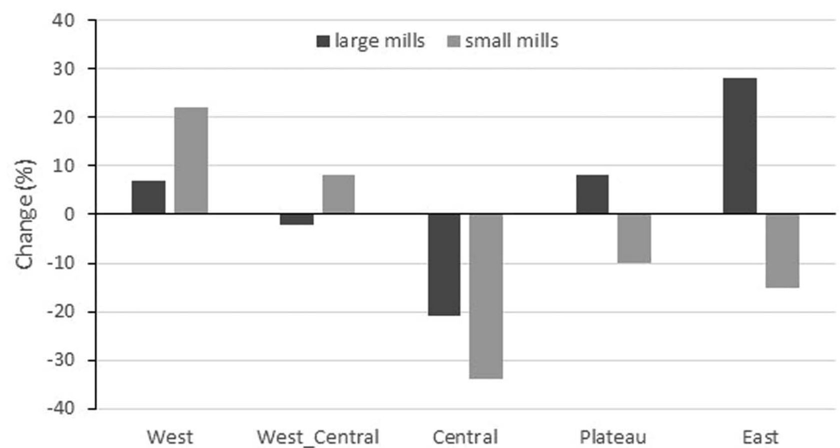

Figure 12. Percentage change in average mill procurement distance by mill size category, 1999 to 2011.

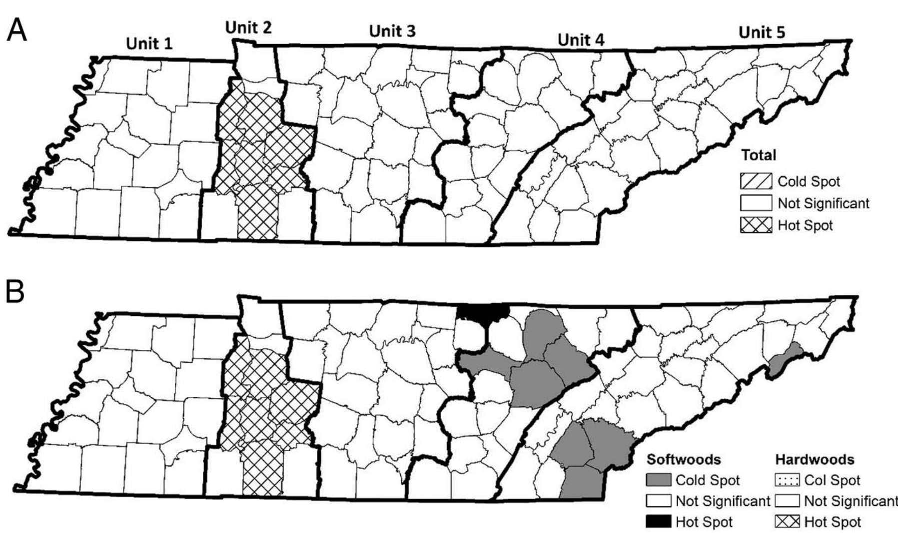

Figure 13. Hot-spot map of wood procurement change between 1999 and 2011 for (A) total volume and (B) by major species group.

analysis provide an indication of likely impact of mill concentration on resource demand.

Information on sawlog input distribution, resulting from wood procurement distribution analyses such as the one developed in this article, should be critical to decision-making agents. Identifying areas with high and low sawlog demand allows state foresters to direct efforts more efficiently and to promote sustainable resource use and availability to satisfy demands over time. Likewise, the visualization of mill procurement across the state provides information to timberland managers and wood procurement agents assessing markets and supply availability. Findings from our analysis can also prove valuable to those examining potential for future mill locations because results provide clear evidence of sawlog demand distribution changes, identifying the areas across the state where these were found significant. The switch in mill distribution from a dispersed to a concentrated location pattern also signals a change in employment distribution, which could have a significant impact on rural communities around the state's East and West units where sawmill presence more sharply declined.

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