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ORIGINAL ARTICLE

Improving County Sawlog Removal Population Estimates using Historical and Distance-Based Mill Procurement Data in the Southern US

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Abstract
The Timber Products Output (TPO) survey, administered by the Forest Inventory and Analysis (FIA) program of the USDA Forest Service, collects data annually from primary wood processing mills. The survey collects data on the volume of roundwood received and residues generated by the primary forest industry by major tree species and counties of harvest. Prior to 2019, the TPO survey was implemented as a full census of all active mills, with varying frequencies across FIA regions. For Southern FIA, TPO surveys of non-pulp mills were delivered every other year. From 2019 forward, TPO transitioned to a national program, with all FIA regions adopting an annual sample survey. The sample methodology involves stratification of the mill population by state, primary roundwood product and mill measure-of-size. Current methodology assigns population county roundwood removal volume estimates only to the counties in which wood was procured by the sampled mills, which can lead to either underestimation or overestimation of actual county volumes. This study evaluates two proposed methods that leverage auxiliary information to improve population county roundwood removal estimates: (1) the Historical Procurement method, which incorporates historical mill-county procurement information and (2) the Radius Procurement method, which incorporates mill-county distance data. We conducted Monte Carlo analysis to test the performance of these two methods, using TPO data from sawmills canvassed in 2011 and 2013 across 11 states in the Southern FIA. Our results showed that both proposed methods achieved improved accuracy in county sawlog removal estimates, compared to the current methodology.

Keywords Survey · Sampling · Precision · Sawmill · Woodshed · Small area estimation · Timber industry

Extended author information available on the last page of the article

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Introduction

The National Resource Use Monitoring component of the USDA Forest Service (Forest Service) Forest Inventory and Analysis (FIA) program manages two data collection efforts to compile information to further characterize timber harvests: the Timber Products Output (TPO) survey and the Harvest Utilization Study (HUS). The TPO survey collects data from primary wood processing mills (i.e., mills that process roundwood in log form, bolt form, or chipped roundwood) to generate estimates of roundwood removed by product at county and state levels along with mill residue by-product generation, and the cross-regional movement of industrial roundwood. "Receipts" refers to the total roundwood volume received by mills, while roundwood “Removal" represents the total roundwood volume harvested from a specific county.

Prior to 2019, TPO surveys were delivered to all active primary wood-using mills on a periodic basis with different regional frequencies. Surveys for roundwood products other than pulpwood were conducted every 2 years in the South. To improve accuracy on a temporal scale, the program shifted to an annualized survey across all regions starting in 2019. The sample frame (mill list) used for sampling is updated annually, in cooperation with state and university partners. Mill samples are selected using a stratified random sampling design. Mills are grouped and stratified by state and roundwood product and then allocated to strata based on a measure-of-size (MOS). Currently, the MOS used, is the mills' most recent volume of roundwood receipts. The aim is to sample 40 percent of the population, giving higher sample probability to larger mills, as previous canvasses have shown that a small number of mills account for a large portion of production (Westfall et al. 2022). Within each state-roundwood product stratum, the MOS get sorted in descending order, mills with a MOS above a predetermined threshold are sampled with certainty (e.g., South samples with certainty all mills with a MOS at or above 10,000 thousand cubic feet (MCF)). Remaining mills are then further stratified such that each stratum has a roughly equivalent total MOS, and two mills are selected at random from each stratum.

The current annual sampling design provides estimates of timber products roundwood removals at the state and county population levels. Although county-level population estimators for roundwood removals remain unbiased, they exhibit relatively high variance compared to the state population estimates, especially in counties with a limited number of mills or low roundwood production (Coulston et al. 2018). Annual county-level estimates frequently show discontinuities since expansion factors amplify volumes from sampled mills, while contributions from non-sampled mills remain unaccounted for. Researchers can improve these estimators' using models that incorporate auxiliary data under the design framework, known as model-assisted estimators (Särndal et al. 2003). In forest inventory, model-assisted sampling frequently employs various auxiliary data sources such as satellite imagery, and lidar data (e.g., Strunk et al. 2012; Ståhl et al. 2016; McRoberts et al. 2022) to enhance population estimator efficiency and maintain approximate unbiasedness when auxiliary data is known for the entire population. The effectiveness of this approach also depends on the strength of the relationship between the auxiliary variable and the county removal volume. The historical mill-county procurement represents a promising auxiliary data source for improving county roundwood product removal estimates, as it is available for most sampling units and shows a strong correlation with current procurement patterns, making it a suitable candidate for model-assisted estimation.

Among the types of TPO primary mills (sawmills, veneer mills, pulp mills, composite panel mills, biomass plants, log home mills, piling mills, pole mills, post mills, residential fuelwood studies and miscellaneous mills), sawmills have the highest number of sampled strata (Westfall & Coulston 2022) and the highest mean error (Coulston et al. 2018). From 2011–2017, sawlog removal represents a significant portion of total removals, accounting for 32 percent of roundwood removals whereas pulpwood and veneer represent 46 and 6 percent of industrial roundwood removal in the southern US, respectively (Durham and Cyprian 2024). Though pulpwood accounts for the highest percentage of roundwood removals, all pulp mills are surveyed annually, meaning that the county procurement estimates for this mill type are accurate. Therefore, improving the accuracy of county sawlog removal estimates should be prioritized, as it could greatly decrease overall errors in county roundwood removal estimates. While alternative county removal data sources, such as FIA inventory (Forest Service, available at: https://apps.fs.usda.gov/fiadb-api/evalidator) and remote sensing can provide county removal estimates, they lack information of removals by species and roundwood product usage categories and often lack temporal accuracy due to multi-year reporting intervals.

The southern United States is the world's largest timber-producing region and is expected to maintain its dominance (Prestemon and Abt 2002), producing approximately 10 percent of the world's total industrial roundwood (USDA Forest Service 2023). Southern forests have distinct growth patterns, successional trajectories, and disturbance regimes (Oswalt et al. 2019). It is essential to have accurate data on county sawlog roundwood removals because, when integrated with county standing volume, it supports effective land use planning and management for multiple objectives such as recreation, wildlife habitat, carbon storage, and the production of multiple timber products. For instance, small and low-quality woody materials left on sites and sawmill residues serve as the primary feedstock for wood pellet production in the renewable energy sector (Dale et al. 2017). The southeastern US generates 74% of total US wood pellet production, sourced from two fuelshed procurement zones that cover specific coastal plain counties across NC, SC, VA, GA, and FL (Hodges et al. 2019). Precise and reliable data on county sawlog production can enhance wood-basket analyses, refine wood supply planning, and enable producers to sustainably meet the growing demand for products like wood pellets.

Several efforts have been explored to improve TPO estimation accuracy. Young (2020) investigated alternative certainty mill boundaries (thresholds) and found that selecting other certainty thresholds based on desired population precision marginally improved state roundwood volume estimate precision compared with the predetermined certainty threshold. Westfall and Coulston (2022) investigated how correlated samples improve the precision of year-to-year changes in total roundwood volume across 12 southern state strata. Their results demonstrated smaller standard errors compared to estimates derived from independent samples. However, little attention has been given to enhancing estimation precision at the county level, particularly through improved sampling designs or better utilization of spatial procurement information. Currently, when mills do not provide explicit county-level procurement data but instead report only a general procurement radius, the approach is to use an ad-hoc model to estimate county volumes from procurement radius information and forest inventory data. This model from procurement radius is useful as a practical workaround, allowing for reasonable estimates in the absence of detailed sourcing information.

Recognizing these gaps, our study focused on the parameter of interest which is sawlog removal volume at the county level. We examined the estimation errors associated with current TPO methodology for this parameter and proposed two alternative methods in model-assisted framework by incorporating auxiliary data: historical mill-county procurement data and mill-county distance data. These auxiliary datasets, available for most mills in the population, are used to predict county-level allocations for non-sampled mills. The predictions are then combined with observed data from sampled mills to produce county totals. The Historical Procurement (HP) and Radius Procurement (RP) methods apply predictions directly to assign volumes to non-sampled mills, which may reduce variance but introduces potential model bias. We then examined the asymptotically design-unbiased method, Historical Procurement Ratio (HPR), which uses the same historical procurement information as HP to form the model predictions but scales the residuals by design-expansion weights. We compared the overall variances obtained from Monte Carlo sampling simulation and design-based variances based on the established sampling design. The study utilized full canvass 2011 and 2013 TPO sawmill survey data from 11 southern states. We treated the 2013 TPO canvass data as the true population to evaluate results using the current and the proposed methods. We used 2011 mill receipt data for stratified sampling and as the historical mill-county procurement volume.

The predictive power of historical procurement data depends on the temporal stability of mill procurement patterns. In counties where mill procurement areas shift substantially over time, historical allocation proportions may be less representative of current sourcing. Also, mills that consistently draw from a broad set of counties are less affected by changes in any single county's supply, allowing historical allocation proportions to be more reliable. In this study, we investigated spatial entropy of how evenly roundwood is procured across a mill's potential woodshed and examined changes in the mill procurement boundaries to capture temporal shifts in sourcing areas. We used subset of sawmills that reported detailed wood draw counties in 2011, 2013, and 2015 for this procurement dynamic analysis.

Methods

County Removal Volume

Timber Products Output (TPO) Method

The TPO program currently employs a stratified random sampling design, selecting approximately 40% of the population of roundwood receiving facilities each year (Westfall et al. 2022). The program divides the population of all roundwood receiving facilities into subpopulations based on the state where the facility resides and the primary roundwood product the facility receives. The sampling design further stratifies facilities within each state–product subpopulation by MOS. Facilities with a MOS greater than a predetermined certainty threshold (for example, 10,000 MCF for facilities in southern states), are placed into certainty strata with only one facility in the stratum, where they are always sampled. The remaining facilities are binned into strata with the objective that the total cumulative MOS within each stratum is approximately equal. In strata with one or two facilities, the program enumerates and includes all facilities in the sample: in strata with more than two facilities, the program randomly samples exactly 2 facilities. From the sampled facilities, the program collects data on their total roundwood receipts and the county of wood origin. In each sampled stratum, the program expands the county roundwood volumes from sampled facilities using a sampling weight, which is the total number of facilities (N_k) in the stratum divided by number of facilities sampled (n_k). For example, suppose subpopulation of 100 sawmills in AL contain 21 strata with 1 certainty stratum from mill's MOS greater than certainty threshold, 5 completely enumerated strata containing exactly 2 mills, and 15 strata containing more than 2 mills. Suppose a stratum contains 3 mills, and 2 mills are sampled, each sampled mill must be weighted to account for the mill that was not sampled. In this case, the sampling weight 1.5 is multiplied by the sampled mill volumes to estimate total volume for this stratum.

Using this notation, the population total of sawlog roundwood for county i is the sum of that county's subpopulation totals across every state-product(sawlog) domain. Under the current TPO methodology, the county sawlog volume estimator ($\widehat{Y}_i^{TPO}$) for county i is calculated as the summation of observed sawlog volume drawn y_{ijk} from county i by the mills j in the stratum k, each multiplied by their sampling weights.

$$\widehat{Y}_i^{TPO} = \sum\nolimits_k \sum\nolimits_{j\in S_k} \frac{N_k}{n_k} y_{ijk}$$

When S_k is simple random sample set of n_k mills from total number of N_k mills in stratum k.

The design variance of this TPO county sawlog volume estimator is given by:

$$Var\left(\widehat{Y}_i^{TPO}\right) = \sum_k \frac{N_k^2}{n_k}(1 - \frac{n_k}{N_k})s_{ik}^{TPO^2}$$

where: $s_{ik}^{TPO^2} = \frac{1}{n_k-1}\sum\nolimits_{j\in S_k}\left(y_{ijk} - \overline{y}_{ik}\right)^2$,

and $s_{ik}^{TPO^2}$ is the sample variance of county volumes for county i in stratum k,

and $\overline{y}_{ik}$ is the average sampled volume from county i in stratum k.

Historical Procurement (HP) Method

We propose a method that utilizes the most recent county draw information to construct county allocation shares for non-sampled mills. For each non-sampled mill, we first determine the proportion of its historical procurement volume coming from each county. These proportions are then used to allocate an estimated total mill volume which was derived from the sampled mills in the same stratum.

The county allocation weight, x_{ijk} representing the fraction of mill j's receipts in stratum k that were historically drawn from county i:

$$x_{ijk} = {}^{v_{ijk}} \Big/ {}_{\sum_l v_{ljk}}$$

where v_{ijk} is the historical volume drawn from county i by mill j
and $\sum_l v_{ljk}$ represents the total historical volume drawn in mill j.

Radius Procurement (RP) Method

The proposed RP method uses a simplified procurement model assuming that every county within a predetermined woodshed supplies an equal share of roundwood to non-sampled mills. For exploration analysis, we defined a woodshed as encompassing counties whose centroids lie within a Euclidean distance of less than 25 miles from a non-sampled mill. Each county within the woodshed is assigned equal removal proportion.

Similar to HP, the county allocation weight x_{ijk} for mill j, county i, and stratum k is:

$$x_{ijk} = {}^{a_{ijk}} \Big/ {}_{\sum_l a_{ljk}}$$

where

$$a_{ijk} = \begin{cases} 1; & \textit{if centroid of county i is within the } 25 \textit{mile radius of mill j} \\ 0; & \textit{otherwise} \end{cases}$$

and $\sum_l a_{ljk}$ represents the total number of counties whose centroids fall within the 25-mile radius woodshed of mill j.

Then estimator of sawlog volume ($\widehat{Y}_i^{HP/RP}$) for county i under either HP or RP methods is defined as

$$\widehat{Y}_i^{HP/RP} = \sum_k \left(\sum_{j \in S_k} y_{ijk} + \sum_{j \notin S_k} \widehat{y}_{ijk} \right) = \sum_k \sum_j \widehat{y}_{ijk} + \sum_k \sum_{j \in S_k} \left(y_{ijk} - \widehat{y}_{ijk} \right)$$

where the predicted volume $\widehat{y}_{ijk}$ from county i for mill j in the stratum k is

$$\widehat{y}_{ijk} = x_{ijk} \cdot \overline{y}_k$$

and $\overline{y}_k$ is the average mill volume from sample mills in stratum k,

$$\overline{y}_k = \sum_{j\in S_k}\sum_i \frac{y_{ijk}}{n_k}.$$

The design-based variance of the estimator is:

$$Var\left(\widehat{Y}_i^{HP/RP}\right) = \sum_k n_k(1-\frac{n_k}{N_k})s_{ik}^{HP/RP^2}$$

when $s_{ik}^{HP/RP^2} = \frac{1}{n_k-1}\sum_{j\in S_k}\left(e_{ijk}-\overline{e}_{ik}\right)^2$

and $e_{ijk} = y_{ijk}$-$\widehat{y}_{ijk}$; $\overline{e}_{ik}$ is the mean prediction error in county i in the stratum k.

Note that the $\widehat{Y}_i^{HP/RP}$ is a biased estimator with the relative bias order $O(\frac{1}{N})$ which diminishes as the number of mills in a stratum increases.

Historical Procurement Ratio (HPR) Method

To consider the unbiased estimator with historical procurement information, we evaluated the model-assisted ratio estimator method. Like the HP method, it uses historical mill–county procurement data to generate predictions. However, it differs by scaling the residual term with the full design expansion weight $\frac{N_k}{n_k}$ to preserve unbiasedness under the sampling design.

The HPR estimator of sawlog volume in county i is:

$$\widehat{Y}_i^{HPR} = \sum_k\sum_j \widehat{y}_{ijk} + \sum_k\sum_{j\in S_k}\frac{N_k}{n_k}\left(y_{ijk}-\widehat{y}_{ijk}\right)$$

where the predicted volume is:

$$\widehat{y}_{ijk} = \widehat{B}_{ik}\cdot v_{ijk}$$

when $\widehat{B}_{ik} = \frac{\sum_{j\in S_k} y_{ijk}}{\sum_{j\in S_k} v_{ijk}}$ is the ratio of observed volume to historical volume for county i within indices stratum k when county i is represented among sampled mills in stratum k (i.e., $n_{ik} > 0$);

and $\widehat{B}_{ik} = \frac{\sum_{j\in S_k}\sum_l y_{ljk}}{\sum_{j\in S_k}\sum_l v_{ljk}}$ is the pooled ratio of observed volume to historical volume across all counties that supply to sample mills in stratum k, used when county i has no sampled observation in stratum k (i.e., $n_{ik} = 0$).

$$Var\left(\widehat{Y}_i^{HPR}\right) = \sum_k \frac{N_k^2}{n_k}(1-\frac{n_k}{N_k})s_{ik}^{HPR^2}$$

When $s_{ik}^{HPR^2} = \frac{1}{n_k-1}\sum_{j\in S_k}\left(e_{ijk}-\overline{e}_{ik}\right)^2$

And $e_{ijk} = y_{ijk}$-$\widehat{y}_{ijk}$; $\overline{e}_{ik}$ is the mean projection error for county i in the stratum k

Note: we omitted the method notation in x_{ijk}, $\widehat{y}_{ijk}$, e_{ijk}, $\overline{e}_{ik}$

Illustration

To illustrate these three methods (TPO, HP, and RP), consider a hypothetical stratum with three mills, each with a 2011 MOS of 1,000 MCF. Mills 1 and 2 are randomly selected for the 2013 mill sample, while mill 3 is not selected ($S_k = \{1,2\}$). Figure 1(a) shows procurement volume notation and counties supplying each mill, and Table 1 compares county volume estimates across the three methods. Total volumes across all methods are the same, but the county volumes differ. The TPO method applies the stratum sampling weight $\frac{N_k}{n_k} = 1.5$ to the reported volume from all counties supplying wood to sampled mills (Fig. 1(b)). In comparison, the HP method reports the sampled mills' volumes from their respective procuring counties, while the non-sampled mill (mill# 3) uses the average volume of the sampled mills as its own mill volume and allocates to its county volumes according to its most recent county procurement proportions (Fig. 1(c)). Likewise, the RP method uses the average volume from the sampled mills as non-sampled mill volume and allocates this volume equally among all counties whose centroids lie within 25 miles of

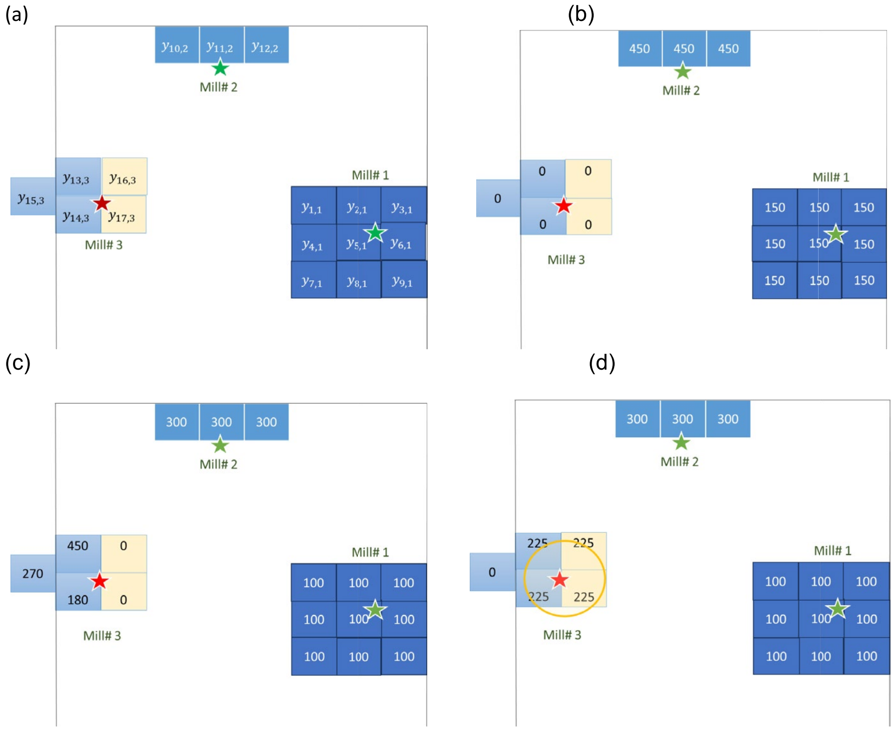

Fig. 1 (**a**) Hypothetical county draw map of a 3-mill stratum (k is omitted here), ($S_k = \{1,2\}$); y_{ij} is the sawlog volume sourced from county i for mill j. Stars indicate the locations of the three mills, while rectangles represent individual counties in a state.(**b**) Sawlog volume estimates $\hat{y}_{ij}$ from TPO method. (**c**) Sawlog volume estimates $\hat{y}_{ij}$ from HP method. (**d**) Sawlog volume estimates $\hat{y}_{ij}$ from RP method. The circle illustrates a 25-mile sourcing radius from the mill

Table 1 Hypothetical sawlog volume, y_{ij}, representing the volume (MCF) drawn from county i for mill j. The "Reported" columns are the observed volumes for 2011 and 2013. The "Estimated 2013" columns present the predicted volumes for 2013 under the current TPO method and proposed HP and RP methods

	Reported		Estimated 2013		
	2011	2013	TPO	HP	RP
$y_{1,1}$	200	100	150	100	100
$y_{2,1}$	100	100	150	100	100
$y_{3,1}$	100	100	150	100	100
$y_{4,1}$	100	100	150	100	100
$y_{5,1}$	100	100	150	100	100
$y_{6,1}$	100	100	150	100	100
$y_{7,1}$	100	100	150	100	100
$y_{8,1}$	100	100	150	100	100
$y_{9,1}$	100	100	150	100	100
$y_{10,2}$	500	300	450	300	300
$y_{11,2}$	200	300	450	300	300
$y_{12,2}$	300	300	450	300	300
$y_{13,3}$	500	400	0	450	225
$y_{14,3}$	200	300	0	180	225
$y_{15,3}$	300	200	0	270	0
$y_{16,3}$	0	0	0	0	225
$y_{17,3}$	0	0	0	0	225

the non-sampled mill. As shown in Fig. 1(d), the RP method distributes county volumes to 2 of the 3 supplying counties ($i=13$, 14) and 2 additional non-supplying counties ($i=16$, 17).

Simulation Study

The simulation analysis calculated and compared the design variances of county sawlog volume estimates from the current TPO, HP, RP, and HPR methods with simulation variances, which represent the actual variability observed across repeated samples. We conducted Monte Carlo simulations using TPO census data restricted to mills active in all four canvass years (2011, 2013, 2015, and 2017) across 11 southern states (Alabama, Arkansas, Georgia, Florida, Kentucky, Louisiana, Mississippi, North Carolina, Oklahoma, South Carolina, and Virginia). Texas did not participate in the TPO program in those years and Tennessee was omitted due to lack of 2013 data. The study treated the 2013 data as the true population and utilized the 2011 data as historical auxiliary information and MOS for the sampling frame. We then incorporated the 2015 and 2017 datasets to conduct sensitivity analyses. There were 771 sawmills with information in all canvass years drawing roundwood from 904 counties. The median and mean of county sawlog volumes of 2013 data were 1,538 and 2,412 MCF, respectively. County sawlog volume estimates were evaluated for 5,000 replications (R). The simulation variance, a.k.a., mean squared error (MSE) for sawlog volume estimate in county i was

$$MSE_i = \frac{1}{R}\sum_{r=1}^{R}(\hat{Y}_i - \theta_i)^2$$

where θ_i is the true sawlog volume in the county i.

The error in sawlog volume estimate can be represented by the root mean squared error (RMSE) for county i as a square root of the MSE.

$$RMSE_i = \sqrt{MSE_i}$$

Sensitivity Analysis

To evaluate the robustness of each method and determine whether the proposed methods consistently outperform the current TPO method, we conducted a sensitivity analysis. In stratified random sampling, the efficiency of models also depends on stratification variables whose characteristics are likely to have a significant impact on the target variable. A reduction in correlation between stratification variable and target variable decreases the estimation precision. In addition, the model-assisted framework can exhibit substantial performance variations when the underlying relationships between auxiliary variables and target variables weaken over time (McRoberts et al. 2013).

In order to explore this, we investigated temporal stability and correlation strength that could affect method performances. For temporal stability sensitivity analysis, we evaluated estimation performance across extended temporal periods in all three methods: TPO, HP, and RP. We applied the 2011 mill receipts, originally used as the MOS for the 2013 estimates, to estimate county volumes for 2015 and 2017. The 2011 mill receipts served dual roles in the HP method: as stratification variable (MOS) and as auxiliary data.

For correlation degradation analysis, we tested how the methods perform when the auxiliary data become less predictive of current conditions. Our baseline analysis used 2011 mill receipts that had strong correlation with 2013 receipts ($\rho = 0.9$), representing ideal conditions where historical data closely predict current patterns. To simulate real-world scenarios where auxiliary data quality degrades such as from structural breaks or missing data, we artificially weakened this relationship by using log-transformed 2011 mill receipts as the auxiliary variable. Correspondingly, the certainty threshold was also adjusted to the log scale to maintain consistent stratification criteria. This transformation reduced the correlation with 2013 receipts to $\rho = 0.6$, mimicking situations where historical procurement patterns become less reliable predictors of current mill behavior.

Procurement Dynamics

To ensure the mills' historical procurement patterns remain a defensible proxy for current behavior, we analyzed the spatial diversity and temporal stability of procurement patterns. This analysis addresses two key questions: (1) how spatially diverse are mill procurement patterns? and (2) how stable are these patterns over time? We examined sawmill procurement characteristics using Batty's spatial entropy (Batty 1974). It serves as an indicator of how broadly or uniformly a mill draws roundwood from its surrounding county landscape. High entropy values indicate diffuse, diversified sourcing patterns across multiple counties, while low values signal concentrated procurement from fewer counties. We define the sourcing area as a 150-mile radius around each mill, ensuring coverage of all possible supplying counties. The spatial entropy $H(f_j)$ of mill j is calculated as:

$$H(f_j) = \sum_i p(f_{ij}) \cdot \ln\left[\frac{A_{ij}}{p(f_{ij})}\right]$$

where f_{ij} is the event that sawlog come from county i to mill j with the probability $p(f_{ij})$,

$p(f_{ij}) = \frac{v_{ij}}{\sum_l v_{lj}}$ which is the county allocation proportion in the HP context. And A_{ij} is the area of county i within mill j's 150-mile radius woodshed.

The procurement patterns may exhibit stability over time or fluctuate due to various economic, ecological or other factors. To examine temporal dynamics, we used procurement boundary, defined as the maximum Euclidean distance from each mill to the farthest supplying county boundary, to assess how mill sourcing areas change over time. Boundary differences were calculated for three periods from survey years 2011, 2013 and 2015. We obtained the first one-period boundary difference (2011–1-d) by subtracting the 2011 mill boundary from the 2013 mill boundary. Similarly, we computed the second one-period boundary difference (2013–1-d) by subtracting the 2015 mill boundary from the 2013 mill boundary. We obtained the two-period boundary difference (2011–2-d) by subtracting the 2015 mill boundary from the 2011 mill boundary. We plotted histograms of the mill boundary differences and computed correlations of these differences to measure the degree of similarity between successive procurement boundaries. This analysis used a subset of 288 sawmills that reported county procurement volumes in all three survey years (2011, 2013, and 2015). We calculated Batty's spatial entropy using only the 2011 data to establish spatial diversity measures, while the temporal boundary analysis utilized procurement data from all three years to assess stability over time.

Results

Variances of County Production Estimates

Table 2 compares the simulation (MSE) and design-based (Vhat) variances for four estimation methods—TPO, HP, RP, and HPR—based on 2,500 simulation runs across 948 counties. The simulation variances capture the overall observed sampling variability of each estimator across simulations. The design-based variances represent the average of the design-based variance estimates calculated from each simulation's sample. The variance estimates across counties are highly right-skewed. The

TPO method has the highest simulation variance among all methods, with a median MSE_TPO well above 10^5. The HP and RP methods show substantially lower simulation variances. The HPR method has the highest mean simulation variance due to extreme values in a few counties. Across all methods, the design-based variances are at least 10 times smaller than and underestimate their corresponding simulation variances. The medians of design-based variances are very small showing that majority of the county estimate variances are close to zero.

County Removal Volume

Figure 2 shows the actual 2013 county sawlog volumes drawn by mills. We examined county sawlog removal estimate errors (i.e., the RMSE) from three methods based on 5,000 simulations (Table 3). The TPO method has the highest mean RMSE (619) and the highest median RMSE (374), indicating that it is the least precise method, while the RP approach performs better than the current TPO estimation method with a lower mean RMSE (414). The HP method stands out as the most accurate, with the lowest mean RMSE (261) and median RMSE (146) among the three methods. Figure 3 exhibits that RMSE from the current TPO approach are high in western AL counties and in the Piedmont Plateau counties in SC and NC. The number of counties with high RMSE (> 1500) is fewer for the HP and RP methods than for the TPO method. A few counties in AL and VA show high RMSE for the HP method and clusters of high RMSE are shown in MS, AL and SC for the RP method. There are 904 counties with wood draw information, but the RMSEs from all three estimation methods are calculated for 948 counties, including counties used in the HP and RP methods but not included in the actual wood draw data.

The weak correlation between MOS and actual mill receipts reduces the performance in the stratification and increases the within-strata variance. The HP method is less sensitive to decreases in the correlation between MOS and mill receipts compared with the current TPO and RP methods, showing a 24 percent increase in RMSE versus 32 and 58 percent, respectively. However, the HP method is the most sensitive over longer temporal scales. The percentage changes in RMSE for county

Table 2 Summary statistics of simulation variances (MSE) and design-based variances (Vhat) of TPO, HP, RP and HPR methods based on 948 county sawlog volume estimates from 2,500 Monte-Carlo simulations

	MSE_TPO	MSE_HP	MSE_RP	MSE_HPR	Vhat_TPO	Vhat_HP	Vhat_RP	Vhat_HPR
Mean	1.5E+06	1.3E+05	1.7E+05	4.9E+07	4.7E+04	1.2E+04	5.8E+04	4.5E+04
SD	1.3E+07	4.6E+05	4.9E+05	6.9E+08	2.4E+05	1.1E+05	4.0E+05	5.4E+05
25pct	1.1E+04	8.6E+02	8.1E+03	4.8E+02	0	0	0	0
Median	1.4E+05	1.2E+04	4.7E+04	1.1E+04	0	3	10	0
75pct	6.6E+05	6.1E+04	1.4E+05	1.1E+05	8.5E+03	3.6E+02	2.0E+03	1.5E+03
95pct	3.6E+06	6.5E+05	6.8E+05	3.3E+06	1.9E+05	3.0E+04	1.5E+05	8.7E+04
Max	3.0E+08	6.8E+06	7.7E+06	1.9E+10	3.6E+06	2.6E+06	7.4E+06	1.1E+07

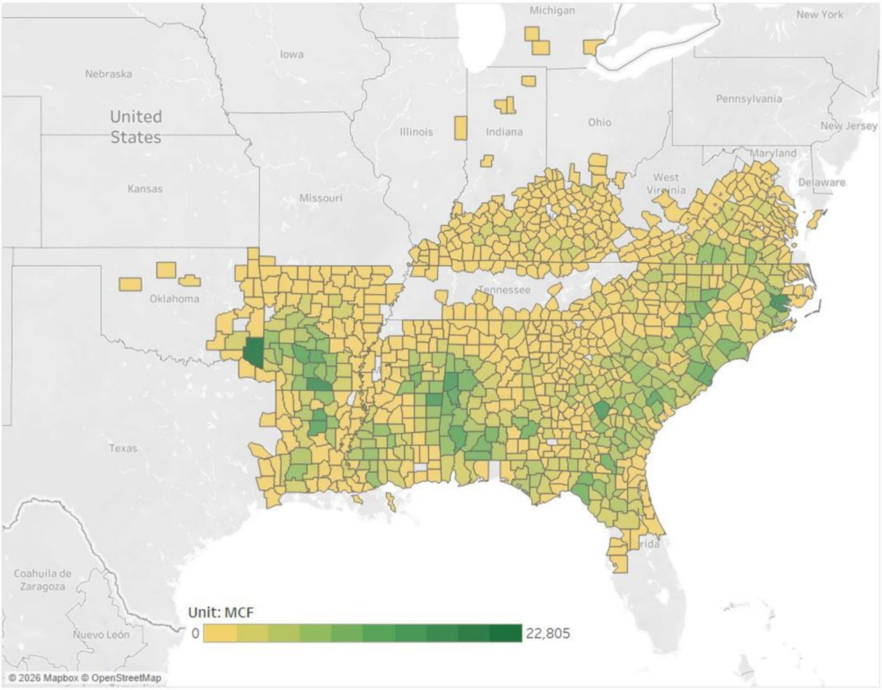

Fig. 2 Observed county sawlog removal volumes in 2013 ($n=904$ counties)

Table 3 Summary statistics of the RMSE (unit: MCF) of county sawlog volume estimates from the current method (TPO), Historical Procurement method (HP), and Radius Procurement method (RP). Results include baseline RMSEs for 2013 and sensitivity scenarios with weaker MOS–mill-receipt correlation ($\rho=0.6$) and temporal extensions applied to 2015 and 2017 data

Method	Mean	SD	25pct	Median	75pct	95pct	Max
TPO	619	975	106	374	808	1,874	15,288
HP	261	351	40	146	331	959	2,986
RP	414	433	143	301	534	1,319	3,731
TPO ($\rho=0.6$)	819	965	180	494	1,055	2,706	6,802
HP ($\rho=0.6$)	324	457	56	157	407	1,230	3,617
RP ($\rho=0.6$)	654	738	166	414	901	2,011	7,655
TPO (Year 2015)	786	1,017	150	463	982	2,687	8,516
HP (Year 2015)	405	563	76	215	491	1,543	5,936
RP (Year 2015)	553	591	143	363	730	1,802	3,840
TPO (Year 2017)	807	1,416	55	390	984	2,610	16,393
HP (Year 2017)	530	727	82	284	664	1,888	6,743
RP (Year 2017)	683	749	145	484	956	2,055	6,987

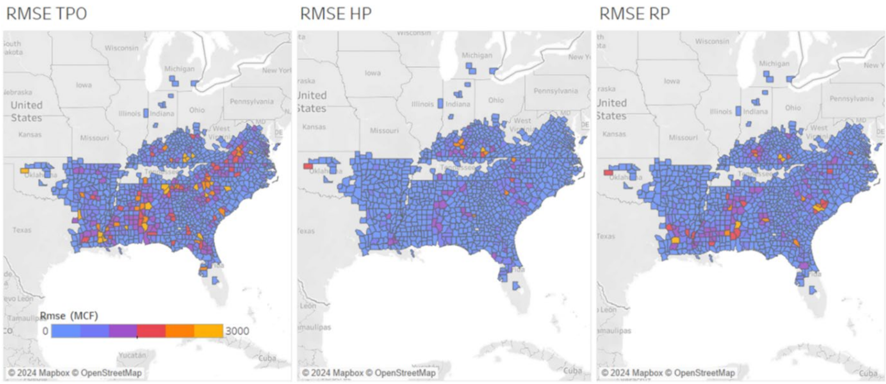

Fig. 3 RMSE (unit: MCF) of county sawlog volume estimates (from left to right: TPO, Historical Procurement (HP), and Radius Procurement (RP); $n = 948$ counties)

sawlog estimates in 2015 and 2017, compared with the 2013 RMSE derived from the same method, increased by 30 percent for both years using the TPO method, by 34 and 65 percent using the RP method, and by 55 and 103 percent using the HP method.

Procurement Dynamics

Figure 4 shows Batty's spatial entropy for 288 mills in 2011. The mean mill entropy is 7.6 and the maximum mill entropy is 9.6. The theoretical maximum Batty's entropy that a mill can have in the sourcing area with 150-miles sourcing radius is 11.17, which represents an even roundwood draw across the sourcing area. Most mills have more than half of the maximum entropy (5.5). The entropy distribution is nearly normal but slightly left-skewed with a few mills having highly concentrated procurement areas.

A subset of mill county procurement data from 288 mills which provided detailed procurement information in 2011, 2013, and 2015 was selected for mill procurement boundary shift analysis. The mean mill boundary distance was 69 miles for 2011 and 71 miles for both 2013 and 2015. In the preliminary analysis (result not shown), the 3 distributions of procurement boundaries across the 3 years were not significantly different according to the Kolmogorov–Smirnov test. Two one-period boundary differences (2011–1-d, 2013–1-d) and a two-period boundary difference (2011–2-d) were calculated. Histograms of the mill boundary differences are heavily centered at zero in all three measures (Fig. 5), indicating that changes in mill boundaries are small. There is strong correlation (0.8297) between the first two-period difference and first one-period difference (2011–2-d and 2011–1-d) but weak correlation (0.3045) between first two-period difference and second one-period difference (2011–2-d and 2013–1-d) (Table 4). The results show a very weak correlation (−0.279) between the one-period differences (2011–1-d and 2013–1-d).

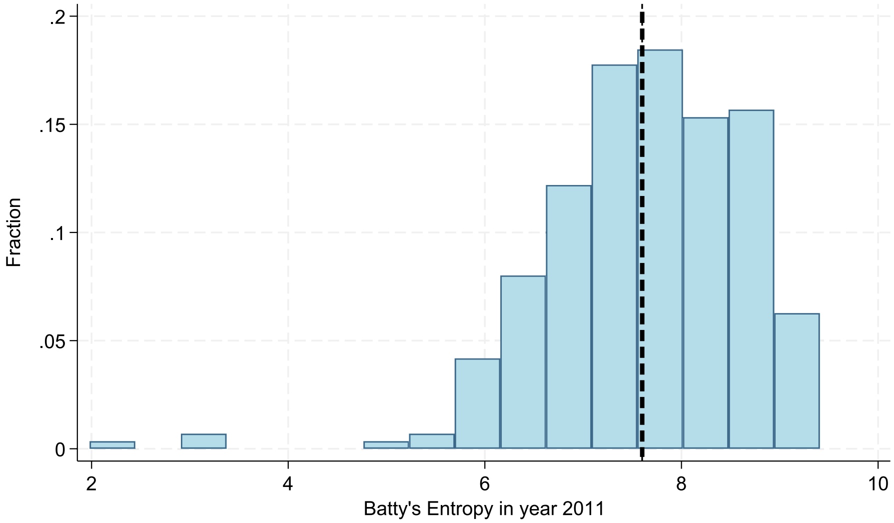

Fig. 4 Distribution of Batty's spatial entropy values for mill procurement in 2011 across 288 mills; the dashed line indicates the mean entropy

Discussion

Although the estimates of annual sawlog production at the county level from the current TPO method may appear patchy and discontinuous, the estimator is design-unbiased. Over multiple survey years, the year-to-year variability tends to average out due to the random sampling design. However, in any single year, the TPO

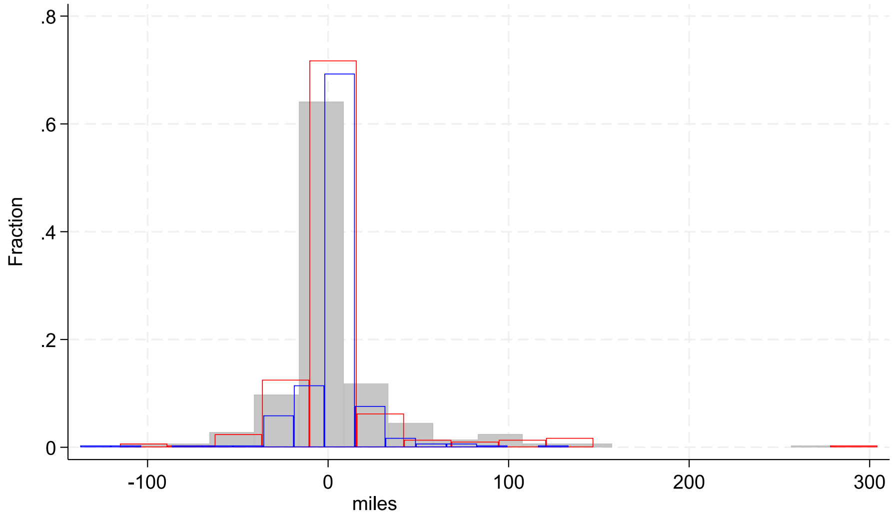

Fig. 5 Histograms of mill radius boundary differences (miles) comparing 2011–1-d (red), 2013–1-d (blue), and 2011–2-d (gray filled)

estimates can be highly volatile. This is because the TPO method assigns production volumes only to counties supplying sampled mills, while counties of supplying non-sampled mills receive no volume, resulting in many zeros and discontinuities. In contrast, the model-assisted methods (HP, RP, and HPR), incorporate auxiliary information, such as historical procurement patterns and geographic information, to predict volume contributions to counties that supplying to non-sampled mills. This allows counties supplying non-sampled mills to receive a nonzero estimate, producing a more realistic map of procurement in a single year.

The HP and RP estimators are model-based methods that use predictions from auxiliary models but omit the design-based weights in the residual expansion component. This omission reduces variance. As a result, both HP and RP estimators show lower simulation variances. However, since these estimators disregard the design weights, they are no longer design-unbiased, and their validity depends on the correctness of the working model. Our result shows a substantial reduction in simulation variances in HP and RP, implying that the model biases are negligible relative to the gain in variance reduction.

The HPR estimator was developed to restore design validity by combining model predictions with residuals expanded using design weights. This method is asymptotically design-unbiased. However, if residuals are large or highly variable, especially in small sample strata, the expansion weights amplify their effect, leading to high simulation variance. In this dataset, the HPR method shows even higher mean simulation variance than the TPO method. This instability undermines the intended efficiency gains of the model-assisted approach and suggests this method is not a reliable choice.

The primary objective with auxiliary data is to increase the precision of population estimates of county removals. The HP model is superior in prediction by taking full advantage of the model efficiency with small bias while the HPR method amplifies the residuals with the sampling weights to guarantee unbiasedness even though the bias is negligible to begin with. The design variances are lower than the simulation variances indicating that the design-based variances underestimate the observed ground truth variances. One contributor to this underestimation is the presence of strata that contain only one or two sampled mills, leading to zero or underestimated within-stratum sample variances.

The high RMSE observed in counties with high sawlog removal volumes is expected across all methods due to the high volumes in these regions; southwest AR, eastern MS, western AL, and the coastal Atlantic of NC, SC, FL, where larger

Table 4 Pairwise Pearson's correlation matrix of mill radius boundary differences: 2011–1-canvass difference (2011–1-d), 2013–1-canvass difference (2013–1-d), and 2011–2-canvass difference (2011–2-d)

	2011–1-d	2013–1-d	2011–2-d
2011–1-d	1		
2013–1-d	−0.279	1	
2011–2-d	0.8297	0.3045	1

volumes naturally lead to larger absolute errors. However, the current TPO method also exhibits high RMSE in counties with low sawlog removals, particularly in the Piedmont Plateau. As noted by Coulston et al. (2018), counties with lower harvesting activities, fewer mills, or limited roundwood removal tend to have greater inaccuracies. The two proposed alternative methods for estimating county sawlog removal demonstrate improvements over the current method in counties with high errors. The HP method demonstrates better alignment with measured removal patterns by incorporating past procurement data, making it particularly effective in regions with high variation or low harvest removals. The RP method improves accuracy by using spatial proximity to estimate roundwood distribution, which helps mitigate errors in underreported areas.

The HP method can be used when data on roundwood volumes sourced by mills are available. Applying the RP method would also improve the accuracy of the estimation, especially if information on mill procurement radii is provided by mills. As seen in the Northern TPO survey, the procurement radius question shows a relatively high response rate (Markowski-Lindsay et al. 2023). County procurement allocation within the procurement radius has been explored in other research areas, such as roundwood supply competition and sustainability (i.e., Parajuli et al. 2021; Gc et al. 2023). Mill procurement radius could be derived from regional or cluster models. For example, Brown (2015) developed models to derive procurement radii from mill total receipts and number of employees in GA primary mills. Our results demonstrate that county roundwood estimation can be efficiently improved with mill procurement information. The inclusion of spatial information generally could also help enhance precision in the county roundwood estimates.

The sensitivity analysis revealed that a reduction in MOS correlation would decrease the precision of roundwood estimation because the design approaches a simple random sampling, where no correlation exists in the selection process. A reduction in correlation from 0.9 to 0.6 leads to a 30% increase in RMSE for the TPO and HP methods with an even greater impact on the RP method. This suggests that the RP method is sensitive to high within-strata variance. The RMSE in the TPO method aligns with the findings in Coulston et al. (2018), which constructed strata using a 0.85 MOS-mill receipt correlation and denoted that MOS within 25% of mill receipts would reduce RMSE by 30%. Using 2011 mill receipts as MOS in estimating county sawlog volumes over longer temporal periods results in less precise performance for both the TPO and RP methods due to the reduced effectiveness of MOS in stratification. Mills in the same stratum with similar roundwood receipts in 2011 can have disparate roundwood receipts in 2015 and 2017 compared with roundwood receipts in 2013. The HP method is the most sensitive in longer temporal periods due to compounding errors in both stratification and allocation of county volume proportion processes.

The most recent mill-county procurement data could be from too far back in time and have high variability in procurement dynamics. Spatial entropy analysis reveals that most mills are not highly concentrated spatially. The mean value of Batty's entropy is approximately 70% of the theoretical maximum, indicating that procurement patterns are moderately diversified, either across the sourcing area or evenly in share among counties. Mills with higher entropy are more likely to exhibit stable sourcing boundaries and have less volatile year-to-year allocation patterns. This reflects a diversification effect. When a mill sources from many counties, the impact of a supply disruption is diluted. High entropy may signal greater resilience and procurement stability over time.

The mill procurement boundary was analyzed to capture the temporal dynamics in procurement patterns. The distribution of the change in mill boundaries is clustered and centered at zero with a few events where large deviations occur as outliers. The two-period difference has a strong correlation with the first one-period difference but is weakly correlated with the second one-period difference, indicating a short-term persistence behavior. The change in mill procurement radius over longer temporal scale is more strongly associated with the short-term change. The weak negative correlation between the 2 one-period differences suggests the deviation tends to reverse or indicating a mean-reverting process. In other words, when the boundary expands in one period, there is a small likelihood that it will contract in the following period. Additionally, without evidence of lag dependence, the change in mill boundaries could not be predicted. The mill boundary depends heavily on its previous value; consequently, using the most recent mill-county procurement is the most rational approach. However, as the temporal gap between the procurement data and the estimation period increases, estimation errors are likely to rise.

The application of the HP method to TPO southern US data is feasible due to the availability of historical procurement data in the database. However, it is important to recognize that a model effective in one region may not perform well in others as mill procurement practices and forest structures vary significantly across regions. Establishing a consistent methodology is crucial for broader applicability. In this study, the RP method serves as a preliminary exploration of using mill location information in comparison to the existing TPO method, and we found that it enhances accuracy in high-error counties, suggesting that the inclusion of spatial procurement information is a promising direction for improving county-level estimation accuracy. The RP method is relatively straightforward to implement, relying on procurement radius that may be influenced by factors such as mill capacity, forest inventory volume, road networks, or timber prices. Note that the 25-mile woodshed radius is measured from a mill to the county centroids, while the boundary distance is measured from a mill to the farthest point of procurement county polygons. In our study, the average mill boundary distance based on 288 mills is 70 miles, although it varies by sub-region. For comparison, a study conducted in the northern states found that the average boundary radius was 37 miles (Anderson and Germain 2007), while a study in the Western states reported it as 60 miles (Affleck and Gaines 2024). Understanding these regional differences in the procurement radius is important, as they reflect the underlying variation in forest structure, timber markets and mill density. Further analysis can explore these differences, underlying factors, and their implications in roundwood removal estimation.

Conclusion and Recommendation

To enhance the precision of county-level roundwood estimates, the TPO program can utilize this study as a framework to evaluate future alternative approaches. Our analysis indicates that incorporating historical mill-county procurement data significantly improves the accuracy of county roundwood production estimates. However, the accuracy of this method is contingent upon the recency and reliability of the procurement data, highlighting the importance of using the most up-to-date information available. As the TPO program continues with its current sampling approach, historical procurement data will become increasingly outdated since not every mill is sampled annually. The availability of recent procurement data for any given mill depends on whether that mill has been selected for sampling in recent cycles. This creates a potential degradation in data quality over time: some mills may only have procurement data that is several years old, while others may lack recent data entirely. In this study, we did not account for several non-sampling errors, such as mill nonresponse and incomplete coverage due to mills closing or newly emerging, which may further affect the quality and representativeness of historical auxiliary data in practice. Model-based estimators are efficient if the model is correctly specified but can be severely biased if the model is misspecified or if underlying assumptions become invalid due to outdated auxiliary data.

Future work could explore strategies to mitigate the risks associated with model misspecification, such as pooling multiple historical canvasses to stabilize procurement proportions, developing nonresponse adjustments for mills missing historical data, or blending historical procurement with other auxiliary sources (e.g., forest inventory, ownership, or transportation networks) within a model-assisted or calibration framework. Further investigation into current patterns of historical procurement is recommended to assess its applicability across the entire southern region. Additionally, further analysis is needed to explore the impact of historical procurement under varying levels of mill sampling probabilities, particularly for mills with low inclusion probabilities.

Incorporating county allocation factors within procurement boundaries could also improve the accuracy of roundwood estimates. It allows us to quantify timber sourcing from each county within the mill's procurement radius, rather than uniformly distributing the total volume across the entire procurement area. The refined methods can help our understanding of driving forces behind timber sourcing and identifying areas at risk of resource depletion, which is critical for forest resource planning and monitoring programs. Given that the TPO program provides annual timber product removal data to support market demand analyses and policy evaluations, enhancing the accuracy of county-level sawlog estimates is important to deepen the understanding of the forest sector and improve strategic decision-making.

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Data availability Mill location data is available through National Resource Use Monitoring (NRUM) program Toolkit which can be found at https://research.fs.usda.gov/products/dataandtools/timber-products-output-tpo-one-click-factsheets. However, individual mill information is held strictly confidential with only industry data summarized at county and state levels.

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