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Annual Monitoring of US Timber Production: Rationale and Design

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Understanding roundwood production in the United States at fine spatial and temporal scales is needed to support a range of analyses for decision making. Currently, estimates of county-level roundwood production are available at various time intervals for different regions of the country and for different products. Here we present our reasoning for moving to an annual timber products monitoring program and further present a comparison of sample designs to facilitate an annual program without increased effort. We found that both probability proportional to size and stratified simple random sampling designs were viable options, but the stratified simple random sampling design provided more flexibility. This flexibility was deemed important to target emerging markets and to enable sampling with certainty of specific firms. Our results lay the foundations for moving to an annual timber products output monitoring design in support of market, sustainability, and policy analyses as well as projections.

Keywords: Industrial roundwood, forest sector, sampling, sustainability

Wood product markets affect forest sector jobs (Hodges et al. 2012, Woodall et al. 2012, Sorenson et al. 2016), shape the composition and structure of future forests (Wear et al. 2016), and are strong drivers of investments in forest management (FAO 2009). Monitoring timber products output (TPO) is key to understanding the current utilization of raw material (industrial roundwood; see Table 1 for background) to support these markets. In the United States, TPO monitoring has been a constituent program within the USDA Forest Service, Forest Inventory and Analysis program (FIA) since 1948. The goal of this effort is to estimate the amount of roundwood removed by product at the county and state level along with the cross-regional movement of industrial roundwood (Bentley and Johnson 2011). Estimates from the TPO program have provided the essential foundation for US timber market analyses and projections (e.g., Adams and Haynes 1996, Buongiorno 1996, McCarl et al. 2000, Abt et al. 2009, Ince et al. 2011), sustainability analyses (e.g., Wear and Greis 2002, USDA Forest Service 2012, Wear and Greis 2013, Shifley and Moser 2016), policy analysis (Boyd and Hyde 1989, Haynes 2003, Wear and Coulston 2015), and local wood basket analysis of potential market expansion. The usefulness of any timber market analysis, forest sustainability assessment, and ultimately any policy analysis in the forest sector is constrained by the quality and precision of these essential data.

The objective of this article is to describe a new approach to TPO data collection and estimation that is efficient in supporting timber market and forest assessment work. There are several alternative sample-based and remote sensing-based approaches that capture some information related to timber product removals from forests but would be inadequate for obtaining information on industrial roundwood by product. For example, remote sensing approaches or FIA inventory approaches can be used to estimate the area of harvesting (Coulston et al. 2015, Moisen et al. 2016) but not the output of specific products. Remote sensing can provide more

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Table 1. Terminology used in timber products output monitoring.

Term	Definition
Bioenergy/fuelwood	Roundwood products and mill residue byproducts used to produce some form of energy (heat, steam, etc.) in residential, industrial, or institutional settings
Byproducts	Primary wood products, e.g., pulp chips, animal bedding, and fuelwood, recycled material from mill residues
Composite panels	Roundwood products manufactured into chips, wafers, strands, flakes, shavings, or sawdust and then reconstituted into a variety of panel and engineered lumber products
Industrial roundwood products	Any primary use of the main stem of a tree, such as sawlogs, pulpwood, and veneer logs, intended to be processed into primary wood products such as lumber, wood pulp, or sheathing, at primary wood-using mills
Post, poles, pilings	Roundwood products milled (cut or peeled) into standard sizes (lengths and circumferences) to be put in the ground to provide vertical and lateral support in buildings, foundations, utility lines, and fences. May also include nonindustrial (unmilled) products.
Pulpwood	A roundwood product that will be reduced to individual wood fibers by chemical or mechanical means. The fibers are used to make a broad generic group of pulp products that includes paper products, as well as fiberboard, insulating board, and paperboard.
Sawlog	A roundwood product, usually 8 feet in length or longer, processed into a variety of sawn products such as lumber, cants, pallets, railroad ties, and timbers
Veneer log	A roundwood product either rotary cut, sliced, stamped, or sawn into a variety of veneer products such as plywood, finished panels, veneer sheets, or sheathing

precise estimates of the timing of harvest than estimates from the FIA inventory but cannot provide estimates of volume by product. FIA inventory data can be used to estimate average annual removal volumes over a 5-, 7-, or 10-year period (Coulston et al. 2015) but not for a single year and product—FIA field plot data can only provide removal estimates by tree species and size, which provides limited insights into actual uses. Because estimates of actual product use cannot be constructed from harvests estimated by traditional inventory or remote sensing approaches, an auxiliary approach is needed to define TPO flows.

TPO monitoring by the US Forest Service began in 1948 as part of the FIA program (Bentley and Johnson 2011) in response to timber supply concerns following WWII, and information from TPO provided estimates of removals to complement the first forest inventories. Methodologies have evolved over time, and the current approach relies on a census of all primary wood using mills/facilities. Primary wood using facilities, defined as mills that process roundwood in log form, bolt form, or as chipped roundwood (Bentley and Johnson 2011), receive a questionnaire focused on obtaining volumes by product (e.g., sawlog, pulpwood, veneer logs, poles, and logs used for composite board products) and species group (e.g., hardwood, softwood) received by the mill and its county of origin. The implementation of the TPO census varies by product class and region. Because of their size and small number, pulp mills are currently canvassed every year. The remaining mills are canvassed on a periodic basis with different regional frequencies. The South has a 2-year frequency, the North has a 3–5-year frequency, and the West has a 5–7-year frequency. This variable frequency creates complications and limits the precision and regional consistency of estimates of US product use. Nonresponse is also an issue with a census-based approach. Current response rates in the South ranged from approximately 60% to 100% depending on state. Conducting a census does not always result in a response for each mill, which means the census estimates have non-quantifiable error.

Rapid technological change in forest products, dynamic housing cycles, and increasing demand for mill residues increases the need for timely, spatially explicit mill consumption data. Emerging and hidden demands as well as market shifts cause spatial and temporal changes in timber product mixes. In the past 25 years, for example, oriented strand board has largely displaced the market share of plywood. Over the same time period, input demands have declined, and species mixes in the paper sector have shifted, while lumber output has strongly shifted from West Coast to southern species in response to harvesting policy shifts on public forests. Wood-based bioenergy is an emergent industry partially driven by the export of wood pellets from the eastern United States. There is a need to monitor timber products at fine temporal and spatial scales to quantify trends and changes in markets and the resulting effects on forest composition and structure.

Current approaches to constructing TPO estimates are based on a census and implemented at variable frequencies across the nation. This limits our capacity for timely and accurate market and forest assessments in the United States. Further, there is a need to integrate TPO information with harvest/removal information from the FIA inventory so that volume of wood removed from forests and delivered to mills can be reconciled. This is particularly important because growth, removals, and mortality estimates from the FIA inventory are lagged by a minimum of 5 years under a 5-panel design based on the midpoint of the remeasurement period. For example, suppose there is a time 1 measurement of the FIA panel design available for 2006–2010 and a time 2 measurement of the complete panel design available from 2011 to 2015 (Table 2). Under a linear trend, the approximate year that average annual removal estimates represent is circa 2010–2011 (Van Deusen 2002). Given a coordinated sample design, TPO monitoring can provide up-to-date estimates of forest inventory removals and product usage and greatly

Management and Policy Implications

Monitoring timber production in a timely and consistent fashion across the United States is essential to understanding how forests support wood product markets, the sustainability of the resource, and the potential impacts of emerging markets. Consistent monitoring is needed from the county scale to the national scale. Here we present the rationale and a statistical design for timber production monitoring on an annual time-step. Estimates arising from the proposed design are expected to more effectively and consistently inform US timber market analyses and projections, sustainability, policy, and local wood basket analysis of potential market expansion.

Table 2. Schematic of FIA rotating panel design under a five-panel inventory system. Time 1 measurement is denoted by the light gray shading. Time 2 measurement denoted by dark gray shading. The x's denote the measurement year of each panel.

	Panel				
Year	A	B	C	D	E
2006	x				
2007		x			
2008			x		
2009				x	
2010					x
2011	x				
2012		x			
2013			x		
2014				x	
2015					x

enhance the value of the national FIA inventory. In the remainder of this article, we describe annual TPO monitoring methods designed to provide annual estimates (and standard errors) of timber product outputs in the United States.

Techniques to Move to an Annual TPO Program

As noted earlier, the goal of the TPO program is to provide estimates of roundwood removal by product, species group, and source location. These data are procured from each mill. This is accomplished either directly from individual mill questionnaires or in some cases through a single contact within the corporate structure of companies that own numerous mills. Data for each mill is collected for each source location (county) from which they draw wood. For example, a sawmill in state 1 may respond to the questionnaire that they consumed 300,000 cubic feet of hardwood sawlogs. They further report that the source location of this roundwood was 20% from county A in state 1, 60% from county B in state 1, 15% from county C in state 1, and 5% from county D in state 2. When these types of data are collected from all mills, the total production of county A in state 1 (for example) can be estimated as the sum of each mill's consumption that came from county A in state 1. In the work presented here, per county estimates of production and per state estimates of production are considered domains. Further, estimates can also be created for an individual product (e.g., sawlogs). Other ancillary data are also collected from mills such as information on residues and byproducts. However, the primary goal of the TPO program is to estimate roundwood removals at county and aggregate (e.g., multi-county woodshed, state) scales, and thus the focus of this manuscript is also to this end.

One approach for an annual TPO program is to shift from the periodic census to an annual census of primary wood-using facilities. However, this assumes that an up-to-date mill list is available, resources are available to conduct the census, and all mills will respond. Sample-based approaches are a clear alternative to a complete census and can provide reduced cost, greater speed, greater scope, and quantifiable precision (Cochran 1977). Non-response is an issue to be considered in any survey. A census with non-response leads to a sample without a design, which affects quantifying precision, whereas sample-based approaches allow the practitioner to appropriately adjust for non-response using design-compatible methods. Some initial sample designs for estimating mill receipts at the state level are presented and discussed by Brown and Oderwald (2012). The focus here differs from the work by Brown and Oderwald (2012) because our interest is in estimating production at the county and state level rather than mill receipts at the state level. In this paper, we consider a sample design to include both a sample selection process and estimation process as suggested by Kish (1995).

Potential TPO sample designs and a census assume a finite population of mills, which can be enumerated to construct the sampling frame. There are several national mill lists available for the United States. These include the TPO mill list maintained by FIA, the University of Georgia Center for Forest Business Forest Industry Shapefiles (UGA 2016), and others such as the Wood$_2$Energy list (https://www.wood2energy.org/). These lists may also contain information such as primary product, production capacity, and number of employees, which facilitates using stratified and probability proportional to size sampling designs. The potential for frame error will depend on the source, the update frequency, and the completeness of each list with respect to the target population (primary wood-using facilities that use roundwood from the United States).

Cochran (1977) suggests that a sample-based approach provides the opportunity for surveyors to focus on collecting high-quality data because of a reduced workload. However, there are other relevant approaches to ensure that high-quality data are collected. Modern forest industry firms, particularly larger corporations, maintain electronic databases that likely contain sufficient information needed for the TPO survey. Working with this cohort of forest industry firms to develop automated data transfer approaches would also ensure that high-quality data are collected and allow surveyors to focus on mills that do not maintain databases or choose to fill out the traditional survey.

Sample Designs: Methods

Two applicable sample designs for TPO monitoring are stratified random sampling (STSI) and probability proportional to size sampling (PPS). Our particular implementation of PPS sampling follows the Tille method (Tille 1996). Each of these techniques requires the mill list (sampling frame) to have some measure of size (MOS) available. We also employ a simple random sample (SI) for reference. Our goal was to test flexible and operationally feasible sample designs and understand their statistical properties. To accomplish this goal, we base our analysis on the 2011 TPO canvass for the southeastern United States (Figure 1). There were N=1363 mills in the test data. We only considered the portion of these mill's receipts within our study area as roundwood production. A summary of mill receipts, state roundwood production, and county roundwood production summary statistics are presented in Table 3. For testing purposes, we consider these data to represent the "true" population and sample the true population in a Monte Carlo setting to assess mean square error (MSE) and bias.

Estimators and Sample Selection

Here we use the π estimator as described by Särndal et al. (1992) for simple random sample (SI), stratified simple random sample (STSI), and probability proportional to size (PPS) designs. We selected this approach for compactness and because our primary interest is in domain estimates. That is, we sample mills based on a sample selection process (e.g., SI), but we are generally interested in estimating per-county and per-state production in total and by timber product. These are domain estimates, and the use of the π estimator allows for a rather simple extension for estimating domain totals. The calculation of inclusion probabilities for SI, STSI, and PPS, as discussed in the subsequent paragraphs, allows us to present a single estimator. Under the π estimator, the estimate of the population total $\hat{Y}$, is:

$$\hat{Y} = \sum_{s} \frac{y_k}{\pi_k}$$

where s is the sample of k=l=1 to n mills, y_k is the observed value for mill receipts from mill k, and π_k is the first-order inclusion probability for mill k. The estimated variance of $\hat{Y}$ is:

$$\widehat{V(\hat{Y})} = \sum\sum_{s} \breve{\Delta}_{kl}\,\tilde{y}_k\,\tilde{y}_l = \sum_{k\in s} \breve{\Delta}_{kk}\,\tilde{y}_k\,\tilde{y}_k + \sum_{\substack{k\in s \\ k\neq l}}\sum_{\substack{l\in s \\ k\neq l}} \breve{\Delta}_{kl}\,\tilde{y}_k\,\tilde{y}_l$$

where $\breve{y}_k = y_k/\pi_k$, $\breve{y}_l = y_l/\pi_l$, and $\breve{\Delta}_{kl} = \Delta_{kl}/\pi_{kl}$ where π_{kl} are the second-order inclusion probabilities for mills k and l and $\Delta_{kl} = \pi_{kl} - \pi_k\,\pi_l$. The estimate of a domain (d) total ($\widehat{Y_d}$) and the estimated variance of $\widehat{Y_d}$, ($\widehat{V(\widehat{Y_d})}$), are

$$\widehat{Y_d} = \sum_{sd} \frac{y_{kd}}{\pi_{kd}} \text{ and } \widehat{V(\widehat{Y_d})} = \sum\sum_{sd} \breve{\Delta}_{kld}\,\widetilde{Y_{kd}}\,\widetilde{Y_{ld}}, \text{ respectively}$$

Under the SI, STSI, and PPS designs, each element in the population can be given a probability of inclusion in the sample. The three sample selection approaches (SI, STSI, PPS) use different methods to determine the inclusion probability. The simplest example is the SI approach, where $\pi_k = n/N$, where N is the population size. The second-order inclusion probability under SI is $\pi_{kl} = n(n\text{-}1)/N(N\text{-}1)$. Under our implementation both the STSI and PPS approaches required a MOS (x) for each element in N. For STSI, x is used to form H = 1,…,h strata, which are to be sampled at a specified n_h. A further description of strata construction for two STSI designs is provided in the subsequent paragraphs, but for each stratum h, $\pi_{hk} = n_h/N_h$ and $\pi_{hkl} = n_h(n_h\text{-}1)/N_h(N_h\text{-}1)$, which leads to an SI sample within strata. For PPS, x is used to calculate inclusion probabilities proportional to x and the sample is drawn using an elimination method developed by Tille (1996). With PPS, one calculates π_k proportional to x by (1) calculating $n{\cdot}x_k/\sum x$ for each of the N elements in the population, and (2) for any $\pi_k > 1$ the value π_k is set to one. Steps (1) and (2) are repeated based on the remaining elements ($\pi_k < 1$) until all values of π_k are in [>0,1]. The elimination procedure is an N-n step process where one element is removed at each step until the desired sample size is obtained (Table 4 illustrates the inclusion probabilities based on an MOS for a small example). We point the interested reader to Tille (1996) for further details on this method, including the calculation of second-order inclusion probabilities. Our implementation of this method was performed using the R (R Core Team, 2015) Sampling package (Tille and Matei 2015).

For the work presented here, the MOS was modeled mill receipts (x). This measure was developed using simple linear regression based on the number of employees at each mill to predict receipts. This model was constructed for the sole purpose of constructing strata based on volumes rather than number of employees. The efficiency of the STSI and PPS designs is based on the correlation between the x and the variables for which estimates are needed. The correlation between x and actual mill receipts was ρ~0.85 based on the 2011 TPO data (Figure 2), which was approximately the same as the correlation between the number of employees and mill receipts.

Two different stratification approaches were examined. The first approach (STSI) was based on creating many approximately equal-sized strata of MOS. The second approach (STSI_{DH}) followed Brown and Oderwald (2012), where the cumulative square-root frequency method (Dalenius and Hodges 1959) was used to define strata boundaries based on the MOS and Neyman allocation was used to allocate the sample.

Strata for STSI were developed by first creating a sampled-with-certainty strata and then by creating approximately equal strata sizes in terms of cumulative modeled mill receipts (x) by product. This stratification approach approximates a PPS approach. Each mill with x> 10 million cubic feet per year was in its own stratum (N_h=n_h=1) and therefore was sampled with certainty (141 mills). We denote the sample size of this portion of the sample as n_c. The number of remaining elements in the sample are the n_u and n=n_c+n_u. For the remaining mills, we developed the strata based on

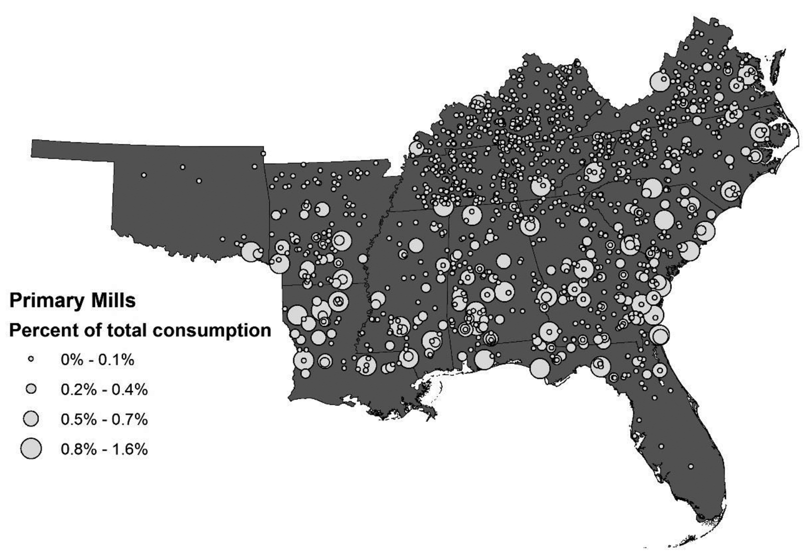

Figure 1. The percent of regional roundwood consumption of primary mills in the 12-state study area of the southeastern United States.

the x and primary product. To construct the strata for each primary product: (i) place x in descending order = dx. (ii) Calculate the target strata size as $t=2 \cdot \sum x / n_u$. (iii) Cumulate dx until the size >=t. This denotes the boundary of the first stratum. Starting at the next element in dx after the stratum boundary, repeat (iii) to identify the next stratum boundary and repeat until the end of dx is reached. Two elements are then randomly selected without replacement from each stratum. Table 4 illustrates STSI stratum boundaries and the inclusion probabilities based on an MOS for a small example when no certainty strata are used.

The $STSI_{DH}$ approach was a three-step process to (1) determine number of strata to use, (2) determine strata boundaries, and (3) allocate the sample. We created a single sampled-with-certainty stratum for the 141 mills with x>10 million cubic feet of mill receipts per year. As suggested by Brown and Oderwald (2012), we used hierarchical clustering to identify the number of clusters for the remaining mills. This technique relies on the similarity among items (mills) to form relatively homogeneous groups. We used the Ward's (1963) clustering algorithm to form the clusters based on the number of employees and consumption of each mill. Both the number of employees and mill consumption were standardized to a mean of zero with unit variance for this analysis. We used the cubic clustering criterion (CCC) (Sarle 1983) and the pseudo t^2 (Duda and Hart 1973) to determine the number of clusters (H). We calculated the bin size (b) as the min(H·15, u), where u is the number of unique values of x as suggested by Rivest and Baillargeon (2017). The frequency in each bin was then found and the square root of the frequency ($\sqrt{f}$) was calculated. Next, the cumulative sum of $\sqrt{f}$ was calculated. The approximate strata break points were calculated as $sb=\sum\sqrt{f} / H$. Final stratum boundaries are found by selecting the bins where the cumulative frequency is closest to $1 \cdot sb$, $2 \cdot sb$,,,$(H-1) \cdot sb$. The sample size for each stratum was then calculated via Neyman allocation, where $n_h=n(N_h S_h)/[\sum(N_h S_h)]$, where S_h is the standard deviation of the x within strata h. Table 4 illustrates $STSI_{DH}$ stratum boundaries and the inclusion probabilities based on an MOS for a small example.

Table 3. Summary statistics of population mill receipts, state production, and county production.

Variable	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
	(million cubic feet)					
Mill receipts	0.00	0.16	0.64	4.93	2.15	105.50
County production	0.00	1.14	3.91	6.82	10.01	57.14
State production	72.02	365.20	559.60	551.70	667.70	1,218.00

Monte Carlo Analysis

We performed a Monte Carlo analysis to quantify the empirical MSE, empirical bias, and the empirical variance of the estimate under three sampling intensities. This approach allowed us to approximate the true error of domain estimates arising from each sampling design at three different sampling intensities. We tested sampling intensities of 15%, 25%, and 50%. We selected these sampling intensities because they would allow for an annual sampling effort without increasing the surveyor's effort, as defined by the average number of mills contacted per year, under a 6–7-year, 4–5-year, and 2-year periodic survey, respectively. For each sampling intensity and sample design, the Monte Carlo analyses proceeded as follows: (1) Draw a sample of size n from the population. (2) Construct domain estimates (i.e., estimate the total product output and total by product for each individual county and each individual state). (3) Repeat (1) and (2) R=5000 times. In this manner, there was a distribution of 5000 point estimates for each timber product (e.g., pulpwood, sawlogs, poles, and total product) for each of the 971 counties and 12 states in the study area.

The empirical MSE for each sample design (PPS, SI, STSI, $STSI_{DH}$) for each domain was

$$MSE_d = \frac{\sum_{r=1}^{R}\left(\hat{Y}_d - Y_d\right)^2}{R}.$$

where Y_d was the true total for the domain of interest. The empirical bias was

$$bias_d = \frac{\sum_{r=1}^{R}\left(\hat{Y}_d - Y_d\right)}{R}.$$

Table 4. Example inclusion probabilities and sample selection for the SI, PPS, STSI, and $STSI_{DH}$ designs for a sample of n=6 from a population of N=16. The stratum boundaries for the STSI and $STSI_{DH}$ are denoted by the gray and white shadings. Under the STSI design, each stratum is approximately 27 units of MOS. The $STSI_{DH}$ design was implemented with H=2 strata and bin size of 6, and the sample was allocated via Neyman allocation. The selected samples are denoted by the bold font under each design.

	PPS	STSI		STSIDH		SI
Measure of Size	Inclusion Probability	Stratum	Inclusion Probability	Stratum	Inclusion Probability	Inclusion Probability
10	**0.73**	1	**0.67**	1	**0.40**	0.38
9	**0.66**	1	**0.67**	1	0.40	**0.38**
9	0.66	1	0.67	1	0.40	0.38
8	**0.59**	2	0.40	1	**0.40**	0.38
7	0.51	2	**0.40**	1	0.40	**0.38**
5	0.37	2	0.40	2	0.36	**0.38**
5	0.37	2	0.40	2	**0.36**	0.38
4	**0.29**	2	**0.40**	2	0.36	0.38
4	**0.29**	3	**0.25**	2	0.36	**0.38**
3	0.22	3	0.25	2	**0.36**	0.38
3	0.22	3	0.25	2	**0.36**	**0.38**
3	0.22	3	0.25	2	0.36	0.38
3	**0.22**	3	0.25	2	0.36	0.38
3	0.22	3	0.25	2	0.36	0.38
3	0.22	3	0.25	2	**0.36**	0.38
3	0.22	3	**0.25**	2	0.36	**0.38**

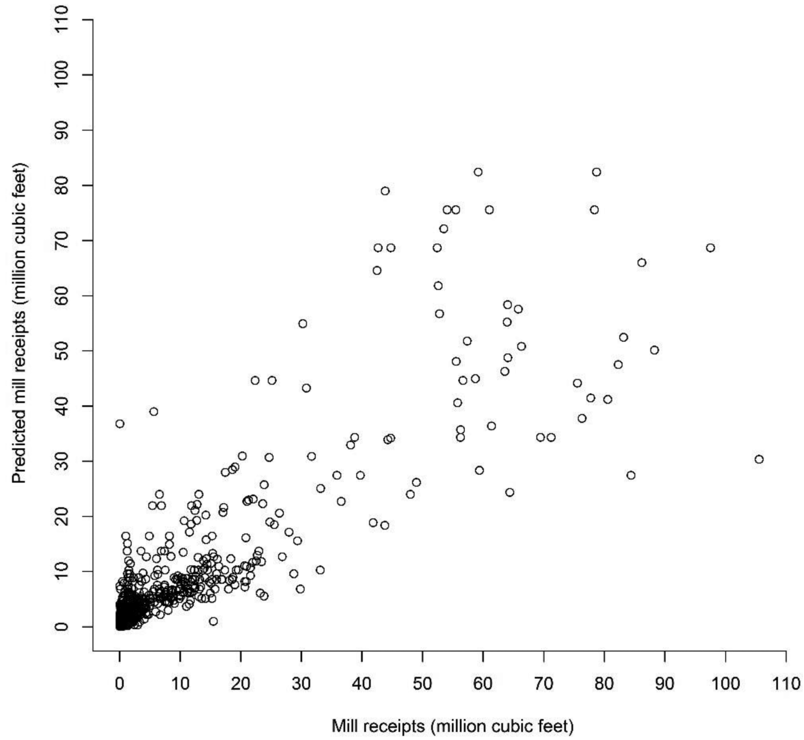

Figure 2. Relationship between modeled mill receipts and actual mill receipts (million cubic feet).

The suggested empirical variance of the estimate (VE_d) was

$$VE_d = MSE_d - bias_d^{\,2}.$$

Sample Designs: Results

We tested two different stratified designs, STSI and $\mathrm{STSI_{DH}}$. For the STSI design, the number of strata depended on the sample size because, with the exception of the sampled-with-certainty strata, two units per strata were sampled. This resulted in 432 strata under *sf*=0.5, 243 strata under *sf*=0.25, and 176 strata under *sf*=0.15. The number of strata for the $\mathrm{STSI_{DH}}$ design was based on a hierarchical cluster analysis, as suggested by Brown and Oderwald (2012). We extended this approach to include a sampled-with-certainty stratum (x>10 million cubic feet). Mills that were not included in the certainty stratum were used for the cluster analysis to determine the number of strata. We identified the significant groupings by examining when the pseudo t^2 index was less than the pseudo t^2 critical value. We then examined the CCC index for this subset of grouping. This resulted in selecting the 12-cluster solution, and 13 strata (12 strata from cluster analysis and one sampled-with-certainty strata) were subsequently used for the $\mathrm{STSI_{DH}}$ design.

To compare the results, we examined quantiles of RMSE=$MSE^{0.5}$ at the county level, state level, by product, sample design, and sampling fraction. We note that our approach is different than estimating the variance for quantiles and other order statistics. The PPS, STSI, and $\mathrm{STSI_{DH}}$ designs performed similarly in terms of total roundwood production and outperformed the SI design (Tables 5 and 6). In terms of RMSE, the county-level precision was similar for the $\mathrm{STSI_{DH}}$, STSI, and PPS designs across the 5000 Monte Carlo replications and sampling fractions (Table 5). For example, at the 0.25 sampling fraction the first quartile of RMSE was 0.6 million cubic feet for the PPS, STSI, and $\mathrm{STSI_{DH}}$ designs. The third quartile was 2.1, 2.2, and 2.2 million cubic feet for PPS, STSI, and $\mathrm{STSI_{DH}}$, respectively. However, the PPS design had notably smaller RMSE than the STSI design at the state level across sampling fractions (Table 5). The PPS also had lower median, mean, 3rd quantile, and maximum RMSEs than the $\mathrm{STSI_{DH}}$ design. For example, the median state-level RMSE was 72.9, 98.5, and 93 million cubic feet for the PPS, STSI, and $\mathrm{STSI_{DH}}$ designs, respectively, under a 0.15 sampling fraction. Because the SI design was predominantly included to provide context for STSI, $\mathrm{STSI_{DH}}$, and PPS design, we only report results for estimating total product output using the SI design where on average the SI had a 3–12-fold increase in RMSE.

We also examined the RMSE for certain products for the PPS, STSI, and $\mathrm{STSI_{DH}}$ designs. RMSE was relatively consistent between STSI, PPS, and $\mathrm{STSI_{DH}}$ designs across sampling fractions for sawlogs for county-level estimates (Table 5). The maximum county RMSE was an exception where the PPS design tended to have smaller maximum RMSE than both the STSI or $\mathrm{STSI_{DH}}$ designs and the STSI design tended to have a smaller maximum RMSE than the $\mathrm{STSI_{DH}}$ design. At the state level, for sawlogs, the STSI design had consistently smaller RMSE than the PPS or $\mathrm{STSI_{DH}}$ design (Table 5).

Pulp mills use large amounts of pulpwood, and because of their size their inclusion probabilities were typically larger than for any other mill types and often were in the range of 0.9–1.0, depending on sampling fraction. However, the STSI and $\mathrm{STSI_{DH}}$ designs used a sampled-with-certainty threshold of 10 million cubic feet modeled mill capacity, which ensured that 73 of the 76 pulp mills were sampled across sampling intensities. This was different than the PPS approach where, as the sampling fraction decreased, the proportion of pulpmills sampled also decreased. This led to smaller RMSE for the STSI and $\mathrm{STSI_{DH}}$ designs (Tables 5 and 6). With respect to poles, the STSI approach generally had smaller RMSE across sampling fractions at the state level (Table 6). This was because the STSI

Table 5. Quantiles of RMSE across 971 counties under PPS, SI, STSTDH, and STSI designs at three sampling intensities for three selected products and total product.

Product	Method	Sampling Fraction	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
			(million cubic feet)					
Total	PPS	0.15	0.0	1.1	2.3	2.9	3.9	41.3
		0.25	0.0	0.6	1.2	1.5	2.1	27.3
		0.50	0.0	0.1	0.3	0.4	0.5	11.7
	SI	0.15	0.0	1.5	4.6	7.7	11.2	55.4
		0.25	0.0	1.1	3.4	5.6	8.1	40.3
		0.50	0.0	0.6	1.9	3.2	4.7	23.4
	STSI	0.15	0.0	1.1	2.5	3.4	4.4	47.1
		0.25	0.0	0.6	1.2	1.7	2.2	30.5
		0.50	0.0	0.1	0.3	0.6	0.7	8.6
	STSIDH	0.15	0.0	1.1	2.4	3.4	4.7	44.5
		0.25	0.0	0.6	1.2	1.6	2.2	25.6
		0.50	0.0	0.1	0.3	0.4	0.5	12.8
Pulpwood	PPS	0.15	0.0	0.0	0.0	0.3	0.1	5.4
		0.25	0.0	0.0	0.0	0.0	0.0	4.1
		0.50	0.0	0.0	0.0	0.0	0.0	1.9
	STSI	0.15	0.0	0.0	0.0	0.0	0.0	0.7
		0.25	0.0	0.0	0.0	0.0	0.0	0.7
		0.50	0.0	0.0	0.0	0.0	0.0	0.7
	STSIDH	0.15	0.0	0.0	0.0	0.0	0.0	4.8
		0.25	0.0	0.0	0.0	0.0	0.0	2.5
		0.50	0.0	0.0	0.0	0.0	0.0	1.3
Saw logs	PPS	0.15	0.0	1.0	2.0	2.5	3.3	21.0
		0.25	0.0	0.5	1.1	1.3	1.8	8.4
		0.50	0.0	0.1	0.2	0.3	0.5	3.3
	STSI	0.15	0.0	1.1	2.1	2.7	3.6	25.6
		0.25	0.0	0.5	1.0	1.3	1.7	10.4
		0.50	0.0	0.1	0.2	0.3	0.4	2.8
	STSIDH	0.15	0.0	1.0	2.1	2.9	3.9	33.3
		0.25	0.0	0.5	1.0	1.4	1.9	15.2
		0.50	0.0	0.1	0.2	0.3	0.5	2.9
Poles	PPS	0.15	0.0	0.1	0.2	0.6	0.6	40.7
		0.25	0.0	0.1	0.2	0.4	0.4	26.3
		0.50	0.0	0.0	0.1	0.2	0.2	11.7
	STSI	0.15	0.0	0.1	0.2	0.5	0.4	31.9
		0.25	0.0	0.1	0.1	0.4	0.3	29.9
		0.50	0.0	0.0	0.1	0.2	0.2	8.5
	STSIDH	0.15	0.0	0.1	0.3	0.7	0.6	43.9
		0.25	0.0	0.1	0.1	0.4	0.3	25.3
		0.50	0.0	0.0	0.1	0.2	0.2	12.7

design was stratified by product and MOS (x). By applying this stratification approach, minor products such as poles were ensured to be in the sample at a specified rate, which decreased RMSE. However, this purposive stratum construction for minor products likely led to some of the increase in state-level total product RMSE.

The efficiency of each design is partially related to the proportion of total mill receipts sampled. Under the SI design, each mill, regardless of size, had an equal probability of being selected in the sample, which means that the proportion of mill receipts sampled was approximately equal to the sampling fraction. This was not the case for the PPS, STSI, and STSI_{DH} designs. For example, at the 0.15 sampling fraction, the PPS, STSI, and STSI_{DH} designs sampled 0.69, 0.73, and 0.72 of the total mill receipts, respectively. At the 0.5 sampling fraction, the PPS, STSI, and STS_{DH} designs resulted in sampling 0.96, 0.93, and 0.95 of total mill receipts, respectively.

MSE was a function of the bias and the variance of the estimate. We examined the contribution of bias^2 to MSE for PPS, STSI, and STSI_{DH} designs. The contribution was defined as $100 \cdot \text{bias}^2/\text{MSE}$. For county-level domain estimates, bias^2 contributed less than 1% to overall MSE. Similarly, bias^2 typically accounted for less than 0.5% of the MSE at the state level. This suggests that the estimated variance of $\hat{Y}_d$ should reflect the MSE for a domain. However, when examining county-level domain estimates, we found that occasionally the estimated variance of $\hat{Y}_d$ was substantially lower than the MSE for the domain. This primarily occurred in counties where harvest for products was a rare event, and only one mill drew a small portion of its total roundwood receipts from that county.

Observations on Sampling Frame Error, Measures of Size, and Non-Response

Sampling frame error is an important consideration for the sample designs we tested. In our work, frame error arises when the mill list is imperfect. We expect that frame errors will likely result from both under-coverage and over-coverage of small mills. For example, if a mill has closed but remains in the sample frame, then over-coverage occurs. If a mill opens or reopens but is not included in the sample frame, then under-coverage occurs. Over-coverage has the potential to be accounted for because some of the closed mills may be selected as part of the sample. However, under-coverage is more problematic because they are completely unknown. We hypothesize that under-coverage and over-coverage will mainly be an issue for small mills because large mills are easily identified due to the typical volumes of wood they process but small mills are more difficult to

Table 6. Quantiles of RMSE across 12 states under PPS, SI, STSTDH, and STSI designs at three sampling intensities for three selected products and total product.

Product	Method	Sampling Fraction	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
			(million cubic feet)					
Total	PPS	0.15	27.9	61.4	72.9	70.7	79.3	134.3
		0.25	12.8	32.3	34.6	36.0	38.0	72.9
		0.50	2.3	6.5	9.4	9.2	10.1	22.9
	SI	0.15	49.1	186.8	277.8	266.7	360.0	472.7
		0.25	35.9	135.8	198.8	194.1	265.7	344.6
		0.50	20.6	79.4	116.0	112.6	151.6	201.4
	STSI	0.15	33.9	71.5	98.5	91.6	109.8	156.8
		0.25	16.5	37.7	49.5	47.3	56.2	82.7
		0.50	7.0	15.3	21.0	20.7	26.8	34.9
	STSIDH	0.15	43.1	82.4	93.0	90.8	101.2	155.0
		0.25	19.9	38.9	43.2	42.9	46.0	79.3
		0.50	2.3	7.0	8.7	9.5	10.2	25.6
Pulpwood	PPS	0.15	0.0	4.8	11.1	12.4	15.1	38.5
		0.25	0.0	0.0	0.0	1.5	0.0	17.8
		0.50	0.0	0.0	0.0	0.7	0.0	8.1
	STSI	0.15	0.0	0.0	0.0	0.3	0.0	3.0
		0.25	0.0	0.0	0.0	0.3	0.0	3.0
		0.50	0.0	0.0	0.0	0.3	0.0	3.0
	STSIDH	0.15	0.0	0.0	0.0	1.9	0.0	20.8
		0.25	0.0	0.0	0.0	1.0	0.0	10.9
		0.50	0.0	0.0	0.0	0.5	0.0	5.6
Saw logs	PPS	0.15	26.2	45.7	54.2	56.3	69.8	83.4
		0.25	11.3	22.2	30.2	28.4	33.2	43.9
		0.50	1.5	4.2	6.0	6.2	9.0	11.0
	STSI	0.15	32.3	48.5	55.9	59.3	70.7	91.6
		0.25	13.3	22.0	25.7	26.7	31.4	43.5
		0.50	1.2	3.7	5.9	5.6	7.8	9.0
	STSIDH	0.15	41.1	60.3	64.6	70.0	80.9	113.6
		0.25	18.9	28.4	30.2	33.0	37.6	53.2
		0.50	1.6	4.1	6.9	6.7	9.0	10.6
Poles	PPS	0.15	0.4	2.0	3.8	11.8	7.9	75.2
		0.25	0.2	1.4	2.6	7.7	5.3	48.6
		0.50	0.0	0.5	1.1	3.4	2.4	21.6
	STSI	0.15	0.1	2.3	2.9	8.6	3.9	58.3
		0.25	0.1	1.4	2.1	7.7	3.8	54.4
		0.50	0.0	0.5	1.0	2.6	2.0	15.2
	STSIDH	0.15	1.7	3.1	4.3	13.8	8.7	81.4
		0.25	0.9	1.7	2.2	7.7	4.7	46.7
		0.50	0.0	0.8	1.1	3.8	2.4	23.5

identify and track and may operate in an ephemeral nature. Under-coverage will lead to a negative bias in the estimate of the total, and over-coverage will lead to a positive bias in the estimate of a total. This is because each mill's sampled value is expanded by π_k^{-1}. For example, under SI $\pi_k^{-1}=N/n$ and when there is under-coverage, N is smaller than the true population size, resulting in sampling weights being too small. The opposite holds for over-coverage. Under the STSI design, however, frame errors depend on how strata are constructed. We constructed strata based on mill primary product and the measure of size. With this approach, frame errors in small sawmills, for example, will not affect estimates of totals for large sawmills or pulpmills. This is because each stratum has a weight of N_h/n_h and is unaffected by frame errors in other strata.

With the exception of the SI design, the sample designs tested required an MOS. As the correlation between MOS and the variable of interest decreases, these designs will approach an SI. In our example, we used modeled mill receipts as our measure of size (Figure 2). Increased precision can be achieved by using an improved MOS. For example, based on simulation, if an MOS was available that was within ±25% of mill receipts, the median RMSE for county-level total product estimates in Table 5 would be reduced by 30% across sampling fractions. The work presented here relies on mill receipts predicted from the number of employees at each mill. This approach can be improved by using a mill's previous receipts (when available) as a predictor variable. Unfortunately, previous mill receipts were not available for this analysis; however, one critical area of future research is on testing alternative MOSs to further increase precision of estimates.

Many of the recommended steps for minimizing non-response are already followed as part of the TPO program. These steps include: (1) evaluating the questionnaire to ensure that questions are understandable and follow a logical format, (2) evaluation of respondent's burden, (3) a communication plan that informs respondents of the importance of the survey, and (4) a follow-up schedule for cases of both unit and item non-response, including reminders and/or in-person visits. As Kish (1995) and Cochran (1977) suggest, sample-based approaches offer the practitioner the opportunity to focus efforts on collecting high-quality data rather than ensuring that data is collected for all units in the population. In short, this focus on collecting high-quality data allows the practitioner to conduct follow-up in-person visits to non-responders, which is one of the more effective ways to minimize non-response. With the exception of the SI design, the sample designs tested focus on collecting data from larger mills with greater probability. Anecdotally, non-response typically arises from smaller mills (e.g., small hardwood sawmills), and because the relevant designs sample these smaller mills with lower probability, the chances of non-response in the overall sample decrease. Regardless, non-response is still likely to occur.

The typical design-based approaches for non-response require an assumption regarding the distribution of the non-response and/or modeling the probability of response based on auxiliary information in order to recalibrate sampling weights. For example, under the $STSI_{DH}$ design, if the practitioner ignores the non-response (i.e., just accepts the decrease in n), then by default the non-response is assumed to occur at random within stratum (i.e., the mean of the observed sample equals the mean of the unobserved sample). This assumption, depending on the mechanism driving the non-response, may or may not be tenable. Future efforts should focus on developing a formal non-response plan and testing the applicability of various approaches for non-response.

Discussion

Our results suggest that PPS, $STSI_{DH}$, and STSI sample designs provided viable alternatives to conducting a complete census in order to achieve annual TPO monitoring. While the results in terms of RMSE and bias were similar for the approaches, their viability in a production monitoring system differ. The STSI design is more flexible and is less complicated when compared to the PPS and $STSI_{DH}$ designs. For example, the STSI approach easily allows for different characteristics among states, different approaches for emerging markets, and modification of strata under non-response. This may include the construction of specific stratum so that assumptions of missing at random are tenable. On the other hand, PPS designs require adjusting inclusion probabilities under non-response and are less purposive in terms of sampling with certainty. The $STSI_{DH}$ design offers some of the flexibility that the STSI design does but is more cumbersome and less intuitive to implement, particularly with respect to the cluster analysis to determine the number of strata. Because the STSI, $STSI_{DH}$, and PPS designs had relatively similar performance overall, but the STSI design is simpler and more flexible operationally, we recommend the STSI design for nationwide testing to support annual TPO monitoring.

In this research, we have presented the precision of the tested designs and sampling fractions in terms of RMSE for total production at the state and county levels as well as for select timber products. Clearly the precision of estimates differs with respect to the domain being estimated. The precision guidelines for the FIA program are documented in USDA Forest Service (1970). These guidelines suggest that the precision of estimates of annual timber cut should be as close as practicable to 5% sampling error per 1 billion cubic feet of annual timber cut in the east and 10% sampling error per 1 billion cubic feet of annual timber cut in the west. Our results suggest that these precision requirements could be easily met based on the sample designs tested. For example, the STSI design under the 0.5 sampling fraction produced estimates for sawlogs in South Carolina with a 1.5% sampling error given an observed total of 172 million cubic feet. In South Carolina, the sampling error rose to 11.8% for the STSI design under a 0.25 sampling fraction. However, based on the model provided by Bechtold and Patterson (2005), the 11.8% sample error per 172 million cubic translates to approximately 1.5% sampling error per billion cubic feet. This suggests that in the study area the required precision can be obtained with less than a 0.5 sampling fraction.

Alternative estimators for small domains should be tested. There are sources of ancillary data that may increase the precision of TPO domain estimates. For example, there are modeled data based on remotely sensed information that may predict the area of stand-clearing events by county (Moisen et al. 2016). However, a closer examination is warranted to understand confusion between harvesting and development (Coulston et al. 2014). There are also substantial efforts aimed at predicting harvest probabilities for each FIA inventory plot based on observed timber market information, mean annual increment, and other information that restricts harvest on some sites (USDA Forest Service 2012). Hypothetically, these predictions can be used to understand likelihood of harvest or the supply of volume that would likely be harvested under observed market prices. In either case, the predictions may be used to help increase the precision of domain estimates based on alternative estimators. These include small area estimation techniques (Rao 2015), model-assisted estimators, ratio estimators (Brown and Oderwald 2012), and synthetic estimators (Särndal et al. 1992).

The FIA program has experience with shifting from a periodic design to an annual design. From the 1930s through the 1990s, the FIA program conducted periodic timberland surveys at the state level. The frequency of these surveys was also variable among regions. However, through a set of recommendations provided by the first and second blue ribbon panels (AFPA 1998), the FIA program shifted to an annual design and extended from a timberland emphasis to a forestland focus across all ownerships. The effort to annualize the TPO survey is a similar situation. Through a number of partner and stakeholder meetings, which included representatives from the US government, state governments, non-governmental organizations, forest industry, and academia, the shift from a periodic TPO effort to an annual TPO effort was recommended. The work presented here represents the first steps in adopting these recommendations.

Future research is needed. We have noted the need for additional research on measures of size, alternative estimators, and non-response. In addition to these items, some components of the TPO program were not tested as part of this research. This includes estimates of mill residues and byproducts. Also, the forest sector is different in different parts of the country. The proposed sample design should be tested in those regions to ensure that precision guidelines can be met. When considering national application of the sampling design, a single base-level sampling intensity should be developed. However, flexibility at the state level should also be maintained so that individual states may choose to intensify their sample. These key research items should be addressed as part of shifting toward an annual sample-based timber products monitoring program.

The combination of an efficient sample design and efficient data collection protocols (e.g., electronic, automated data transfers) presents the opportunity to deliver timely annual timber product removals data. Edgar et al. (2015) demonstrated that these types of data can be collected and published within one year. A more efficient TPO effort offers several advantages. Timely annual timber product removal information allows users to place these removals within the context of economic conditions, market prices, and production of forest products. Timber product demand is also linked. For example, market shifts in demand for structural lumber influence sawmill consumption of sawlogs and hence residue availability. Reductions in sawmill residues such as sawdust and shavings affect the availability of those residues for pellet production, which can lead to substituting roundwood for residue in order to meet pellet demand. Temporally dense estimates of timber product output can capture these emerging roundwood demand shifts. Likewise, a flexible statistical design such as the stratified approach described in this paper allows for the practitioner to purposively include strata for emerging products. Further, spatially explicit estimates of actual timber product removals when combined with inventory data and land use change information allow for the exploration of the effects of land use change on roundwood availability. An annual TPO effort will increase knowledge of the forest sector and enhance our capability for both strategic and tactical analyses to not only understand markets and forest sector employment, but also understand the opportunities for forest management and how these factors will shape future forests.

Conclusions/Recommendations

Current annual estimates of timber products output are needed to inform both public and private sector decision making and analyses including market, sustainability, and policy analyses across a range of spatial scales. Under the current TPO program, only pulpmills are canvassed annually and remaining mills are canvassed at a variable frequency. While the current TPO program aims to be a complete census, there is non-response, which means the current approach is a *de facto* sample. Shifting the TPO program to an annual design will provide more timely and consistent information across spatial scales. Employing an efficient sample design offers the opportunity for this shift with little increase in data collection effort and further allows for statistical inference. We found that a stratified simple random sample offers a flexible approach to annual TPO monitoring that can be easily implemented. Further efficiencies can be realized by working with key industry partners on automated data transfer approaches, which will allow increased effort on smaller mills, which typically drive non-response rates. We recommend that the TPO program continue this line of research to shift to an annual sample design in order to provide needed up-to-date information consistently across the United States.

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