Estimating Current Forest Attributes from Paneled Inventory Data Using Plot-Level Imputation: A Study from the Pacific Northwest

Bianca N.I. Eskelson, Hailemariam Temesgen, and Tara M. Barrett

Abstract: Information on current forest condition is essential to assess and characterize resources and to support resource management and policy decisions. The 1998 Farm Bill mandates the US Forest Service to conduct annual inventories to provide annual updates of each state's forest. In annual inventories, the sample size of 1 year (panel) is only a portion of the full sample and therefore the precision of the estimations for any given year is low. To achieve higher precision, the Forest Inventory and Analysis program uses a moving average (MA), which combines the data of multiple panels, as default estimator. The MA can result in biased estimates of current conditions and alternative methods are sought. Alternatives to MA have not yet been explored in the Pacific Northwest. Data from Oregon and Washington national forests were used to examine a weighted moving average (WMA) and three imputation approaches: most similar neighbor, gradient nearest neighbor, and randomForest (RF). Using the most recent measurements of the variables of interest as ancillary variables, RF provided almost unbiased estimates that were comparable to those of the MA and WMA estimators in terms of root mean square error. FOR. SCI. 55(1):64-71.

Keywords: moving average, weighted moving average, nearest neighbor imputation, missing panels

Initiated by the Agricultural Research, Extension, and Education Reform Act of 1998 (PL 105-185), the Forest Inventory and Analysis (FIA) program of the US Forest Service has switched from periodic inventories that varied from state to state to a consistent nationwide annual inventory. A portion of the inventory of the nation's forests is now conducted annually within each state. The fraction of the plots measured annually is 10% in the western United States and 20% in the eastern United States.

The precision of the estimates of current status and changes in the forest resources using only data from the panel of plots measured in the current year has been found to be unacceptable because of the small annual sample size (Mckoberts and Hansen 1999). There have been efforts to combine data of multiple panels to achieve a higher precision. The current FIA default estimator is a moving average (MA), which is operationally convenient and requires few assumptions (Gartner and Reams 2001). The MA approach can improve the precision of the estimates by using data from the panels measured in the most recent years. However, MA reflects an average of conditions over the past 10 years rather than current forest conditions, resulting in a bias of the current year's population parameter (McRoberts 2000, Johnson et al. 2003). The MA estimates can be improved with a weighted moving average (WMA), which weighs panels that were measured more recently more heavily than those measured earlier (Roesch and Reams 1999). Other approaches to combine data from all panels include updating unmeasured panel data to the current year using growth models (Lessard et al. 2001, McRoberts 2001), time series models (Johnson et al. 2003) or mixed estimation (Van Deusen 1996, 1999, 2002, Scott et al. 1999); filling in missing panel data using tree- and plot-level imputation techniques (Gartner and Reams 2001, 2002, McRoberts 2001); or modifying the annual inventory of interpenetrating, nonoverlapping panels to an inventory system with balanced annual partial remeasurements so that estimators based on sampling with partial replacement can be used (Scott et al. 1999, Arner et al. 2004).

There is a need to develop new methods that will be included in the annual inventory system according to their performance (Reams et al. 1999). Because spatial, temporal, and forest characteristics differ within and among regions, it is unclear whether any single technique will work for all regions (Patterson and Reams 2005), and it is necessary to evaluate different methods in all regions. Studies comparing different alternatives to the MA approach for estimating current forest attributes in the Pacific Northwest (PNW) are still lacking, whereas a variety of methods have been tested in the other regions of the United States (Van Deusen 1996, 1997, 1999, 2002, Lessard et al. 2001, McRoberts 2001, Arner et al. 2004).

The imputation and modeling approaches examined by McRoberts (2001) asserted that model development requires a greater resource investment than development of an imputation procedure. As the difference in the estimation results was negligible, it is reasonable to focus on investigating and improving the imputation techniques. McRoberts

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(2001) pointed out that development of models might be facilitated as soon as the annual inventory is established for several years and provides calibration data from fixed-radius FIA plots at 5- or 10-year intervals. Unlike modeling approaches, imputation techniques require reference data at the application phase. An advantage, however, is that they update themselves when data are added or removed from the database (Sironen et al. 2003), and the reference data will increase every year after establishment of the annual inventory.

Depending on the intended use, tree- and plot-level imputation techniques differ in their predictive abilities and suitability (Gartner and Reams 2002). If diameter distributions by species are required, tree-level imputation will be necessary. Therefore, tree-level imputation may be more suitable for complex uneven-aged multispecies stands, for which detailed information in the form of tree lists is needed to describe the stand structure. Only tree-level imputation techniques allow determination of the distribution of individual tree growth and mortality, individual tree size change. and change by species and tree size classes. In a separate study. we are comparing the performance of tree-level and plot-level imputation.

The objectives of this study were to use paneled data from the PNW to estimate current forest attributes with the FIA default method and compare the MA results with estimates based only on the data from the current panel and to examine three different plot-level imputation methods to fill in values for the missing panels as well as a WMA and assess their performance against MA.

Methods

Data

The data used in this study consist of 618 plots from six national forests and were collected as part of the PNW region Current Vegetation Survey (CVS) of the US Forest Service. The plots were installed between 1993 and 1997 and remeasured in 2000. The particular national forests sampled were the Colville (28 plots), Mount Hood (Ill plots), Ochoco (82 plots), Rogue River (70 plots), Wallowa-Whitman (199 plots), and Winema (128 plots) (Table 1).

Panel data are a special case of inventory data with measurements taken at different times. To mimic a panel system with the available data the plots were assigned to the following panels: panel 1 (P1) were those measured in 1993 and 1994; panel 2 (P2) were those measured in 1995; panel 3 (P3) were those measured in 1996 and 1997; and panel 4 (P4) were a part of those measured in 2000. All plots were measured in the year 2000, but for the simulations 25% of the plots were randomly assigned to P4 and the remaining 75% of the plots belong to P1, P2, and P3 on the basis of their year of installation. This randomization resulted in P1, P2, and P3 having different sizes in each iteration. P1, P2, and P3 lack data for the national forests Rogue River, Coleville, and Winema, respectively, because no data were collected in those forests in the corresponding years (Table 1).

The basic CVS sampling unit is 1 ha in size. Five plots are installed in each sampling unit with each plot consisting of three permanent circular, nested subplots of different sizes. Which trees are measured in each of the three nested subplots depends on their diameter at breast height in cm (dbh). Max et al. (1996) provided a detailed description of the inventory. In this study only live trees with dbh of 12.7 em or larger were used. Missing heights in m (HT) were filled using height models developed in Barrett (2006). Volume and biomass equations from the US Forest Service were used to calculate gross cubic-meter volume and total gross oven-dry weight biomass (US Department of Agriculture 2000). For each plot, basal area in m^2/ha (BAl, stems per ha (SPH), volume in m^3/ha (VOL), and biomass in tons per ha (BIOT) were calculated and summarized (Table 2).

A total of 33 species were present on the plots (Table 3). The most frequently encountered species were Douglas-fir (*Pseudotsuga menziesii* [Mirb.] Franco), ponderosa pine (*Pinus ponderosa* C. Lawson), grand fir (*Abies grandis* [Douglas ex D. Don] Lindl.), lodgepole pine (*Pinus contorta* Douglas ex Louden), white fir (*Abies concolor* [Gord. & Glend.] Lindl. ex Hildebr.), and western hemlock (Tsuga heterophylla [Raf.] Sarg.), in decreasing order.

Thematic Mapper (TM) images from 2000 were extracted from the National Land Cover Database 2001 (Homer et al. 2004) and were used as ancillary data. The raw imagery bands 1-5 and band 7 (TM I, TM2, TM3, TM4, TM5, and TM7) as well as the Tasseled Cap (TC) transformations of the six axes (TC 1-TC6) were used. The normalized difference vegetation index and three commonly used band ratios (band 4 to band 3 [R43], band 5 to band 4 [R54], and band 5 to band 7 [R57]) were calculated. Tree canopy cover was extracted from the National Land Cover Database 2001 (Homer et al. 2004).

Climate and topography variables were used as another source of ancillary data. Elevation in m (EL) was recorded as part of the CVS inventory. Annual precipitation (ANNPRE) and mean annual temperature (ANNTMP) (Table 2) were extracted from DAYMET Daily Surface Weather Data

Table 1. Number of plots measured by year of installation and national forest and corresponding panel assignment

Year of Installation	Colville	Mt. Hood	Ochoco	Rogue River	Wallowa-Whitman	Winema	Total	Assigned panel
1993	7	0	0	0	0	0	7	1
1994	4	9	23	0	99	94	229	1
1995	0	51	41	20	77	34	223	2
1996	16	51	18	50	23	0	158	3
1997	1	0	0	0	0	0	1	3
Total	28	111	82	70	199	128	618	

All plots listed were remeasured in 2000.

Table 2. **Summary of plot-level variables**

Variable	Minimum	Mean	Maximum	Standard
BA (m^2/ha)	0.24	24.32	105.35	19.00
SPH (stems/ha)	1	305	1517	221
Volume (m^3/ha)	0.66	224.82	1444.74	221.04
Total gross oven dry weight biomass (tons/ha)	0.58	134.09	800.64	132.64
Canopy cover (%)	0	54	97	29
Slope (%)	0	23	83	17
Elevation (m)	274	1389	2377	321
Annual precipitation (ln cm) (scaled × 100)	577	683	817	48
Mean annual temperature (°C) (scaled × 100)	60	579	1067	166

Table 3. Tree species found in this study

Scientific name	Common name	Frequency
Abies amabilis (Douglas ex Louden) Douglas ex Forbes	Pacific silver fir	913
Abies concolor (Gord. & Glend.) Lindl. ex Hildebr.	White fir	2,325
Abies grandis (Douglas ex D. Don) Lindl.	Grand fir	2,935
Abies lasiocarpa (Hook.) Nutt.	Subalpine fir	645
Abies × shastensis (Lemmon) Lemmon [*magnifica × procera*]	Shasta red fir	854
Abies procera Rehder	Noble fir	245
Acer macrophyllum Pursh	Bigleaf maple	93
Alnus rubra Bong.	Red alder	81
Arbutus menziesii Pursh	Pacific madrone	126
Betula papyrifera Marsh. var. *commutata* (Regel) Fernald	Paper birch	6
Castanopsis chrysophylla (Douglas ex Hook.) A. DC.	Golden chinquapin	71
Calocedrus decurrens (Torr.) Florin	Incense cedar	140
Cornus nuttallii Audubon ex Torr. & A. Gray	Pacific dogwood	3
Juniperus occidentalis Hook.	Western juniper	517
Larix occidentalis Nutt.	Western larch	801
Pinus albicaulis Engelm.	Whitebark pine	96
Pinus attenuata Lemmon	Knobcone pine	14
Pinus contorta Douglas ex Louden	Lodgepole pine	2,758
Picea engelmannii Parry ex Engelm.	Engelmann spruce	651
Pinus lambertiana Douglas	Sugar pine	177
Pinus monticola Douglas ex D. Don	Western white pine	78
Pinus ponderosa C. Lawson	Ponderosa pine	5,040
Populus balsamifera L. ssp. *trichocarpa* (Torr. & A. Gray ex Hook.) Brayshaw	Black cottonwood	5
Populus tremuloides Michx.	Quaking aspen	33
Prunus emarginata (Douglas ex Hook.) D. Dietr.	Bitter cherry	2
Pseudotsuga menziesii (Mirb.) Franco	Douglas-fir	8,202
Quercus chrysolepis Liebm.	Canyon live oak	184
Quercus garryana Douglas ex Hook.	Oregon white oak	11
Quercus kelloggii Newberry	California black oak	8
Taxus brevifolia Nutt.	Pacific yew	35
Thuja plicata Donn ex D. Don	Western redcedar	577
Tsuga heterophylla (Raf.) Sarg.	Western hemlock	2,123
Tsuga mertensiana (Bong.) Carrière	Mountain hemlock	960

and Climatological Summaries (Thornton et al. 1997, Thornton and Running 1999). Slope (%) and aspect (degrees) were derived from a 30-m digital elevation model using Arc Workstation GRID surface functions and commands (Environmental Systems Research Institute 1991).

Plot-Level Imputation Techniques

The available 618 plots were randomly split without replacement into 154 plots (25%) constituting P4 and 464 plots (75%) that, on the basis of the year of their first measurement, belong to P1, P2, and P3.

Using the data from P4, the mean values of the variables of interest (Y) for the year 2000 (SAMPLE25 estimator) were calculated as

$$\bar{Y}_{\mathrm{SAMPLE25}} = \sum_{i:Y_i \in \mathrm{P4}} Y_{t,i} \Big/ n_4, \tag{1}$$

where $Y_{t,i}$ is the observed Y value of the ith plot at time t, which is the year 2000, and n_4 is the number of plots in P4.

The MA estimator, the FIA default method, was also used to calculate the current mean values for the variables of interest:

$$\bar{Y}_{\mathrm{MA(4)}} = 0.25 * \bar{Y}_{t-3,i} + 0.25 * \bar{Y}_{t-2,i} + 0.25 * \bar{Y}_{t-1,i} + 0.25 * \bar{Y}_{t,i}, \tag{2}$$

where $\bar{Y}_{t-3,i}$; $\bar{Y}_{t-2,i}$ $\bar{Y}_{t-1,i}$, and $\bar{Y}_{t,i}$ are the mean values of the variables of interest of P1, P2, P3, and P4, respectively. This

MA(4) estimator will be referred to as MA in the following. The MA takes into account the fact that the panels include different numbers of plots. The following WMA takes the varying number of plots per panel into account and allows allocation of weights declining with time lapsed since the most recent measurement:

$$\bar{Y}_{\mathrm{WMA}(4)} = w_{t-3} * \bar{Y}_{t-3,i} + w_{t-2} * \bar{Y}_{t-2,i} + w_{t-1} * \bar{Y}_{t-1,i} + w_t * \bar{Y}_{t,i}, \tag{3}$$

where w_{t-3}, w_{t-2}, w_{t-1}, and w_t are the weights of P1, P2, P3, and P4, respectively. Larger weights were chosen for P3 and P4 ($w_{t-1} = w_t = 0.3$) than for P1 and P2 ($w_{t-3} = w_{t-2} = 0.2$). WMA(4) will be referred to as WMA.

Nearest neighbor (NN) imputation methods are donor-based methods in which the imputed value is either a value that was actually observed for another plot or the average of values for more than one plot. Forest attributes that are measured on all plots are referred to as ancillary variables. Variables of interest are those forest attributes that are only measured on a subset of plots. Plots with measured ancillary variables and variables of interest are called reference plots, and target plots are those that only have ancillary variables measured. In this study, the target plots were assumed to be nonsampled plots lacking inventory data (panels 1-3). The reference plots constituted the pool of potential plots with ground and ancillary data (P4), which could be selected to impute the inventory data for the target plots.

The most similar neighbor (MSN) method (Moeur and Stage 1995) has been shown to provide reasonable imputation results for forest attributes (Moeur and Stage 1995, LeMay and Temesgen 2005). The gradient nearest neighbor (GNN) method (Ohmann and Gregory 2002) has been used successfully to map forest composition and structure (Ohmann and Gregory 2002, Ohmann et al. 2007). The randomForest (RF) method (Crookston and Finley 2008) has been found to provide a flexible and robust alternative to traditional NN imputation methods such as MSN and GNN for estimating forest attributes such as BA and SPH (Hudak et al. 2008). MSN, GNN, and RF were examined using the yaImpute R package version 1.0-6 (Crookston and Finley 2008). For MSN and GNN, the similarity between reference and target plots is defined using a weighted Euclidean distance:

$$D_{ij}^2 = (X_i - X_j)W(X_i - X_j)', \tag{4}$$

where W is the weight matrix, X_i is a vector of standardized values of the ancillary variables for the ith target plot, and X_j is a vector of standardized values of ancillary variables for the jth reference plot. The ancillary variables for both target and reference plots were standardized using the mean and variance of the ancillary variables of the reference plots.

For MSN, the weight used is $W = \Gamma\Lambda^2\Gamma'$ where Γ is the matrix of standardized canonical coefficients for the ancillary variables and Λ^2 is the diagonal matrix of squared canonical correlations between ancillary attributes and ground variables (Moeur and Stage 1995). The "most similar" reference plot is hence selected on the basis of similarity of the ancillary data, weighted by the correlations to the ground data. The ground data of the reference plot with the smallest distance is then imputed to the target plot. The GNN uses a projected ordination of the ancillary data based on canonical correspondence analysis (CCA) to assign the weights (Ohmann and Gregory 2002).

The RF method is a classification and regression tree method (Breiman 2001). The data and variables are randomly and iteratively sampled to generate a large group, or forest, of classification and regression trees. For RF two observations are considered similar if they tend to end up in the same terminal nodes in a forest of classification and regression trees. The distance measure is 1 minus the proportion of trees where a target observation is in the same terminal node as a reference observation (Crookston and Finley 2008, Hudak et al. 2008).

Instead of filling in the missing values for panels 1 to 3 with their previous measurements, as was done in the MA calculation, MSN, GNN, and RF were explored to impute the missing values and then estimate the overall mean of the variables of interest for the year 2000:

$$\bar{Y}_{\mathrm{IMP}} = \left[\sum_{i:Y_i \in P1} Y_{\mathrm{imp},i} + \sum_{i:Y_i \in P2} Y_{\mathrm{imp},i} + \sum_{i:Y_i \in P3} Y_{\mathrm{imp},i} + \sum_{i:Y_i \in P4} Y_{t,i} \right] \Big/ n, \tag{5}$$

where IMP refers to the NN imputation method used and $Y_{\mathrm{imp},i}$ is the imputed Y value for the ith plot.

BA, SPH, VOL, and BIOT were used as variables of interest, and SAMPLE25, MA, WMA, and the three imputation methods were compared on the basis of the overall means of the variables of interest in the year 2000 (see Equations 1-3 and 5).

Two sets of ancillary variables were tested for the imputation methods. The first set included climate, topography, and satellite data and the second set consisted of the previous measurements of the variables of interest that were taken at measurement occasion 1 in the years 1993 to 1997 (BAoccl, SPHoccl, VOLoccl, and BIOToccl).

The methods were compared by randomly splitting the available data of 618 plots into 154 reference and 464 target plots, applying each method, determining mean estimates for the variables of interest in the year 2000 (see Equations 1-3 and 5), and comparing the estimates to the observed mean values of the variables of interest in the year 2000:

$$\bar{Y}_{\mathrm{OBS}} = \sum_{i=1}^{n} Y_{t,i} \Big/ n, \tag{6}$$

where $Y_{t,i}$ is the observed Y value of the ith plot at time t, which is the year 2000.

The basis of evaluation was accuracy, as expressed by the root mean square error (RMSE), and bias, calculated as the mean difference between the estimates and the observed mean values (Equation 6) from 500 iterations of randomly splitting the data. Five hundred iterations were considered sufficient because other studies have found RMSE and bias to stabilize at approximately 200 iterations (e.g., Arner et al.

2004). Both RMSE and bias were expressed as a percentage of the observed mean for each variable of interest:

$$\text{Bias\%} = \frac{\sum_{i=1}^{n} (\text{est}_i - \text{obs}_i) \Big/ m}{\sum_{i=1}^{n} \text{obs}_i \Big/ m} * 100 \qquad (7)$$

$$\text{RMSE\%} = \frac{\sqrt{\sum_{i=1}^{n} (\text{est}_i - \text{obs}_i) \Big/ m}}{\sum_{i=1}^{n} \text{obs}_i \Big/ m} * 100 \qquad (8)$$

where $m = 500$.

Results

For BA and SPH, the RMSE values of MA were about half the size of those observed for SAMPLE25. For VOL and BIOT, the RMSE values for MA were about one-third of those observed for SAMPLE25. SAMPLE25 results were virtually unbiased with absolute values of 0.13% and less. Bias for the MA results ranged from -2.63% for SPH to - 1.98% for BIOT. MA estimates were very precise, and the bias contributed most to the RMSE. The opposite was true for the virtually unbiased SAMPLE25 estimates, for which the variance contributed most to the RMSE (Table 4). WMA reduced the bias and with that the RMSE for SPH even further. For BA, VOL, and BIOT, the bias became positive and the RMSE values increased for VOL and BIOT compared with those of the MA (Table 4).

When climate, topography, and satellite data were used as ancillary variables, MSN provided better results than SAMPLE25 in terms of RMSE for BA, VOL, and BIOT but worse results than MA and WMA. MSN imputation resulted in negligible bias with absolute values less than 0.3%, hence, outperforming the MA and WMA results in terms of bias. The variance contributed most to the RMSE values of the MSN estimates (Table 4). With climate, topography, and satellite data as ancillary variables, RF provided slightly better results than MSN in terms of RMSE for all four variables of interest. With values ranging from 0.26 to 0.89% bias was slightly larger than for MSN but still negligible. As for SAMPLE25 and MSN, the variance contributed most to the RMSE (Table 4). GNN imputation results were by far the worst when climate, topography, and satellite data were used as ancillary variables with RMSE values of approximately 15% and positive bias of approximately 10% (Table 4).

When BAoccl, SPHoccl, VOLoccl, and BIOToccl were used as ancillary variables, the MSN results had a negative bias ranging between -2.90 and -4.56%. The bias contributed most to the RMSE values, which were still slightly better than those of SAMPLE25. However, MA and WMA now outperformed MSN both in terms of bias and RMSE (Table 5). RF results improved both in terms of bias and RMSE when previous measurements were used as ancillary variables and outperformed MA in terms of bias and RMSE. RF also provided better results than WMA in terms of bias for all four variables of interest and for VOL and BIOT in terms of RMSE (Table 5). GNN estimates were even worse with the second set of ancillary variables, resulting in large positive bias exceeding 29% and large RMSE values exceeding 36% (Table 5).

Discussion

The SAMPLE25 estimator should provide unbiased estimates. In this study the bias was not equal to zero but reached values up to 0.13%. If all possible subsamples of size 154 were taken, SAMPLE25 should result in a bias of zero. Because not all possible subsamples were taken, the negligible bias observed for the method in this study was probably due to the number of iterations that were performed.

As found in other studies (Van Deusen 2002, Arner et al. 2004), MA, the PIA default estimator, resulted in improvements in terms of RMSE compared with use of only the current panel as the basis of estimating current forest attributes. However, MA resulted in negatively biased estimates. This bias is commonly referred to as lag bias, which arises because the MA estimator tends to underestimate current forest conditions. In the given example, the 4-year gap between P3 and P4 increased the lag bias, and it is expected that the lag bias would have been smaller for a regular four-panel inventory where panels are only a year apart. Most studies on the MA performance have been done in other regions where the inventory cycle is 5 years, and the lag bias of the MA has been found to be more than compensated for by a reduction in variance for a 5-year inventory cycle by "borrowing" strength in terms of sample size from previous years (Johnson et al. 2003).

MA provides unbiased estimates for the midpoint of the

Table 4. Imputation results for the set of ancillary variables that included climate, topography, and satellite data

	BA		SPH		VOL		BIOT	
Method	% bias	% RMSE	% bias	% RMSE	% bias	% RMSE	% bias	% RMSE
SAMPLE25	−0.02	5.29	0.13	5.05	−0.08	6.59	−0.06	6.67
MA	−2.54	2.60	−2.63	2.68	−1.92	2.06	−1.98	2.12
WMA (0.2, 0.2, 0.3, 0.3)*	0.58	0.98	−1.58	1.74	2.51	2.71	2.58	2.78
MSN	0.05	3.73	0.29	5.13	−0.19	5.01	−0.15	4.97
GNN	10.14	15.10	10.11	14.89	8.97	15.72	9.67	16.35
RF	0.44	3.60	0.89	4.99	0.37	4.96	0.26	4.89

* Weights for the WMA are given in parentheses as follows (w_{t-3}, w_{t-2}, w_{t-1}, and w_t).

Table 5. Imputation results for using occasion 1 measurements of the variables of interest (BAoccl, SPHoccl, VOLocc1, and BIOToccl) as ancillary data

Method	BA		SPH		VOL		BIOT	
	% bias	% RMSE	% bias	% RMSE	% bias	% RMSE	% bias	% RMSE
SAMPLE25	−0.02	5.29	0.13	5.05	−0.08	6.59	−0.06	6.67
MA	−2.54	2.60	−2.63	2.68	−1.92	2.06	−1.98	2.12
WMA (0.2, 0.2, 0.3, 0.3)*	0.58	0.98	−1.58	1.74	2.51	2.71	2.58	2.78
MSN	−3.91	4.35	−2.90	3.68	−4.41	4.97	−4.56	5.09
GNN	30.67	36.12	43.92	51.48	29.55	36.57	34.53	41.09
RF	−0.30	1.58	−0.85	2.78	−0.06	1.90	−0.09	1.79

* Weights for the WMA are given in parentheses as follows (w_{t-3}, w_{t-2}, w_{t-1}, and w_t).

period and is hence not valid as end of period estimator.. When used as an end of period estimator as done by FIA and in this study, the MA has the tendency to mask temporal trends (Roesch and Reams 1999) and provide biased estimates for the end of the period. One approach to solving this problem is to apply weights that give more weight to the most recently measured panels. This was done for the WMA, which provided improved estimates in terms of bias and RMSE for BA and SPH but increased bias and RMSE values for VOL and BIOT compared with MA. The selection of the weights poses a problem that is not yet solved. Choosing appropriate weights requires knowledge of the trend inherent in the data, which is hardly ever known. Breidt (1999) presented models that can be used for selecting the weights somewhat objectively. Amer et al. (2004) found an increase in RMSE for mean volume and mean annual volume change with increasing larger weights for recent years, and Johnson et al. (2003) have shown that equal weights lead to the lowest RMSE in most situations.

P1, P2, and P3 lack data for the national forests Rogue River, Coleville, and Winema, respectively (Table 1), which suggests that the panels may not have accurately characterized the population of interest.. This feature could have been exacerbated by the random assignment of plots to P4. MA assumes that each yearly sample covers the population of interest (Johnson and Williams 2004). Hence, the MA results in this study may have been compromised by this data feature. PIA plots are assigned to the panels in a systematic manner, so that each PIA panel covers the population of interest systematically, which ensures that the annual sample maintains its spatial properties. Hence, the performance of the MA estimator using actual PIA data is expected to be better than in the given example.

Longer inventory cycles will have negative effects on the performance of the MA and WMA estimators in terms of bias (Johnson et al. 2003). Hence, it is questionable whether the MA estimator is optimal for the PNW region where the inventory cycle length is 10 years. However, if the lag bias could be corrected, the MA and WMA estimators could provide RMSE values substantially lower than those of the SAMPLE25 estimator..

Three plot-level imputation techniques were examined; these performed differently in terms of bias and RMSE compared with the SAMPLE25, MA, and WMA estimators. Although MSN imputation using climate, topography, and satellite data improved the results compared with the SAMPLE25 estimates in terms of RMSE for BA, VOL, and BIOT, the improvements in RMSE seemed minor considering the computational expenses of applying imputation techniques. Using imputation techniques is questionable if the improvements are not substantial.. MA and WMA estimators outperformed MSN imputation in terms of RMSE when climate, topography, and satellite data were used as ancillary data and in both bias and RMSE when previous measurements were used as ancillary data. Hence, the results of this study did not indicate any advantage of MSN imputation over the MA and WMA estimators.

GNN results were not close to those obtained by SAMPLE25, MA, WMA, MSN, or RF, which may be due to the fact that CCA requires the use of environmental factors for the ordination. GNN has been developed for pixel imputation (Ohmann and Gregory 2002), and it is possible that gradients in the environmental factors are not picked up when plot-level data are being used in combination with the available climate, topography, and satellite data. GNN should not be used with previous measurements as ancillary data because those do not provide any environmental factors that are necessary for the CCA step in the GNN analysis. This explains the bad results achieved by GNN with previous measurements as ancillary variables (see Table 5).

The results of this study support the findings of Hudak et al. (2008) that RF represents a robust alternative to traditional imputation methods. In this study, RF was the only imputation method that provided results that could compete with the results of the MA and WMA estimators. When RF was used with previous measurements as ancillary variables, it outperformed the WMA estimates not only in terms of bias but also in terms of RMSE for two of the four variables of interest. This finding suggests further exploration of this method with different data sets.

In a 10-panel inventory system, using previous measurements as ancillary variables is expected to result in overpredictions of the variables of interest.. The current panel is used as reference data and its previous measurements are 10 years old. The previous measurements of the remaining nine panels constituting the target data are 1-9 years old. Matching on previous measurements will result in overpredicting growth. Using an updated MA as introduced by Gartner and Reams (2002), in which only the panels that have the most outdated measurements are being updated, may avoid the problem of overprediction when previous measurements are being used as ancillary variables. In a 10-panel system, the first 5 panels would be updated with imputation methods based on previous measurements as ancillary variables for estimating the status of the variables of interest in year to. Then an MA would be calculated based on the updated values of panels 1 through 5 and the measurements obtained for panels 6 through 10.

The efficiency of the imputation methods depends on the strengths of relationships between the variables of interest and the ancillary data. The data in this study showed only weak association between forest inventory attributes and ancillary variables from TM images, climate, and topography data. The findings of this study do not provide any incentive to prefer the use of NN imputation methods that employ climate, topography, and satellite data as ancillary variables over the use of MA and WMA estimators. Data of higher quality than those derived from TM images could have the potential to improve the NN imputation techniques. Variables derived from light detection and ranging (LiDAR) data are an example (e.g., Hudak et al. 2008).

Throughout all estimation methods, RMSE was larger for VOL and BIOT than for BA. The poorer results for VOL and BIOT may be due to the fact that these two variables are transformations of both tree DBH and HT, and, therefore, they are three-dimensional variables on the landscape. BA, on the other hand, is a two-dimensional variable because it is based only on the DBH measurements. Many of the ancillary variables available in this study for imputation are themselves only two-dimensional variables. Again, three-dimensional LiDAR data have the potential to improve the imputation techniques for VOL and BIOT.

The results of the imputation methods may have been impaired by a combination of the number of plots used as reference stands (P4, 154 plots) and the large number of species and forest types in the six national forests that were used in this study. The diversity in the data and the small number of plots suggest that it was probably not easy to find good matches in some of the cases. Because imputation methods do not extrapolate and only interpolate when $k >$ 1 (Crookston et al. 2002), it is important that the reference data span the full range of the population in the space of the ancillary variables without any large gaps. If this is not given, the availability of similar reference observations may be reduced and imputation error increases (Stage and Crookston 2007). The random assignment of plots to P4 may have resulted in plot combinations for P4 that did not represent the population well, which would have negatively influenced the performance of the imputation methods. PIA annual inventory data assure systematic coverage of the population of interest for each panel so that it seems more likely to find good matches, and an improvement of imputation results could be expected.

Conclusions

Compared with the SAMPLE25 estimator, the MA estimator improved the estimates in terms of RMSE and worsened the estimates in terms of bias. The WMA estimator improved the results for two of the variables of interest compared with the MA. The performance of the MA and WMA estimators should be explored using an actual to-year inventory system to examine the increase in lag bias for a long inventory cycle. Different weighting schemes in a lO-year inventory system need to be explored for the WMA estimator.

With the available ancillary data, MSN and GNN could not compete with any of the other estimation methods. RF results were best when previous measurements of the variables of interest were used as ancillary variables and outperformed the MA and WMA estimators in terms of bias and were comparable in terms of RMSE. Using RF imputation with previous measurements as ancillary variables might provide an approximately unbiased alternative to the biased MA and WMA estimators in the PNW. Because overprediction of the variables of interest may occur, more research on the behavior of this method in a 10-panel system is warranted.

For the MA and WMA estimates, the variance was very small and bias contributed most to the RMSE values. **If** the lag bias could be corrected, the RMSE values would be reduced substantially, and the MA and WMA estimators may outperform all other methods. Methods for correcting the MA and WMA lag bias should be sought. If the lag bias is not corrected for, users should be aware that they are estimating a midpoint value rather than an end of period value when they use the MA estimator.

Because of the data structure and the random assignment of plots to P4, the panels did not always represent the population well. This had impacts on the MA and WMA estimates as well as on the NN imputation results. All methods are expected to show improved results when actual FIA data are used because FIA panels provide complete coverage of the population with equal number of plots for each year.

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