

Small-Area Estimation of County-Level Forest Attributes Using Ground Data and Remote Sensed Auxiliary Information

Michael E. Goerndt, Vicente J. Monleon, and Hailemariam Temesgen

Abstract: Small-area estimation (SAE) is a concept that has considerable potential for precise estimation of forest ecosystem attributes in partitioned forest populations. In this study, several estimators were compared as SAE techniques for 12 counties in the northern Oregon Coast range. The estimators that were compared consisted of three indirect estimators, multiple linear regression (MLR), gradient nearest neighbor imputation (GNN), and most similar neighbor imputation (MSN), and five composite estimators based on MLR, MSN, and GNN with county-level direct estimates. Forest attributes of interest were density (trees/ha), basal area (m²/ha), cubic volume (m³/ha), quadratic mean diameter (cm), and average height of 100 largest trees per ha. The sample consisted of 680 annual Forest Inventory Analysis plots, a spatially balanced sample across all conditions and ownerships. The auxiliary data consisted of 16 Landsat variables, a land cover classification, tree cover, and elevation. Overall, the composite estimators were superior when both precision and bias of estimation were considered. FOR. SCI. 59(5):536–548.

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FOREST MANAGERS AND PRACTITIONERS OFTEN PARTITION large forested populations into smaller areas of interest for forest management objectives. Large inventory programs, such as the Forest Inventory Analysis (FIA) of the US Department of Agriculture, are also interested in estimating forest attributes for areas smaller than the state or national level. Typically, this is done by deriving direct estimators from the plots sampled within the area of interest. However, it is often difficult to obtain precise direct estimators of forest attributes within relatively small areas that may contain few plots.

Small-area estimation (SAE) is a concept that is relatively new to forestry but has considerable potential for precise estimation of forest ecosystem attributes. Much of the demand to assess SAE has arisen from the need for precise and accurate estimators of forest attributes at varying spatial scales. SAE techniques attempt to obtain estimators in situations in which there is insufficient ground data to achieve the desired level of precision for direct estimators (Costa et al. 2003). Through FIA, it is possible to classify larger areas as populations containing smaller areas of interest (e.g., individual counties or subcounties). Note that the term “small area” does not necessarily pertain to the physical size of the area but rather the sample size representing it.

There are different methods of SAE, the validity of which greatly depends on the structure and composition of both the small area and the available auxiliary information (Best et al. 2007). Traditionally, SAE has been divided into

three categories: direct estimation, indirect estimation, and composite estimation (Rao 2003, Costa et al. 2003, 2004, Best et al. 2007). A direct estimator is an estimator that uses data taken directly from the small area of interest. This implies that there needs to be a sample taken from all areas of interest to effectively use direct estimation (Best et al. 2007).

Indirect estimators do not necessarily require that an adequate sample is taken for each area of interest. They use auxiliary information both within and outside the study area to derive a model for the population and then base estimation on this model (Heady et al. 2003, Rao 2003, p. 57, Best et al. 2007). One common indirect estimator used for SAE is multiple linear regression (MLR), but other methods such as nearest neighbor imputation have also been used in forestry (Moeur and Stage 1995, Moeur 2000, LeMay and Temesgen 2005, Hudak et al. 2008). If linear regression is used, the coefficients of the model are applied to mean or total values of the auxiliary variables within the small area of interest (Fuller and Rao 2001, Rao 2003).

A composite estimator is a method that can incorporate strength from both direct and indirect estimation; it usually consists of a weighted sum or mean of a direct estimator and an indirect estimator for the small area of interest. A typical form of composite estimation for SAE uses a regression-based indirect estimate and a direct estimate for each small area of interest (Fuller and Rao 2001). The reason for using such an estimator is to balance the potential bias of the

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synthetic estimator with the lower precision of the direct estimator (Slud and Maiti 2006).

One of the main methods of composite estimation is a unit-level empirical best linear unbiased predictor (EBLUP). With use of a 1-fold nested error (linear mixed) model, EBLUP has both an indirect component with fixed effects and a random effects coefficient. This is accomplished by splitting the model variance into within-area and between-area variance (Rao 2003, p. 95–113, Breidenbach and Astrup 2012). One drawback of obtaining indirect estimates through standard MLR is that small areas can sometimes have strong individual effects not indicative of the overall population. EBLUP attempts to compensate for this deficiency by predicting random effects for the small areas based on one or more of the auxiliary variables. Unlike an area-level EBLUP, a unit-level EBLUP allows the auxiliary variables to be directly linked with the observational units of the population sample, such as individual plots (Rao 2003, Chapter 5, Goerndt et al. 2011).

A common alternative to regression-based approaches to SAE is nearest neighbor (NN) imputation. Imputation is defined as the replacement of missing or nonsampled measurements for a unit with measurements from a unit with similar characteristics (Van Deusen 1997). NN imputation methods rely on a measurement of the distance between units or areas of interest based on auxiliary information through some form of canonical correlation analysis (Moer and Stage 1995, Moer et al. 1999, Eskelson et al. 2009). Two prevalent methods of NN imputation for forest attributes are most similar neighbor (MSN) (Moer and Stage 1995, Moer 2000, LeMay and Temesgen 2005, Hudak et al. 2008) and gradient nearest neighbor (GNN) (Ohmann and Gregory 2002). As with MSN, GNN typically uses only one neighbor for imputation. The primary difference between these two methods is that GNN uses a canonical correspondence analysis (CCA) as opposed to a canonical correlation analysis to estimate the distance metric.

All forms of SAE that have been described require auxiliary data to be directly linked with observational units (plots) on the ground. For spatially large populations (e.g., counties and subregions), it has become increasingly common to use remote sensed data for the entire population. One form of remote sensed auxiliary information that has been shown to be effective for implementing SAE techniques is light detection and ranging (LiDAR) data (Goerndt et al. 2011). However, LiDAR is limited as to its availability for large regions. Landsat TM and Landsat ETM+ data, on the other hand, are readily available nationwide and can be useful for estimating forest attributes (Meng et al. 2007, 2009, Hudak et al. 2008).

The primary goal of this study was to compare selected SAE methods to obtain precise and accurate county-level estimates for selected forest attributes within a large region. The specific objectives were to examine the performance of three indirect estimation methods (MLR, GNN, and MSN), examine the performance of composite estimators, including EBLUP, using direct estimates and each of the aforementioned indirect estimates, and compare the selected methods with regard to the estimation of attributes of interest for the individual counties. The variables of interest for

this study are total stem volume (CuVol, $\text{m}^3 \text{ ha}^{-1}$), mean height of largest (dbh) 100 trees/ha (Ht, m), quadratic mean diameter (QDBH, cm), basal area (BA, $\text{m}^2 \text{ ha}^{-1}$), and density (live stems ha^{-1}). Ht was chosen because it is a common height metric used in the Pacific Northwest.

Methods

Study Area

The population of interest for this study consisted of an area of approximately 2,250,000 ha in western Oregon. The main tree species are conifers, including Douglas fir (*Pseudotsuga menziesii* [Mirb.] Franco), grand fir (*Abies grandis* [Dougl. ex D. Don] Lindl.), western hemlock (*Tsuga heterophylla* [Raf.] Sarg.), and western redcedar (*Thuja plicata* Donn ex D. Don) as apex species. The primary deciduous species are bigleaf maple (*Acer macrophyllum* Pursh) and red alder (*Alnus rubra* Bong.). This population was selected as a collection of 12 counties and subcounties representing the forested area of the northwestern coastal range of Oregon with the Willamette Valley and the Oregon coast as eastern and western boundaries, respectively. Of the original nine counties that make up this region, Lane, Tillamook, and Lincoln counties were considerably larger than the other counties. Therefore, these counties were split into subcounties based primarily on their relative size and the boundaries of the smaller adjacent counties. An alternative method for defining subcounties would have been to divide them so that each subcounty would have equal FIA sample sizes. It was decided that the chosen method would be more realistic with regard to arbitrary features (landscape, waterways, and topography) that are typically used to define county boundaries. A description of the individual subcounties (counties) and location information for the population of interest are given in Figure 1.

Field Data

The field data used in this study consisted of annual FIA plots measured between 2002 and 2008. This sample is the first seven panels of the FIA annual inventory and thus constitutes 70% of the full FIA sample for the counties of interest. The ground data included all forested and nonforested FIA plots within the region. Note that the 6-year time span in which the FIA plots were measured could potentially lead to slight bias. However, the bias should be negligible because the auxiliary data (Landsat) used for this study were collected in 2006, as described in the next section. The final FIA data set for the population of interest consisted of 680 plots. All pertinent tree information for the FIA plots was obtained from four 7.32-m radius subplots for trees with dbh between 12.7 and 76.2 cm and four 17.95-m radius macro-plots for trees with dbh ≥ 76.2 cm. A summary of selected stand attributes by county/subcounty is given in Table 1. Many attributes have fairly large SDs, denoting a high degree of within-county variability.

Landsat Data

The Landsat data used for this study was Landsat 5 TM collected between July 7 and Aug. 1, 2006. From the

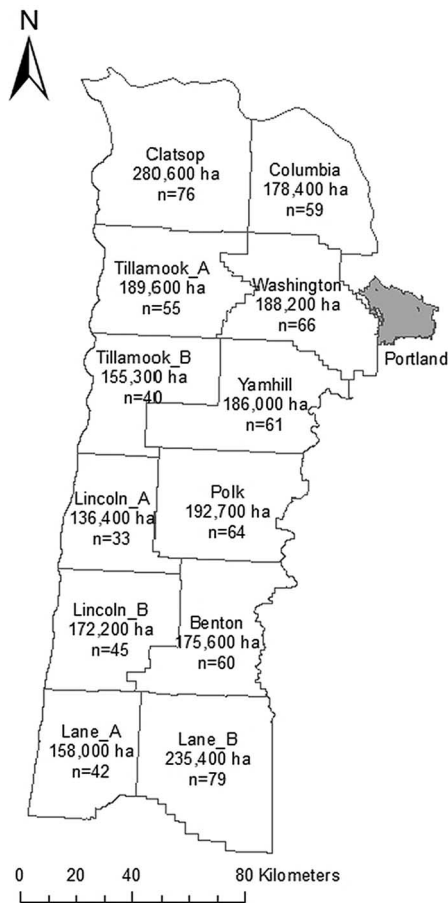


Figure 1. Map of population with county names, areas (ha), and FIA sample sizes (*n*).

original Landsat data, six of the original bands including bands 1 through 5 (B1–B5) and band 7 (B7) were extracted. Geometric rectification and radiometric correction were conducted by the USDA Forest Service Remote Sensing Applications Center in 2006. There are several transformations of Landsat imagery correlated with certain characteristics of landscape vegetative structure (Wilson and Sader 2002, Healey et al. 2005). One type of Landsat transformation included in this study was tasseled-cap (TC) transformation. TC transformation is accomplished through the combination of all nonthermal TM bands with coefficients derived from spectral analyses (Crist and Ciccone 1984). In past studies, TM bands used in TC transformation of Landsat have been shown to be correlated with forest disturbance (Olthof et al. 2004, Healey et al. 2005). TC transformations are designed to optimize the visualization of three important factors: brightness, greenness, and wetness (Crist and Ciccone 1984). These factors are primarily represented by the first three of six TC variables (TC1–TC6), whereas the fourth generally represents haze and the fifth and six are considered “noise” variables. Although the first three TC variables are considered to be the most important for vegetation studies, all six of the TC variables were considered as possible auxiliary variables in the analysis. The normalized difference vegetation index (NDVI) is a very simple Landsat band function that can be important in describing

forest health and vigor (Gillespie 2005). More specifically, NDVI has been shown to be effective in describing factors such as crown closure, forest density, and tree species diversity (Feeley et al. 2005). NDVI was calculated using the following equation

$$\text{NDVI} = \frac{B4 - B3}{B4 + B3} \quad (1)$$

where B3 and B4 are TM bands 3 and 4, respectively.

In addition to those Landsat bands and transformations, there are several simple band ratios that can be useful for describing forest characteristics. The band ratios used in this study were B4/B3 (R1), B5/B4 (R2), and B7/B5 (R3). The combined purpose of these ratios is to enhance the features of forest cover, bare soil, and water to better contrast them on the landscape (Wilson and Sader 2002, Olthof et al. 2004). The spatial resolution of all Landsat bands used in this study was 30×30 m. For each FIA plot, Landsat values were obtained by taking the average of the nine pixel values intersecting the plot. Landsat variables values were obtained for every pixel located within the population.

Other Auxiliary Data

In addition to Landsat variables, several auxiliary variables were used in the analysis. Cover was derived from the National Land Coverage Database (NLCD), which classifies individual Landsat pixels into cover types (e.g., coniferous forest, deciduous forest, shrub/scrub, wetlands, urban development, and cultivated fields) (NLCD 2001, Homer et al. 2007). The Cover variable is an indicator of whether an area is forested (“1”) or nonforested (“0”). For this study, pixels classified as “forested” included coniferous forest, deciduous forest, mixed forest, shrub/scrub, and woody wetlands. Plot-level values for Cover were calculated as the cover type of the majority of pixels intersecting each plot. Another variable included in the analysis and derived from NLCD was forest canopy percentage (Canopy) (NLCD 2001, Nowak and Greenfield 2010). Canopy values for each plot were calculated as an average of the pixel values intersecting each plot. Note that there is some potential for bias in using the NLCD because it was collected 5 years before the Landsat data. Any bias issues would most likely be caused by newly developed areas not indicated on the NLCD coverage. Elevation (Elev) was derived from digital elevation models (DEM) obtained from the US Geographical Survey (US Geographical Survey 2001, Dorren et al. 2003). As with Canopy, Elev for each plot was calculated as an average of the DEM pixel values intersecting each plot.

Simulation

The primary assumption for SAE is that there is an insufficient sample size within each small area of interest to obtain precise direct estimates. The individual counties used in this study contain anywhere from 33 to 79 FIA plots (Figure 1). It was necessary to simulate smaller sample sizes to assess the performance of the estimators as the sample size increased or decreased and to facilitate validation of the estimators using direct county estimates of the attributes from the full samples as a surrogate for census information.

Table 1. Selected forest attributes by county.

County	No.	<i>n</i>	Density (trees/ha)	BA (m ² /ha)	CuVol (m ³ /ha)	QDBH (cm)	Ht (m)
Benton	1	60	201.3 (204)	23.2 (25.4)	277.2 (357.3)	29.4 (31.1)	20.2 (18.6)
Clatsop	2	76	357.8 (299.8)	24.3 (21.8)	227.1 (254.1)	25.3 (19.5)	17.8 (12.7)
Columbia	3	59	262.4 (267.7)	16.6 (18.9)	157.7 (222.2)	18.7 (17.7)	14.7 (14.1)
Lane_A	4	42	298.3 (185.7)	37.4 (26.6)	437.4 (379.3)	48.1 (30.7)	30.2 (16.7)
Lane_B	5	79	214.7 (236.7)	18.1 (20.1)	198.1 (248.1)	23.8 (24)	17.9 (16.6)
Lincoln_A	6	33	330.0 (341)	21.6 (19.4)	201.3 (216.5)	28.1 (26.1)	18.2 (13.8)
Lincoln_B	7	45	331.3 (259.5)	30.9 (24.6)	351.4 (372.5)	37.5 (29.7)	25.2 (18.3)
Polk	8	64	183.7 (277.4)	13.8 (20.6)	145.3 (262.5)	18.0 (25.1)	12.2 (15.6)
Tillamook_A	9	55	348.4 (268)	30.6 (18.9)	311.1 (217.8)	32.7 (17.1)	24.8 (12.4)
Tillamook_B	10	40	266.6 (261.4)	26.9 (20.8)	301.2 (280.2)	40.1 (30.3)	25.1 (16.1)
Washington	11	66	192.6 (246.1)	17.4 (20.8)	181.0 (231.9)	19.9 (22.8)	15.1 (16.2)
Yamhill	12	61	158.0 (234.1)	16.6 (21.6)	195.2 (290.9)	27.6 (31.9)	17.1 (18.7)

Data are means (SD); *n* = 680.

Therefore, the simulation of reduced sample sizes was done by randomly selecting FIA plots from each county using 20, 30, and 40% sampling intensities for 500 iterations. Direct estimates in the form of county-level means were calculated for each attribute at all sampling intensities as well as for the full samples. The estimators were assessed for the three sampling intensities separately. County-level direct estimates based on the full sample for each attribute were retained as validation data for each estimator in the absence of census information.

Statistical Analysis

MLR Models

Unit-level (plot-level) MLR models using the full sample data were calculated as an initial template (variable list) for creating both the MLR estimates and the EBLUP models. The attributes of interest were assessed for transformations (e.g., log transformation and square root transformation) using residual plots. Models were selected using a subset regression technique that identifies the explanatory variables that create the best-fitting linear regression models according to the Bayesian information criterion (BIC) using an exhaustive search. This was performed using the *regsubsets()* tool available in the *leaps()* package for *R()* (Lumley 2009, R Development Core Team 2008). The resulting output contained information for a total of 70 possible models ranked by BIC. Any model that had a variance inflation factor score greater than 9.5 was automatically dropped from the final list (Goerndt et al. 2011). The variable sets derived from this step were used to calculate regression coefficients by using both the full sample and each subsample selected in the simulation. The regression coefficients estimated by using the full sample and subsamples were applied to the county-specific means for all pixels of the auxiliary variables to calculate the indirect (synthetic-type) estimates (Rao 2003, p. 46, 79). Whereas MLR_A was calculated using the full sample, MLR_B was calculated using 20, 30, and 40% subsamples.

EBLUP Models

The unit-level EBLUP is based on a 1-fold nested error linear regression model with the following form (Rao 2003, p. 78)

$$y_{ij} = x'_{ij}\beta + v_i + e_{ij}, \quad (2)$$

where y_{ij} is the attribute value for FIA plot j in county i , x_{ij} is a vector of values for selected auxiliary variables for FIA plot j in county i , β is a vector of regression coefficients, v_i is the area-specific random effect for county i , and e_{ij} are independent and identically distributed random variables independent of v_i .

The 1-fold nested error models were fit using the *lme* tool from the *nlme* package for R (R Development Core Team 2008). The final model for each attribute was chosen by assessing the BIC value from each possible model and choosing the model with the lowest BIC. To obtain attribute EBLUPs for each county, the fixed coefficients and the random county effect obtained from the respective unit-level model were used to form an estimate of the following form (Rao 2003, p. 80)

$$\bar{Y}_i = \bar{X}'_i\beta + \hat{v}_i, \quad (3)$$

where \bar{X}_i is a vector of auxiliary values in the form of overall area-specific means from all Landsat and auxiliary pixels within county i , β is a vector of regression coefficients, and v_i is the area-specific random effect for county i calculated as

$$\begin{aligned} \hat{v}_i &= \frac{\hat{\sigma}_v^2}{\hat{\sigma}_e^2 + n_i\hat{\sigma}_v^2} \sum_{j=1}^{n_i} (y_{ij} - x'_{ij}\hat{\beta}) \\ &= \frac{n_i\hat{\sigma}_v^2}{\hat{\sigma}_e^2 + n_i\hat{\sigma}_v^2} (\bar{y}_i - \bar{X}'_i\hat{\beta}) \end{aligned} \quad (4)$$

where \bar{y}_i is the mean of y_{ij} for county i , $\hat{\sigma}_e^2$ and $\hat{\sigma}_v^2$ are the estimated variances of e and v , and n_i is the number of plots in the county (Battese et al. 1988, Rao 2003, p. 79, Costa et al. 2009). This leads to Equation 3 being calculated as

$$\begin{aligned} \bar{Y}_i &= \bar{X}'_i\hat{\beta} + \hat{v}_i = \bar{X}'_i\hat{\beta} + \frac{n_i\hat{\sigma}_v^2}{\hat{\sigma}_e^2 + n_i\hat{\sigma}_v^2} (\bar{y}_i - \bar{X}'_i\hat{\beta}) \\ &= \left(1 - \frac{n_i\hat{\sigma}_v^2}{\hat{\sigma}_e^2 + n_i\hat{\sigma}_v^2}\right)\bar{X}'_i\hat{\beta} + \frac{n_i\hat{\sigma}_v^2}{\hat{\sigma}_e^2 + n_i\hat{\sigma}_v^2}\bar{y}_i, \end{aligned} \quad (5)$$

Equation 5 demonstrates how the nature of v_i (Equation 4) causes EBLUP to actually be a composite estimator derived

from a direct component (\bar{y}_i) and indirect component ($X_i'\beta$). Note that setting $v_i = 0$ and use of the subsampled data results in the calculation of MLR_B (Rao 2003, pg. 78).

The primary purpose of using EBLUP as opposed to MLR for deriving county-level estimates is to capitalize on the between-county variation in the data to improve estimation. Although Landsat data can be fairly informative regarding some forest attributes such as density and BA, it is suspected that other attributes such as QDBH and Ht will contain variation that cannot be explained by the Landsat auxiliary data. However, EBLUP may adjust for some of this variation by accounting for strong individual effects that may exist in the counties themselves (e.g., variation in forest attributes between counties not explained by explanatory variables).

Imputation (MSN and GNN)

Both MSN and GNN imputation were assessed as alternatives to MLR indirect estimation of forest attributes, because imputation methods are widely used in forestry (Moeur and Stage 1995, Moeur 2000, Ohmann and Gregory 2002, LeMay and Temesgen 2005). Rather than use standard MSN imputation, we used a “modified” MSN, which imputes values to the unit (pixel) level rather than to the county level. This allowed for a more direct comparison between the performance of MSN and GNN. The distance metric used for MSN imputation had the following form (Moeur and Stage 1995, Temesgen et al. 2003, LeMay and Temesgen 2005)

$$d_{ij}^2 = (X_i - X_j)' \Gamma \Lambda^2 \Gamma' (X_i - X_j), \quad (6)$$

where X_i is the vector of auxiliary variables for the i th plot, X_j is the vector of auxiliary variables for the j th reference plot, Γ is a matrix of standardized canonical coefficients for the X variables, and Λ^2 is a diagonal matrix of squared canonical correlations. For GNN, the weights ($\Gamma \Lambda^2 \Gamma'$) were assigned by using a projected ordination of the auxiliary data based on CCA (Ohmann and Gregory 2002, Eskelson et al. 2009). The set of X variables for this analysis consisted of a matrix of the Landsat-derived auxiliary variables (Table 2), whereas the set of Y variables was a matrix of values for all five attributes of interest. The canonical correlations are created using both the X and Y variables.

All calculations for MSN and GNN were performed using the *yalmpute()* tool for *R()* (Crookston and Finley 2007, R Development Core Team 2008). MSN and GNN

Table 2. Landsat and auxiliary variables used in all imputations.

Description	Specific variables
Original Landsat bands	B1 B2 B7
Landsat ratios and functions	R1–R3 NDVI
Landsat transformations (TC)	TC1–TC6
Auxiliary variables	Cover Canopy Elevation

estimates were obtained by imputing values to all pixels within each county using only FIA plots located in forested areas as defined by NLCD. Similar to Ohmann and Gregory (2002), attribute values for nonforested pixels were set to 0 by masking nonforested land using NLCD forested and nonforested classifications described earlier (e.g., coniferous forest, shrub/scrub, and woody wetland). This makes the classification of NLCD an integral part of the estimates derived from MSN and GNN. The final MSN and GNN estimates were obtained by calculating the county-level mean of all pixel-based (forested and nonforested) attribute values (Ohmann and Gregory 2002). Because of the exorbitant amount of time and computing resources that would be needed to impute values to more than 20,000,000 pixels over 500 iterations, MSN and GNN were applied using only the full sample.

Composite Estimators

In addition to EBLUP, four other composite estimators were analyzed in this study. For every sampling intensity, each composite estimator was calculated using the reduced sample direct estimate and one of the aforementioned indirect estimates for each county. Individually, the composite estimators (CE) will be referred to hereafter as MLR_CE_A, MLR_CE_B, MSN_CE, and GNN_CE based on the indirect estimation components MLR_B, MSN, and GNN, respectively. The composite estimators for each variable of interest were developed using Equation 7 (Rao, 2003, p. 57)

$$\hat{Y}_{iCP} = \phi_i \hat{Y}_{i2} + (1 - \phi_i) \hat{Y}_{i1}, \quad (7)$$

where \hat{Y}_{iCP} is the composite estimate of the attribute for the i th county, \hat{Y}_{i1} is the direct estimate of the attribute for the i th county, \hat{Y}_{i2} is the indirect estimate of the i th county, and ϕ_i is the weight calculated for the i th county. The weights for MLR_CE_B, MSN_CE, and GNN_CE were calculated using a variation of a method described by Costa et al. (2003, 2009)

$$\hat{\phi}_i = \frac{\hat{\psi}_i}{\hat{\psi}_i + (\hat{Y}_{i2} - \hat{Y}_{i1})^2}, \quad (8)$$

with

$$\hat{\psi}_i = \frac{V_c}{n_i}, \quad (9)$$

and

$$V_e = \frac{\sum_i^m a_i s_i^2}{\sum_i^m a_i}, \quad (10)$$

where a_i is the total area (ha) in county i , s_i^2 is the sample variance for county i , V_e is the weighted sample variance for county i , and n_i is the ground sample size for county i . Note that $\hat{\psi}_i$ is a form of “smoothed” variance that provides stability to the weights. Although sample variance can be used, it is considered to be somewhat unstable and can sometimes be severely inflated compared with $(\hat{Y}_{i2} - \hat{Y}_{i1})^2$ (Costa et al. 2003). To assess the difference in precision and

bias, MLR_CE_A was estimated using s_i^2 in place of V_e to derive the weights. In so doing, MLR_CE_A uses a weighting strategy very similar to that used by Costa et al. (2009). The weighting method shown in Equation 8 differs slightly from the one presented by Costa et al. (2003) in that it uses the individual county-level difference between the indirect estimate and direct estimate instead of a mean difference across all counties. Although slightly less stable, this form of weighting should make the composite estimators more versatile with regard to weights. The weighting strategy described in Equation 8 shows that the greater $(\hat{Y}_{i2} - \hat{Y}_{i1})^2$ is relative to $\hat{\Psi}_i$, the greater the influence the direct estimate will have on the final estimate. The ultimate purpose of calculating composite estimates is to balance the potential bias of an indirect estimator against the instability of a direct estimator (Rao 2003, p. 57). This is an important aspect to consider when indirect estimators for forest attributes based on Landsat auxiliary information are used.

The MLR_A, MSN, and GNN indirect estimates (\hat{Y}_{i1} in Equation 7) were all calculated using the full sample from the population instead of the subsample. The purpose of MLR_A was to calculate a regression-based full sample counterpart estimate for direct comparison with MSN and GNN, which could not be calculated using subsamples. The implication is that the full sample estimates will most likely perform consistently better than the subsample-based estimates simply because they use more information. However, the composite estimates for MLR_A, MSN, and GNN were calculated using the subsamples for the direct estimator component. In this way, the comparison between the estimators extends to situations in which individual county samples are assumed to be inadequate regardless of whether the indirect component is estimated with either the full sample or a subsample.

Validation

County-level full sample direct estimates were used for validation at the county level for each estimator. To compare the estimators for each sampling intensity, performance statistics were calculated based on the full set of plots from each county, including relative root mean squared error (RRMSE) and relative bias (RB). Because most of the estimators were evaluated over 500 subsamples, the performance statistics needed to be calculated accordingly. Overall performance was assessed using RRMSE (Rao 2003, p. 62, Datta et al. 2005)

$$\text{RRMSE} = \frac{1}{m} \sum_i^m (\text{RMSE}_i / \hat{Y}_{iO}), \quad (11)$$

with

$$\text{RMSE}_i = \sqrt{\frac{1}{R} \sum_{r=1}^R (\hat{Y}_{iP} - \hat{Y}_{iO})^2}, \quad (12)$$

where RMSE_i is the root mean squared error for county i , m is the number of counties, R is the number of subsamples (iterations), \hat{Y}_{iP} is the predicted value for county i , and \hat{Y}_{iO}

is the full sample direct estimate for county i . Similarly, overall bias was assessed using relative bias calculated as

$$\text{RB} = \frac{1}{m} \sum_{i=1}^m (\text{RB}_i), \quad (13)$$

with

$$\text{RB}_i = \frac{1}{R} \sum_{r=1}^R \left(\frac{\hat{Y}_{iP} - \hat{Y}_{iO}}{\hat{Y}_{iO}} \right), \quad (14)$$

where RB_i is the relative bias squared error for county i . Because MLR_A, MSN, and GNN were not based on subsampling, the same statistics were calculated based on the single estimate for each county. This was necessary to properly compare the performance of these estimators with the estimators that were dependent on subsampling.

Results and Discussion

The final MLR models were fairly consistent in that they all included Canopy as a significant predictor variable. Most of the MLR models also included R3 and Elev as significant variables. Table 3 shows regression coefficients and summary statistics for the MLR_A models calculated from the full sample, as well as lists of auxiliary variables chosen in the preliminary MLR assessment of the attributes.

The residual plots indicated that transformations were not needed. The same variables were identified as significant in the models for both CuVol and Ht with the exception of TC4 and Cover. TC4 and TC5 are generally considered to be less useful for most applications than TC1–TC3. Table 3 shows that variables such as TC4 and TC5 can be significant in estimating several forest attributes after the effects of other important Landsat variables are accounted for. Similarly, the auxiliary variables of Canopy and Elev were significant for most attributes. As stated previously, the sets of variables identified in Table 3 were used to evaluate MLR_B, EBLUP, and the composite estimators using an MLR_B component.

Because there were five different forest attributes included in the canonical correlation for MSN and GNN, five canonical covariates (axes) were created for determining distance. The analysis for each method indicated that three of the axes were highly significant. BA, QDBH, and Ht had the highest canonical correlations with the auxiliary data, whereas Density and CuVol had the lowest. Performance statistics for each county-level attribute by estimation method and sampling intensity are given for imputation-based estimators and regression-based estimators in Tables 4 and 5 respectively.

Indirect Estimation

Full Sample Estimates

One of the first noticeable characteristics is the difference in performance of GNN and MSN compared with that of MLR_A (Tables 4 and 5). With the exception of density, GNN and MSN yielded lower RRMSE values than MLR_A. However, MLR_A consistently had lower bias

Table 3. Regression coefficients for MLR_A models using the full sample.

Coefficient	Density (trees/ha)	BA (m ² /ha)	CuVol (m ³ /ha)	QDBH (cm)	Ht (m)
Intercept	-1182.8 (110.1)	-0.018 (0.18)	-719.4 (131.9)	-61.1 (13.9)	-0.46 (7.4)
B4			-0.15 (0.02)	-0.01 (0.002)	-0.006 (0.0008)
R3		1.2 (0.12)	9.9 (0.98)	0.59 (0.1)	0.41 (0.053)
TC2		-0.02 (0.002)			
TC4	-0.8 (0.11)	-0.5 (0.009)	-0.2 (0.12)		
Cover				-0.8 (3.3)	1.8 (1.7)
Canopy	1.8 (0.24)	0.22 (0.021)	2.4 (0.31)	0.15 (0.04)	0.13 (0.019)
Elev		0.0043 (0.002)	0.05 (0.02)		0.0029 (0.0008)
R ² (adj) %	43	54	44	37	55
RMSE	200.6	15.3	216.3	21.1	11.1

SEs of coefficients are given in parentheses.

than MSN and GNN. In addition, with the exception of density, GNN tended to have higher values than MSN for both RRMSE and RB. Both GNN and MSN have a strong tendency for underestimation compared with MLR_A, although RB tends to be negative in most cases for MLR_A as well. There are several possible reasons for the greater bias of GNN compared with that for MSN and MLR_A. We classified forest areas as having one of several NLCD land cover classes including coniferous forest, deciduous forest, mixed forest, shrub/scrub, and woody wetlands. Cases of

areas actually containing some trees being classified as nonforest either by the land cover classes we chose or by error in the NLCD coverage are entirely possible and would contribute to underestimation in both GNN and MSN (Smith et al. 2003). However, when MSN and GNN are calculated without using a mask for nonforested areas, the RRMSE and RB values are much greater than those shown in Table 5, especially for GNN. There have also been other documented cases for which GNN had considerably higher bias than MSN, such as those described by Eskelson et al.

Table 4. Estimated RRMSE and RB of all regression-based estimates and DE for each attribute of interest by sampling intensity.

	20%		30%		40%	
	RRMSE	RB	RRMSE	RB	RRMSE	RB
Density (trees/ha)						
MLR_A*	8.9	0.48	8.9	0.48	8.9	0.48
MLR_B	11.4	0.48	10.6	-0.11	10.2	0.36
EBLUP	12.1	0.13	10.6	-0.45	10.1	0.03
MLR_CE_A	11.7	-0.48	10.2	-0.53	9.8	0.11
MLR_CE_B	15.6	0.28	12.3	-0.41	10.4	0.04
DE	26.8	-0.05	20.6	-0.6	16.7	-0.3
BA (m ² /ha)						
MLR_A*	15.7	-3.9	15.7	-3.9	15.7	-3.9
MLR_B	16.9	-3.6	16.4	-4.1	16.3	-3.9
EBLUP	16.7	-3.9	15.5	-4.4	15.1	-4.3
MLR_CE_A	16.1	-4.1	15.4	-4.2	15.2	-3.9
MLR_CE_B	17.9	-2.3	14.7	-2.4	12.8	-2.2
DE	26.3	-0.4	19.9	-0.2	16.4	-0.2
CuVol (m ³ /ha)						
MLR_A*	18.4	-3.2	18.4	-3.2	18.4	-3.2
MLR_B	21.1	-3.1	19.9	-3.3	19.6	-3.2
EBLUP	20.2	-3.8	18.1	-4.3	16.8	-4.3
MLR_CE_A	20.4	-5.1	18.8	-4.3	18.3	-3.8
MLR_CE_B	21.8	-2.2	17.8	-2.1	15.5	-2
DE	31.4	-0.4	23.9	-0.08	19.5	-0.2
QDBH (cm)						
MLR_A*	18.1	-1.3	18.1	-1.3	18.1	-1.3
MLR_B	19.9	-0.52	19	-1.1	18.8	-1.2
EBLUP	17.5	-1.3	15.1	-2.1	13.4	-2.3
MLR_CE_A	18.2	-1.9	17.8	-2.1	17.1	-1.9
MLR_CE_B	18.4	-0.72	14.9	-1.1	12.9	-1.1
DE	24.6	0.2	18.7	0.08	15.3	-0.08
Ht (m)						
MLR_A*	14.1	-3.2	14.1	-3.2	14.1	-3.2
MLR_B	15.4	-2.9	14.8	-3.2	14.7	-3.3
EBLUP	14.1	-3.2	12.5	-3.6	11.5	-3.7
MLR_CE_A	14.3	-2.8	13.7	-3.1	13.7	-3.2
MLR_CE_B	15.4	-1.7	12.6	-1.8	11.1	-1.8
DE	22.2	-0.04	16.9	0.05	13.8	-0.2

* No subsampling.

Table 5. Estimated RRMSE and RB of all imputation-based estimates and DE for each attribute of interest by sampling intensity.

	20%		30%		40%	
	RRMSE	RB	RRMSE	RB	RRMSE	RB
Density (trees/ha)						
MSN*	13.4	-13.2	13.4	-13.2	13.4	-13.2
GNN*	7.2	-4.8	7.2	-4.8	7.2	-4.8
MSN_CE	16.3	-6.1	13.4	-6.3	11.6	-6
GNN_CE	14.3	-2.3	11.2	-2.6	9.3	-2.5
DE	26.8	-0.05	20.6	-0.6	16.7	-0.3
BA (m ² /ha)						
MSN*	12.8	-10.1	12.8	-10.1	12.8	-10.1
GNN*	14.8	-13.7	14.8	-13.7	14.8	-13.7
MSN_CE	16.6	-4.8	13.6	-4.7	11.7	-4.4
GNN_CE	17.6	-6.1	14.4	-5.8	12.6	-5.4
DE	26.3	-0.4	19.9	-0.2	16.4	-0.2
CuVol (m ³ /ha)						
MSN*	14.6	-6.7	14.6	-6.7	14.6	-6.7
GNN*	17.8	-16.5	17.8	-16.5	17.8	-16.5
MSN_CE	19.1	-3.4	15.5	-3.3	13.4	-3.3
GNN_CE	21.2	-7.2	17.4	-6.7	15.2	-6.2
DE	31.4	-0.4	23.9	-0.08	19.5	-0.2
QDBH (cm)						
MSN*	13.7	-4.4	13.7	-4.4	13.7	-4.4
GNN*	15	-7.2	15	-7.2	15	-7.2
MSN_CE	16.1	-2.1	13.1	-2.2	11.4	-2.1
GNN_CE	16.8	-3.1	13.7	-3.1	11.9	-2.9
DE	24.6	0.2	18.7	0.08	15.3	-0.08
Ht (m)						
MSN*	11.7	-7.2	11.7	-7.2	11.7	-7.2
GNN*	13.2	-12.4	13.2	-12.4	13.2	-12.4
MSN_CE	13.7	-3.4	11.4	-3.4	9.9	-3.4
GNN_CE	15.2	-5.3	12.5	-5.1	10.9	-4.8
DE	22.2	-0.04	16.9	0.05	13.8	-0.2

* No subsampling.

(2009) in which for some attributes GNN had RB 5 times greater than that of MSN, a magnitude of difference not experienced in this study. The indirect estimators usually achieved greater precision than the direct estimates for low sampling intensities, albeit the former are based on a much larger sample size.

Subsample Estimates

The one indirect estimate derived entirely from the subsamples was MLR_B. As expected, MLR_B tended to have a slightly higher RRMSE than MLR_A, particularly at low sampling intensities (Table 4). Interestingly, this was often not the case for RB, which for many attributes and sampling intensities was “slightly” lower for MLR_B than MLR_A. This may have been caused by the relatively high proportion of zero observations in the data from nonforested plots, the truncating effects of which were probably negligible for many subsamples, depending on which plots were randomly chosen. Most significant is the performance of the indirect estimator compared with the direct estimates. For the 20% sampling intensity, the RRMSE of the model-based, indirect estimator was substantially better than that of the direct estimator. However, as the sample size increased, the performance of the direct estimator improved relative to that of the indirect estimator, especially for QDBH and Ht. The direct estimator is design-unbiased, and, therefore, the rel-

ative bias was negligible and always smaller than that of all other estimators.

Composite Estimation

In contrast to the other subsample-dependent composite estimators, EBLUP has the greatest tendency to mimic the performance of MLR_B for most attributes and most sampling intensities. In this study, EBLUP was very similar to MLR_B in terms of RRMSE and RB in many cases (Table 4). This result is due to extremely small values of the estimated random effects (e.g., $v_i = 0.00001 - 0.22$) that were most likely caused by a disparity between within-county variation and between-county variation. EBLUP is highly dependent on the between-area variation, which describes differences in the attribute of interest that independent variables cannot explain. According to Equation 4, small random effects can be caused by small values of σ_v^2 , relative to σ_e^2 , reflecting a disproportionately large within-county variation compared with the between-county variation. This can have the effect of creating a very small ratio (weight) $\lambda = \sigma_v^2/\sigma_e^2$, where $\sigma_v^2/\sigma_e^2 = n_i\sigma_v^2 = \lambda/(1 + n_i\lambda)$. Based on the full sample, σ_e^2 was between 4 times (QDBH) and 100 times (density) σ_v^2 . Therefore, the weight assigned to the direct estimator in Equation 5 was always lower than 0.25 and was typically much lower when subsamples due to higher values for σ_e^2 were used.

In terms of precision, the composite estimators generally mirrored the performance of their respective indirect estimation components; this was more evident for MLR_CE_A than for MLR_CE_B. Much of the difference in precision observed between MLR and MSN dissipated greatly with the calculation of composite estimates. Composite estimation did not produce greater precision than indirect estimation for MSN in most cases, but substantially decreased the relative bias. This was a contrast to MLR_CE_A and MLR_CE_B, which achieved greater precision than did MLR_B in many cases, particularly at sampling intensities greater than 20%. This effect may be due to the fact that MSN was estimated with the entire sample, whereas both the DE component of MSN_CE and the MLR-based estimates were computed with a fraction of the sample. One key observation is that there is a difference in performance between MLR_CE_A and MLR_CE_B, particularly for precision. MLR_CE_B has a tendency to outperform MLR_CE_A in terms of precision for higher sampling intensities but often not for low sampling intensities. This difference in performance is primarily the result of fundamental differences between the weighting strategies of the two composite estimators and will be addressed more thoroughly later.

County-Level Estimation

Although the statistics shown in Tables 4 and 5 are informative as to the overall performance of the estimators, the main objective of SAE is to produce estimates for individual counties. The county-level RRMSE and RB for the best subsampled estimators (Tables 4 and 5), including MLR_B, MLR_CP_A, and MLR_CP_B, and direct estimation were compared for a sampling intensity that showed a great difference between the estimators (20%) (Figures 2 and 3). For each figure, the counties were sorted in an ascending sequence based on the mean absolute deviation of MLR_B from the full sample direct estimates for each attribute of interest.

Precision (RRMSE)

As seen in the summary statistics in Table 4, it is difficult to pinpoint any single estimator that is superior in terms of precision for all attributes in all counties. However, there are some very distinct trends that can be observed in Figure 2. First, it is apparent that in precision, DE is generally inferior to all model-based estimators in most cases, particularly for Density, but it is not appreciably worse for QDBH. One possible explanation for this is the poorer model performance of QDBH shown in Table 3, based on adjusted R^2 . MLR_B is consistently the most precise estimator for counties with low absolute deviation, but this quickly changes at mid-range to high deviation. In addition, EBLUP, MLR_CE_A, and MLR_CE_B tend to more closely mimic MLR_B for counties with low deviation, usually in the same general order, because a lower absolute deviation of MLR leads to a higher weight on the indirect component of composite estimators.

MLR_CE_B does not follow the pattern of MLR_B

nearly as much as do EBLUP and MLR_CE_A. More specifically, MLR_CE_B tends to be more stable with regard to precision and actually uses DE more heavily than MLR_CE_A. This difference is a result of the use of the smoothed variance estimator (Equation 9) for deriving the weights of MLR_CE_B. Because the variance component of the weighting method is itself a weighted mean, MLR_CE_B tends to weight the direct estimation component much more heavily than does MLR_CE_A. As a result, RRMSE varies less from county to county for MLR_CE_B than it does for any of the other composite estimators. This inherent stability, which was the primary reason to use a smoothed variance, has an even greater effect on RB, as will be discussed shortly.

Although the county-level values of RRMSE do not identify one particular estimator as superior to the others, use of a composite estimator has an apparent advantage in terms of precision. With the exception of counties with very low absolute deviation of MLR_B, the composite estimators tend to have the highest deviation, particularly MLR_CE_B. RRMSE demonstrates the benefits of using either indirect estimation or composite prediction over direct estimation; one of the most important comparisons between the different indirect and composite methods is bias. This is also important when imputation is considered as an SAE method because MSN and GNN were shown to have substantially higher RB (Table 5) than all estimators illustrated in Figure 1 even though the full sample was used to calculate MSN and GNN.

Bias (RB)

Note that DE was not included in the comparison of bias because direct estimation is design unbiased. The overall differences in RB for these estimators are more intuitive than are the differences for RRMSE. As expected, the composite prediction outperformed indirect estimation for almost all counties and attributes, because the primary purpose of composite prediction is to balance the inherent bias of an indirect estimator with the low precision of a direct estimator. By far, the most stable estimator for bias was MLR_CE_B for all counties and all attributes. This stability, caused by a tendency for MLR_CE_B to weight the direct estimation component more heavily, was also the primary reason that this estimator was consistently superior in terms of bias.

Best Estimator

Although the summary statistics and graphs have shown that both indirect estimation and composite prediction can produce relatively precise and low biased estimates, the question of which estimator is the best remains. It is clear from Figure 3 that MLR_CE_B is superior to all other methods with regard to bias. However, one has to consider both precision and bias when choosing an SAE method. The determination of which estimator is best based on precision is far less intuitive than that for bias. This was most likely caused by two factors: poor overall performance of regression models and homogeneity between counties for some

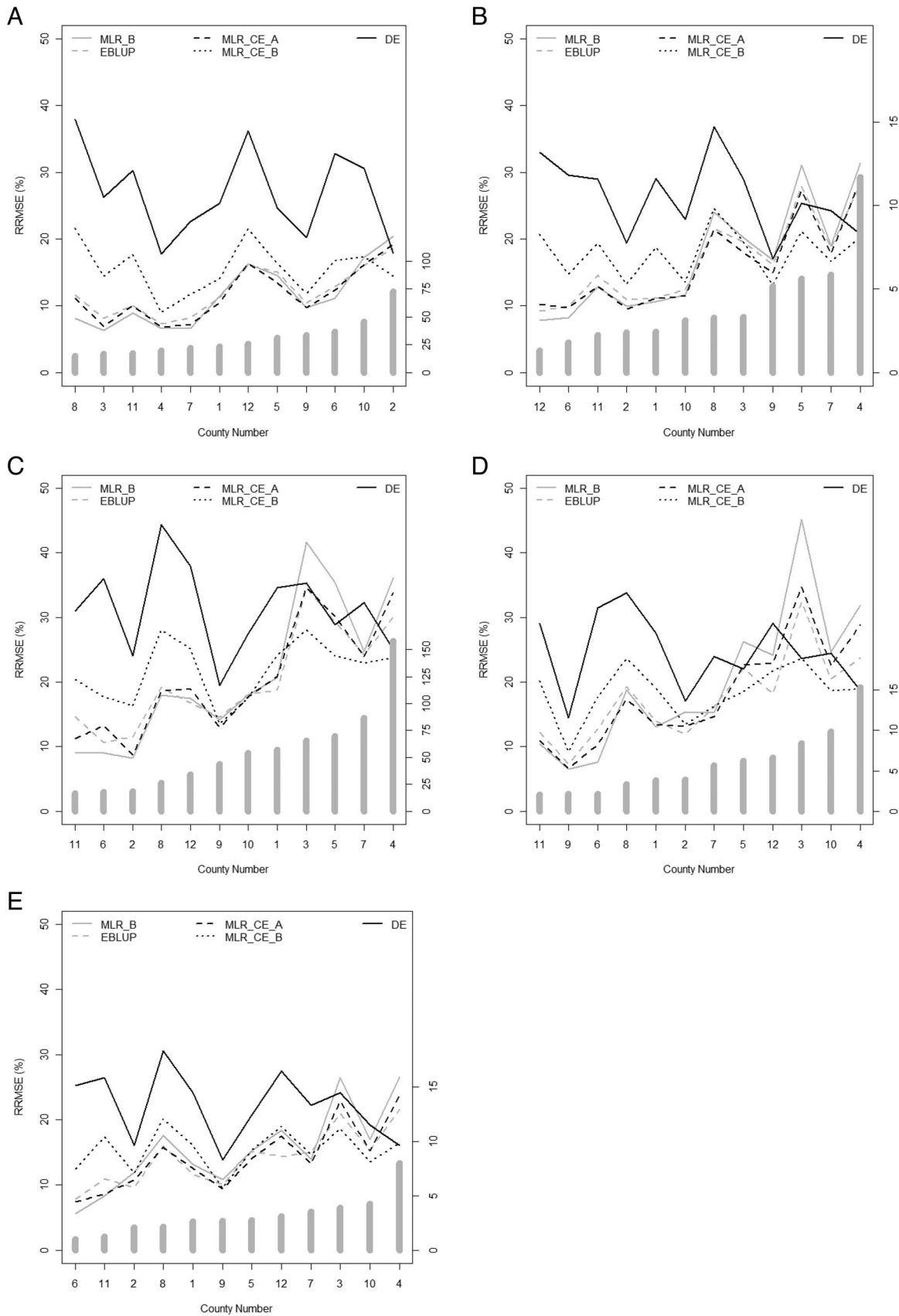


Figure 2. Plots of RRMSE% at 20% sampling intensity MLR_B, EBLUP, MLR_CE_A, MLR_CE_B, and DE for (A) trees/ha, (B) BA, (C) CuVol, (D) QDBH, and (E) Ht. The horizontal axis shows county number (Table 1), and the right axis represents mean absolute deviation of MLR_B from the full sample mean.

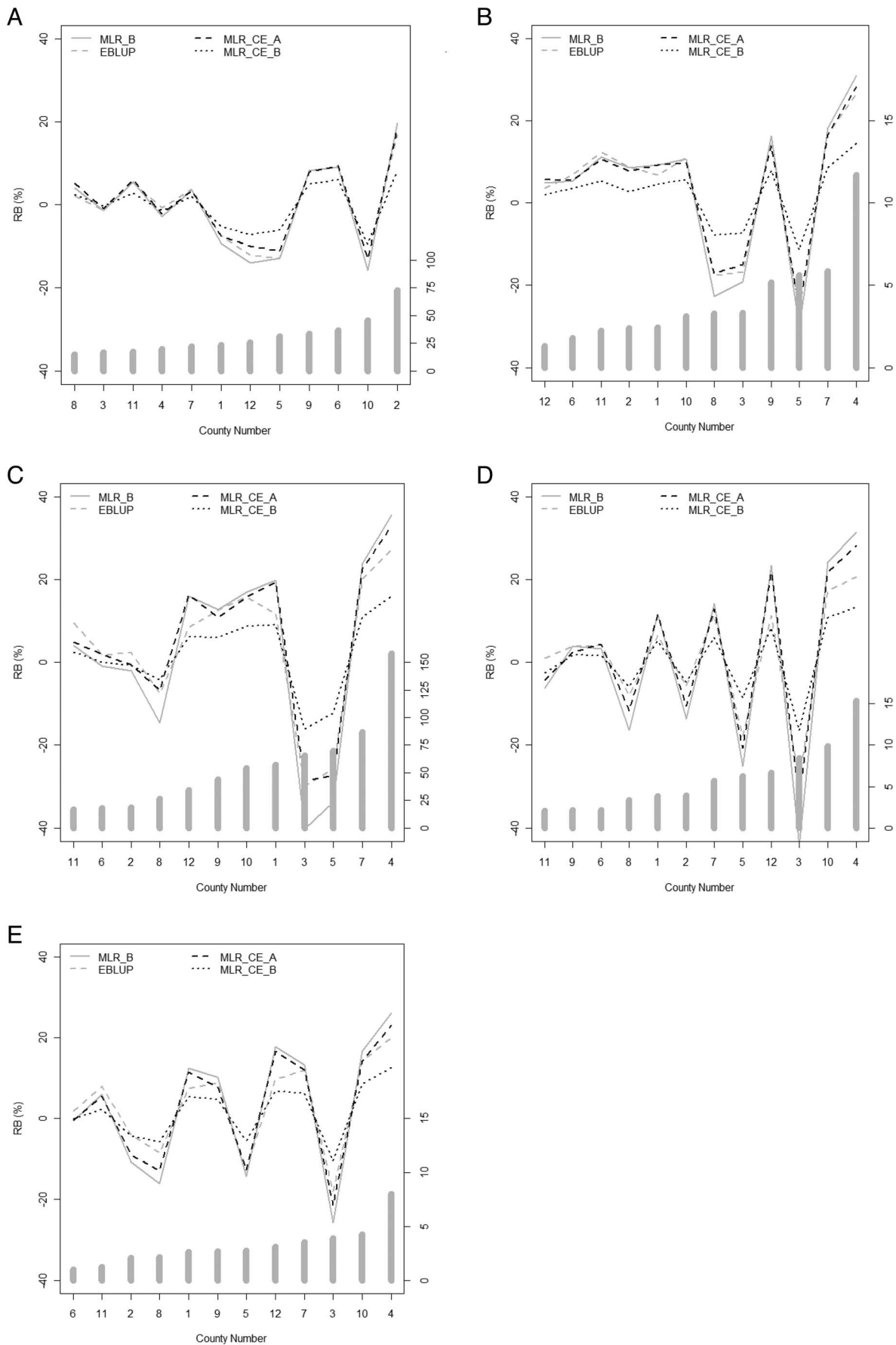


Figure 3. Plots of RB% at 20% sampling intensity MLR_B, EBLUP, MLR_CE_A, and MLR_CE_B for (A) trees/ha, (B) BA, (C) CuVol, (D) QDBH, and (E) Ht. The horizontal axis shows county number (Table 1), and the right axis represents mean absolute deviation of MLR_B from the full sample mean.

forest attributes. The fact that the overall performance of the regression models was relatively low (Table 3) is the most likely reason and was primarily caused by the fact that Landsat metrics are not as highly correlated with many forest attributes as are some more advanced forms of remote-sensed data such as LiDAR (Goerndt et al. 2011). This is particularly important when the precision of estimation is considered, because the higher precision of most composite prediction methods compared with that of direct estimation is a result of the indirect (model-based) component. Relative homogeneity between counties was observed for most of the attributes used in this study, especially for Density and Ht (Table 1), which had an adverse effect on the estimation of random effects for EBLUP.

Based on the results of the analysis, MLR_CE_A and MLR_CE_B are superior estimators in terms of precision. Even on a county-level basis, MLR_CE_B is superior to all other estimators examined in this study with regard to bias. Any of the aforementioned composite estimators has the demonstrated capability to derive estimates of forest attributes with relatively high precision and low bias. MLR_CE_B could probably be considered the best overall estimator examined in this study, although it does not always obtain higher precision than some of the other estimators.

Conclusion

SAE can provide precise and accurate estimates of forest attributes for areas of interest within populations of varying spatial scales. The large-scale availability of modern remotely sensed auxiliary information such as Landsat, NLCD, and DEMs is the key to accomplishing the goal of applying effective SAE techniques to forestry problems. The SAE techniques examined in this study have provided considerable evidence that indirect and composite estimators based on auxiliary information from a regional population can provide precise estimates of many forest attributes at the county level. It was also found that the success of SAE for county-level forest attributes was greatly dependent on the use of composite estimations that could account for strong individual effects within the counties where they exist.

This study showed that the model-based indirect estimators and composite estimators were all sufficient for obtaining county-level estimates that had relatively low bias and were more precise than direct estimates. This result led to composite estimators that had high precision and low bias compared with those of direct estimation. EBLUP, MLR_CE_A, MLR_CE_B, and MLR_B all yielded more precise estimates with fairly low bias for all attributes than did direct estimation. However, MLR_CE_B was consistently the best composite estimator with regard to bias. Composite methods obtained lower bias for all attributes in most counties than did indirect estimation. Unlike the regression-based estimators, GNN and MSN both had a tendency for consistent underestimation for each county, with substantially greater RB overall.

The estimators used in this study were developed based on two general situations: there is a sufficient sample size

for the population as a whole, and there is an insufficient sample size for all counties of interest. For full sample estimates, the results showed that MLR_A was superior to GNN and MSN in terms of bias but not in terms of precision, indicating a distinct tradeoff between use of regression-based or imputation-based indirect estimators. However, most disparity in bias between the imputation estimators and MLR_A was adjusted for in the creation of GNN_CE and MSN_CE, while still maintaining higher precision than that of MLR_A for most attributes. In addition, all three indirect estimators using the full sample consistently had higher precision than DE in most cases. It was also shown that the MLR_CE_B performed better than its indirect component (MLR_B) in precision and bias for most sampling intensities. This result indicates that use of the modeling techniques in this study in conjunction with Landsat auxiliary information can produce relatively precise and low-bias composite estimators that are well suited to both situations. The analyses also showed that composite estimators based on regression generally performed better than composite estimators based on imputation, especially for bias. This study has shown that SAE is fairly successful in estimating several county-level forest attributes with high precision and relatively low bias.

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