Accuracy Assessment of FIA's Nationwide Biomass Mapping Products: Results From the North Central FIA Region

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Abstract.—The Remote Sensing Band of the Forest Inventory and Analysis (FIA) program has developed a nationwide map of forest biomass to be distributed as a geospatial raster data set with 250-meter spatial resolution. The accuracy of the forest biomass map depends on both an intermediate forest/nonforest classification and the biomass estimation. For the North Central FIA region, we assessed the accuracy of the forest classification and biomass estimation using three approaches: (1) per pixel percent correctly classified; (2) comparisons of pixel- and FIA plot-based estimations within delineated areas; and (3) utility for stratified estimation of FIA attributes. Results showed the forest/nonforest map to be accurate based on all three assessments, while the forest biomass map performed well only for area estimates.

Introduction

The mission of the Forest Inventory and Analysis (FIA) program is to provide statistical information about America's forests. In the past, much of this information was summarized in statistical reports covering large areas, which offered little insight into describing where forest attributes occur on the ground. With improvements in geospatial technologies and the increased availability of remotely sensed imagery, developing maps of predicted forest attributes across landscapes is now feasible. During the summer of 2003, the Remote Sensing Band (RSB)—an interregional working group of the FIA program—developed a nationwide forest biomass map. The purpose of this mapping effort was to predict forest biomass across the Nation by combining FIA measurements with remotely sensed imagery and other raster data sets. This effort produced two mapping products: a forest/nonforest (FNF) map and the forest biomass map itself. Although this mapping effort is notable, its utility depends on the accuracy of the resulting products. In this article, we report and discuss results related to our validation of the portions of the FNF and biomass maps in the North Central FIA (NCFIA) region. We assessed accuracy using the following approaches: (1) per pixel correctly classified, (2) comparisons of pixel-based and FIA plot-based estimates within delineated areas, and (3) utility for stratified estimation of FIA attributes.

Biomass Mapping Effort

Forest/nonforest classes and continuous estimates of biomass were mapped at a 250-meter spatial resolution across the continental United States, Alaska, and Puerto Rico. FIA attributes were integrated with spectral information from a variety of data layers collectively referred to as the national geospatial predictor data set. These data layers included Moderate Resolution Imaging Spectroradiometer (MODIS) reflectance data; MODIS derivatives such as Enhanced Vegetation Index, Normalized Difference Vegetation Index, and Vegetation Continuous Fields (Hansen *et al.* 2002); derivatives of the National Land Cover Data of 1992 (NLCD92), a 30-meter spatial resolution land cover product of the Multi-Resolution Land Characterization Consortium derived from nominal 1992 Landsat Thematic Mapper (TM) imagery (Vogelmann *et al.* 2001); and elevation, precipitation, and temperature data.

Software from a suite of data mining packages developed by RuleQuest Research was used for creating models specific to mapping zones developed for the National Land Cover Data of 2000 (Homer *et al.* 2002). See5, a data mining software package, was used for modeling forest land by combining FNF data observed on FIA plots with corresponding information from the predictor data set to produce decision trees or rule sets (RuleQuest Research 1997). Using a custom software interface tool developed by the Forest Service's Remote Sensing

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Applications Center (RSAC), we incorporated these decision trees or rule sets with ERDAS IMAGINE image processing software to assign each 250-meter pixel to either a forest or nonforest class.

Modeling and mapping of biomass was performed in a similar manner, but relied on Cubist, RuleQuest Research's data mining software package for deriving predictive models of continuous response variables (RuleQuest Research 1997). The Cubist rule-based linear models were used for predicting gross biomass of all live trees (oven-dry tons/acre). Again, the models were brought into ERDAS IMAGINE using the custom-built RSAC tool to map the biomass predictions for each pixel. Because the model was predicting forest biomass values, biomass was mapped only on forest land, and the FNF map was used to mask appropriate nonforest areas.

Accuracy Assessment

Per Pixel

FNF Map

Because the FNF map included discrete classes, the accuracy assessment for the FNF map used only FIA plots that were both single condition (either 100-percent forested or 100-percent nonforested) and independent of the plots used to train the model (10 percent were randomly selected from the total plots available). For pixels containing these "test" plot locations, predicted forest or nonforest classes were extracted and compared to observed forest or nonforest assignments reported for those specific plots. Results were tabulated in a confusion matrix. Originally, assessments were to be performed for each State. Based on a rule of thumb proposed by Congalton and Green (1999), which suggests at least 50 sample points per class for accuracy assessment, however, some States were combined into larger areas. One of these aggregations included Iowa (IA) and the Plain States (PS): North Dakota (ND), South Dakota (SD), Nebraska (NE), and Kansas (KS). Indiana (IN) and Illinois (IL) were also combined into a single area. Per State assessments were performed for the remaining four States in NCFIA: Michigan (MI), Minnesota (MN), Missouri (MO), and Wisconsin (WI). In addition, a regionwide assessment was conducted.

Four accuracy measures were calculated from the confusion matrix: (1) overall accuracy, (2) producer's accuracy, (3) user's accuracy, and (4) Kappa. Overall accuracy, a measure of the accuracy across all classes, is calculated as the ratio of the total number of correctly classified reference points to the total number of reference points. Producer's accuracy, which describes how well the classification matched the reference data for each class individually, is calculated as the ratio of the number of correctly classified reference points for a class to the total number of reference points for that class. User's accuracy, also referred to as mapping accuracy, measures the likelihood that an area assigned to a class will actually be that class when visited in the field. This number is calculated as the ratio of the number of correctly classified reference points for a class to the total of reference points classified as that class. The Kappa, or KHAT statistic, measures the percent improvement the classification has over a classification based purely on a random assignment of pixels to classes (Congalton and Green 1999, Jensen 1996, Lillesand and Kiefer 2000).

Forest Biomass

Cubist, the data mining software used to model biomass, produces three measures for assessing model accuracy. These measures—average error, relative error, and correlation coefficient—are based on all model predictions. Average error is calculated as the average absolute difference between observed and predicted values. Relative error is the ratio of the average error to the average absolute difference between observed values and the mean value of the training observations. A relative error value near to or greater than 1 indicates little or no improvement by the model over the assignment of the mean of the observed values to each case. The correlation coefficient (r) describes the linear relationship between observed and predicted values. These three measures were also recalculated for the independent validation data set, using only plots with 100-percent forest condition and located in pixels classified as "forest" in the FNF map. Assessment was performed on the regionwide map.

Plot- Versus Pixel-Based Area Estimates

Although per pixel accuracy assessments are important for validating maps at the local level, area estimates can provide an indication of correctness for larger areas. Reese *et al.* (2002)

reported that using a k-Nearest Neighbor (kNN) algorithm with SPOT 3 and Landsat TM/Enhanced Thematic Mapper Plus data performed poorly at the pixel level but produced acceptable results for larger area estimates of wood volume and biomass in Sweden's forests. For our study, we assessed accuracy of area estimates by comparing FIA plot-based estimates to RSB map-based estimates. This comparison, relative difference (RD), was calculated as:

$$\text{RD} = \frac{(predicted - observed)}{observed}$$

Because FIA plot-based estimates are based on a sample, 95-percent confidence limits were calculated for each estimate and compared to the RSB map-based estimates.

FNF Map

Total and forested pixel counts were determined for each State in the 11-State NCFIA region. Proportion forest land area for a State was computed as the ratio of the number of forested pixels in a State to the total number of pixels in that State. A consistent intensity of FIA plots in a State was used to calculate estimates of plot-based proportion forest area based on the assumption of simple random sampling (SRS). For comparison to another map product, estimates of statewide proportion forest land were calculated using the NLCD92. The NLCD92 data set consists of 21 land cover classes. We aggregated these classes into forest and nonforest, as recommended by McRoberts *et al.* (2002), and computed statewide proportion forest land, as was done for the RSB FNF map. In addition, RD was calculated to compare plot-based estimates to NLCD92-based estimates.

Forest Biomass

Pixel-based area estimates for forest biomass were calculated in much the same way as forest area estimates. The mean biomass in tons/acre was calculated for an area using all pixels classed as forest in the RSB FNF map in the area. Plot-based estimates included only plots that had a forested condition.

Stratified Estimation

NCFIA currently uses a stratified estimation (post-sampling stratification) approach that incorporates satellite-imagery-derived land cover classification data for improving the precision of FIA estimates (McRoberts *et al.* 2002). According to Hansen (2001), "The sampling errors of the area estimates are very dependent on the quality of the stratification" (Hansen 2001, 45). We assessed the accuracies of the mapping products by examining their utility for stratified estimation. This was accomplished by comparing the precision of a stratified estimate using map-based strata to the precision of estimates based on SRS.

For SRS, plot-based estimates calculated for the area estimate comparisons discussed above were used. The variance estimates were then calculated to determine the precision of each SRS estimate. For stratified estimation, the same plots used in the SRS technique were assigned to strata based on overlays of the stratification layers. Again, the estimate, $\bar{\rho}$, and associated variance estimate, Var ($\bar{\rho}$), were calculated, but this time Cochran's (1977) formulas for stratified analyses were used:

$$\bar{\rho} = A\sum_{j=1}^{J} W_j \hat{P}_j$$

and

$$\text{Var}(\bar{\rho}) = A^2 \sum_{j=1}^{J} W_j^2 \hat{\sigma}_j^2 / n_j$$

where:

A is total area,

j=1,…,J denotes stratum,

W_j is the weight for the jth stratum calculated as the ratio of the number of pixels assigned to the jth stratum to the total number of pixels for all strata,

$\hat{P}_i$ denotes the mean proportion forest land for plots assigned to the jth stratum,

$\hat{\sigma}_j^2$ is the within-stratum variance for the jth stratum calculated as:

$$\hat{\sigma}_j^2 = \frac{1}{n_j - 1} \sum_{i=1}^{nj} (P_{ij} - \hat{P}_j)^2$$

where:

P_{ij} is the proportion forest land observed by the field crew for the ith plot in the jth stratum, and

n_j is the number of plots assigned to the jth stratum.

FIA precision estimates are scaled to a constant area to report precisions for estimation units of varying sizes. These precisions, as a percent estimate per million acres of forest land or a percent per billion tons of biomass, were calculated as follows:

$$PREC = \frac{(sampling\ error)\sqrt{estimated\ attribute}}{\sqrt{standard}}$$

Relative efficiency (RE) of the stratified estimation precision to the SRS precision is calculated as:

$$RE = \left(\frac{SE(SRS)}{SE(stratified\ estimation)} \right)^2$$

FNF Map

Using a consistent intensity of FIA plots from the first annual inventory, a SRS estimate of forest land area was calculated for each State. The FNF map was used as a stratification layer to compute a stratified estimate of forest land area. Two stratification layers were derived from this map. The first was a two-stratum layer created using the forest and nonforest classes directly. The second was a four-stratum layer that included two interior classes, forest and nonforest, and two edge classes, one located adjacent to forest interior and the other adjacent to nonforest interior. The four-strata layer required manipulation of the FNF map including (1) a division of each 250-meter pixel into 25 50-meter pixels, and (2) a search and recode operation to reassign the first tier of 50-meter pixels adjacent to each interior class located along the transition zone to its respective edge class. This same procedure was repeated for the entire 11-State FIA region, using FIA plots from fiscal year (FY) 2001, the only year for which annual plot data are available across all 11 States.

Forest Biomass

Per area estimates of forest biomass were computed for the entire NCFIA region. Plots from a single year of the annual inventory FY 2001 were used. To create the stratification layer, the continuous biomass values were aggregated into three biomass classes representing low, medium, and high biomass. Class breaks were based on those proposed for distribution in the RSB national map: less than 30 tons/acre (low), 30–50 tons/acre (medium), and greater than 50 tons/acre (high). These class breaks are comparable to one standard deviation of the predicted data in the NCFIA region. A per pixel accuracy assessment of these biomass classes was performed using observed values from FIA plot data grouped in the same classes as test data.

Results

FNF Map

Per Pixel

Table 1 shows a summary of the results for the per pixel correctly classified assessment of the RSB FNF map. Overall accuracies for all areas were good, exceeding the 85-percent minimum described as acceptable by Anderson (1971) for land cover classifications. For many areas, overall accuracy exceeded 90 percent. When compared to the reference data (producer's accuracy), the nonforest class had relatively high values (88 percent or higher) in all analysis areas. The accuracy of the forest class tended to reflect the abundance of forest land in that area, because classifications of sparsely forested areas (PS and IA) performed poorly, while classifications of more heavily forested areas (MI, MN, MO, and WI) performed better. The mapping accuracy (user's accuracy) exhibited a similar trend. Except for the PS and IA area (Kappa = 43 percent), the classifications performed better than a random assignment of pixels to classes (Kappa > 70 percent).

Table 1.—*Confusion matrix summary for the FNF map based on a per pixel accuracy assessment.*

Analysis area	Overall accuracy (%)	Producer's accuracy (%)		User's accuracy (%)		Kappa (%)
		Forest	Nonforest	Forest	Nonforest	
MI	91	92	89	90	91	81
MN	89	91	88	84	93	78
MO	88	77	94	88	88	73
IL and IN	95	82	97	77	98	77
PS and IA	98	40	99	48	99	43
Region	94	84	96	86	96	81

Table 2.—*Comparison of proportion forest area estimates.*

Analysis area	Proportion forest land			Relative difference (%) to plot-based	
	RSB map-based	NLCD92 map-based	Annual plot-based	RSB map-based	NLCD92 map-based
IL	0.09	0.15	0.11	–25	31
IN	0.14	0.20	0.19	–25	7
IA	0.04	0.08	0.07	–35	19
KS	0.02	0.04	0.04	–49	–13
MI	0.51	0.56	0.52	–3	7
MN	0.29	0.36	0.29	0	22
MO	0.28	0.39	0.32	–11	21
NE	0.01	0.02	0.03	–76	–23
ND	0.01	0.04	0.02	–67	144
SD	0.03	0.06	0.03	–12	62
WI	0.41	0.47	0.44	–7	6
Region	0.16	0.20	0.18	–11	11

Table 3.—*Comparison of RSB map-based forest proportion to plot-based 95-percent confidence limits (C. I.)*

Analysis area	RSB map-based	Plot-based 95-percent C.I.	
		Lower	Upper
IL	0.09	0.10	0.13
IN	0.14	0.18	0.20
IA	0.04	0.06	0.08
KS	0.02	0.04	0.05
MI	0.51	0.51	0.54
MN	0.29	0.28	0.30
MO	0.28	0.31	0.33
NE	0.01	0.02	0.03
ND	0.01	0.01	0.02
SD	0.03	0.03	0.04
WI	0.41	0.43	0.46
Region	0.16	0.17	0.19

Plot- Versus Pixel-based Per Area Estimates

Table 2 shows the RSB map-based, NLCD92 map-based, and plot-based proportion forest area estimates. Compared to the plot-based estimates, the RSB map-based forest land estimates underestimate all areas except MN. For MN, the estimates were within 1 percent. The relative difference between the plot- and RSB map-based estimates tended to reflect the abundance of forest land calculated for an area, so that more heavily forested areas had closer estimates, and more sparsely forested areas had greater differences between estimates. Conversely, the NLCD92 map-based estimates tended to overestimate forest area when compared to the plot-based estimates except for two sparsely forest areas, KS and NE. For most States/areas, the RSB map-based estimates were below the range of the 95-percent confidence limits for the plot-based estimates (table 3).

Stratified Estimation

Table 4 reports the forest area estimates in thousands of acres for the SRS, RSB map two- and four-class stratifications, and NCFIA's reported estimates for FY 2002 that use an NLCD92-derived classification to assign plots to strata. As was expected, the estimates were all comparable with stratified estimates and within a few percent of the SRS estimates. The RSB FNF map improved the precision of the estimates over the SRS for all States and the entire NCFIA region. Table 5 lists these precisions and the relative efficiencies of the stratified estimates. Because an improvement in precision for most States was obtained using the four-class stratification over the two-class stratification, the relative efficiency was calculated only for the four-class stratification. Sparsely forested States such as NE, ND, IA, and KS showed a slight improvement in precision over the SRS (relative efficiency was less than 1.5), while heavily forested States, such as MI, MN, MO, and WI, showed a greater improvement, which is consistent with the poorer accuracies seen with the other two assessment methods described above. Also, increased sampling intensity in these four heavily forested States most likely contributed to this improvement. Stratified estimation using the NLCD92-based stratification layer achieved higher precisions for all analysis areas except one, SD (relative efficiency of 2.14 compared to 3.72 when the RSB FNF map was used as a stratification layer).

Table 4.—*Estimated forest area (1,000 acres) based on an assumption of simple random sampling (SRS) and stratified estimation.*

Analysis area	SRS	Stratified estimation		
		RSB map two-class	RSB map four-class	NCFIA four-class
IL	4,097	4,180	4,275	4,260
IN	4,359	4,216	4,223	4,545
IA	2,492	2,524	2,567	2,699
KS	2,172	2,171	2,175	2,229
MI	19,618	19,752	19,710	19,349
MN	15,922	16,394	16,416	16,353
MO	14,231	14,544	14,570	14,464
NE	1,355	1,443	1,449	1,364
ND	744	731	716	823
SD	1,700	1,702	1,705	1,714
WI	15,894	15,982	15,941	16,016
Region	82,390	81,755	81,924	83,815

Forest Biomass

Per Pixel (Continuous)

Average error of the Cubist biomass model predictions was about 20 tons/acre, meaning that, on average, the predicted value differed from the observed value by plus or minus 20 tons/acre. The relative error was 0.88. Because values nearing 1.0 indicate little improvement of the predicted values over the assignment of the observed mean to all cases, this result might indicate that the modeling tended to predict values close to the mean. The correlation coefficient was calculated as 0.4. Figure 1 is a scatter diagram of the predicted biomass values plotted against the observed biomass values with a “least squares” trendline and r^2 statistic. Initial observations show a positive correlation between the observed and predicted values, but the range of the predicted values (10–60 tons/acre) did not match that of the observed value range (0–286 tons/acre). Correlation was poor with $r^2 = 0.16$.

Table 5.—*Precisions of forest area estimates as a percent per million acres and relative efficiency of map-based precisions over precisions based on the assumption of simple random sampling (SRS).*

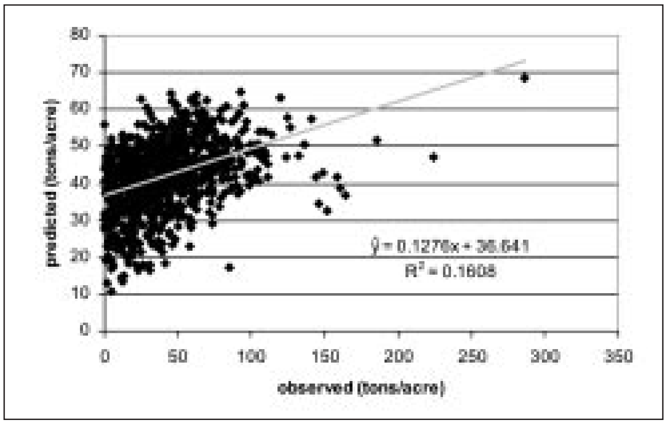
Analysis area	FIA precision[a]				Relative efficiency	
	Simple random sampling	RSB map two-class	RSB map four-class	NLCD92 four-class	RSB map four-class	NLCD92 four-clas
IL	6.74	4.96	4.82	3.98	1.95	2.88
IN	6.48	4.60	4.38	3.66	2.19	3.13
IA	6.92	5.88	5.87	4.39	1.39	2.48
KS	6.83	6.50	6.44	5.47	1.13	1.56
MI	2.40	1.45	1.43	1.34	2.82	3.21
MN	4.75	2.89	2.84	2.57	2.80	3.41
MO	5.56	4.11	3.96	3.16	1.97	3.08
NE	6.95	6.28	6.31	5.97	1.21	1.36
ND	7.02	6.42	6.42	6.12	1.19	1.32
SD	7.37	3.88	3.82	5.04	3.72	2.14
WI	3.87	2.64	2.58	2.19	2.25	3.14
Region	5.83	3.60	3.56	N/A	2.69	N/A

a Calculated as a percent per million acres of forest land.
N/A = not available.

Per Pixel (Classed)

Overall accuracy for the classed biomass map was poor with only about 40 percent of the reference points correctly classified. The error matrix in figure 2 shows that the majority of the error occurred in the low and high biomass classes because of a bias in the map toward the medium biomass class. Although the reference data included an almost equal number of points observed in each class, the classification showed the majority of the reference data (about 69 percent) predicted in the medium class. This bias is evident in the producer's accuracies of 73 percent for the medium class and 24 and 32 percent, respectively, for the low and high classes. The Kappa statistic of 14 percent indicates that the classification was not much of an improvement over a random assignment of classes to pixels.

Figure 1.—*Scatter diagram of observed biomass values versus predicted biomass values.*



Plot- Versus Pixel-based Per Area Estimates

Table 6 provides average biomass estimates by State and region based on the RSB biomass map and the FIA plot data. For many States and regionwide, the predicted average biomass per acre was within 10 percent of the observed average biomass, with estimates for two States, MO and NE, within less than 1 percent. Many of the pixel-based estimates were within the 95-percent confidence limits of plot-based estimates. Exceptions included areas with RD greater than 0.04.

Figure 2.—*Confusion matrix for classed biomass map.*

Classification	Reference Low	Reference Medium	Reference High	Total	Producer's Accuracy	User's Accuracy
Low	87	32	19	138	23.7%	63.0%
Medium	259	212	215	686	72.9%	30.9%
High	21	47	110	178	32.0%	61.8%
Total	367	291	344	1002		

Table 6.—*Pixel- versus plot-based estimates of average biomass per acre by analysis area.*

Analysis area	Mean biomass (tons/acre)		Relative difference (%)	Plot-based 95 percent C.I.	
	RSB map	Plot-based		Lower	Upper
IL	50.66	52.34	–3	48.17	56.51
IN	53.37	60.76	–12	57.68	63.84
IA	45.01	46.06	–2	42.09	50.03
KS	39.84	41.04	–3	35.89	46.19
MI	45.66	50.16	–9	48.21	52.11
MO	45.07	45.29	0	44.06	46.53
NE	36.92	36.77	0	30.23	43.31
ND	29.24	28.62	2	21.52	35.72
SD	25.94	21.79	19	18.91	24.68
WI	43.81	45.18	–3	43.60	46.77
Region	42.43	44.87	–5	43.64	46.10

Stratified Estimation

Estimates of total biomass for the entire region were comparable between the SRS (3.73 billion tons) and stratified estimation (3.35 billion tons). Using biomass classes for stratification did little to improve the precision of total biomass stratified estimation with an RE of 1.08.

Conclusions

The 11-State NCFIA portion of the RSB FNF map exhibited favorable results for all three measures of accuracy assessment used in this study. The map appears to have a consistent negative bias, however, relative to plot-based estimates. Bias was smaller in more heavily forested States and larger in more sparsely forested States. In contrast, the 30-meter NLCD92 FNF map was positively biased relative to plot-based estimates, with magnitude of bias being less dependent on the amount of forest land within a State. The coarser spatial resolution of the RSB map (250-meter) versus the NLCD92 map (30-meter) may partially account for the different bias trends in these two image-based maps. Mayaux and Lambin (1995) related bias in image-based estimates to "effects of spatial aggregation."

Although sums of biomass pixel values produced unbiased estimates of statewide forest biomass for most NCFIA States, individual pixel predictions tended to underestimate high biomass and overestimate low biomass with high correlations occurring in the middle values, similar to observations made by Reese *et al.* (2002). Given this observation, the minimal gain in precision over SRS estimates achieved when using biomass classes as strata for stratified estimation is not surprising. Additional work is needed to determine spatial scales at which the RSB FNF and biomass maps are biased or unbiased and compare precision of estimates derived from these maps to estimates derived from the FIA inventory.

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