

APPLICATION OF AN ASSESSMENT PROTOCOL TO EXTENSIVE SPECIES AND TOTAL BASAL AREA PER ACRE DATASETS FOR THE EASTERN COTERMINOUS UNITED STATES

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ABSTRACT

We recently developed an assessment protocol that provides information on the magnitude, location, frequency and type of error in geospatial datasets of continuous variables (Riemann et al. 2010). The protocol consists of a suite of assessment metrics which include an examination of data distributions and areas estimates, at several scales, examining each in the form of maps, graphics, and summary statistics. In this study we have applied this protocol to the modeled total and species-level basal area/acre datasets recently completed for the eastern coterminous United States (Wilson et al. in review). We were interested in the answers to two questions: (1) how can assessment results be effectively presented over extensive areas, and (2) what is the accuracy of modeled datasets of much less common forest characteristics such as the presence of an individual species, and what might that tell us about the limitations of the current modeled dataset for other less common variables. Results from this study will help fine-tune the type of assessments applied and how they are presented in the metadata available with all geospatial datasets produced by Forest Inventory and Analysis (FIA).

Keywords: Accuracy assessment, uncertainty, geospatial data, continuous variables, species distribution

INTRODUCTION

Modeled geospatial datasets benefit greatly from detailed accuracy assessment. Every geospatial dataset is a model of real conditions on the ground and thus inevitably contains some error. This error can take the form of truncated distributions, a loss of local variability, and/or an underestimation or overestimation of values that can be random (unsystematic error) or represent a bias (systematic error) across the entire dataset or in some areas. Similarly, the type of error present and its magnitude frequently varies with scale, and by the subpopulation being examined. Such inaccuracies do not usually render a modeled dataset useless, but these errors do affect interpretation and

appropriate use of the dataset, and may suggest different approaches for iterative improvement of the modeled geospatial dataset. In addition, for an assessment to be truly effective it must be consistent, to facilitate the comparison of results between datasets of the same variable, and timely, ideally available as soon as the dataset itself. In a previous study we developed a protocol for assessing geospatial datasets of continuous variables (Riemann et al. 2010). This protocol consists of a suite of assessment metrics that together describe the location of errors, the frequency of errors, the magnitude of errors, and the type/nature of errors (Foody 2002) (Canter 1997), and improves timeliness by taking advantage of USFS Forest Inventory and Analysis' (FIA's) existing extensive plot database as the reference data source.

U.S. Forest Inventory and Analysis (FIA) is in the process of developing a broad set of modeled geospatial datasets of forest characteristics across the entire United States, and needs to provide information on the accuracies of those datasets in the accompanying metadata as soon as datasets are released. One such set of datasets has been produced using an approach developed by Wilson et al. (in review) and will soon be available for the coterminous United States.

In this study we applied the existing assessment protocol to the eastern half of this extensive modeled geospatial dataset, and in particular to datasets of total basal area/acre (ba/acre) as well as six individual tree species ba/acre. We were interested in: 1) how assessment results could be most effectively presented for such extensive areas, and 2) the accuracy of individual species datasets given the wide range in their frequency of occurrence, in their spatial patterns of distribution, and in their level of canopy and/or basal area dominance in the stands in which they occur.

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DESCRIPTION OF THE ASSESSMENT PROTOCOL

The protocol recommends a suite of assessments, including:

- assessment of data distributions – at several scales
- assessment of overall agreement of area estimates – at several scales
- examining differences in local variability
- examining spatial and distribution patterns of local differences

First, assessment of data distributions is accomplished by comparing the empirical cumulative distribution functions (ecdf's) of the modeled and reference datasets. A Kolomogorov-Smirnov (KS) statistic can also be used to summarize the largest distance between the two curves (Figure 1a). Second, assessment of overall agreement of estimates is accomplished by comparing a scatterplot of model-derived vs. FIA plot-based estimates against the 1:1 line (Figure 1b). Metrics can be calculated from this scatterplot to quantitatively describe the overall agreement (agreement coefficient, AC), systematic agreement (AC_{sys}), unsystematic agreement (AC_{uns}), and root mean square error (RMSE) (Ji and Gallo 2006). Systematic agreement quantifies the difference between the 1:1 line and the geometric mean functional relationship (GMFR) regression line, which describes the level of bias present. Unsystematic agreement quantifies the level of scatter about the GMFR regression line, which describes the magnitude of remaining random or unexplained error. The GMFR regression line is used instead of the linear regression line because GMFR is a symmetric regression model that assumes both X and Y datasets are subject to error, unlike least squares regression. All three agreement coefficient metrics are symmetric and standardized, facilitating easy comparison between datasets. RMSE values are also symmetric, and are in data units, providing a measure of the magnitude of the error in data units. As many studies have pointed out, dataset accuracy changes with scale (e.g. (Blackard et al. 2008), (Nelson et al. 2009)). Thus, these first two assessments should be calculated at a range of scales to provide information on how dataset accuracy changes with scale. We have recommended choosing that scale at which we have reasonable confidence in FIA estimates (216,500 ha), plus one or two below and above that (Riemann et al. 2010).

The third assessment examines differences in local variability (figure 1c), and the fourth examines the spatial and distribution patterns of local differences between the modeled and reference datasets, (figures 1d,e). These last two assessments can be effective if calculated at a scale at which a sufficient number of FIA plots are available to have reasonable confidence in the FIA plot-based estimates for mean, standard deviation, and a reasonably small confidence interval. When working with hexagons as the spatial unit,

a hexagon 50 kilometers in diameter is 216,500 hectares in size and contains an average of 35 FIA plots (forest and nonforest) per hexagon. A full description of all metrics can be found in Riemann et al. (2010). A complete description of the Agreement Coefficient metrics can be found in Ji and Gallo (2006).

The last two assessments calculate and present assessment results for local areas (i.e. at a fixed scale defining that local area) and can thus be easily expanded to cover large map extents without any loss of descriptive power for local areas. The first two assessments, however, are initially calculated for the dataset as a whole, making them less valuable as the extent of the dataset increases. Thus, when working with datasets as extensive as the Eastern CONTinental United States (ECONUS), calculating these metrics for the dataset as a whole is not sufficient. Over such a large area both the type and magnitude of errors can and will vary by region, and thus the summary metrics should be calculated and available by smaller regions as well as the dataset as a whole, which requires choosing both the regions of assessment and the scale at which it will be assessed.

In this study we calculated assessments using both level 3 ecoregions and 3.5 million ha hexagons to examine any differences resulting from choice of region. We selected the 78,100 ha scale because of its reasonably high comparative accuracies reported in the dataset-wide assessment (Figure 2)— $AC=0.95$, $AC_{sys}=1.0$, $AC_{uns}=0.95$. The 78,100 ha scale also represents a compromise between having a sufficient number of plots within each hexagon (an average of 20) so that the FIA estimate is a reasonably robust estimate of the mean for the area, and having a sufficient number of hexagons within each region so that there are enough points from which to calculate reasonably robust assessment metrics for each region, whether level 3 ecoregions or 3.5 million ha hex-regions are used (Figure 3). With respect to the choice of region, ecoregions have the advantage of including the entire land area, and of dividing the area by one characteristic which could contribute to differences in accuracy, such as different ecosystem types. However, they have the disadvantage of varying widely in area (which means one cannot simply use the histogram to display the amount of area in each error category), of sometimes being very long and narrow and even containing exclusions which inevitably translates into a greater number of summary units (the 78,100 ha hexagons) that include area from neighboring ecoregions. Using a 3.5 million ha hexagon as the region of assessment has the advantage of being equal land area unless we include the edge hexagons that reach beyond the extent of the land area and plot data in the study. They have the disadvantage of not being based on any factor suspected of affecting accuracy other than geographic location, however since there could be many factors, perhaps this is a less important criteria.

DESCRIPTION OF THE DATASETS

In this paper we assess datasets generated for the Eastern CONTinental United States (ECONUS) using an approach developed by Wilson et al. (in review), which is a modification of the gradient nearest neighbor technique developed by Ohmann and Gregory (2002). The approach uses MODIS (MODerate-resolution Imaging Spectroradiometer) composites taken from the entire growing season to take advantage of phenological differences between species, along with climate and topographic variables. The datasets are both modeled and output at a resolution of 250m (6.25 ha, 15.44 acre) grid cells. The technique uses a weighted nearest-neighbor approach, using the 2nd through 7th nearest neighbors, moderated by the proportion of forest pixels from the 2001 National Land Cover Dataset (NLCD2001) within each grid cell. All grid cells have modeled estimates regardless of the proportion of forestland present within them. The approach modeled entire plots, and thus the full suite of variables (volume, individual species basal area, stand size structure, etc.) are essentially modeled together. The plot data used did not record tree data on nonforest plots even if trees occurred (Wilson et al. in review). Knowing basic details about the method used to produce the geospatial dataset being examined provides valuable information about model assumptions, data used, known smoothing applied, characteristics optimized for, etc., that can help interpretation of assessment results and the sources of different types of error found.

RESULTS/DISCUSSION

ASSESSMENT OF MODELED TOTAL BASAL AREA PER ACRE DATASET

Figure 2 presents results from the comparative assessments of data distribution and area estimates across four different spatial scales. From the information provided by the scatterplots and ecdf plots in figure 2, it is apparent that the modeled dataset is closely approximating plot-based estimates for total basal area by the 78,100 hectare scale when the entire dataset is assessed together. Agreement coefficient values are greater than 0.90 by that scale, and KS distance values are very small from the 78,100 to 3.5 million ha scales.

In the choropleth map of local differences between model- and plot-based means at the 216,500 scale (Figure 4), 74 percent of the hexagon means are within the bounds of the 90th CI. Differences larger than that appear to be relatively scattered across the dataset, although there is more tendency for the modeled dataset to overestimate total ba/acre present (23 percent of the hexagons) than underestimate (3 percent of the hexagons), when compared to the plot-based estimate.

The modeled dataset tends to overestimate with respect to plot-based means in areas with low or no total tree ba/acre inventoried by the plots, such as the plains areas in the western side of the study area or southeastern Michigan. This is not surprising, given that basal area is modeled for pixels with tree cover, even if those trees do not fall within FIA's definition of 'forest land.' In the graph of local differences sorted by increasing plot mean (figure 5), there does not seem to be much difference in this pattern across the range of ba/acre values.

With respect to local variability (figure 6), the modeled dataset appears to retain the general pattern of local variability across the study area, but frequently underestimates that variability. This difference will reflect the difference in sample unit size between the two datasets – here between FIA plots measuring the landscape at a 0.06 ha scale, and the modeled dataset describing the landscape at a 6.25 ha scale. However, local variability is considered a sufficiently important characteristic of modeled geospatial datasets to warrant its assessment as a description of the level of local spatial variability present in the modeled dataset, with the plot-based results providing an indication of the smaller-scale variability likely to be present in the real population.

The accuracy presented in figure 2 for the entire area is relatively high, with agreement values at the 78,100 ha scale of 0.95 for AC, 1.0 for AC_{sys} , 0.95 for AC_{uns} , 4.35 (sq. feet per acre) for RMSE, and 0.13 for KS. Figure 7 presents these four assessment metrics for the same 78,100 ha scale by ecoregion and by 3.5 million ha hexagon. It is clear from these results that regional agreement metrics vary widely. For example, while national AC = 0.95, regional AC ranges from less than 0.4 to 1.0. Lowest values predominate in the northern plains region where the lowest total ba/acre is found, however moderately to very low AC values are also found in the northeast and east sections as well. Systematic agreement metric values (AC_{sys}), indicating the level and location of any bias present are much higher overall. However AC_{sys} values still range from 0.76 to 1.0 when calculated by local region, as compared to a national AC_{sys} value of 1.0. Ecoregions with high AC_{uns} values are those with the highest scatter about the GMFR regression line – suggesting those that are currently the most difficult to model given the current set of predictor variables used. Unsystematic agreement (AC_{uns}) values are more similar in range and distribution to AC values, indicating the general dominance of unsystematic error in the overall AC values, with of course a few exceptions. When examined regionally, the magnitude of RMSE values appear to largely track the magnitude of total tree ba/acre present in each local region, with larger errors in areas with higher total ba/acre values. This is entirely understandable given that RMSE values are expressed in data units. The maps of KS distances are

strongly driven by those areas where the plots measured no tree ba/acre and the model estimated some ba/acre greater than zero. Given the fact that FIA plots do not record any tree ba/acre if the plot is defined as ‘nonforest’ even if trees are present, while the data used in the modeling includes tree cover on all lands, it is understandable that this may occur. Thus, it would be helpful if one could calculate the KS distance between the two ecdf’s excluding that difference in the y-intercept, because we may be more interested in differences between the ecdf’s at other places in the plot, rather than the understandable and probably often reasonable differences in the y-intercept due to modeling ba/acre where the plots did not measure any. With the datasets examined here, original data distributions were very closely captured by the modeled dataset, so the only difference was really in the y-intercept. However this is not always the case (see Riemann et al. 2010).

Some differences in results did occur when a different region was used. The most noticeable example was in the systematic agreement (AC_{sys}) maps. Here the northwestern corner of the study area changes from having moderate to relatively high systematic agreement if examined by level 3 ecoregion, to having much lower systematic agreement if examined by 3.5 million ha hexagon. There are several ecoregions that appear very different across many of the maps, such as those along the New York/Pennsylvania border, and a long thin ecoregion down the Appalachian mountains in east central U.S. This is likely due to the small size or long, thin shape of the ecoregions in question, and may be an example of the ecoregions picking up specific areas with different characteristics, while the hexagon includes enough adjacent area to smooth over these differences. Overall, the ecoregion maps indicate that users in the northeast corner may want to improve both the systematic and unsystematic error in many places, whereas the hexagon maps do not draw your attention to that area. Given their equal area and shape, the hexagons may provide a better idea of the spatial patterning of errors, with the cost that errors specifically associated with other region types may not appear as clearly.

ASSESSMENT FOR SPECIES BASAL AREA PER ACRE

Forestland occurs on many FIA plots in United States. Individual tree species, however, represent variables that are much less common. Even sugar maple, a relatively common species, occurs only 7.5 percent of FIA plots in the ECONUS area. Factors affecting how well an individual species is modeled include the number of plots available to model with, whether those plots reflect the full range of variation present over the study area, how dominant that species is where it occurs, and how correlated that species is with respect to the predictor variables used. In this situation, rare species, those with less specific site characteristics,

those in the understory (when working with remotely sensed predictor variables), and those that occur at low densities when they do occur tend to be the most difficult to model accurately when they are modeled independently. One of the characteristics of the nearest neighbor techniques used to generate the modeled datasets being assessed here is that each species is not modeled independently, but rather all species are modeled concurrently. Thus, a relatively rare species which might not have a sufficient number of plots to model well on its own, may achieve a higher accuracy due to its correlation with other species which are more visible or site-specific.

We assessed the modeled ba/acre datasets for six individual tree species, and present four of these species, sugar maple, flowering dogwood, eastern red cedar, and river birch, in more detail in figures 8-11. Results for selected summary metrics for all six species are presented in table 1.

Sugar maple occurs on 7.5 percent of FIA plots in the ECONUS area, has a maximum ba/acre value of 188.7 square feet per acre, and a mean of 14.4 percent ba/acre where it occurs. Figure 8 presents assessment results in terms of the scatterplot across four scales, and the comparison of modeled means to plot-based confidence intervals. The ecdf plot is not shown because it is so dominated by the large number of zero areas over this large an area that it has little story to tell. Assessment results for sugar maple are in general similar to the total ba/acre dataset, with AC values greater than .90 by the 216,500 ha scale, and AC_{sys} values greater than 0.95 by the 8660 ha scale. The percentage of estimates at the 216,500 ha scale falling within, above, and below the 90th plot-based confidence interval are also similar to results for the total ba/acre dataset, although the spatial distribution of those values is of course somewhat different. Modeled estimates for sugar maple at this scale are much more likely to overestimate plot-based estimates in areas where it occurs at lower ba/acre levels, and underestimate plot-based estimates in areas where it occurs at higher ba/acre levels.

Flowering dogwood is an intermediate and understory species that never reaches a very large size. It occurs on only 3.8 percent of ECONUS plots, and of the six species examined it has the lowest maximum ba/acre (42.8 sq. feet per acre) and mean percent basal area/acre (2.6 percent) where it does occur. Yet, despite this, dogwood was relatively well modeled (figure 9, table 1), reaching our target AC and AC_{sys} values set for this study by the 866,025 ha and 78,100 ha scales, respectively. Seventy-five percent of the modeled dataset is within the 90th CI at the 216,500 ha scale, and the model more often overestimates dogwood in the remaining hexagons with respect to the plot-based means. The fact that dogwood does report relatively high accuracies despite its rarity may be due to its correlations

with associated species, although we did not investigate this specifically in time for this study.

Eastern red cedar occurs on 3.2 percent of ECONUS plots, similar to dogwood, although it has higher ba/acre values and represents a larger proportion of the stands where it occurs (figure 10, table 1). Results are similar to dogwood, with the exception that the model much more frequently predicts eastern red cedar in hexagons where the plots record none. Given the habit of cedar to occupy old field locations that may not yet qualify as forestland and thus not be recorded by FIA plots, this may be an example of the model picking up more of the species actually present than the FIA plots are detecting when they record trees on FIA-defined “forestland” only.

River Birch is an example of an extremely rare species, occurring on only 0.4 percent of ECONUS plots (figure 11, table 1). Because of the large number of hexagons without any inventoried or predicted river birch, a high percentage of modeled estimates at the 216,500 ha scale still fall within the 90th CI. However the scatterplots and agreement metrics reveal much higher systematic and random error, reflected in the low AC_{sys} and AC_{uns} (and AC) values, respectively. River birch is an example of a species that has poor overall accuracy in the modeled dataset, probably because of its rarity within the study area, and perhaps in combination with a wide spatial distribution and/or lack of association with other more common species. Regional examination of species assessment results would undoubtedly provide valuable additional information for users and should be added to the standard assessment protocol.

CONCLUSION

Results indicated important regional differences in assessment metrics. For extensive geospatial datasets such as these ECONUS datasets, calculating additional agreement metrics by region better characterizes geographic differences in the magnitude and types of errors present in the modeled geospatial dataset. This may be sufficient basic information for the metadata, particularly when used in combination with dataset-wide scatterplot and ecdf results across several different scales. For application in a specific area, a user may want to additionally examine the scatterplots and ecdf plots at multiple scales for the specific area of interest to gain more insight into accuracy at that location as you move across spatial scales.

There are many factors affecting the accuracy of an individual tree species, one of which is its rarity within the study area. Application of the protocol to individual

species from the modeled pGNN dataset indicates a general tendency toward decreasing accuracy as a species becomes less common, although the threshold seems very low. In this ECONUS-wide assessment, modeled species datasets appeared to be reasonably accurate even when species occurred on only 3–4 percent of the plots, but were substantially less accurate when a species occurred on less than 1 percent of the plots. From our quick examination here of only six species, there did not appear to be a similar relationship between level of accuracy and low basal/area per acre values or low relative dominance. Results of the species assessment provide some indication of the scale(s) at which modeled datasets of rarer variables (e.g. river birch, occurrence of downed wood, etc.) are most consistent with the data from FIA plots. Regional assessment of accuracy will be important with individual species datasets, as assessment results may vary widely from the national values, particularly where a species is locally rare.

This study further develops the minimum information that should be included in the standard metadata available with every FIA geospatial dataset. In addition to indicating the true accuracy of the dataset with respect to the real population on the ground, this assessment protocol provides an explicit description of how summaries generated from a modeled dataset relate to summaries generated directly from the FIA plot data.

ACKNOWLEDGEMENTS

The authors wish to thank Matt Gregory, Mark Nelson, and Kevin Megown for their thoughtful reviews.

LITERATURE CITED

- Blackard, J.A.;** Finco, M.V.; Helmer, E.H. [and others]. 2008. Mapping U.S. forest biomass using nationwide forest inventory data and moderate resolution information. *Remote Sensing of Environment*. 112(4):1658-1677.
- Caners, F.** 1997. Evaluating the uncertainty of area estimates derived from fuzzy land-cover classification. *PE&RS, Photogrammetric Engineering & Remote Sensing*. 63:403-414.
- Foody, G.** 2002. Status of land cover classification accuracy assessment. *Remote Sensing of Environment*. 80(1):185-201.
- Ji, L.;** Gallo, K. 2006. An agreement coefficient for image comparison. *Photogramm. Eng. Remote Sens.* 72(7):823-833.
- Nelson, M.D.;** McRoberts, R.E.; Holden, G.R.; Bauer, M.E. 2009. Effects of satellite image spatial aggregation and resolution on estimates of forest land area. *International Journal of Remote Sensing*. 30(8):1913-1940.

Ohmann, J.L.; Gregory, M.J. 2002. Predictive mapping of forest composition and structure with direct gradient analysis and nearest-neighbor imputation in coastal Oregon, U.S.A. *Can. J. For. Res.* . 32(4):725-741.

Wilson, B.T.; Lister, A.J.; Riemann, R. in review. A nearest-neighbor imputation approach to large area mapping of tree species distributions using field sampled data. *Remote Sensing of Environment.*

Riemann, R.; Wilson, B.T.; Lister, A.; Parks, S. 2010. An effective assessment protocol for continuous geospatial datasets of forest characteristics using USFS Forest Inventory and Analysis (FIA) data. *Remote Sensing of Environment.* 114(10):2337-2352.

Table 1—Selected assessment results for six individual species, sorted by decreasing agreement (AC and AC_{sys})

species	percent of ECONUS plots on which it occurs	maximum ba/acre value (sq. ft per acre)	mean % ba/acre value where it occurs	scale at which AC > 0.90 (hectares)	scale at which AC _{sys} > 0.95 (hectares)	percent of modeled dataset within 90th CI at 216,500 ha scale	percent of dataset ABOVE 90th plot CI at 216,500 ha scale	percent of dataset BELOW 90th plot CI at 216,500 ha scale
sugar maple	7.5	188.7	14.4	216,500	8660	71	25	3
black cherry	7.9	178.2	5	866,025	78100	68	29	3
flowering dogwood	3.8	42.8	2.6	866,025	78,100	75	24	1
eastern red cedar	3.2	104.6	7.3	866,025	78,100	50	47	2
bitternut hickory	1.6	67.2	5.7	3.5 million	866,025	69	29	1
river birch	0.4	95.6	8.6	AC=0.85 at 3.5 million	3.5 million	67	32	1

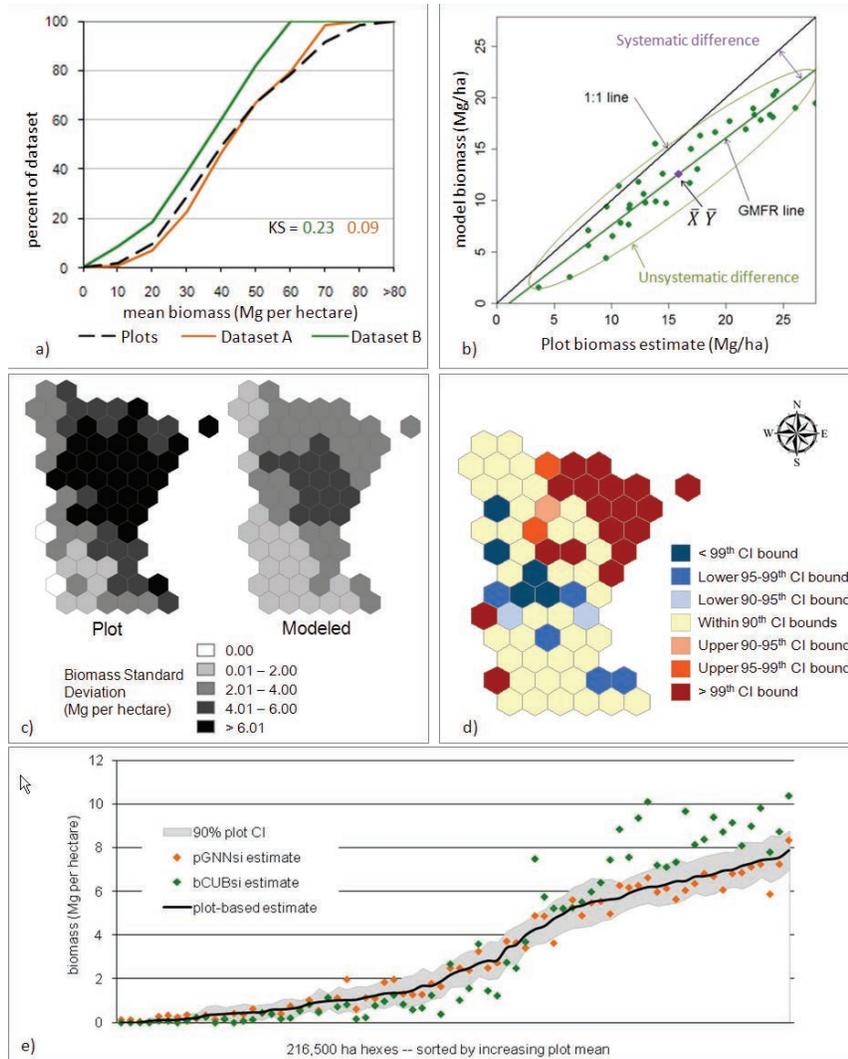


Figure 1—Example assessment protocol used: a) assessment of data distributions with KS distance metrics, b) assessment of agreement between model- and plot-based means—in this example, $AC = 0.80$, $AC_{sys} = 0.84$, and $AC_{uns} = 0.96$, and $RMSE = 3.9$, c) comparing local variability, d) spatial pattern of local differences with respect to plot-based confidence intervals, e) pattern of those differences across the range of biomass values. Example is from assessing modeled datasets of biomass in Minnesota.

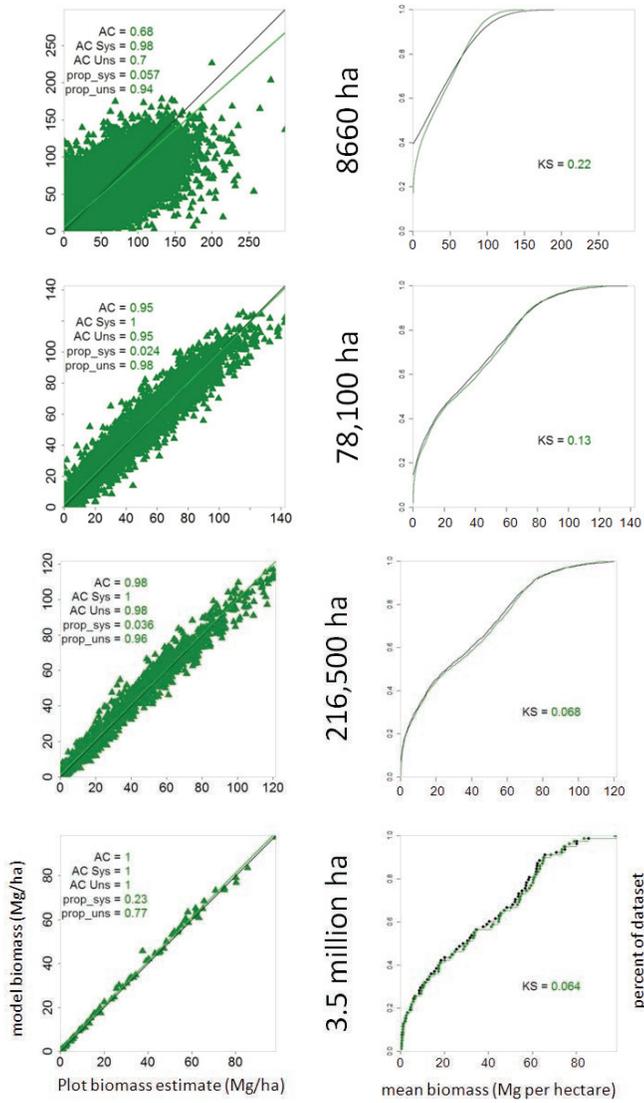


Figure 2—Scatterplots and ecdf plots of ECONUS total ba/acre across four scales.

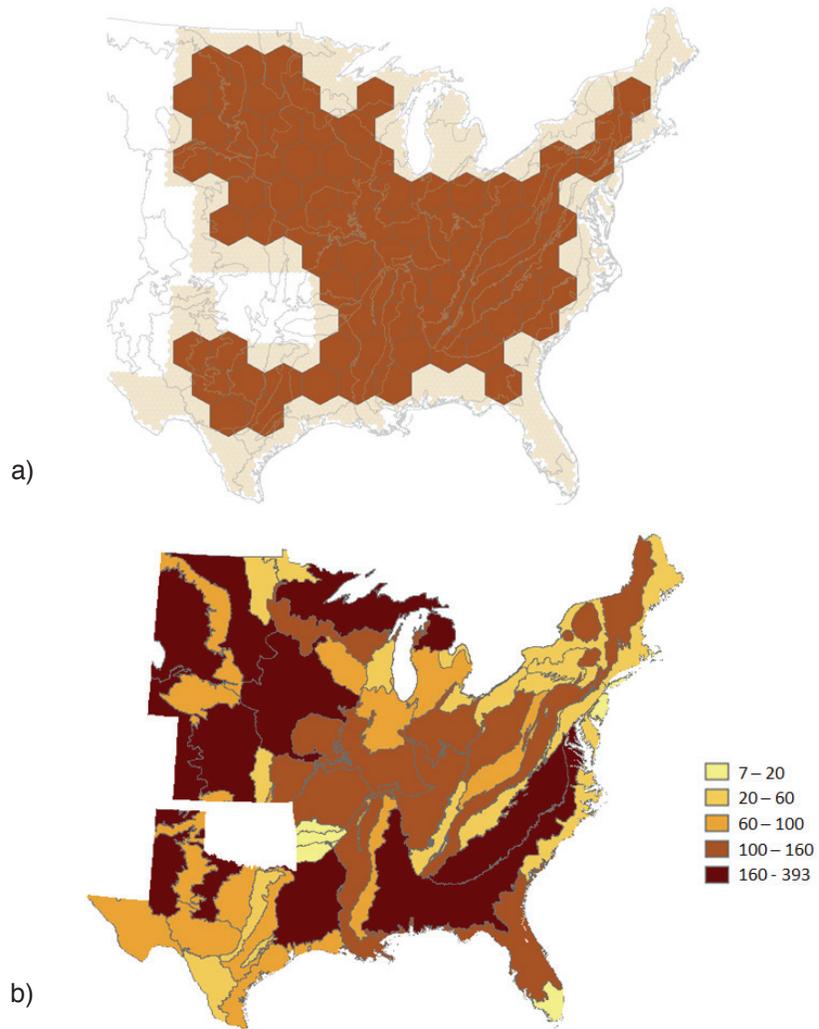


Figure 3—Number of 78,100 ha hexagons within each scale examined: a) 216,500 ha hexagons, where $n = 42-45$, and b) level 3 ecoregions.

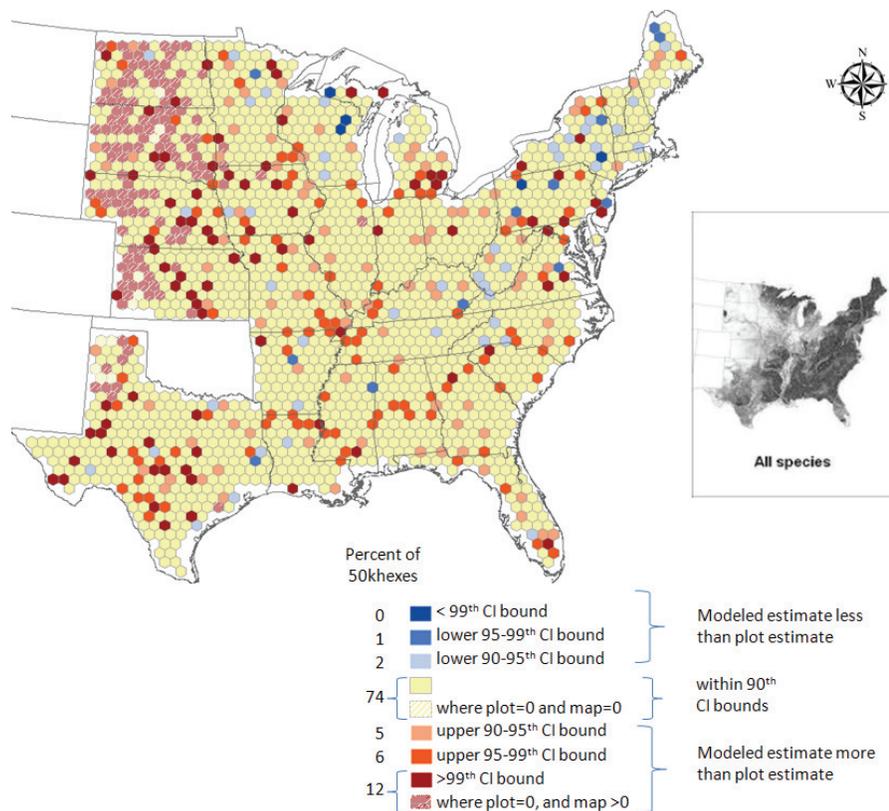


Figure 4—Choropleth map of differences between mapped estimates and plot-based means and confidence intervals for ECONUS at the 216,500 ha scale.

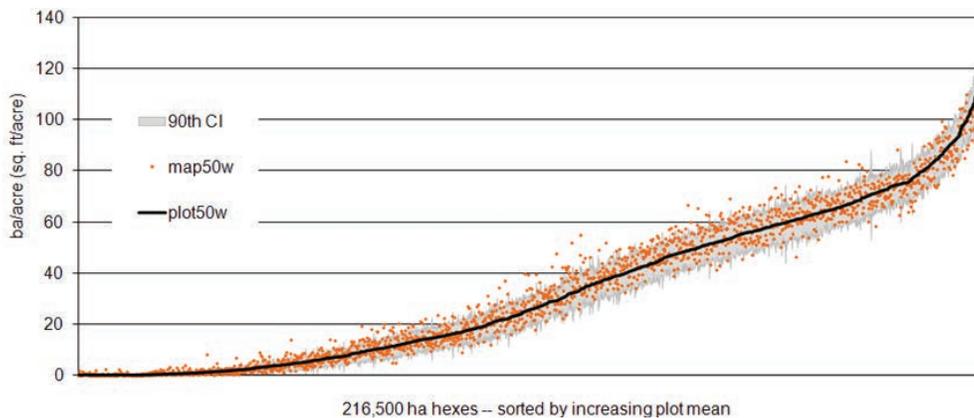


Figure 5—Differences between mapped estimates and plot-based means and confidence intervals for ECONUS at the 216,500 ha scale, as graphed across the distribution of plot mean values.

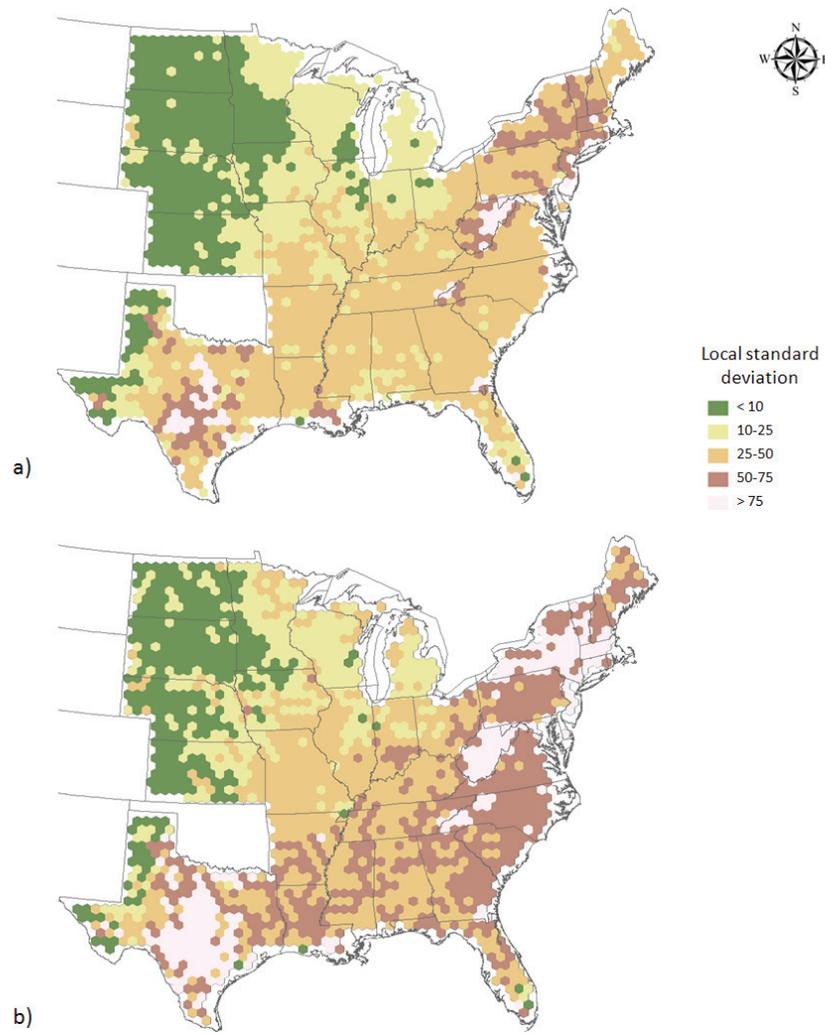


Figure 6—Choropleth map of differences in local spatial variability of ECONUS estimates, as described by the standard deviation of modeled (a) or plot-based (b) values at the 216,500 ha scale.

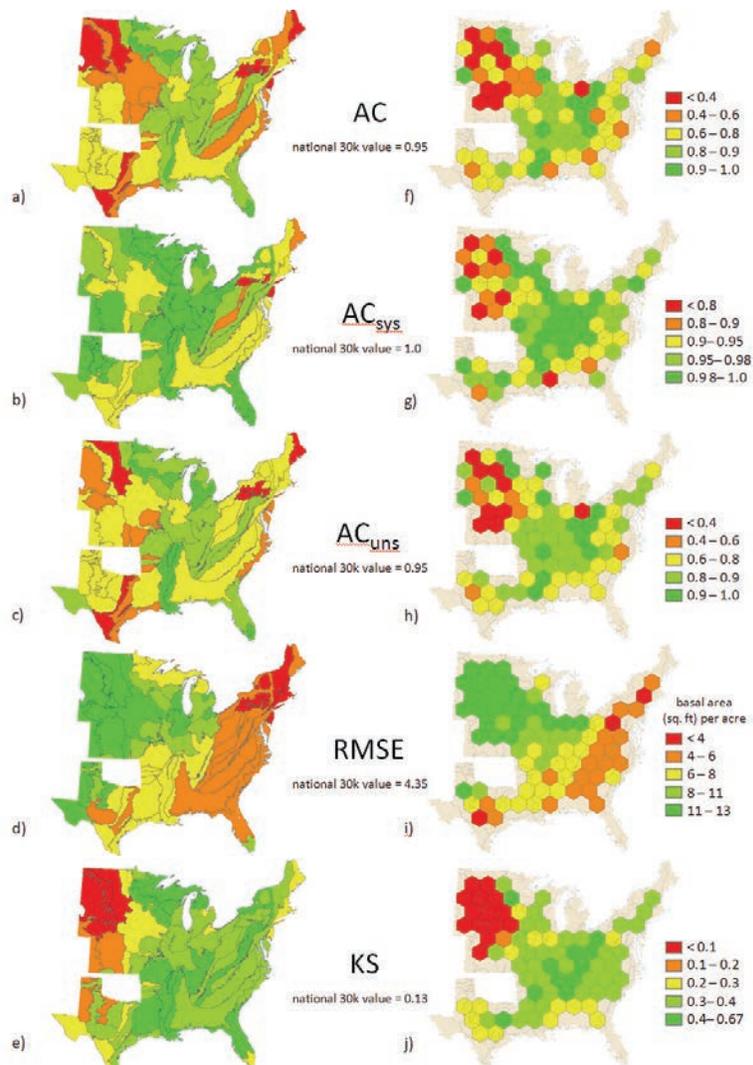


Figure 7—Maps of agreement metrics for the ECONUS dataset, summarized by ecoregion (a-e), and 3.5 million ha hexagon (f-j).

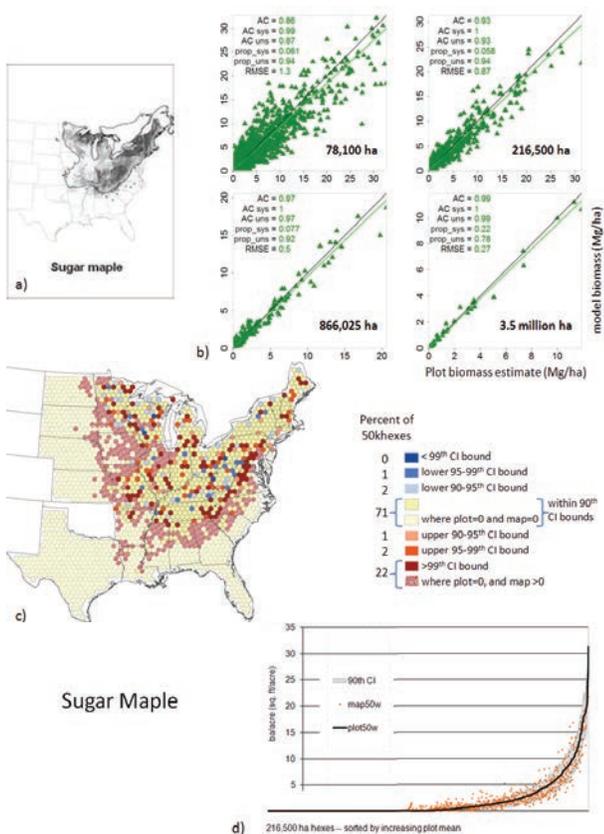


Figure 8—Assessment results for the ECONUS sugar maple dataset: a) map of modeled distribution, b) comparison of model- to plot-based means across four scales, c) magnitude and spatial pattern local differences at the 216,500 ha scale, and d) magnitude and distribution pattern of local differences across the range of sugar maple ba/acre values.

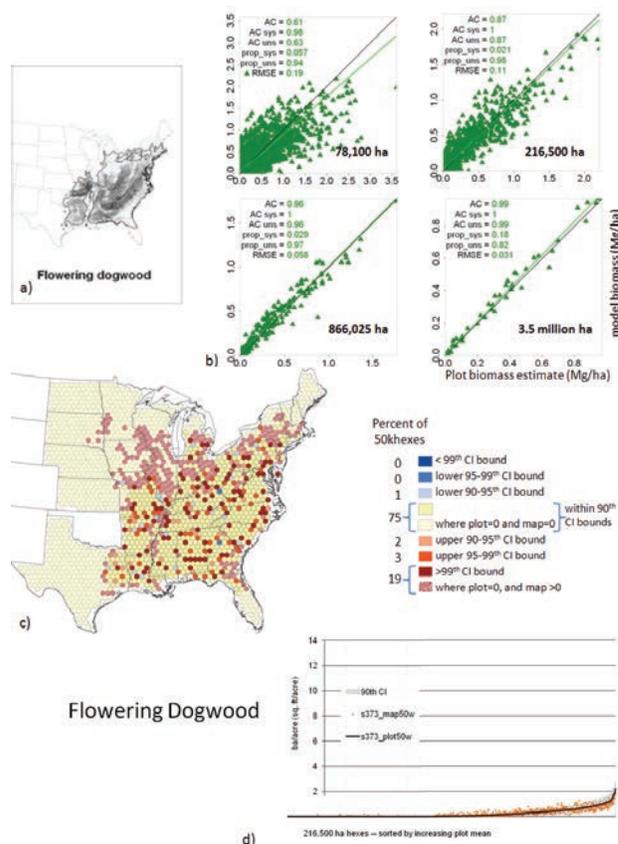


Figure 9—Assessment results for flowering dogwood: a) map of modeled distribution, b) comparison of model- to plot-based means across four scales, c) magnitude and spatial pattern local differences at the 216,500 ha scale, and d) magnitude and distribution pattern of local differences across the range of sugar maple ba/acre values.

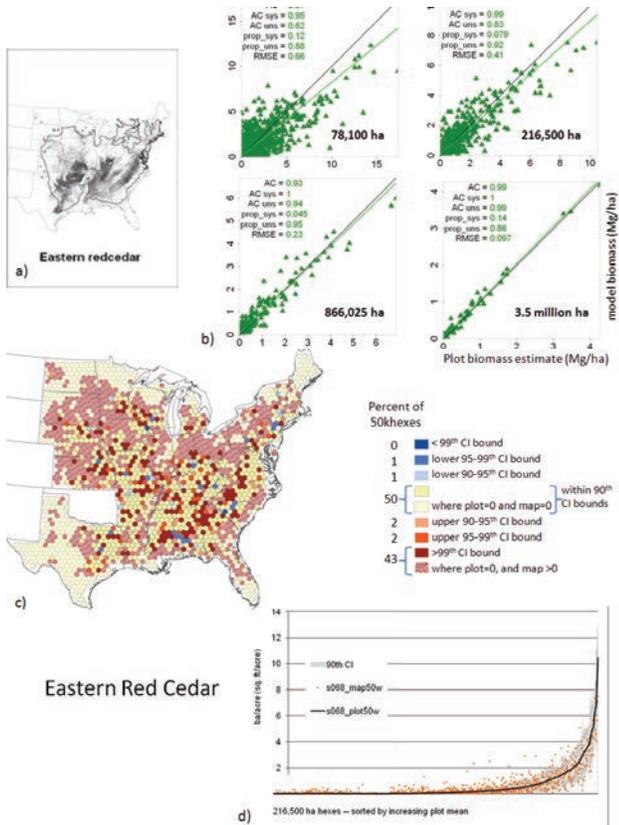


Figure 10—Assessment results for eastern red cedar: a) map of modeled distribution, b) comparison of model- to plot-based means across four scales, c) magnitude and spatial pattern local differences at the 216,500 ha scale, and d) magnitude and distribution pattern of local differences across the range of sugar maple ba/acre values.

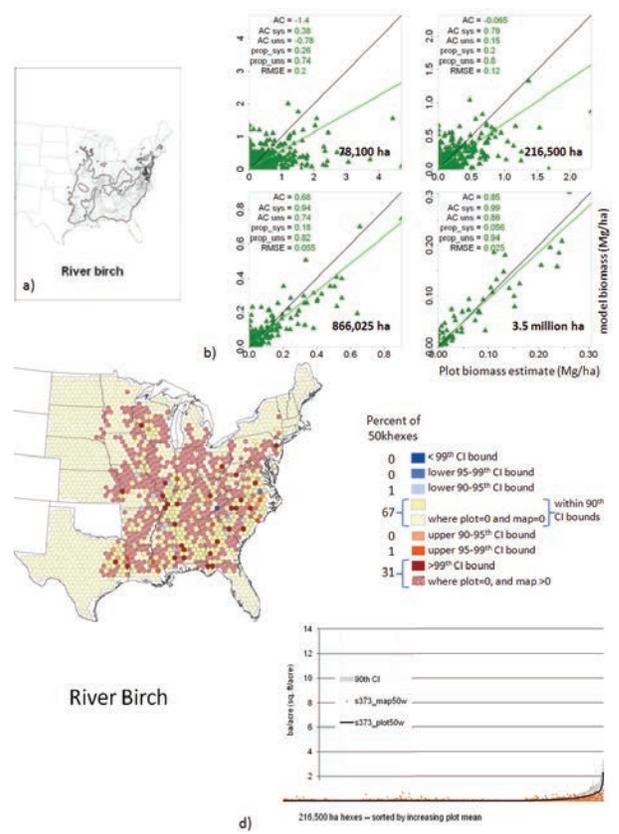


Figure 11—Assessment results for river birch: a) map of modeled distribution, b) comparison of model- to plot-based means across four scales, c) magnitude and spatial pattern local differences at the 216,500 ha scale, and d) magnitude and distribution pattern of local differences across the range of sugar maple ba/acre values.