Weighted analysis methods for mapped plot forest inventory data: Tables, regressions, maps and graphs

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ABSTRACT

Weighted estimation methods for analysis of mapped plot forest inventory data are discussed. The appropriate weighting scheme can vary depending on the type of analysis and graphical display. Both statistical issues and user expectations need to be considered in these methods. A weighting scheme is proposed that balances statistical considerations and the logical expectations of users. The methods described here are being used in an online forest carbon estimation tool. Example applications are presented to demonstrate the methods.

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1. Introduction

Analysis methods for mapped plot forest inventory data are important because the USDA Forest Service Forest Inventory and Analysis (FIA) program (Bechtold and Patterson, 2005) has installed hundreds of thousands of such plots throughout the US and its territories. In addition, mapped plots are being used by some state agencies and individual owners (Van Deusen, 2009). Mapped plots require the delineation of areas within the plot, called a condition, with distinct land-based characteristics in terms of forest type, land use and structure, for example, FIA makes these data available in an online public database called the FIADB (Anon., 2010; Smith et al., 2006), which users can download and analyze in a number of ways. Generally, analyses of FIADB data can be categorized based on the intended output such as: tabular, regression, maps or graphs.

Often, graphs and maps involve similar considerations that focus on a combination of statistical issues and user needs for understandable, timely, and objective information. Instead of downloading the data for analysis elsewhere, users of FIA data often prefer using online analysis tools that allow them to customize and download output in usable form. The methods described here were developed to provide forest carbon information, which has been in increasing demand to the point where an automated information system is necessary to satisfy user requests. These methods are shared by the Carbon OnLine Estimator (COLE) (Proctor et al., 2005;

NCASI, 2010), and a newer version that features a ®Google Maps interface (G-COLE). Total carbon stocks and carbon density (ton per area) are output in a consistent way across analysis methods. FIA has several online tools (USDA, 2010) which draw data from the FIADB, including Evalidator, which creates tables, and FIDO, which creates tables and maps. Currently, Evalidator outputs total population carbon estimates only in tables, whereas carbon output is not yet a feature of the FIDO tool.

Mapped plot data (Van Deusen, 2004; Bechtold and Patterson, 2005) bring some complications to the analysis, because FIA plots can be subdivided into one or more conditions. Thus, the one plot becomes multiple observations, each based on an area of less than a plot. A proper analysis of the data needs to take this into consideration. Weighted approaches are appropriate when fitting these data to equations, and when developing estimates for tabular output. Graphs and maps may not use weights, but they need to be produced with regard to mapped plot characteristics. In this study, we further discuss the issues, and propose solutions that unify the underlying methods while producing the various outputs.

2. Background

A variety of methods may be used to analyze mapped plot forest inventory data depending on how the data are being analyzed and displayed. However, all approaches must handle the special characteristics of mapped plot data in a way that allows for a meaningful analysis. For example, a user generally expects 1 point per plot on a graph, not 1 point per condition. A regression analysis should

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be weighted to reflect different condition proportions and possibly different plot expansion factors as well.

The most recent compilation of statistical methods that FIA follows is published in the "Green-Book" (Bechtold and Patterson, 2005). The Green-Book presents methods for tabular analysis, but does not specifically consider methods for graphs, regressions or maps. The methods for tables presented here are similar to Green-Book methods, but we emphasize using weights and plot condition measurements that are adjusted to ensure unbiasedness and that rows and columns logically sum to the correct totals.

Graphical displays such as box plots and *xy* plots are generally referred to here as graphs to differentiate a graphical display from a field plot. Data intended for graphs should often be handled differently than for tables or regressions. It may not be appropriate to display a point for each mapped plot condition. Doing so could lead to having more than one point per field plot, which might confuse interpretation. Likewise, a very small condition may have few trees and should not necessarily be displayed alongside full plot conditions without some adjustment. Examples are provided using output from the online tools.

3. Weighted tabular estimation

A mapped plot forest inventory results in measurements for each condition, *c*, within each plot, *i*. The analysis involves the condition measurements, y_{ic}, and the condition proportions, a_{ic}, where the proportions on each plot sum to 1.0. These data can be described with the following simple model (Van Deusen, 2004),

$$y_{ic} = a_{ic}\mu_c + \epsilon_{ic} \tag{1}$$

where μ_c is the expected value for condition *c*, and the random error ϵ_{ic} has mean 0 and assumed variance $a_i\sigma_c^2$. We assume throughout that y_{ic} has already been expanded to a per acre or per hectare value. For example, with 10th hectare plots, the actual plot condition measurements should have been multiplied by 10 to make them represent per hectare values.

Weighted estimation also requires that each plot be assigned a weight. Often, it is meaningful to interpret this weight as an expansion factor denoting the number of acres or hectares a plot represents. FIA installs 1 plot for (approximately) every 6000 acres (1 ha = 2.47 acres). Therefore, we would expect the expansion factor for FIA plots to be close to 6000 when working in English units. Most single owner inventories would have a higher sampling intensity, say 1 plot for every 100 acres, but weighted analysis follows the same template regardless of the sample intensity.

3.1. Weighted estimates of the mean

A weighted estimator was presented (Van Deusen, 2007) that used plot expansion factors as weights and estimates the condition total, $\hat{T}_c$, without bias,

$$E\left[\sum_{i=1}^n e_i y_{ic}\right] = \mu_c \sum_{i=1}^n e_i a_{ic} \tag{2}$$

where e_i is the plot expansion factor, *n* is number of plots in the inventory or the number of plots that contain some condition *c* (either interpretation of *n* gives the same result). The expectation on the right side of Eq. (2) follows directly from Eq. (1). It is the logical estimate for the condition total, which is to multiply the mean μ_c by the sum of the expansion factors adjusted with the condition proportions. It follows immediately that an unbiased weighted estimate of the mean is,

$$\hat{\mu}_c = \frac{\sum_{i=1}^n e_i y_{ic}}{\sum_{i=1}^n e_i a_{ic}} \tag{3}$$

In order to simplify the weighted estimator notation, we define a set of adjusted weights, $w_{ic} = a_{ic}e_i$ and corresponding adjusted condition measurements, $\tilde{y}_{ic} = y_{ic}/a_{ic}$. This results in the following estimator for the mean,

$$\hat{\mu}_c = \frac{\sum_{i=1}^n w_{ic}\tilde{y}_{ic}}{\sum_{i=1}^n w_{ic}} \tag{4}$$

Although Eq. (4) is just a reformulation of Eq. (3), we show below that the adjusted weights and condition measurements have value beyond their obvious use for creating tabular results where rows and columns logically add to the totals.

3.2. Weighted variance estimates

The weighted total, $\hat{T}_c$, and the weighted mean (Eqs. (2) and (3)) are related as follows,

$$\hat{\mu}_c = \frac{\hat{T}_c}{\hat{A}_c} \tag{5}$$

where $\hat{A}_c$ is an estimate of the area in condition *c*. With mapped plots, a forest condition area estimate is

$$\hat{A}_c = \sum_{i=1}^n w_{ic} \tag{6}$$

We are ignoring the contribution to variance from $\hat{A}_c$ in what follows, but interested readers can see (Zarnoch and Bechtold, 2000) for ideas on how to incorporate this additional variance component.

The variance of the weighted total (Eq. (2)) is

$$v(\hat{T}_c) = v\left(\sum_{i=1}^n w_{ic}\tilde{y}_{ic}\right) = \sum_{i=1}^n e_i^2\sigma_c^2 \tag{7}$$

where σ_c^2 can be estimated for each table cell from the plots that fall into that cell or category. The suggested estimator from (Van Deusen, 2004) can be used to estimate the variance component in Eq. (7)

$$\hat{\sigma}_c^2 = \frac{\sum_{i\in c}^n \hat{\varepsilon}_i^2}{\sum_{i\in c}^n a_i - 1} \tag{8}$$

where $\hat{\varepsilon}_i = y_i - a_i\hat{\mu}_c$, and $i \in c$ denotes that the summation is over the plots that contain the same category or condition.

The variance of the weighted mean follows immediately from the relationship in Eq. (5) and is

$$v(\hat{\mu}_c) = \frac{v(\hat{T}_c)}{\hat{A}_c^2} \tag{9}$$

4. Combining conditions for graphs

Conditions should generally be combined so that each mapped plot only contributes one observation to the graph. The adjusted condition measurements, $\tilde{y}_{ic}$, represent per hectare expected values. For example, when the condition covers 50% of the plot one expects it to have half the value of a like condition that covers the full plot. In general, the partial condition measurement should be divided by the condition proportion to make it approximate a full plot value. The original condition measurements, y_{ic}, may have already been adjusted to represent per acre or hectare values in the dataset by dividing by the full plot size, e.g. values for 10th hectare plots have been divided by 0.1. Clearly, adjusting small conditions (slivers) to per hectare values can give results that might be hard to find on an actual full hectare of that particular condition. For example, a small sliver that contains a few large trees could result in an extremely large per hectare value.

Table 1

Pseudo data from three mapped plots. The columns are: y—condition measurements, a—condition proportions, e—plot expansion factors and c—condition codes.

Plot	y	a	e	c
1	y_{11}	0.4	100	1
1	y_{12}	0.6	100	2
2	y_{21}	1.0	100	1
3	y_{31}	0.2	100	1
3	y_{32}	0.7	100	2
3	y_{33}	0.1	100	3

To clarify these ideas, consider the pseudo data (Table 1) that might arise from three mapped plots. Actual values are assigned for expansion factors and condition proportions, but the condition measurements are denoted generically as y_{ic}. The suggested method for presenting condition measurements on a graph is to create one measurement per plot. Suppose the pseudo data (Table 1) are to be used to create an *xy* plot for filtered plot characteristics which are exhibited by conditions 2 and 3. Only plots 1 and 3 contain conditions 2 and 3, so there should be 2 points on the graph. Plot 1 would contribute $\tilde{y}_{12} = y_{12}/0.6$ and plot 3 would contribute $(y_{32} + y_{33})/(0.7 + 0.1)$. Therefore, graphs depend on how the data are filtered by the user and must be created dynamically. For this example, the user filtered for conditions 2 and 3, which required those conditions to be combined such that each plot containing some of either condition would contribute a single observation to the graphical display.

Mapped plot observations that have been filtered for characteristics so that more than 1 condition is included will be denoted by $\tilde{y}_{if}$, where

$$\tilde{y}_{if} = \frac{\sum_{c \in f} y_{ic}}{\sum_{c \in f} a_{ic}} \tag{10}$$

Note that $\tilde{y}_{ic}$ is a special case of $\tilde{y}_{if}$, occuring when there is only 1 condition. Graphs should generally display a value that corresponds to $\tilde{y}_{if}$, so that each mapped plot only contributes one observation.

The corresponding weight for filtered observations is simply,

$$w_{if} = e_i \sum_{c \in f} a_{ic} \tag{11}$$

Thus, proper results for graphs depend on combining conditions according to the user defined filters prior to display. Tabular analysis will give the same results whether applied to the filtered observations, $\tilde{y}_{if}$, and weights, w_{if}, or individual condition values, $\tilde{y}_{ic}$ and w_{ic}, because conditions are combined during the summation process. Regression analysis also requires that conditions be combined to produce proper results.

5. Weighted regression

Weighted regression analysis and graphical analysis should both be applied to filtered mapped plot data as defined by Eqs. (10) and (11). Each mapped plot should contribute a single observation to any given weighted regression analysis. Otherwise, the degrees of freedom in the analysis of variance will be inflated.

Consider using mapped plot data in a regression analysis where the objective is to estimate the parameter vector, β_c, in the following linear equation,

$$Y_c = X\beta_c + V_c \tag{12}$$

where Y_c is a vector of condition c observations (from mapped plots), X is a matrix of concomitant variables and V_c is a vector of error terms.

It makes sense to apply weighted regression methods to observations that have different expansion factors. Also, it would not be reasonable to treat a condition which is only a mere sliver of a plot the same as an observation from a full plot. Consider the basic matrix formula for weighted linear regression,

$$\hat{\beta}_c = \left[X'W_c^{-1}X\right]^{-1} X'W_c^{-1}Y_c \tag{13}$$

where W_c is a matrix of weights.

Our proposal is to let $W_c = 1/diag(w_{1c}, \ldots, w_{nc})$, i.e. a diagonal matrix consisting of the inverse of the weights defined in Eq. (11). This weighting scheme results in weights being proportional to the product of the condition proportion and the plot expansion factor. Therefore, conditions of large proportions on plots with large expansion factors get more weight in the analysis. If all plots have the same expansion factor, then the weights are equal to condition proportions, which is intuitively reasonable. In fact, it might be appropriate to set all expansion factors to a constant, say 1.0, for some regression analyses. There is no statistical reason for plot expansion factors to weight the analysis when the plot selection probability was independent of the expansion factor, which is the case with the FIA survey. Recall that tabular analysis involves expansion factors so that tables add to the correct totals, which is logically (not theoretically) motivated.

It can also be shown that Eq. (4) is a special case of Eq. (13) when $Y_c = (\tilde{y}_{1f}, \ldots, \tilde{y}_{nf})$ and X is set to a vector of ones. Therefore, this approach to weighted regression produces estimates from mapped plot data that are compatible with weighted tabular estimates when the observations and associated weights are, $(\tilde{y}_{if}, w_{if})$. In particular, this weighted regression strategy results in minimizing the following weighted sum of squared residuals,

$$\sum_{i=1}^{n} w_{if}(\tilde{y}_{if} - x_i \hat{\beta}_c)^2 \tag{14}$$

where x_i is the ith row of the X matrix. This weighting scheme can be applied to nonlinear regression as well.

5.1. Exceptions to the one observation per plot rule

There is a situation that calls for an exception to the rule of one observation per plot for a regression analysis. This is when there is a categorical independent variable. For example, suppose one is interested in predicting total above-ground carbon as a function of owner group. There could be plots that have conditions with different owners. Suppose a plot overlaps Federally-owned and Private land. In this case, the plot has to contribute two observations to the analysis.

In general, it is reasonable to treat FIA plot observations as if they are independent in a regression analysis. This is not the case in the situation where a plot contributes more than one observation to the analysis. Clearly, multiple observations from the same plot are not independent. Ignoring this dependence between observations from conditions on the same plot does not bias the parameter estimates. However, it does lead to overly optimistic variance estimates.

6. Growth, removals and mortality

In general, growth, removals and mortality (GRM) estimates do not require new techniques. However, GRM data may require different weights. This is largely due to the fact that some mapped plots may be newly installed and therefore have no data to contribute to a GRM analysis. The number of plots with current measurements will always be at least as large as the number of plots that have current and past measurements. Therefore, a GRM analysis will often use a subset of the plots that would contribute to an analysis of current values.
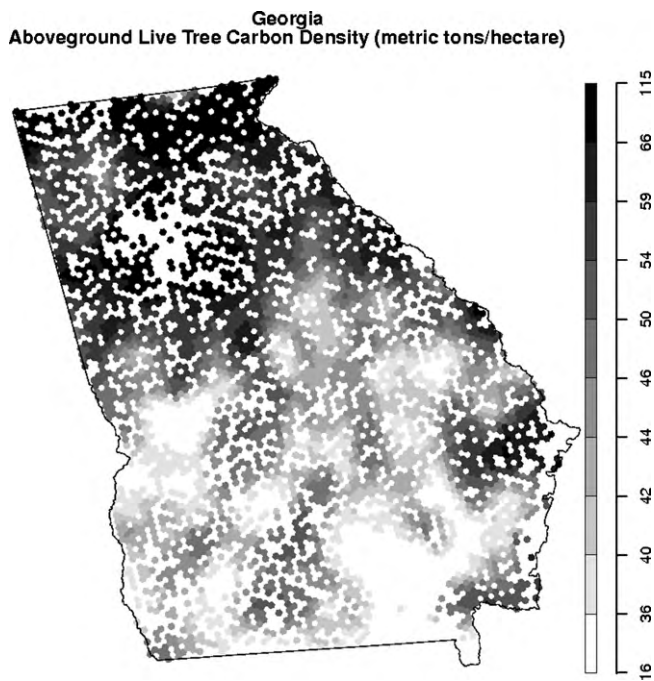
Georgia
Aboveground Live Tree Carbon Density (metric tons/hectare)

Fig. 1. Hexagon map of above-ground live tree carbon (ton/ha) in Georgia, 2006.

6.1. Defining plot expansion factors

Plot expansion factors for COLE are derived from values in the FIADB. It is possible to determine the current FIA estimate of forest land area for each county in the US from the FIADB. COLE weights are then derived so the weights for all forested plots in a county add to the FIA estimate of forest land area for that county. This equation, applicable to any set of plots within a well defined polygon or political region, is,

$$w_p = \frac{A_p}{n_p} \tag{15}$$

where w_p is the weight to assign to each plot that falls within the polygon, A_p is the forest area of the polygon and n_p is the number of plots in polygon p. The area, A_p, is fixed but the number of plots, n_p, may be different for GRM and non-GRM analyses.

7. Example applications

The example results are generated with COLE (NCASI, 2010) and FIADB (Anon., 2010) data that were current as of Monday, August 16, 12:57:15, 2010 for the state of Georgia. We begin by generating a map of hexagons (Fig. 1) where each hexagon covers 5937 acres (2402.6 ha). Hexagons that include only non-forested conditions are blank; hexagons that include a forested condition are colored. Each FIA plot that includes a forested condition is assigned to the nearest hexagon's center. The data are preprocessed so that each FIA plot contributes one observation that corresponds to $\hat{y}_{if}$ (Eq. (10)). A loess smoothing procedure from

the **R** statistical package (RDCT, 2010) is applied to improve the appearance.

We apply the weighted estimation procedure to produce a table (Table 2) of above-ground carbon density (live trees without foliage). The per hectare means use Eq. (4) and the standard errors are based on Eq. (9).

Carbon totals (Table 3) are computed with Eq. (2) with standard errors based on Eq. (7). The rows and columns add to the correct totals as they should with the weighted estimators. The "All" cells (Table 3) were computed independently to verify that the totals add correctly, apart from small differences due to rounding to the nearest tonne.

We use the average measurement year as the estimate for year. To calculate this, the number of plots by measurement year table (Table 4) is printed out by COLE when the Table – Means analysis function is chosen. By weighting measurement year by number of plots, we estimate the average measurement year for these data is 2005.6, which we round up to 2006.

Finally, we look at a weighted regression analysis and do a comparison of those results with the weighted means (Table 2). The linear model is fitting live tree above-ground carbon (*treeAGC*) to indicator variables for owner group and stand origin (natural or planted), i.e. *treeAGC* = *f*(OWNGRPCD + STDORGCD). This approach absorbs the first level of each categorical variable into the intercept. Therefore, the coefficient for the intercept (Table 5) corresponds to the USDA Forest Service natural stand category as computed by the weighted mean method (Table 2).

The other coefficients (Table 5) can be interpreted as deviations from the Forest Service natural stand category. For example, the mean for Natural Private stands is derived by adding the private coefficient to the intercept (77.281 – 25.646 = 51.635 ton/ha). The planted coefficient indicates the expected difference between a natural and a planted stand, regardless of owner.

It might seem odd that the planted stand coefficient is negative, since we expect plantations to produce more wood than natural stands. However, these are stock, not production estimates, and if age is included in the model the planted coefficient becomes positive. The results in Table 5 reflect the fact that plantations on average are younger than the typical natural forest stand, especially if it is on Forest Service land.

8. Discussion

FIA annual inventory data can be analyzed in a number of ways. Methods were presented to unify tabular, graphical and regression analyses, which can all be used to summarize and understand FIA survey data. The methods presented here are not identical to the methods that FIA uses (Bechtold and Patterson, 2005), but these methods still produce unbiased estimates with variances that can be estimated.

The fact that there are alternative methods for the analysis of FIA data should not be surprising or disturbing. It is known that uniformly minimum variance estimators do not generally exist for survey samples from finite populations (Godambe, 1970). Regardless, the methods presented here are very similar to FIA (Bechtold and Patterson, 2005) methods, but leave out some of the compli-

Table 2

Above-ground live tree (no foliage) carbon density (ton/ha) by owner group and stand origin for all forest land in Georgia, 2006. Standard errors are in parentheses.

	Natural	Planted	All
USDA Forest Service	77.27 (2.77)	62.97 (23.16)	76.64 (2.81)
Other federal	62.03 (3.37)	49.84 (13.23)	61.6 (3.28)
State and local	62.04 (4.26)	35.37 (4.67)	56.29 (3.62)
Private	52.02 (0.84)	31.44 (0.76)	45.03 (0.63)
All	53.99 (0.79)	31.73 (0.75)	46.94 (0.61)

Table 3
Total above-ground live tree (no foliage) carbon (ton) by owner group and stand origin for all forestland in Georgia, 2006. Standard errors in parentheses.

	Natural	Planted	All
USDA Forest Service	25,372,107 (911,054)	944,046 (347,188)	26,316,153 (966,683)
Other federal	17,957,137 (983,133)	539,322 (143,190)	18,496,459 (992,831)
State and local	13,498,838 (936,750)	2,111,547 (287,643)	15,610,385 (1,019,532)
Private	309,312,168 (5,079,044)	96,043,616 (2,344,580)	405,355,785 (5,787,401)
All	366,140,251 (5,396,259)	99,638,530 (2,391,475)	465,778,782 (60,144,832)

Table 4
Number of plots by measurement year by owner group for all forest land in Georgia, 2006.

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
USDA Forest Service	6	2	–	–	–	24	23	35	34	21
Other federal	4	1	–	–	–	23	34	30	18	23
State and local	4	1	–	–	–	31	25	30	25	12
Private	119	60	1	3	4	694	874	953	914	497

Table 5
Linear model results for total above-ground live tree (no foliage) carbon (ton) by owner group (OWNGRPCD) and stand origin (STDORGCD) for all forestland in Georgia, 2006.

Coefficient	Estimate	Std. error	t value
Intercept	77.281	2.524	30.616
OWNGRPCD:other federal	−14.959	3.679	−4.066
OWNGRPCD:state and local	−16.799	3.761	−4.466
OWNGRPCD:private	−25.646	2.589	−9.904
STDORGCD:planted	−20.255	1.012	−20.010

cations that result from FIA's use of stratified estimators. The FIA analysis method (Bechtold and Patterson, 2005) based on double sampling for stratification adds components to the variance estimator that are not required in the methods proposed here.

There are four FIA strata (Bechtold and Patterson, 2005): forest, non-forest, forest/non-forest-edge, and non-forest/forest-edge. FIA plots are laid out on a grid and post-stratification is accomplished by assigning each plot to a stratum determined from (Vogelmann et al., 1998) USGS National Land Cover data (NLCD). However, much of the variance reduction could be obtained with just two strata, forest and non-forest. The FIA strata involving proximity to forest-edge are somewhat subtle and hard to identify. The approach described here uses only forest land plots and ignores the strata, which immediately simplifies the analysis.

While the stratification might reduce variance at a state level, it's likely to have little impact with smaller sample sizes, because assigning plots to strata is inherently uncertain. It is difficult to match an FIA plot consisting of four circular subplots located 37 m apart that collectively total one-fifteenth of a hectare to a 30 m² NLCD pixel.

9. Conclusions

The methods presented here apply statistical principles in a practical way that enhances the value of forest survey data. Implementing these methods in a web tool allows users to develop statistically-sound estimates based on data chosen for their needs. Tabular and weighted regression estimates can be presented with standard errors for tests of statistical significance. Presentation of results from individual FIA plots (Fig. 1), may provide useful information about geographic patterns. Graphic display of individual observations can enhance understanding of advanced statistical analysis and promote comparative interpretation among plots.

The estimation methods are useful for summarizing current status from forest survey data. They are also useful for assessing GRM data based on a set of current and previous plot measurements. More sophisticated methods (Van Deusen, 1999) should

be employed when data are available from multiple remeasurements of the same plot or multiple inventories over time. The FIA annual inventory is maturing to where multiple plot remeasurements are becoming available for a number of states. Use of these data in the near future will require addressing analytical needs for remeasurements.

It should be clear from the methods presented here that FIA data are flexible and can be processed with understandable analytical procedures. The example applications were generated from an online tool that implements these methods. This makes it possible for users to quickly access FIA data for their region of interest and to obtain a range of valid summary results. Online tools are useful, but there will always be users who need to go beyond what an online tool can offer. It is hoped that the methods described here will help users to achieve their analysis objectives with FIA data, regardless of what they might be.

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