Quantifying Forest Soil Physical Variables Potentially Important for Site Growth Analyses

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ABSTRACT: *Accurate mean plot values of forest soil factors are required for use as independent variables in site-growth analyses. Adequate accuracy is often difficult to attain because soils are inherently widely variable. Estimates of the variability of appropriate soil factors influencing growth can be used to determine the sampling intensity required to secure accurate mean plot values. A study was conducted to determine the plot means and variation of bulk density, texture, and gross moisture weights within plots associated with the longleaf pine (*Pinus palustris *Mill.) forest type in south Alabama. Included in the study were three different soil series (Troup, Norfolk, and Esto), at each of three topographic positions (lower, mid, and upper slope). Soil texture was the most variable among the properties studied and gross moisture weights the least variable. Results provide a means of estimating forest soil sampling intensity for use in site growth analyses. South. J. Appl. For. 28(1):5–11.*

Key Words: Longleaf pine, forest soils, soil variability, soil sampling.

Before site evaluation schemes can be of practical value to forestry, the degree of variability of forest soils and the accuracy of mean plot values for soil factors must be determined (Mader 1963). This is necessary, as estimates of soil moisture and/or site productivity are only as accurate as the plot mean values of the independent soil variables on which they are based. The desired accuracy and precision can be difficult to obtain because forest soils often lack uniformity, even within taxonomic units. The few attempts made towards a solution to this problem have indicated that soil factors affecting tree growth typically vary widely within a study area, greatly reducing the precision of site index estimation based on soil type. Accurate mean plot values of soil factors can be obtained with statistically sufficient replication but, due to the high degree of variability of forest soils, it may not be physically or economically feasible to sample and analyze the large number of plots or subplots required. Moreover, differences in variability among soil factors necessitate different sampling intensities to obtain the same levels of precision and accuracy for each factor.

Mader and Owen (1961), Clutter and Ike (1962), and Ike and Clutter (1968) discuss problems associated with soil variability and suggest approaches and analyses that might be employed. They suggest sampling soil factors in duplicate for each study site and analyzing components of variance to determine within- and among-plot variation of means, in order to estimate the sampling intensities required to achieve precision targets. Since this time, Mroz and Reed (1991) presented a theoretical application of these ideas, but we found only two studies, both out of the Northeast, reporting actual applications to forest soils. Mader (1963) confirmed the importance of soils variability data in planning future surveys and identified the need for more efficient soil sampling methods, particularly with respect to quantifying relationships between soils and tree growth. Mollitor et al. (1980) studied components of variance within and between plots for a number of soil parameters on flood-plain soils and concluded that similar methodology might be used to gain sampling efficiencies on other soils.

The study reported herein was initiated shortly after Mader's (1963) article was published. In 1966, the Southern Research

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Station (USDA Forest Service) and T.R. Miller Mill Company established a study to quantify within- and between-plot variability and their influence on the confidence in estimates of soil parameters, including bulk density, texture, and water availability, for soils of the longleaf pine (*Pinus pulustris* Mill.) forest type. Located on the Escambia Experimental Forest, near Brewton Alabama, a set of 18 1/10 ac plots cut across three soil series (Troup, Norfolk, and Esto) and three slope positions (lower, mid, and upper). The study data also served to describe the soils in the areas sampled. To our knowledge, no one has since undertaken the intensive field sampling and rigorous laboratory analyses necessary to fulfill this need in the Southeast.

Although considerable time has elapsed since these efforts, there remains a need to establish sound estimates of soil physical properties at both small and larger scales. Small-scale estimates are critical to growth and yield estimation and correlation and regression analyses relating soil property estimates to tree growth. Larger scale estimates are required for accurate mapping of soil properties at the stand and forest levels. The data reported herein should aid foresters in optimizing soil samples with respect to spatial variability in future studies of soils or site index.

Methods

Field Collection

The study was carried out on three soil series and at each of three topographic positions (upper, mid, and lower slope). The soil series were the Esto (clayey, kaolinitic, thermic Typic Paleudult), the Troup (loamy, siliceous, thermic Grossarenic Paleudult), and the Norfolk (fine-loamy, siliceous, thermic Typic Paleudult). These soil series were used because they are three of the more extensive soil series on the Escambia Experimental Forest that could be found in three topographic positions and of three different families. In addition, these series are representative of soils across the Southeast, occurring in every state with longleaf pine. The conditions of the longleaf pine stands were fully stocked, free from insect and disease damage and experienced periodic prescribed fire.

On each soil series-slope position combination, two replicate 1/10 ac plots were established, for a total of 18 plots. At each plot, a soil pit was dug at a random location beside or below, but 6 ft upslope from, each of two moisture probe access tube locations. Care was exercised to disturb the surrounding area as little as possible. The soil profile was described and each horizon sampled by obtaining two undisturbed cores and a bulk sample. The two core samples were removed from the midpoint of the horizon, whereas the bulk sample of about 500 grams was taken as a vertical slice through the thickness of the horizon. The core samples were placed in weighing cans and the bulk samples in plastic freezer bags for transport to the laboratory.

Laboratory Procedure

Bulk density values on the undisturbed core samples were obtained from oven-dry data. The hydrometer method of Bouyoucos (195 1) was followed for texture analysis. However, a major modification was made where sands were separated from clays by wet sieving, using a 300-mesh sieve, after the samples had been mechanically dispersed. This eliminated the sands from the hydrometer cylinder. Silt percentage was obtained as the difference between the sum of the sand and clay percentage, and 100%. Table 1 presents the mean values for the measured soil variables by soil series.

Statistical Analysis

Variables describing soil properties were averaged across soil horizons in each profile, weighted by horizon thickness. Texture measures were averaged across E, A3, B 1, B21, and B2 horizons. Separate A (E, A3) and B (B 1, B21, B2) averages were calculated for bulk density and gross moisture weight variables. The resulting means were then subjected to analysis of variance (ANOVA) to separate variance components relating to each of the sampling stages.

The sampling stages accounted for included soil series (S), slope position(T), plot orreplicate (R), profile (P), and sample (E). The original sampling design was summarized by a linear model that accounted for both slope position and the interaction between slope and soil series ($S \times T$):

$$Y_{ijklm} = \mu + S_i + T_j + ST_{ij} + R_{(ij)k} + P_{(ijk)l} + E_{(ijkl)m} \quad (1)$$

where Y_{ijklm} is the measured soil property associated with the ith soil series (S), $i = 1..3$, jth slope position (T), $j = 1..3$, kth plot *(R)*, $k = 1...r_{ij}$, lth profile (P), $l = 1...p_{ijk}$, and mth sample (E), $m = 1..n_{ijkl}$. Soil series (S) and slope (T) are considered fixed effects. Plot (R), profile (P), and sample (E) are random, nested effects; plots are nested within soil series x slope combinations, profiles within plots, and samples within profiles.

In application of this model to the data, the interaction between slope position and soil series was not significant in all cases ($P > 0.237$). With the ST term removed from the model, slope position was also found to be insignificant ($P > 0.135$) and removed, leading to the simplified version of model (1):

Table 1. Mean and range values for soil variables measured for each soil series (based on *n* = 24 samples per series).

Variable	Soil series: Troup	Norfolk	Esto
% Sand	80.8 (56.6-86.6)	69.6 (54.3-82.5)	48.1 (23.0–78.8)
% Silt	14.2 (9.2-22.1)	19.1 (12.8–30.4)	33.0 (7.9-55.2)
% Clay	5.0 (2.7-21.3)	11.3 (1.6-21.9)	18.9 (5.8-34.9)
Depth to B-horizon (in.)	10.5 (4-20)	10.7 (6-28)	12.5 (6–33)
Bulk density (A-horizon)	1.41 (1.20-1.63)	1.40 (1.21-1.53)	1.45 (1.29-1.61)
Bulk density (B-horizon)	1.59 (1.44-1.76)	1.64 (1.50-1.80)	1.60 (1.44–1.83)

$$Y_{ijkl} = \mu + S_i + R_{(i)j} + P_{(ij)k} + E_{(ijk)l} \quad (2)$$

where Y_{ijkl} is the measured soil property associated with the ith soil series (S), $i = 1...3$, jth plot (R), $j = 1... r_i$, kth profile (P), $k = 1...p_{ij}$, and lth sample (E), $l = 1...n_{ijk}$.

The variance components of (2) were then used to study the effects of sample size on the estimation precision of (a) soil series means, and (b) plot means. To do this, expressions for the expected mean squares of (2) were combined with the formulas for the standard errors of series, plot, and profile means. To illustrate, the expected mean squares of (2) are:

$$MSR = \sigma_E^2 + n\sigma_P^2 + pn\sigma_R^2, \quad (3)$$

$$MSP = \sigma_E^2 + n\sigma_P^2 \quad (4)$$

and

$$MSE = \sigma_E^2 \quad (5)$$

where MS = mean square, R, P, and E are as defined above, σ^2 is a variance component, n = the number of samples taken from a profile, and p = the number of profiles observed in a plot. These expected mean squares were generated using the algorithm outlined by Hicks (1982).

The formulas for the standard errors of series, plot, and profile means are given by (Steel and Torrie 1980):

$$s_{\bar{S}} = \sqrt{\frac{MSR}{rpn}}, \quad (6)$$

$$s_{\bar{R}} = \sqrt{\frac{MSP}{pn}} \quad (7)$$

$$s_{\bar{P}} = \sqrt{\frac{MSE}{n}} \quad (8)$$

where s = standard error, S, R, P, n, and p are as previously defined, and r = the number of plots within a soil series. Combining (3), (4), and (5) with (6), (7), and (8), respectively, leads to:

$$s_{\bar{S}}^2 = \frac{MSR}{rpn} = \frac{s_E^2 + ns_P^2 + pns_R^2}{rpn} = \frac{s_E^2}{rpn} + \frac{s_P^2}{rp} + \frac{s_R^2}{r} \quad (9)$$

$$s_{\bar{R}}^2 = \frac{MSP}{pn} = \frac{s_E^2 + ns_P^2}{pn} = \frac{s_E^2}{pn} + \frac{s_P^2}{p}, \quad (10)$$

and

$$s_{\bar{P}}^2 = \frac{MSE}{n} = \frac{s_E^2}{n} \quad (11)$$

where s_R^2, s_P^2, and s_E^2 are estimates for σ_R^2, σ_P^2, and σ_E^2, respectively.

Equations (9), (10), and (11) were used to determine the optimum allocation of sample sizes, n, p, and r to minimize the standard error of a soil series or plot mean. Further, these equations were used to determine the sample sizes required to estimate the various soil properties to within ± 5 % (in some cases ± 10 %) of the mean 95 times out of 100.

Numerical Example

Application of the above formulas is illustrated using the property, percentage of sand. From analysis of variance of the collected data and model (2), MSR = 471.23, MSP = 60.15, and MSE = 10.86. With the existing sample sizes, $r = 6$, $p = 2$, and $n = 2$, the application of (6), (7), and (8) give the standard errors $s_{\bar{S}} = 4.43$, $s_{\bar{R}} = 3.88$, and $s_{\bar{P}} = 2.33$. Then, from the expected mean squares [(3), (4), and (5)]:

$$\sigma_E^2 \approx MSE = 10.86,$$

$$\sigma_P^2 \approx \frac{MSP - MSE}{n} = \frac{60.15 - 10.86}{2} = 24.64,$$

and

$$\sigma_R^2 \approx \frac{MSR - MSP}{pn} = \frac{471.23 - 60.15}{4} = 102.77$$

Therefore, the variation in percentage sand among samples within a profile is approximately 10.86, among profiles within a plot is 24.64, and among plots within a soil series is 102.77. Figure 1 is a schematic representation of these different component variances.

Returning to (9), (10), and (11), it can be shown that the standard error for an estimate will be minimized when sampling effort is focused on the highest level of replication; plots for a series mean, profiles for a plot mean. This is reflected in Table 2, where all possible allocations of the existing sample are listed with their corresponding standard errors for soil series and plot means. For a soil series mean, the best way that our rpn = 24 samples could have been apportioned is $r = 24$, $p = 1$ and $n = 1$:

$$s_{\bar{S}} = \sqrt{\frac{10.86}{24} + \frac{24.64}{24} + \frac{102.77}{24}} = 2.40$$

leading to a standard error considerably smaller than the 4.43 achieved with $r = 6$, $p = 2$ and $n = 2$. Similarly, focusing sampling efforts on the number of profiles maximizes the precision of a plot mean. Of course, the most efficient allocation of sample, profile, and plot replicates will always depend on the relative cost of each of these.

A more practical use of Equations (9) and (10) lies in determination of the number of soil samples required to estimate a plot mean for sand content, with a 95% confidence interval of, say, $\pm$ 5%. If we assume $n = 1$, then p can be determined from (10):

$$95\ \%\ \mathrm{CI} = \pm 5 = \pm t_{(0.05/2,\, p-1)} \times s_{\bar{R}}$$

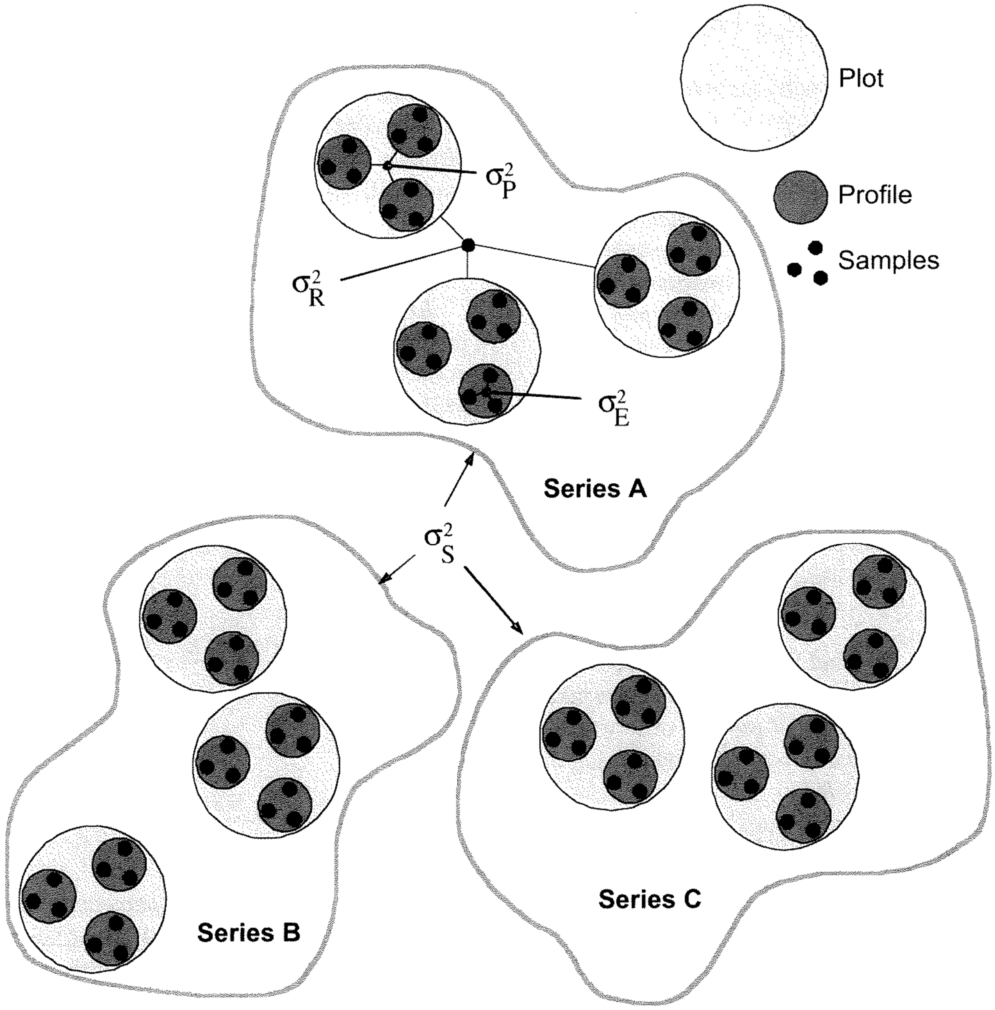

Figure 1. Schematic view of sample, profile, plot, and soil series variance components in a three-stage sampling design.

$$5^2 = t^2_{(0.05/2,p-1)} \times \left(\frac{s_E^2 + s_P^2}{p}\right),$$

since $n = 1$.

Then, substituting an appropriate value for t,

$$p = \frac{2.37^2\ x(10.861\text{-}24.64)}{5'} = 7\ 98 \approx 8.$$

Therefore, evaluating eight profiles per plot should yield plot means for percent sand that have a sampling precision of ± 5%.

Similarly, the number of plots required to yield equally precise series means can be computed from Equation (9). Assuming $n = 1$, and $p = 8$:

$$95\%\ \mathrm{CI} = \pm 5 = \pm t_{(0.05/2\ ,r-1)} \times s_{\bar{S}}$$

$$5^2 = t^2_{(0.05/2,r-1)} \times \left(\frac{s_E^2}{rpn} + \frac{s_P^2}{rp} + \frac{s_R^2}{r}\right)$$

$$5^2 = t^2_{(0.05/2,r-1)} \times \left(\frac{10.86}{8r} \frac{24.64}{8r} + \frac{8 \times 102.77}{8r}\right)$$

Then, substituting an appropriate value fort,

$$r = \frac{2.07^2 \times (10.86 + 24.64 + 8 \times 102.77)}{8 \times 5^2} = 18.4 \approx 19$$

With eight profiles per plot and 19 plots, a series mean for sand content should be estimated with a precision of ±5%. Armed with estimates for the different sampling variances, one can thus design a soil sample to meet very specific needs.

Results and Discussion

The values listed for s_E^2, s_P^2, and s_R^2 in Table 3 estimate the variances among samples, profiles, and plots within each soil series (Figure 1), respectively, as these were installed in this investigation. These values approach what might be expected in repeated sampling using a similar protocol. The F-tests for the plot and profile variances (P_R, and P_P, Table 3) provide insight into the efficiency of the sampling protocol, given the soil conditions encountered.

Table 2. Possible allocations of 24 soil samples and their corresponding effects on soil series and profile means for percent sand content. Italic rows indicate allocation leading to the lowest standard error; bold rows identify the combination used.

	Soil series mean					Plot mean		
$s_{\bar{S}}$	Samples n	Profiles p	Plots r	Total	$s_{\bar{R}}$	Samples n	Profiles p	Total
2.40	1	1	24	24	5.96	1	1	1
3.17		2	12	24	4.21	1	2	2
3.78			8	24	3.44	1	3	3
4.31		4	6	24	2.98	1	4	4
5.21		6	4	24	2.43	1	6	6
5.98		8		24	2.11	1	8	8
1.27		12	2	24	1.72	1	12	12
10.21		24		24	1.22	1	24	24
3.33	2		12	24	5.48	2	1	2
4.43	2	2	6	24	3.88	2	2	4
5.31	2	3	4	24	3.17	2	3	6
6.06	2	4		24	2.74	2	4	8
7.34	2	6	2	24	2.24	2	6	12
10.26	2	12		24	1.58	2	12	24
4.05	3		8	24	5.32	3	1	3
5.41	3	2	4	24	3.76	3	2	6
7.41	3	4	2	24	2.66	3	4	12
10.31	3	8		24	1.88	3	8	24
4.66	4		6	24	5.23	4	1	4
6.23	4		3	24	3.70	4	2	8
7.48	4		2	24	3.02	4	3	12
10.36	4			24	2.14	4	6	24
6.55	8			24	5.10	8	1	8
10.56	8	3		24	2.94	8	3	24
8.01	12		2	24	5.05	12	1	12
10.75	12	2	1	24	3.57	12	2	24
11.31	24	1	1	24	5.01	24	1	24

In cluster or multistage sampling, the objective is to maximize within-cluster variation to minimize betweerr-cluster variation. For efficient series estimates, for example, one would want to maximize within plot variation (i.e., variation between profiles) to minimize variation between plots. The fact that s_R^2 was statistically significant (i.e., > 0, $P_R < 0.05$) for all soil properties but gross moisture weight (0 atmospheres, A horizon) suggests that a larger plot size than that used (i.e., greater distance between profiles, Figure 1) may offer some gains in efficiency if series estimation is the goal. Regardless, the sample protocol used enabled distinction between soil series in all cases but depth to B, bulk density (A and B), and gross moisture weight (0 atmospheres, A and B horizons) ($P_S < 0.04$). Coefficients of variation were quite small (< 4%) for these insignificant variables, so it is possible that they are not distinguishing properties of the soil series studied.

Estimates for somewhat smaller areas (e.g., growth and yield plots) may require a shift in focus to maximizing variation within profiles and minimizing variation between. From this perspective, smaller plots (i.e., minimal distance between profiles, Figure 1) will likely give the greatest efficiency. For the properties bulk density (A horizon) and gross moisture weight (A horizon), the distribution of samples in the protocol used generally provided for elevated between sample variances (s_E^2) and relatively small between-profile variances ($P_P > 0.097$). This suggests that these properties were variable at small spatial scales (i.e., within profiles), but largely homogeneous at the plot level. Given similar soil conditions, future applications of this sample design should generally lead to sound plot estimates for these variables. In contrast, the other properties tended to be less variable at small spatial scales and more variable between profiles. Although s_P^2 was generally not greater than approximately two times s_E^2, this serves as a reminder that variation between profiles could erode the efficiency of plot-level estimates, given slightly different conditions.

The data suggest that the texture of these soils might generally be quantified to within ±5% on plots by sampling 5 to 8 soil profiles (Table 3). The percentage of sand was the most variable, requiring the higher number of profiles. For series means of the same precision, between 8 and 19 plots would be required if they were subsampled (with 5 to 8 profiles) and 10 to 24 plots required if they are each based on a single profile. In contrast, depth to B was highly variable, requiring a large number of profiles and/or plots (>30) to attain precision approaching ± 1.1" (±10 % of the mean). Bulk density in the A horizon requires approximately seven profiles to attain a plot mean with 95% confidence limits of ±0.07 gm cm^{-3} and six such plots to attain a series mean of similar precision. B-horizon estimates were somewhat less variable, requiring slightly fewer samples. Gross moisture weight was the least variable of the properties studied, typically requiring four to five profiles per plot for 95% confidence limits equal to ± 5% of the mean plot value. Series estimates require four to

Table 3. Summary of sampling statistics for the range of soil properties studied.

		From analysis of variance* variability among:						
Characteristic	Horizon	Samples s_E^2	Profiles s_P^2	Plots s_R^2	Overall mean	Series P_S	Plots P_R	Profiles P_P
% Sand	A, B	10.86	24.64	102.77	66.16	0.0004	0.0001	0.000 1
% Silt	A, B	4.28	11.30	50.79	22.13	0.0018	0.0001	0.0001
% Clay	A, B	7.16	6.63	33.39	11.72	0.0053	0.0001	0.0036
Depth to B (in.)	A	10.35	6.72	11.49	11.24	0.6488	0.0161	0.0165
Bulk density	A	0.0040	0.0012	0.0032	1.42	0.4240	0.0154	0.1079
	B	0.0015	0.0011	0.0061	1.61	0.5658	0.0001	0.0121
M.R. @ 0†	A	6.75	2.22	1.44	126	0.2817	0.1993	0.097 1
	B	2.72	1.19	7.91	133	0.2165	0.0001	0.0535
M.R. @ 0.10	A	11.26	2.36	12.82	118	0.0326	0.0024	0.1817
	B	3.86	4.28	19.48	128	0.0228	0.0001	0.0014
M.R. @ 0.33	A	10.50	2.97	8.76	115	0.0358	0.0116	0.1234
	B	3.76	4.74	19.34	126	0.0146	0.0001	0.0006
M.R. @ 1.0	A	10.86	2.09	5.81	113	0.0123	0.0308	0.1982
	B	4.11	5.35	17.94	124	0.0076	0.0003	0.0006
M.R. @ 3.0	A	10.55	2.21	5.25	112	0.0212	0.0393	0.1817
	B	4.33	5.43	17.16	123	0.0074	0.0005	0.0007
M.R. @ 15.0	A	10.53	1.74	5.13	111	0.0283	0.0354	0.2277
	B	3.86	5.58	18.02	123	0.0108	0.0003	0.0003

		Based on ANOVA, number of samples required for estimating						
		Plot mean			Series mean			
		$s_{\bar{R}}$	95 CI(±)††	Profiles p (n = 1)	$s_{\bar{S}}$	95% CI(±)††	Plots r (n=1,	Plots r (n=1, p=1)
% Sand	A. B	-3.88	5	8	4.43	5	19	24
% Silt	A; B	2.59	5	5	3.10	5	11	13
% Clay	A, B	2.26	5	5	2.53	5	8	10
Depth to B (in.)	A	2.44	1.12	55	1.70	1.12	39	92
Bulk density	A	0.0404	0.07	7	0.0283	0.07	6	9
	B	0.0303	0.08	4	0.0341	0.08	7	8
M.R. @ 0†	A	1.67	6.28	4	0.84	6.28	3	4
	B	1.13	6.65	3	1.24	6.65	4	4
M.R. @ 0.10	A	2.00	5.89	4	1.67	5.89	5	6
	B	1.76	6.38	4	1.94	6.38	5	6
M.R. @ 0.33	A	2.03	5.74	5	1.46	5.74	4	6
	B	1.82	6.28	4	1.94	6.28	5	6
M.R. @ 1.0	A	1.94	5.64	5	1.26	5.64	4	5
	B	1.93	6.22	4	1.90	6.22	5	6
M.R. @ 3.0	A	1.93	5.59	5	1.22	5.59	4	5
	B	1.95	6.13	4	1.87	6.13	5	6
M.R. @ 15.0	A	1.87	5.56	4	1.20	5.56	4	5
	B	1.94	6.15	4	1.91	6.15	5	6

* From model [2], P_s, P_R, and P_P are probabilities of a greater F-value for Series, Plots, and Profiles, respectively.
† Gross moisture weight at specified atmospheric pressure.
†† 95 % confidence limits specified as a target for future sampling precision (generally ± 5 or 10% of the mean).
¶ P = the sample size in terms of the number of profiles, previously computed for a plot mean.

five plots of four to five profiles per plot, or about six randomly placed profiles for the same degree of precision. A-horizon estimates tended to be slightly more variable than B in the data collected. If conventional practice involves averaging 10 profiles per plot, our results suggest that this may be somewhat more than necessary and that efficiencies may be gained by transferring some of this sampling effort to additional plot assessment.

Mader (1963) and Mollitor et al. (1980) conducted similar studies in forest soils of the Northeast, each looking at a wide array of soil properties. With similar sampling designs to those employed by this study, the major conclusions of these studies were consistent with the above:

- Variability between plots was greater than variation within plots.
- Within-plot variation appears to be, for most soil properties, of a magnitude that would not deter plot-level correlation and regression analyses.
- Two profiles per plot are generally insufficient to satisfactorily estimate most soil properties. in Mader's (1963) soils of agricultural origin, estimated sample sizes suggested for bulk density and texture were similar to those reported in Table 3, given equivalent levels of precision (±10% with 95% confidence). Flood plain soils, however, exhibited greater variability, requiring two to three times the number of samples to achieve the same precision (Mollitor et al. 1980).

Mader (1963) also hypothesized that properties of the lower horizons may be more uniform than those at the surface because of less disturbance and effects of microtopography. While his data did not support this hypothesis, ours did. In the cases of bulk density, and moisture retention, where separate A- and B-horizon estimates were obtained, A-horizon estimates were slightly more variable than B-estimates. Previous agricultural use on Mader's soils may have led to greater mixing of the upper layers and, therefore, more homogeneity than typical of the undisturbed soils studied herein. Mollitor *et al.* (I 980) found a similar mixing effect in the upper layers of flood plain soils, these being more uniform than subsurface soils.

The results of this and related studies provide strong evidence that soil sampling efficiency can be improved through knowledge of the spatial variability in soils. We assert that, prior to any significant evaluation of forest soils, a preliminary survey be undertaken to quantify spatial variability in the soil parameters of interest. Such an effort would undoubtedly amount to a wise investment, for only with this prior information can the larger survey be designed with optimum and efficient allocation of samples to address the specific study objectives at hand.

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