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Double Sampling Increases the Efficiency of Forest Floor Inventories for Arizona Ponderosa Pine Forests

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Abstract. Stand and natural fuel conditions were sampled in ponderosa pine forests in northern and central Arizona to develop predictive fuel depth and loading equations. Litter and duff depths can be estimated from measurements of stand density (basal area, stand density index). Although woody fuel loading did not correlate well with stand variables, correlations were found among loadings of different woody fuel size classes, so that results from a planar intersect tally of certain single woody fuel size classes may be used to predict the loadings in certain other size classes. The relatively low precision of estimates from these predictive equations can be substantially increased by applying them in a double sampling scheme. Making use of these predictive relationships, managers can devise simple, rapid, and cost-effective fuel inventories that focus on the fuel category of interest. Fuel loads can be estimated at a desired precision with reduced investment of time and funds compared to a more comprehensive direct fuel inventory.

Keywords: Fuel inventory; Double sampling; Ponderosa pine; Arizona.

Introduction

The forest floor, consisting of litter, duff, and downed dead woody material, plays a crucial role in many ecosystem processes. Information on the quantity and quality of forest floor components may be obtained with specific inventory procedures (Brown et al. 1982), but managers often cannot invest the funds or time for sampling large areas. The objective of the present study was to develop an efficient method incorporating predictive relationships in a double sampling scheme to estimate forest floor depth and woody debris loading. Although the data examined in detail pertain to fuels in southwestern ponderosa pine, the double sampling procedure could improve efficiency of fuel sampling in other forest types as well.

Forest floor characteristics of interest are litter (L layer), duff (F and H layers), and woody material. In fire management, woody material is classified by diameter and time response to moisture changes as 1-hour (0 to 0.62 cm diameter), 10-hour (0.62 to 2.54 cm), 100-hour (2.54 to 7.62 cm) and 1000-hour (over 7.62 cm) timelag fuels. The largest class is subdivided into sound and rotten categories. For simplicity, woody fuels are referred to by timelag class rather than diameter range. These groups form the standard classification for fuel inventories (Brown et al. 1982) and fire behavior fuel models (Burgan and Rothermel 1984).

Different forest floor components are important to managers in different ways. Litter and duff depths are valuable in estimation of interception of precipitation and erosion potential (Baker 1990), habitat of various species, including insects, which require litter or duff for all or part of their life cycles (Schmid et al. 1981), and cycling of nutrients (Covington and Sackett 1986). Duff depth is important in prescriptions for controlled burning, which is commonly designed to reduce duff depth (Harrington 1987) or to expose mineral soil to enhance pine seedling establishment (Haase 1986). The small size classes of woody fuels, together with litter, carry the flaming front, respond quickly to moisture changes, and are key inputs to fire behavior fuel models (Burgan and Rothermel 1984). Larger size classes of woody fuels are especially important in smoldering time (Brown and See 1981) and localized soil heating (Covington and Sackett 1990).

Aldon (1968) and Ffolliott et al. (1968) reported a relationship between ponderosa pine basal area and forest floor loading and depth for specific sites. Equations to predict forest floor depth from basal area on a selectively harvested site on basalt soils in central Arizona were developed with coefficients of determination (r^2) between 0.35 and 0.53 (Ffolliott et al. 1968). In a more extensive study across Arizona and New Mexico, ponderosa pine forest floors were sampled by

Sackett (1979), who found variability too high to create any predictive models, even though only stands without obvious human-caused disturbance within the last 20 years were sampled. A similar study in the northern Rocky Mountains showed numerous significant correlations among stand and forest floor variables, but again high variability precluded the development of predictive models (Brown and See 1981). Sackett and Haase (1991) stratified ponderosa pine stands in northern Arizona into small even-sized groups and predicted forest floor loading (total of litter, duff, and woody fuels under 2.54 cm diameter) from average tree height, average tree diameter, and soil parent material (basalt or sedimentary).

Presently, managers requiring information on natural ponderosa fuels in order to evaluate fire behavior, risk, fuel treatments, or burning prescriptions in Arizona must choose between: (1) a comprehensive inventory of forest floor and woody fuels (Brown et al. 1982); (2) applying predictive equations from stand inventory data under constraints of limited predictive capability (Ffolliott et al. 1968) or extensive stratification (Sackett and Haase 1991); (3) using a photo guide for estimating post-harvest residues developed in the Black Hills, South Dakota (USDA 1990), but commonly applied for fuel inventory in the Southwest (Al Braddock, USDA Forest Service, personal communication 1992); or (4) proceeding with only general vegetation type information (e.g., Fule and Bradshaw 1992). The option of conducting a complete inventory may be excluded by budgetary limitations. For example, an economic analysis by Barrager et al. (1982) estimated the value of improved fuel information on Mount Hood National Forest to range from \$0.02 per ha for general fire planning to \$79 per ha for evaluation of complex postharvest alternatives, suggesting that high investment in detailed fuel inventory is best suited for high value or high risk sites. The relatively limited choices which remain do not reflect inadequate research efforts but rather the great natural diversity of forest conditions and history. Application of predictive equations within a double-sampling context may be an intermediate alternative, less costly than an inventory but providing increased precision compared to the estimates offered by the other choices.

Methods

Data were collected in two field seasons, 1989 and 1992, in forests which met the criteria of no evident disturbance within 20 years (Sackett 1979). The 1989 sampling was done on the ponderosa pine forest of the North Rim, Grand Canyon National Park, and the Bar M watershed, Coconino National Forest. The North Rim is closed to harvesting and grazing, while the Bar M area was selectively harvested in 1948 and is subject to grazing. Elevations ranged from 2200 to 2500 meters on the North Rim and 2100 to 2300 meters at Bar M. Sedimentary soils (limestone) occur on the North Rim; basalt soils at Bar M.

Fixed plots of 10 $\times$ 20 meters were randomly located by overlaying site maps with a grid and choosing random coordinates. Each point were located on the ground and used to fix the sample plot 30 meters away in a random direction. Acceptable plots were at least 10% forested and had no apparent recent disturbance. Approximately 10% of the points were rejected due to recent fire or insufficient cover. All plots were within the ponderosa pine type. Measurements were taken on 33 North Rim plots and 11 Bar M plots.

Woody fuels and litter and duff depth were inventoried on each plot with three parallel 16 m planar transects (Brown et al. 1982). Large woody fuels (1000 hour class) were tallied along the full 16 m of each transect, while smaller woody fuels were tallied on 8 m per transect and litter and duff depths were measured every 2 m. Tree measurements included species and diameter at breast height of all trees over 1.37 m. Height, crown length, and an increment core were measured on a 10% subsample of trees. Overstory type (mature, pole, seedling), canopy closure, slope, aspect, and elevation were also recorded.

Preliminary analysis of the 1989 results indicated that several stand variables, including age, height, growth rate, and crown length, contributed less than stand density (basal area, trees per hectare, stand density index) to the explanation of fuel variation. Therefore additional data were collected in 1992 with a simplified method concentrating on stand density at a study site in the Gus Pearson Natural Area, Fort Valley Experimental Forest, Coconino National Forest. The Pearson site is closed to harvesting and grazing. Elevation at the site is 2200 to 2250 meters; soils are basaltic. Circular fixed plots of 10 meter diameter were randomly distributed within 3 overstory types: trees over 120 years, trees under 120 years, and small forest openings (50 to 150 m^2) with few trees but containing woody fuels and pine litter from the surrounding forest. Measurements were taken on 56 Pearson plots. Tree measurements included species and diameter at breast height of all trees over 1.37 m. Fuels were inventoried with two perpendicular 5 m planar transects per plot. All woody fuels were tallied along the 5 m transects and litter and duff depths measured every meter. Overstory type and elevation were also recorded.

For all sites, mean fuel loadings by size class per plot were calculated using the method of Brown (1974) with southwestern ponderosa pine woody fuel average squared diameters and specific gravities (Sackett 1980). Mean litter and duff depths were calculated per plot. Stand characteristics calculated from diameter measurements included basal area (BA, m^2/ha), trees per hectare (TPH), and quadratic mean diameter (QD, cm). Stand density index was calculated as $SDI = TPH(QD/25.4)^{1.605}$ (McTague and Patton 1989).

Regressions were developed with SYSTAT statistical software (Wilkinson 1988). Logarithmic and weighted transforms, and indicator variables, were tested for improving the models. Residuals were examined for violation of regression assumptions. Models were validated by splitting the data set and comparing predicted mean square errors from models made with one set to the mean square error observed in applying the models to the other set (Snee 1977).

Results

Since differences among sedimentary and basalt sites in Arizona have been observed in studies of ponderosa fuels (Ffolliott et al. 1968, 1976; Sackett and Haase, 1991), multivariate analysis of variance (MANOVA) was chosen to examine the effect of site on the complete fuel and stand matrices. The alpha level for all statistical tests was 0.05. Following an overall determination of a statistically significant difference among sites using the Wilk's lambda statistic, the MANOVA univariate F-values were examined for individual comparisons among fuel and stand variables. The MANOVA indicated that overall fuel characteristics were significantly different between the sedimentary and basalt sites (Wilk's lambda = 0.705, p = 0.000). Forest floor depth, woody fuel loadings, and univariate F-test results are shown in Table 1. The MANOVA indicated that overall stand characteristics were also significantly different between the sedimentary and basalt sites (Wilk's lambda = 0.313, p= 0.000). Table 2 gives the stand characteristics and univariate F-test results. Despite the different sampling plot designs and past harvesting history on the two basalt sites, stand variables on these sites were not significantly different. The basalt fuel complexes were significantly different overall (Wilk's lambda = 0.684, p = 0.001) but the difference was probably due primarily to the 1-hour woody fuel class, since it was the only category found significantly different by the univariate F-test.

Depth prediction equations for litter, duff, and the total forest floor are shown in Table 3. An indicator variable, SITE, which separated the basalt and sedimentary sites, was significant in the litter model. In general, stand variables were good predictors of forest floor depth but not of woody fuel loading, either by separate size classes or in total. However, different size classes of woody fuels were found to be strongly correlated with one another so that loading from one size class may be used to predict another. A series of relationships among the woody fuel classes is shown in Table 4. One hour fuel loading can be used to predict 10-hour loading (equation 4). Alternately, 100-hour fuel loading can be used to predict 1 and 10-hour loadings (equations 5 and 6). Finally, Table 4 shows relationships between the smaller fuel classes and total woody fuel loading. Equation 7 through 9 give three alternatives for predicting total woody fuel loading from 1-hour, 100-hour, and 1000-hour loading respectively. One data point was considered an outlier due to an extremely high 1000-hour fuel loading approximately 8 standard deviations above the mean. It was excluded from the data set for models including 1000-hour fuels or total fuels only (equations 7 - 9 in Table 4) because it had very high leverage, increasing r^2 values to 0.99. The indicator variable SITE was significant in several of the woody fuel models.

Table 1. Forest Floor and Woody Fuels.

	Total Plots N = 100 Mean	S.E.	Basalt Plots N = 67 Mean[1]	S.E.	Sedimentary Plots N = 33 Mean	S.E.
	cm[2]					
Litter Depth	1.05	0.038	1.17 a	0.095	0.377 b	0.040
Duff Depth	3.99	0.255	4.12 c	0.358	3.71 c	0.270
	metric tons ha^{-1}					
1-hour Woody	0.378	0.0509	0.491 d	0.072	0.150 e	0.0106
10-hour Woody	1.59	0.225	1.97 f	0.326	0.832 g	0.557
100-hour Woody	4.43	0.856	5.44 h	1.26	2.37 h	0.298
1000-hour Sound	1.75	0.484	0.94 i	0.395	3.41 j	1.19
1000-hour Rotten	6.06	3.08	6.49 k	4.48	5.19 k	2.26
Total Woody Fuels	14.2	3.33	15.3 l	4.78	12.0 l	2.87

[1] Within a row, means followed by the same letter are not significantly different ($p < 0.05$).
[2] Measured to approximately the nearest one-third cm; extra decimal places are from averaging.

Table 2. Stand Characteristics

	Total Plots N = 100 Mean	S.E.	Basalt Plots N = 67 Mean[1]	S.E.	Sedimentary Plots N = 33 Mean	S.E.
Basal Area ($m^2 ha^{-1}$)	52.6	4.52	54.8 a	6.40	48.2 a	4.47
Trees per Hectare	2360	285	3040 b	388	979 c	200
Stand Density Index	839	68.3	1079 d	87.2	349 e	26.3

[1] Within a row, means followed by the same letter are not significantly different ($p < 0.05$).

Table 3. Estimation of Forest Floor Depth

	R_A^2	N	S.E.E.
[1] DUFF = 1.60 + 0.0455 BA	.65	100	1.52
[2] LITTER = 0.856 + 0.000295 SDI - 0.17 SITE	.43	100	0.29
[3] FLOOR = 2.49 + 0.0484 BA	.62	100	1.67

DUFF = Duff Depth (cm)
LITTER = Litter Depth (cm)
FLOOR = Total Forest Floor Depth [Litter + Duff] (cm)
BA = Basal Area (m^2 ha^{-1})
SDI = Stand Density Index
SITE (indicator variable) = 0 for Basalt Site
= 1 for Sedimentary Site
R_A^2 = Adjusted Coefficient of Determination
S.E.E. = Standard Error of Estimate (cm)

Discussion

Woody fuel loading results in Table 1 are similar to mean southwestern ponderosa pine loadings reported by Sackett (1979) in the 1 through 100-hour classes; heavy woody fuel loadings were 25% (sound fuels) to 50% (rotten fuels) of the southwestern average. Higher variance was observed in fuel and stand variables on basalt sites than on sedimentary sites. This difference may be due to the change in sample plot layout, stand history between the formerly-harvested Bar M site and the unharvested Pearson site, or inherent productivity differences. Compared to Ffolliott et al.'s (1968) equation for forest floor depth, equation 3 in Table 3 is significantly different (t-test, $p < 0.05$) in slope and intercept. However, the study site of Ffolliott et al. (1968) did not meet the criterion of 20 or more years free from disturbance applied by Sackett (1979) and in the present study.

Litter, duff, and forest floor depths may be calculated from timber inventory data for sites with appropriate physical and stand history characteristics using the equations in Table 3. Woody fuel estimates using the models in Table 4 require the addition of a planar transect to each field inventory plot, increasing the complexity and cost of the procedure. However, because a tally of planar intersections of as few as one woody fuel size class could be sufficient for management needs, the planar transect inventory could be simpler and faster than a complete sample of all woody fuel classes (Brown et al. 1982). For example, a tally of 100-hour fuels along a 5 m transect, with subsequent prediction of 1-hour, 10-hour, and total woody fuel loading using equations in Table 4, is expected to be less costly than a complete tally along a 15 m transect. The woody fuel class of primary interest should be chosen for sampling on the planar transect. Estimates of additional fuels generated from current or planned management activities could be added to the sampled or predicted natural fuel loadings (Puckett et al. 1979), although variance could increase greatly. While the precision of estimates from the equations in Tables 3 and 4 is likely to be low given the relatively low r^2 values and high standard errors shown, the explanatory power of the equations is comparable to that of similar equations previously reported, if indeed variability permitted any to be made (Ffolliott et al. 1968 and 1976, Sackett 1979, Brown and See 1981). The higher explanatory power of the equations developed by Sackett and Haase (1991), on the other hand, reflects the detailed sampling stratification and combination of duff, litter, and woody fuels under 2.54 cm diameter fuel classes into a single total fuel loading value.

Table 4. Estimation of Woody Fuel Loadings

	R_A^2	N	S.E.E.
[4] F10 = 0.328 + 3.34 F1	.57	100	1.490
[5] F1 = 0.276 + 0.0394 F100 - 0.219 SITE	.52	100	0.355
[6] F10 = 0.738 + 0.193 F100	.53	100	1.540
[7] FT = 0.245 + 17.1 F1 + 6.93 SITE	.27	99	13.400
[8] FT = 1.43 F100 + 3.65 (SITE*F100)	.53	99	10.700
[9] FT = 6.26 + 1.02 F1000	.52	99	10.800

F1 = 1-hour Fuel Loading (ton ha^{-1})
F10 = 10-hour Fuel Loading (ton ha^{-1})
F100 = 100-hour Fuel Loading (ton ha^{-1})
FT = Total Woody Fuel Loading (ton ha^{-1})
F1000 = 1000-hour Woody Fuel Loading [Sound + Rotten] (ton ha^{-1})
SITE (indicator variable) = 0 for Basalt Site
= 1 for Sedimentary Site
R_A^2 = Adjusted Coefficient of Determination
S.E.E. = Standard Error of Estimate (ton ha^{-1})

The precision of estimates from the equations in Tables 3 and 4 would be enhanced by applying them in a double sampling context, as is often done in scales ranging from that of remote sensing (e.g., Paine 1981) to that of individual organisms (e.g., Andariese and Covington 1986). Double sampling methods are widely used in the U.S. for estimation of herbaceous and litter fuels (Brown et al. 1982) and other vegetation sampling (Francis et al. 1979). Double sampling in fuel estimation rests upon a theoretical foundation of allometry, the mathematical and functional interrelationships of the growth and structure of organism components (e.g., the relationship between canopy mass and sapwood area, Grier and Waring 1974). Although most allometric studies have been conducted at the individual organism level, others have explored ecosystem level allometry (including litterfall and dead organic accumulations, e.g., Olson 1963, Covington 1981). Two facts suggest that allometry might serve as a foundation for improved understanding of forest floor and down woody biomass interrelationships. First, litterfall components are functionally related to plant biomass components (Kercher and Axelrod 1984, Keane et al.

1990), and second, the balance between litterfall production and decomposition varies with litterfall dimensions (Harmon et al. 1986). Thus it might be possible to develop useful allometric relations among woody litter and forest floor components as well as with live tree measurements. In this manner one could use detailed inventory on one or more of the components and extrapolate using allometric equations for the others.

In the present case, fuel information may be obtained from timber inventory for a relatively small extra cost. Taking a subsample or "double" sample of fuel measurements on some of the timber inventory points will improve the precision of the fuel estimate, give the manager control over confidence limits and the desired sampling error, and allow calculation of the cost of fuel information. An example is discussed below for estimation of duff depth. Analogous methods may be used for the other models in Tables 3 and 4.

Estimates of duff depth on suitable sites can be made from a timber inventory based on variable radius sample points by computing basal area and applying equation 1 from Table 3. Stratifying duff depth estimates by established timber strata will give less variable results and allow the manager to map fuels by stand boundaries. If duff depth is measured on a random subset of inventory plots, a double sampling regression estimate of the mean duff depths may be calculated. An illustrative data set was developed by measuring basal area on 100 variable-radius sample points (N = 100) on a 200 ha ponderosa pine site with natural fuels within the Fort Valley Experimental Forest, Coconino National Forest. Duff depth at each sample point was calculated using equation 1. Duff depth was measured at 1 m intervals along a random-direction 5 m transect at a randomly-selected 30 of the 100 points (n = 30 double sampled points). The average duff depth was computed at each double sample point. Figure 1 shows the 30 predicted and observed duff depth pairs. Calibration through linear regression of observed depth (y) on predicted depth (x) gives:

$$\begin{aligned} y_i &= \bar{y} + b(x_i - \bar{x}) \\ &= 2.953 + 1.296(x_i - 3.355) \quad r = .744 \qquad (10) \end{aligned}$$

where: $\bar{y}$ = mean observed duff depth on the double sample points
$\bar{x}$ = mean predicted duff depth on the double sampling points
b = slope of regression line
r = correlation coefficient

Due to the variability observed in the data, the least-squares regression curve does not pass through the origin as might be expected with a more highly precise estimator. Nonetheless, the correlation between the observed and predicted values is the basis for applying double sampling to reduce variance (Francis et al. 1979). As long as some correlation exists, double sampling will always reduce variance compared to simple random sampling of a given number of field sampling points (deVries 1986).

The estimated population mean duff depth $\bar{Y}$ is now calculated by substituting $\bar{X}$ for x_i in equation 10 above:

$$\bar{Y} = 2.953 + 1.296(3.286 - 3.355) = 2.864$$

and the estimated variance of $\bar{Y}$ is (de Vries 1986):

$$\begin{aligned} \mathrm{var}(\bar{Y}) &= s_y^2\,[n^{-1} - (N - n)(r^2)/(Nn)] \\ &= (1.907)[30^{-1} - (100 - 30)(0.553)/(100)(30)] \\ &= 0.0390 \qquad (11) \end{aligned}$$

where: s_y^2 = variance of observed duff depth
N = large sample
n = double sample

The double sampling standard error of the mean, $s(\bar{Y}) = [\mathrm{var}(\bar{Y})]^{0.5} = 0.1974$, is approximately 22% less than the standard error of the mean from the 30 samples, $s(\bar{y}) = [s_y^2/n]^{0.5} = 0.2521$. The double sampling estimator of the mean therefore is more precise: taking the 90% confidence interval with $t_{0.1,100} \approx 1.67$, the double sampling estimate is $\bar{Y} = 2.864 \pm 0.330$ while the 90% confidence interval with $t_{0.1,30} = 1.70$ around the 30 sampled points is $\bar{y} = 2.953 \pm 0.429$.

Cost information will now be included to determine the best ratio of predicted to observed points and the relative efficiency of the sampling scheme. If the example data in Figure 1 were from a preliminary survey, an optimal number of sample and subsample points could be calculated to reach an estimate of specified precision at minimal cost. Assume that the cost of predicting duff depth from basal area data is C. This value is the cost of applying equation 1 to a data set and should be trivial (for example, $0.01 per point). Then estimate the marginal cost of measuring duff depth along with a basal area inventory in the field. This cost, c, is the extra cost of taking a duff measurement (for example, $1.50 per plot to measure the duff in 5 places and average). The cost of the basal area inventory itself is not included. The optimum ratio, R, of predicted duff points to measured duff points in a double sampling scheme, using the example cost and r^2 values, is (Paine 1981):

$$\begin{aligned} R &= 1/[(\{1 - r^2\}/r^2)(C/c)]^{0.5} \\ &= 1/[(\{1 - 0.553\}/0.553)(0.01/1.50)]^{0.5} \\ &= 13.622 \qquad (12) \end{aligned}$$

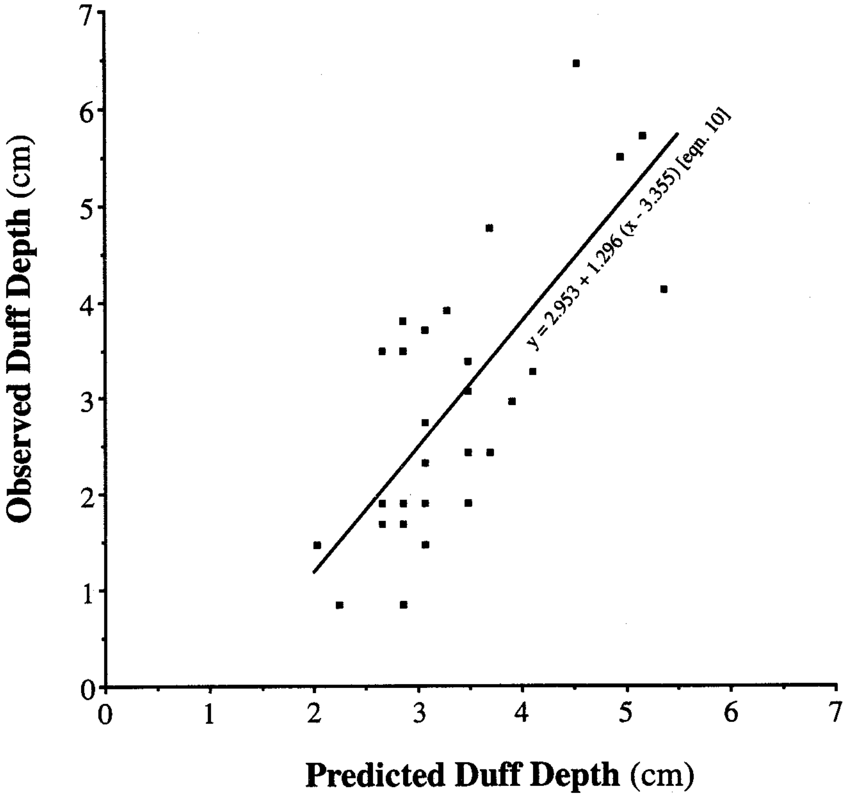

Figure 1. Predicted and observed duff depth at 30 double sample points. Predicted Values: N = 100, $\bar{X} = 3.286$, $s_x^2 = 0.555$. Double Sample Predicted Values: n = 30, $\bar{x} = 3.355$, $s_x^2 = 0.627$. Double Sample observed Values: n = 30, $\bar{y} = 2.953$, $s_y^2 = 1.907$.

where: R = optimum ratio of predicted to observed duff depth points
r^2 = coefficient of determination of regression equation (10)
C = cost of predicting duff depth at one point
c = marginal cost of measuring duff depth at one point

meaning that the double sample of duff depth should be taken on approximately 14% of all variable radius inventory points.

The efficiency, E, of this double sample is a dimensionless number used to compare different double sample schemes. In general, the higher the correlation between the predicted and observed values (equation (10)), the higher the efficiency (Paine 1981). Using values from the example, the efficiency is (Paine 1981):

$$\begin{aligned} E &= (c/C)/[(\{1 - r^2\}\{c/C\})^{0.5} + r]^2 \\ &= (1.50/0.01)/[(\{1 - 0.553\}\{1.50/0.01\})^{0.5} + 0.744]^2 \\ &= 1.882 \end{aligned} \quad (13)$$

where: E = efficiency of the double sample; other variables are as in (12) above.

The number of double sample field points n_f required for an estimate with a specified percent sampling error at a given confidence level can now be determined. Calculate the coefficient of variation of duff depth from the field plots ($[s_y^2]^{0.5}/y$). Choose the desired sampling error DSE (for example, 10% of the mean) and t value for the confidence level (90% confidence, $t \approx 1.67$). Applying the example and R and E values calculated above, the calculation is (Paine 1981):

$$\begin{aligned} n_f &= [CV]^2[t]^2/[DSE]^2 \times c/\{E[c + (R)(C)]\} \\ &= [47]^2[1.67]^2/[10]^2 \times 1.50/\{1.882[1.50 + (13.622)(0.01)]\} \\ &= 30.009 \approx 30 \end{aligned} \quad (14)$$

where: n_f = number of double sample field points
CV = coefficient of variation of double sample field measurements
t = confidence level t value
DSE = desired sampling error
E = efficiency of the double sample
R = optimal ratio of predicted to observed double sample points
C = cost of prediction
c = marginal cost of measurement

and the number of prediction points, n_p, is $(R)(n_f)$ = 409. Total cost for the duff depth information is (409)($0.01) + (30)($1.50) = $49.09. To achieve the same precision with field sampling alone, the number of points required is:

$$n = ([CV]^2[t]^2)/[DSE]^2 = 61.6 \approx 62$$

costing $93.00 or 89% more. The costs of prediction and observation may appear difficult to estimate prior to application of the method, but the number of field observation points is rather insensitive to a range of costs. In the example above, reducing the field measurement cost, c, to $0.50 gives $n_f = 32$, while increasing the cost to $3.00 gives $n_f = 29$. For comparison, current compensation to U.S. Forest Service contractors for stand examination inventory based on variable-radius sampling in the Southwest is approximately $8.00 to $14.00 per point (William F. Stansfield, personal communication 1993). Further analysis in a particular management situation could explore the effects of other fuel measurements, sensitivity to confidence level changes, and comparison to the cost of a dedicated fuel inventory.

Extending the analysis beyond the natural Arizona ponderosa pine fuels in this study, the double sampling approach could prove useful with other predictive equations or in other geographic areas or forest types where predictive methods are available. Predictions need not be based on equations; any method which results in correlation between predicted and observed values may be useful if the cost of obtaining the predicted (auxiliary) variable is sufficiently low compared to the cost of direct sampling. For instance, the common double sampling application of weight estimation of herbaceous production depends on ocular estimates for prediction (Francis et al. 1979). The detailed example worked out in this study is intended to clarify the method and assist managers in design and nalysis of double sampling schemes for fuel inventories.

Conclusion

Since information on forest floor characteristics can be expensive or difficult to obtain, the ability to predict these characteristics from limited data would be useful to managers. Even under the constraints of reduced disturbance and small plot size followed in this study, a great deal of variation was observed in natural ponderosa pine forest floors with no disturbance within 20 years on sedimentary and basalt soils in northern and central Arizona. However, the allometric relationships between forest stand characteristics and litter and duff depth, as well as among the different woody fuel size classes, can be applied to create predictive equations for these site. These equations are not precise due to high variability in fuels and stand characteristics, but when used with double sampling the combination gives equivalent results at reduced cost compared to field sampling alone. In regions or fuel types where other predictive relationships exist, they may be applied in analogous fashion. Investment can be further controlled by adjusting the confidence level and desired sampling error to reflect the relative values-at-risk and fire hazard in different sampled areas. The method described here is not a comprehensive plan for fuel inventory; rather it is intended to expand the alternatives available to managers who must make decisions under conditions of high variability and limited resources.

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