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Stratification of Regional Sampling by Model-Predicted Changes of Carbon Stocks in Forested Mineral Soils

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Monitoring changes in soil C has recently received interest due to reporting under the Kyoto Protocol. Model-based approaches to estimate changes in soil C stocks exist, but they cannot fully replace repeated measurements. Measuring changes in soil C is laborious due to small expected changes and large spatial variation. Stratification of soil sampling allows the reduction of sample size without reducing precision. If there are no previous measurements, the stratification can be made with model-predictions of target variable. Our aim was to present a simulation-based stratification method, and to estimate how much stratification of inventory plots could improve the efficiency of the sampling. The effect of large uncertainties related to soil C change measurements and simulated predictions was targeted since they may considerably decrease the efficiency of stratification. According to our simulations, stratification can be useful with a feasible soil sample number if other uncertainties (simulated predictions and forecasted forest management) can be controlled. For example, the optimal (Neyman) allocation of plots to 4 strata with 10 soil samples from each plot (unpaired repeated sampling) reduced the standard error (SE) of the stratified mean by 9–34% from that of simple random sampling, depending on the assumptions of uncertainties. When the uncertainties of measurements and simulations were not accounted for in the division to strata, the decreases of SEs were 2–9 units less. Stratified sampling scheme that accounts for the uncertainties in measured material and in the correlates (simulated predictions) is recommended for the sampling design of soil C stock changes.

Keywords anticipated variance, forest soil, monitoring, repeated measurement, soil carbon, soil survey, stratified sampling, uncertainty
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1 Introduction

Monitoring of carbon stocks in soil has become a topical issue due to reporting requirements set by the Climate Convention and Kyoto Protocol (UNFCCC 1992, UNFCCC 1997). Repeated measurements provide a direct way to assess possible changes in soil C stocks. The measurement-based estimates of soil C changes can be used in national inventory submissions to the UNFCCC, or they can be used for evaluation of models that provide these estimates (Peltoniemi et al. 2007).

Measuring changes in soil C is notoriously difficult and laborious. Typically, the changes are small, and their estimation by repeated measurements is impaired by large heterogeneity of soil C stocks that is already present within small distances (Palmer et al. 2002, Conen et al. 2004). Consequently, a large number of soil samples are required to detect the change in soil C significantly, or a very long period of time is needed for the change to become detectable (e.g. Hungate et al. 1996, Garten and Wullschleger 1999, Conen et al. 2003, Conen et al. 2004, Smith 2004). On regional or national scale this means that soil surveys need to measure a very large number of sample plots to provide reliable estimates of averages. There is a great need to improve the efficiency of large-scale soil C sampling, especially in forest soils where the spatial variation is generally higher than on cultivated land (Conant et al. 2003).

Stratification provides a way to improve efficiency of sampling, i.e., to reduce the number of sample plots needed without reducing precision, or to estimate the parameters of interest more precisely with the same effort (see e.g. Cochran 1977, Rao 2000). The idea of stratification is to group similar sites into the same stratum, and to conduct independent samplings within each stratum to estimate stratum means. Usually, a selected number of sampled sites (sample plots) per stratum are either equal to each others, or proportional to stratum size, or based on stratum size and variance (optimal i.e Neyman allocation). An unbiased estimate of the population mean is obtained as a weighted average of the stratum means with weights proportional to the stratum sizes. Stratification is particularly useful if it yields strata that either have a small variance or a small size.

Soil carbon is an essential ecosystem variable. When changes in soil C occur, they are most likely to occur also in other ecosystem properties, such as pH, N, K, P, Fe, Al, or S (Bormann et al. 1995, Chen and Li 2003) either because they are dynamically linked, they share the same driving agent, or they all are sensitive to disturbances such as harvests or forest fires. Therefore, stratification of sampling according to predicted change in soil C is likely to enhance the probability of detecting change also in other variables.

Before stratification takes place, one should know what features make individuals of a population similar to each other. In our case, it means similarity in terms of changes in soil C stocks. Before comprehensive measured material is available, one can estimate this similarity with models of ecosystem and soil, e.g. *Century*, *RothC* and *Motti*/*Yasso* (Parton et al. 1987, Coleman and Jenkinson 1996, Peltoniemi et al. 2004, Liski et al. 2005, Salminen et al. 2005). Models can be considered to provide a synthesis of current process understanding. We call this approach model-based stratification.

Typically, regional soil C measurements are conducted on a systematic grid or a systematic sub-sample of a grid that is established to monitor several ecosystem properties. These sampling designs may be soil surveys or forest inventories (e.g. Ståhl et al. 2004, Bellamy et al. 2005, O'Neill et al. 2005), or even grids established for monitoring the effects of atmospheric pollution in Europe (ICP Level 1, Arrouays et al. 2001). Systematic (sub-)selection of plots has merits, but it may not be optimal regarding the detection of changes in soil C. For example, stratification of plots with data on land management decreases the time for changes to become detectable (Saby and Arrouays 2004).

Stratification based on model-predicted changes in soil C is a feasible approach to decrease sampling variance, when a sub-sample of an existing grid of sample plots is selected for measuring changes in soil C stock. But how useful is this approach considering that there are large uncertainties in both measurements of soil C changes and predictions used for stratification?

The objectives of this study were i) to present a novel application of process-based stand-soil model to sampling design for soil C changes, and ii) to estimate how much model-based stratification (with different sampling schemes) can be expected to improve the sampling efficiency when both soil measurements and simulated predictions contain considerable uncertainties, and when they are accounted for in the stratification.

2 Materials and Methods

2.1 Simulations for Changes in Soil C

Simulations were made on permanent sample plots established by National Forest Inventory (NFI) (Mäkipää and Heikkinen 2003). They form nearly a uniform grid covering all land-area of Finland. Spacing of the grid is denser in Southern Finland. Altogether, there are 3009 plots on forestry land, of which 1911 are on mineral soils. Plots that missed data on tree species or age were neglected, as were the most northern plots that were outside the parameterization range of the models used for providing stratification correlates. Consequently, our target population consisted of 1719 plots.

Growth of each stand was simulated with *Motti* stand simulator (Hynynen et al. 2002, Matala et al. 2003, Hynynen et al. 2005). For each stand, *Motti* was given a location and an altitude of the stand, dominant tree species, site fertility (according to Cajander 1949), and mean annual temperature sum with 5ºC threshold at given location (estimated with a model of Ojansuu and Henttonen 1983). Initialization of trees was made with typical seedling stand (by diameter class and height) under measured conditions. Stand simulations were run assuming standard forest management regime; stands were thinned with a basal area vs. height criteria, or clear-cut when the volume weighted mean diameter of trees was achieved (Tapio 2001)

In *Motti*, biomass is estimated for each tree class separately (by diameter class and height), and for compartments of stem, branches, needles, roots (Marklund 1988). Fine-root biomass (<2 mm) is estimated with a relation $(0.1+0.0018\,t)\,b_f$, where t is age of the tree (years) and b_f is foliage biomass (Vanninen and Mäkelä 1999). These estimates were used for both standing and harvested trees.

Estimates of annual litter production were obtained by multiplying the biomasses with turnover rates (Liski et al. 2006). Estimates of harvest residues were calculated for each removed tree. For each removed tree in a stand, most of the stem wood was removed from forest (according to share of merchantable wood estimated by *Motti*); the rest of the stem and 100% of other biomass compartments were left in the forest as harvest residues.

Soil C was simulated for each stand with the soil carbon model *Yasso* (Liski et al. 2005). Yasso is a dynamic seven-pool soil carbon model that takes litter as input and simulates decomposition of litter based on litter quality, temperature sum, and summer drought (precipitation – potential evapotranspiration). In this study, soil C (litter, organic layer and mineral soil 0–100 cm) was represented with a sum of all model compartments of *Yasso* (Liski et al. 2005). Mean values of climatic variables from the period 1961–1990 were used to estimate temperature sum and summer drought (Ojansuu and Henttonen 1983)

Soil model was initialized for each stand separately, by feeding repeatedly the litter time series estimated with *Motti* for typical rotation period. Rotation started with a clear cut and ended one year before the next clear cut. Iteration was stopped when all model pools differed less than 1% between the final and the previous simulation cycle at the end of the rotation. This eliminated the potential long term trend in simulated soil C. By this we assumed that the changes during the final rotation are considerably larger than what could occur, for example, due to previous land use (which we did not know).

The result of these simulations are plot specific curves, $C_i(t)$, of C stock ($\mathrm{kg \cdot m^{-2}}$) as a function of stand age, t, for each of the 1719 permanent sample plots, i (see Fig. 1 for one example). The target variable, y, is the change in soil C stock during a hypothetical sampling period of $\Delta t=$ 10 years. In the simplest case, where all sources of uncertainty were ignored, $y_i=C_i(t_{1i})-C_i(t_{0i})$, where t_{0i} was set to $t_{i,\mathrm{obs}}$, the stand age at plot i obtained from inventory data and $t_{1i}=t_{0i}+\Delta t$.

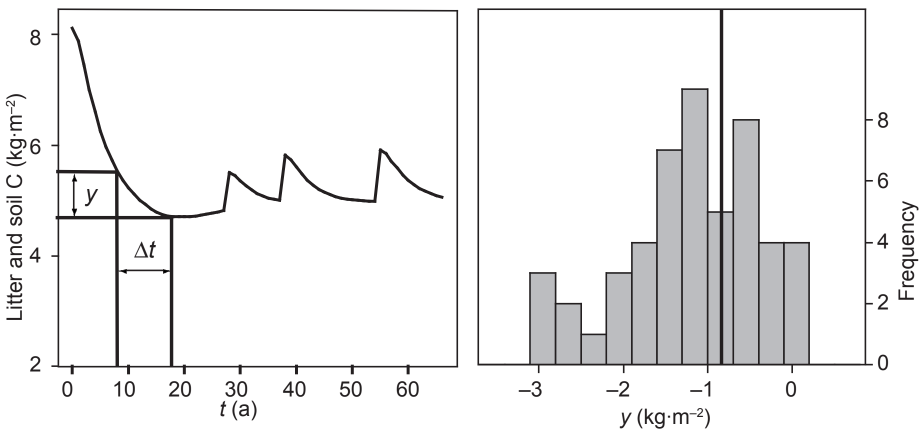

Fig 1. Example of simulated litter and soil C stock over rotation (left panel). High value of soil C at the start of the rotation is due to harvest residues, three peaks between 30 and 60 years represent thinning residues. Right panel shows the effect of scenario uncertainty, the simulated distribution of y_is when 50 random samples were drawn from age distribution, t_{0i} ~ N(8a, 5a). The vertical line shows the predicted value C_i(18a) – C_i(8a).

If the measured stand age t_{0i} was higher than the length of the simulated rotation period for the plot, the stand was considered old-growth, and y_i was determined from the last ten years of rotation. If t_{0i} was less than 10 years shorter than the rotation, then $y_i = C_i(t_{0i} + \Delta t - \text{length of rotation}) - C_i(t_{0i})$.

Sources of uncertainty were accounted for by adding random variation both to t_{0i} and to y_i as explained in the following sections.

2.2 Stratification and Sampling Variance

Suppose then that the C stock change, y, would actually be measured on a given number of sample plots, n, a subset of the total population of N = 1719 plots. The population is assumed to be divided into G strata with N_g plots in stratum g, and n_g plots are randomly selected to be measured from each stratum g with restriction

$$\sum_{g=1}^{G} n_g = n \tag{1}$$

The stratified estimator of the population mean is

$$\hat{y}_{\text{str}} = \sum_{g=1}^{G} W_g \bar{y}_g , \tag{2}$$

where $W_g = N_g / N$ and $\bar{y}_g$ is the sample mean in stratum g. Our aim was to quantify the anticipated sampling variance of $\hat{y}_{\text{str}}$ under various stratified sampling schemes, which determine the number of strata, G, the stratification of the population and the sample sizes within each stratum, n_g, (the allocation), and under various assumptions concerning the uncertainty of the predicted y_i's. The results are presented for the case n = 250.

Let us first consider the case, where the prediction and measurement errors are ignored. Approximately optimal stratum boundaries are then obtained using cumulative function, $F(y)$, calculated from the square root of probability density function, $f(y)$ (Dalenius and Hodges Jr. 1959, Cochran 1977):

$$F(y) = \int_{\min\{y_i\}}^{y} \sqrt{f(w)}\,dw \qquad y \in \left[\min\{y_i\}, \max\{y_i\}\right] \tag{3}$$

with density $f(w)$ estimated from the distribution of predicted C stock changes, y_i, over all plots. Equal sized intervals, which form the strata, are divided on F-scale. The optimal number of strata is strongly case dependent, but empirical results rarely support more than 6 strata (Cochran 1977). In this study, we varied the number of strata, G, from 1 to 7.

Equal, proportional, and Neyman allocation were considered in determining the proportions, $p_g = n_g / n$ of the samples to be allocated to each stratum, g. In equal allocation, $p_g = 1/G$ for all g, in proportional allocation, $p_g = W_g$, and in Neyman allocation,

$$p_g = \frac{W_g S_g}{\sum_{g=1}^{G} W_g S_g} \tag{4}$$

where S_g is the standard deviation of y_i's in stratum g. In each case the sampling variance of the stratified estimator $\hat{y}_{\text{str}}$ is

$$V = \sum_{g=1}^{G} W_g^2 \frac{1-f_g}{n_g} S_g^2 \tag{5}$$

where $f_g = n_g / N_g$ (Rao 2000).

2.3 Uncertainties

Ignoring uncertainty in predictions of y_i can result in unrealistically small within stratum standard deviations S_g, which has a complex effect on the comparison of variances of the mean, V, associated with different sampling schemes. The overall distribution of the measured C stock changes is also likely to be more dispersed than that of the predictions y_i, which affects the optimal stratum boundaries. We therefore suggest that the determination of stratum boundaries, the allocation of sample plots, and the computation of anticipated variance should be based on modified predictions y'_i, to which prediction and measurement errors have been added.

Simulation Uncertainty

It is fair to admit that the simulated predictions of soil C stock changes are far from precise. Therefore, we implemented simulation uncertainty into the predictions of y_i. This uncertainty represents all the error sources that are related to the simulated predictions, e.g. the limited ability of the model to represent real variation in the soil C stock changes between the plots, and the uncertainty due to choice of the model.

Simulation uncertainty was implemented by

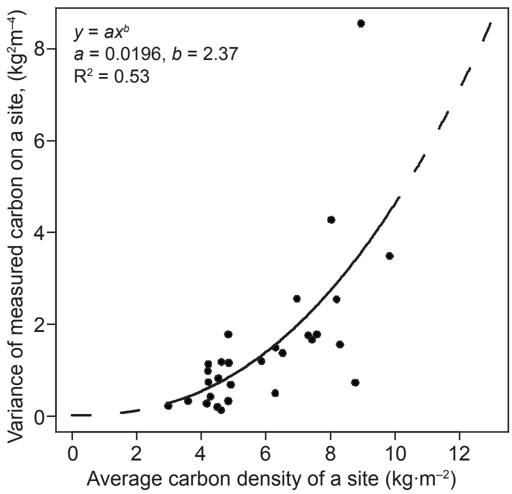

Fig 2. Within plot variance of soil C stock measurements as a function of the measured mean carbon stock on a plot. Dash line represents extrapolation towards small and large stocks of carbon. Data from Liski and Westman (1995).

adding to the predicted changes y_i random normally distributed noise with standard deviation $\sigma_{\text{sim},i} = (50 \text{ g} \cdot \text{m}^{-2} + 0.10\ y_i) \cdot A$, for $A = 1$, 5, and 10. The minimum uncertainty in the simulated material is therefore 50 g of C per 10 years, which corresponds to an average change (over rotation length) in organic layer C change measured from a chronosequence of sites in southern Finland (Peltoniemi et al. 2004). Minimum of 10% of simulated change was added to admit that simulating rapidly changing ecosystem variables may be more difficult than simulating nearly stable ecosystems.

Measurement Uncertainty

Based on empirical data on measured soil C stocks (org. layer + mineral soil 0–100 cm; 30 sites, each with 6 sample cores) (Liski and Westman 1995), we assumed that the variance in single measurements of soil C stock is multiplicative to the measured mean stock size: $\ln(\sigma^2) = a + b \ln(C)$. Parameters a and b were estimated by fitting a linear model to the log-transformed C and σ^2 values (Fig. 2) and correction residual variance/2 was added to a so that the back-transformed predictions $\sigma^2(C) = e^a C^b$ are unbiased.

To estimate the measurement error of soil C stock change due to within site variation of soil C, we assumed an unpaired repeated sampling with m soil samples taken at each plot both at the beginning and at the end of the monitoring period. Combining the two assumptions, the measurement error variance of the plot-level change in soil C stock is

$$\sigma^2_{\mathrm{meas},i} = \frac{\sigma^2(C_i(t_{0i})) + \sigma^2(C_i(t_{1i}))}{m} \qquad (6)$$

where $\sigma^2(C_i(t))$ is the stock variance calculated from predicted stock at time t with equation presented in Fig. 2.

Scenario Uncertainty

Scenario uncertainty stems from the uncertainty of projecting the future forest management of the plots, and the fact that our predictions of the current state of the stands are uncertain.

Scenario uncertainty was implemented by simulating 50 different populations of plots by simulating 50 scenarios of soil C changes for each of the 1719 plots. Scenarios were constructed by drawing the t_{0i}s as random samples from the normal distribution $N(t_{i,\mathrm{obs}}, \sigma_{\mathrm{sce}})$ instead of using the measured ages $t_{i,\mathrm{obs}}$ as such. Varying measured age instead of timing of harvests was considered as an adequate representation of scenario uncertainty. The varying assumptions of scenario uncertainty refer to the applied standard deviations of $\sigma_{\mathrm{sce}} = 2.5$, 5, or 10 a,

Combining Sources of Uncertainty

The effects of these sources of uncertainty were combined by means of simulations. We created 27 sets of 50 populations of N sample plots with simulated C stock changes y'_i each set corresponding to one combination of $\sigma_{\mathrm{sce}} = 2.5, 5, 10$ a, A = 1, 5, 10, and m = 1, 10, Inf. The y'_i were simulated independently by

1. drawing a random 'starting age' t_{0i} from $N(t_{i,\mathrm{obs}}, \sigma^2_{\mathrm{sce}})$,
2. computing the corresponding predicted change as $y_i = C_i(t_{1i}) - C_i(t_{0i})$, where $t_{1i} = t_{0i} + \Delta t$, and
3. setting $y'_i = y_i + e_{\mathrm{sim},i} + e_{\mathrm{meas},i}$, where $e_{\mathrm{sim},i}$ and $e_{\mathrm{meas},i}$ were drawn from $N(0, \sigma^2_{\mathrm{sim},i})$, and $N(0, \sigma^2_{\mathrm{meas},i})$, respectively.

One of the populations in each set (corresponding to combinations of σ_{sce}, A, m) was exceptional so that $t_{0i} = t_{i,\mathrm{obs}}$. The stratum boundaries for G = 2,…,7 and within stratum variances for Neyman allocation were computed using that specific population. For each combination of σ_{sce}, A, m, G and allocation method, 49 different values of V, the sampling variance of the stratified estimator $\hat{y}_{\mathrm{str}}$ were obtained by calculating S_gs (in Eq. 5) from the 49 simulated populations the stratum to which a plot belongs being determined by the original prediction y_i. The results are plotted as standard errors of stratified means relative to those of simple random sampling, $\mathrm{SE}/\mathrm{SE}_{\mathrm{srs}} = \sqrt{V}/\sqrt{V_{\mathrm{srs}}}$.

The results of stratification that accounted for the uncertainty assumptions of measurements and simulations were compared to a 'naive stratification' where ignoring simulation and measurement uncertainty, stratum boundaries and allocations were determined purely on the basis of the original predictions y_i.

3 Results

3.1 Strata

Very large negative or positive predictions of soil C change, y_i, were classified to outermost strata (Fig. 3). The number of plots in outermost strata was consistently and remarkably smaller than the number of plots in innermost strata. Also the variances S_g^2 of the outermost strata were consistently and remarkably larger than the variances of innermost strata. The outermost y_is were related to simulated peaks in Fig. 1 caused by harvests and thinnings.

Stratum boundaries were more evenly distributed along y-axis when the uncertainty of the measurements was high (m = 1 in Fig. 3). Without any uncertainties, the widths of thinnest strata were approximately 0.5 kg·m^{-2}(10a)$^{-1}$ when the material was divided into 7 strata.

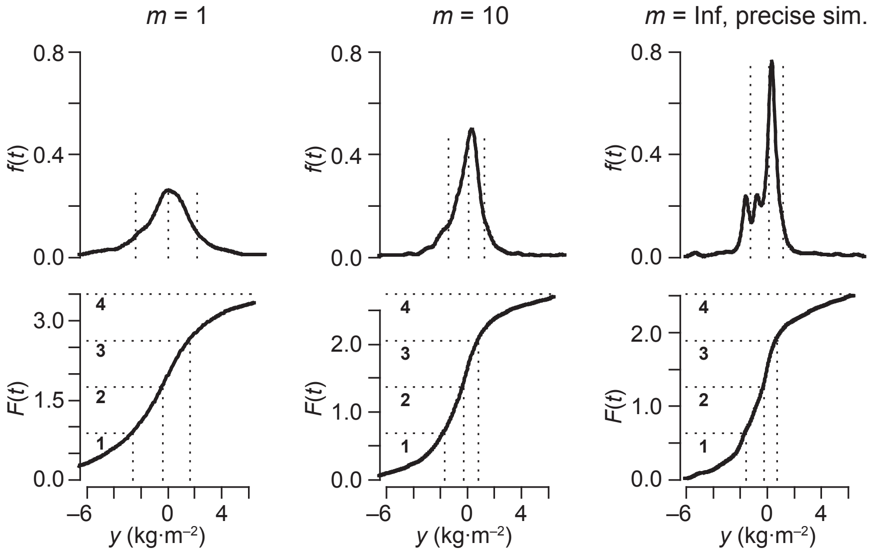

Fig 3. Stratification of sample plots is based on cumulative function (below). Corresponding probability densities are shown above. Examples are shown for stratification to 4 strata with default assumptions of simulation uncertainty (A = 1) and very uncertain soil measurements m = 1 (left), feasible soil sample number, m = 10 (middle) and with 'naive stratification' without simulation uncertainties and with m = Inf (right).

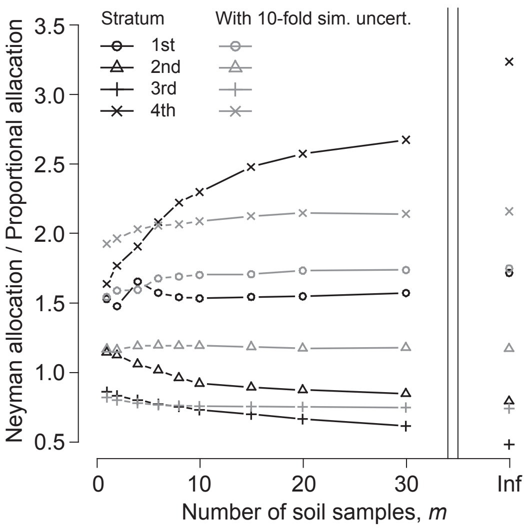

Fig 4. Optimal sample allocation (Neyman) relative to proportional allocation (i.e. to relative stratum size) as a function of the number of soil samples, m (with default simulation uncertainty A = 1, and 10-fold simulation uncertainty, A = 10).

Optimal sample allocation to strata was closer to proportional allocation with small m than with large m (Fig. 4). Increasing uncertainty of the simulated y'_i had a similar effect.

3.2 Precision and Sampling

Neyman allocation performed better than the proportional and equal allocation, especially when $G>2$, and when the uncertainties of measurements (high m) and scenarios were small (Fig. 5). Equal allocation performed poorly when the simulation, measurement and scenario uncertainties were high.

The efficiency of stratification reduced when the measurement and simulation uncertainties were not accounted for in the division of material to strata (naive stratification), especially when the uncertainties of measurements and simulations were large, and there were many strata (Fig. 5). For example, with m = 10, σ_{sce} = 5, A = 1, stratification accounting for the uncertainties led to 15, 25, and 28% reductions of the average SE of mean relative to SRS, for G = 2,4,7, respectively,

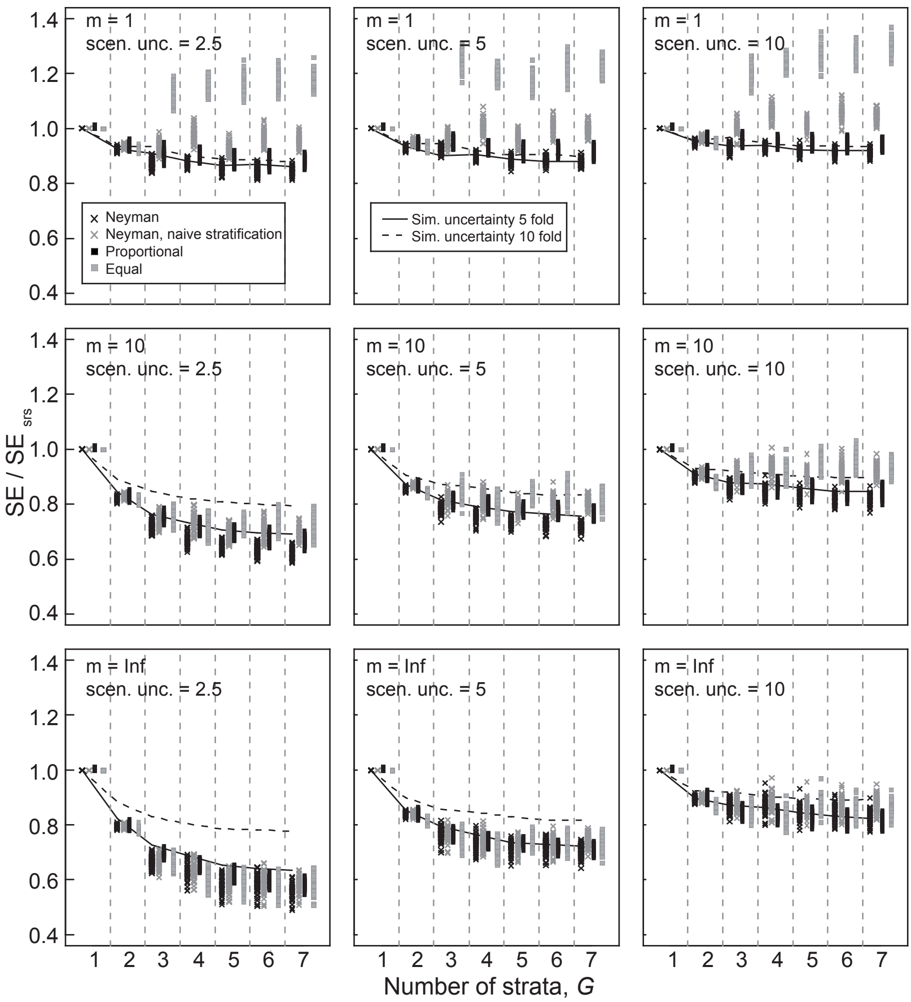

Fig 5. Efficiency of stratified sampling and three allocation methods relative to simple random sampling with different numbers of strata, G, (x-axis), based on sampling variances of the stratified estimator in sets of 50 populations simulated with different numbers of soil samples (m = 1, 10 or Inf), and different assumptions of scenario uncertainty (2.5, 5 or 10 years). Each of these variances is plotted for the case of default simulation uncertainty A = 1, while solid and dash lines represent the results of Neyman allocation (comparable to ×) when simulation uncertainties were further increased to A = 5 (solid) and A = 10 (dash).

but naive stratification only to 13, 18, and 19% reductions.

Increasing number of strata, G, generally increased the sampling efficiency (Fig. 5). The increase of sampling efficiency was less pronounced and saturated faster when the uncertainties of measurements, simulations, and scenario were high.

Increasing precision of measurements of y (i.e. increasing m) increased the efficiency of stratification (Fig. 5). With a practically feasible number of soil samples (m = 10), stratifications were clearly beneficial with all assumptions of uncertainties. For example, with $G=4$ and $m=10$ the mean stratification gains relative to SRS were 34, 25, and 15%, for scenario uncertainties of

2.5, 5, and 10 years, respectively. However, these gains were reduced to 18, 14 and 9% when the simulation uncertainties were increased to 10-fold (i.e. $A = 10$). The role of simulation uncertainties (solid and dash lines) stood out more clearly when the measurement and scenario uncertainties were low.

Distributions of expected Neyman sampling gain were wider than those of proportional allocation, especially when the m was large (Fig. 5). With large m, strata contained less plots, which lead to less reliable estimates of S_g s, and n_g s that had relatively large probability of performing very well or very poorly in independent target populations (different scenarios) that were sampled to estimate the reported SEs. Proportional allocation is not based on S_g s of strata, thus its expected sampling efficiencies are more robust.

4 Discussion

Large uncertainties of soil measurements, scenarios, and simulations affect the stratification of sampling, and decrease its efficiency. However, some improvements of sampling efficiency can be obtained if uncertainty of soil C stock estimates is controlled by taking an adequate number of soil samples per plot. For efficient soil sampling design the number of soil samples should be determined, and uncertainties of stratification correlates should be quantified before the stratification takes place.

The estimation of standard errors of stratified sampling based on simulated material includes some stochastic factors. Therefore, the stratum boundaries, allocation of plots, and estimated SEs and especially their confidence limits slightly differ each time the simulated sampling is repeated. General trends of the effects of the number of strata (G), number of soil samples (m), and the uncertainties related to possible forest management scenarios still hold.

Relatively small number of plots in outermost strata has a large effect on the mean soil C stock change, y_i, of all plots. Disproportionately intensive sampling of outermost strata that were mostly consisted of harvested or thinned plots was suggested by Neyman allocation. Since the sampling of these strata is emphasized, they have a large effect on the expected stratification efficiency. The efficiency of stratified sampling can be expected to increase if forest management is predictable and very large positive or negative changes in soil C can be predicted reliably.

In this study, we used a simple relation to estimate the measurement error of soil C change, y_i (Fig. 2). Theoretically, the most precise estimate for temporal change at the plot scale can be obtained by cokriging (Papritz and Flühler 1994). However, in practice, where m are small and there is no information on spatial autocorrelation, stratified random sampling with two samples per strata is recommended (Papritz and Webster 1995). If these sampling methods were applied on plots, they would likely improve the efficiency of model based stratification, similar to what occurred by increasing m.

Models are often highly averaging and they cannot capture all variation present in nature with just a few parameters (in our case: tree species, temperature, location, altitude, soil fertility, litter quality, harvests, and age at measurement). Therefore, we embedded a random error component to soil C change predictions, y_i, which had a low limit of 5 $g \cdot m^{-2} a^{-1}$. The low limit parallels with the long-term average C accumulation rate to organic layer measured from chronosequences in boreal forests (Wardle et al. 2003, Peltoniemi et al. 2004), and it is a magnitude smaller than the thinnest strata in this study (~50 $g \cdot m^{-2} a^{-1}$). Furthermore, we tested the effect of even more uncertain model predictions, by multiplying the previous assumption by A=5 or 10. Our study suggests that simulation estimates are useful for the purposes of stratification although they would be far from precise. Uncertainties of scenarios and measurements reduce the expected stratification gain at least as much.

Increasing number of strata lead to reduced variance of the mean (via smaller within strata variances) but this decrease saturated with larger G. If the estimates that stratification is based on (simulated y) are uncertain, the gain in precision of the mean estimate by increasing G becomes soon negligible (Cochran 1977). Based on the results of this study, we would like to add that also the uncertainties of measurements (that are notoriously high for soil sampling) affect the selection of *G*. Often 4 or 5 strata should be enough for soil sampling stratification.

Time-dependent stratification criteria, such as changes in ecosystem properties, are not usually recommended for selection of plots for permanent monitoring (Scott 1998). However, in our simulations, changes in soil C were closely related to time (mostly due to simulated effect of harvests and thinnings), and it seems important to take that into account. Further studies are needed on applicability, usefulness and cost-efficiency of a method that stratifies plots by their average susceptibility to change. Similarly, also options that plots are recycled at certain intervals or that plots have varying sampling period lengths need further studying.

Soils under different land-use can store varying amount of carbon, and a change in land-use can lead to long-term accumulation or depletion of carbon (Post and Kwon 2000). In our study this effect was not accounted for since there was no information on the history of plots, although recent land-use changes may lead to large changes in soil carbon. Similarly, some of the plots or some regions can be more vulnerable to climate change, or may face larger changes or variability in climatic conditions in future than other plots or regions. Both of these effects could promote the selection of some plots in the stratified sampling design.

There is a strong political interest towards reporting changes in all carbon pools, one of which is soil carbon (UNFCCC 1992, UNFCCC 1997). Therefore, stratification based on one target variable, soil C change, may become a reasonable option when soil inventories are developed. Furthermore, one could assume that the changes in other soil properties are correlated (negatively or positively) with changes in soil carbon, and that also their monitoring would be facilitated with this stratification. The cross-correlation may be due to dynamic coupling of parameters, or by the fact that most of the changes occur when forest ecosystem is disturbed in some manner (in this study by harvests, but also by climate change, fires, tillage, etc.). If neither of these applies, for example, if one would like to stratify sampling using two criteria, forest health, and soil C change, one has to determine importance of each target parameter. Methods for multi-criteria stratification have been presented by Yates (1960) and Cochran (1977).

Forest ecosystem models provide a synthesis of current data and knowledge on ecosystem functioning, but their application can be challenging due to large input data requirements. Empirical models are often less demanding in input data requirements, but they require measurements of target variable. Models in various forms can provide efficient tools to plan sampling optimally since strata variances that are required for Neyman allocation can be anticipated using the modelled data appended with uncertainties. In this study, we made the stratification for soil C change measurements, but this kind of approach and conclusions should apply for many other ecosystem properties that can be modelled.

Despite the large uncertainties of soil modelling, measurements, and scenarios of future harvests, the sampling efficiency of soil C changes can be improved with stratification and optimal allocation of samples to some extent. In large inventories, also small improvements in sampling efficiency of uncertain target parameters, such as soil C change, may lead to large cost reductions.

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List of symbols.

Variable	Unit	Explanation
t	a	Time, t_0 (and t_{obs}) for hypothetical 1st soil sampling, and t_1 for 2nd.
b_f	kg	Foliage biomass
C_i	kg·m^{-2}	Carbon stock of litter and soil per unit area, from litter layer down to 100 cm depth.
i		Subscript that denotes a plot
y	kg·m^{-2}	Change in litter and soil C stock during a hypothetical sampling period of Δt = 10 a
n		Number of sampled plots in a stratification scheme
n_g		Number of sampled plots allocated to a stratum g
N		Total number of plots in the population
N_g		Stratum size, i.e. total number of plots in the stratum
G		Number of strata in the stratification scheme
g		Subscript that denotes a stratum
W_g		Number of plots in the stratum relative to the total number of plots, N_g/N
$F(y)$	kg·m^{-2}	Cumulative function of $f(y)$
$f(y)$	kg·m^{-2}	Probability density function of y
p_g		Allocated plots to the stratum relative to number of plots that will be sampled, n_g/n
S_g	kg·m^{-2}	Standard deviation of y within the stratum g
f_g		Allocated plots relative to the stratum size
V	kg^{2}m^{-4}	Variance of the mean of y
$\sigma_{sim,i}$	kg·m^{-2}	Anticipated uncertainty of the simulated y_i (standard deviation, in carbon)
A		Scaling factor to increase the simulation uncertainty
a, b		Parameters for empirical equation to anticipate the measurement uncertainty of soil C stock in plots
σ^2	kg^{2}m^{-4}	Anticipated variance of the plot's soil C stock measurement
$\sigma^2_{meas,i}$	kg^{2}m^{-4}	Anticipated variance of the mean of measured y_i in the plot i (in carbon)
m		Number of soil samples collected from each plot
σ_{sce}	a	Anticipated uncertainty of timing of thinnings and harvests (scenario uncertainty)
y'_i	kg·m^{-2}	Simulated estimate for the litter and soil C stock change in a plot i
$e_{sim,i}$	kg·m^{-2}	Error term of y'_i, which represents the simulation uncertainty
$e_{meas,i}$	kg·m^{-2}	Error term of y'_i, which represents the uncertainty of empirical soil C change estimate
SE	kg·m^{-2}	Standard error of the stratified mean of y, obtained with various sampling schemes

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