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Soil Carbon Dynamics During Stand Rotation in Boreal Forests

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ABSTRACT

The utilisation of forest resources is frequently criticised for its adverse environmental impacts. In particular, the widespread use of rotation forestry practices, including clear-cutting, is viewed as a threat to ecosystems. Clear-cutting has short-term impacts that turn the forest into a net carbon (C) source, but such modifications to the ecosystem also have long-term effects. Any analyses of alternative management approaches should include at least one full rotation, which requires model extrapolations. In this study, we used data from a well-documented series of long-term forest monitoring sites in Finland (ICP Forests Level II), focusing on two recent clear-cut sites—one dominated by Scots pine and the other by Norway spruce. These data were utilised to constrain a soil C model and to extrapolate two future scenarios: rotation forestry and set-aside (unmanaged). We simulated these scenarios over a period exceeding one full rotation and compared the outcomes. Although the stand thinning events did not heavily affect the C balance of the studied sites, clear-cutting did. Each clear-cut event caused a negative soil organic carbon (SOC) balance for many decades. It took between 37 and 69 years (for Norway spruce and Scots pine, respectively) to reach a break-even point in which soil C losses compensated for C uptake. Emissions from coarse harvest residuals represented the greatest C source after clear-cutting, followed by fine roots and then foliage. When comparing such a scenario with a set-aside scenario, the soil C budget of the managed stand after clear-cut was negative until the first thinning or even until the following clear-cut, while the set-aside was always a C sink in soil. Thus, scenario analyses of forest C sequestration that disregard long-term soil C dynamics following management interventions may lead to biased conclusions. As a management regime, rotation forestry was relatively ineffective when evaluated considering C sequestration as an important ecosystem service.

1 | Introduction

1.1 | Should We Manage Forests as a Tool for Climate Change Mitigation?

The idea that managed forests can serve as a significant tool in the fight against climate change was put forward decades ago (Canadell and Raupach 2008). More recently, the idea of climate-smart forestry (CSF) consolidated the concept, aiming to enhance the resilience of forests to global changes, contribute to climate change mitigation and adaptation, and maintain the productive role of forest ecosystems (Hetemäki and Verkerk 2022; Verkerk et al. 2022). However, considering public perception, forestry is still often seen as negative even when considering approaches alternative to clear-cutting (St-Laurent et al. 2018). Regarding the climate change mitigation potential, Rametsteiner et al. (2008) found that people in the European Union preferred forest conservation over

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Summary

- Stand regeneration impact on ecosystems' C balance is debated.
- Assessing such impact requires a long-term perspective.
- SOC stocks after clear-cutting took several decades to recover.

active management. In contrast, some active forest management regimes increase carbon (C) sequestration more than no management or even protection when product extraction is managed responsibly (Pukkala 2017). The controversy becomes even more heated when it comes to conventional rotation forestry with clear-cuttings.

1.2 | Clear-Cutting Impacts on Soil C Stocks and Emissions

In Fennoscandia, rotation forestry is applied in 90% of forests (Heinonen et al. 2020; Kronberg et al. 2016). Such a prevalent management regime implies resistance towards change, although it has been shown to have adverse effects on aquatic ecosystems of the catchment (Palviainen et al. 2014), biodiversity, and visual appearance of forests (Chaudhary et al. 2016), and their soil organic carbon (SOC) balance (Mäkipää et al. 2023). Although some previous studies have shown minimal differences in the C balance between rotation forestry and alternative methods, such as continuous cover forestry (Lundmark et al. 2016), the literature generally tends to agree that rotation forestry is reducing the overall C stocks of forest ecosystems (Ola et al. 2024), but this may vary depending on the economic objectives considered.

Some authors have claimed that it is possible to manage a stand conventionally while increasing C stocks compared to current management (Parkatti et al. 2024). This claim is controversial, as several studies have shown that clear-cutting causes an immediate increase in greenhouse gas (GHG) emissions from forest SOC stocks (Kolari et al. 2004; Korkiakoski et al. 2019; Vestin et al. 2020), turning a potential GHG-neutral ecosystem or sink into a source. However, such an effect may be limited in time since forest and understorey vegetation recover. How long such emissions would be sustained determines the total GHG balance of forest rotation and management, such as thinning (Aslan et al. 2024), which depends on the amount of C released during the source phase and how fast forest regeneration turns the forest into a sink. Even if the forest achieves neutrality by balancing emission and uptake, the emissions of the initial phase can be significant and have a relevant weight on the total C budget of the forest after a few years (Rebane et al. 2020). Measurements by both Peichl et al. (2022) and Grelle et al. (2023) found that the time required for a forest to offset the emissions of the immediate phase after clear-cut would be approximately 18 years, while Lindroth (2023) was more pessimistic and suggested 39 years.

A regenerating forest stand is a dynamic system in rapid change. The rate of net primary production in both managed and unmanaged old-growth forests decreases with stand age, while the stand continues to sequester C (Gundersen et al. 2021). Therefore, a comparison between this management approach and a more conservation-oriented approach requires a perspective able to capture this variation over time. To understand the impact of clear-cutting on the global C cycle, we should consider the C balance of rotation forestry in comparison with a reference scenario over a full rotation period.

1.3 | Modelling Soil C Stocks for Long-Term Storage

The C balance of a stand is heavily dependent on the C balance of its soil. Living trees are an important component of forest C stock. However, they are less than half of the total C stock of the forest ecosystem in boreal forests, and their management is determined by production needs in commercial forestry. The C stock in tree stems and mineral soil is estimated to be the largest (30% and 28%, respectively), while the organic layer is the third largest (13%) component (Merilä et al. 2024). Together, the C in mineral soil and litter layers represent soil organic C (SOC) stocks, which is the largest C pool in boreal forests and can be managed relatively independently from production. As such, managing the dynamics of the SOC pool is a central tool for minimising the climate impacts of forestry. Although long-term data to produce reliable statistical models and even direct observations are available for estimating the aboveground C component, the SOC component is more difficult to determine. The SOC observations are more difficult and, consequently, this pool has not been the object of the same number of measurements despite its importance. Determining the long-term impact of forest management on SOC stocks is therefore a crucial step towards assessing the total GHG impact of forest management.

The long rotation time of forests (decades or centuries) makes it particularly difficult to measure the SOC balance of a forest ecosystem on a relevant time scale (Yamulki et al. 2021), which would require extensive long-term campaigns that are quite expensive. Techniques to directly measure the GHG fluxes from a whole stand have been performed over two decades, which makes it possible to constrain the SOC fluxes and, therefore, their dynamics (Pastorello et al. 2020). However, there is no available time series lasting as long as one full rotation period, and this knowledge gap prevents the use of such measurements directly to assess the C balance consequences of forest management. SOC is dynamic and varies following extensive changes, such as clear-cutting. Due to the ecological changes caused by management, the SOC balance across 1, 10 or 100 years from a clear-cut event would differ, and to obtain a robust picture, we need to integrate our estimates across at least 1 full rotation period. Models can be used to fill this gap. By coupling a simulation of aboveground management and above- and belowground litter production with a C decomposition model, we can estimate the impact of different management practices on the SOC balance of the stand over the time scale of a forest rotation. However, the main variables driving the model are C inputs, and they are rather uncertain, in particular fine roots (Lehtonen and Heikkinen 2016). Therefore, it is necessary to also account for this uncertainty to draw any conclusion from the model.

1.4 | Possible Solutions

To produce robust estimates of the impact of clear-cutting on the C balance of a stand, we can combine a process-based SOC decomposition model with detailed data sources and drive it with growth predictions for extrapolating future scenarios that can span over at least one rotation period. The Level II sites of the UNECE ICP Forests network provide a good source of data for this purpose, with numerous measurements of aboveground biomass. In Finland, some ICP II sites also provide repeated SOC measurements over almost three decades (Lindroos et al. 2022). These can be an important source of information as additional constraints for a model, reducing prediction uncertainty. Two of these sites in particular, Scots pine (*Pinus sylvestris* L.) and Norway spruce (*Picea abies* L. Karst) dominated stands, have recently been regenerated (with natural regeneration) after clear-cutting. We coupled aboveground measurements and biomass estimates derived from the forest simulator Motti (Salminen et al. 2005; Siipilehto et al. 2014) with the Yasso07 (Tuomi et al. 2011) organic matter decomposition model, a widely used model for boreal forests, which has a long utilisation history and continuous development and validation (Hernández et al. 2017; Karhu et al. 2011; Yousefpour et al. 2019). We then assimilated all the information in the available data within a Bayesian framework designed to assess the uncertainty of the assumptions in the input estimation and model initialisation. Relying on a Bayesian approach also allowed us to consider uncertainty in the input estimates and to propagate such uncertainty in the prediction. We could then extrapolate future predictions comparing clear-cutting against a set-aside forest conservation scenario, which was used as a relative baseline.

1.5 | Objectives of the Study

The overall objective was to quantify the responses of forest soil C stock to clear-cutting and regeneration over a timeframe of at least one rotation cycle to answer the question "what are the consequences of rotation forestry for soil C stocks when compared with a reference of non-managed forest?" As a secondary aim, by reconstructing the C balance of a clear-cut area over its whole rotation period after regeneration, we aimed to determine when (and if) the soil C losses caused by clear-cutting are balanced by increased C uptake from recovering forest growth.

2 | Material and Methods

2.1 | Sites and Measurements

We calibrated and tested our model at 2 forest sites (*Pinus sylvestris* and *Picea abies* dominated), managed as monocultures, which were regenerated after clear-cutting in 2017. Logging residuals were left on site in both sites. The sites are in Juupajoki, Finland, and they belong to the European intensive forest monitoring network (Level II), established under the UNECE ICP Forests monitoring programme (Lorenz and Fischer 2013; Merilä et al. 2014). The forest site type based on the ground vegetation composition of the dominant species (Cajander 1949; Pohjanmies et al. 2020) was *Vaccinium vitis-idaea* type (VT) (pine site) and *Oxalis acetocella–Vaccinium myrtillus* type (OMT) (spruce site). The soil type for the pine site was poorly developed Arenosol (IUSS Working Group 2006), and the soil texture was sorted sand. The soil type for the spruce site was Arenosol (IUSS Working Group 2006), and the soil texture was unsorted till with a dominant fraction of sand. Both soils showed some podzolic features. The ICP Level II sites include many measurements of aboveground vegetation, which were used to drive our model. Recently, Lindroos et al. (2022) published a study on the same sites where they measured the trends in SOC stocks over the last 20 years. We used their data as the target variable of our model.

2.2 | Estimating C Inputs Into the Soil

The input of C to the soil was estimated with a collection of functions from the above- and belowground biomass. These functions come from different sources and were mostly based on an implementation by Ťupek et al. (2023). We partially recoded and reorganised both the main model functions and the input estimation functions into an experimental R package (accessible at https://github.com/ilmenichetti/YaYasso), whose documentation also contains a detailed description of each function, including references. When measurements were available (until the last sampled point, right after the clear-cut event), we relied on them to drive the biomass functions, while from that point on, we relied on the aboveground biomass simulations described in the next paragraph.

When functions were species-specific and applied at the plot level (e.g., fine roots), we considered the dominant species as monoculture, given that these stands were managed as such, and therefore, eventual errors due to unwanted species growing in between thinnings would be small. The workflow of the simulation of C inputs to the soil began with simulating the biomass components, distinguishing fine roots, woody roots, stumps, stems, stem bark, branches, foliage and ground vegetation. For most components, we relied on the functions described by Repola (2009), which were developed in Finland and are therefore likely to represent local conditions. Ground vegetation was simulated based on coverage data, with functions developed by Lehtonen using data from Salemaa et al. (2013). Litter inputs were estimated from the aboveground biomass and then partitioned into the AWEN pools (see Decomposition Model section), with the functions reported in Liski et al. (2009). Logging residuals were assumed to be left on site. We assumed that the commercial part of the stems was always removed, but that all other components (including stem residuals) returned to the soil as litter. Tree mortality was recorded for each site by tree, and we used these data to estimate the amount of deadwood and the amount of C returned to the soil (minus the stem and bark). The time series characterising the aboveground biomass were neither complete nor regular due to sampling at irregular intervals; therefore, we interpolated to estimate a continuous time series. This was achieved with linear interpolation, which was chosen over more refined methods (e.g., spline) to make any bias due to interpolation more controllable and regular over time. We interpolated linearly between the available values and then extrapolated outside these values by repeating the closest value.

2.3 | Simulation of Future Management Scenarios

For the two clear-cut sites, we simulated future stand management for both clear-cut and set-aside scenarios (under current climate) with the Motti stand simulator software, developed at the Natural Resources Institute Finland (Luke). Motti is a forest management and decision support tool that consists of stand-level models and distance-independent individual-tree models for predicting stand dynamics structures (Hynynen et al. 2014; Salminen et al. 2005; Siipilehto et al. 2014). The growth and yield models of the Motti stand simulator are based on extensive empirical data covering all commercial tree species (Hynynen et al. 2002). The predicted responses to different forest management practices are based on empirical data that cover all common forest management practices applied in practical forestry in Finland over recent decades (Hynynen et al. 2002). We extended our simulations to cover at least one forest rotation, as this is the time period over which the variance in fluxes (and, therefore, SOC) manifests. Consequently, a representative timescale was considered for integration. The choice to include the set-aside scenario was motivated by the need to offer some baseline to compare the clear-cut with.

2.4 | Decomposition Model

The soil model we relied upon was Yasso07, and we based our work on the implementation by Ťupek et al. (2023) for the input functions recoded and reorganised in the same experimental R package. Yasso is a first-order compartmental decomposition model. First order means that the decomposition rate is proportional to the amount of C in the pool, so no microbial feedback is considered in the model. The model is based on a set of differential equations, which were written in matrix form in this implementation. This enabled the main model structure to be implemented within the framework offered by the package *SoilR* (Sierra et al. 2014). This implementation makes it relatively easy to derive an analytical steady-state solution (determined by assuming constant inputs and climate).

The model included five pools (C_A, C_W, C_E, C_N, C_H), whose definitions are grounded in chemical fractionation principles. The first three were relatively fast decaying: A was the acidic pool, W was the water-soluble pool; and E was the ethanol-soluble pool. The last two were relatively slow decaying: N was the non-hydrolysable pool and H was the "humus" pool. Each of the pools decomposes with a certain kinetic term, while only the first 4 pools receive input from the litter based on its chemical composition. The latter was peculiar in Yasso compared to other similarly structured compartmental models, making it relatively easy to distribute the inputs based on chemical analyses of the litter.

The model could be written in matrix form, as follows:

$$\frac{d\mathbf{C}}{dt} = \mathbf{I} + \xi(t) \cdot \mathbf{A} \cdot \mathbf{C} \tag{1}$$

where $\mathbf{C}$ is the vector of the pools, $\mathbf{I}$ is the vector of the inputs, $\mathbf{A}$ is the transfer matrix, and $\xi(t)$ is a scalar representing the climate modifier (which, in this case, is calculated from the mean annual temperature and the annual mean of the monthly accumulated precipitation).

Writing the matrices in extended form, the model becomes:

$$\frac{d\mathbf{C}}{dt} = \frac{d}{dt}\begin{pmatrix} C_A \\ C_W \\ C_E \\ C_N \\ C_H \end{pmatrix} = \begin{pmatrix} I_A \\ I_W \\ I_E \\ I_N \\ 0 \end{pmatrix} + \xi(t)\begin{pmatrix} -k_A & a_{W,A}k_W & a_{E,A}k_E & a_{N,A}k_N & 0 \\ a_{A,W}k_A & -k_W & a_{E,W}k_E & a_{N,W}k_N & 0 \\ a_{A,E}k_A & a_{W,E}k_W & -k_E & a_{N,E}k_N & 0 \\ a_{A,N}k_A & a_{W,N}k_W & a_{E,N}k_E & -k_N & 0 \\ a_H k_A & a_H k_W & a_H k_E & a_H k_N & -k_H \end{pmatrix}\begin{pmatrix} C_A \\ C_W \\ C_E \\ C_N \\ C_H \end{pmatrix} \tag{2}$$

More than other models of the same class (compartmental, first-order decomposition kinetics), this model is expected to present high equifinality because of the many feedback fluxes. In this context, equifinality means that different sets of model parameters, even substantially different ones, produce the same outcome for the predicted variable. This makes it challenging to distinguish between these parameter sets during calibration. When models have interacting parameters, such as various input fractions that interact with each other and the decomposition kinetics to produce a certain SOC stock, it becomes difficult to discriminate an optimal parameter solution based on a single observed variable (two points in time of SOC stocks in this case). We therefore limited the scope of our uncertainty analysis to the input components.

The model was run, in annual steps, for 3 separate components: foliage, fine roots component and coarse woody component (anything that is not foliage or fine roots). The 3 components were run in parallel, and their contribution to SOC was assessed individually and then summed to obtain the total SOC, which was then compared with the measurements.

Model initialisation was solved analytically with the steady-state solution, assuming the average of the estimated inputs and climate of the whole simulation period as constants. The steady-state solution was determined by inverting matrix $\mathbf{A}$ and multiplying it by input vector $\mathbf{I}$ after assuming $\xi(t) = \overline{\xi}$ as a constant and incorporating it into $\mathbf{A}$ as scalar. The steady-state solution is then $\mathbf{C_{ss}} = -\frac{1}{\overline{\xi}} \cdot \mathbf{A}^{-1} \cdot \mathbf{I}$ and was solved numerically in this form for each of the 3 components in order to determine the initial proportion between the model pools.

Yasso kinetics are influenced by the diameter of the litter and the chemical composition of the litter. Although the latter is already considered by function partitioning the litter input into the first 4 Yasso pools (A, W, E and N), the first needs to be specified as a model parameter. We therefore divided the litter into 3 components, each represented by a separate instance from the model and receiving different inputs, foliage, fine roots and coarse component, assigning a separate average diameter to each of them. Stumps and stems are usually also considered separately. However, in our case, tree mortality was very low (and absent in most plots), while stems were harvested. Thus, we incorporated them into the coarse component. Foliage and fine roots conventionally have a diameter of 0, but for our purposes, we kept them separated to assign them different priors (described in the following paragraphs). The coarse component was considered to have an average diameter of 2 cm.

2.4.1 | Model Initialisation

Initial conditions are one of the biggest drivers of the variance of SOC simulations (Menichetti et al. 2019; Peltoniemi et al. 2006) and are at the same time the most uncertain since they are a consequence of decades of previous inputs before the start of any experiment, and we usually lack information about such history. Therefore, we included model initialisation uncertainty in the calibration by representing the uncertainty with a linear multiplier of the initial biomass pools. This linear multiplier was considered uncertain and variable at each site.

Initially, the proportions between the pools (which relate to initial SOC *quality* or *recalcitrance*) were determined by the analytical steady-state solution of the SOC decay model. The initial SOC content was then rescaled so that the sum of all pools could match the measured initial value, and the uncertainty term was then applied as a linear multiplier (centred at 1). This choice, particularly the rescaling, was motivated by the main aim of the study, which was to compare the differences between the two management approaches. Thus, it focused more on their relative differences than absolute amounts. By doing so, we minimised the impact of eventual regular biases on the measurements of SOC, such as an underestimation that might be caused by stoniness (Merilä et al. 2014). In the case of a regular underestimation of measured SOC, initialising the model based on the estimated inputs at an assumed equilibrium might impact the initial trends (since the predicted initial SOC would then be much higher than that of the measurements, leading unavoidably to simulated losses and biased posterior distributions for the model to match such trend). For the steady-state solutions, we assumed the average inputs from the last five years before the cut as constants.

The equilibrium assumption, of course, has its drawbacks since the ecosystems at the start of the simulation could indeed depart from it; since the considered stands were close to maturity, this error should be relatively small. However, this assumption was needed to allow the model to utilise some of the information available in the recorded time series to constrain initialisation, which would otherwise have been completely unconstrained.

2.5 | Implementation of the Bayesian Framework

The decomposition model was calibrated using a Bayesian approach by adding error terms to the input estimation and model initialisation. We assumed the standard Yasso07 kinetics (Tuomi et al. 2011), including the climate reduction functions, outside the Bayesian framework, since a full uncertainty analysis of the model was outside the scope of the present study, and model kinetics were therefore considered deterministic values (according to the original Yasso parameterisation, Liski et al. 2009). Instead, we focused on all other uncertainty sources, namely the input fractions and model initialisation. We defined priors expressing our uncertainty for each of these sources, which we then updated with the data. The error terms were linear multipliers of the estimates and, therefore, all centred on a mean of 1, equivalent to no error in the estimate, which was the null hypothesis in this case. The aim was to test how much the posteriors would deviate from the null hypothesis within the assumptions. All uncertainty terms were applied to both the steady-state solution and the transient solution of the model.

Bayesian calibration was built around the *BayesianTools* package (Hartig et al. 2023). The package offers a variety of samplers, and we relied on the differential evolution Markov chain Monte Carlo (DE-MCMC) sampler (Storn and Price 1997). We ran 4 chains of 5000 samples each. We assessed model convergence with the conventional Gelman–Rubin test (Gelman and Rubin 1992) and considered the maximum $\hat{R}$ across all considered parameters as the diagnostic criterion. We considered the model to be converged when $\hat{R} < 1.1$ for all parameters.

After sampling, the resulting population of chains was assembled into a single series of parameter sets and thinned by randomly resampling 1 of every 10 values. After that, we utilised the resulting matrix of parameter sets to run simulations for each parameter set, and we assessed the uncertainty bounds of the posterior simulation by considering the maximum and minimum of these simulations. The choice of minimum and maximum over-confidence intervals for the uncertainty bounds is for more cautiously privileging robustness over statistical resolution. The posterior probability distributions converge to accurately represent the real underlying probability distribution due to the properties of the sampler, and the minima and maxima should not be affected by outlier parameter sets.

We considered all input terms uncertain, as well as the model initialisation parameters.

$$\frac{d\mathbf{C}_{\boldsymbol{j},\boldsymbol{k}}}{dt} = \mathbf{I}_{\boldsymbol{j},\boldsymbol{k}} \cdot \varepsilon_{j,k} + \xi(t) \cdot \mathbf{A} \cdot \mathbf{C}_{\boldsymbol{j},\boldsymbol{k}} \tag{3}$$

where j corresponds to the site index (spruce or pine) and k to each of the three components. Each error term ε is associated with a specific component (so foliage, coarse and fine roots) and site.

Uncertainty of model initialisation was considered as a separate error term, also by site:

$$\mathbf{C}_{\mathbf{t0,j}} = \mathrm{SOC}_{t0,j} \cdot \varepsilon_{\mathrm{SOC},j} \tag{4}$$

Initialisation uncertainty was considered only concerning the total C mass, but the proportion between the pools was determined with the analytical solution as described above.

All error terms were defined with a truncated normal distribution centred at 1 and with a coefficient of variation of 25% for the input uncertainty and 100% for the initialisation uncertainty terms. The lower limits of the truncated normal were set to 0.25 (so 25% of the initial estimated value) for the input uncertainty terms and 0 (so 0% of the initial estimated value) for the initialisation uncertainty terms, while the upper limits were set to 2 (so 200% of the initial estimated value) in all cases. The choice of truncated normal was a compromise between the need to retain information from previous modelling studies (which are point estimates), which would suggest using narrow normal distributions, and the need to provide more conservative estimates of the ranges of values for output variables. We assigned a set of uncertainty terms for pine and another independent set for spruce, so each term was species-specific. All choices for the prior parameterisation of the error functions were aimed at exploring what was identified as a reasonable cautious coefficient of variation, mediating the need to maintain the information in the original functions to deal with the lack of data with the need to consider the uncertainty of the input estimation. Our results are therefore all conditional on this assumption.

2.5.1 | Likelihood Function

We calculated the log-likelihood values as follows:

$$ll_j = \sum \log\left[\mathcal{N}\left(\text{obs} = \text{SOC}_{\text{obs}_{j,i}}, \mu = \text{SOC}_{\text{sim}_{j,i}}, \sigma\right)\right] \qquad (5)$$

where $\mathcal{N}(\text{obs}, \mu, \sigma)$ represents the normal distribution with mean μ and standard deviation σ, and obs are all the observations (so three sampling occasions for each statistical unit), while SOC_{sim} are the simulated SOC stocks at the time of each observation. The term j denotes the site (pine or spruce), and the term i denotes the observation index for each site. The parameter σ, representing the uncertainty of the SOC estimates, was also a parameter of the Bayesian model (also defined by a truncated normal centred on 0.5, but closer to a uniform because of the deviation set to 5, and limits 0 and 1) and assumed to be constant across sites (so not stratified by site). We calibrated against each measurement point in Lindroos et al. (2022), so that all the information on the variance between each replicate was already considered into the calibration directly; the term σ represents therefore unknown uncertainties (e.g., sampling biases).

2.6 | Model Analysis

To analyse the information gain from the calibration for the different parameters, we calculated the Kullbach–Leibler (KL) divergence between the prior and posterior for each parameter. This measure enabled the evaluation of the difference between two probability distributions and was particularly useful in the context of Bayesian analysis to assess how much information is gained when updating from a prior distribution to a posterior distribution.

The KL divergence between the prior and posterior distributions was calculated using the following formula:

$$D_{\text{KL}}(P \parallel Q) = \sum_{i=1}^{N} p(x_i) \log\left(\frac{p(x_i)}{q(x_i)}\right) \qquad (6)$$

where $p(x_i)$ and $q(x_i)$ are the probability densities of the prior and posterior distributions, respectively, evaluated at the common points x_i. The sum is taken over all N points in the grid. The KL divergence $D_{\text{KL}}(P \parallel Q)$ quantifies the expected number of additional bits required to encode samples from P using the code optimised for Q. In this context, it represents the information gain achieved by updating the prior distribution to the posterior distribution after observing the data.

By considering the information gain of different parameters, we also assessed their relative importance in explaining the observed variance, which we assumed to be proportional to the information gain.

3 | Results

3.1 | Clear-Cut Impact on Soil C Stock and Recovery Time

The model was able to describe the SOC changes at each site relatively well (Figure 1). It also predicted a slight increase in SOC over a full rotation in all cases, particularly for the spruce forest ecosystem.

Clear-cutting resulted in a very quick release of organic matter from the harvest residuals left on a site. Clear-cutting had a strong impact on the soil C stock of the sites, with a strong increase in the C stock in the first year (peaking at 106.1 Mg C ha^{-1} for pine and 82.4 Mg C ha^{-1} for spruce, with an increase at clear-cuts of 33.5% and 31.8% from the previous year for pine and spruce, respectively), followed by a fast decrease in the immediate years after clear-cutting (Figure 1). Such a decrease reached

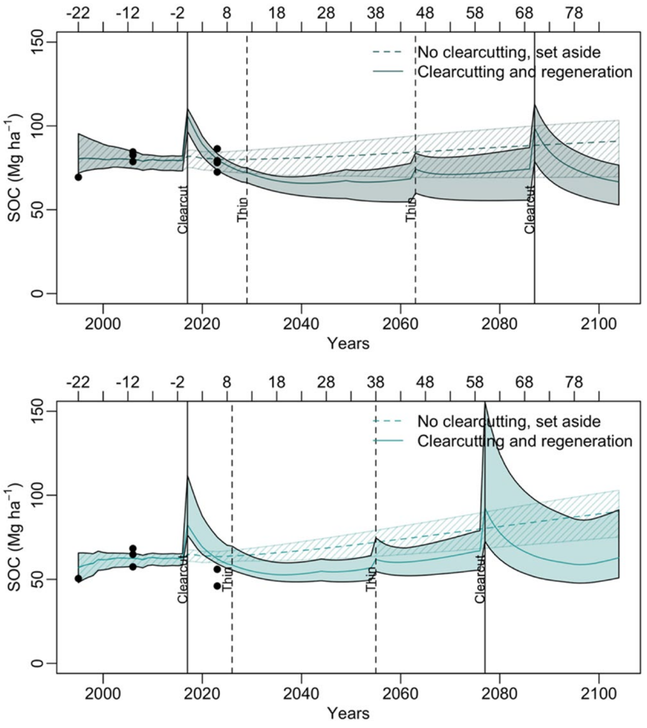

FIGURE 1 | Simulation of SOC in Scots pine (above) and Norway spruce (below) forest ecosystems. Bands represent the 95% confidence interval of predictions calculated based on the 95th percentile of the MCMC runs. Dots represent measured SOC stocks.

the same level as the year before the clear-cut (considering the mean over the MCMCs of the simulation) after 8 and 7 years for pine and spruce, respectively, after which it still decreased and did not recover until the next thinning. In the reference set-aside scenario, the SOC stock of the soil kept increasing and was always higher than the clear-cut scenario until the following clear-cut, considering the mean of predictions.

The harvest residues generated an initial increase in SOC compared to the set-aside scenario due to a sudden influx of litter (Figure 1). Although the average litter input in the 23 years before the clear-cut was 0.53 and 0.64 Mg ha^{-1} year^{-1} for Scots pine and Norway spruce stands, respectively, the clear-cut produced a sudden pulse of organic matter of 25.8 and 35.8 Mg ha^{-1} year^{-1} for pine and spruce, respectively. This means that during the clear-cut, the pine stand generated a litter pulse 49 times bigger than usual, while the spruce stand was 56 times bigger than usual. In the Scots pine stand, the average C stocks over the whole rotation period (60 years for pine and 70 years for spruce) of the managed stand were 74.2 Mg ha^{-1} SOC and 33.2 Mg ha^{-1} aboveground biomass, while in the set-aside stand, the average C stock was 83.6 Mg ha^{-1} SOC and 107.9 Mg ha^{-1} aboveground biomass. In the managed Norway spruce stand, the average C stock over the whole simulated period was 61.5 Mg ha^{-1} SOC and 52.9 Mg ha^{-1} aboveground biomass, while in the set-aside ecosystem, the average C stock was 72.2 Mg ha^{-1} SOC and 169.9 Mg ha^{-1} aboveground biomass.

The time needed for the site C sequestration to completely offset the soil C lost due to the clear-cut event was several decades (Figure 1). The model estimated that at the Scots pine site, the soil C stock would not recover before the subsequent clear-cut, so this neutrality point would be reached after 69 years during the following clear-cut, while the Norway spruce site would reach it after 37 years during a thinning, resulting in major C input from harvest residues (Figure 2).

The clear-cut site always accumulated less C in the soil than the set-aside site, except for a short burst of a few years in correspondence with each clear-cut event and, to a much lesser extent, thinning (Figure 3). The average C sequestration over the whole simulation was 3.21 Mg ha^{-1} year^{-1} (set-aside) and −6.15 Mg ha^{-1} year^{-1} (clear-cut) for pine and 15.41 Mg ha^{-1} year^{-1} (set-aside) and 4.69 Mg ha^{-1} year^{-1} (clear-cut) for spruce (Figure 2).

3.2 | Clear-Cut Impact on GHG Exchanges From Each Forest Ecosystem

Emissions oscillated over time, clearly following management events, and were generally dominated by the coarse woody component (Figure 4). In agreement with the clear-cut events, the model simulated a very high peak in all fluxes from the three components but a much bigger increase in the flux from the coarse component than the others due to the harvesting

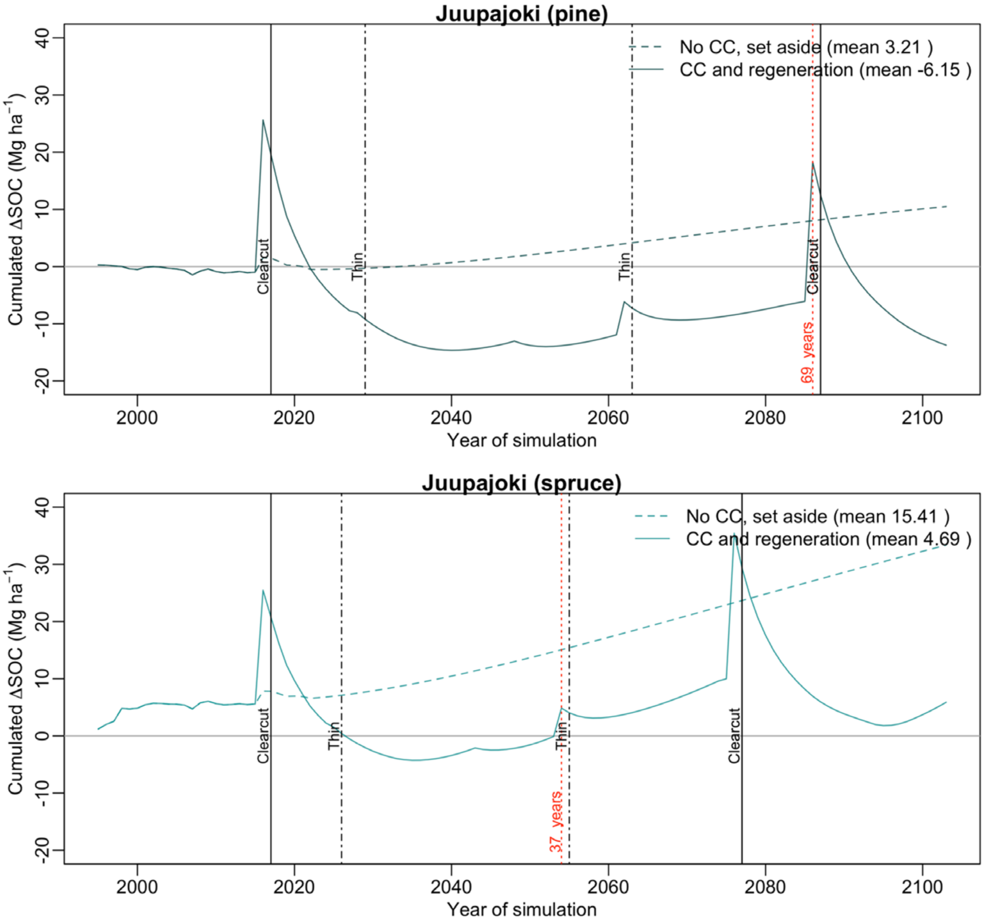

FIGURE 2 | SOC balance (mean over each MCMC) of the Scots pine and Norway spruce sites, calculated as the cumulative sum of the differences in SOC between each year (ΔSOC). The red thin, dashed line represents the time needed for each site to recover to pre-clear-cut levels of C.

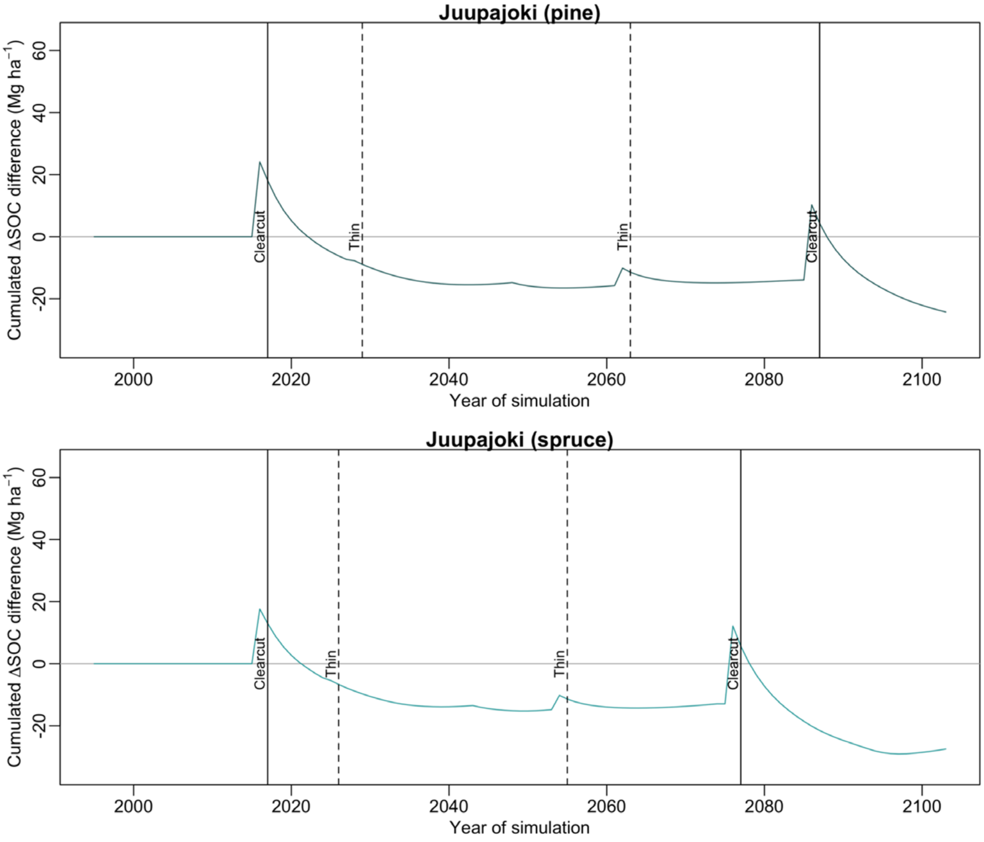

FIGURE 3 | Comparison of the SOC differences (mean over each MCMC) over time between the two alternative scenarios (cumulated ΔSOC of the clear-cut minus cumulated ΔSOC of the set-aside scenario). Positive values mean that the clear-cut sequesters more C than the set-aside scenario.

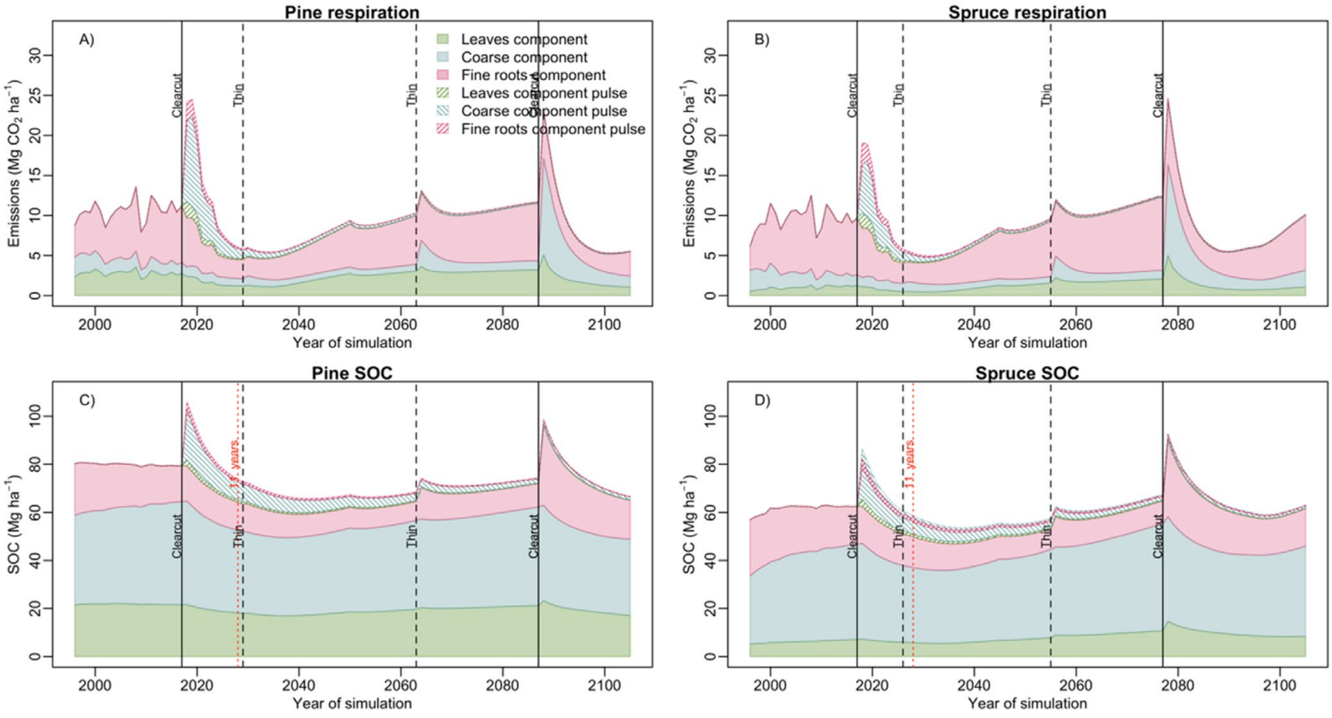

FIGURE 4 | Average decomposition emissions from soils for each component (A and B), and variation of the soil organic carbon stock (SOC) (C and D) in Scots pine and Norway spruce stands managed according to practices applied in conventional rotation forestry (clear-cutting and 2 stand thinnings). Vertical black lines denote the time of the clear-cut (continuous) and thinnings (dashed). The vertical red, fine dashed line indicates the time when 90% of the clear-cut pulse has been decomposed.

residuals. Emissions from the foliage component peaked for both sites in the year of the clear-cut, while from fine roots and coarse components, the peak was one year after clear-cut.

Of the decomposing pulse of organic material coming from the harvest residues on the clear-cut of the Scots pine system, based on results shown in Figure 4 foliage accounted for 2.8 Mg ha^{-1} of C (10.3% of the total), fine roots for 3.5 Mg ha^{-1} of C (12.8% of the total) and the coarse component for 21.1 Mg ha^{-1} of C (76.9% of the total). In the Norway spruce system, foliage accounted for 3.1 Mg ha^{-1} of C (15.0% of the total), fine roots for 4 Mg ha^{-1} of C (19.5% of the total) and the coarse component for 13.3 Mg ha^{-1} of C (65.5% of the total). In both pine and spruce, 90% of the pulse of organic matter entered with the clear-cut was decomposed after 11 years.

Still based on the results shown in Figure 4 during the first 5 years after clear-cutting, average emissions from harvest residues averaged to 3.7 Mg CO_2 ha^{-1} year^{-1} in Scots pine stand and 2.9 Mg CO_2 ha^{-1} year^{-1} in Norway spruce stand, while emissions from initial soil C stock averaged from 3.5 Mg CO_2 ha^{-1} year^{-1} in Norway spruce stand to 3.3 Mg CO_2 ha^{-1} year^{-1} in Scots pine stand (Figure 4).

3.3 | Model Posteriors and Model Sensitivity

The model posteriors for foliage and coarse components were generally much narrower than the priors, and there seemed to be some separation between the pine and spruce sites (Supplement 1–6 in Supporting Information), with pine generally needing slightly higher inputs than those previously estimated. This is particularly true for the coarse component inputs. For fine roots, the uncertainty remained high, particularly for spruce. The KL divergence was generally high for the initialisation uncertainty term (Supplement 2 in Supporting Information), particularly for spruce. The initialisation parameters granted, for each of the species considered, the most information gain, suggesting that they were the most important in determining model likelihood (or, in other terms, model fitness was most sensitive to them).

4 | Discussion

4.1 | Clear-Cutting Modifies Organic Matter Fluxes and Reduces Total Soil C Stocks

The harvest residues generated a sudden increase in the C fluxes to the soil, impacting SOC. However, this increase in SOC was very short-lived, lasting only a few years (Figure 1). At the same time, SOC stocks, not supported by a constant influx from large living trees, were also reduced. This caused a much lower overall C sequestration for the clear-cut site when compared to the set-aside site over the whole length of the simulation, with negative estimated values when averaging across all simulations of the Monte Carlo realisations in some years for the spruce stand and most often after the clear-cut for the pine stand, indicating that the system recorded a net C loss until that point. A difference of 0 indicates that the balance is neutral and that the system recovered all of the C that was present at the beginning of the simulation. These results also indicate that an extended rotation length would increase the average soil C stock over a rotation period. Although these averages are sensitive both to the simulation assumptions and to the choice of the length over which averages were calculated, the relative comparison between the two scenarios is quite robust and makes it clear that clear-cutting is not an optimal approach when the objective is to maximise C sequestration. This agrees with the conclusions of recent modelling studies (Ameray et al. 2023) and measurements (Grelle et al. 2023; Lindroth 2023; Peichl et al. 2022). Despite the initial positive effects on C sequestration after a clear-cut due to the system being set in earlier successional stages, the overall result is a decrease in C sequestration, particularly for SOC, due to the absence of large living trees, which contribute to continuous C input through litterfall and root turnover (Goulden et al. 2011).

The ratio between aboveground biomass and average SOC stock was 0.44 in rotation forestry and 1.3 in the set-aside for pine and 0.85 in rotation forestry and 2.3 in the set-aside for the spruce stand. Thus, there was a relative shift towards a bigger relative proportion of organic matter stored in the SOC because of the clear-cut. However, the absolute total C amount with set-aside management increased from 107.5 to 191.4 Mg ha^{-1} for pine and from 114.5 to 242.0 Mg ha^{-1} for spruce. Although we observed a relative shift towards more SOC and less aboveground C caused by rotation forestry, there was a substantial decrease in the average total C stored in the ecosystem.

Forest soil C stock declined after clear-cutting, at a rate of 1.4 and 1.6 Mg ha^{-1} year^{-1} for Norway spruce and Scots pine, respectively, when considering the time from the clear-cut event to the next inflection point (in which the balance shifted from positive to negative), which was after 20 and 25 years for Norway spruce and Scots pine, respectively. The time needed for site C sequestration to completely offset the soil C lost due to the removal of living trees during clear-cut was several decades, which means that soil C stocks will be, in general, oscillating around a lower mean average value under rotation compared with more conservative approaches. The impact of clear-cutting is debated in the literature, particularly when discussing it against alternative management approaches (Lehtonen et al. 2023; Lundmark et al. 2016). Our estimates of the time needed for the site C balance to completely offset the C lost due to the clear-cut event are in line with the most pessimistic estimates (specifically Lindroth 2023) and compared to estimates based on measurements alone (Grelle et al. 2023; Peichl et al. 2022), our results are much more pessimistic. Similar conclusions, specifically about the decrease of forest floor C stocks for decades after clear-cut, were also recently reached by analysing large national forest inventory datasets from Sweden, Denmark, Finland, Norway and Canada (Johannesson et al. 2025). Thus, even if the growth rates after a clear-cut are high since the forest is set back to the first phases of the ecological succession, when considering the initial soil C losses after the clear-cut, this still represents a net cost in terms of C sequestration of the system when considering the overall rotation length.

Just a few years after harvest, the SOC balance of the sites was already negative and remained negative for multiple decades. Forest harvesting with clear-cutting results in a massive amount of C stored in trees being decomposed or removed as harvest residuals. Removing logging residuals for bioenergy purposes has negative impacts for forest C stocks (particularly SOC, e.g., Mäkipää et al. 2015), and the impact is higher for slow decomposing residuals, such as stumps, because quickly decomposing residuals, such as leaves and small branches, disappear in a few years (Repo et al. 2011).

In our case, the simulation of the fluxes from the forest ecosystems presented a huge spike in the first 2–5 years after the clear-cut event. The coarse residuals had a longer-lasting impact and were by far the biggest contributor to the total emissions. The effect of this spike in C inputs coming from logging residuals was observed in the SOC simulation, in which the SOC balance of the site was positive for the first years after the event (Figure 1), but the effect was short-lived.

4.2 | Relative Impact of Clear-Cutting Compared to a Set-Aside Scenario

When comparing the balance of the managed forest regenerated by clear-cutting to the set-aside scenario, our results were not surprising, as the set-aside scenario sequestered more C than rotation forestry. Over the length of the whole simulation, this additional sequestered C showed an average of 12.5%–17.2% of the SOC for the clear-cut or approximately 9.2 and 10.6 Mg ha^{-1} C for pine and spruce, respectively. More extensive changes were observed when considering the total C stocks of the stand, with about 84.0 and 127.6 Mg ha^{-1} C for pine and spruce, respectively.

We also need to consider that the pine site produced around 215 Mg ha^{-1} C of timber, which corresponded to 108 Mg ha^{-1} C, while the spruce site produced 297 Mg ha^{-1} C of timber (wood by-products not destined to sawmills) that can be used for energy and, therefore, has some substitution effect. Even without considering the substitution effect of energy from wood waste harvesting and assuming that only timber is taken from the stand, to calculate the impact of a clear-cut compared to a set-aside scenario, we would need to include this C mass and consider it dynamically by determining its half-life. Currently, 61% of the biomass and C of the harvested timber in Finland is burned and directly emitted as CO_2 since all side streams of the forest industry are efficiently used for bioenergy production (Suomen virallinen tilasto 2023). Only 13% is in saw timber (Suomen virallinen tilasto 2023), of which a small part is stored in wood products with long lifespans (Liski et al. 2001). Thus, considering current product utilisation, any additional C storage effect would be quite limited. Mäkipää et al. (2015) reported that harvesting decreased the forest C stock by 26.8 Mg C ha^{-1}, on average, over the rotation period. If harvested forest residues were used for energy production instead of fossil fuels, emissions declined by 19 Mg C ha^{-1}. Thus, Mäkipää et al. (2015) suggested that using forest residues for energy production led to a net increase in C emissions since the soil C stock decreased more than that by which bioenergy reduces fossil emissions for energy production.

4.3 | Study Limitations

As indicated by KL divergence, the most crucial assumptions for the simulation of the ecosystem C balance are the ones connected to model initialisation. Starting from an initial state of SOC, either particularly high or particularly low, determines the trend of the simulation, and therefore, the trend is highly sensitive to the model initialisation assumptions. Nevertheless, over such a long time scale, SOC is ultimately determined (at least several decades after the start of the simulation) by the estimated inputs over the length of the simulation (Peltoniemi et al. 2006). Our approach of rescaling the initial state on the measured SOC was chosen to maximise robustness in modelling the correct directions of the trajectories (at the cost of a less accurate estimation of the absolute amounts), but still relying on the available information to constrain it at least to some extent. Assuming a steady-state is always problematic in a managed forest since it is always a dynamic situation. The management aim in commercial stands is to maximise production, and this usually means that the ecosystem tends to be regenerated with a clear-cut when soil is approaching a balance between inputs and C release in decomposition. Soil organic matter still takes decades after clear-cut to reach the equilibrium determined by a new level of (steady) inputs, particularly when considering SOC quality (represented in Yasso by the distribution of the pools). Given that managed sites tend not to spend much time in an ecological climax state (if at all), it is unlikely that the initial distribution of the SOC pools given by the steady-state solution perfectly represents the organic matter quality at the start of the simulation. Eventual errors in the initialisation, particularly concerning organic matter quality, should be compensated by the calibration, although most likely introducing slight biases in the input posteriors, and should therefore not heavily impact the trends of the simulation. If the model initialisation was wrong, this would have an influence on the kinetics, but this influence would be a regular bias affecting both scenarios at the same time and not affecting the directions of the trends. Such an impact would also be proportional to how wrong the steady-state assumption is, and although it is unlikely that the sites are exactly at steady-state at the beginning of the simulations, the fact that the stands are quite close to maturity at that point suggests that such an assumption is still relatively close to reality.

A more difficult problem related to initialisation is a potential error in the initially measured SOC stocks (Häkkinen et al. 2011; Ťupek et al. 2019). As mentioned in Lindroos et al. (2022), the stoniness in the two sites causes large uncertainties in the measurements of SOC stocks. This is because sampling with an auger becomes extremely difficult when there are stones, which might cause biases in sampling since sampling tends to focus on areas characterised by the same micro-topography. Although the SOC stocks have been corrected to account for stoniness by normalising the values for the actual volume of mineral soil (minus the stones), the absolute values must be considered with caution due to the difficulties in sampling very stony soils. However, in any case, eventual biases should be regularly affecting the whole time series, and therefore, the trends and relative comparisons between management approaches should still be reliable.

Additionally, future scenarios contain uncertainty. The set-aside scenarios with long-term predicted periods are especially out of the range for which the forest simulator Motti has been validated, and this might increase uncertainty in our reference scenario. Commonly used biomass models are based on more mature stands and are not necessarily suitable for the initial growth stage (Repola et al. 2024).

Concerning the assumptions around the priors expressing the input estimate uncertainty terms, these are to be considered cornerstones to interpret the results, which depend on them to some extent. Exploring around a 25% coefficient of variation of the inputs was considered a reasonable prudential estimation of a potential error to test, thus missing reliable information on such error, and the whole approach was designed to avoid full reliance on the input function estimates, as we would have done, considering them as fully deterministic.

Although SOC stocks are also affected by environmental changes, such as atmospheric nitrogen deposition and climate change, these were not in the scope of this study, which focused on providing scientific evidence to plan forest management-related policies. This study examined the effects of forest management on SOC stocks, which is politically relevant for science-based decision-making about forest management decisions that directly affect forest C sequestration (as shown in this study). Since future climate, resulting ecological interactions and nitrogen deposition include relevant uncertainties, broadening our scope to include uncertain future scenarios would have diluted the political significance and applicability of our study. These factors are nevertheless likely to impact both scenarios considered in this study, and therefore, the relative comparison would still apply as a result.

5 | Conclusions

Rotation forestry with regeneration after clear-cutting has a strong impact on the C balance of the sites, with a strong decrease in the soil C stock in the first years (following a short-lived sharp increase caused by the undecomposed C inputs coming from the clear-cut) or even decades after the event. If the changes in soil C stock during the early decades after clear-cutting are not accounted for in the assessment of the forest's climate effect and only the tree stand is considered, the rate of forest C sequestration is seriously overestimated. For both the Scots pine and the Norway spruce sites, the time needed for the site C balance to completely offset the C lost due to the clear-cut event amounted to several decades, thus slightly longer than the most pessimistic estimates found in the literature. Therefore, clear-cutting has a huge cost in terms of GHG emissions when considering the forest ecosystem as the boundaries of the system. These emissions were, in our case, substantial, around 100 $\mathrm{Mg\,ha^{-1}}$ C for both pine and spruce stands over 80 years, and the contribution of the coarse component in them was the largest. Our results are limited to the C budget of a forest and do not consider what happens outside these boundaries. However, such results should raise attention. Although thinning events (which could also be associated with alternative management strategies, such as continuous cover forestry) were much less impacted on the GHG budget of the considered systems, clear-cutting appeared to be a relatively ineffective management regime when considering C storage as an important ecosystem service. Management regimes allowing larger aboveground biomass stocks, such as continuous cover forestry with moderate thinning intensities, might offer a C storage capacity much closer to a set-aside scenario while still retaining most, if not all, productive capacity. In general, considering forest C sequestration over the short term and disregarding long-term soil C dynamics following management interventions may lead to biased conclusions.

Author Contributions

Lorenzo Menichetti: conceptualization, methodology, software, formal analysis, visualization, validation, investigation, writing – original draft, writing – review and editing. **Aleksi Lehtonen:** conceptualization, investigation, methodology, validation, software, writing – review and editing, writing – original draft. **Antti-Jussi Lindroos:** conceptualization, data curation, writing – review and editing, funding acquisition, formal analysis, investigation, writing – original draft. **Päivi Merilä:** methodology, validation, writing – review and editing. **Saija Huuskonen:** methodology, validation, writing – review and editing. **Liisa Ukonmaanaho:** data curation. **Raisa Mäkipää:** conceptualization, methodology, data curation, supervision, funding acquisition, project administration, resources, writing – review and editing, validation, investigation, writing – original draft.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that supports the findings of this study are available in the Supporting Information of this article.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.