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Predicted changes in soil organic carbon stocks following afforestation of agricultural mineral soils in hemiboreal Latvia using Yasso20 model

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Abstract

Afforestation of agricultural land on mineral soils is a promising carbon farming measure in managed ecosystems for climate change mitigation; it remains an ongoing land-use change practice in Latvia, supported by both historical and current land management and climate policies. However, quantitative assessment of soil organic carbon (SOC) stock changes following afforestation, based either on repeated field measurements or modelling approaches evaluated against independent empirical data, remains limited for the hemiboreal vegetation region of Europe. The objective of this study was to quantify SOC stock changes following afforestation of agricultural mineral soils in Latvia using the Yasso20 model parameterised with nationally representative input data and evaluated against independent field measurements. The model predicted a rapid increase in SOC stocks during the first 20 years following afforestation, averaging 0.62 t C ha^{-1} $year^{-1}$, followed by a substantially slower increase that persisted for at least the subsequent 180 years, averaging 0.041 t C ha^{-1} $year^{-1}$. The predicted rapid SOC accumulation during the first 20 years following afforestation closely matched the mean measured SOC stock increase of 0.58 t C ha^{-1} $year^{-1}$ in established forest stands, supporting the plausibility of the model results. The model indicated a tendency towards the highest and most consistent SOC stock increase potential in coniferous species, whilst aspen was also highly competitive due to its rapid growth, with field measurements likewise indicating higher SOC stocks in coniferous and aspen stands.

Keywords: mineral soil; soil carbon stock changes; afforestation; Yasso20

Introduction

The role of soil is emphasised as essential not only for maintaining biodiversity, supporting ecosystem functions (Delgado-Baquerizo et al. 2025) and ensuring agricultural productivity (Xing et al. 2025), but also as a significant organic carbon (OC) sink under the urgent need to mitigate climate change (IPCC 2023). Afforestation is considered one of the most promising carbon farming measures in managed ecosystems (Chiti et al. 2026) and a key nature-based strategy to mitigate climate change in the land use, land use change and forestry (LULUCF) sector, primarily through the sequestration and storage of atmospheric carbon dioxide (CO_2) into new tree biomass (and subsequently in wood products) and secondarily through the potential to increase soil organic carbon (SOC) stock (Hasegawa et al. 2024, Liang et al. 2025). However, soils play a dual role as both sources and sinks of CO_2. The balance between these two opposing processes (CO_2 efflux from soil heterotrophic respiration and C input into soil through dead wood, plant litter, and root exudation) determines the temporal variability in SOC stock changes following afforestation (Paul et al. 2002). Furthermore, the effect of afforesting agricultural land on SOC stock changes varies with climate, tree species, site preparation, previous land use, soil fertility, clay content and other soil physicochemical parameters, management, and other factors (Paul et al. 2002, Tupek et al. 2021, Chiti et al. 2026).

In Latvia, the area of forest land has increased from around 24% in 1914 (Vasiļevskis 2007, Tērauds et al. 2011) to 51% (3,293 kha) in 2024, including 176 kha of land converted to forest land in the past 20 years (Skrebele et al. 2025). Afforestation is a continuing land-use change practice in Latvia, supported by land management and climate policies. For instance, under Latvia's National Energy and Climate Plan for 2021–2030, it is predicted that an additional 75 kha of less productive agricultural land with mineral soils will be afforested by 2030 (LR Ministru kabinets 2021). Given the significant extent of both historically and planned afforested land, estimating changes in SOC stocks in agricultural mineral soils following afforestation is necessary for a more accurate impact assessment and

evaluation of the total contribution to CO_2 emission reduction in Latvia's LULUCF sector.

Empirically grounded data on SOC stock changes in mineral soils in Latvia are limited. Although inventory data on SOC stocks in forest and agricultural lands are available, systematic and continuous monitoring of SOC stock changes is largely lacking. There is no long-term national-level soil carbon monitoring programme; however, some individual studies exist. In particular, mineral soil plots in forest land established under the BioSoil project in 2006 have been revisited twice, in 2012 and 2025, providing repeated measurements of SOC stock for forest soils. For agricultural soils, several inventory projects have been conducted, but without repeated measurements at the same sites. While these data are insufficient to characterise SOC stock changes across different land uses in full, land-use change, and management regimes, they provide independent information against which modelling results can be evaluated. In addition, several efforts monitor soils at the European scale, for instance, the Land Use/Cover Area Frame Survey (Orgiazzi et al. 2018). However, its current potential to estimate SOC stock changes across afforested lands remains limited (Deroo et al. 2024), due to the lack of monitoring plots specifically located in afforested areas and insufficient information on key soil variables, such as bulk density, which has only been assessed since the 2018 survey, despite being essential for estimating SOC stock changes. Thus, due to insufficient national-level and broader empirical data, changes in SOC stocks following the afforestation of agricultural land cannot be estimated without modelling. Alongside other models, the Yasso soil carbon model (Viskari et al. 2022) has been used to report SOC stock changes on forest and agricultural lands in several European countries (Astover et al. 2021) and has been identified as a suitable tool for national greenhouse gas (GHG) reporting under the United Nations Framework Convention on Climate Change (UNFCCC) framework (Eggleston et al. 2006, IPCC 2019).

The objective of this study was to quantify changes in SOC stock following the afforestation of agricultural mineral soils in Latvia using the Yasso20 model, parameterised with nationally representative input data, and evaluated against independent field measurements.

Material and methods

Model description

Yasso20 is a process-based SOC model that predicts SOC stocks and their temporal changes using OC inputs from litter and meteorological data (air temperature and precipitation). The model considers litter carbon according to its chemical composition, partitioning inputs into humus (H), acid-hydrolysable (A), water-soluble (W), ethanol-soluble (E), and non-soluble, non-hydrolysable lignin-like (N) compound groups. Decomposition rates of these compound groups depend on climatic conditions and litter characteristics, including litter size. During decomposition, carbon is either released to the atmosphere as CO_2 or transferred between compound groups, with part of the decomposed material forming more stable soil organic matter in mineral soils. Through these processes, Yasso20 predicts SOC stocks and their temporal changes. Yasso20 model runs can be initialised either by defining an initial SOC stock and its distribution among AWEN fractions or by predicting a long-term historical steady-state SOC stock using historical mean meteorological conditions and characteristic mean carbon inputs to soil. The model is well-suited to Latvian conditions, as its parameters have been calibrated using diverse global datasets on litter decomposition, woody debris decay, and SOC measurements, spanning a wide range of temperate and boreal climates. The Yasso20 model was applied using its default parameterisation; details of the model structure and calibration are provided by Viskari et al. (2022).

Model scenarios

To characterise afforestation, we made model runs for afforestation of agricultural land (cropland and grassland) with mineral soil with silver birch (*Betula pendula* Roth), aspen (*Populus tremula* L.), black alder (*Alnus glutinosa* (L.) Gaertn.), grey alder (*Alnus incana* (L.) Moench), Scots pine (*Pinus sylvestris* L.), and Norway spruce (*Picea abies* (L.) H. Karst.). Although Yasso20 is a deterministic model, 20 model iterations were performed for each scenario to leverage the probabilistic nature of the AGM forest growth model (Lazdiņš et al. 2019). The AGM model incorporates probabilistic features that represent variation in stand development and management, including harvesting periodicity observed in Latvia, based on National Forest Inventory data (National Forest Monitoring). Accordingly, 20 different AGM outputs for each scenario were used to derive Yasso20 input values and to characterise variability in SOC stock change predictions. For each scenario, Yasso20 was used to predict SOC stocks over 200 years following afforestation. All scenarios assumed afforestation in 2024.

Input data

The annual OC inputs to soil (foliar litter, natural mortality of aboveground and belowground vascular ground vegetation and fine roots of trees, deadwood from natural mortality and above- and belowground harvesting residues) used in the predictions were derived from Latvian-specific studies, as well as the AGM forest stand growth model (Lazdiņš et al. 2019), which is based on local empirical measurements, including the National Forest Inventory (LSFRI 'Silava' 2023, Šņepsts et al. 2026). The AGM model provided species-specific stand development parameters across successive forest management cycles, including the effects of clearcutting when stands have met the final-felling age or mean-diameter criteria specified in Latvian regulations, and thinning regimes reflecting

observed forest-management practices. Typical simulated management cycles included one or two thinnings followed by clearcutting at approximately 71–101 years, except for aspen, for which final felling is permitted from 41 years of age (LR Saeima 2000). It generated output values for carbon stock in annual deadwood from natural mortality, as well as in aboveground and belowground harvesting residues, including stumps, coarse roots, and fine roots. To convert the mass of aboveground harvesting residues into the amount of C input to the soil, a coefficient of 0.4 was applied, based on the assumption that 60% of non-merchantable wood residues are removed from the forest. The size of annual coarse litter was calculated as a weighted average, assuming a mean branch diameter of 4 cm, and that the diameter of material from natural mortality and below-ground biomass harvesting residues corresponds to half of the breast-height diameter of the average tree at the time of the harvest. In addition, AGM results on stand basal area and age dynamics were used as proxies to estimate carbon input to the soil from foliar litter and ground vegetation. Input by foliar litter was based on the relationship with the stand basal area reported by Bārdule et al. (2021). Data on annual carbon input from fine-root turnover were obtained from the studies of Butlers et al. (2022, 2025); the analysis assumed that fine-root production equals fine-root mortality, and – due to limited data on parameter variability for specific stands – averaged static values were used. Static values were also used to characterise the annual carbon input to the soil from aboveground and belowground vascular ground vegetation (Table S1); values measured in clear-cut areas were applied to stands up to 20 years of age (Butlers et al. 2022, 2025). Carbon input was allocated to AWEN fractions using the coefficients listed in Table S2.

Meteorological data were retrieved from the open data portal of the Latvian Environment, Geology and Meteorology Centre and included monthly mean air temperature and annual precipitation data from 2024 to 2050. For the period beyond 2050, climate inputs were extrapolated using the mean values from the preceding 10-year period (LVĢMC 2026).

Model runs were initialised using observation-count-weighted mean SOC stocks at 0–40 and 0–80 cm depths of 83.3 and 99.1 t C ha^{-1} for croplands, and 86.0 and 102.9 t C ha^{-1} for grasslands, respectively, based on inventory measurements (Table S3; Bardule et al. 2017, Petaja et al. 2024). Initial SOC stocks were partitioned among AWEN pools using model-predicted steady-state proportions based on historical mean meteorological conditions (Table S4) and characteristic ground vegetation C stocks of 4.70 t C ha^{-1} $year^{-1}$ for croplands and 3.36 t C ha^{-1} $year^{-1}$ for grasslands, consistent with national GHG inventory assumptions (Eggleston et al. 2006, Purviņa et al. 2024, Bārdule et al. 2025).

AGM model outputs describing species-specific stand development and harvesting patterns for all scenarios and their replicates, together with the litter carbon inputs derived from these outputs and used in Yasso20, and detailed Yasso20 simulation outputs, are available online (Butlers 2026). Table S5 summarises Yasso20 carbon input data sources and assumptions.

Uncertainty and evaluation of predictions

Annual SOC stock change rates were estimated using linear regression on the results of individual model runs. Mean rates (slopes) were calculated across replicates of the specific scenario, and uncertainty was expressed as the standard deviation of the derived slope values. The resulting variation in SOC outcomes reflects the sensitivity of Yasso20 predictions to input uncertainty. The SOC stock change trends were estimated and evaluated separately for the first 20 years after afforestation to align with the land-use change period commonly used in national inventory reporting (Eggleston et al. 2006), and for the subsequent period to characterise longer-term dynamics.

To assess the precision of the modelled results, predicted SOC stock changes were compared with results from repeated measurements of the BioSoil forest mineral soil monitoring plots ($n = 43$; Butlers 2026). The agreement between BioSoil measurements and predicted SOC stocks and stock change slopes was evaluated using an independent, unpaired comparison. Measured SOC values were pooled within each soil layer, while predicted SOC stocks were grouped by soil layer and post-afforestation period using a 20-year threshold. Differences between measured and predicted distributions were quantified using Welch's two-sample t-test and *Cohen's d* effect size, calculated using the pooled standard deviation of measured and predicted values. Smaller absolute *Cohen's d* values were interpreted as better agreement between measured and predicted SOC stocks.

Results

Predictions showed the same SOC accumulation trajectory for cropland and grassland afforestation, characterised by a rapid increase in mineral soil SOC stocks during the first 20 years. In subsequent years, SOC accumulation slowed considerably. Predicted SOC stocks continued to increase throughout the entire prediction period, with no steady state reached during the 200-year simulation period (Figure 1). The only exception was afforestation with black alder, when model runs were initialised based on SOC stock in the 0–80 cm soil layer.

Hereafter, predicted SOC stocks and their changes are presented for model runs initialised using carbon stock in the 0–80 cm soil layer, unless stated otherwise. Results from model runs initialised using SOC stock in the 0–40 cm layer are provided in the Supplementary. The highest SOC stock increase rate during the first 20 years after afforestation was predicted for aspen, at 0.68 ± 0.22 t C ha^{-1} $year^{-1}$ (Figure 2, Table S6). Lower, but mutually comparable, initial SOC stock increases

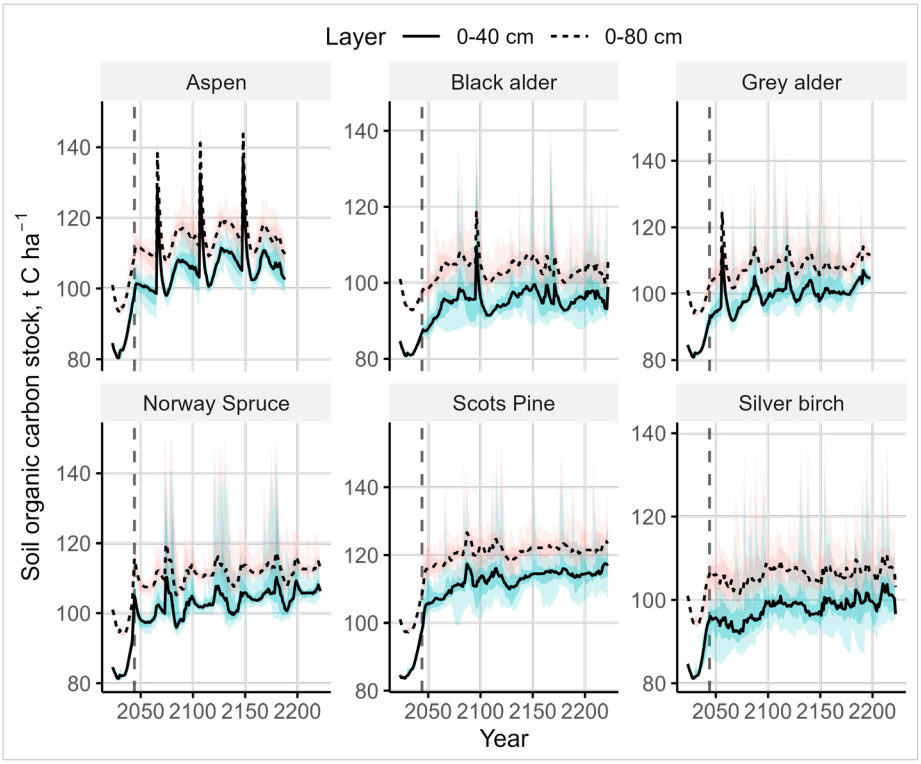

Figure 1. Predicted soil organic carbon stocks and associated variation

The black lines show the median trajectory of soil organic carbon stock across model runs. The shaded areas correspond to the 25–75% and 5–95% interquartile ranges. The vertical dashed line indicates the point in time corresponding to 20 years after afforestation.

were predicted for Norway spruce, Scots pine, and silver birch, with a mean rate of 0.47 ± 0.07 t C ha^{-1} year^{-1}. In contrast, substantially lower rates were estimated for grey alder (0.22 ± 0.15 t C ha^{-1} year^{-1}) and black alder (–0.03 ± 0.06 t C ha^{-1} year^{-1}).

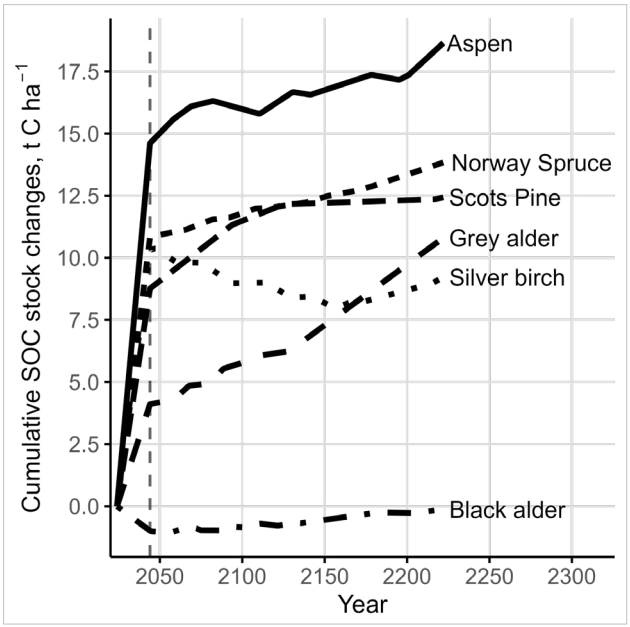

Figure 2. Cumulative soil organic carbon (SOC) stock change in the soil layer 0–80 cm following afforestation by different tree species, reconstructed from piecewise linear trends estimated for individual predictions

The vertical dashed line marks 20 years after afforestation. SOC stock changes in the soil layer 0–40 are indicated in Table S6 and Figure S1.

Beyond 20 years after afforestation, the mean increase in SOC stock across species was 0.02 ± 0.01 t C ha^{-1} year^{-1}. Despite relatively similar overall trends, dominant tree species exhibited distinct rates of SOC stock increase during this period (Table S6). Grey alder showed the highest mean SOC stock increase rate in the post-20-year period (0.027 ± 0.037 t C ha^{-1} year^{-1}). Despite lower initial accumulation, predicted SOC stocks in grey alder stands approached those predicted for Norway spruce and Scots pine later in the simulation (Figure 1). In contrast, silver birch, which exhibited relatively rapid SOC accumulation in the early afforestation phase, showed highly uncertain SOC stock increases in the post-20-year period (0.015 ± 0.039 t C ha^{-1} year^{-1}). Increased variability in SOC stock change was also observed for aspen (Figure 3). Similarly, although median prediction for black alder indicates continued SOC accumulation, stocks did not increase continuously in all model replicates (Figure S2). In contrast, long-term increases in SOC stock were predicted to be consistently sustained across the other species. Norway spruce exhibited the lowest variability in predicted SOC stock increase rates among the species analysed (Figure S2).

The mean predicted SOC stock over years 20–200 was 110.8 ± 9.1 t C ha^{-1} in afforested croplands and 112.7 ± 9.1 t C ha^{-1} in afforested grasslands (Table S7). Median predicted SOC stocks in the post-20-year period were 114.0 t C ha^{-1} for Norway spruce, while Scots pine showed even higher long-term SOC stocks, with a median of 120.9 t C ha^{-1} and a 75th percentile reaching 124.3 t C ha^{-1}. Black alder had the lowest median

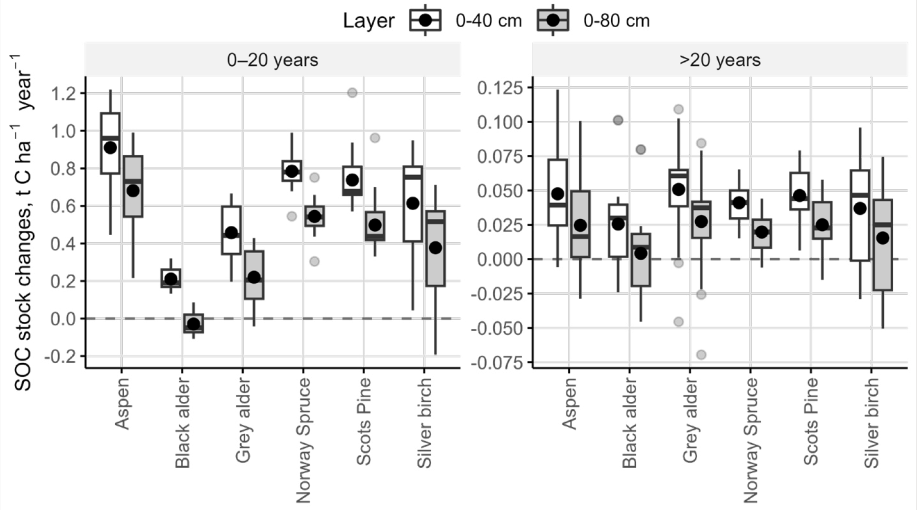

Figure 3. Variation in rates of change in linear soil carbon stock across predictions

The boxes designate the interquartile range (IQR), while the whiskers show the 5th to 95th percentile range. Black dots mark the mean values, horizontal lines inside the boxes indicate the medians, and grey dots outside the whiskers represent outliers. The horizontal dashed line denotes zero change.

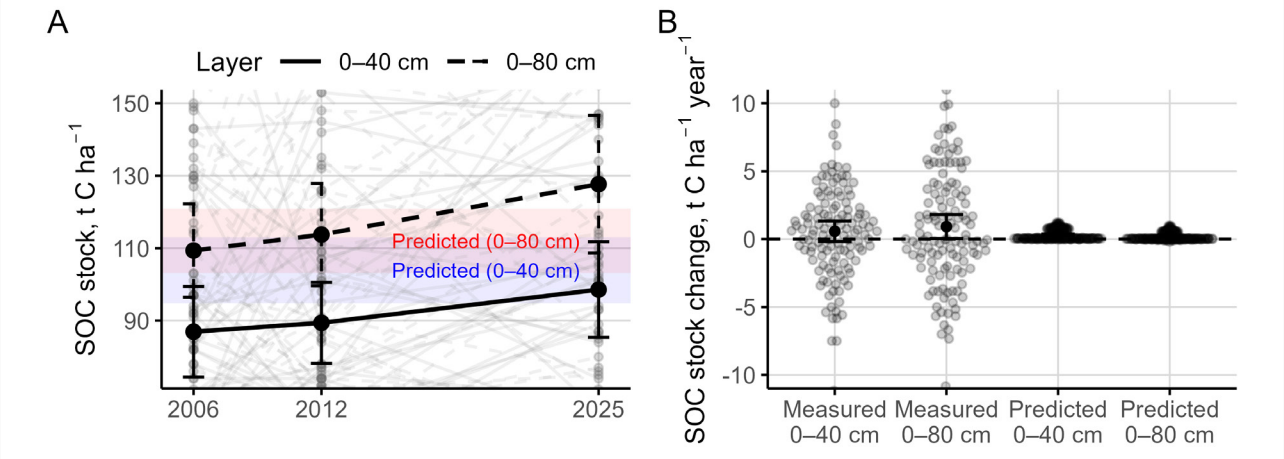

Figure 4. Measured soil organic carbon stocks (SOC) and annual change rates in mineral soils compared with Yasso model predictions

(A) SOC stocks measured in forest land in 2006, 2012, and 2025. Grey lines and points represent individual BioSoil monitoring plots, while black points and error bars indicate the mean SOC stock across plots with 95% confidence intervals. Shaded areas denote the range of median SOC stocks predicted by Yasso model run replicates over the 200 years after afforestation for the 0–40 cm (blue) and 0–80 cm (red) soil layers (Tables S8 and S9). (B) Annual SOC stock change rates based on measured data (aggregated across all BioSoil periods) and model-predicted values for 0–40 cm and 0–80 cm layers. Points represent individual observations, and error bars show the 95% confidence interval.

predicted SOC stock of 103.1 t C ha^{-1}, although these values did not differ substantially from those predicted for grey alder and silver birch (Tables S8 and S9).

Comparison of model results with independent repeated measurements acquired in BioSoil plots indicated good correspondence. The closest agreement between the distributions of measured and predicted SOC stocks was observed for the 0–80 cm layer (*Cohen's d* = –0.141), with mean values of 117 and 112 t C ha^{-1}, respectively (Figure 4A, Table S10). The distributions of measured and predicted SOC stock change rates were closely aligned across all depths and time periods, with *Cohen's d* remaining below 0.3 in all cases. The best agreement was observed for the 0–40 cm layer during the 0–20 years period (*Cohen's d* = 0.014), where the measured and predicted SOC stock change rates were nearly identical, both approximating 0.6 t C ha^{-1} year^{-1} (Figure 4B, Table S11).

Discussion

Comparison of predicted results with independent data

SOC stocks predicted by Yasso20, which, according to Liski et al. (2005), represent the organic F/H layer together with the uppermost 1 m of the mineral soil profile, were comparable with SOC stocks measured in established forest stands in Latvia. Field measurements have shown SOC stocks (litter layer plus 0–80 cm soil layer) of 126–128 t C ha^{-1} in mature Norway spruce and aspen stands on dry mineral soils, 112 t C ha^{-1} in Scots pine stands, and 104 t C ha^{-1} in birch stands (Ķēniņa et al. 2023). These values were generally consistent with the predicted SOC stocks for the 0–80 cm layer, which ranged from median values of 103 to 121 t C ha^{-1}.

The observed tendencies were also broadly comparable, with coniferous stands generally showing higher SOC stocks than deciduous stands. The plausibility of the predicted SOC stock levels was further supported by their agreement with BioSoil measurements, indicating that Yasso20-predicted SOC stocks were more closely aligned with measured SOC stocks in the 0–80 cm layer than in the 0–40 cm layer. These observations provided confidence that Yasso20 can reproduce SOC stock levels under hemiboreal conditions and generate SOC stock estimates consistent with independent field measurements, supporting the interpretation that its results represent SOC stocks approximately within the upper 1 m of the soil profile.

Nevertheless, comparison based solely on absolute SOC stock values is limited, as the primary objective of the modelling is to predict changes in SOC stocks. A more practical approach to model evaluation is to compare long-term monitored changes in SOC stock, which directly reflect temporal dynamics but require substantially more resources than single-time SOC stock inventories. Currently, the best available data for Latvia are repeated SOC stock measurements from 43 BioSoil forest mineral soil plots between 2006 and 2025, which showed agreement with Yasso20 predictions. However, although the closest agreement between measured and predicted SOC stocks was identified for the 0–80 cm layer in stands older than 20 years (117 ± 51 vs. 112 ± 9 t C ha^{-1}), measured SOC stock change rates agreed most closely with predictions for the 0–40 cm layer during the first 20 years after afforestation (both approximately 0.6 t C ha^{-1} year^{-1}). Predictions initialised with SOC stocks from the deeper soil layer yielded lower accumulation rates than those measured in established forest stands, suggesting that model initialisation using deep-soil SOC stocks may underestimate SOC accumulation following afforestation.

Model initialisation

These observations highlight the importance of the Yasso20 model initialisation approach for SOC modelling results, a finding also reported in previous studies. (e.g. Palosuo et al. 2016). Considering that the primary objective of such modelling exercises is to predict changes in SOC stocks, the most appropriate Yasso20 initialisation approach is the one that best replicates observed SOC stock changes. Initialisation using SOC stocks from the 0–40 cm layer appears more appropriate for estimating SOC stock changes, as the resulting predictions showed the closest agreement with measured SOC stock change rates in this layer, whilst the historical litter-input approach also yielded plausible initial SOC stocks for croplands at the same depth. The model runs to derive the initial AWENH composition from assumed agricultural litter carbon inputs (see "Materials and methods") predicted steady-state SOC stocks of 87.0 t C ha^{-1} for croplands and 65.9 t C ha^{-1} for grasslands. The cropland estimate was close to both the measured mean used for initialisation in the 0–40 cm layer (83.0 t C ha^{-1}) and the value applied in the Latvian GHG inventory (85.60 t C ha^{-1}; Skrebele et al. 2024).

Instead of explicitly defining initial SOC stocks, as was done in this study, a potentially more robust approach would be to model initialisation based on historical litter carbon inputs, provided that such an approach can reproduce observed steady-state SOC stocks in agricultural lands. However, because steady-state SOC stocks in grasslands could not be successfully replicated, this approach currently remains limited by insufficient knowledge regarding litter carbon inputs in agricultural systems. Addressing these gaps through targeted data collection would enable modelling of afforestation without explicitly defining initial SOC stocks. Instead, SOC dynamics could be predicted in full based on litter inputs before and after land-use change, allowing more robust comparisons with independent SOC stock measurements, which would no longer be used as model inputs.

Predicted SOC stock change tendencies

Irrespective of whether the model was initialised using measured SOC stocks from the 0–40 or 0–80 cm soil layer, Yasso20 consistently predicted a sharp decline in SOC stocks during the first years after afforestation, followed by a rapid increase over the subsequent approximately 20 years. It remains uncertain whether the immediate decrease in SOC stocks reflects limitations in model parameterisation or input data, or whether it represents a realistic initial response to afforestation. Field measurements show that an initial decline in SOC after afforestation can occur (e.g. Paul et al. 2002, based on 43 published or unpublished studies, encompassing 204 sites). This effect is primarily associated with soil mechanical disturbance and damage caused by site preparation. Petaja et al. (2023), in a study based on field measurements conducted in Latvia, reported an initial decline in SOC stocks after afforestation, associated with decreased soil bulk density. This can be explained by reduced soil compaction from livestock and machinery, increased total porosity (the presence of macropores), and increased soil organic matter content (Yaşar Korkanç 2014). However, mechanical disturbances are not explicitly represented in the Yasso20 model; therefore, it remains probable that the predicted initial SOC decrease is rather related to model performance under the applied setup.

Rerunning the model with constant ground-vegetation litter inputs throughout stand development retained the rapid SOC increase during the first approximately 20 years. This indicates that the assumption that ground vegetation litter measured in clearcuts applies to stands up to 20 years of age is not responsible for the tendency toward rapid increases in SOC stock in the first decades. Rather, the results suggest that approximately 20 years are required for soils to respond to changing litter input dynamics and to approach a new soil carbon balance equilibrium. This interpretation is supported by the observation that, irrespective of the dominant tree species, a characteristic rapid increase

in SOC stocks occurred within the first 20 years, despite differences in the pace of initial carbon stock accumulation. Notably, the identified ~ 20-year soil C balance adjustment period corresponds well with the IPCC default assumption that soils reach a new steady-state SOC level within 20 years following land-use change (Eggleston et al. 2006). Furthermore, assumptions of increased vegetation biomass in young stands were also applied during subsequent rotations. The prediction period covered three to six forest management cycles, depending on species.

However, these assumptions did not induce similarly rapid SOC shifts; instead, the largest SOC changes were associated with harvesting events, which triggered both rapid SOC increases and declines. Such tendencies raise concerns that the default Yasso20 parameterisation may decompose coarse litter too rapidly, which does not fully correspond with decomposition observations in Latvia. Studies have shown that coniferous stumps decompose over approximately 92 years, deciduous stumps over 38 years, and harvesting residues in coniferous stands over approximately 40 years. Similarly, the half-decomposition period of above-ground coarse deadwood particles has been estimated at 67 years in pine stands and 51 years in spruce stands (Lazdiņš et al. 2015). Comparable slow decomposition dynamics of coarse woody debris have been observed in the boreal region (Shorohova et al. 2008, Menichetti et al. 2021). Adjusting the model parameterisation to better reflect observed decomposition dynamics of coarse litter could increase the estimated contribution of harvesting residues to SOC stock accumulation following afforestation and forest management activities.

Importance of input data quality

Previous Yasso20 modelling exercises commonly rely on tree litter as the sole source of soil carbon input, as forest science data in many countries are sufficient to quantify tree-related dynamic carbon inputs to soil accurately. However, contributions from ground vegetation are still often excluded (e.g. Menichetti et al. 2025), which are associated with increased soil carbon inputs from ground vegetation litter (Butlers et al. 2022). The removal of canopy trees during harvesting reduces competition for light, nutrients, and water, thereby promoting rapid development of ground vegetation, including root systems, which in turn enhances soil carbon inputs via ground vegetation litter, potentially even exceeding those in mature forest stands (Butlers et al. 2022, Lazdiņš et al. 2024). Our experience demonstrates that ignoring carbon inputs from ground vegetation not only underestimates SOC stocks but also overestimates initial SOC losses after afforestation or clearcutting, as ground vegetation represents the dominant source of soil carbon inputs during early stand development (Butlers et al. 2022). The impact of these biases can be particularly pronounced when modelling is limited to a single forest management cycle. Therefore, this study highlights the importance of further refining knowledge on ground vegetation litter dynamics in response to stand development and management events to enable continued improvement in SOC stock predictions. Furthermore, it is important to account for additional aspects that promote litter input, for example, silvicultural operations such as agrotechnical tending and stand composition management, which were not included in this modelling exercise because such knowledge is not available. In Latvia, agrotechnical tending is commonly carried out once or twice during the first two to three years after afforestation or reforestation. These activities can further increase litter inputs into soil, and accounting for this effect could mitigate, or even avoid, the potentially overestimated initial decline in SOC stocks currently predicted to occur immediately after afforestation or reforestation. In addition, further knowledge is needed on canopy litter inputs in young stands, as linear reductions had to be assumed for this litter component in stands with a basal area below 10 m^2 ha^{-1}. Improved understanding of understory biomass and litter dynamics throughout stand development is also required. Furthermore, fine-root mortality dynamics remain poorly understood, particularly in relation to stand conditions such as soil fertility and tree stand characteristics. Addressing these issues can further advance understanding of carbon cycling in forest ecosystems.

Interpretation of the results

The approach of multiple model run iterations reflecting variability in stand development trajectories, consistent with typical forest management practices in Latvia, allows the results to be interpreted at the national scale. Considering that Yasso20 predictions indicate continued increases in SOC stocks for at least 200 years following afforestation, and that approximately half of the current forest land in Latvia was agricultural land at the beginning of the 20th century (Tērauds et al. 2011), it is likely that mineral soils in Latvia are, on average, still accumulating SOC. This tendency therefore extends beyond areas classified as recently afforested and also applies to historically established forest land. Due to the deterministic structure of the Yasso20 model and identical assumptions for initial AWENH pool distribution and stand development, predicted SOC stock trajectories for cropland and grassland followed the same trends and differed only by the small offset in initial SOC stocks (Δ = 2.7–3.8 t C ha^{-1}), which is negligible considering the underlying data variation. Consequently, because cropland and grassland have similar initial SOC stocks, the predicted SOC response to afforestation is also similar for both land-use types, and the results apply to agricultural land afforestation in general, regardless of initial land use. The high SOC stock accumulation observed under aspen and grey alder can be attributed to their rapid growth rates and the resulting relatively short forest management rotation cycles, which are reflected in increased rates of carbon input to the soil. This suggests that SOC accumulation in other species could likewise be enhanced

by shorter rotation cycles, as harvesting residues contribute considerably (14%) to total litter inputs over a rotation. However, to more accurately assess the impacts of reforestation and afforestation, the effects of soil preparation on SOC stocks should be evaluated, as the frequency of disturbance-related impacts on SOC would increase with these activities.

Limitations of the results

The predictions are conditional on the model structure and the assumptions used for initialisation and future climate. Under the applied parameterisation, Yasso20 does not explicitly account for soil texture or associated differences in SOC changes. Model runs were initialised using mean SOC stocks for cropland and grassland pooled across different mineral soils; consequently, the predictions do not represent the full variability in initial SOC stocks or afforestation responses associated with soil texture, fertility, and other soil properties. Although the overall mean SOC stocks used for initialisation reported by Petaja et al. (2024) and Bardule et al. (2017) were broadly comparable (Table S3), Petaja et al. (2024) reported mean SOC stocks ranging from 48 to 90 t C ha^{-1} in the 0–40 cm layer across WRB soil groups in agricultural mineral soils. Such variation in initial SOC stocks could substantially influence the magnitude and trajectory of predicted SOC stock changes following afforestation. Furthermore, we held climate inputs after 2050 constant at the mean conditions of the preceding decade. The subsequent simulations therefore describe long-term SOC dynamics under this assumed climate, while continued changes in temperature and precipitation could alter decomposition rates and predicted SOC accumulation. Finally, we evaluated model results against independent, unpaired BioSoil measurements from established forest stands. This comparison provides evidence regarding the plausibility of predicted SOC stocks and stock change rates under Latvian forest conditions, however, does not directly validate predictions for individual sites or SOC dynamics following the conversion of agricultural land to forest.

Conclusions

Owing to species-specific stand growth rates and the resulting harvest frequency, different rates of increase in soil organic carbon (SOC) stock are predicted across tree species. However, a common pattern is observed: mineral SOC stocks increase rapidly during the first 20 years after afforestation, followed by a substantially slower but persistent increase lasting at least 200 years. Coniferous species demonstrate the greatest long-term potential for SOC accumulation. In contrast, aspen, due to its rapid growth, is associated with the most rapid SOC increase during the initial decades following afforestation. The predicted mean SOC stock increase during the first 20 years following afforestation aligned with the measured SOC stock increase in forest lands, both of which approximated 0.6 t C ha^{-1} $year^{-1}$. Harvesting-related carbon inputs accounted for approximately 14% of total soil carbon inputs, suggesting that increased forest management intensity may potentially enhance carbon input to soil.

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Supplementary

Table S1. Annual carbon input (t C ha^{-1}) from natural fine-root turnover and ground vegetation

Dominant tree species	Tree fine roots	Ground vegetation	
		Aboveground	Belowground
Black alder	0.44	0.84	1.30
Birch	0.63	0.72	1.18
Pine	1.64	1.08	1.79
Spruce	0.76	0.90	0.97
Deciduous	0.54	0.77	1.24
Clearcut	-	2.22	1.12

Table S2. Proportion of litter carbon allocated to the AWENH fractions

Litter type	Dominant tree species	A	W	E	N
Coarse litter*	Pine	0.46	0.02	0.08	0.43
	Spruce	0.67	0.02	0.01	0.31
	Deciduous	0.65	0.015	0.015	0.32
Foliar litter	Pine	0.52	0.18	0.09	0.22
	Spruce	0.48	0.13	0.07	0.32
	Deciduous	0.41	0.20	0.10	0.30
Fine roots	Pine	0.58	0.13	0.06	0.23
	Spruce	0.55	0.13	0.07	0.25
	Deciduous	0.51	0.05	0.05	0.39
Ground vegetation	All	0.46	0.32	0.04	0.18

Note: * deadwood by natural mortality and aboveground and belowground (stumps, coarse roots) harvesting residues.

Table S3. Soil carbon stock determined by direct measurements

Land use	Soil layer, cm	C stock, t C ha^{-1}	Observations	Source
Cropland	0–40	83.91	120	Bardule et al. 2017
		82.78	152	Petaja et al. 2024
		83.28	272	Weighted average
	0–80	99.10	120	Bardule et al. 2017
Grass-land	0–40	89.40	120	Bardule et al. 2017
		76.95	45	Petaja et al. 2024
		86.00	165	Weighted average
	0–80	102.90	120	Bārdule et al. 2017

Table S4. Meteorological input values used to predict initial soil organic carbon stocks in agricultural soils

Month	Air temperature, ºC	Precipitation, mm
January	–5.5	650
February	–5.3	
March	–1.7	
April	4.8	
May	10.8	
June	14.6	
July	16.9	
August	16.0	
September	11.8	
October	6.5	
November	1.2	
December	–3.1	

Table S5. Yasso20 carbon input data sources and assumptions

Source	Source and assumption
Foliar litter	Empirical data from Bārdule et al. (2021)
Deadwood from natural mortality (aboveground and belowground)	AGM forest stand growth model (Lazdiņš et al. 2019) output data used directly
Belowground deadwood by harvesting	
Fine roots of trees by harvesting	
Aboveground harvesting residues	AGM forest stand growth model (Lazdiņš et al. 2019) output recalculated, assuming that 40% of residues are left on the site
Fine roots of trees by natural mortality	Empirical data from Butlers et al. (2022, 2025), assuming that fine-root production equals mortality
Ground vegetation (aboveground and belowground)	Empirical data from Butlers et al. (2022, 2025), assuming that clearcut values apply to stands up to 20 years of age

Table S6. Descriptive statistics of linear regression slopes characterising annual soil organic carbon stock changes following afforestation (t C ha^{-1} year^{-1})

Years after afforestation	Species	Soil layer, cm	Mean	*SD*	Median	Min	Max
≤ 20	Aspen	0–40	0.910	0.225	0.960	0.445	1.220
	Norway spruce		0.785	0.094	0.780	0.545	0.990
	Scots pine		0.738	0.150	0.677	0.571	1.203
	Grey alder		0.457	0.150	0.443	0.196	0.666
	Silver birch		0.614	0.271	0.753	0.044	0.949
	Black alder		0.210	0.059	0.191	0.133	0.320
	All		0.619	0.288	-	-	-
	Aspen	0–80	0.681	0.225	0.731	0.216	0.990
	Norway spruce		0.544	0.094	0.541	0.304	0.751
	Scots pine		0.498	0.151	0.438	0.331	0.962
	Grey alder		0.220	0.150	0.205	–0.041	0.429
	Silver birch		0.377	0.271	0.516	–0.193	0.712
	Black alder		–0.029	0.060	–0.049	–0.108	0.086
	All		0.382	0.289	-	-	-
> 20	Aspen	0–40	0.048	0.037	0.039	-0.006	0.124
	Norway spruce		0.041	0.015	0.041	0.015	0.065
	Scots pine		0.046	0.019	0.044	0.006	0.079
	Grey alder		0.051	0.037	0.061	–0.046	0.109
	Silver birch		0.037	0.039	0.046	–0.029	0.096
	Black alder		0.026	0.034	0.030	–0.024	0.101
	All		0.041	0.032	-	-	-
	Aspen	0–80	0.025	0.037	0.016	–0.029	0.101
	Norway spruce		0.020	0.015	0.020	–0.006	0.044
	Scots pine		0.025	0.019	0.023	–0.015	0.058
	Grey alder		0.027	0.037	0.037	–0.070	0.084
	Silver birch		0.015	0.039	0.025	–0.050	0.075
	Black alder		0.004	0.034	0.009	–0.045	0.080
	All		0.019	0.032	-	-	-

Table S7. Mean soil organic carbon stock (t C ha^{-1} ± *SD*) during the period following the first 20 years after afforestation

Land use	Soil layer, cm	Before afforestation	Aspen	Birch	Grey alder	Spruce	Black alder	Pine	Average
Cropland	0 –40	83.3	105.7 ± 7.2	98.2 ± 7.5	99.9 ± 7.1	104.3 ± 7.9	95.4 ± 7.1	112.5 ± 6.9	102.7 ± 7.2
Grassland		86.0	107.1 ± 7.1	99.5 ± 7.5	101.3 ± 7.1	105.6 ± 7.9	96.8 ± 7.1	113.8 ± 6.9	104.1 ± 9.3
Cropland	0–80	99.1	114.0 ± 7.0	106.2 ± 7.3	108.3 ± 7.0	112.3 ± 7.7	103.3 ± 7.0	120.4 ± 6.7	110.8 ± 9.1
Grassland		102.9	115.9 ± 6.9	108.1 ± 7.3	110.3 ± 6.9	114.2 ± 7.6	105.2 ± 7.0	122.2 ± 6.7	112.7 ± 9.1

Table S8. Median and quantiles of predicted soil organic carbon stocks during the period > 20 years after afforestation for model runs initialised with carbon stock in the 0–40 cm soil layer (t C ha^{-1})

Species	Soil organic carbon stock, t C ha^{-1}		
	Median	Quantile	
		75	90
Aspen	105.6	110.0	114.2
Norway spruce	103.4	107.2	113.1
Scots pine	113.0	116.3	119.8
Grey alder	99.4	103.2	108.7
Silver birch	97.9	102.0	106.4
Black alder	94.8	99.0	103.5

Table S9. Median and quantiles of predicted soil organic carbon stocks during the period > 20 years after afforestation for model runs initialised with carbon stock in the 0–80 cm soil layer (t C ha^{-1})

Species	Soil organic carbon stock, t C ha^{-1}		
	Median	Quantile	
		75	90
Aspen	114.0	118.3	122.6
Norway spruce	111.5	115.1	121.0
Scots pine	120.9	124.3	127.9
Grey alder	108.0	111.8	117.2
Silver birch	106.3	110.2	114.5
Black alder	103.1	107.2	111.8

Table S10. Comparison of mean measured and predicted SOC stocks for 0–20 and > 20 years after afforestation (t C ha^{-1})

Layer, cm	Period	n	Mean	sd	*p*	*Cohen's d*
0–40	Measured	129	91.626	40.08	-	-
	0–20 years	5,040	85.034	4.577	0.064	–0.231
	> 20 years	39,498	103.334	9.344	0.001	0.402
0–80	Measured	129	116.922	50.786	-	-
	0–20 years	5,040	97.7	4.17	< 0.001	–0.533
	> 20 years	39,498	111.76	9.187	0.25	–0.141

Table S11. Comparison of mean measured and predicted SOC stock changes for 0–20 and > 20 years after afforestation (t C ha^{-1} year^{-1})

Layer, cm	Period	n	Mean	sd	*p*	*Cohen's d*
0–40	Measured	129	0.576	4.344	-	-
	0–20 years	120	0.619	0.288	0,911	0,014
	> 20 years	120	0.041	0.032	0,165	–0,174
0–80	Measured	129	0.923	5.065	-	-
	0–20 years	120	0.382	0.289	0,228	–0,151
	> 20 years	120	0.019	0.032	0,045	–0,252

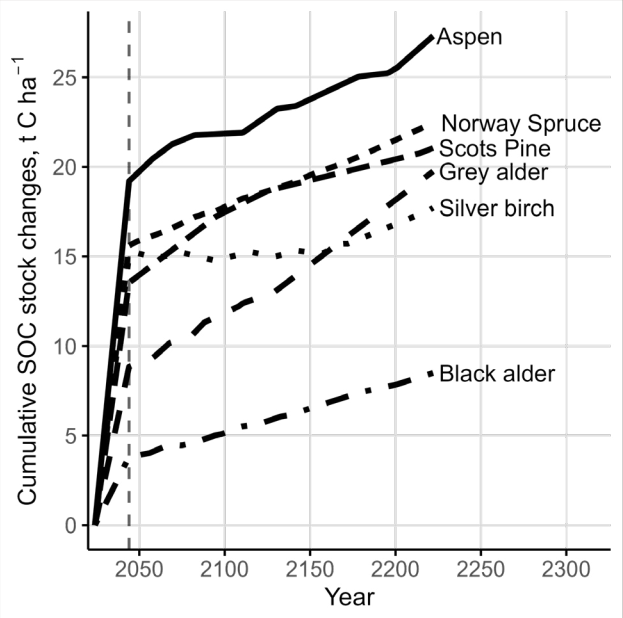

Figure S1. Cumulative soil organic carbon (SOC) stock change in the soil layer 0–40 cm following afforestation with tree species, reconstructed from piecewise linear trends estimated for individual predictions

The vertical dashed line marks 20 years after afforestation.

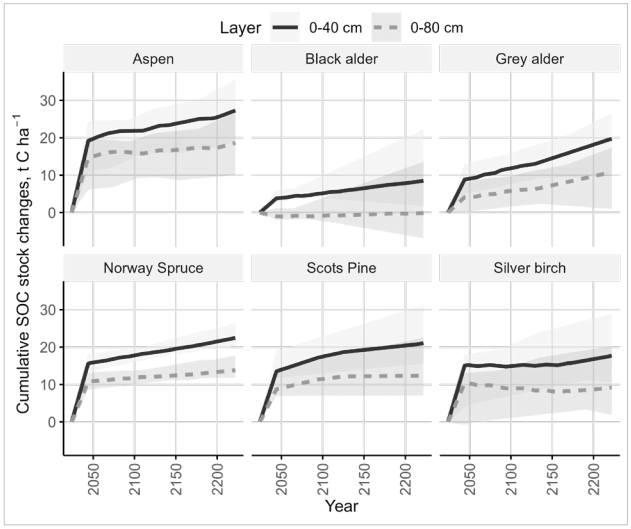

Figure S2. Cumulative soil organic carbon (SOC) stock changes (t C ha^{-1}) predicted over time following afforestation, stratified by dominant tree species

Solid lines represent median estimates, while shaded ribbons indicate the 5th–95th percentile range of model predictions. The vertical dashed line marks 20 years after afforestation.