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YSSP Report
Young Scientists Summer Program

The case for incorporating soil nutrient availability into large-scale forest management models

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Abstract

The availability of nutrients exerts major control on ecosystem structure, functioning and responses to global change. Process-based ecosystem models therefore increasingly incorporate nutrient cycles, but forest and other ecosystem modules in integrated assessment models, used to advise policy making based on trade-offs and feedbacks within and among economy, agriculture, forestry etc., nutrient availability is usually poorly accounted for. Here, we explored whether in a statistical random forest model predicting site productivity, replacing soil type by key soil properties (organic layer C:N ratio, upper soil organic carbon concentration (SOC), organic layer pH) would improve predictions across Swedish and European forests. We found substantial variation in the key soil properties and a nutrient availability metric (which à priori integrated the same soil properties), both among and within soil types. Because of the within-soil type variation in nutrient availability, both random forest models using soil properties and these using the nutrient availability metric predicted significantly better forest site productivity than the soil type-fed models across Sweden and Europe. We recommend the inclusion of often available, resource-use related soil properties such as C:N, SOC and pH into random forests that feed into integrated assessment models. Substituting individual soil properties by an à priori defined nutrient availability metric can reduce overfitting in statistical random forest models.

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Introduction

The availability of nutrients exerts strong control on the structure and functioning of forests and other terrestrial ecosystems. Increasing nutrient availability not only positively influences biomass production (Bergh *et al.*, 1999; 2005), but also promotes aboveground carbon allocation (Ågren & Franklin, 2003), can suppress soil respiration (Janssens *et al.*, 2002 - but see Zhou *et al.*, 2014), enhances the dominance of competitive species at the expense of stress-tolerant species in diverse communities (Hautier *et al.*, 2009), and it has an overall unimodal effect on biodiversity (Fraser *et al.*, 2015). Because of its influences on the C and other biogeochemical cycles, as well as on biodiversity, nutrient availability is also recognized as a key modifier of ecosystem responses to global change. For instance, ample availability of nutrients reinforces the CO_2 fertilization effect (Terrer *et al.*, 2019), but can increase ecosystem sensitivity to droughts (Van Sundert *et al.*, 2021).

Progressively more ecosystem models account for nutrient availability. In predominantly process-based models, such as land surface models (LSMs) used for i.e., climate change projections, the nitrogen (N) (Lawrence *et al.*, 2019) and occasionally also phosphorus (P) cycles (Fleischer *et al.*, 2020; Sun *et al.*, 2021) are increasingly explicitly included (but see Canadell *et al.*, 2021: about half of CMIP6 LSMs still are C-only models). Nutrient pools in biota and soil are calculated per time step as a function of in- and output processes, analogous to the fashion in which the C cycle is represented (Thomas *et al.*, 2015). An advantage of such approach is that it allows for addressing interactions among biogeochemical cycles that feed back to the overall functioning of ecosystems over time. However, each additional incorporated nutrient substantially raises model complexity since nutrient pools are determined by an extensive number of processes that are often not fully understood and have not sufficiently been measured in the field (Vicca *et al.*, 2018).

Integrated assessment models combine modules originating from various disciplines (e.g. economics, forestry, energy science, agronomy, ...) to investigate trade-offs and feedbacks among landscape-scale processes and policy decisions. For example, bio-energy can be used as a means to substitute fossil fuels, but large-scale deployment can reduce regional land C sinks (Böttcher *et al.*, 2012) and come into competition with crop production (Smith *et al.*, 2019), depending on additional policy decisions such as regulations, carbon pricing, etc. (Kindermann *et al.*, 2006). In integrated assessment modeling, fully process-based forest models are rarely used because of their high computational demands. Instead, simpler large-scale forest models are used which do not explicitly address nutrient limitation of net primary productivity in forest ecosystems. Instead, some indirectly account for nutrients' influence on forest functioning by including soil type as one of the environmental and forest features influencing site productivity (e.g. Kindermann, 2018). While nutrient availability indeed differs among soil types (e.g. sandy podzols are generally nutrient poorer than fine textured, young cambisols - IUSS Working Group WRB, 2015), the possibility exists that accounting for within-soil type variation in nutrient availability-relevant soil properties (e.g. C:N ratio, soil organic carbon concentration (SOC), pH – Van Sundert *et al.*, 2020) may significantly improve estimates of site productivity, without inflating model complexity.

Here, we investigated whether the inclusion of widely available soil properties into random forest models improves forest site productivity estimates across Swedish and European forests, compared to using soil type only (along with climate, species and stand age). We also compare an approach combining individual soil properties indicative of the nutrient status (organic layer C:N, 0-20 cm SOC, organic layer pH) in the random forest models, vs à priori integrating the same soil properties in a nutrient availability metric developed by Van Sundert *et al.* (2018; 2020), updated from an earlier agriculture-focused metric of IIASA & FAO (2012). Finally, we examined the performance of these bottom-up random forest models based on environmental features (incl. soil) vs alternative site productivity estimates based on remote sensing-derived height assessments for Swedish forests.

Methods

Data sources

Data from Swedish and European forest and soil inventories were used to calibrate and evaluate random forest models predicting site productivity. The Swedish dataset comprised spruce (n = 2219) and pine (n = 1869) forest productivity data (mean annual volume increment) from the Swedish National Forest Inventory (Lundin, 2011), soil property data on the same locations from the Swedish Forest Soil Inventory (Olsson, 1999; Lundin, 2011) and mean annual precipitation data derived from EC–JRC– MARS (http://spirits.jrc.ec.europa.eu/). The growing season temperature sum (TSUM) was calculated based on site coordinates and elevation, following an empirical equation by Odin *et al.* (1983), updated to the current climate, available at https://www.skogskunskap.se/. More details on the Swedish dataset were described in Van Sundert *et al.* (2018). European data from spruce-, pine-, beech- and oak-dominated forests (five-year averaged productivity, soil properties, climate, age) were available from the ICP Forests dataset, see also Van Sundert *et al.* (2020).

Exploring soil property variation among and within soil types

We used the R software (R Core Team, 2019) for all analyses. First, soil properties (organic layer C:N ratio, 0-20 cm SOC, organic layer pH) and the nutrient availability metric were plotted by soil type (package ggplot 2 – Wickham, 2016) to visualize variation in nutrient availability-related variables within and among soil types. Differences in soil properties and nutrient availability were then compared through ANOVAs and Tukey's post-hoc test. Positively skewed variables were log-transformed to reach the assumption of normality.

Random forest model estimates, evaluation and comparison with an alternative

Statistical random forests can be used to empirically predict site productivity based on environmental and stand-specific features, such as climate, soil type or nutrient status, and dominant species (Breiman, 2001). The resulting site productivity index can then feed into a forest module of an integrated assessment model, where it co-influences forest functioning along with dynamic processes (e.g. wood harvesting). The random forests method consists of building a set of decision trees, each trained on a random subset of the given dataset. Interactions among covariates and non-linear relationships are taken into account (Stekhoven & Buhlmann, 2012).

We used random forest outputs (R packages caret – Kuhn, 2021, randomForest – Liaw & Wiener, 2002, and randomForestSRC – Ishwaran & Kogalur, 2007; 2021; Ishwaran *et al.*, 2008) to assess variable importance (out-of-bag MSE), and predict forest site productivity in training and validation datasets. A random subset of 75% of the Swedish and European datasets was used for training vs 25% for validation. In the Swedish dataset, calibration was done based on southern sites only (TSUM > 1200°C days), with most variation in site conditions, because of heteroscedasticity in the dataset for the entire country: in the north, where productivity was low, also the variance was low in absolute terms, in contrast to southern sites. Evaluations were then performed for both the southern Swedish validation dataset only, as well as the entire dataset for Sweden, taking à priori into account that potential biases may occur in predictions of northern sites outside of the training range.

Model performance was expressed as R^2, i.e. the quadrat of the correlation coefficient between observation and prediction. Model performances were compared among models with alternative explanatory variables (soil type vs soil properties vs nutrient availability metric) and, in Sweden, against an alternative method estimating site productivity per 1x1 km pixel based on LiDAR height measurements vs. stand age and height-development curves (Franklin *et al.*, 2020).

Results and Discussion

Soil property variation within and among soil types

In both the Swedish and European forest datasets, significant differences emerged in average soil property values between different soil types, such that organic soil C:N ratio was minimal for Cambisols and Umbrisols, and greatest for Podzols (Figs. 1a and S1a; pine Sweden - $F_{7,1848}$ = 28.00, P < 0.001; spruce Sweden – $F_{7,2203}$ = 78.59, P < 0.001; Europe – $F_{5,90}$ = 3.51, P = 0.006), thus indicating high and low N availability, respectively (Thomas *et al.*, 2015). Cambisols and Podzols also exhibited significant contrast in organic soil pH (Figs. 1c and S1c) across both datasets (pine Sweden - $F_{7,1848}$ = 55.65, P < 0.001; spruce Sweden – $F_{7,2203}$ = 70.82, P < 0.001; Europe – $F_{5,90}$ = 13.79, P < 0.001). Organic Histosols, present in the Swedish but absent in the European dataset, evidently showed the maximum SOC (Fig. 1b; pine Sweden - $F_{7,1848}$ = 199.83, P < 0.001; spruce Sweden – $F_{7,2203}$ = 179.12, P < 0.001).

Also within soil types, substantial variation in key soil properties occurred, to such extent that multiple soil types showed overlap in C:N ratio (Figs. 1a and S1a), SOC (Fig. 1b and S1b) and pH (Fig. 1c and S1c), and consequently also in the nutrient availability metric. This overlap in soil properties among soil types may indicate that analyses and also models addressing nutrient availability in more detail than soil type may allow more thorough investigation of ecosystems processes with regard to the nutrient status, and potentially use the identified relationships to make more accurate and precise predictions of site productivity.

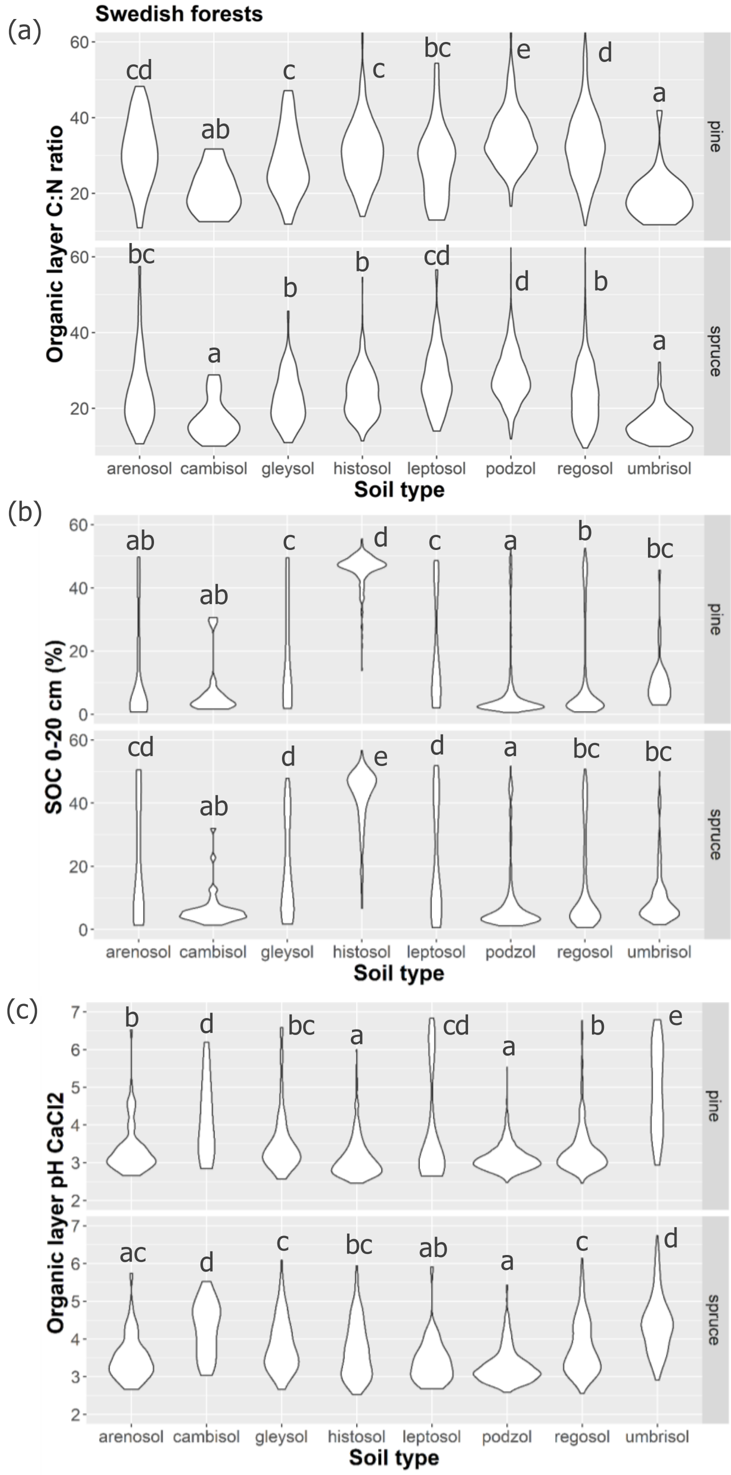

Figure 1 | Soil properties by soil type in Swedish pine and spruce dominated forests. Letters indicate significantly different groups (α = 0.05).

Predicting site productivity: soil type vs soil properties vs nutrient metric

Soil type is commonly used in forest modules of integrated assessment models (e.g. Kindermann, 2018). In forest models used by IIASA (e.g. global forest model G4M), soil type is one of the variables often feeding into a random forest model, based on which site productivity is estimated per pixel. In order to explore whether random forest model performance would improve when replacing soil type by soil properties, and whether reasons exist to à priori integrate soil properties into a nutrient availability metric, random forests were calibrated and compared.

Results indicated that random forest predictions based on soil type performed worse at estimating measured productivity in Swedish and European forests compared to models using soil properties, individually or integrated in a nutrient availability metric (Tables 1-3, Fig. 2). Moreover, assessments of variable importance through MSE showed that in the European soil type model, climate, age and species were more important predictors than soil, whereas in the European soil property/metric models, soil nutrient availability was more important than climate and forest stand features. Taken together, the enhanced predictive power of the random forest models including soil properties as well as the increased relevance of soil nutrient limitation in these models strongly suggest that if the necessary soil property data are available (which is at least for some or for all here discussed soil properties the case for various spatial scales, e.g. global - FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012, Europe - Ballabio *et al.*, 2019, Sweden - Olsson, 1999; Lundin, 2011), large-scale forest management models would benefit from incorporating nutrient availability-relevant soil variables such as C:N ratio, SOC and pH, either individually or as components of a calculated nutrient availability metric.

Table 1 | Soil type based random forest model performance (squared correlation coefficient R^2 - range based on three times running the code) to predict spruce and pine forest mean annual increment (MAI) in Sweden and spruce, pine, beech and oak current annual increment (CAI) in Europe (m^3 ha^{-1} yr^{-1}). Predictors were soil type, growing season temperature sum, mean annual precipitation and species in the Swedish dataset, and soil type, mean annual temperature, mean annual precipitation, species and stand age in the European dataset.

Training dataset	R^2 training dataset	R^2 South Sweden (validation)	R^2 Entire Sweden	R^2 Europe (validation)
South Sweden	0.76 – 0.78	0.70 – 0.75	0.54 – 0.55	-
Europe	0.86	-	-	75% training dataset: 0.19 – 0.71 50% training dataset: 0.35 – 0.47

Table 2 | Nutrient availability metric based random forest model performance (squared correlation coefficient R^2 - range based on three times running the code) to predict spruce and pine forest mean annual increment (MAI) in Sweden and spruce, pine, beech and oak current annual increment (CAI) in Europe (m^3 ha^{-1} yr^{-1}). Predictors were the nutrient availability metric, growing season temperature sum, mean annual precipitation and species in the Swedish dataset, and the nutrient availability metric, mean annual temperature, mean annual precipitation, species and stand age in the European dataset.

Training dataset	R^2 training dataset	R^2 South Sweden (validation)	R^2 Entire Sweden	R^2 Europe (validation)
South Sweden	0.80 – 0.81	0.71 – 0.75	0.57 – 0.58	-
Europe	0.88 – 0.89	-	-	75% training dataset: 0.40 – 0.81 50% training dataset: 0.47 – 0.69

Table 3 | Soil properties based random forest model performance (squared correlation coefficient R^2 - range based on three times running the code) to predict spruce and pine forest mean annual increment (MAI) in Sweden and spruce, pine, beech and oak current annual increment (CAI) in Europe (m^3 ha^{-1} yr^{-1}). Predictors were soil properties, growing season temperature sum, mean annual precipitation and species in the Swedish dataset, and soil properties, mean annual temperature, mean annual precipitation, species and stand age in the European dataset.

Training dataset	R^2 training dataset	R^2 South Sweden (validation)	R^2 Entire Sweden	R^2 Europe (validation)
South Sweden	0.95	0.74 – 0.77	0.72	-
Europe	0.93	-	-	75% training dataset: 0.38 – 0.85 50% training dataset: 0.26 – 0.53

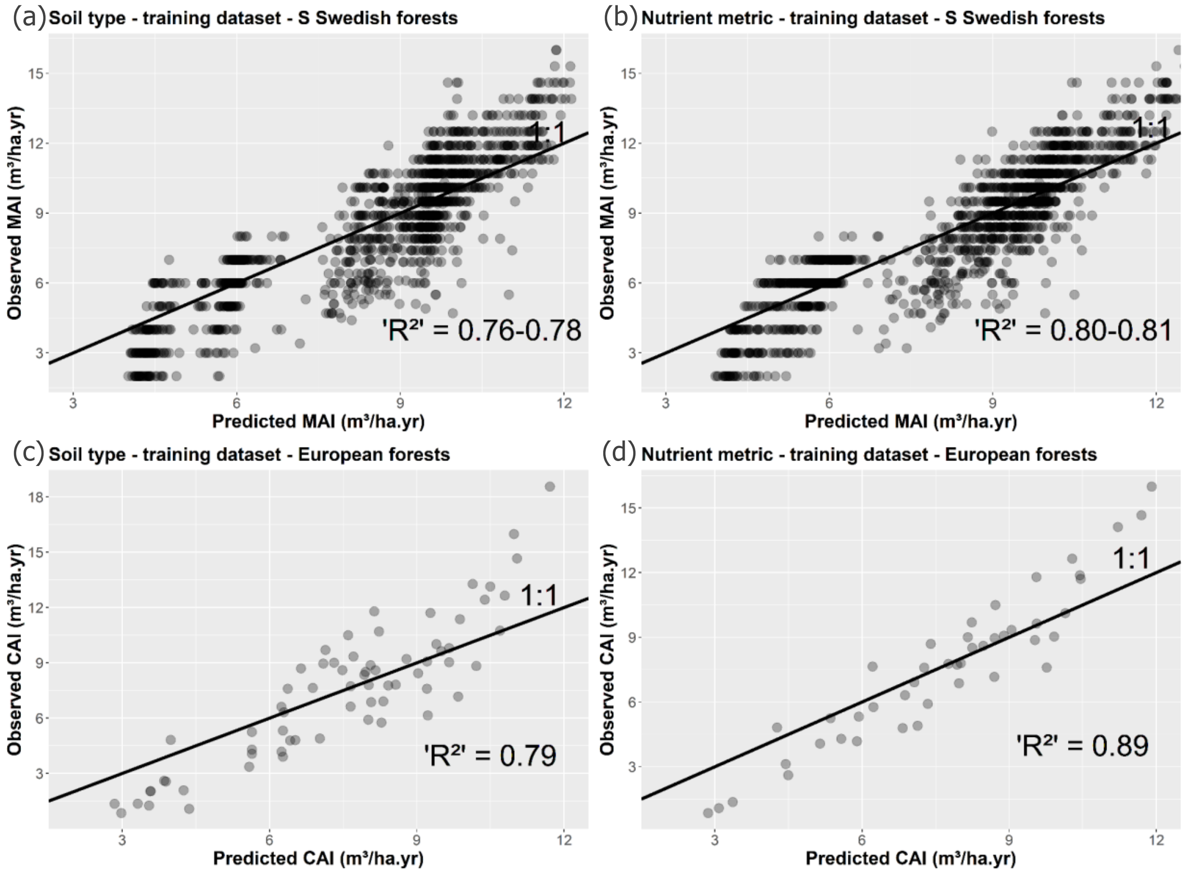

Figure 2 | Soil type vs nutrient availability metric based random forest model performance (squared correlation coefficient *R^2* - range based on three times running the code) in the training datasets. Response variables were spruce and pine forest mean annual increment (MAI) in Sweden and spruce, pine, beech and oak current annual increment (CAI) in Europe (m^3 ha^{-1} yr^{-1}). Predictors were soil type vs the nutrient availability metric, growing season temperature sum, mean annual precipitation and species in the Swedish dataset, and soil type vs the nutrient availability metric, mean annual temperature, mean annual precipitation, species and stand age in the European dataset.

Compared to using a nutrient availability metric, random forest models trained on individual soil properties performed better against their training dataset (Tables 2 vs 3). However, when site productivity of new data points (i.e. a validation dataset) was predicted, individual soil property models became less reliable: in the European forest dataset, predictions using individual soil properties underperformed predictions based on the nutrient availability metric (Tables 2 vs 3, Fig. 3). Such result aligns with the fact that a random forest model not using a pre-defined nutrient metric has more freedom to combine the three soil properties, such that predictions will fit the training data better. This, however, increases the probability of overfitting: optimal mathematical combinations from a training dataset may partly reflect coincidence, rather than actual among-predictor interactions and eventual influences on forest productivity. In this context, the nutrient availability metric, which was developed based on forest data as well as theoretical considerations (IIASA & FAO, 2012; Van Sundert *et al.*, 2018; 2020), can act as a more reliable alternative applicable to temperate and boreal forests that reduces overfitting.

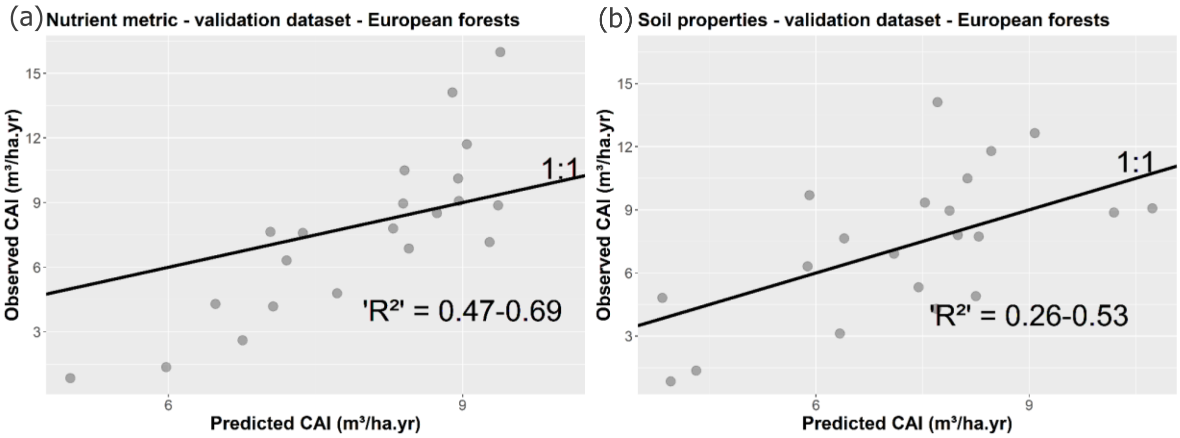

Figure 3 | Nutrient availability metric vs soil property based random forest model performance (squared correlation coefficient R^2 - range based on three times running the code) in the European validation dataset. The response variable was spruce, pine, beech and oak current annual increment (CAI - m^3 ha^{-1} yr^{-1}). Predictors were the nutrient availability metric vs soil properties, mean annual temperature, mean annual precipitation, species and stand age.

Predicting site productivity: random forest vs alternatives

For certain integrated assessment model applications, it can be assumed that the average environment remains stable and is unlikely to influence further model processes and outcomes. In such cases, explicitly incorporating soil type, nutrient availability or even climate may not be necessary if alternatives exist to estimate inter-annual averaged site productivity for each pixel in the study region of interest. Franklin *et al.* (2020), for example, conducted a model-based study on trade-offs between moose populations in Sweden and the choice between planting of spruce vs pine. Site productivity (mean annual volume increment) for spruce and pine across Sweden was estimated in this study by combining LiDAR-based height estimates (www.skogsstyrelsen.se/nyhetslista/nu-ska-sveriges-skogar-laserskannas/) with ground-based stand age measurements, and applying height development curves (e.g. Ekö *et al.*, 2008; Mensah *et al.*, 2021) in each pixel with a 1x1 km dimension.

Contrasting performance of the nutrient metric random forest model against the LiDAR remote sensing estimates ("IIASA estimates") for validation data points indicated that the bottom-up approach using the metric and other environmental variables resulted in the most accurate productivity estimates in southern Sweden (Fig. 4a vs 4b). We therefore suggest that even in studies where soil and climate (change) are not of primary interest, explicitly including such environmental features can substantially improve predictions of other (response) variables, such as site productivity. Both better expressions of nutrient availability and remote sensing products should further enhance future predictions of forest productivity and other ecosystem processes.

When considering entire Sweden (i.e. not only the southern region), the IIASA-estimates performed better than bottom-up random forest approaches using the nutrient availability metric, soil properties or soil type. Random forest predictions particularly overestimated site productivity in low-productive sites (Fig. 4c vs 4d). This pattern can be explained by the heteroscedastic nature of the Swedish dataset: variance increased along with the mean, i.e. the reason why the Swedish data were split into regions à priori to avoid violating assumptions of random forest modeling. For future research, we suggest addressing heteroscedasticity by adding a parameter that modifies the variance as a function of the mean (Carrol & Ruppert, 1988). Considering the results from southern Sweden, it is likely that such heteroscedasticity-corrected random forest model would perform better than the IIASA-estimates.

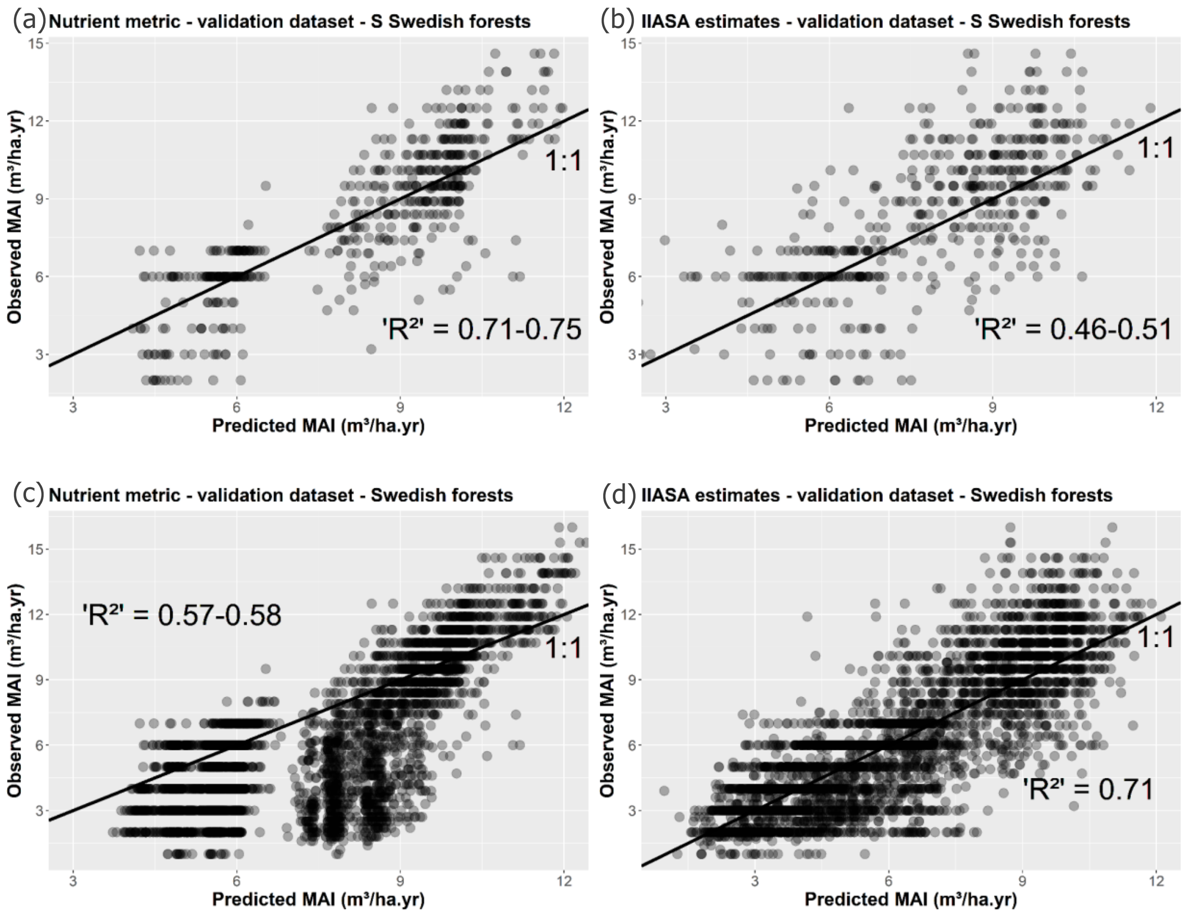

Figure 4 | Nutrient availability metric based random forest model performance vs performance of alternative estimation by IIASA (squared correlation coefficient R^2 - range based on three times running the code) based on LiDAR-derived tree height estimates across Sweden, height-development curves and conversion to volume. Response variables were spruce and pine forest mean annual increment (MAI - m^3 ha^{-1} yr^{-1}). Predictors of the random forest model were the nutrient availability metric, growing season temperature sum, mean annual precipitation and species.

Conclusion and recommendations

In the present study, we made the case for incorporating nutrient availability more explicitly into forest modules of integrated assessment models. Such explicit accounting for nutrients is possible by including soil properties indicative of the nutrient status, such as soil C:N ratio, SOC and pH, which depend substantially less on species than for example leaf stoichiometry despite plant-soil feedbacks (Van Sundert *et al.*, 2021). Statistical random forest models can estimate site productivity per pixel based on forest and environmental features including these soil properties, either each one individually or à priori integrated through a nutrient availability metric that avoids overfitting. The metric used here applies particularly to temperate and boreal forests. Further improvements to the metric, e.g. by more explicitly incorporating P availability (through C:P ratio, ... – Achat *et al.*, 2012) could expand the regional scale of application. A better representation of nutrient availability in integrated assessment models should improve model estimates of forest productivity and C storage, thus allowing to (i) compare model outputs with in-situ observations and experimental metaanalyses; and to (ii) address relationships of nutrient availability with predictions of forest productivity under projected climate change scenarios.

Regional (Olsson, 1999; Lundin, 2011), continental (Ballabio *et al.*, 2019) and global scale soil maps and datasets (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012) are available that allow including soil nutrient availability in predictions of ecosystem site productivity. Some of these maps and datasets explicitly present soil properties, but a common barrier to the usefulness of these data is the regular lack of separation of organic vs mineral soil layer properties, and reporting of thicknesses where such organic layer is present. Therefore, we recommend separate sampling, measuring and presenting of organic vs mineral soil layers and their properties for proposed soil inventories and future map development.

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Supplement

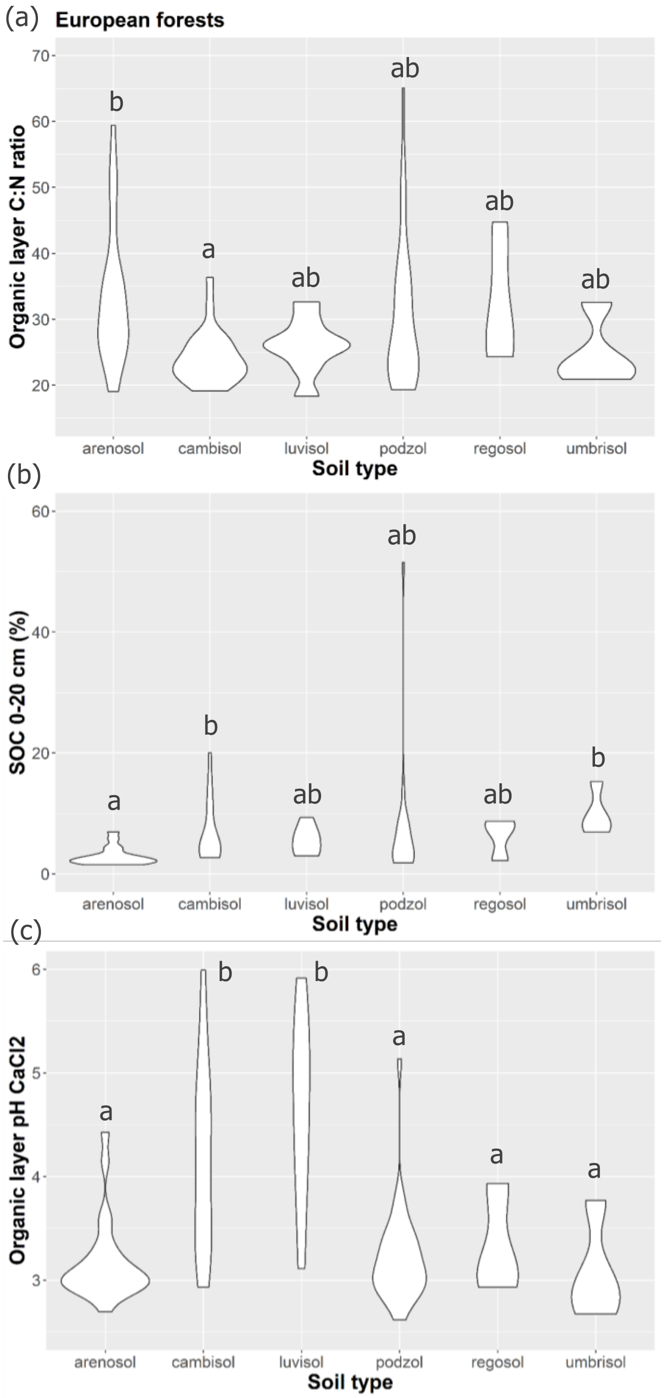

Figure S1 | Soil properties by soil type in European forests. Letters indicate significantly different groups (α = 0.05).