

# Improved prediction of soil organic carbon sequestration potentials in Austrian arable soils as simulated by multi-model ensembles

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## Introduction and framework

Modeling is a useful approach to estimating SOC stocks and their dynamics for large areas, where sampling is not possible or economically viable, such as future climate and management scenarios, as well as large areas. SOC models differ in their complexity, assumptions and performance which makes the selection of an appropriate model more difficult. Large differences in SOC predictions and their direction are associated with SOC model and allometric function choice (Keel et al., 2017; Riggers et al., 2019). In a recent publication, the use of multi-model ensembles as used in other scientific domains was successfully applied by Riggers et al. (2019) based on permanent agricultural monitoring sites in Germany. In this work we performed a similar analysis, combining four SOC models and five allometric equations to determine the optimal SOC model ensemble for more precise, future regional modelling studies based on published long term experimental data.

## Materials & Methods

We evaluated 20 possible model combinations on 53 treatments of 7 LTEs (Fig. 1), primarily in the main agricultural regions of Austria based on average mean error (AME), mean error (ME) and root mean square error (RMSE) of the linear SOC trends to reduce the influence of differing experimental durations.

The four selected SOC models are multi compartment, process-based models described extensively in their own publications and in Riggers et al. (2019). The initialization procedures were applied as described in the former publication to minimize differences. Allometric functions estimate C inputs as a function of generally available parameters, such as yield but are calibrated against different datasets or based on different assumptions, such as the consideration of root exudates.  
**Selected models:**  
 • Rothamsted Carbon Turnover Model (RothC) (Coleman et al., 1997)  
 • Yasso07 (Tuomi et al., 2009)  
 • Introductory Carbon Balance Model 2 (ICBM2) (Kätterer und Andrén, 2001; Poeplau et al., 2015)  
 • C-Tool (Taghizadeh-Toosi et al., 2014)

**Selected allometric equations:** Bolinder, BZE, IPCC, CCB, C-Tool (cited in Riggers et al., 2019)

The multi-model ensemble was selected by reducing the full ensemble by one component, calculating RMSE and AME and removing the one that improved the ensemble iteratively until no improvement could be achieved. Implementation of SOC models, allometric functions, data analysis and visualization was performed with R (R Core Team, 2023) with „sorcing“ and „ggpubr“.

## Sites & Treatments

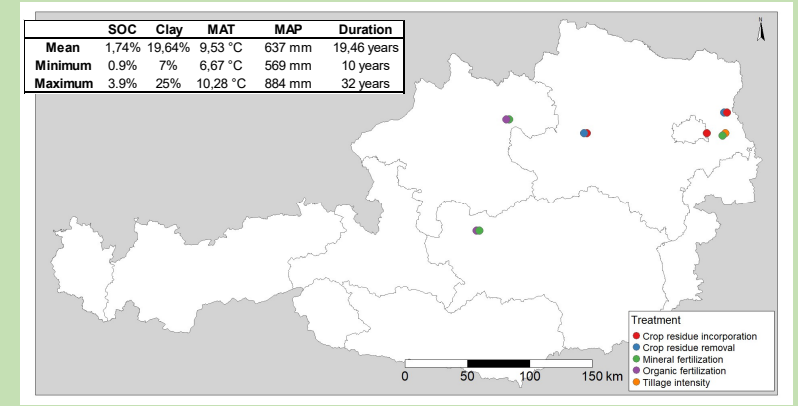


Figure 1: Long-term experimental sites used for validation. The horizontally overlapping points indicate the same site but different treatments for enhanced visualization.

## Results & Discussion

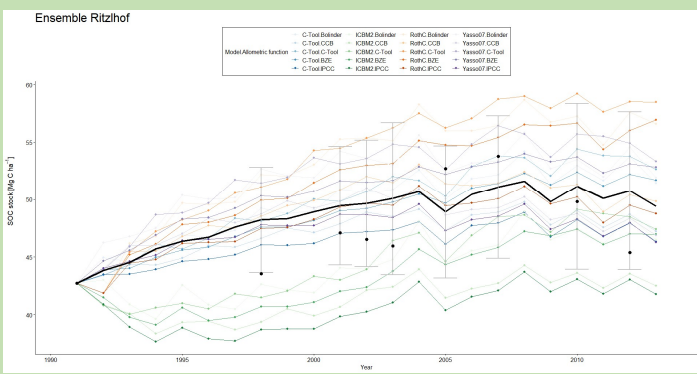


Figure 4: Mean SOC stock dynamics from 1992-2012 of the organic amendment long term experiment at Ritzhof (n treatments = 12) as predicted by the 20 model combinations. The bold, dark line displays the SOC dynamics as predicted by the selected multi-model ensemble. Gray whiskers indicate the confidence interval of the modeled time series at the time of measurement. The dark, bold points display the mean measured SOC value reported in the publication.

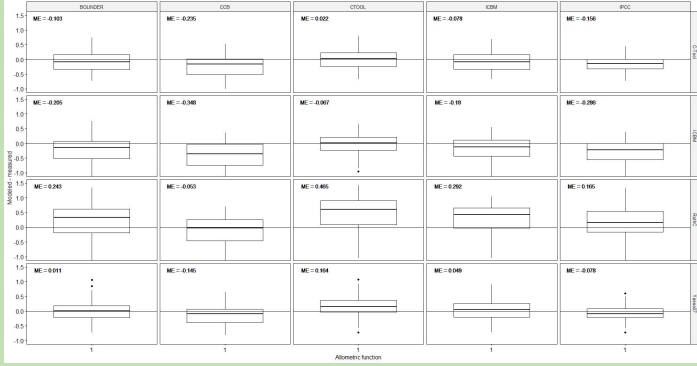


Figure 3: Mean errors by allometric function (left to right) and SOC model (top to bottom). The horizontal line indicates a perfect overlap between modeled and measured values (Model error = 0).

- Mean C inputs estimated by allometric functions ranged from 1.82 Mg C ha<sup>-1</sup> (IPCC) to 3.70 Mg C ha<sup>-1</sup> (C-Tool).
- A one-way ANOVA revealed the means to differ significantly (p < 0.001). Post-hoc LSD test revealed that all means differed between allometric functions, except between BZE and Bolinder (Fig. 2).
- Contrary to the findings in Riggers et al. (2019), a majority (60 %) of ensemble members slightly underestimated SOC trends (Fig. 3), which can be attributed to lower carbon inputs estimated in this study.

Table 1. Summary of model evaluation parameters.

Parameter	Range	Lowest	Highest
ME	-0.348 Mg C ha <sup>-1</sup> yr <sup>-1</sup>	ICBM_CCB	RothC_C-Tool
	0.465 Mg C ha <sup>-1</sup> yr <sup>-1</sup>		
AME	0.212 Mg C ha <sup>-1</sup> yr <sup>-1</sup>	Yasso07_IPCC	RothC_Ctool
	0.591 Mg C ha <sup>-1</sup> yr <sup>-1</sup>		
RMSE	0.229 Mg C ha <sup>-1</sup> yr <sup>-1</sup>	Yasso07_IPCC	RothC_Ctool
	0.661 Mg C ha <sup>-1</sup> yr <sup>-1</sup>		

- A two-way ANOVA showed model errors to be significantly dependent on both model and allometric function choice (p < 0.001). The **effect size** of model error was **larger for model choice** than for allometric function, with Eta<sup>2</sup> of 0.13 and 0.07, respectively.
- The total model ensemble (n = 20) had an AME of 0.264 Mg C ha<sup>-1</sup> yr<sup>-1</sup>, and an RMSE of 0.317 Mg C ha<sup>-1</sup> yr<sup>-1</sup>, **outperforming 85% and 90% of the single model combinations**, respectively (Fig. 4). The iterative selection process yielded a final ensemble of four members, with an AME of 0.167 and RMSE of 0.250, which represent a decrease of 36,7% and 21,1%, respectively.
- The results confirm the usefulness of MME for modelling SOC dynamics and underline the way forward presented by Riggers et al. (2019).

## Conclusions

- Large uncertainties associated with model choice. SOC model choice had a larger effect compared to allometric function selection
- Significant improvements in terms of AME and RMSE can be achieved by the use of multi-model ensembles for SOC sequestration potential modeling
- Multi-model ensembles could potentially substitute the lengthy, cumbersome and region-specific procedure of calibrating single models for modelling carbon sequestration potentials

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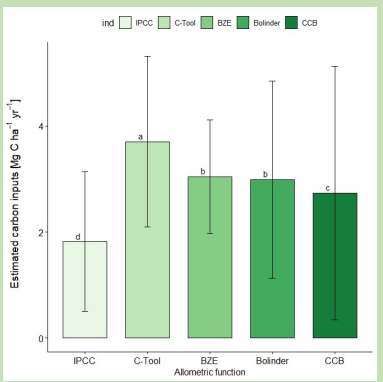


Figure 2: Mean aboveground and belowground (0-25 cm) carbon inputs estimated by five allometric functions for all sites and crop types. Error bars indicate standard deviations. Different letters indicate significant differences (p < 0.05) as evaluated by LSD post-hoc test.

