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Modelling soil carbon development in Swedish coniferous forest soils—An uncertainty analysis of parameters and model estimates using the GLUE method

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ABSTRACT

Boreal forest soils such as those in Sweden contain a large active carbon stock. Hence, a relatively small change in this stock can have a major impact on the Swedish national CO_2 balance. Understanding of the uncertainties in the estimations of soil carbon pools is critical for accurately assessing changes in carbon stocks in the national reports to UNFCCC and the Kyoto Protocol. Our objective was to analyse the parameter uncertainties of simulated estimates of the soil organic carbon (SOC) development between 1994 and 2002 in Swedish coniferous forests with the Q model. Both the sensitivity of model parameters and the uncertainties in simulations were assessed. Data of forests with Norway spruce, Scots pine and Lodgepole pine, from the Swedish Forest Soil Inventory (SFSI) were used. Data of 12 Swedish counties were used to calibrate parameter settings; and data from another 11 counties to validate. The "limits of acceptability" within GLUE were set at the 95% confidence interval for the annual, mean measured SOC at county scale. The calibration procedure reduced the parameter uncertainties and reshaped the distributions of the parameters county-specific. The average measured and simulated SOC amounts varied from 60 t C ha^{-1} in northern to 140 t C ha^{-1} in the southern Sweden. The calibrated model simulated the soil carbon pool within the limits of acceptability for all calibration counties except for one county during one year. The efficiency of the calibrated model varied strongly; for five out of 12 counties the model estimates agreed well with measurements, for two counties agreement was moderate and for five counties the agreement was poor. The lack of agreement can be explained with the high inter-annual variability of the down-scaled measured SOC estimates and changes in forest areas over time. We conclude that, although we succeed in reducing the uncertainty in the model estimates, calibrating of a regional scale process-oriented model using a national scale dataset is a sensitive balance between introducing and reducing uncertainties. Parameter distributions showed to be scale sensitive and county specific. Further analysis of uncertainties in the methods used for reporting SOC changes to the UNFCCC and Kyoto protocol is recommended.

1. Introduction

Forest soils in temperate and boreal climates contain large quantities of soil organic carbon (SOC) and boreal and temperate forests have been pointed out as important carbon sinks in the global carbon balance (Raich and Schlesinger, 1992; Goodale et al., 2002). Forest soils in Sweden represent a carbon pool of 2200 Tg C with an average carbon content of 82 t C ha^{-1} and a total area of 27 M ha that fulfils the FAO definition of forest land (Olsson et al., 2009). Sweden reports changes in dead organic matter (DOM) and SOC with data from the repeated Swedish Forest Soil Inventory (SFSI) to the United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol (UNFCCC, 1992, 1997; SEPA, 2009). As the total soil carbon pool is approximately two orders of magnitude larger than Swedish annual emissions, relatively small changes induced by climatic and/or management changes have the potential to affect the national greenhouse gas balance. If the expected changes are small a large inventory sample size is required to detect significant changes (Peltoniemi et al., 2004; SEPA, 2009). Vertical and horizontal spatial variability in soil horizons, C concentration and bulk density give rise to uncertainties in the estimates of SOC stocks and changes (Ellert et al., 2001; Wilding et al., 2001). There is a need for assessing uncertainties in the estimations of soil carbon development in Swedish forest soils in order to determine the level of certainty of the reported values and to verify the estimated changes by independent methods.

Process-based modelling offers an alternative way of estimating the SOC development in forest soils. However, model simulations are also associated with uncertainties and it is important that these uncertainties are communicated so that policy makers are aware

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of the degree of uncertainty of the information (Walker et al., 2003). A model assessment should include all three aspects of sensitivity analysis, calibration, and validation to test whether the model is suitable for its intended use (Rykiel, 1996) and whether the results are consistent with observational data (Oreskes et al., 1994). Peltoniemi et al. (2007) reviewed six widely applied carbon models and concluded that uncertainty analyses of models and model results are rarely applied in forest soil carbon modelling. One calibration and uncertainty estimation methodology is the Generalized Likelihood Uncertainty Estimation (GLUE) (Beven and Binley, 1992). It has been tested and successfully applied in many disciplines analysing uncertainty in models (Schulz et al., 1999; Cameron et al., 1999; Martinez-Vilalta et al., 2002; Larsbo et al., 2005; Beven, 2006; Mitchell et al., 2009; Piñol et al., 2009; Juston et al., 2009). Juston et al. (2010) made a GLUE application in soil organic carbon modelling of a long-term agricultural experiment. GLUE is based on the "equifinality" concept, meaning different inputs and parameterizations lead to equally good and acceptable performances of a model due to the interactions of different parameters: this rejects the idea of one "optimum" model parameterization. The GLUE method describes the model output uncertainties relative to measured observations. The core of the GLUE method is that once a likelihood measure (a measure of performance of the model) has been decided, a range of acceptable models (a specific model structure with specific input and parameterization) can be determined. In order to take into account uncertainty in observations in the analysis of model uncertainty, the "limit of acceptability" approach has been developed within the GLUE methodology (Beven, 2006). The accepted simulations are retained to determine the uncertainty bounds of the model outputs and the posterior parameter distributions (Smith et al., 2008).

In this study, the process-oriented Q model (Rolff and Ågren, 1999) was used, because it has previously been applied in soil carbon modelling of forest ecosystems at a national scale in Sweden (Ågren and Hyvönen, 2003; Ågren et al., 2007). A sensitivity analysis of the Q model by Hyvönen et al. (1998) determined an optimum parameter set through varying individual parameters "one-at-a-time", a so-called local analysis. However, this approach neglects possible parameter interactions and might have discarded different parameter combinations that result in good model performance. We choose to use the GLUE method because it includes uncertainty in model structure and parameters simultaneously in a transparent way. Moreover, in combination with Monte Carlo simulations, the uncertainty of all parameters can be assessed simultaneously, a so-called global assessment, which guarantees that all possible parameter interactions and parameter combinations are taken into account. One disadvantage of the GLUE method is that it is not possible to generate true confidence limits since the uncertainty analysis is made on accepted simulations with a subjective criterion.

The aim of this study was to assess the effects of parameter uncertainties on the estimates of soil carbon stocks in Swedish coniferous forests with data from SFSI and the Q model. Data from coniferous forest stands either dominated by Scots pine (*Pinus sylvestris*) and Lodgepole pine (*Pinus contorta*) or by Norway spruce (*Picea abies*) were used. The Q model was calibrated with data of 12 counties using the GLUE technique. The 95% confidence intervals of the measurements were used as limits of acceptance. The performance of the model was assessed by validating the model on 11 other counties (Fig. 1). Standard statistical measures such as, root mean squared error (RMSE) and model efficiency (ME), were used for analysing the model performance for both accepted calibrated and validated estimates. Finally, the usefulness of model estimates relative to estimates from measurement was discussed.

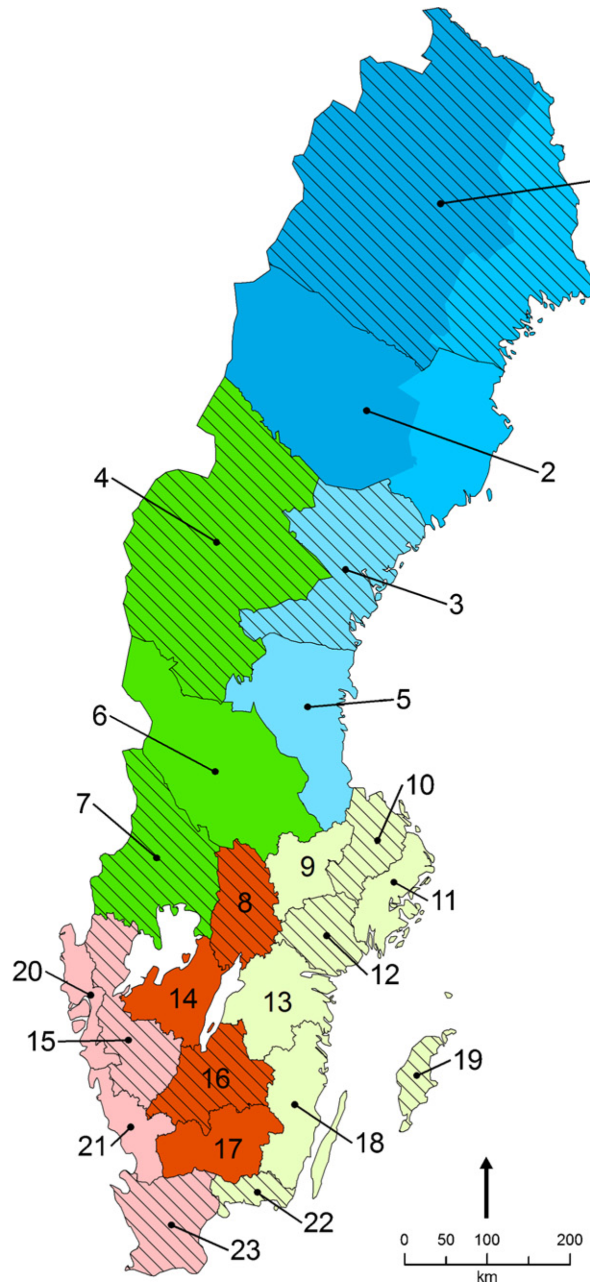

Fig. 1. Division of Sweden into climatic regions and counties for calibration and validation. The lined marked counties were included in the calibration and the remainder in the validation. The division into climatic regions is represented by different colours of the counties. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of the article.)

2. Materials and methods

2.1. The model

The carbon amounts in Swedish forest soils during the period 1994–2002 were estimated with the process-oriented dynamic decomposition model Q (Rolff and Ågren, 1999; Hyvönen and Ågren, 2001; Ågren et al., 2007). This version of the model calculates decomposition of three different litter fractions with specific decomposition rates with the litter fractions being characterized by their initial qualities. When litter decomposes, carbon is mineralised and the mineralisation rate decreases when the quality of the litter fraction decreases. The decomposition rate changes between