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The simple AMG model accurately simulates organic carbon storage in soils after repeated application of exogenous organic matter

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Abstract

Repeated application of exogenous organic matter (EOM) contributes to soil organic carbon (SOC) stocks in cropped soils. Simple and robust models such as the AMG model are useful tools for predicting the effects of various EOM practices on SOC. In AMG, EOM is characterized by a single parameter: the isohumic coefficient K_1, which represents the proportion of carbon that is humified and incorporated into SOC. The AMG model has been validated under various pedoclimatic conditions and cropping systems, but has not yet been tested with data from long-term field experiments where EOM is regularly applied. The calibration of the EOM parameter K_1 also remains an issue. In this study, AMG was used to simulate SOC stocks in seven long-term field experiments with EOM application. AMG simulated changes in SOC stocks with a mean *RMSE* of 3.0 t C ha^{-1} (the difference in SOC stocks between treatments with and without EOM). The optimized K_1 values were highly correlated (R^2=0.62) with the indicator of remaining organic carbon (I_{ROC}), which is measured by laboratory analysis. The present study (i) demonstrated the ability of the AMG model to accurately simulate changes in SOC stocks in long-term field experiments with regular EOM application and (ii) validated the parameterization of EOM in AMG using I_{ROC}, which is routinely measured by commercial laboratories. Twenty-six different EOM types representing a wide range of EOM sources were parameterized using more than 600 I_{ROC} values. The AMG model could thus be used to predict the SOC increase following EOM addition with a very simple calibration.

Keywords: organic amendment, organic fertilizer, EOM, soil organic carbon stock, model, AMG.

1 Introduction

Exogenous organic matter (EOM) is organic matter that is not directly derived from crops but applied to soil as an organic fertilizer or organic amendment to improve soil fertility. EOM includes animal manures and other organic matter from urban or industrial activities, often treated to produce compost and anaerobic digestates. Depending on its characteristics, the use of EOM may increase the short-term and long-term nutrient supply (Gómez-Muñoz et al., 2017), increase soil organic matter (SOM) stocks (Zavattaro et al., 2017) and improve soil quality (Eden et al., 2017; Obriot et al., 2016). An increase in soil organic carbon (SOC) stocks also contributes to reduced atmospheric CO_2 concentration (Maillard and Angers, 2014) provided that EOM had not been applied to the soil before (Powlson et al., 2011). Repeated EOM application in field experiments increase SOM stocks, depending on EOM type and characteristics, and the amount and frequency of EOM application (Bhogal et al., 2018; Maltas et al., 2018). The physico-chemical characteristics of applied EOM, such as nitrogen and lignin content, affect their initial rate of decomposition, whereas their influence in the longer term is uncertain (Dignac et al., 2017). Additionally, specific site conditions (e.g., soil texture and climate) influence the potential soil carbon storage.

Models simulating soil carbon turnover are useful for predicting and comparing different EOM application practices and their efficiency in increasing SOM stocks. The simpler these models are, the more likely they are to be used by farming advisors. Several models have been developed over the past decades, including, the Hénin-Dupuis (Hénin and Dupuis, 1945), Roth-C (Jenkinson and Rayner, 1977), Century (Parton et al., 1987), ICBM (Andrén and Kätterer, 1997) and C-TOOL (Taghizadeh-Toosi et al., 2014) models. The AMG model (Andriulo et al., 1999) was developed in the late 1990s to improve the Hénin-Dupuis model. Compared to the Roth-C and Century models, AMG uses a simpler representation of organic matter with only three pools: organic inputs (crop residues, roots or EOMs); an active SOM pool, which is supplied by humified organic inputs and undergoes mineralization; and a stable SOM pool, taken to be inert at the considered timescale (decades). AMG has been parameterized and validated for a wide range of cropping systems and pedoclimatic conditions (Bouthier et al., 2014; Clivot et al., 2019; Saffih-Hdadi and Mary, 2008). It is widely used in France by farming advisors, researchers, teachers and students as it has a dedicated online version (http://www.simeos-amg.org/). However, its ability to simulate the effects of repeated EOM application on the long-term evolution of SOC stocks has not yet been verified. An update of the EOM parameters is also needed due to the recent development of the model (AMGv2). This version involves new formalisms and changes in some parameter values (Clivot et al., 2019). Moreover, because of the required increase in organic waste recycling in Europe (Directive 2018/851 of the European Parliament and of the Council) and in anaerobic digestion of both urban and agricultural wastes, the use of certain types of EOM is increasing together with the diversity of available EOM. Therefore, parameters for a wider range of EOM types are needed to facilitate AMG use by both researchers and stakeholders. The parameterization of EOM has previously been linked to the Roth-C model using field data from long-term experiments (Dechow et al., 2019; Peltre et al., 2012). However, long-term field trials are scarce and other methods based on laboratory analysis are needed to parameterize AMG. The indicator of residual organic carbon (I_{ROC}) (Lashermes et al., 2009) is calculated from biochemical fractions of EOM (Van Soest and Wine, 1967) and the proportion of EOM carbon mineralized during 3 days of incubation with soil. I_{ROC} has been defined as a predictor of the EOM residual carbon after long-term incubation of EOM with soil under controlled conditions. Peltre et al. (2012) used I_{ROC} to predict the partition of EOM into the different carbon pools of the Roth-C model. Preliminary results also indicate its potential use for parameterizing EOM in AMG (Bouthier et al., 2014).

The objectives of this study were (i) to evaluate the ability of the AMG model to accurately simulate SOC stock evolution in long-term field experiments where EOM is regularly applied, (ii) to validate a method for EOM parameterization in AMG from laboratory analysis, and (iii) to use this method to parameterize a wide range of EOM types in AMG.

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2 Materials and Methods

2.1 Field data

Data from seven long-term field experiments were used for this study: Askov K2 in Denmark (Bruun et al., 2003; Christensen and Johnston, 1997), Colmar in eastern France (Obriot, 2016), QualiAgro in northern France (Obriot et al., 2016; Peltre et al., 2012), La Jaillière in western France (Bouthier and Trochard, 2015), SERAIL in southern France (Peltre et al., 2012), Broadbalk at Rothamsted Research in southern England (Jenkinson and Rayner, 1977; Perryman et al., 2018) and Ultuna in central Sweden (Gerzabek et al., 1997; Karhu et al., 2012; Kätterer et al., 2011). These seven experiments cover a wide range of durations, climates, soils, crop rotations and EOM types (Tables 1 and 2). More details about each experiment can be found in the references given above.

Carbon inputs from plants were divided into aboveground and belowground inputs. Belowground carbon inputs (roots and exudates) were computed for each treatment and year according to the measured crop yields and allometric relationships (Clivot et al., 2019) adapted from Bolinder et al. (2007). For aboveground carbon, allometric relationships were also used for the Askov and SERAIL experiments, whereas carbon inputs were directly estimated from biomass measurements in the field for the QualiAgro, Colmar, La Jaillière, Ultuna and Rothamsted experiments.

The EOM carbon inputs were computed from the known amount of applied EOM and the dry matter and carbon content of the EOM. When these variables were not determined every year, mean values of the available data were used to estimate carbon inputs from EOM.

The SOC stocks were calculated by using SOC content and soil mass over the sampling depth, by considering an equivalent soil mass (Ellert and Bettany, 1995). When the soil bulk density changed over time (QualiAgro, Ultuna and Rothamsted experiments), SOC stocks were estimated by adding a variable amount of subsoil. In the Askov, Colmar, La Jaillière and SERAIL experiments, bulk density remained constant and SOC stocks were computed with a constant soil depth. If any rock fragments were present (as at La Jaillière), the bulk density of the fine soil was used, and the rock fragment fraction was subtracted from the soil volume to compute the SOC stocks, as suggested by Poeplau et al. (2017).

2.2 AMG model

The AMG model originally developed by Andriulo et al. (1999) simulates the dynamics of SOC stocks at an annual time step in response to climate and cropping systems. A full description of the AMGv2 model version used in this study is given by Clivot et al. (2019) along with its validation under various pedoclimatic and cropping conditions. Only the main principles are described below.

AMG considers three carbon pools (Figure **1**): (i) a pool including carbon inputs from crop residues, roots and EOM, (ii) an active carbon pool and (iii) a stable carbon pool. A fixed proportion, K_1, of the carbon inputs is humified yearly and allocated to the active carbon pool. The remaining 1-K_1 is mineralized as CO_2. Aboveground crop residues, roots, EOM are each characterized by the specific K_1 parameter (also termed isohumic coefficient). The active carbon pool decomposes according to first-order kinetics with a rate constant k affected by mean annual water balance and air temperature, soil clay and carbonate contents, soil pH and the C to N ratio of SOM (Clivot et al., 2017). The stable carbon pool is taken to be inert during the simulated period. The initial proportion of stable carbon is preset by default to 65% of the total SOC in long-term arable soils. The aboveground and belowground carbon inputs from plants are estimated by allometric relationships (Clivot et al., 2019) adapted from Bolinder et al. (2007) or directly as measured field data if available. The stocks are computed for a soil depth given as input data. AMG can be described by the following set of equations (Clivot et al., 2019):

$$QC = QC_S + QC_A \qquad (1)$$

$$\frac{dQC_A}{dt} = \sum_i mi\ K_{1i} - k\ QC_A \qquad (2)$$

where QC is the total SOC stock (t ha^{-1}), QC_A and QC_S are the C stocks of the active and stable C pools (t ha^{-1}), respectively, m_i is the annual C input from organic residue i (t ha^{-1} yr^{-1}), K_{1i} is its isohumic coefficient (the fraction of C inputs which is incorporated in SOM after 1 year) and k is the mineralization rate constant of the active C pool (yr^{-1})

2.3 Determination of the coefficient K_1 in long-term field experiments

2.3.1 EOM K_1 optimization

The K_1 value of each EOM type was estimated by fitting the model to the time series of differences in SOC stocks between the EOM treatments and the control treatments, i.e., the additional SOC storage in the treatments with EOM, designated ΔSOC stocks. The optimization was performed in R with the “optim” function and the “L-BFGS-B” method (Byrd et al., 1995) by minimizing the sum of squared differences between the observed and simulated ΔSOC stocks, with K_1 varying between 0 and 100%.

Using ΔSOC stocks instead of SOC stocks prevents the effects of a poor parameterization of the initial proportion of stable soil organic carbon, as suggested by Peltre et al. (2012). It also reduces the risk of bias, since any bias that occurred in simulating the SOC stocks of the control treatment is expected to also occur when simulating the EOM treatment. Beyond EOM inputs, we also considered the differences in crop residue input among treatments to explain ΔSOC stocks, since the carbon input from crop residues was input data specific to each treatment.

All other parameters of the model were kept as the default values to preserve the consistency of the model and the general applicability of the optimized EOM K_1 values. This included the K_1 values of aboveground crop residues and roots (Table S3 in Clivot et al., 2019). Finally, for the field experiments in which soil pH and soil C to N ratio changed over time, these changes were considered in the model input data.

2.3.2 Model evaluation

The model performance was first evaluated in control treatments without EOM (ASK_CT+N, COL_CT+N, QUA_CT-N and QUA_CT+N, LAJA_CT+N, ROTH_CT_S0 and ROTH_CT_S1, SER_CT_eqC and SER_CT_eqH, ULT_CT-N and ULT_CT+N). Indeed, because organic carbon from EOM is incorporated in SOC, it was important to verify the ability of the model to accurately simulate the evolution of SOC stocks under the various soil, climate and cropping system conditions. The mean error (*ME*), root mean square error (*RMSE*), relative *RMSE* (*RRMSE*), coefficient of determination (R^2) and model efficiency (*EF*) were thus computed using the observed and simulated SOC stocks in each control treatment (Equations 3 to 7). The model performance for each treatment with EOM was then assessed by using the same statistical criteria.

$$ME = \frac{1}{n} \cdot \sum_{i=1}^{n} (O_i - S_i) \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} (O_i - S_i)^2} \quad (4)$$

$$RRMSE = RMSE/\bar{O} \quad (5)$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}((O_i-\bar{O})\cdot(S_i-\bar{S}))}{\sqrt{\sum_{i=1}^{n}(O_i-\bar{O})^2}\cdot\sqrt{\sum_{i=1}^{n}(S_i-\bar{S})^2}}\right)^2 \quad (6)$$

$$EF = 1 - \frac{\sum_{i=1}^{n}(O_i-S_i)^2}{\sum_{i=1}^{n}(O_i-\bar{O})^2} \quad (7)$$

where *O* and *S* are the observed and simulated values, respectively, and *n* is the number of observations. $\bar{O}$ and $\bar{S}$ are the means of the observations and simulations, respectively.

2.4 Using I_{ROC} to model SOC stocks

The indicator of residual organic carbon (I_{ROC}) is computed from the biochemical fractions of EOM (Van Soest and Wine, 1967) and from the proportion of organic carbon mineralized during 3 days of soil incubation (Lashermes et al., 2009). I_{ROC} was defined as a predictor of the EOM residual carbon after long-term incubation of EOM with soil under controlled conditions.

The I_{ROC} values of the EOM types applied in the field experiments were available only for 4 out of the 7 experiments: Colmar, QualiAgro (one I_{ROC} value per EOM type and per application year), Ultuna (three I_{ROC} values per EOM type corresponding to three pooled samples of different years of application) and SERAIL (one or two I_{ROC} values per EOM type corresponding to one or two application years). When several I_{ROC} values were available for a given EOM type in a field experiment, the mean of the I_{ROC} values was used as the K_1 value in AMG. For the 4 experiments with measured I_{ROC} values, the relationship between the optimized K_1 values based on field data (section 2.3) and the I_{ROC} values of the EOM was investigated by calculating the coefficient of determination (R^2), mean error (*ME*) and root mean square error (*RMSE*). The I_{ROC} values of the EOM were also directly used as K_1 input values in AMG (without any rescaling). The model performance was assessed under the same conditions as previously described (section 2.3.2) and compared to the model performance with optimized K_1.

2.5 The I_{ROC} database

The original database developed by Lashermes et al. (2009) provided K_1 values for EOM types for which we did not have any field estimates. This database was expanded with additional I_{ROC} values from various research projects. Thus, the database contained more than 600 EOM types from 5 main groups: livestock liquid and solid manures (n=106), anaerobic digestates (n=54), sewage sludge (n=71), composts (n=352) and others (n=69). Most frequently used EOM types were present in the database; however, there were limited number of values for cattle slurry (n=5) considering its relative abundance and for different types of digestates (from 2 to 9 depending on the type of digestates).

3 Results

3.1 Evaluation of the AMG model for the control treatments

The performance of the AMG model for the control treatments without EOM application was good for the Colmar, QualiAgro, La Jaillière, SERAIL and Ultuna experiments. In these treatments, the *RMSE* was equal to or lower than 3 t C ha^{-1} and the *RRMSE* was lower than 10% (electronic supplementary material, appendices A and B). The model thus succeeded in representing the decrease in SOC stocks at La Jaillière (CT_N), Ultuna (CT_N and CT), SERAIL (CT_EQC and CT_EQH), and QualiAgro (CT_N-), and the nearly constant SOC stocks at Colmar (CT_N) and QualiAgro (CT_N+). For Askov and Rothamsted, the model performance was worse, with an *RMSE* between 4 and 5 t C ha^{-1} in all control treatments (*RRMSE* from 19% to 30%). The model failed to simulate the increase in SOC stocks at Askov (CT_N) and overestimated the decrease in SOC stocks at Rothamsted (CT_S0 and CT_S1). If we consider all treatments and experiments, the simulation bias (*ME*) remained low, smaller than 1 t C ha^{-1}, except for the Askov, Rothamsted, Ultuna (T0) and La Jaillière experiments.

3.2 Simulation of ΔSOC stocks with the optimized EOM K_1 value

Using the optimized values of K_1, AMG succeeded in simulating the dynamics of ΔSOC stocks in all treatments and experiments, except in two treatments at QualiAgro (BIO_N+, BIO_N-) and one at SERAIL (GW_EQH) which were underestimated (Figure **2**). This was confirmed by the low *ME* values (Table **3**), except those for the underestimated treatments (*ME* higher than 3.5 t C/ha). The *RMSE* remained low, with minimum, mean and maximum values of 0.5, 3.0 and 8.2 t C ha^{-1} respectively. Except for two treatments at La Jaillière

(POM, CPOM), which had very low variability in ΔSOC stocks, and the SERAIL experiment, for which the dynamics of ΔSOC stocks were very noisy, the R^2 values were high (>0.6) to very high, indicating a good simulation of the variability of ΔSOC stocks. For example, the initial increase followed by stability in ΔSOC stocks at Rothamsted was well simulated, as was the initial increase at La Jaillère followed by a decrease in ΔSOC stocks after the cessation of EOM application. The model efficiency (*EF)* exhibited the same trends as R^2.

3.3 Determination of isohumic coefficient (K_1) values from long-term field experiments

The optimized K_1 values varied greatly among EOM types. For example, the lowest value was 8% for the poultry manure at La Jaillière, while values of 100% were found for several EOM types including green waste and sludge compost at QualiAgro (Table **3**). The mean optimized K_1 for all treatments was 63%. For a given type of EOM, a large variation also existed. For example, the optimized K_1 value of cattle manure varied from 44% (FYM treatment at Ultuna) to 99% (FYM_N+ at QualiAgro), with a mean value of 66%.

3.4 Prediction of K_1 with I_{ROC}

Based on the four experiments for which I_{ROC} values of EOM were available, the I_{ROC} indicator appeared to be an acceptable predictor of K_1 (Figure 3). *ME* and *RMSE* between K_1 and I_{ROC} were low for SERAIL and Ultuna (e.g., *RMSE* equal to 11% for Ultuna) but higher for Colmar and QualiAgro (Table 4). The I_{ROC} value systematically underestimated the optimized K_1 (*ME*=-30%) for QualiAgro. Within each experiment, the variation in K_1 was well explained by the variability in I_{ROC} (R^2 = 0.73 - 0.95). Considering all experiments together, the I_{ROC} explained slightly less of the K_1 variability (R^2 = 0.62).

3.5 Simulations of C storage from EOM with K_1 values equal to I_{ROC}

The I_{ROC} values were used as input K_1 values in AMG to simulate the ΔSOC stocks for the four experiments for which I_{ROC} values were available. *RMSE* logically increased in all treatments when replacing optimized K_1 with I_{ROC} (Figure **4**). The mean *RMSE* increased from 3.0 to 4.9 t C ha^{-1}, with a minimal increase of 0.01 t C ha^{-1} for the FYM_EQH treatment at SERAIL and a maximal increase of 5.4 t C ha^{-1} for the treatment PEA+N at Ultuna. The largest increases in *RMSE* were associated with experiments with very high ∆SOC stocks (more than 50 t C ha^{-1} for PEA+N at Ultuna, for example), and thus the *RMSE* increases were relatively low.

3.6 Definition of a database of reference K_1 values for AMG

Using the I_{ROC} database (section 2.5), some marked differences among EOM types appeared, (Figure 5, appendix D in electronic supplementary material). For example, the median I_{ROC} values of chicken droppings, cattle manure and green waste compost were 16%, 67% and 82%, respectively. Variability was also found within a given type of EOM: for example, the I_{ROC} values for cattle manure ranged from 21% to 79%. Some EOM types were grouped when an insufficient amount of data existed and if the differences among these EOMs were low. For example, all anaerobic digestates were grouped into one type. Another group was sewage sludge from urban wastewater treatment plants. Finally, we proposed a default K_1 value for 26 EOM types: 9 types of livestock manure, 1 type of digestate, 2 types of sewage sludge, 13 types of compost and 1 type of other EOM.

4 Discussion

4.1 The accurate simulation by AMG of SOC stock evolution after repeated applications of EOM

Many authors have observed an increase in SOC stocks following EOM addition, the increase being dependent on the amount and type of EOM applied (Bhogal et al., 2018; Maltas et al., 2018). The importance of the type of EOM in explaining differences in SOC storage was confirmed in experiments where various EOM types applied similar carbon inputs (Gerzabek et al., 1997). AMG succeeded in simulating these increases in SOC stocks with various EOM types and under various pedoclimatic conditions and cropping systems (Figure **2**), for example, in the Ultuna and QualiAgro experiments. The ability of the AMG model to simulate the additional SOC stocks from EOM addition (ΔSOC stocks) was satisfactory. The mean *RMSE* value (3.0 t C ha^{-1}) was comparable to the mean standard deviation of the SOC measurements in the different experiments (2.1 t C ha^{-1} in QualiAgro, 2.5 t C ha^{-1} for Colmar). This mean *RMSE* for ΔSOC stocks was also comparable to that obtained by Peltre et al. (2012) with the Roth-C model. These authors found a mean *RMSE* of 3.2 t C ha^{-1} in the Askov, QualiAgro (1998-2009 only), Ultuna and SERAIL experiments. Even if EOM K_1 values were optimized to minimize the *RMSE* of ΔSOC stocks, the *RMSE* of the simulated SOC stocks compared to the actual SOC stocks (electronic supplementary material, appendix C) was also similar to that found in other modeling studies. Karhu et al. (2012) reported *RMSE* values of SOC stocks between 2.5 and 10.3 t C ha^{-1} for different treatments in the Ultuna experiment (from 2.1 to 6.6 t C ha^{-1} for the same treatments in our study). Begum et al. (2017) obtained an *RRMSE* of 8.9% for the FYM treatment of the Rothamsted experiment (FYM_S1), compared with 13.0% obtained in our study with AMG. These simulations could have been further improved if we had optimized the size of the stable SOC pool. However, this would not have affected the simulation of the ΔSOC stocks.

Finally, the mean *RMSE* that we obtained in simulating ΔSOC stocks for all EOM types (3.0 t C ha^{-1}) was close to the *RMSE* obtained for SOC stocks in the control treatments without EOM in our study (2.7 t C ha^{-1}). The mean RMSE from simulating ΔSOC stocks was also close to the mean *RMSE* obtained by Clivot et al. (2019) with the AMG model on a dataset of 60 treatments located at 20 sites in France (2.6 t C ha^{-1}). However, the mean *RMSE* for SOC stocks with EOM application (4.3 t C ha^{-1}, electronic supplementary material, appendix C) was higher. It is recalled that EOM K_1 values were not optimized to minimize the *RMSE* for SOC stocks but rather to minimize the RMSE for ΔSOC stocks. Indeed, the poor modeling performance for the control treatments at Rothamsted and Askov also impacted the *RMSE* of SOC stocks for treatments with EOM (but not that of ΔSOC stocks). The poor simulation of these control treatments could be related to inappropriate allometric coefficients used for old crop varieties at Rothamsted and to the very low initial C content in the subsoil used at the Askov experiment, for which the SOC mineralization function was not adapted.

4.2 Variability and prediction of the K_1 isohumic coefficient for EOM

The optimized K_1 values showed high variability among types of EOM, from 8% to 100%, with a mean value of 63%. Most of the EOM K_1 values were higher than the K_1 values of aboveground residues (from 22% to 32%) and roots (40%) (Clivot et al., 2019). This finding confirms that certain EOM types make a greater contribution to SOC than crop residues, as suggested by several authors (Kätterer et al., 2011; Kong et al., 2005), even if the continuation of this greater contribution in the long term is debated (Maillard and Angers, 2014).

The variability in EOM K_1 values well reflected the difference in stability of different EOM types, as approximated by their I_{ROC} value (Figure 3). Using the I_{ROC} indicator as a predictor of K_1 only slightly decreased model performance (Figure **4**). The largest increases in *RMSE* were associated with experiments with very high ΔSOC stocks. The small *RMSE* values confirmed the usefulness of I_{ROC} for parameterizing soil carbon models, as shown by Peltre et al. (2012) with Roth-C. In comparison to the parameters used for this latter study, the use of I_{ROC} was easier: I_{ROC} was directly used to derive K_1 values in AMG without any rescaling, whereas several regressions were needed to predict the Roth-C EOM parameters. Some studies used other laboratory measurements to calibrate EOM in soil carbon models. Mondini et al. (2017) used EOM incubations to predict the partition coefficients and mineralization rates of EOM in Roth-C. Pansu et al. (2017) used ^{13}C nuclear magnetic resonance spectra to estimate the parameters of the TAO model. In comparison to these studies, the advantages of I_{ROC} are that it is a standardized (XP U44-162 standard), inexpensive method, and is already being conducted by several commercial laboratories.

4.3 The need for further improvement of the AMG formalism for EOM?

Even if the performance of AMG in simulating the effects of EOM on SOC stocks was generally satisfying, AMG failed to simulate the substantial increase in SOC stocks observed in some treatments of the QualiAgro experiment (+24 t C ha^{-1} in 20 years for the BIO_N+ treatment), even with the maximal K_1 value (K_1 = 100%). In AMG, organic carbon from EOM is incorporated into the active SOC pool the year following EOM application and is then mineralized at the same rate as the native active SOC pool. The result for QualiAgro suggests that SOC derived from EOM could have a slower mineralization rate than the native SOC. This hypothesis is supported by other modeling studies: tests done with the STICS soil-crop model showed that a slower decomposition constant was needed to accurately simulate the SOC stocks in QualiAgro (Levavasseur et al., in prep). Noirot-Cosson et al. (2016) also calibrated a slower decomposition rate constant for EOM than for SOC to simulate the QualiAgro experiment with the CERES-EGC model. Peltre et al. (2017) observed a higher thermal stability of organic matter in EOM-amended soils. Yu et al. (2012) indicated a lower specific mineralization rate in EOM-amended soils, but Liu et al. (2018) found the opposite result.

Although the isohumic coefficient K_1 was generally well predicted by the I_{ROC} indicator, significant residual variability remained. Some very different K_1 values were optimized for similar EOM types in different experiments. For example, the optimized K_1 for cattle manure varied greatly among the different experiments. Part of this variability is certainly due to the true variability in OM stability, which could be related to differences in bedding materials and storage duration (Helgason et al., 2005). More surprisingly, we observed an unexplained variability in the K_1 of the green waste and sludge compost at QualiAgro and Colmar. Although the compost often came from the same producer, the optimized K_1 values were very different, at 100% and 41%, respectively. This unexplained variability in K_1 indicates that some factors not considered in the AMG model affected the storage of carbon from EOM. Zhang et al. (2018) showed that accounting for the effects of litter stoichiometry and soil N availability may improve the simulation of SOM formation with the CENTURY model. Peltre et al. (2012) suggested that changes in soil pH may explain some of the larger simulation errors obtained with Roth-C. In our case, the evolution of pH was explicitly considered in the AMG model (annual soil pH was a model input). Brilli et al. (2017) also indicated that poor consideration of soil water conditions may lead to erroneous SOC modeling. The simple annual water balance used in the AMG model to account for the effect of climate on SOC dynamics might be a cause of some poor simulations. For example, in Colmar, the effect of common thunderstorms in summer is not well represented by an annual water balance.

Finally, even if the AMG formalisms could be improved, AMG performed as well as other models in the literature despite its simpler formalisms. The simple formalisms of the AMG model make it possible for it to be a calibration-free model that is already easy to use outside of academic research, especially thanks to the online tool (http://www.simeos-amg.org/). Therefore, the need to modify the formalisms of AMG to more accurately simulate the effects of EOM should be carefully investigated in other field experiments from both the modeling and the soil chemistry points of view.

5 Conclusion

Using the AMG model, we simulated the evolution of SOC stocks in seven long-term field experiments with repeated applications of different EOM types. The good model performance confirmed its ability to adequately simulate long-term effects of EOM application on SOC stocks. The only EOM parameter in AMG, the isohumic coefficient K_1, was optimized for each EOM to minimize the difference in SOC stocks between treatments with and without EOM. These optimized K_1 values were well correlated with the organic matter stability of EOM, approximated by the indicator of residual organic carbon in soil (I_{ROC}). This indicator is routinely analyzed by commercial laboratories. The I_{ROC} value could be used directly as the EOM K_1 value in AMG while maintaining satisfactory model performance. A database of I_{ROC} values was used to parameterize 26 types of EOM in AMG, which can thus be used by stakeholders to model the effects of different EOM practices.

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7 Tables

Table 1 Main general characteristics of the experiments used in this study

Experiment	Location	Considered period	Soil type (FAO)	Sampling depth (cm)	Soil clay content (%)	Soil $CaCO_3$ content (%)	Mean initial SOC stock (t C ha^{-1})	Mean annual temperature (°C)	Mean annual P-PET (mm)	Crop rotation
Askov (ASK)	Askov, Denmark (55°28’ N, 9°55’ E)	1956-1986 (31 years)	Dystric Arenosol	25	3	0	11	7.5	466	Silage maize – spring barley – fiber flax – winter wheat
Colmar (COL)	Colmar, France (48°06’ N, 7°33’ E)	2000-2013 (14 years)	Calcosol	28	18	12	45	11.4	-252	Grain maize – winter wheat – sugar beet - spring barley
QualiAgro (QUA)	Feucherolles, France (48°52’ N, 1°57’ E)	1998-2017 (20 years)	Luvisol	29	17	0	43	10.7	44	Grain maize – winter wheat
La Jaillière 2 (LAJA)	Loireauxence, France (47°45’ N, 0°96’ W)	1995-2009 (15 years)	Gleyic Cambisol	25	21	0	37	12.6	53	Silage maize – winter wheat
Rothamsted Broadbalk (ROTH)	Harpenden, UK (51°48’ N, 0°22’ W)	1843-2010 (168 years)	Chromic Luvisol	23	28	2	29	9.1	80	Winter wheat
SERAIL (SER)	Brindas, France (45°43’ N, 4°42’ E)	1995-2009 (15 years)	Luvisol	27	17	0	38	12.9	-135	Vegetables in rotation
Ultuna (ULT)	Uppsala, Sweden (59°82’ N, 17°65’ E)	1956-1991 (36 years)	Eutric Cambisol	20	37	0	43	5.4	-39	Several years of spring cereals (oat, wheat, barley) followed by one year of rape or mustard

Table 2 Description of the treatments in the different experiments used in this study

Experiment	Treatment	EOM type	Mean EOM amount (t C ha^{-1})	EOM return period (year)	Mineral fertilization or straw management differences
Askov (ASK)	FYM	Cattle farmyard manure	2.3	1	Mineral N fertilization
	PEA	White sphagnum peat	3.2	1	Mineral N fertilization
	SAW	Sawdust	3.2	1	Mineral N fertilization
	STR	Cereal straw	3.0	1	Mineral N fertilization
	CT+N	-	-	-	Mineral N fertilization
Colmar (COL)	GWS+N	Green waste and sewage sludge cocompost	2.2	2	Mineral N fertilization
	CT+N	-	-	-	Mineral N fertilization
QualiAgro (QUA)	BIO-N	Compost of green waste and home-sorted organic fraction of municipal solid waste	3.6	2	Low mineral N fertilization
	BIO+N	Compost of green waste and home-sorted organic fraction of municipal solid waste	3.6	2	Optimal mineral N fertilization
	GWS-N	Green waste and sewage sludge cocompost	4.0	2	Low mineral N fertilization
	GWS+N	Green waste and sewage sludge cocompost	4.0	2	Optimal mineral N fertilization
	MSW-N	Compost of mechanically separated organic fractions from residual waste after selective collection of dry and clean packaging	3.5	2	Low mineral N fertilization
	MSW+N	Compost of mechanically separated organic fractions from residual waste after selective collection of dry and clean packaging	3.5	2	Optimal mineral N fertilization
	FYM-N	Cattle farmyard manure	3.7	2	Low mineral N fertilization
	FYM+N	Cattle farmyard manure	3.7	2	Optimal mineral N fertilization
	CT-N	-	-	-	Low mineral N fertilization
	CT+N	-	-	-	Optimal mineral N fertilization
La Jaillière 2 (LAJA)	CM	Cattle farmyard manure	2.4	1 (until 2004)	Mineral P fertilization
	PIM	Pig farmyard manure	1.8	1 (until 2004)	Mineral P fertilization
	POM	Poultry farmyard manure	1.6	1 (until 2004)	Mineral P fertilization
	CCM	Composted cattle farmyard manure	1.9	1 (until 2004)	Mineral P fertilization
	CPIM	Composted pig farmyard manure	1.7	1 (until 2004)	Mineral P fertilization
	CPOM	Composted poultry farmyard manure	1.6	1 (until 2004)	Mineral P fertilization

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Experiment	Treatment	EOM type	Mean EOM amount (t C ha^{-1})	EOM return period (year)	Mineral fertilization or straw management differences
	CT+N	-	-	-	Mineral NP fertilization
Rothamsted Broadbalk (ROTH)	FYM_S0	Cattle farmyard manure	3.0	1	Section 0: straw incorporated since 1986
	FYM_S1	Cattle farmyard manure	3.0	1	Section 1: straw removed
	CT_S0	-	-	-	Section 0: straw incorporated since 1986
	CT_S1	-	-	-	Section 1: straw removed
SERAIL (SER)	FUM_eqC	Cattle farmyard manure	2.6	1	P K Ca Mg
	FUM_eqH	Cattle farmyard manure	2.6	1	P K Ca Mg
	FUMT_eqC	Pelletized cattle farmyard manure	2.6	1	P K Ca Mg
	FUMT_eqH	Pelletized cattle farmyard manure	2.7	1	P K Ca Mg
	CDV_eqC	Green waste compost	2.6	1	P K Ca Mg
	CDV_eqH	Green waste compost	1.6	1	P K Ca Mg
	ALGO_eqC	Algoforestier: compost of bark, poultry manure, liquid manure and algae	2.6	1	P K Ca Mg
	ALGO_eqH	Algoforestier: compost of bark, poultry manure, liquid manure and algae	2.0	1	P K Ca Mg
	VEGET_eqC	Végethumus: compost of coffee pulp cakes (90%), sheep manure and wool waste	2.6	1	P K Ca Mg
	VEGET_eqH	Végethumus: compost of coffee pulp cakes (90%), sheep manure and wool waste	1.4	1	P K Ca Mg
	FUM_eqH	Cattle farmyard manure	2.6	1	P K Ca Mg
	CT_eqC	-	-	-	P K Ca Mg
	CT_eqH	-	-	-	P K Ca Mg
Ultuna (ULT)	FYM	Cattle farmyard manure	3.8	2	-
	FYM+P	Cattle farmyard manure	3.8	2	P
	GM	Green manure	3.5	2	-
	PEA	White sphagnum peat	3.9	2	-
	PEA+N	White sphagnum peat	3.9	2	Mineral N
	SAW	Sawdust	3.7	2	-
	SAW+N	Sawdust	3.7	2	Mineral N
	SLU	Anaerobically digested sewage sludge	3.7	2	-
	STR	Cereal straw	3.5	2	-
	STR+N	Cereal straw	3.5	2	Mineral N
	CT-N	-	-	-	-

Experiment	Treatment	EOM type	Mean EOM amount (t C ha^{-1})	EOM return period (year)	Mineral fertilization or straw management differences
	CT+N	-	-	-	Mineral N

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Table 3 Model performance in simulating ΔSOC stocks in the treatments with EOM in the seven long-term field experiments. The optimized value of the isohumic coefficient K_1 is given for each EOM type

Experiment	Treatment	EOM	ME (t C ha^{-1})	RMSE (t C ha^{a-1})	RRMSE (%)	R^2	EF	K_1 (%)
ASK	FYM	Cattle manure	0.09	1.32	11	0.96	0.96	63
ASK	PEA	Peat	0.80	4.91	20	0.89	0.88	86
ASK	SAW	Sawdust	-0.22	1.92	15	0.88	0.88	42
ASK	STR	Straw	0.19	1.47	15	0.94	0.93	40
COL	GWS_N+	Green waste and sludge compost	0.08	0.50	23	0.84	0.83	43
LAJA2	CM	Cattle manure	0.01	1.03	39	0.77	0.77	47
LAJA2	PIM	Pig manure	0.01	0.53	16	0.81	0.81	46
LAJA2	POM	Poultry manure	0.08	0.78	85	0.01	-0.08	8
LAJA2	CCM	Composted cattle manure	0.02	0.87	35	0.75	0.75	47
LAJA2	CPIM	Composted pig manure	0.06	0.91	54	0.71	0.71	50
LAJA2	CPOM	Composted poultry manure	0.00	0.65	-122	0.19	0.19	15
QUA	BIO_N-	Green waste and biowaste compost	-4.21	5.82	40	0.94	0.59	100
QUA	BIO_N+	Green waste and biowaste compost	-3.50	5.50	41	0.92	0.60	100
QUA	FYM_N-	Cattle manure	0.27	1.91	16	0.93	0.92	97
QUA	FYM_N+	Cattle manure	0.10	1.69	15	0.92	0.92	99
QUA	GWS_N-	Green waste and sludge compost	-1.20	3.09	21	0.94	0.90	100
QUA	GWS_N+	Green waste and sludge compost	-0.47	3.56	26	0.89	0.86	100
QUA	MSW_N-	Municipal solid waste compost	0.16	2.39	29	0.79	0.79	83
QUA	MSW_N+	Municipal solid waste compost	0.26	2.23	34	0.79	0.78	81
ROTH	FYM_S0	Cattle manure	0.08	6.59	17	0.75	0.75	74
ROTH	FYM_S1	Cattle manure	0.00	8.20	21	0.67	0.67	78
SER	ALGO_EQC	Algoforestier compost	-0.42	3.74	39	0.55	0.53	69
SER	ALGO_EQH	Algoforestier compost	-0.18	3.83	40	0.59	0.58	98
SER	FYM_EQC	Cattle manure	-0.44	3.10	64	0.57	0.54	56
SER	FYM_EQH	Cattle manure	-0.81	3.99	90	0.31	0.21	52
SER	GW_EQC	Green waste compost	-0.23	4.08	34	0.77	0.76	100
SER	GW_EQH	Green waste compost	-4.32	7.41	61	0.75	0.29	100
SER	PFYM_EQC	Pelletized cattle manure	0.11	2.01	47	0.71	0.71	40
SER	PFYM_EQH	Pelletized cattle manure	0.07	1.55	37	0.80	0.80	40
SER	VEGET_EQC	Végéthumus compost	-1.49	5.01	79	0.18	-0.20	60
SER	VEGET_EQH	Végéthumus compost	-2.40	4.83	70	0.30	0.04	100
ULT	FYM	Cattle manure	-0.38	2.61	15	0.86	0.83	44
ULT	FYM_P	Cattle manure	-0.32	2.42	13	0.89	0.87	46
ULT	GM	Green manure	-0.42	2.16	21	0.77	0.66	28
ULT	PEA	Peat	-0.31	4.16	14	0.88	0.88	78
ULT	PEA_N	Peat	0.07	4.52	13	0.90	0.90	86
ULT	SAW	Sawdust	-0.10	1.61	12	0.91	0.91	38
ULT	SAW_N	Sawdust	-0.06	1.62	11	0.91	0.91	37
ULT	SLU	Sludge	-0.86	5.46	19	0.73	0.66	66

Experiment	Treatment	EOM	ME (t C ha^{-1})	RMSE (t C ha^{a-1})	RRMSE (%)	R^2	EF	K_1 (%)
ULT	STR	Straw	-0.37	1.79	21	0.63	0.45	21
ULT	STR_N	Straw	-0.12	1.32	13	0.87	0.86	27
Min	-	-	-4.32	0.50	-122	0.01	-0.20	8
Mean	-	-	-0.50	3.00	28	0.74	0.67	63
Max	-	-	0.80	8.20	90	0.96	0.96	100

Table 4 Mean error (*ME*), root mean square error (*RMSE*) and coefficient of determination (R^2) between the I_{ROC} indicator and the optimized K_1 for all treatments of experiments for which I_{ROC} values were available

Experiment	ME (%)	RMSE (%)	R^2
COL	24	24	-
QUA	-30	30	0.95
SER	-3	13	0.73
ULT	-2	11	0.73
All	-9	19	0.62

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8 Figure captions

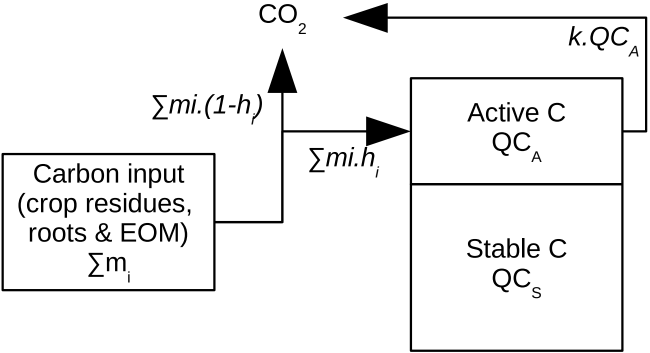
Figure 1 Conceptual diagram of the AMG model. The organic carbon inputs (*m*) from crop residues, roots or EOM are either mineralized (1-K_1 fraction) or incorporated (K_1 fraction) into the active soil organic carbon pool (Active C, QC_A). The active organic carbon pool mineralizes according to first-order kinetics with the *k* decay constant. The stable organic carbon pool (Stable C, QC_S) is considered completely inert (created with LibreOffice Draw)

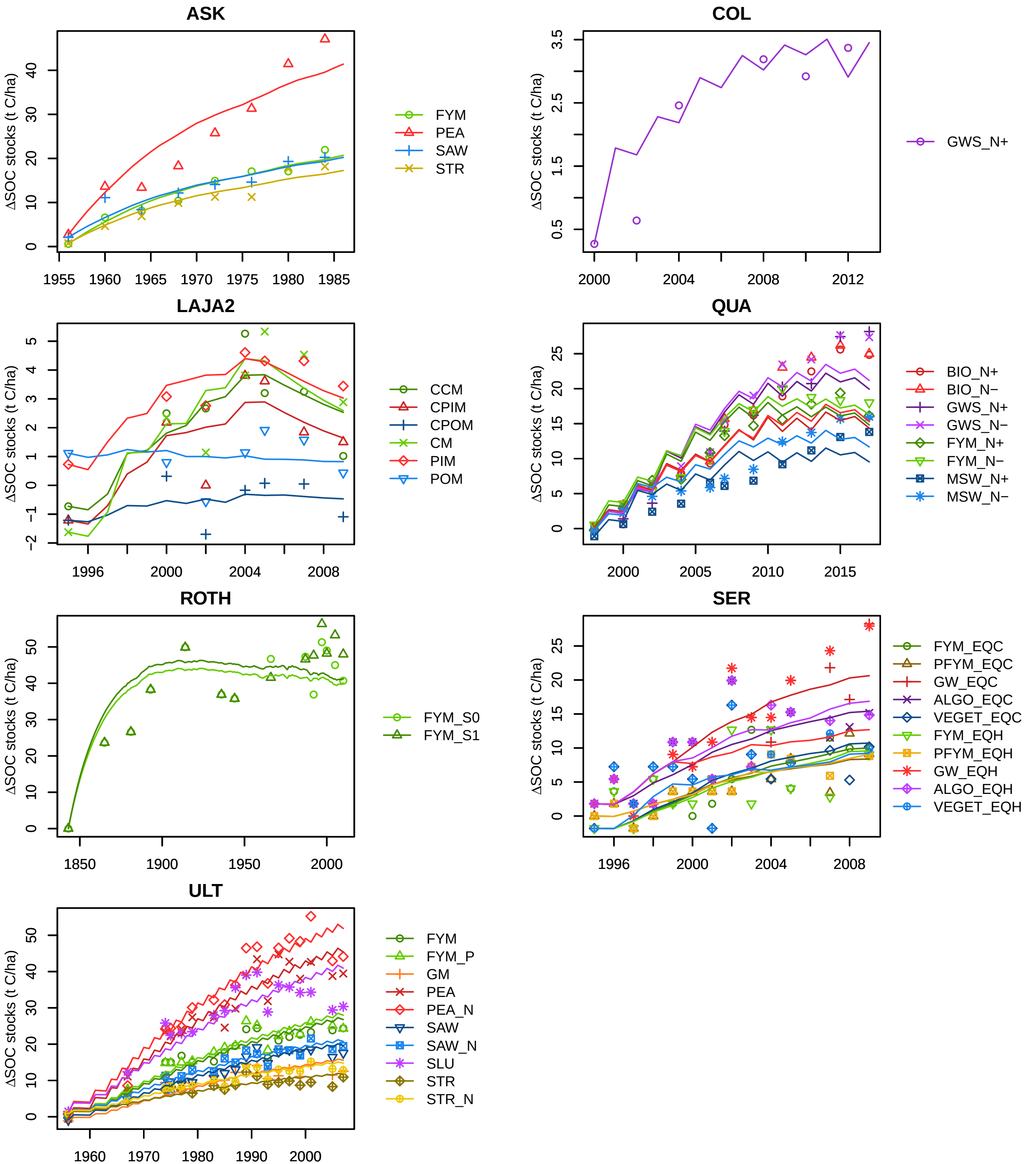
Figure 2 Observed (dots) and simulated (lines) differences in SOC stocks (ΔSOC stocks) between the treatments with EOM and without EOM (controls) for the seven long-term field experiments (created with R)

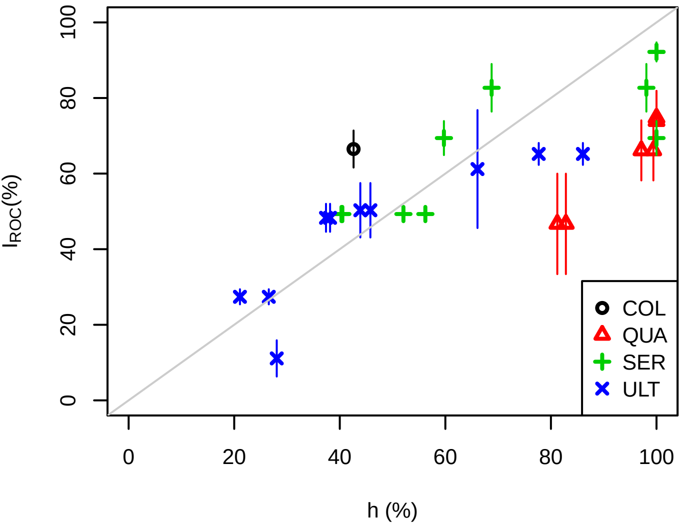
Figure 3 Relationship between the optimized value of the isohumic coefficient K_1 and the I_{ROC} indicator in the long-term field experiments of Colmar (COL), QualiAgro (QUA), SERAIL (SER) and Ultuna (ULT). Error bars around the mean I_{ROC} values represent the standard deviations (when available) (created with R)

Figure 4 Root mean square error (*RMSE*) between simulated and observed differences in SOC stocks in treatments with and without EOM (ΔSOC stocks) in four long-term experiments. The isohumic K_1 coefficient was either optimized (black bars) or equal to I_{ROC} (gray bars) (created with R)

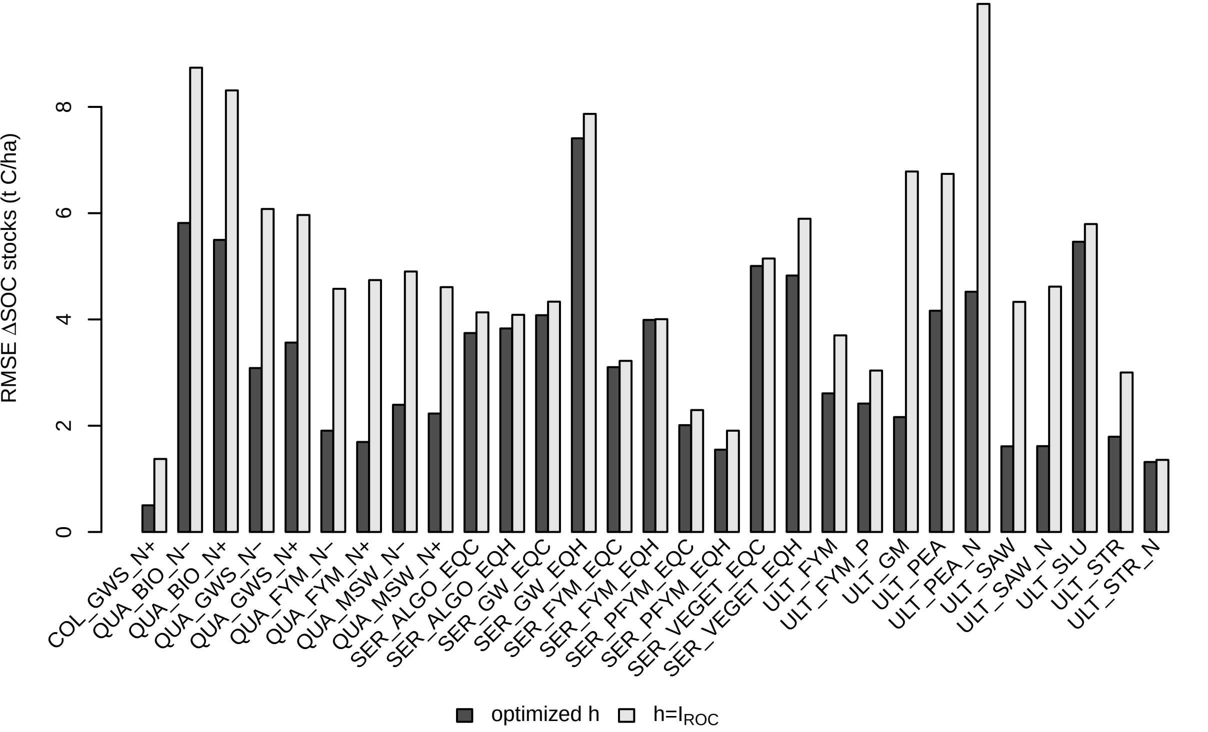
Figure 5 Distribution of I_{ROC} values for certain EOM types from the database and median values of I_{ROC} proposed as reference K_1 values for AMG (in red). *n* represents the number of I_{ROC} values for a given EOM. DIG=anaerobic digestate, SS=urban sewage sludge, CM=cattle manure, HM=horse manure, PIS=pig slurry, CD=chicken droppings, GWC=green waste compost, CCM=composted cattle manure (created with R)

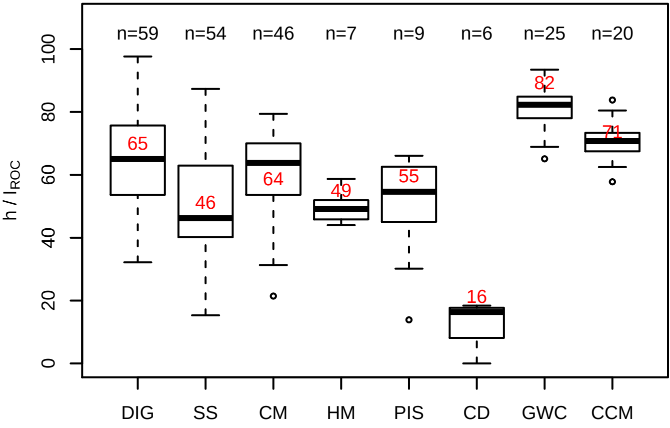

CO_2
$k.QC_A$
$\sum mi.(1-h_i)$
Active C
QC_A
$\sum mi.h_i$
Carbon input
(crop residues,
roots & EOM)
$\sum m_i$
Stable C
QC_S


ASK
ΔSOC stocks (t C/ha)
FYM
PEA
SAW
STR
COL
GWS_N+
LAJA2
CCM
CPIM
CPOM
CM
PIM
POM
QUA
BIO_N+
BIO_N−
GWS_N+
GWS_N−
FYM_N+
FYM_N−
MSW_N+
MSW_N−
ROTH
FYM_S0
FYM_S1
SER
FYM_EQC
PFYM_EQC
GW_EQC
ALGO_EQC
VEGET_EQC
FYM_EQH
PFYM_EQH
GW_EQH
ALGO_EQH
VEGET_EQH
ULT
FYM
FYM_P
GM
PEA
PEA_N
SAW
SAW_N
SLU
STR
STR_N



COL
QUA
SER
ULT
$I_{ROC}(\%)$
h (%)
0
20
40
60
80
100
0
20
40
60
80
100


RMSE ΔSOC stocks (t C/ha)
0
2
4
6
8
COL_GWS_N+
QUA_BIO_N–
QUA_BIO_N+
QUA_GWS_N–
QUA_GWS_N+
QUA_FYM_N–
QUA_FYM_N+
QUA_MSW_N–
QUA_MSW_N+
SER_ALGO_EQC
SER_ALGO_EQH
SER_GW_EQC
SER_GW_EQH
SER_FYM_EQC
SER_FYM_EQH
SER_PFYM_EQC
SER_PFYM_EQH
SER_VEGET_EQC
SER_VEGET_EQH
ULT_FYM
ULT_FYM_P
ULT_GM
ULT_PEA
ULT_PEA_N
ULT_SAW
ULT_SAW_N
ULT_SLU
ULT_STR
ULT_STR_N
optimized h
h=I_ROC


n=59
n=54
n=46
n=7
n=9
n=6
n=25
n=20
65
46
64
49
55
16
82
71
h / l_{ROC}
0
20
40
60
80
100
DIG
SS
CM
HM
PIS
CD
GWC
CCM