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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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35

## 36 **Abstract**

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

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

## 58 **1 Introduction**

59 Exogenous organic matter (EOM) is organic matter that is not directly derived from crops but  
60 applied to soil as an organic fertilizer or organic amendment to improve soil fertility. EOM

61 includes animal manures and other organic matter from urban or industrial activities, often  
62 treated to produce compost and anaerobic digestates. Depending on its characteristics, the  
63 use of EOM may increase the short-term and long-term nutrient supply (Gómez-Muñoz et al.,  
64 2017), increase soil organic matter (SOM) stocks (Zavattaro et al., 2017) and improve soil  
65 quality (Eden et al., 2017; Obriot et al., 2016). An increase in soil organic carbon (SOC)  
66 stocks also contributes to reduced atmospheric CO<sub>2</sub> concentration (Maillard and Angers,  
67 2014) provided that EOM had not been applied to the soil before (Powlson et al., 2011).  
68 Repeated EOM application in field experiments increase SOM stocks, depending on EOM  
69 type and characteristics, and the amount and frequency of EOM application (Bhogal et al.,  
70 2018; Maltas et al., 2018). The physico-chemical characteristics of applied EOM, such as  
71 nitrogen and lignin content, affect their initial rate of decomposition, whereas their influence  
72 in the longer term is uncertain (Dignac et al., 2017). Additionally, specific site conditions (e.g.,  
73 soil texture and climate) influence the potential soil carbon storage.

74 Models simulating soil carbon turnover are useful for predicting and comparing different EOM  
75 application practices and their efficiency in increasing SOM stocks. The simpler these  
76 models are, the more likely they are to be used by farming advisors. Several models have  
77 been developed over the past decades, including, the Hénin-Dupuis (Hénin and Dupuis,  
78 1945), Roth-C (Jenkinson and Rayner, 1977), Century (Parton et al., 1987), ICBM (Andrén  
79 and Kätterer, 1997) and C-TOOL (Taghizadeh-Toosi et al., 2014) models. The AMG model  
80 (Andriulo et al., 1999) was developed in the late 1990s to improve the Hénin-Dupuis model.  
81 Compared to the Roth-C and Century models, AMG uses a simpler representation of organic  
82 matter with only three pools: organic inputs (crop residues, roots or EOMs); an active SOM  
83 pool, which is supplied by humified organic inputs and undergoes mineralization; and a  
84 stable SOM pool, taken to be inert at the considered timescale (decades). AMG has been  
85 parameterized and validated for a wide range of cropping systems and pedoclimatic  
86 conditions (Bouthier et al., 2014; Clivot et al., 2019; Saffih-Hdadi and Mary, 2008). It is widely

87 used in France by farming advisors, researchers, teachers and students as it has a  
88 dedicated online version (<http://www.simeos-amg.org/>). However, its ability to simulate the  
89 effects of repeated EOM application on the long-term evolution of SOC stocks has not yet  
90 been verified. An update of the EOM parameters is also needed due to the recent  
91 development of the model (AMGv2). This version involves new formalisms and changes in  
92 some parameter values (Clivot et al., 2019). Moreover, because of the required increase in  
93 organic waste recycling in Europe (Directive 2018/851 of the European Parliament and of the  
94 Council) and in anaerobic digestion of both urban and agricultural wastes, the use of certain  
95 types of EOM is increasing together with the diversity of available EOM. Therefore,  
96 parameters for a wider range of EOM types are needed to facilitate AMG use by both  
97 researchers and stakeholders. The parameterization of EOM has previously been linked to  
98 the Roth-C model using field data from long-term experiments (Dechow et al., 2019; Peltre et  
99 al., 2012). However, long-term field trials are scarce and other methods based on laboratory  
100 analysis are needed to parameterize AMG. The indicator of residual organic carbon ( $I_{ROC}$ )  
101 (Lashermes et al., 2009) is calculated from biochemical fractions of EOM (Van Soest and  
102 Wine, 1967) and the proportion of EOM carbon mineralized during 3 days of incubation with  
103 soil.  $I_{ROC}$  has been defined as a predictor of the EOM residual carbon after long-term  
104 incubation of EOM with soil under controlled conditions. Peltre et al. (2012) used  $I_{ROC}$  to  
105 predict the partition of EOM into the different carbon pools of the Roth-C model. Preliminary  
106 results also indicate its potential use for parameterizing EOM in AMG (Bouthier et al., 2014).

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

## 111 **2 Materials and Methods**

### 112 **2.1 Field data**

113 Data from seven long-term field experiments were used for this study: Askov K2 in Denmark  
114 (Bruun et al., 2003; Christensen and Johnston, 1997), Colmar in eastern France (Obriot,  
115 2016), QualiAgro in northern France (Obriot et al., 2016; Peltre et al., 2012), La Jaillière in  
116 western France (Bouthier and Trochard, 2015), SERAIL in southern France (Peltre et al.,  
117 2012), Broadbalk at Rothamsted Research in southern England (Jenkinson and Rayner,  
118 1977; Perryman et al., 2018) and Ultuna in central Sweden (Gerzabek et al., 1997; Karhu et  
119 al., 2012; Kätterer et al., 2011). These seven experiments cover a wide range of durations,  
120 climates, soils, crop rotations and EOM types (Tables 1 and 2). More details about each  
121 experiment can be found in the references given above.

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

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

132 The SOC stocks were calculated by using SOC content and soil mass over the sampling  
133 depth, by considering an equivalent soil mass (Ellert and Bettany, 1995). When the soil bulk  
134 density changed over time (QualiAgro, Ultuna and Rothamsted experiments), SOC stocks  
135 were estimated by adding a variable amount of subsoil. In the Askov, Colmar, La Jaillière

136 and SERAIL experiments, bulk density remained constant and SOC stocks were computed  
137 with a constant soil depth. If any rock fragments were present (as at La Jaillière), the bulk  
138 density of the fine soil was used, and the rock fragment fraction was subtracted from the soil  
139 volume to compute the SOC stocks, as suggested by Poeplau et al. (2017).

## 140 **2.2 AMG model**

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

146 AMG considers three carbon pools (Figure 1): (i) a pool including carbon inputs from crop  
147 residues, roots and EOM, (ii) an active carbon pool and (iii) a stable carbon pool. A fixed  
148 proportion,  $K_1$ , of the carbon inputs is humified yearly and allocated to the active carbon pool.  
149 The remaining  $1-K_1$  is mineralized as  $\text{CO}_2$ . Aboveground crop residues, roots, EOM are each  
150 characterized by the specific  $K_1$  parameter (also termed isohumic coefficient). The active  
151 carbon pool decomposes according to first-order kinetics with a rate constant  $k$  affected by  
152 mean annual water balance and air temperature, soil clay and carbonate contents, soil pH  
153 and the C to N ratio of SOM (Clivot et al., 2017). The stable carbon pool is taken to be inert  
154 during the simulated period. The initial proportion of stable carbon is preset by default to 65%  
155 of the total SOC in long-term arable soils. The aboveground and belowground carbon inputs  
156 from plants are estimated by allometric relationships (Clivot et al., 2019) adapted from  
157 Bolinder et al. (2007) or directly as measured field data if available. The stocks are computed  
158 for a soil depth given as input data. AMG can be described by the following set of equations  
159 (Clivot et al., 2019):

$$160 \quad QC = QC_S + QC_A \quad (1)$$



$$161 \quad \frac{dQC_A}{dt} = \sum_i m_i K_{1i} - k QC_A \quad (2)$$

162 where  $QC$  is the total SOC stock ( $\text{t ha}^{-1}$ ),  $QC_A$  and  $QC_S$  are the C stocks of the active and  
163 stable C pools ( $\text{t ha}^{-1}$ ), respectively,  $m_i$  is the annual C input from organic residue  $i$  ( $\text{t ha}^{-1}$   
164  $\text{yr}^{-1}$ ),  $K_{1i}$  is its isohumic coefficient (the fraction of C inputs which is incorporated in SOM after  
165 1 year) and  $k$  is the mineralization rate constant of the active C pool ( $\text{yr}^{-1}$ )

## 166 **2.3 Determination of the coefficient $K_1$ in long-term field experiments**

### 167 *2.3.1 EOM $K_1$ optimization*

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

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

181 All other parameters of the model were kept as the default values to preserve the  
182 consistency of the model and the general applicability of the optimized EOM  $K_1$  values. This  
183 included the  $K_1$  values of aboveground crop residues and roots (Table S3 in Clivot et al.,

184 2019). Finally, for the field experiments in which soil pH and soil C to N ratio changed over  
185 time, these changes were considered in the model input data.

### 186 2.3.2 Model evaluation

187 The model performance was first evaluated in control treatments without EOM (ASK\_CT+N,  
188 COL\_CT+N, QUA\_CT-N and QUA\_CT+N, LAJA\_CT+N, ROTH\_CT\_S0 and ROTH\_CT\_S1,  
189 SER\_CT\_eqC and SER\_CT\_eqH, ULT\_CT-N and ULT\_CT+N). Indeed, because organic  
190 carbon from EOM is incorporated in SOC, it was important to verify the ability of the model to  
191 accurately simulate the evolution of SOC stocks under the various soil, climate and cropping  
192 system conditions. The mean error (*ME*), root mean square error (*RMSE*), relative *RMSE*  
193 (*RRMSE*), coefficient of determination (*R*<sup>2</sup>) and model efficiency (*EF*) were thus computed  
194 using the observed and simulated SOC stocks in each control treatment (Equations 3 to 7).  
195 The model performance for each treatment with EOM was then assessed by using the same  
196 statistical criteria.

$$197 \quad ME = \frac{1}{n} \cdot \sum_{i=1}^n (O_i - S_i) \quad (3)$$

$$198 \quad RMSE = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^n (O_i - S_i)^2} \quad (4)$$

$$199 \quad RRMSE = RMSE / \bar{O} \quad (5)$$

$$200 \quad R^2 = \left( \frac{\sum_{i=1}^n ((O_i - \bar{O}) \cdot (S_i - \bar{S}))}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2} \cdot \sqrt{\sum_{i=1}^n (S_i - \bar{S})^2}} \right)^2 \quad (6)$$

$$201 \quad EF = 1 - \frac{\sum_{i=1}^n (O_i - S_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (7)$$

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

## 204 **2.4 Using $I_{ROC}$ to model SOC stocks**

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

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

## 223 **2.5 The $I_{ROC}$ database**

224 The original database developed by Lashermes et al. (2009) provided  $K_1$  values for EOM  
225 types for which we did not have any field estimates. This database was expanded with  
226 additional  $I_{ROC}$  values from various research projects. Thus, the database contained more  
227 than 600 EOM types from 5 main groups: livestock liquid and solid manures (n=106),  
228 anaerobic digestates (n=54), sewage sludge (n=71), composts (n=352) and others (n=69).  
229 Most frequently used EOM types were present in the database; however, there were limited

230 number of values for cattle slurry (n=5) considering its relative abundance and for different  
231 types of digestates (from 2 to 9 depending on the type of digestates).

## 232 **3 Results**

### 233 **3.1 Evaluation of the AMG model for the control treatments**

234 The performance of the AMG model for the control treatments without EOM application was  
235 good for the Colmar, QualiAgro, La Jaillière, SERAIL and Ultuna experiments. In these  
236 treatments, the *RMSE* was equal to or lower than 3 t C ha<sup>-1</sup> and the *RRMSE* was lower than  
237 10% (electronic supplementary material, appendices A and B). The model thus succeeded in  
238 representing the decrease in SOC stocks at La Jaillière (CT\_N), Ultuna (CT\_N and CT),  
239 SERAIL (CT\_EQC and CT\_EQH), and QualiAgro (CT\_N-), and the nearly constant SOC  
240 stocks at Colmar (CT\_N) and QualiAgro (CT\_N+). For Askov and Rothamsted, the model  
241 performance was worse, with an *RMSE* between 4 and 5 t C ha<sup>-1</sup> in all control treatments  
242 (*RRMSE* from 19% to 30%). The model failed to simulate the increase in SOC stocks at  
243 Askov (CT\_N) and overestimated the decrease in SOC stocks at Rothamsted (CT\_S0 and  
244 CT\_S1). If we consider all treatments and experiments, the simulation bias (*ME*) remained  
245 low, smaller than 1 t C ha<sup>-1</sup>, except for the Askov, Rothamsted, Ultuna (T0) and La Jaillière  
246 experiments.

### 247 **3.2 Simulation of $\Delta$ SOC stocks with the optimized EOM $K_1$ value**

248 Using the optimized values of  $K_1$ , AMG succeeded in simulating the dynamics of  $\Delta$ SOC  
249 stocks in all treatments and experiments, except in two treatments at QualiAgro (BIO\_N+,  
250 BIO\_N-) and one at SERAIL (GW\_EQH) which were underestimated (Figure 2). This was  
251 confirmed by the low *ME* values (Table 3), except those for the underestimated treatments  
252 (*ME* higher than 3.5 t C/ha). The *RMSE* remained low, with minimum, mean and maximum  
253 values of 0.5, 3.0 and 8.2 t C ha<sup>-1</sup> respectively. Except for two treatments at La Jaillière

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

### 260 **3.3 Determination of isohumic coefficient ( $K_1$ ) values from long-term field** 261 **experiments**

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

### 268 **3.4 Prediction of $K_1$ with $I_{ROC}$**

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

### 276 **3.5 Simulations of C storage from EOM with $K_1$ values equal to $I_{ROC}$**

277 The  $I_{ROC}$  values were used as input  $K_1$  values in AMG to simulate the  $\Delta$ SOC stocks for the  
278 four experiments for which  $I_{ROC}$  values were available.  $RMSE$  logically increased in all

279 treatments when replacing optimized  $K_1$  with  $I_{ROC}$  (Figure 4). The mean  $RMSE$  increased  
280 from 3.0 to 4.9 t C ha<sup>-1</sup>, with a minimal increase of 0.01 t C ha<sup>-1</sup> for the FYM\_EQH treatment  
281 at SERAIL and a maximal increase of 5.4 t C ha<sup>-1</sup> for the treatment PEA+N at Ultuna. The  
282 largest increases in  $RMSE$  were associated with experiments with very high  $\Delta SOC$  stocks  
283 (more than 50 t C ha<sup>-1</sup> for PEA+N at Ultuna, for example), and thus the  $RMSE$  increases  
284 were relatively low.

### 285 **3.6 Definition of a database of reference $K_1$ values for AMG**

286 Using the  $I_{ROC}$  database (section 2.5), some marked differences among EOM types  
287 appeared, (Figure 5, appendix D in electronic supplementary material). For example, the  
288 median  $I_{ROC}$  values of chicken droppings, cattle manure and green waste compost were 16%,  
289 67% and 82%, respectively. Variability was also found within a given type of EOM: for  
290 example, the  $I_{ROC}$  values for cattle manure ranged from 21% to 79%. Some EOM types were  
291 grouped when an insufficient amount of data existed and if the differences among these  
292 EOMs were low. For example, all anaerobic digestates were grouped into one type. Another  
293 group was sewage sludge from urban wastewater treatment plants. Finally, we proposed a  
294 default  $K_1$  value for 26 EOM types: 9 types of livestock manure, 1 type of digestate, 2 types  
295 of sewage sludge, 13 types of compost and 1 type of other EOM.

## 296 **4 Discussion**

### 297 **4.1 The accurate simulation by AMG of SOC stock evolution after repeated** 298 **applications of EOM**

299 Many authors have observed an increase in SOC stocks following EOM addition, the  
300 increase being dependent on the amount and type of EOM applied (Bhogal et al., 2018;  
301 Maltas et al., 2018). The importance of the type of EOM in explaining differences in SOC  
302 storage was confirmed in experiments where various EOM types applied similar carbon

303 inputs (Gerzabek et al., 1997). AMG succeeded in simulating these increases in SOC stocks  
304 with various EOM types and under various pedoclimatic conditions and cropping systems  
305 (Figure 2), for example, in the Ultuna and QualiAgro experiments. The ability of the AMG  
306 model to simulate the additional SOC stocks from EOM addition ( $\Delta$ SOC stocks) was  
307 satisfactory. The mean *RMSE* value ( $3.0 \text{ t C ha}^{-1}$ ) was comparable to the mean standard  
308 deviation of the SOC measurements in the different experiments ( $2.1 \text{ t C ha}^{-1}$  in QualiAgro,  
309  $2.5 \text{ t C ha}^{-1}$  for Colmar). This mean *RMSE* for  $\Delta$ SOC stocks was also comparable to that  
310 obtained by Peltre et al. (2012) with the Roth-C model. These authors found a mean *RMSE*  
311 of  $3.2 \text{ t C ha}^{-1}$  in the Askov, QualiAgro (1998-2009 only), Ultuna and SERAIL experiments.  
312 Even if EOM  $K_1$  values were optimized to minimize the *RMSE* of  $\Delta$ SOC stocks, the *RMSE* of  
313 the simulated SOC stocks compared to the actual SOC stocks (electronic supplementary  
314 material, appendix C) was also similar to that found in other modeling studies. Karhu et al.  
315 (2012) reported *RMSE* values of SOC stocks between  $2.5$  and  $10.3 \text{ t C ha}^{-1}$  for different  
316 treatments in the Ultuna experiment (from  $2.1$  to  $6.6 \text{ t C ha}^{-1}$  for the same treatments in our  
317 study). Begum et al. (2017) obtained an *RRMSE* of 8.9% for the FYM treatment of the  
318 Rothamsted experiment (FYM\_S1), compared with 13.0% obtained in our study with AMG.  
319 These simulations could have been further improved if we had optimized the size of the  
320 stable SOC pool. However, this would not have affected the simulation of the  $\Delta$ SOC stocks.

321 Finally, the mean *RMSE* that we obtained in simulating  $\Delta$ SOC stocks for all EOM types  
322 ( $3.0 \text{ t C ha}^{-1}$ ) was close to the *RMSE* obtained for SOC stocks in the control treatments  
323 without EOM in our study ( $2.7 \text{ t C ha}^{-1}$ ). The mean *RMSE* from simulating  $\Delta$ SOC stocks was  
324 also close to the mean *RMSE* obtained by Clivot et al. (2019) with the AMG model on a  
325 dataset of 60 treatments located at 20 sites in France ( $2.6 \text{ t C ha}^{-1}$ ). However, the mean  
326 *RMSE* for SOC stocks with EOM application ( $4.3 \text{ t C ha}^{-1}$ , electronic supplementary material,  
327 appendix C) was higher. It is recalled that EOM  $K_1$  values were not optimized to minimize the  
328 *RMSE* for SOC stocks but rather to minimize the *RMSE* for  $\Delta$ SOC stocks. Indeed, the poor

329 modeling performance for the control treatments at Rothamsted and Askov also impacted the  
330 *RMSE* of SOC stocks for treatments with EOM (but not that of  $\Delta$ SOC stocks). The poor  
331 simulation of these control treatments could be related to inappropriate allometric coefficients  
332 used for old crop varieties at Rothamsted and to the very low initial C content in the subsoil  
333 used at the Askov experiment, for which the SOC mineralization function was not adapted.

#### 334 **4.2 Variability and prediction of the $K_1$ isohumic coefficient for EOM**

335 The optimized  $K_1$  values showed high variability among types of EOM, from 8% to 100%,  
336 with a mean value of 63%. Most of the EOM  $K_1$  values were higher than the  $K_1$  values of  
337 aboveground residues (from 22% to 32%) and roots (40%) (Clivot et al., 2019). This finding  
338 confirms that certain EOM types make a greater contribution to SOC than crop residues, as  
339 suggested by several authors (Kätterer et al., 2011; Kong et al., 2005), even if the  
340 continuation of this greater contribution in the long term is debated (Maillard and Angers,  
341 2014).

342 The variability in EOM  $K_1$  values well reflected the difference in stability of different EOM  
343 types, as approximated by their  $I_{ROC}$  value (Figure 3). Using the  $I_{ROC}$  indicator as a predictor  
344 of  $K_1$  only slightly decreased model performance (Figure 4). The largest increases in *RMSE*  
345 were associated with experiments with very high  $\Delta$ SOC stocks. The small *RMSE* values  
346 confirmed the usefulness of  $I_{ROC}$  for parameterizing soil carbon models, as shown by Peltre  
347 et al. (2012) with Roth-C. In comparison to the parameters used for this latter study, the use  
348 of  $I_{ROC}$  was easier:  $I_{ROC}$  was directly used to derive  $K_1$  values in AMG without any rescaling,  
349 whereas several regressions were needed to predict the Roth-C EOM parameters. Some  
350 studies used other laboratory measurements to calibrate EOM in soil carbon models.  
351 Mondini et al. (2017) used EOM incubations to predict the partition coefficients and  
352 mineralization rates of EOM in Roth-C. Pansu et al. (2017) used  $^{13}\text{C}$  nuclear magnetic  
353 resonance spectra to estimate the parameters of the TAO model. In comparison to these



354 studies, the advantages of  $I_{ROC}$  are that it is a standardized (XP U44-162 standard),  
355 inexpensive method, and is already being conducted by several commercial laboratories.

#### 356 **4.3 The need for further improvement of the AMG formalism for EOM?**

357 Even if the performance of AMG in simulating the effects of EOM on SOC stocks was  
358 generally satisfying, AMG failed to simulate the substantial increase in SOC stocks observed  
359 in some treatments of the QualiAgro experiment (+24 t C ha<sup>-1</sup> in 20 years for the BIO\_N+  
360 treatment), even with the maximal  $K_1$  value ( $K_1 = 100\%$ ). In AMG, organic carbon from EOM  
361 is incorporated into the active SOC pool the year following EOM application and is then  
362 mineralized at the same rate as the native active SOC pool. The result for QualiAgro  
363 suggests that SOC derived from EOM could have a slower mineralization rate than the native  
364 SOC. This hypothesis is supported by other modeling studies: tests done with the STICS  
365 soil-crop model showed that a slower decomposition constant was needed to accurately  
366 simulate the SOC stocks in QualiAgro (Levavasseur et al., in prep). Noirot-Cosson et al.  
367 (2016) also calibrated a slower decomposition rate constant for EOM than for SOC to  
368 simulate the QualiAgro experiment with the CERES-EGC model. Peltre et al. (2017)  
369 observed a higher thermal stability of organic matter in EOM-amended soils. Yu et al. (2012)  
370 indicated a lower specific mineralization rate in EOM-amended soils, but Liu et al. (2018)  
371 found the opposite result.

372 Although the isohumic coefficient  $K_1$  was generally well predicted by the  $I_{ROC}$  indicator,  
373 significant residual variability remained. Some very different  $K_1$  values were optimized for  
374 similar EOM types in different experiments. For example, the optimized  $K_1$  for cattle manure  
375 varied greatly among the different experiments. Part of this variability is certainly due to the  
376 true variability in OM stability, which could be related to differences in bedding materials and  
377 storage duration (Helgason et al., 2005). More surprisingly, we observed an unexplained  
378 variability in the  $K_1$  of the green waste and sludge compost at QualiAgro and Colmar.  
379 Although the compost often came from the same producer, the optimized  $K_1$  values were

380 very different, at 100% and 41%, respectively. This unexplained variability in  $K_1$  indicates that  
381 some factors not considered in the AMG model affected the storage of carbon from EOM.  
382 Zhang et al. (2018) showed that accounting for the effects of litter stoichiometry and soil N  
383 availability may improve the simulation of SOM formation with the CENTURY model. Peltre  
384 et al. (2012) suggested that changes in soil pH may explain some of the larger simulation  
385 errors obtained with Roth-C. In our case, the evolution of pH was explicitly considered in the  
386 AMG model (annual soil pH was a model input). Brillì et al. (2017) also indicated that poor  
387 consideration of soil water conditions may lead to erroneous SOC modeling. The simple  
388 annual water balance used in the AMG model to account for the effect of climate on SOC  
389 dynamics might be a cause of some poor simulations. For example, in Colmar, the effect of  
390 common thunderstorms in summer is not well represented by an annual water balance.

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

## 398 **5 Conclusion**

399 Using the AMG model, we simulated the evolution of SOC stocks in seven long-term field  
400 experiments with repeated applications of different EOM types. The good model performance  
401 confirmed its ability to adequately simulate long-term effects of EOM application on SOC  
402 stocks. The only EOM parameter in AMG, the isohumic coefficient  $K_1$ , was optimized for each  
403 EOM to minimize the difference in SOC stocks between treatments with and without EOM.  
404 These optimized  $K_1$  values were well correlated with the organic matter stability of EOM,

405 approximated by the indicator of residual organic carbon in soil ( $I_{ROC}$ ). This indicator is  
406 routinely analyzed by commercial laboratories. The  $I_{ROC}$  value could be used directly as the  
407 EOM  $K_f$  value in AMG while maintaining satisfactory model performance. A database of  $I_{ROC}$   
408 values was used to parameterize 26 types of EOM in AMG, which can thus be used by  
409 stakeholders to model the effects of different EOM practices.

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573

574 **7 Tables**

575 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 <sub>3</sub> content (%)	Mean initial SOC stock (t C ha <sup>-1</sup> )	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)	Calcisol	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 Jaillièrè 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

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

Experiment	Treatment	EOM type	Mean EOM amount (t C ha <sup>-1</sup> )	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
			3.5	2	Optimal mineral N fertilization
	FYM-N	Cattle farmyard manure	3.7	2	Low mineral N fertilization
			3.7	2	Optimal mineral N fertilization
	CT-N	-	-	-	Low mineral N fertilization
	CT+N	-	-	-	Optimal mineral N fertilization
La Jaillièrè 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

Experiment	Treatment	EOM type	Mean EOM amount (t C ha <sup>-1</sup> )	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 <sup>-1</sup> )	EOM return period (year)	Mineral fertilization or straw management differences
	CT+N	-	-	-	Mineral N

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581 Table 3 Model performance in simulating  $\Delta$ SOC stocks in the treatments with EOM in the seven long-  
582 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 <sup>-1</sup> )	RMSE (t C ha <sup>a-1</sup> )	RRMSE (%)	R <sup>2</sup>	EF	K <sub>1</sub> (%)
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 <sup>-1</sup> )	RMSE (t C ha <sup>a-1</sup> )	RRMSE (%)	R <sup>2</sup>	EF	K <sub>1</sub> (%)
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

583

584 Table 4 Mean error (*ME*), root mean square error (*RMSE*) and coefficient of determination (*R*<sup>2</sup>)  
 585 between the *I*<sub>ROC</sub> indicator and the optimized *K*<sub>1</sub> for all treatments of experiments for which *I*<sub>ROC</sub> values  
 586 were available

Experiment	ME (%)	RMSE (%)	R <sup>2</sup>
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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588



## 589 **8 Figure captions**

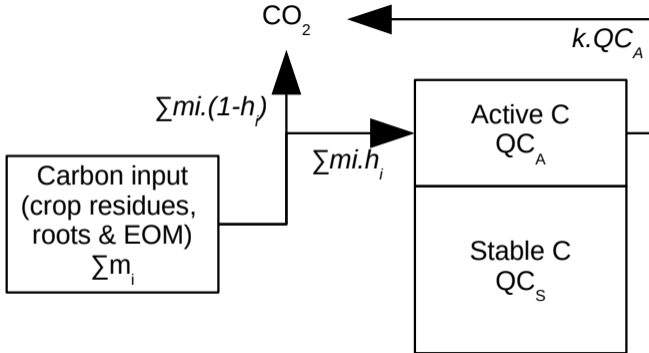
590 Figure 1 Conceptual diagram of the AMG model. The organic carbon inputs ( $m$ ) from crop residues,  
591 roots or EOM are either mineralized ( $1-K_1$  fraction) or incorporated ( $K_1$  fraction) into the active soil  
592 organic carbon pool (Active C,  $QC_A$ ). The active organic carbon pool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

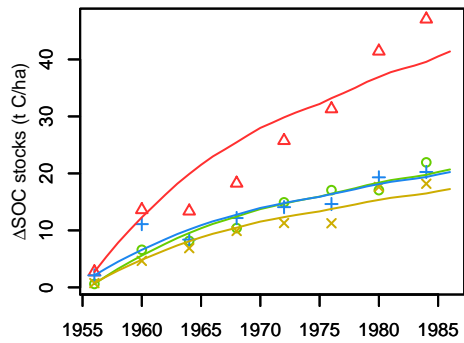
595 Figure 2 Observed (dots) and simulated (lines) differences in SOC stocks ( $\Delta$ SOC stocks) between the  
596 treatments with EOM and without EOM (controls) for the seven long-term field experiments (created  
597 with R)

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

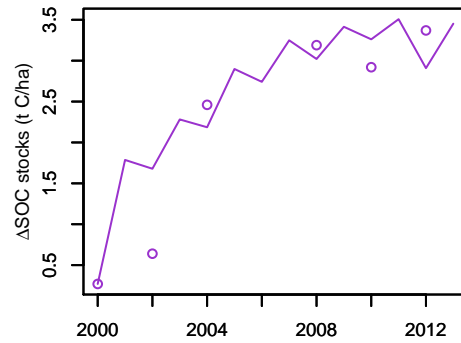
602 Figure 4 Root mean square error ( $RMSE$ ) between simulated and observed differences in SOC stocks  
603 in treatments with and without EOM ( $\Delta$ SOC stocks) in four long-term experiments. The isohumic  $K_1$   
604 coefficient was either optimized (black bars) or equal to  $I_{ROC}$  (gray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

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

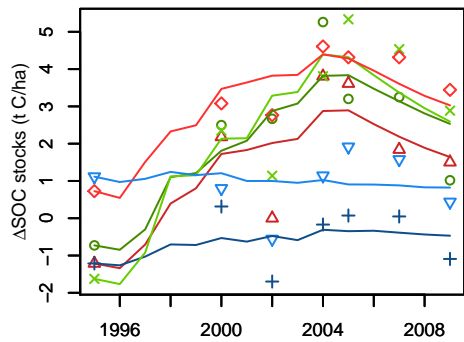


**ASK**

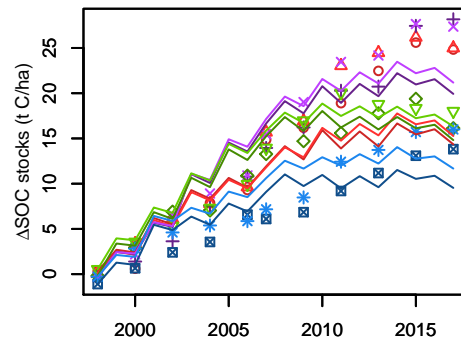
○ FYM  
 ▲ PEA  
 + SAW  
 × STR

**COL**

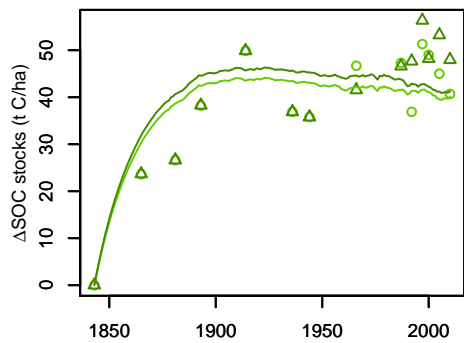
○ GWS\_N+

**LAJA2**

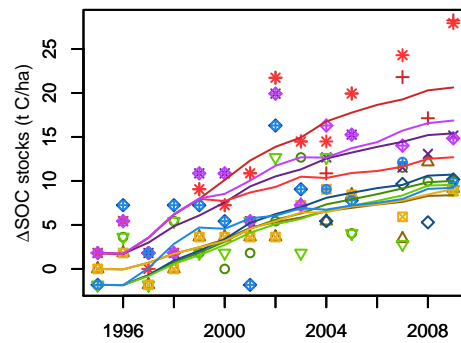
○ CCM  
 ▲ CPIM  
 + CPOM  
 × CM  
 ◆ PIM  
 ▼ POM

**QUA**

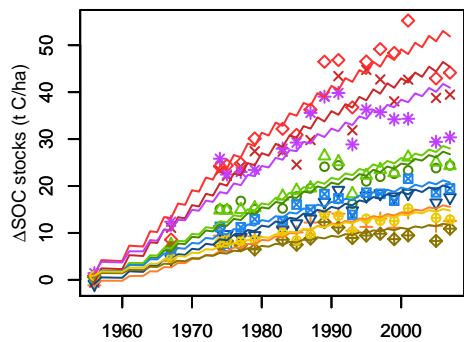
○ BIO\_N+  
 ▲ BIO\_N-  
 + GWS\_N+  
 × GWS\_N-  
 ◆ FYM\_N+  
 ▼ FYM\_N-  
 ■ MSW\_N+  
 \* MSW\_N-

**ROTH**

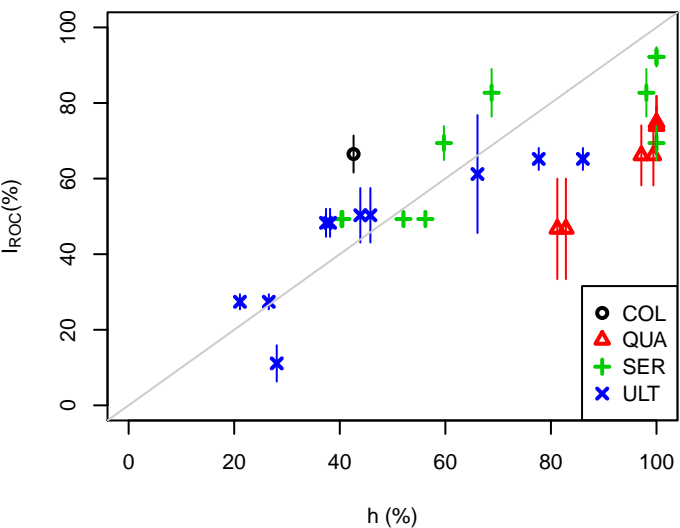
○ FYM\_S0  
 ▲ FYM\_S1

**SER**

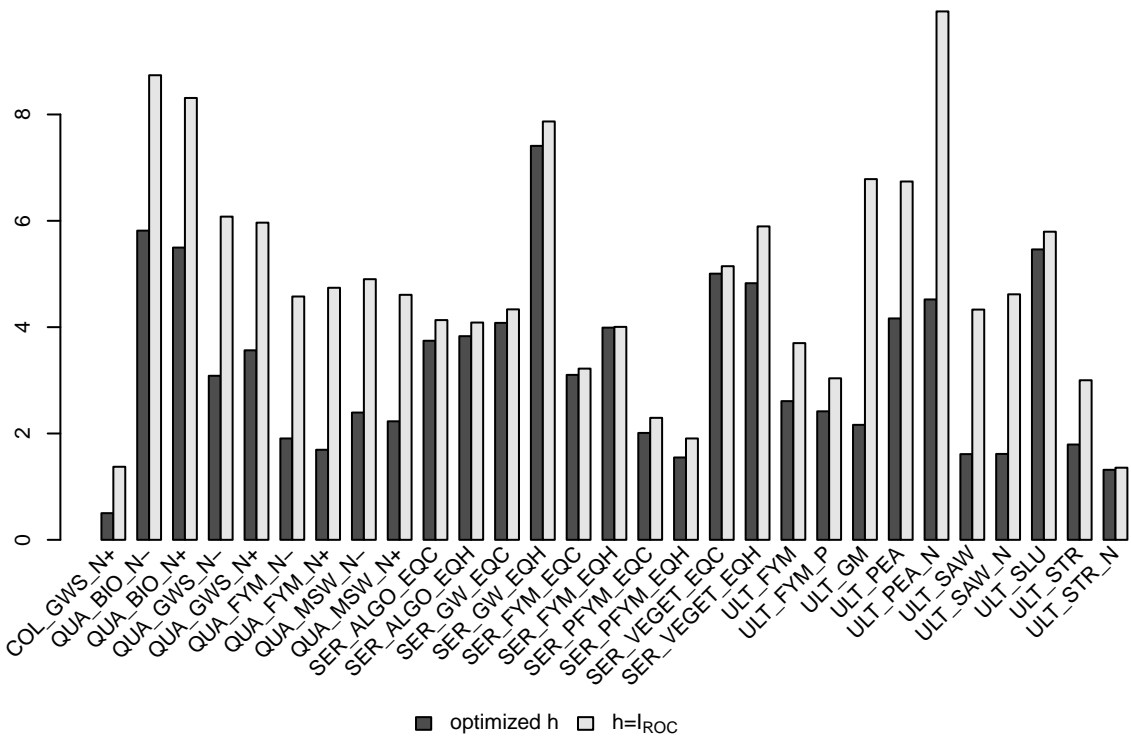
○ FYM\_EQC  
 ▲ PFYM\_EQC  
 + GW\_EQC  
 × ALGO\_EQC  
 ◆ VEGET\_EQC  
 ▼ FYM\_EQH  
 ■ PFYM\_EQH  
 \* GW\_EQH  
 ◆ ALGO\_EQH  
 \* VEGET\_EQH

**ULT**

○ FYM  
 ▲ FYM\_P  
 + GM  
 × PEA  
 ◆ PEA\_N  
 ▼ SAW  
 ■ SAW\_N  
 \* SLU  
 ◆ STR  
 \* STR\_N



RMSE  $\Delta$ SOC stocks (t C/ha)



■ optimized h    □ h=lROC

