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

Florent Levavasseur, Bruno Mary, Bent Christensen, Annie Duparque, Fabien Ferchaud, Thomas Kätterer, Hélène Lagrange, Denis Montenach, Camille Resseguier, Sabine Houot

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5    Florent Levavasseur[1*], Bruno Mary[2], Bent T Christensen[3], Annie Duparque[4], Fabien

6    Ferchaud[2], Thomas Kätterer[5], Hélène Lagrange[6], Denis Montenach[7], Camille Resseguier[1],

7    Sabine Houot[1]

8    [1] UMR INRA AgroParisTech ECOSYS, Université Paris-Saclay, 78850 Thiverval-Grignon,

9    France

10    [2] BioEcoAgro Joint Research Unit, INRAE, Université de Liège, Université de Lille,

11    Université de Picardie Jules Verne, 02000 Barenton-Bugny, France

12    [3] Department of Agroecology, AU Foulum, Aarhus University, Tjele, Denmark

13    [4] Agro-Transfert Ressources et Territoires, 80200 Estrées-Mons, France

14    [5] Department of Ecology, Swedish University of Agricultural Sciences, Uppsala, Sweden

15    [6] ARVALIS-Institut du Végétal, 31450 Baziège, France

16    [7] UE INRA 0871 Service d'expérimentation Agronomique et Viticole, Colmar, France

17    * Corresponding author: florent.levavasseur@inra.fr

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## 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$^{-1}$ (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.

## 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 $CO_2$ 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.

## 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

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).

## 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 $CO_2$. 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  $QC = QC_S + QC_A$ (1)

7

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

162    where $QC$ is the total SOC stock (t ha$^{-1}$), $QC_A$ and $QC_S$ are the C stocks of the active and

163    stable C pools (t ha$^{-1}$), respectively, $m_i$ is the annual C input from organic residue i (t ha$^{-1}$

164    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 (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 ΔSOC 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 ΔSOC stocks, with $K_1$ varying between 0 and 100%.

174    Using ΔSOC 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 ΔSOC 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 (*R²*) 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 $ME = \frac{1}{n} \cdot \sum_{i=1}^{n}(O_i - S_i)$      (3)

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

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

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

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

10

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).

# 3   Results

232

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

233

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$^{-1}$ 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$^{-1}$ 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$^{-1}$, except for the Askov, Rothamsted, Ultuna (T0) and La Jaillière

246    experiments.

### 3.2   Simulation of ΔSOC stocks with the optimized EOM $K_1$ value

247

248    Using the optimized values of $K_1$, AMG succeeded in simulating the dynamics of ΔSOC

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$^{-1}$ respectively. Except for two treatments at La Jaillière

254  (POM, CPOM), which had very low variability in ΔSOC stocks, and the SERAIL experiment,

255  for which the dynamics of ΔSOC stocks were very noisy, the R² values were high (>0.6) to

256  very high, indicating a good simulation of the variability of ΔSOC stocks. For example, the

257  initial increase followed by stability in ΔSOC stocks at Rothamsted was well simulated, as

258  was the initial increase at La Jaillère followed by a decrease in ΔSOC stocks after the

259  cessation of EOM application. The model efficiency (*EF)* exhibited the same trends as *R².*

260  **3.3 Determination of isohumic coefficient (*K₁*) 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 *K₁* 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 $I_{ROC}$ (*R²* = 0.73 - 0.95). Considering all experiments together, the $I_{ROC}$

275  explained slightly less of the $K_1$ variability (*R²* = 0.62).

276  **3.5 Simulations of C storage from EOM with *K₁* values equal to *I$_{ROC}$***

277  The $I_{ROC}$ values were used as input $K_1$ values in AMG to simulate the ΔSOC 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$^{-1}$, with a minimal increase of 0.01 t C ha$^{-1}$ for the FYM_EQH treatment

281  at SERAIL and a maximal increase of 5.4 t C ha$^{-1}$ for the treatment PEA+N at Ultuna. The

282  largest increases in *RMSE* were associated with experiments with very high ∆SOC stocks

283  (more than 50 t C ha$^{-1}$ 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 (ΔSOC stocks) was

307    satisfactory. The mean *RMSE* value (3.0 t C ha$^{-1}$) was comparable to the mean standard

308    deviation of the SOC measurements in the different experiments (2.1 t C ha$^{-1}$ in QualiAgro,

309    2.5 t C ha$^{-1}$ for Colmar). This mean *RMSE* for ΔSOC 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 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 ΔSOC 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 t C ha$^{-1}$ for different

316    treatments in the Ultuna experiment (from 2.1 to 6.6 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 ΔSOC stocks.

321    Finally, the mean *RMSE* that we obtained in simulating ΔSOC stocks for all EOM types

322    (3.0 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 t C ha$^{-1}$). The mean RMSE from simulating ΔSOC 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 t C ha$^{-1}$). However, the mean

326    *RMSE* for SOC stocks with EOM application (4.3 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 ΔSOC 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 ΔSOC 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 ΔSOC 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 $^{13}C$ 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.

### 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$^{-1}$ 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). Brilli 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.


## 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 $K_1$ 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.

## 6  References

410

411  Andrén, O., Kätterer, T., 1997. Icbm: The Introductory Carbon Balance Model for Exploration

412  of Soil Carbon Balances. Ecol. Appl. 7, 1226–1236. https://doi.org/10.1890/1051-

413  0761(1997)007[1226:ITICBM]2.0.CO;2

414  Andriulo, A., Mary, B., Guerif, J., 1999. Modelling soil carbon dynamics with various cropping

415  sequences on the rolling pampas. Agron. Sustain. Dev. 19, 365–377.

416  https://doi.org/10.1051/agro:19990504

417  Begum, K., Kuhnert, M., Yeluripati, J., Glendining, M., Smith, P., 2017. Simulating soil carbon

418  sequestration from long term fertilizer and manure additions under continuous wheat using

419  the DailyDayCent model. Nutr. Cycl. Agroecosystems 109, 291–302.

420  https://doi.org/10.1007/s10705-017-9888-0

421  Bhogal, A., Nicholson, F.A., Rollett, A., Taylor, M., Litterick, A., Whittingham, M.J., Williams,

422  J.R., 2018. Improvements in the Quality of Agricultural Soils Following Organic Material

423  Additions Depend on Both the Quantity and Quality of the Materials Applied. Front. Sustain.

424  Food Syst. 2. https://doi.org/10.3389/fsufs.2018.00009

425  Bolinder, M.A., Janzen, H.H., Gregorich, E.G., Angers, D.A., VandenBygaart, A.J., 2007. An

426  approach for estimating net primary productivity and annual carbon inputs to soil for common

427  agricultural crops in Canada. Agric. Ecosyst. Environ. 118, 29–42.

428  https://doi.org/10.1016/j.agee.2006.05.013

429   Bouthier, A., Duparque, A., Mary, B., Sagot, S., Trochard, R., Levert, M., Houot, S., Damay,
430   N., Denoroy, P., Dinh, J.-L., Blin, B., Ganteil, F., 2014. Adaptation et mise en œuvre du
431   modèle de calcul de bilan humique à long terme AMG dans une large gamme de systèmes
432   de grandes cultures et de polyculture-élevage. Innov. Agron. 34, 125–139.

433   Bouthier, A., Trochard, R., 2015. Incidence d'apports répétés d'engrais de ferme sur la
434   fertilité physique, chimique et microbiologique des sols sous rotation de cultures annuelles et
435   sous prairie temporaire. Fourrages 223, 211–219.

436   Brilli, L., Bechini, L., Bindi, M., Carozzi, M., Cavalli, D., Conant, R., Dorich, C.D., Doro, L.,
437   Ehrhardt, F., Farina, R., Ferrise, R., Fitton, N., Francaviglia, R., Grace, P., Iocola, I., Klumpp,
438   K., Léonard, J., Martin, R., Massad, R.S., Recous, S., Seddaiu, G., Sharp, J., Smith, P.,
439   Smith, W.N., Soussana, J.-F., Bellocchi, G., 2017. Review and analysis of strengths and
440   weaknesses of agro-ecosystem models for simulating C and N fluxes. Sci. Total Environ.
441   598, 445–470. https://doi.org/10.1016/j.scitotenv.2017.03.208

442   Bruun, S., Christensen, B.T., Hansen, E.M., Magid, J., Jensen, L.S., 2003. Calibration and
443   validation of the soil organic matter dynamics of the Daisy model with data from the Askov
444   long-term experiments. Soil Biol. Biochem. 35, 67–76. https://doi.org/10.1016/S0038-
445   0717(02)00237-7

446   Byrd, R., Lu, P., Nocedal, J., Zhu, C., 1995. A Limited Memory Algorithm for Bound
447   Constrained    Optimization.    SIAM    J.    Sci.    Comput.    16,    1190–1208.
448   https://doi.org/10.1137/0916069

449   Christensen, B.T., Johnston, A.E., 1997. Chapter 18 Soil organic matter and soil quality—
450   Lessons learned from long-term experiments at Askov and Rothamsted, in: Gregorich, E.G.,
451   Carter, M.R. (Eds.), Developments in Soil Science, Soil Quality for Crop Production and
452   Ecosystem Health. Elsevier, pp. 399–430. https://doi.org/10.1016/S0166-2481(97)80045-1

453    Clivot, H., Mary, B., Valé, M., Cohan, J.-P., Champolivier, L., Piraux, F., Laurent, F., Justes,

454    E., 2017. Quantifying in situ and modeling net nitrogen mineralization from soil organic

455    matter in arable cropping systems. Soil Biol. Biochem. 111, 44–59.

456    https://doi.org/10.1016/j.soilbio.2017.03.010

457    Clivot, H., Mouny, J.-C., Duparque, A., Dinh, J.-L., Denoroy, P., Houot, S., Vertès, F.,

458    Trochard, R., Bouthier, A., Sagot, S., Mary, B., 2019. Modeling soil organic carbon evolution

459    in long-term arable experiments with AMG model. Environ. Model. Softw. 118, 99–113.

460    https://doi.org/10.1016/j.envsoft.2019.04.004

461    Dechow, R., Franko, U., Kätterer, T., Kolbe, H., 2019. Evaluation of the RothC model as a

462    prognostic tool for the prediction of SOC trends in response to management practices on

463    arable land. Geoderma 337, 463–478. https://doi.org/10.1016/j.geoderma.2018.10.001

464    Dignac, M.-F., Derrien, D., Barré, P., Barot, S., Cécillon, L., Chenu, C., Chevallier, T.,

465    Freschet, G.T., Garnier, P., Guenet, B., Hedde, M., Klumpp, K., Lashermes, G., Maron, P.-

466    A., Nunan, N., Roumet, C., Basile-Doelsch, I., 2017. Increasing soil carbon storage:

467    mechanisms, effects of agricultural practices and proxies. A review. Agron. Sustain. Dev. 37,

468    14. https://doi.org/10.1007/s13593-017-0421-2

469    Eden, M., Gerke, H.H., Houot, S., 2017. Organic waste recycling in agriculture and related

470    effects on soil water retention and plant available water: a review. Agron. Sustain. Dev. 37,

471    11. https://doi.org/10.1007/s13593-017-0419-9

472    Gerzabek, M. h., Pichlmayer, F., Kirchmann, H., Haberhauer, G., 1997. The response of soil

473    organic matter to manure amendments in a long-term experiment at Ultuna, Sweden. Eur. J.

474    Soil Sci. 48, 273–282. https://doi.org/10.1111/j.1365-2389.1997.tb00547.x

475    Gómez-Muñoz, B., Magid, J., Jensen, L.S., 2017. Nitrogen turnover, crop use efficiency and

476    soil fertility in a long-term field experiment amended with different qualities of urban and

477    agricultural    waste.    Agric.    Ecosyst.    Environ.    240,    300–313.
478    https://doi.org/10.1016/j.agee.2017.01.030

479    Helgason, B.L., Larney, F.J., Janzen, H.H., 2005. Estimating carbon retention in soils
480    amended with composted beef cattle manure. Can. J. Soil Sci. 85, 39–46.
481    https://doi.org/10.4141/S04-049

482    Hénin, S., Dupuis, M., 1945. Essai de bilan de la matière organique du sol. Ann. Agron. 15,
483    17–29.

484    Jenkinson, D.S., Rayner, J.H., 1977. The Turnover of Soil Organic Matter in Some of the
485    Rothamsted Classical Experiments. Soil Sci. 123. https://doi.org/10.1097/00010694-
486    200606001-00018

487    Karhu, K., Gärdenäs, A.I., Heikkinen, J., Vanhala, P., Tuomi, M., Liski, J., 2012. Impacts of
488    organic amendments on carbon stocks of an agricultural soil — Comparison of model-
489    simulations    to    measurements.    Geoderma    189–190,    606–616.
490    https://doi.org/10.1016/j.geoderma.2012.06.007

491    Kätterer, T., Bolinder, M.A., Andrén, O., Kirchmann, H., Menichetti, L., 2011. Roots
492    contribute more to refractory soil organic matter than above-ground crop residues, as
493    revealed by a long-term field experiment. Agric. Ecosyst. Environ. 141, 184–192.
494    https://doi.org/10.1016/j.agee.2011.02.029

495    Kong, A.Y.Y., Six, J., Bryant, D.C., Denison, R.F., van Kessel, C., 2005. The Relationship
496    between Carbon Input, Aggregation, and Soil Organic Carbon Stabilization in Sustainable
497    Cropping    Systems.    Soil    Sci.    Soc.    Am.    J.    69,    1078–1085.
498    https://doi.org/10.2136/sssaj2004.0215

499    Lashermes, G., Nicolardot, B., Parnaudeau, V., Thuriès, L., Chaussod, R., Guillotin, M.L.,
500    Linères, M., Mary, B., Metzger, L., Morvan, T., Tricaud, A., Villette, C., Houot, S., 2009.

501    Indicator of potential residual carbon in soils after exogenous organic matter application. Eur.

502    J. Soil Sci. 60, 297–310. https://doi.org/10.1111/j.1365-2389.2008.01110.x

503    Liu, H., Zhang, J., Ai, Z., Wu, Y., Xu, H., Li, Q., Xue, S., Liu, G., 2018. 16-Year fertilization

504    changes the dynamics of soil oxidizable organic carbon fractions and the stability of soil

505    organic carbon in soybean-corn agroecosystem. Agric. Ecosyst. Environ. 265, 320–330.

506    https://doi.org/10.1016/j.agee.2018.06.032

507    Maillard, É., Angers, D.A., 2014. Animal manure application and soil organic carbon stocks: a

508    meta-analysis. Glob. Change Biol. 20, 666–679. https://doi.org/10.1111/gcb.12438

509    Maltas, A., Kebli, H., Oberholzer, H.R., Weisskopf, P., Sinaj, S., 2018. The effects of organic

510    and mineral fertilizers on carbon sequestration, soil properties, and crop yields from a long-

511    term field experiment under a Swiss conventional farming system. Land Degrad. Dev. 29,

512    926–938. https://doi.org/10.1002/ldr.2913

513    Mondini, C., Cayuela, M.L., Sinicco, T., Fornasier, F., Galvez, A., Sánchez-Monedero, M.A.,

514    2017. Modification of the RothC model to simulate soil C mineralization of exogenous organic

515    matter. Biogeosciences 14, 3253–3274. https://doi.org/10.5194/bg-14-3253-2017

516    Noirot-Cosson, P.E., Vaudour, E., Gilliot, J.M., Gabrielle, B., Houot, S., 2016. Modelling the

517    long-term effect of urban waste compost applications on carbon and nitrogen dynamics in

518    temperate cropland. Soil Biol. Biochem. 94, 138–153.

519    https://doi.org/10.1016/j.soilbio.2015.11.014

520    Obriot, F., 2016. Epandage de produits residuaires organiques et fonctionnement biologique

521    des sols: De la quantification des impacts sur les cycles carbone et azote a l'evaluation

522    multicritere de la pratique a l'echelle de la parcelle (PhD thesis). AgroParisTech.

523    Obriot, F., Stauffer, M., Goubard, Y., Cheviron, N., Peres, G., Eden, M., Revallier, A.,

524    Vieublé-Gonod, L., Houot, S., 2016. Multi-criteria indices to evaluate the effects of repeated

525    organic amendment applications on soil and crop quality. Agric. Ecosyst. Environ. 232, 165–

526    178. https://doi.org/10.1016/j.agee.2016.08.004

527    Pansu, M., Thuriès, L.J.-M., Soares, V.F., Simões, M.L., Neto, L.M., 2017. Modelling the

528    transformation of organic materials in soil with nuclear magnetic resonance spectra. Eur. J.

529    Soil Sci. 68, 90–104. https://doi.org/10.1111/ejss.12405

530    Parton, W.J., Schimel, D.S., Cole, C.V., Ojima, D.S., 1987. Analysis of Factors Controlling

531    Soil Organic Matter Levels in Great Plains Grasslands 1. Soil Sci. Soc. Am. J. 51, 1173–

532    1179. https://doi.org/10.2136/sssaj1987.03615995005100050015x

533    Peltre, C., Christensen, B.T., Dragon, S., Icard, C., Kätterer, T., Houot, S., 2012. RothC

534    simulation of carbon accumulation in soil after repeated application of widely different organic

535    amendments. Soil Biol. Biochem. 52, 49–60. https://doi.org/10.1016/j.soilbio.2012.03.023

536    Peltre, C., Gregorich, E.G., Bruun, S., Jensen, L.S., Magid, J., 2017. Repeated application of

537    organic waste affects soil organic matter composition: Evidence from thermal analysis, FTIR-

538    PAS, amino sugars and lignin biomarkers. Soil Biol. Biochem. 104, 117–127.

539    https://doi.org/10.1016/j.soilbio.2016.10.016

540    Perryman, S.A.M., Castells-Brooke, N.I.D., Glendining, M.J., Goulding, K.W.T., Hawkesford,

541    M.J., Macdonald, A.J., Ostler, R.J., Poulton, P.R., Rawlings, C.J., Scott, T., Verrier, P.J.,

542    2018. The electronic Rothamsted Archive (e-RA), an online resource for data from the

543    Rothamsted        long-term        experiments.        Sci.        Data        5,        180072.

544    https://doi.org/10.1038/sdata.2018.72

545    Poeplau, C., Vos, C., Don, A., 2017. Soil organic carbon stocks are systematically

546    overestimated by misuse of the parameters bulk density and rock fragment content. SOIL 3,

547    61–66. https://doi.org/10.5194/soil-3-61-2017

548     Powlson, D.S., Whitmore, A.P., Goulding, K.W.T., 2011. Soil carbon sequestration to

549     mitigate climate change: a critical re-examination to identify the true and the false. Eur. J.

550     Soil Sci. 62, 42–55. https://doi.org/10.1111/j.1365-2389.2010.01342.x

551     Saffih-Hdadi, K., Mary, B., 2008. Modeling consequences of straw residues export on soil

552     organic carbon. Soil Biol. Biochem. 40, 594–607.

553     https://doi.org/10.1016/j.soilbio.2007.08.022

554     Taghizadeh-Toosi, A., Christensen, B.T., Hutchings, N.J., Vejlin, J., Kätterer, T., Glendining,

555     M., Olesen, J.E., 2014. C-TOOL: A simple model for simulating whole-profile carbon storage

556     in temperate agricultural soils. Ecol. Model. 292, 11–25.

557     https://doi.org/10.1016/j.ecolmodel.2014.08.016

558     Van Soest, P.J., Wine, R.H., 1967. Use of detergents in the analysis of fibrous feeds. IV.

559     Determination of plant cell-wall constituents. J. Assoc. Off. Anal. Chem. 50, 50–55.

560     Yu, H., Ding, W., Luo, J., Geng, R., Ghani, A., Cai, Z., 2012. Effects of long-term compost

561     and fertilizer application on stability of aggregate-associated organic carbon in an intensively

562     cultivated sandy loam soil. Biol. Fertil. Soils 48, 325–336. https://doi.org/10.1007/s00374-

563     011-0629-2

564     Zavattaro, L., Bechini, L., Grignani, C., van Evert, F.K., Mallast, J., Spiegel, H., Sandén, T.,

565     Pecio, A., Giráldez Cervera, J.V., Guzmán, G., Vanderlinden, K., D'Hose, T., Ruysschaert,

566     G., ten Berge, H.F.M., 2017. Agronomic effects of bovine manure: A review of long-term

567     European field experiments. Eur. J. Agron. 90, 127–138.

568     https://doi.org/10.1016/j.eja.2017.07.010

569     Zhang, H., Goll, D.S., Manzoni, S., Ciais, P., Guenet, B., Huang, Y., 2018. Modeling the

570     effects of litter stoichiometry and soil mineral N availability on soil organic matter formation

571    using    CENTURY-CUE    (v1.0).    Geosci.    Model    Dev.    11,    4779–4796.

572    https://doi.org/10.5194/gmd-11-4779-2018

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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 $CaCO_3$ 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 |

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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⁻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 |

27

| 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 |

579

580

581    Table 3 Model performance in simulating ∆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$^{-1}$) | 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 |

583

584  Table 4 Mean error (*ME*), root mean square error (*RMSE*) and coefficient of determination (*R²*)

585  between the *I$_{ROC}$* indicator and the optimized *K$_1$* for all treatments of experiments for which *I$_{ROC}$* values

586  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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588

## 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 ($\Delta$SOC 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 ($\Delta$SOC 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)
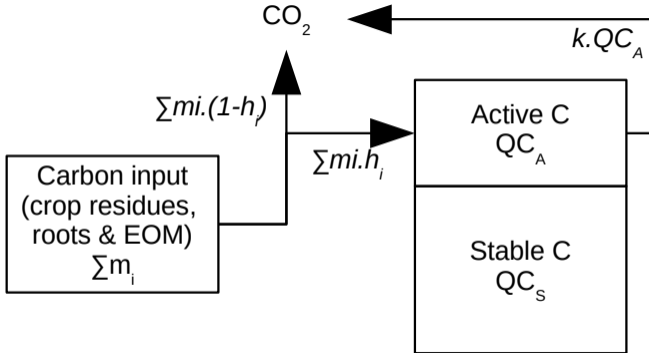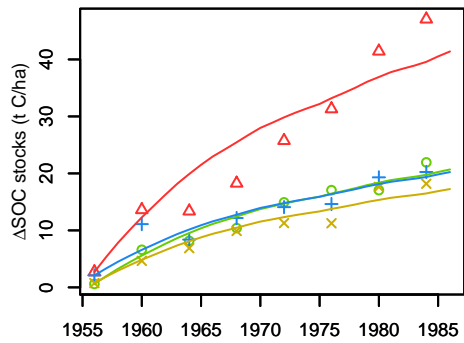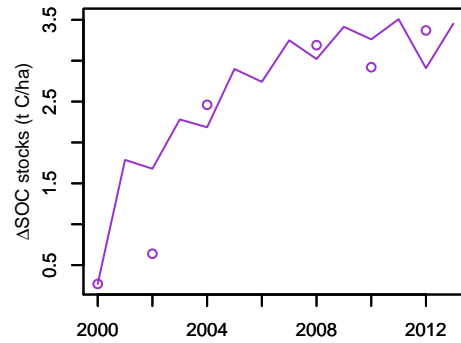
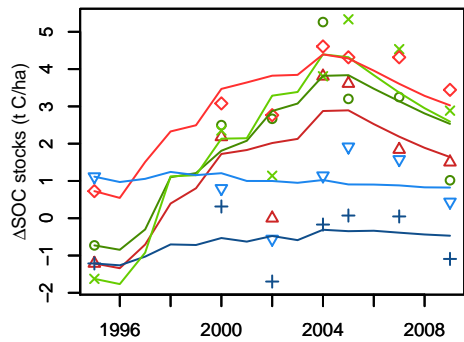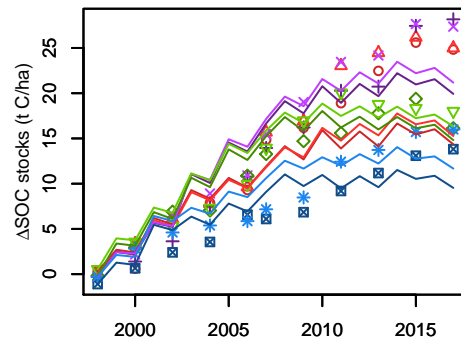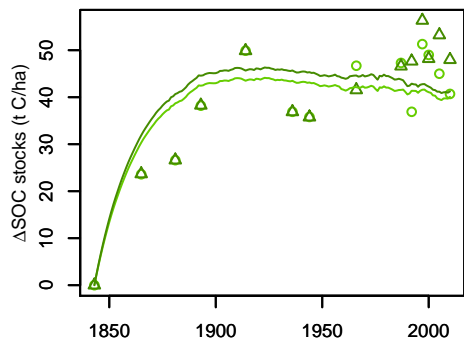Carbon input (crop residues, roots & EOM) $\sum m_i$

$\sum m_i \cdot (1-h_i)$

$\sum m_i \cdot h_i$

$CO_2$

$k \cdot QC_A$

Active C $QC_A$

Stable C $QC_S$
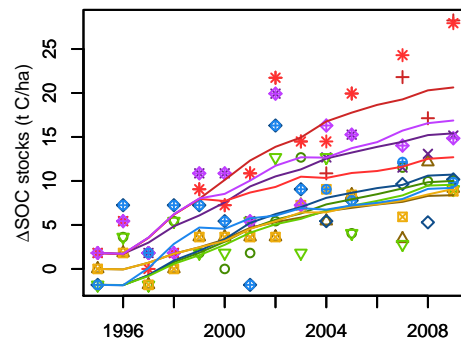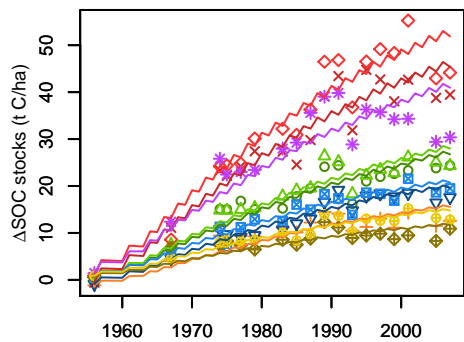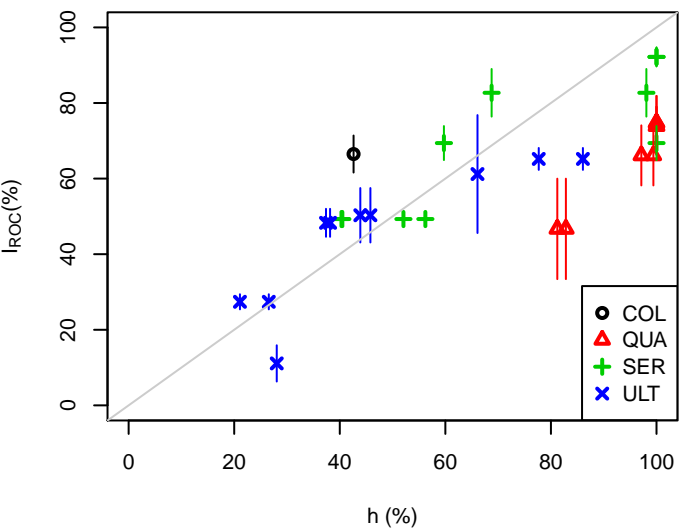
RMSE ΔSOC stocks (t C/ha)

optimized h    h=I$_{ROC}$

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