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1 **Modeling soil organic carbon evolution in long-term arable experiments with AMG**
2 **model**

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19 **Abstract**

20 Reliable models predicting soil organic carbon (SOC) evolution are required to better manage
21 cropping systems with the objectives of mitigating climate change and improving soil quality.
22 In this study, data from 60 selected long-term field trials conducted in arable systems in France
23 were used to evaluate a revised version of AMG model integrating a new mineralization
24 submodel. The drivers of SOC evolution identified using Random Forest analysis were
25 consistent with those considered in AMG. The model with its default parameterization
26 simulated accurately the changes in SOC stocks over time, the relative model error (*RRMSE*
27 = 5.3%) being comparable to the measurement error (*CV* = 4.3%). Model performance was
28 little affected by the choice of plant C input estimation method, but was improved by a site
29 specific optimization of SOC pool partitioning. AMG shows a good potential for predicting SOC
30 evolution in scenarios varying in climate, soil properties and crop management.

31 **Highlights:**

- 32 • SOC evolution in 60 long-term French trials was analyzed and simulated
33 • On average, SOC stocks declined between 1970 and 2015 at a rate of -0.20 t C/ha/yr
34 • Drivers of SOC evolution were similar in Random Forest analysis and AMG model
35 • Implementing a new mineralization module in AMG improved SOC evolution predictions
36 • Optimizing site-specific stable C pool could further improve model performance

37 **Keywords:** soil organic carbon; mineralization; soil carbon storage; carbon inputs; AMG model

38 **1. Introduction**

39 Soils are fundamental to many provisioning and regulating ecosystem services, the prediction
40 of which requires improving our understanding of soil processes and their modeling (Smith et
41 al., 2015; Vereecken et al., 2016). In agricultural systems, soil organic matter (SOM) plays a
42 crucial role in soil structure, quality and fertility for crop production (Tiessen et al., 1994;
43 Reeves, 1997). SOM also constitutes an important reservoir of carbon (C) whose dynamics
44 can significantly impact the global C cycle (Heimann and Reichstein, 2008). Soil organic
45 carbon (SOC) can act as a sink or source of atmospheric C and has therefore the potential of
46 mitigating climate change by increasing C storage in agricultural soils (Paustian et al., 1997,
47 2016), leading to the recent “4 per mille” initiative (www.4p1000.org). Croplands, which are
48 depleted in SOC compared to grasslands and forests (Smith, 2008; Poeplau et al., 2011), have
49 a great potential for C sequestration (Lal and Bruce, 1999; Smith, 2004).

50 SOC dynamics in arable systems is mainly driven by i) C inputs into soils from crop residues
51 and organic amendments generating newly-formed SOM (Kuzyakov and Domanski, 2000;
52 Mandal et al., 2007; Maillard and Angers, 2014) and ii) C outputs due to SOM decomposition
53 and erosion. The unbalance between these two opposite fluxes determines soil C decline or
54 accumulation. An accurate estimation of C inputs and the consideration of the relevant drivers
55 of SOM mineralization and stabilization are therefore needed to better predict SOC stock
56 evolutions, which are primarily under the influence of pedoclimatic conditions and agricultural
57 practices (Stockmann et al., 2013; Dignac et al., 2017). SOC turns over slowly and variations
58 in SOC stocks can only be reliably detected on the mid or long-term in most cases. There is
59 consequently a need for long-term experiments (LTEs) to calibrate and validate mathematical
60 models able to reproduce accurately SOC dynamics and reliably predict future SOC
61 evolutions.

62 Numerous and various soil biogeochemical models featuring different levels of complexity
63 have been designed to simulate SOC dynamics (Falloon and Smith, 2000; Manzoni and
64 Porporato, 2009; Campbell and Paustian, 2015). These models can be used to predict SOC

65 stock evolution, better understand their driving factors and test methods and hypotheses
66 regarding i) estimates of plant C inputs into soils (Taghizadeh-Toosi et al., 2016; Keel et al.,
67 2017), and ii) mineralization of SOM and its partitioning into functional C pools (Zimmermann
68 et al., 2007; Herbst et al., 2018). Among the diversity of soil C models, simple process-oriented
69 models may have some advantages compared to more complex ones or organism-oriented
70 models (Stockmann et al., 2013). They require a lower number of input variables and have
71 been designed to simulate SOC evolutions with a reduced set of functions and parameters
72 reflecting the main processes driving SOC dynamics. They can be applied to a larger number
73 of experiments and/or over longer time and spatial scales. When correctly calibrated, they may
74 represent a good compromise between complexity and reliability for general applications and
75 could be used as decision support tools to help managing SOC in arable systems.

76 The aim of this study was to enhance the reliability of AMG, a simple model simulating soil C
77 at annual time steps (Andriulo et al., 1999), in predicting SOC stock evolution in topsoils from
78 arable cropping systems. AMG was previously shown to satisfactorily simulate the effects of
79 straw residue export on SOC in various cropping systems and pedoclimatic conditions (Saffih-
80 Hdadi and Mary, 2008) and the effects of alternative arable systems (Autret et al., 2016). It
81 was also used as a tool for designing innovative cropping systems (Colnenne-David and Doré,
82 2015; Dufossé et al., 2016). In this work, we evaluated a revised version of AMG, in which was
83 implemented a new model of SOM mineralization calibrated for the prediction of N
84 mineralization in arable soils (Clivot et al., 2017). We hypothesized that the main identified
85 driving factors of soil organic N mineralization could apply for the prediction of SOC
86 mineralization due to a tight soil C and N coupling (Zaehle, 2013) and could also improve the
87 modeling of SOC dynamics. We analyzed the impact of two major sources of uncertainty in
88 SOC modeling using several methods related to i) estimation of aboveground (AG) and
89 belowground (BG) plant C inputs and ii) partitioning of total SOC between active and stable
90 pools, and the relevance of these methods for AMG model.

91 **2. Material and methods**

92 **2.1. Experimental sites**

93 In a first step, we compiled all the available LTEs carried out in arable cropping systems in
94 France by research teams or extension services since 1970, in which SOC had been measured
95 at several dates. They represented 455 treatments spread over 53 sites. We then selected the
96 most reliable experiments by applying the following criteria: number of replicates ≥ 3 ; number
97 of measurement dates ≥ 3 ; experiment duration ≥ 8 years; mean coefficient of variation of SOC
98 measurements $\leq 10\%$; rock fragment content nil or measured. The selection leads to a reduced
99 dataset of 60 treatments located in 20 sites (Figure 1), covering however a large diversity of
100 pedoclimatic conditions (Table S1), crop rotation types and practices (Table S2) representative
101 of most French arable systems.

102 The field experiments were carried out between 1970 and 2015, lasting between 8 and 41
103 years (median value of 22 years) (Table 1). The mean annual temperature observed during
104 the field trials ranged from 9.9 to 13.5°C (median value of 11.0°C). The annual precipitation
105 ranged from 637 to 1285 mm (median 753 mm) and potential evapotranspiration from 637 to
106 947 mm (median 721 mm). The field trials exhibited contrasting soil physicochemical
107 parameters. The clay content ranged from 43 to 308 g kg⁻¹ (median 214 g kg⁻¹), silt content
108 from 95 to 781 g kg⁻¹ (median 528 g kg⁻¹), sand content from 12 to 791 g kg⁻¹ (median 140 g
109 kg⁻¹) and CaCO₃ content of soils varied from 0 to 781 g kg⁻¹ (median 0 g kg⁻¹). Soil pH varied
110 between 5.6 and 8.3 (median 6.8). Bulk density ranged from 1.20 to 1.52 g cm⁻³ (median 1.40
111 g cm⁻³). Initial soil organic C (SOC) stocks in the topsoils (ploughed layer, 0-20 to 0-30 cm)
112 varied widely, from 25 to 105 t C ha⁻¹ (median 44 t C ha⁻¹).

113 Cropping systems encountered in the 60 treatments were cereal-based rotations with legumes
114 and/or oilseed crops (32% of the cropping systems), grain maize/winter wheat rotations (27%),
115 rotations with silage maize (23%, including 3 out of 14 treatments in monoculture), grain maize
116 monocultures (10%), cereals/sugarbeet rotations with legumes and/or rapeseed (7%) and 1
117 treatment was a bare fallow soil. Winter cover crops were occasionally grown in 10 treatments
118 (17%) on 3 different sites. Straw residues were regularly exported in 38% of the treatments

119 and returned to soil in 62% of them. Exogenous organic matters (EOM) were applied as
120 manure or slurry in 11 treatments (18%) from 5 different sites. Crops were grown with
121 conventional N rate applications providing a positive N balance in most situations. Seven sites
122 included variations in P or K fertilization rate but they did not reveal major effects on yield or
123 aboveground plant biomass production. Conventional tillage with full inversion ploughing was
124 conducted in all treatments except 6 treatments from the BOIG-site where soils were
125 maintained under no-till. Past land use of the investigated sites was cropland except the 5
126 treatments from the KERB-site which were previously under sown grassland. Details on
127 cropping systems can be found in Table S2.

128 **2.2. Soil physicochemical analyses**

129 For each field trial, top soil layers were sampled in 3 to 4 replicates on several occasions to
130 determine soil physicochemical characteristics and SOC stocks. The sampling depth varied
131 between 20 and 30 cm (median 28 cm), and was equal or greater than the greatest ploughing
132 depth recorded during the study. For each soil characterization, several soil cores were
133 collected and mixed together to obtain a representative composite sample. Particle-size
134 distribution was determined on non-decarbonated soil samples using the pipette method
135 according to NF ISO 11277. Soil CaCO₃ content was quantified by a volumetric method
136 following NF ISO 10693 and soil pH was measured at a 1:5 soil/water ratio (NF ISO 10390).
137 Soil bulk density (BD) was determined either by the cylinder method or the gamma radiation
138 method (Blake, 1965) or estimated according to the soil pedological class. The determination
139 of soil organic C (SOC) was performed by colorimetry after sulfochromic oxidation (NF ISO
140 14235). Soil organic N (SON) was quantified following NF ISO 11261, by using the Kjeldahl
141 method after sulfuric acid digestion. In the later years, the dry combustion method was used
142 to determine total C and N at some sites. The two different methods were shown to produce
143 very close estimates of SOC and SON concentrations (Dimassi et al., 2014) and were therefore
144 not distinguished later.

145 The SOC stock (QC , expressed in $t\ C\ ha^{-1}$) at the considered soil depth z (m) was calculated
146 as follows (Poepflau et al., 2017):

$$QC(z) = C \cdot z \cdot BD \cdot (1 - R_f) \cdot 10 \quad (1)$$

147 where C is the SOC content ($g\ C\ kg^{-1}$), BD is the bulk density of fine earth ($g\ cm^{-3}$) and R_f the
148 volumetric fraction of rock fragments ($> 2\ mm$) unaccounted for in the analysis.

149 **2.3. Climatic data**

150 For each experimental site, mean annual air temperature ($^{\circ}C$) and annual cumulative
151 precipitation (mm) and potential evapotranspiration (PET in mm, Penman, 1948) were
152 calculated using daily data obtained from the closest weather station (the distance between
153 the experimental sites and the weather stations varied from 0 to 55 km, on average 11 km).

154 **2.4. AMG model**

155 2.4.1. Model description

156 AMG is a model designed to simulate soil C dynamics at an annual time step (Andriulo et al.,
157 1999; Saffih-Hdadi and Mary, 2008). The model considers three organic matter (OM)
158 compartments: fresh OM (FOM) coming from crop residues or organic amendments which can
159 be decomposed or humified, and SOM which is divided into active (C_A) and stable C pools
160 (C_S). Humified FOM is allocated to C_A , which is affected by the mineralization process. C_S is
161 considered completely recalcitrant to mineralization during the prediction time ($< 100\ yrs$).

162 AMG can be described by this set of equations:

$$QC = QC_S + QC_A \quad (2)$$

$$\frac{dQC_A}{dt} = \sum_i m_i h_i - kQC_A \quad (3)$$

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

167 simulating separately the C originating from C₃ or C₄ crops using ¹³C natural isotopic
168 abundance measurements (Appendix A).

169 2.4.2. SOC pool partitioning

170 In the default parameterization, the initial proportion of the stable pool (C_S/C_0) was set at 65%
171 of total C for conditions of land use with a long-term arable history (Saffih-Hdadi and Mary,
172 2008). In the case of arable soils with a long-term grassland history, C_S/C_0 was assumed to be
173 lower as suggested by Huggins et al. (1998) and was set by default at 40% of initial SOC
174 content, this value corresponding to the lower limit of optimum values found earlier for
175 simulating SOC evolutions with AMG (Saffih-Hdadi and Mary, 2008).

176 2.4.3. Environmental functions

177 In AMGv1, the mineralization rate k of the active C pool depends on climatic conditions and
178 soil characteristics and is calculated using environmental functions as follows:

$$k_{AMGv1} = k_0 \cdot f(T) \cdot f(H) \cdot f(A) \cdot f(CaCO_3) \quad (4)$$

179 where k_0 is the potential mineralization rate (yr⁻¹), $f(T)$ is a function of mean annual air
180 temperature (°C) and $f(H)$ is a function used as a proxy to describe the effects of soil moisture.
181 $f(H)$ is a function of the annual water inputs (precipitation and irrigation water) and PET. $f(A)$
182 and $f(CaCO_3)$ are reduction rate functions of clay and CaCO₃ contents on SOM mineralization,
183 respectively.

184 In AMGv2, we implemented the model of SOM mineralization recently developed for the
185 prediction of N mineralization in arable soils (Clivot et al., 2017), so that the mineralization rate
186 k is calculated in this modified version following this equation:

$$k_{AMGv2} = k_0 \cdot f(T) \cdot f(H) \cdot f(A) \cdot f(CaCO_3) \cdot f(pH) \cdot f(C/N) \quad (5)$$

187 where $f(T)$, $f(H)$, $f(A)$ and $f(CaCO_3)$ are the same functions than in AMGv1, the parameter
188 values of $f(A)$ and $f(CaCO_3)$ differing slightly between the two versions. In AMGv2, the
189 additional functions $f(pH)$ and $f(C/N)$ describe the effects of soil pH (increasing function) and
190 C:N ratio (Gaussian function) on SOM mineralization. The soil functions $f(A)$ and $f(CaCO_3)$ and
191 their associated parameters in AMGv1 are similar to those used in the v8.5 and earlier version

192 of the STICS model (Coucheney et al., 2015), while those in AMGv2 are corresponding to the
193 mineralization model developed in Clivot et al. (2017), except the parameterization of $(CaCO_3)$,
194 which has been optimized independently using mineralized N data in chalky soils (unpublished
195 data). The potential mineralization rate k_0 was the only parameter optimized with AMG for the
196 calibration of each version of the model. All the functions and parameters are detailed in
197 supplementary material (Appendix A).

198 2.4.4. Calculation of carbon inputs

199 We adapted to French experimental data the approach described in Bolinder et al. (2007) to
200 calculate relative annual C allocation coefficients in the different plant parts in order to estimate
201 aboveground (AG) and belowground (BG) C inputs from crops residues. Plant aboveground C
202 was calculated according to measured dry matter yield (Y_P expressed in $t\ ha^{-1}\ yr^{-1}$) and mean
203 harvest index (HI , grain to aerial biomass (including grain) ratio) obtained from a compilation
204 of data from French experiments. Plant C in straw and stubble (C_S) was calculated using a C
205 content of $0.44\ g\ g^{-1}$ in the aboveground plant material (Redin et al., 2014):

$$C_S = Y_P \cdot \frac{1 - HI}{HI} \cdot 0.44 \quad (6)$$

206 Aboveground C inputs (C_{AG}) depend on the fraction of C_S (P_S) that is returned to the soil:

$$C_{AG} = P_S \cdot C_S \quad (7)$$

207 P_S value being equal to 1 when all crop residues are left in the field or lower than 1 when a part
208 of C_S is exported. P_S values were determined for the different crops in case of straw residues
209 export (P_{SE}) and correspond to the fraction of C_S , represented by stubble and chaff, that is left
210 to the soil. P_{SE} values for the different crops are reported in Table S3.

211 For BG input estimates, two C pools were calculated: 1) plant C in roots (C_R) and 2) plant C in
212 extra-root material (C_E) which corresponds to organic matter deriving from root-turnover and
213 root exudates. C_R for the different crops were calculated using shoot-to-root ratios (SR)
214 compiled in Bolinder et al. (2007) and completed by French experimental data, assuming a C
215 content of $0.40\ g\ g^{-1}$ in the BG plant material (Boiffin et al., 1986), lower than in AG crop
216 residues (Buyanovsky and Wagner, 1986):

$$C_R = \frac{Y_P}{SR \cdot HI} \cdot 0.40 \quad (8)$$

217 Extra-root C inputs were calculated following the assumption made by Bolinder et al. (2007):

$$C_E = 0.65 \cdot C_R \quad (9)$$

218 In order to estimate BG inputs, we used the asymptotic equation of Gale and Grigal (1987) to
 219 determine the cumulative BG input fraction (BG_F) from the soil surface to a considered depth
 220 (cm):

$$BG_{F-Depth} = 1 - \beta^{Depth} \quad (10)$$

221 where β is a crop-specific parameter determined using the root distributions for temperate
 222 agricultural crops reported in Fan et al. (2016). Calculated β values are reported in Table S3.

223 The depth was set at 30 cm to calculate BG inputs (C_{BG}):

$$C_{BG} = BG_{F-30} \cdot (C_R + C_E) \quad (11)$$

224 Calculated BG inputs, expressed in t C ha⁻¹, were further corrected for site-specific considered
 225 depth (20 to 30 cm in this study) by the AMG model. Relative annual C allocation coefficients
 226 obtained for the crops encountered in our experiments are reported in Table S3. C inputs from
 227 exogenous organic matter (EOM) were calculated according to the amount of organic
 228 amendment applied and to measured C content conversion coefficients and were expressed
 229 in t C ha⁻¹.

230 2.4.5. Humification coefficients

231 Humification coefficients of AG crop residues were calculated as in the STICS model
 232 (Coucheney et al., 2015) using their specific average C/N ratio (Machet et al., 2017) and the
 233 functions and parameterization described in Justes et al. (2009), low C/N ratio of crop residues
 234 promoting humification. The calculated humification coefficients, ranging from 0.22 (for a C/N
 235 ratio of 82) to 0.31 (for a C/N ratio of 22) for the different crops, are reported in Table S3.

236 We assumed that root derived C contributed more to stored SOC than the same amount of C
 237 derived from AG crop residues (Balesdent and Balabane, 1996; Ghafoor et al., 2017; Kätterer
 238 et al., 2011). We calculated a value of 0.39 for the humification coefficient of BG inputs, both
 239 using the data of Balesdent and Balabane (1996) and Kristiansen et al. (2005) with ¹³C tracing

240 and root incubation experiments described in Justes et al. (2009). It corresponds to a relative
241 contribution of BG material to humified C 26% to 77% greater than that of AG residues. This
242 range is in accordance with the data compiled by Rasse et al. (2005) who found an average
243 of 30% increase of humification coefficient for root compared to shoot material in incubation
244 studies.

245 Humification coefficients of diverse EOMs were determined by soil incubations and inverse
246 modeling in AMG simulations performed on field-experiments. They were used for the
247 parameterization of EOMs applied into soils of this study. Humification coefficients used were
248 0.52 and 0.53 for bovine and pig manure respectively, and 0.50 and 0.15 for bovine and pig
249 slurry, respectively (Bouthier et al., 2014).

250 **2.5. Model simulations**

251 2.5.1. Modeling steps

252 Prior to simulations of SOC stock evolutions with AMG model, we first used Random Forest
253 (RF) regression analysis as a mean to identify relevant variables (Hapfelmeier and Ulm, 2013)
254 driving SOC stock change rates in our experiments. SOC stock change rate, as the response
255 variable, was calculated as the slope of the linear regression of SOC stocks against time in
256 each trial. Selected input variables for the RF analysis were related to climatic conditions
257 (mean annual temperature, cumulative precipitation and PET), soil characteristics (initial SOC
258 stock, soil pH, C:N ratio, clay, silt, sand and CaCO₃ contents) and agricultural practices
259 (frequencies in the rotation of straw residue export, bare fallow or winter cover crops and mean
260 annual EOM applications). RF was run in R Software version 3.3.0 (R Core Team, 2016) using
261 the *randomForest* package (Liaw and Wiener, 2002), the number of trees being set to *ntree* =
262 100,000 to ensure convergence, while the other parameters were set to their default values.
263 The performance in predicting SOC stock change rates by RF was compared with that
264 obtained with the two model versions (AMGv1 and AMGv2) against the database. After this
265 first step in which we analyzed SOC stock change rates, we focused on the simulations of soil
266 C stocks with AMG model. The quality of prediction of AMGv1 and AMGv2 was compared to

267 the SOC evolution measured in the 60 field trials. Using AMGv2, we evaluated the effects of
268 alternative methods for estimating plant C inputs (2.5.2) and for setting the initial stable C pool
269 proportion (2.5.3). We also performed a sensitivity analysis of AMGv2 outputs to the different
270 input variables (see part 2.6.2).

271 2.5.2. Assessment of plant C inputs

272 Using AMGv2, we evaluated the effects of alternative methods for estimating plant C inputs.
273 Keel et al. (2017) have pointed out the importance of the method of calculation of C inputs in
274 modeling performance. We compared three methods for estimating aboveground plant C
275 inputs (R, A1 and A2) and three methods for calculating belowground crop residues (B1-B3).
276 In the reference method R (detailed in part 2.4.4), fixed HI values were used to calculate
277 aboveground C inputs (C_{AG}) regardless of crop yields. In method A1, harvest index was
278 calculated as a function of crop yield using coefficients from Fan et al. (2017) who found linear
279 correlations between HI and crop yields and suggested that these relationships should improve
280 estimations of crop residue inputs in cold continental climates. Method A2 was similar to A1,
281 but used “local coefficients” for four major crops (wheat, winter barley, maize and pea) derived
282 from French experimental data. The Bolinder approach was used for crop species which were
283 not referenced by Fan et al. (2017). All coefficients are reported in Table S4.

284 Recent studies suggested that belowground inputs (C_{BG}) should be estimated regardless of
285 crop yield or aboveground biomass using crop specific fixed values and/or dependent on
286 farming systems (Taghizadeh-Toosi et al., 2016; Hirte et al., 2017; Hu et al., 2018). In the three
287 methods B, aboveground inputs (C_{AG}) were calculated using the reference approach while BG
288 input estimates (C_{BG}) were fixed for each crop species. In method B1, C_{BG} was calculated for
289 each crop as the average of all C_{BG} estimates obtained for this crop in our database with the
290 reference approach. Method B2 was similar but C_{BG} was decreased by 50% whereas it was
291 increased by 50% in method B3, in order to account for uncertainties on the shoot:root ratio
292 estimates which show a coefficient of variation close to 50% (Bolinder et al., 2007). In all three
293 methods, the belowground estimates included the dead root material (C_R) and the extra-root

294 material (C_E), the latter being assumed to represent 65% of root material, as proposed by
295 Bolinder et al. (2007). The potential mineralization rate k_0 was re-optimized for each method.

296 2.5.3. Assessment of the size of the stable C pool

297 Using AMGv2, we compared three methods (M1-M3) of parameterization of the initial stable
298 pool fraction (C_S/C_0). In method M1, fixed values of C_S/C_0 were compared with those often
299 recommended in other models as previously performed in Saffih-Hdadi and Mary (2008): we
300 compared three values covering the range of usually reported values: 65%, 40% and 10% for
301 soils with a long-term arable history. The proportion was reduced by 40% in soils with a long-
302 term grassland history. For each parameter set, the potential mineralization rate k_0 was
303 optimized giving three different k_0 values.

304 In method M2, we tested the hypothesis that C_S/C_0 is not constant but rather a decreasing
305 function of SOC stock, suggesting that the active C pool could be proportionally higher in soils
306 with high SOC content. We evaluated this hypothesis using the following empirical function:

$$\frac{C_S}{C_0} = P_S \cdot e^{-p \cdot QC_0} \quad (12)$$

307 where QC_0 is the initial SOC stock (t C ha⁻¹). The parameter p was set at one of three values
308 (0.001, 0.005 and 0.010) and the parameter P_S (the proportion of C_S/C_0 for very low SOC
309 stocks) was optimized each time, while k_0 was fixed at its default value.

310 In method M3, C_S/C_0 was optimized separately in each of the 20 sites, assuming that all
311 treatments of the same site had a similar stable C pool, using each of the three values of
312 parameter k_0 determined in method M1.

313 2.6. Model evaluation

314 2.6.1. Statistical criteria

315 Statistical measurements of agreement between observed SOC stock change rates and
316 predictions made by the RF and AMG models were performed by calculating the mean
317 difference (MD , simulated minus observed value), the modeling efficiency (EF), the index of
318 agreement ($d1$), the root mean squared error ($RMSE$) and the relative root mean squared error

319 (*RRMSE*) (Smith et al., 1996; Wallach, 2006; Willmott et al., 1985). The average values of *MD*
320 and *RMSE* obtained in each experiment were used to calibrate the potential mineralization rate
321 k_0 , which has to be optimized for each version of the model. A trial-and-error method was
322 applied to determine the k_0 value that allowed to minimize both criteria. The same procedure
323 was performed to determine the best values of parameters that were optimized when
324 assessing the different C input calculation methods and when optimizing the C pool
325 partitioning.

326 The predictive quality of AMGv1 and AMGv2 models was assessed by calculating the root
327 mean squared error of prediction (*RMSEP*) using leave-one-out cross-validation (Stone, 1974).
328 The evaluation was carried out each time on one site excluded from the calibration of k_0 , which
329 was optimized using the data of the 19 remaining sites. The mean *RMSEP* of the 20 situations
330 was computed to compare the predictive quality of AMGv1 et AMGv2.

331 The coefficient of variation (*CV*) of measured SOC stocks was used to compare the
332 measurement error with the relative model error (*RRMSE*).

333 2.6.2. Sensitivity analysis to input variables

334 We adapted the method conducted by Poeplau (2016) for the sensitivity analysis of RothC
335 model. We analyzed the sensitivity of AMGv2 outputs to a 20% increase in several variables
336 related to C inputs (crop yields, aboveground and belowground C inputs) and SOM
337 mineralization (rainfall, PET, initial size of the active C pool, soil C:N ratio, clay and CaCO₃
338 contents), except for temperature and pH which were increased by 2°C and 1 unit, respectively.
339 To this end, we simulated the SOC stock evolutions of reference scenarios for all 60 treatments
340 over an extended period of 100 years. We calculated for each treatment the difference in SOC
341 stocks at the end of the simulation (steady state) between a modified scenario (increase of a
342 variable) and the reference one and analyzed the variations observed for the 60 treatments on
343 model outputs.

344 3. Results

345 **3.1. Drivers and prediction of SOC stock change rates**

346 For the 60 treatments, measured SOC stock changes ranged from -24.0 to +7.1 t C ha⁻¹
347 between the start and the end of experiments (Table 1). Annual SOC stock change rates varied
348 from -1.01 to +0.45 t C ha⁻¹ yr⁻¹; the median and mean rates were -0.08 and -0.20 t C ha⁻¹ yr⁻¹,
349 respectively. The linear regression made to calculate these rates is meaningful, since the
350 *RMSE* was small (1.2 t C ha⁻¹) compared to the mean standard deviation of measurements
351 (2.3 t C ha⁻¹), indicating that the general evolution of SOC was more or less linear over time.
352 The distribution of SOC change rates was skewed towards negative values (Figure 2). The
353 interval [-0.1, 0.1] t C ha⁻¹ yr⁻¹ corresponds to the mean standard deviation of measurements
354 and can be considered as a SOC stock stability range. It represented 42% of situations. SOC
355 declined in 49% of situations and SOC increase occurred in the remaining 10% of situations.
356 The Random Forest (RF) analysis revealed that the initial C stock was the most important
357 variable in predicting SOC stock change rate (Figure 3A); indeed, the two variables are
358 negatively correlated (Pearson $r = -0.59$, $p < 0.001$). The variables related to climate
359 (precipitation, PET and temperature) were the second most important factor followed by the
360 management of crop residues and soil parameters (clay, pH and C/N). The remaining input
361 variables had less importance in the RF model applied on our dataset. Significant correlations
362 were found between SOC stock change rate and precipitation ($r = -0.44$, $p < 0.001$) and PET
363 ($r = 0.37$, $p < 0.01$) but no clear relationship was found with the other variables.
364 Measured rates of SOC stock change were compared with predicted rates either by the RF
365 model (Figure 3B) or by simulations performed by AMG models: AMGv1 (Figure 3C) and
366 AMGv2 (Figure 3D). The closeness of fit to the 1:1 line shows that there was no marked bias
367 in the predictions made by the three models, *MD* varying between 0.00 and -0.05 t C ha⁻¹ yr⁻¹.
368 The range of predicted rates was narrower for RF than for measured values. Overall, the
369 statistical criteria revealed that AMGv2 performed better in predicting SOC stock change rates
370 than RF and AMGv1 showing a higher modeling efficiency (*EF*) and index of agreement (*d1*),
371 and a lower modeling error (*RMSE*).

372 **3.2. Modeling SOC stock dynamics with AMG model**

373 An example of SOC stock evolution and simulation performed by AMGv2 on one experiment
374 at the Boigneville site is illustrated in Figure 4. The model reproduced well the dynamics of
375 total SOC stocks, accounting for the effects of straw residue export which led to a slight
376 decrease in C stock between 1982 and 1994 and the change in crop rotation which occurred
377 in 1998. It also simulated satisfactorily the evolution of C stocks originating from C₃ and C₄
378 crops, particularly the decrease in C₄ stock after changing the 2-year wheat-maize rotation to
379 a 4-year rotation without C₄ crops.

380 The ability of AMGv1 and AMGv2 to predict SOC stock evolution was evaluated in the 60 field
381 treatments (Figure 5). Figures 5A and B show the absence of marked bias in the simulation of
382 total SOC stock with both model versions. Figures 5C and 5D show that there was no increase
383 in model error over time for the different C stocks simulated by both AMG versions. The mean
384 modeling error was lower for AMGv2 than for AMGv1, *RMSE* being respectively 2.6 and 3.2 t
385 C ha⁻¹ for total SOC stocks. The mean modeling error for C₃ stocks was also smaller for AMGv2
386 (*MD* = -0.5 and *RMSE* = 2.9 t C ha⁻¹) than for AMGv1 (*MD* = -1.1 and *RMSE* = 3.9 t C ha⁻¹).
387 The predictive quality of AMGv2 was better than that of AMGv1, *RMSEP* being respectively
388 2.7 and 3.5 t C ha⁻¹ for total SOC stocks, when estimated using a cross-validation method.
389 Compared to AMGv1, the modified version AMGv2, including the new mineralization function
390 established on a completely independent dataset, was found to improve the prediction of SOC
391 evolutions on long-term experiments.

392 AMGv2 was also tested on the database reported by Saffih-Hdadi and Mary (2008). We
393 obtained a similar quality of fit than that found by these authors with the previous AMG version
394 (mean *RMSE* of 1.6 t C ha⁻¹ for both versions). All results validated the reliability of this new
395 version, which was therefore used in the following analyses.

396 **3.3. Sensitivity analysis of AMGv2 model**

397 The sensitivity analysis of AMGv2 was conducted on steady state situations. The reference
398 scenario simulating the 60 treatments over a 100-year period predicted that the proportion of

399 active pool C would reach an asymptotic value close to the initial value (35% of total C) for
400 situations either with no export of straw biomass or with straw removal but receiving EOM
401 applications (Figure S1). The proportion of active C would, on average, stabilize around 20%
402 of SOC for situations with systematic straw residue removal.

403 The final SOC stocks simulated for this reference scenario were compared with those obtained
404 in alternative scenarios in which one variable related to C input or SOM mineralization
405 (depending on climate and soil properties) was increased. The mean SOC difference at steady
406 state between the alternative and reference scenarios ranged from -4.1 to +2.7 t C ha⁻¹,
407 depending on the input variable modified (Figure 6). Variations in crop yield had a rather
408 marked effect on SOC stocks (mean +2.7 t C ha⁻¹), and corresponded to the sum of
409 aboveground and belowground C effects. The model was particularly sensitive to changes in
410 temperature, soil pH and C/N ratio, whereas changes in precipitation and PET affected very
411 little the SOC stocks. The largest variability between sites in model response concerned soil
412 pH. The initial size of the active C pool was also an important factor determining SOC stock at
413 steady state. This emphasizes the importance of the variables with the largest uncertainty, *i.e.*
414 plant C inputs calculated from crop yields and the initial SOC pool partitioning.

415 **3.4. Impact of alternative methods for estimating plant C inputs**

416 We evaluated the effect of alternative methods for estimating AG and BG plant C inputs on
417 SOC modeling with AMGv2, compared to the reference R (Table 2). Method A1, which
418 considered variable harvest indexes depending on crop yields, increased slightly model error
419 for the simulation of soil C stocks, *RMSE* being of 2.6 vs 2.8 t C ha⁻¹ for R and A1 methods,
420 respectively. Method A2, which used local coefficients for calculating harvest indexes,
421 produced slightly better simulations (*RMSE* = 2.7 t C ha⁻¹) than A1 but did not improve SOC
422 simulation compared to the reference. The alternative method of calculation of belowground
423 inputs, in which root biomass was assumed to be only species dependent, did not affect much
424 the quality of fit, as can be seen with method B1. However, when root biomass was reduced
425 by 50% (method B2), SOC stock predictions were slightly improved for total SOC (*RMSE* =

426 2.5 t C ha⁻¹) and particularly for C₄ stocks for which the bias observed in the reference method
427 disappeared. Conversely, a 50% increase in root C input (method B3) resulted in a poor quality
428 of fit, both for total SOC and C₄ stocks. It must be noticed that the reduction of root input in
429 method B2 is accompanied by a reduction in the potential mineralization rate k_0 which drops
430 from 0.29 to 0.24 yr⁻¹.

431 **3.5. Impact of alternative methods for initializing the stable SOC pool**

432 Three alternative methods (M1-M3) were assessed using AMGv2 for setting the size of the
433 initial stable SOC pool (Table 3). Method M1 compares the effects of three values for the initial
434 stable pool proportion (C_S/C_0). Results show that decreasing C_S/C_0 from the default value of
435 0.65 (for sites with long-term arable history) to 0.40 or 0.10 decreased the quality of fit for the
436 simulations of total SOC, particularly for C₃ and C₄ stocks, increasing both the bias and the
437 *RMSE*. The mineralization rates k_0 , optimized for each initial C_S/C_0 value (0.65, 0.40 and 0.10),
438 dropped from 0.29 to 0.17 and 0.11 yr⁻¹, respectively.

439 In method M2, we tested the hypothesis that C_S/C_0 could be a decreasing (exponential)
440 function of SOC stock. One parameter of this function (p) was fixed and the other (P_S) was
441 optimized. This hypothesis proved to be inappropriate since model performance declined
442 compared to the reference whatever the value of parameter p . The quality of fit decreased
443 gradually as the slope of the exponential function increased.

444 In method M3, the size of the stable C pool was supposed to be site specific. The optimized
445 mineralization rates k_0 obtained in method M1 were used as fixed parameters whereas C_S/C_0
446 was optimized for each site. This assumption resulted in a decreased model error for the
447 simulations of total SOC stocks compared to the reference approach, whatever the k_0 value.

448 The *RMSE* obtained with the default k_0 value of 0.29 yr⁻¹ was 1.8 t C ha⁻¹, lower than those
449 obtained for k_0 values of 0.17 and 0.11 yr⁻¹ (*RMSE* = 2.0 and 2.4 t C ha⁻¹, respectively). In
450 addition, these alternative k_0 values (corresponding to low values of C_S/C_0) did not allow to
451 simulate C₃ and C₄ stocks and generated an important bias on each stock (up to 3.5 t C ha⁻¹).

452 The variability of C_S/C_0 values optimized on each site for each k_0 value is shown in Figure 7.

453 The median C_S/C_0 values obtained for the 20 sites (0.63, 0.37 and 0.08) were close to the
454 single values initially applied to all sites (0.65, 0.40 and 0.10). The variability of C_S/C_0 between
455 sites was much lower for the default value of k_0 (0.29 yr^{-1}) than for the two other settings.

456 **4. Discussion**

457 **4.1. Observed SOC evolution in arable cropping systems**

458 The dataset considered in this study covers a period ranging from 1970 to 2015, the average
459 being a 24-year period (1980-2003). It covers the diversity of arable cropping systems
460 practiced in France during these years, with regard to crop rotations, tillage practices, crop
461 residue management, N fertilization and crop yields. During the more recent years, an
462 evolution towards a higher frequency of catch crop cultivation and a slight reduction in tillage
463 operations and intensity was observed. Our results showed on average a slight decrease in
464 SOC stocks (mean rate of change = $-0.20 \text{ t C ha}^{-1} \text{ yr}^{-1}$). This decrease could be attributed to
465 the legacy effect of conversion from grass to arable land over the past 25 years with
466 comparatively lower organic matter restitution levels. In many regions, the areas devoted to
467 permanent meadows have declined regularly as exemplified in the Seine-Normandie Basin
468 between 1971 and 2013 in North of France (Beaudoin et al., 2018). Steinmann et al. (2016)
469 observed a drastic decline under arable crops in Germany between 1989 and 2015, which was
470 also mainly attributed to grassland conversion to cropland. This is consistent with other results
471 obtained on conventional arable systems under temperate climate. For example, Saffih-Hdadi
472 and Mary (2007) gathered a set of 391 agricultural fields monitored several times in Picardie
473 (Northern France) during the 1970-1997 period and found a mean decrease rate of -0.08 t C
474 $\text{ha}^{-1} \text{ yr}^{-1}$. In Belgium, Goidts and van Wesemael, (2007) reported a decrease of $-0.11 \text{ t C ha}^{-1}$
475 yr^{-1} in arable crops during 50 years (1955-2005) confirmed by Meersmans et al. (2011) who
476 observed a mean decrease of $-0.09 \text{ t C ha}^{-1} \text{ yr}^{-1}$ from 1960 to 2006.

477 **4.2. Drivers of SOC dynamics**

478 The main drivers of SOC dynamics identified by RF were the soil characteristics (initial SOC
479 stock, texture, ...), the agricultural practices (residue management, cover crops, EOM) and the
480 climate (precipitation, temperature). The initial SOC stock was a main factor as shown by the
481 RF analysis and the negative correlation between SOC change rates and the initial SOC stock.
482 Such a strong negative relationship was already pointed out by Goidts and van Wesemael,
483 (2007), Zhao et al. (2013) and Luo et al. (2017). It suggests that soils with the highest SOC
484 contents, with past grassland or having received important amounts of EOM, were not yet at
485 equilibrium and are still declining. This is consistent with Oberholzer et al. (2014) who found
486 that SOC content was still declining even 60 years after the conversion of grassland to
487 cropland. Post et al. (2008) have pointed out the importance of an accurate determination of
488 initial SOC stock in the propagation of uncertainty in SOM models.

489 Residue management (straw removal vs retention) was also an important factor identified by
490 both RF and AMG model. This confirms the results obtained by Saffih and Mary (2008) and
491 Liu et al. (2014). Reducing residue removal increased SOC in most wheat cropping systems
492 studied in Australia by Zhao et al. (2013) and Luo et al. (2017).

493 The impact of climatic factors was more surprising: the temperature effect was consistent
494 between RF analysis and AMG model, but not precipitation, which was an influent factor in RF
495 but not in AMG. This apparent contradiction is due to the fact that precipitation was strongly
496 correlated with initial SOC content ($r = 0.59$, $p < 0.001$). In fact, running the RF analysis without
497 this variable explained as much variance than with it. The small sensitivity of AMG model
498 reflects the moderate range of water balance ($P-PET$ varied from -290 to 595 mm yr^{-1}) in all
499 sites, without dry situations such as described by Luo et al. (2017). Indeed, we confirmed the
500 absence of improvement in model performance when recalibrating this function. Taghizadeh-
501 Toosi et al. (2014) also found that there was no need to account for moisture effects in the C-
502 TOOL model to simulate the data obtained in three LTEs of Northern Europe.

503 Finally, two other soil characteristics were identified as being influent on SOC evolution: the
504 C/N ratio and soil pH. Both were identified in this study by the Random Forest analysis and

505 previously as drivers of organic N mineralization (for more discussion see Clivot et al., 2017),
506 justifying the implementation of these variables and their effect in AMGv2.

507 The model could simulate the LTEs without considering nitrogen (N) availability as a possible
508 driver of SOC evolution, as suggested by the C:N stoichiometry observed in SOM composition
509 (van Groenigen et al., 2017). This may result from the positive N surplus observed in most of
510 our experiments, but a possible limitation should be considered in other experiments,
511 particularly those receiving low N inputs.

512 **4.3. Reliability of AMG model**

513 The new AMG version was found to better predict SOC stock change rates than RF and
514 AMGv1. The general evolution of SOC was found to be more or less linear over time. However,
515 on the contrary to AMG, RF is a statistical model which cannot capture subtle changes in SOC
516 through time since RF, as used in this study, cannot take into account annual variations of
517 climate and C inputs. In AMGv2, the implementation of two additional variables (soil pH and
518 C/N ratio), previously identified as drivers of SOM mineralization (Clivot et al., 2017) but not
519 considered in AMGv1, slightly improved the quality of SOC predictions, since the relative root
520 mean square error (*RRMSE*) decreased from 6.1% for AMGv1 to 5.3% for AMGv2. This result
521 was obtained with a common set of parameters for all sites, without any site-specific
522 calibration. This model error was only slightly greater than the mean coefficient of variation of
523 measurements which was 4.3%. Furthermore, the model error did not increase with time,
524 showing that there was no significant drift over time. The model error is comparable to that
525 obtained on other LTEs with other models. Smith et al. (1997) compared nine models on 7
526 LTEs and found a *RRMSE* varying between 6.5% and 10% for the best 6 models. Falloon and
527 Smith (2002) simulated 6 LTEs and obtained a mean *RRMSE* of 6.8% for Century and 9.9%
528 for RothC. The CCB model (Franko et al., 2011), evaluated on 40 sites in central Europe,
529 showed a mean *RRMSE* of 8.5%. Taghizadeh-Toosi et al. (2014) evaluated the C-TOOL model
530 on 3 LTEs in Northern Europe and obtained a mean *RRMSE* of 6.1% for topsoils. Using the

531 Century model, Dimassi et al. (2018) obtained a RRMSE of 13.1% on a subset of our database
532 with 6 LTEs.

533 Datasets including ^{13}C natural tracing experiments (with C_4 and C_3 plants) are essential to
534 better evaluate SOM models, because they allow to characterize separately the decrease
535 in «old» SOM and the increase in newly formed SOM (Balesdent, 1996). The AMG model was
536 shown to simulate well the evolution of C_3 and C_4 stocks in the experiments which included C_4
537 plants, showing its ability to simulate the two components of SOC change.

538 **4.4. Uncertainties in plant C input estimates**

539 C input estimates in our study are close to those obtained in comparable climatic conditions,
540 reported by Wiesmeier et al. (2014) in Germany for cereals (3.2 vs 3.1 t C ha⁻¹ yr⁻¹) and for
541 other crops (2.7 vs 2.3 t C ha⁻¹ yr⁻¹). These inputs, which represent annually 5.3% of SOC on
542 average, include uncertainties on aboveground inputs, particularly on the harvest index. The
543 model performance was little sensitive to the method of calculation: the model did not perform
544 better when using a variable HI calibrated with French references compared to the original
545 Bolinder method with a fixed HI. Comparing five different methods, Keel et al (2017) also found
546 that the Bolinder method gave the best predictions of SOC evolution using the C-TOOL model.
547 However, the greatest uncertainties about C input are those relating to belowground C. For
548 root biomass estimates, we found little difference in model performance when using allometric
549 equations (R) or fixed biomass (B1). Taghizadeh-Toosi et al. (2016) made the same
550 comparison with the C-TOOL model and obtained a better quality of fit when using the fixed
551 root biomass option. Recent studies suggest that root biomass could be independent of aerial
552 biomass, questioning the rationale of allometric relationships. Hirte et al. (2018) found that N
553 fertilization rate affects the below:above ground ratio of wheat and maize but does not modify
554 the belowground C inputs. Komainda et al. (2018) found no effect of N fertilization on root
555 biomass and turnover in two cultivars of maize. Hu et al. (2018) even found larger root biomass
556 of cereals and catch crops in organic farming than in conventional systems, in spite of a lower

557 aerial biomass. Therefore, using a fixed amount of root biomass depending on crop species
558 only seems to be a preferable option for simulating SOC evolution.

559 Concerning the BG inputs, our results show that model performance (including the prediction
560 of C_4 stocks) markedly declined when increasing BG inputs beyond the default fixed root
561 biomass (method B1). This indicates that the contribution of root and extra root material (65%
562 of root material, *i.e.* 40% of BG inputs) to the humified C input is set at its maximum and could
563 even be overestimated. A similar conclusion on extra root C was drawn by Poeplau (2016)
564 with the RothC model, while results from a recent field study (Hirte et al., 2018) suggest that
565 the proportion of rhizodeposition of total BG inputs for maize and wheat should be higher (on
566 average 55% in the topsoil for net rhizodeposition C) than the widely adopted value of 40%.
567 However, besides the uncertainty on the amount of extra root material deposited, it should be
568 noticed that the humification coefficient applied to this fraction in our model is equivalent to that
569 of roots, whereas root exudates are very labile substances and might contribute less to SOC
570 formation.

571 **4.5. Initializing the size of the stable SOC pool**

572 The sensitivity analysis indicated that the initial setting of the inert SOC pool had a large impact
573 on model outputs, confirming previous studies (*e.g.* Puhlmann et al., 2007). The site-specific
574 adjustment of SOC pools gave better simulations than default parameterization, since the
575 *RRMSE* reduced from 5.3 to 3.7% as previously observed with Century and RothC models
576 (Falloon and Smith, 2002). However, the lack of information on the past land use (particularly
577 the grassland history) did not allow us to calculate a more precise initial partitioning of SOC
578 between pools.

579 During the calibration phase, the optimization of the size of the recalcitrant C pool (either inert
580 or having a residence time greater than 1,000 years) is highly dependent on the value of the
581 potential rate constant of the active C pool, because both are correlated. The strong correlation
582 between the two parameters may even result in equifinality, *i.e.* leading to similar model
583 performance for widely varying paired parameter values (Luo et al., 2016). This was not the

584 case with our dataset and model, since the model error increased significantly, particularly for
585 the C₄ stocks simulations, when the initial stable pool fraction was reduced from 65% to 10%.
586 The mean value found in optimizing the site-specific C_S/C₀ was 60 ±18% for sites with a long-
587 term arable history and was found to be lower (*i.e.* 47%) for the site with long-term grassland
588 history. This result confirms the default parameterization established earlier (Saffih-Hdadi and
589 Mary, 2008).

590 Chemical methods have been proposed to characterize the more stable SOC fractions with a
591 limited success (Helfrich et al., 2007; von Lützow et al., 2007). Combining particle size
592 fractionation and chemical analysis was more successful in separating SOC into fractions with
593 different turnover rates (Poeplau et al., 2018) and in matching measurable C fractions and
594 model pools (Zimmermann et al., 2007; Herbst et al., 2018). New methods such as thermal
595 analysis are also promising: they could allow identifying fractions having a residence time of
596 about 20 years (Soucémariadin et al., 2018), these latter corresponding to the residence
597 time in our experiments (varying from 7 to 26 years). Data from long-term bare fallow
598 experiments (Barré et al., 2010) can also be combined with thermal analysis to quantify the
599 size of centennially persistent SOC pool (Cécillon et al., 2018) in order to better calibrate soil
600 C models.

601 **5. Conclusion**

602 The modified version of AMG model including the new function of SOM mineralization was
603 found to improve the prediction of SOC evolution compared to the previous version. The model
604 could simulate SOC stock dynamics in LTEs conducted in French conventional arable systems
605 with a mean relative model error of 5.3%. The results strengthen the importance of SOC pool
606 partitioning and therefore the need of methods that would allow to measure functional C
607 fractions to better initialize soil C model simulations. The model performance appeared to be
608 little sensitive to the method of plant C input estimation. Considering root C inputs independent
609 of aerial biomass production as shown by recent studies was found to perform as well as

610 allometric relationships, suggesting that using a fixed amount of root biomass depending on
611 crop species should be preferred in the model. AMG demonstrates a good potential for
612 predicting SOC evolution in scenarios varying in climate, soil properties and management for
613 conventional arable cropping systems. The next objective will be to improve the ability of AMG
614 for modeling other systems such as low input or organic systems, cropping systems including
615 perennial species or permanent grasslands in order to extend the validity domain of the model
616 to simulate contrasting agricultural systems.

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- 628 Andriulo, A., Mary, B., Guerif, J., 1999. Modelling soil carbon dynamics with various cropping
629 sequences on the rolling pampas. *Agronomie* 19, 365–377.
630 <https://doi.org/10.1051/agro:19990504>
- 631 Autret, B., Mary, B., Chenu, C., Balabane, M., Girardin, C., Bertrand, M., Grandeau, G.,
632 Beaudoin, N., 2016. Alternative arable cropping systems: A key to increase soil organic
633 carbon storage? Results from a 16 year field experiment. *Agric. Ecosyst. Environ.* 232,
634 150–164. <https://doi.org/10.1016/j.agee.2016.07.008>
- 635 Balesdent, J., 1996. The significance of organic separates to carbon dynamics and its
636 modelling in some cultivated soils. *Eur. J. Soil Sci.* 47, 485–493.
637 <https://doi.org/10.1111/j.1365-2389.1996.tb01848.x>
- 638 Balesdent, J., Balabane, M., 1996. Major contribution of roots to soil carbon storage inferred
639 from maize cultivated soils. *Soil Biol. Biochem.* 28, 1261–1263.
640 [https://doi.org/10.1016/0038-0717\(96\)00112-5](https://doi.org/10.1016/0038-0717(96)00112-5)
- 641 Balesdent, J., Mariotti, A., Guillet, B., 1987. Natural ¹³C abundance as a tracer for studies of
642 soil organic matter dynamics. *Soil Biol. Biochem.* 19, 25–30.
643 [https://doi.org/10.1016/0038-0717\(87\)90120-9](https://doi.org/10.1016/0038-0717(87)90120-9)
- 644 Barré, P., Eglin, T., Christensen, B.T., Ciais, P., Houot, S., Kätterer, T., van Oort, F., Peylin,
645 P., Poulton, P.R., Romanenkov, V., Chenu, C., 2010. Quantifying and isolating stable
646 soil organic carbon using long-term bare fallow experiments. *Biogeosciences* 7, 3839–
647 3850. <https://doi.org/10.5194/bg-7-3839-2010>
- 648 Beaudoin, N., Gallois, N., Viennot, P., Le Bas, C., Puech, T., Schott, C., Buis, S., Mary, B.,
649 2018. Evaluation of a spatialized agronomic model in predicting yield and N leaching
650 at the scale of the Seine-Normandie Basin. *Environ. Sci. Pollut. Res.* 25, 23529–23558.
651 <https://doi.org/10.1007/s11356-016-7478-3>
- 652 Blake, G.R., 1965. Bulk density. *Methods Soil Anal. Part 1 Phys. Mineral. Prop. Stat. Meas.*
653 *Sampl.* 374–390.
- 654 Boiffin, J., Zagbahi, J.K., Sebillotte, M., 1986. Systèmes de culture et statut organique des sols
655 dans le Noyonnais : application du modèle de Hénin-Dupuis. *Agronomie* 6, 437–446.
656 <https://doi.org/10.1051/agro:19860503>
- 657 Bolinder, M.A., Janzen, H.H., Gregorich, E.G., Angers, D.A., VandenBygaart, A.J., 2007. An
658 approach for estimating net primary productivity and annual carbon inputs to soil for
659 common agricultural crops in Canada. *Agric. Ecosyst. Environ.* 118, 29–42.
660 <https://doi.org/10.1016/j.agee.2006.05.013>
- 661 Bouthier, A., Duparque, A., Mary, B., Sagot, S., Trochard, R., Levert, M., Houot, S., Damay,
662 N., Denoroy, P., Dinh, J.-L., Blin, B., Ganteil, F., 2014. Adaptation et mise en oeuvre
663 du modèle de calcul de bilan humique à long terme AMG dans une large gamme de
664 systèmes de grandes cultures et de polyculture-élevage. *Innov. Agron.* 34, 125–139.
- 665 Buyanovsky, G.A., Wagner, G.H., 1986. Post-harvest residue input to cropland. *Plant Soil* 93,
666 57–65. <https://doi.org/10.1007/BF02377145>
- 667 Campbell, E.E., Paustian, K., 2015. Current developments in soil organic matter modeling and
668 the expansion of model applications: a review. *Environ. Res. Lett.* 10, 123004.
669 <https://doi.org/10.1088/1748-9326/10/12/123004>
- 670 Cécillon, L., Baudin, F., Chenu, C., Houot, S., Jolivet, R., Kätterer, T., Lutfalla, S., Macdonald,
671 A., van Oort, F., Plante, A.F., Savignac, F., Soucémariadin, L.N., Barré, P., 2018. A
672 model based on Rock-Eval thermal analysis to quantify the size of the centennially
673 persistent organic carbon pool in temperate soils. *Biogeosciences* 15, 2835–2849.
674 <https://doi.org/10.5194/bg-15-2835-2018>
- 675 Clivot, H., Mary, B., Valé, M., Cohan, J.-P., Champolivier, L., Piraux, F., Laurent, F., Justes,
676 E., 2017. Quantifying in situ and modeling net nitrogen mineralization from soil organic
677 matter in arable cropping systems. *Soil Biol. Biochem.* 111, 44–59.
678 <https://doi.org/10.1016/j.soilbio.2017.03.010>

679 Colnenne-David, C., Doré, T., 2015. Designing innovative productive cropping systems with
680 quantified and ambitious environmental goals. *Renew. Agric. Food Syst.* 30, 487–502.
681 <https://doi.org/10.1017/S1742170514000313>

682 Coucheney, E., Buis, S., Launay, M., Constantin, J., Mary, B., García de Cortázar-Atauri, I.,
683 Ripoche, D., Beaudoin, N., Ruget, F., Andrianarisoa, K.S., Le Bas, C., Justes, E.,
684 Léonard, J., 2015. Accuracy, robustness and behavior of the STICS soil–crop model
685 for plant, water and nitrogen outputs: Evaluation over a wide range of agro-
686 environmental conditions in France. *Environ. Model. Softw.* 64, 177–190.
687 <https://doi.org/10.1016/j.envsoft.2014.11.024>

688 Dignac, M.-F., Derrien, D., Barré, P., Barot, S., Céillon, L., Chenu, C., Chevallier, T., Freschet,
689 G.T., Garnier, P., Guenet, B., Hedde, M., Klumpp, K., Lashermes, G., Maron, P.-A.,
690 Nunan, N., Roumet, C., Basile-Doelsch, I., 2017. Increasing soil carbon storage:
691 mechanisms, effects of agricultural practices and proxies. A review. *Agron. Sustain.*
692 *Dev.* 37, 14. <https://doi.org/10.1007/s13593-017-0421-2>

693 Dimassi, B., Guenet, B., Saby, N.P.A., Munoz, F., Bardy, M., Millet, F., Martin, M.P., 2018. The
694 impacts of CENTURY model initialization scenarios on soil organic carbon dynamics
695 simulation in French long-term experiments. *Geoderma* 311, 25–36.
696 <https://doi.org/10.1016/j.geoderma.2017.09.038>

697 Dimassi, B., Mary, B., Wylleman, R., Labreuche, J., Couture, D., Piraux, F., Cohan, J.-P., 2014.
698 Long-term effect of contrasted tillage and crop management on soil carbon dynamics
699 during 41 years. *Agric. Ecosyst. Environ.* 188, 134–146.
700 <https://doi.org/10.1016/j.agee.2014.02.014>

701 Dufossé, K., Drouet, J.-L., Gabrielle, B., 2016. Agro-ecosystem modeling can aid in the
702 optimization of biomass feedstock supply. *Environ. Model. Softw.* 85, 139–155.
703 <https://doi.org/10.1016/j.envsoft.2016.07.014>

704 Falloon, P., Smith, P., 2002. Simulating SOC changes in long-term experiments with RothC
705 and CENTURY: model evaluation for a regional scale application. *Soil Use Manag.* 18,
706 101–111. <https://doi.org/10.1111/j.1475-2743.2002.tb00227.x>

707 Falloon, P.D., Smith, P., 2000. Modelling refractory soil organic matter. *Biol. Fertil. Soils* 30,
708 388–398. <https://doi.org/10.1007/s003740050019>

709 Fan, J., McConkey, B., Janzen, H., Townley-Smith, L., Wang, H., 2017. Harvest index–yield
710 relationship for estimating crop residue in cold continental climates. *Field Crops Res.*
711 204, 153–157. <https://doi.org/10.1016/j.fcr.2017.01.014>

712 Fan, J., McConkey, B., Wang, H., Janzen, H., 2016. Root distribution by depth for temperate
713 agricultural crops. *Field Crops Res.* 189, 68–74.
714 <https://doi.org/10.1016/j.fcr.2016.02.013>

715 Franko, U., Kolbe, H., Thiel, E., Ließ, E., 2011. Multi-site validation of a soil organic matter
716 model for arable fields based on generally available input data. *Geoderma* 166, 119–
717 134. <https://doi.org/10.1016/j.geoderma.2011.07.019>

718 Gale, M.R., Grigal, D.F., 1987. Vertical root distributions of northern tree species in relation to
719 successional status. *Can. J. For. Res.* 17, 829–834. <https://doi.org/10.1139/x87-131>

720 Ghafoor, A., Poeplau, C., Kätterer, T., 2017. Fate of straw- and root-derived carbon in a
721 Swedish agricultural soil. *Biol. Fertil. Soils* 53, 257–267.
722 <https://doi.org/10.1007/s00374-016-1168-7>

723 Goidts, E., van Wesemael, B., 2007. Regional assessment of soil organic carbon changes
724 under agriculture in Southern Belgium (1955–2005). *Geoderma* 141, 341–354.
725 <https://doi.org/10.1016/j.geoderma.2007.06.013>

726 Hapfelmeier, A., Ulm, K., 2013. A new variable selection approach using Random Forests.
727 *Comput. Stat. Data Anal.* 60, 50–69. <https://doi.org/10.1016/j.csda.2012.09.020>

728 Heimann, M., Reichstein, M., 2008. Terrestrial ecosystem carbon dynamics and climate
729 feedbacks. *Nature* 451, 289–292. <https://doi.org/10.1038/nature06591>

730 Helfrich M., Flessa H., Mikutta R., Dreves A., Ludwig B., 2007. Comparison of chemical
731 fractionation methods for isolating stable soil organic carbon pools. *Eur. J. Soil Sci.* 58,
732 1316–1329. <https://doi.org/10.1111/j.1365-2389.2007.00926.x>

733 Herbst, M., Welp, G., Macdonald, A., Jate, M., Hädicke, A., Scherer, H., Gaiser, T., Herrmann,
734 F., Amelung, W., Vanderborght, J., 2018. Correspondence of measured soil carbon
735 fractions and RothC pools for equilibrium and non-equilibrium states. *Geoderma* 314,
736 37–46. <https://doi.org/10.1016/j.geoderma.2017.10.047>

737 Hirte, J., Leifeld, J., Abiven, S., Oberholzer, H.-R., Mayer, J., 2018. Below ground carbon inputs
738 to soil via root biomass and rhizodeposition of field-grown maize and wheat at harvest
739 are independent of net primary productivity. *Agric. Ecosyst. Environ.* 265, 556–566.
740 <https://doi.org/10.1016/j.agee.2018.07.010>

741 Hirte, J., Leifeld, J., Abiven, S., Oberholzer, H.-R., Mayer, J., 2017. Agricultural management
742 affects below ground carbon input estimations. Presented at the EGU General
743 Assembly Conference Abstracts, p. 9748.

744 Hu, T., Sørensen, P., Wahlström, E.M., Chirinda, N., Sharif, B., Li, X., Olesen, J.E., 2018. Root
745 biomass in cereals, catch crops and weeds can be reliably estimated without
746 considering aboveground biomass. *Agric. Ecosyst. Environ.* 251, 141–148.
747 <https://doi.org/10.1016/j.agee.2017.09.024>

748 Huggins, D.R., Buyanovsky, G.A., Wagner, G.H., Brown, J.R., Darmody, R.G., Peck, T.R.,
749 Lesoing, G.W., Vanotti, M.B., Bundy, L.G., 1998. Soil organic C in the tallgrass prairie-
750 derived region of the corn belt: effects of long-term crop management. *Soil Tillage Res.*
751 47, 219–234. [https://doi.org/10.1016/S0167-1987\(98\)00108-1](https://doi.org/10.1016/S0167-1987(98)00108-1)

752 Justes, E., Mary, B., Nicolardot, B., 2009. Quantifying and modelling C and N mineralization
753 kinetics of catch crop residues in soil: parameterization of the residue decomposition
754 module of STICS model for mature and non mature residues. *Plant Soil* 325, 171–185.
755 <https://doi.org/10.1007/s11104-009-9966-4>

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

760 Keel, S.G., Leifeld, J., Mayer, J., Taghizadeh-Toosi, A., Olesen, J.E., 2017. Large uncertainty
761 in soil carbon modelling related to method of calculation of plant carbon input in
762 agricultural systems. *Eur. J. Soil Sci.* 68, 953–963. <https://doi.org/10.1111/ejss.12454>

763 Komainda, M., Taube, F., Kluß, C., Herrmann, A., 2018. The effects of maize (*Zea mays* L.)
764 hybrid and harvest date on above- and belowground biomass dynamics, forage yield
765 and quality – A trade-off for carbon inputs? *Eur. J. Agron.* 92, 51–62.
766 <https://doi.org/10.1016/j.eja.2017.10.003>

767 Kristiansen, S.M., Hansen, E.M., Jensen, L.S., Christensen, B.T., 2005. Natural ¹³C
768 abundance and carbon storage in Danish soils under continuous silage maize. *Eur. J.*
769 *Agron.* 22, 107–117. <https://doi.org/10.1016/j.eja.2004.01.002>

770 Kuzyakov, Y., Domanski, G., 2000. Carbon input by plants into the soil. *Review. J. Plant Nutr.*
771 *Soil Sci.* 163, 421–431. [https://doi.org/10.1002/1522-2624\(200008\)163:4<421::AID-](https://doi.org/10.1002/1522-2624(200008)163:4<421::AID-JPLN421>3.0.CO;2-R)
772 [JPLN421>3.0.CO;2-R](https://doi.org/10.1002/1522-2624(200008)163:4<421::AID-JPLN421>3.0.CO;2-R)

773 Lal, R., Bruce, J.P., 1999. The potential of world cropland soils to sequester C and mitigate the
774 greenhouse effect. *Environ. Sci. Policy* 2, 177–185. [https://doi.org/10.1016/S1462-](https://doi.org/10.1016/S1462-9011(99)00012-X)
775 [9011\(99\)00012-X](https://doi.org/10.1016/S1462-9011(99)00012-X)

776 Liaw, A., Wiener, M., 2002. Classification and regression by randomForest. *R News* 2, 18–22.

777 Liu, C., Lu, M., Cui, J., Li, B., Fang, C., 2014. Effects of straw carbon input on carbon dynamics
778 in agricultural soils: a meta-analysis. *Glob. Change Biol.* 20, 1366–1381.
779 <https://doi.org/10.1111/gcb.12517>

780 Luo, Z., Feng, W., Luo, Y., Baldock, J., Wang, E., 2017. Soil organic carbon dynamics jointly
781 controlled by climate, carbon inputs, soil properties and soil carbon fractions. *Glob.*
782 *Change Biol.* n/a-n/a. <https://doi.org/10.1111/gcb.13767>

783 Luo, Z., Wang, E., Shao, Q., Conyers, M.K., Liu, D.L., 2016. Confidence in soil carbon
784 predictions undermined by the uncertainties in observations and model
785 parameterisation. *Environ. Model. Softw.* 80, 26–32.
786 <https://doi.org/10.1016/j.envsoft.2016.02.013>

787 Machet, J.-M., Dubrulle, P., Damay, N., Duval, R., Julien, J.-L., Recous, S., 2017. A Dynamic
788 Decision-Making Tool for Calculating the Optimal Rates of N Application for 40 Annual
789 Crops While Minimising the Residual Level of Mineral N at Harvest. *Agronomy* 7, 73.
790 <https://doi.org/10.3390/agronomy7040073>

791 Maillard, É., Angers, D.A., 2014. Animal manure application and soil organic carbon stocks: a
792 meta-analysis. *Glob. Change Biol.* 20, 666–679. <https://doi.org/10.1111/gcb.12438>

793 Mandal, B., Majumder, B., Bandyopadhyay, P.K., Hazra, G.C., Gangopadhyay, A.,
794 Samantaray, R.N., Mishra, A.K., Chaudhury, J., Saha, M.N., Kundu, S., 2007. The
795 potential of cropping systems and soil amendments for carbon sequestration in soils
796 under long-term experiments in subtropical India. *Glob. Change Biol.* 13, 357–369.
797 <https://doi.org/10.1111/j.1365-2486.2006.01309.x>

798 Manzoni, S., Porporato, A., 2009. Soil carbon and nitrogen mineralization: Theory and models
799 across scales. *Soil Biol. Biochem.* 41, 1355–1379.
800 <https://doi.org/10.1016/j.soilbio.2009.02.031>

801 Meersmans, J., Van WESEMAEL, B., Goidts, E., Van MOLLE, M., De BAETS, S., De RIDDER,
802 F., 2011. Spatial analysis of soil organic carbon evolution in Belgian croplands and
803 grasslands, 1960–2006. *Glob. Change Biol.* 17, 466–479.
804 <https://doi.org/10.1111/j.1365-2486.2010.02183.x>

805 Oberholzer, H.R., Leifeld, J., Mayer, J., 2014. Changes in soil carbon and crop yield over 60
806 years in the Zurich Organic Fertilization Experiment, following land-use change from
807 grassland to cropland. *J. Plant Nutr. Soil Sci.* 177, 696–704.
808 <https://doi.org/10.1002/jpln.201300385>

809 Paustian, K., Andrén, O., Janzen, H.H., Lal, R., Smith, P., Tian, G., Tiessen, H., Van Noordwijk,
810 M., Woomer, P.L., 1997. Agricultural soils as a sink to mitigate CO₂ emissions. *Soil*
811 *Use Manag.* 13, 230–244. <https://doi.org/10.1111/j.1475-2743.1997.tb00594.x>

812 Paustian, K., Lehmann, J., Ogle, S., Reay, D., Robertson, G.P., Smith, P., 2016. Climate-smart
813 soils. *Nature* 532, 49–57. <https://doi.org/10.1038/nature17174>

814 Penman, H.L., 1948. Natural evaporation from open water, bare soil and grass. *Proc R Soc*
815 *Lond A* 193, 120–145. <https://doi.org/10.1098/rspa.1948.0037>

816 Poeplau, C., 2016. Estimating root: shoot ratio and soil carbon inputs in temperate grasslands
817 with the RothC model. *Plant Soil* 407, 293–305. [https://doi.org/10.1007/s11104-016-](https://doi.org/10.1007/s11104-016-3017-8)
818 [3017-8](https://doi.org/10.1007/s11104-016-3017-8)

819 Poeplau, C., Don, A., Six, J., Kaiser, M., Benbi, D., Chenu, C., Cotrufo, M.F., Derrien, D.,
820 Gioacchini, P., Grand, S., Gregorich, E., Griepentrog, M., Gunina, A., Haddix, M.,
821 Kuzyakov, Y., Kühnel, A., Macdonald, L.M., Soong, J., Trigalet, S., Vermeire, M.-L.,
822 Rovira, P., van Wesemael, B., Wiesmeier, M., Yeasmin, S., Yevdokimov, I., Nieder, R.,
823 2018. Isolating organic carbon fractions with varying turnover rates in temperate
824 agricultural soils – A comprehensive method comparison. *Soil Biol. Biochem.* 125, 10–
825 26. <https://doi.org/10.1016/j.soilbio.2018.06.025>

826 Poeplau, C., Don, A., Vesterdal, L., Leifeld, J., Van Wesemael, B., Schumacher, J., Gensior,
827 A., 2011. Temporal dynamics of soil organic carbon after land-use change in the
828 temperate zone – carbon response functions as a model approach. *Glob. Change Biol.*
829 17, 2415–2427. <https://doi.org/10.1111/j.1365-2486.2011.02408.x>

830 Poeplau, C., Vos, C., Don, A., 2017. Soil organic carbon stocks are systematically
831 overestimated by misuse of the parameters bulk density and rock fragment content.
832 *SOIL* 3, 61–66. <https://doi.org/10.5194/soil-3-61-2017>

833 Post, J., Hattermann, F.F., Krysanova, V., Suckow, F., 2008. Parameter and input data
834 uncertainty estimation for the assessment of long-term soil organic carbon dynamics.
835 *Environ. Model. Softw.* 23, 125–138. <https://doi.org/10.1016/j.envsoft.2007.05.010>

836 Puhlmann, M., Kuka, K., Franko, U., 2007. Comparison of methods for the estimation of inert
837 carbon suitable for initialisation of the CANDY model, in: *Modelling Water and Nutrient*
838 *Dynamics in Soil–Crop Systems*. Springer, Dordrecht, pp. 209–218.
839 https://doi.org/10.1007/978-1-4020-4479-3_15

840 R Core Team, 2016. R: A Language and Environment for Statistical Computing. *WwwR-Proj.*

841 Rasse, D.P., Rumpel, C., Dignac, M.-F., 2005. Is soil carbon mostly root carbon? Mechanisms
842 for a specific stabilisation. *Plant Soil* 269, 341–356. [https://doi.org/10.1007/s11104-](https://doi.org/10.1007/s11104-004-0907-y)
843 [004-0907-y](https://doi.org/10.1007/s11104-004-0907-y)

844 Redin, M., Recous, S., Aita, C., Dietrich, G., Skolaude, A.C., Ludke, W.H., Schmatz, R.,
845 Giacomini, S.J., 2014. How the chemical composition and heterogeneity of crop
846 residue mixtures decomposing at the soil surface affects C and N mineralization. *Soil*
847 *Biol. Biochem.* 78, 65–75. <https://doi.org/10.1016/j.soilbio.2014.07.014>

848 Reeves, D.W., 1997. The role of soil organic matter in maintaining soil quality in continuous
849 cropping systems. *Soil Tillage Res.*, XIVth ISTRO Conference on Agroecological and
850 Economical Aspects of Soil Tillage 43, 131–167. [https://doi.org/10.1016/S0167-](https://doi.org/10.1016/S0167-1987(97)00038-X)
851 [1987\(97\)00038-X](https://doi.org/10.1016/S0167-1987(97)00038-X)

852 Saffih-Hdadi, K., Mary, B., 2008. Modeling consequences of straw residues export on soil
853 organic carbon. *Soil Biol. Biochem.* 40, 594–607.
854 <https://doi.org/10.1016/j.soilbio.2007.08.022>

855 Saffih-Hdadi, K., Mary, B., 2007. Préviation de l'évolution des stocks de carbone organique
856 pour différentes pratiques d'exportation des pailles. Application à l'estimation de la
857 disponibilité en paille pour le département de l'Aisne. Rapport final Contrat Cartopailles.
858 INRA.

859 Smith, J., Smith, P., Addiscott, T., 1996. Quantitative methods to evaluate and compare Soil
860 Organic Matter (SOM) Models, in: Powlson, D.S., Smith, P., Smith, J.U. (Eds.),
861 Evaluation of Soil Organic Matter Models, NATO ASI Series. Springer Berlin
862 Heidelberg, pp. 181–199. https://doi.org/10.1007/978-3-642-61094-3_13

863 Smith, P., 2008. Land use change and soil organic carbon dynamics. *Nutr. Cycl.*
864 *Agroecosystems* 81, 169–178. <https://doi.org/10.1007/s10705-007-9138-y>

865 Smith, P., 2004. Carbon sequestration in croplands: the potential in Europe and the global
866 context. *Eur. J. Agron.* 20, 229–236. <https://doi.org/10.1016/j.eja.2003.08.002>

867 Smith, P., Cotrufo, M.F., Rumpel, C., Paustian, K., Kuikman, P.J., Elliott, J.A., McDowell, R.,
868 Griffiths, R.I., Asakawa, S., Bustamante, M., House, J.I., Sobocká, J., Harper, R., Pan,
869 G., West, P.C., Gerber, J.S., Clark, J.M., Adhya, T., Scholes, R.J., Scholes, M.C., 2015.
870 Biogeochemical cycles and biodiversity as key drivers of ecosystem services provided
871 by soils. *SOIL* 1, 665–685. <https://doi.org/10.5194/soil-1-665-2015>

872 Smith, P., Smith, J.U., Powlson, D.S., McGill, W.B., Arah, J.R.M., Chertov, O.G., Coleman, K.,
873 Franko, U., Frolking, S., Jenkinson, D.S., Jensen, L.S., Kelly, R.H., Klein-Gunnewiek,
874 H., Komarov, A.S., Li, C., Molina, J.A.E., Mueller, T., Parton, W.J., Thornley, J.H.M.,
875 Whitmore, A.P., 1997. A comparison of the performance of nine soil organic matter
876 models using datasets from seven long-term experiments. *Geoderma, Evaluation and*
877 *Comparison of Soil Organic Matter Models* 81, 153–225.
878 [https://doi.org/10.1016/S0016-7061\(97\)00087-6](https://doi.org/10.1016/S0016-7061(97)00087-6)

879 Soucémariadin, L., Cécillon, L., Chenu, C., Baudin, F., Nicolas, M., Girardin, C., Barré, P.,
880 2018. Is Rock-Eval 6 thermal analysis a good indicator of soil organic carbon lability?
881 – A method-comparison study in forest soils. *Soil Biol. Biochem.* 117, 108–116.
882 <https://doi.org/10.1016/j.soilbio.2017.10.025>

883 Steinmann, T., Welp, G., Holbeck, B., Amelung, W., 2016. Long-term development of organic
884 carbon contents in arable soil of North Rhine–Westphalia, Germany, 1979–2015. *Eur.*
885 *J. Soil Sci.* 67, 616–623. <https://doi.org/10.1111/ejss.12376>

886 Stockmann, U., Adams, M.A., Crawford, J.W., Field, D.J., Henakaarchchi, N., Jenkins, M.,
887 Minasny, B., McBratney, A.B., Courcelles, V. de R. de, Singh, K., Wheeler, I., Abbott,
888 L., Angers, D.A., Baldock, J., Bird, M., Brookes, P.C., Chenu, C., Jastrow, J.D., Lal, R.,
889 Lehmann, J., O'Donnell, A.G., Parton, W.J., Whitehead, D., Zimmermann, M., 2013.
890 The knowns, known unknowns and unknowns of sequestration of soil organic carbon.
891 *Agric. Ecosyst. Environ.* 164, 80–99. <https://doi.org/10.1016/j.agee.2012.10.001>

892 Stone, M., 1974. Cross-Validatory Choice and Assessment of Statistical Predictions. *J. R. Stat.*
893 *Soc. Ser. B Methodol.* 36, 111–147.

894 Taghizadeh-Toosi, A., Christensen, B.T., Glendining, M., Olesen, J.E., 2016. Consolidating
895 soil carbon turnover models by improved estimates of belowground carbon input. *Sci.*
896 *Rep.* 6, 32568. <https://doi.org/10.1038/srep32568>

897 Taghizadeh-Toosi, A., Christensen, B.T., Hutchings, N.J., Vejlin, J., Kätterer, T., Glendining,
898 M., Olesen, J.E., 2014. C-TOOL: A simple model for simulating whole-profile carbon
899 storage in temperate agricultural soils. *Ecol. Model.* 292, 11–25.
900 <https://doi.org/10.1016/j.ecolmodel.2014.08.016>

901 Tiessen, H., Cuevas, E., Chacon, P., 1994. The role of soil organic matter in sustaining soil
902 fertility. *Nature* 371, 783–785. <https://doi.org/10.1038/371783a0>

903 van Groenigen, J.W., van Kessel, C., Hungate, B.A., Oenema, O., Powlson, D.S., van
904 Groenigen, K.J., 2017. Sequestering Soil Organic Carbon: A Nitrogen Dilemma.
905 *Environ. Sci. Technol.* <https://doi.org/10.1021/acs.est.7b01427>

906 Vereecken, H., Schnepf, A., Hopmans, J.W., Javaux, M., Or, D., Roose, T., Vanderborght, J.,
907 Young, M.H., Amelung, W., Aitkenhead, M., Allison, S.D., Assouline, S., Baveye, P.,
908 Berli, M., Brüggemann, N., Finke, P., Flury, M., Gaiser, T., Govers, G., Ghezzehei, T.,
909 Hallett, P., Hendricks Franssen, H.J., Heppell, J., Horn, R., Huisman, J.A., Jacques,
910 D., Jonard, F., Kollet, S., Lafolie, F., Lamorski, K., Leitner, D., McBratney, A., Minasny,
911 B., Montzka, C., Nowak, W., Pachepsky, Y., Padarian, J., Romano, N., Roth, K.,
912 Rothfuss, Y., Rowe, E.C., Schwen, A., Šimůnek, J., Tiktak, A., Van Dam, J., van der
913 Zee, S.E.A.T.M., Vogel, H.J., Vrugt, J.A., Wöhling, T., Young, I.M., 2016. Modeling Soil
914 Processes: Review, Key Challenges, and New Perspectives. *Vadose Zone J.* 15, 0.
915 <https://doi.org/10.2136/vzj2015.09.0131>

916 von Lützow, M., Kögel-Knabner, I., Ekschmitt, K., Flessa, H., Guggenberger, G., Matzner, E.,
917 Marschner, B., 2007. SOM fractionation methods: Relevance to functional pools and to
918 stabilization mechanisms. *Soil Biol. Biochem.* 39, 2183–2207.
919 <https://doi.org/10.1016/j.soilbio.2007.03.007>

920 Wallach, D., 2006. Evaluating crop models. *Work. Dyn. Crop Models Elsevier Amst.* 11–53.

921 Wiesmeier, M., Hübner, R., Dechow, R., Maier, H., Spörlein, P., Geuß, U., Hangen, E., Reischl,
922 A., Schilling, B., von Lützow, M., Kögel-Knabner, I., 2014. Estimation of past and recent
923 carbon input by crops into agricultural soils of southeast Germany. *Eur. J. Agron.* 61,
924 10–23. <https://doi.org/10.1016/j.eja.2014.08.001>

925 Willmott, C.J., Ackleson, S.G., Davis, R.E., Feddema, J.J., Klink, K.M., Legates, D.R.,
926 O'Donnell, J., Rowe, C.M., 1985. Statistics for the evaluation and comparison of
927 models. *J. Geophys. Res.* 90, 8995. <https://doi.org/10.1029/JC090iC05p08995>

928 Zaehle, S., 2013. Terrestrial nitrogen–carbon cycle interactions at the global scale. *Philos.*
929 *Trans. R. Soc. Lond. B Biol. Sci.* 368, 20130125.
930 <https://doi.org/10.1098/rstb.2013.0125>

931 Zhao, G., Bryan, B.A., King, D., Luo, Z., Wang, E., Song, X., Yu, Q., 2013. Impact of agricultural
932 management practices on soil organic carbon: simulation of Australian wheat systems.
933 *Glob. Change Biol.* 19, 1585–1597. <https://doi.org/10.1111/gcb.12145>

934 Zimmermann, M., Leifeld, J., Schmidt, M.W.I., Smith, P., Fuhrer, J., 2007. Measured soil
935 organic matter fractions can be related to pools in the RothC model. *Eur. J. Soil Sci.*
936 58, 658–667. <https://doi.org/10.1111/j.1365-2389.2006.00855.x>

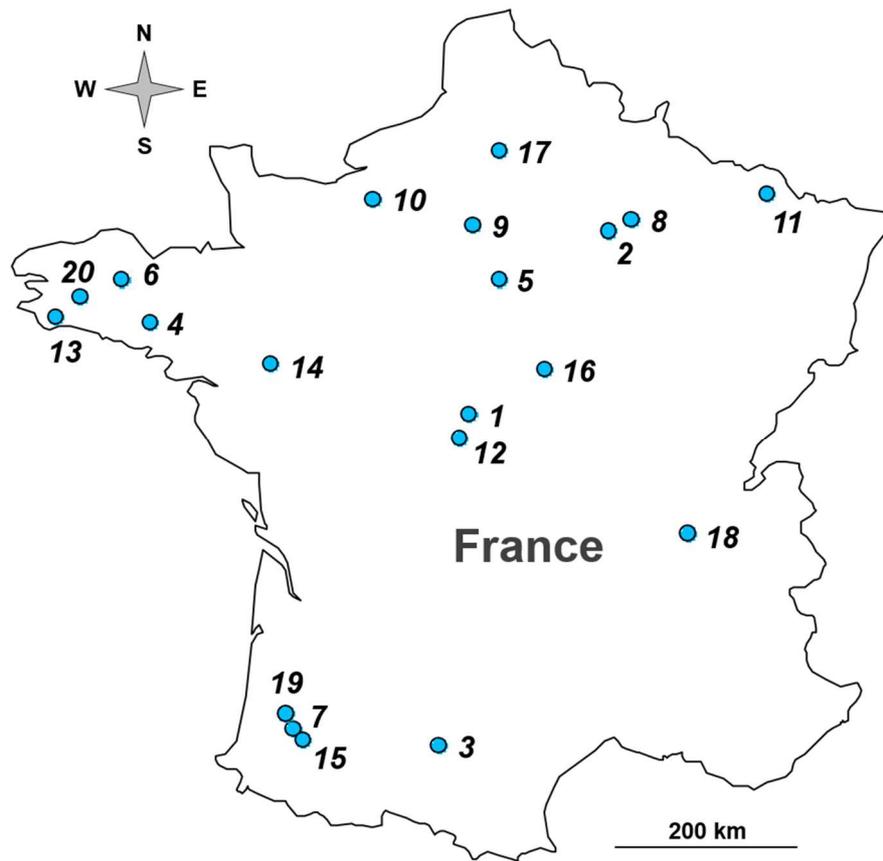


Figure 1. Location of the 60 field trials distributed among 20 sites in France. The correspondence between site numbers and field-experiments is defined in Tables S1 and S2.

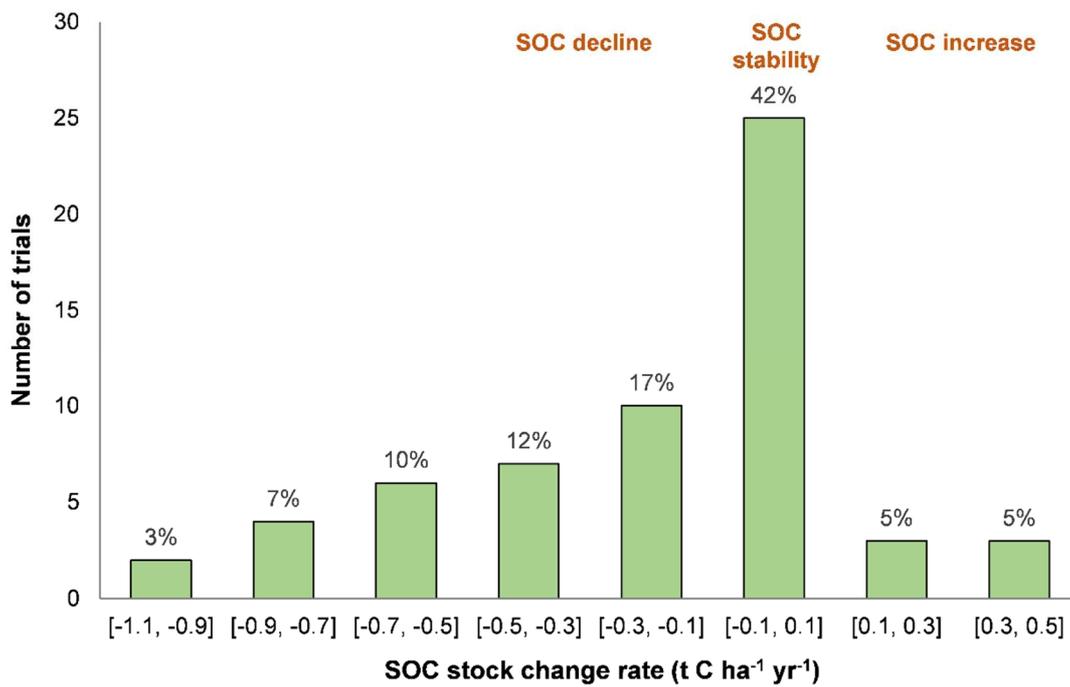


Figure 2. Distribution histogram of SOC stock change rates over the 60 field trials

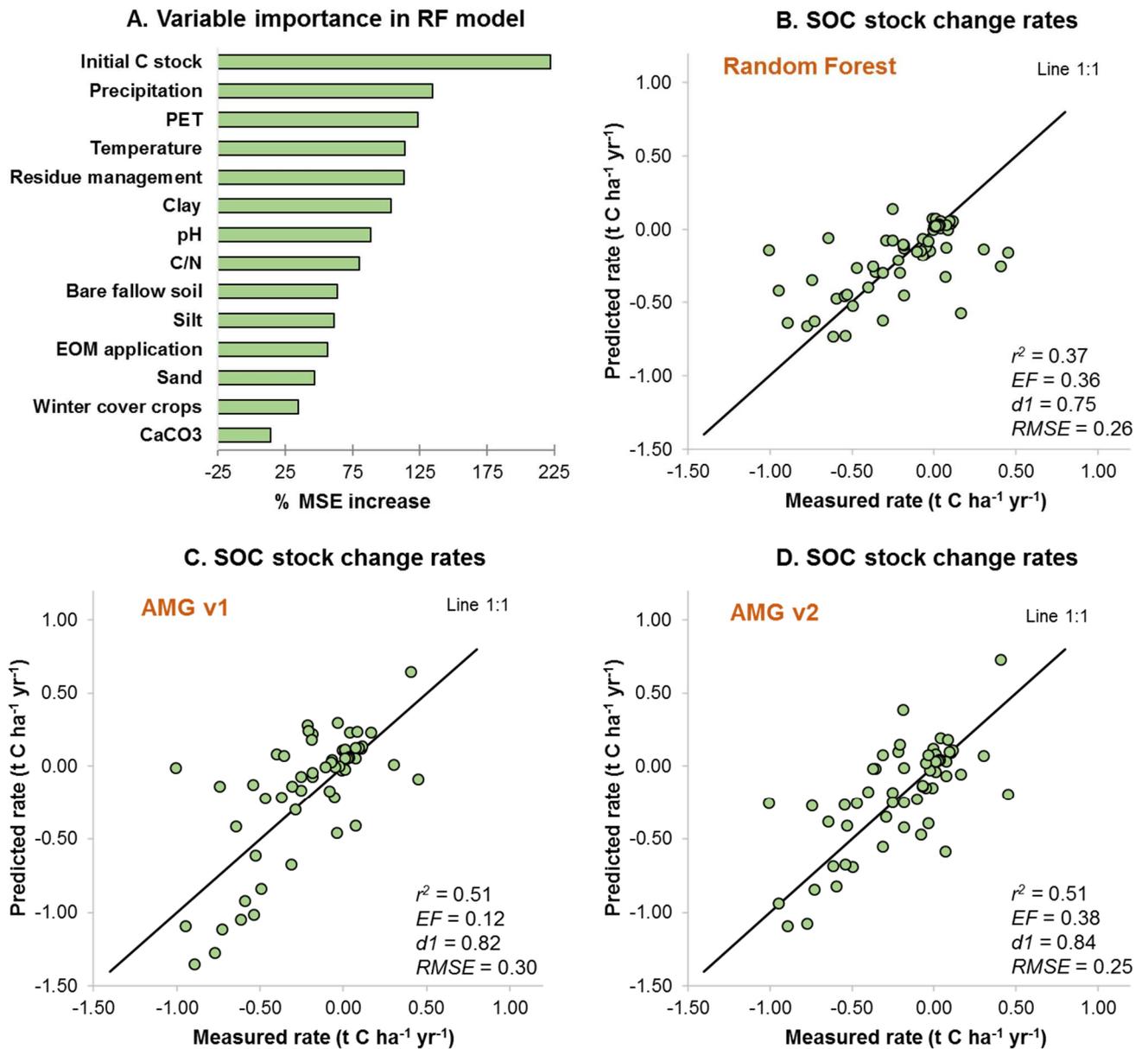


Figure 3. Variable importance in a random forest (RF) model predicting SOC stock change rates for the 60 field trials (A) and observed vs predicted variations obtained with the Random Forest (B), AMGv1 (C) and AMGv2 (D) models. SOC: soil organic carbon, EF : modeling efficiency, $d1$: index of agreement, $RMSE$: root mean squared error of the model.

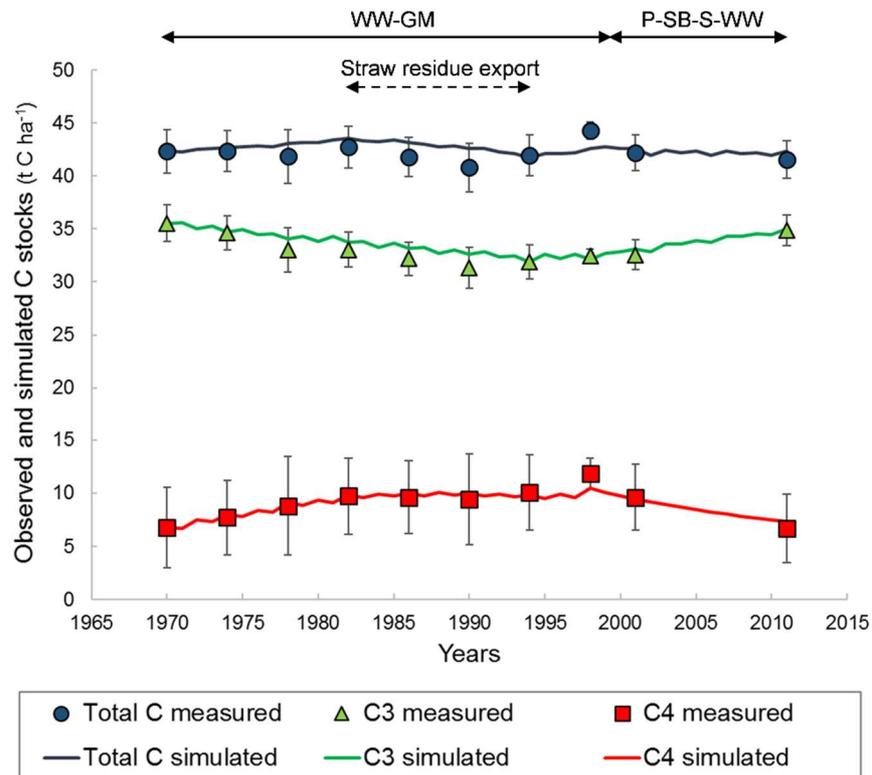


Figure 4. Example of observations (symbols) and simulations performed by AMG (solid lines) of SOC stock evolutions in the upper soil layer (29 cm depth) of one treatment of the Boigneville long-term experiment (BOIG_A_CM4_L0). Circles represent total SOC stocks, while triangles and squares represent C stocks originating from C₃ and C₄ crops, respectively. Crop abbreviations: WW = Winter Wheat, GM = Grain Maize, P = Pea, SB = Spring Barley, S = Sugarbeet. Error bars are measured SD.

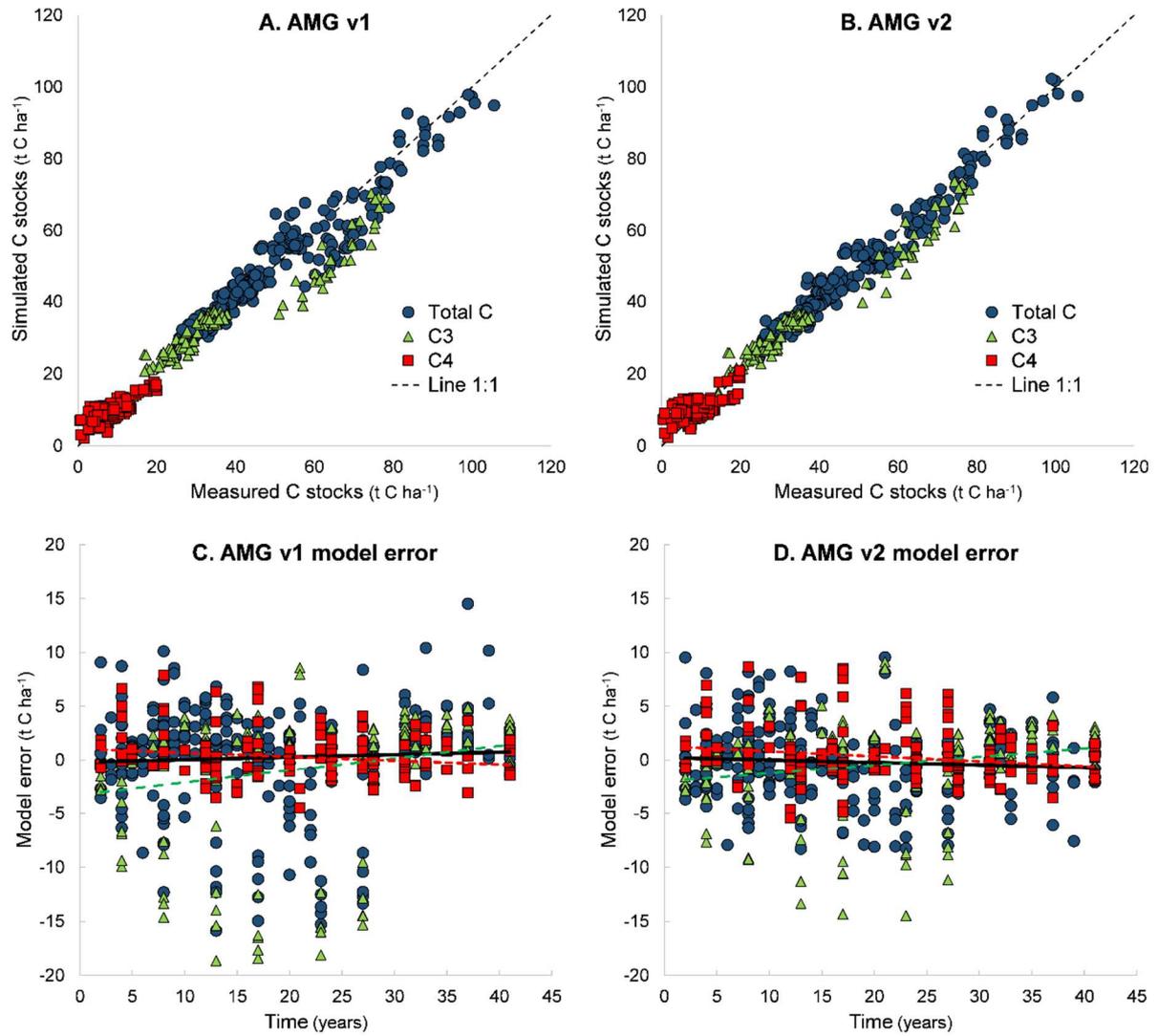


Figure 5. Measured vs predicted SOC stocks by the AMGv1 (A) and AMGv2 (B) models and error (difference between simulated and measured SOC stocks) over time of AMGv1 (C) and AMGv2 (D) for all sampling dates of the 60 field-trials. Circles represent total SOC stocks, while triangles and squares represent C stocks originating from C3 and C4 crops, respectively. The solid line represents the regression line between model error and time for total C, while the red and green dotted lines represent the regressions for C originating from C₄ and C₃ crops, respectively.

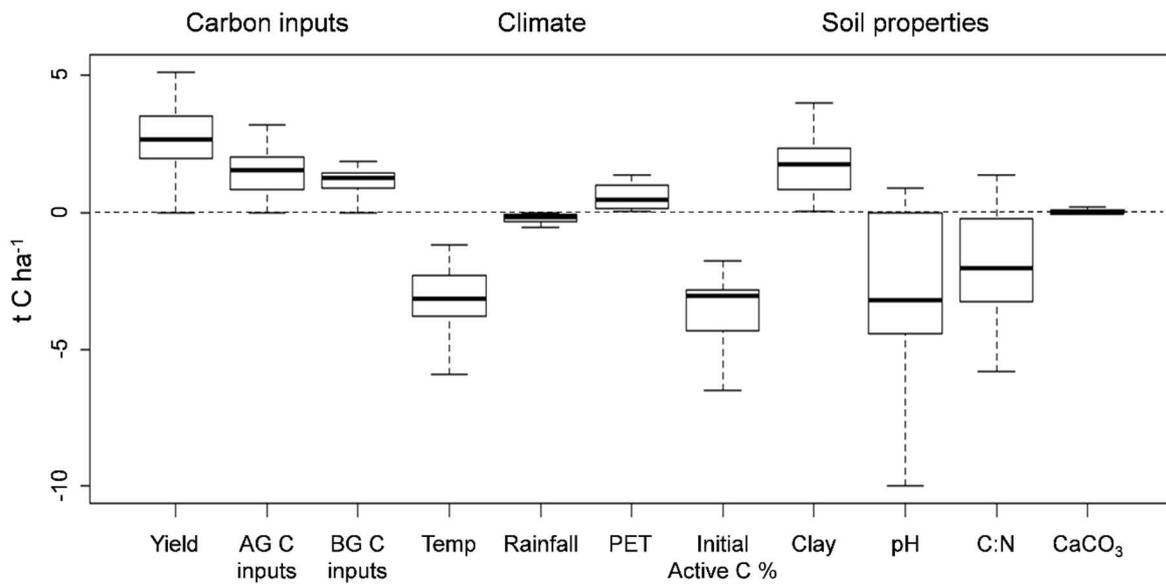


Figure 6. Boxplots showing the sensitivity of the AMGv2 model to 20% increase in different variables/parameters related to C inputs and SOM mineralization, excepting temperature and pH which were increased by 2°C and 1 pH unit, respectively. Boxplots represent the variations of the differences between the modified scenario (increase of the variable) and the reference scenario for all 60 trials over an extended period of 100 years. The dotted line represents the result for the simulation of final SOC stocks in the reference scenario with unmodified data and parameters. Boxplots show median and quartiles, while whiskers represent samples lying within 1.5 times the interquartile range. Extreme outliers are not shown.

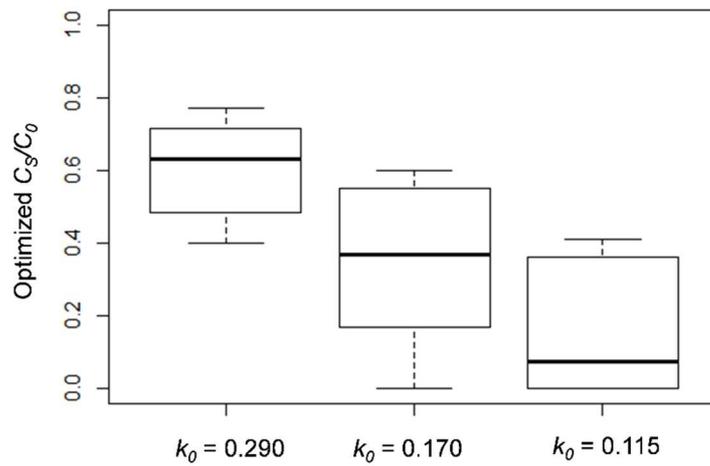


Figure 7. Variability of the initial stable C pool proportion (C_s/C_0) optimized for each site ($n = 20$) for three different values of the potential mineralization rate (k_0). Boxplots show median and quartiles, while whiskers represent samples lying within 1.5 times the interquartile range. Extreme outliers are not shown.

Table 1. SOC stock variations, mean climatic conditions and soil physicochemical parameters measured for the 60 field trials.

	Units	Min	Max	Median	Mean	SD
<i>SOC stock variations</i>						
Considered soil depth	cm	20	30	28	27	3
Initial SOC stock	t C ha ⁻¹	25.1	115.3	43.8	53.5	21.2
SOC stock changes (final-initial)	t C ha ⁻¹	-24.0	7.1	-1.2	-3.6	7.3
Experiment duration	yr	8	41	22	24	12
Annual SOC stock change rates	t C ha ⁻¹ yr ⁻¹	-1.01	0.45	-0.08	-0.20	0.33
<i>Annual climatic conditions</i>						
Mean temperature	°C	9.9	13.5	11.0	11.5	1.1
Cumulative Precipitation	mm	637	1285	753	840	220
Cumulative PET	mm	637	947	721	722	77
Precipitation-PET	mm	-290	595	37	117	252
<i>Soil properties</i>						
Clay	g kg ⁻¹	43	308	214	197	76
Silt	g kg ⁻¹	95	781	528	488	176
Sand	g kg ⁻¹	12	791	140	233	194
CaCO ₃	g kg ⁻¹	0	781	0	82	209
pH		5.6	8.3	6.8	7.0	0.9
C/N		7.8	13.0	9.1	9.4	1.1
Initial SOC content	g kg ⁻¹	7.2	32.9	14.1	15.8	6.8
Bulk density	g cm ⁻³	1.20	1.52	1.40	1.38	0.08
Rock fragment	%	0	39	0	7	10

PET: potential evapotranspiration, SOC: soil organic carbon

Table 2. Evaluation of the quality of fit obtained with AMGv2 using different methods for estimating aboveground and belowground C inputs.

Method for estimating C inputs	Harvest Index	Aboveground C inputs	Belowground C inputs	Optimized k0 value yr ⁻¹	Total MD t C ha ⁻¹
R. Reference method (Bolinder et al., 2007)	HI = f(species)	$C_{AG} = f(\text{species}, Y, HI)$	$C_{BG} = f(\text{species}, Y, HI, SR)$	0.29	-0.1
A1. HI function of yield (Fan et al, 2017)	HI = f(species, Y)	$C_{AG} = f(\text{species}, Y, HI)$	$C_{BG} = f(\text{species}, Y, HI, SR)$	0.32	-0.1
A2. HI function of yield (local coefficients)	HI = f(species, Y)	$C_{AG} = f(\text{species}, Y, HI)$	$C_{BG} = f(\text{species}, Y, HI, SR)$	0.30	0.0
B1. Fixed root biomass	HI = f(species)	$C_{AG} = f(\text{species}, Y, HI)$	$C_{BG} = f(\text{species})$	0.29	0.0
B2. Fixed root biomass - 50%	HI = f(species)	$C_{AG} = f(\text{species}, Y, HI)$	$C_{BG} = 0.5^* f(\text{species})$	0.24	-0.1
B3. Fixed root biomass + 50%	HI = f(species)	$C_{AG} = f(\text{species}, Y, HI)$	$C_{BG} = 1.5^* f(\text{species})$	0.34	0.0

Y = crop yield; HI = harvest index; SR = shoot:root ratio

* whole database (60 field trials)

** subset (27 field trials)

Table 3. Evaluation of the quality of fit obtained with AMGv2 using three methods and three parameterizations for setting the size of the initial stable pool proportion (C_S/C_0).

Method	Initial stable pool fraction (C_S/C_0)	Fixed parameter	Fixed parameter	Optimized parameter	Total SOC		SOC-C3		SOC-C4		
					MD	RM SE	MD	RM SE	MD	RM SE	
					tC ha ⁻¹						
M1	Constant	Fixed	C_S/C_0 0.65*	k_0 0.290	-0.1	2.6	-0.5	2.9	0.4	2.0	
		Fixed	C_S/C_0 0.40*	k_0 0.170	0.0	2.9	-1.5	2.3	2.3	2.9	
		Fixed	C_S/C_0 0.10*	k_0 0.115	-0.1	3.3	-2.5	3.2	3.5	4.2	
M2	Variable	$C_S/C_0 = P_s \cdot \exp(-p \cdot QC_0)$	k_0 0.290	p 0.001	P_s 0.66	0.0	2.9	0.6	2.1	0.4	2.0
		$C_S/C_0 = P_s \cdot \exp(-p \cdot QC_0)$	k_0 0.290	p 0.005	P_s 0.83	-0.1	3.4	1.0	2.5	0.4	2.0
		$C_S/C_0 = P_s \cdot \exp(-p \cdot QC_0)$	k_0 0.290	p 0.010	P_s 1.00	-1.3	4.1	0.1	2.9	0.4	2.0
M3	Site specific	Fixed	k_0 0.290	C_S/C_0 Site specific**	0.1	1.8	-0.4	2.3	0.4	2.0	
		Fixed	k_0 0.170	C_S/C_0 Site specific**	0.1	2.0	-2.3	2.9	2.3	2.9	
		Fixed	k_0 0.115	C_S/C_0 Site specific**	0.7	2.4	-2.6	3.3	3.5	4.2	

* Values reduced by 40% in the site with long term grassland history

** The variabilities of C_S/C_0 values optimized for the 20 sites are shown in figure 7

Line in bold corresponds to the reference method