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1 **Quantifying and simulating carbon and nitrogen**
2 **mineralization from diverse exogenous organic matters**

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17 **Running Title:** C and N mineralization from EOM

18

19 **Abstract**

20 The potential contributions of exogenous organic matters (EOMs) to soil organic C and
21 mineral N supply depend on their C and N mineralization, which can be assessed in
22 laboratory incubations. Such incubations are essential to calibrate decomposition models,
23 because not all EOMs can be tested in the field. However, EOM incubations are resource-
24 intensive. Therefore, easily measurable EOM characteristics that can be useful to predict
25 EOM behavior are needed.

26 We quantified C and N mineralization during the incubation of 663 EOMs from five
27 groups (animal manures, composts, sewage sludges, digestates, and others). This
28 represents one of the largest and diversified set of EOM incubations. The C and N
29 mineralization varied widely between and within EOM subgroups. We simulated C and N
30 mineralization with a simple generic decomposition model. Three calibration methods
31 were compared. Individual EOM calibration of the model yielded good model
32 performances, while the use of a unique parameter set per EOM subgroup decreased the
33 model performance, and the use of two EOM characteristics to estimate model parameters
34 gave an intermediate model performance (average RMSE-C values of 32, 99 and
35 65 mg C g⁻¹ added C and average RMSE-N values of 50, 126 and 110 mg N g⁻¹ added N,
36 respectively).

37 Because of the EOM variability, individual EOM calibration based on incubation remains
38 the recommended method for predicting most accurately the C and N mineralization of
39 EOMs. However, the two alternative calibration methods are sufficient for the simulation
40 of EOMs without incubation data to obtain reasonable model performances.

41 **Keywords:** organic amendment, fertilizer, model, organic matter, soil, decomposition, N
42 mineralization

43 **Highlights:**

44 C and N mineralization in 663 exogenous organic matters was quantified under controlled
45 conditions

46 C and N mineralization varied widely between and among the subgroups of exogenous
47 organic matters

48 A simple generic model can predict the variability in C and N mineralization from EOMs

49 A calibration was proposed for 26 EOM subgroups using their biochemical characteristics.

50 **1 Introduction**

51 Exogenous organic matter (EOM) is characterized as various residual organic matters
52 applied to soil as organic fertilizers or organic amendments. They encompass animal
53 manures and urban and industrial organic wastes and can be used raw or after treatments
54 (e.g., composting or anaerobic digestion). The contribution of EOM carbon (C) to soil
55 organic carbon (SOC) and EOM nitrogen (N) to the mineral N supply available to crops
56 has been extensively studied, especially in long-term field experiments (Gerzabek et al.,
57 1997; Gómez-Muñoz et al., 2017). A better characterization of the large diversity of EOM
58 is however needed to better quantify their potential for soil carbon storage, especially
59 EOMs that have been submitted to treatments such as composting or anaerobic digestion
60 (Chenu et al., 2019). Due to the limited number of EOMs, cropping systems, and climate
61 and soil conditions that can be tested *in situ*, many authors have used EOM incubations to
62 quantify the C and N mineralization of EOMs in soil under controlled conditions (Lazicki
63 et al., 2020; Mondini et al., 2017; Noirot-Cosson et al., 2017). The kinetics obtained during
64 laboratory incubations can be used to predict C and N mineralization in field or greenhouse
65 conditions with additional accounting for the effect of environmental factors (soil
66 temperature, water content, etc.) (Delin et al., 2012; Gale et al., 2006; Pinto et al., 2020).

67 However, a comparison of the C and N mineralization kinetics of a wide range of common
68 types of EOM, integrating their variability, is still lacking. EOM incubations can also be
69 used to calibrate EOM decomposition modules in soil-crop models (Noirot-Cosson et al.,
70 2016), which allows us to predict the impact of EOM applications under field conditions.
71 Calibrations for many EOMs have yet to be proposed for the decomposition modules of
72 soil-crop models, which often do not consider the diversity of and variability in EOMs.
73 Due to the workload involved in laboratory incubations (several months of incubation are
74 needed), the use of easily available EOM characteristics (e.g. biochemical fractions and
75 C:N ratios) to predict C and N mineralization should be encouraged (Delin et al., 2012;
76 Lashermes et al., 2009, 2010; Lazicki et al., 2020; Morvan & Nicolardot, 2009; Pansu &
77 Thuriès, 2003; Parnaudeau et al., 2004). The use of these characteristics for calibrating
78 decomposition modules in soil-crop models should allow prediction not only of the final
79 mineralization but also the mineralization dynamics; therefore, they need to be validated
80 for a wide range of EOMs.

81 The aim of this work was to quantify the C and N mineralization of a wide range of EOMs
82 during laboratory incubations, to test the ability of a simple generic decomposition model
83 to simulate their C and N mineralization, and to propose some simple calibration methods
84 of the model in order to avoid the use of long and costly laboratory incubations.

85 **2 Materials and methods**

86 *2.1 EOM database*

87 The EOM database compiles the results of 663 EOM incubations in soil over at least 90
88 days under controlled laboratory conditions. The EOM incubations were performed in
89 various research projects for many years and were not all conducted with exactly the same
90 procedure. However, most incubations were carried out according to a standard method

91 (AFNOR, 2009): the equivalent of 25 g of dry soil was mixed with the EOM added at a
92 rate corresponding to 2 g organic C kg⁻¹ dry soil. The EOM was dried and ground to a
93 particle size of 1 mm. Mineral N was added in excess to avoid any mineral N deficiency,
94 which could have limited the EOM decomposition rate, and to highlight the potential N
95 immobilization (Recous et al., 1995). The temperature was maintained at 28°C, and the
96 gravimetric water content was equivalent to the field capacity (pF = 2.5). A few
97 incubations were performed under different conditions (e.g., a temperature of 15°C and a
98 longer duration and/or with the addition of fresh EOM) (Table S1, Appendix B, online
99 supporting information). Most soils used in the incubations were loamy and noncalcareous
100 with a low carbon content (mean soil carbon content equal to 11.6 g kg⁻¹, mean soil organic
101 C:N equal to 9.8) (Table S2, Appendix B, online supporting information).

102 In each incubation, the CO₂ evolved and the soil mineral N were measured to determine
103 the mineralized C and N. The net C and N mineralized from each EOM were computed by
104 subtracting the mineralized C and N of an unamended soil (control). The proportions of the
105 net mineralized C and N from the EOMs were obtained by dividing the net C and N
106 mineralized from each EOM by the total amount of added organic C and organic N by the
107 EOM, respectively. We thus hypothesized the absence of a priming effect (Bol et al.,
108 2003).

109 The EOMs were classified into 5 groups: livestock manures (n=103), composts (n=337),
110 anaerobic digestates (n=54), sewage sludges (n=70) and others (n=99). Each EOM group
111 was divided into different EOM subgroups (from 1 to 8). Only digestates were not
112 subdivided into different subgroups because of the limited number of digestates in the
113 database compared to the diversity of digestates according to process (solid or liquid state),
114 post-treatment (phase separation or not), and digested waste (animal manures, urban
115 wastes) and the non-significant differences in C and N mineralization among these factors.

116 Each EOM was described by its organic C content, its organic and mineral N contents and
117 its $C_{org}:N_{org}$ ratio (Table 1). For 608 of the 663 incubated EOMs, the biochemical fractions
118 of the EOM (Van Soest & Wine, 1967) were also available. These biochemical fractions
119 combined with the proportion of EOM organic C mineralized during 3 days of incubation
120 in soil allowed the computation of the I_{ROC} value, which is an indicator of the proportion of
121 the EOM organic matter remaining in soils over the long term after application (Lashermes
122 et al., 2009) (Equation 1).

$$123 \quad I_{ROC} = 44.5 + 0.5 SOL - 0.2 CEL + 0.7 LIC - 2.3 C_{3d} \quad (1)$$

124 where SOL , CEL , and LIC are the soluble, cellulose-like and lignin-like fractions
125 (percentage of the total organic matter) and C_{3d} is the percentage of organic C mineralized
126 during 3 days of incubation in soil (percentage of the total C)

127 Finally, to estimate the contributions of organic C from the EOMs to the soil organic
128 matter and of organic N from the EOMs to the soil mineral N, the mineralized organic
129 carbon and the mineralized organic nitrogen after a period of incubation equivalent to one
130 year in field conditions based on mean annual temperature were computed. This equivalent
131 incubation duration was determined by using the concept of “normalized” time (Mary et
132 al., 1996), which modifies the incubation time with correction factors based on soil
133 temperature and soil water content. The correction factors of the STICS model were used
134 (Brisson et al., 2008) (see section 2.2 and Appendix A). The mean annual temperature in
135 the field applied was 12°C, corresponding to the mean annual temperature in central
136 France, while a constant soil water content equivalent to field capacity was used. The
137 observed quantity of C and N mineralized were not modified, only the corresponding
138 incubation time. For example, 89 days of incubation at 28°C and field capacity
139 corresponded to 365 days in the field at 12°C and field capacity.

140 2.2 *EOM decomposition model*

141 We used a simple generic decomposition model based on the residue decomposition
142 module of the STICS model. This model was initially developed for crop residues
143 (Nicolardot et al., 2001). In this study, we used a modified version of the STICS
144 decomposition module, adapted from Levavasseur et al. (2021), which allowed a better
145 simulation of C and N mineralization from EOMs of various origins.

146 The soil organic matter is subdivided into five pools (Figure 1). EOM C is divided into
147 labile (RES_1) and recalcitrant (RES_2) pools (with RES standing for “residues”). The
148 allocation of nitrogen between these two pools can be different, with each pool having its
149 own C:N ratio (CN_{res1} and CN_{res2}). This allocation is defined by a single parameter, a_{CN1} ,
150 which is the ratio between CN_{res1} and CN_{res} , where CN_{res} is the C:N ratio of the EOM as a
151 whole. The labile pool decomposes according to first-order kinetics with the
152 decomposition constant K_{res} , while the recalcitrant pool is directly incorporated into the
153 active organic matter pool. The decomposed labile pool is either mineralized or assimilated
154 by the zymogenous microbial biomass pool (with an assimilation yield Y). Soil mineral N
155 may be immobilized if the C:N ratio of the labile pool (CN_{res1}) greatly exceeds that of the
156 microbial biomass (CN_{bio}). The microbial biomass decays according to first-order kinetics,
157 with the decomposition constant K_{bio} . The decomposed biomass is either mineralized or
158 incorporated in the active soil organic matter, with the humification yield H . The soil
159 mineral N may be immobilized during this decay process depending on the C:N ratio of the
160 newly formed active soil organic matter, which is set as equal to the initial C:N ratio of the
161 soil organic matter. The active soil organic matter decomposes according to first-order
162 kinetics, with the decomposition constant K_a that depends on soil type (Clivot et al., 2017).
163 In this study, however, the K_a constant was optimized to minimize the simulation error of
164 the mineralized C and N in the control treatment, which did not include EOM in the

165 incubation. The stable soil organic matter pool is assumed to be inert at the century time
166 scale. With this model, the proportion of mineralized C and N is the sum of three
167 exponential terms (Appendix A, online supporting information).

168 2.3 Model calibration

169 Three methods of calibration (i.e., the adjustment of the model parameters) were tested.
170 M1 included a calibration specific to each EOM, wherein the unknown decomposition
171 parameters were optimized for each EOM separately. M2 included a calibration per EOM
172 subgroup, assuming that all EOMs of the same subgroup had the same optimized
173 decomposition parameters. M3 included a calibration per EOM subgroup based on
174 measured EOM characteristics. For the M3 method, the results of the M1 calibration
175 method were used to derive linear relationships between optimized decomposition
176 parameters and two EOM characteristics (I_{ROC} and C_{3d}) for all the EOMs together. The
177 parameters of these linear relationships were further optimized in calibration method M3,
178 i.e., the decomposition parameters were predicted by using linear relationships with EOM
179 characteristics. Simple linear functions with only I_{ROC} and C_{3d} were selected; other types of
180 functions and other EOM characteristics available in the database (e.g., lignin content) did
181 not significantly improve the prediction of the EOM parameters. As for the M2 method,
182 the interest of the M3 method is to avoid the need for an additional experimental
183 incubation for each new EOM (i.e., an EOM not in the database). In addition to M2, the
184 objective of the M3 method is to use easily available EOM characteristics to improve the
185 calibration within each EOM subgroup.

186 The upper and lower limits of the optimized parameters were mainly determined according
187 to the literature. K_{res} varied between 0.005 and 0.7 day⁻¹. These values prevented both an
188 accumulation of the labile pool in soil (which would not be consistent) and unrealistic
189 decomposition in only a few days. K_{bio} was set at 0.0076 day⁻¹ according to Justes et al.

190 (2009), assuming that the zymogenous biomass had the same decay rate for EOMs and
191 crop residues. The assimilation yield (Y) varied between 0.1 and 0.6 (Lee & Schmidt,
192 2014; Sauvadet et al., 2018; Spohn et al., 2016). The mean value of the humification yield
193 (H) optimized with calibration method M1 was 0.88. Preliminary tests indicated that fixing
194 H at this value for all EOMs did not significantly decrease model performances (Table S3,
195 Appendix B, online supporting information) due to compensation between H , Y and RES_1 .
196 This high and constant H value is consistent with the primary role of microbial necromass
197 in soil organic matter formation (Miltner et al., 2012). CN_{bio} was fixed at 7, according to
198 the mean value reported in the literature and because the C:N ratio of microbial biomass is
199 not expected to change markedly (Mooshammer et al., 2014). Fixing CN_{bio} at this value for
200 all EOMs did not significantly decrease model performances (Table S3, Appendix B,
201 online supporting information). RES_1 and RES_2 varied between 0 and 1, allowing EOM to
202 be completely labile or recalcitrant. CN_{res1} and CN_{res2} were defined as positive and to
203 ensure the nitrogen mass balance (relative to the total amount of N in the EOMs).
204 For each method of model calibration, the parameters were optimized to minimize the sum
205 of the root mean square errors ($RMSEs$) for the mineralized C and N (Equation 2).

$$206 \quad RMSE = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^n (O_i - S_i)^2} \quad (2)$$

207 where S_i and O_i are the simulated and observed values for the same measurement date (i)
208 and n is the number of measurement dates. The optimized (K_{res}) or fixed (K_{bio})
209 decomposition rates were corrected with the temperature and soil water content functions
210 (Brisson et al., 2008; Mary et al., 1996) (Appendix A) to take into account the effect of
211 these factors.

212 The “optim” function in R with the “L-BFGS-B” method was used for optimization (Byrd
213 et al., 1995), giving a lower and an upper bound to each parameter, as mentioned above.

214 2.4 Model validation

215 Calibration method M1 could not be validated on an independent dataset, and the
216 calibration was specific to each EOM. We assessed the performances of calibration
217 methods M2 and M3 by using V-fold cross-validation with three replicates. Each EOM
218 subgroup was randomly divided into three different subsamples. Two subsamples were
219 used for calibration, and the third subsample was used for validation. We repeated this
220 operation three times, changing the validation subsample each time, and then repeated
221 these three operations three times by changing the random division of the sample to avoid
222 any sampling effects in the results.

223 The performances of the model for calibration and validation were assessed with three
224 different statistical criteria: the *RMSE*, the mean error (*ME*), and the coefficient of
225 determination (R^2) (Equations 2, 3 and 4). These criteria were computed for each
226 incubation and then averaged.

227
$$ME = \frac{1}{n} \cdot \sum_{i=1}^n (O_i - S_i) \quad (3)$$

228
$$R^2 = \left(\frac{\sum_{i=1}^n ((O_i - \bar{O}) \cdot (S_i - \bar{S}))}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2} \cdot \sqrt{\sum_{i=1}^n (S_i - \bar{S})^2}} \right)^2 \quad (4)$$

229 where S_i and O_i are the simulated and observed values for the same measurement date (i)
230 and n is the number of measurement dates. \bar{O} and \bar{S} are the means of the observations and
231 simulations, respectively.

232 **3 Results**

233 3.1 Observed C and N mineralization

234 For a given EOM group, the C and N mineralization varied widely between the different
235 EOMs (Figure 2). For example, for animal manures, the mineralized C varied between 0

236 and 500 mg C g⁻¹ added C and the mineralized N varied between -500 and 500 mg N g⁻¹
237 added N after twenty days of incubation. Among animal manures, chicken droppings
238 (AM_CD) produced the greatest net mineralization, while horse manure decomposition
239 resulted in a net N immobilization.

240 The calculation of mineralized C after an incubation duration equivalent to one year in the
241 field allows an easy assessment of the potential EOM contribution to C storage in soil (the
242 lower the mineralized C is, the higher the contribution) (Figure 3). Compared to all other
243 EOMs, the lowest values were obtained for composts, with a median C mineralization
244 equal to 181, 270, 372, 403 and 456 mg C g⁻¹ added C for composts, digestates, animal
245 manures, sewage sludges and other EOMs, respectively. However, a large variability was
246 found within the EOM groups. For example, composts of municipal solid waste (C_MSW)
247 exhibited a higher C mineralization (median value of 324 mg C g⁻¹ added C) than the
248 average, while composts of green waste (C_GW) showed a very low C mineralization,
249 equal to 108 mg C g⁻¹ added C. Differences in the mineralized C after an incubation
250 duration equivalent to one year in the field also appeared among animal manures: chicken
251 droppings, pig slurries and horse manures had median values of 545, 448 and 432 mg C g⁻¹
252 added C, respectively, and were more mineralizable than bovine manure (258 mg C g⁻¹
253 added C). If we consider all the EOM subgroups, the mineralized C after an incubation
254 duration equivalent to one year in the field appeared to be well correlated with the *I_{ROC}* (R^2
255 = 0.67, Table S4, Appendix B, online supporting information). For specific EOM
256 subgroups, the *I_{ROC}* was also significantly correlated with mineralized C, except for some
257 EOM subgroups with low mineralization (e.g., green waste compost (C_GW), Table S4,
258 Appendix B, online supporting information).

259 The calculation of net mineralized N after an incubation duration equivalent to one year in
260 the field allowed us to compare the fertilizing values of the various EOMs (Figure 3).

261 Composts and digestates were characterized by a small net mineralization, which varied
262 between -104 and 76 mg N g⁻¹ added N. The short-term N fertilizing value of these EOMs
263 thus relied on their mineral nitrogen content only, which was very low for most composts
264 (except, e.g., C_GWS and C_PIS) but high for digestates (Table 1). Wide variability was
265 found among the animal manures: horse manure decomposition resulted in strong N
266 immobilization (-419 mg N g⁻¹ added N), while chicken droppings produced important net
267 N mineralization (304 mg N g⁻¹ added N). Moderate amounts of N were mineralized from
268 bovine and pig manures (52 and 100 mg N g⁻¹ added N, respectively), which had small
269 mineral N contents. The three sewage sludge subgroups exhibited a high mineralized N
270 (278 to 432 mg N g⁻¹ added N). The last group of EOMs (“others”) exhibited variable N
271 mineralization, which is consistent with the highly diverse EOMs within this group,
272 ranging from vegetal residues (e.g., bark) that mainly immobilized N to algae and animal
273 residues (e.g., feather meal) that mainly mineralized N. The variability in the net
274 mineralized N after an incubation duration equivalent to one year in the field for all the
275 EOM subgroups was partly related to that of $C:N_{org}$ ($R^2 = 0.32$, Table S4, Appendix B,
276 online supporting information). However, the relationship between the mineralized N and
277 $C:N_{org}$ varied widely among the EOM subgroups: a good correlation was observed for
278 some EOM subgroups (e.g., $R^2 = 0.89$ for C_PIS and $R^2 = 0.92$ for OTH_AR) to the
279 absence of a relationship for other EOMs (e.g., $R^2 = 0$ for AM_HM and SS_AGR).

280 3.2 Prediction of C and N mineralization

281 The simulation of C and N mineralization with a calibration specific to each EOM (M1)
282 gave very good results. The observed variability was very well accounted for (Figure 4):
283 the determination coefficient was 0.92 for C and 0.68 for N, the bias was very low
284 (5 mg C g⁻¹ added C and 2 mg N g⁻¹ added N) and the *RMSE* values were 32 mg C g⁻¹

285 ¹ added C and 50 mg N g⁻¹ added N (Table 2), which were less than twofold the mean
286 standard deviation of the observations (17 mg C g⁻¹ added C and 39 mg N g⁻¹ added N).

287 When using method M2, which included a calibration per EOM subgroup (i.e., all the
288 EOMs within the same EOM subgroup had the same optimized parameters), the observed
289 variability in C and N mineralization was still reproduced by the model (Figure 4), but the
290 *R*² of the cross-validation for N mineralization decreased to 0.52. A slight bias was
291 observed for C (-11 mg C g⁻¹ added C), and the *RMSE* increased by a 2- to 3-fold factor for
292 both C and N (Table 2).

293 When the calibration was based on EOM characteristics (including EOM subgroup) (M3),
294 the model performance based on the validation dataset was better than the performance
295 observed for method M2, since the *RMSE* of mineralized C dropped from 99 to 65 mg C g⁻¹
296 ¹ added C and the *RMSE* of mineralized N decreased from 126 to 110 mg N g⁻¹ added N.

297 Regardless of the calibration method, the model performance strongly varied with EOM
298 subgroup (Tables S3 and S4, Appendix B, online supporting information). For example,
299 the highest *RMSE* was often associated with the EOM that had the highest mineralization
300 (e.g. algae (OTH_ALG) and agri-industrial wastewater (OTH_AGRWW)).

301 3.3 Parameters of the calibration per EOM subgroup

302 For calibration method M2, a set of parameters was proposed for each EOM subgroup
303 (Table 3). In the absence of a specific incubation for a given EOM or of its characteristics
304 (e.g., *I*_{ROC}), these parameters can be used to simulate C and N mineralization with
305 acceptable accuracy (section 3.2). The parameters greatly varied according to EOM
306 subgroup. The labile fraction of the residues (*RES*_l) varied between 0.13 for the green
307 waste compost (C_GW) and 1.00 for vinasse (OTH_VIN) and algae (OTH_ALG). The
308 microbial assimilation yield (*Y*) ranged from 0.10 (for example, in chicken droppings

309 (AM_CD)) to 0.60 in green waste and sludge compost (C_GWS). The parameter aCN_l was
310 greater than 1 for all EOMs except SS_AGR, indicating that the C:N ratio of the labile
311 pool (CN_{res1}) was greater than the C:N ratio of the recalcitrant pool (CN_{res2}). The
312 corresponding simulated C and N mineralization dynamics for the different EOM
313 subgroups are presented in Figure S1 (Appendix C, online supporting information).

314 3.4 Parameters of the calibration per EOM subgroup and with EOM characteristics

315 For calibration method M3, the relationships between the model parameters and EOM
316 characteristics were established by considering the significant relationships observed
317 between the optimized parameters of EOM in the first calibration method (M1) and EOM
318 characteristics (Figure S2). The labile fractions of the EOMs (RES_l) decreased with
319 increasing values of I_{ROC} ($R^2=0.61$ with EOM subgroup as a covariable, $R^2 = 0.49$ for all
320 the EOMs together). The decomposition rate (K_{res}) increased with C_{3d} according to a
321 logarithmic relationship ($R^2 = 0.34$ with EOM subgroup as a covariable, $R^2 = 0.21$ for all
322 the EOMs together). The other significant relationships were not considered because they
323 did not improve the residual variance. The aforementioned linear relationships were
324 introduced in calibration method M3 to predict the EOM parameters of the model (Table 4
325 and Table S7, Appendix B, online supporting information). EOM subgroup was added as a
326 covariable due to the systematic improvement in R^2 when using it.

327 4 Discussion

328 4.1 Variability in EOM C and N mineralization

329 The comparison of a wide range of EOMs highlighted some important differences in C and
330 N mineralization among the EOMs (Figure 2, Figure 3). While C mineralization from the
331 EOMs was generally low for composts, C mineralization can be high for certain EOMs,
332 such as chicken droppings, animal residues or vinasses. The rate of N mineralization from

333 the EOMs exhibited even more variability between EOM subgroups (e.g., important net N
334 mineralization for chicken droppings and strong net N immobilization for horse manure).
335 Considering the organic N content of these two EOMs (Table 1), their typical water
336 content (60% and 30%, respectively, personal data) and their typical application rate (20
337 and 3 t ha⁻¹, respectively, personal data), the input of organic N would represent
338 approximately 100 kg ha⁻¹ in both cases, thus leading to a net immobilization of
339 42 kg N ha⁻¹ for horse manure and a net mineralization of 30 kg N ha⁻¹ for chicken
340 droppings after one year in the field. Despite the high immobilization caused by horse
341 manure in the first phase, this EOM could have a fertilizing value during the second phase,
342 in which N is slowly released (Figure 2). Moreover, it is important to highlight that these
343 high values of N immobilization represents only the potential immobilization, which can
344 be reached only when the soil mineral N content is large enough and is a nonlimiting factor
345 in decomposition. The hierarchy of amendment and fertilizing values between the EOM
346 subgroups is in line with existing literature (Lazicki et al., 2020; Mondini et al., 2017;
347 Noirot-Cosson et al., 2017), even though the comparison of so many EOM subgroups is
348 rare. The hierarchy of mineralized C and N after an incubation duration equivalent to one
349 year in the field between the EOM subgroups also reflected their contribution to the SOC
350 (inverse relationship) observed in the field by various authors (Gerzabek et al., 1997;
351 Levavasseur et al., 2020) and to N short-term supply (Gutser et al., 2005).

352 In addition to the differences between EOM subgroups, a high variability in C and N
353 mineralization existed inside each EOM subgroup (Figure 3). This result highlighted the
354 need for a detailed characterization of EOMs, either through laboratory incubations, or
355 with indicators that are easier to retrieve, such as the *I_{ROC}* indicator based on biochemical
356 fractionation (Lashermes et al., 2009), to determine the contribution of EOMs to SOC. We
357 found a strong correlation between the mineralized C after an incubation duration

358 equivalent to one year in the field and I_{ROC} ($R^2 = 0.67$), which was expected because I_{ROC}
359 was defined as a predictor of residual C in soils under laboratory incubation. Our study,
360 however, validates the interest of I_{ROC} for a wider range of EOMs, including for some
361 EOM subgroups not used in the I_{ROC} calibration such as digestates (R^2 between mineralized
362 C and I_{ROC} equal to 0.62). The mineralized N after an incubation duration equivalent to one
363 year in the field was less but significantly correlated with EOM characteristics (R^2 with
364 CN_{res} equal to 0.32), and the correlation was higher for some EOM subgroups (e.g., animal
365 residues (OTH_AR)). This result contradicts a study showing that CN_{res} was a good
366 predictor of N mineralization ($R^2 = 0.94$) (Lazicki et al., 2020) but confirms another study
367 pointing out that CN_{res} is not sufficient for predicting the N mineralization of EOMs of
368 various qualities (Bonanomi et al., 2019). The limited capacity of this parameter to predict
369 N mineralization could be explained by the great diversity of EOMs used in our study. For
370 example, some anaerobic digestates exhibited low CN_{res} and induced N immobilization, in
371 opposition to other EOM with low CN_{res} like sewage sludge. Moreover, the use of
372 incubations realized in different experimental conditions in our study (temperature, water
373 content) and their “standardization” using the concept of normalized time (Mary et al.,
374 1996) could partly weaken the relationship between EOM characteristics and EOM
375 mineralization for all the incubation taken together, even if most of the EOM incubation
376 that we used were realized in similar conditions (Tables S1 and S2).

377 Despite the interest in EOM characteristics, they were not sufficient to predict the
378 dynamics of C and N mineralization in various soil and climate conditions, which required
379 the use of a well-calibrated decomposition model.

380 4.2 Model performance

381 The calibration of individual EOMs in the model yielded good model performances for all
382 the EOM subgroups, with $RMSE$ values equal to 32 mg C g⁻¹ added C and 50 mg N g⁻¹

383 ¹ added N and an R^2 equal to 0.92 and 0.68 for C and N mineralization, respectively. These
384 performances are similar to those reported for other models for a less diverse groups of
385 EOMs (Gale et al., 2006; Mohanty et al., 2011; Mondini et al., 2017). It is also comparable
386 to the performance obtained with the STICS model for crop residues (Justes et al., 2009).
387 When the same set of parameters was used for all the EOMs of the same EOM subgroup,
388 the model performances decreased for C and N, due to the diversity of EOMs within each
389 subgroup. The simulation of C mineralization was improved when the EOM characteristics
390 (I_{ROC} and C_{3ds}) were accounted for in the model parameterization. However, the EOM
391 characteristics were not sufficient for the determination of decomposition parameters
392 capable of simulating the N mineralization kinetics very accurately. Such a result was
393 found by Noirot-Cosson et al. (2017) and Monhanty et al. (2011).

394 Regarding the model performances within the three calibration methods, we recommend
395 that a specific EOM laboratory incubation is used to calibrate the model (M1 method) and
396 to most accurately predict its potential behavior in the field, when the user considers a
397 specific EOM (Figure 5). However, model users often do not have any information on the
398 particular EOM, except the quantity applied. In that case, we showed that a calibration
399 depending only on its subgroup (M2 method) bring some insights that are sufficient to test
400 some global EOM application scenarios. We do not recommend to use the M2 “default”
401 method to simulate accurately the effects of a specific EOM in case of repeated application
402 so as not to accumulate over time the error in the estimates. As an alternative to the latter
403 case, we highly recommend the addition of EOM easily measurable characteristics to
404 calibrate the model (M3 method), as tested in Levavasseur et al. (2021) for the simulation
405 of a long term experiment. The quality of the calibration methods M2 and M3 varied
406 according to the considered EOM subgroup (Table S5 and S6). We recommend the user to
407 consider the EOM subgroup to determine whether a specific calibration of the modeled

408 EOM (M1) is required or not and to put it in perspective with the objective and
409 characteristics of the modeling study (e.g., importance of EOM application in the
410 scenarios).

411 Other EOM characteristics not considered here might contribute to improving the
412 prediction of EOM model parameters and, subsequently, the simulation of C and N
413 mineralization. For example, the C:N ratio of biochemical fractions has been shown to be
414 useful in predicting N mineralization (Morvan & Nicolardot, 2009; Parnaudeau et al.,
415 2004) as well as ¹³C-CPMAS NMR spectral regions (Bonanomi et al., 2019; Pansu et al.,
416 2017). However, these characteristics were not available in the EOM database we used and
417 are not usually available outside research laboratories. The identification of readily
418 available EOM characteristics that can be used to calibrate decomposition models remains
419 a challenge.

420 *4.3 Model hypotheses*

421 The modification of the STICS model proposed by Levavasseur et al. (2021) to model
422 EOM decomposition was used to simulate a wide range of EOM decomposition levels in
423 our study. This modification includes the addition of a recalcitrant pool of EOM that is
424 directly incorporated in the soil active OM and is not assimilated by the microbial biomass,
425 assuming that this recalcitrant pool results from the previous digestion of raw matter by
426 microbial biomass (in animal guts or during treatments). This pool is considered to have
427 the same dynamics as the active pool in the STICS model. Several authors have
428 hypothesized that EOM is composed of at least two dynamic pools (Gijsman et al., 2002;
429 Mondini et al., 2017) to simulate EOM decomposition; however, this distinction was not
430 necessary for simulating crop residue decomposition in the STICS model, which
431 considered a single dynamic pool (Justes et al., 2009). Whereas the decay rate of the
432 recalcitrant pool of EOM was optimized and inferior to the decay rate of the soil active

433 OM in the study of Levvasseur et al. (2021), this decay rate was set equal to that of the
434 soil active OM in the present study. This simplification caused some overestimation of C
435 mineralization for very stable EOMs, such as composts (Figure 4). The plateau of C
436 mineralization usually observed in laboratory incubations could not be properly simulated
437 with this model. However, this modification was made to limit the number of parameters in
438 the STICS model. Moreover, several authors have suggested that SOM stability after EOM
439 application is not modified (Liu et al., 2018; Luan et al., 2019), even though another study
440 suggested the opposite (Peltre et al., 2017). Levvasseur et al. (2020) successfully
441 simulated carbon storage in long-term field experiments with EOM application using the
442 AMG model without assuming a greater stability of EOM in comparison to that of SOM.
443 Because the STICS and AMG formalisms for SOC are very similar (i.e., SOC is divided
444 into an active and a stable pool, and the mineralization function is the same) (Clivot et al.,
445 2019), the STICS model should also allow the simulation of C and N dynamics of EOMs
446 without assuming a greater stability of those EOMs, i.e., by allocating EOMs only to soil
447 active OM (either directly, or after soil microbial biomass assimilation, Figure 1). Directly
448 allocating the recalcitrant fractions of EOMs to soil active OM could change the soil C:N
449 ratio after repeated applications of the EOMs. This effect is consistent with the fact that
450 soil C:N usually increases with SOC content (Mooshammer et al., 2014). Other
451 simplifications made in our study include the use of a constant humification yield (H) of
452 microbial necromass and a constant C:N ratio of microbial biomass (CN_{bio}), in line with
453 recent knowledge about SOM formation (Miltner et al., 2012; Mooshammer et al., 2014).
454 However, the H value retained in our study is higher than the value reported in the study of
455 Miltner et al. (2012). Concerning the decay rate of the labile pool K_{res} , the calibration
456 method M1 gave some optimized values equal to the minimal (0.005 day^{-1}) or maximal
457 (0.7 day^{-1}) value for some EOM (Figure S2). The use of lower minimal and higher

458 maximal values could improve the simulation. However, we decided to keep these limits to
459 prevent both an accumulation of the labile pool in soil (which would not be consistent) and
460 unrealistic decomposition in only a few days.

461 The use of EOM incubations to calibrate the decomposition module of the STICS model
462 and predict EOM decomposition under field conditions requires some correction factors
463 regarding water content and temperature. The use of EOM incubations run under different
464 conditions (temperature, soil water content, soil type) could have introduced errors into the
465 EOM calibration, because of the uncertainty associated with these correction factors.
466 However, most of the EOM incubations used in this study were realized in similar
467 conditions (loamy soil, 28°C, water content close to or equal to field capacity, Tables S1
468 and S2). The effects of soil type, water content, temperature and N mineral availability are
469 already taken into account in the STICS soil-crop model to calculate EOM mineralization
470 *in situ* (Brisson et al., 2008). The correction factors should allow the extrapolation of
471 laboratory incubations to field conditions (Gale et al., 2006). However, laboratory
472 incubations are usually realized with dried and crushed EOM, which can influence the
473 mineralization of C and, especially, N (Le Roux et al., 2016). Correction factors that
474 consider EOM preparation before incubation should also be proposed.

475 Finally, beyond the STICS users, the decomposition module (Appendix A) and the
476 calibrations proposed in this paper could be used outside the STICS model to predict the C
477 and N mineralization of a large diversity of EOMs.

478 **5 Conclusions**

479 We quantified the C and N mineralization of a wide range of EOMs based on a database of
480 more than 600 EOM incubations, from five groups (animal manures, composts, sewage
481 sludges, digestates, and others) and 26 subgroups (e.g., bovine manure, green waste

482 compost). This represents one of the largest and most diversified syntheses of EOM
483 incubation data. The results indicated a wide diversity in EOM contributions to C storage
484 in soil and N supply for crops, both between EOM subgroups and within EOMs of the
485 same subgroup. The EOM incubations were used to calibrate a simple generic
486 decomposition model included in the STICS soil-crop model to simulate EOM
487 decomposition. Individual EOM calibration yielded the best model performances for the
488 simulation of C and N mineralization and is the recommended calibration method of the
489 STICS model for accurate simulations of scenarios of application of a specific EOM in
490 field conditions. In the absence of EOM incubation data, we proposed two calibration
491 methods for the 26 different subgroups of EOMs in the STICS model: using either a
492 unique calibration per EOM subgroup or EOM characteristics as predictors of model
493 parameters. Although these two calibration methods decreased model performances, they
494 allow the prediction with a reasonable performance of the EOM contribution to soil C
495 storage or to mineral N supply to determine the best practices for their use (amount, period
496 of application, fertilized crops, etc.). Future research is needed to better predict the EOM
497 parameters from easily available EOM characteristics and verify the extrapolation of
498 laboratory incubation to field conditions.

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502

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- 663
- 664

665 **8 Tables**

666

667 **Table 1** Main characteristics of the EOM database

Group	Subgroup	Code	No. of samples	C _{org} (g kg ⁻¹ DM)		N _{org} (g kg ⁻¹ DM)		C _{org} :N _{org}		N _{min} (g kg ⁻¹ DM)		I _{ROC} * (%)	
				Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Animal manures	Bovine manure	AM_BM	45	359	69	21.1	5.2	18.1	6.5	1.3	1.4	59	13
	Bovine slurry	AM_BS	3	360	25	33.7	11.2	12.0	5.2	25.6	11.3	51	6
	Chicken droppings	AM_CD	8	398	147	45.2	17.4	9.6	3.8	2.9	2.2	27	21
	Horse manure	AM_HM	8	407	41	12.4	2.4	33.6	5.5	0.5	0.5	50	5
	Other manures	AM_OTH	8	366	75	32.9	12.8	12.9	5.2	24.8	40.0	58	8
	Pig manure	AM_PIM	6	428	29	18.1	3.9	24.9	6.9	2.4	1.8	57	12
	Pig slurry	AM_PIS	10	409	106	37.8	17.1	11.9	3.6	30.7	30.2	47	10
	Poultry manure	AM_POM	15	353	66	26.1	8.5	14.2	3.0	4.0	4.6	47	19
Composts	Composted animal manure	C_AM	39	322	81	22.0	6.8	14.9	5.4	1.4	1.8	67	14
	Biowaste and green waste compost	C_BIO	52	212	61	16.3	4.5	13.1	2.4	0.4	0.6	75	9
	Green waste compost	C_GW	25	247	57	15.7	5.3	18.2	11.0	0.3	1.3	80	7
	Green waste and animal manure compost	C_GW+AM	9	213	98	17.6	8.7	12.4	2.1	2.1	2.1	62	12
	Green waste and sludge compost	C_GWS	71	257	64	20.0	5.2	13.6	4.8	2.2	1.8	79	10
	Municipal solid waste compost	C_MSW	89	253	72	13.1	4.1	20.1	5.8	0.8	1.0	55	15
	Other composts	C_OTH	41	299	112	17.5	8.7	23.4	22.6	1.0	1.5	69	15
	Pig slurry compost (various cosubstrates)	C_PIS	11	338	66	22.0	10.3	18.9	10.0	3.9	4.3	64	13
Digestates	All digestates	DIG	54	346	90	26.6	15.1	15.9	7.1	36.4	66.3	66	13
Sewage sludges	Agro-industrial sludges	SS_AGR	11	235	143	28.6	24.4	24.5	33.8	3.3	6.2	52	15
	Other sludges	SS_OTH	6	341	42	41.4	18.0	10.5	7.2	2.4	2.0	61	3
	Urban sludges	SS_URB	53	294	86	39.4	17.5	8.9	7.1	4.4	6.1	49	17
Others	Agro-industrial wastewater	OTH_AGRWW	23	312	158	8.7	0.7	23.4	19.1	10.0	8.3	-	-
	Algae	OTH_ALG	5	155	51	13.0	4.3	12.4	1.9	0.1	0.0	21	22
	Animal residues (feather meal, etc.)	OTH_AR	6	476	61	103.4	59.5	7.7	6.7	5.9	7.0	51	23
	Others	OTH_OTH	38	293	132	37.0	37.2	13.8	10.9	3.6	8.5	46	23
	Sugarbeet vinasse	OTH_VIN	8	352	26	34.0	7.9	11.9	2.9	1.2	0.7	-	-
	Vegetal residues (bark, grape marc, etc.)	OTH_VR	19	483	47	22.7	17.7	38.5	31.4	0.5	1.4	63	16

668 * Indicator of residual organic carbon in soils (Lashermes et al., 2009)

669 **Table 2** Model performance per incubation for all the EOMs together according to the
670 calibration method (mean calibration and validation performance of the cross-validation
671 iterations for methods M2 and M3) (ME: mean error, RMSE: root mean square error, R²:
672 coefficient of determination).

Calibration method	Evaluation dataset	Carbon mineralization (mg C g ⁻¹ added C)			Nitrogen mineralization (mg N g ⁻¹ added N)		
		ME	RMSE	R ²	ME	RMSE	R ²
M1: Individual EOM calibration	Calibration	5	32	0.92	2	50	0.68
M2: Calibration per EOM subgroup	Calibration	-12	91	0.91	6	111	0.54
	Validation	-11	99	0.91	4	126	0.52
M3: Calibration with EOM characteristics	Calibration	-7	58	0.92	11	96	0.54
	Validation	-7	65	0.92	11	110	0.52

673

674

675 **Table 3** Optimized parameters for the STICS decomposition module per EOM subgroup
 676 (obtained with the whole EOM dataset used for calibration method M2). K_{bio} , H and CN_{bio}
 677 were fixed at 0.0076 day^{-1} , 0.88 and 7.0, respectively. The meaning of the EOM subgroup can
 678 be found in Table 1.

EOM subgroup	$K_{res} \text{ (day}^{-1}\text{)}$	RES_1	Y	a_{CN1}
AM_BM	0.025	0.24	0.32	3.09
AM_BS	0.062	0.42	0.39	2.14
AM_CD	0.077	0.46	0.10	1.37
AM_HM	0.028	0.48	0.31	10.00
AM_OTH	0.005	1.00	0.53	1.02
AM_PIM	0.011	0.25	0.35	1.14
AM_PIS	0.048	0.40	0.10	5.25
AM_POM	0.055	0.46	0.34	1.99
C_AM	0.005	0.33	0.44	2.07
C_BIO	0.005	0.16	0.50	10.00
C_GW	0.005	0.13	0.60	10.00
C_GW+AM	0.026	0.29	0.56	10.00
C_GWS	0.005	0.18	0.60	5.58
C_MSW	0.059	0.44	0.50	1.65
C_OTH	0.005	0.19	0.58	4.29
C_PIS	0.036	0.34	0.57	1.04
DIG	0.024	0.24	0.25	10.00
SS_AGR	0.090	0.29	0.20	0.76
SS_OTH	0.076	0.48	0.52	1.04
SS_URB	0.072	0.53	0.40	1.21
OTH_AGRWW	0.141	0.64	0.38	1.71
OTH_ALG	0.069	1.00	0.25	2.38
OTH_AR	0.068	0.77	0.45	1.27
OTH_OTH	0.069	0.45	0.33	1.45
OTH_VIN	0.114	1.00	0.45	1.12
OTH_VR	0.013	0.35	0.39	10.00

679

680

681 **Table 4** Calibration for the STICS model per EOM subgroup and according to the EOM
682 characteristics (M3) (the numerical values of α_{res1} , β_{res1} , α_{kres} , β_{kres} , Y , a_{CN1} per EOM subgroup
683 are given in Table S7)

Parameter	Calibration per EOM subgroup
RES_1	$\alpha_{res1} + \beta_{res1} \times I_{ROC}$
RES_2	$1 - RES_2$
K_{res}	$\exp(\alpha_{kres} + \beta_{kres} \times C_{3d})$
K_{bio}	0.0076
Y	Y
H	0.88
CN_{bio}	7.0
a_{CN1}	a_{CN1}

684

685

686 **9 Figure legends**

687 **Figure 1** Decomposition model of EOM in the modified version of the STICS model. The C
688 fluxes are represented as solid black lines, and the N fluxes are represented as dashed gray
689 lines.

690 RES_1 and RES_2 are the proportions of C from the EOMs in the labile pool and recalcitrant
691 pools, respectively, with $RES_2 = 1 - RES_1$

692 CN_{res} , CN_{res1} and CN_{res2} are the C:N ratios of the EOM and the labile and recalcitrant pools,
693 respectively, and a_{CN1} is the ratio $CN_{res1} : CN_{res}$

694 K_{res1} is the decomposition rate of the labile pool

695 Y is the C assimilation yield of the labile pool

696 CN_{bio} , CN_a and CN_s are the C:N ratios of the microbial biomass, and active and stable pools,
697 respectively

698 K_{bio} and K_a are the decay rates of the zymogenous biomass and the active soil organic matter
699 pools, respectively

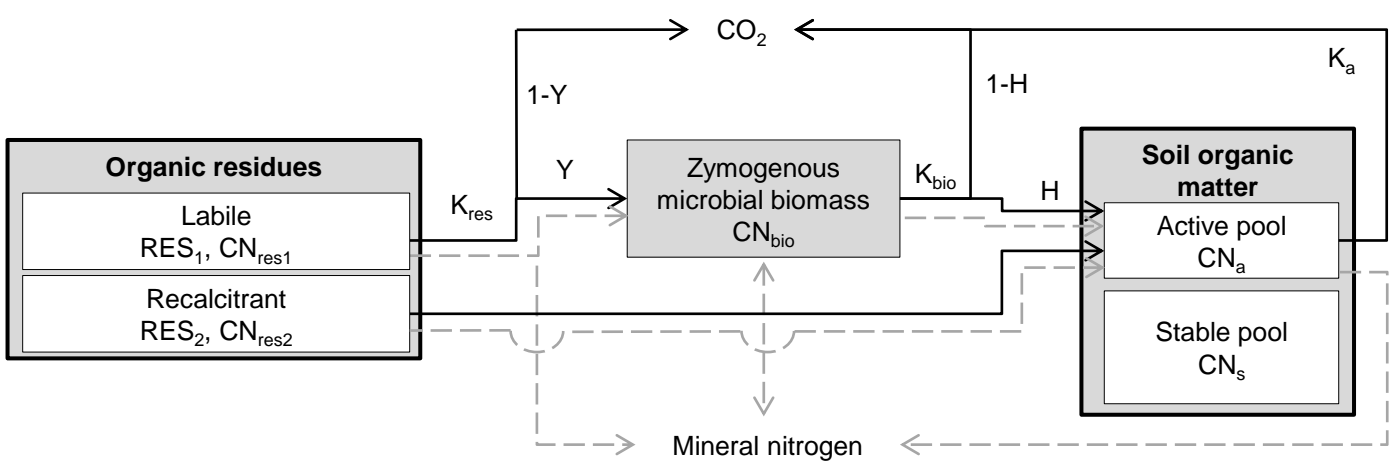
700 H is the C humification yield.

701 **Figure 2** Observed mineralized organic carbon and nitrogen for the different groups of EOMs
702 in laboratory incubations. Each gray line represents an EOM incubation, while the colored
703 lines represent fitted local polynomial regressions per EOM subgroup (performed with the
704 loess function in R). Very few data on N mineralization are lower than -100% and the Y-axis
705 was cut to -100% to improve the visibility. The meaning of the EOM subgroup abbreviations
706 can be found in Table 1.

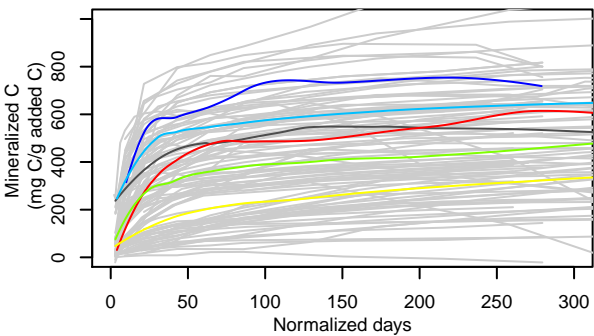
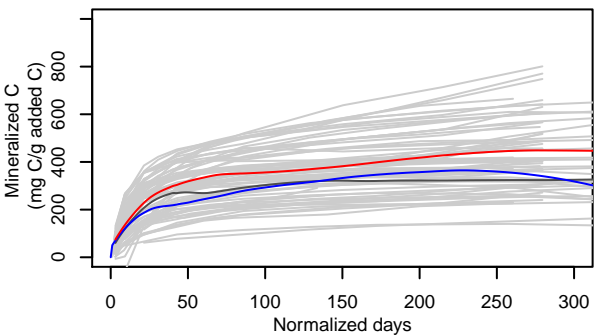
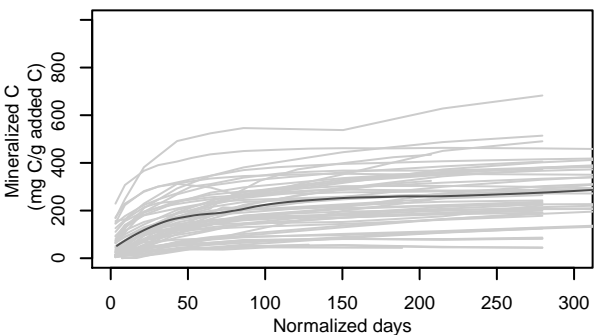
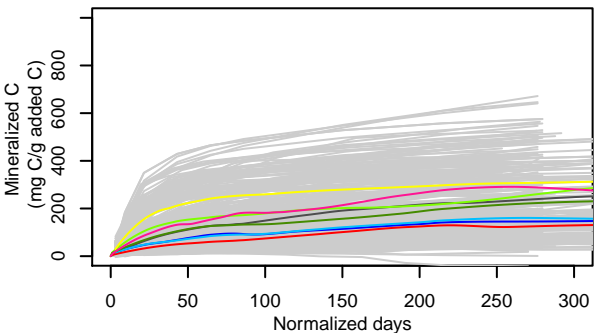
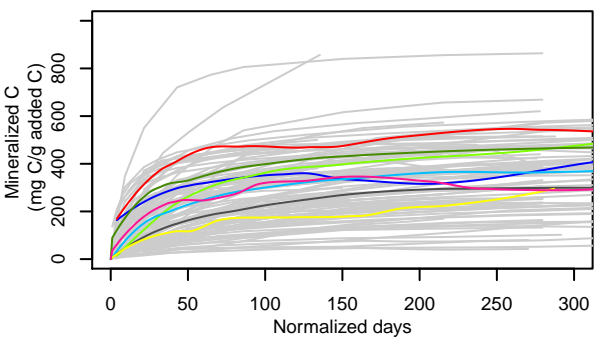
707 **Figure 3** Observed mineralized carbon and net mineralized nitrogen for each EOM group and
708 subgroup after incubation for a duration equivalent to one year under field conditions. The
709 meaning of the EOM subgroup abbreviations can be found in Table 1.

710 **Figure 4** Observed and simulated values of carbon and nitrogen mineralization for each EOM
711 and sampling date, according to the calibration method (results obtained by using the whole
712 EOM dataset for calibration).

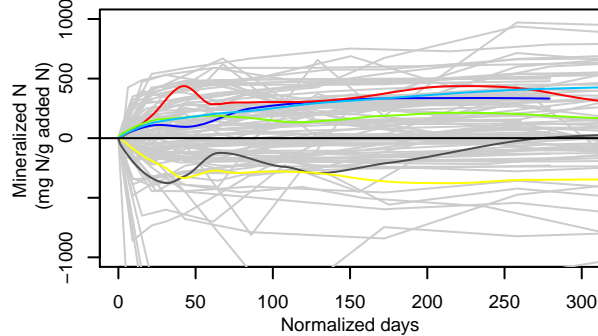
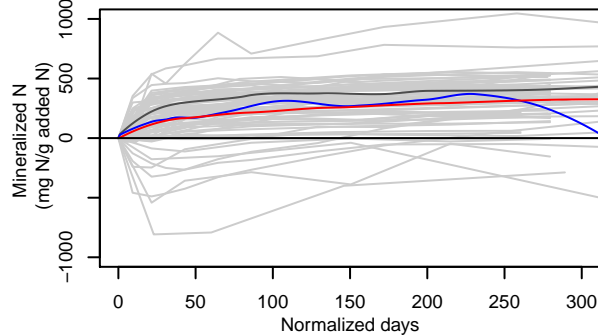
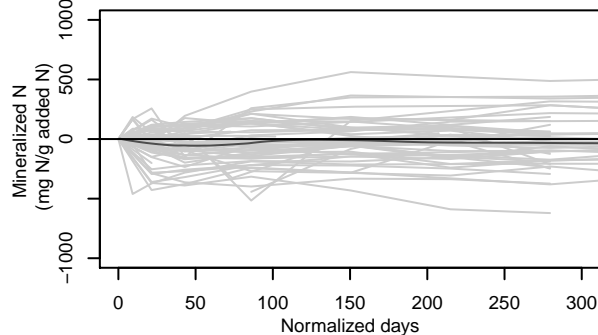
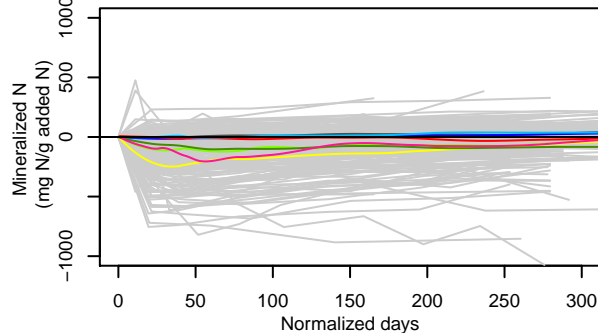
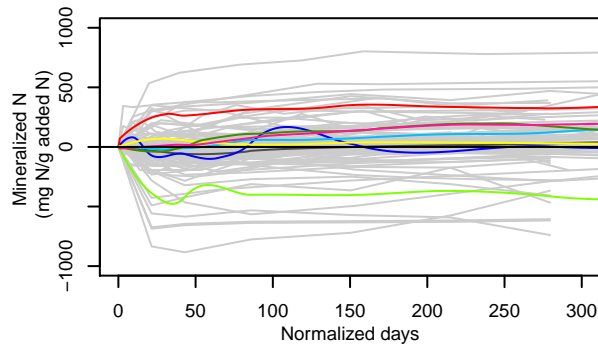
713 **Figure 5.** Conceptual diagram for the calibration of an EOM in the decomposition model.



Carbon mineralization



Nitrogen mineralization



Animal manures

— AM_BM
— AM_BS
— AM_CD
— AM_HM
— AM_OTH
— AM_PIM
— AM_PIS
— AM_POM

Composts

— C_AM
— C_BIO
— C_GW
— C_GW+AM
— C_GWS
— C_MSW
— C_OTH
— C_PIS

Digestates

— DIG

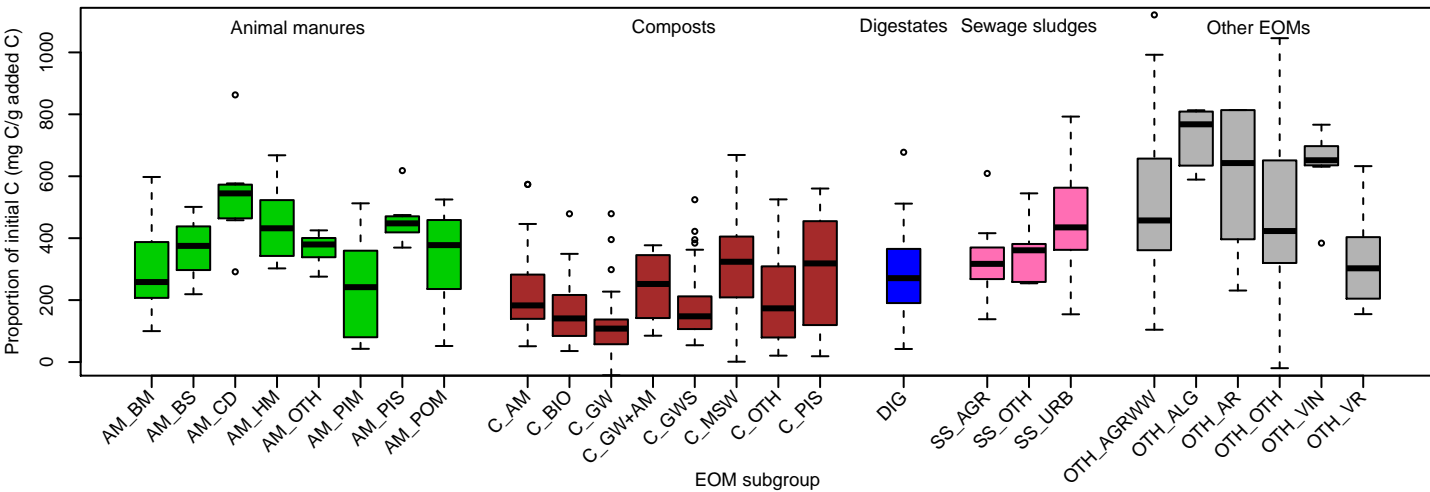
Sewage sludges

— SS_AGR
— SS_OTH
— SS_URB

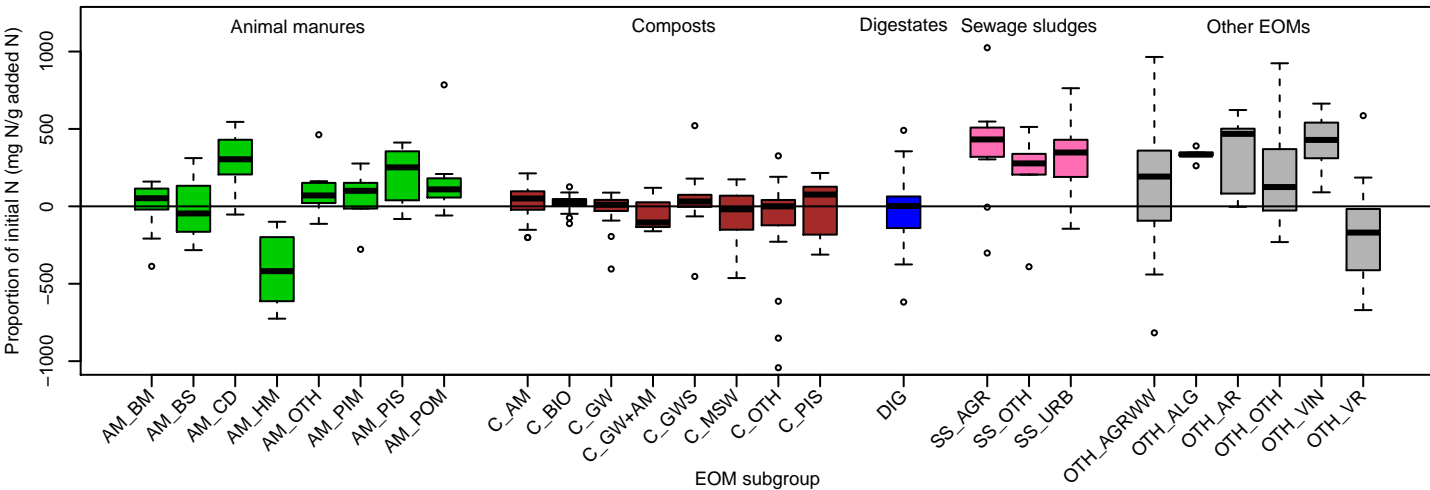
Other EOMs

— OTH_AGRWW
— OTH_ALG
— OTH_AR
— OTH_OTH
— OTH_VIN
— OTH_VR

Net mineralized organic C

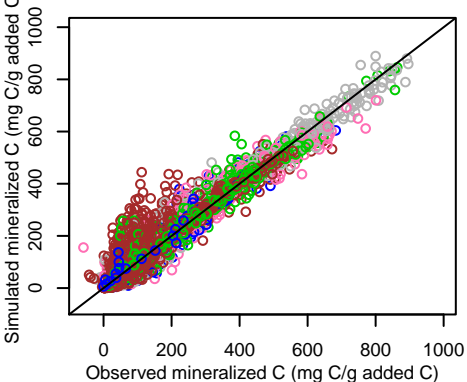


Net mineralized organic N

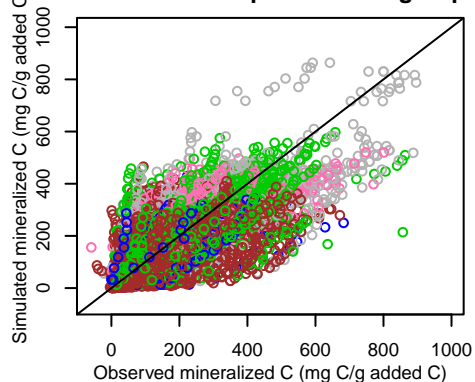


Carbon mineralization

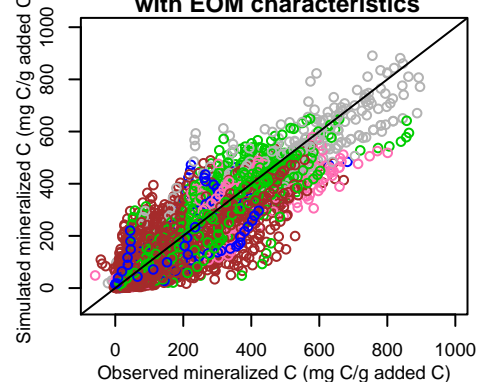
M1: individual EOM calibration



M2: calibration per EOM subgroup

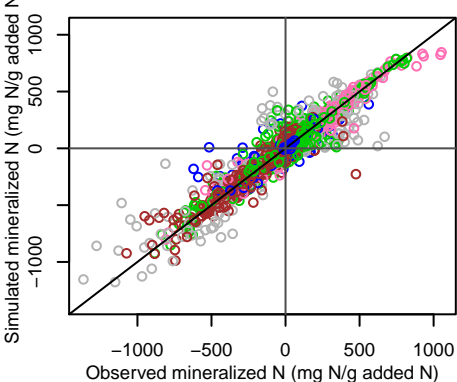


M3: calibration per EOM subgroup with EOM characteristics

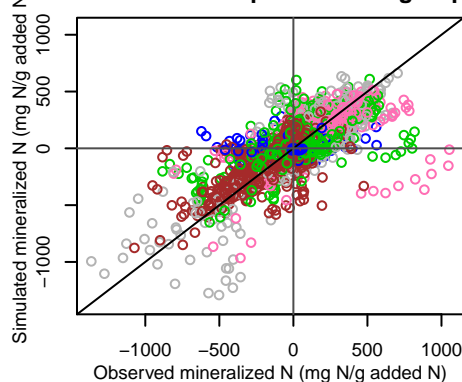


Nitrogen mineralization

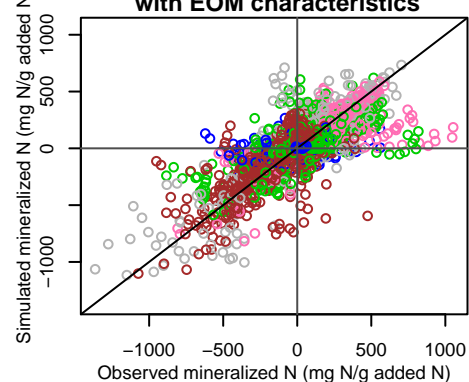
M1: individual EOM calibration



M2: calibration per EOM subgroup



M3: calibration per EOM subgroup with EOM characteristics



● Animal manures ● Composts ● Digestates ● Sewage sludges ● Other EOMs

Experimental data from laboratory incubation for the considered EOM ?

No

Yes

Characteristics (I_{ROC} and C_{3d}) of EOM and subgroup of EOM

Yes

No

Method 1. Specific calibration of the model for the considered EOM

- *Best accuracy*
- *Recommended method for an accurate simulation of a specific experiment with repeated EOM application*

Method 2. Default model parameter values proposed for the EOM subgroup

- *Lowest accuracy*
- *Sufficient for the simulation of general scenarios of EOM application*

Method 3. Model parameters based on the EOM characteristics within each subgroup of EOM

- *Intermediate accuracy*
- *Recommended method for the simulation of a specific experiment in absence of an EOM incubation*