

1 **Towards a representation of priming on soil carbon**
2 **decomposition in the global land biosphere model**
3 **ORCHIDEE (version 1.9.5.2).**

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13 **Abstract**

14 Priming of soil carbon decomposition encompasses different processes through which
15 the decomposition of native (already present) soil organic matter is amplified through the
16 addition of new organic matter, with new inputs typically being more labile than the native
17 soil organic matter. Evidence for priming comes from laboratory and field experiments, but to
18 date there is no estimate of its impact at global scale and under the current anthropogenic
19 perturbation of the carbon cycle. Current soil carbon decomposition models do not include
20 priming mechanisms, thereby introducing uncertainty when extrapolating short-term local
21 observations to ecosystem and regional to global scale. In this study we present a simple
22 conceptual model of decomposition priming, called PRIM, able to reproduce laboratory
23 (incubation) and field (litter manipulation) priming experiments. Parameters for this model
24 were first optimized against data from 20 soil incubation experiments using a Bayesian
25 framework. The optimized parameter values were evaluated against another set of soil
26 incubation data independent from the ones used for calibration and the PRIM model
27 reproduced the soil incubations data better than the original, CENTURY-type soil
28 decomposition model, whose decomposition equations are based only on first order kinetics.
29 We then compared the PRIM model and the standard first order decay model incorporated
30 into the global land biosphere model ORCHIDEE. A test of both models was performed at
31 ecosystem scale using litter manipulation experiments from 5 sites. Although both versions
32 were equally able to reproduce observed decay rates of litter, only ORCHIDEE-PRIM could
33 simulate the observed priming ($R^2=0.54$) in cases where litter was added or removed. This
34 result suggests that a conceptually simple and numerically tractable representation of priming
35 adapted to global models is able to capture the sign and magnitude of the priming of litter and
36 soil organic matter.

37

38 Keywords: soil carbon decomposition, global land biosphere model, priming effect, climate
39 change.

40 **1. Introduction**

41 Soils are the largest reservoir of organic carbon (C) on land, holding three times as
42 much as plant biomass globally (MEA, 2005). The dynamics of long-term soil organic matter
43 formation (Schmidt et al., 2011) and its decomposition on time scales of future climate
44 change (Jones et al. 2003) both remain poorly understood. The lack of a mechanistic
45 understanding of soil carbon dynamics on time scales going from years to centuries induces
46 important differences in the future projections of the global land carbon storage among global
47 land biosphere models (Todd-Brown et al., 2013).

48 Different conceptual models have been proposed to explain empirical data on soil
49 carbon decomposition, mainly incubation experiments (Wutzler and Reichstein, 2008;
50 Manzoni and Porporato, 2009). Those conceptual models are usually calibrated to fit data (i.e.
51 measurements of stock evolution or fluxes) from experiments on soil incubation, and on time
52 scales going from hours to days (Panikov and Sizova, 1996; Blagodatsky and Richter 1998).
53 It was shown by Wutzler and Reichstein (2008) that conceptual decomposition models
54 accounting for interactions between labile and more recalcitrant microbial-related carbon,
55 often called “priming effects”, could better fit data from incubation experiments acquired over
56 periods of about 100 days.

57 The conceptual models of soil carbon decomposition encapsulated in global land
58 biosphere models usually ignore interactions between labile and recalcitrant carbon. All
59 global land biosphere models part of the Earth System Models used for IPCC climate
60 projections are based on donor-pool dominant transfer and first order decay (Luo et al. 2015).
61 Many of those global land biosphere models have soil carbon modules derived from the
62 CENTURY (Parton et al., 1988) and RothC (Coleman and Jenkinson, 1999) models, in which
63 the first order decay rates of different pools are modulated by soil temperature and moisture,
64 as well as by soil texture (Friedlingstein et al., 2006).

65 Although the conceptual models with priming showed a more realistic behavior than
66 first order decay models when applied to short term incubation data, one may still wonder if
67 priming significantly influences the dynamics of soil carbon on time scales ranging from
68 years to decades, and at large spatial scales. On the one hand, incorporating priming in a
69 global land biosphere model has the disadvantage of introducing new parameters that are
70 difficult to constrain and of generating a more complex - but unproven - dynamical behavior
71 than the first order decay models. On the other hand, if the performances of first order decay
72 models are not satisfactory at the large scale, structural changes of soil carbon models are
73 needed and must be carefully tested.

74 The current situation with first-order decay dynamics in global land biosphere is that
75 out of the 11 Earth System models used for the IPCC-AR5 CMIP5 simulations and
76 benchmarked by Todd-Brown et al., (2013) against a global soil organic carbon (SOC) map,
77 only six succeeded in representing the total mean C stocks at the global scale, but all failed to
78 reproduce the spatial heterogeneity of SOC stocks as well as the SOC distribution under
79 different vegetation cover (Todd-Brown et al., 2013). Possible causes of model failure include
80 both errors in model structure but also errors in the different parameters controlling soil
81 carbon dynamics. The optimization of the parameters of a first order decay model against a
82 global SOC map could only partly reduce regional discrepancies with observations, with the
83 optimized model explaining only 41% of the global variability of SOC (Hararuk et al., 2014).
84 On the other hand, the use of a structurally different model that accounted for microbial
85 biomass was shown to produce a rather realistic large-scale SOC variability, but very different
86 soil carbon dynamics in response to future climate change (Wieder et al., 2013). This
87 illustrates that model structure matters a lot for the simulation of the current distribution of
88 soil carbon and its future evolution in response to climate and CO₂ changes.

89 Discrepancies between global land biosphere model predictions and observations are
90 partially due to models lacking key mechanisms controlling SOC dynamics (Schmidt et al.,

91 2011). One example is the interactions with the N cycle. The majority of the ESMs used for
92 the IPCC-AR5 CMIP5 Earth System simulations did not represent explicitly the nitrogen
93 cycle, but the two ESMs with an explicit nitrogen cycle did not result either in a better
94 simulations of current SOC (Todd-Brown et al., 2013). Another example is the role of
95 microorganisms. The first order kinetics used in most models obviates the role that microbial
96 decomposers are known to play in controlling SOC mineralization (Cleveland et al., 2007;
97 Garcia-Pausas and Paterson 2011), but their activities is controlled by physical and chemical
98 drivers (Kemmit et al., 2008). Therefore, ESMs have significant gaps in reproducing the
99 mechanisms related to microbial dynamics such as priming (see definition below), the object
100 of this study.

101 Soil C priming is defined as a modification of SOC decomposition rates when fresh
102 organic C (FOC) is added (Kuzyakov et al., 2000). Priming is almost ubiquitously observed in
103 ecosystem studies where organic matter inputs are altered in laboratory incubations (reviewed
104 by Blagodatskaya and Kuzyakov 2008) or directly on the field (Boone et al., 1998; Borken et
105 al., 2002; Chemidlin-Prévost-Bouré et al., 2010; Subke et al., 2004; Sulzman et al., 2005;
106 Xiao et al., 2015). Priming can occasionally be negative but most commonly has a stimulative
107 effect on the decomposition of organic matter that decomposes. Several mechanisms may be
108 involved in controlling priming (Fontaine et al., 2003; Blagodatskaya and Kuzyakov 2008,
109 Guenet et al., 2010b), and conceptual models of priming can have substantial number of
110 parameters making their parameterization quite complex at large scales (Wutzler and
111 Reichstein, 2013). Wutzler and Reichstein (2008) proposed conceptual models summarized
112 into different equations to introduce priming without using too many parameters, but in all
113 cases an explicit representation of microbial biomass was required. Recently, Guenet et al.,
114 (2013a) modified the equation proposed by Wutzler and Reichstein (2008) to represent
115 priming without an explicit representation of microbial biomass, assuming that microbial
116 biomass is always at equilibrium with FOC. This assumption is suitable for being

117 incorporated into ESMs since it adds only one more free parameter compared to the first order
118 kinetic models. This priming scheme was incorporated into the global land biosphere model
119 ORCHIDEE, with the priming parameters statistically calibrated to reproduce the same
120 equilibrium state (in terms of C stocks, after spin up of the model) than the standard version
121 based on CENTURY (Guenet et al., 2013b). Despite its calibration ensuring the same initial
122 state of SOC for England and Wales, the version of ORCHIDEE with priming resulted in a
123 loss of SOC during the late 20th Century, in better agreement with inventory data (Bellamy et
124 al., 2005) than the standard version which produced a continuous SOC gain. In that study,
125 however, the parameters of the priming model were not based on observations but tuned
126 instead to equilibrium SOC values. The objectives of this study are therefore:

- 127 • To derive optimal parameter values of a priming model (PRIM) with C inputs
128 forced by data by using a Bayesian method (Tarantola, 1987) with priors and
129 data from 20 different soil incubations.
- 130 • To introduce the calibrated PRIM model into the ORCHIDEE ecosystem
131 model version AR5 and evaluate the new version ORCHIDEE-PRIM against
132 independent *in situ* litter manipulation experiments at ecosystem scale.
- 133 • To assess if the priming model significantly improves the simulation of SOC
134 mineralization compared to the standard first order decay model used in
135 ORCHIDEE, on time scales of months to years.

136

136

137 2. Materials and Methods

138 The material and methods section is summarized in Fig. 1.

139 2.1 Models presentation

140 2.1.1 Soil carbon priming model PRIM

141 To represent priming, we used the ORCHIDEE soil decomposition module, which is
142 similar to CENTURY (Parton et al., 1988). It has three carbon pools (active, slow and
143 passive) and two litter pools (metabolic and structural). SOC decomposition is modulated by
144 soil temperature and moisture functions. Active SOC decomposition is further modulated by
145 a clay function. These functions are the same as in CENTURY but they are driven by soil
146 physical variables calculated at a daily time step by the soil physics of ORCHIDEE (Krinner
147 et al., 2005). In the PRIM model, we replaced the CENTURY decomposition equations by
148 those developed by Guenet et al. (2013a) to simulate a priming effect:

$$149 \quad (1) \quad \frac{dSOC_{Active}}{dt} = I - k_{SOC_{Active}} \times SOC \times (1 - e^{-c \times (Litter_C)}) \times \theta \times \tau \times \gamma$$

$$150 \quad (2) \quad \frac{dSOC_{Slow}}{dt} = I - k_{SOC_{Slow}} \times SOC \times (1 - e^{-c \times (Litter_C + SOC_{Active})}) \times \theta \times \tau$$

$$151 \quad (3) \quad \frac{dSOC_{Passive}}{dt} = I - k_{SOC_{Passive}} \times SOC \times (1 - e^{-c \times (Litter_C + SOC_{Active} + SOC_{Slow})}) \times \theta \times \tau$$

152 with I being the input of C into the pool considered, k_{SOC} the SOC decomposition rate for the
153 active, the slow and the passive pool, $Litter_C$, the sum of all the litter pools of the model. θ ,
154 τ , and γ are the soil moisture function, the temperature function and the clay function
155 modulating decomposition, respectively. c is a parameter controlling the impact of the fresh
156 organic carbon (FOC) pool on the SOC mineralization rate. Here, we considered that FOC
157 represents all the carbon from pools more labile than the pool being affected as shown in
158 equation (1) to (3). Therefore, FOC is only litter for the active SOC pool, but for the slow
159 SOC pool, FOC is the sum of the litter and the active SOC pool. Finally, for the passive SOC

160 pool, FOC is the litter and the active and slow carbon pools. The decomposition of the first
161 donor litter pool is described using first order kinetics (4):

162

$$163 \quad (4) \quad \frac{dLitter_C}{dt} = I - k_{Litter_C} \times Litter_C \times \theta \times \tau$$

164

165 In the Wutzler and Reichstein (2008) equation, the SOC mineralization was described by:

$$166 \quad (5) \quad \frac{dSOC}{dt} = I - k_{SOC} \times SOC \times (1 - e^{-c \times MB})$$

167 with *MB* being the microbial biomass. Unlike Wutzler and Reichstein (2008), our
168 model does not explicitly simulate *MB* but assumes that MB equilibrates with FOC thus the
169 relationship between MB and FOC is linear. Consequently, we represent priming using a
170 direct relationship between FOC and SOC mineralization. Finally, the moisture, temperature
171 and clay functions are described by equation (6), (7) and (8), respectively with *soil_moisture*
172 in m³ H₂O m⁻³ of soil, *soil_temperature* in Kelvin and *clay* in %wt :

$$173 \quad (6) \quad \theta = \max(0.25, \min(1, -1.1 \times soil_moisture^2 + 2.4 \times soil_moisture + 0.29))$$

$$174 \quad (7) \quad \tau = \exp(0.69 \times (soil_temperature - 303)/10)$$

$$175 \quad (8) \quad \gamma = 1 - 0.75 \times clay$$

176

177 **2.1.2 ORCHIDEE and ORCHIDEE-PRIM**

178 ORCHIDEE is a process-based global land biosphere model that calculates the fluxes
179 of CO₂, H₂O, and heat between the terrestrial land and the atmosphere. The time step of the
180 model is 1/2-hour, and the variations of H₂O and C pools are calculated on a daily basis. The
181 model has been evaluated at different scales (sites, regions, globes) and under different
182 climates from the tropics to northern boreal zones (Krinner et al., 2005; Ciais et al., 2005;

183 Santaren et al., 2007; Piao et al., 2006). ORCHIDEE results from the coupling of three
184 different sub-models. The first one is called SVAT SECHIBA and describes soil water budget
185 and turbulent fluxes of energy and water between the atmosphere and the biosphere
186 (Ducoudré et al., 1993; de Rosnay and Polcher, 1998). The second one is derived from the
187 dynamic global vegetation model LPJ (Sitch et al., 2003) and deals with vegetation dynamics
188 (fire, sapling establishment, light competition, tree mortality, and climatic criteria for the
189 introduction or elimination of plant functional types). The last, called STOMATE (Saclay
190 Toulouse Orsay Model for the Analysis of Terrestrial Ecosystems) deals with phenology and
191 carbon dynamics of the terrestrial biosphere. Twelve plant functional types (PFT) are used to
192 classify the vegetation. Each PFT dynamic is controlled by similar set of governing equations
193 but using different parameter values. Only the leafy season onset and offset, are PFT-specific
194 (Krinner et al., 2005).

195 The simulation of SOC in ORCHIDEE version is based on CENTURY (Parton et al.,
196 1988) as described above. No vertical description of the SOC is included in the ORCHIDEE
197 version used here. In ORCHIDEE-PRIM we replaced CENTURY by the PRIM model
198 described in section 2.1.1.

199

200 **2.2** Data description

201 **2.2.1** Incubation experiments to calibrate the priming model

202 We optimized the PRIM parameters and the ORCHIDEE soil module parameters
203 using data from soil incubation experiments where FOC was added and the priming effect
204 was measured by comparing a control study without FOC with a perturbation study with FOC
205 (table 1). The data come from 20 incubations (from nine studies) of duration going from one
206 week to 10 months. The incubated soil samples have very different characteristics (table 1)
207 and came from different ecosystems (grassland, cropland, broadleaf forest, needleleaf forest,

208 savannah). However, the great majority of the data used to optimize the model were obtained
209 from temperate soils. In the incubation experiments, added FOC was labeled with ^{13}C or ^{14}C
210 and therefore the respired CO_2 fluxes coming from either SOC already present before the
211 FOC amendments or from the FOC induced priming of SOC pools was estimated separately.
212 We used only incubations performed during at least 7 days to eliminate all studies that
213 potentially observed apparent priming effects. Apparent priming is a replacement of the ^{12}C in
214 microbial biomass with labeled carbon isotopes, a short- term artifact due to the amendment
215 of labeled material to an unlabelled soil (Blagodatskaya and Kuzyakov, 2008). Moreover, we
216 used only studies that reported cumulative respired CO_2 fluxes in order to optimize the
217 priming parameters against the extra CO_2 fluxes obtained at the end of the experiment and not
218 those resulting from short-term priming dynamics, since cumulative mineralization integrates
219 the different processes occurring during incubation. Finally, several treatments might be
220 performed in the studies used to optimize the model (different soils, different types and
221 amount of FOC). When the treatments performed differed on aspects reproducible by the
222 model (amounts of FOC added, different clay content in the soils used, etc.) we considered all
223 the treatments. In the opposite case we averaged the results of the different treatments to
224 perform the optimization except in case where the treatments clearly impact the results
225 without the possibility to reproduce the experimental design with the model (addition of
226 mineral N for instance).

227 We also use the control incubations without FOC amendments to evaluate both
228 models. We extracted data from the figures of original publications (Table 1) using
229 GraphClick version 3.0 . Several input variables are needed to run the soil model, as described
230 in section 2.1.1. When data were not available from the surveyed publications, we obtained
231 them from the databases normally used for running ORCHIDEE, except for the C:N ratio of
232 FOC and for clay content where data came from Rodal et al., (1960) and from USDA
233 (<http://soils.usda.gov/technical/classification/osd/index.html>), respectively. The three

234 carbon pools of CENTURY are not measurable (Six et al., 2002), so we cannot estimate how
235 much C of in each pool is present in the incubated samples. To calculate the distribution of C
236 among the three pools of the model we ran ORCHIDEE until equilibrium was reached at the
237 sites where soil samples were taken and calculated the percentage of each pool.

238 **2.2.2 Incubation data used for evaluation of the priming model**

239 A first evaluation of the soil carbon model with and without priming is performed at
240 the scale of soil samples against independent data from the large database of soil incubations
241 (300 in total) published by Moyano et al., (2012). Within this database we selected the
242 experiments where all the inputs necessary to run the two soil carbon models were available
243 (clay, content, moisture, temperature, SOC content at the beginning of the incubation) and
244 where cumulative mineralization or mineralization rates associated to the time step between
245 two measurements were reported. We removed all the studies without information on the
246 location since geographical coordinates are necessary to run ORCHIDEE and thus estimate
247 the initial fraction of each pool. We selected only data coming from experiments without
248 important soil manipulation (e.g. compaction, litter amendments). The model evaluation was
249 performed against a set of 164 independent incubation experiments.

250 **2.2.3 Ecosystem-level data used for evaluation of the priming model**

251 A second evaluation of the ORCHIDEE-PRIM model was performed at ecosystem scale
252 against observations of four litter manipulation experiments (Boone et al., 1998; Chemidlin-
253 Prévost-Bouré et al., 2010; Subke et al., 2004; Sulzman et al., 2005) and one compost
254 amendment experiment (Borken et al., 2002). In the litter experiments, two treatments and a
255 control are generally performed. The treatments are total exclusion of above ground litter
256 using nets to prevent fresh litter from falling onto the soil, often transplanting the collected
257 fresh litter to create a second treatment with doubled aboveground litter inputs (Boone et al.,
258 1998; Chemidlin-Prévost-Bouré et al., 2010; Sulzman et al., 2005). For the compost

259 amendment experiment by Borken et al. (2002), 1.4 kg C m⁻² (and a zero-addition control) of
 260 compost was added to the soil. These studies are presented in table 3. When information
 261 about soil clay content was not available in the original study, we extracted it from Zobler
 262 (1986). The data measured at field scale are the soil CO₂ efflux including the heterotrophic
 263 respiration but also root respiration in the same flux without clear separation of the two
 264 components.

265 **2.3 Optimization procedure**

266 For PRIM, the 6 parameters optimized are turnover rate (k_{SOC}) and priming parameters
 267 c for each of the three pools (table 2). For the ORCHIDEE soil module, only the three k_{SOC}
 268 values are optimized. The same parameters are optimized against the priming incubations
 269 dataset described in 2.2.1. Since optimizations were performed using soil incubations data
 270 obtained at optimal temperature and soil moisture, we did not optimize the parameters related
 271 to the eq. (6) and (7) because the range of observations was quite limited. Optimization was
 272 performed in the framework of the Bayesian inversion method with priors (Tarantola, 1987)
 273 as described by Santaren et al., (2007) using assimilating all data streams in the same cost
 274 function. Assuming that all uncertainties follow Gaussian distributions (parameter error,
 275 measurement error, model error), the optimized parameters correspond to a set minimizing the
 276 following quadratic cost function:

277

$$278 \quad (9) \quad J(\mathbf{x}) = \frac{1}{2} \left[(\mathbf{y} - \mathbf{H}(\mathbf{x}))' \mathbf{R}^{-1} (\mathbf{y} - \mathbf{H}(\mathbf{x})) + (\mathbf{x} - \mathbf{x}_b)' \mathbf{P}_b^{-1} (\mathbf{x} - \mathbf{x}_b) \right]$$

279 The cost function defined by equation (9) contains both the mismatch between model
 280 outputs and observed data, and the mismatch between optimized parameters and the prior
 281 values. The mismatch is weighted by errors of each quantity. \mathbf{x} is the of unknown parameters
 282 vector, \mathbf{x}_b the prior values, \mathbf{y} the observations vector and $\mathbf{H}(\mathbf{x})$ the model outputs. \mathbf{P}_b is the

283 prior parameter error variances/covariances, and \mathbf{R} contains the observational error
284 variances/covariances which represents both measurement uncertainty and model uncertainty.

285 To minimize the cost function, we used a gradient-based iterative algorithm, called L-
286 BFGS-B (Zhu et al., 1995). A range of values for all the parameters is prescribed by called L-
287 BFGS-B. At each iteration, the cost function $J(x)$ gradient is calculated, with respect to the six
288 parameters. When $J(x)$ is minimized, using a classic finite difference method, we further
289 calculated the posterior error covariance matrix on the parameters P_a from the prior error
290 covariance matrices and the Jacobian of the model at the minimum of the cost function, using
291 the linearity assumption (Tarantola, 1987). When error correlations are close to 1 it suggests
292 that the observations do not permit to clearly separate the effect of two parameters.

293 The model $H(x)$ is non linear and therefore the approach to minimize the cost function
294 is sensitive to potential local minima. We get around by performing 30 optimizations with
295 different sets of prior parameter randomly distributed within their variation range. We then
296 used the case providing the lowest cost function. This approach reduces drastically the
297 sensitivity to potential local minima as illustrated in Santaren et al. (2014).

298 We defined the prior ranges of decomposition rates using literature data (Parton et al.,
299 1988; Gignoux et al., 2001). However, only two studies already estimated the c parameter
300 before (Guenet et al, 2013a, Guenet et al., 2013b), its prior value is therefore considered as
301 non-informative and we set a large error on the prior (50%). As for the variance of the model-
302 data mismatch term in the cost function of equation (9), note that with our formalism this
303 error should include both the model error (for instance the model capability to represent the
304 measurement) and the measurement error. Given that the error on the measurements was
305 difficult to estimate precisely for each study, we fixed it to 5% of the mean observed CO_2 flux
306 assuming that all incubation data were independent. At its minimum, $J(x)$ should be close to

307 half the number of observations (reduced χ^2 of one). We assumed that all errors (the
308 observations and on the a priori parameters) are uncorrelated.

309

310 **2.4 Simulations protocol**

311 **2.4.1 Simulation protocol for the soil priming model PRIM**

312 Simulations were performed for each incubation experiment presented in 2.2.1 (table
313 1) as well as for the evaluation sites in 2.2.2. The simulations of the stand-alone PRIM carbon
314 model (i.e. unplugged from the ORCHIDEE full ecosystem model) were run at a daily time
315 step using FOC inputs from table 1 or from the Moyano et al., (2012) database. No spin-up
316 was performed. We started the simulation by prescribing to the soil carbon models with and
317 without priming an initial amount of SOC equal to that measured in the study considered,
318 distributed among active, slow and passive pools as explained in section 2.2.1 At each time
319 step we increment the cumulative heterotrophic respiration coming from SOC mineralization,
320 so that this cumulative simulated CO₂ flux can be compared to data from the end of the
321 incubation experiment. Simulations were performed using R 3.0.2.

322

323 **2.4.2 Simulation protocol for ORCHIDEE-PRIM and ORCHIDEE**

324 We ran ORCHIDEE and ORCHIDEE-PRIM at each litter manipulation site presented
325 in table 3 using 6 hourly climate data obtained from the combination of two existing datasets:
326 the Climate Research Unit (CRU) (Mitchell et al. 2004) and the National Centers for
327 Environmental Prediction (NCEP) (Kalnay et al., 1996). Both models were run using the first
328 ten years of the climate forcing (1901-1909) repeated in a loop, and an atmospheric CO₂ value
329 corresponding to the year 1901. When the simulated relative yearly change of the SOC stock
330 was less than 0.01%, we considered that SOC equilibrium was reached. Once pre-industrial
331 equilibrium was reached in each grid point, we run transient simulations from 1901 until the

332 beginning of the manipulation experiment assuming no land use change driven by
333 reconstructed climate and observed CO₂. Then when the simulation reached the year at which
334 the litter manipulation experiment began, we modified the input of above-ground litter in the
335 same proportion than in the actual manipulation experiments, Finally, we ran the model for
336 each treatment during a period corresponding to duration of each experiment.

337

338 **2.5 Model evaluation**

339 The model evaluation was performed in two steps. First, we evaluated separately
340 PRIM and the standard first order decay model with their optimized parameters, as stand
341 alone decomposition models, i.e. unplugged from the ORCHIDEE ecosystem model. To
342 evaluate the stand-alone soil models, we used incubation data coming from Moyano et al.,
343 (2012) as described in 2.2.2. Secondly, we evaluated ORCHIDEE and ORCHIDEE-PRIM,
344 against litter manipulation experiments (see 2.2.3).

345 To compare model outputs with data we used different metrics. First a linear mixed
346 effect model with intercept value forced to zero using model outputs as the variable to
347 explain, and data as the fixed effect and the study where data came from as random effect.
348 This approach aimed to take into account the fact that incubations performed within the same
349 study are not independent because they were performed and analyzed by the same team. The
350 linear-mixed effect model gives the slope of the relationship as output. A slope close to one
351 indicates that the model reproduces the data well. Then, we used the Normalized Standard
352 Deviation (*NSD*) or ratio of model to observed standard deviations ; *NSD* = 1 means that the
353 model perfectly reproduces the observed standard deviations across experiments:

$$(10) \quad NSD = \frac{\sqrt{\frac{1}{n} \times \sum_{i=1}^n (x_i - \bar{x})^2}}{\sqrt{\frac{1}{n} \times \sum_{i=1}^n (o_i - \bar{o})^2}}$$

355 where x refers to the model value, o to the observed value and n the number of
356 samples. Finally, we compared model performance using the Bayesian Information Criterion
357 (BIC) to take into account that the PRIM soil model has three more priming parameters (one
358 per pool) than the standard model:

$$359 \quad (11) \quad BIC = \log(MSD) \times n + \log(n) \times p$$

360 with MSD being the mean squared deviation derived from equation (12), n the number
361 of data used to evaluate the model, and p the number of parameters of the soil model.

$$362 \quad (12) \quad MSD = \frac{\sum (m - o)^2}{n}$$

363 with o the observed values, m the values calculated by the model and n the number of
364 observations. The lowest is the BIC the better the model is.

365 **3. Results**

366 **3.1 Optimized parameters of the priming model**

367 The parameters obtained after optimization using incubation data described in section
368 2.2.1 are given in Table 2. The turnover times ranged from a few months (0.30 ± 0.15 year)
369 for the active pool to 462.0 ± 233.8 years for the passive pool, the slow pool being
370 intermediate with 1.12 ± 0.01 years. The priming parameters indicated a decreasing
371 sensitivity with increasing turnover time. The parameter c values were 493.7 ± 246.8 , $194.0 \pm$
372 97.0 and 136.5 ± 68.3 for the active, slow and passive pools, respectively. Errors correspond
373 to the estimates from the linear assumption at the minimum of $J(x)$. For both, the correlation
374 between parameters was low (data not shown).

375 After optimization, both models with and without priming parameterization were able
376 to reproduce the cumulative mineralization measured in the different incubations where FOC
377 was added well (Fig. 2, top panel). The slope of the linear regression between optimized
378 model output and incubation measurements was 1.13 for PRIM and 0.93 for the ORCHIDEE

379 soil module. The NSD value (1.80 and 1.52 for PRIM and the standard soil module,
380 respectively) showed that the models overestimated the variance after optimization. When
381 both models were evaluated against the same incubation experiments but without FOM
382 addition, the PRIM model slightly over-estimated accumulated mineralization (Fig. 2 middle
383 panel), as indicated by the value of the slope (1.05). Nevertheless, it performed better than the
384 standard soil module, which underestimated the soil mineralization as indicated by the value
385 of the slope (0.72). The PRIM soil model reproduced quite well the observed priming effect
386 (section 2.2.1) as shown in Fig. 2 (lower panel) with a slope value (1.07). PRIM largely
387 overestimated however the variance of data as indicated by the NSD value (3.14). As
388 expected, the standard soil module was totally unable to reproduce priming (Fig. 2, lower
389 panel).

390 **3.2** Standard soil module vs. PRIM against incubations data

391 To evaluate the performance of PRIM we tested it against data from soil incubation
392 experiments independent from those used for optimization (see section 2.2.2). We did the
393 same with the standard soil module (Fig. 3). The standard soil module tended to overestimate
394 accumulated mineralization as indicated by a slope value of 1.32 and to underestimate the
395 cross-experiments variance by more than 50% (NSD=0.44). PRIM performed slightly better,
396 but underestimated accumulated mineralization (slope 0.80). The optimized PRIM
397 underestimated the variance by 29%, but the NSD value (0.71) was closer to 1 compared to
398 the standard model. Using the BIC index, which takes into account the higher number of
399 parameters of PRIM, this model still performed better (BIC values of 546.2 vs. 347.4 for
400 standard and PRIM, respectively).

401

402 **3.3** ORCHIDEE vs. ORCHIDEE-PRIM comparison using *in situ* datasets

403 When tested at ecosystem-level against litter manipulation experiments, 4 studies x 3
404 treatments and 1 study with 2 treatments. Both ORCHIDEE and ORCHIDEE-PRIM
405 performed generally well to reproduce the soil CO₂ efflux (Fig. 4). Generally, both versions
406 showed similar performance as indicated by the values of slopes and NSD presented in table
407 4. The mean slopes are 0.98 for ORCHIDEE-PRIM against 0.97 for ORCHIDEE, and the
408 mean NSD are 1.26 and 1.27, respectively. It must be noted that slope values were generally
409 lower for the treatments excluding litter compared to control and double litter inputs (Table
410 4). No particular differences of the NSD values were observed between the different litter
411 input regimes. Nevertheless, the BIC index was always higher for ORCHIDEE-PRIM
412 because three more parameters were used by this version compared to ORCHIDEE.

413 ORCHIDEE-PRIM was able to reproduce the priming observed defined as the
414 difference of CO₂ efflux coming from SOC only with or without litter (Fig. 5), but tended to
415 underestimate its intensity as indicated by the slope value lower than one (0.55). The variance
416 between experiments calculated for priming was overestimated as shown by the NSD value of
417 1.29. It must be noted that priming was not calculated for ORCHIDEE since the structure of
418 its soil decomposition model does not include a priming mechanisms.

419 **4. Discussion**

420 4.1 PRIM in the context of other soil priming conceptual models

421 Priming is a complex phenomenon controlled by several mechanisms, such as N
422 mining by microbial communities with different growth strategies, competition between
423 microbial groups for substrate, energy limitations, etc. (Kuzyakov et al., 200; Fontaine et al.,
424 2003; Guenet et al., 2010b). Priming may have important consequences on the feedbacks
425 between climate and C cycle (Schmidt et al., 2011) and it is therefore crucial to better
426 quantify the C fluxes due to priming, especially at large scale (i.e, continental to global).
427 Several models have been developed to describe soil C mineralization with a representation of
428 priming (Gignoux et al., 2001; Fontaine and Barot, 2005; Neill and Gignoux, 2006; Moorhead

429 and Sinsabaugh, 2006; Wutzler and Reichstein, 2008; Neill and Guenet, 2010; Blagodatsky et
430 al., 2010) and such models generally succeeded at reproducing short-term data, mainly
431 incubation. However, to our knowledge, they have never been tested in a range of contrasted
432 situations (different soil types, different FOC amount and chemical composition, different
433 temperature and soil moisture, etc.). Here, we used most of the available incubation data
434 respecting the criteria described in the material and method section. Moreover, previous
435 priming models all needed a high number of parameters compared to PRIM. For these two
436 reasons, the conceptual soil models accounting for soil priming were thus far not included in
437 global land biosphere models (Wutzler and Reichstein, 2008) and very few studies of soil
438 priming at global scale have been performed (Foereid et al., 2014). Here, using a simple
439 scheme with only three additional parameters than the standard soil module of ORCHIDEE,
440 we were able to reproduce priming but also soil mineralization data coming from very
441 different incubation studies performed with different soils at different temperature and
442 moisture, with different time length, etc. The PRIM soil model, which is a microbial steady-
443 state model, might not be able to reproduce short-term response to abrupt change of FOC
444 inputs but with negligible bias over the long term (Wutzler and Reichstein 2013). However, it
445 might have similar performances than more complex models to reproduce long-term trends of
446 FOC inputs (Wutzler and Reichstein 2013). PRIM performed better than the standard soil
447 module to reproduce soil incubation data used to optimize, but it must be noted that the BIC
448 values indicate that the improvement observed with PRIM may be simply due to a higher
449 number of parameters. Nevertheless, when using independent soil incubations data from the
450 one used to optimize the model the improvement is quite clear with BIC values much lower
451 with PRIM than with the standard soil module (347.4 and 546.2, respectively). Furthermore,
452 PRIM was not able to fully catch the observed variability of priming. As discussed above,
453 priming is a complex phenomenon resulting from the interactions of different mechanisms
454 that we summarized in a very simple equation. Therefore, PRIM is probably good in
455 representing a general trends but not all the complexity of the phenomenon. Nevertheless, the

456 use of the PRIM soil model seems justified since it increases only slightly the number of
457 parameter of a global land biosphere model and since the parameter values were obtained
458 after optimization on data coming from incubations performed in a range of soils and
459 conditions (different soil types, different ecosystems, different temperatures, different
460 moistures, different amount and type of FOC amended, etc.).

461

462 **4.2** ORCHIDEE vs. ORCHIDEE-PRIM

463 **4.2.1** Cross sites evaluation

464 ORCHIDEE-PRIM exhibited similar performance than ORCHIDEE when simulating
465 litter manipulation experiments. It must be noted that both versions share the same scheme for
466 primary production (controlling soil C input by litter), soil temperature and moisture function.
467 The similar performance obtained by the two versions may be due to a model bias for these
468 quantities as well as poorly constrained site histories and climate forcing errors. Since primary
469 production is the main driver of the C input into the soil, the soil CO₂ efflux calculated by the
470 models was largely driven by the capacity of the model to reproduce the observed primary
471 production. In particular, both models largely underestimated the soil CO₂ efflux when litter
472 was removed (Table 4), but obtained good results when litter was kept or when litter was
473 added. This suggests that both models performed quite well when reproducing soil CO₂
474 efflux, but this was due to bias compensation, meaning that the fraction of CO₂ coming from
475 soil mineralization and root respiration was underestimated and the fraction of CO₂ coming
476 from litter mineralization was overestimated. Moreover, the modification of the litter cover
477 may change the soil humidity and temperature and these effects were not represented in the
478 models.

479 Finally, the use of microbial steady state model like ORCHIDEE-PRIM present
480 several advantages compared to explicit microbial models. Wieder et al., (2015) identified
481 several challenges related to the incorporation of explicit microbial models in ESMs. In
482 particular, it may induce unrealistic temporal oscillations in response to small perturbations

483 and it needs much more parameter than the classical approach. With ORCHIDEE-PRIM these
484 two difficulties are resolved since we only add three more parameters and because the model
485 is not subject to short-term oscillations.

486

487 **5. Conclusion**

488

489 Regarding the several processes that may lead to priming, the satisfactory performance
490 of ORCHIDEE-PRIM compared to observations from both laboratory incubation and field
491 litter manipulation experiments suggests that the simple PRIM conceptual model simulates
492 well the magnitude of observed priming. Consequently, ORCHIDEE-PRIM has the potential
493 to quantify the impact of priming on the soil C cycle at large scales. Nevertheless,
494 ORCHIDEE-PRIM underestimates the priming intensity as shown by the slope value (0.55),
495 indicating that the model still misses important mechanisms explaining the observations. In
496 particular, N availability is an important driver of priming, inducing higher priming when N
497 availability is reduced (Fontaine et al., 2004; Blagodatskaya et al., 2007). The role of N in the
498 priming intensity as well as the extra N mineralization induced by priming and its effect on
499 primary production may represent the next addition to the soil representation in a land surface
500 model by adding a control on the *c* parameter depending on the mineral N availability and on
501 the C:N ratio of the considered pool. Nevertheless, some detailed information on the N
502 dynamic in priming effect experiments would be necessary to do so and very few authors
503 reported the impact of priming effect on N dynamic after FOC additions.

504

505

506 **Code availability**

507 For ORCHIDEE, the main part of the code was written by Krinner et al., (2005). The
508 version used here is the 1.9.5.2 version. In this version, compared to the one presented in

509 Krinner et al., (2005), the albedo representation was improved (Hourdin et al., pers. com.), a
510 routing scheme controlling the flux of water from land surface to the ocean was added (Ngo-
511 Duc et al., 2007) and the dynamic of vegetation was modified (Viovy et al., pers. com.).
512 Furthermore, since 2005 the code has been parallelized. A detailed documentation and the
513 code can be provided upon request to the corresponding author.

514 ORCHIDEE-PRIM is derived from ORCHIDEE with the modifications presented in
515 the section 2.1.2. A detailed description can be found in Guenet et al., (2013). The code is
516 available upon request to the corresponding author.

517

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712

713 Figure legends

714 Figure 1: Summarizing scheme of the methods

715 Figure 2: Scatter plot between data and the PRIM model outputs for the incubations with FOC
716 amendment (a), without FOC amendment (b) and for priming effect (c). The dataset used here
717 are the similar to those used for optimization (a) or are the control incubations (b) and are
718 described in section (2.2.1). Red lines indicate the 1:1 line. Different symbol indicate different
719 studies.

720 Figure 3: Scatter plot between independent data from optimization (dataset describes in
721 section 2.2.2) and the soil module of ORCHIDEE outputs (a) or between data and the PRIM
722 model outputs (b). Red lines indicate the 1:1 line.

723 Figure 4: Soil CO₂ efflux calculated by ORCHIDEE on the left side and by ORCHIDEE-
724 PRIM on the right side for the data coming from Boone et al., (1998) (a), from Boroken et al.,
725 (2002) (b), from Chemidlin-Prévost-Bourré et al., (2010) (c), from Subke et al., (2004) (d)
726 and from Sulzman et al., (2005) (e). Red lines indicate the 1:1 line, black, dashed and dotted
727 lines correspond to control, litter exclusion and litter amendment situations respectively.

728 Figure 5: Scatter plot between the priming effect measured and the priming effect calculated
729 by ORCHIDEE-PRIM. Red line indicate the 1:1 line and different symbol indicate different
730 studies.

731

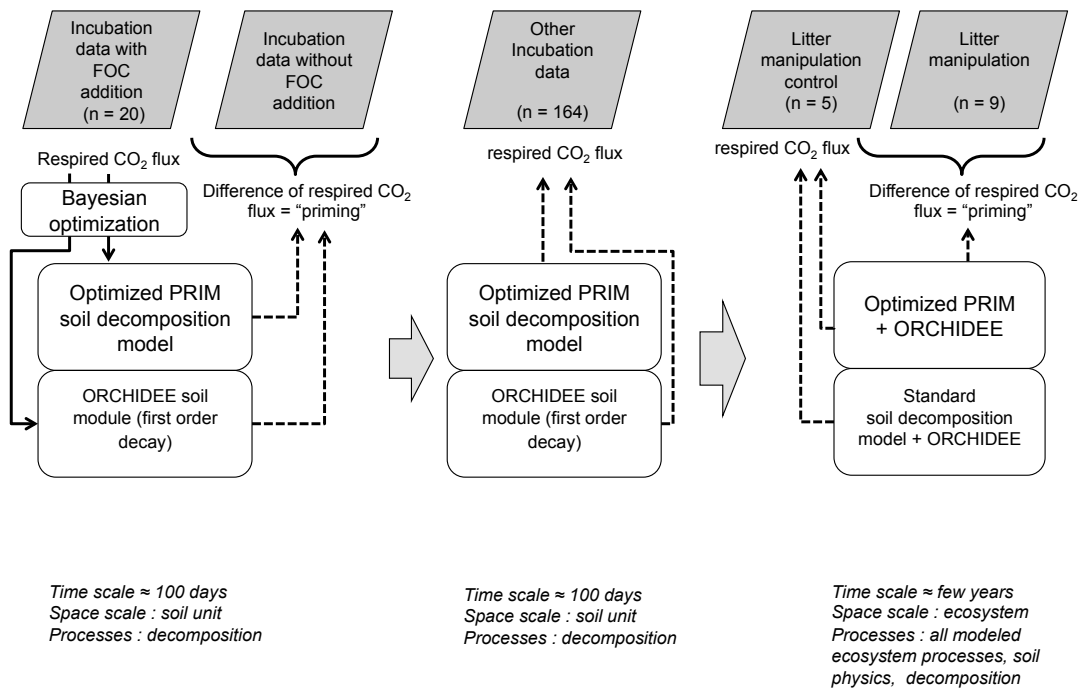


Figure 1

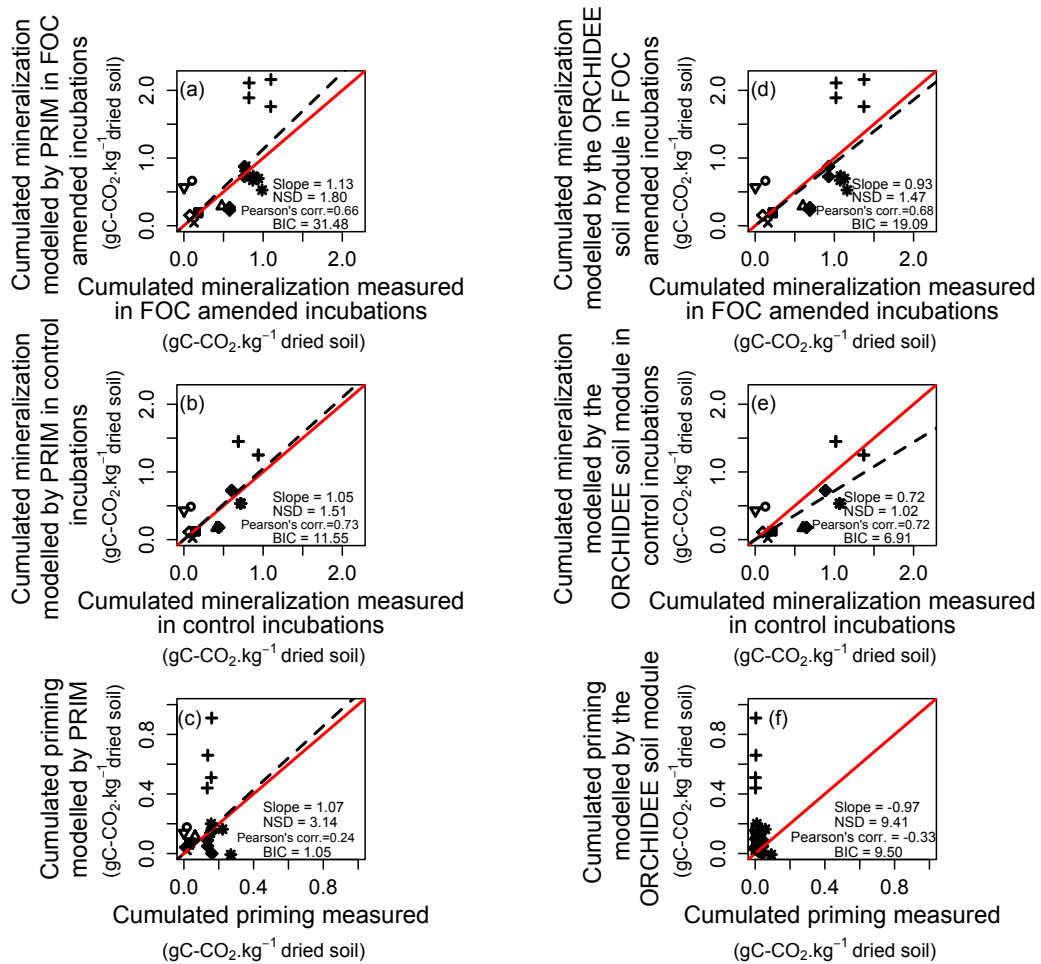


Figure 2

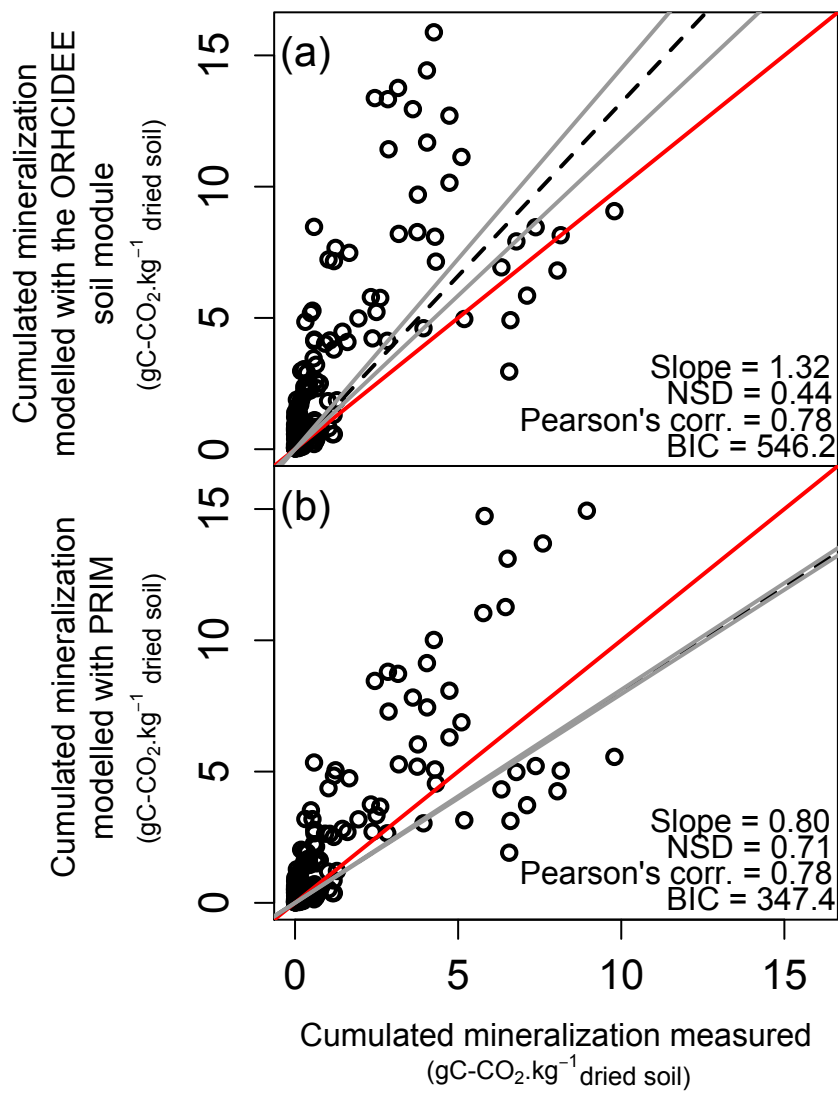


Figure 3

ORCHIDEE ORCHIDEE-PRIM

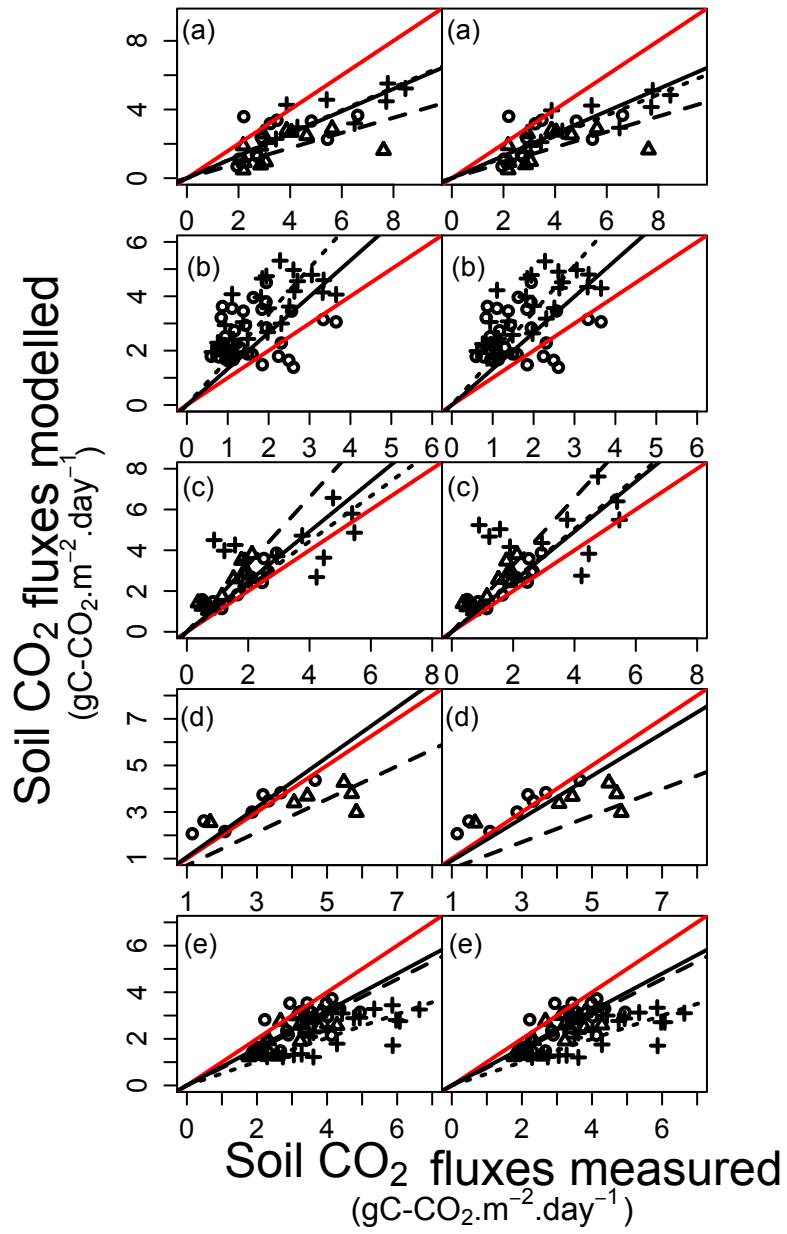


Figure 4

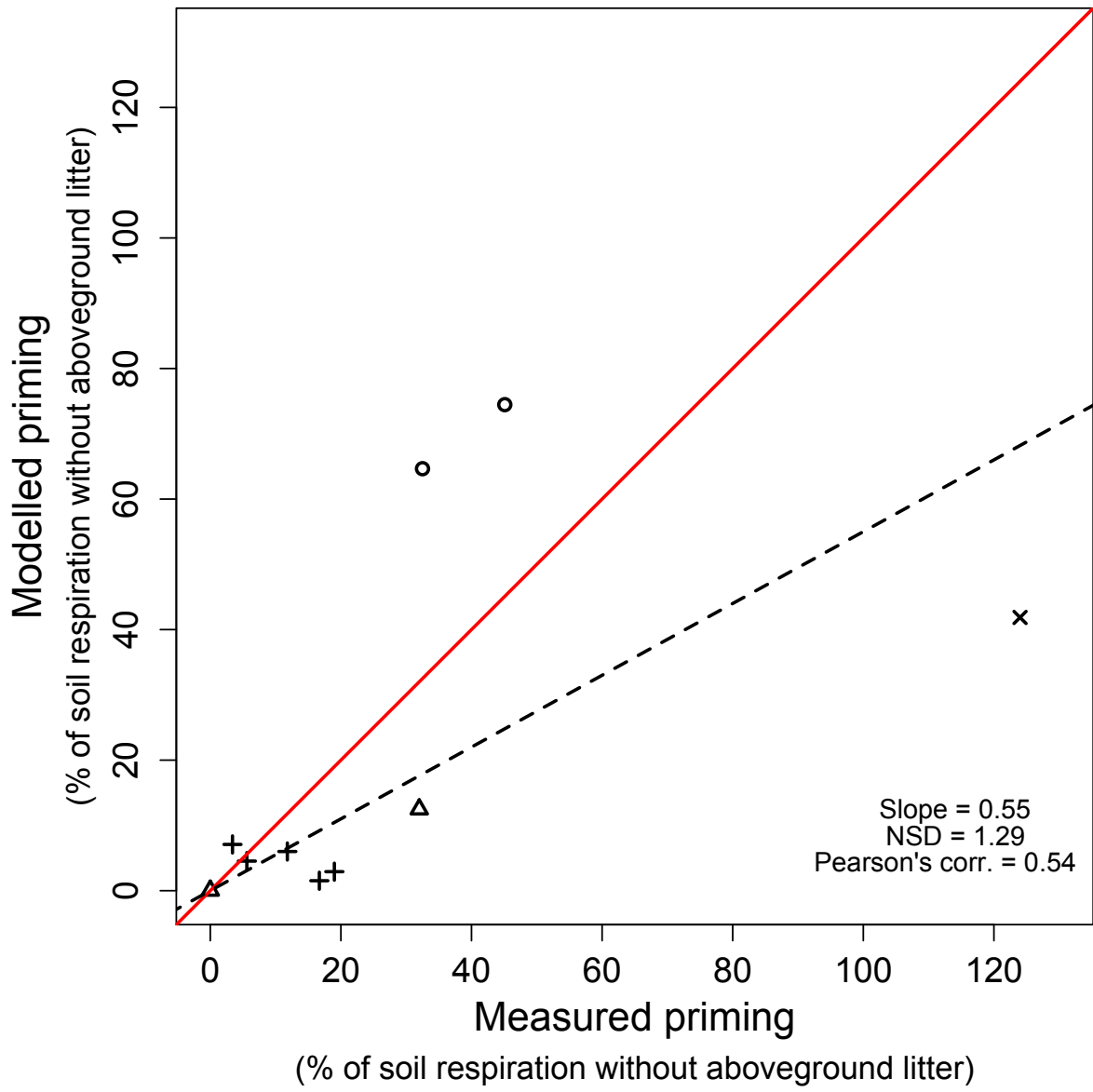


Figure 5

710 Table 1: Description of the studies used to optimize the model parameters

Study	Incubations	Study site	FOC types	Amount of FOC amended (g C kg ⁻¹ dry soil)	Lignin:C ratio of FOC	C:N ratio of FOC	Soil clay content (%)	Temperature (K)	Moisture (% of Field Capacity)	Incubation length (days)	SOC content (g C kg ⁻¹ dry soil)
Bell et al., (2003)	Experience 1 averaged over the 4 soils tested	Ralston, Washington State, USA	Wheat straw	1.54	0.22*	128*	0.08	298.15	0.2	31	10.1
Blagodatskaya et al., (2007)	GL treatment	Ramon, Voronezh region, Russia	Glucose	0.0487	0	0	0.2*	295.15	0.6	14	50
Conde et al., (2005)	Soil A+ Maize	Former lake Texcoco in the valley of Mexico City (Mexico)	Maize	1	0.575	39.8	0.22	295.15	0.55	28	53
	Soil A + Glucose	former lake Texcoco in the valley of Mexico City (Mexico)	Glucose	1	0	0	0.22	295.15	0.55	28	53
	Soil B + Maize	former lake Texcoco in the valley of Mexico City (Mexico)	Maize	1	0.575	39.8	0.054	295.15	0.55	28	38.8
	Soil B + Glucose	former lake Texcoco in the valley of	Glucose	1	0	0	0.054	295.15	0.55	28	38.8

		Mexico City (Mexico)									
De Nobili et al., (2001)	Experiment 1 with Soil 2	Rothamsted experimental station, UK	Cellulose	1	0	0	0.24	298.15	0.5	11	14.8
Falchini et al., (2003)	Average over the tree treatments	Grassland in Tuscany, Italy	Oxalix acid/ Glutamic acid/ Glucose	0.1815	0	0	0.14	298.15	0.5	7	16.6
Fontaine et al., (2004)	Only one incubation	Lamto experimental station, Ivory Coast	Cellulose	0.495	0	0	0.1	231.15	0.032	70	10.5
Guenet et al., (2010)	S1 without N amendment	La cage experimental station, France	Wheat Straw	1.5	0.22*	44	0.167	293.15	0.17	80	10.4
	S2 without N amendment	La cage experimental station, France	Wheat Straw	2.2	0.22*	44	0.167	293.15	0.17	80	10.4
	S3 without N amendment	La cage experimental station, France	Wheat Straw	3.2	0.22*	44	0.167	293.15	0.17	80	10.4
Guenet et al., (2012)	Arable soil with high cellulose input	Closeaux experimental station, France	Cellulose	5	0	0	0.167	293.15	0.19	209	19.9
	Arable soil with high wheat straw input	Closeaux experimental station, France	Wheat Straw	5	0.22*	98	0.167	293.15	0.19	209	19.9

	Arable soil with low cellulose input	Closeaux experimental station, France	Cellulose	0.5	0	0	0.167	293.15	0.19	209	19.9
	Arable soil with low wheat straw input	Closeaux experimental station, France	Wheat Straw	0.5	0.22*	98	0.167	293.15	0.19	209	19.9
Harmer & Marschner (2005)	Dystric cambisol (A horizon) + Alanine	Steigerwald, Bavaria, Germany	Alanine	13.3	0	3	0.14	293.15	0.6	26	44
	Dystric cambisol (A horizon)+ Fructose	Steigerwald, Bavaria, Germany	Fructose	13.3	0	0	0.14	293.15	0.6	26	44
	Haplic podzol (EA horizon) + Alanine	Fichtelgebirge, Bavaria, Germany	Alanine	13.3	0	3	0.104	293.15	0.6	26	32
	Haplic podzol (EA horizon) + Fructose	Fichtelgebirge, Bavaria, Germany	Fructose	13.3	0	0	0.104	293.15	0.6	26	32

711 *estimated values

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713 Table 2: Model parameters summary for PRIM and the ORCHIDEE soil module

Model parameter	Meaning	SOC pools	Prior range	Posterior modes \pm s.d. (prior modes) for PRIM	Posterior modes \pm s.d. (prior modes) for the ORCHIDEE soil module
k _{soc}	Turnover rate of SOM (d)	Active	10 ⁻³ -0.5	0.30 \pm 0.15 (0.31)	0.43 \pm 0.22 (0.43)
		Slow	0.5-5	1.12 \pm 0.01 (4.51)	0.50 \pm 0.09 (2.39)
		Passive	5-500	462.0 \pm 233.8 (467.55)	40.17 \pm 22.19 (44.39)
c	Influence of the FOM carbon pool in the SOM mineralization (priming parameter)	Active	2.10 ⁻⁴ -500	493.7 \pm 246.8 (493.7)	NA
		Slow	2.10 ⁻⁴ -500	194.0 \pm 97.0 (194.0)	NA
		Passive	2.10 ⁻⁴ -500	136.5 \pm 68.3 (136.5)	NA

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716 **Table 3:** Description of the studies used to evaluate the model

Study	Treatments performed	Ecosystems	Sites Names (Coordinates)	Treatment performed in:	CO₂ monitored between:	Soil clay content (%)	Soil silt content (%)	Soil sand content (%)
Boone et al., (1998)	No litter/Double litter/ Control	Deciduous forest	Harvard forest, Petersham, Massachusetts, USA (42°30' N,72°12' W)	January 1990	June 1994- June 1995	25*	30*	45*
Borken et al. (2002)	Compost amendment/ Control	Needleleaf forest	Solling, Norway (51°46'N, 9°34'E)	August 1997	September 1997- December 1999	3	23	74
Chemidlin-Prévost-Bouré et al., (2010)	No litter/Double litter/ Control	Deciduous forest	Barbeau National Forest, France (48°29'N,02°47'E)	March 2006	May 2006- March 2007	19.3	38.8	41.9
Subke et al., (2004)	Double litter/ Control	Needleleaf forest	Wetzstein, Thüringisches Schiefergebirge, Germany (50°30'N 11°10'E)	April 2002	April 2002(three weeks after treatment) - October 2002	70*	18*	12*
Sulzman et al., (2005)	No litter/Double litter/ Control	Needleleaf forest	H.J. Andrews Experimental Forest, Oregon, USA (44°15'N, 122°10'W)	January 1997	July 2001- December 2003	25*	30*	45*

717 *estimated values

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719 Table 4: Model performances for each evaluation sites

		Boone et al., (1998)				Borken et al., (2002)			Chemidlin-Prévost-Bouré et al., (2010)				Subke et al., (2004)			Sulzman et al., (2005)			
		All data	No litter	Control	Double litter	All data	Compost	Control	All data	No litter	Control	Double litter	All data	No litter	Control	All data	No litter	Control	Double litter
ORCHIDEE	slope	0.56	0.45	0.65	0.66	0.65	1.68	1.33	0.55	1.65	1.23	1.11	0.48	0.72	1.07	0.60	0.77	0.80	0.51
	NSD	1.43	1.86	1.37	1.48	0.77	0.79	0.87	1.03	0.70	0.97	1.56	1.85	1.65	1.41	1.53	1.10	1.08	1.68
	BIC	103.4	57.9	49.3	53.8	116.8	84.0	74.9	73.1	39.4	29.1	52.2	45.9	38.3	24.3	109.9	39.9	42.4	78.3
ORCHIDEE-PRIM	slope	0.55	0.45	0.65	0.61	0.67	1.71	1.33	0.54	1.64	1.23	1.26	0.48	0.71	1.07	0.58	0.76	0.80	0.50
	NSD	1.53	1.85	1.37	1.59	0.77	0.79	0.86	0.86	0.70	0.97	1.30	1.86	1.66	1.41	1.55	1.10	1.09	1.76
	BIC	116.3	64.9	56.5	63.46	131.1	95.9	85.0	96.1	46.2	36.3	65.1	54.3	44.6	30.5	124.1	48.2	51.3	88.1

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