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A comprehensive analysis of CO₂ exchanges in agro-ecosystems based on a generic soil-crop model-derived methodology

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Abstract

Carbon emissions in agriculture play a major role in climate change. Modelling studies enable to investigate the impacts of climate change in crops, accounting for soil organic carbon feedbacks and CO₂ concentrations. But it is primordial that crop models properly consider the CO₂ exchanges at the level of crop rotations beyond the cycle of a single crop. With this goal in mind, we used the outputs of the soil-crop model STICS in its standard pre-parameterized version to model (i) the Gross Primary Productivity (GPP), derived from the autotrophic respiration and the Net Primary Productivity, which is computed through the daily change in plant carbon (C) pools; (ii) the Ecosystem Respiration (RECO), with the autotrophic component being derived from the plant biomass, plant nitrogen concentration and GPP, and the heterotrophic component from the mineralization of residues and organic matter; and (iii) the Net Ecosystem Exchange, equal to the sum of GPP and RECO. The comparison of simulations with field observations indicates that the model is able to simulate accurately daily CO₂ fluxes originating from a long-term and diversified crop rotation (efficiency EF equal to 0.79 for GPP, 0.59 for RECO and 0.67 for NEE). Concerning the evaluation of the cumulated fluxes over the 16-year rotation, the model is able to evaluate it accurately for RECO, with a slight underestimation (normalized deviation ND = 15.7%), and very accurately for GPP (ND = 5.12%). But for NEE, the relative overestimation is higher (ND = 62.2%), indicating that a more precise estimation of HR is required to obtain reliable net C budgets. The model also succeeds to capture the trends in the influence of several environmental drivers on CO₂ fluxes. It globally proves to be a valuable tool in the investigation of CO₂ exchanges of crop rotations in historical and future climatic conditions.

Keywords: Net Ecosystem Exchange; Crop model; Gross Primary Productivity; Autotrophic respiration; Heterotrophic respiration; Carbon balance

39 **1. Introduction**

40 Climate change causes widespread negative impacts, not only on ecosystems but also on people,
41 settlements and infrastructure. Among these, extreme events such as heatwaves, heavy precipitations,
42 droughts, fires, etc. are impacting ecosystems, human health and the economy and causing
43 humanitarian crises. Furthermore, these effects are expected to intensify with a very high level of
44 confidence (IPCC, 2022).

45 Among greenhouse gases, that are directly responsible for climate change, CO₂ emissions
46 constitute 75% of global net anthropogenic emissions (IPCC, 2013). Agricultural lands generate very
47 large CO₂ fluxes, but the balance between their source and sink capacities is subject to large
48 uncertainties and high annual and spatial variability (Smith et al., 2007; Wattenbach et al., 2010).
49 Globally, soils are known to store more than twice as much carbon as is contained in the vegetation or
50 the atmosphere (Bellamy et al., 2005). Croplands have thus potential to mitigate climate change, but
51 this requires a deep understanding of soil CO₂ fluxes and how agricultural management and
52 environmental variables affect them.

53 The two major CO₂ fluxes between the atmosphere and the terrestrial biosphere result from the
54 photosynthesis by vegetation and the respiration from autotrophic and heterotrophic organisms
55 (Klosterhalfen et al., 2017). It is photosynthesis that is the primary source of carbon (C) in ecosystems,
56 by fixing C in plants and adding it to soil as above- and belowground organic matter (Bolinder et al.,
57 2007). This amount of C fixed is referred to as the Gross Primary Productivity (GPP). About half of
58 this photosynthetically fixed carbon is lost by internal plant metabolism for plant growth and
59 maintenance processes. These processes are called the Autotrophic Respiration (AR) (Kirschbaum and
60 Mueller, 2001). The difference between GPP and AR is called Net Primary Productivity (NPP). The
61 other part of the respiration is called Heterotrophic Respiration (HR). It refers to the carbon that is lost
62 by all organisms in ecosystems other than plants: animals that live aboveground, but mostly all macro-
63 and micro-organisms that live in the soil and the litter and decompose organic matter. The sum of the
64 autotrophic and heterotrophic respirations is referred to as Ecosystem Respiration (RECO). Finally,
65 Net Ecosystem Exchange (NEE) is the balance between photosynthesis, that fixes carbon, and

66 respiration, that releases it.

67 The standardization of eddy-covariance measurements (Aubinet et al., 1999) has allowed the
68 development of regional flux-tower networks (such as EUROFLUX which later morphed into
69 CARBOEUROPE and ICOS, or AMERIFLUX) that produce standardized and long-term observations
70 on the carbon balance of various terrestrial ecosystems (Baldocchi et al., 2008). They have notably led
71 to studies investigating the carbon budgets of crops using datasets ranging from one to multiple
72 experimental sites and from one cropping season to full crop rotations. Globally, agro-ecosystems had
73 negative annual NEE, indicating that the plants sequester more carbon than what is respired. However,
74 they were found to be C sources when considering Net Biome Production (NBP) that also considers
75 lateral C fluxes such as manure and harvest (Aubinet et al., 2009; Kutsch et al., 2010; Buysse et al.,
76 2017; Dold et al., 2017). Such C losses lead to a decrease in soil organic carbon (SOC) stocks,
77 threatening soils fertility on the long term but also potential of crops for climate mitigation.

78 Globally, longer-term studies are necessary to consider the inter-annual variability of C fluxes in
79 agro-ecosystems, which is large and influenced by genetics (e.g. crop type), environment (e.g.
80 radiation, temperature or water availability) and management (e.g. tillage) (Chi et al., 2016; Buysse et
81 al., 2017). The determination of GPP and RECO fluxes may require combining altogether the use of
82 eddy-covariance with soil chambers measurements, which is both time- and money-consuming and
83 does not allow to deal easily with plot scales (Vuichard et al., 2016). An alternative consists in using
84 partitioning methods such as non-linear regressions, look-up tables or statistical analyses, which might
85 induce some errors (Smith et al., 2010). Moreover, if one wants to separate soil respiration into its
86 autotrophic and heterotrophic components, additional experimental effort is needed, for example
87 keeping a plot without vegetation nor roots in order to have a heterotrophic-only respiration area
88 (Suleau et al., 2011), at the cost of high labour requirements. This is why it is particularly interesting
89 to be able to estimate the components of CO₂ fluxes from a crop modelling-based approach.

90 Process-based models are essential research tools for extrapolating field results in both time and
91 space. They not only allow assessing the impact of climate change on these systems through the
92 account for soil-plant feedback mechanisms considering notably the interaction between soil organic

93 carbon and carbon dioxide (Basso et al., 2018), but also their potential to mitigate it (Kang et al., 2009;
94 Rosenzweig et al., 2014; Asseng et al., 2015; Lobell et al., 2017). They also help to represent current
95 understanding of the impacts of drivers such as temperature or water content on agronomic and
96 physical processes (Sándor et al., 2020).

97 Several process-based models like Agro-C (Huang et al., 2009), DNDC (Li et al., 2005), SPAC
98 (Sus et al., 2010) or ORCHIDEE-STICS (Krinner et al., 2005) have already been developed for
99 modelling CO₂ fluxes of the soil-plant system and compared to each other (Wattenbach et al., 2010;
100 Lokupitiya et al., 2016; Sándor et al., 2020). It appears that most of these models either under- or
101 overpredict CO₂ fluxes, with the most precise models limited either in their range of simulated crops
102 or in their type of modelled flux (GPP or RECO). This restrains their ability to simulate the full carbon
103 balance of diversified crop rotations. This is why simulating CO₂ fluxes with a process-based model
104 such as the soil-crop model STICS (Brisson et al., 2008), already able to simulate a wide range of
105 agronomic and environmental indicators in various agro-environmental conditions (Coucheney et al.,
106 2015), might be profitable.

107 Several methods are used to model these CO₂ fluxes. Heterotrophic respiration is computed via
108 the mineralization of humus, mulch and residues, with a dependence on different factors such as
109 temperature (Tuomi et al., 2008), moisture availability or quality and supply of decomposable
110 substrate material (Trumbore, 2006).

111 GPP and/or NPP are usually calculated by multiplying the amount of solar radiation intercepted
112 by a coefficient of conversion of this radiation into biomass, this coefficient depending on several
113 factors such as green leaf nitrogen content, air temperature, soil moisture and atmospheric CO₂
114 concentration (Kirschbaum and Mueller, 2001; Huang et al., 2009). If it is NPP that is calculated, GPP
115 will be obtained by adding autotrophic respiration, whereas if GPP is directly derived, respiration is
116 implicitly taken into account into the parameterization of growth functions.

117 To model crop respiration, a first simple approach involves using photosynthesis (GPP) and
118 multiplying it by a respiration:photosynthesis ratio. This ratio of respiration to gross photosynthesis
119 might be assumed to be constant over a wide range of plant sizes and growth rates, CO₂ concentrations

120 and temperatures, but this could induce modelling uncertainties since whole-plant chambers
121 measurements reported that this ratio might vary from 0.35 to 0.6 (Kirschbaum and Mueller, 2001;
122 Gifford, 1995). A second approach to derive plant respiration consists in partitioning respiration into
123 the components of growth and maintenance (Amthor, 1984). The growth respiration allows the
124 synthesis of new tissues, while the maintenance respiration represents the cost of maintaining the
125 existing biomass, i.e. the costs of protein synthesis and replacement, membrane repair and the
126 maintenance of ion gradients. The advantage of this approach is that growth costs are fixed for a unit
127 of new tissue whereas maintenance respiration varies with environment (e.g. temperature), protein
128 turnover, plant species and even organs (greater in roots than in the shoot) (Amthor, 1984; Ryan,
129 1991). However, it remains theoretical since maintenance and growth respiration are not biochemically
130 distinct and cannot be differentiated experimentally. To consider the energy requirement for
131 maintenance due to protein turnover, we can take advantage of the correlation between maintenance
132 respiration and tissue nitrogen concentration (Ryan, 1991; Sun et al., 2007).

133 In this paper, we present an innovative methodology to model the CO₂ exchanges of a crop
134 rotation. Data recorded over a 16-year crop rotation at the ICOS site of Lonzée in Belgium (BE-LON),
135 comprising winter wheat, sugarbeet, potato, maize and cover crops, allow to calibrate and validate our
136 approach. The soil-crop model STICS is used to model the crop rotation and as a basis to derive CO₂
137 fluxes. The objectives of this study are (i) to elaborate the methodology to compute GPP, RECO and
138 NEE; (ii) to assess its validity and accuracy by a comparison with observed CO₂ fluxes; and (iii) to
139 discuss the influence of various environmental drivers on crop rotations CO₂ fluxes, based on both
140 field observations and simulations.

141 **2. Material and Methods**

142 ***2.1. Site description***

143 The BE-LON experimental site is situated in Lonzée, about 45 km at the south-east of Brussels
144 in Belgium (50°33'08''N, 4°44'42''E, 165 m asl). It belongs to the Integrated Carbon Observations
145 Systems (ICOS) network, a European infrastructure, since the 17th November of 2017. Fluxes and
146 meteorological variables were measured with eddy-covariance following ICOS protocols, except for

147 the period before 2014 when CARBOEUROPE-IP and FLUXNET network standards were used
148 (Buysse et al., 2017). The measured fluxes, after correction, filtering and gap-filling, provide the NEE,
149 following the ONEFlux processing pipeline methodology (Pastorello et al., 2020). The later
150 partitioning of experimentally measured NEE into GPP and RECO components was conducted
151 following the procedures used and described by Reichstein et al. (2005). Both raw fluxes
152 measurements and treated fluxes are available in Heinesch et al. (2021). Later in the manuscript, we
153 will refer to these fluxes as *observed*, despite GPP and RECO being computed from NEE which was
154 the only flux actually measured on the field.

155 In Lonzée, the climate is temperate maritime (classified as Cfb in the Köppen classification;
156 Köppen, 1984). Mean annual temperature and precipitation are about 10°C and 800 mm respectively.

157 The field of BE-LON experimental site covers about 12 ha on a fairly flat plateau with a
158 quadrilateral shape. The soil is classified as a Luvisol with, in August 2007, a soil organic C stock of
159 46.7 tC ha⁻¹ over the 0-30 cm soil layer (Buysse et al., 2017). Records indicate that the field has been
160 cultivated for over 80 years. Since 2004, crop rotation has been stabilized to the following 4-year
161 sequence: sugarbeet, winter wheat, seed potatoes and winter wheat. An exception occurred in 2012
162 when sugarbeet was replaced by maize. Mustard was sown as cover crop and N trap in 2009, 2013,
163 2015 and 2017 (Table A1 in Appendices). Fertilization, mainly as nitrogen, and pesticide applications
164 for weeding, growth regulator, control of insects and fungal followed Belgian common practices
165 (Buysse et al., 2017). Regular soil tillage, namely 25-cm deep tillage after each winter wheat crop, was
166 practiced.

167 The dataset that was used includes both agronomic and environmental data. The first category
168 comprises Leaf Area Index (LAI), shoot biomass, yield, and N concentration in the plant and in the
169 grain. The latter involves soil organic carbon, standard meteorological variables, evapotranspiration
170 and CO₂ fluxes (GPP, RECO and NEE).

171 Further details about the BE-LON experimental site, crop management activities and data
172 collection procedures are available e.g. in Aubinet et al. (2009), Suleau et al. (2011) or Buysse et al.
173 (2017).

174 **2.2. The STICS soil-crop model (v9.2)**

175 In this study, we used the standard version 9.2 of STICS (*Simulateur multIdisciplinaire pour*
176 *les Cultures Standard* in French); see Beaudoin et al. (2022) for a detailed description of the different
177 versions of the model. STICS is a soil-crop model which computes changes in both agronomic (e.g.
178 biomass and yield) and environmental variables (e.g. soil organic carbon, nitrate leaching, soil water
179 and nitrogen, etc.) from input variables and parameters relating to weather conditions, soils and
180 cropping systems (Brisson et al., 2009). It is a process-based model that simulates plant growth as well
181 as water, C and N fluxes. Biomass is computed from the radiation intercepted by foliage (LAI), that is
182 incremented on a daily basis as a logistic function of phasic development. The amount of N taken up
183 by the plant is assumed to be the daily minimum between soil N supply and crop N demand.

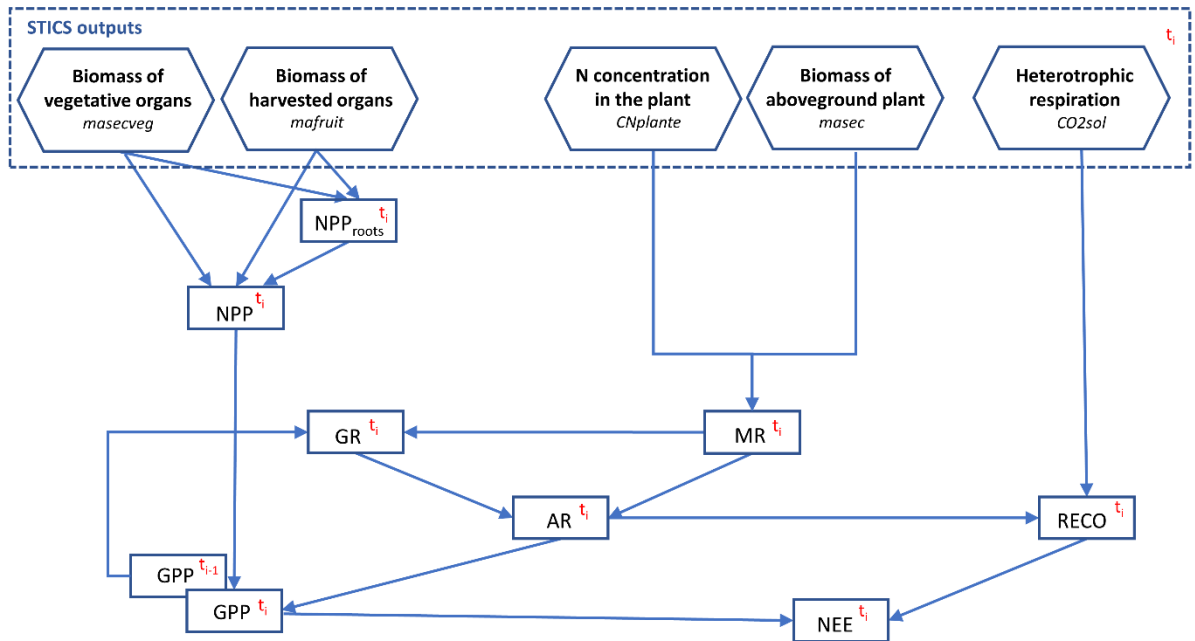
184 STICS does not explicitly simulate neither GPP nor autotrophic respiration since it relies on the
185 concept of radiation use efficiency that combines photosynthesis and respiration. Yet it explicitly
186 simulates heterotrophic respiration from mineralization of all crop residues and soil organic matter
187 (humus). The decomposition of residues follows a first-order kinetics, with a rate depending on their
188 nature, their C:N ratio, soil temperature, water and mineral nitrogen content. The decomposition of
189 humified organic matter depends on a mineralization rate constant (calculated according to the soil
190 characteristics) that is multiplied by stress factors accounting for the effects of soil temperature and
191 moisture.

192 **2.3. Deriving GPP, AR and NEE from STICS output variables**

193 The Gross Primary Productivity is the sum of the Net Primary Productivity and the autotrophic
194 respiration (Kirschbaum and Mueller, 2001). Taking as a convention that fluxes towards the soil are
195 regarded as negative and those leaving from the soil as positive (as e.g. in Buysse et al. (2017)), this
196 gives:

$$GPP = NPP - AR \#(1)$$

197 The approach used to compute the different CO₂ fluxes from STICS outputs is represented on
198 Figure 1 and detailed hereafter..



199

200 **Figure 1. Overview of the methodology used to compute the different CO₂ fluxes from STICS**
 201 **outputs. STICS variables are written in italic.**

202 **2.3.1 Net Primary Productivity**

203 NPP is the daily change in the total carbon content (TCC) of the aboveground and belowground
 204 parts of the plant. Considering the different biomass pools in STICS (Brisson et al., 2009), a first
 205 method to compute the TCC is:

$$TCC = masecveg * 0.42 + mafruit * 0.44 + msrac * 0.38 + mafeuiltombe * 0.42 \#(2)$$

206 with the STICS variables *masecveg*, *mafruit*, *msrac* and *mafeuiltombe* standing for the biomass of
 207 respectively vegetative organs, harvested organs, roots and fallen leaves due to senescence, and where
 208 each pool is multiplied by a carbon content coefficient, as defined in the STICS model.

209 However, this first method reveals limitations, that we hypothesize to be linked to (i) the uncertainty
 210 associated with the simulated roots biomass and C content, which might be of importance since a
 211 significant proportion of NPP is allocated to belowground plant parts (Bolinder et al., 2007; Pausch
 212 and Kuzyakov, 2018), and (ii) the carbon fraction being actually different between crops. Indeed, root
 213 biomass is not explicitly simulated at a daily time-step in STICS v9.2 (it is only calculated at harvest
 214 when roots become belowground crop residues). Furthermore, STICS assumes the carbon fraction as
 215 constant, but it actually varies, especially for the carbon contained in harvested organs (Penning de
 216 Vries, 1989).

217 To address these limitations, we chose to not use directly the roots biomass simulated by
218 STICS, because (i) we lacked field data to validate belowground simulations, and, most of all, (ii) we
219 wanted to use the standard version of STICS to avoid overfitting and keep generality and usability. In
220 the standard parameterization of STICS, there is no dependence between root length expansion and
221 shoot growth, which is indispensable to obtain a reliable soil-crop C balance. Instead, to derive
222 belowground NPP, we used a constant coefficient coming from shoot-root ratios and harvest indices. It
223 allowed to estimate NPP due to roots based on aboveground organs simulations, following the
224 coefficients for several crops including sugarbeet, potato and maize provided by Bolinder et al. (2007)
225 and Bolinder et al. (2015). As mentioned in these papers, this allows the approach to be easily
226 transferable and updated with new experimental results. Rhizodeposition was considered, as carbon is
227 exudated into the soil from the extra-root component (Asseng et al., 1997; Bolinder et al., 2007). For
228 mustard used as cover crop, a shoot-root ratio of 5 was used, from De Baets et al. (2011). For winter
229 wheat, we took benefit from the more extensive literature to use a dynamic shoot-root ratio evolving
230 along the crop season, following the coefficients used in Asseng et al. (1997) which also consider
231 exudation. This dynamic shoot-root ratio is equal to 0.66 before the maximal rate of leaf growth (end
232 of juvenile phase), 2.33 between the maximal rate of leaf growth and flowering and 3 after flowering.
233 This is in accordance with the constant value of 2.46 proposed by Bolinder et al. (2007). All allocation
234 coefficients used for computing carbon stored in roots and rhizodeposition from aboveground
235 vegetative biomass are summarized in Table A2. Secondly, for the carbon contained in harvested
236 organs (linked to *mafruit*), a carbon fraction specific to each crop, lying in the interval 0.42-0.45, was
237 proposed (Penning De Vries et al, 1989). Two reasons explain this choice. Firstly, not referring to the
238 carbon content of harvested organs prescribed within STICS is not problematic, since i) our module is
239 external to the crop model and ii) these organs are exported and therefore not returned to the soil.
240 Secondly, while the model is known to be reliable as a source of biomass simulation (Coucheney et
241 al., 2015), as it uses a constant carbon fraction within harvested organs for all crops (equal to 0.44), we
242 believe that it is not as trustworthy for carbon estimates across a crop rotation including a diversity of
243 plants (sugarbeet, wheat, etc.).

244 **2.3.2 Autotrophic respiration**

245 For the autotrophic respiration calculation, we separated it between its two components for
246 growth (GR) and maintenance (MR):

$$AR = GR + MR \#(3)$$

247 Growth respiration is the CO₂ emitted resulting from growth processes that convert glucose into
248 other organic components (Penning de Vries, 1989). Therefore, from the amount of glucose required
249 to synthesize 1g of plant material, Ruimy et al. (1996) found a growth coefficient of 0.28 (€
250 [0.25, 0.29]), based on various natural ecosystems and various organs. This role of glucose molecules,
251 serving as building components for virtually all organic constituents, is common and almost constant
252 to all plants (Penning de Vries, 1972; Amthor, 1984; Penning de Vries, 1989; Ryan, 1991; Poorter,
253 1994).

254 To compute GR, we used the equation of the ORCHIDEE model described in Krinner et al.
255 (2005) and Vuichard et al. (2016). A fixed fraction (28%) of the available carbon for growth (GPP-
256 MR) was used for GR. As highlighted in Figure 1, GPP, AR and GR are interlinked. To deal with
257 computation issues, we computed GR at day *i* as being a function of GPP at day *i-1*, such a correlation
258 being suggested in Suleau et al. (2011):

$$GR_i = (GPP_{i-1} - MR_i) * 0.28 \#(4)$$

259 Initial values GPP₁ and GR₁ are null since we started the simulations in STICS, specific to each
260 crop season, before sowing.

261 **2.3.3 Maintenance respiration**

262 To simulate maintenance respiration, we used the correlation between plant maintenance
263 respiration and tissue N, as reported by Ryan (1991). This relationship conceives that a major energy
264 demand for plant tissue maintenance is for protein turnover, to support protein repair and replacement
265 (Ryan et al., 1991; Kirschbaum and Mueller, 2001; Sun et al., 2007). Following Amthor (2000),
266 Kirschbaum and Mueller (2001) and Sun et al. (2007), we used the following relationship between the
267 maintenance respiration MR [kg C m⁻² day⁻¹], the aboveground plant biomass W [kg m⁻²], the
268 environmental temperature T [°C] and the tissue N content [%]:

$$MR = (aN + b) * Q_{10}^{\frac{T-25}{10}} * W \#(5)$$

269 with Q_{10} a temperature coefficient of respiration equal to 2 (the Q_{10} value and the reference
 270 temperature are widely confirmed by the literature, e.g. in Vandendriessche (2000)). Sun et al. (2007)
 271 found from pot experiments, for wheat and rice and for the aboveground AR, coefficients a and b
 272 respectively equal to 2.16 and -0.66 (when converted to the units we used). These are also used for
 273 several crops in the Agro-C model (Huang et al., 2009).

274 However, since we made the choice to compute AR from its maintenance and growth
 275 components, we need to calculate the coefficients a and b of Eq. (5) for maintenance respiration only.
 276 We took benefit from our long-term dataset to separate it into randomly selected independent
 277 calibration and validation sets for each crop (Table A3). Since the amount of data did not allow an
 278 independent validation for maize and cover crops, we decided to use for these crops the coefficients
 279 obtained from winter wheat. It appeared that the coefficients should be fitted separately for winter
 280 wheat, sugarbeet and potato. Indeed physiological differences exist between organs respiration rates.
 281 For example, Amthor (1984) indicated that the maintenance respiration coefficient is greater in roots
 282 than in the shoot, and Suleau et al. (2011) suggested that the storage organs of sugarbeet respire less
 283 than fine roots.

284 For the fitting process, we started from the equality

$$RECO = HR + GR + MR \#(6)$$

285 and substituted GR and MR by their expressions in Eq. (4) and Eq. (5), leading to the following
 286 relationship:

$$\Leftrightarrow RECO - HR = (GPP - MR) * 0.28 + MR \#(7)$$

$$\Leftrightarrow RECO - HR = 0.28 * GPP + (1 - 0.28) * (aN + b) * Q_{10}^{\frac{T-25}{10}} * W \#(8)$$

287 where all indicators are replaced by their estimated values except for RECO which is observed. This
 288 allowed to estimate by linear regression the values of the coefficients a and b for the different crops
 289 with the following equality, with i and $i-1$ indicating the day:

$$\Leftrightarrow aN_{sim_i} + b = \frac{RECO_{obs_i} - HR_{sim_i} - 0.28 * GPP_{sim_{i-1}}}{(1 - 0.28) * Q_{10}^{\frac{T_i - 25}{10}} * W_{sim_i}} \#(9)$$

290 We finally computed total autotrophic respiration with Eq. (3).

291 **2.3.4 Net Ecosystem Exchange**

292 Using the soil heterotrophic respiration (HR) simulated by STICS, we computed the Net
293 Ecosystem Exchange (NEE) with

$$NEE = AR (> 0) + HR(> 0) + GPP (< 0) \#(10)$$

294 One should note that, if its objective is to compute NEE with no regard to autotrophic
295 respiration, combining Eqs. (1) and (10), it is similar to compute NEE with

$$NEE = HR (> 0) + NPP (< 0) \#(11)$$

296 **2.4. Environmental drivers of NEE**

297 NEE is known to vary between cropping years, even for a given crop (Aubinet et al., 2009;
298 Buysse et al., 2017). The BE-LON dataset allowed us to study the influence of environmental factors
299 on NEE inter-annual variability. Indeed, the same management was applied to same crops for different
300 cropping years. As in the study of Buysse et al. (2017), we explored using linear regressions between
301 seasonal NEE (from emergence to harvest) and environmental drivers such as (i) the number of days
302 of active vegetation (NDAV), i.e. days when daily GPP was in absolute value over a certain threshold
303 estimated to be optimal to avoid the influence of weeds that the model is unable to reproduce (50 g C
304 m⁻² d⁻¹ for winter wheat and 10 g C m⁻² d⁻¹ for the other crops as in Ceschia et al. (2010) and Buysse et
305 al. (2017)), (ii) the cumulated radiation (Q_{cum}) during active vegetation period, (iii) the average air
306 temperature (T_{air,av}) during the active vegetation period, (iv) the water balance (precipitation minus
307 evapotranspiration) and (v) the SPEI. The Standardized Precipitation-Evapotranspiration Index (SPEI)
308 characterizes the onset, duration and magnitude of a drought based on the difference between
309 precipitations and evapotranspiration (Vicente-Serrano et al., 2010). It then captures the impact of
310 temperature on water demand. Correlations were tested for the SPEI at different months as well as for
311 different durations.

2.5. Crop model parameterization and validation

2.5.1 Parameterization

Soil parameters initializing the simulations originated from observations used to define a standard profile, because no initial values were available. For the plants, we used the standard parameters provided with STICS v9.2 that were validated on the large and diversified datasets of the STICS core team (Beaudoin et al., 2022). Few slight modifications were made for winter wheat, according to Dumont et al. (2016), and for potato, according to M. Launay (personal communication). All simulations files related to soil and plant parameterization, crop management and outputs are available in Appendix A3.

2.5.2 Validation

To evaluate the accuracy of the model simulations, three different indicators were used: the Root Mean Square Error (RMSE), the Model Efficiency (EF) and the Normalized Deviation (ND):

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

with S_i the simulations and O_i the observations. We consider that the model is adequate for a given variable of interest if $EF \geq 0.5$ and $|ND| \leq 0.1$ (Beaudoin et al., 2008). A graphical analysis based on RMSE decomposition between its systematic (RMSEs) and unsystematic (RMSEu) components (Willmott et al., 1981), initially proposed in Taylor (2001), was used to assess model global performance. They were calculated as follows:

$$RMSEs = \sqrt{\frac{1}{n} \sum_{i=1}^n (\bar{S}_i - O_i)^2}$$
$$RMSEu = \sqrt{\frac{1}{n} \sum_{i=1}^n (S_i - \bar{S}_i)^2}$$

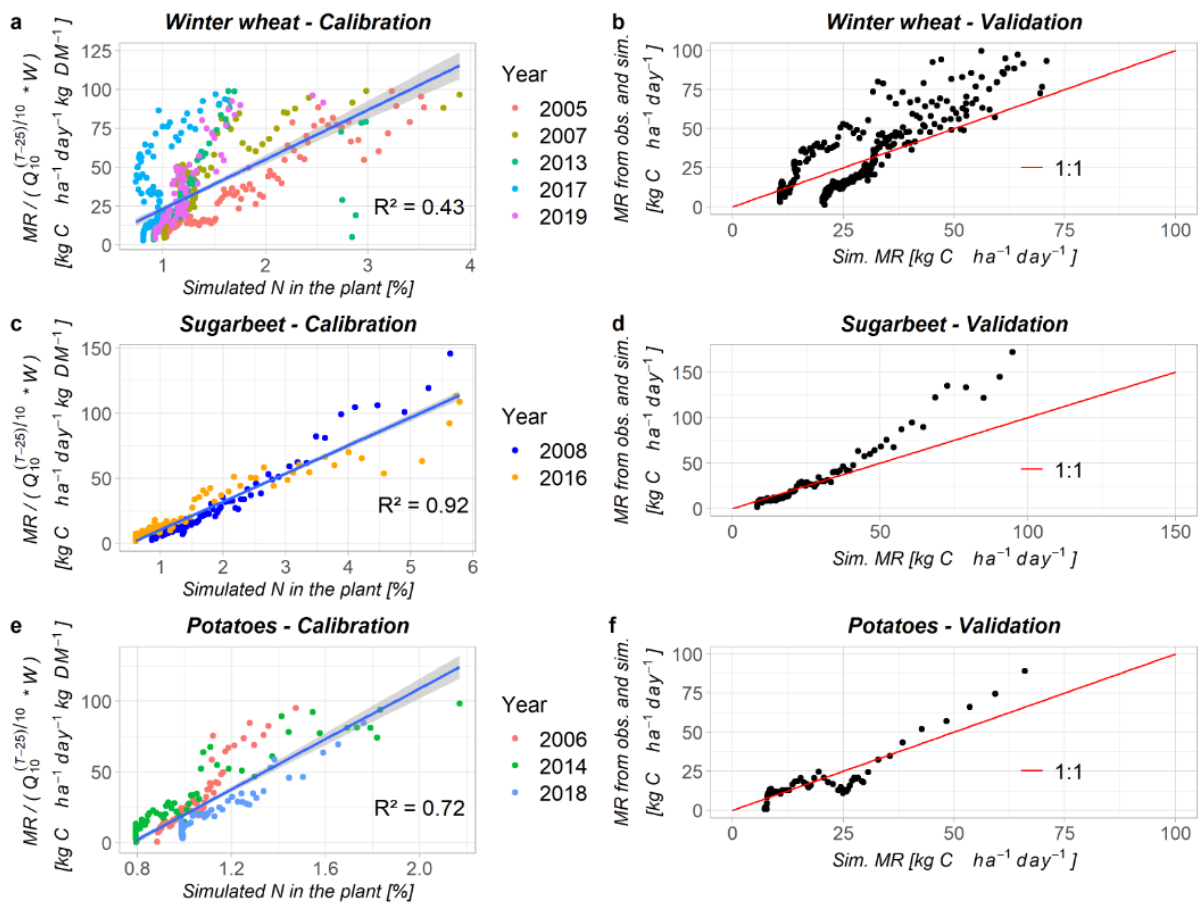
with $\bar{S}_i = c_1 + d_1 * O_i$ the linear regression of observed versus simulated values. This was

330 utilized for example by Coucheney et al. (2015), which established criteria allowing to qualify an
 331 indicator simulation as *satisfactory*, *good* or *very good*. RMSE components were standardized to
 332 compare the performance of simulation between variables having different units.

333 We also used the parameters c_2 and d_2 of the linear regression $\bar{O}_i = c_2 + d_2 * S_i$ of simulated
 334 versus observed values as supplementary indicators of the goodness of fit: the intercept c_2 and the
 335 slope d_2 being as close as possible to respectively 0 and 1 (Pineiro et al., 2008).

336 3. Results and Discussion

337 3.1. Relationship between plant N concentration and maintenance respiration



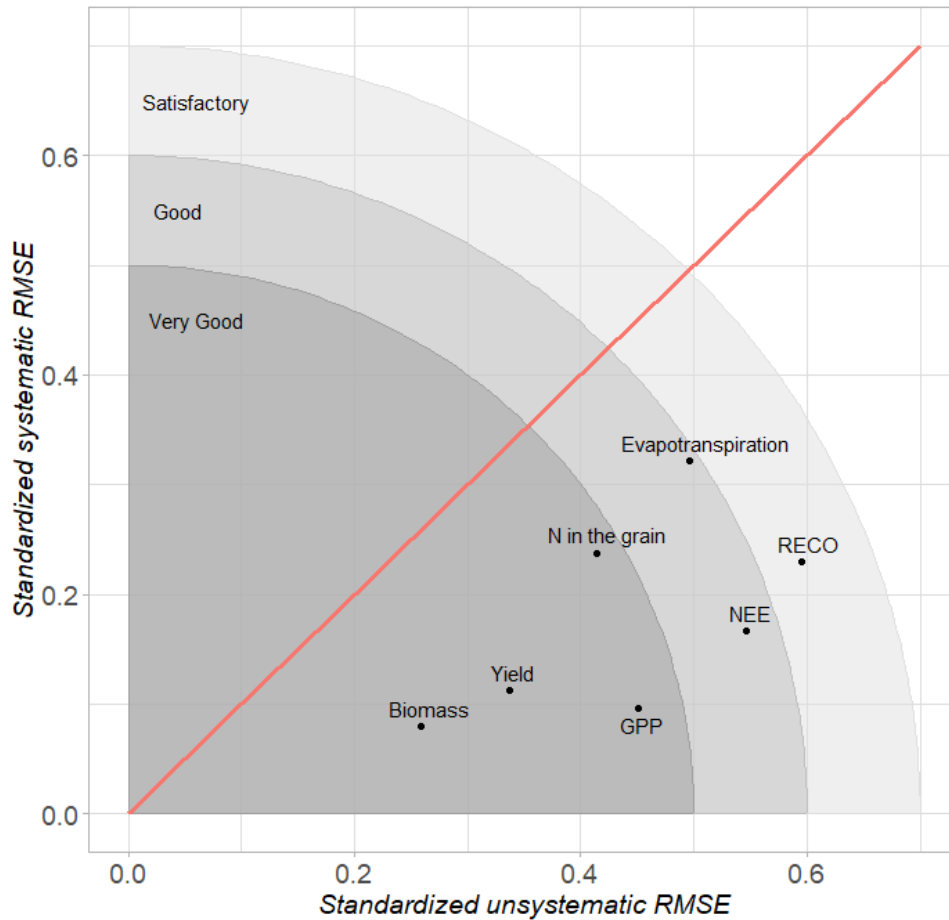
338
 339 **Figure 2.** Fitting results to compute maintenance respiration (MR) from plant N concentration
 340 for winter wheat (2a and 2b), sugarbeet (2c and 2d) and potatoes (2e and 2f). Fig. 2a, 2c and 2e
 341 show, for each crop, the relationship between plant N concentration and simulated MR (divided
 342 by the Q_{10} -coefficient and biomass W) in the calibration set, with in blue the linear regression
 343 and its 95%-confidence interval. Fig. 2b, 2d and 2f compare, in the independent validation set,
 344 the simulated MR on the x-axis, and the MR computed with observed RECO (as defined in Eq.
 345 (9)) on the y-axis. Regression coefficients and goodness of fit indicators are summarized in Table
 346 A4.

347 As illustrated in Fig. 2, calibration proved that the model is adequate to predict maintenance

348 respiration (R^2 between 0.43 and 0.92 for calibration), with however a higher variability in winter
349 wheat response (Fig. 2a). Such a variability may be caused by the different varieties that were sown
350 and/or different turnover rates for the enzymatic processes of respiration (Ryan, 1991). Similarly, the
351 potato cropping season of 2006 (red points in Fig. 2e) is seen to observe a different respiration rate
352 compared to the two other seasons. We believe it is because of the different cultivar sown during that
353 year (cv. Spunta) compared to 2014 and 2018 cropping seasons (cv. Draga). Bouma et al. (1992)
354 indicated that differences in potato leaf respiration rates between cultivars might be due to contrasted
355 general metabolic activity due to different optima for temperature. The maintenance coefficient a ,
356 which represents the dependence of maintenance respiration (per unit of dry matter) on nitrogen
357 content, is higher for potato compared to the two other crops (Table A4). This might be due to (i) the
358 lower variability of simulated N concentration in its aboveground tissues, (ii) the difference of
359 maintenance respiration rates between above- and belowground parts of the plant (Amthor, 1984), and
360 (iii) the energy cost associated to nocturnal carbohydrate export (proportional to the total dark
361 respiration) within starch-storing species (Bouma et al., 1995). Validation confirmed the model
362 pertinence (Fig. 2b, 2d, 2f and Table A4).

363 **3.2. Model performance**

364 The STICS model satisfactorily simulated the agronomic indicators that are involved in CO_2
365 fluxes computation: shoot biomass, yield, N concentration in the grain and evapotranspiration were all
366 well simulated (Fig. 3). We see on Figure 3 that the RMSE is largely dominated by its unsystematic
367 component, indicating that model errors are mainly related to data dispersion rather than due to a
368 systematic bias in the model (Willmott, 1981; Coucheney et al., 2015). For the soil organic carbon,
369 field observations were only made in 2007 and 2017, but they confirm that soil C content simulations
370 were realistic over the long-term period (Fig. A1). The ‘good’ simulation of daily evapotranspiration
371 ($EF = 0.65$), and the ‘very good’ simulation associated to the prediction of biomass and yield ($EF \geq$
372 0.88) and to N concentration in harvested organs ($EF = 0.73$ for the grain) provided a reliable basis
373 to further proceed with CO_2 fluxes modelling.



374

375 **Figure 3. Model performance for the main indicators over the 16-year dataset in Lonzée**
 376 **(Belgium).**

377 Calculation performance of daily GPP, RECO and NEE ranged from satisfactory to very good

378 (Fig. 3). Figure 4 illustrates the advantages of the approach allowing to distinguish the different pools

379 in GPP allocation (Fig. 4a) and RECO (Fig. 4b). For each cropping season, the dynamics of the

380 observed and simulated CO₂ fluxes (GPP, RECO and NEE) are available in Appendix A2. Globally,

381 we noticed that a bias in GPP estimation during the growth period was often concomitant with a

382 similar bias in RECO estimation; these underestimations are illustrated respectively on Fig. 4a and

383 Fig. 4b. As exemplified on Fig. 4c, these mismatches might compensate for each other and provide a

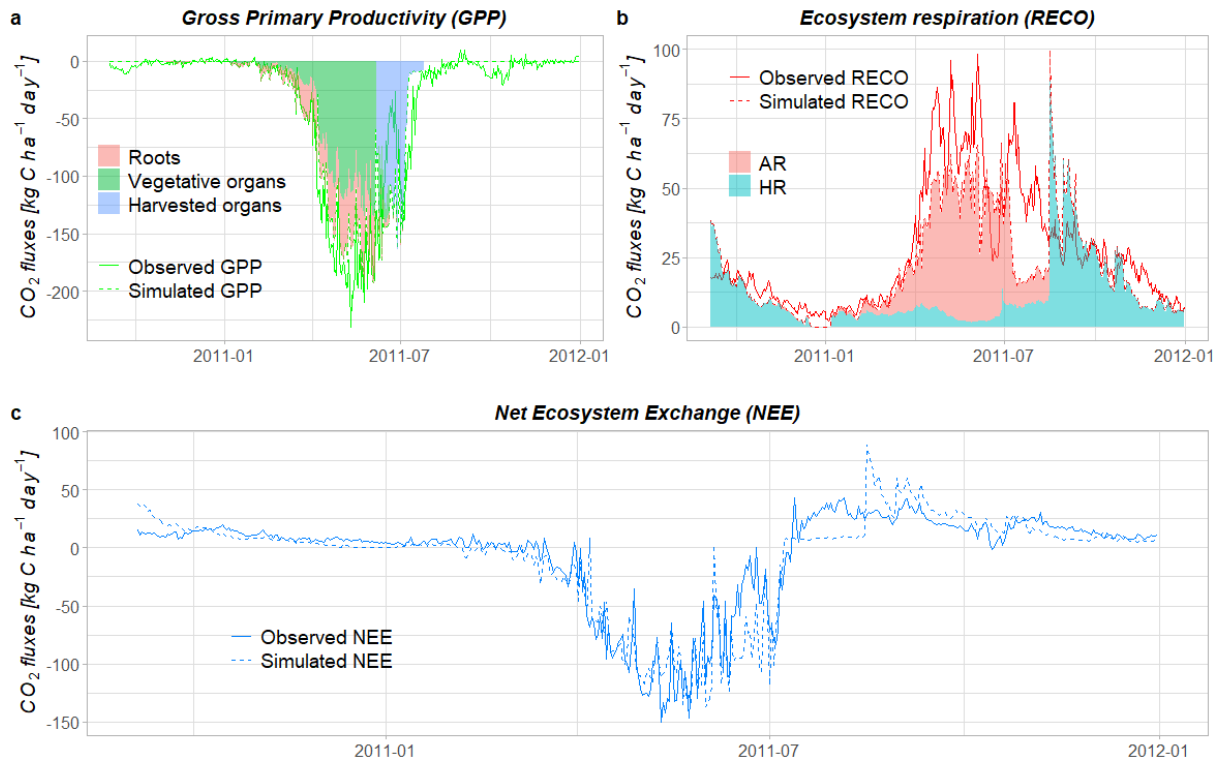
384 better estimation of NEE. For RECO, an underestimation of plant nitrogen content, that would induce

385 an underestimation of maintenance respiration, might be at play – see e.g. Fig. A2. However, too few

386 data were available for the validation of total plant N uptake over the different crops. Therefore, the

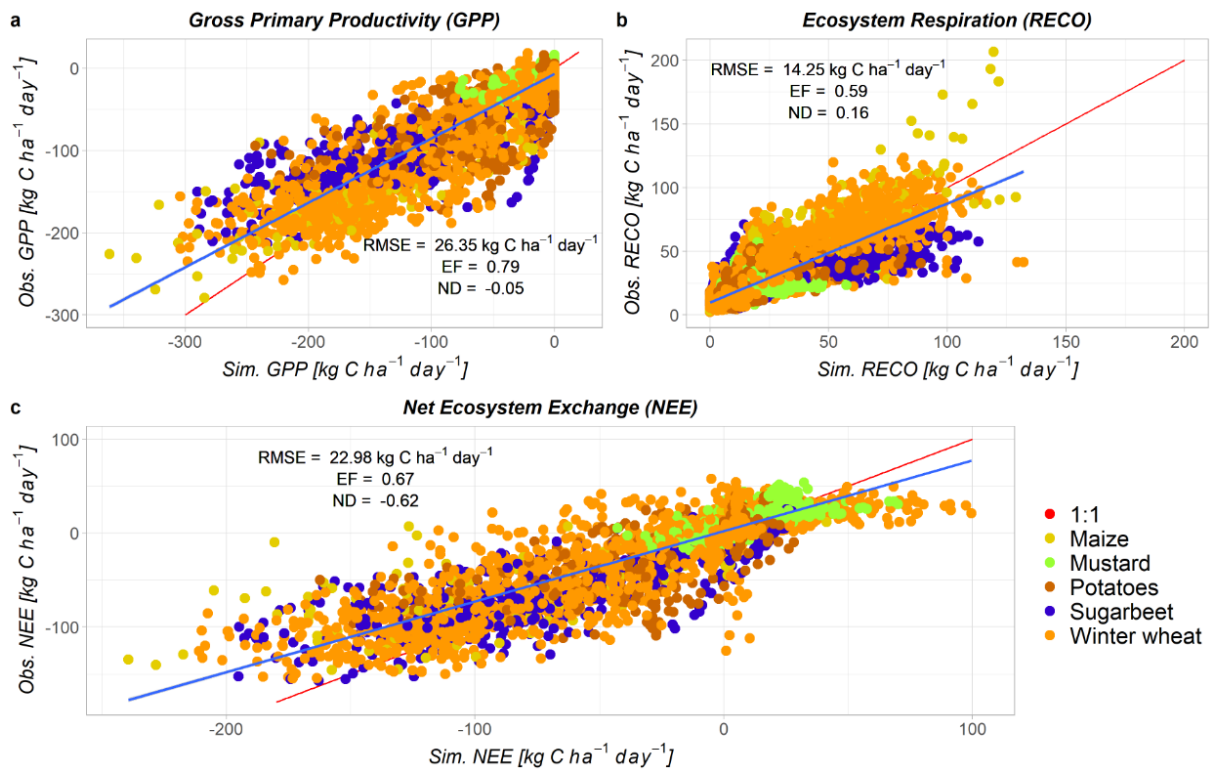
387 standard parameterization of each crop was used to simulate plant N uptake. We believe this might be

388 a point of attention for future researches and improvement of our methodology.



389

390 **Figure 4. Dynamics of the CO₂ fluxes related to NEE, GPP and RECO, observed and simulated,**
 391 **for the winter wheat cropping season of 2010-2011. For GPP and RECO, the contribution of the**
 392 **different pools or sources to the global fluxes are presented.**



393

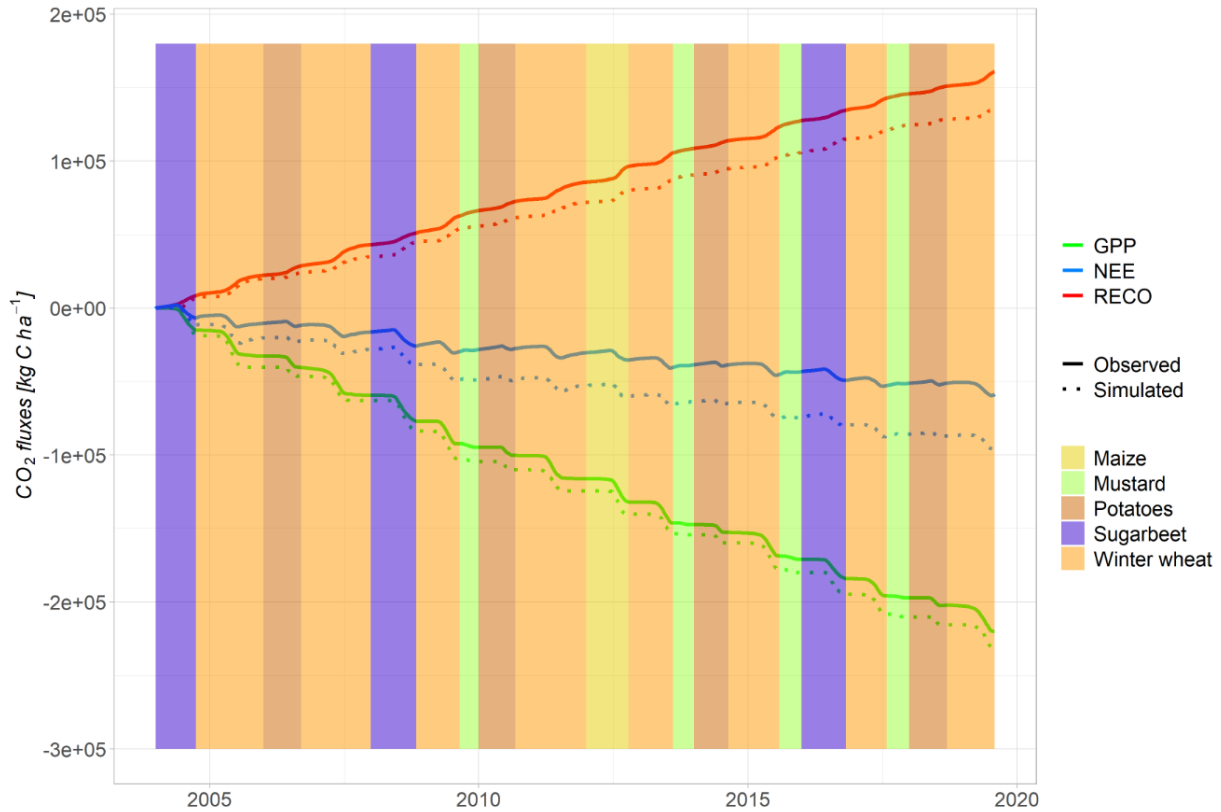
394 **Figure 5. Comparison between observations and simulations for a) GPP b) RECO and c) NEE.**
 395 **The red line represents the ideal 1:1 trajectory and the blue line designates the linear regression**
 396 **of observations-simulations pairs.**

397 All three global efficiencies for CO₂ fluxes simulation were satisfactory to very good (Table 1).
398 Yet while the model offered good results on RMSEs, EF and ND criteria, the goodness of fit
399 indicators c_2 and d_2 - respectively statistically different from 0 and 1 (Table 1) - suggest that the
400 model would benefit from additional calibration for plant parameterization. Potatoes and cover crops
401 results were slightly less satisfying than other crops (Table A5). For potatoes, this might be due to the
402 different varieties that were sown, all simulated with the same standard parameters. For cover crops,
403 few agronomic data such as LAI, biomass or N content were available to validate the simulations.
404 Underestimations of RECO were notably noticed for some cover crop seasons (Appendix A2). Hence
405 errors in CO₂ fluxes estimations can be ascribed to a bias in biomass and/or N content simulations at
406 daily time scale impacting the inferred calculations of CO₂ fluxes. Regarding future research, we
407 recommend to investigate further on the calibration related to the winter periods and/or cover crop
408 seasons. Indeed we noticed that RECO was also sometimes underestimated over the early winter
409 months of winter wheat seasons (Appendix A2). Since HR is predominant at these periods, it might be
410 valuable to explore further the parameterization of mineralization rates. Moreover, we used for cover
411 crops the coefficients between plant N concentration and maintenance respiration derived for winter
412 wheat, but we believe that specific calibration of these coefficients for mustard cover crop would be
413 helpful. We lacked data to investigate further these suggested improvements, but we believe they
414 might be worth to be explored in future work.

	GPP	RECO	NEE
RMSE	26.35	14.25	22.98
EF	0.79	0.59	0.67
ND	-0.05	0.16	-0.62
Intercept c_2	-6.82 [-7.48, -6.15]	9.73 [9.27, 10.19]	2.27 [1.76, 2.78]
Slope d_2	0.78 [0.78, 0.79]	0.78 [0.76, 0.79]	0.75 [0.74, 0.76]

415 **Table 1. Global performance indicators for CO₂ fluxes modelling. RMSE is given in [kg C ha⁻¹**

416 day^{-1}]. The coefficients of the regression of all daily points with simulated C flux in abscissa and
 417 observed one in ordinate axis, c_2 (in $[\text{kg C ha}^{-1} \text{ day}^{-1}]$) and d_2 , are given with their 95%-
 418 confidence interval.



419
 420 **Figure 6. Cumulated CO₂ fluxes for the whole 16-year period. We use as convention that fluxes**
 421 **towards the soil are regarded as negative and those leaving from the soil as positive.**

422 We see with Figure 6, that illustrates cumulated CO₂ fluxes for the 16-year period, and with ND
 423 criteria of Figure 5, summarized in Tables 1 and A5 (for separate crops), that the model might be
 424 considered as satisfying to elaborate the cumulated fluxes of a long-term and diversified crop rotation,
 425 with a global error equal to 5.12% for GPP (overestimated in absolute value) and 15.7% for RECO
 426 (underestimated). It is possible that our overestimation of GPP might be slightly greater than observed
 427 on Fig. 5 and Fig. 6 since the model does not consider weeds nor crop re-growth after harvest. Yet the
 428 observations might include the CO₂ fluxes they generate, and this tends to increase (in absolute value)
 429 GPP (Ceschia et al., 2010; Sus et al., 2010; Klosterhalfen et al., 2017; Pique et al., 2020).

430 ND was much greater for NEE (62.2%). This poor performance might be explained by the
 431 presence in daily NEE of both positive and negative values, leading to lower absolute mean value and
 432 therefore to a relative error much greater. However, in this case, reliable crop rotations NEE budgets
 433 would require, in view of the ND value associated to RECO, better estimates of HR (since NEE does

434 not involve AR), as already suggested above. This is in accordance with Vuichard et al. (2016) which
435 indicated that current crop models fail to establish precise net CO₂ fluxes budgets and that a bias in
436 NEE budgets is often explained by a bias in RECO. This suggests that the model is more suitable to
437 establish comparisons between crops, environments and management rather than to provide absolute
438 carbon budgets.

439 We compared our results with those obtained by the multi-models and multi-sites comparisons
440 of Sándor et al. (2020) and Wattenbach et al. (2010) (Table A6). Sándor et al. (2020) compared
441 individually 23 models at three different cropping sites, with full calibration based on data such as
442 biomass, phenology, soil temperature, moisture, mineral N, N₂O emissions and soil organic C and N
443 flux. They also compared the multi-model median (MMM) describing the models ensemble
444 performance (with some models specialized in one or two kinds of CO₂ fluxes). Wattenbach et al.
445 (2010) compared four models at five cropping sites. Globally, our approach performed better on
446 RECO, GPP and NEE, even if one must retain that our study dataset is limited to one experimental
447 site. Our approach is however outperformed for NEE prediction by the Soil Plant Atmosphere model
448 (SPA), which obtained better results for GPP and NEE in Wattenbach et al. (2010). This model is
449 specialized in predicting photosynthesis and water balance (Williams et al., 1996) and requires a
450 granular parameterization since it uses very fine temporal and spatial scales (30 min time step, ten
451 canopy and twenty soil layers, leaf-level photosynthesis and transpiration) (Williams et al., 2000;
452 Wattenbach et al., 2010).

453 We also compared our results with those of the ORCHIDEE-STICS model. It combines the
454 ORCHIDEE ecosystem model to STICS (Li et al., 2011). The main difference between ORCHIDEE-
455 STICS and our methodology lies in the calculation of maintenance respiration (MR), which we based
456 on a linear relationship between N content in biomass and MR with a Q_{10} -Van't Hoff equation
457 temperature dependence, whereas the ORCHIDEE model estimates MR as a function of the C:N ratio
458 of each tissue plus a linear increase with the temperature (Krinner et al., 2005). The ORCHIDEE
459 model also computes photosynthesis with a 30 min time step at the canopy scale. ORCHIDEE-STICS
460 was used at seven wheat cropping seasons in Vuichard et al. (2016) and five maize cropping seasons

461 in Li et al. (2011) (Table A6). Our approach performed globally better, both for winter wheat and
 462 maize, even if one must notice that studies concerned different agro-environmental conditions. When
 463 compared with the model ORCHIDEE-CROP, a small variant of ORCHIDEE-STICS, it appeared
 464 graphically -the study does not report indicators- that our approach performed better for estimating
 465 NEE for the 2006-07 wheat cropping season at the same experimental site of BE-LON (Wu et al.,
 466 2016).

467 **3.3. Roots NPP**

468 As detailed above, roots NPP was computed from shoot-root ratios rather than from root
 469 biomass simulated by STICS. This choice was motivated by the desire to use the standard version
 470 (v9.2) released, for generality and usability purposes. In that version, all crops are parameterized
 471 without dependence of root length expansion on shoot growth, which might be detrimental to roots C
 472 balance simulation. The proposed methodology allows to obtain reliable C simulations without any
 473 specific parameterization relative to plant roots. This is interesting because of the typical difficulty to
 474 gather roots experimental data. Our results reported that the importance of roots and rhizodeposition
 475 into global NPP ranges in average from 24.3% for winter wheat to only 2.15% for potato and 0.7% for
 476 sugarbeet. For wheat, this is in line with Bolinder et al. (2007), that estimated to 19.6% the relative
 477 proportion of NPP due to roots and rhizodeposition. For sugarbeet and potatoes, this is also consistent
 478 with Bolinder et al. (2015), that provided the shoot-root ratios that we used for these crops and
 479 estimated this relative proportion to 2.5% for potato and 1.7% for sugarbeet, suggesting that it is much
 480 lower for root crops than for other annual crops. However, whereas our objective was to estimate NPP
 481 continuously along the growing season, Bolinder et al. (2015) focused on estimating annual C inputs
 482 to soil, hence not considering for example coarse lateral roots that are attached to the beet (because it
 483 is removed at harvest). This suggests that roots NPP might be slightly higher for sugarbeet than
 484 estimated from our methodology.

485 **3.4. NEE inter-annual variability and relation to driving variables**

variable1, variable2	β_1		β_2		γ		R^2		p	
	Obs.	Sim.	Obs.	Sim.	Obs.	Sim.	Obs.	Sim.	Obs.	Sim.

Winter wheat cropping seasons (n = 8)										
NDAV	-150.63 (53.68)	-161.32 (25.38)	-	-	9314 (5533)	7485 (2645)	0.57	0.87	0.03**	7.1e-4**
Q _{cum}	-4.33 (2.79)	-15.95 (1.69)	-	-	-4261 (1866)	1340 (1127)	0.29	0.94	0.172	7.9e-5**
Q _{cum} , T _{air, av}	-4.21 (3.03)	-15.98 (1.85)	244 (611.1)	-74.78 (373.37)	-7777 (9034)	2418 (5519)	0.31	0.94	0.398	9.7e-4**
Potato cropping seasons (n = 4)										
T _{air, av}	174.7 (142.7)	198.3 (105.1)	-	-	-5491 (2419)	-6283 (1782)	0.43	0.64	0.288	0.199
Q _{cum} , T _{air, av}	-2.67 (3.18)	-2.33 (1.99)	137.1 (161.02)	165.46 (100.42)	-3863 (3262)	-4863 (2034)	0.67	0.85	0.579	0.389
Surgarbeet cropping seasons (n = 3)										
NDAV	-205.59 (64.69)	40.1 (133.8)	-	-	22798 (9950)	-15649 (18030)	0.91	0.08	0.194	0.815
T _{air, av}	1318.9 (460.5)	804 (1514)	-	-	-29639 (7202)	-23255 (23685)	0.89	0.22	0.214	0.689
SPEI-3 in month preceding harvest	-822.6 (1875.9)	-2602 (1041)	-	-	-9571 (2198)	-12731 (1220)	0.16	0.86	0.737	0.243
Cover crop periods (n = 4)										
NDAV	0.47 (3.74)	-27.29 (8.11)	-	-	214 (243)	1646 (537)	0.008	0.85	0.829	0.078*
Q _{cum}	1.42 (1.37)	-10.55 (3.72)	-	-	-199 (148)	703 (401)	0.35	0.80	0.408	0.105
Q _{cum} , T _{air, av}	1.23 (1.62)	-11.18 (3.93)	-84.5 (122.42)	-274.32 (297.27)	717 (1339)	3678 (3251)	0.56	0.89	0.663	0.328

486 **Table 2. Regression coefficients of the relation $NEE = \beta_1 \text{variable1} + \beta_2 \text{variable2}$ for the**
487 **different crops between crop emergence and harvest. Only the regressions that are significant (** p**
488 **< 0.05, * p < 0.1) or almost significant for at least the observations and/or the simulations are**
489 **displayed. β_1 is expressed in $\text{kg C ha}^{-1} \text{d}^{-1}$ with variable1 = NDAV, in $\text{kg C ha}^{-1} (\text{MJ m}^{-2})^{-1}$ with**
490 **variable1 = Q_{cum}, in $\text{kg C ha}^{-1} \text{°C}^{-1}$ with variable1 = T_{air, av} and in kg C ha^{-1} with variable1 = SPEI-3. β_2 is**
491 **expressed in $\text{kg C ha}^{-1} \text{°C}^{-1}$. Values between brackets are the standard errors of the coefficients.**

492 Globally, most significant correlations were found for winter wheat, which is explained by its
493 higher number of cropping seasons. Yet global trends were similar between crops.

494 For winter wheat and cover crops, NDAV was negatively correlated with NEE, indicating a
495 greater C sequestration when the number of active vegetation days increases (Table 2 and Fig. A3a).
496 Similar behaviour was reported by Ceschia et al. (2010) and Buysse et al. (2017), the latter reporting
497 an R²-value of 0.58 when considering all winter wheat cropping seasons between 2005 and 2015. This

498 result emphasizes the importance of extending the vegetation period whenever it is possible, e.g. by
499 early sowing or long cover crops, for greater environmental performance such as C sequestration.

500 Based on simulations, NEE was also correlated with the photosynthetic active radiation
501 intercepted by the canopy, Q_{cum} (Table 2 and Fig. A3b). The correlation was even stronger when the
502 regression also included air temperature. This relates to the positive influence of these two drivers on
503 crop growth. No significant correlation was found based on observations.

504 No significant correlations were found either between NEE and any SPEI. However, for
505 sugarbeet, a non-significant correlation ($R^2 = 0.86$, $p = 0.243$) between simulations and the SPEI-3,
506 based on the last 3 months preceding harvest (i.e. August or September), was suggested (correlation
507 significance is difficult to satisfy because of the low number of sugarbeet cropping seasons). A wetter
508 end of the cropping season, leading to a higher SPEI-3, was associated to an increase in C
509 sequestration, suggesting that the better water availability increased crop growth (Shrestha et al.,
510 2010).

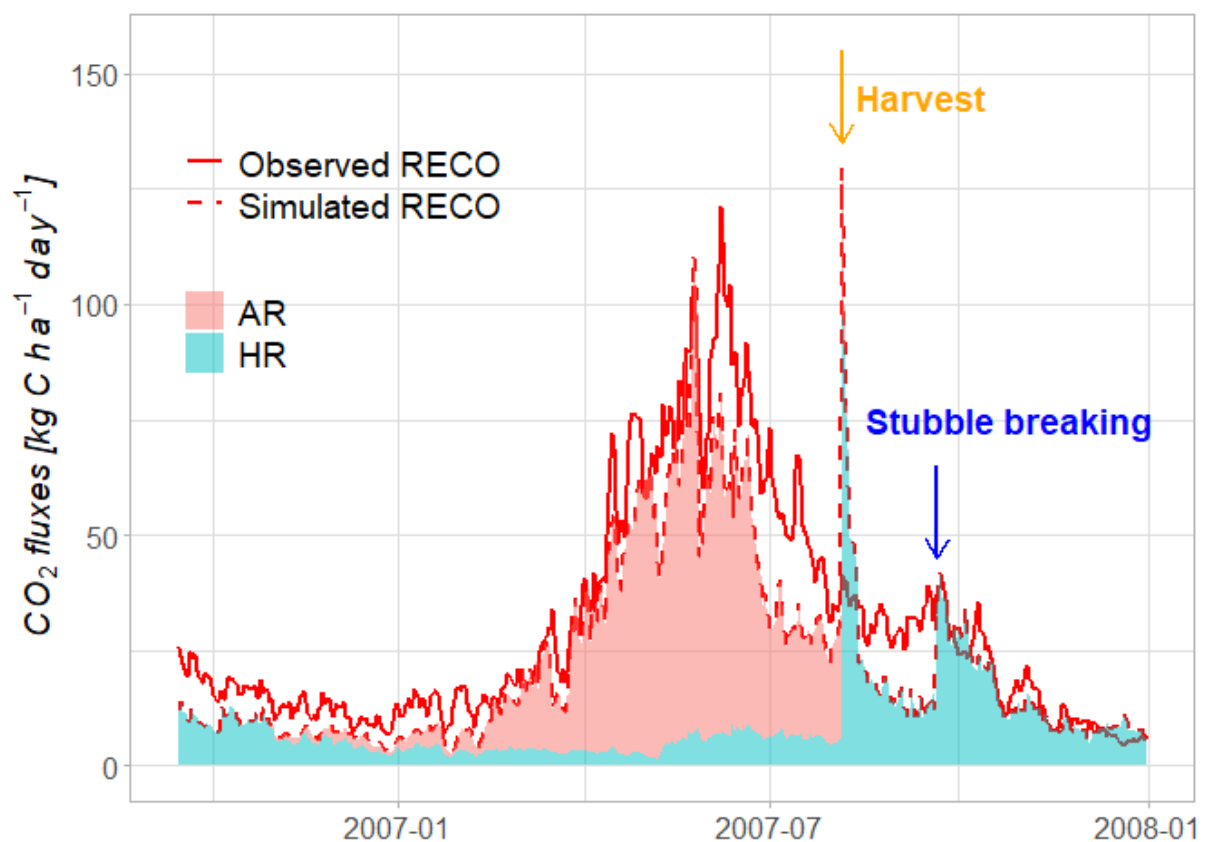
511 Globally, we observed that, except in some cases for potato and sugarbeet, correlations, even
512 when not significant, were higher when obtained from the simulated NEE than from the observed one.
513 The model is deterministic and process-based; therefore it is coherent that simulated physiological
514 processes and our new external algorithms are found to be correlated to driving variables. However, in
515 real life, external events might increase the dispersion of observed values and decrease the strength of
516 the correlation. Such events might be material failure, gap filling, wheat lodging that would slow down
517 maturity and increase the growing period, etc.

518 ***3.5. Respiration components***

519 **3.5.1 Influence of management operations on heterotrophic respiration**

520 As exemplified on Figure 7, we noticed that there was a systematic peak in simulated HR when
521 crops were harvested. We believe that this is associated to two modelling assumptions. Firstly, organic
522 residues mineralization rate might be overestimated, which would also explain the sudden peak at
523 stubble breaking not observed in the field. Indeed mineralization rates used in STICS were calibrated
524 on really finely crushed residues whereas crop residues in the field often form bigger pieces

525 (Nicolardot et al., 2001). STICS tends to overestimate carbon mineralization, and a previous
526 sensitivity analysis showed that the decomposition rate of residues has an influence on the shape of the
527 kinetics at the beginning of decomposition (Nicolardot et al., 2001). Secondly, in STICS v9.2, root
528 biomass is computed at harvest and returned to the soil as belowground residues. This might
529 contribute to the simulated HR peak at harvest, not observed in field data because part of the roots
530 actually died along the season before harvest.



531

532 **Figure 7. Ecosystem respiration during the 2006-07 season of winter wheat. The arrows show the**
533 **harvest (in orange) and the stubble breaking (in blue) dates.**

534 3.5.2 Contribution of autotrophic to total respiration

535 We compared the mean daily ratios of autotrophic respiration to total ecosystem respiration for
536 specific seasons (Table A7). The work of Suleau et al. (2011), performed at the same experimental site
537 of BE-LON with soil chambers, allows us to compare the respective importance of observed versus
538 simulated autotrophic and heterotrophic components of ecosystem respiration. The comparison

539 between observations and simulations gave very satisfying results (Table A7), except for potatoes for
540 which the difference was greater. The global AR/RECO ratios obtained for the different crops (Table
541 A7) seem to confirm the assumption of Buysse et al. (2017) which suggested that the autotrophic
542 contribution of sugarbeet to total ecosystem respiration is lower than the one for maize and winter
543 wheat. The reported domination of the autotrophic component of ecosystem respiration is also
544 confirmed by many studies such as Moureaux et al. (2008), Wang et al. (2015) and Demyan et al.
545 (2016). Suleau et al. (2011) suggested that this is due to the relatively low SOC level and limited
546 manure input which are typical of the loam region where BE-LON is situated.

547 **3.5.3 Influence of temperature on respiration components**

548 Partitioning of respiration allows us to investigate the influence of temperature on respiration
549 components. They all include a dependance on temperature in their calculation, directly for MR (Eq.
550 (5)) and for HR (with an exponential increase in mineralization rates with higher soil temperatures
551 (Brisson et al. (2009))), and indirectly for GR (depending on GPP and MR). Such a dependance is thus
552 induced by the parameters that we use in our methodology and in the STICS model, and can be
553 compared with field or lab experiments results. Figure A4 presents the evolution of AR and HR with
554 the soil temperature for winter wheat, the most represented crop in our dataset. Using Van't Hoff
555 equation, we obtained $Q_{10} = 2.49$ ($\in [2.3, 2.71]$ with 95%-confidence) for HR and $Q_{10} = 2.93$ (\in
556 $[2.74, 3.15]$) for AR. This contrasts with Suleau et al. (2011) which found a bigger correlation with
557 temperature for HR than for AR ($Q_{10} = 2.11$ for HR and $Q_{10} = 1.76$ for AR). They however utilized
558 only one crop season (against eight in our study) and warned that their results were difficult to
559 generalize. Zhang et al. (2020) suggested that soil respiration, including HR but also below-ground
560 AR, is largely influenced by soil temperature whereas above-ground AR is largely influenced by air
561 temperature. Very few studies investigate the autotrophic component of respiration, and as Suleau et
562 al. (2011), we believe that field or laboratory experiments that would directly measure AR (instead of
563 estimating it for example with root exclusion zones) would be helpful.

564 In an attempt to push further the analysis, we investigated the potential interactive effect of
565 respiration sensitivity to temperature with soil moisture. We found that the soil water content (SWC),

566 in the first horizon 0-30cm, was a factor significantly improving linear models that correlate AR/HR
567 with soil temperature ($R^2 = 0.51$ and $p < 0.01$ for AR, $R^2 = 0.34$ and $p < 0.01$ for HR). By taking the
568 first order derivative of these models with respect to soil temperature, it appeared that the sensitivity of
569 HR to soil temperature depends on SWC, but it is not the case for AR which includes above-ground
570 plant respiration (Fig. A5). This goes in line with Zhang et al. (2013) which also found a correlation
571 between HR and SWC but no significant impact of SWC on soil autotrophic respiration. We found
572 that the soil temperature significantly decreases as SWC increases ($R^2 = 0.32$, $p < 0.01$). Therefore
573 we would have expected that the temperature sensitivity of HR would decrease as SWC increases (and
574 not the opposite as illustrated with the brown line of Fig. A5), since a decrease of SWC is correlated
575 with an increase of soil temperature and that the mineralization rate exponentially increases with
576 temperature in the STICS model (Brisson et al., 2009). But this means that, in our temperate soil, the
577 effect of SWC on HR, inducing an increase in HR with increasing SWC, is more important than
578 temperature, as represented by the coefficients of the regression y_2 (Fig. A5). As suggested above with
579 Q_{10} relationships, the sensitivity of AR to soil temperature is almost always greater than for HR, except
580 when the soil water content is above field capacity, i.e. 30%. As Ding et al. (2007), we believe that
581 further study is required to investigate the interaction between soil moisture and temperature on CO_2
582 fluxes, which seems important for future modelling efforts.

583 **4. Conclusions**

584 The present study demonstrates that it is possible, from the outputs of a soil-crop model (STICS
585 in this study), to obtain a reliable estimation of CO_2 fluxes originating from a diversified crop rotation,
586 with model efficiencies ranging from satisfactory to very good. The genericity of the proposed
587 methodology makes it transferable to any soil-crop model. It computes separately the evolution of
588 photosynthesis (GPP) and ecosystem respiration (RECO). This could help verifying the partitioning of
589 the NEE observed with eddy covariance into GPP and RECO components, since many different
590 statistical flux-partitioning methods exist (Moffat et al., 2007; Desai et al., 2008; Smith et al., 2010;
591 Wohlfahrt and Galvagno, 2017). Moreover, the identification of autotrophic and heterotrophic
592 components of RECO is useful to predict the evolution of RECO with climate and/or soil- and crop

593 management (Trumbore, 2006). Measuring that on-field is not possible with eddy covariance and
594 requires the combined use of soil chambers (Suleau et al., 2011; Zhang et al., 2013; Whang et al.,
595 2015), that are time- and energy-consuming. Process-based models are key tools to extrapolate these
596 results. We emphasize the importance of delivering accurate simulations of biomass, yields and
597 nitrogen concentration prior reliable CO₂ fluxes estimations, with a particular attention to crop
598 residues management and operations that have a significative impact on these fluxes.

599 The model was proven to capture the inter- and intra-annual variability of CO₂ fluxes associated
600 to several environmental drivers. It turns out to be a suitable tool for investigating these trends
601 whereas field observations sometimes miss them because of the influence of external events or data
602 inconsistency. We believe that the proposed methodology might be used to project the CO₂ exchanges
603 of various crop rotations under different management schemes and climate change scenarios, to
604 investigate the impact of crop rotations on climate change but also their potential of adaptation and
605 mitigation.

606 Yet we believe that there is still room for improvement. A new version of STICS (v10) offers
607 the possibility to consider the daily N allocation to roots, as well as the daily computation of roots
608 mortality and soil restitution. It should help to use roots biomass simulations directly in NPP
609 computation. This might enhance our estimation of roots NPP which was based, for crops other than
610 winter wheat, on a constant average shoot-root ratio measured near plant maturity.

611 Further validation with other agricultural systems, such as crops in varied pedo-climatic
612 conditions but also grasslands, would be interesting to fully validate our methodology. A granular
613 analysis of the model performance under contrasted management practices might also be relevant (e.g.
614 tillage or cover crops). The ever increasing impacts of climate change should motivate us in
615 conducting such research for an ever better understanding of the role of agricultural systems in
616 ecosystem carbon exchanges.

617 **5. Declarations of interest**

618 The authors declare no conflicts of interest.

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625 **7. References**

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877

8. Appendices

878

A1. Supplementary Tables and Figures

Crops	Sowing date	Harvest date
Sugarbeet	30-03-04	29-09-04
Winter wheat	14-10-04	3-08-05
Potatoes	1-05-06	15-09-06
Winter wheat	13-10-06	5-08-07
Sugarbeet	22-04-08	4-11-08
Winter wheat	13-11-08	7-08-09
Cover crop (mustard)	1-09-09	1-12-09
Potatoes	25-04-10	5-09-10
Winter wheat	14-10-10	16-08-11
Maize	14-05-12	13-10-12
Winter wheat	25-10-12	12-08-13
Cover crop (mustard)	5-09-13	15-11-13
Potatoes	7-04-14	22-08-14
Winter wheat	15-10-14	2-08-15
Cover crop (mustard)	26-08-15	9-12-15
Sugarbeet	12-04-16	27-10-16
Winter wheat	29-10-16	30-07-17
Cover crop (mustard)	7-09-17	6-12-17
Potatoes	23-04-18	11-09-18
Winter wheat	10-10-18	30-07-19

879

Table A1. 16-year crop rotation at the experimental site of Lonzée (Belgium). More information is available in Buysse et al. (2017).

880

881

Crop		Roots + rhizodeposition coefficient
Winter wheat	Before maximal rate of leaf growth (end of juvenile phase)	1.5
	Between maximal rate of leaf growth and flowering	0.43
	After flowering	0.33
Sugarbeet		0.05
Potato		0.11
Maize		0.59
Mustard cover crop		0.2

882 **Table A2. Coefficient used to compute carbon pool contained in roots and rhizodeposition, as**
883 **described in NPP computation (Section 2.3.1). The coefficient is multiplied to aerial vegetative**
884 **organs biomass.**

885

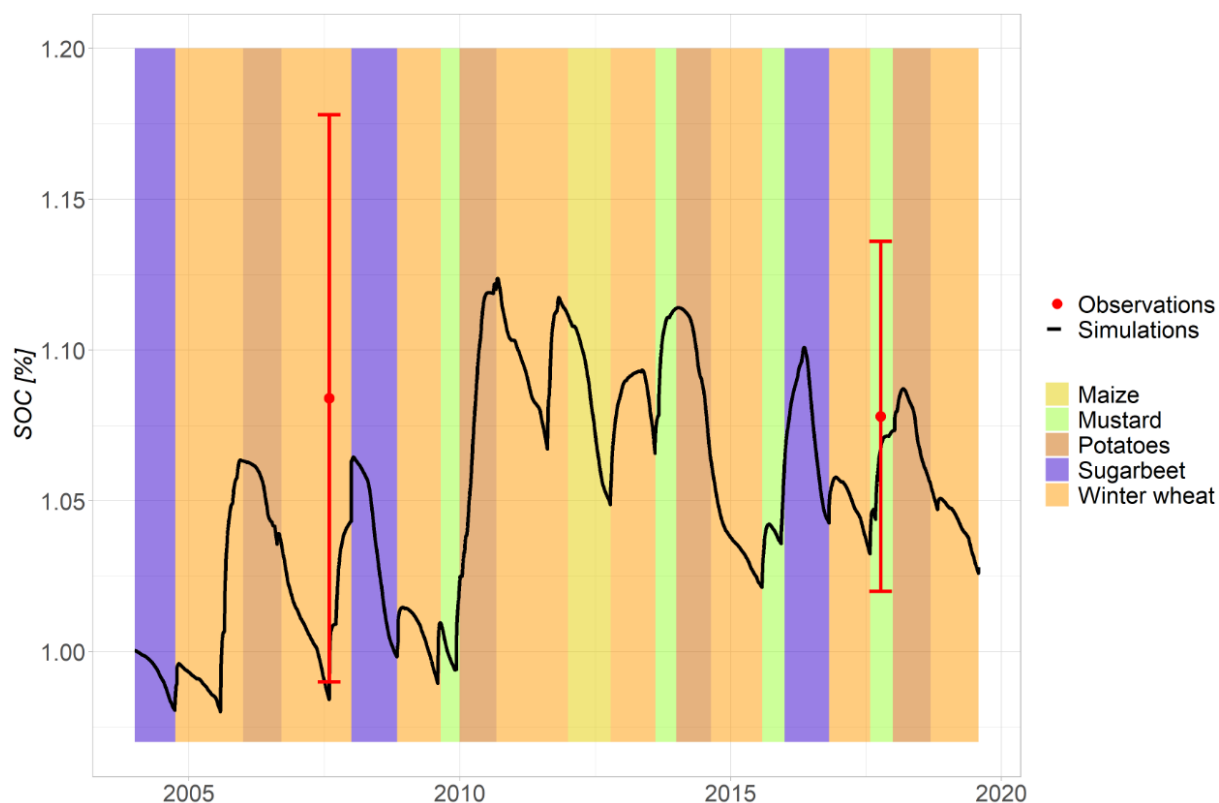
Crop	Crop seasons used for calibration	Crop seasons used for validation
Winter wheat	2004-05, 2006-07, 2012-13, 2016-17, 2018-19	2008-09, 2010-11, 2014-15
Sugarbeet	2008, 2016	2004
Potatoes	2006, 2014, 2018	2010

886 **Table A3. Calibration and validation sets for the fitting process used to compute coefficients of**
887 **maintenance respiration.**

888

Crop	Calibration			Validation		
	<i>a</i> [kg C ha ⁻¹ day ⁻¹ / % of N in the plant / kg DM]	<i>b</i> [kg C ha ⁻¹ day ⁻¹]	R ²	EF	ND	RMSE [kg C ha ⁻¹ day ⁻¹]
Winter wheat	3.18 (2.86, 3.51)	-0.87 (-1.32, -0.41)	0.43	0.66	0.08	142.8
Sugarbeet	2.15 (2.08, 2.23)	-1.10 (-1.23, -0.97)	0.92	0.78	0.14	159.8
Potatoes	8.90 (8.19, 9.6)	-6.91 (-7.65, -6.17)	0.72	0.82	-0.11	70.8

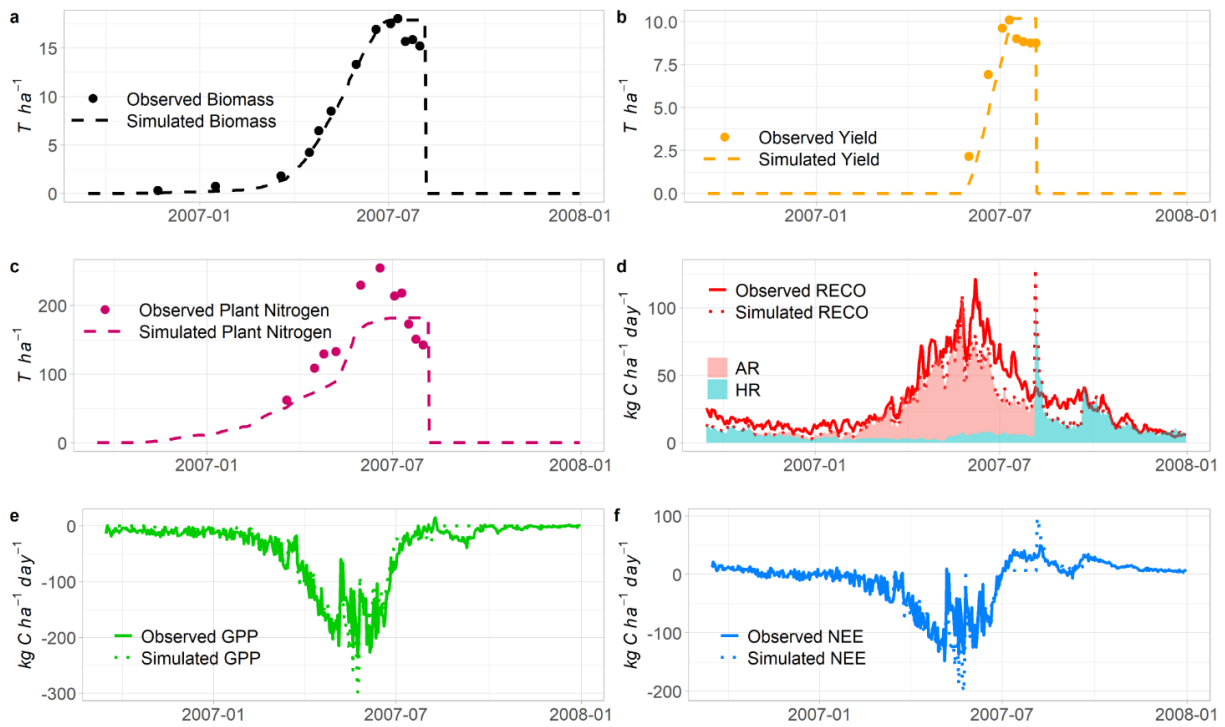
890 **Table A4. Linear regression of Eq. (9) results. The regression coefficients *a* and *b* are displayed**
891 **for each of the three crops fitted separately on calibration datasets, with their 95%-confidence**
892 **interval. Indicators EF, ND and RMSE show the model performance on an independent**
893 **validation dataset.**



894 **Figure A1. Soil organic carbon dynamics. The two field observations, in 2007 and 2017, are**
895 **given with their standard deviation.**

897

898



899

900 **Figure A2. Comparison between observations and simulations for a) total aerial biomass, b)**
 901 **yield, c) plant nitrogen content, d) RECO, e) GPP and f) NEE, for the winter wheat cropping**
 902 **season of 2006-2007.**

903

904

		RMSE [kg C ha ⁻¹ day ⁻¹]	EF	ND
Winter wheat	NEE	23.70	0.69	-0.59
	RECO	13.33	0.72	0.19
	GPP	24.17	0.85	-0.04
Potatoes	NEE	19.68	0.54	-5.53
	RECO	11.69	0.37	0.24
	GPP	25.44	0.60	0.07
Sugarbeet	NEE	25.36	0.69	-0.26
	RECO	18.07	-0.34	-0.11
	GPP	37.35	0.60	-0.18
Maize	NEE	32.92	0.36	-0.57
	RECO	20.32	0.72	0.27
	GPP	32.41	0.80	0.01
Cover crop	NEE	12.06	0.37	0.32

	RECO	12.25	-0.61	0.19
	GPP	8.85	0.56	0.08

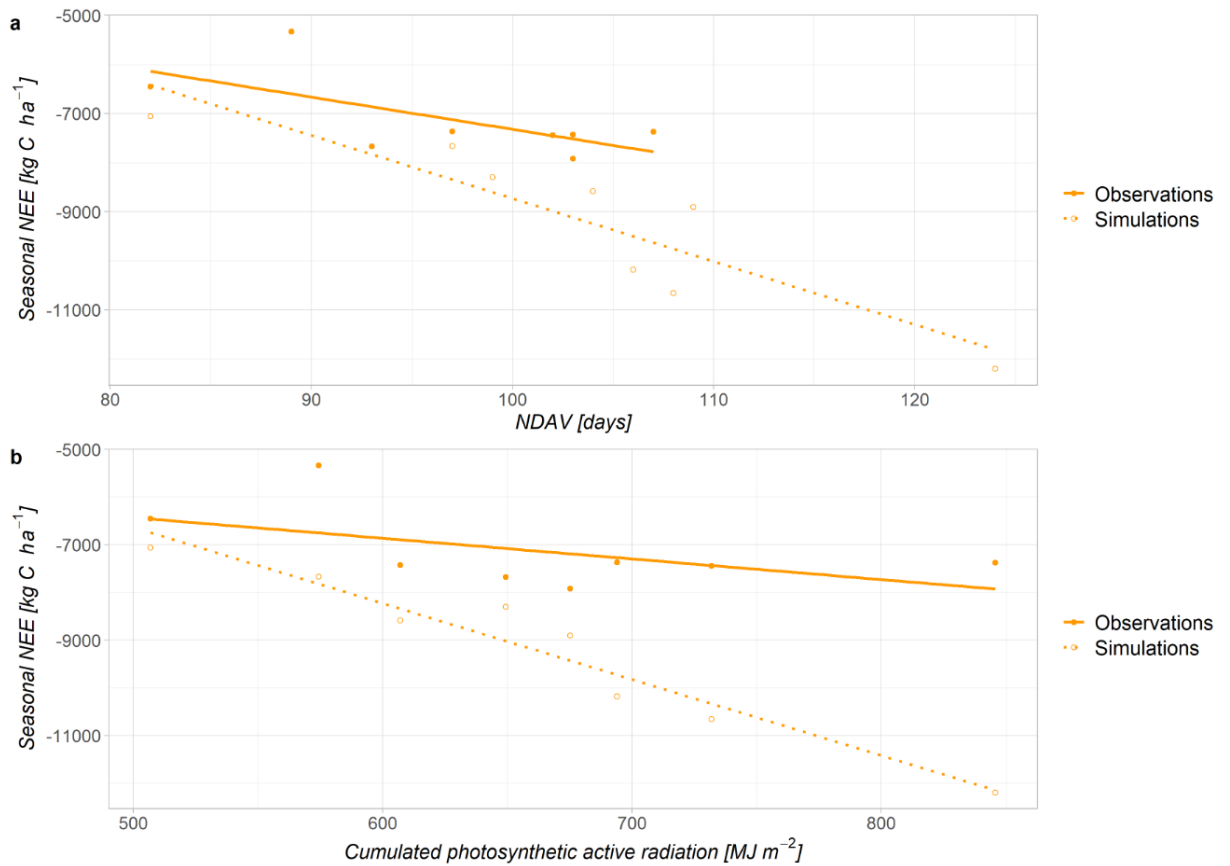
905

Table A5. Performance indicators for CO₂ fluxes modelling for the different crops.

ALL CROPS	Our results at Lonzée experimental site	Sándor et al. (2020) Model comparison	Wattenbach et al. (2010) Model comparison
Crops	Winter wheat, sugarbeet, potatoes, maize, mustard cover crop	Spring wheat, soybean, rapeseed, maize, spring wheat, triticale, phacelia, rice	Winter wheat
Crop sites	1	3	5
Total years of data	16	19	5
GPP	EF = 0.79	Best EF between 0.43 and 0.44 MMM EF between 0.32 and 0.58	Best mean EF = 0.69 Mean of mean EFs = 0.65
RECO	EF = 0.59	Best EF between -100.46 and 0.37 MMM EF between -3.53 and 0.03	Best mean EF = 0.44 Mean of mean EFs = -0.14
NEE	EF = 0.67	Best EF between 0.15 and 0.26 MMM EF between 0.22 and 0.55	Best mean EF = 0.76 Mean of mean EFs = 0.55
WINTER WHEAT	Our results at Lonzée experimental site	Vuichard et al. (2016) ORCHIDEE-STICS	
Crops	Subset with winter wheat	Winter wheat	
Crop sites	1	7	
Total years of data	8	7	
GPP	Mean R = 0.95 Best R = 0.97 Worst R = 0.88	Mean R = 0.91 Best R = 0.97 Worst R = 0.80	
RECO	Mean R = 0.89 Best R = 0.95 Worst R = 0.76	Mean R = 0.88 Best R = 0.95 Worst R = 0.76	
NEE	Mean R = 0.90 Best R = 0.95 Worst R = 0.80	Mean R = 0.87 Best R = 0.95 Worst R = 0.74	
MAIZE	Our results at Lonzée experimental site	Li et al. (2011) ORCHIDEE-STICS	
Crops	Subset with maize	Maize	
Crop sites	1	5	
Total years of data	1	5	
GPP	$R^2 = 0.88$	Mean $R^2 = 0.58$ Best $R^2 = 0.83$ Worst $R^2 = 0.32$	
RECO	$R^2 = 0.79$	Mean $R^2 = 0.42$ Best $R^2 = 0.81$ Worst $R^2 = 0.03$	
NEE	$R^2 = 0.72$	Mean $R^2 = 0.55$ Best $R^2 = 0.73$ Worst $R^2 = 0.23$	

907 **Table A6. Comparison of CO₂ fluxes simulations performance with other CO₂ fluxes simulations**
908 **studies. For the winter wheat, we used the goodness of fit indicator R as in Vuichard et al.**
909 **(2016), from Taylor (2001). For the maize, we used the goodness of fit indicator R^2 as in Li et al.**
910 **(2011). One must be aware that R^2 differs from the efficiency EF , used in this present study.**

911



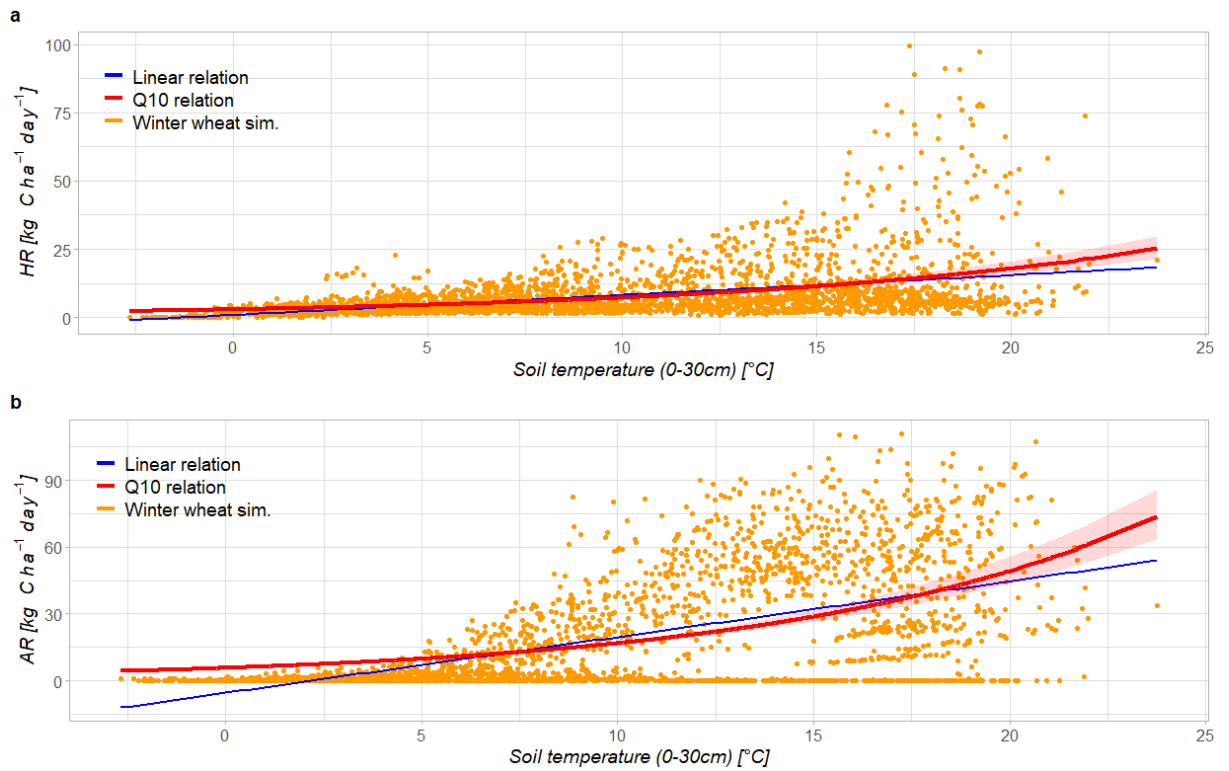
912

913 **Figure A3. Correlation between cumulated seasonal NEE and a) the number of days of active**
 914 **vegetation (NDAV) b) the cumulated photosynthetic active radiation intercepted by the canopy**
 915 **(Qcum), for winter wheat (WW) between emergence and harvest.**

916

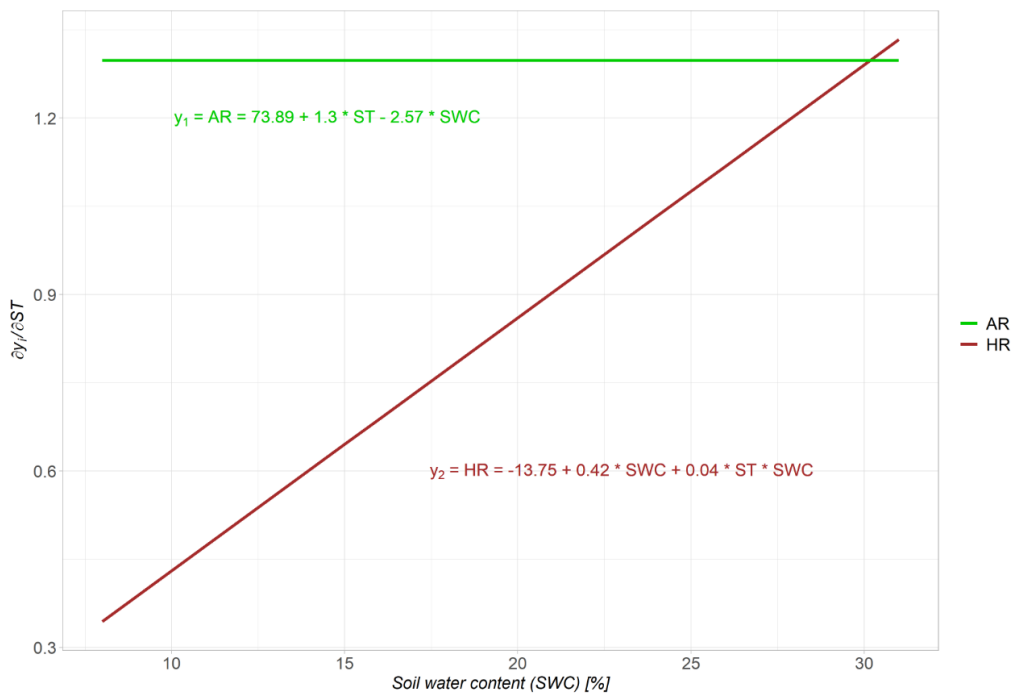
Crop season	Observed AR/RECO (Suleau et al., 2011)	Computed AR/RECO
Potatoes 2006 (DOY 153-220)	67%	81%
Winter wheat 2006-07 (DOY 92-200)	89%	89%
Sugarbeet 2008 (DOY 136-262)	62%	64%
Computed total AR/total RECO (between emergence and harvest)		
Maize	81.9%	
Potatoes	64.8%	
Winter wheat	80.6%	
Sugarbeet	76.8%	

917 **Table A7. Ratios of AR to RECO. For the single seasons, means were computed over the**
 918 **observations periods of Suleau et al. (2011). For the global crop percentages, means were**
 919 **computed between crop emergence and harvest.**



920

921 **Figure A4. Correlation between daily respiration components (HR and AR) and soil temperature**
 922 **(over the soil profile 0-30cm) for winter wheat. The Q10 relationship is represented with its 95%-**
 923 **confidence interval.**



924

925 **Figure A5. Temperature sensitivity for AR and HR as a function of soil water content in the first**
 926 **horizon (0-30cm). The sensitivity is expressed as the first order derivative of the linear models y_1**
 927 **and y_2 with respect to soil temperature. The x -axis takes the range of simulated SWC values**
 928 **throughout the whole experiment.**

929 ***A2. Comparisons between observed and simulated CO₂ fluxes***

930 For each cropping season, the dynamics of the observed and simulated CO₂ fluxes (GPP, RECO
931 and NEE) are available in the following shared repository:
932 <https://doi.org/10.6084/m9.figshare.23540472>.

933 ***A3. STICS simulations data***

934 All inputs and outputs, soil and plant parameterization and crop management files that were
935 used for simulating the BE-LON field experiment with the soil-crop model STICS are available in the
936 following shared repository: <https://doi.org/10.6084/m9.figshare.23260772>.

937