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1 Coupling biophysical and micro-economic models to
2 assess the effect of mitigation measures on greenhouse
3 gas emissions from agriculture

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Abstract

Agricultural soils are a major source of atmospheric nitrous oxide (N₂O), a potent greenhouse gas (GHG). Because N₂O emissions strongly depend on soil type, climate, and crop management, their inventory requires the combination of biophysical and economic modeling, to simulate farmers' behavior. Here, we coupled a biophysical soil-crop model, CERES-EGC, with an economic farm type supply model, AROPAj, at the regional scale in northern France. Response curves of N₂O emissions to fertilizer nitrogen (Nf) inputs were generated with CERES-EGC, and linearized to obtain emission factors. The latter ranged from 0.001 to 0.0225 kg N₂O-N kg⁻¹ Nf, depending on soil and crop type, compared to the fixed 0.0125 value of the IPCC guidelines.

The modeled emission factors were fed into the economic model AROPAj which relates farm-level GHG emissions to production factors. This resulted in a N₂O efflux 20% lower than with the default IPCC method. The costs of abating GHG emissions from agriculture were calculated using a first-best tax on GHG emissions, and a second-best tax on their presumed factors (livestock size and fertilizer inputs). The first-best taxation was relatively efficient, achieving an 8% reduction with a tax of 11 €/t-CO₂-equivalent, compared to 68 €/t-CO₂ eq for the same target with the second-best scheme.

Keywords: nitrous oxide, agro-ecosystem model, economic modeling, greenhouse gas, mitigation measures

Abbreviations: GHG – Greenhouse Gas ; Nf – Fertilizer nitrogen ; IPCC – Intergovernmental Panel on Climate Change ; CAP – Common Agricultural Policy ; FADN – Farm Accountancy Data Network ; t-CO₂-eq – t DM-CO₂-equivalent ; LU – Livestock Unit; CERES-EGC: agro-ecosystem model simulating N₂O emissions; STICS: agro-ecosystem model simulating crop yields; AROPAj: economic farm model including GHG emissions; NOE: algorithm predicting N₂O emissions from soil drivers.

1 Introduction

1.1 N₂O emissions in agriculture

The global abundance of nitrous oxide (N₂O) in the atmosphere was 319.2 ppb in 2004, and had been increasing at a rate of 0.74 ppb per year over the past decade WMO and WDCGG (2006). Nitrous oxide is a potent greenhouse gas, with a global warming potential about 300 times higher than the carbon dioxide (CO₂). It is the third contributor to anthropogenic global warming, after CO₂ and methane (CH₄). Nitrous oxide is naturally emitted from soils and oceans, but human activities also contribute a third of its overall release (WMO and WDCGG, 2006). Policy measures aiming at abating anthropogenic emissions of N₂O are thus being actively sought. At the country level, the agricultural sector is generally the first anthropogenic source of N₂O. In France, its share was estimated at 76% in 2004 (CITEPA, 2008), when summing the emissions related to land-use and to the use of synthetic fertilizer nitrogen (Nf). Agricultural N₂O emissions are known to depend on Nf inputs of to a large extent (Houghton et al., 1996). Besides, excessive use of fertilizer N is also responsible for the increase of nitrate leaching (Beaudoin et al., 2005; Schnebelen et al., 2004) and ammonia (NH₃) emissions (Herrmann et al., 2001). Nitrate pollution of groundwater is a well-known environmental problem, particularly harmful for aquatic ecosystems, while NH₃ is a major atmospheric pollutant with impacts on atmospheric chemistry and on the stability and the biodiversity of terrestrial and aquatic ecosystems (Asman et al., 1998). However, the emission of these reactive N compounds are not solely related to fertilizer inputs, inasmuch as they occur throughout the N cycle in the soil. Complex processes involving soil microbiology affect the dynamics of inorganic and organic forms of nitrogen in the soil, with the result that N losses by arable systems are tightly related to environmental conditions, and chiefly climatic sequence and soil type.

66 **1.2 Coupling economic and biophysical models to assess N₂O emissions**

67 The Kyoto protocol (1997) is an agreement made under the United Nations Framework Conven-
68 tion on Climate Change. It requires signatory countries to inventory and report emissions for a
69 set of greenhouse gases (GHG), including N₂O on an annual basis to monitor their time course.
70 Guidelines were set up by the Intergovernmental Panel on Climate Change (IPCC) to help these
71 countries in their national inventories (Houghton et al., 1996), with a tiered approach. The sim-
72 plest and most used methodology provided by the IPCC (Tier 1) relies on generic, fixed factors
73 to convert national statistics on economic activities into GHG emissions. Because these factors
74 are default ones, they should not be considered as an exclusive standard. Caution is expressed in
75 the guidelines regarding "the default assumptions and data which are not always appropriate for
76 specific national contexts". The development of alternative methodologies, as permitted under
77 the Tiers 2 & 3 of the latest IPCC guidelines (IPCC, 2006), thus appears as a promising way to
78 assess GHG emissions more accurately.

79
80 The major shortcoming of the IPCC default method lies in its ignoring the complexity of the
81 microbiological processes responsible for N₂O emissions (nitrification and denitrification; Fire-
82 stone and Davidson 1989). Also, it is necessary to take into account the effects of soil charac-
83 teristics, climate, crop management and land use in the assessment of the N₂O emissions (Granli
84 and Bockman, 1995; Smith et al., 1998; Ruser et al., 2001), and their variability in both space
85 and time (Kaiser et al., 1998; Dobbie et al., 1999; Smith et al., 2004).

86 Contrary to the IPCC Tier 1 method, biophysical soil-crop models have the potential to deal with
87 these drivers, and may be used to assess more accurately the amounts of N₂O emitted from agri-
88 cultural soils, in relation to crop management (Neufeldt et al., 2006). As those models integrate
89 the complexity of nitrogen cycles pathways in the soil-crop-atmosphere system, they are also
90 expected to provide a rather fine assessment of other forms of N losses as well (among which

91 NO_3^- , NH_3 and NO). However, while there exist spatially-explicit maps for the biophysical input
92 parameters of these models (including soil properties and climatic data), information on crop
93 management on the same mapping units proves much more challenging to infer because of the
94 variety of agricultural production systems present within a given geographical zone. Such data
95 are usually obtained through field surveys, regional statistics or farm accountancy data, but their
96 scales do not match that of the spatial units relevant to the biophysical processes at stake (Leip
97 et al., 2008). Intersecting the two levels practically implies the use of agricultural fields as ele-
98 mentary objects. Economic models at the farm level provide a unique means of predicting and
99 scaling down management data from aggregated statistics. Coupling economic and biophysical
100 models has therefore emerged as a promising route to address the environmental impacts of agri-
101 culture and their regulation (Vatn et al., 1999; Godard et al., 2008), tackling the issue of spatial
102 and temporal variability in environmental losses. However, because economic and biophysical
103 models do not operate at the same level, disaggregation techniques are required to generate man-
104 agement information at the scale relevant to biophysical processes. These include econometrics,
105 Bayesian inference of spatial distribution parameters based on physical co-variables (Leip et al.,
106 2008), and expert knowledge (Godard et al., 2008; Godard, 2005).

107

108 Recent work has underlined the usefulness of such coupling in the estimation of GHG emissions
109 from agriculture at regional (Neufeldt et al., 2006) to continental (Leip et al., 2008) level. The
110 latter authors fed outputs from economic modeling of agricultural activities at farm or regional
111 level to a biophysical model, DNDC (Li et al., 1992), to predict the GHG balances of statistically
112 representative farms or homogeneous simulation units. They highlighted the large variability of
113 N_2O emissions across landscape, soil, climate characteristics and farming systems. However,
114 they did not address the effects of taking this variability into account when designing policies to
115 regulate GHG emissions from agriculture, which is the focus of this paper. In principle, it should

116 allow more accurate studies on the effects of public policies, because agro-ecosystem models
117 can deal with heterogeneities occurring at finer scales.

118 **1.3 Modeling the efficiency of mitigation measures for greenhouse gas emis-** 119 **sions from agriculture**

120 For countries having ratified the Kyoto Protocol, there is a need to investigate the efficiency of
121 GHG mitigation measures, including their economic costs. Economic models have a capacity to
122 simulate the impact of various policy scenarios of the agricultural sector, in our case. Coupling
123 them with biophysical agro-ecosystem models is thus a promising way to appraise the efficiency
124 of pollution mitigation policies, and of GHG emissions in particular. Economic regulation aim-
125 ing at mitigating environmental damage leads to consider two standardized taxing schemes: a
126 first-best scheme levying a tax on the direct damage, such as the quantity of pollutants dumped
127 into the environment; and a second-best scheme taxing the presumed factors of the damages in-
128 curred (Henry, 1989; De Cara and Jayet, 2000b). First-best taxing allows a very tight linkage
129 with damages, and thereby theoretically the best economic efficiency in its abatement. It usu-
130 ally refers to an ideal world where information is fully accessible and transaction costs are as
131 small as possible. Although the underlying assumptions are never satisfied in the real world, the
132 first-best option provides the 'best possible world' reference. Namely, in our case, this situation
133 refers to a world where farmers do actually optimize their N fertilizing level to maximize their
134 profit, based on their knowledge of the relationships between yield and GHG emissions and Nf
135 rates. It implies they would make the most of the information currently provided to AROPAj
136 by the biophysical models. This reference corresponds to what could be expected in terms of
137 welfare, including environmental economics, when the best options are implemented into the
138 system. However, it requires a detailed knowledge of the actual damage, an information which
139 is very costly if not impossible to obtain. In practice, it is thus more convenient to consider the

140 production factors presumed to be responsible for the damage, which may be better-known and
141 measurable. This leads to the implementation of a second-best taxation, which usually results
142 in a loss in the efficiency of the mitigation measure ¹. Second best options are obviously more
143 relevant for policy makers, and incur a loss of welfare which is interesting to assess. Here, we
144 investigated two possible measures for the reduction of GHG emissions from agriculture, using
145 either a first-best tax on the GHG emissions or a second-best tax on their presumed management
146 factors.

147

148 Godard et al. (Godard et al., 2008; Godard, 2005) coupled the biophysical crop-model STICS
149 (Brisson et al., 1998) and the economic farm type model AROPAj (De Cara and Jayet, 2000a),
150 which is based on the European data of the Farm Accountancy Data Network (FADN; see section
151 2.2 for a detailed presentation). This linkage made it possible to simulate the response of crop
152 yields to fertilizer nitrogen (Nf), in various regions of the European Union (EU), and thereby
153 predict the effect of various GHG emissions taxation scenarios on farmers' crop management
154 practices. Currently, with the AROPAj model, the consequences in terms of GHG emissions at
155 the farm type level were estimated using the optimized Nf doses and the IPCC default emission
156 factor of 1.25% for N₂O (whereby 1.25% of applied Nf is evolved as N₂O).

157

158 Here, we set out to further the analysis by using a biophysical crop model to predict the N₂O emis-
159 sions, instead of the fixed emission factor of the IPCC Tier 1 methodology. Such an approach
160 allows for improved relationships between farming activities and N pollution, and should ben-
161 efit the economic analysis of GHG emissions and mitigation. This is especially relevant since
162 agriculture is a major contributor to N₂O emissions. This paper thus focuses on the derivation of
163 N₂O emission functions and on the impact of their implementation in an agricultural economic
164 model, regarding GHG emissions and the efficiency of two GHG taxation schemes. Ideally, the

165 same biophysical model could have been used to simulate both the response of crop yields
166 to Nf and the emissions of N₂O. However, because the STICS model does not simulate N₂O
167 emissions as yet, we had to use another one for N₂O. We selected the CERES-EGC crop model
168 (Gabrielle et al., 2006a) for the coupling, as it struck a good balance between process description
169 level and ease of use.

170 The objectives of this work were thus three-fold: i/ to build response curves relating N₂O emis-
171 sions from cropland to fertilizer N application rates using the CERES-EGC model, ii/ to input
172 these results to the economic model AROPAj to assess the regional N₂O emissions from agricul-
173 ture, and iii/ to investigate the effects of various mitigation measures. We focused on the Picardie
174 region in Northern France, but the following methodology could easily be extrapolated to any
175 FADN region within the EU.

176 **2 Materials and Methods**

177 **2.1 The biophysical model CERES-EGC**

178 CERES-EGC was adapted from the CERES family of soil-crop models, which have been ex-
179 tensively tested worldwide for more than 20 years (see Jones et al. (2005) for a review). This
180 particular version focuses on environmental outputs (nitrate leaching, gaseous emissions of N₂O,
181 ammonia and nitrogen oxides). It comprises sub-models that simulate the major processes gov-
182 erning the cycles of water, carbon and nitrogen in soil-crop systems, on a daily time step. A
183 physical module simulates the transfer of heat, water and nitrate down the soil profile, as well
184 as soil evaporation, plant water uptake and transpiration in relation to climatic demand. Water
185 infiltrates down the soil profile following a tipping-bucket approach, and may be redistributed
186 upwards after evapo-transpiration has dried some soil layers. In both of these equations, the
187 generalized Darcy's law has subsequently been introduced in order to better simulate water dy-
188 namics in fine-textured soils. A microbiological module simulates the turnover of organic matter

189 in the plough layer, involving both mineralization and immobilization of inorganic N (Gabrielle
190 and Kengni, 1996). Ammonia volatilization is calculated using a classical resistance model for
191 turbulent transport between the soil surface and the atmosphere, and physico-chemical equilib-
192 riums in the liquid and gaseous phases of the topsoil, as a function of soil pH and ammonium
193 concentration. The model is available for a wide range of crops, and was tested against experi-
194 mental data for a broad range of agronomic and pedoclimatic situations, mostly in France and in
195 Europe, for the simulation of crop yields, soil water and N dynamics, nitrate leaching, or gaseous
196 losses (Gabrielle and Kengni, 1996; Gabrielle et al., 2002; Rolland et al., 2008). In particular, it
197 was used to simulate N₂O emissions from wheat crops at the field and regional scales (Gabrielle
198 et al., 2006a,b; Gabrielle and Gagnaire, 2007), using a large database of field-scale observations
199 over Northern France (Lehuger et al., 2008). Figure 1 presents a general schematic of the model,
200 with the various modules involved.

201

202

203

[Figure 1 about here.]

204 NOE is the semi-empirical sub-model used in CERES-EGC to simulate the production and re-
205 duction of N₂O in agricultural soils (Hénault et al., 2005). NOE simulates N₂O release through
206 the denitrification and nitrification pathways. The total denitrification of soil NO₃⁻ is calculated
207 as the product of a soil-specific potential rate with three unit-less factors related to soil water
208 content, nitrate content and temperature. The fraction of denitrified nitrate that evolves as N₂O is
209 then considered as constant for a given soil type. Nitrification is modeled as a Michaëlis-Menten
210 reaction, with NH₄⁺ as substrate. The corresponding rate is multiplied by unit-less modifiers
211 related to soil water content and temperature. A soil-specific proportion of total nitrification
212 evolves as N₂O.

213 **2.2 The AROPAj economic farm-type model**

214 AROPAj is a linear programming model which simulates the agricultural supply of the European
215 Union regions (De Cara and Jayet, 2000a; Godard et al., 2008). For a given economic situation
216 (i.e. a set of prices, taxes and policy measures), it provides an assessment of the type and amount
217 of the agricultural products delivered on the markets. This model is mostly used to study the
218 successive reforms of the Common Agricultural Policy (CAP) of the European Union (Jayet and
219 Labonne, 2005), but it has been used also to address global agro-environmental problems such
220 as agricultural GHG emissions (De Cara et al., 2005).

221

222 AROPAj is built as a set of independent sub-models, each of them simulating the behavior of
223 a category of producers as related to a 'farm-type' (Chakir et al., 2005). The farm types result
224 from the clustering of individual farms described in the Farm Accounting Data Network (FADN),
225 using (i) FADN normalized farm types, (ii) elevation class, and (iii) normalized economic size.
226 Clustering is done at the FADN-Region level. Farm types are weighted by a parameter estimated
227 through the individual weights provided by the FADN. These farm types are statistically repre-
228 sentative of actual production systems at the regional level, and reflect the behavior of the farmers
229 assuming that they optimize their gross margin. A detailed presentation of the AROPAj model
230 is available in (Chakir et al., 2005; De Cara and Jayet, 2000a), while additional information is
231 also provided by deliverables from the GENEDEC project¹. In the version of the AROPAj model
232 used in this study, French agriculture is divided into 131 farm types, among which 4 are located
233 in the Picardie Region.

234 Figure 2 presents a schematic of the AROPAj model, detailing its input parameters, constraints,
235 and outputs. The variables taken into account in AROPAj include the area of each crop (among
236 a total of 32 crop activities), the livestock size per animal type (with 31 pre-defined classes),

¹<http://www.grignon.inra.fr/economie-publique/genedec/eng/enpub.htm>

237 the quantity of meat, milk, grains or other crop types produced, the quantity of animal feed pur-
238 chased, and the opportunity cost of land.

239

240

241

[Figure 2 about here.]

242 AROPAj includes a GHG calculation module inventorying around 20 sources of CH₄ and N₂O
243 from livestock and arable farming, based on the IPCC Tier 1 guidelines. Methane is produced
244 by enteric fermentation of mono-gastric livestock, manure management, and rice cultivation. Ni-
245 trous oxide is mostly produced by agricultural soils as a result of mineral Nf application, manure
246 application as well as soil incorporation of crop residues. The model assumes that the most im-
247 portant factors behind GHG emissions may be assumed to be livestock size (for CH₄ and N₂O),
248 and nitrogen fertilizer use (for N₂O) (De Cara et al., 2005). By default, N₂O emissions from
249 soils are assumed proportional to Nf inputs (Bouwman, 1996), ignoring the background emis-
250 sions (considered non-anthropogenic). Thus, N₂O emissions represent a fixed fraction of the
251 inputs. This fraction, referred to as the emission factor, is set to 1.25% by default in the Tier 1
252 methodology (Houghton et al., 1996). However, the emission factor may be varied in AROPAj,
253 in order to explore alternative estimation methods.

254

255 In the implementation of AROPAj we used, it is important to note that the utilized arable area
256 for each farm-type is constant. Also, cattle farmers have the possibility to adjust their livestock
257 within a range from 85% up to 115% of their initial size. Within AROPAj it is possible to in-
258 troduce various mitigation measures, such as taxes on GHG emissions, on animals or on the
259 fertilizer N use, and to examine their effects on the model outputs.

260 **2.3 Coupling CERES-EGC and AROPAj**

261 **2.3.1 Principles of the coupling : Nf-response curves**

The coupling is based on the introduction in AROPAj of two mathematical relationships, relating Nf rates to crop yields and N₂O emissions, respectively. The former were generated with the methodology developed by Godard et al. (2008), by running the STICS model over a range of Nf rates for various possible combinations of other crop production factors (soil type, crop management practices, climate) specific to each farm type. The methodology to determine those factors and the input data is detailed in Godard et al. (2008). Thus, a series of points (Nf rate and crop yield) were obtained for each crop in all farm types, and an exponential function was fitted to these series. Such a form of function met economic requirements for the estimation of a mathematical optimum (ie, a concave shape with 1st derivative greater than 0), being altogether consistent with the expected agronomic response (Godard et al., 2008). Hence, the following function was selected :

$$Y(Nf) = Y_{max} - (Y_{max} - Y_{min}) \times e^{-\tau Nf} \quad (1)$$

262 where Y(Nf) is the crop yield (in t ha⁻¹), Nf is the fertilizer N rate (kg N ha⁻¹), τ the rate of
263 increase (curvature) of the yield function, and Ymin and Ymax are the minimum and maximum
264 (asymptotic) yields, respectively. This relationship was derived by running the STICS model
265 with the same input data and adjustment procedure as Godard et al. (2008).

266

267 The relationship between N₂O emissions and Nf was generated by running the CERES-EGC
268 models in the same conditions as with the yield response curve, namely the same biophysical
269 inputs and Nf range for each crop in all farm types. The resulting yearly N₂O emissions curves
270 were regressed against Nf assuming a straight-line, following the 'emission factor' approach of
271 the IPCC Tier 1 methodology.

272 **2.3.2 Simulation scenarios with the coupled models AROPAj and CERES-EGC**

273 The two relationships Nf-yield response curve and N₂O emission factor were fed into the AROPAj
274 model. The yield response curves were input in the form of the exponential function given in
275 eq. 1, specific for each crop of each farm type, as were with the N₂O emission factors generated
276 with the CERES-EGC simulations. An exception was made for the crops not simulated with
277 CERES-EGC, in which case the IPCC default value of 1.25% was used. The CAP agenda 2000
278 scenario (De Cara et al., 2005) was implemented in the economic model that was also run under
279 a set of taxation rules, in which case the farmers could be expected to adjust their fertilizer doses
280 taking into account these new economic environment. The objective of this paper was to study
281 the variation of N₂O emissions and the effect on them of various taxation scenarios, under vari-
282 ous modeling assumptions relating the biophysical model CERES-EGC and the economic model
283 AROPAj . After having checked the consistency of the yield-Nf response curves obtained with
284 the CERES-EGC and the STICS models, the N₂O emissions factors were computed from the
285 CERES-EGC simulations. Two simulation scenarios for crop yields and two simulation scenar-
286 ios for N₂O emission factors were tested. In the first variant for yields (referred to as EXOG in
287 the following), the yields were considered constant and fixed at the values given in the FADN for
288 each crop and farm type. The total nitrogen fertilizer inputs were estimated based on the costs of
289 each crop and farm type, as extracted from the FADN data. In the second variant for crop yields
290 (noted ENDOG), the yields and the fertilizers rates were calculated by optimizing the field's
291 gross margins based on the response curves. This led to solve simple mathematical programs of
292 the type ' $max_{Nf} [p Y(Nf) - w Nf]$ subject to $Nf \geq 0$ ', where Nf is fertilizer N input rate, p
293 is the crop selling price, Y(Nf) is the crop yield, and w is the market price of fertilizer N. Within
294 this "ENDOG" scenario, changes in fertilizer costs due to taxes on this commodity are expected
295 to alter the optimum Nf rate. For comparison with the IPCC method, the N₂O emissions of the
296 farm types were assessed with AROPAj either with the default emission factor (noted IPCC) or

297 with the CERES-EGC derived emission factors (noted CERES). Table 1 summarizes the four
298 simulation scenarios tested with the AROPAj micro-economic model.

299 [Table 1 about here.]

300 **2.4 Crop simulations at the regional level**

301 Since this work directly follows that of Godard et al., and involves comparison with her results,
302 we chose the same simulation conditions. We focused on the Picardie region (northern France),
303 which is characterized by an important agricultural activity based on intensive cereal, sugar beet,
304 potato, oil and protein-producing crops. Its climate is temperate and mild, with marine influence.
305 The annual rainfall is 630 mm, and the mean annual air temperature is 10.6 °C. In the AROPAj
306 model, the Picardie region is represented by four farm types (CrPi1, CrPi2, CaPi1, and CaPi2)
307 representing, respectively, 2819, 4786, 2116, and 1002 real farms. They involve both arable and
308 arable-livestock farming. The harvest year of the simulations is 1997 because the economic data
309 used by AROPAj are derived from the FADN data for this particular year. Since all farm types
310 belong to the same AROPAj altitude class (namely, less than 300 meters above sea level), we
311 considered only one set of daily weather data for the whole Picardie region (Godard et al., 2008).
312 We used weather data for the years 1995 through 1997, to take into account the preceding crop.
313 The main data sources and methods to estimate inputs for the biophysical models are listed in
314 Table 2. Readers are referred to Godard et al. (2008) for a full description of these databases. The
315 characteristics of the cases studied in Picardie are presented in Tables 3 (for the farm types and
316 crops) and 4 for soils' properties. CERES-EGC uses the same soil parameters as STICS with
317 the exception of specific additional parameters needed by the nitrification and denitrification
318 routines. Those were obtained from references involving similar soil types, as listed in Table 4.

319 [Table 2 about here.]

320 Simulations with the CERES-EGC model for the studied cases for yield and N₂O Nf-response
321 curves were carried out with yearly Nf rates varying from 0 to 400 kg N ha⁻¹, in 20 kg N ha⁻¹
322 increments.

323 [Table 3 about here.]

324 [Table 4 about here.]

325 The variation in the earliness implies a variation in the dates of the phenological stages of the
326 crops, and thus in the fertilizers application dates (Godard, 2005). We started the simulations
327 upon sowing of the preceding crop in order to smooth out the effects of initial soil conditions
328 setting. The preceding crop was either a non-fertilized pea or a fertilized soft wheat. Since we
329 focused on N-losses in relation to Nf application, and because the processes in the nitrogen cycle
330 responsible for the various N-losses do not instantly respond to Nf inputs, it may be relevant
331 to include the N losses occurring over the next few years of the crop rotation. However, as the
332 economic model only takes into account the year of the FADN data (1997, in this case), we only
333 used the N-loss estimates for this year.

334 Not all crops grown in Picardie could be simulated by the CERES-EGC model: such was the case
335 for potato and sunflower, which have not yet been implemented in the model. However, as shown
336 in Table 5, we worked with the major crops present in Picardie: wheat, barley, maize, rapeseed
337 and sugar beet cultivation made up 74% of the total arable area of the region in 1997 (AGRESTE,
338 1997). For the crops that were not simulated with CERES-EGC, we kept the default yield and Nf
339 values, i.e. the ones from the FADN of the year 1997. Since there was some livestock farming
340 in the region, manure N was taken into account in the yield response curves simulated by STICS
341 (Godard et al., 2008). Emissions of GHG from manure handling and spreading are included
342 in AROPAj, based on IPCC guidelines and regional coefficients. Since CERES-EGC was not
343 used to simulate the direct emissions of N₂O resulting from manure application, there were no

344 modeled emission factors for manure N input and we used the IPCC Tier 1 emission factor of
345 0.0125 kg N-N₂O kg⁻¹ Nf.

346 [Table 5 about here.]

347 **3 Results and discussion**

348 **3.1 Response of N₂O emissions to nitrogen fertilizer inputs**

349 **3.1.1 Simulation of N₂O emissions across crops and farm types**

350 [Figure 3 about here.]

351 Figure 3 presents the N₂O emissions simulated with the CERES-EGC crop-model, for Nf rates
352 varying from 0 to 400 kg N ha⁻¹, in the various regional cases. Generally, N₂O emissions in-
353 creased as Nf increased. Strong differences occurred between the cases in the magnitude of
354 the N₂O emissions. For a 400 kg N ha⁻¹ fertilizer input, N₂O emissions reached as much as
355 3.5 kg N₂O-N ha⁻¹ for soft wheat, and nearly 11 kg N₂O-N ha⁻¹ for sugar beet. In the medium
356 range of Nf (around 200 kg N ha⁻¹) corresponding to the actual application rates determined
357 with the Nf yield response curves (Godard et al., 2008), the emissions rates ranged from 0.60
358 for winter barley to 7.61 kg N₂O-N ha⁻¹, and averaged about 2.94 kg N₂O-N ha⁻¹ across the
359 various cases. This value is very close to the average flux of 2.7 kg N₂O-N ha⁻¹ reported by
360 (Leip et al., 2008) for the whole of France with a similar mean application rate (201 kg N ha⁻¹),
361 and to the 1.94-2.53 kg N₂O-N ha⁻¹ range by (Neufeldt et al., 2006) for the Baden-Wurtemberg
362 region of Germany.

363 There was a stark contrast between winter- and spring-sown crops, with emissions being higher
364 by a factor of 2 for the latter compared to the former. This may be explained by the fact that Nf
365 application occurred later in the season for spring crops, when temperature conditions are more
366 conducive for nitrification and denitrification. These processes may also be enhanced because

367 of the build-up of inorganic N from spring mineralization of soil organic matter under the bare
368 soil preceding the planting of spring crops. However, this may be a specific to the environmental
369 conditions of Picardie. In Baden-Wurtemberg, an opposite trend was noted with winter cereals
370 emitting slightly more N₂O than spring types (Neufeldt et al., 2006). This highlights the interplay
371 between climate, soil conditions and crop management which may produce different outcomes
372 depending on their respective dynamics.

373 Besides, the response pattern to the Nf input differed significantly between cases, to the extent
374 that in a 2 cases out of 12 (involving soft wheat crops) the model simulated a decrease of N₂O
375 emissions when Nf increased. This may be seen for case 6 on Figure 3, and was actually due to
376 the fractionation scheme for fertilizer application, which changed around that rate. Under a total
377 dose of 80 kg N ha⁻¹, fertilizer was applied all at once in mid-April, whereas it was split into 2
378 applications (early March and mid-April) above. This split resulted in a higher growth potential
379 for the wheat in early spring, and a higher N use efficiency (and hence lower emissions) following
380 subsequent Nf inputs. This feedback leading to counter-intuitive results may still be an artefact
381 of the model simulations, but nevertheless reflects the long-established agronomic principle that
382 split applications increase Nf use efficiency. The resulting regression curve was somewhat sen-
383 sitive to the 4 first data points, since shifting them down to force a monotonic response increased
384 its slope from 0.58% to 0.70%. This slight variation would have had limited consequences in the
385 economic modeling, and we kept the original simulation curves to maintain the consistency of
386 the models' coupling. Note that the economic model uses the regression coefficients (and not the
387 jagged simulation line itself). Other than that, the response curves obtained with CERES-EGC
388 for the different cases varied according to of one or several of their specific parameters: soil and
389 crop types, sowing date, and previous crop.

390

391 The straight lines (noted *Bouwman assessment*) on Figure 3 represent the N₂O emissions as-

392 sessments according to the equation $E_{N_2O} = 1 + 0.0125 * Nf$, with E_{N_2O} is the annual direct
393 emission of N_2O (kg N- N_2O ha⁻¹) and Nf the fertilizer N rate (kg Nf ha⁻¹) (Bouwman, 1996).
394 This linear model is used as the default IPCC methodology (Tier 1) (Houghton et al., 1996),
395 and represents the current calculation of the N_2O emissions in the AROPAj economic model,
396 with the difference that the background emissions (in the absence Nf inputs) are not taken into
397 account. The Bouwman equation and the CERES-EGC response curves never matched, whether
398 regarding the background emission rates or the slope of the curves. Depending on the cases, the
399 former led to either lower or higher estimates than those resulting from the biophysical modeling.
400 Such discrepancies were also noted in a study on N_2O emissions from winter wheat crops in a
401 neighboring region, where the modeled N_2O emissions were 40% to 80% lower than estimated
402 with the Tier 1 emission factor (Gabrielle et al., 2006b). When compared with observations at the
403 field-scale, the CERES-EGC model had a mean deviation typically ranging (in absolute values)
404 from less than 1 to 5 g N- N_2O ha⁻¹ d⁻¹ (Gabrielle et al., 2006a,b), which may be considered as
405 resulting in unbiased predictions at the yearly scale given the high temporal variability of these
406 fluxes (Hénault et al., 2005). These gaps between the two estimation methods also stress the im-
407 portance of a finer assessment of the N_2O emissions with a biophysical model that can take into
408 account regional variations in soil and climate conditions, along with crop management practices.

409

410 While CERES-EGC model was only applied to one year, the inter-annual variability of climate
411 was likely to affect its simulation of N_2O emissions in the long run. In a study on GHG emis-
412 sions from arable crops in the same region, Gabrielle and Gagnaire (2007) found coefficients of
413 variations of up to 80% across the years when running the same model on a 30-yr series of past
414 weather data. However, the differences between crops were persistent over the years, as did the
415 discrepancies between the IPCC Tier 1 estimates and the modeled emissions. Thus, inter-annual
416 variability should not undermine the tendency obtained with the particular year we used here

417 when comparing our biophysical/economic modeling with approaches that fully ignore soil and
418 climate variability. From a quantitative point of view, and to put our particular simulation year
419 into prospective, it should lastly be mentioned that it led to N₂O emission levels 30% lower than
420 the 30-yr average for the cases simulated here. Thus, the discrepancies with the IPCC Tier 1
421 estimates were probably slightly over-emphasized.

422 **3.1.2 Regression analysis and link with economic model**

423 The N₂O response curves simulated by CERES-EGC for the various cases were input to the eco-
424 nomic model AROPAj in the form of linear regression coefficients. Note that the rather variable
425 levels of background emissions, in the absence of fertilizer inputs (ranging from 0.37 to 3.67 kg
426 N₂O-N ha⁻¹), were not input to AROPAj, since they were deemed natural and not anthropogenic.
427 However, the fact that they varied across crops (contrary to the Bouwman (1996) equation) un-
428 derlines the arbitrary limitation of this convention. Table 6 presents the characteristics of the
429 linear regressions of N₂O emissions against Nf inputs.

430 [Table 6 about here.]

431 The linear regressions fitted the N₂O emission response curves rather well, with R-squared values
432 ranging above 0.80 in 8 cases out of 12. Such pattern was also reported by Neufeldt et al. (2006)
433 with the biophysical model DNDC in the Baden-Wurtemberg region of Germany, with an R^2
434 of 0.79 for the same types of crops and Nf rates ranging from 40 to 250 kg N ha⁻¹. However,
435 for two cases involving soft wheat, the N₂O emissions curves presented an important dip (see
436 case 6 on Figure 3). This particular pattern in the response curve was ignored by the linear
437 regression, and resulted in poorer R^2 values. Non-linear models were also tested, including an
438 exponential model, which achieved a better fit and a lower residual standard error. However,
439 the latter remained relatively low and acceptable with the linear models, being for instance of
440 only 0.13 kg N₂O-N ha⁻¹ for the wheat crops, i.e. less than 10% of the annual total for the

441 optimal fertilizer rate. We reverted to the linear model, considering it sufficient to address the
442 first-order effect of our approach, which stems from the slope of the regression curve being in
443 sharp contrast with the Tier 1 IPCC emission factor. Deviations from the linear response curves
444 are a second-order effect, which would be worth tackling in future work.

445 **3.2 Impacts of response functions to nitrogen input in economic modeling.**

446 **3.2.1 Regional GHG emissions and economic margins**

447 [Figure 4 about here.]

448 [Figure 5 about here.]

449 Figures 4 and 5 present the AROPAj results for the N₂O emissions and the global GHG emis-
450 sions for the whole Picardie region. The emission factors obtained with CERES-EGC led to a
451 reduced estimate of N₂O emissions, whether with the exogenous or endogenous yields, with a
452 20% decrease compared to the IPCC estimate. Whatever the emission factors, the emissions of
453 N₂O were also 30% lower with the endogenous yields than with the exogenous ones. This could
454 be expected, since the use of yield response curves allowed a higher efficiency of fertilizer use
455 by crops, and thus led to an overall reduction in fertilizer consumption by farmers. With the en-
456 dogenous yields, the model was also more reactive to the CAP 'Agenda 2000' scenario, resulting
457 in changes in the management of each farm type: the areas allocated to each crop were slightly
458 modified, as well as crop yields, so were the GHG emissions.

459 Total GHG emissions followed the same pattern as the N₂O emissions across the simulation sce-
460 narios (Figure 5), being lower with the CERES-EGC emission factors compared to the IPCC
461 one, and lowest with the endogenous yields. Obviously, GHG emissions from animals were not
462 affected by the choice of the N₂O emission factors. On the one hand, as was expected, the gross
463 margins, crop areas and crop productivity levels calculated by AROPAj were not impacted by
464 the changes in N₂O emissions' estimates (IPCC vs CERES). On the other hand, changes in the

465 yield assessment method in AROPAj (EXOG vs ENDOG) strongly affected the AROPAj results.
466 The total gross margin increased by 5% with the endogenous method compared to the exoge-
467 nous one, reflecting the higher efficiency of Nf inputs and marketable yield levels permitted by
468 the yield response curves. This increase was higher for the arable crops specialized farm types
469 (CrPi1 and CrPi2), and lower for the livestock-oriented farm types. The total arable area of the
470 farm types was not modified because the AROPAj model considers them as constant. Never-
471 theless, the breakdown of arable area among crops was modified: there was a slight increase in
472 cereal crops, industrial crops and pea, and a decrease in fodder crops.

473 **3.2.2 Mitigation measures and taxation schemes**

474 Various tax policies may be implemented within AROPAj, using different parameter sets. In
475 order to mitigate the total GHG emissions, and thereby the emissions of N₂O, we enforced two
476 taxation schemes: a first-best scheme directly taxing the GHG emissions; and a second-best
477 scheme taxing the presumed factors behind the GHG emissions.

478 **Direct taxation of GHG emissions**

479 [Figure 6 about here.]

480 We studied for each of the simulation scenarios presented in Table 1 the effects of an increasing
481 tax on the GHG emissions, ranging from 0 to 100 € per t-CO₂-eq. Figure 6 presents the results
482 for the Picardie region regarding the total GHG emissions and their abatement. As expected,
483 the GHG emissions decreased as the tax level increased, for all simulation scenarios. The major
484 difference between the scenarios was due to the yield assessment method: GHG emissions were
485 significantly higher with the exogenous method than with the endogenous one. This could be
486 expected since farmers have more degrees of freedom available with the endogenous yield deter-
487 mination to maximize N use efficiency and abate GHG emissions than with the fixed, exogenous

488 yields. The rate of abatement was also higher with the endogenous yields. However, these pat-
489 terns were affected by the N₂O emission factors, which drastically changed the magnitude of the
490 emissions, and to a minor extent the abatement rates. Examination of the level of tax needed to
491 achieve a given target of GHG mitigation corroborates this analysis. The three horizontal lines
492 on Figure 6 present three mitigation targets of 4, 8 and 12% compared to the baseline emissions
493 (ie in the absence of GHG-related taxes). Their intersection with the GHG emission curves ob-
494 tained with the four simulation scenarios provide an estimate of the tax level required to meet
495 these targets, which are quantified in Table 7.

496 [Table 7 about here.]

497 Higher taxes on GHG emissions were necessary to reach a given mitigation target with the ex-
498 ogenous yield assessment compared to the endogenous one. This gap widened as the mitigation
499 target increased: taxes with the exogenous yields were twice higher than with the endogenous
500 yields for the 4% mitigation target, and 3 to 4 times higher for the 8% target. Differences between
501 the N₂O assessment methods were also evidenced. Generally, the tax level needed to achieve a
502 given mitigation target was slightly higher when using the CERES-EGC emission factors than
503 the IPCC one, and this gap widened as the mitigation target increased.

504

505

506 [Figure 7 about here.]

507 The same tendencies were observed with the total gross margin for the whole Picardie region
508 and its response to increasing tax on GHG emissions (Figure 7). There was a notable difference
509 between the two yield assessment methods, with a higher gross margin with the endogenous
510 yields. In addition, the reduction in the gross margin as the tax increased was significantly lower
511 with the endogenous method than with the exogenous one. Indeed, the former allows a better

512 reactivity of the farmer to changes in crop prices, and thereby to political measures. These gross
513 margin results also evidence small differences due to the use of the CERES-EGC emission factor,
514 which became more pronounced as the tax level increased.

515 This first-best tax on GHG emissions allows the public regulator to reach ambitious target of
516 environmental damage abatement. However, such taxation is very costly to implement because
517 each farmer's GHG emissions must be precisely known. Economically and practically speaking,
518 it is unfeasible to measure these GHG emissions on each arable field. That is why we also
519 compared that first-best scheme with its alternative, a second-best scheme taxing the presumed
520 factors of the environmental damage.

521 **Taxing the presumed factors of the GHG emissions**

522 AROPAj calculates the emissions of two GHG: methane (CH₄) and N₂O. Because farming activ-
523 ities are globally affected by any change in the economic environment, changes in land allocation
524 between marketed crops, fodder crops and pastures (linked to livestock farming) have to be im-
525 plemented in our framework. We thus included the methane emissions and livestock activities in
526 the below results. As livestock or nitrogen fertilizer consumption are easily observable factors
527 (through the CAP or the markets), they may serve as a basis for a second-best GHG mitigation
528 policy. It would lead to tax the livestock population and the fertilizer use of each farm type. We
529 thus implemented such a scheme in the AROPAj model, and its effects on GHG emissions using
530 the four simulation scenarios of Table 1.

531

532

[Figure 8 about here.]

533 Figure 8 presents the results of AROPAj simulations with a combination of two taxes: one on
534 Livestock Units ² (in €/LU) and one on nitrogen fertilizer input (in €/t Nf). The curves present
535 the combined tax needed to reach a certain level of reduction (2 to 12% reduction of the total

536 GHG emissions - in relation to the baseline level of emissions). Similar to the first-best taxa-
537 tion, important differences occurred between the exogenous and endogenous yield assessment
538 methods. With the exogenous yields, reasonable mitigation targets were harder to reach: a 2%
539 or higher reduction in GHG emissions required both taxes on LU and Nf to be higher than
540 200 €/per LU or t Nf). With the endogenous yields, such tax levels make it possible to abate
541 the emissions by more than 10%. It is important to note that in the current implementation of
542 AROPAj , contrary to crop yields, animal productions are not optimized against their production
543 factors. The production levels of meat or milk are not related to the levels of animal feed sup-
544 ply. Obviously, such assessment would confer more reactivity to the model, and a more realistic
545 response to the second-best taxation. The graphs also show an effect of the method used for the
546 assessment of N₂O emissions. Overall, the taxes were higher with the CERES-EGC emission
547 factors than with the IPCC one for the same reduction target. Using the endogenous yields, a
548 12% reduction of the GHG emissions was attained with a tax on fertilizer N ranging from 180
549 to 250 €/t N with the IPCC emission factor, compared to a 240 to 250 €/t N range with the
550 CERES-EGC emission factors.

551

552 Second-best taxes should be quite high to reach a given target of GHG emission abatement,
553 much higher than the first-best tax when expressed in €/t-CO₂ eq abated through the physical
554 relationship between the factor and the emission. For an 8% reduction in GHG emissions, the
555 first-best tax was around 11 €/t-CO₂ eq, whereas the second-best tax could reach as high as
556 125 €/t N and 110 €/LU. Considering that 1 t of Nf produces about 4 t-CO₂ eq, and that 1 LU
557 produces 3 t-CO₂ eq, the equivalent tax on GHG emissions for the second-best taxation would be
558 68 €/t-CO₂ eq, *i.e.* 6 times higher than the first-best tax. Moreover, the relative efficiency of the
559 second best tax scheme compared to first-best one may be highly dependent on the abatement
560 target. Therefore, an analysis of costs and profits of the various taxation policies needs to be

561 done in order to compare the efficiency of the 2 taxes more rigorously.

562 **4 Conclusion**

563 The IPCC Tier 1 methodology is currently widely used to assess greenhouse gas emissions - and
564 in particular N₂O emissions from agriculture. However, this methodology is relatively imprecise
565 when used at the regional scale as it ignores the effect of the local environment. This paper
566 explored an alternative methodology to assess the N₂O emissions by coupling a biophysical soil-
567 crop model to a micro-economic farm model. The biophysical model CERES-EGC enabled a
568 fine assessment of N₂O emissions, as related to local environmental conditions, and the eco-
569 nomic model AROPAj enabled the generalization of the N₂O results at the level of farm types
570 representative of actual farms. The paper also studied possible policy measures to mitigate GHG
571 emissions.

572

573 A series of cases representing different soil and crop management characteristics was set up in
574 the Picardie region, based on an analysis of various comprehensive databases. Response curves
575 of N₂O emissions to Nf inputs were built for these cases, and fitted with a a linear regression
576 function. The slopes of these regressions ranged from 0.10% to 2.25% depending on the cases,
577 whereas the IPCC default method considered a constant 1.25% emission factor. These slopes
578 were input to the economic model AROPAj as new emission factors depending on crop type and
579 farm type. Four simulation scenarios were run with AROPAj: crop yields were either exogenous
580 or endogenous using yield response curves to nitrogen input, and the N₂O emission factors were
581 either obtained from the biophysical model or set at the IPCC value. The use of the modeled
582 emission factors resulted in a 20% decrease in the magnitude of N₂O emissions compared to
583 the IPCC estimate. Thus, taking into account the yield response functions to Nf inputs appeared
584 beneficial to the economic modeling.

585

586 AROPAj allowed us to study two different greenhouse gas mitigation measures: a first-best
587 tax on GHG emissions, and a second-best tax on the presumed factors of the GHG emissions
588 (livestock and Nf inputs). Interestingly, the simulation variants (using exogenous or endogenous
589 yields, and IPCC or CERES-EGC N₂O emission factors) had a marked influence in the response
590 to taxes, and thereby in the conclusions that could be drawn on the efficiency of the mitigation
591 policies. With the first-best scheme, the discrepancies between the scenarios led to a tax range
592 of 11 to 53 €/t-CO₂ eq for an 8% reduction of the GHG emissions. The gap was firstly due to
593 the yield assessment method: the reduction of the GHG emissions was more pronounced with
594 the endogenous yields as the tax increased. For high level of taxes (up to 50 €/t-CO₂ eq), dif-
595 ferences due to the N₂O emission factors started to appear. A similar pattern was observed with
596 the second-best taxation scheme. Endogenous yields conferred a higher reactivity to the model,
597 and mitigation targets were easier to reach than with the exogenous yields. However, the taxes
598 were higher than with the first-best taxation: an 8% abatement of GHG emissions required, for
599 instance, a tax of 110 € per livestock unit and a tax of 125 € per ton of fertilizer N. However, a
600 detailed analysis of the costs and profits of each taxation scheme should be undertaken to com-
601 pare the 2 types of taxation, and measure their respective efficiency.

602

603 The method we proposed here needs to be extended to a wider set of EU regions and crop types
604 to improve its operational status. It also has the potential to address environmental impacts, such
605 as related to the emissions of NH₃ and NO₃⁻, which could be easily introduced into the economic
606 analysis. It could also be interesting to use the best-fit model (which is not necessarily linear) to
607 describe the response of N losses to Nf inputs, and introduce these functions in AROPAj. Imple-
608 menting response functions of animal production (meat and milk) to animal feed supply levels
609 in AROPAj is also an important issue, allowing a more realistic response of farmers to GHG

610 taxation schemes.

611 **Notes**

613 ¹The theoretical economic second-best world is quite large and complex. In the wide body of literature on the
614 subject, we refer readers to Henry (1989) for a review.

615 ²Livestock Unit (LU) is a unit used in order to compare livestock size of different species or category of animals.
616 It is based on the feeding demand of the animals.

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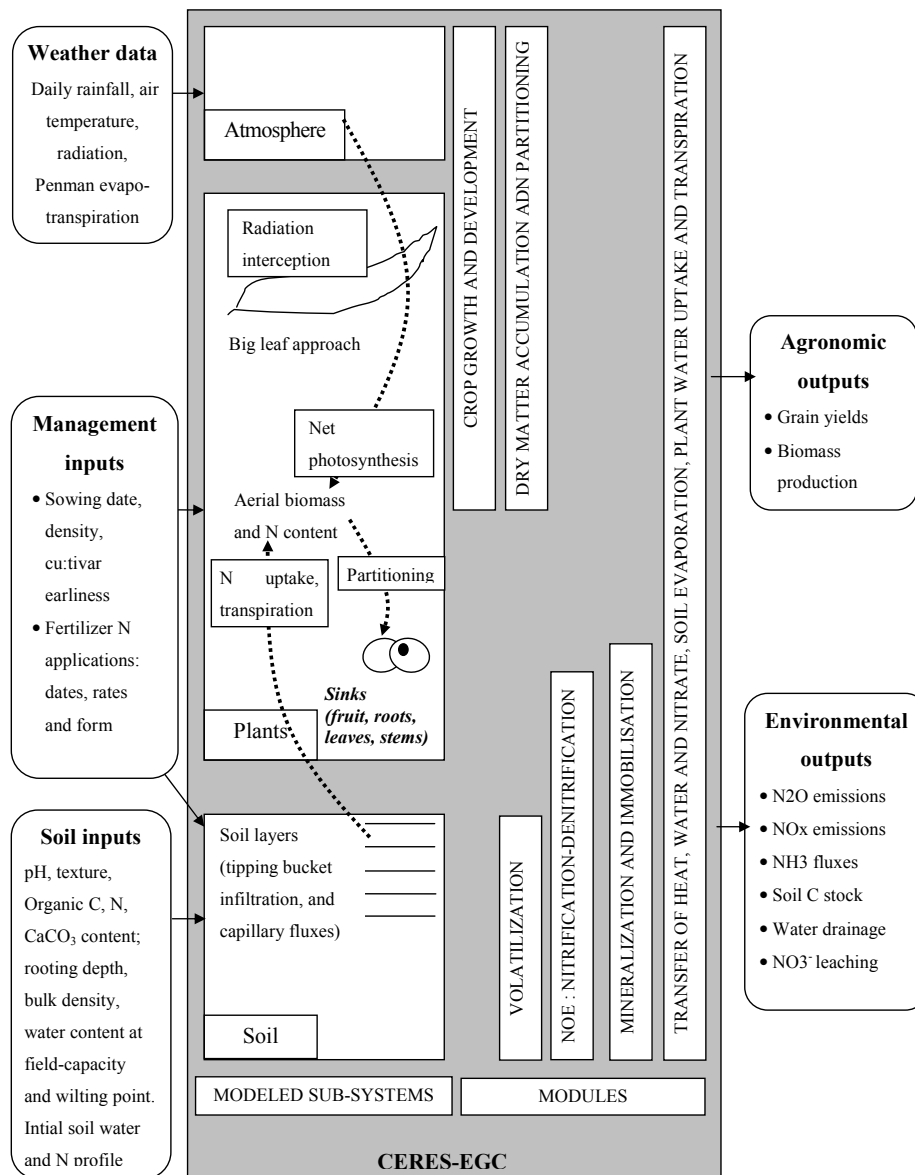


Figure 1: Schematic of the CERES-EGC model: inputs, compartments, modules and outputs.

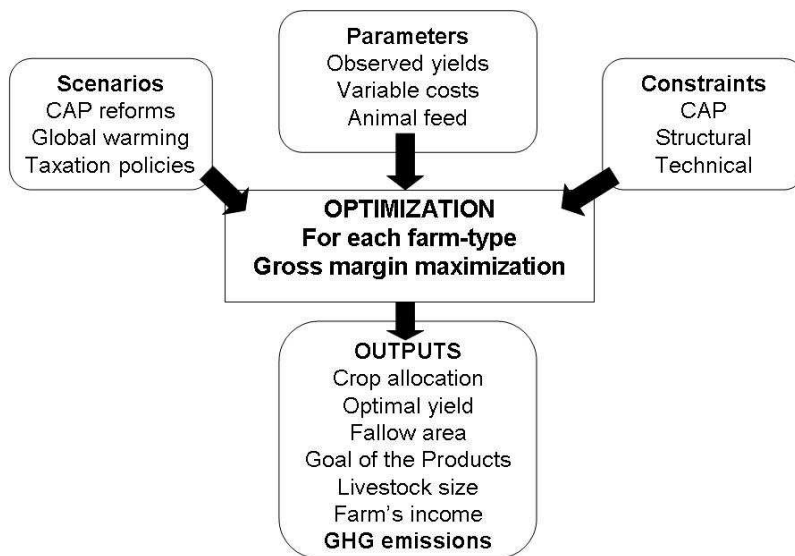
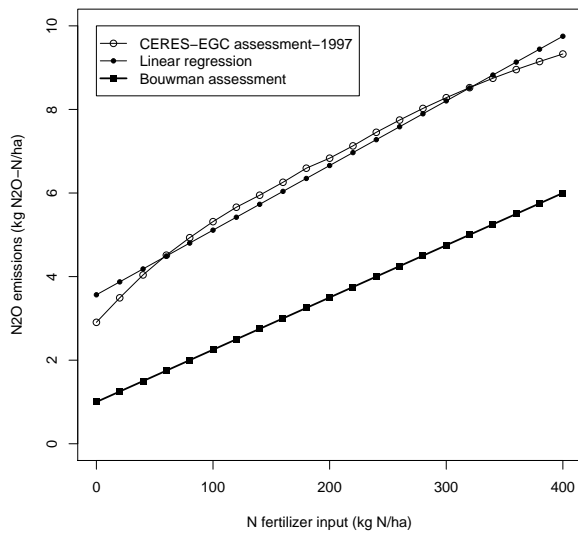
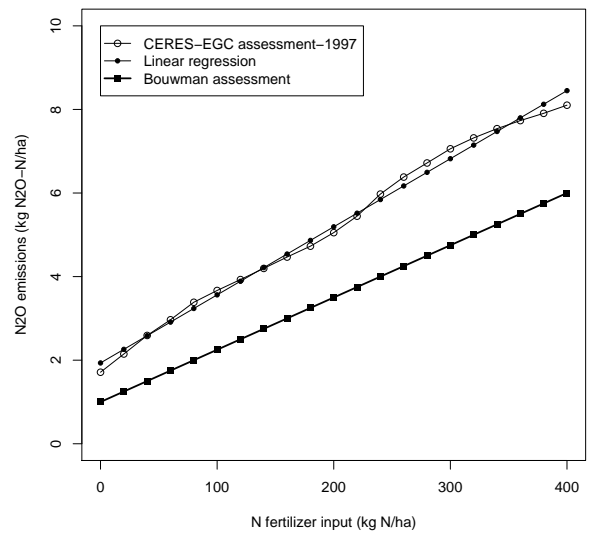


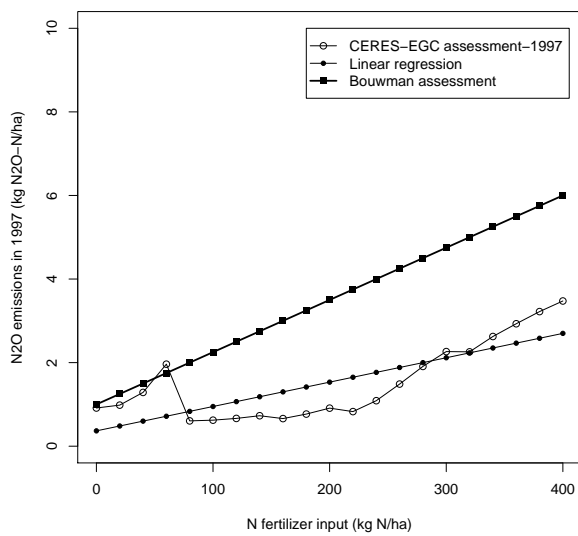
Figure 2: Schematic of the AROPAj model.



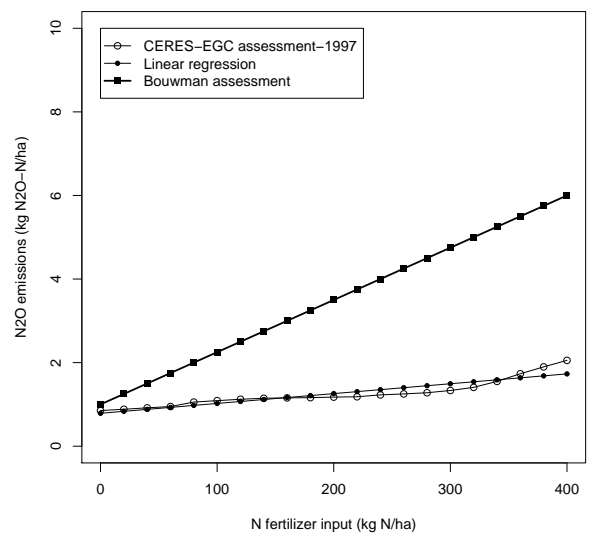
Case 2: Maize



Case 5: Spring barley



Case 6: Soft wheat



Case 12: Winter barley

Figure 3: Response curves of N₂O emissions to Nf input, as simulated by CERES-EGC. The resulting linear regression and IPCC Tier 1 estimation lines (noted Bouwman) are also depicted.

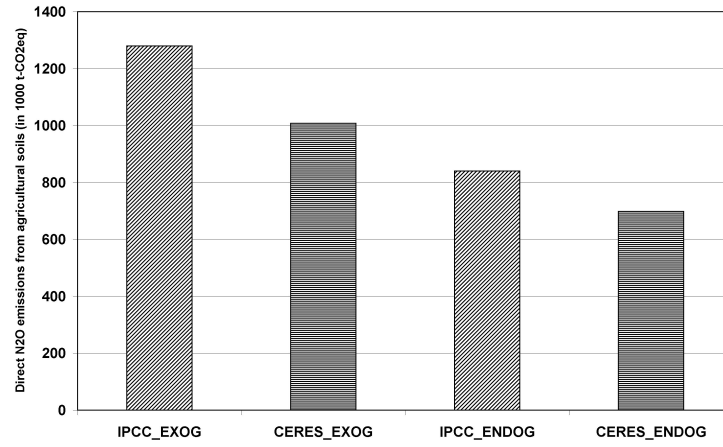


Figure 4: N₂O emissions from synthetic fertilizers (in 1000 t of CO₂-eq.) for the Picardie region.

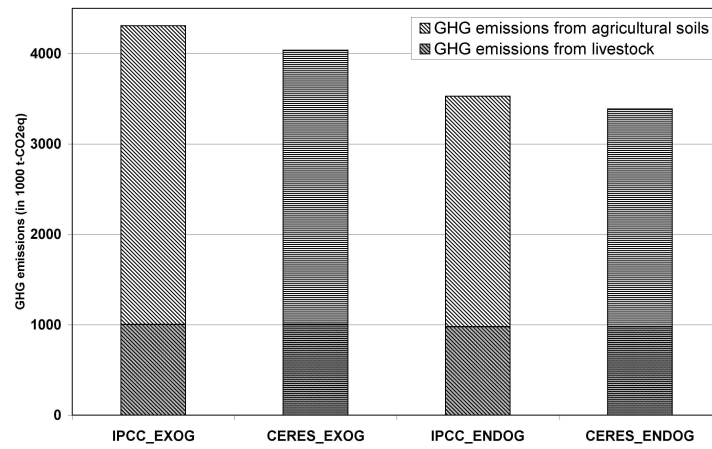


Figure 5: Global GHG (N₂O and CH₄) emissions from agriculture for the Picardie region (in 1000 t of CO₂-eq.), as calculated by the AROPAj model for the various yield and N₂O estimation methods.

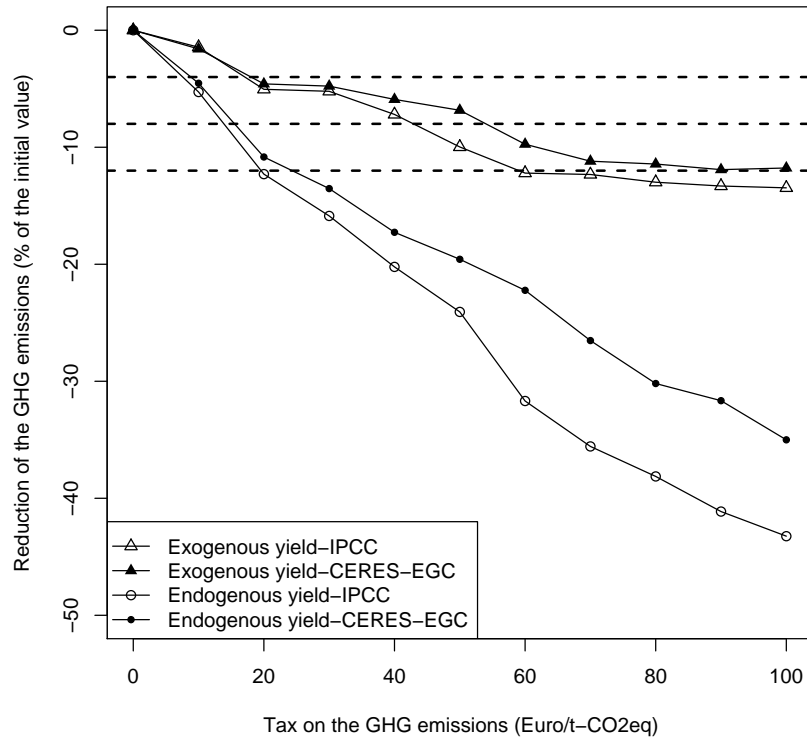


Figure 6: Effect of a direct taxation of GHG emissions on the relative reduction of GHG emissions from agriculture in the Picardie region. The horizontal lines refer to target abatement levels of 4, 8 and 12%, resp.

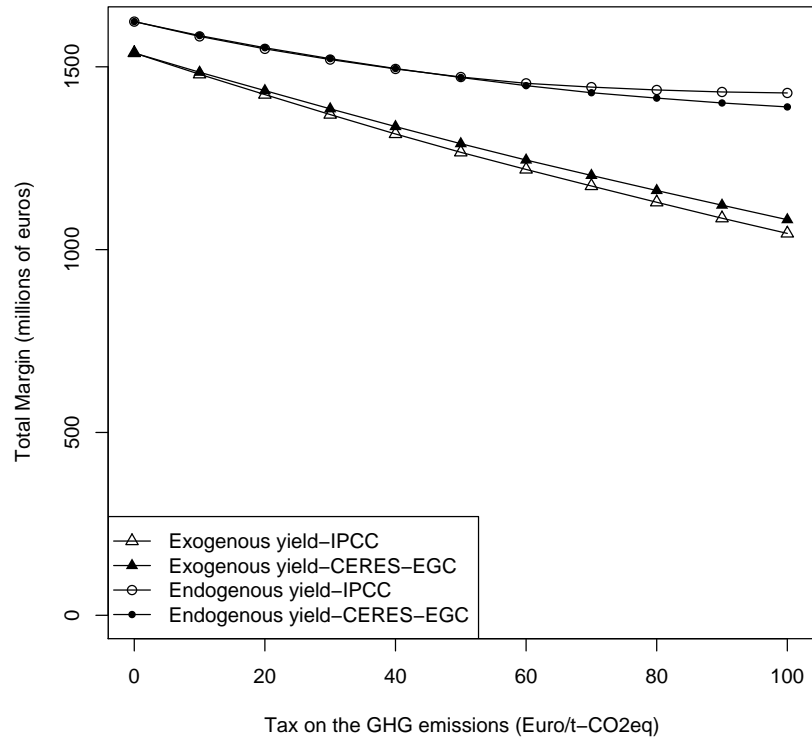


Figure 7: Variations of the total gross margin of Picardie agriculture with increasing taxes on GHG emissions.

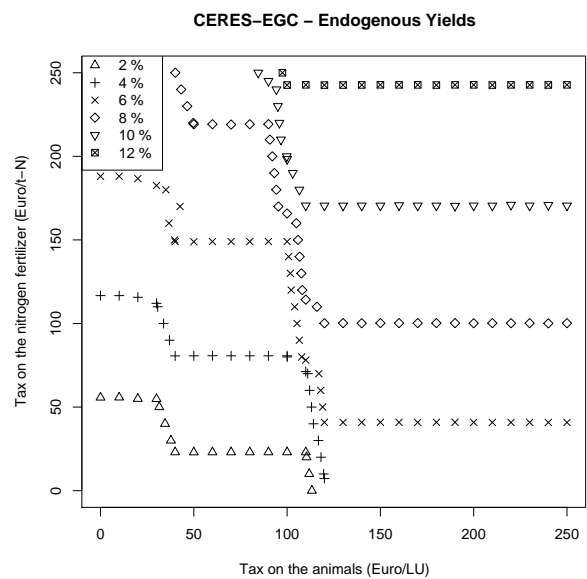
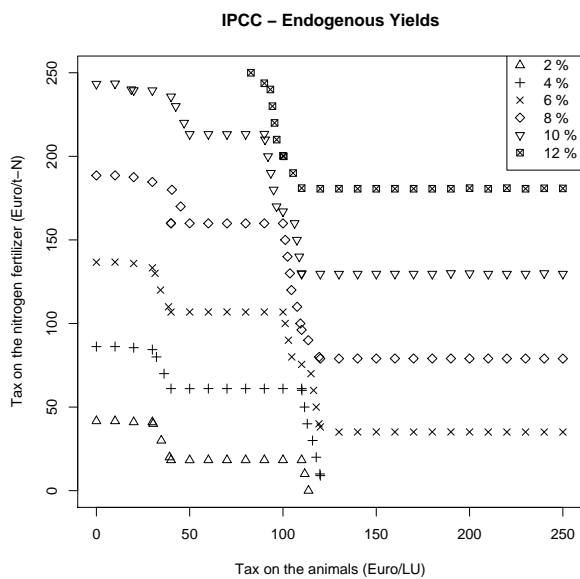
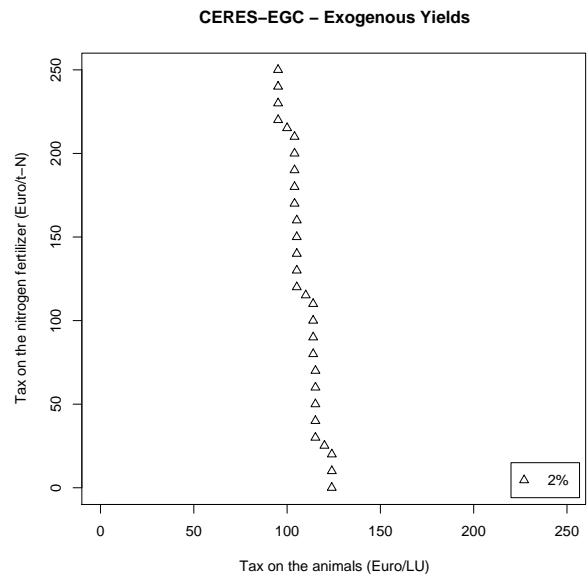
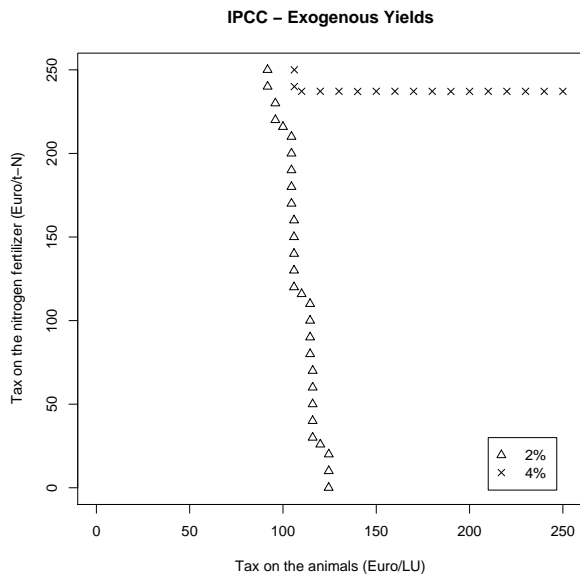


Figure 8: Tax levels required to achieve various mitigation targets with the coupled second-best taxes on livestock units (LU) and on fertilizer N inputs, for the Picardie region, with the various crop yield and N₂O estimation methods. EXOG means that crop yields are kept constant for any one farm type while ENDOG uses the yield response curves. These methods are combined with two variants for N₂O emissions: the IPCC Tier 1 emission factor, or the CERES-EGC derived factors.

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769 emissions. 49

| | Yield | N ₂ O emissions |
|-------------|------------|--|
| IPCC-EXOG | Exogenous | 1.25% of Nf inputs |
| CERES-EXOG | Exogenous | Fraction of Nf inputs depending on crop and farm types |
| IPCC-ENDOG | Endogenous | 1.25 % of Nf inputs |
| CERES-ENDOG | Endogenous | Fraction of Nf inputs depending on crop and farm types |

Table 1: Characteristics of the AROPAj simulations regarding the yields and N₂O emissions estimation methods.

| Inputs | Main information sources | Determination method |
|-------------------------------|--|---|
| Climate | MARS ¹ Project database (van der Groot, 1998) | Climatic conditions based on altitude class |
| Soil | - 1:1,000,000 European geographical soil database (King et al., 1994) - Corine Land Cover 2000 ² | Aggregation of soil types with identical STICS parameters and largest areas within the Picardie region |
| Earliness ³ group | Lorgeou and Souverain (2008) | Selection of one cultivar and one earliness group depending on the crop, |
| Sowing date | - Phenological MARS Project database (Willekens et al., 1998) - Expert knowledge | and on the weight of the earliness factor in the cultivar choice (Godard et al., 2008) |
| Preceding crop | | Wheat (non N-fixing crop) or pea (N-fixing crop) |
| Synthetic fertilizer N inputs | Expert knowledge and decision rules | Fertilizer type(s) fully determined, splitting of Nf applications according to development stages (based on degree-days). |
| Organic N inputs | - Expert knowledge and rules - FADN ⁴ | Rates and types of manure spread estimated from priority order and livestock estimations by AROPAj from FADN |

Table 2: Summary of the sources and methods for the determination of the STICS input data used for CERES-EGC (adapted from Godard et al. 2008).

1: MARS: Monitoring Agriculture from Remote Sensing.

2: <http://www.ifen.fr/bases-de-donnees/occupation-du-sol.html>

3: Earliness is a characteristic of a crop cultivar defining its maturity date.

4: FADN: Farm Accountancy Data Network.

| Case | Crop | Farm type | Soil | Earliness Group ¹ | Sowing date | Preceding Crop ² |
|---------------------|---------------|--------------------|------|------------------------------|--------------|-----------------------------|
| Spring crops | | | | | | |
| 1 | Maize | CrPi1, CaPi1 | 1969 | 2 | 5 May 1997 | Wheat |
| 2 | Maize | CrPi2 | 1974 | 1 | 5 May 1997 | Pea |
| 3 | Sugar beet | CrPi 1-2, CaPi 1-2 | 1974 | RA ³ | 2 Apr. 1997 | Wheat |
| 4 | Spring Barley | CrPi1 | 1042 | RA | 16 Mar. 1997 | Wheat |
| 5 | Spring Barley | CaPi2 | 1974 | RA | 2 Feb. 1997 | Pea |
| Winter crops | | | | | | |
| 6 | Soft wheat | CrPi1, CaPi 1-2 | 1042 | 1 | 15 Oct. 1996 | Pea |
| 7 | Soft wheat | CrPi2 | 1974 | 2 | 15 Oct. 1996 | Pea |
| 8 | Rapeseed | CrPi1 | 1042 | RA | 30 Aug. 1996 | Pea |
| 9 | Rapeseed | CrPi2, CaPi1 | 1974 | RA | 30 Aug. 1996 | Pea |
| 10 | Rapeseed | CaPi2 | 1974 | RA | 27 Aug. 1996 | Wheat |
| 11 | Winter Barley | CrPi2 | 1792 | RA | 31 Oct. 1996 | Wheat |
| 12 | Winter Barley | CaPi1 | 1974 | RA | 31 Oct. 1996 | Pea |

1: Earliness is a characteristic of a crop cultivar defining its maturity date. It determines the dates of the various management intervention during the crop growing cycle. Cultivars belonging to 'earliness group 1' have an earlier maturity than those of 'earliness group 2'.

2: The preceding crop 'Pea' is not fertilized whereas 'Wheat' is fertilized with 200 kg N ha⁻¹.

3: RA: regional average.

Table 3: Characteristics of the various simulation cases in Picardie. Farm types CrPi1 and SCrPi2 specialize in arable crops, whereas farm types CaPi1 and CaPi2 are mixed livestock-arable farms. Soil characteristics are given in Table 4.

| Soil code | FAO Classification ¹ | PAW ² mm | pH value | Organic carbon g kg ⁻¹ | CaCO ₃ content g kg ⁻¹ | PDR ³ kg N ha ⁻¹ d ⁻¹ |
|-----------|---------------------------------|---------------------|----------|-----------------------------------|--|--|
| 1042 | <i>Eutric Fluvisol</i> | 150.6 | 6.5 | 10 | 10 | 8.0 |
| 1792 | <i>Calcic Cambisol</i> | 118.4 | 8.0 | 18 | 50 | 3.4 |
| 1969 | <i>Orthic Luvisol</i> | 189.6 | 6.5 | 10 | 0 | 16.0 |
| 1974 | <i>Calcaric Eutric Cambisol</i> | 114 | 7.0 | 10 | 20 | 6.0 |

¹: FAO-UNESCO (1974)

²PAW: Plant Available Water.

³PDR: Potential Denitrification Rate (Hénault et al., 2005).

Table 4: Codes and selected characteristics of the soils used in the Picardie simulations.

| Crop type | Area (ha) |
|---------------|-----------|
| Soft wheat | 502 343 |
| Maize | 35 100 |
| Sugar beet | 166 855 |
| Rapeseed | 37 839 |
| Spring barley | 39 286 |
| Winter barley | 91 183 |
| Total | 872 606 |

Table 5: Crop types simulated with CERES-EGC and cultivated area in Picardie (AGRESTE, 1997). The area covered by these 6 crops made up 74 % of the regional utilized arable area.

| Case | Crop type | a % | b kg N ₂ ON ha ⁻¹ | Residual standard error | Adjusted R-squared |
|------|---------------|--------|--|----------------------------|-----------------------|
| 1 | Maize | 0.83 | 1.01 | 0.36 | 0.89 |
| 2 | Maize | 1.55 | 3.56 | 0.26 | 0.98 |
| 3 | Sugar beet | 1.98 | 3.67 | 0.42 | 0.97 |
| 4 | Spring Barley | 2.25 | 1.73 | 0.61 | 0.95 |
| 5 | Spring Barley | 1.63 | 1.93 | 0.17 | 0.99 |
| 6 | Wheat | 0.58 | 0.37 | 0.60 | 0.58 |
| 7 | Wheat | 0.46 | 0.42 | 0.25 | 0.84 |
| 8 | Rapeseed | 0.21 | 2.74 | 0.71 | 0.08 |
| 9 | Rapeseed | 0.29 | 0.93 | 0.48 | 0.35 |
| 10 | Rapeseed | 0.31 | 1.09 | 0.51 | 0.34 |
| 11 | Winter Barley | 0.10 | 0.39 | 0.03 | 0.95 |
| 12 | Winter Barley | 0.24 | 0.79 | 0.13 | 0.83 |

Table 6: Coefficients of the linear regressions of N₂O emissions against fertilizer N rates (Nf). The regression equation reads: $E_{N_2O} = a \times Nf + b$, where E_{N_2O} are the N₂O emissions in kg N₂ON ha⁻¹.

| GHG emissions reduction | Exogenous Yields | | Endogenous Yields | |
|-------------------------|------------------|-----------|-------------------|-----------|
| | IPCC | CERES-EGC | IPCC | CERES-EGC |
| 4% | 14.5 | 14 | 6.9 | 8 |
| 8% | 46 | 53 | 10.8 | 11 |
| 12% | 59 | 85 | 19 | 24 |

Table 7: Tax levels (in euros/t-CO₂-eq) required to achieve a set of GHG mitigation targets, as calculated with AROPAj with various methods to estimate yield and N₂O emissions.