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Development of marginal emission factors for N losses from agricultural soils with the DNDC–CAPRI meta-model

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ABSTRACT

The article discusses marginal emission factors for N losses from agricultural soils, with rape and wheat as examples, and presents results for EU15 as high-resolution maps and aggregated to Member State level. The results are generated by linking the economic model for the agricultural sector CAPRI (Common Agricultural Policy Regional Impact) with spatial down-scaling, and a statistical meta-model for the bio-physical model DNDC (DeNitrification–DeComposition). For a given agro-economic scenario, CAPRI supplies for each crop the crop share, yield and fertilizer application rate spatially downscaled to clusters of 1 km × 1 km grid cells. The results from CAPRI are processed by a meta-model of DNDC to estimate the local greenhouse gas emissions from the soil. DNDC is a dynamic process-oriented model, which estimates trace gas fluxes and nutrient turnover in agricultural soils. The fit of the regressions is typically very good (~$0.95R^2$ for the majority of the regressions), and all coefficients are significant at 99% probability. The meta-model allows a seamless integration between the economic and the bio-physical models, offering additional benefit such as the site-specific calibration of the bio-physical model ensuring the match between simulated and observed yield at the grid-level.

The meta-model is used to calculate marginal emission factors for a 1 kg ha^{-1} increase of mineral N and manure fertilizer rates for rape and wheat, at different levels of fertilization. They show that for Western European farming practice, only a small fraction of extra nitrogen fertilizer would go into increased yields: most of it would be emitted to the environment. The largest spatial variability is observed for N_2O emissions. The derivation of marginal emission factors is just one of the many possible uses for the linked regionalized agro-economic and soil chemistry model, which exploits to a large extent both geo-referenced and regionally available statistical information at European scale.

1. Introduction

Agricultural and agri-environmental policies have simultaneous economic, social and environmental impacts. Impact analysis of the typically complex and non-linear interactions is often based on simulation models designed to address specific questions. However, these models are rarely linked together and often fail to cover the whole range of impacts. This article describes the transparent integration of a soil biogeochemistry (or "bio-physical") model into an agro-economic model through a meta-model, and highlights its utility for environmental impact assessment by deriving marginal greenhouse gas emission factors for the increasing use of nitrogen fertilizers.

The large-scale application of bio-physical models needs to balance resolution in space and time against processing-time and data storage requirements. Examples for large-scale approaches therefore use either larger grid cells of e.g., 10 km × 10 km, averaging over site characteristics (e.g., Grizzetti et al., 2007), or limit the delineation features to keep the number of sites manageable (e.g., Adler et al., 2007). Often only some important crops are captured in the analysis. An alternative to the application of the bio-physical models are meta-models giving an approximation of the input/output behaviour of the underlying simulation model (Kleijnen, 2006). Bouzaher et al. (1993) define meta-modelling as "a statistical method to abstract away from unnecessary details for regional analysis by approximating outcomes of a complex simulation model through statistically validated parametric forms".

In the domain of bio-economic analysis, meta-modelling dates back to the days where processor time was scarcer than today, e.g., Bouzaher et al. (1993), Furtan et al. (1995) and Carriquiry et al. (1998). Its main advantages are typically faster execution, reduced storage needs and easier integration into other processes. In view of global and inter-sectoral challenges such as mitigation of global warming, combined application of

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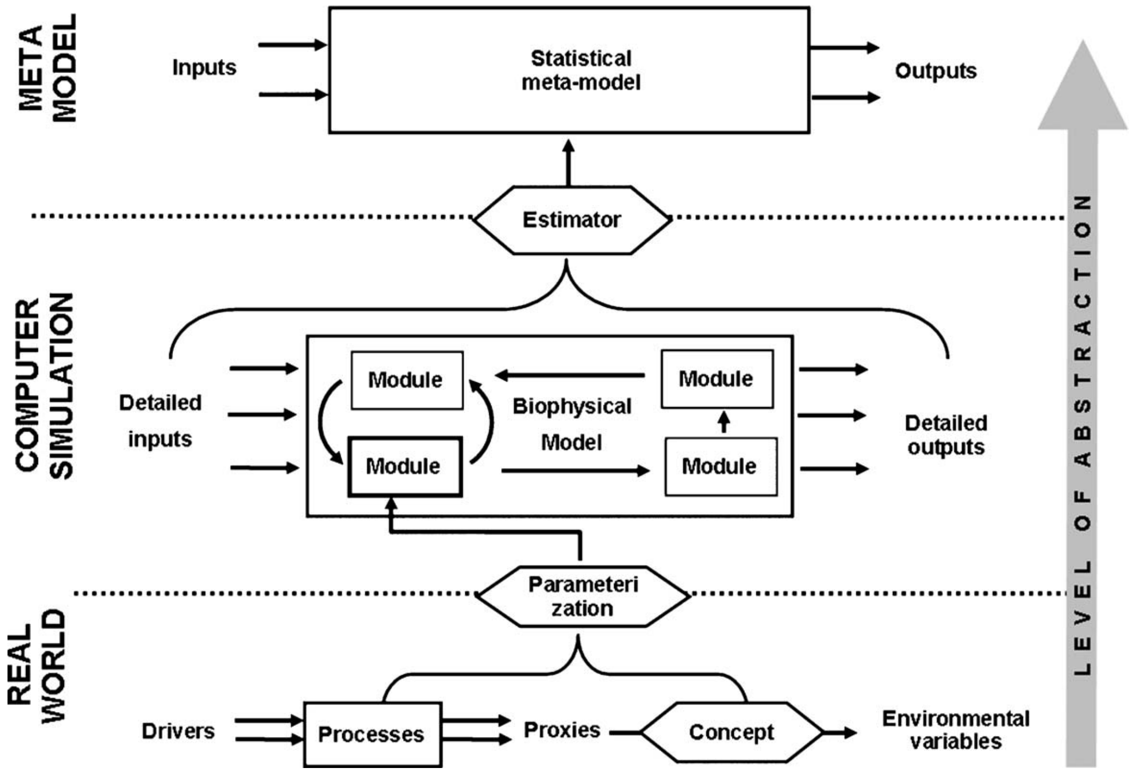

Fig. 1. Conceptual representation of the increasing level of abstraction from real-world phenomena over bio-physical models, meta-models up to the integrated modelling framework.

different models across scales and domains is seen as a key tool for integrated policy impact assessment. Here, meta-modelling might facilitate integration and application of the models applied. Additionally, for agricultural bio-economic analysis, it allows a large number of site–crop combinations and farm practices to be simulated, and thus decreases aggregation bias resulting from reduced spatial variance and/or concentration on major crops.

The main objective of this article is to present the newly developed DNDC–CAPRI meta-model that allows combining the strengths of two very different models, the agro-economic model CAPRI and the biogeochemistry model DNDC into a model chain, depicted in Fig. 1. At the bottom are real-world observations e.g., from field experiments on specific phenomena which allow to develop the individual components of the bio-physical model. Each component simulates observed relations between selected inputs and outputs, typically based on empirically derived equations, and may work on its own scale in time and space. A computer simulation model such as DNDC is a framework linking such components, each describing in mathematical terms the relationships between selected drivers and environmental variables. Both the individual components and the overall framework simplify from real-world processes due to the aggregation as well as by the limited scientific understanding of the process, which both also impact on the accuracy of its results.

Developing a meta-model abstracts further from the real world by solely maintaining numerical relation between (certain and partly simplified) inputs and selected outputs of the bio-physical model. Typically, a meta-model works at a higher scale than the model itself: DNDC runs at (sub-)daily temporal resolution while the DNDC–CAPRI meta-model uses annual data, while keeping the spatial resolution at the original level of 1×1 grid cell clusters level. Very often, the meta-model becomes a component in yet another computer simulation framework, in the present case, in the model chain of CAPRI.

Due to their simplified nature, meta-models are able to perform a large number of simulations using relatively little resources and allow for fast-responding scenario analyses, an important feature for policy decision tools.

The article discusses the development of the CAPRI–DNDC meta-model and its integration into the CAPRI model chain, and highlights its usability by deriving marginal emission factors for nitrogen fertilizer application. The first section on methods discusses the underlying data sources, generating an observation sample for the regression analysis, estimation and site-specific calibration of the meta-model and how the marginal emission factors are derived. The result section presents the explanatory power of the regression models. Next, marginal emission factors for different nitrogen pathways are shown for wheat and rape seed (1) simulated over fertilizer application rates at the mean of the observation sample, (2) at fertilizer application rates from the database for all sites both as maps and distribution diagrams, and (3) aggregated to country level. The third section first compares the newly developed model chain to other frameworks with similar aims, and its results and findings to other Pan-European analysis and large-scale approaches. The article closes with selected conclusions.

2. Methods

A statistical meta-model is developed, which is seamlessly integrated into the CAPRI/DNDC-EUROPE framework described by Leip et al. (2008). This framework combines two existing models, the economic CAPRI model and the bio-physical model DNDC, together with a down-scaling procedure. Here, a meta-model for DNDC-simulation results is added as a new element. The meta-model feeds back into the disaggregation procedure thus ensuring virtually complete consistency between the two modelling systems involved and simplifying the application of the CAPRI/DNDC-EUROPE framework.

2.1. Database of disaggregated information from the CAPRI model

CAPRI (see Britz and Witzke, 2008) is an economic model developed to analyze the impacts of changes in European (or international) agricultural policies and markets on European agriculture and global agricultural markets. Its typical application consists in analyzing impacts of counterfactual scenarios at the medium term (8–10 years) against a so-called reference run which captures the most probable development under the current active law. Operational since 1999, it has been regularly applied for policy impact analysis.

A down-scaling process disaggregates consistently all major elements of the regional CAPRI data set to sub-regional processing units covering the agricultural area of the European Union. The calculation units used are fractions of administrative regions that are uniform with respect to soil, slope and land cover. These about 180,000 so-called Homogenous Spatial Mapping Units (HSMUs) are clusters of 1 km $\times$ 1 km pixels.

The down-scaling procedure has been described in detail by Leip et al. (2008) and Kempen et al. (2005, 2007) and comprises:

- *Crop shares* for each HSMU—based on binary Maximum Likelihood regression models of growing each crop as a function of local factors.
- *Crop yield* combining regional production data and productivities in the spatial calculation unit incorporating information on potential irrigated and rainfed crop yields (Genovese et al., 2007) and irrigation shares (Siebert et al., 2005).
- *Animal stocking densities* for 13 ruminant and non-ruminants animal types considering the possibility of fodder transport across the borders of the individual HSMUs.
- *Manure nitrogen application rates* taking into account nitrogen losses from animal housing and manure management systems, which are estimated according to the MITERRA-EUROPE (Oenema et al., 2007) and Regional Air Pollution Information and Simulation (RAINS) (Klimont and Brink, 2004) models.
- Nitrogen input from crop residues, biological fixation and atmospheric deposition.
- *Application rates of synthetic fertilizer nitrogen*, based on the difference between the crop nutrient need and all non-mineral nitrogen sources, corrected by typical loss rates, and a factor based on soil properties.

All results recover weighted averages for administrative regions based on Highest Posterior Density estimators (Heckelei et al., 2005), consistent either to statistical data *ex post* or CAPRI projection or simulation results *ex ante*.

2.2. Creating a pool of DNDC emissions results for deriving the meta-model

DNDC is a dynamic, process-oriented model to predict trace gas fluxes and nutrient turnover in agricultural soils (Li et al., 1992, 1994; Li, 2000). It consists of three major sub-models: (1) soil climate, (2) crop growth, and (3) soil biogeochemistry including sub-modules for the decomposition of organic material, nitrification, denitrification, and fermentation. It is able to track the fate of nitrogen and delivers the observation space to the statistical response surface. The model is driven by environmental (daily weather), ecological (nitrogen deposition) and management (land use, fertilizer application, field operations) factors which are provided by the spatial down-scaling component (3.3), complemented by further information such as planting dates.

Originally developed to run at the plot scale, the model has been successfully applied at both the plot scales (see for example Li et al., 2005) and also used for several regional applications in many areas of the world (e.g., Pathak et al., 2005; Tonitto et al., 2007; Xu-Ri et al., 2003) and has been intensively tested and applied under European conditions (e.g., Brown et al., 2002; Butterbach-Bahl et al., 2004; Edwards et al., 2007; Mulligan, 2006; Neufeldt et al., 2006; Sleutel et al., 2006).

Table 1
Number of observations in the space generated with the DNDC-simulations.

	Rainfed	Irrigated
BARL	1664	832
MAIZ	2469	1948
POTA	3314	3130
SUGB	2000	1572
PULS	4322	1004
RAPE	2418	730
SUNF	3100	1560
OFAR	3110	2506
WHEA	6586	3706
CERE	5990	1124
VEGPRM	3811	3439

According to Carriquiry et al. (1998), the simulation experiments used for the construction of a meta-model must "generate output that is representative of the study area, so that inferences for the area can be drawn with acceptable statistical reliability". Here, a pool of reference that results from full DNDC simulations for each crop was created, covering the variance in climatic and soil parameters.

DNDC simulations were performed on a selection of crop–site combinations using the same criteria as in Leip et al. (2008) on a total 11,063 combinations of crops and environmental conditions. For each of these combinations, eight different scenarios were simulated by setting both mineral and organic nitrogen application rates to 0% and 100% of the rate determined from the down-scaling process as discussed above, both under rainfed conditions and under full irrigation where applicable. Full irrigation, for a DNDC simulation, is obtained by adding daily the appropriate quantity of water to keep the crop without water stress. That meant that in total about 90,000 observations are available to generate the meta-model.

2.3. Statistical set-up of the meta-model

The main challenge in designing the meta-model of DNDC is to find those parameters available at HSMU level which contribute most to the variance of the DNDC outputs. Because of the highly non-linear relations in the bio-physical model appropriate numerical transformation of the inputs were added to the design problem (Table 1).

Regression functions were estimated for total annual values of 13 outputs[1] of DNDC (nitrogen leaching, nitrogen release during mineralization of organic matter, nitrogen uptake of the crop, gas losses as N_2, N_2O, NO and NH_3, total nitrification plus denitrification gas losses ($N_2 + N_2O + NO$), total nitrogen losses, water uptake by the crop, water leached, water evaporated and water transpired) and for 11 crops or groups of crops (wheat, barley, maize, other cereals, rape seed, sunflowers, pulses, potatoes, sugar beet, vegetables and annual grassland), and, where applicable, for irrigated and non-irrigated agriculture, leading to 198 regression models. The irrigated/non-irrigated distinction was introduced as the impact of rainfall on the different processes in DNDC naturally depends on whether additional irrigation water is used or not.

The following 14 parameters were used as explanatory variables: organic and inorganic nitrogen application rates, annual averages of monthly minimum and maximum temperatures, annual and three-monthly accumulated precipitation, or annual evaporation from a open water surface (E_0) and evapo-transpiration from grass (ET_0),

[1] Of which four relating to the water balance are not discussed in the paper.

soil organic carbon content, soil pH and packing density, clay content, and the optimum potential yield. Variables were offered in linear form, as logs, as squares and as square root. Furthermore, the product of any two variables was presented to the estimator. Given the importance of soil organic carbon for DNDC's simulation behaviour, additional explanatory variables were constructed by multiplying each variable both with the log and the square of soil organic carbon. That meant that each regression model could choose a suitable set of regressors from close to 200 potential candidates.

The selection was based on backward elimination using two criteria simultaneously. First, any regressors not significant at the 99.9% confidence level were excluded, starting with the least significant ones. Second, in order to avoid over-fitting, the least significant regressor was dropped as long as the adjusted R^2 was increasing. This guarantees that any explanatory variable must have a statistically significant impact. Each of the meta-model equations comprises between 50 and 100 regressors.

2.4. Site-specific calibration

In the meta-model, inconsistencies are being created as parameters like crop yields are produced both from the down-scaling process and from the crop-growth module of DNDC with significant repercussions on the N-budget. As a solution to this problem, one key parameter in DNDC is automatically recalibrated to fit the yields as derived in the down-scaling procedure. Conceptually, the process can be described as follows. Assume an estimated relationship between the yield simulated by the bio-physical model, y^*, and two separate vectors of independent variables, α' and β'

$$y^* = f(\alpha', \beta') + \varepsilon \tag{1}$$

where in average over the observation sample, the error term will be zero. The vector α' may comprise those parameters which the researcher is uncertain about and which are typically used for manual calibration of the bio-physical model. Furthermore, it is required that the elements of α' are not subject to consistency conditions as e.g., the fertilizer application rates. For any given crop–site combination, the down-scaling part will deliver a local yield y', which in almost any case will lead to $y' \neq y^*$. Inverting the relation, those values for the crop parameters α with a given site-specific properties and farming practice β' are derived that let the bio-physical model simulate a yield of y':

$$\alpha = f^{-1}(y', \beta') \tag{2}$$

In the case of DNDC, that process is especially simple as the simulated yields are driven by an optimum potential yield, so that only one element on α needs to be calibrated (see Fig. 2). The un-calibrated simulation response is shown in red. In the chosen example, the potential yield α' is too high, so that for the given site-specific values β', a yield of y^* is simulated, which is greater than the observed one y'. Such an overestimation at fixed N input would mean that total N fluxes to the environment would be underestimated. By reducing the potential yield to the blue dotted line α, based on an inversion of the regression function for the yield, the bio-physical model and the meta-model will simulate the observed yield y'.

2.5. Reducing estimation errors by integrating results for aggregated pathways

A further problem of a meta-model is that each flux-component is estimated separately so that the mass budget of nitrogen is not necessarily closed, in contrast to the original results from the bio-physical model. To overcome this problem the meta-model estimates also total nitrogen losses, which can be done with a

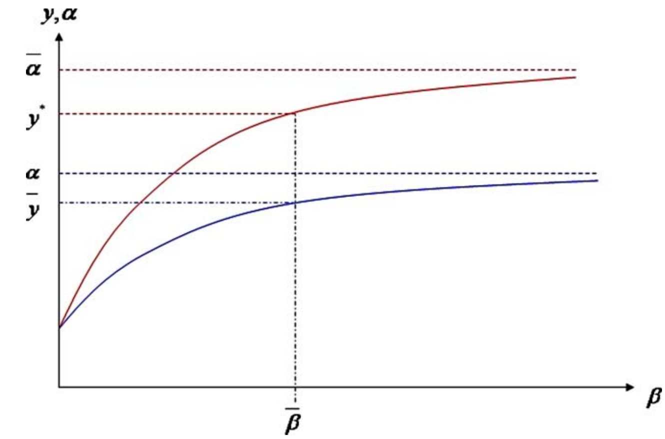

Fig. 2. Calibration to observed farming practise (fertilizer application rate and realized yield) by shifting the potential yield.

higher level of confidence, and the error is then distributed over the individual loss terms.

Let the balance components be elements of the vector **x**. For each simulated crop–site combination, DNDC will yield $\Sigma_i x_i = 0$, but the regression models will typically give: $\Sigma_i x_i = \varepsilon$. The aim is to get a vector of corrected values x^* where the balance holds again and some distance function between the raw estimates and consistent ones is minimized.

$$\min D(x', x*), st. \Sigma_i x_i = 0 \tag{3}$$

This is achieved by distributing the error to the elements of **x**, using the unexplained variance as weights, however under some safety rules which prevent e.g., negative balance estimates or correction beyond what was observed as a minimum and maximum in the observation sample. During the correction, nitrogen crop removal with harvested material is however kept constant to ensure that the consistency with the regional surplus calculation is not lost.

2.6. Derivation of marginal emission factors

Let $F_{i,j,k}$ be the simulated dependent variable i (for example N_2O emissions), in kg N ha^{-1}, at the relative application rates j (for example at 50% relative to the figures determined during the down-scaling procedure) for mineral and k for organic nitrogen. Let $F_{i,j+x,k}$ be the same at mineral nitrogen application rate increased by x kilogram. The Marginal Emission Factor $F_{\text{marg,min},i,j}$ is then defined as:

$$F_{\text{marg},i,\text{min},j} = \frac{F_{i,j+x,k} - F_{i,j,k}}{x} \tag{4}$$

For all model runs presented in the following, x was set to 1 kg N. For a linear relationship as assumed for example in the IPCC guidelines (see e.g., IPCC, 2000), $F_{\text{marg,min}}$ is a constant.

In order to investigate whether identical emission factors for organic and mineral nitrogen are appropriate, scenarios are added which derive $F_{i,\text{min,man}+1}$ in order to calculate the analogous marginal emission factor for manure nitrogen:

$$F_{\text{marg},i,\text{man},k} = \frac{F_{i,j,k} - F_{i,j,k}}{x} \tag{5}$$

3. Results

3.1. Explanatory power of the regression functions

The DNDC–CAPRI meta-model explained typically a rather large part of the variance of the DNDC simulations (see Table 2).

Table 2
Coefficients of determination of the DNDC–CAPRI meta-model versus DNDC-simulation results. R^2 below 80% in italic, and all above 95% in bold.

		N-leaching	N-mineralized	N_2	N_2O	NH_3	NO	N-denitrific.	N-surplus	N-crop uptake
Barley	Rainfed	**0.977**	**0.997**	**0.963**	*0.787*	**0.982**	0.940	**0.955**	**0.997**	**0.978**
	Irrigated	**0.964**	**0.999**	**0.972**	0.882	**0.991**	**0.969**	**0.957**	**0.999**	**0.985**
Maize	Rainfed	0.914	**0.993**	*0.792*	0.830	**0.983**	0.946	0.846	**0.990**	**0.984**
	Irrigated	0.877	**0.997**	*0.772*	0.888	**0.983**	**0.961**	0.884	**0.990**	**0.988**
Potatoes	Rainfed	0.923	**0.997**	0.932	0.867	**0.984**	**0.964**	0.928	**0.989**	**0.996**
	Irrigated	0.911	**0.998**	0.937	0.915	**0.984**	**0.969**	0.941	**0.989**	**0.996**
Sugarbeet	Rainfed	0.929	**0.992**	0.932	0.932	**0.988**	**0.967**	0.944	**0.991**	**0.991**
	Irrigated	0.899	**0.991**	0.909	0.924	**0.991**	**0.976**	0.932	**0.990**	**0.994**
Pulses	Rainfed	**0.974**	**0.989**	0.930	*0.794*	**0.975**	0.928	0.925	**0.994**	0.852
	Irrigated	**0.981**	**0.997**	0.949	0.908	**0.983**	**0.968**	**0.964**	**1.000**	**0.963**
Rape seed	Rainfed	**0.977**	**0.993**	0.934	0.866	**0.969**	0.946	0.935	**0.996**	**0.960**
	Irrigated	**0.989**	**0.999**	0.926	0.934	**0.992**	**0.980**	0.945	**0.999**	**0.986**
Sunflower	Rainfed	**0.969**	**0.994**	0.928	0.810	**0.980**	0.924	0.927	**0.998**	**0.976**
	Irrigated	**0.962**	**0.996**	**0.953**	0.910	**0.990**	**0.959**	**0.958**	**0.999**	**0.986**
Fodder production	Rainfed	**0.978**	**0.972**	0.942	*0.776*	**0.964**	0.940	0.933	**0.999**	0.919
	Irrigated	**0.978**	**0.967**	0.820	*0.783*	**0.966**	0.944	0.825	**0.999**	0.912
Wheat	Rainfed	**0.963**	**0.959**	0.800	*0.751*	**0.966**	0.900	0.822	**0.989**	0.898
	Irrigated	**0.962**	**0.976**	0.842	0.845	**0.980**	0.926	0.887	**0.994**	0.912
Other cereals	Rainfed	0.917	**0.974**	0.851	*0.742*	0.943	0.919	0.878	**0.982**	0.925
	Irrigated	**0.953**	**0.988**	0.945	0.908	**0.988**	**0.971**	**0.960**	**0.993**	**0.974**
Vegetables	Rainfed	0.945	**0.995**	0.917	0.845	**0.984**	0.946	0.919	**0.989**	**0.964**
	Irrigated	0.945	**0.996**	0.841	0.828	**0.986**	**0.954**	0.859	**0.990**	**0.964**

Considering all regression functions (for all crops and DNDC outputs estimated), about 40% of the obtained R^2 values were above 0.95. For another 32% of the regressions, R^2 was above 85% and only in 10% of the cases below 75%.

The comparison between the results for different fluxes of nitrogen obtained with the meta-model for EU15 and the corresponding fluxes simulated with the DNDC model is shown for wheat (Fig. 3) and rape seed (Fig. 4). The scatter diagrams

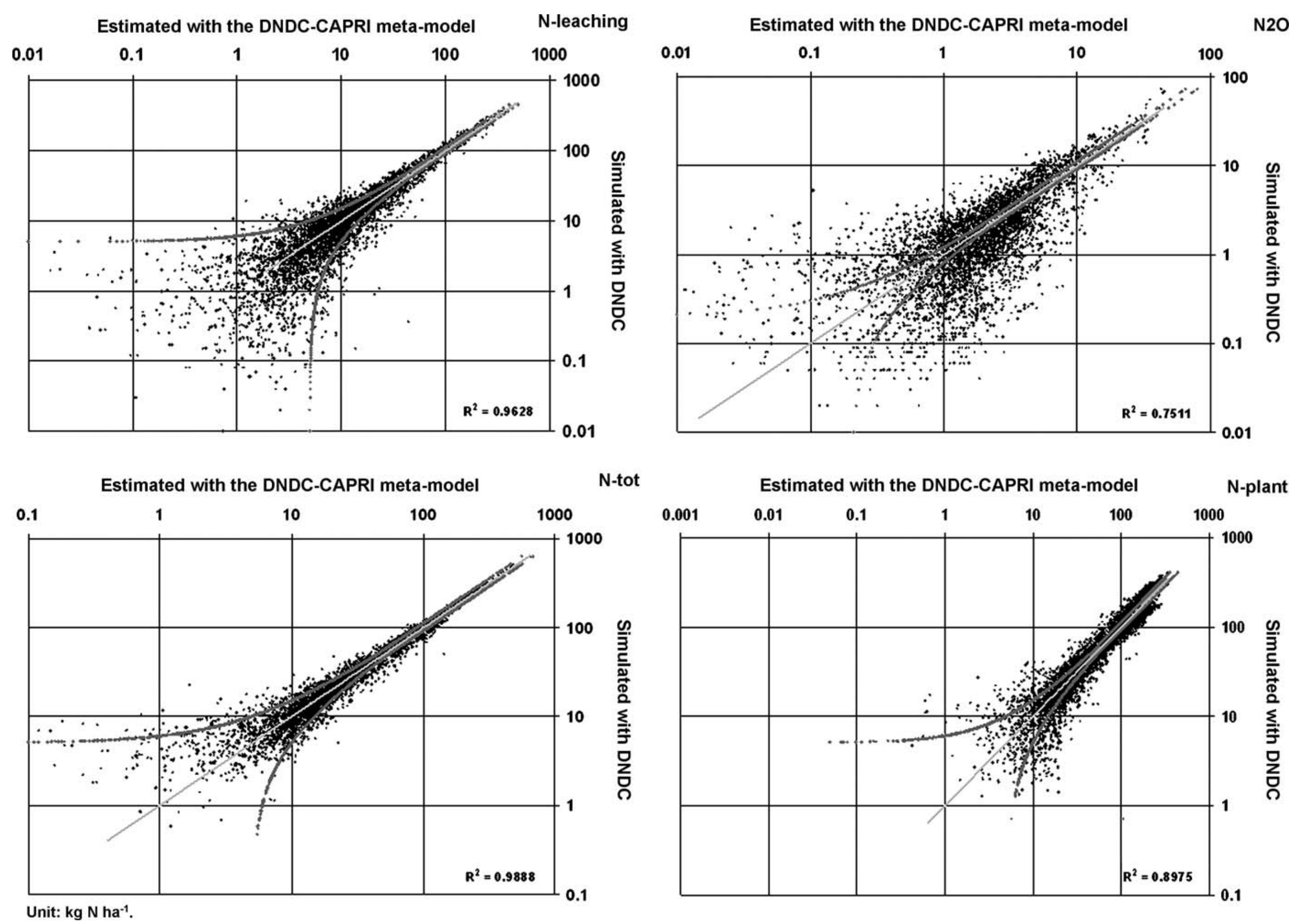

Fig. 3. Nitrogen losses for the cultivation of wheat. The scatter diagrams show the losses estimated with the DNDC–CAPRI meta-model versus the results of the DNDC. The correlation coefficient (trend line in light grey) is given in each panel. A window enclosing all values being closer to the DNDC simulation than 10% with a minimum of a fixed amount of nitrogen is shown in grey dots. The minimum distance is 0.1 kg N ha^{-1} for N_2O and 5 kg N ha^{-1} for N-leaching, N-tot (total N losses) and N in plant biomass.

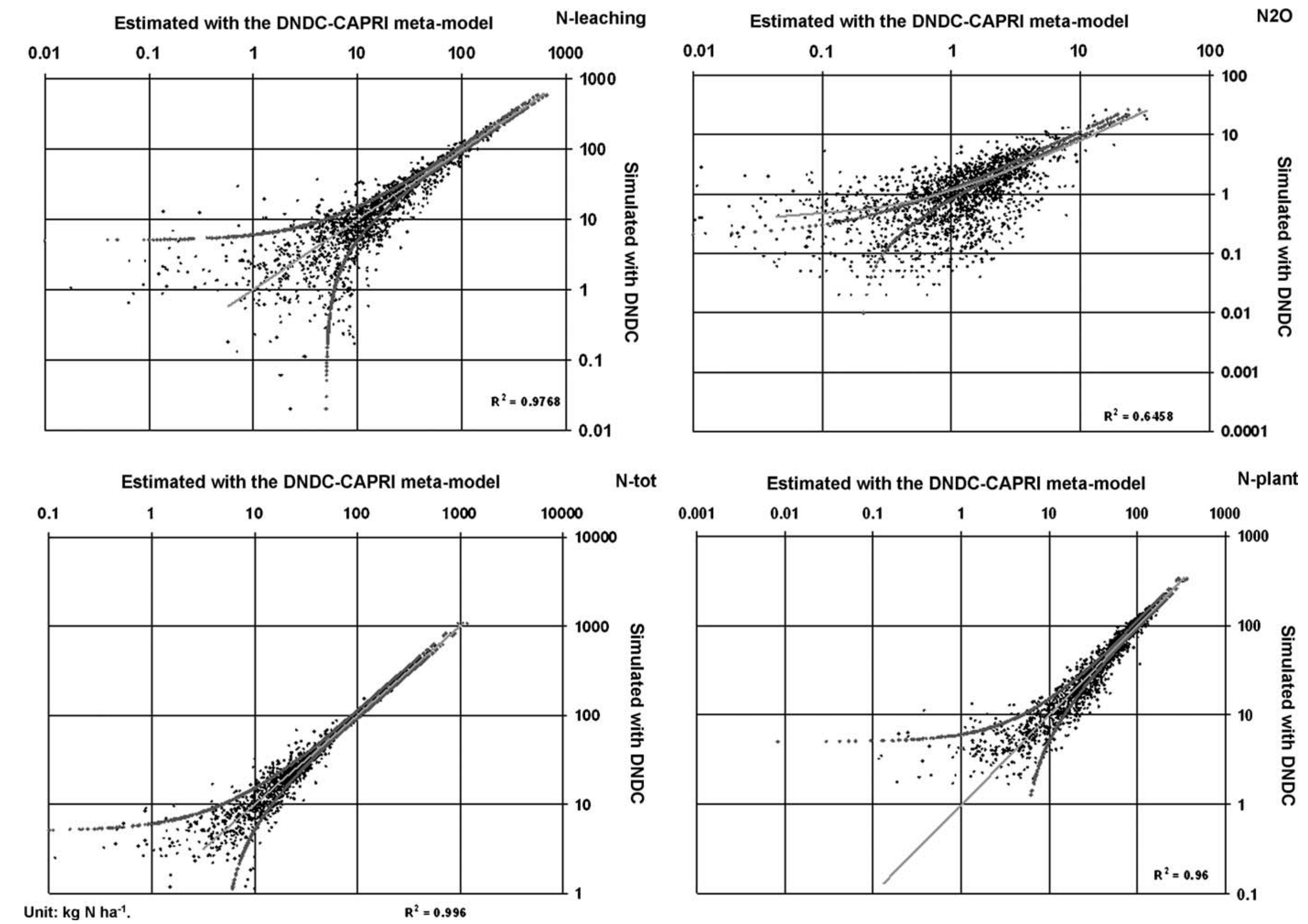

Fig. 4. Nitrogen losses for the cultivation of rape seed. The scatter diagrams show the losses estimated with the DNDC–CAPRI meta-model versus the results of the DNDC. The correlation coefficient (trend line in light grey) is given in each panel. A window enclosing all values being closer to the DNDC simulation than 10% with a minimum of a fixed amount of nitrogen is shown in grey dots. The minimum distance is 0.1 kg N ha^{-1} for N_2O and 5 kg N ha^{-1} for N-leaching, N-tot (total N losses) and N in plant biomass.

underline that for small values relative errors may be rather high: a result of using ordinary least squares regressions. The scatter diagrams show also a subjective estimate of the corridor of uncertainty in the DNDC-simulation results. This is bounded by a 10% proportional uncertainty (due to the inaccuracies in the DNDC methodology) combined with an absolute uncertainty calculated from the estimated error range of the input data. This absolute uncertainty was subjectively chosen at 0.1 kg N ha^{-1} for N_2O fluxes and at 5 kg N ha^{-1} for the 'large' nitrogen fluxes: N-leaching, N in plant biomass and total N losses through gaseous emissions or nitrogen leaching.

3.2. Simulation behaviour of the meta-model around the mean of the observation sample

The general behaviour of the meta-model is analyzed by performing simulations on one virtual, but representative site for wheat and rape seed, defined by mean values for all environmental characteristics (i.e., 25% and 28% clay content, 3.9% and 2.5% organic carbon, a bulk density of 1.3 and 1.4, and a pH of 7.5 and 7.9 for the simulations of rape seed and wheat, respectively). Fig. 5 shows how yields and emissions of nitrogen react to increased mineral fertilizer doses up to 300 kg N ha^{-1}. Results are for rainfed agriculture, which dominates for both crops in the EU.

More than 80% of the first kilogram of mineral nitrogen applied is converted into plant biomass (black square). Yields continue to respond to higher application rates, however with rapidly decreasing marginal returns letting marginal losses increase. The right panels of Fig. 5 report the marginal emission factors, representing the partitioning of one additional kilogram of nitrogen applied. At the maximum simulated application rates, yield increases become insignificant and almost all the nitrogen additionally applied is lost to the environment. According to the meta-model, the plateau of the nitrogen biomass is reached earlier for rape seed cultivation (at around 150 kg N ha^{-1}, with 34 kg N ha^{-1} contained in manure applied in all scenarios), than for the cultivation of wheat (at around 300 kg N ha^{-1} with 13 kg N ha^{-1} manure applied). The results of rape seed correspond well with the European average nitrogen application rates (of 150 kg N ha^{-1}) indicating that the meta-model catches well the agro-economic situation in Europe.

In this example, the range of marginal emission factors for NO and N_2O fluxes are relatively small; for NO fluxes, these decrease from 0.3% to 0.15% of mineral fertilizer applied to rape seed fields, and these are stable at 0.25% for nitrogen applied to wheat fields. Marginal emission factors of N_2O also decrease with increasing application rates of mineral fertilizer nitrogen for these representative conditions, from 2.6% to 1.4% for rape seed and 1.6% to 1.3% for wheat fields.

3.3. Marginal emissions factors at HSMU level

The maps in Fig. 6 show marginal leaching and N_2O fluxes for the application of one additional kg of mineral fertilizer nitrogen

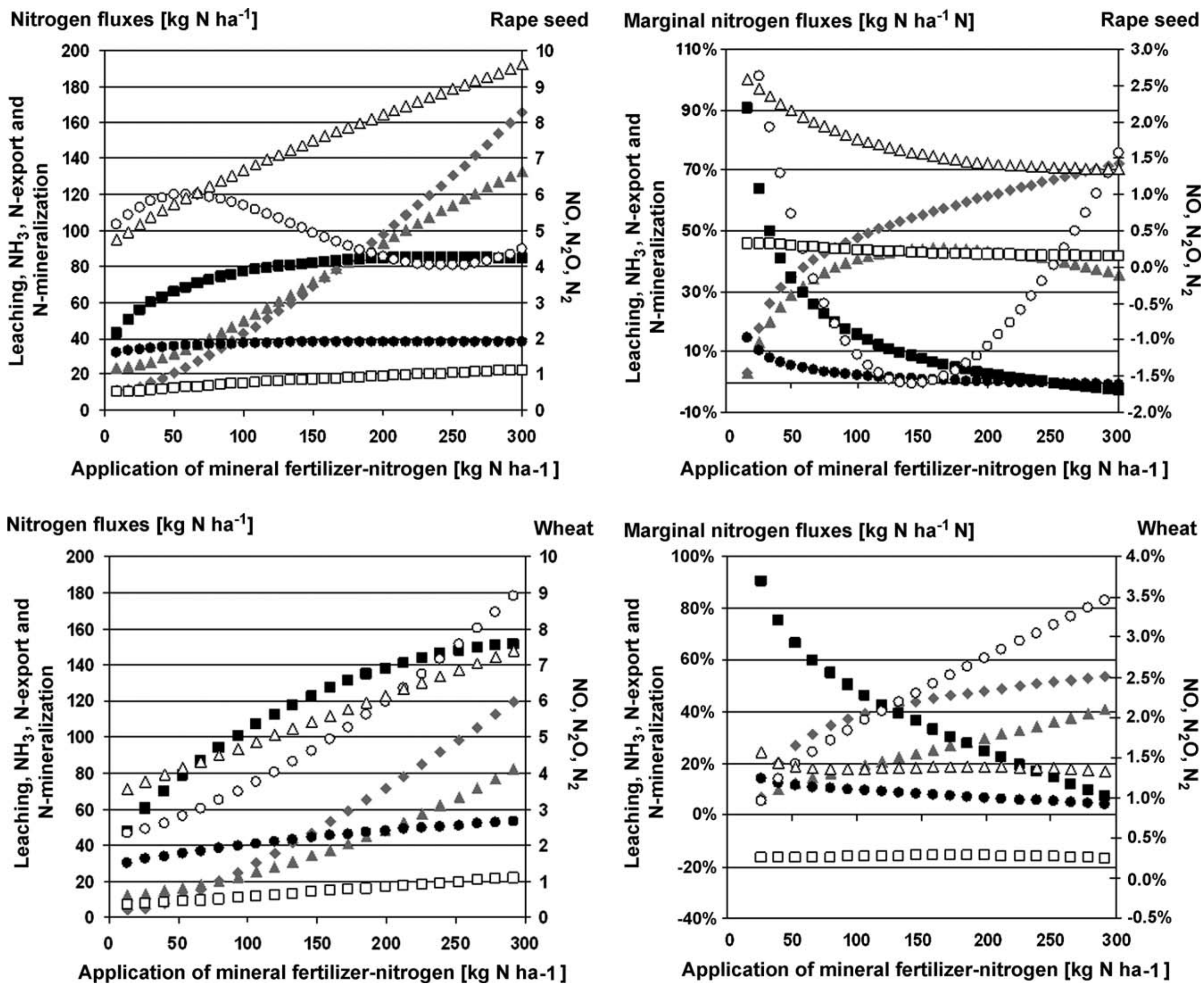

Fig. 5. Impact of changing mineral fertilizer-nitrogen application rates on total nitrogen fluxes (left-hand panels) or marginal nitrogen fluxes (percent of additional nitrogen lost to pathway) for rape seed (upper panels) and wheat (lower panels) cultivation. On the left *y*-axis: (■) nitrogen in plant biomass; (▲) N-leaching, (●) N-mineralization, (◆) NH_3 and on the right *y*-axis: (○) N_2, (□) NO, (△) N_2O.

for the cultivation of rape seed at the currently estimated average farming practice. Some care must be taken when interpreting the maps as large HSMUs may only comprise a small share of rape seed cultivated. In Scandinavian countries, to give an example, high marginal emission factors coincide with small crop shares.

Changes in N_2O emissions caused by the application of one more kilogram of mineral nitrogen range from small reductions of N_2O for some HSMUs to increases of N_2O emissions by up to more than 5% of the additional N input. The spatial distribution of emission hot-spots is very similar for the cultivation of rape seed and wheat (not shown), in contrast to the spatial distribution of the application rate of nitrogen (not shown), indicating the importance of the environmental factors. Most important factor appears to the soil organic carbon content (for example in Scandinavia, Wales, Northern Germany) and fertilizer application rates (for example in the Po Valley, Italy, Southern Germany and Bretagne, France).

Fig. 7 shows the cumulative distribution of marginal emission factors over area of rape seed and wheat cultivation. Nitrogen leaching rates significantly below 20% of additional nitrogen input are occurring on less than 20% of cultivated area, with marginal nitrogen leaching rates being larger for rape seed field than for wheat fields. Under current practices, there are 10% of the cultivated area where marginal nitrate leaching losses account for 60% or more of the last kilogram of added mineral nitrogen. Also, leaching rates from additional manure applied tend to be higher than the corresponding rates for mineral fertilizer. A different picture is obtained for the marginal N_2O flux rates, as here emissions from wheat fields were not depending on the type of nitrogen input, whereas for rape seed cultivation considerably higher marginal emission rates are simulated for the additional application of manure nitrogen compared to mineral fertilizer. For a considerable fraction of the area, additional input of nitrogen reduces N_2O fluxes, but with significant values only for manure applied on wheat fields.

3.4. Marginal emissions factors at country level

Table 3 reports aggregated marginal emission factors at the country level at the currently estimated average farming practice for an incremental addition of 1 kg of mineral fertilizer nitrogen and manure nitrogen. The aggregation per crop takes the estimated shares of crops per processing unit into account, and thus summarizes over soil types, climate and fertilizer application rates in accordance to estimated site-specific yield. Deviations between the sum of total emissions (N-tot) and nitrogen removal with plant material (N-plant) from unity are possible because (i) changes in nitrogen stocks in soils and in nitrogen fixation are not

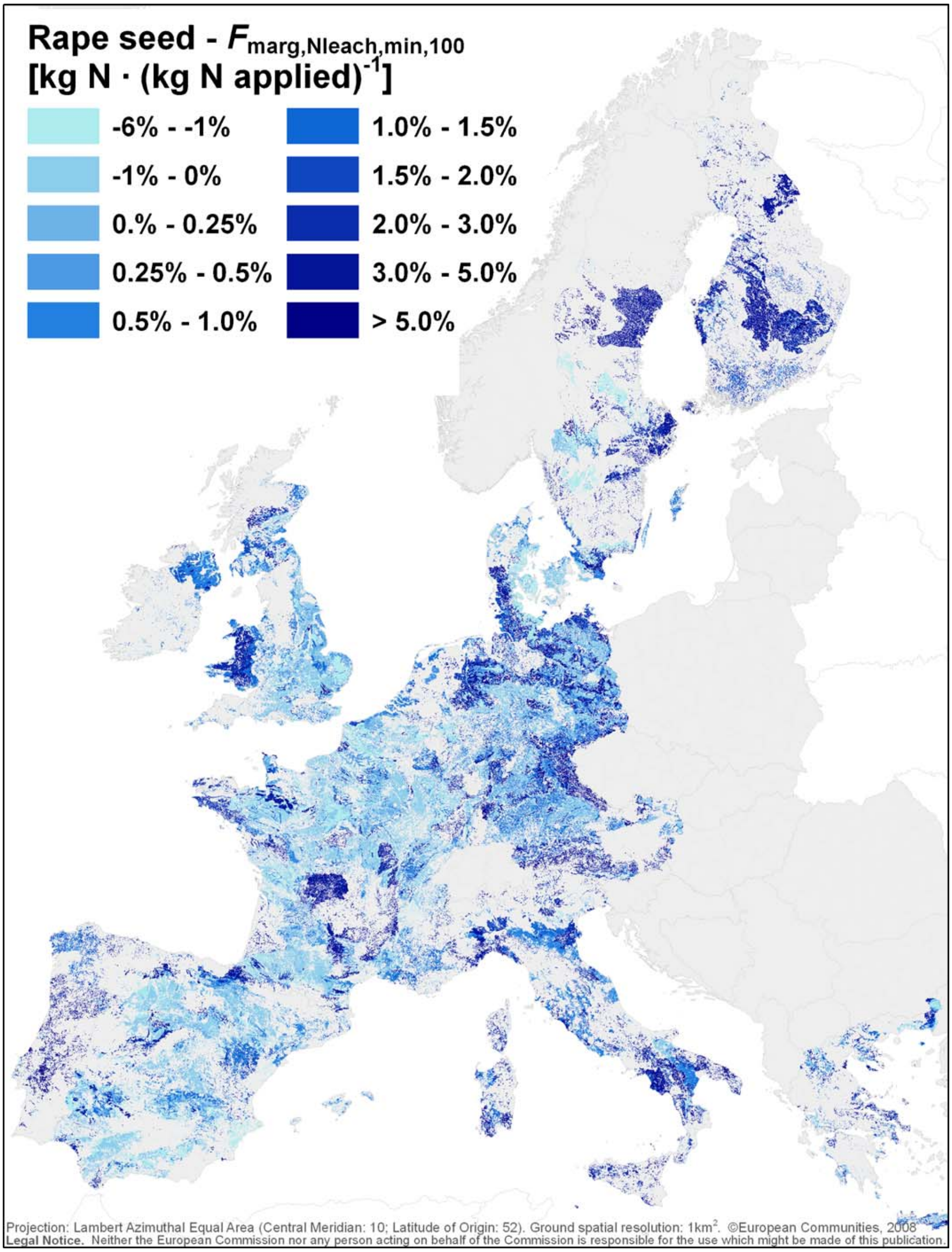

Fig. 6. Marginal emission factor of N_2O in EU15 at the HSMU level for rape seed. Application rates of nitrogen correspond to current farming practices (year 2000). The marginal emission factors are expressed in percent of 1 kg of mineral fertilizer nitrogen applied incrementally. Note that HSMUs also with a small share of the respective crop cultivated are coloured.

covered by the meta-model explicitly, but rather used to implicitly close the balance and (ii) the meta-model (when calculating marginal emission factors) may indeed introduce some small error in the consistent mass flows of DNDC by estimating each nitrogen flux separately.

Extra manure applied to rape seed cultivation, has a much higher marginal emission factor than mineral N in some countries, such as Austria and Spain. But in others (e.g., Scandinavia), the addition of manure nitrogen leads to a reduction of total N_2O, while the latter is in general also found for application to wheat, there is a general tendency of smaller F_{marg} for manure than for mineral fertilizers, with the exception of Mediterranean countries.

4. Discussion

4.1. Methodological approach

The combination of economic and bio-physical models is more and more recognized as a powerful tool for policy decision support (e.g., Schneider et al., 2007; van Vuuren et al., 2006; Vatn et al., 2006). Yet, the challenges are large and different choices had to be made. Erisman et al. (2002), for example, developed a comprehensive decision support system (NitroGenius) for the Netherlands, but policy and farm management decisions were to be made by the "player". Also very comprehensive is the ECEMOD system (Vatn et al., 2006) comprising losses of nitrogen phosphorus, as

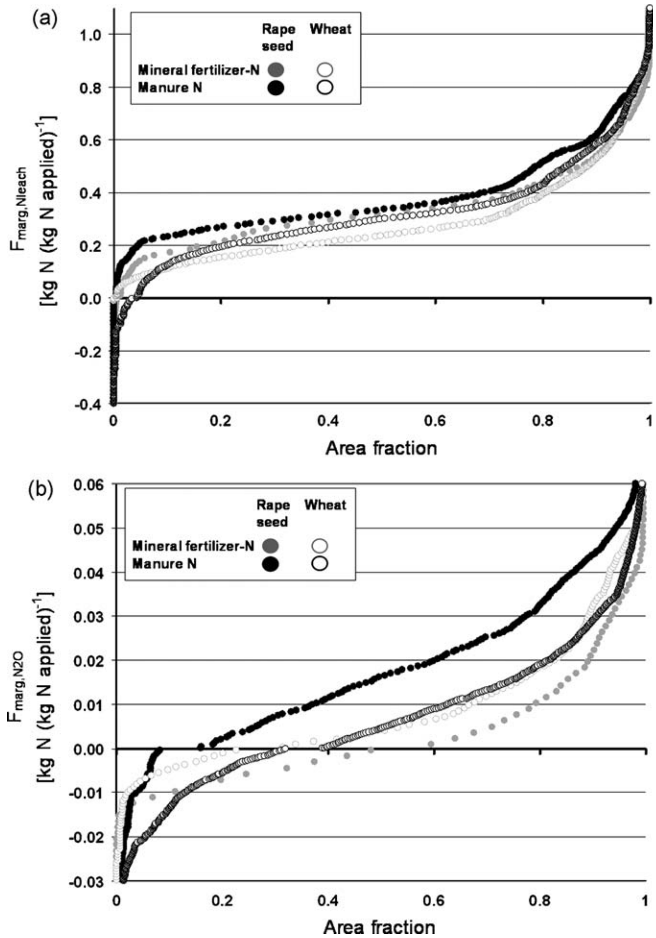

Fig. 7. Marginal emission factors for (a) N-leaching and (b) N_2O fluxes at current farming practices (year 2000) for the incremental addition of 1 kg mineral fertilizer or manure nitrogen to rape seed and wheat fields. The marginal emission factors are plotted against the cumulative area with lower or equal marginal emissions.

well as pesticides and soil carbon development, but applications so far were restricted to relatively small study areas in Norway. Schneider et al. (2007) assess the agricultural and environmental impact of carbon prices, by applying a US agricultural sector and greenhouse gas mitigation model to a limited number of regional aggregates and land type classes. Neufeldt et al. (2006) linked DNDC to an economic model at a disaggregated scale, relying however on very detailed input data for the German state of Baden-Württemberg. The DNDC–CAPRI meta-model allows us to combine the flexibility and Pan-European extent of the economic model CAPRI with the process-understanding and level of detail of the bio-physical model.

The statistical calibration procedure for the yields simulated with the DNDC meta-model (see Section 2.4) offers an elegant and efficient way to ensure mutual consistency between the statistically down-scaled regional yields and the simulation behaviour of the meta-model. The simple equation structure of the meta-model renders site-specific calibration easy, if sufficient variance in the parameters used for calibration is given. Within limits this method allows also including technical progress in scenario calculations of the meta-model, for example higher yields per hectare or more draught resistant cultivars.

Additionally, the DNDC–CAPRI meta-model is able to construct nitrogen response curves for virtually all possible crop–site-management combinations in Europe, without being constrained to pre-defined functional forms or a limited sample (see Godard et al., 2008; Rajsic and Weersink, 2008). These features make the DNDC–CAPRI meta-model unique and powerful as a decision support tool.

The predictive power of the meta-model was generally very good. There were a few cases, particularly for estimated N_2O fluxes, where R^2 was less than 0.8. The present version of the DNDC–CAPRI meta-model is based on DNDC simulations with only one year of weather data available (see Leip et al., 2008). For the meta-model, however, long-term averaged climatic drivers per HSMU were used as explanatory variables. For N_2O fluxes, however, the timing of precipitation event and the occurrence freeze/thaws events is often more decisive than the annual climate parameters (e.g., Skiba and

Table 3
Marginal emission factors for the incremental application of 1 kg of mineral fertilizer and manure nitrogen, respectively, at average mineral and organic fertilization rates.

	N input		N-leaching		N_2O		N-tot		N-plant	
	Mineral	Manure	Mineral	Manure	Mineral	Manure	Mineral	Manure	Mineral	Manure
(a) Rape seed										
Austria	78	2	0.34	0.32	1.77%	3.12%	0.71	0.32	0.25	0.22
Belgium	136	34	0.40	0.48	0.38%	2.25%	0.71	0.83	0.23	0.24
Denmark	111	23	0.19	0.22	0.40%	−0.81%	0.70	0.84	0.19	0.25
Finland	90	3	0.40	0.47	2.43%	−2.20%	0.73	0.95	0.12	0.25
France	151	7	0.41	0.48	0.53%	3.18%	0.75	0.33	0.19	0.20
Germany	165	11	0.39	0.48	1.18%	2.23%	0.79	0.92	0.15	0.16
Greece	92	5	0.42	0.59	0.88%	3.75%	0.70	0.77	0.29	0.24
Ireland	134	7	0.64	0.75	0.91%	1.43%	0.77	0.33	0.21	0.20
Italy	25	2	0.25	0.33	1.23%	4.02%	0.68	0.70	0.37	0.25
Netherland	55	5	0.41	0.58	1.54%	2.63%	0.85	0.97	0.05	0.06
Portugal	2	2	0.43	0.51	0.63%	5.08%	0.63	0.72	0.28	0.36
Spain	128	14	0.33	0.43	0.05%	3.38%	0.80	0.90	0.16	0.14
Sweden	39	6	0.41	0.50	2.69%	−0.25%	0.66	0.72	0.35	0.29
UK	173	11	0.46	0.54	0.78%	1.04%	0.78	0.92	0.13	0.17
(b) Wheat										
Austria	103	20	0.27	0.26	1.15%	0.55%	0.59	0.72	0.38	0.37
Belgium	206	43	0.39	0.31	0.88%	−0.26%	0.59	0.90	0.16	0.35
Denmark	150	90	0.39	0.38	0.56%	−0.52%	0.74	1.02	0.01	0.21
Finland	102	51	0.61	0.54	3.28%	−1.40%	0.66	0.93	0.06	0.29
France	161	32	0.36	0.42	0.89%	1.40%	0.85	0.91	0.13	0.06
Germany	156	35	0.37	0.40	1.49%	0.79%	0.78	0.83	0.20	0.16
Greece	45	10	0.30	0.38	2.40%	0.72%	0.71	0.82	0.22	0.18
Ireland	187	28	0.62	0.69	1.66%	1.24%	0.82	0.87	0.12	0.10
Italy	68	11	0.37	0.44	0.85%	2.39%	0.85	0.87	0.15	0.05
Netherland	216	61	0.66	0.59	1.87%	1.77%	0.84	1.11	−0.07	0.09

Table 3 (*Continued*)

	N input		N-leaching		N_2O		N-tot		N-plant	
	Mineral	Manure	Mineral	Manure	Mineral	Manure	Mineral	Manure	Mineral	Manure
Portugal	29	13	0.24	0.35	1.29%	1.71%	0.68	0.59	0.36	0.16
Spain	70	24	0.24	0.32	1.25%	1.89%	0.91	0.94	0.11	−0.04
Sweden	122	23	0.52	0.46	2.88%	0.08%	0.61	0.34	0.13	0.34
UK	206	33	0.50	0.55	0.96%	0.73%	0.89	1.02	−0.01	0.02

Smith, 2000) and mirrors the general problem in estimating N_2O emissions with statistical models (Heuvelink, 2008). Recently, a new database with daily observations for 1900–2000 has been processed (Orlandini and Leip, 2008), and their integration and the development of more elaborated climate indicators will almost certainly further increase the explanatory power of the meta-model. Predictions of the meta-model becomes also more scattered for low simulated fluxes (see Figs. 8 and 9). This is a direct effect of using ordinary least squares regressions. One could tackle this problem by regressing using the logs of the dependent variables. However, then the absolute errors for the *larger* values of emissions would increase. As the meta-model is introduced to estimate the overall environmental impacts of farming, reducing absolute errors was deemed more relevant. The predictive power of total N losses exceeds that of single pathways so that errors can be further minimized by scaling single N loss terms to the total N loss according to the uncertainty of the prediction (see also Section 2.5), thus closing the N-budget.

4.2. Simulation results

Marginal emission factors as discussed here are not directly comparable with overall average emission factors from IPCC. The latter are designed to derive total emissions for different parts of the economy, at current average practice. By contrast, marginal emission factors are the appropriate measure to assess the impact of changes in practices. They are fundamental in assessing possible mitigation strategies under the Kyoto protocol and need to be integrated into accounting methodologies to account for simultaneous changes in activity levels and activity practices.

Nevertheless, we found that under current farming practices median marginal loss of nitrates by leaching are close to the IPCC default of 30% of applied nitrogen. The picture is different for N_2O fluxes, where median losses from nitrogen applied as manure on rape seed field are higher (1.5% of applied N) and lower for wheat fields (0.5% of applied nitrogen, regardless of fertilizer type) and

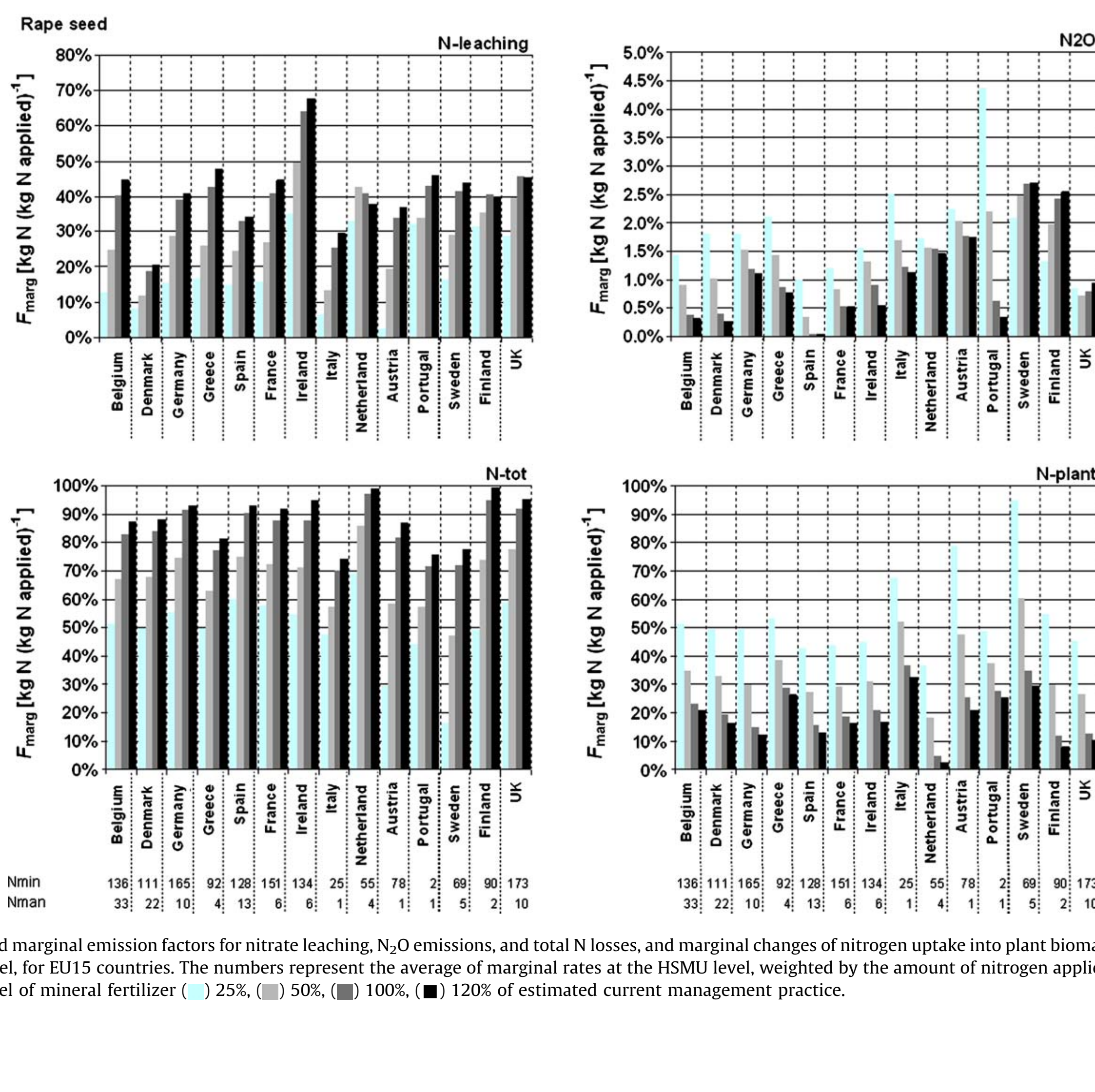

Fig. 8. Rape seed marginal emission factors for nitrate leaching, N_2O emissions, and total N losses, and marginal changes of nitrogen uptake into plant biomass, aggregated to the country level, for EU15 countries. The numbers represent the average of marginal rates at the HSMU level, weighted by the amount of nitrogen applied (in kg N ha^{-1}). Application level of mineral fertilizer ( ) 25%, ( ) 50%, ( ) 100%, ( ) 120% of estimated current management practice.

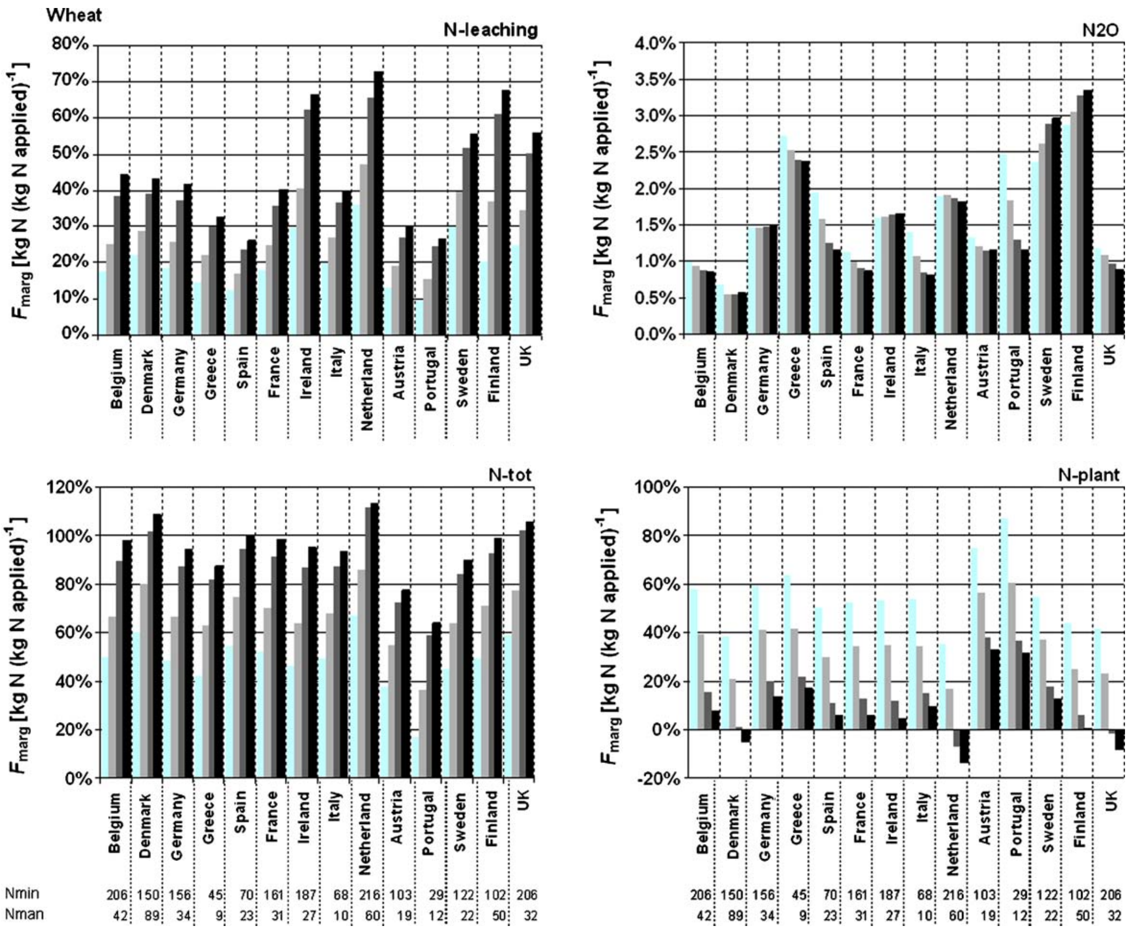

Fig. 9. Wheat marginal emission factors for nitrate leaching, N_2O emissions, and total N losses, and marginal changes of nitrogen uptake into plant biomass, aggregated to the country level, for EU15 countries. The numbers represent the average of marginal rates at the HSMU level, weighted by the amount of nitrogen applied (in kg N ha^{-1}). Application level of mineral fertilizer ( ) 25%, ( ) 50%, ( ) 100%, (■) 120% of estimated current management practice.

additional mineral fertilizer nitrogen added to rape seed field did not lead to additional N_2O fluxes.

The concept of marginal environmental impact is not new. Leip and Mulligan (2005) for example concluded that the marginal emission factors for N_2O are a function of the nitrogen application rate and that different emission factors should be used for mineral fertilizer and manure nitrogen. Mean N_2O emission factors for mineral fertilizer-nitrogen were 0.014 ± 0.017 kg N–N_2O/N without the additional application of manure and 0.0020 ± 0.0021 kg N–N_2O/N if manure was applied, in consistency with the results of the meta-model in this study. However, while Leip and Mulligan (2005) found lower N_2O emission rates for the application of manure nitrogen than of mineral fertilizer nitrogen, our study gives on the average higher total marginal losses for the addition of manure nitrogen and a very diverse picture for N_2O emissions (see Table 3). This can be explained by the higher level of ammonia volatilization (see e.g., IPCC, 2006), and because manure enhances the mineralization process by delivering substrate and thus consuming oxygen, which favours the creation of anaerobic microsites (e.g., Parkin, 1987). On the other hand, nitrogen contained in manure is also stabilized and less prone to be attacked by denitrifying micro-organisms.

Marginal rates of nitrogen leaching are higher for rape seed than for wheat. This reflects the seasonality of the processes. While rape seed is a winter crop and fertilizer application is thus simulated in autumn, much of the wheat is grown over summer and nitrogen is applied during the season when precipitation is less intensive. Generally, simulated NH_3 fluxes are relatively high and N_2 fluxes relatively low compared to other large-scale estimates (see e.g., Galloway et al., 2004; Velthof et al., 2009). This might be explained by the fact that a majority of studies so far focused on N_2O rather than NH_3, while only few experimental data of N_2 fluxes exist. The marginal N_2O emission factors are particularly characterized by high variability over small distances. This confirms the dependence of N_2O fluxes on local factors, especially soil type and weather conditions. As discussed above, this already made it difficult to explain some part of the variability in the DNDC data using climatic explanatory variables in the meta-model, so that one can assume that the "real" scatter of the data – at the chosen scale of representation – is even higher.

One important outcome of such an analysis is the relationship between Nitrogen Use Efficiency (NUE) and nitrogen input. At low input levels, NUE can be as high as 80% but quickly falls to low and very low values for input levels that are reflecting current farm practices. These finding are consistent with the (global) NUEs reported by Erisman et al. (2008) of 80% in the 1960s and 30% around the year 2000. Still today, nitrogen fertilizer application rates are largely variable. The use of default factors will lead to serious bias in estimating impacts on the environment. In some of the 'new' Member States of the European Union, for example, average yields and fertilizer application rates are still relatively modest compared to EU15. Here, according to DNDC simulations, total nitrogen losses in relative and absolute terms from fertilizer application will be considerably lower than in the old Member States.

Previous analyses of Leip and Mulligan (2005) was carried out running the DNDC model at the regional level and thus does not reflect the full spatial variability of environmental conditions encountered in Europe. For such detailed analyses, application of the original biogeochemistry model is too resource intensive. To our knowledge, the DNDC–CAPRI meta-model is the first model able not only to both reflect all major drivers of nitrogen flow pathways once applied to agricultural soils, but also fast enough to allow a sufficient number calculations for the development of marginal emission factors and their variability in space. The policy debate concerns the best use of resources (both natural and economic) for alternative pathways describing incremental changes from the current situation. Integrated environmental impact indicators often have only weak power for efficient and (spatially targeted) decision support.

5. Conclusion

A meta-model was developed able to perform detailed analysis of the environmental impact of arable cropping and results shown for the example of marginal change of the environmental pressure related to nitrogen losses. The meta-model is flexibly integrated into the agro-economic model CAPRI and thus can be easily used for scenario analysis, while at the same time running at the highly disaggregated scale reproducing to a high degree the variability of N losses simulated with the biogeochemistry model DNDC. Full consistency across the models is assured through a calibration procedure that matches the aggregated simulated yields for each calculation unit with regional statistics.

Marginal emission factors provide a more meaningful term to assess the impact of incremental changes in the agricultural system than IPCC-like emission factors. Marginal nitrous oxide fluxes caused by the applications of mineral fertilizer nitrogen generally decrease with increasing levels of N-application; however for wheat the effect was much smaller than the range of average emission factors calculated for the individual countries. For nitrate leaching, marginal fractions strongly increase with the level of N-application, but differences between countries are less important. These findings, if they can be confirmed by other studies, could support the assumption of the IPCC methodology that direct N_2O emission factors are crop-dependent but to a lesser degree a function of the N-application level, though highly variable in space. On the other hand, given the high large difference in N_2O emission factors across countries and between fertilizer types, national greenhouse gas inventories could be significantly improved if robust national emission factors could be developed. For indirect N_2O emissions through nitrate leaching, however, one leaching fraction might work for all the countries in EU15, if the level of nitrogen application is taken into account.

The findings presented might also be relevant for the current policy debate, for example on expansion of bio-fuel production. As the set-aside obligation has already phased out, expansion of the agricultural area is limited. Particularly for the EU15 countries, increased aggregate production of agricultural commodities will hence only be possible through higher yields. The results show that, with current cultivars, yield increases will lead to significant increases in the marginal pressure on the environment. Technical progress could reduce marginal emission factors, but would also be possible without the additional demand.

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