Estimation of Greenhouse Gas coefficients per Commodity and World Region to Capture Emission Leakage in European Agriculture

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Estimation of Greenhouse Gas coefficients per Commodity and World Region to Capture Emission Leakage in European Agriculture

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This paper presents a novel methodology to estimate greenhouse gas emission coefficients for agricultural commodities produced in the whole world, differentiated by region of production (regional disaggregation as defined by the Food and Agriculture Organization). For the European Member States (MS), emission coefficients per activity and product are borrowed from previous studies with the CAPRI modelling system. Emission coefficients for non-EU regions are here estimated within a Bayesian econometric framework for traded agricultural commodities by using (i) the existing estimates for the EU regions per gas source and product as a-priori information, (ii) time series on emission inventories per gas source and region from the Emission Database for Global Atmospheric Research (EDGAR), and (iii) time series on key production indicators from FAOSTAT. The estimator proposed uses emission factors in similar European regions as prior information in order to resolve the ill-posedness inherent to the estimation problem. As a result a complete set of GHG emission coefficients is estimated for 177 countries, 25 products and 10 emission sources. By combining them with production and trade statistics, emission trade balances for those regions are calculated.

KEYWORDS: Bayesian econometrics, agriculture, greenhouse gas emissions, emission leakage

1. Introduction

Greenhouse gas (GHG) emissions have seized increasing room in the public debate. The UN meeting on global climate change in Copenhagen in December 2009 was the largest UN conference ever in terms of number of participants, and no news media could ignore the ongoing negotiations.
GHG emissions need to be studied at a global scale for two reasons. Firstly, the effects of GHG emissions are global. Secondly, the integration of global commodity markets imply that ambitious abatement concessions in one part of the world may lead to changed trade flows and global production patterns, thereby affecting GHG emissions in other parts of the world. This implies that efforts on emission abatement by a specific world region ('emission bubble') have to be analysed together with their indirect effects on additional emissions in other parts of the world (the so-called emission leakage).
This paper provides a detailed and consistent methodology on the estimation of GHG emission coefficients per commodity and region for the entire world in order to aid quantification of GHG emissions and the effects of GHG abatement policies on a global scale. Estimated results are provided

such as to enhance global trade analyses in the field of GHG abatement policies to cover GHG emission leakage.
Several studies exist that provide estimates of emission coefficients for different regions and commodities, or even for the entire world. (see Hyman et al, 2003; Johnson et al. 2003; Ogino et al. 2003; FAO, 2010). Nevertheless, this study, focusing specifically on agriculture, provides a unique coverage in terms of commodities and regions. The estimates are based on inventories compiled at the Institute of Environmental Sustainability (EDGAR database[1]) following the methodology proposed by the International Panel on Climate Change (IPCC). These are then disaggregated to agricultural commodities using (i) supply tables from the FAOSTAT for agricultural commodities outside the EU, (ii) detailed computations of emission coefficients per gas source and region in the EU-27, and (iii) additional expert information on key determinants per world region (e.g. yields, management techniques and temperature).
The disaggregation is made using a Bayesian estimator that has been developed specifically for this purpose. The estimation problem is that of filling a matrix of emission coefficients given production weighted row sums. It resembles the economic problem of estimating a Social Accounting Matrix given row and column sums, as discussed by Golan et al. (1994).

2. Methodology

This paper aims at computing commodity specific GHG emission coefficients for a set of 177 FAO world regions (EU excluded) and 25 agricultural commodities. Bottom-up computation of so many emission coefficients would be prohibitively expensive. Instead, we propose an estimation method that uses of (1) existing GHG emission inventories per region, (2) production data per region, and (3) existing disaggregated emission coefficients for the EU countries and expert judgments to derive a complete dataset. The Bayesian approach proposed selects point estimates for coefficients by maximizing a prior probability distribution derived from existing information (e.g. from other models or case studies) and expert information on the precision of the prior modes, subject to moment (data) constraints requiring consistency with existing aggregate inventories reported in the EDGAR database . This is in line with the general approach for inference in ill-posed inverse problems described by O’Sullivan (1986). The necessary prior information on GHG emission coefficients is calculated with the CAPRI (Common Agricultural Policy Regionalized Impact) model at product level, i.e. emissions per kg of meat of litre of milk.

[1] EDGAR database v4.00, including data of agricultural emissions for 1970-2005 for all available countries split by IPCC categories

Derivation of commodity emission factors for the EU

CAPRI is a large-scale comparative-static agricultural sector model with a focus on EU27 but covering global trade with agricultural products as well (Britz and Witzke, 2008). The supply module consists of about 250 independent aggregate optimisation models representing all regional agricultural activities in a Nuts 2 region (28 crop and 13 animal activities). The market module consists of a spatial, non-stochastic global multi-commodity model for 40 primary and processed agricultural products, covering 40 countries or country blocks. The link between the supply and market modules is based on an iterative procedure.

The specific structure of CAPRI is suitable for the analysis of GHG emissions. The regional supply models capture links between agricultural production activities in detail and allow, based on the differentiated lists of production activities, inputs and outputs to define environmental effects of agriculture in response to changes in the policy or market environment. The CAPRI model incorporates a detailed nutrient flow model per activity and region (including explicit feeding and fertilizing activities, i.e. balancing of nutrient needs and availability) and calculates endogenously yields per agricultural activity endogenously. With this information, it calculates endogenously GHG emission coefficients following the IPCC guidelines (IPCC 2006). As relevant output, emission inventories are calculated for MS, mimicking the reporting on emissions by the EU to the UNFCCC (Pérez Domínguez 2006; Pérez Domínguez et al. 2007, Pérez Domínguez et al. 2009).

In this paper, and based on the previous information, CAPRI has been used to compute emission coefficients per commodity in the EU (see Figure 1, where darker shaded matrices are given data). Emission coefficients per activity in CAPRI (matrix A) are utilized together with coefficients of marketable outputs (matrix O) to compute output factors per commodity (matrix B).

Figure 1. Computation of GHG emission coefficients for the EU

		Emission type (p)			Commodity (i)			Activity level
		1	...	t	1	...	N	
Activity j	1	**A** $[m \times t]$			**O** $[m \times n]$			**L** $[m \times 1]$
	...							
	m							
Content (c)	Energy				**V** $[1 \times n]$			
Output level					**X** $[1 \times n]$			
Emission type (p)	1				**B** $[t \times n]$			
	...							
	t							

Since some activities have several marketable outputs (e.g. meat and milk from dairy cows), the emissions of each activity may need to be distributed among several commodities. That is done based on the energy content shares of the different outputs in total energy contents in outputs of the activity. The contents of energy are available in vector V.
The computation of each element of B is then given by equations (1). In words, the emission factor $b_{i,p}$ for each commodity i and emission type p is computed as the sum of emissions from all activities (j), weighted by the share $s_{j,i,p}$ of the outputs of each activity's output of emission type p that is attributable to product i, divided by total production x of product i. The shares s are computed using the contents v_i of energy.

$$b_{i,p} = \frac{\sum_j \left(l_j a_{j,p} s_{j,i,p} \right)}{x_i}, \text{ where } s_{j,i,p} = \frac{o_{j,i} v_i}{\sum_{ii} o_{j,ii} v_{ii}} \quad (1)$$

Additional remarks shall be done regarding the conversion of emission coefficients from activities to commodities in CAPRI:
- *Consideration of internal animal activities.* CAPRI incorporates a semi-dynamic herd flow model with allocation of young animal activities (see Britz et al. 2008, p.34). These animals are sources of emissions but are not traded in CAPRI outside the EU (they are also not recorded in trade statistics). Therefore, it is important to consistently distribute their emissions to the final products so that (1) no emissions are left out of the system (e.g. emissions from raising calves), and (2) emissions are correctly distributed between their different outputs (e.g. beef/milk, poultry/eggs)[2].

[2] For the calculation of emission coefficients per product all input and output animal activities that were produced in the year are considered. Differently, in a life cycle analysis (LCA), all emissions directly related to the output are accounted for (e.g. we slaughter 500 suckler cows to beef and account the emissions of 500 input heifers, 500 input calves and 500 output calves in the year).

- *Splitting of emissions from multi-output activities* (e.g. beef and milk from suckler cows). Input/output coefficients are available in the supply module of CAPRI and, therefore, separation of emissions is straightforward. The only differentiation has to be made on the weights used for the different types of emission sources (e.g. for calculating coefficients for methane emissions from enteric fermentation in beef we use as weight ' net energy growth'; for milk we would use 'net energy lactation' as weight).
- *Consideration of non-tradable feedstock commodities* (e.g. grass, fodder maize, straw). As in the case of internal animal activities, these products are not traded and we need to map their related emissions (e.g. nitrous oxide emissions from mineral fertilizer application on the field) to the output of the animal activities where this product is used (e.g. beef).
- *Separation of raw and processed commodities.* In CAPRI we calculate emissions at farm gate (i.e. emissions from transport or packaging from food products are not included) and only for raw products to avoid double counting (e.g. emissions from cow milk production can be found in cheese or skimmed milk powder). Nevertheless, in trade statistics we can find three kinds of products: (a) there is only data on production and trade of the raw product, so there is no problem and we can use the EU prior coefficients; (b) we have only processed products, so that we need to calculate emission coefficients for secondary products, and (c) we have raw and processed products, so that we can have double counting (e.g. emissions from oilseeds production should not also be allocated to vegetable oils)[3].

Weighting of emission factors to different regional characteristics

The average emission factors per commodity computed for all EU regions are used as prior information in the rest of the world. Differing natural conditions (climate, and soil), production mixes and agricultural managements in the different parts of the world suggest that weighting the EU emission coefficients per commodity so that regions of the EU that are similar to the foreign region receive a higher weight would increase the accuracy of the estimation. For this, a possibility is to use regional information on emissions and production characteristics in the EU available in CAPRI, and regress the effect of certain variables on emission coefficients. This would allow the extrapolation of weighting parameters to non-EU regions. We could use the following information:

[3] At the time of completeness of this draft paper the calculation of multipliers for intermediate animal activities and processed products was not completed. The authors will correspondingly update the paper and incorporate this information as soon as possible.

Table 1. Additional information for re-scaling prior emission coefficients4

Code	Additional information
N2OMAN	Pasture shares, shares of liquid systems (IPCC) and nitrogen excretion per head
N2OGRA	Pasture shares (IPCC)
N2OSYN	Synthetic fertilizer application per crop (data from the International Fertilizer Association))
CH4EN2	Milk/beef/poultry/pigf yields (available at FAO country level), share of time on pastures (available from IPCC per continent)
CH4MA2	Average temperature per zone, share of liquid manure management systems (IPCC) and yields (FAO)

Estimation of emission factors for non-EU countries

The world is partitioned into 177 regions (excluding the EU) where EDGAR data is available, listed in table A3 of the annex. Let R denote the set of regions. For a subset of the regions, denoted by R^a, data on per commodity emission factors are available, whereas for the remaining regions R^b, no previous estimates are available or the available estimates are incomplete or not consistently adding up to existing inventories for the whole region reported by EDGAR.

Let K denote the positions of the EDGAR inventories. The elements of K are listed in table 2. Furthermore, let J denote the set of commodities, listed in table 3, for which the estimations are to be performed. Inventories are available for broad product aggregates indexed by a, and we denote the mapping from commodities to aggregates by J(a) = {j: "j belongs to aggregate a"}. We want to estimate emission factors per region, commodity and emission category β_{rjk} for all $r \in R^b$, $j \in J$ and $k \in K$ that are "as consistent as possible" with available annual inventories per year t,

$$\varepsilon_{rkat} \sum_{j \in J(a)} \beta_{rjk} x_{rjt} = Y_{rkat} \quad \text{for all } r \in R^b \text{ and all k, a, t} \qquad (2)$$

where x_{rj} is the total production of commodity j in region r, and ε_{rkat} is a multiplicative equation error. A multiplicative error was chosen based on the assumption that when the inventories Y were computed the errors in those computations were proportional to the magnitude of production, and that the errors in the production data is much smaller than the other errors in the computation. Only those years where there was both production data x and inventory data Y were used in the estimation.

The estimation problem as described above is generally ill-posed, because the number of emission factors to estimate is greater than the number of

[4] At the time of completeness of this draft paper, these regressions have not been completed. The authors will correspondingly update the paper and incorporate this information as soon as possible.

constraints except if the region produces fewer commodities than there are years of inventory and production data.
To resolve the ill-posedness, additional information about the values of the emission factors is used, as discussed above, i.e. derived from existing emission computations for EU regions available in the CAPRI model. The prior density of the emission factors is assumed to be such that its mode is equal to the weighted average emission factor of the EU and its precision inversely proportional to the variance of the weighted mean and proportional to the prior total emissions attributable to each product. The latter requirement is chosen because it implies that if for some emission type k, the variance of the weighted means of the commodity specific emission factors are equal, and only a single year t is available for the estimation, then changing both factors with the same proportion of the mode will result in the same reduction in the posterior density, making the prior in a sense less informative when combined with the likelihood function below. The functional form of the prior density function is discussed in a separate section below. The equation errors ε are assumed to come from normal distribution with mean 1 and standard deviation of $0.1(T - t + 1)$, implying, by the three-sigma-rule, that essentially all outcomes are in the range 0.7 to 1.3 in the last year but with greater dispersion in earlier years to render the estimation less sensitive to an unspecified trend error. The following Bayesian estimator is proposed in order to ensure consistency with any existing IPCC inventories and at the same time using any available prior information:

$$\max f\left(\mathbf{Y}_r \mid \mathbf{x}_r, \boldsymbol{\beta}_r \boldsymbol{\varepsilon}_r\right) p(\boldsymbol{\beta}_r \mid \mathbf{x}_r) p(\boldsymbol{\varepsilon}_r) \text{ for each } r \in R^b \tag{3}$$

where $p(\cdot)$ are the prior density functions, and the likelihood function $f(Y_r|x_r,\beta_r,\varepsilon_r)$ is defined by

$$f\left(\mathbf{Y}_r \mid \mathbf{x}_r, \boldsymbol{\beta}_r, \boldsymbol{\varepsilon}_r\right) = \begin{cases} 1 & \text{if } \varepsilon_{rkat} \sum_{j \in J(a)} \beta_{rjk} x_{rjt} = Y_{rkat} \\ 0 & \text{otherwise} \end{cases} . \tag{4}$$

The likelihood function (4) implies that any matrix β_r and error matrix ε_r that together with the production row vector x_r satisfy the data constraint (2) are equally likely as any other to be the true emission factor matrix, whereas matrices not satisfying it are considered completely unlikely to be the true matrix. The posterior mode is used as point estimate of the emission factors. The posterior density function could be used to derive further inference about the parameters, such as posterior mean and variance, in a way similar to that described by Jansson and Heckelei (2010).

Prior density function for β

We were given the following expression of prior information from researchers involved in the computation of GHG inventories: *"If the a-priori emission factor for commodity i is d times as reliable as that for commodity j, and the given inventory is such that there is a mis-match between a-priori information and data, then the necessary adjustment of a-priori factors shall be such that the factor for commodity j is d times more adjusted than that for commodity i."*

The statement above refers to the behaviour of the point estimate resulting from the posterior mode estimation, and it can be used to derive the functional form of the prior density function. Assuming for simplicity that there is a single inventory Y and production data x_j for j = 1...J, and no equation error present, we note that the first order conditions to the problem

$$\arg\max_{h}\left\{\sum_j -d_j\alpha_j\left(h_j-1\right)^2 : \sum_j \tilde{\beta}_j h_j x_j = Y\right\} \tag{5}$$

where α_j are unknown parameters of the prior density function for β, imply that

$$\frac{d_i\alpha_i\left(h_i-1\right)}{d_j\alpha_j\left(h_j-1\right)} = \frac{\tilde{\beta}_i x_i}{\tilde{\beta}_j x_j}$$

The verbal statement of the prior requires that

$$\frac{h_i-1}{h_j-1} = \frac{d_i}{d_j},$$

and it is easily seen that this is obtained if $\frac{\alpha_i}{\alpha_j} = \frac{\tilde{\beta}_i x_i}{\tilde{\beta}_j x_j}$. Since the objective function of (5) is the logarithm of the kernel of a normal density function, and the maximum is constant under monotonous transformations such as logarithms, this leads us to choosing the prior density

$$f\left(\beta_i \mid \mathbf{x}, \tilde{\beta}_i\right) = C\exp\left[-d_i \frac{x_i\tilde{\beta}_i}{\sum_j x_j\tilde{\beta}_j}\left(\frac{\beta_i}{\tilde{\beta}_i}-1\right)^2\right] \tag{6}$$

where C is a scaling factor which would make the function integrate to 1, $\tilde{\beta}$ is the prior mode defined by the mean emission factor computed for the EU, and d is the reliability index defined as the inverse of the variance of $\tilde{\beta}$.The chosen prior satisfies the verbal definition only with a single observation and no equation error. With many observation and equation errors, the data (Y) will increasingly determine the estimates, making the prior less and less relevant.

3. Data and methodology

Database on emissions

For our estimation exercise, we have used the EDGAR v4.0 database (http://edgar.jrc.ec.europa.eu), which covers 35 years (1970-2005) of greenhouse gas emissions by country and emission sector. The dataset does not only cover carbon dioxide (CO2) but also the other relevant greenhouse gases: methane (CH4), nitrous oxide (N2O), hydrofluorcarbons (HFCs), perfluorcarbons (PFCs) and sulfur hexafluoride (SF6). As the most relevant gases for agriculture, in our paper we concentrate on the estimation of emission coefficients for different sources for N2O and CH4 (see Table A1 in the Annexes). The EDGAR set of inventories were compiled from the perspective of providing good quality reference estimates of anthropogenic emission sources per source category, based on scientifically sound input data and recent guidelines on emission calculation methodologies. This was done be using (a) international statistics as activity data, since these are comparable between countries in definition and units, (b) emission factors from the relevant scientific literature, also common across countries when judged comparable, and (c) grid maps for allocating sectoral emissions of a country to a grid, in principle common per sector, thus achieving spatial consistency per sector across compounds and years. (Van Aardenne et al. 2001; Olivier et al. 1996))

Production and trade statistics

FAOSTAT (http://www.faostat.fao.org/) provides time-series and cross sectional data relating to food and agriculture for some 200 countries. Supply utilisation accounts (SUAs) are time series data dealing with statistics on supply (production, imports and stock changes) and utilisation (exports, feed + seed, food, and other use-including waste) which are kept physically together to allow the matching of food availability with food use. The statistical framework of SUAs has been developed with the aim of providing a useful statistical tool for the preparation, conduct and appraisal of government action aimed at developing and improving the agricultural and food sectors of national economies. The TradeSTAT module provides comprehensive, comparable and up-to-date annual trade statistics by country, region and economic country groups for about 600 individual food and agriculture commodities since 1961.

4. Results

The expected result of this research is a comprehensive set of GHG coefficients, disaggregated by product and region and consistent with existing EDGAR emission inventories. Such a dataset is highly valuable in itself, as it allows comparing agricultural across different countries on a product basis. Yet the final use envisaged for the results is to contribute to the ongoing discussion about emission leakage (IPCC 2003).

As summary information, the presented exercise makes use of 46892 observations (information from EDGAR over countries, emission sources and years) and returns 18456 emission coefficients. In Table 2 we present a selection of results for 4 commodities, 4 countries and 2 emission sources[5].

Table 2. Emission coefficients for selected countries, products and gas sources (in kg of methane or nitrous oxide per ton of product)

		Potatoes			Wheat			Beef			Cow milk		
		pmod	amod	nobs	pmod	amod	nobs	pmod	amod	nobs	pmod	amod	nobs
USA	N2OSYN	0.06	0.06	14.00	0.29	0.30	14.00	2.08	2.36	14.00	0.06	0.28	18.00
	CH4EN2	-	-	-	-	-	-	680.10	415.79	14.00	21.11	21.88	18.00
Canada	N2OSYN	0.06	0.06	14.00	0.29	0.29	14.00	2.08	2.22	14.00	0.06	0.31	18.00
	CH4EN2	-	-	-	-	-	-	680.10	570.59	14.00	21.11	21.63	18.00
Argentina	N2OSYN	0.06	0.06	14.00	0.29	0.27	14.00	2.08	1.80	14.00	0.06	0.10	18.00
	CH4EN2	-	-	-	-	-	-	680.10	923.15	14.00	21.11	35.93	18.00
China	N2OSYN	0.06	0.06	14.00	0.29	0.31	14.00	2.08	2.61	14.00	0.06	1.82	18.00
	CH4EN2	-	-	-	-	-	-	680.10	1,047.21	14.00	21.11	45.40	18.00

Note: pmod: prior mode for the emission coefficient (calculated for the EU27), amod: average estimated emission coefficient (over years), nobs: number of observations (years of EDGAR data for the estimated emission source). Acronyms for emission sources are described in the annexes (see Table A1).

The presented results show that a ton of beef produced in United States implies 415 kg of enteric fermentation methane emissions (whereas the prior information from the EU27 is 680 kg of methane). By doing a back of the envelope calculation, we can see that an average ‘beef producing activity’[6] in the EU27 is producing 0.25 tons of beef and emits around 104 kg of methane. Out of the estimation we can deduct that, based on the existing information on emission inventories (EDGAR) and production figures (FAOSTAT), enteric fermentation emissions per beef producing activity in the US are higher than in the EU and/or beef yields are lower in the US with respect to the EU. We also observe a higher allocation of enteric fermentation emissions to milk production in the US than in the EU (21.88 and 21.11 kg of methane respectively). Implausible results can be observed for Argentina and China (923/1047 kg of methane per ton of beef and 36/45 kg of methane per ton of milk), what can be provoked by a mis-match between emission inventories and production statistics.

[5] The full set of results is available from the authors upon request.

[6] Here we include the whole cattle chain, including beef production from bulls (low and high weight), suckler cows, fattening calves, fattening heifers and dairy cows.

In the case of nitrous oxide emitted through the synthetic fertilizer application, emission coefficients for crop products range between 0.06 for potatoes and 0.29 for wheat. Beef and milk production has also been allocated emissions from synthetic fertilizer application indirectly through feeding.

Table 3. GHG Emission trade balances for selected countries and commodities (in thousand tons of carbon dioxide equivalents)

	Wheat			Beef		
	Produced	Imported	Exported	Produced	Imported	Exported
European Union 27	15499	309	2690	114179	8165	1495
Argentina	1838	0	815	93767	148	15502
USA	6380	5	382	151479	24697	3541
Canada	2444	1	357	31381	661	13667

In **Error! Reference source not found.** we have printed the net GHG emissions for selected countries, computed using the estimated emission factors together with harmonized production and trade data of the CAPRI model. For the calculation of emissions in imports and exports, the estimated emission coefficients are multiplied by the bilateral trade flows between all countries. This provides a link between trade and emission abatement policies: depending on the emission intensity by agricultural activities in different parts of the world, trade liberalisation policies might affect emission abatement efforts. For instance, mitigation efforts within the EU may result in higher production costs, higher production prices, reduced consumption and increased imports from outside the EU. Of particular interest are the highly protected beef and dairy sectors.

5. Final remarks

The methodology presented allows firstly for a comprehensive analysis of emission mitigation policies in Europe, including potential net imports of GHG emissions through trade of agricultural commodities with other parts of the world. Secondly, the conversion of GHG emission coefficients from activity to product, is a cumbersome but crucial milestone towards the study of life cycle analysis of emissions in agriculture. The increasing concerns about the environmental effects of livestock production in Europe (see FAO, 2006) have motivated the use of alternative approaches to calculate emission inventories than the guidelines provided by the IPCC. The work here presented is currently linked to the development of a LCA emission accounting framework in the CAPRI model. Last but not least, the provided emission coefficients can be certainly of valuable use by other trade models (partial or general equilibrium ones), so that emission leakage is also incorporated to their scenario analysis of GHG emission abatement policies.

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7. Annexes

Table A1. Emission sources modelled in CAPRI (IPCC Tier 2 categories)

N2OMAN	Direct nitrous oxide emissions stemming from manure management and application except grazing (IPCC)
N2OGRA	Direct nitrous oxide emissions stemming from manure management on grazing (IPCC)
N2OSYN	Direct nitrous oxide emissions from synthetic fertilizer application (IPCC)
N2OHIS	Direct nitrous oxide emissions from cultivation of histosols (IPCC via Miterra)
N2OLEA	Indirect nitrous oxide emissions from leaching (IPCC via Miterra)
N2OCRO	Direct nitrous oxide emissions from crop residues (IPCC)
N2OFIX	Direct nitrous oxide emissions from nitrogen fixing crops (IPCC)
N2OAMM	Indirect nitrous oxide emissions from ammonia volatilisation (IPCC)
N2OAPP	Direct nitrous oxide emissions from fertilizer application not including grassland (IPCC)
N2ODEP	Direct nitrous oxide emissions from atmosferic deposition (IPCC)
CH4EN2	Methane emissions from enteric fermentation (IPCC)
CH4MA2	Methane emissions from manure management (IPCC)
CH4RIC	Methane emissions from rice production (IPCC)

Table A2. Commodities in estimation

Rye	Table grapes	Concentrated milk
Barley	Table olives	Rice
Oats	Table wine	Sugar
Maize	Wheat	Rape oil
other cereals	Beef	Sunflower oil
Rapeseed	Pork meat	Soya oil
Sunflower	Sheep and goat meat	Olive oil
Soybean	Eggs	Palm oil
Pulses	Poultry	Rape seed cake
Potatoes	Whey powder	Sunflower seed cake
Textiles	Casein	Soya cake
Tobacco	Whole milk powder	Distilled dried grains from bio-ethanol production
Tomatoes	Butter	Raw milk at dairy
Other vegetables	Skimmed milk powder	Protein rich feed (by-products of milling and brewing industry)
Apples pears peaches	Cheese	Energy rich feed (by-products of sugar-beet processing), manioc, cassava etc.
Other fruits	Fresh milk products	
Citrus	Cream	

Table A3. Regions for which emission factors are estimated

Afghanistan	Gabon	Norway
Albania	Gambia	Oman
Algeria	Georgia	Pakistan
American Samoa	Germany	Panama
Angola	Ghana	Papua New Guinea
Antigua and Barbuda	Greece	Paraguay
Argentina	Greenland	Peru
Armenia	Grenada	Philippines
Australia	Guadeloupe	Poland
Austria	Guam	Portugal
Azerbaijan, Republic of	Guatemala	Puerto Rico
Bahamas	Guinea	Qatar
Bahrain	Guinea-Bissau	Reunion
Bangladesh	Guyana	Romania
Barbados	Haiti	Russian Federation
Belarus	Honduras	Rwanda
Belgium-Luxembourg	Hungary	Saint Kitts and Nevis
Belize	Iceland	Saint Lucia
Benin	India	Saint Vincent, Grenadines
Bermuda	Iran, Islamic Rep of	Samoa
Bhutan	Ireland	Sao Tome and Principe
Bolivia	Israel	Saudi Arabia
Bosnia and Herzegovina	Italy	Senegal
Botswana	Jamaica	Serbia and Montenegro
Brazil	Japan	Seychelles
Brunei Darussalam	Jordan	Sierra Leone
Bulgaria	Kazakhstan	Singapore
Burkina Faso	Kenya	Slovakia
Burundi	Kiribati	Slovenia
Cambodia	Korea, Dem People s Rep	Solomon Islands
Cameroon	Korea, Republic of	Somalia
Canada	Kuwait	South Africa
Cape Verde	Kyrgyzstan	Spain
Cayman Islands	Laos	Sri Lanka
Central African Republic	Latvia	Sudan
Chad	Lebanon	Suriname
Chile	Lesotho	Swaziland
China	Liberia	Sweden
China, Mainland	Libyan Arab Jamahiriya	Switzerland

China, Taiwan Prov of	Lithuania	Syrian Arab Republic
Colombia	Macedonia,The Fmr Yug Rp	Tajikistan
Comoros	Madagascar	Tanzania, United Rep of
Congo, Dem Republic of	Malawi	Thailand
Congo, Republic of	Malaysia	Timor-Leste
Cook Islands	Maldives	Togo
Costa Rica	Mali	Tokelau
Côte d Ivoire	Malta	Tonga
Croatia	Martinique	Trinidad and Tobago
Cuba	Mauritania	Tunisia
Cyprus	Mauritius	Turkey
Czech Republic	Mexico	Turkmenistan
Denmark	Moldova, Republic of	Tuvalu
Djibouti	Mongolia	Uganda
Dominica	Montserrat	Ukraine
Dominican Republic	Morocco	United Arab Emirates
Ecuador	Mozambique	United Kingdom
Egypt	Myanmar	United States of America
El Salvador	Namibia	Uruguay
Equatorial Guinea	Nauru	US Virgin Islands
Eritrea	Nepal	Uzbekistan
Estonia	Netherlands	Wallis and Futuna Is
Ethiopia	Netherlands Antilles	Vanuatu
Faeroe Islands	New Caledonia	Venezuela, Boliv Rep of
Fiji Islands	New Zealand	Western Sahara
Finland	Nicaragua	Viet Nam
France	Niger	Yemen
French Guiana	Nigeria	Zambia
French Polynesia	Niue	Zimbabwe