Raport Badawczy

Research Report

RB/20/2016

Spatial distribution and associated uncertainties of GHG emissions from agriculture sector in Poland

N. Charkovska, J. Horabik-Pyzel,
R. Bun, O. Danylo, Z. Nahorski,
M. Jonas

Instytut Badań Systemowych
Polska Akademia Nauk

Systems Research Institute
Polish Academy of Sciences

POLSKA AKADEMIA NAUK

Instytut Badań Systemowych

ul. Newelska 6

01-447 Warszawa

tel.: (+48) (22) 3810100

fax: (+48) (22) 3810105

Kierownik Zakładu zgłaszający pracę:
Prof. dr hab. inż. Zbigniew Nahorski

Warszawa 2016

Spatial distribution and associated uncertainties of GHG emissions from agriculture sector in Poland

Nadiia Charkovska[1], Joanna Horabik-Pyzel[2], Rostyslav Bun[1,3], Olha Danylo[1,4], Zbigniew Nahorski[1,5], Matthias Jonas[4]

[1]Lviv Polytechnic National University, Lviv, Ukraine

[2]Systems Research Institute of the Polish Academy of Sciences, Warsaw, Poland

[3]Academy of Business, Dąbrowa Górnicza, Poland

[4]International Institute for Applied Systems Analysis, Laxenburg, Austria

[5]Warsaw School of Information Technology, Warszawa, Poland

(Corresponding author – Zbigniew Nahorski,

email: Zbigniew.Nahorski@ibspan.waw.pl)

Abstract

Agricultural activity, which plays a significant role as a source and sink of greenhouse gases (GHGs), displays a meaningful geographical pattern. Thus, spatially resolved inventories are important for efficient design of GHG mitigation processes. This study develops a geoinformation approach to a spatial inventory of GHG emissions from agricultural sector in Poland, following the categories of the IPCC guidelines. Using the Corine Land Cover data, a digital map of emission sources is built, with elementary objects that are split up by administrative boundaries. Various procedures have been developed for disaggregation of available emission activity data down to a level of elementary objects, taking into account the specifics of animal nutrition. In particular, for spatial allocation of livestock census data from district to municipality level, we present a novel approach based on the conditional autoregressive structure. In addition, we quantify uncertainties associated with the developed spatial inventory at a level of voivodeships. Due to asymmetric distribution of uncertainties of input parameters (CH4 and N2O emission factors), the Monte Carlo method has been applied. The proposed technique allows us to discuss factors driving a geographical distribution of GHG emission levels for different categories of agricultural sector.

Keywords: GHG emissions, spatial inventory, spatial cadastre, energy sector, uncertainty, geo-information system.

1. Introduction

During the last century the environment has experienced a lot of irreversible changes. Global climate change seriously impacted economies of many world countries and humanity in general. Most of scientists in the field of climate changes research affirm that climate change is largely, except natural factors, influenced by results of anthropogenic action. According to the latest assessment report of the IPCC, the human activity, with 95-100% degree of confidence is the main reason of climate changes after 1950. In effect, in Ukraine and Poland, for example, more frequent droughts and floods are observed, which are the main reason of agriculture productivity reduction. The anthropogenic factors cause increasing concentration of the greenhouse gases (GHG) in the Earth's atmosphere and its pollution with the tiniest solid particles. Apart from the energy sector, a significant share in terms of GHG emissions belongs to agricultural activity. It is believed (Wollenburg et al., 2016) that achieving the 2°C limit target will not be possible without significant reduction of emission from the agriculture section, mainly of non-CO_2 GHGs.

Agriculture is mainly a source of three greenhouse gases: CO_2, CH_4, and N_2O, and also a sink of CO_2 that is not considered in the modelling described in this paper. Emissions from the agriculture activities have been a subject of many studies, see e.g. a review by Snyder et al. (2009). Some types of emissions raised higher interest due to its more complicated nature (Ogle et al., 2013). Measurements of N_2O emission in Europe from several grassland sites located in different countries is reported by Soussana et al. (2007), and from the arable land, obtained from simulations using the DNDC-Europe model by Leip et al. (2011). Methane emission from the agricultural activity in China was analyzed by Fu & Gu (2010). Emission from the livestock sector in EU were calculated using the CAPRI model by Weiss & Leip (2012). Herrero et al. (2015) published a review of the problems connected with impacts of the livestock on environment. A lot of data on emissions can be also found in papers on mitigation potentials in agriculture (Burnay et al., 2010; Gerber et al., 2016; Herrero et al., 2016; Fitton et al., 2011; Johnson et al., 2007; Smith et al., 2008). In all papers large spatial variations of emissions, due to e.g. different type of soils, different climatic parameters, water conditions, or different fertilizer types and manure management practices, are stressed.

The IPCC has developed a universal methodology of GHG inventory in different categories of anthropogenic activity (IPCC, 2016). Using these methods allows forming national reports of GHG emissions at the level of the whole country. But the general methods are ineffective for evaluation of emissions at the regional level, because they do not take into account the specifics of emission processes and irregularity of territorial distribution of the emission sources. At the same time, in order to plan the strategic development of individual regions, it is more useful to build spatial emission inventories on small areas of territory. Although in all the above studies the spatial or spatiotemporal analysis is presented, it is usually confined to bigger territories. An approach close in spirit to that described in the present paper is delineated in Yao et al. (2006) for estimates of methane emissions from rice paddies in China, with resolution of 10 km×10 km.

For spatial analysis of GHG emissions and estimation of many parameters the correlation between some proxy data can be used. Kim & Dall'erba (2014) studied spatial correlation of fossil fuel CO_2 emission from crop production in US and found that it is high. This phenomenon may be likely the case for other emissions in the agriculture sector as well. This means that in advanced analysis geostatistical modelling is worth considering, like using universal kriging (Young et al., 2016) or autoregressive methods, conditional (Horabik & Nahorski, 2010) or spatial (Kim & Dall'erba, 2014) autoregression models.

The GHG inventories are associated with some uncertainties which play a key role in market mechanisms and other applications. Therefore any GHG inventory loses in its meaning without the uncertainty analysis of input and output data (statistical information about the results of anthropogenic activity, the emission factors, the emission estimates etc.) (Bun et al., 2007).

Following IPCC recommendations, uncertainties of the compiled emissions were assessed in some papers. For example, Zhang et al. (2014) and Zhu et al. (2016) performed uncertainty calculations for rice paddies and livestock, respectively. Quite typically, they used Monte Carlo method for it. A more sophisticated analysis was applied by Berdanier & Conant (2012). They used data from 32 national emission inventories and a model for emission of N_2O from soils to estimate regional model parameter distributions using Bayesian Markov chain

Monte Carlo method, and in particular such parameters as mineral N fertilizer inputs, animal manure N input, and crop residue N input. The model allowed computation of emission distributions, and as consequence, uncertainties of emission estimates.

In this paper we present an approach for spatial inventory of GHG emissions in agriculture sector in Poland. We analyse the sources of emissions in terms of their spatial representation for all categories of this sector covered by IPCC Guidelines (IPCC, 2006). In the agriculture sector the emission sources are the area-type (diffused) objects. The digital maps of these sources are built using Corine Land Cover vector map (EEA, 2000) as polygons, without using any regular grid, contrary to usual practice. Such elementary objects are split up by administrative boundaries of regions (voivodeships), districts (powiats), and municipalities (gminas); to keep the administrative assignment of each elementary object. Then we create an algorithms for calculating GHG emissions from these objects using the activity data and the emission coefficient. For the activity data assessment, we have developed algorithms for disaggregation of available statistical data to the lowest possible level of elementary objects.

In particular, for spatial allocation of livestock census data from district to municipality level, we present a novel approach based on the conditional autoregressive structure. In case of national GHG inventories, relevant information about low resolution activity data needs to be acquired from national/regional totals. A procedure of allocation into smaller spatial units (like districts, municipalities, and finally grid cells) differs among various emission sectors. A common approach though, is a spatial allocation made in a proportion to some related indicators that are available in a finer grid.

In this study, a statistical scaling method is developed in order to support the procedure of compiling high resolution activity data. We propose a method for allocating GHG activity data to finer spatial scales, conditional on covariate information, such as land use, observable in a fine grid. The proposition is suitable for spatially correlated, area emission sources.

Regarding an assumption on residual covariance, we apply the structure suitable for area data, i.e. the conditional autoregressive (CAR) model. We demonstrate usefulness of the proposed technique for the agricultural sector of GHG national inventory in Poland. The example considers an allocation of livestock data (a number of horses) from district to municipality level. This contribution extends the basic model (Horabik & Nahorski, 2014a) for the case of various regression models in each region (here voivodeship).

Using created digital maps and mathematical models we carried out spatial inventory of emissions for each elementary object and got sets of geospatial data on GHG emissions caused by enteric fermentation, manure management, agricultural soils etc., according to the agriculture sector structure in the IPCC Guidelines. The maximum resolution of this spatial inventory is determined by the resolution of the used digital maps of land use and in our case does not exceed 100 m.

These results together with the results of spatial inventory of greenhouse gases from electricity and heat production, the extraction and processing of fossil fuels, in the residential sector, and other categories of anthropogenic activity (Topylko et al., 2017; Danylo et al., 2017) made it possible to get a high resolution pattern of GHG emissions in Poland (Bun et al., 2017).

2. The specificity of greenhouse gases emissions processes

Agricultural fields are examples of area emission/absorption sources. In this study this group also includes the territories where a large number of small point emission sources (animals owned by individual households) are concentrated, and territories of agricultural households, where agricultural work is conducted.

Animal sector, as one of the subsectors of agriculture, plays a very important ecological, economic and social role in various parts of the world. The emissions of GHG from animal sector occur as a result of the animals enteric fermentation (dairy and non-dairy cattle, sheep, goats, horses and pigs), and also of the decomposition, collection, storage and use of animal manure in various storage systems (manure reservoir in solid and liquid forms separately). Highest methane emissions from enteric fermentation are produced in large quantities during the digestive process of ruminants. Total emissions from enteric fermentation can be derived from the energy content of feed intake that is lost as methane. The decomposition of the organic material contained in the animal manure in the anaerobic environment produces methane through the action of methanogenic bacteria when large numbers of livestock are managed in confined areas. As far, the scientific literature has not evaluated the long-term trend of GHG emissions from animal sector separately for developed and developing countries (Caro et al., 2014).

Besides the areas with animals, also the cultivated lands (arable lands) manured by various kinds of fertilizers can be regarded as the area-type sources of emissions, where the processes of leaching and runoff of nitrous oxide, among other nitrogen compounds, take place.

An analysis of statistical information of livestock numbers in Poland in 2010 showed that in one municipality (gmina) the number of pigs was over 800 thousands (Agricultural census, 2010). Despite strong criticism of environmentalists in this gmina, in 2004 two new large pig farms were opened. This case and many others show that emission territorial distribution in animal subsector is essentially non-uniform. That is why spatial analysis of GHG emissions is needed to give the experts and authorities a tool to take effective measures for reducing emissions in areas where they are high (Charkovska & Bun, 2014).

3. Mathematical models for spatial inventory

During modeling the emission processes in animal subsector in Poland (in IPCC categories "Enteric Fermentation" and "Decomposition, collection, storage and use of animal manure") several assumptions were taken. In particular, as there is no possibility to monitor emissions from individual animals, the total emissions from all animals of one species within each rural locality in general were estimated. In the proposed mathematical models it was taken into account that the Polish statistical data on livestock and poultry are published separately for the agricultural enterprises and the households in municipalities (gminas).

Starting with the latter case, it is assumed that the number of animals in the households are distributed in rural settlements proportionally to the gmina rural population. The ratio of the population in the analyzed elementary object and the population in gmina can be calculated as:

$$V(\delta_n) = \frac{p(\delta_n)\cdot area(R_{3,n_3} \cap \delta_n)}{P(R_{3,n_3})}, \quad n = \overline{1, N}, \tag{1}$$

where $V(\delta_n)$ is the requested share of the population in the n-th elementary object δ_n; N is the total number of such objects; $p(\delta_n)$ is the population density in the n-th elementary object; $P(R_{3,n_3})$ is the number of people in gmina R_{3,n_3}; R_{3,n_3} is the third level of administrative unit (gmina), which includes the n-th elementary object, that is $\delta_n \subset R_{3,n_3}$ (geographical object δ_n is within the geographic object R_{3,n_3}), $n_3 \in \left[\overline{1, N_3}\right]$, and N_3 is the number of gminas in Poland; *area* (δ) is the area of object δ, $\cap$ is the operation of intersection of the common area of two geographic objects. The parameter $V(\delta_n)$ is then used as an indicator for disaggregation of the known statistical data on the number of animal livestock in the households within the gmina to the level of elementary objects.

As far as the agricultural enterprises are considered, the farms use agricultural lands. Then the statistical data on livestock and poultry within these farms are disaggregated to the level of elementary objects in proportion to the area of agricultural land (arable land, grassland, etc.) belonging to the farm, using the formula:

$$S(\delta_n) = \frac{\sum\limits_{f_i \in F} area(f_i \cap \delta_n)}{\sum\limits_{f_j \in F} area(f_j \cap R_{3,n_3})}, \quad \forall f_i \cap \delta_n \neq 0, \quad f_j \cap R_{3,n_3} \neq 0, \quad n = \overline{1, N}, \qquad (2)$$

where $S(\delta_n)$ is the ratio of the sum of areas of agricultural lands, $f_i \in F$, that are located within the elementary area δ_n and the sum of such areas of the lands in the gmina R_{3,n_3}, which contains this elementary object, that is $\delta_n \subset R_{3,n_3}$, F is the set of agricultural land elements in the digital map of land use for the whole country.

The methane emissions from enteric fermentation of animals in the households and agricultural enterprises can be calculated using the following mathematical model:

$$E_{EntFerm}^{CH_4}(\delta_n) = \sum_{t=1}^{T}\left[A_t^{ind}(R_{3,n_3}) \times V_t(\delta_n) + A_t^{agr}(R_{3,n_3}) \times S_t(\delta_n)\right] \times$$
$$\times K_t^{CH_4}(\delta_n), \; n = \overline{1, N},$$

where $E_{EntFerm}^{CH_4}(\delta_n)$ is the total annual emission of methane in the n-th elementary object δ_n; $A_t^{ind}(R_{3,n_3})$ and $A_t^{agr}(R_{3,n_3})$ are the statistical data on the number of the t-th animal species (dairy cattle, non-dairy cattle, sheep, goats, horses, pigs, poultry) in individual rural households, denoted by *ind* in the superscript, and agricultural enterprises (*agr* in the superscript) for the chosen year in gmina R_{3,n_3}, which contains the elementary object δ_n; $V_t(\delta_n)$ and $S_t(\delta_n)$ are the coefficients calculated using formulas (1) and (2) for disaggregation of the gmina level livestock data for the t-th animal species in the households and agricultural farms, from R_{3,n_3} to the level of elementary object δ_n; $K_t^{CH_4}(\delta_n)$ is the coefficient of methane emission from enteric fermentation for the t-th animal species in the n-th elementary object (it depends on the climate zone, in which this object is located); *EntFerm* is the index that stands for the emissions from the enteric fermentation.

Besides the described above animal subsector, also the emissions from agricultural soils take place in the agricultural sector. Such arable lands are considered as area-type emission sources. In particular, the nitrous oxide emissions from agricultural soils occur when the microbial processes of nitrification and denitrification in the soils take place, and include direct soil emissions, indirect soil emissions, and emissions induced by grazing animals. During modeling the emission processes in soil subsector in Poland (in category "Direct soil emissions") we computed the total nitrogen input for (1) synthetic fertilizer use per-hectare nitrogen input and the area planted in crop; (2) animal waste applied to soils as fertilizer (using as statistical data the number of each animal type and the annual per-head amount of nitrogen produced by animal type), (3) nitrogen fixation by N-fixing crops (using statistical data on sown areas of different N-fixing crops, mainly pulses) and (4) nitrogen content of crop residues. The total amount of nitrogen input is corrected to account for the fraction of nitrogen that volatilizes as NO_x and NH_3. Emission estimate is obtained by multiplying the corrected nitrogen input and the emission factor.

4. Inventory livestock dataset

The presented above approach uses agricultural data from the municipalities (gminas), especially the number of livestock as the activity data. However, such data sometimes (for some species of animals, like poultry, for example) are not available and must be assessed by disaggregation of the data published for a higher level administrative unit, in our case districts (powiats). Certainly, the simple disaggregation proportional to the population can be done. But in this section we present a more sophisticated method that takes into account spatial correlation of the data, what enables obtaining more accurate disaggregation.

As an example of application of this method we consider a livestock dataset (cattle, pigs, horses, poultry, etc.) for the territory of Poland, based on the agricultural census 2010, and available from the Central Statistical Office of Poland - Local Data Bank (BDL, 2016). The goal is to allocate relevant livestock amounts from districts (*powiats*) to municipalities (*gminas*).

In particular, for horses, the data are available also in municipalities, and this fact enables us to verify the proposed disaggregation method. Therefore, in what follows we consider the task of disaggregation of the number of horses reported for 314 districts into 2171 municipalities, taking advantage of the covariate information observable for municipalities. Only rural municipalities are considered in the study.

As explanatory variables we use population density (denoted x_1) and land use information. For the latter, the CORINE Land Cover map, available from the European Environment Agency (EEA, 2000), was employed. For each rural municipality we calculate the area of the agricultural classes, which may be related to livestock farming. Three CORINE classes were considered (the CORINE class numbers are given in brackets):

- Arable land (2.1); denoted x_2;
- Pastures (2.3); denoted x_3;
- Heterogeneous agricultural areas (2.4); denoted x_4.

The results of the disaggregation with the proposed procedure are further compared with the results of simple allocation proportional to population of municipalities. This approach is called here *naïve*.

5. The disaggregation framework

This technique is needed for the assessment of activity data (number of livestock in our case) at the lowest administrative level or fine grid on the basis of available statistical data at the higher level or another grid, and correlation with some other data as proxy.

5.1 The basic model

First, the model is specified on a level of *fine* grid. Let Y_i denote a random variable associated with an unknown value of interest y_i defined at each cell i for $i = 1,...,n$ of a fine grid (n denotes the overall number of cells in a fine grid). The random variables Y_i are assumed to follow the Gaussian distribution with the mean μ_i and variance σ_Y^2

$$Y_i|\mu_i \sim Gau\left(\mu_i, \sigma_Y^2\right).$$

Given the values μ_i and σ_Y^2, the random variables Y_i are assumed independent. The mean $\boldsymbol{\mu} = \{\mu_i\}_{i=1}^n$ represents the true process underlying emissions, and the (unknown) observations are related to this process through a measurement error with the variance σ_Y^2. The approach to modeling μ_i expresses an assumption that available covariates explain part of the spatial pattern, and the remaining part is captured through a spatial dependence. The conditional autocorrelation (CAR) scheme follows an assumption of similar random effects in adjacent cells, and it is given through the specification of full conditional distribution functions of μ_i for $i = 1,...,n$

$$\mu_i|\mu_{-i} \sim Gau\left(\boldsymbol{x}_i^T\boldsymbol{\beta} + \rho\cdot\sum_{\substack{j=1\\ j\neq i}}^n \frac{w_{ij}}{w_{i+}}\left(\mu_j - \boldsymbol{x}_j^T\boldsymbol{\beta}\right), \frac{\tau^2}{w_{i+}}\right),$$

where μ_i denotes all elements in $\boldsymbol{\mu}$ but μ_i, w_{ij} are the adjacency weights ($w_{ij} = 1$ if j is a neighbour of i and 0 otherwise, also $w_{ii} = 0$); $w_{i+} = \sum_j w_{ij}$ is the number of neighbours of an area i; $\boldsymbol{x}_i^T\boldsymbol{\beta}$ is a regression component with proxy information available for area i and a respective vector of regression coefficients; τ^2 is a variance parameter. Thus, the mean of the conditional distribution $\mu_i|\mu_{-i}$ consists of the regression part and the second summand, which is proportional to the average values of remainders $\mu_j - \boldsymbol{x}_i^T\boldsymbol{\beta}$ for neighbouring sites (i.e. when $w_{ij} = 1$). The proportion is calibrated with the parameter ρ, reflecting strength of a spatial association. Furthermore, the variance of the conditional distribution $\mu_i|\mu_{-i}$ is inversely proportional to the number of neighbours w_{i+}.

The joint distribution of the process $\boldsymbol{\mu}$ is the following (for the derivation see Kaiser et al. (2002)):

$$\boldsymbol{\mu} \sim Gau\left(\boldsymbol{X\beta}, \tau^2(\boldsymbol{D} - \rho\boldsymbol{W})^{-1}\right), \tag{3}$$

where $\boldsymbol{D}$ is an $n\times n$ diagonal matrix with w_{i+} on the diagonal; and $\boldsymbol{W}$ is an $n\times n$ matrix with adjacency weights w_{ij}. Equivalently, we can write (3) as

$$\mu = X\beta + \varepsilon, \quad \varepsilon \sim Gau_n(\mathbf{0}, \mathbf{\Omega}), \tag{4}$$

with $\mathbf{\Omega} = \tau^2(\boldsymbol{D} - \rho \boldsymbol{W})^{-1}$.

The model for a *coarse* grid of (aggregated) observed data is obtained by multiplication of (4) with the $N \times n$ *aggregation matrix* $\boldsymbol{C}$, where N is a number of observations in a coarse grid

$$\boldsymbol{C}\mu = \boldsymbol{C}X\beta + \boldsymbol{C}\varepsilon, \quad \boldsymbol{C}\varepsilon \sim Gau_n\left(\mathbf{0}, \boldsymbol{C}\mathbf{\Omega}\boldsymbol{C}^T\right).$$

The aggregation matrix $\boldsymbol{C}$ consists of 0's and 1's, indicating which cells have to be aligned together. The random variable $\lambda = \boldsymbol{C}\mu$ is treated as the mean process for variables $\boldsymbol{Z} = \{Z_i\}_{i=1}^N$ associated with observations $z = \{z_i\}_{i=1}^N$ of the aggregated model (in a coarse grid)

$$\boldsymbol{Z}|\lambda \sim Gau_N\left(\lambda, \sigma_Z^2 \boldsymbol{I}_N\right).$$

Also at this level, the underlying process λ is related to $\boldsymbol{Z}$ through a measurement error with variance σ_Z^2.

Model parameters β, σ_Z^2, τ^2 and ρ are estimated with the maximum likelihood method based on the joint unconditional distribution of observed random variables $\boldsymbol{Z}$:

$$\boldsymbol{Z} \sim Gau_N\left(\boldsymbol{C}X\beta, \sigma_Z^2 \boldsymbol{I}_N + \boldsymbol{C}\mathbf{\Omega}\boldsymbol{C}^T\right). \tag{5}$$

The log likelihood function associated with (5) is formulated, and the analytical derivation is limited to the regression coefficients β; further maximization of the profile log likelihood is performed numerically.

As to the prediction of missing values in a fine grid, the underlying mean process μ is of our primary interest. The predictors optimal in terms of the mean squared error are given by the conditional expected value $E(\mu|z)$. The joint distribution of $(\mu, \boldsymbol{Z})$ is

$$\begin{bmatrix} \mu \\ \boldsymbol{Z} \end{bmatrix} \sim Gau_{n+N}\left(\begin{bmatrix} X\beta \\ \boldsymbol{C}X\beta \end{bmatrix}, \begin{bmatrix} \mathbf{\Omega} & \mathbf{\Omega}\boldsymbol{C}^T \\ \mathbf{\Omega}\boldsymbol{C} & \sigma_Z^2 \boldsymbol{I}_N + \boldsymbol{C}\mathbf{\Omega}\boldsymbol{C}^T \end{bmatrix}\right). \tag{6}$$

The distribution (6) yields both the predictor $\widehat{E(\mu|z)}$ and its error $\widehat{Var(\mu|z)}$

$$\widehat{E(\mu|z)} = X\hat{\beta} + \hat{\Omega}C^T\left(\widehat{\sigma_Z^2}I_N + C\hat{\Omega}C^T\right)^{-1}[z - CX\hat{\beta}],$$

$$\widehat{Var(\mu|z)} = \hat{\Omega} - \hat{\Omega}C^T\left(\widehat{\sigma_Z^2}I_N + C\hat{\Omega}C^T\right)^{-1}C\hat{\Omega}.$$

The standard errors of parameter estimators are calculated with the Fisher information matrix based on the log likelihood function, see (Horabik & Nahorski, 2014b).

5.2. Results of disaggregation

First, Table 1 presents the estimation results (parameters with their standard errors) for the models with and without a spatial component, denoted CAR and LM (linear model) respectively. Note that in this setting the variable β_2 (land use class *Arable land*) turned out to be statistically insignificant. Introduction of the spatial CAR structure increased the standard error of estimated parameters, as compared with LM model.

Table 1. Maximum likelihood estimates

	CAR	LM

	Estimate	Std. Error	Estimate	Std. Error
β_0	8.525	0.1605	-6.981	0.0389
β_1	3.517	0.0148	1.932	0.0042
β_2	–	–	–	–
β_3	0.916	0.0034	1.786	0.0010
β_4	3.912	0.0055	5.032	0.0013
σ_Z^2	0.961	0.4052	1.506	0.1202
τ^2	1.683	0.1569	–	–
ρ	0.9889	2.62e-06	–	–

However, let us assess goodness of fit for these models in Table 2. It contains the analysis of residuals ($d_i = y_i - y_i^*$, where y_i^* are the predicted values) for the considered models. We report the mean squared error *mse*, the minimum and maximum values of d_i as well as the sample correlation coefficient r between the predicted and observed values. From here, it is obvious that the spatial CAR structure considerably improves the results obtained with the model of independent errors LM. For comparison, we also include the results obtained with the allocation proportional to population in municipalities, called *naïve* (NV). It is a straightforward and commonly used approach in this area of application. Here we note that the NV approach provides reasonable results, but the CAR model outperforms it in terms of all the reported criteria. The decrease of the mean squared error is from 3374.4 for NV to 3069.4 for CAR, which gives 9% improvement. From the maps of predicted values for the models CAR and NV it is difficult to spot a meaningful difference, so only the former is presented in Fig. 1.

Table 2. Analysis of residuals ($d_i = y_i - y_i^*$)

	mse	$\min(d_i)$	$\max(d_i)$	r
CAR	3069.4	-275	469	0.784
LM	5641.2	-357	522	0.555
NV	3374.4	-475	403	0.766

a) b)

Figure 15.3.1. Original data in municipalities (a), as well as predicted values for the model CAR (b).

The CAR technique provides good disaggregation of the correlated activity data from district to municipality levels, better than the disaggregation proportional to one variable. In the example considered, the improvement amounts to 9%. But this value will depend on the spatial correlation strength of the activity data. In particular, when they are very weakly correlated, application of the CAR technique may not improve disaggregation.

6. The results of spatial GHG inventory from agriculture

Developed mathematical models and disaggregation algorithms gave the opportunity to obtain spatial estimates of GHG emissions for each source category in the agricultural sector. The results of computational experiments showed that the largest methane emissions in the agricultural sector occurred as a result of enteric fermentation of farm animals, such as dairy and non-dairy cattle. In such a way, the results of spatial inventory were obtained at the level of elementary areas (see an example in Fig. 2), and at the level of arable lands (see an example in Fig. 3). The spatial inventory results can be aggregated to the larger area-type objects like the voivodeship in Poland (see Fig. 4). The total GHG emissions in the agriculture sector are presented in Fig. 5. Geospatial data on GHG emissions in the agriculture sector in Poland are available in Supplementary Materials {link will be provided}.

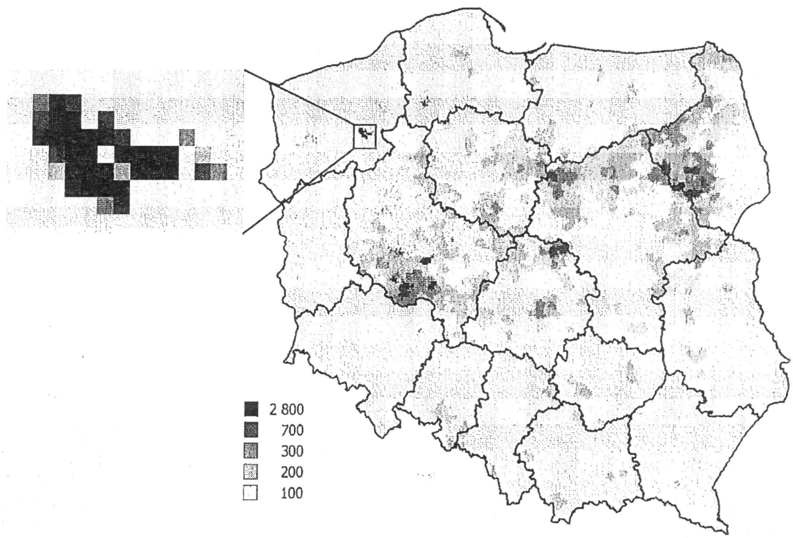

Figure 2. The specific total GHG emissions in animal sector in Poland (elementary areas 2 km x 22 km; Mg/km^2, CO_2-equivalent, 2010)

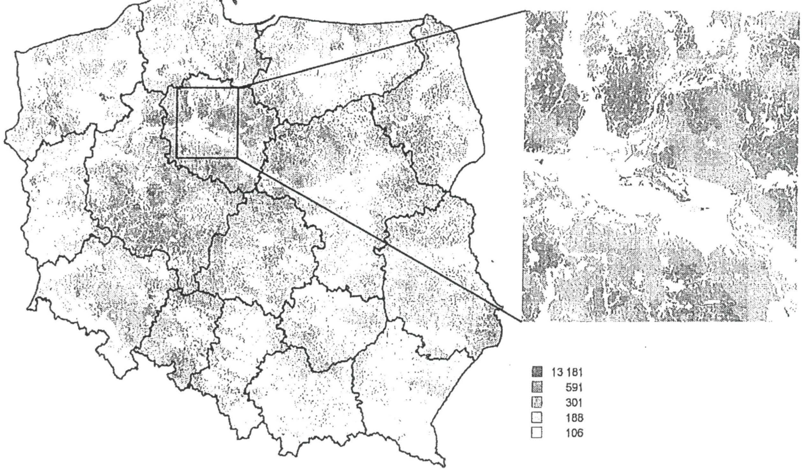

Figure 3. Specific N_2O emissions from fertilization of arable lands in Poland (kg/km^2, 2010)

The biggest emissions of methane in the animal subsector are in the Mazovian voivodeship (80,694 tons), Greater Poland (60,956 tons), and Podlaskie (66,266 tons), while the least is in the Lubusz voivodeship (5,190 tons (see Fig. 4). The total emissions of methane from enteric fermentation of all species in 2010 amounted to 434.7 thousand tons, that is 75% of total emissions of this gases in animal sector, and the rest of 25% is caused by decomposition of manure.

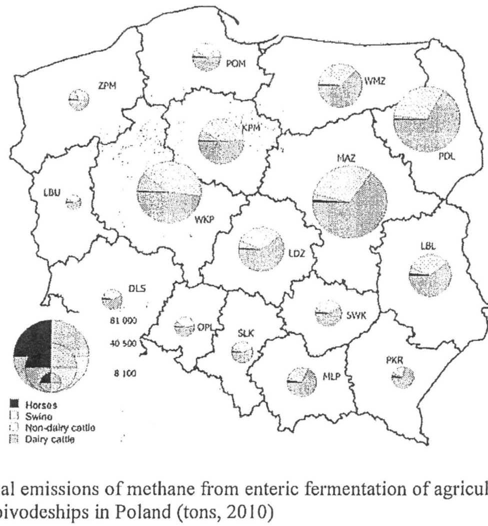

Figure 4. Annual emissions of methane from enteric fermentation of agricultural animals in the voivodeships in Poland (tons, 2010)

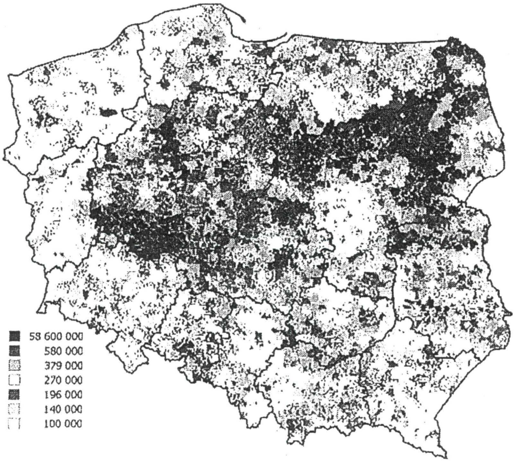

Figure 5. The specific total GHG emissions in the agriculture sector in Poland (elementary areas 2 km x 2 km, kg CO_2-equivalent, 2010)

7. Uncertainty analysis

Uncertainty of GHG emissions represents a lack of knowledge about the true value of emissions for a certain area. Total uncertainty of emission modelling depends on uncertainties of all input parameters. These uncertainties may be combined into a total uncertainty estimate of the inventory using the statistical tools specified in IPCC 2006 methodology (IPCC, 2006). For such an analysis it is important to have uncertainty ranges for emission coefficients, statistical data and other parameters of the inventory process (IPCC, 2001).

Uncertainty estimates of total emissions at the country level play very important role in the practical implementation of international agreements regarding the reduction of GHG emissions. Scientific investigations show that these uncertainties are not constant, and depend on two main factors: 'knowledge increase' about GHG emission/absorption processes and structural changes in GHG emissions. Therefore, increasing knowledge on uncertainty and on reasons for its change is very important for uncertainties reduction in GHG national inventories (Boychuk & Bun, 2014).

Input data for developed mathematical models of spatial inventory are not known exactly, and they can be simulated as random variables. For example, the statistical data on livestock population (activity data) and the specific animal species' GHG emission factors can be modelled as random variables. Currently, one of the main methods of modelling GHG emission uncertainty is the Monte Carlo method. Its advantage is the ability of using the information on uncertainty of the input parameters in estimating uncertainty in GHG emissions for different areas, regions and the country as a whole.

The resulting emission uncertainties in the agricultural sector were analysed at the level of regions (voivodeship), particularly from enteric fermentation of farm animals (cows, non-dairy cattle, sheep, goats, horses and pigs). As for the uncertainty of statistical data on these animal livestock, it should be noted that the accuracy of the data depends mainly on the completeness and reliability of the national census methods. In addition, there are different rules in the census for accounting of agricultural animals that live shorter than a year, such as pigs, so they should be considered during analysis of emissions uncertainty. Another source of emission uncertainty from the livestock is the use of uncertain data in the formulas to calculate methane emission factor. In the implemented mathematical models of GHG emissions evaluation, the statistical data are used, which uncertainty range for animal calculation is 5% (symmetrical distribution). For modelling GHG emissions in the category "Enteric Fermentation" by the Monte-Carlo method the methane emission factor for agricultural animals (IPCC, 2001) and appropriate uncertainty ranges (50%, symmetrical, normal distribution) were used.

Applying the implemented geospatial database and the developed approach to analysis of uncertainties of GHG emissions, computational experiments were performed to calculate the GHG emission uncertainty from enteric fermentation of agricultural livestock using the Monte Carlo method. The results were calculated for Polish voivodeships according to statistical data from 2010. Results are presented in Table 3. The emission uncertainties range from -50,043% to + 50,51% for CH_4 emissions from enteric fermentation. The verification of the correctness of realized mathematical and software tools was carried out using Polish national annual reports (NIR, 2012) on GHG emission at the country level as a whole. The obtained results show a high uncertainty of inventory results in the agricultural sector in 2010.

These results can be used in calculation of the total uncertainty of regional or national emissions for all categories of anthropogenic activities, and give the authorities an opportunity to take into account this factor in inspection of the data prepared for reporting in connection with international agreements on reduction of GHG emissions.

Table 3. Input data for the uncertainty analysis of methane emissions from enteric fermentation in region of Poland (2010)

Voivodeship	CH_4 emissions (tons) and the limits of uncertainty range (%)					
	Dairy cattle	Non-dairy cattle	Pigs	Horses	Sheep	Goats
Lower Silesian	4677,6 -50,08 +50,47	3181,7 -50,10 +50,50	524,2 -50,09 +50,47	201,9 -50,10 +50,46	103,8 -50,10 +50,42	32,91 -50,09 +50,44
Kuyavian-Pomeranian	17137,8 -50,05 +50,46	14140,4 -50,09 +50,45	2686,2 -50,08 +50,48	173,2 -50,08 +50,45	110,1 -50,08 +50,45	15,06 -50,06 +50,46
Lublin	18242,9 -50,09 +50,44	9938,1 -50,08 +50,44	1508,6 -50,11 +50,50	542,6 -50,07 +50,43	135,03 -50,07 +50,46	63,63 -50,108 +50,46
Lubusz	2876,2 -50,10 +50,46	2114,1 -50,10 +50,48	298,5 -50,06 +50,47	109,7 -50,09 +50,44	32,9 -50,09 +50,43	9,76 -50,10 +50,45
Łódż	21022,3 -50,12 +50,49	11708,3 -50,09 +50,46	1954,5 -50,13 +50,46	270,4 -50,10 +50,46	121,4 -50,05 +50,43	25,60 -50,09 +50,45
Lesser Poland	10953,5 -50,09 +50,45	4366,4 -50,12 +50,48	539,8 -50,12 +50,43	383,7 -50,09 +50,43	547,8 -50,12 +50,47	89,53 -50,09 +50,44

Masovian	52696,3 -50,08	25256,1 -50,11 +50,44	2115,4 -50,08 +50,46	857,2 -50,10 +50,49	72,2 -50,09 +50,48	31,12 -50,10 +50,48
Opole	4700,1 -50,05 +50,46	3664,5 -50,08 +50,45	904,3 -50,09 +50,46	74,0 -50,09 +50,47	24,2 -50,11 +50,48	14,88 -50,10 +50,45
Subcarpathian	7267,5 -50,06 +50,48	2080,2 -50,08 +50,46	451,1 -50,11 +50,47	320,3 -50,05 +50,48	151,9 -50,10 +50,45	77,09 -50,10 +50,44
Podlaskie	44420,4 -50,07 +50,41	20667,7 -50,08 +50,44	826,9 -50,09 +50,48	362,0 -50,07 +50,46	174,1 -50,13 +50,47	15,02 -50,12 +50,47
Pomeranian	7429,1 -50,1 +50,43	5943,5 -50,07 +50,45	1261,4 -50,1 +50,48	253,3 -50,09 +50,46	137,1 -50,12 +50,45	13,78 -50,08 +50,46
Silesian	5237,5 -50,11 +50,44	3670,9 -50,05 +50,45	523,6 -50,11 +50,47	154,4 -50,09 +50,44	114,3 -50,10 +50,47	43,04 -50,12 +50,48
Świętokrzyskie	7750,2 -50,09 +50,46	5063,0 -50,10 +50,45	605,8 -50,08 +50,47	212,3 -50,10 +50,45	33,9 -50,08 +50,41	27,24 -50,08 +50,47
Warmian-Masurian	20541,9 -50,05 +50,46	11379,7 -50,09 +50,48	1021,8 -50,10 +50,48	300,6 -50,11 +50,42	85,4 -50,08 +50,45	19,38 -50,07 +50,45
Greater Poland	29537,6 -50,1 +50,49	26493,8 -50,06 +50,42	5877,3 -50,10 +50,47	378,3 -50,08 +50,49	198,5 -50,11 +50,46	92,52 -50,05 +50,49
West Pomeranian	4236,2 -50,11 +50,48	3040,09 -50,09 +50,44	1816,7 -50,16 +50,45	159,9 -50,09 +50,48	103,8 -50,07 +50,48	15,69 -50,07 +50,47

8. Conclusions

The main GHG emission processes in the agriculture sector in Poland, in particular from animal enteric fermentation, are analyzed in this paper. Mathematical models for disaggregation of the emission processes from these sources to the scale of the elementary objects of fixed size are used for performing a spatial inventory of GHG emissions.

For this purpose the study presents also the first attempt to apply the spatial scaling model for the GHG inventory in Poland. The task was to allocate spatially correlated data to finer spatial scales, conditional on covariate information observable in a fine grid. The results of the disaggregation with the proposed procedure were compared with the allocation proportional to population; an improvement of 9% in terms of the mean squared error was obtained. The proposed method provided good results for livestock activity data of agricultural sector. The method proved to be feasible for disaggregation from districts to municipalities.

Using proposed methods and geoinformation system tools, a geospatial database of statistical information on the number of livestock in Polish regions is formed. As a result of numerical experiments, the estimates of methane emissions by animals at the level of elementary areas with resolution 100m are obtained. With the purpose of visualization on maps these results were aggregate to the grid 2 km x 2 km in size.

The results indicate that the highest specific total GHG emissions in the animal sector in Poland are in the Central and North-East Poland. But the highest specific emission, reaching 2800 kg km^{-2} yr^{-1} in CO_2-equivalent in 2010, is in the municipality of Wierzchowo in the West Pomeranian voivodship, where large pig farms are located. The highest specific N_2O emissions from fertilization of arable lands are in some areas of the Kuyavian-Pomeranian voivodship and reach 13,180 kg km^{-2} yr^{-1} in CO_2-equivalent. In all voivodships, emission of methane from dairy cattle enteric fermentation prevails, with the share of more than 50%.

The obtained results on uncertainty analysis of methane emissions from enteric fermentation by animal species in the Polish regions show quite high ranges of uncertainties. It considerably impacts the uncertainty of the total regional or national emissions from all categories of anthropogenic activity. The uncertainty assessments at the level of elementary objects is hampered by lack of knowledge about uncertainty of some disaggregation parameters from the municipality to the elementary object / grid levels.

Identifying agricultural territories or administrative regions that have the greatest influence on overall emissions from agricultural activity, opens new opportunities for improving the inventory process by investments in solutions to decrease the uncertainty in the input parameters (statistical data, emission coefficients).

Acknowledgement

The study was partly conducted within the European Union FP7 Marie Curie Actions IRSES project No. 247645, acronym GESAPU.

References

Agricultural census 2010 by holdings headquater; Livestock (cattle, pigs, horses, poultry), Available online at: http://www.stat.gov.pl

BDL, 2016. Bank Danych Lokalnych (Local Data Bank), GUS, Warsaw, Poland, Available at: http://stat.gov.pl/bdl

Berdanier A.B., and Conant R. (2012) Regionally differentiated estimates of cropland N_2O emissions reduce uncertainty in global calculations. Global Change Biology, 18: 928-935.

Boychuk Kh., and Bun R. (2014) Regional spatial cadastres of GHG emissions in Energy sector: Accounting for uncertainty, Climatic Change, 124(3), 561-574.

Bun R., Gusti M., Kujii L., Tokar O., Tsybrivskyy Ya., and Bun A. (2007) Spatial GHG inventory: Analysis of uncertainty sources. A case study for Ukraine, Water, Air, & Soil Pollution: Focus, Springer Netherlands, 7(4-5): 483-494.

Bun R., Nahorski Z., Horabik-Pyzel J., Danylo O., See L., Charkovska N., Topylko P., Halushchak M., Lesiv M., Valakh M., and Striamets O. (2017) Developing a high resolution spatial inventory of GHG emissions for Poland from stationary and mobile sources (this issue).

Burnay J.A., Davis S.J., and Lobell D.B. (2010) Greenhouse gas mitigation by agricultural intensification. PNAS, 107(26): 12052-12057.

Caro D., Davis S.J., Bastianoni S., and Caldeira K. (2014) Global and regional trends in greenhouse gas emissions from livestock, Climatic Change, 126, 203-216.

Charkovska N.V., and Bun R.A. (2014) Mathematical modeling and spatial analysis of GHG emissions processes from Agriculture sector of Poland, Proceedings of the International Conference on Environmental Observations, Modeling and Information Systems (ENVIROMIS-2014), Tomsk, Russia, SCERT, 76-77.

Danylo O., Bun R., See L., Topylko P., Xiangyang X., Charkovska N., and Tymków P. (2017) Accounting uncertainty for spatial modeling of greenhouse gas emissions in the residential sector: fuel combustion and heat production (this issue).

EEA, 2000. European Environment Agency, Corine Land Cover 2000. http://www.eea.europa.eu/data-and-maps/data

Fitton N., Ejerenwa C.P., Bhogal A., Edgington P., Black H., Lilly A., Barraclough D., Worral F., Hillier J., and Smith P. (2011) Greenhouse gas mitigation potential of agricultural land in Great Britain. Soil use and Management, 27: 491-501.

Fu Ch., and Yu G. (2010) Estimation and spatiotemporal analysis of methane emissions from agriculture in China. Environmental Management, 46: 618-632.

Gerber J.S., Carlsson K.M., Makowski D., Mueller N.D., de Cortazar-Atauri I.G., Havlík P., Herrero M., Launay M., O'Connell Ch.S., Smith P., and West P. (2016) Spatially explicit estimates of N_2O emissions from cropland suggest climate mitigation opportunities from improved fertilizer management. Global Change Biology, 22: 3383-3394.

IPCC (2001) Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories, Penman Jim, Dina Kruger, Ian Galbally et al.

Herrero M., Wirsenius S., Henderson B., Rigolot C., Thornton Ph., Havlík P., de Boer I., and Gerber P.J. (2015) Livestock and the environment: What have we learned in the past decade? Annual Review of Environment and Resources, 40: 177-202.

Herrero M., Henderson B., Havlík P., Thornton Ph.K., Conant R.T., Smith P., Wirsenius S., Hristov A.N., Gerber P., Gill M., Butterbach-Bahl K., Valin H., Garnett T., and Stehfest E. (2016) Greenhouse gas mitigation potentials in the livestock sector. Nature Climate Change, 6: 452-461.

Horabik J., and Nahorski Z. (2010) A statistical model for spatial inventory data: a case study of N_2O emissions in multicipalities of Southern Norway. Climatic Change, 103: 236-276.

Horabik J., and Nahorski Z. (2014a) Improving resolution of a spatial air pollution inventory with a statistical inference approach, Climatic Change 124: 575-589.

Horabik J., and Nahorski Z. (2014b) The Cramér-Rao lower bound for the estimated parameters in a spatial disaggregation model for areal data. In: D. Filev et al.: Intelligent Systems 2014, Springer International Publishing, pp. 661-668.

IPCC (2006) IPCC Guidelines for National Greenhouse Gas Inventories, Prepared by the National Greenhouse Gas Inventories Programme, Eggleston HS, Buendia L, Miwa K, Ngara T, Tanabe K (eds)

Johnson J.M.-F., Franzluebbers A.J., Weyers Sh.L., and Reicosky D.C. (2007) Agricultural opportunities to mitigate greenhouse gas emissions. Environmental Pollutions, 150: 107-124.

Kaiser M.S., Daniels M.J., Furakawa K., and Dixon P. (2002) Analysis of particulate matter air pollution using Markov random field models of spatial dependence, Environmetrics 13: 615-628.

Kim T., and Dall'erba S. (2014) Spatio-temporal association of fossil fuel CO_2 emissions from crop production across US counties. Agriculture, Ecosystems and Environment, 183: 69-77.

Ogle S.M., Buendia L., Butterbach-Bahl K., Breidt F.J., Martman M., Yagi K., Nayamuth R., Spencer Sh., Wirth T., and Smith P. (2013) Advancing national greenhouse gas inventories for agriculture in developing countries: improving activity data, emission factors and software technology. Environmental Research Letters, 8: 015030, doi: 10.1088/1748-9326/8/1/015030.

Leip A., Busto M., and Winiwarter W. (2011) Developing spatially stratified N_2O emission factors for Europe. Environmental Pollution, 159: 3223-3232.

NIR (2012) Poland's National Inventory Report 2012, KOBIZE, Warsaw, 358 p., Available online at: http://unfccc.int/national_reports

Smith P., Martino D., Cai Z., Gwary D., Janzen H., Kumar P., McCarl B., Ogle S., O'Mara F., Rice Ch., Scholes B., Sirotenko O., Howden M., McAllister T., Pan G., Romanenkov V., Schneider U., Towprayoon S., Wittenbach M., and Smith J. (2008) Greenhouse gas mitigation in agriculture. Philosophical Transactions of the Royal Society B, 363: 789-813.

Snyder C.S., Bruulsema T.W., Jensen T.L., and Fixen P.E. (2009) Review of greenhouse gas emissions from crop production systems and fertilizer management effects. Agriculture, Ecosystems and Environment, 133(3-4): 247-266.

Soussana J.F., Allard V., Pilegaard K., Ambus P., Amman C., Campbell C., Ceschia E., Clifton-Brown J., Czobel S., Dominigues R., Flechard C., Fuhrer J., Hensen A., Horvath L., Jones M., Kasper

G., Martin C., Nagy Z., Neftel A., Raschi A., Baronti S., Rees R.M., Skiba U., Stefani P., Manca G., Sutton M., Tuba Z., and Valentini R. (2007) Full accounting of the greenhouse gas (CO_2, N_2O, CH_4) budget of nine European grassland sites. *Agriculture Ecosystems & Environment*, 121:121-134.

Topylko P., Halushchak M., Bun R., Oda T., Lesiv M., Danylo O., and Jonas M. (2017) Spatial greenhouse gas inventory and uncertainty analysis: A case study of electricity generation and fossil fuels processing (this issue).

Weiss F., and Leip A. (2012) Greenhouse gas emissions from the EU livestock sector: A life cycle assessment carried out with the CAPRI model. Agriculture, Ecosystems and Environments, 149: 124-134.

Wollenberg E., Richards M., Smith P., Havlík P., Obersteiner M., Tubiello F.N., Herold M., Gerber P., Carter S., Reisinger A., van Vuuren D., Dickie A., Neufeldt H., Sander B.O., Wassmann R., Sommer R., Amonette J.E., Falcucci A., Herrero M., Opio C., Roman-Cuesta R., Stehfest E., Westhoek H., Ortiz-Monasterio I., Sapkota T., Rufino M.C., Thornton P.K., Verchot L., West P.C., Soussana J.-F., Baedeker T., Sadler M., Vermeulen S., and Campbell B.M. (2016) Reducing emissions from agriculture to meet the 2°C target. *Global Change Biology*, doi: 10.1111/gcb.13340.

Yao H., Wen Zh., Xunhua Zh., Shenghui H., and Yongqiang Y. (2006) Estimates of methane emissions from Chinese rice paddies by linking a model do GIS database. Acta Ecologica Sinica, 26(4): 980-988.

Young M.T., Bechle M.J., Sampson P.D., Szpiro A.A., Marshall J.D., Sheppard L., and Kaufman J.D. (2016) Satellite-based NO_2 and model validation in a national prediction model based on universal kriging and land-use regression. Environmental Science & Technology, 50: 3686-3694.

Zhang W., Zhang Q., Huang Y., Li T.T., Bian J.Y., and Han P.F. (2014) Uncertainties in estimating regional methane emissions from rice paddies due to data scarcity in the modelling approach. Geoscientific Model Development, 7: 1211-1224.

Zhu B., Kros J., Lesschen J.P., Staritsky I.G., and de Vries W. (2016) Assessment of uncertainties in greenhouse gas emission profiles of livestock sectors in Africa, Latin America and Europe. Regional Environmental Change, 16: 1571-1582.