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High resolution spatial distribution and associated uncertainties of greenhouse gas emissions from the agricultural sector

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Abstract

Agricultural activity plays a significant role in the atmospheric carbon balance as a source and sink of greenhouse gases (GHGs) and has high mitigation potential. The agricultural emissions display evident geographical differences in the regional, national, and even local levels, not only due to spatially differentiated activity, but also due to very geographically different emission coefficients. Thus, spatially resolved inventories are important for obtaining better estimates of emission content and design of GHG mitigation processes to adapt to global carbon rise in the atmosphere. This study develops a geoinformation approach to a high resolution spatial inventory of GHG emissions from the agricultural sector, following the categories of the IPCC guidelines. Using the Corine Land Cover data, a digital map of emission sources is built, with elementary areal objects that are split up by administrative boundaries. Various procedures are developed for disaggregation of available emission activity data down to a level of elementary emission objects, conditional on covariate information, such as land use, observable in the elementary object scale. Among them, a statistical scaling method suitable for spatially correlated areal emission sources is applied. As an example of implementation of this approach, the spatial distribution of CH_4 and N_2O emissions was obtained for areal emission sources in the agriculture sector in Poland with a spatial resolution of 100 m. We calculated the specific total emissions for different types of animal and manure systems as well as the total emissions in CO_2-equivalent. We demonstrated that the emission sources are located highly non-uniformly and the emissions from them vary substantially, so that average data may provide insufficient approximation. In our case, over 11% smaller emission was estimated using spatial approach as compared with the National Inventory Report where average data were used. In addition, we quantified uncertainties associated with the developed spatial inventory and analysed the dominant components in total emission uncertainties in the agriculture sector. We used the activity data from the lowest possible (municipal) level. The depth of disaggregation of these data to the level of arable lands is minimal, and hence the relative uncertainty of spatial inventory is smaller when comparing with traditional gridded emissions. The proposed technique allows us to discuss factors driving the geographical distribution of GHG emissions for different categories of the agricultural sector. This may be particularly useful in high resolution modelling of GHGs dispersion in the atmosphere.

Keywords: GHG emissions, spatial inventory, agriculture sector, uncertainty, geo-information system, high resolution (big) data.

1. Introduction

During the last century, the environment has experienced significant global climate change (IPCC 2014). By now, research has affirmed that to a large extent, climate change is the result of anthropogenic activities (Cook et al. 2016). According to the latest assessment report of the Intergovernmental Panel on Climate Change (IPCC), human activities have to be attributed to be the main reason of this change, with above 95% degree of confidence (IPCC 2013). Global climate change

has seriously impacted the economy of a number of countries and, consequently, humanity as such. For example, higher frequencies of droughts and floods have been observed universally, causing significant reductions in agricultural production (Lesk et al. 2016). In turn, agricultural production causes considerable amounts of greenhouse gases (GHG) and mainly carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) (IPCC 2006). Therefore, achieving the 2°C limit target will not be possible without a significant reduction of GHG emissions from the agriculture sector (Wollenburg et al. 2016).

The share of the agricultural sector in global total GHG emissions is about 13% (in 2012). Agriculture is responsible for 53% of global non-CO_2 emissions, and therefore it has essential mitigation potential and costs of reducing GHG emissions (Beach et al. 2016; Gerber et al. 2016; Johnson et al. 2007; Smith et al. 2008). Due to meteorological conditions, development level and many other factors, the share of agricultural emissions is not the same around the World. This can be illustrated by the example of the European Union (EU) member states where Ireland has the largest share of the agricultural sector in its total GHG emissions (30.77%), while the smallest is in Malta (3.23%), with the average share for EU equal 10.35% (in 2012) (AGHGS 2017). At the same time, in the absolute terms the largest emissions in the agriculture sector are in France (89.3 million tonnes of CO_2-equivalent), Germany (69.5), United Kingdom (51.8), and Spain (37.7). Poland, with 36.7 million tonnes of CO_2-equivalent is in the fifth place.

If we consider non fossil fuel GHG emissions, the main categories of GHG emissions in the agriculture are enteric fermentation, manure management and agricultural soil (IPCC 2006). The livestock farming plays an important ecological, economic and social role in various parts of the world (Havlík et al. 2015). According to IPCC (2006) the emissions of GHG from the animal sector are mainly a result of enteric fermentation (dairy and non-dairy cattle, sheep, goats, horses and pigs) where methane emissions are produced in large quantities during the digestive process of ruminants, and decomposition, collection, storage and use of animal manure in various storage systems (manure reservoir in solid and liquid forms, separately). So far, science has not evaluated the long-term trend of GHG emissions from the animal sector separately for developed and developing countries (Caro et al. 2014). Apart from livestock, cultivated lands (arable lands) manured by various kinds of fertilisers can be regarded as areal sources of emissions, with leaching and runoff of nitrous oxide and other nitrogen compounds (Butterbach-Bahl et al. 2013).

Emissions from agricultural activities have been a subject of many studies, see e.g. a review by Snyder et al. (2009). Some types of emissions have attracted higher attention from the scientific community due to their more complex nature (Ogle et al. 2013). For example, Herrero et al. (2015) published a review of the problems resulting from the livestock production. The publications emphasise the large spatial variations of emissions, due to e.g. different soil types, different climatic parameters and water conditions or different fertilisation strategies and manure management practices. Some publications are devoted to regional or national studies. For example, methane emissions from agricultural activities in China have been analysed by Fu & Gu (2010); measurements of N_2O emissions in Europe from several grassland sites have been reported by Soussana et al. (2007); N_2O emissions from arable land, calculated by simulations using the DNDC-Europe model, have been evaluated by Leip et al. (2011); emissions from the livestock sector in the EU have been calculated using the CAPRI model by Weiss & Leip (2012). As far as gridded emissions are concerned, Yao et al. (2006) estimated methane emissions from rice paddies in China, with a spatial resolution of 10 km

×10 km; EDGAR (2017) published gridded emissions from enteric fermentation, manure management, and agricultural soil with a spatial resolution of 0.1°×0.1° latitude and longitude (about 11×11 km for the equator).

In order to plan the strategic development of individual regions and evaluate their mitigation potential, it is more adequate to build spatial emission inventories on small areas of the territory, see e.g. Trombetti et al. (2017). This is one of main reasons why estimation of emissions with high spatial resolution is a subject of many studies, but a vast majority of them dealt with emissions from fossil fuels consumption, see the list of references in Bun et al. (2018). At the same time, well-focussed and more intensive emission mitigations, when applied widespread, will have in effect a positive impact on achieving the global target limit of GHG concentration in the atmosphere.

Although all of the above mentioned studies related to agriculture have adopted a spatial or spatiotemporal approach, this is usually confined to larger territories. Therefore a special interest exists for mapping GHG emissions in the main categories of the agriculture sector with resolution that matches spatial differentiability of agricultural activity.

The IPCC has developed a universal methodology of GHG inventory in different categories of anthropogenic activity, including agriculture (IPCC, 2006), that standardises procedures of preparing national inventory reports of GHG emissions at the country level. However, these methods are ineffective in the evaluation of emissions at the local level, because they do not take into account the specificity of emission processes and irregularity of territorial distribution of the emission sources.

Relevant information about high resolution activity data needs to be acquired from national/regional totals. A common approach of the spatial allocation of data into smaller spatial units (such as districts, municipalities and finally grid cells) is their disaggregation in proportion to some related indicators (proxies) that are available in a finer scale. Kim & Dall'erba (2014) found a high spatial correlation of fossil fuel CO_2 emissions from crop production in the US; this might also apply to other GHG emissions in the agricultural sector. So, in advanced analysis, it is worth considering the correlation between some proxy data, for example using tools of geostatistical modelling such as universal kriging (Young et al. 2016) or autoregressive methods, and among them conditional (Horabik & Nahorski, 2010) or spatial (Kim & Dall'erba, 2014) autoregression models.

The IPCC (2001) recommends the uncertainty analysis of any GHG inventory due to its possible high values. This analysis can be mostly used also for GHG spatial inventory (Bun et al. 2007). Following the IPCC (2001) recommendations, uncertainties of the compiled emissions have been assessed in some papers. For example, Zhang et al. (2014) and Zhu et al. (2016) performed uncertainty calculations for rice paddies and livestock, respectively, applying the Monte Carlo method. Berdanier & Conant (2012) used data from 32 national emission inventories and a model for emission of N_2O from soils to estimate regional model parameter distributions using the Bayesian Markov Chain Monte Carlo method to compute emission distributions.

The main objective of this study is to develop an approach for high resolution spatial inventory of GHG emissions in the agriculture sector using statistical data and land cover map. This approach is implemented in the agricultural sector of Poland, to manifest its ability of achieving the goal. Using the created digital maps of emission sources and mathematical models, we carried out an inventory of emissions and obtained sets of geospatial GHG emission data for each elementary

areal object due to enteric fermentation, manure management, agricultural soils, etc., according to the agricultural 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. Uncertainty of calculated emissions is estimated and their mitigation potential is evaluated.

For disaggregation of activity data published for higher level administrative units (districts) to the municipalities level, we applied an original conditional autocorrelation (CAR) method that is based on Horabik & Nahorski (2015) approach, and takes into account spatial correlation of the data, thereby enabling us to obtain more accurate disaggregation.

The approach to spatial inventory presented in this study can be used for many other countries. It particularly fits to countries with nonhomogeneous agricultural structure, which is the case of Poland.

2. Input data

2.1. Study area description

Poland, one of EU countries, covers an area of 312 km^2 with a population of over 38 million people. It is divided administratively to 16 provinces (voivodeships), 380 districts (powiats), and 2478 municipalities (gminas), the latter include urban (302), urban-rural (621), and rural (1555) municipalities (PBI 2017). Two latter types are considered in the study.

Poland plays a significant role in the European agriculture, as it has a high potential for intensification and technological advancement as compared to western EU countries. At the same time, it is much more similar to many developing countries within and out of EU. That is why it is an interesting case for investigations.

Polish agrotechnical practices diverse a lot spatially due to different traditions in territories annexed to three neighboring countries during partition of the Polish-Lithuanian Commonwealth at the end of the 18th century that lasted for 123 years. This diverse still exists despite a century from restoration of Polish independence after the 1st World War.

Big recent changes in the Polish agriculture have occurred since start of the economic transformation to the market economy in 1989 and later when Poland became a member state of the European Union in 2004. The main restructuring was connected with privatization of the arable land (95,6% according to the 2010 census), its concentration in larger farms and commercialization (CSOP 2010). On the other hand, quick urbanization caused partitions of many arable land and their use for housing and recreation. Nevertheless, traditional small farms still prevail. In 2010 the average farm acreage was 6.85 ha (CSOP 2010).

Despite recent development there is still big potential for further intensification of the Polish agriculture. For this, however, strategic decisions are needed. Territory of Poland is located in the temperate climatic zone with strong influence of polar and tropical air masses from the north-south direction, and maritime and continental from the west-east one. Polish agriculture is partly temperature- and partly water-restricted. Climate change models predict increase of vegetation period length but at the same time drier condition in most of the Polish territory and in a consequence decrease of crop yields (Szwed et al. 2010). So, thorough changes in agrotechnical practices will be needed. Emissions of GHG can be used in them as one of the considered criteria.

2.2. Input datasets

In the spatial analysis of emission processes in the animal subsector in Poland we took into account the IPCC (2006) categories 4.A 'Enteric Fermentation' and 4.B 'Decomposition, Collection, Storage and Use of Animal Manure'). In the plant growing subsector we considered the categories 4.D 'Agricultural Soils' and 4.F 'Field Burning of Agricultural Residues'. According to the basic IPCC (2006) approach, the GHG emissions depend on activity data and emission factors, which were provided for the study area. We also used high resolution maps of analyzed territory, and implemented procedures for disaggregation of the data to smaller plots with a homogeneous agricultural activity.

Statistical data on animal stocks were taken from Local Data Bank (BDL 2017), which contains data on number of heads for dairy cattle, non-dairy cattle, sheep, goats, horses, swines, and poultry, acquired from Agricultural Census 2010 (CSOP 2010). These data are given separately for farms and households. The data were gathered for the lowest administrative level of municipalities. The data which were available only for the districts, like horses and goats, were disaggregated to the municipality level using our own developed method described in the next section.

The following input data were used for the considered GHG categories:
- category 'Enteric Fermentation': the map of rural settlements; number of dairy cattle, non-dairy cattle, sheep, swine, poultry, goat, and horse heads at municipal level (BDL 2017); emission coefficients (NIR 2012; IPCC 2006), and areas of rural settlements as proxy data;
- category 'Manure Management': the maps of rural settlements and arable lands (EEA 2006); number of animals at municipal level (BDL 2016); data on nitrogen excretion per animal waste management system and emission coefficients (NIR 2012; IPCC 2006), and areas of rural settlements and arable lands as proxy data;
- category 'Agricultural Soils': the map of arable lands (EEA 2006); data on nitrogen input from agricultural processes, area of cultivated organic soil at national and provincial levels (CSOP 2010; NIR 2012); emission coefficients (IPCC 2006), and areas of arable lands as proxy data;
- category 'Field Burning of Agricultural Residues': the map of arable lands (EEA 2006); activity data according to IPCC (2006) at national and provincial levels (CSOP 2010; NIR 2012); emission coefficients (IPCC 2006).

From Corine Land Cover 2006 map (EEA 2006) we used the classes 2.1 'Arable Land', 2.3 'Pastures', and 2.4 'Heterogeneous Agricultural Areas'. This raster map with a resolution of 100 m was converted to a vector one. The accuracy of this product is 87.82% (Büttner et al. 2012).

3. Research methods

The main idea of our approach consists in developing a methodology to compile the spatial inventory of GHG emissions directly on the level of emission sources. The gridded emissions (Fig. 1) are calculated only at the final stage, for presentation. Therefore our main attempt was in proper definitions of possibly homogenous emission sources. Agricultural fields/pastures are examples of such area emission sources. In the animal subsector (in the IPCC categories 'Enteric Fermentation' and 'Decomposition, Collection, Storage and Use of Animal

Manure'), there is no practical possibility to monitor emissions from individual animals, so the total emissions from all animals of one species within each rural locality in general were treated as one emission source. In the proposed mathematical models, it was also taken into account that statistical data on livestock and poultry are published separately for the agricultural enterprises and the households in municipalities.
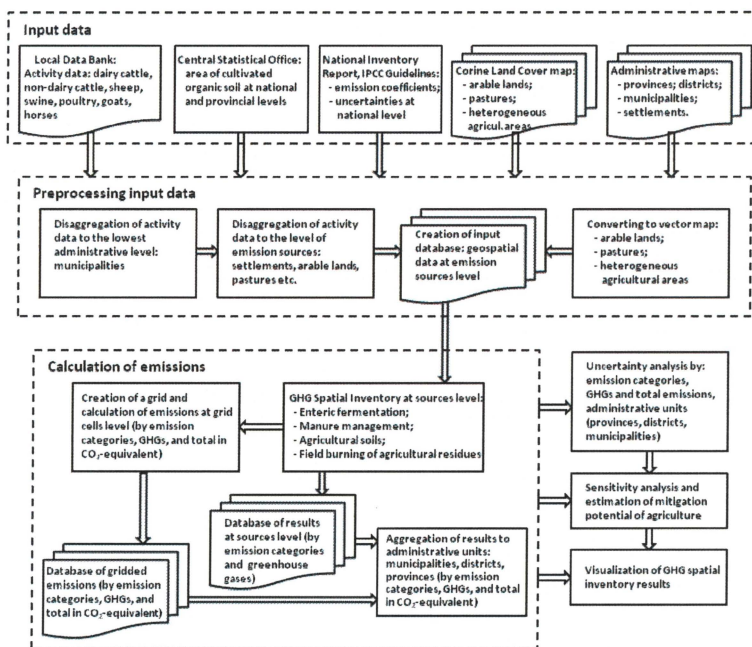

Figure 1. Flow chart of geoinformation approach to high resolution spatial inventory of GHG in the agriculture sector

We analyze the sources of spatial emissions for all categories of the agriculture sector covered by the IPCC (2006) guidelines, treating emission sources as areal (diffused) objects. The digital maps of these sources are built using Corine Land Cover vector map (EEA, 2006) as polygons, without using any regular grid, contrary to usual practice. Such elementary areal objects (polygons) are split up by administrative boundaries of regions (voivodeships in Poland), districts (powiats) and municipalities (gminas). Subsequently, we create algorithms for calculating GHG emissions from these objects using the activity data and the emission coefficients.

Pre-processing input data includes:

– converting land cover map to a vector format, in order to have a possibility to keep information on administrative assignment of each settlement, agricultural land etc. without loss of accuracy;

– disaggregation of the statistical/activity data on livestock and poultry to the municipalities level (only for species given in (BDL 2017) solely on the district level, e.g. horses and goats);

– disaggregation of statistical data from municipalities to emission sources level (arable lands, pastures, and rural settlements).
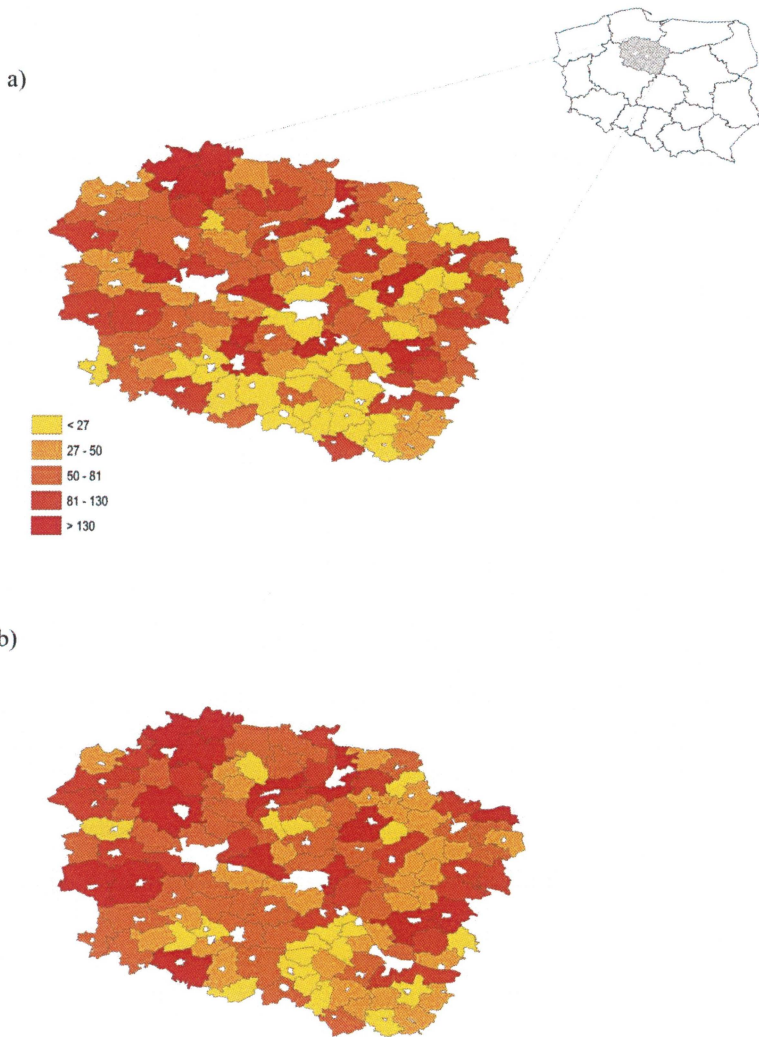
a)

	< 27
	27 - 50
	50 - 81
	81 - 130
	> 130

b)

Figure 2. Original data on number of horses in municipalities of Kuyavian-Pomeranian province (a) as well as predicted values for the model CAR (b)

For the activity data assessment, we developed algorithms for disaggregation of available statistical data to the lowest possible level of elementary areas. In particular, for spatial allocation of livestock census data from district to

municipality level, we present a novel approach based on the conditional autoregressive (CAR) structure, following the basic model proposed by Horabik & Nahorski (2014). Regarding an assumption on residual covariance, it allows for allocating GHG activity data to finer spatial scales, conditional on covariate information, such as land use, observable in a coarse grid (see Appendix). We demonstrate the usefulness of the proposed technique for GHG spatial inventory in the agricultural sector, using as an example an allocation of livestock data (cattle, pigs, horses, poultry, etc.) from the district to the municipality level in Poland, based on the agricultural census 2010 (BDL 2017). In particular, for horses, the data were available also in municipalities, and this fact enabled us to validate the proposed disaggregation model. Only rural and urban-rural municipalities (according to official administrative classification) were considered here.

As explanatory (proxy) variables, we used the average population density within municipalities and land use information. For the latter, the Corine Land Cover map (EEA 2006) was employed. For each municipality, we calculated the area of the agricultural classes, which may be related to livestock farming. Three Corine classes were considered (the class numbers are given in brackets): arable land (2.1), pastures (2.3), and heterogeneous agricultural areas (2.4). These proxy variables were statistically tested in the model for their significance and insignificant ones were dropped. The estimation results (parameters with their standard errors) are presented in the Appendix (Table 3). The models with and without a spatial component, denoted CAR and LM (linear model), are compared. We also added the results obtained for allocation proportional to population in municipalities, called there *naïve* (NV) which is a straightforward and commonly used approach.

Taking into account the residuals, the mean squared error, and the sample correlation coefficient between the predicted and observed values, we demonstrated that the spatial CAR structure considerably improves the results obtained by using the LM model, see Table 4 in the Appendix. 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 ranged from 3,374.4 for NV to 3,069.4 for CAR, with an improvement of 9%. Fig. 2 presents the maps with data on number of horses in municipalities (a) as well as the values predicted with the model CAR (b). For better visibility, Fig. 2 shows the maps for a single province (Kuyavian-Pomeranian), although the disaggregation was made for the whole territory of Poland. It should be noted that the obtained improvement depends on the spatial correlation strength of the activity data. In particular, with weak correlations, application of the CAR technique may not improve disaggregation.

For final disaggregation of activity data from municipality level to the level of emission sources, it was assumed that the animals in the households in municipality settlements are distributed proportionally to the rural population (the rural population map was created using corresponding polygons of Corine land cover vector map (EEA, 2006) after the removal of polygons of cities; accordingly, the rural population of the municipalities was disaggregated between rural settlements in proportion to their area). The ratio of the population in each analysed areal emission source (settlement in this case) and the population in municipality was used as a proxy for disaggregation of the number of animal livestock in the households within the municipality to the level of emission sources.

The statistical data on livestock and poultry within agricultural enterprises were therefore disaggregated to the level of emission sources (arable land, grassland, etc. in this case) in proportion to the area of these lands belonging to the

farm. The ratio of the area of each agricultural land and the sum of such areas of the lands in the municipality was used as a proxy for disaggregation of the number of animal livestock in the farms within the municipality to the level of emission sources.

The total annual emission of methane from enteric fermentation of animals in the households and agricultural enterprises within elementary area δ_n were calculated using the model:

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

where $A_t^{ind}(R_{3,n_3})$ 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 municipality R_m, which contains the elementary area δ_n; $V_t(\delta_n)$ and $S_t(\delta_n)$ are the mentioned above ratios for the population and agricultural land in an analysed elementary area δ_n, used for disaggregation of the municipality level livestock data on the t-th animal species in the households and agricultural farms from municipality R_m to the level of the elementary area; $K_t^{CH_4}(\delta_n)$ is the coefficient of methane emission from enteric fermentation for the t-th animal species in the n-th elementary area (depending on the climate zone in which this area is located); $EntFerm$ represents the emissions from enteric fermentation.

To calculate emissions from agricultural soils we considered the arable lands treated as areal emission sources. In particular, nitrous oxide emissions from agricultural soils occur when the microbial processes of nitrification and denitrification in the soils take place. They include direct soil emissions, indirect soil emissions and emissions induced by grazing animals. When modelling the emission processes in the soil subsector (in the category 'Direct soil emissions'), we computed the total nitrogen inputs for (1) synthetic fertiliser applied, converted to the amount of nitrogen used per-hectare of the planted crop; (2) animal waste applied to soils as fertiliser (using as statistical data the number of each animal type and the annual per-head amount of nitrogen produced by an 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 was corrected to account for the fraction of nitrogen that volatilises as NO_x and NH_3. Emission estimates were obtained by multiplying the corrected nitrogen input with the emission factor.

We treated grid cells as polygons in the vector map to combine the calculated methane and nitrous oxide emissions from diverse sources in animal and soil subsectors to estimate the total emissions in the agriculture sector. Because vector maps were used, it was possible to divide the grid cells into smaller areas when they belonged to more than one municipality. The grid size may be arbitrary. It depends on the task solved and it is of no importance at this stage, as our spatial inventory has been done at the level of emission sources. However, the final grid size cannot be smaller than 100 m, because applied land cover map was of this resolution. Nevertheless, the emission results that are coded in vector maps, can be easily aggregated to the levels of municipalities, districts and provinces without loss of accuracy.

4. Results

4.1. The spatially explicit GHG inventories for Poland

Implementing the above mathematical models and disaggregation algorithms, we obtained spatial estimates of GHG emissions for each IPCC source category in the agricultural sector in Poland, i.e. '4A. Enteric Fermentation', '4B. Manure Management', '4D. Agricultural Soils' and '4F. Burning of Agricultural Residues'. The inventory was calculated at the level of polygons as areal emission sources (rural settlements, arable lands and pastures). Full geospatial data for all emission categories at the level of the areal emission sources as well as at that of the grid (2 x 2 km) are available in Supplementary Materials.
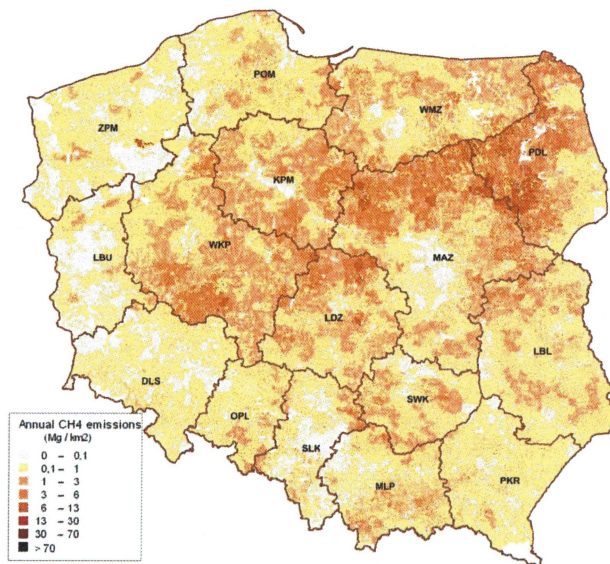

Figure 3. Spatial distribution of annual emissions of methane from enteric fermentation of agricultural animals in Poland (Mg/km², 2010)

Livestock. The largest emissions in the agricultural sector are from enteric fermentation by farm and household animals, such as dairy and non-dairy cattle (see Fig. 3 and Fig. 4). The total emissions of CH_4 from enteric fermentation of all species in 2010 amount to 434.7 Gg, representing 75% of the total emissions in the animal sector. The remaining 25% (145.0 Gg) are caused by decomposition of animal manure. The highest methane emissions from enteric fermentation are found in the Masovian, Greater Poland and Podlaskie provinces, while the lowest are observed in the Lubusz province (Table 1). The highest CH_4 emissions from decomposing manure (IPCC categories 4B1-4B9) are in Greater Poland, Masovian, and Kuyavian-Pomeranian provinces.

The total national emissions of nitrous oxide from the storage and use of animal waste (4B11-4B12 categories) amount to 12.3 Gg (21.2% of total N_2O emission in the agricultural sector): 0.1 Gg for the liquid waste and 12.2 Gg for the solid waste, respectively (Table 1).

Table 1. Annual GHG emissions in the agriculture sector in Poland at the level of provinces (2010)

Province	Enteric fermentation	Manure management		Agricultural soils	Burning of agricultural residues		Total
	CH_4 (Gg)	CH_4 (Gg)	N_2O (Gg)	N_2O (Gg)	CH_4 (Mg)	N_2O (Mg)	CO_2-eq,Gg
Lower Silesian	8.27	3.13	0.23	4.37	45.20	0.0521	1,656.46
Kuyavian-Pomeranian	33.88	14.36	1.10	5.03	54.34	0.0686	3,035.13
Lublin	30.11	9.83	0.84	3.85	64.15	0.112	2,396.62
Lubusz	5.19	2.11	0.15	1.68	13.03	0.0112	728.29
Łódź	34.92	12.55	1.03	3.85	48.49	0.0785	2,641.86
Lesser Poland	16.28	4.43	0.41	1.40	13.66	0.0253	1,058.58
Masovian	80.71	19.22	1.98	6.40	95.07	0.161	4,999.51
Opole	9.09	4.67	0.32	1.03	30.53	0.0314	749.05
Subcarpathian	10.10	3.50	0.28	1.02	12.34	0.0205	729.21
Podlaskie	66.27	11.15	1.48	2.51	22.23	0.0206	3,126.70
Pomeranian	14.53	6.35	0.46	3.82	26.14	0.0297	1,795.85
Silesian	9.51	3.62	0.27	1.20	11.44	0.0125	763.65
Świętokrzyskie	13.61	4.13	0.36	0.84	23.35	0.0446	802.19
Warmian-Masurian	32.98	7.97	0.82	2.12	26.12	0.0226	1,902.07
Greater Poland	60.96	30.62	2.14	5.09	79.60	0.0969	4,444.49
West Pomeranian	8.40	7.35	0.42	2.32	37.45	0.0356	1,211.97
Poland	434.81	145.01	12.29	46.53	603.14	0.823	32,141.63

Total specific GHG CO_2-equivalent emissions from the animal sector (4A and 4B subsectors) are illustrated in Fig. 5. Our results show that the distribution of GHG emissions is highly uneven. The greatest emissions are in the rural municipality Wierzchowo (id 3203052) in West Pomeranian province. In this municipality, livestock numbers in 2010 are as follows: pigs 829,597, total cattle 595, dairy cattle (cows) 229, goats 14, sheep 22, horses 23, poultry 5,369. The municipality of Wierzchowo covers an area of 230.2 km²; total annual emissions in the municipality in 2010 amount to 183,408.6 $Mg_{CO2\text{-}eq}$. Therefore, the average annual emission per unit of area is 796.7 $Mg_{CO2\text{-}eq}$/km²/yr. The municipality Wierzchowo consists of 79 grid cells of the area 2 km×2 km. In 27 of them, see Fig. 5, the highest specific emissions are between 700 and 2,756 $Mg_{CO2\text{-}eq}$/km²/yr. This exemplifies a significant local variety of emission magnitude. In the remaining 52 cells, there are mainly forests and no agricultural activity. The total 183,408.6 $Mg_{CO2\text{-}eq}$ emission consists of:

1) CH_4 emission from enteric fermentation of all species owned by the rural population, which is 41.92 Mg_{CH4} (1,048.0 Mg_{CO2-eq});
2) CH_4 emission from enteric fermentation of all species owned by agricultural households, which is 1,000.3 Mg_{CH4} (25,008.4 Mg_{CO2-eq});
3) CH_4 emission from decomposition of manure of all species, which is 3,995.3 Mg_{CH4} (99,882.1 Mg_{CO2-eq});
4) N_2O emission from collection, storage and use of liquid waste, which is 3.29 Mg_{N2O} (980.1 Mg_{CO2-eq});
5) N_2O emissions from collection, storage and use of solid waste, which is 189.56 Mg_{N2O} (56,490.0 Mg_{CO2-eq}).
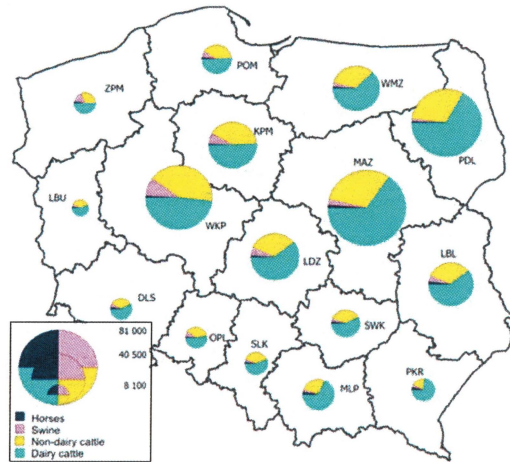
Figure 4. Annual emissions of methane from enteric fermentation of agricultural animals in the provinces in Poland (Mg, 2010). The size of the circles is proportional to emissions, see the scale in the legend. The colours show the share of emissions of the marked species.

Cropland. The shares of N_2O emissions in the agricultural soils categories are 73%, 25%, and 2% for direct emissions (4D1 category), indirect emissions (4D2) and grazing livestock (4D3), respectively. Direct soil emissions are due to synthetic fertiliser usage (54% of total N_2O emission in 4D1 category), animal wastes application (34%), cultivation of N-fixing crops (pulses) (1%), cultivation of other crops (10%), and application of sewage sludge (1%). As an example of the most important category, the N_2O emissions from category "4D1. Direct Soil Emissions" at the level of arable lands are presented in Fig. 6. Geospatial results for emissions in other categories are available in Supplementary Materials.

The share of N_2O emissions from the IPCC category '4F. Burning Residues of Crops in the Fields' in the total emissions from the agricultural sector is relatively small, 0.001%, that is 0.6 Gg_{CO2-eq}. It completes the structure of the emission in this sector (Table 1).
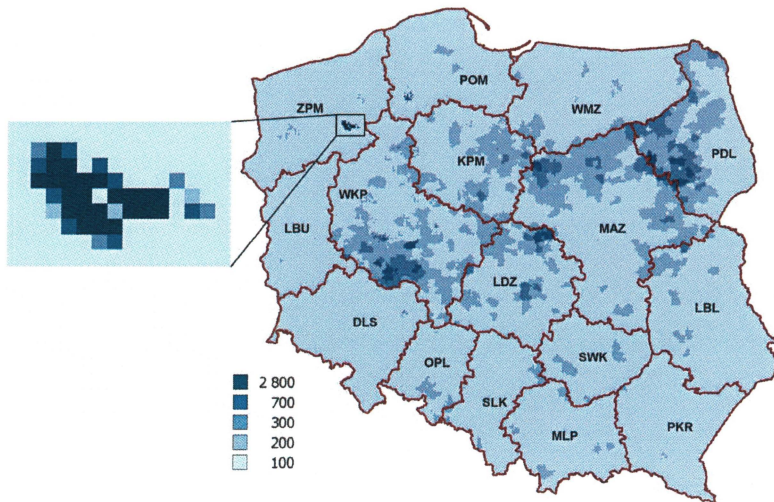
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Figure 5. Specific total GHG emissions in the livestock sector in Poland and the rural municipality Wierzchowo, with the highest emissions (grid 2 x 2 km; Mg/cell/yr, CO_2-equivalent, 2010)
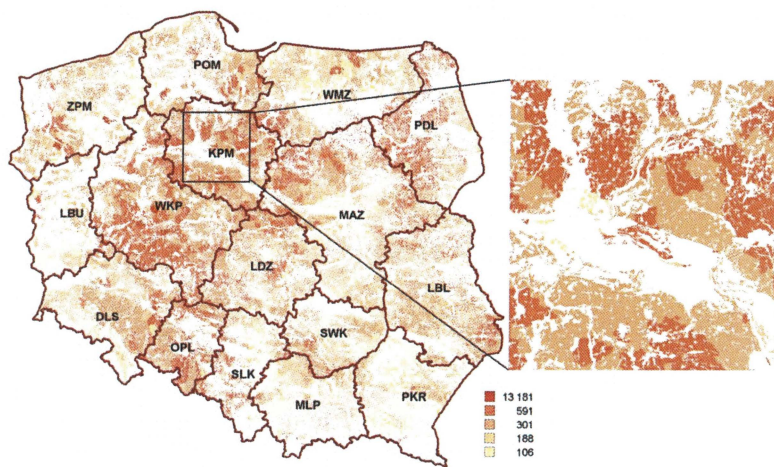

Figure 6. Specific N_2O emissions from IPCC "4D1.Direct Soil Emission" category in Poland (at the level of arable lands as areal emission sources, kg/km^2/yr, 2010)
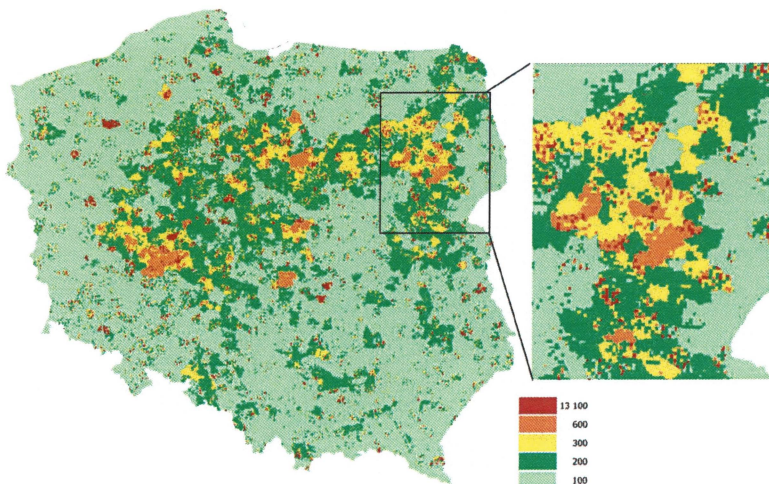
Figure 7. Specific total N$_2$O emissions in the agricultural sector in Poland (grid 2 x 2 km, kg N$_2$O/km^2/yr, 2010)
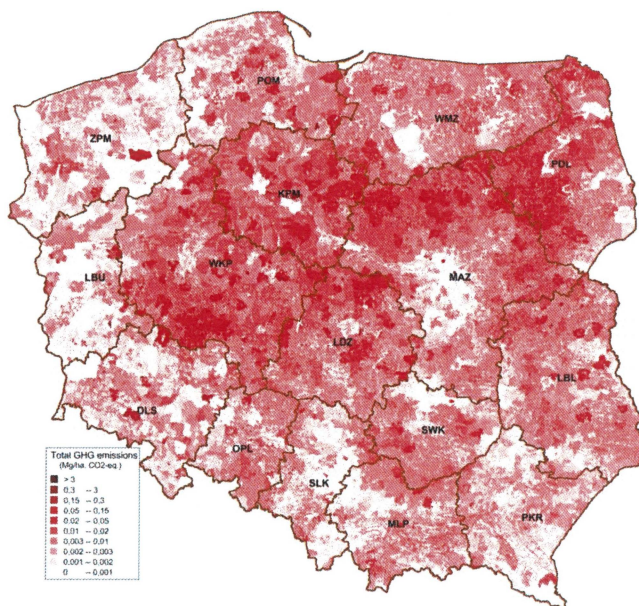

Figure 8. Specific total GHG emissions in the agricultural sector in Poland (at the level of emission sources: arable lands, settlements, Mg CO$_2$-equivalent/ha/yr, 2010)

Total emissions. To calculate specific total CH$_4$ and N$_2$O emissions in categories, for different types of animal and manure systems, as well as to easily calculate total emissions in CO$_2$-equivalent for different territories, the results are aggregated in a regular grid of 2 km×2 km, as described in detail in Bun et al.

(2018). Subsequently, the results were aggregated to the larger areas, for example the provinces, when needed.

The specific total N_2O emissions in the agricultural sector in Poland are presented in Fig. 7 in the regular grid of 2 km×2 km. Total emissions of nitrous oxide in this sector amount to 57.84 Gg. The agricultural soils are the main sources of N_2O emissions, with a share of 78.76% or 45.56 Gg_{N2O}. The highest emissions of N_2O from agricultural soils are found in the Masovian, Greater Poland and Kuyavian-Pomeranian provinces, and the lowest emissions in the Świętokrzyskie province.

Total GHG emissions in the Polish agricultural sector in the 2 km×2 km grid are presented in Fig. 8. In 2010, the major emissions from agricultural activities occur in the Masovian province, representing approximately 15.6% of total emissions in Poland; the lowest emissions occur in the Lubuskie province.

Table 2. Comparison of partial inventories of this study with NIR data

	This study, Gg	NIR, Gg	Relative difference, %
Enteric fermentation, CH_4	434.81	439.16	0.99
Manure management, CH_4	145.01	143.91	0.76
Manure management, N_2O	12.28	16.81	26.9
Agricultural soils, N_2O	46.55	55.30	15.8

Comparison with NIR data. The calculated emissions were then aggregated to the whole territory of Poland and compared with the Polish annual national inventory report on GHG emissions for 2010 (NIR 2012). Table 2 contains comparison of the inventories compiled in this study with those published by NIR. The inventories for CH_4 are quite close each other. Those for N_2O, known for high uncertainty, differ more. But all of them are well within the uncertainty range calculated in the next section. In the spatial inventory, we used activity data and emission parameters at the level of municipalities, which provides more accurate data than those obtained in the national inventory, where average values are used. In general, our inventories provide lower values than those compiled by NIR, particularly for the N_2O emissions. When converted to CO_2-eq emissions using global warming potentials (IPCC 2007), the total for all emissions in our calculations is 32,026.8 Gg CO_2-eq versus 36,065.5 Gg CO_2-eq given by NIR, so the relative difference equals 11.2 %. This is in surprisingly good agreement with 12% reduction of CO_2 emission estimate obtained by revision of local activity data and emission coefficients, although in a different category of fossil fuel combustion and cement production, and distant country of China (Liu et al. 2015).

4.2. Uncertainty analysis

Uncertainty of GHG emissions represents a lack of knowledge about the actual value of emissions, for a certain area. The total uncertainty of the inventory is calculated using uncertainties of all input parameters using the statistical tools specified in the IPCC (2006) methodology. For this, uncertainty ranges for emission coefficients, statistical data and other parameters of the inventory process are needed (IPCC 2001).

Uncertainty estimates of total emissions at the country level are important in analysis of the reduction of GHG emissions. The uncertainties are not constant and depend on the two main factors 'knowledge increase' about GHG emission/absorption processes and 'structural changes' in GHG emissions (Jonas et al. 2018). Therefore, increasing knowledge on uncertainty and on reasons for its change is important for the reduction of uncertainties in national GHG inventories (Boychuk & Bun 2014; Jarnicka & Nahorski 2018).

Input data for spatial inventory are not exactly known but can be simulated as random variables with known (estimated or assumed) distributions. For example, the livestock population (activity data) and the specific animal species' GHG emission factors can be modelled as random variables. This allows for modelling GHG emission uncertainty using the Monte Carlo method.

We analysed emission uncertainties in the agricultural sector at the level of provinces, focussing on enteric fermentation of farm animals (cows, non-dairy cattle, sheep, goats, horses and pigs). The uncertainty of statistical data on the animal livestock depends mainly on the completeness and reliability of the national census methods including different accounting rules for agricultural animals that live shorter than one year, such as pigs. Another source of uncertainty are uncertain data in the formulas for calculating the methane emission factor.
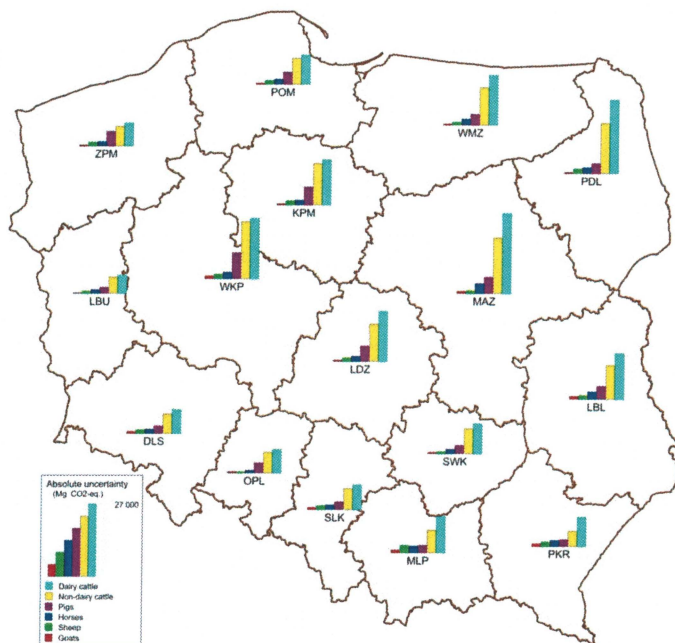

Figure 9. Absolute uncertainties of methane emission from enteric fermentation of livestock in provinces of Poland (calculated as 1/2 of 95% confidential interval, Mg CO_2-equivalent, square root scale, 2010)

In the implemented mathematical models of GHG emission evaluation, the uncertainty range of the statistical data used for animal calculation are of ±5% (normal distribution, 95% confidence interval). 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%, normal distribution, 95% confidence interval) were used. With this data, the absolute uncertainties, i.e. half of 95% confidential interval, were calculated for Polish provinces using the Monte Carlo method for the statistical data from 2010 (Fig. 9). The highest absolute uncertainties were found for the Mazowian province followed by the Podlaskie province and by the Greater Poland province. The smallest absolute uncertainties are in the Lubusz province. However, the relative uncertainties were similar across provinces and close to 50%.

5. Discussion

In this study spatial analysis of the main GHG emission processes in the agricultural sector in Poland is performed, in particular from animal enteric fermentation, manure management, agricultural soils, and burning of agricultural residues. For this, we consider rural settlements, arable lands and pastures as emission sources. For each emission category we build mathematical models that take into consideration activity data and emission factors as the input data. These data were basically acquired from the lowest possible level of municipalities. Some statistical data on livestock numbers were, however, available only at the district level. To disaggregate them to the municipality level we used a novel conditional autoregressive method, following the basic model presented by Horabik & Nahorski (2014). The municipality level activity data were further disaggregated to the elementary areal emission sources using as proxy the land cover and population density data, that allowed us to build a georeferenced database of activity data and emission factors and compile high resolution spatial inventory of GHG in the agriculture sector.

The results of this study indicate that the highest specific total GHG emissions in the animal sector in Poland, calculated from the 2 km×2 km cell level, occurred in the central and northeastern parts of the country. The highest specific emission, reaching 700 Mg km^{-2} yr^{-1} of CO_2-equivalent in 2010, occurred in the municipality of Wierzchowo in the West Pomeranian province, where large pig farms are located. An analysis of statistical information on livestock numbers in Poland in 2010 showed that in this municipality, the number of pigs exceeded 800,000 (CSOP 2010). This case and many others show that territorial emission distribution in the animal subsector is highly non-uniform. Therefore, spatial analysis of GHG emissions provides more accurate local data and is a helpful tool in taking effective policy measures to mitigate emissions.

The highest average specific emission, by which we mean specific emission calculated from the province level data, of CH_4 for the animal sector is in the northeast of Poland, in Podlaskie province (3.85 Mg$_{CH4}$/km^2), and the lowest in the west provinces near Germany border, namely Lubuskie (0.52 Mg$_{CH4}$/km^2), Lower Silesian, and West Pomeranian provinces. In sparsely populated Podlaskie province the per capita emission of methane in the animal sector is 65 kg, while in densely populated industrial Silesian province only 2.8 kg. In all provinces emission of methane from dairy cattle enteric fermentation prevails and exceeds 50%.

The highest specific N_2O emissions from manure management occurred in some areas of the Kuyavian-Pomeranian province and reached average 13.18 Mg km^{-2} yr^{-1} in CO_2-equivalent. In this province there is also the highest average specific direct emissions of nitrous oxide from soils (82.9 Mg km^{-2} yr^{-1} in CO_2-eq),

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while the lowest is in forested Subcarpathian province (17.0 Mg km^{-2} yr^{-1} in CO_2-eq).

The average specific emission of total GHG in the agriculture sector calculated from the whole Poland spatial inventory data is equal to 102.5 Mg km^{-2} yr^{-1} in CO_2-eq, but its distribution is highly spatially nonhomogeneous, from 169.6 Mg km^{-2} yr^{-1} in CO_2-eq in the Kuyavian-Pomeranian province with intensive agriculture and animal breeding, to 41.0 Mg km^{-2} yr^{-1} in Subcarpathian province. The highest per capita emission is in Podlaskie province (2.62 Mg yr^{-1} in CO_2-eq), and smallest in Silesian province (0.16 Mg yr^{-1}), with country average 0.84 Mg yr^{-1}.

In all provinces, the highest absolute uncertainties were found for methane emission from enteric fermentation of dairy and non-dairy cattle (the largest absolute uncertainties of emissions are in Masovian province: 26.6 and 12.7 Mg yr^{-1} in CO_2-eq, respectively). The absolute uncertainties for methane emission from enteric fermentation of pigs are smaller, followed by uncertainties of methane emission from enteric fermentation of horses and sheep. However, the relative emission uncertainties were fairly uniform in the provinces and close to $\pm 50\%$ for all methane emissions from enteric fermentation. These uncertainties are greater than estimated e.g. by Zhu at al. (2016), who estimated the methane emission uncertainty for EU-27 to be 16-19%, but our results are for small territories, so less statistical averaging occurs.

6. Conclusions

The basic meaning of this study is in presenting a method of spatially resolved inventory of GHG emissions from the agricultural activity. These kind of emissions are highly uneven in space, as documented above, both because of very differentiated spatially activity and of differentiated emission coefficients. This is connected with different soil, water availability, and meteorological conditions, as well as with agrotechnical practices that are much different in Polish regions, to big extent as a result of their different historical development. Highly space dependent conditions are, however, quite typical factors influencing agricultural production in many regions of the world.

Spatial inventory allows for spatially specific use of emission coefficients that improves inventory accuracy as opposed to using average coefficients for big territories in a country level inventory. Preparation of a spatial inventory requires, however, disaggregation of activity data that are usually acquired from statistical reports for different administrative units. To minimize as much as possible uncertainty introduced by disaggregation, we use as low level of statistical data as only known. Moreover, for data which are known only on higher level, we use more accurate disaggregation method that takes into account spatial correlation of emissions. It is perhaps worth to add that statistical data are usually gathered with much better spatial resolution than those published by statistical offices. This gives room for further improvement of the final accuracy of spatial inventory.

Taking into account high uncertainty of the GHG emissions from the agricultural activity, more accurate inventory can help in better constraining atmospheric concentrations of GHG connected with emission fluxes. Apart of possibly higher accuracy of the spatial inventory itself, it provides unique possibility of giving input data to atmospheric dispersion models that enable confrontation of predicted increment in local atmospheric concentration with the real one. Using inverse modelling, it is in principle possible to further improve the

accuracy of emissions, see Berdanier & Conant (2012), who reduced this way uncertainty of N_2O emissions in world regions up to 65%.

In comparison to the approaches of other studies, like Gerber et al. (2016), Leip et al. (2011) or Yao et al. (2006), our approach improves considerably the spatial resolution of GHG spatial inventory, which is possible by a novel and more detailed modelling and processing of the source (elementary object) emissions. Additional improvement of accuracy is obtained due to an applied statistical disaggregation method for activity data, developed by the authors, that takes into account the spatial autocorrelation of the emissions.

The obtained results on uncertainty analysis of methane emissions from enteric fermentation by animal species in the Polish regions show relatively high uncertainties of ±50%. This considerably impacts the uncertainty of the total regional or national emissions from all categories of anthropogenic activities. 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.

The basic idea of the method presented in this study consists in analysis of emissions from possibly homogenous elementary areal sources. This elementary emission sources are modeled in vector maps as polygons. It gives possibility to keep information on the administrative localization together with the emission sources that finally allows us to aggregate the results to the levels of municipalities, districts or provinces without loss of accuracy. This paper presents implementation of this approach for high resolution spatial analysis of GHG emission in the agricultural sector of Poland. It can be, however, used for any other countries or regions, taking into consideration their specificity of gathering statistical data on the lowest administrative levels and knowledge of the corresponding emission factors.

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 and emission coefficients). The most important is reduction of the emission coefficient uncertainties that play a key role in assessing uncertainty of the total emissions in the agriculture sector. Better estimates of the total uncertainty of regional or national emissions for all categories of anthropogenic activities would provide the authorities with data useful in reporting GHG emissions.

Spatial inventory of GHG emissions from agriculture is highly helpful in supporting local mitigation strategies, to find an optimal solution to satisfy usually contradictory goals of environmental protection on one side, and usage of agriculture potential for intensification and technological advancement on the other. However, as argued by Burney at al. (2010), the net effect of agricultural intensification for higher crop yields avoids emission of carbon. This opens a possibility to a win-win solution of higher productivity and smaller net emission, in which local adaptation policies add to global reduction of the atmospheric carbon.

Acknowledgement

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Appendix

The disaggregation framework: The basic conditional autocorrelation model

As explanatory variables, we used population density (denoted x_1) and land use information (Corine Land Cover map (EEA 2006)). For each rural municipality, we calculated the area of the agricultural classes, which may be related to livestock farming. Three Corine classes were considered:

- arable land, denoted x_2;
- pastures, denoted x_3;
- heterogeneous agricultural areas, denoted x_4.

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

$$Y_i|\mu_i \sim Gau\left(\mu_i, \sigma_Y^2\right). \tag{1}$$

Given the values μ_i and σ_Y^2, the random variables Y_i are assumed independent. The mean $\mu = \{\mu_i\}_{i=1}^n$ 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 modelling μ_i expresses an assumption that available covariates explain part of the spatial pattern and that 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 $i = 1,...,n$

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

where μ_i denotes all elements in μ; 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; $x_i^T\beta$ 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 $\mu_j - x_i^T\beta$ 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 μ is the following (for the derivation see Kaiser et al. (2002))

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

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

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

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

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

$$C\mu = CX\beta + C\varepsilon, \quad C\varepsilon \sim Gau_n\left(0, C\Omega C^T\right).$$

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

$$Z|\lambda \sim Gau_N\left(\lambda, \sigma_Z^2 I_N\right).$$

Also at this level, the underlying process λ is related to 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 Z:

$$Z \sim Gau_N\left(CX\beta, \sigma_Z^2 I_N + C\Omega C^T\right). \tag{5}$$

The log likelihood function associated with (5) is formulated, and the analytical derivation is limited to the regression coefficients β; further maximisation 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 (μ, Z) is

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

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

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

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

The standard errors of parameter estimators are calculated with the Fisher information matrix based on the log likelihood function, see Horabik & Nahorski (2015).

Table 3 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 the LM model.

Table 3. Maximum likelihood estimates of the spatial (CAR) and linear (LM) models parameters

	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	–	–

The goodness of fit is described in Table 4, which contains the results of 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.

Table 4. Analysis of residuals ($d_i = y_i - y_i^*$) of the spatial (CAR), linear (LM), and *naïve* (NV) models

	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