4th International Workshop
on Uncertainty in Atmospheric Emissions
7-9 October 2015, Krakow, Poland

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About the Workshop

The assessment of greenhouse gases and air pollutants (indirect GHGs) emitted to and removed from the atmosphere is high on the political and scientific agendas. Building on the UN climate process, the international community strives to address the long-term challenge of climate change collectively and comprehensively, and to take concrete and timely action that proves sustainable and robust in the future. Under the umbrella of the UN Framework Convention on Climate Change, mainly developed country parties to the Convention have, since the mid-1990s, published annual or periodic inventories of emissions and removals, and continued to do so after the Kyoto Protocol to the Convention ceased in 2012. Policymakers use these inventories to develop strategies and policies for emission reductions and to track the progress of those strategies and policies. Where formal commitments to limit emissions exist, regulatory agencies and corporations rely on emission inventories to establish compliance records.

However, as increasing international concern and cooperation aim at policy-oriented solutions to the climate change problem, a number of issues circulating around uncertainty have come to the fore, which were undervalued or left unmentioned at the time of the Kyoto Protocol but require adequate recognition under a workable and legislated successor agreement. Accounting and verification of emissions in space and time, compliance with emission reduction commitments, risk of exceeding future temperature targets, evaluating effects of mitigation versus adaptation versus intensity of induced impacts at home and elsewhere, and accounting of traded emission permits are to name but a few.

The *4th International Workshop on Uncertainty in Atmospheric Emissions* is jointly organized by the *Systems Research Institute of the Polish Academy of Sciences*, the Austrian-based *International Institute for Applied Systems Analysis*, and the *Lviv Polytechnic National University*. The 4th Uncertainty Workshop follows up and expands on the scope of the earlier Uncertainty Workshops – the *1st Workshop* in 2004 in Warsaw, Poland; the *2nd Workshop* in 2007 in Laxenburg, Austria; and the *3rd Workshop* in 2010 in Lviv, Ukraine.

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Integration of multi-source information in disaggregation of spatial emission data

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Abstract

Quantification of CO_2 emissions at fine spatial scales is advantageous for many environmental, physical, and socio-economic analyzes; in principle it can be easily integrated with other data in gridded format. It is especially important for better assessment of carbon cycle and climate change. Some possibilities exist for incorporation of the additional knowledge to improve the results and their uncertainty. There is, for example, a constant progress in assessment of local emissions from observations done in the atmosphere. This information can possibly help in improving disaggregated emission estimates. This paper discusses these questions and outline possibility of using these additional knowledge for improving estimation of emissions in fine scales.

Keywords: Greenhouse gases emissions, spatially resolved data, disaggregation, integration of multi-model results

1. Introduction

This paper is meant as a discussion paper which attempts to overview the research results that can be used in improving spatial gridded GHG estimates at a fine resolution by using existing or possible to obtain information coming from different sources. This problem is intrinsically connected with uncertainties of the used information, as it is quite intuitionally evident that a more sure information should be more credited in integration of knowledge than a less sure one, and therefore the former should be more weighted in the final result than the latter.

Quantification of GHG emissions at fine spatial scales is advantageous for many environmental, physical, and socio-economic analyzes; in principle, it can be easily integrated with other data in a gridded format. This is especially important for improved assessment of carbon and other chemical component cycles and climate change. To better understand the transport of different pollutants atmospheric dispersion models are used. This way influence of emissions can be confronted with the atmospheric concentration measurements. In this modelling two factors are considered to be mainly responsible for modelling errors: emission accuracy and meteorology. This is the reason for a battle for high accuracy gridded emission estimates.

In some applications, of particular importance are estimations of fossil fuel CO_2 fluxes, which are used to quantitatively estimate CO_2 sources and sinks, see e.g. [5]. A few institutions gather data on emissions from fossil fuels at national levels, like the US Department of Energy Carbon Dioxide Information Analysis Center (CDIAC) [6, 50]; the International Energy Agency (IEA) [35]. IPCC gathers data from national GHG inventories within the Kyoto Protocol agreement and its continuation [36]. British Petroleum company compiles energy statistics [7] that can be conveniently used for estimation of national CO_2 emissions. These datasets have been used for estimating global sources and sinks on a regional (e.g. continental) scale, [2, 11, 29, 59, 63, 64]. Their resolution is, however, too small to be directly useful for very fine emission grids.

Much less data are available on emissions in the below-national scales. Some countries publish data for provinces, but their scale is still too rough compared with other contemporary studies, like those presented in the sequel. Spatial disaggregation of emissions introduces additional uncertainty to a developed inventory. This is why the option of using additional information to reduce this uncertainty is of great interest.

A common approach to disaggregation of emissions is a usage of proxy data, which are most often areas of fine grids or population therein. However, independent estimates of GHG fluxes, like inverse modeling or eddy covariance, provide opportunity to incorporate additional knowledge and provide more comprehensive spatial quantification of carbon budget. Evidently, there is a mismatch between distinct approaches to estimation of fluxes. In general, there are two kinds of estimates: it can be either accounting of emissions (bottom-up) or by measuring concentrations of CO_2 and inferring about original emission fluxes (top-down). Merging such datasets is a challenging task due to incomplete accounting and uncertainties underlying each of the methods. Moreover, one should take into account various spatial scales and different scarcity of data. This paper outlines several methods, discusses advantages and limitations of using them for improving inventory emission estimates in fine scales, and review methods used for combining uncertain data sets, highlighting the issues related to spatial dimension of the task.

2. Disaggregation based on proxy data

2.1. Basic research stream

Disaggregation methods for obtaining high-resolution emissions typically use proxy data available in finer scales. The most straightforward approach to estimate data in a fine scale is to disaggregate national emissions proportionally to gridded population information, see e.g. [1, 55, 67] or in some cases proportionally to the area. Another proxy data are the satellite observations of nighttime lights [16, 17]. Direct use of these proxy data does not allow for very fine resolutions, as emissions from some sources, like power plants, do not correlate well with proxies. That is why Oda and Maksyutov [53] extracted emissions from point sources before disaggregating the non-point emissions proportionally to the nightlight distribution, and integrated them again to obtain 1km × 1km emission data. Rayner et al. [61] used a modified Kaya identity, in which emissions are modeled as a product of population density, per capita economic activity, energy intensity of economy, and carbon intensity of energy to predict emissions from several sectors, namely energy, manufacturing, transport (broken to land, sea, and air emissions).

A very high resolution of emission cadasters (2km × 2km grid) was obtained for Poland within the 7th FP GESAPU project [24]. It resulted from a detailed analysis of information from various sources, published by governmental and research agencies, as well as energy or industry plants (e.g. taking part in emission trading scheme); the analysis was followed by disaggregation on activity levels and precise modeling, see [8, 9]. At present, this approach to disaggregation seems to provide the best results. Nevertheless, the relevant procedure, like gathering data from numerous sources and publications or individual disaggregation of multitude of variables, requires immense input of human work, so this approach is as far suitable rather only for regions of a country or a few countries.

The GESAPU approach allows for rather straightforward assessment of uncertainty of disaggregated data, following the IPCC guidelines Tier 1 (error propagation) or Tier

2 (Monte Carlo method) methodology ([37, 38]. Again, Bun et al. [9] and accompanying papers ([12, 13, 30, 71] provide details of the analysis. As well, it is based on individual examination of all sources and sinks. Hogue et al. [31] discuss problems of doing similar analysis using existing global databases. Oda et al. [54] proposes a method of calculating uncertainty parameters. This method will be mentioned in the sequel.

2.2. Extensions

An intrinsic possibility is to use more than one proxy data for disaggregation. This can be done using linear regression function. The problem is to estimate its parameters, as no data for the fine resolution grid are given usually. Using data from other regions is questionable. Ghosh et al. [25] calculated the correlation between the nighttime lights and the Vulcan data [28] compiled for USA with the resolution 10km × 10km, and then used this correlation to calculate disaggregated emissions for other countries, but this approach did not provide satisfactory results. An ad-hoc method was proposed to improve this approach.

A method to use regression function, in a more general context of spatially autocorrelated data, was proposed in [32]. Its idea is to estimate the regression function parameters for the coarse grid and use them in the regression function for the fine grid. This method works well when the coarse and fine grid cell areas differ not more than a few to a dozen times ([32, 34]). But its range of applicability depends very much on the similarity of correlations on different area scales.

This methods enables automatic calculation of uncertainty distribution arising from statistical inference, see [33].

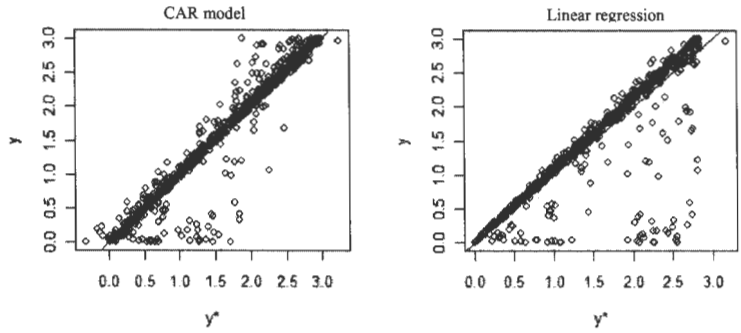

Figure 1. Predicted (y^*) versus observed (y) values

Figure 1 presents scatterplots of predicted values versus observations for original ammonia data in 5km × 5km grid as well as the values disaggregated from 10km × 10km grid. For the disaggregation from 10km×10km to 5km×5km grids, the mean square error (MSE) was 0.064 (conditional autocorrelation (CAR) model) and 0.186 (regression). Although introduction of spatial dependence evidently improved accuracy of prediction, the linear reggression method gives pretty good match.

A problem with using regression function is in estimating zero emissions, i.e. emissions (or activities) for the cells where they do not exist. This problem, known also under the name semicontinuous variables, clumped-at-zero or zero-inflated data, can also happen in the disaggregation proportional to one proxy variable, but it is more

acute for the multivariable case. In this problem a variable has a continuous probability distribution for positive values and a nonzero probability mass at zero. Simple cutting off of the negative values is perhaps operative, but scientifically not well justified. Min & Agresti [52] discuss this problem and review methods of dealing with it. They will be not discussed here.

3. Other sources of information

3.1. Atmospheric observations

Two kind of observations can be of value to constrain inventory estimates and perhaps improve their accuracies. One is measurement of the specific gas concentration or mixing ratio. An example can be found in [75]. The problem is to partition the estimated atmospheric load obtained possibly from subtracting a background concentration, to emission sources. This is typically done using the inversion methods to estimate CO_2 fluxes. For this, the Bayes estimator is generally applied ([18, 68]). To use the inversion method, the function which relates emission with concentration (footprints) is needed. It is typically computed using the atmospheric dispersion models and is finally of the linear form

$$\boldsymbol{y}_{\text{obs}} = \mathbf{H}\boldsymbol{x} + \boldsymbol{\psi} \tag{1}$$

where $\boldsymbol{y}_{\text{obs}}$ is an m-vector of the measured atmospheric concentrations (mixing ratios) in the receptor points, in space and time, above the background value, $\boldsymbol{x}$ is an n-vector of fluxes (emissions) from sources in the region considered, and $\mathbf{H}$ is the matrix that relates emissions in sources to the measurements. The elements of the $m \times n$ matrix $\mathbf{H}$ are computed using a transport model. It is assumed that they are constant in the considered time period, which may be a rough approximation. $\boldsymbol{\psi}$ is an m-vector of uncertainties of the relation (10); it is modeled as a random variable with the Gaussian distribution

$$p(\boldsymbol{\psi}) = \left[(2\pi)^m \det \mathbf{C}_y\right]^{-1} \exp\left\{-\frac{1}{2}\boldsymbol{\psi}^T \mathbf{C}_y^{-1}\boldsymbol{\psi}\right\} \tag{2}$$

The real fluxes are unknown but it is assumed that uncertain information on fluxes $\boldsymbol{x}_{\text{prior}}$ is given, so that

$$\boldsymbol{x} = \boldsymbol{x}_{\text{prior}} + \boldsymbol{\vartheta} \tag{3}$$

where again, the uncertainty is modeled as a random vector with the Gaussian distribution, independent on $p(\boldsymbol{\psi})$,

$$p(\boldsymbol{\vartheta}) = [(2\pi)^m \det \mathbf{C}_x]^{-1} \exp\left\{-\frac{1}{2}\boldsymbol{\vartheta}^T \mathbf{C}_x^{-1}\boldsymbol{\vartheta}\right\} \tag{4}$$

Using the Bayes theory the conditional probability $p(\boldsymbol{x}|\boldsymbol{y}_{\text{obs}})$ is given by

$$p(\boldsymbol{x}|\boldsymbol{y}_{\text{obs}}) = \frac{p(\boldsymbol{y}_{\text{obs}}|\boldsymbol{x})p(\boldsymbol{x})}{p(\boldsymbol{y}_{\text{obs}})} \tag{5}$$

It is proportional to

$$p(\boldsymbol{x}|\boldsymbol{y}_{\text{obs}}) \sim \exp\left\{-\frac{1}{2}\left[(\boldsymbol{y}_{\text{obs}} - \mathbf{H}\boldsymbol{x})^T \mathbf{C}_y^{-1}(\boldsymbol{y}_{\text{obs}} - \mathbf{H}\boldsymbol{x}) + (\boldsymbol{x} - \boldsymbol{x}_{\text{prior}})^T \mathbf{C}_x^{-1}(\boldsymbol{x} - \boldsymbol{x}_{\text{prior}})\right]\right\} \tag{6}$$

After some manipulations the value $\hat{\boldsymbol{x}}$ which maximizes the above conditional probability is obtained which gives the Bayes estimator of the fluxes

$$\hat{\boldsymbol{x}} = \boldsymbol{x}_{\text{prior}} + \left(\mathbf{H}^T \mathbf{C}_y^{-1}\mathbf{H} + \mathbf{C}_x^{-1}\right)^{-1} \mathbf{H}^T \mathbf{C}_y^{-1}\left(\boldsymbol{y}_{\text{obs}} - \mathbf{H}\boldsymbol{x}_{\text{prior}}\right) \tag{7}$$

The statistical uncertainty of the Bayesian estimator can be calculated as a covariance matrix

$$\hat{\mathbf{C}}_x = \left(\mathbf{H}^T \mathbf{C}_y^{-1}\mathbf{H} + \mathbf{C}_x^{-1}\right)^{-1} = \mathbf{C}_x - \mathbf{C}_x\mathbf{H}^T\left(\mathbf{H}\mathbf{C}_x\mathbf{H}^T + \mathbf{C}_y\right)^{-1}\mathbf{H}\mathbf{C}_x \tag{8}$$

The estimate $\hat{\boldsymbol{x}}$ is the sum of the prior estimate plus a correction, which depends on the deviation of observations from their predicted values. This correction improves the initial estimate of fluxes (e.g. obtained from disaggregation of the inventory estimates). The expression (8) informs us that the errors of the improved estimates (the values on the diagonal of $\widehat{\mathbf{C}}_x$) are not bigger (and very likely smaller) than the errors of the á priori estimate.

To use the above expressions, one has to know estimates of the covariance matrices $\widehat{\mathbf{C}}_x$ and $\mathbf{C}_y$. This issue is discussed in numerous papers, e.g. [45, 57, 63]. Various methods of finding appropriate values have been proposed; very often diagonal matrices have been used. Exponential decay of covariance values, both in space and/or time, has been found to match the reality better. Michalak et al. [51] develop a maximum likelihood method for estimating the covariance parameters. The likelihood function is formulated and the Cramér-Rao bound is derived.

The idea to use the likelihood function approach has been also used in the so-called geostatistical inverse modelling [27]. In this setting, instead of using prior information, emissions are modelled as linear combinations of trends. More advanced modelling of the fluxes has been proposed in the so-called assimilation data method proposed by Kaminski et al. [39], and then used e.g. in [60]. In this method, a more thorough model of emissions from the biosphere is included.

The above expressions have been used mostly in flux inversion studies. Ciais et al. [14] provide various comments on practical applications of this sort of methods. Peylin et al. [57] use them for estimating monthly European CO_2 fluxes and report 60% reduction of errors. Rivier et al. [63] apply them for estimating monthly fluxes of CO_2 from the biosphere and ocean for the global and European scale. The Bayesian estimate errors are reduced therein by 76% for the western and southern Europe, and by 56% for the central Europe. Lauvaux et al. [45] give inversion results for a 300km × 300km region in the South-West of France near Bordeaux with the 8km × 8km resolution of CO_2 fluxes, reporting about 50% error reduction. Continuous measurements were taken in two towers, and two aircrafts measuring CO_2 were used. Thompson et al. [70] estimated the N_2O fluxes in the western and central Europe. With only one in-situ measurement point used for inversion, they obtained between 30% and 60% error reduction for Germany.

The idea of atmospheric inversion methods is very general, and it can be used for improving estimates given any additional information in a suitable form. Atmospheric measurements are rather rare in space, so it may be difficult to obtain significant improvement for a very fine spatial grid for large areas. However, using local measurements and fine gridded a priori data the good resolutions can be achieved. For example, Gałkowski [21] obtained this way emission estimates with the resolution of few kilometers using measurements performed the stations in Kraków, and at Kasprowy Wierch located on a mountain in Polish Tatras (1989 m a.s.l.) some 100 km south of Kraków. This resolution is only a few times coarser than the very fine resolutions of 1-2 km, which have been obtained by using inventory data and disaggregation based on proxies.

Atmospheric inversion methods seem nowadays to be the most important approaches used to constrain estimates of emission fluxes from the biosphere.

3.2. Measurements of tracers

Measurement of tracers connected with emissions helps to identify better the fluxes. The most important tracer is ^{14}C isotope. The ^{14}C isotope is produced by cosmic

radiation in the upper atmosphere, and then it is transported down and absorbed by living organisms. The ^{14}C isotope decays in time of a few hundred years (its half-life equals approximately 5700 years), while the fossil fuels come from organisms which lived million to hundred million years ago. Intensive burning of the fossil fuels dilutes the atmospheric concentration of the ^{14}C isotope [66]. This way (a lack of) ^{14}C isotope may be used as a tracer of fossil fuel originated CO_2 emissions, and the rate of dilution can be used to assess local/regional/global emissions of fossil fuel CO_2.

The ^{14}C isotope has not been the only tracer of CO_2 emissions considered. Also, SF_6 and CO have been investigated [22, 47, 72], but ^{14}C has been found to be the most useful and directly available. Lopez et al. [49] used additional tracers of CO, NO_x, and $^{13}CO_2$, besides that of $^{14}CO_2$, to estimate relative fossil fuel (from liquid and gas combustion) and biosphere fossil fuel (from biofuels, human and plant respiration) CO_2 in Paris, and got good agreement.

Estimation of the fossil fuel CO_2 basically comes from two mass balance equations, for CO_2 and ^{14}C (or $^{14}CO_2$), which are presented in the concentration form (or, more often, in the mixing ratio form; the mixing ratio s is defined as $s = \rho_c/\rho_a$, where ρ_c is a CO_2 density and ρ_a is the air density)

$$CO_2^{obs} = CO_2^{bg} + CO_2^{ff} + CO_2^{bio} + CO_2^{other} \tag{9}$$

$$^{14}C^{obs} = {}^{14}C^{bg} + {}^{14}C^{ff} + {}^{14}C^{bio} + {}^{14}C^{other} \tag{10}$$

where the superscripts stand for, respectively, the observed (^{obs}) mixing ratio, background (^{bg}) mixing ratio – without the local fossil fuel emission, fossil fuel (^{ff}) mixing ratio, biosphere (photosynthesis and heterotrophic respiration) component (^{bio}), and other components, like those coming from burning of biomass, nuclear industry or ocean (^{other}). The ^{14}C isotope is typically measured as a relative difference between the (^{13}C corrected) sample and absolute rate [40, 65]

$$\Delta^{14}C = \frac{\left(\frac{^{14}C}{C}\right)_{obs} - \left(\frac{^{14}C}{C}\right)_{abs}}{\left(\frac{^{14}C}{C}\right)_{abs}} \tag{11}$$

where the absolute ($_{abs}$) value is the absolute radiocarbon standard ($1.176 \cdot 10^{-12}$ mol^{14}C/molC), related to oxalic acid activity. Equation (11) is usually expressed in per mill (‰) and written as

$$\Delta^{14}C = \left[\frac{\left(\frac{^{14}C}{C}\right)_{obs}}{\left(\frac{^{14}C}{C}\right)_{abs}} - 1\right] \cdot 1000\ [‰] \tag{12}$$

After some transformation the following final equation can be obtained

$$\Delta^{14}C^{obs}CO_2^{obs} = \Delta^{14}C^{bg}CO_2^{bg} + \Delta^{14}C^{ff}CO_2^{ff} + \Delta^{14}C^{bio}CO_2^{bio} + \Delta^{14}C^{other}CO_2^{other} \tag{13}$$

From (9), the concentration of one component can be calculated and inserted to (13). The choice of the eliminated component depends in principle on possibility of measuring the values in the equations, and the case considered. For example, having eliminated CO_2^{obs}, the equation for CO_2^{ff} is found as follows

$$CO_2^{ff} = \frac{(\Delta^{14}C^{obs} - \Delta^{14}C^{bg})\cdot CO_2^{bg}}{\Delta^{14}C^{ff} - \Delta^{14}C^{obs}} + \frac{(\Delta^{14}C^{obs} - \Delta^{14}C^{bio})\cdot CO_2^{bio}}{\Delta^{14}C^{ff} - \Delta^{14}C^{obs}} + \frac{(\Delta^{14}C^{obs} - \Delta^{14}C^{other})\cdot CO_2^{other}}{\Delta^{14}C^{ff} - \Delta^{14}C^{obs}}$$

As the concentration (and mixing ratio) of ^{14}C in the fossil fuel CO_2 is equal to 0, then from (11) we have $\Delta^{14}Cff = -1000$. It is often assumed that $CO_2^{other} = 0$, particularly when a site is far from other sources. Other assumptions may be appropriate for the area

considered, as this methodology can be applied to the studies of different scales, ranging from the global ones to small-scale.

Various authors discuss assumptions and assess underlying uncertainties. Turnbull et al. [73] present a systematic discussion and quantify uncertainties using modelling and the above equations.

Another important aspect is the choice of location for measurements of background values. Since the measurements are usually taken for long time periods, the background values are taken from observations at high-altitude sites. In Europe, commonly used background observations come from the High Alpine Research station Jungfraujoch at 3450 m a.s.l. in the Swiss Alps. Other local sites considered in Europe are the Vermunt station in Austria (1800 m a.s.l.) and the Schauinsland in Germany (1205 m a.s.l.). In Poland, there is an observation site at Kasprowy Wierch (1989 m a.s.l.) in the High Tatra Mountains, which can be used as a regional reference station [44]. Turnbull et al. [73] estimate differences of 1-3 ‰ due to the choice of a background site.

The resolution of CO_2^{ff} determination depends, first of all, on a spatial distribution of $\Delta^{14}C^{ff}$measurements. The $\Delta^{14}C^{ff}$ measuring observation stations are rather scarce. For instance, in 2008 there were only 10 measurement sites in Europe [56]. Much better spatial resolution can be obtained using measurements in plant materials, like corn leaves, rice, grape wine ethanol, grass, tree leaves, and tree rings. Most of them allow only for annual estimation, so measurements have to be done for many years to get longer time series. Only wine ethanol and tree rings enable historical records. This way Palstra et al. [56] was able to measure ^{14}C in 165 different wines from 32 different regions in 9 different European countries. The measurements were compared with those obtained from a regional atmospheric transport model, predicting fossil fuel CO2 with the resolution 55km × 55km, with a good compatibility. Riley et al. [62] used measurements from winter annual grasses collected at 128 sites across California, USA, to model transport of fossil fuel CO_2 by using a regional transport model with the resolution 36km × 36km. These resolutions are still not high enough to be directly useful in very fine gridded cells and need to be disaggregated for this or used for improving estimates in coarser grid.

3.3. Direct local measurements of fluxes

The fluxes can be also measured. The fluxes from big chimneys are actually estimated with quite good accuracy. But also fluxes coming from the biosphere or urban environment can be measured using several methods. Observations from the flux towers are taken above the plant canopies, and use the so-called eddy covariance method. The basic idea of the eddy covariance can be found in [10]. Foken & Wichura [19] discuss the connected errors. Other possible measurements use chamber system, see an example in [75], to measure fluxes coming from the soil.

The flux tower observations could be a perfect way to provide very high resolution emission fluxes from the biosphere both in space and time provided that a net of flux towers is dense enough. Unfortunately, flux towers are rather scarce. Even over the large area of USA and Canada, only 36 flux tower observations are reported [58]. Their use can be therefore rather considered in the future, when more flux towers are constructed. At present, they are used mainly for an assessment of biosphere emission models, see [3] or [58].

When using local flux measurements, particularly coming from the soil, some problems may arise with high spatial variability of the obtained results For example, Gałkowski [21] reports three times difference between measurements of nitrous oxide fluxes from the soil in a distance of few meters.

To be useful in estimation of areal data, the point measurements have to be interpolated. Geostatistical methods, like Kriging [15, 23], are usually applied. It is, however, suitable only for homogeneous fields. Bayesian melding [20] is a method that can cope with usual inhomogeneity of pollution fields, see e.g. [48]. These methods have been developed to include time dependence, [4, 46].

4. Combining multi-model estimates

There are many different ways to combine results of models. Three groups are distinguished in this paper, although the authors do not claim that they cover all published methods.

Averaging. Simple averages, see e.g. Oda (2015), can be quite efficient. Weighted averages

$$\bar{x} = \frac{\sum_i w_i x_i}{\sum_i w_i}$$

perform usually better, but the weights w_i have to be defined in them. Usual method of determining weights from the historical differences between the model output and observations cannot be used, as observations of real emission values do not exist. The situation is a bit similar to combining models in climate projections, see [41, 69] for review of the methods used there. As the models use projections for the future, both the discrepancies of the model output from the ensemble mean in the current time and in the future are considered there. For example, in reliability ensemble average method proposed in [26] the weights are calculated as the product of two terms inversely proportional to the absolute values of these discrepancies. Adaptation to emission models could use only one discrepancy. The calculations can follow iteratively.

Bayesian approach. The Bayesian methodology proposed in the atmospheric inversion may be applied for combining model results, which give independent information complementing each other. In this case, the following function has to be minimized

$$J = (\boldsymbol{y}_{\text{obs}} - \boldsymbol{x})^T \mathbf{C}_y^{-1} (\boldsymbol{y}_{\text{obs}} - \boldsymbol{x}) + (\boldsymbol{x} - \boldsymbol{x}_{\text{prior}})^T \mathbf{C}_x^{-1} (\boldsymbol{x} - \boldsymbol{x}_{\text{prior}}) \tag{14}$$

where $\boldsymbol{y}_{\text{obs}}$ is the vector of the emission estimates from the first model and $\boldsymbol{x}_{\text{prior}}$ is the vector of estimates from the second one. The solution of the minimization problem is

$$\hat{\boldsymbol{x}} = \boldsymbol{x}_{\text{prior}} + \left(\mathbf{C}_y^{-1} + \mathbf{C}_x^{-1}\right)^{-1} \mathbf{C}_y^{-1} (\boldsymbol{y}_{\text{obs}} - \boldsymbol{x}_{\text{prior}}) = \boldsymbol{x}_{\text{prior}} + \mathbf{C}_x (\mathbf{C}_y + \mathbf{C}_x)^{-1} (\boldsymbol{y}_{\text{obs}} - \boldsymbol{x}_{\text{prior}}) \tag{15}$$

and the estimate of the improved estimate covariance matrix takes the form

$$\hat{\mathbf{C}}_x = \left(\mathbf{C}_y^{-1} + \mathbf{C}_x^{-1}\right)^{-1} = \mathbf{C}_x - \mathbf{C}_x (\mathbf{C}_x + \mathbf{C}_y)^{-1} \mathbf{C}_x \tag{16}$$

Particularly simple computations are obtained for diagonal covariance matrices $\mathbf{C}_x$ and $\mathbf{C}_y$. In this case the above formulae read

$$\hat{x}_i = x_{i,\text{prior}} + \frac{c_{ii,x}}{c_{ii,x} + c_{ii,y}} \left(y_{i,\text{obs}} - x_{i,\text{prior}}\right), \qquad i = 1, \ldots, n \tag{17}$$

$$\hat{c}_{ii,x} = \frac{1}{\frac{1}{c_{ii,x}} + \frac{1}{c_{ii,y}}} = \frac{c_{ii,x} c_{ii,y}}{c_{ii,x} + c_{ii,y}}, \qquad i = 1, \ldots, n \tag{18}$$

It is readily seen that $\hat{c}_{ii,x} \leq c_{ii,x}$ and $\hat{c}_{ii,x} \leq c_{ii,y}$. This procedure can be generalized to more than two models.

Joint probability distribution approach. This approach has been proposed by Kryazhimsky [42]. In his approach no weighting is used. He operates on the joint probability distribution (multivariable distribution) obtained as the product of the distributions of individual distributions under assumption of their independence, as in the bivariate case

$$p(x,y) = p(x)p(y)$$

although the method can be applied to a higher multivariate distribution as well. In opposition to the two previously mentioned ones, this approach has been as yet not extensively evaluated in practical applications. It was used in [43] for combining estimates of net primary production of forest obtained from two models.

5. Final remarks

A preliminary review of possibilities of using additional knowledge to improve fine gridded estimates of GHG emissions is presented. Besides the mentioned above, there may be still more information that can help in better estimation of gridded emissions, but not dealt with in the paper. Different constraints on local emission (like lack of specific sources in the cells) can be possibly used in obtaining better accuracy. There may be, for example, independent emission assessments done on part of considered regions. Also some common sense knowledge can be used. One of important problems connected with integration of different knowledge is mismatch of the grids used in different studies, often spotted in real applications. These problems are discussed [74], who also presents an approach based on artificial intelligence methods to solve them. Many practical difficulties are also pointed to in [31].

A basic question is how much all additional knowledge can improve the estimates obtained by using proxy variables. This probably will depend on specific case. Not much can be probably expected in the case of industrial emissions, particularly of the carbon dioxide gas. However, for such emissions like nitrous oxide, N_2O, from the biosphere, which is very poorly estimated by present techniques, introduction of, say, atmospheric inversion methods can perhaps give a considerable improvement. These questions can be solved only by investigations of specific cases. This makes the area for interesting research projects.

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