4th International Workshop
on Uncertainty in Atmospheric Emissions

7-9 October 2015, Krakow, Poland

PROCEEDINGS

4th International Workshop on Uncertainty in Atmospheric Emissions

7–9 October 2015, Kraków, Poland

PROCEEDINGS

Warszawa 2015

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

Printed from the material submitted by the authors.

ISBN 83-894-7557-X
EAN 9788389475572

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.

Steering Committee

Rostyslav BUN (Lviv Polytechnic National University, UA)
Matthias JONAS (International Institute for Applied Systems Analysis, AT)
Zbigniew NAHORSKI (Polish Academy of Sciences, PL) – Chair

Scientific Committee

Evgueni GORDOV (Siberian Center for Environmental Research & Training, RU)
Piotr HOLNICKI-SZULC (Polish Academy of Sciences, PL)
Joanna HORABIK-PYZEL (Polish Academy of Sciences, PL)
Olgierd HRYNIEWICZ (Polish Academy of Sciences, PL)
Katarzyna JUDA-REZLER (Warsaw University of Technology, PL)
Petro LAKYDA (National University of Life and Environmental Sciences of Ukraine, UA)
Myroslava LESIV (Lviv Polytechnic National University, UA)
Gregg MARLAND (Appalachian State University, USA)
Sten NILSSON (Forest Sector Insights AB, SE)
Tom ODA (Univ. Space Research Association, NASA Goddard Space Flight Center, USA)
Stefan PICKL (Universität der Bundeswehr München, Germany)
Elena ROVENSKAYA (International Institute for Applied Systems Analysis, AT)
Kazimierz RÓŻAŃSKI (AGH University of Science and Technology in Cracow, PL)
Dmitry SCHEPASCHENKO (International Institute for Applied Systems Analysis, AT)
Anatoly SHVIDENKO (International Institute for Applied Systems Analysis, AT)
Jacek SKOŚKIEWICZ (National Centre for Emissions Management, PL)
Philippe THUNIS (EC Joint Research Centre Ispra, EU)
Marialuisa VOLTA (University of Brescia, IT)

Local Organizing Committee

Joanna HORABIK-PYZEL
Jolanta JARNICKA - Chair
Weronika RADZISZEWSKA
Jörg VERSTRAETE

A method for estimating time evolution of precision and accuracy of greenhouse gases inventories from revised reports

Jolanta Jarnicka[1], Zbigniew Nahorski[1]

[1] Systems Research Institute, Polish Academy of Sciences,
Warsaw, Poland
Jolanta.Jarnicka@ibspan.waw.pl, Zbigniew.Nahorski@ibspan.waw.pl

Abstract

In the paper a statistical method for estimating the evolution of GHG inventories is proposed. For estimation the revisions of inventories published in consecutive years are used. Data from the National Inventory Reports up to 2007, and then up to 2014 are analyzed. A parametric model and a procedure for estimating parameters are described, and examples of their applications are presented. As a result, statistically significant trajectories of standard deviations are obtained and clear improvement of inventory accuracy in time is observed.

Keywords: greenhouse gases inventories, uncertainty, modeling

1. Introduction

According to the United Nations Framework Convention on Climate Change (UNFCCC) and its Kyoto Protocol, each of the cosignatories is obliged to provide annual data on greenhouse gas inventory. Each report contains data from a given year and revisions of past data, whenever required, but it also has to deal with uncertainties. Data for previous years are revised when more precise information is obtained. This means that revisions made in different years use different knowledge, and hence uncertainties in different revisions are incomparable. The question therefore arises, whether it is possible to compare and organize data on GHG emission, to get as much information about the unknown uncertainty as possible. Disscussion on that problem can be found e.g. in [1], [2], [3], and many others.

The goal of that paper is an attempt to find an answer to that question, by proposing an alternative method of uncertainty assessment. This is done by analyzing how the uncertainty of the inventory reports changes over the consecutive yearly revisions. Based on the data from the National Inventory Reports up to 2007 and then the data up to 2014, in view of revisions of inventories published in consecutive years, we observed significant improvement of inventory accuracies in time. The results obtained indicate a clear learning effect in inventory calculation.

In Section 2 we present the idea of interpreting the data and propose a parametric model, that describes the uncertainty structure in the inventory reports. Section 3 contains the results of fitting the model to data from the National Inventory Reports for Austria. Conclusions are given in Section 4.

2. Presentation of the model

We analyze data from the national inventory reports. Let E^n – denote the inventory data for the country i, in the year n revised in the year y, and let Y – denote the last year, when the revision is made. For a given country i all the inventory data form a table, in which each row contains consecutive revisions of the data for a given year (Table 1).

Table 1. Indexing the data

$$
\begin{array}{ccccccccc}
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
\cdots & E^{n-1}_{y,i} & E^{n}_{y,i} & E^{n+1}_{y,i} & \cdots & E^{y}_{y,i} & 0 & \cdots & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
\cdots & E^{n-1}_{Y,i} & E^{n}_{Y,i} & E^{n+1}_{Y,i} & \cdots & E^{y}_{Y,i} & E^{y+1}_{Y,i} & \cdots & E^{Y}_{Y,i}
\end{array}
$$

We use the fact that, each revision data, for a given country, forms a realization of a stochastic process. These stochastic processes for a fixed country are different, but related. They form a bunch of stochastic processes. An example is given in Figure 1, presenting data from the National Inventory Reports for Austria. The data refers to CO_2 emissions in the years 1990-2005 (i.e. reported up to 2007), and revisions performed every year, from 1999-2005.

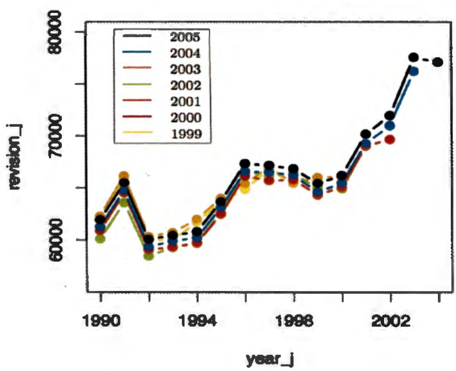

Figure 1. Revisions of the National Inventory Reports data on CO_2 emissions, 1999-2005, Austria.

For a given country *i*, we model any revision data to be composed of the "real" emission, which we call the "deterministic" fraction and a "stochastic" fraction, related to our lack of knowledge and imprecision of observation of the real emission. We assume that the uncertainty is related to the stochastic part of the model.

$$E^{n}_{Y,i} = D^{n}_{Y,i} + S^{n}_{Y,i}, \qquad S^{n}_{Y,i} \sim \mathcal{N}(0, \sigma_{Y,i}),$$

where E – stands for the emission inventory, D – for its deterministic fraction, S – for the stochastic fraction, and n – is the year, for which the revised data were recalculated. Similarly, if $y_j < Y$,

$$E^{n}_{y_j,i} = D^{n}_{Y,i} + S^{n}_{y_j,i}, \qquad \text{with} \quad S^{n}_{y_j,i} \sim \mathcal{N}\left(m^{n}_{y_j,i}, \sigma^{n}_{y_j,i}\right),$$

where the mean values and standard deviations are of the form

$$m^n_{y_j,i} = a_i(Y - y_j), \qquad \sigma^n_{y_j,i} = \sigma_{Y,i} + b_i f(Y - y_j), \quad b_i \neq 0.$$

and f is a function, such that

$$f(Y - y_j) > -\frac{\sigma_{Y,i}}{b_i}.$$

The parameters a_i and b_i, for a country i, associated with the stochastic fraction $S^n_{y_j,i}$ can be estimated from the data, together with $\sigma_{Y,i}$. Parameter a_i describes a shift in the accuracy of the inventory gathering, and b_i – a shift of the precision level. They both depend on the difference between the revision year y_j, and the most recent revision year Y, due to the learning. To find the deterministic fraction$D^n_{Y,i}$, the smoothing splines can be used, as presented in [4]. This approach, when applied to the most recently revised data $E^n_{Y,i}$will give not only the estimate of the deterministic fraction, but also an estimate of the variance $\sigma^2_{Y,i}$.

Algorithm for a fixed country i

Fix i and consider all the inventory data $E^n_{y_j,i}$ in the year n for $n = 1, \ldots, N_j$, revised in the year y_j, $j = 1, \ldots, J$. For a fixed country i, the procedure can be described as follows.

1. For the most recently revised inventory data E^n_Y **calculate the smoothing spline** Sp_Y **and estimate the variance** σ^2_Y of the stochastic fraction S^n_Y.
2. **Subtract the spline** Sp_Y**, built on the data from the year** Y**, from all earlier revisions** $E^n_{y_j}$, $y_j < Y$, calculating differences
$$v^n_j = E^n_{y_j} - \mathrm{Sp}_Y, \quad n = 1, \ldots, N_j, \; j = 1, \ldots, J.$$
For some years the difference v does not exist, due to lack of revised inventories in this year. These years are skipped from the sequence of N_j data.
We consider the following <u>model</u>:

(1) $$v^n_j \sim \mathcal{N}\Big(m_j, \sigma_j\Big), \quad n = 1, \ldots, N_j, \quad j = 1, \ldots, J,$$

where

(2) $$m_j = a(Y - y_j), \quad \sigma_j = \sigma_Y - b\,(Y - y_j)^{c+1}, \quad b \neq 0.$$

Assume also that differences (1) are independent.

3. **Estimate parameters a, b, and c** (and hence m_j and σ_j, $j = 1, \ldots, J$ in (2)) in the following three-step procedure.

<u>Step 1.</u> Estimate parameters α_j and β_j, $j = 1, \ldots, J$ in the model

$$m_j = \alpha_j(Y - y_j), \quad \sigma_j = \widehat{\sigma}_Y + \beta_j\,(Y - y_j), \quad \beta_j \neq 0,$$

using Maximum Likelihood estimators

$$\widehat{\alpha}_j = \frac{1}{N_j(Y - y_j)} \sum_{n=1}^{N_j} v^n_j, \qquad \widehat{\beta}_j = \frac{\left(\sqrt{\frac{1}{N_j}\sum_{n=1}^{N_j}\left(v^n_j - \bar{v}_j\right)^2} - \widehat{\sigma}_Y\right)}{(Y - y_j)},$$

where $\bar{v}_j = \frac{1}{N_j}\sum_{n=1}^{N_j} v^n_j$.

Step 2. Use $\widehat{\alpha}_j$, $j = 1, \ldots, J$, obtained in Step 1, to estimate parameter a in the first order autoregressive model

$$\alpha_{j-1} = \frac{1}{\tilde{a}}\alpha_j + \varepsilon_j, \quad |\tilde{a}| < 1,\ \tilde{a} \neq 0, \quad \text{where} \quad \alpha_{J+1} := 0,$$

and ε_j are independent and $\varepsilon_j \sim N(0, \sigma)$. Estimator of the parameter a is then given by

$$\widehat{a} = \frac{1}{\;}$$

Step 3. Use the sequence $\widehat{\beta}_j$, $j = 1, \ldots, J$, obtained in Step 1, to estimate parameters b and c in the regression model

(3) $$\beta_j := -b(Y - y_j)^c, \quad j = 1, \ldots, J, \quad \text{where} \quad b < 0.$$

Since $\beta_j > 0$, $j = 1, \ldots, J$, nonlinear model (3) can be converted into a linear one of the form

$$\ln \beta_j = \ln(-b) + c\ln(Y - y_j),$$

and the parameters $\widetilde{b} := \ln(-b)$ and c can now be estimated using the Least Squares method.

3. Case study - NIR data for Austria

The data analyzed refers to CO_2 emissions in the years 1990 – 2005, and recalculations (revisions), performed every year, from 1999 to 2005. We start with building a smoothing spline Sp_Y for the most recently revised data – from the year $Y = 2005$ (Figure 2).

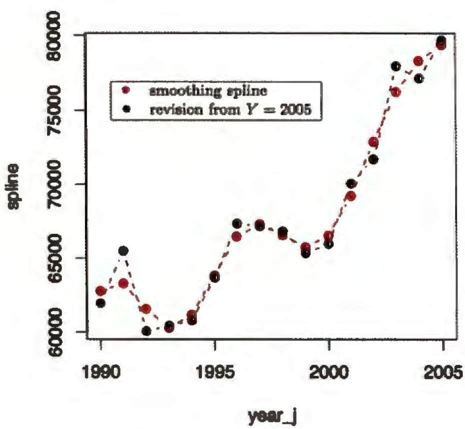

Figure 2. Smoothing spline and data on CO_2 emissions from Austrian NIR, $Y = 2005$

Then, we calculate the differences v_j, between real emissions data, and the spline obtained, and estimate parameters a, b, and c in the model (1) - (2). Having obtained estimates for a, b, and c, we can find sequences of means and standard deviations. The results are presented in Figure 3 and Table 2.

Table 2. Estimates of parameters in the model (1) - (2).

j	1999	2000	2001	2002	2003	2004	parameters
m_j	8.62	7.18	5.74	4.31	2.87	1.44	$\hat{a} = 1.44$
σ_j	1119.33	1099.62	1074.95	1042.20	994.20	906.87	$\hat{b} = 1158.6$, $\hat{c} = -1.11$

Parameter	Estimate	Model fit
a	1.44	$\sigma^2 = 43669$
b	1158.6	St.error=0.056, t-test: p-value=0.000000023, $R^2 = 0.99$
c	-1.11	St.error = 0.045, t-test: p-value=0.0000152

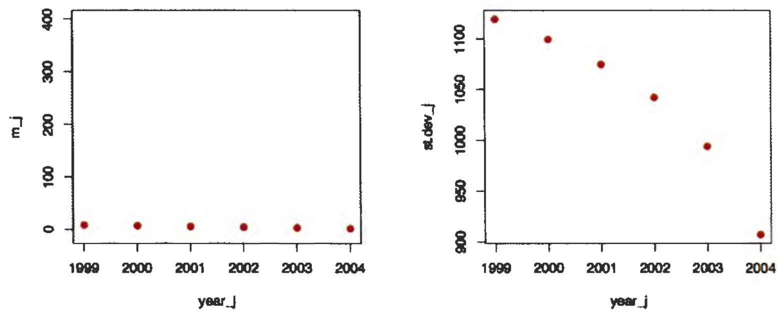

Figure 3. Estimates of m_j and σ_j, j=1999..2004, Austria.

The analysis conducted gives the information about the data considered. The mean values tend to zero and we may take into account the speed of that convergence. The sequence of standard deviations is strictly decreasing, indicating a reduction in the emissions.

The main result – the uncertainty assessment is the sequence of relative values of the form

$$\frac{\hat{\sigma}_j}{\mathrm{Sp}_j},\ j = 1, \ldots, J$$

depicted in Figure 4a), together with the relative uncertainties provided in the National Inventory Report. One can observe that the relative values are significantly smaller than the uncertainties published in the reports, which means that the assessment proposed is more accurate.

For comparison, in Figure 4b) we present the analysis, conducted for the Austrian National Inventory Reports data available up to the year 2014 (i.e. for $Y = 2012$). Also in this case, one can notice that uncertainty assessment obtained using the method proposed is significantly better than those published in the official reports.

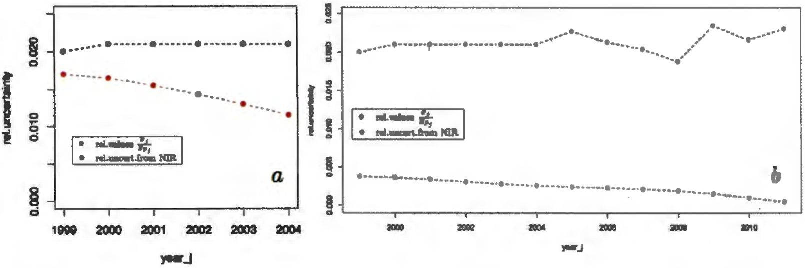

Figure 4. Comparison of relative uncertainty and relative values $\frac{\sigma_j}{Sp_j}$, NIR data on CO_2 emissions, Austria, $a)\ j = 1999 \ldots 2004,\ Y = 2005$ $b)\ j = 1999 \ldots 2011,\ Y = 2012$

4. Conclusions

The method proposed, proved to be a good tool for the uncertainty assessment. It is worth noting that it is based solely on the data, and works without any additional assumptions. It works well in practice (applied to the NIR data for EU countries). However, it is necessary to test larger data sets (as they become available), and other databases.

References

[1] G. Marland (2008), Uncertainties in accounting for CO_2 from fossil fuels. Journal of Industrial Ecology, 12(2):136-139.

[2] G. Marland, K. Hamal, M. Jonas (2009), How uncertain are estimates of CO_2 emissions? Journal of Industrial Ecology, 13(1):4-7.

[3] K. Hamal (2010) Reporting GHG emissions: Change in uncertainty and its relevance for detection of emission changes. Interim Report IR-10-003. IIASA, Laxenburg.

[4] Z. Nahorski, W. Jęda (2007), Processing national CO_2 inventory emission data and their total uncertainty estimates, Water, Air, and Soil Pollution: Focus, 7(4-5):513-527.