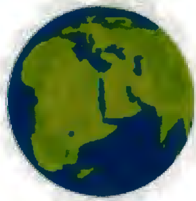

4th International Workshop
on Uncertainty in Atmospheric Emissions

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

Assessing the improvement of greenhouse gases inventories: can we capture diagnostic learning?

Piotr Żebrowski, Matthias Jonas, Elena Rovenskaya

International Institute for Applied Systems Analysis, Advanced Systems Analysis Program, Laxenburg, Austria
Piotr.Zebrowski@iiasa.ac.at

Abstract

Our study aims at modelling the diagnostic learning understood as a gradual improvement of the quality of greenhouse inventories. We quantify this improvement by the speed of convergence of consecutive revisions of emissions estimates to the most recently published ones, which we assume to be close to the true emissions values. On the example of Austria's National Inventory Reports we show that the diagnostic learning process exhibits exponential dynamics.

Keywords: Greenhouse gas emissions, revisions of emissions inventories, learning, uncertainty of emissions estimates

1. Introduction

Signatories to the United Nations Framework Convention on Climate Change (UNFCCC) are obliged to submit annual inventories of their greenhouse gas (GHG) emissions, together with revisions of historical emission estimates. Previous estimates are recalculated whenever errors in inventories were identified and corrected, new data sources were taken into account or new accounting methodologies were employed. Therefore, consecutive revisions of emissions estimates from previous years are thought to reflect the advancement of knowledge in constructing GHG inventories, while the most recent estimates are considered to be accurate. But can we detect this learning process in the historical data of GHG emissions reported to the UNFCCC?

In this work we show on the example of Austria's GHG inventories that indeed we can observe and model the improvement of GHG emission inventories.

2. Diagnostic learning

By diagnostic learning we call the process of gradual improvements in the quality of GHG emissions inventories. This "improvement of quality" we understand as the advancement of knowledge, which is reflected by the increase of accuracy (reduction of bias) and/or precision (reduction of standard deviation) of emissions estimates.

Several attempts have been made to grasp the diagnostic learning in a quantitative way. In Hamal's work [1] the notion of total uncertainty was used. The total uncertainty combines inaccuracy (in relative terms) between the most recent and the most initial estimates of emissions, with the imprecisions of these estimates (lack of precision). Another approach is to analyze the convergence of sequences of estimates reported in the consecutive National Inventory Reports as has been done in Nahorski *et. al.* [2].

In Marland *et. al.* [3] learning was understood as a convergence of revised estimates of emissions towards the more accurate ones. In our work we follow this line of thinking and investigate whether the consecutive revisions of estimates stabilize around certain level (presumed to represent the accurate estimate), and if so, how fast this stabilization level is reached.

A common feature of the approaches presented in [1] and [2] is that is that both methods strived to capture the learning process from one report to another in the uniform way (ensemble approach). However, if one do not consider revised estimates of emissions occurred in different years separately, then the learning process one tries to describe is "contaminated" by structural changes in emissions in different years.

In contrast, our method grasp "pure" learning (unaffected by structural changes) because we model learning process in consecutive revisions of emissions estimates for only one fixed year of emissions at a time. But before we explain our approach to diagnostic learning in detail we first describe the data set we are analysing.

3. The data

We chose to present our method on the case example of Austria as for this country the temporal evolution of revised CO_2 emissions estimates is well pronounced. The data set we are working on has been compiled from the Austria's National Inventory Reports (NIRs) submitted to the UNFCCC in the years 2003-2014.

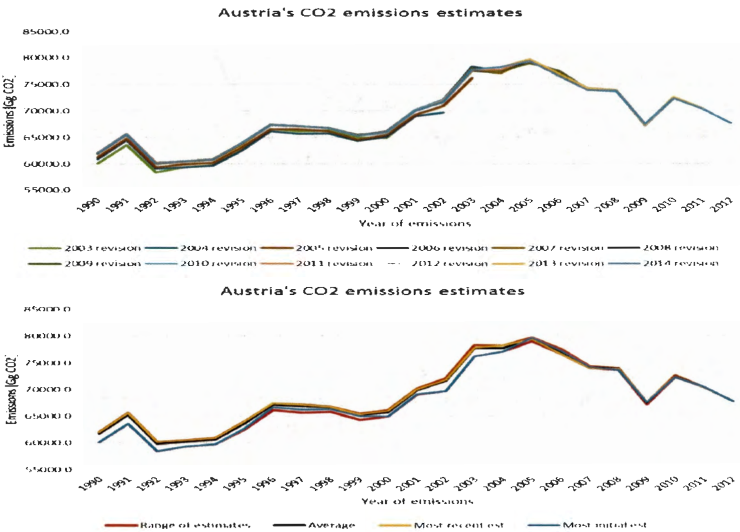

Figure 1. Revisions of the Austria's CO_2 emissions estimates (top panel) and time evolution of ranges of Austria's CO_2 emissions estimates (bottom panel).

It is important to note that our data set may be naturally divided into two parts. Part I contains revised estimates of emissions in the period 1990-2001. It may be organized into 11 sequences, with firs one containing revised estimates of emissions occurred in 1990, second one contains estimates of emissions for 1991 and so on. Each of these sequences consists of estimates published in the years 2003-2014 and thus all of them have the equal length of 12. As a consequence, all most initial estimates in this part comes from the NIR published in 2003 (see Figure 2.). Part II containing the rest of the data (estimates of emissions occurred in the period 2002-2012) can be organized into another 11 sequences in the same way as the part I. The only difference is that all these sequences are of different lengths. The first one, containing estimates of emissions in year 2002, is of the length 11 and the last one has only one element , that is the only available estimate of emissions in year 2012 published in the year 2014.

Figure 1. shows that revised emissions estimates differ slightly revision-wise but clearly follow the emissions path published most recently. However, for each year of emission the revised estimates may behave erratic and in general do not approach the most recent one (assumed to be correct) in the strictly monotonic way. It is also difficult to compare in absolute terms the changes in estimates of emissions that occurred in different years. Thus, in order to see a clearer picture, we assume the most recent estimates as a reference level and work with relative differences of estimates normalized estimates (i.e., values of estimates divided by the most recent ones).

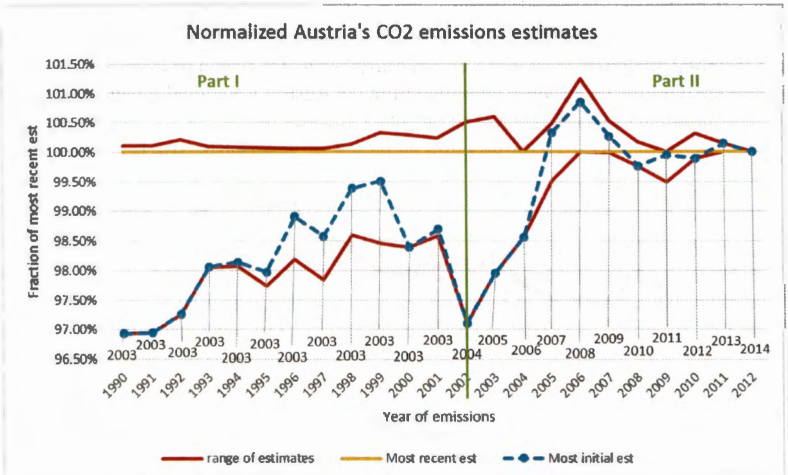

Figure 2. Austria's CO_2 emissions estimates normalized by the most recent estimates. For the most initial estimates line the year of estimate's publications is marked.

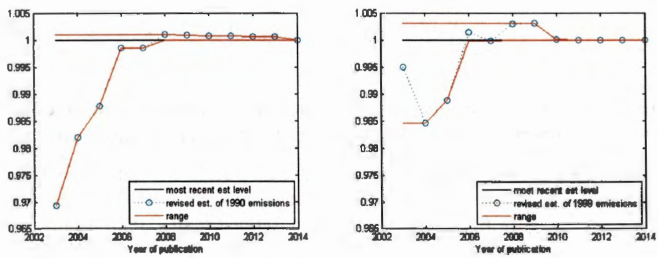

Figure 3. Time evolution of revised estimates of Austria's CO2 emissions in the year 1990 (left panel) and 1999 (right panel).

Figure 2. presents the data after normalization transformation and should be interpreted as follows: for example, initial estimate of the emissions in 1999 were lower

than the most recent one by 0.5% of the most recent estimate, and the range of all revisions spans from 98.5% to 100.3%. How these estimates change from revision to revision is shown on the Figure 3. (left).

After normalization of estimates we clearly see that typically the most initial estimates tend to underestimate emissions, but their subsequent corrections are not always in the direction of the most recent estimate. The range of revised estimates of emissions in a given year carries more information about the variability of these estimates and is a good proxy for the uncertainty of these estimates. Hence, we argue that analysis of the ranges of emissions estimates suits well the purpose of grasping diagnostic learning. Our methodology, which we describe in the following section, is based on this observation.

4. Model of diagnostic learning

4.1. Notation

Let $E_{n,y}$ denotes estimate of emissions in year n revised in year y, with $n = \{1990, \ldots, 2012\}$ and $y = \{n+2, \ldots, Y\}$, where $Y = 2014$ is the year of the last revision ($y \geq n+2$ reflects the fact that inventories are published with 2-year delay). We define

$$m_{n,y} = min\{E_{n,y}, \ldots, E_{n,Y}\} \text{ and } M_{n,y} = max\{E_{n,y}, \ldots, E_{n,Y}\}. \qquad (1)$$

Then $m_{n,y}$ denotes the smallest of the estimates of emissions in year n that were published in years between y and Y. Similarly $M_{n,y}$ denotes the biggest of these estimates. How $m_{n,y}$ and $M_{n,y}$ (normalized by $E_{n,Y}$) change as $y \to Y$ can be seen on the Figure 3. (The lower and upper red lines on the left panel represents evolution of $m_{1990,y}/E_{1990,2014}$ and $M_{1990,y}/E_{1990,2014}$ for y changing from 2003 to 2014. Similarly, the lower and upper red lines on the right panel correspond to $m_{1999,y}/E_{1999,2014}$ and $M_{1999,y}/E_{1999,2014}$, accordingly.)

4.2. Formal approach to diagnostic learning

As mentioned in section 2. we understand diagnostic learning as a convergence

$$E_{n,y} \to E_n \text{ as } y \to \infty, \qquad (2)$$

where E_n is a true but unknown value of emissions that occurred in the year n. In practice, for each year of emissions n we observe only a few initial elements of sequence $E_{n,y}$ (at most 12 for the Part I of the data). However, if convergence (2) holds and the most recent estimate $E_{n,Y}$ is close to the true value E_n then we observe that revisions $E_{n,y}$ stabilize around level $E_{n,Y}$. Ten necessarily also $m_{n,y} \to E_{n,Y}$ and $M_{n,y} \to E_{n,Y}$ as $y \to Y$. Both these effects can be seen of Figure 3.

Let us fix a year of emissions n. As revised estimates $E_{n,y}$ may oscillate around level $E_{n,Y}$, the learning process is more apparent in the evolution of $m_{n,y}$ and $M_{n,y}$ since they converge monotonically to $E_{n,Y}$. The speed of this convergence may be interpreted as the rate of suppression of oscillations of estimates $E_{n,y}$ and the decrease of the difference $M_{n,y} - m_{n,y}$ may be regarded as the decrease of uncertainty.

Figure 2. reveals that the upper ranges of emission estimates $M_{n,y}$ do not vary much between different years of emissions n and in general are only slightly higher (typically by less than 0.5%) than the most recent estimates. Therefore it is the evolution of lower ends of the estimates ranges that reflects the diagnostic learning.

4.3. Modeling diagnostic learning in revisions of emission estimates for each year of emissions separately.

Figure 3. suggests that for each fixed year of emissions n lower end of estimate's range $m_{n,y}$ approaches level $E_{n,Y}$ more rapidly at the beginning and gradually slows down and stabilizes as $y \to Y$. Therefore, for each fixed n, it is natural to choose the exponential dynamics as a model of time evolution of $m_{n,y}$ as $y \to Y$, namely

$$\frac{m_{n,y}}{E_{n,Y}} = 1 - c_n e^{-\lambda_n (y-n-2)} \tag{3}$$

for $y = \{y_0, \dots, Y\}$, where $y_0 \geq n + 2$ is the year of publication of the most initial available estimate of emissions in the year n. The parameter λ_n is the interpreted as the learning rate in the period between y_0 and Y.

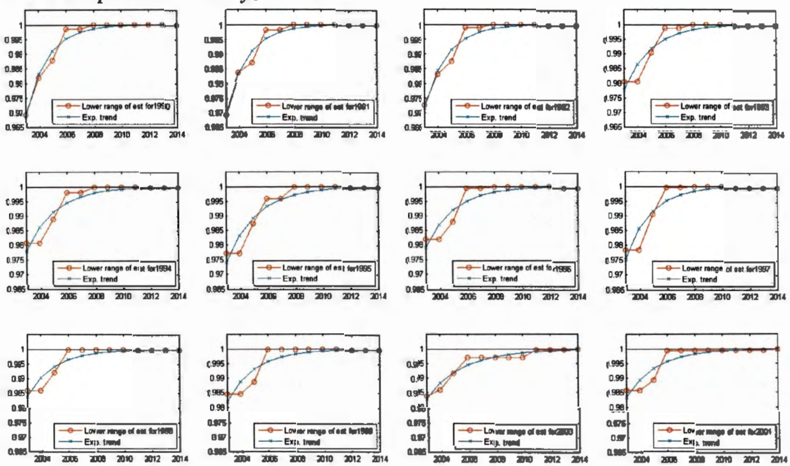

Figure 4. Exponential trends of evolution of lower ends of emissions estimates ranges.

Table 1. Values of learning obtained via formula (3)

Year of emissions n	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**
Learning rate λ_n	0.6251	0.6210	0.5954	0.5043	0.4722	0.4425
Year of emissions n	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**
Learning rate λ_n	0.4815	0.5405	0.5147	0.4786	0.3761	0.4497

We apply the model (3) to each sequence in the Part I of the data (that is to revisions of emissions for years n = 1990, … , 2001, that were published between years y_0=2003 and Y = 2014). The reason for this choice is two-fold. Firstly, all sequences in Part I are of equal length which ensures that the of the trend fit is comparable for all considered samples. Second reason is that all these sequences reflects learning process in the same period, namely the years 2003-2014. On Figure 4. we present the trends in learning obtained from model (3) for the years of emissions covered by the Part I of the data, while Table 1. contains the corresponding learning rates.

4.4. Modeling diagnostic learning revision-wise

In the previous section we applied model (3) to grasp learning in the revised emissions estimates for each one year of emissions covered by the Part I of the data at a time. However, if our model of diagnostic learning is a correct one, we should be able to observe exponential trend in overall improvement of inventories from one revision to another. We perform such consistency check using the Part II of the data.

We suspect that the structural changes in emissions cause only minor differences between learning rates λ_n for different years of emissions n (see Hamal [1]). Therefore it is reasonable to assume that the learning process from revision to revision is uniform for estimates of emissions across all covered years of emissions n.

We calculate the average $\bar{\lambda} = 0.5085$ of all learning rates λ_n given in the Table 1. and interpret it as the approximate uniform learning rate of this overall improvement of all CO_2 inventories published in the period 2003-2014.

Provided this hypothesis is true we should then be able to use our model (3) to grasp diagnostic learning in the Part II of the data. Observe that the lower red line in the Part II of the Figure 2. corresponds to normalized lower ends of the ranges of emissions estimates $m_{n,n+2} / E_{n,Y}$ for the years of emission covered by Part II of the data (n = 2002,..., 2012). Now, if all $m_{n,y} / E_{n,Y}$ behave uniformly for all n as $y \rightarrow Y$, then model (3) and our assumptions yield that

$$\frac{m_{n,n+2}}{E_{n,Y}} = 1 - \bar{c}\, e^{-\bar{\lambda}(n-n_0)} \tag{4}$$

for all $n = \{n_0 = 2002, \ldots, 2014\}$, where parameter $\bar{\lambda}$ is the uniform learning rate describing overall improvement of emissions inventories revision-wise. Thus, if our model is a correct one, value of $\bar{\lambda}$ calculated as the average of learning rates λ_n given in the Table 1. and the value of $\bar{\lambda}$ obtained directly from the Part II of the data via model (4) should match. As Table 2. shows, this indeed is the case.

Table 2. Two independent estimates of the uniform learning rate $\bar{\lambda}$

$\bar{\lambda}$ as the average of λ_n from Table 1.	0.5085
$\bar{\lambda}$ derived from equation (4)	0.4948

This close agreement of independent estimates of uniform learning rate $\bar{\lambda}$ strongly indicates that the model of diagnostic learning presented above is correct.

5. Further research plans.

When deriving equation (4) we assumed that the structural changes have negligible influence on how the learning rates λ_n changes with n. In reality averaging the learning rates over the years of emissions n both explicitly or implicitly (as we have done in case of estimation of $\bar{\lambda}$ with use of equation (4)) is susceptible to structural changes. In future we plan to factor structural changes into the methodology presented above.

References

[1] Hamal, K. (2010). Reporting GHG Emissions: Change in Uncertainty and Its Relevance for Detection of Emission Changes. Interim Report IR-10-003, International Institute for Applied Systems Analysis, Laxenburg

[2] Nahorski, Z., Jarnicka, J. Modeling Uncertainty Structure of Greenhouse Gases Inventories, unpublished manuscript.

[3] Marland, G., Hamal, K., Jonas, M., (2009). How Uncertain Are Estimates of CO2 Emissions? Journal of Industrial Ecology, 13(1) pp. 4-7.