2nd International Workshop on Uncertainty in Greenhouse Gas Inventories

PROCEEDINGS

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About the Workshop

The assessment of greenhouse gases (GHGs) emitted to and removed from the atmosphere is high on both political and scientific agendas internationally. Under the United Nations Framework Convention on Climate Change (UNFCCC), parties to the Convention have published national GHG inventories, or national communications to the UNFCCC, since the early 1990s. Methods for the proper accounting of human-induced GHG sources and sinks at national scales have been stipulated by institutions such as the Intergovernmental Panel on Climate Change (IPCC) and many countries have been producing national assessments for well over a decade. As increasing international concern and cooperation aim at policy-oriented solutions to the climate change problem, however, a number of issues have begun to arise regarding verification and compliance under both proposed and legislated schemes meant to reduce the human-induced global climate impact.

The issues of concern at the 1st International Workshop on Uncertainty in Greenhouse Gas Inventories, held September 24-25, 2004, in Warsaw, Poland, rooted in the level of confidence with which national emission assessments can be performed, as well as the management of uncertainty and its role in developing informed policy. The 1st Workshop covered state-of-the-art research and developments in accounting, verifying and trading of GHG emissions and provided a multidisciplinary forum for international experts to address the methodological uncertainties underlying these activities. The topics of interest covered national GHG emission inventories, bottom-up versus top-down emission analyses, signal processing and detection, verification and compliance, and emission trading schemes.

In the meantime, researchers grow increasingly suspicious about these and other uncertainty issues. In a follow-up workshop, jointly organized by the Austrian-based International Institute for Applied Systems Analysis and the Systems Research Institute of the Polish Academy of Sciences, international experts are invited to address uncertainty issues concerning:

- Achieving reliable GHG emission inventories at national and other scales (facility/entity level, project level, etc.)
- Reporting reliable uncertainties at these scales/levels
- Accounting GHG emissions across spatial scales (regional/continental, national, facility/entity, project, etc.)
- Bottom-up versus top-down emission analyses
- Detecting and analyzing emission changes vis-a-vis their underlying uncertainties
- Reconciling short-term emission commitments and long-term concentration targets
- Verification and compliance
- Trading emissions
- Communicating, negotiating and effectively using uncertainty.

The 2nd International Workshop on Uncertainty in Greenhouse Gas Inventories will take place at the International Institute for Applied Systems Analysis (IIASA) in Laxenburg, Austria.

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Minimizing the Cost of Abatement under Imperfectly Observed Emissions

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Abstract

Marginal abatement curves are the starting point for determining the demand and supply for emission permits. We simulate the market for emissions permits by considering uncertainty in emission inventory reports. The approach taken in this analysis is to enhance the emissions reported in each region by a certain part of their uncertainty when compliance with the Kyoto targets is being proved. While this formulation is not new in the literature, we calculate additional costs that the uncertainty bears apart from costs resulting from shifting the Kyoto targets.

This paper differs from the previous research in data sets and methodology. More scenarios are taken into account. We distinguished five regions and attempted to calculate how much each region will reduce emissions or buy permits and how high are benefits from trading. We also calculate the total benefits, ie. How much the total reduction cost can be decreased by emission trading.

1. Introduction

Implementation of tradable emission permit system can be an efficient strategy for pollution reduction. It introduces a new type of property right, which lets a specified amount of pollutant to be emitted. Thus, the total number of permits held by all sources puts a limit on the total quantity of emissions. Permits can be sold to anyone participating in the permit market. The system is initialized by thecentral decision maker who decide on the number of permits to be put into circulation. As the total number of permits is usually lower than current total emissions, some emitters will receive fewer permits than their current emissions would normally allow.

In general, the literature provides strong support for the use of that kind of markets in environmental policy (Ellerman and Decaux 1998, Fields 2002, Godal 2000, Holtsmark 2002, Tietenberg 1988, McKibbina and Wilcoxen, 2004). Market based instruments have also become increasingly popular among environmental policy makers during the last decade.

To ratify the protocol, the countries listed in Annex B of Kyoto Protocol have agreed to decrease their emissions for about 5 % of the 1990 emission level in the period 2008-2012 (Holtsmark and Maestad 2002). We follow definition of Annex B countries as in the EPPA model, see Ellerman and Decaux 1998, UN Kyoto Protocol. The problem with the Kyoto Protocol is in neglectingin it the uncertainty. For example, we have no evidence that the targets set by the protocol are the optimal levels of greenhouse gas emissions, either for an individual country or for the world as a whole (UN Kyoto Protocol).

We applied data described by Godal (2003) and calculated the total cost of abatement together with final emissions from each country, and the number of emission permits traded by each region or country from Annex B. Emissions of greenhouse gases cannot be observed perfectly, therefore regions can underreport emissions because of underlyinguncertainty. If we consider uncertainty in the data, the reported emissions plus the possible unreported emission must be below the Kyoto target for the region. Therefore, the emission reduction should overshoot the level of uncertainty or at least its fraction, if we agree to bear some risk. Conversely to previous work (Bartoszczuk, , we consider more scenarios: when the risk parameter $\alpha = 0$, 0.1, 0.33 and 0.5.

2. Marginal Abatement Curve

Below we present the economic bases of the emission trading mechanism between two countries. Regional purchase or sale of permits until their marginal costs are equalized: $MAC_1 = MAC_2 = p_2$

This way the aggregate emission reduction is reached at the least cost for the whole market. The difference between the market price and the marginal cost in the absence of trade creates a potential gain that is shared between the two trading regions. This is illustrated in *Figure 1*.

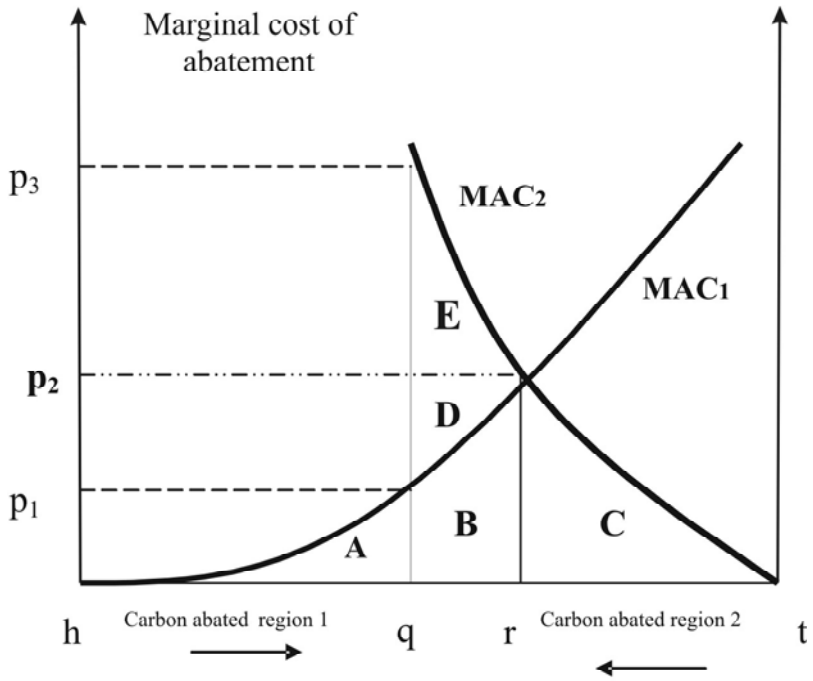

Figure 1. Marginal abatements cost curves for two regions: MAC1 and MAC2

The origin of the marginal cost of control for the first source (MAC1) is the left-hand axis and the origin of the marginal cost of control for the second source (MAC2) is the right-hand axis. The diagram represents all possible allocations of the reduction between the two sources. The left-hand axis represents an allocation of the entire control responsibility to the second region, while the right-hand axis represents a situation, in which the first source bears responsibility (Tietenberg, 1985). Let us assume that initially region "1" must reduce h-q amount of pollution, while region "2" t-q units of pollution (looking from the right side of the axis). Total abatement cost is given by the area below the marginal abatement cost curves MAC1

and MAC2, respectively. Before trading, the total abatement cost for region "1" is the field "A," and for region "2" is the sum of the areas B+C+D+E. Region "2" buys permits to emit more than is allowed (in other word after trades, it reduces only the amount (t-r) instead of the amount (-tq), while region "1" abates more than it is obliged to do (hr), simultaneously selling (qr) permits.

After exchange of permits, costs for both sources is represented by the area (A+B+C). The sum of the area A and B is the cost of control for the first source, while the area C is the cost of control for the second. The area D+E represents the amount saved by emissions trading. The costs of emission reduction is minimized, as the marginal costs are equalized across the emitters. Both regions have incentives to trade, as the marginal cost of control for the second region is higher than that for the first region. The second region will lower its costs as long as it can buy permits from the first region at a price lower than p3. When the price equals p2, neither region would have any further incentive to trade.

Marginal abatement curves are the basis for determining how many permits are needed. In the absence of any trading the region would abate what is consistent with its Kyoto obligation, and the corresponding price would be named "autarkic " marginal abatement costs. If emission trading were a possibility, the region would purchase or sell permits according to the relation of the market price to its autarkic marginal cost.

We distinguish following cases:

- permit price lower than region's autarkic MAC; therefore region wants to buy permits corresponding to quantity difference between the autarkic emission reduction and the domestic abatement it would undertake at the market price,
- permit price is higher than its autarkic marginal cost, it would abate more and sell permits to other region,
- if autarkic MAC is zero, then that region would be only suppliers of permits.

3. Optimization Problem

We consider n regions with emission levels xi (i = 1, 2,...,n). The total costs of holding emissions in region i down to xi is denoted by $C_i(x_i)$ (abatement cost function). We assume that cost functions $C_i(x_i)$ are positive, decreasing, and continuously differentiable for each region. The Kyoto target for each region i is indicated by Ki . The number of emission permits acquired by source is expressed by yi (yi is negative if region i is a net supplier of permits).

The problem is then formulated as follows:

$$\min_{x_i}[\sum_{i=1}^{n} C_i(x_i)] \tag{1}$$

subject to $$x_i + (1-2\alpha)d_i n_i \le K_i + y_i, \quad for \;\; i = 1, 2, ..., n \tag{2}$$

$$\sum_i y_i = 0 \tag{3}$$

The task is to minimize the sum of total emission reduction costs for n regions. There are n+1 side conditions. Equation (2) states that, for each of n regions, reported emissions plus potentially unreported emission, that is, $x_i + (1-2\alpha)d_i n_i$, must be below the Kyoto target K_i modified by the amount of traded permits y_i. The sum of permits bought and sold equals 0, in order to maintain market equilibrium (Equation 3).

To evaluate the comparison we need to consider uncertainty (undershooting)(Horabik and Nahorski 2005). The uncertainty belt is then expressed as $(1-2\alpha)d_i n_i$. The parameter α represents the risk of not satisfying the Kyoto target because of the uncertainty of the inventory report $\alpha \in [0;0.5]$ and it is set so as to be common for all participants. Expression (1-2α) allows the extent to which uncertainty is included in the scheme to be tuned. The relative uncertainty of emission reports is represented by di. As those uncertainties vary for different regions or countries (Winiwarter, 2001) they are also indexed by i. Base-year (1990) emissions at source i are depicted by ni, while xi represents emissions in the commitment year (2010). It should be emphasized that the study takes the year 2010 as representative of the first commitment period, which includes the years 2008 through 2012.

4. Data

In this approach, we present different data set from presented in Bartoszczuk (2005). Regions are aggregated into following five groups: United States (USA); the Organisation of Economic Co-operation and Development (OECD and Europe (OECDE); Japan, Canada-Australia-New Zealand (CANZ); and Eastern Europe (EE) and the former Soviet Union (FSU) (EEFSU). In our approach, to avoid complicated calculations and because of the scarcity of data, we do not consider the stochastic model of uncertainty. We assume arbitrarily that uncertainty coefficient di equals a given percentage of reported emissions in the base year (Godal et al., 2003).

The carbon emission reduction constraints used for this study are based on the commitments made by countries to the Kyoto Protocol. Five of the six EPPA regions belonging to Annex B are obliged to reduce emissions. However, it is predicted that EEFSU emissions will be below the level that this nation committed to under Kyoto. The difference between the EEFSU commitment and expected emissions is often described as “hot air” and it can be sold as a “right to emit.” The carbon emission reduction constraints used for this study are based on the commitments made by countries to the Kyoto Protocol.

The uncertainties vary for different regions or countries. They were presented by Godal (2000).

The curves of marginal abatement costs are of the form: P=aQ, where Q is the amount of abatement in million metric tons of carbon and P is the marginal cost, or shadow price, of carbon in 1985 US dollars. By integration, the total abatement costs C are calculated as c=0.5Q2.

Region	**Base year emissions (MtC/y)**	**Kyoto target %**	**Inventory uncertainty %**	**Marginal costs of abatement ($/tC)**	**Total cost (MUS$)**
USA	1,345	7.0	13	313.7	89,343
OECDE	934	7.9	10	322.7	28,652
JAPAN	274	6.0	15	453.8	21,077
CANZ	217	0.7	20	216.5	10,477
EEFSU	1,337	1.7	30	0	0
SUM	**4107**				**149,549**

Figure 2. Initial emissions, changes in emissions, inventory uncertainty of carbon dioxide in different regions, Kyoto obligation; no risk underreporting included in initial emissions.

	total benefits	billions USD		
Region/alfa	0,50	0,30	0,10	0,00
USA	27	12	4	1
OECDE	9	14	19	23
JAPAN	10	9	9	8
CANZ	1	0	0	1
EEFSU	201	129	72	50
Total	248	164	104	83

	Reduction	MTON		
Region/alfa	0,50	0,30	0,10	0,00
USA	259	427	595	744
OECDE	79	130	181	365
JAPAN	29	48	66	134
CANZ	64	106	148	141
EEFSU	91	150	209	-15
Total	522	861	1200	1368

	Number of permits traded			
Region/alfa	0,50	0,30	0,10	0,00
USA	310	212	114	65
OECDE	99	123	147	158
JAPAN	63	61	58	57
CANZ	33	9	-16	-28
EEFSU	-506	-405	-303	-253
Total				

	Market price of permits		USD/t	
Region/alfa	0,50	0,30	0,10	0,00
USA	142	170	198	212
OECDE	142	170	198	212
JAPAN	142	170	198	212
CANZ	142	170	198	212
EEFSU	142	170	198	212

Figure 3. Results of simulation: benefits from trading (billion USD), reduction (Mtons) and number of permits traded

5. Results of Simulations

Initially, before trade, the highest marginal abatement cost is for Japan, 454 $/ton, and is higher than for OECDE, which is 323 $/ton. For the USA the shadow price equals 313$/ton, as can be calculated from the marginal abatement cost curves. We assume the regions begin to trade and calculate market price of emissions permits. We will present calculations for three scenarios: when parameter α equals 0.5, 0.33, 0.1 and 0.

With uncertainty disregarded ($\alpha = 0.5$), uncertainty involved overshoot fraction ($1\text{-}2\alpha$)= 0 (*Figure 4*). The market shadow price of permits equals $142/ton. Therefore, regions CANZ, OECDE, EET, JPN and USA want to purchase permits equivalent to 506 Mton to avoid an expensive abatement, while EEFSU conduct additional abatement and sell permits (*Figure 3*). In this way, trading brings some gain for regions. The total savings for all regions are $248 billions. EEFSU gain 201 billions and OECD regions 9 billions. Japan imports 63 permits, i.e. 63% of the reduction required by its Kyoto commitment, and spends $10 billions for permits. While Japan benefits $10 billions from emission trading in relation to the no trading case, CANZ gains only $1 billions.

In the second scenario with $\alpha = 0.3$, a risk of 30% that each Party's actual emissions can be above the Kyoto obligation is taken, the results are as follows. The total reported emission reductions (emissions aggregated for all the participants) are 861 MtC/y. However, total cost ($US101 billions) is 2,7 times higher than in first scenario. The market permit price is higher: 170 $/tC. Because of the higher price in our case, permit turnover is higher. One more aspect of emissions trading can be analyzed from the table: the fact that benefits from emissions trading is not evenly distributed among participants. In our analysis, the greatest benefits are obtained by 1) the EEFSU, which provides all the permits on the market with zero costs to itself and 2) OECDE with USA, which imports the most permits and which, without trading, would have to bear high marginal costs (*Figure 3*). For detailed analysis of the distribution of benefits from trade evaluated for another data set, see Bartoszczuk (2005 and 2007).

In the third scenario, coefficient α=0.1. The total cost for all regions is $197 billions, if no trading. In this scenario most countries gain from trading, except CANZ, which gets almost nothing (*Figure 3*). We calculated market price of emissions permits which equals 198$/ton. It is more than in first scenario and in second one. EEFSU exports 303 permits and gains from trading $72 billions. CANZ exports 303 permits and gains from trading almost nothing. Japan reduces only 66 Mtons of carbon, 53% of its commitment, what saves $9 billions. OECDE purchase 147 permits, redeuces 181 tons and gain from trade: $19 billions. Overall, the gain from trading for all countries is $104 billions.

Finally, in the scenario with risk parameter $\alpha = 0$ (ie., when the entire uncertainty belt is taken into account), the total cost of abatement for the analysed countries without trading is $256 billions. In this scenario we add full uncertainty in emission reporting, which are handled as an increased Kyoto reduction target (*Figure 3*). Annex B countries save from trading $83 billions, what is less than in the first scenario (247 billions). The market price of permits is 212 $/ton, which is much more than in the first scenario. The amount of permits traded on the market is lower than in other scenarios by 50%. The countries except EEFSU and CANZ are importers of permits - they purchase permits equivalent to 253 Mtons from EEFSU and CANZ. Regions: OECDE, and JAPAN gain from trading: $22 billions, and $9 billions, respectively. EEFSU gains most, $50 billions (*Figure 3*).

Regarding the sensitivity of the results when we change the degree of included uncertainty, higher abatement is necessary 1368 Mtons versus 522. Quite naturally when we diminish α (i.e., account for more uncertainty, a lower emission level is required by the Kyoto Protocol which, in turn, requires costs to be increased and benefits to be decreased.).

6. Conclusion

The paper shows how important is emission trading in pollution abatement. With emission trading the total abatement cost for all regions is lower. From presented three scenarios it is clear that in first scenario, ie. when the uncertainty is fully omitted (α=0.5), regions derive highest gains from trading system ($248 billions). An increase in necessary emission reduction, due to uncertainty leads to lower supply of permits, and thus higher market shadow prices.

The benefits from emissions trading is not evenly distributed. As it was stated in Ellerman et al. (1998), regions whose autarkic marginal cost is further from the trading equilibrium will benefit more than those regions whose autarkic marginal cost is closer to the equilibrium. The greatest benefit obtains USA that imports more permits than other regions and EEFSU, that exports most of permits.

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Scaling Up from the Stand to Regional Level: An Analysis Based on the Major Forest Species in Ireland

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Abstract

The potential carbon (C) sink capacity of the major Irish forest species, Sitka spruce, was assessed using eddy correlation, detailed inventory measurements and a generalised National C sink model (CARBWARE) to resolve stochastic characteristics at different temporal and spatial scales. Meta-analysis of eddy correlation and stand level inventory estimates of net C stock change showed good agreement between the different stand based estimates over short periods (1-2 years). When data derived from the CARBWARE model were validated against detailed chronosequence data, the largest degree of uncertainty was associated with the estimation of current annual biomass increment (CAI) and soil C pools. Uncertainties in the CAI component of the CARBWARE model were primarily associated with the use of general stand management assumptions due to the lack of information from repeated National forest inventories. The results from this study imply that a large degree of uncertainty is introduced when the spatial representation of C stock change estimates, at the stand level, are scaled up to national or regional level unless inventory data is available to develop generalised forest sink models in an iterative manner.

Key words: *scaling-up, eddy covariance, forest inventory, regional stand-level models*

Introduction

The net exchange of carbon (C) or sequestration by a forest ecosystem over a given period of time is termed net ecosystem productivity (NEP). NEP captures a variety of processes and feedbacks associated with C cycling between the atmosphere, vegetation and soil pools (*Figure 1*).

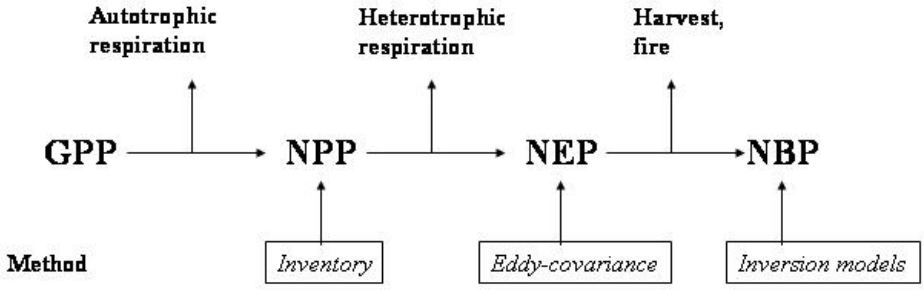

Figure 1: The relationship between different components of ecosystem exchange and associated observation methods (from Ehman et al. 2002). Gross primary productivity (GPP) is the C pool taken up during photosynthesis. Net primary productivity (NPP) is the biomass increment and other lost biomass pools, such as herbivory. Net ecosystem productivity (NEP) represents the net uptake (positive) or loss (negative value) for the entire ecosystem. Net biome productivity (NBP) represents the total uptake or loss of C over for a particular land-use type, including flux changes associated with harvest, thinning or fires.

Eddy covariance is a micro-meteorological technique that directly measures the exchange of CO_2 or net ecosystem productivity (NEP) between the atmosphere and a forest canopy. A major drawback of this technique is an inability to represent large regions with different species cover or age structures. This is primarily due to a lack of replication and poor geographical coverage because of to high capital and operating expenses, unsuitable suitable topography and intensive maintenance requirements. Therefore, National carbon (C) accounting methodologies for reporting to the United Nations Convention on Climate Change and on forest activities relating to the Kyoto Protocol rely on the use of inventory data, biometric and modelling approaches. However, these require independent validation. Theoretically, eddy covariance, inventory-based NEP and generalised stand level model-based measures should provide a similar estimate, but represent independent assessments with unrelated errors. Therefore, such inter-comparisons provide information on the spatial and temporal errors associated in scaling up from the stand to a regional level.
In this paper, we report on a comparison of eddy covariance, stand level inventory and regional stand-level model procedures for assessing NEP of Sitka spruce chronosequence and analyse the sources of uncertainties and errors associated with different approaches.

Methodology

Eddy covariance assessments

Eddy covariance measurements of NEP (-NEE) were made from February 2002 to February 2007 using the EdiSol system described in detail by Moncrieff et al. (1997). Fluxes of sensible heat, water vapour, CO_2 and friction velocity (u-star) were calculated for 30 min periods using the EdiSol software. For detailed information on eddy covariance methodology, gap-filling procedures, footprint and uncertainty analysis refer to Black et al. (2007).

Stand-level inventory approaches

Stand level C stock changes can be accurately assessed using inventory and ecophysiological approaches (NEP_{eco}), based on the estimation of net C balance from heterotrophic and

autotrophic processes (Curtis et al. 2002, Ehman et al. 2002). The NEP_{eco} approach includes an assessment of annual CO_2 losses from the ecosystem, via heterotrophic respiration as well as the net gains from autotrophic processes (Curtis et al. 2002, Ehman et al. 2002):

$$NEP_{eco} = NPP - R_h \quad (1)$$

where NPP is net primary productivity and Rh is heterotrophic respiration due to microbial decomposition of soil organic C, litter, above-ground detritus (AGD) and respiration by consumers:

$$R_h\ (total) = R_{h\ (soil)} + R_{h\ (AGD)} + \mathbf{R}_{h\ (consumers)} \quad (2)$$

Generally, C stored as AGD includes decaying stumps and branches, which may be a particularly significant component in second rotation forests (Kolari et al. 2004) and natural unmanaged stands.

Inventory-based estimates of NPP can be calculated as:

$$NPP = \Delta B + \Delta AGD + D_a + D_b + H + VOC \quad (3)$$

where ΔB is the change in living biomass, ΔAGD is the annual change in dead material, D_a is above-ground litter fall measured as the annual loss of live shoots or branches, D_b is below-ground detritus, defined as fine root turnover, and H is related to herbivore removal of biomass. Losses associated with the emission of volatile organic compounds (VOCs), such as monoterpenes, are not commonly accounted for and assumed to be small.

For the purposed of this study the changes in parameters for NEP_{eco} over a chronosequence of Sitka spruce (yield class 22 $m^3\ ha^{-1}\ yr^{-1}$) growing on wet mineral gley soils was determined using repeat inventory, litter trap and soil respiration measurements. For detailed information on methodologies refer to Black et al. (2007), Saiz et al. (2006, 2007), Tobin et al. (2006), Black and Farrell (2006).

Generalized stand-level models (CARBWARE v. 5.0)

The NEPeco approaches, as discusses above, are often too detailed to parameterise on a regional scale. Therefore, a common approach used to report regional annual C stock changes or interpolate between inventory measurements involves mass-balance (NEP□C) estimates (IPCC, 1996). This is normally based on models/measurements which describe the changes in biomass (□Cb), litter (□C1itter), dead wood (□Cdead wood) and soil (□Csoil) C pools:

$$NEP_{\Delta C} = \Delta C_b + \Delta C_{litter} + \Delta C_{dead\ wood} + \Delta C_{soil} \quad (4)$$

Stand Biomass

The current CARBWARE model describes changes in ΔC_b based on tree-level allometric functions and stand attributes for a Sitka spruce stand according to the British Forestry Commission yield models (Edwards & Christy, 1981; Black & Farrell, 2006). For this exercise, stand attributes, such as age, mean DBH, top height, stocking and timber harvested, for 2m spaced and intermediately thinned Sitka spruce, yield class 22 $m^3\ ha^{-1}\ yr^{-1}$, were used as inputs for the calculation of cumulative stand biomass using species-specific allometric relationships (Black et al., 2004, Black et al., 2007; Tobin et al., 2006; Black & Farrell, 2006).

A modified expo-linear growth function (Monteith, 2000) was used to more accurately simulate growth early years of the rotation and interpolate growth over time.

Stand biomass (*St*) was expressed as:

$$St = Mt\left[\frac{1-e^{-k_s(k_t-t)}}{1-e^{-k_s k_t t}}\right] \quad (5)$$

where

$$Mt = \frac{Cm}{Rm}\ln\left[1+\frac{Co}{Cm}e^{Rmt}\right] \quad (6)$$

Mt is Monteith's function where *Cm* is maximum growth rate, *C*o is initial absolute growth rate and *R*m is the initial relative growth rate and *t* is time (years). Parameters *Cm, Rm, Co,* k_s and k_t were fitted using the least squared optimisation method to estimated stand biomass values.

The current annual increment (ΔC_b) for any given year was then calculated as:

$$\Delta C_b = St_{n+1} - St_n \quad (7)$$

The same approach was used to calculate aboveground and belowground biomass changes (*Figure 2*). On a National basis, the biomass loss due to harvest should be included in the inventory. The CARBWARE model assumes that all C is lost at harvest and does not account for C residence time in harvested wood products (Figure 2). This is in line with the current IPCC good practice guidelines. For the purpose of this exercise, the timber biomass removed at harvest was not accounted for because this represents lateral transfer outside the site footprint (i.e. it represents NBP not NEP). However, biomass losses associated with on site transfer from biomass to litter and dead wood pools were included the model (*Figure 2*).

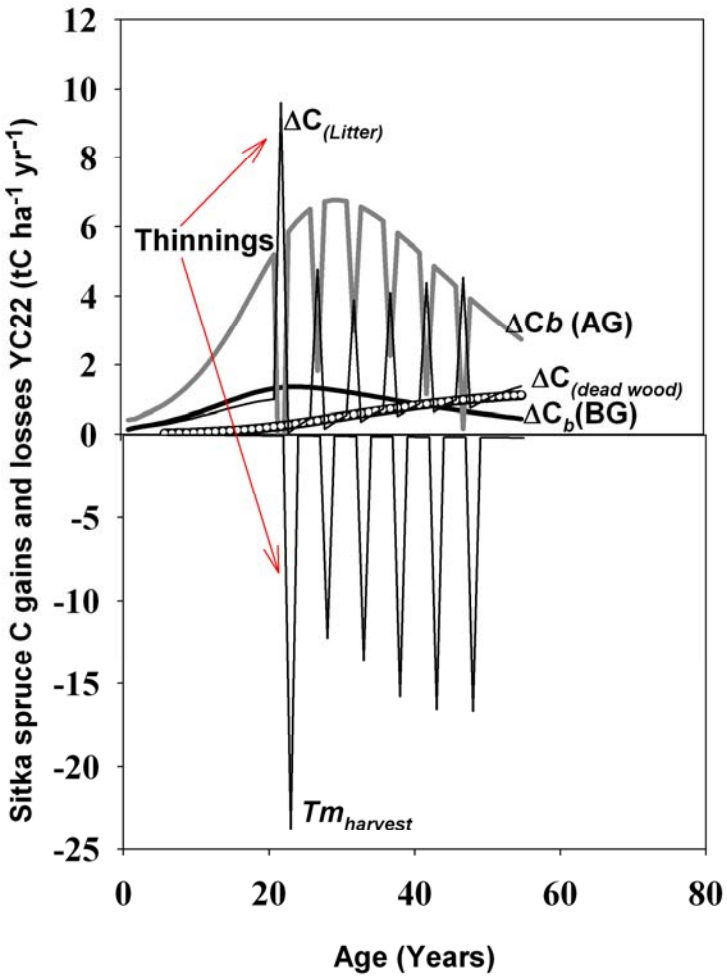

Figure 2: Changes in C gains and losses in the $\Delta C_b + \Delta C_{litter} + \Delta C_{dead\ wood}$ pools over the first rotation of a yield class 22 Sitka spruce stand. The aboveground losses indicated in this graph include timber removal by harvest; however, these were not included for scaling-up comparisons because this loss occurs outside the site footprint.

Other Carbon Pools

Annual litter gains and losses ($\Delta C_{litter} = C_{lgain} - C_{lloss}$) were calculated based on foliar biomass functions, litter fall models (Tobin et al. 2006), estimates of harvest residue and decomposition factors;

$$C_{\lg ain} = (Ft \times Ft) + Br \quad (8)$$

where *FB* is foliage biomass (t C ha-1), *Ft i*s leaf or needle turnover rate (*Ft* = 0.2 (i.e. 5 years) for Sitka spruce, Tobin et al. 2006) and *Br* is brash (harvest residue in the form of branches and needles) added to the litter floor. Brash (*Br* < 7cm diameter) was calculated as:

$$Br = AG_{harvest} - Tm_{harvest} \quad (9)$$

where *AG* (Total biomass – belowground biomass, BG) is aboveground biomass and T*m* is timber cut at harvest (DBH >7cm, t C ha-1).

Emissions from the accumulated litter pool (ΔC_{lloss}) for any given year (*n*) was calculated as a function of litter turn over rates (*Lt*) based on experimental data (*Lt* = 0.14; Saiz et al. 2007);

$$C_{lloss\ (n+n)} = \sum \left[\left(C_{\lg ian\,(n)} \times Lt \right), \left(C_{\lg ain_{(n)}} \times (1 - Lt) \right) + C_{\lg ain_{(n+n)}} \times Lt \right] \quad (10)$$

The dead coarse wood C pool ($C_{dead\ wood}$) includes C gains ($C_{d.gain}$) and decomposition losses ($C_{d.loss}$).

$$C_{d.gain} = st + hr + tr + mort \quad (11)$$

where *mort* is mortality (assumed to occur at a rate of 0.05% from closed canopy (ca. 10 years-old)), *st* and *hr* represent stumps and roots of harvested trees (Total biomass harvest - $AG_{harvest}$) and *tr* is the harvest residue of remaining timber on site after harvest (assumed be 5 % of the biomass from the $Tm_{harvest}$ pool).

Changes in soil C pools over time (ΔC_{soil}) were based on analysis of soil data collected over the chronosequence and 25 other wet mineral gley soil sites afforested with Sitka spruce (Black & Farrell, 2006).

Uncertainty and error estimates of CARBWARE

The uncertainty of estimation for the CARBWARE model only includes model errors (see eq. 1 to 11). There was no information on the model errors in the Edwards and Christy yield tables. The potential error associated with the use of generalised models was expressed as a root mean square error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (obs - pre)^2}{n - p}} \quad (12)$$

where *obs* is the experimental observations and *pre* is the predictions from a model, n = number of observations, p = number of parameters used. In some cases, such as when assumption where made for mortality for example, the uncertainty was assumed to be 10 % the assumed value.

The total standard error of different NEP estimates the following assumption was made (Black et al. 2007);

$$\sigma_x = \sqrt{\sigma^2{}_a + \sigma^2{}_b + \sigma^2{}_c + \sigma^2{}_{n+1}} \quad (13)$$

Results and Discussion

Meta-analysis and inter-comparison of -NEE and NEPeco assessments

A comparison of inventory-based approaches with eddy covariance assessments of NEP, from this and other studies (Black et al 2007, Ehman et al. 2002), shows a good agreement between the two estimates ($p<0.001$, slope = 1.16; *Figure 3*). Small discrepancies between the -NEE and NEP_{eco} based estimates may be related to unaccounted C fluxes associated with VOC,

herbivory and run-off of dissolved organic matter (Goulden et al. 1996; Ehman et al 2002; Ciccoilli et al. 2003).

Generally, the cumulative standard errors were smaller for eddy covariance (6 to 10 %), when compared to NEP_{eco} based estimates (~ 20%, Black et al, 2007; Ehman et al 2002). However, it should be noted that uncertainty estimates are not theoretically additive and a Monte Carlo approach may be warranted here. Also, uncertainty associated with eddy covariance assessments represent measurement and gap filling model errors rather than spatial variations because of the lack if replication of these methodologies (Black et al., 2007). Therefore, means and variances of -NEE and NEP_{eco} estimates may be different because they reflect different spatial and temporal scales and ecosystem components.

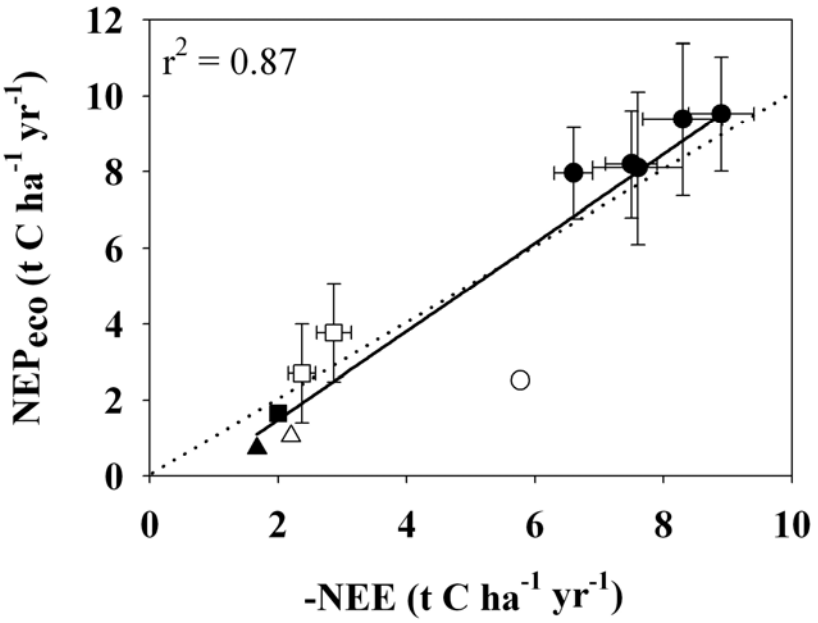

Figure 3: Different inventory-based estimates of NEP compared to eddy covariance (-NEE) measures for various forest sites across Europe and the U.S.A. The solid line represent the linear relationships between NEPeco and –NEE. The dotted line represents the 1:1 slope of the relationship. Different symbols represent data from different sites. The solid circles (●) represents 5 consecutive year measurement of a Sitka spruce site in Ireland. Open squares (□) represents 2 year assessments on a stand at Monroe State Forest, Indiana, USA (Ehman et al. 2002). The other symbols represent deciduous forests in the USA (Curtis et al. 2002); Walker Branch, Tennnesse (○), Harvard Forest, Massachusetts (■), Willow Creek, Wisconsin (▲), and University of Michigan Biological Station, Michigan (△).The error bars represent S.E of –NEE and NEPeco as described by Black et al 2007). In some cases, the S.E. could not be determined because of limited information on uncertainty (Curtis et al. 2002).

Sensitivity analysis

The largest uncertainty associated with the eddy covariance estimates were methodological and model errors. The amount of data missing, due to instrument failure, and discarded, due to unsuitable atmospheric conditions accounted for 16 to 21 % of the annual half hour flux data. The mean error associated with the filling-in of this data with gap-filling models was 7.9 % for the five year period. We suggest that the methodological errors associated with eddy covariance are not well defined. The known errors include lack of good long term energy

closure due to damping, high frequency fluctuations and water storage in the canopy (Black et al. 2007).

The largest source of variance in the NEPeco estimation came from soil processes (i.e. Rh (soil) and Db) and □B. Errors associated with the estimation of soil processes introduced an error of 29 %. We suggest that the introduction of process-based production and transport soil respiration models (Black et al. 2007; Saiz et al. 2007) could reduce the uncertainty of these estimates. The largest uncertainty regarding the estimation of □B included model (RMSE = 8%) and variations in stocking density (S.E = 11.8 %).

Inter-comparison of NEPeco and NEP C assessments

Although there was a good correlation between NEPeco and $NEP_{\Delta C}$ estimates ($p<0.01$, *Figure 4A*), values derived from the CARBWARE model were systematically underestimated in older stands (*Figure 4B*).

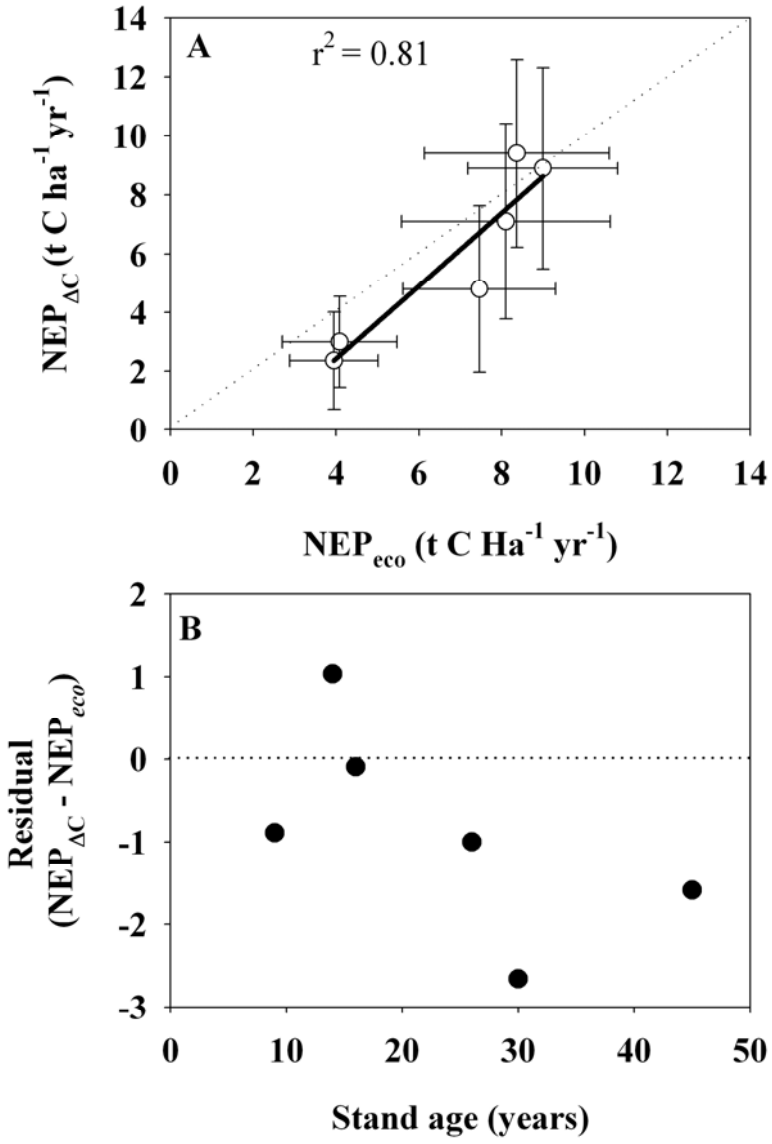

Figure 4: An inter-comparison showing the relationship (A) and differences (B) between inventory-based (NEPeco) and generalised stand models (NEP□C, CARBWARE) estimates across a Sitka spruce chronosequence.

Sources of uncertainty in the current CARBWARE model

Soil (□Csoil, RMSE = 35.4%) and biomass (□Cb, RMSE = 30.1%) stock change estimates represented the largest degree of uncertainty in the CARBWARE model (Figures 5 & 6).

Soils

Estimation of the extent to which forest soils sequester C in the mid to long-term is hindered is by a high degree of spatial heterogeneity and temporal variability. Alternatives to repeated soil assessments over time include the paired-plot (Black et al. 2007; Halliday et al. 2003) and chronosequence-based approaches (Black and Farrell, 2006). Both of these methods are based on the selection of a range of different aged stands and an un-forested site with a representing the same soil type, topography, climatic zone and site productivity and assume that measured changes can be interpolated to represent a soil stock change over time. One of the major criticisms of this approach is that the historical land-use or disturbance events are not considered.

The soil C stocks across 29 afforested sites, ranging from 0 to 49 years old, were extremely variable (*Figure 5*). This may be due to site preparation for afforestation, which disturbs the soil carbon content by exposing lower soil layers to mixing with upper soil layers. Results from this adopted chronosequence approach suggests that the mean soil C sequestration rate is 0.48 t C ha-1 yr-1 over the first 50 years of the rotation, but this was not significant (p = 0.14, *Figure 5*). Despite the large degree of uncertainty in estimating □Csoil, it is unlikely that these small changes resulted in the systematic underestimation of NEP□C using the CARBWARE model (*Figure 4*).

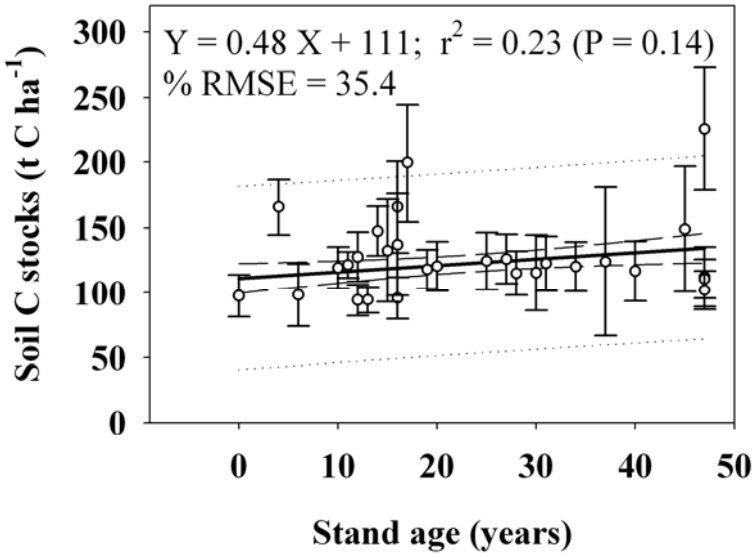

Figure 5: Variation in soil carbon stocks and estimation of ΔC_{soil} using the chronosequence approach (n = 29). The solid line represents the linear change on C stock over time. The dashed and dotted lines represent the 95% confidence and prediction intervals.

Biomass

The current annual biomass increment (CAI) estimates derived from the yield tables and the CARBWARE model (i.e. ΔC_d) was validated against repeat inventory data across the chronosequence (i.e. ΔB, see *Figure 6*). The performance of the expo-linear growth function used in the CARBWARE model was also assessed using the experimental data (ΔB) from the chronosequence (closed symbols, *Figure 6*). It is evident from this analysis that the expo-

linear growth function performed well when compared to observed measures of ΔB (r^2 = 0.91, P < 0.001, RMSE = 5.9 %). However, when the model derived from the experimental data set was validated against the CAI component of the CARBWARE model, the RMSE increased to 30.1%. The large of uncertainty was primarily associated with the underestimation of CAI in older stands, and hence, a systematic underestimation of the total C stock change, using the CARBWARE model (*Figure 4*). It was evident from sensitivity analysis that the failure of the model to capture changes in biomass in old stand is due to differences in stand management activities, particularly thinning intensity. The Christy and Edward yield table assume thinning intensity of 70 % of the yield class on a 5 year cycle, commonly known as the marginal thinning intensity. However, this is not common practice in Irish forests. Stands are generally subjected the first thinning cycle later in the rotation and subsequent thinning is less intensive.

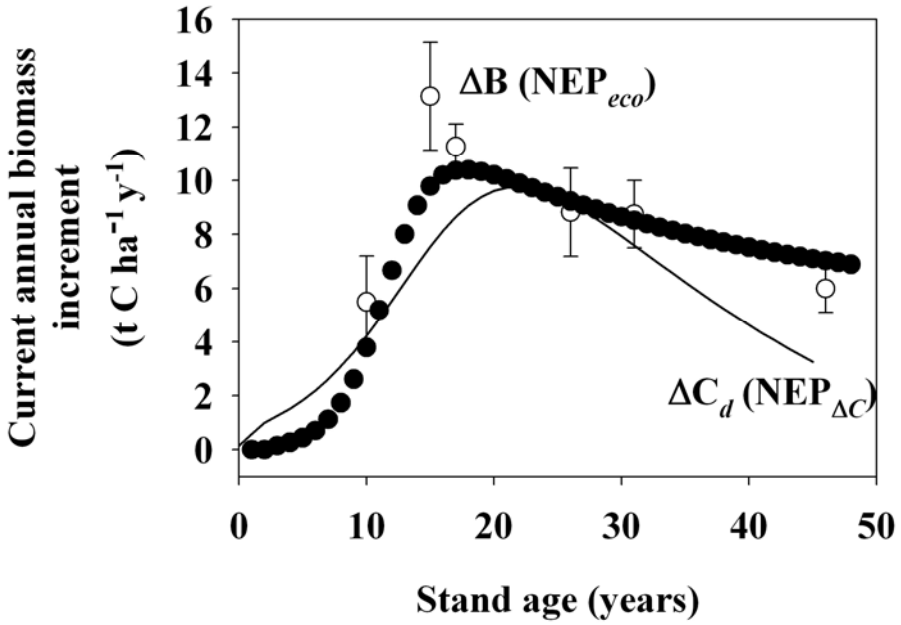

Figure 6: Inter-comparison of current annual biomass increment methods using the NEP_{eco} inventory approach (ΔB,○) and CARBWARE model (ΔC_d, solid line). The solid symbols (●) represents the interpolated ΔB values using the modified expo-linear growth functions (eq. 5, 6 and 7).

Conclusions

The results from this study imply that a large degree of uncertainty is introduced when the spatial representation of C stock change estimates, at the stand level, are scaled up to national or regional level unless inventory data is available to develop generalised forest sink models in an iterative manner. The use of generalised stand-level models introduces a large degree of uncertainty because of limited application across a wide range of silvicultural conditions and management scenarios. Other shortfalls of stand-level models include

- They do not capture inter-annual variation associated biotic and abiotic interactions.
- Stand level models are only applicative to pure species stands. The introduction of mixed species stands in Ireland and Europe may warrant a change to the use of individual tree growth models in the future.

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Verification of Compliance with GHG Emission Targets: Annex I Countries

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Abstract

This study addresses the application of the preparatory detection of uncertain greenhouse gas (GHG) emission changes (also termed emission signals) under the Kyoto Protocol. It is a necessary measure that must be taken prior to/in negotiating the Protocol. Uncertainties are already monitored and are increasingly made available but monitored emissions and uncertainties are still dealt with in isolation. A connection between emission and uncertainty estimates for the purpose of an advanced country evaluation is examined in the present study. The purpose of the study is to advance the monitoring of the GHG emissions reported by the Annex I countries.

Keywords: climate change, GHG inventory, uncertainty, verification, undershooting.

1. Introduction

Industrial development in the last decades resulted in an increase of concentration of greenhouse gases (GHG) in the atmosphere. The Kyoto Protocol to the UN Framework Convention on Climate Change stipulates the reporting of GHG emissions at the scale of countries and keeping them within limits provided by the Protocol.

In order to unify approaches to GHG emissions inventory Intergovernmental Panel on Climate Change developed guidelines for national GHG inventories (IPCC, 1997) and corresponding software (IPCC, 1998). These tools must be used while carrying out national GHG inventory. However these guidelines and software are too general and don't take into account regional properties. Thus the reported emissions are uncertain per se (Bun, 2004). Since it is essential to know how credible these estimates are for a number of important reasons, uncertainties of GHG emission estimates have to be reported as well.

The Kyoto Protocol contemplates emission trading but this requires considering uncertainty of GHG inventories. However, so far GHG emissions and their uncertainties are not interlinked, they are reported independently.

Different concepts exist to assess GHG emission changes in consideration of uncertainty (Jonas et al, 2004; Gillenwater, 2004). In our research we make use of the Undershooting and Verification Time (Und&VT) concept, which has been developed to advance the monitoring of GHG emissions. Under commitment conditions, it requires that a state undershoots its

official Kyoto target by a certain value so that the probability (risk) of not meeting this target is reduced.

We advance the monitoring of GHG emissions and uncertainties that are reported annually by Annex I countries as well as some other countries that have joined the Kyoto Protocol later by evaluating their emission changes and uncertainties jointly. This combined evaluation is useful for policy makers since it supports decision-making with respect to framing GHG emissions policies.

The Und&VT concept is applied with reference a linear path emission targets between the base year and the commitment year. Emissions for the period 2002-2004 are examined in this study. As a first-order approach, it is assumed that countries strive to achieve their Kyoto targets on linear paths, permitting the calculation of annual linear path targets. As a result of applying the U&VT concept, GHG emissions that are required for meeting and undershooting these targets can be derived. Undershooting reduces the risk that the countries' true emissions exceed their linear path targets.

2. Methodology

The idea of the Und&VT concept is to apply undershooting which helps to reduce the probability (called risk) that country's true (but unknown emissions) exceed the committed level. An initial or obligatory undershooting is also introduced, where necessary, so that the countries' emission signals become detectable (i.e., meet the maximal allowable verification time – the reported absolute GHG emissions change exceed the absolute uncertainty of the emissions estimate) before the countries are permitted to make economic use of their excess emission reductions.

Assumptions made in this method are:

- uncertainties at t_1 and t_2 are given in the form of intervals, which take into account that a difference might exist between the true but unknown net emissions and their best estimates;
- the relative uncertainty ρ of a country's net emissions is symmetrical and does not change over time.

Here critical emission reduction/limitation target δ_{crit} is introduced:

$$\delta_{crit} = \begin{cases} \dfrac{\rho}{1+\rho}, & \text{for } x_2 < x_1 \left(\delta_{KP} > 0\right); \\ -\dfrac{\rho}{1-\rho}, & \text{for } x_2 \geq x_1 \left(\delta_{KP} \leq 0\right), \end{cases}$$

where δ_{KP} – emission reduction/limitation target under the Kyoto Protocol (in the case of reduction target, $\delta_{KP} > 0$), x_1, x_2 – emission levels in the beginning and at the end of a period respectively. With the help of δ_{KP} and δ_{crit} four cases are distinguished depending on the sign of δ_{KP} and whether $\delta_{KP} \geq \delta_{crit}$.

In the next step the undershooting (U) and the initial or obligatory undershooting $(\widetilde{U})$, where necessary, is applied. This means that a new (modified) emission limitation/reduction target (δ_{mod}) is calculated:

$$\delta_{mod} = \delta_{KP} + U + \widetilde{U}.$$

This formula is general for all four cases. The difference is in a way of calculating the undershooting. For example in one of the cases ($\delta_{KP} > 0$ and $\delta_{KP} \geq \delta_{crit}$), the modified target is calculated by a formula:

$$\delta_{mod} = \delta_{KP} + U = \delta_{KP} + (1 - \delta_{KP}) \cdot \frac{(1-2\alpha)\rho}{1+(1-2\alpha)\rho},$$

where $\widetilde{U} = 0$; α – risk (probability that true emissions exceed the allowed level). In such a way this risk can be minimized.

In a next step, the required emissions are compared with the countries' actual GHG emissions. This allows drawing conclusions and making projections about the emissions trading situation in the future.

3. National Inventory Results with a Consideration of Uncertainty

The developed methodology was used for analysis of uncertainties of national GHG inventories in the Annex I countries. Calculations were carried out for the period 2002-2004. The input data emissions (excluding LULUCF) and uncertainty estimates were extracted from GHG inventory reports for all the investigated countries (in particular the EU (EEA, 2006), the USA (USEPA, 2006), Russia (Roshydromet, 2006) and Ukraine (Arena-Eco, 2006) and others). However some countries (namely Estonia, Lithuania, Luxembourg, Portugal and Romania) didn't report their uncertainties, therefore total uncertainties of national GHG inventories in these countries were assumed to be 10%.

Figure 1 displays the relative undershooting required for selected and the most illustrative Annex I countries in accordance with the Und&VT concept (risk $\alpha = 10\%$) in 2004 compared to the actual distance to target indicator (DTI), which shows the difference between the reported level of emissions and linear path (base year –commitment year) target. If DTI is positive, GHG emissions in a corresponding state exceed the allowed level, and vice-versa. Thus if country's DTI is less than required undershooting, country's emissions fall below the allowed level and even with the consideration of uncertainty it can be a good emissions seller. Otherwise country must decrease GHG emissions, uncertainty or buy the allowance from another country.

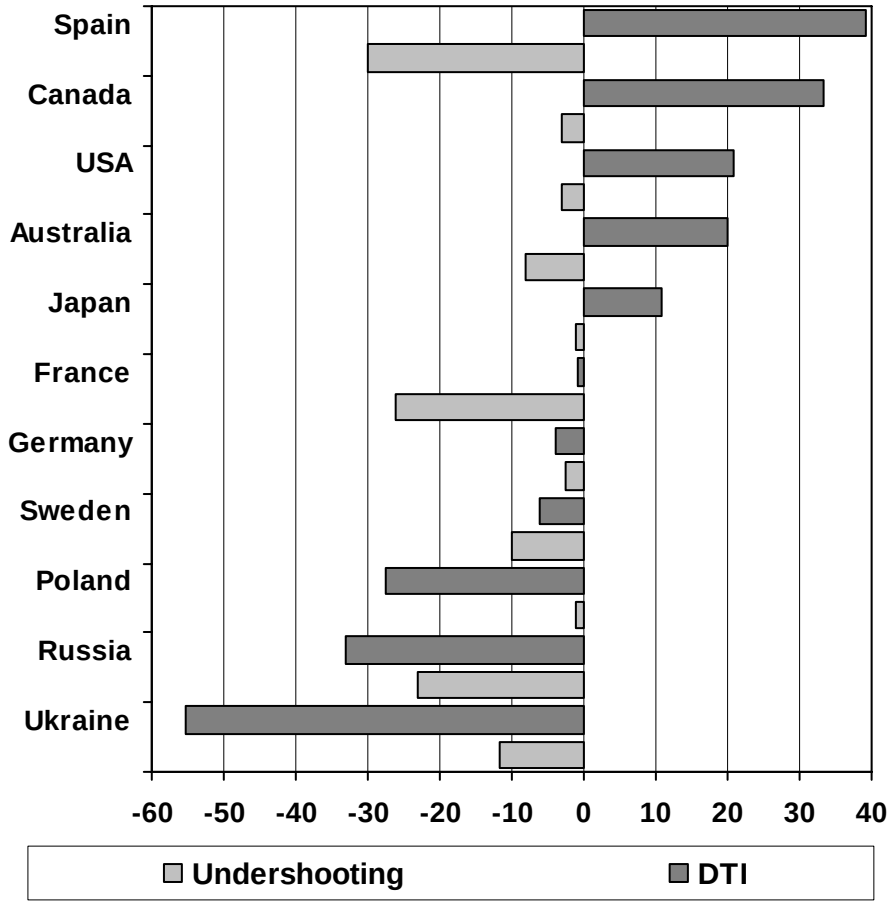

Figure 1. Undershooting required for current levels of uncertainty (for risk $\alpha = 10\%$) in comparison with the actual DTI (in %, relative to the base year emissions)

As it can be seen from the *Figure 1*, some of the presented countries exhibit positive DTI i.e. their emissions exceed the levels allowed by the Protocol. Uncertainty makes the situation in these countries even worse because their DTI with the consideration of uncertainty increases (in some cases significantly, like for Spain, which reported a great uncertainty). Nevertheless for countries with a small uncertainty (e.g. Japan) the required undershooting is little.

Most of the New Independent States, new EU Member States and some other countries exhibit some/considerable undershooting. However, in some cases the realized undershooting is smaller than the uncertainty that underlies the emissions (see *Figure 1*, France and Sweden). Hence, such countries must be rated as less credible emission sellers because of the greater risk of real emissions exceeding allowed (here: linear path) targets; i.e., turning into an emission buyer instead of being an emission seller. The other countries which exhibit negative DTI and appear as potential sellers since, in contrast to the countries like France and Sweden, these countries' emissions are much lower than their targets.\

Figure 2 shows the amounts of GHG emissions which the Annex I countries must buy or can sell, and the amounts the USA must buy and Russia and Ukraine can sell after the Und&VT concept is applied (*Figure 2b*) and without applying it (*Figure 2a*). The corresponding calculations were carried out for the period 2002-2004. It is shown that the USA, Russia and Ukraine are most likely the greatest participants in the GHG emissions market. Russia and

Ukraine can sell more GHG emissions than the rest of Annex I countries together, while the USA must buy more emissions than the rest of Annex I countries.

As shown in the *Figure 2*, overall GHG emissions in the Annex I countries showed a clear tendency to increase. However total GHG emissions in these countries were below the Kyoto target in 2004. Nevertheless taking into account uncertainty of GHG inventories can change the situation to the opposite since the undershooting the Kyoto target is negligible compare to the overall uncertainty. *Figure 2b* shows that the amounts the Annex I parties need to buy is more than twice as much as the amounts they can sell in 2004. At the same time Russia and Ukraine exhibited a significant undershooting so that even after the Und&VT concept is applied they still can sell much of their emission allowances.

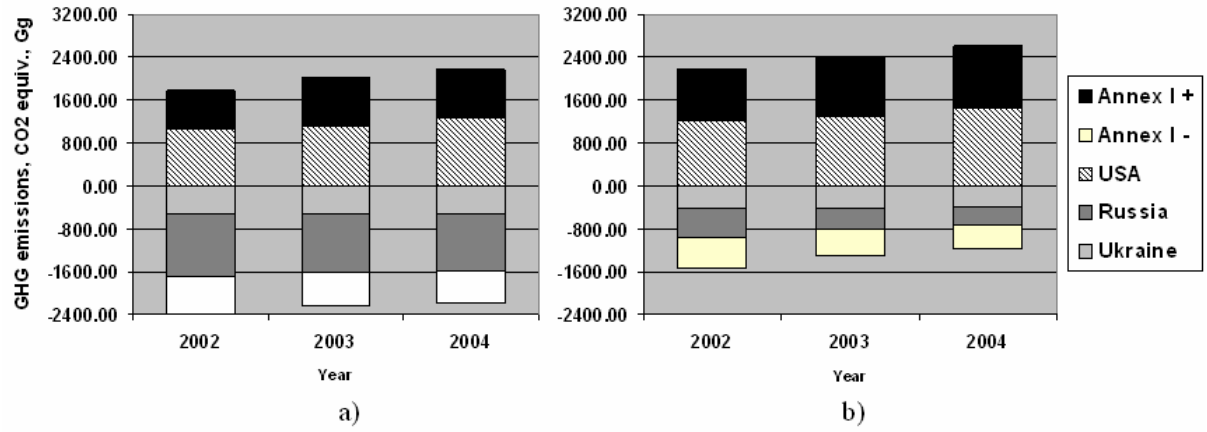

Figure 2. Need for buying and potential in selling GHG emission allowances for Annex I countries, in Gg CO_2 equiv.: a) without uncertainty; b) with uncertainty (for risk $\alpha = 10\%$)

4. Conclusions

The methodology presented in this paper allows analysis of uncertainty of national GHG emissions' inventory. The problem of design of the methodology for dealing with uncertainty of GHG emissions' inventory is urgent, since considering uncertainty is provided by the Kyoto Protocol, but it does not implement approaches for this. Emissions in the Annex I countries are analyzed in this paper with the consideration of uncertainty. This analysis is based on the Undershooting and Verification Time concept. Inventory reports of the Annex I parties were used for this analysis. It is discovered that not all of the countries with the negative DTI can be credible emissions sellers, since the probability that their emissions exceed allowed levels remains. It is shown that some countries (in particular Ukraine and Russia) can sell much of their emissions allowances, since GHG emissions in these countries are much below the Kyoto targets.

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Spatial GHG Inventory on Regional Level: Accounting for Uncertainty

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Abstract

Geoinformation technology for spatial inventory of greenhouse gas on a regional level has been presented. The spatial structure of total emissions in the main sectors, according to economical activity results in some regions of Ukraine has been analyzed, and each administrative unit's contribution to summarized emissions has been estimated. A few scenarios of passing to the alternative types of energy generation are considered and respective structural change in sources of greenhouse gases are analyzed. An influence of these structural changes on the total uncertainty of greenhouse gas inventory results is studied.

Keywords: spatial GHG inventory, energy sector, regional level, uncertainty.

1. Introduction

The problems of greenhouse gases inventory become especially relevant according to formation and analysis of mechanisms of the Kyoto Protocol implementation. Traditional methods of greenhouse gas inventory are mainly directed to estimation of emissions and absorptions on a country scale. Such methods are useful as they enable to trace the countries following international agreements. At the same time the uncertainty of emission sources and absorbers and the uncertainty of basic parameters of these processes reduce the inventory efficiency from the viewpoint of using its results for emission trading purposes.

On the other hand for governmental bodies of every country it is desirable to have a tool, which would enable to analyse the separate constituents of many-sided processes of greenhouse gas emissions and absorptions and thus to find the optimum ways of solving a number of economic or environment protection problems (Bun, 2006). In this work an approach to realisation of a spatial inventory of greenhouse gases (georeferenced cadastres) and uncertainty estimation is developed. The approach is presented using examples of separate regions of Ukraine. Special attention is paid to the spatial inventory in Energy sector, which gives the largest part of total greenhouse gas emissions. An approach to identification of the largest sources of greenhouse gas emissions on the regional level are shown and their contribution to the total uncertainty of inventory results is analyzed.

2. Geo-information Technology of Spatial Inventory

In proposed approach each administrative region is divided into elementary plots (for example, 10 x 10 km), and greenhouse gas inventory is carried out in turn for each plot

following the traditional methodologies (IPCC, 1988). An inventory model in Energy sector is presented in the following form

$$\Delta Y_n = \sum_{m=1}^{M} a_{nm} \Delta x_{nm}, \quad n = 1,...,N, \tag{1}$$

where a_{nm} is the emission factor for the *m*-th activity of the Energy sector in the *n*-th elementary plot, *N* is the total number of elementary plots, Δx_{nm} is the data for the *m*-th human activity in the Energy sector in the *n*-th elementary plot, ΔY_n is the inventory total results for the *n*-th elementary plot. In such a model the input and output data relate to elementary plot and are presented in a form of distributed (geo-referenced) database.

According to traditional methodology (IPCC, 1996) and Ukrainian statistic's specificity the Energy sector (Power, 2002; Fuel, 2005; Industry, 2005; Statistical, 2005) is divided into five categories of greenhouse gas sources (subsectors) ($M = 5$): fuel treatment and electrical energy production (energy industries); residential sector; manufacturing industries and construction; transport; fuel treatment at other sectors.

An important future of such an inventory is that input and output data relate to elementary plots, i.e. they are not lumped. Presented in such a form results accommodate various regional peculiarities and therefore provide the governmental bodies with integrated information on actual territorial distribution of greenhouse gas sources and absorbers (Bun, 2004). Besides, if one sums inventory results for all elementary plots in the boundaries of some region he obtains general inventory results for this region.

The geo-information technology uses the digital maps, geoinformation system MapInfo, and inventory software in Excel. The technology is based on performing the inventory step-by-step for all elementary plots. The digital maps are used for input database forming and for presentation or interpretation of inventory results. Inventory software is used to calculate emissions in each elementary plot.

The developed geoinformation system consists of three main modules. The module *Mod0_MapInfoServer* is used for program MapInfo starting and management. By means of this module the MapInfo window and other windows (legend, information window etc.) are built in the main inventory program, and information interchange between them occur using MapBasic commands. The module *Mod1_Invent* is a programming module with such main functions: input data filling into corresponding cells of Excel-tables (IPCC, 1998); inventory of greenhouse gases, which were emitted in corresponding (selected by user) sector/subsector. Geo-information for each elementary plot using OLE-technology and MapBasic queries is entered in corresponding cells, which are later used by Excel program. The module *Mod2_Maps* has the next functions: queries forming to tables with inventory results, new geo-information layers forming with the elementary plot's inventory results and presenting them on the region digital map, 3-D maps building. The input data for this module are formed by inventory result tables and topographic information from the region's digital map. For each economical activity a separate layer of the digital map is generated.

3. Elementary Plots Forming, and Georeferenced Input Data

Before making the greenhouse gas inventory it is necessary first of all to form the elementary plots. Such an elementary plot is a $l \times l$ km plot, but limited with borders of administrative unit. In borders of each unit a set of elementary plots $l \times l$ km is formed. Besides, it is necessary to form objects, which refer to administrative cities. Total number of elementary plots in region is equal $N = \sum_{r=1}^{R} N_r + N_M$, where N is the total amount of objects; r is the ordinal number of administrative unit, $r = 1,..,R$; R is the amount of units; N_r is the amount of elementary plots in the r-th unit; N_M is the number of objects, which refer to administrative cities. A set of all elementary plots of the region V is a union of sets of elementary plots of regional level and objects V_m for administrative cities

$$V = \left[\bigcup_{r=1}^{R} \{v_{ri}, i = \overline{1, N_r}\} \right] \bigcup \{v_m, m = \overline{1, N_M}\}.$$

For example, the territory of Lviv region of Ukraine is proposed to be "cut" into elementary plots 10×10 km. First of all the map of region was divided into administrative districts and then each district was cut into elementary plots. As a result the elementary plot set was formed on the map of Lviv region. Total amount of objects $N = 420$. It includes objects of $R = 20$ administrative districts and $N_M = 9$ objects for cities.

During spatial modeling and analysis of emissions the input data on each sort of fuel consumption per separate elementary plot is needed. The data on fuel consumption by Energy sector in administrative regions and cities are taken from statistical yearbooks, and are distributed among elementary plots according to certain algorithms. For example, for *residential sector* input data on fuel consumption are distributed among elementary plots proportionally to population in this plot.

4. Spatial Inventory Results

On the basis of formed input data on fuel consumption the geoinformation technology of spatial inventory allows building the geodistributed emission cadastres according to certain methodology on the level of elementary plots. The total emissions of direct acting greenhouse gases (CH_4, N_2O, CO_2) in the Energy sector are calculated using global warming coefficient. As an example, on *Figure 1* the spatial distribution of total emissions in CO2-equivalent for the Lviv region of Ukraine are presented.

Geo-information technology of spatial inventory allows investigation of structure of greenhouse gas emissions by economic activities on the level of elementary plots, administrative units or on the level of region in general. The main carbon dioxide and methane emissions take place in energy industries. That is why it is necessary to make decisions in order to reduce emissions mainly in this sector. The leaders in greenhouse gas emissions are: Lviv agglomeration (31,7 % of all emissions), Kamjanka-Bus'kiy district (16,5 %), and Boryslav-Drogobych agglomeration (12,0 %). Just in the Energy sector of these administrative regions it is necessary to make investments in order to reduce emissions, and to decrease the statistical data uncertainty. Emissions in the rest administrative units don't exceed 500 Gg of CO2-equivalent per year.

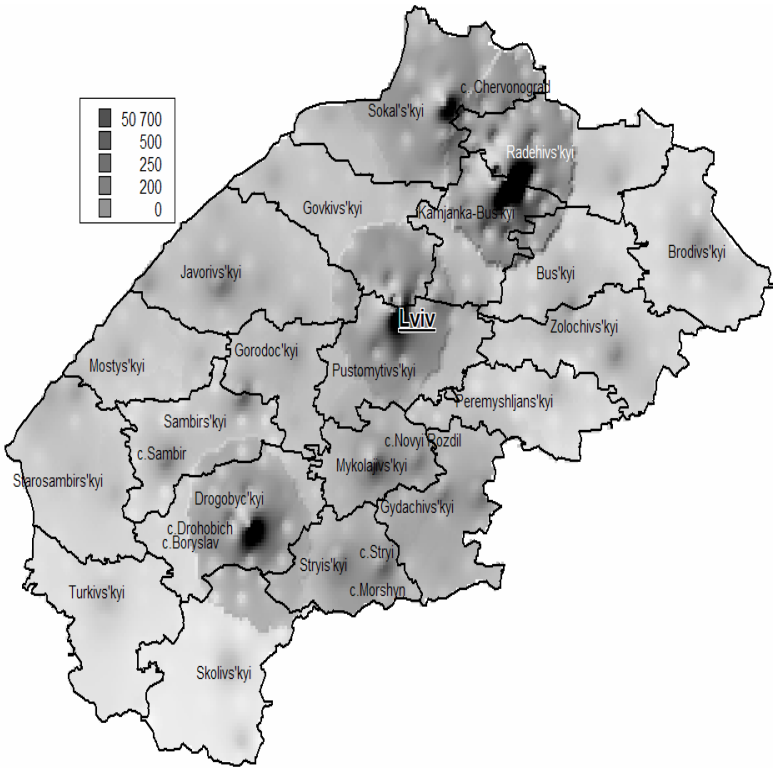

Figure 1.. The map of greenhouse gas emissions in CO_2-equivalent in Energy sector in 2004 (Mg/km^2)

5. The Main Sources Localization and Uncertainty Problem

Geoinformation technology of spatial inventory and analysis of greenhouse gases is very useful for policy makers because it gives additional information about spatial distribution of emission sources. The technology makes possible to identify (to localize) the greatest sources of emissions, and then to investigate their influence on the total regional emissions (for example, as indicated above three leaders for Lviv region).

The greatest sources of emissions are, as a rule, in Energy sector, especially during processes of fuel burning for energy production. Naturally for policy makers is an aspiration for decreasing emissions in this subsector (for example, by transition to alternative energy sources). But inventory results of fuel burning for energy production are characterized by smaller relative uncertainty. Therefore the transition to the other energy sources leads to structural changes in emission sources, and therefore it causes increasing relative uncertainty of total inventory results for the whole administrative region. On the base of presented above results for the Lviv region of Ukraine three largest emission sources of greenhouse gases were identified and then using Monte-Carlo method simulation experiments were carried out to investigate an influence of these leaders on total inventory results.

Figure 2 presents the dependence of relative uncertainty of total inventory results for Lviv region. On abscissa we have the coefficient of transition of three indicated above leaders to alternative energy sources (k=0 – traditional energy generation; k=1 – full transition to alternative sources). For numerical experiments it was assumed that relative uncertainty of greenhouse gas inventory for fuel burning is equal accordingly 7%, 5%, and 3%, but the relative uncertainty of inventory in other subsectors is equal 10%.

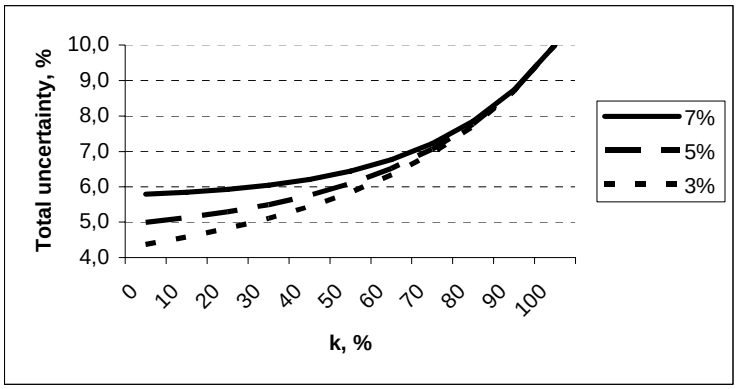

Figure 2. Dependence of total relative uncertainty during transition to alternative energy sources

Here an interesting question appears about combined influence of these two effects: decreasing of emission and increasing of the relative uncertainty. *Figure 3* demonstrates a decreasing of emission caused by transition to alternative energy generation or by other activity (for three indicated leaders), and "corridor" of absolute uncertainty, which has practically the same width (in spite of the fact of increasing of the relative uncertainty).

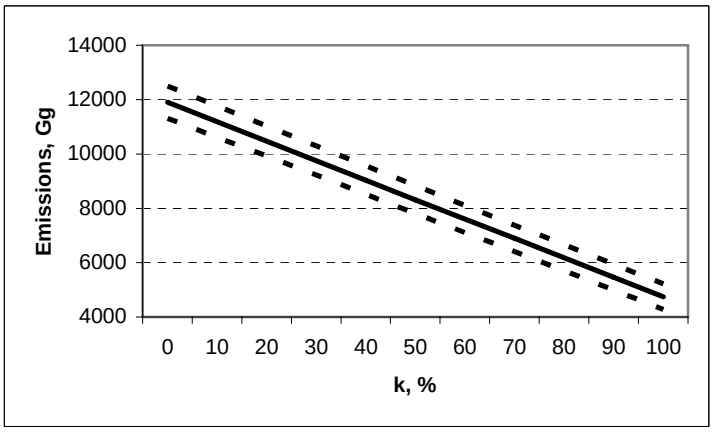

Figure. 3. Decreasing of emission and "corridor" of absolute uncertainty

Decreasing of uncertainty of inventory results for the greatest sources (leaders of emission) also leads to reduction of relative uncertainty of the total inventory results for administrative region. The relative uncertainty of the total inventory as function of relative uncertainty of three leaders for the Lviv region (for three values of the coefficient of transition) is presented on *Figure 4*.

6. Conclusions

Results of greenhouse gas spatial inventory for Energy sector in the Lviv region of Ukraine confirm the assumption about high irregularities of emissions in different administrative units and different subsectors. The results have testified to the importance of spatial inventory for region level. Such an approach to calculation of greenhouse gas emissions better takes into account the differences in economic activity of the separate administrative regions or cities.

The results of spatial inventory gives a possibility to identify the leaders of emissions and to investigate an influence of their uncertainties to the uncertainty of inventory results for the whole region. Therefore policy makers will have an effective tool for supporting decisions on strategic baselines of economic development and environmental policy.

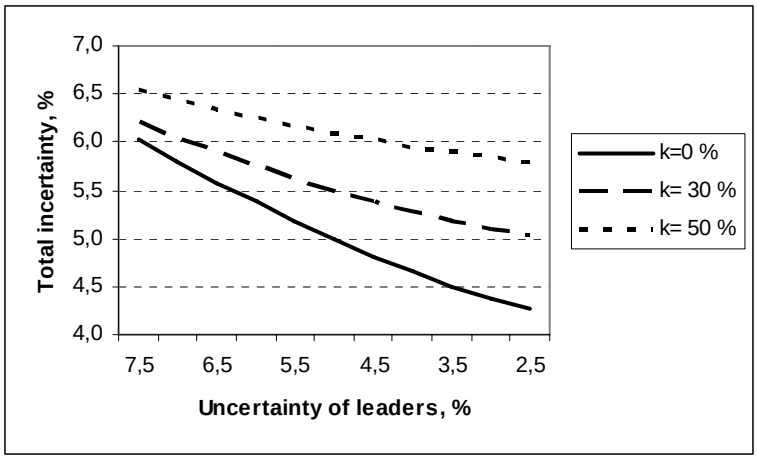

Figure 4. The relative uncertainty of the total inventory results for region as function of the relative uncertainty of leaders

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Component Fluxes of the Carbon Balance of Europe and Their Uncertainty

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Abstract

Quantifying the carbon budget of a continent is a formidable task, which can only be tackled by taking a suite of complementary measurements going from the scale of ecosystems up to the overlying atmosphere, and by using a hierarchy of models to integrate between these scales. An integrated observation strategy is based on a combination of 1) knowledge of ecosystem processes derived from eddy flux towers and ecological studies, 2) spatially extensive and repetitive remote sensing retrievals of biophysical vegetation parameters, 3) ecosystem models driven by variable climate, soil properties, and land cover and 4) atmospheric CO2 and tracers concentration measurements assimilated into transport models.

The CARBOEUROPE and the North American Carbon Plan NACP are maybe the two largest research experiments which have undertaken the deployment of an integrated carbon observation strategy over large land masses with diverse ecosystems, contrasted climate regimes, and nearly ubiquitous fossil fuel emissions. Both experiments rely on dense measurements, and on a combination of top-down and bottom-up measurements, but their sampling strategy is quite different. The atmospheric sampling, especially in the vertical, is much more intensive over North America than over Europe. Yet, the geographic distribution of the C fluxes over the European continent is more complex than over North America, which would deserve a denser atmospheric network. Over Europe, fossil and biospheric fluxes are mixed everywhere, with many small 'hot-spot' areas where high fossil emissions are dispersed over complex terrain, such as for instance the Mediterranean coastal cities, making the detection of atmospheric signals more difficult. Also, the European continent has only one ocean boundary instead of two for North America, which makes the closure of the atmospheric top-down mass balance (REF) more difficult. The density of ecosystem flux towers is on the other hand larger over Europe. Now, the two experiments are running through their mid-term. It is necessary for CARBOEUROPE which involves 400 scientists in very diverse fields, to make a synthesis of the knowledge gained on the European carbon balance. Results from a new assessment of the European carbon balance and component fluxes, and of its driving forces will be presented. It has been initiated as a cooperative work crosscutting among the different tasks and sub-projects of the CARBOEUROPE project.

A quantitative breakdown of the European carbon balance into its component fluxes is provided, including, of course, fossil fuel emissions, but also net primary productivity and decomposition release of CO2, and the other fluxes resulting from harvest, fire disturbances and export to rivers. A detailed regional estimation of these fluxes was not attempted. Also, there are inevitable inconsistencies in the various input dataset and methodologies, which have only be partially harmonized by adjusting the flux estimates to the same domain: the EU area (4.3 106 km2). First, the fossil fuel emissions are discussed, and their regional trends and

errors. Next, we provide ‘best estimates’ of the component carbon fluxes for forests, for croplands and for managed grasslands. We focused on estimating the Net Primary Productivity (NPP) and heterotrophic respiration (HR) component fluxes, and the carbon sequestration efficiency defined as the ratio of NBP to NPP.

Grassland soils were found to be by far the largest C sink per unit area (234 gC m-2 y-1) and show an average uptake rate much larger than the one of forests (50 gC m-2 y-1), despite intensive forest management and C saving sylvicultural practices in western Europe. In contrast, cropland soils are almost C neutral, or a small sink, which implies a downward revision of former estimates of a large source. We also estimated NPP at the continental level using various methods. The most productive ecosystems were found to be the grasslands, followed by croplands and forests. Grasslands also have the largest C sequestration efficiency (= 32%), defined as the ratio of NBP to NPP. This is about twice the value of forests. Overall, we obtain a European NBP of 181 TgC y-1 over the EU area, distributed into 110 TgC y-1 for grasslands, 11 TgC y-1 for croplands and 60 TgC y-1 for forests, three biomes which altogether cover 76% of the total EU area. The total NBP uncertainty, estimated from the range of estimates from different methods, is 129 TgC y-1, decomposed into 77 TgC y-1 for grasslands, 24 TgC y-1 for cropland and 28 TgC y-1 for forests. Other EU vegetated area: shrubland vegetation in Mediterranean areas, wetlands, and urban ecosystems, is not covered by sufficient data for NBP to be safely estimated at the continental level, and deserves further studies.

Uncertainty Ranges and Correlations Assumed in Tier 2 Studies of Several European Countries

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1. Introduction

In response to the IPCC report 'Good Practice Guidance and Uncertainty Management in National Greenhouse Inventories' (IPCC, 2000) various countries carried out comprehensive ("Tier 2") uncertainty analyses. The IPCC report established guidelines describing in detail how uncertainty analysis of National Inventory Reports (NIR) should be conducted. It provides the option to choose between two levels of analysis: Tier 1 is based on the application of simplified error propagation equations, whereas Tier 2 uses comprehensive Monte Carlo techniques at a more detailed level of aggregation. As part of a Dutch Monte Carlo-based uncertainty study (Ramirez *et al.*, 2007) we have compared the uncertainty ranges in activity data and emission factors assumed in several European Tier 2 studies. Such an analysis does not only put the Netherlands assumptions in context (as informal quality control) but also helps to understand differences in uncertainty in total GHG-emissions of different countries. The goal of our research is twofold. Firstly, to compare the differences in uncertainty ranges, probability distribution functions (PDF) and correlations assumed in the input of Tier-2 analyses of six European countries. Secondly, to assess the influence of these differences on the resulting uncertainties of the total greenhouse gas emissions reported by those countries.

2. Methodology

The following countries have been included in our comparison of Tier 2 uncertainty studies: Austria, Flanders (Belgian province), Finland, the Netherlands, Norway and the United Kingdom. The reference year of the Tier 2 studies differ, since most countries do not conduct a Tier 2 uncertainty analysis annually. Furthermore the aggregation level of the analysis differs among the countries, therefore not all values are directly comparable. Since we conducted the comparison in order to put the ranges used in the Dutch TIER analysis in context, the chosen aggregation level for the comparison was the aggregation level of the TIER-1 analysis in the Dutch NIR. The Tier 2 studies included in our comparison are listed in *Table 1*.

3. Uncertainty Comparison of Subsectors

In this section, we focus on Sector 1 (Stationary Combustion) to exemplify the type of results found in our study. The results for all sectors can be found in Ramirez *et al.*, (2007). Sector 1 is responsible for a large share of the greenhouse gas emissions, in the Netherlands it accounts for over 60 % of the reported emissions.

Table 1: Overview of European studies used in this research

Country	Reference year	References	Comments
Austria	1997	Winiwarter et al., 2000 Winiwarter et al., 2001	This study systematically distinguishes between random and systematic uncertainty.
Finland	2003	Monni et al., 2003 Monni et al., 2004 Statistics Finland, 2005	
Flanders (Belgium)	2001	Boogaerts et al., 2004	
Norway	2000	Rypdal et al., 2000	A second Tier 2 study was published later, but since it did not describe detailed methodological aspects (e.g. PDF) we could not used for the purpose of this research
Netherlands	2004	Ramírez et al., 2007	
United Kingdom	2003	Baggott et al., 2005	Aggregation level of uncertainties very different from NL

3.1. Sector 1: Stationary Combustion

Table 2 shows a comparison of the PDFs assumed for the activity data (upper table) and emission factors (lower table). Note that because various countries use different (types of) aggregation levels, not all PDFs are comparable. The level at which one can compare the PDFs is depicted in the table in a graphical way. Hence, a white background colour means that the uncertainty value is well comparable to the Dutch source categories. An orange colour indicates that the PDF is less comparable to the Dutch situation. Although uncertainty data for the Dutch 2004 NIR are available at a more detailed level than the ones shown in *Table 2*, the data has been aggregated to a higher level of aggregation in order facilitate comparison .

Table 2: Uncertainties in activity data, emission factors and PDF in Stationary Combustion

IPCC	Source category	Uncertainty in Activity Data (2 std dev in %) NL	FI	UK	NO	AU-R	AU-S	FL
1A1 l	Energy Industries, liquids	7.6 N	2 N	0.8 .. 24 N	3 N	0.5 N	5U	4.3 N
1A1 s	Energy Industries, solids	1 N	1.5 N	1.2..5.6 N		0.5N	10U	1 N
1A1 g	Energy Industries, gases	1.4 N	1 N	2.4 N	4 N	2 N	5U	2 N
1A1 o	Energy Industries, other fuels	10 N						
1A2 l	Manufacturing Industries and Construction, liquids	1 N	2 N	1.1..25N	3 N	1 N		3.4 N
1A2 s	Manufacturing Industries and Construction, solids	2 N	1.5 N	1.1..5.6N	5 N	1N	8U	1.8 N
1A2 g	Manufacturing Industries and Construction, gases	2 N	1 N	2.4 N	4 N	5 N		2 N
1A4 l	Other Sectors, liquids	20 N	3 N	1.4..24N	3 N			11.6 N
1A4 s	Other Sectors, solids*	50 N	10 N	1.2..5.6 N	20 N			11.7 N
1A4 g	Other Sectors, gases	5 N	5 N	2.4 N				5 N

IPCC	Source category	Uncertainty in Emission factor (2 std dev in %) NL	FI	UK	NO	AU	FL
1A1 l	Energy Industries, liquids	8.4 N	2 N	2..5 N	3 N	0.5 N	2 N
1A1 s	Energy Industries, solids	3.4 N	3 N	3..6 N	7 N	0.5 N	2 N
1A1 g	Energy Industries, gases	1 N	1 N	1 N	7 N	0.5 N	1 N
1A1 o	Energy Industries, other fuels	5 N					
1A2 l	Manufacturing Industries and Construction, liquids	5 N	2 N	2..5 N	3 N	0.5 N	2 N
1A2 s	Manufacturing Industries and Construction, solids	14 N	3 N	3..6 N	7 N	0.5 N	5 N
1A2 g	Manufacturing Industries and Construction, gases	1 N	1 N	1 N	7 N	0.5 N	1 N
1A4 l	Other Sectors, liquids	2 N	2 N	2..3 N	3 N		2 N
1A4 s	Other Sectors, solids*	5 N	5 N	3..6 N	7 N		5 N
1A4 g	Other Sectors, gases	1 N	1 N	1 N			1 N

NL (Netherlands), FI (Finland), UK (United Kingdom), NO (Norway), AU-R (Austria, random), AU-S (Austria, systematic), Fl (Flanders, Belgium)
pdf's N (normal), U (uniform)

From the comparison, we conclude that most of the uncertainties used in the Dutch analysis for the activity data of the sector 1A1 *liquids* are larger than the ones reported for other European countries. This can be understood from the large underlying uncertainties in the activity data of the sub sectors 1A1b *Petroleum Refining* and 1A1c *Manufacture of Solid Fuels* (Olivier et al., 2005). The uncertainty of the sector 1A1 *solids* is comparable to those used in Finland and Flanders. The high (systematic) uncertainties reported by Austria for all sectors are based on a large difference (up to 10%) in the fuel statistics between two major Austrian institutions (Winiwarter et al., 2001). The uncertainty of the Dutch activity data for the sector 1A1 *gases* is higher than that of Finland but lower than for the other European countries.

The uncertainties of carbon dioxide (CO_2) emission factors for stationary combustion are presented in *Table 2*. The uncertainties for the Dutch sector 1A1 *liquids* are significantly higher than in all other European countries. A possible explanation for this is that in the Netherlands 'residual chemical gas' constitutes a large part of this category, especially in the year 2004 (Olivier et al., 2005). The amount of 'residual chemical gas' in this sector is unknown in other countries. For the sector 1A1 *gases*, Norway reports a high uncertainty in the emission factor. At the moment, there is not enough information available to explain this. For the Netherlands, the uncertainties of emission factor in 1A2 for *liquids* and *solids* are slightly higher than those of other countries. This can be explained by a relatively high percentage of residual chemical gas and blast furnace/OF gas.

3.2. Correlations

One of the main differences between a TIER 1 and a Monte Carlo analysis is that correlations can be accounted for. In this study, we have looked at the correlations assumed between PDFs of activity data and emission factors within a given year by country and correlations assumed between different years (i.e. the base year and year of study). Note that not all correlations are applicable in all countries, because of differences in aggregation levels. Main results are:
Most countries, including the Netherlands, fully correlate activity data, when it is used to calculate more than one emission. This is the case for example for number of animals, which are used both for calculating *enteric fermentation* and *manure management*.
Emission factors are correlated if e.g. the same fuel is present in more subcategories.
The activity data is, in most cases, not correlated between base year and end year. Exceptions are histosols in Norway, peat production areas in Finland, solid and other waste and cement production in Austria.
The emission factors between base year and end year are fully correlated in all countries except for some situations in the UK. The exceptions in the UK are related to the level of aggregation and the reference to specific studies for e.g. methane emissions for open cast and coal storage.
Most studies lack a full description of the correlation used and based on the information reported, it seems that correlation are not fully taken into account in most studies.

4. Conclusion

The results of the Monte Carlo analyses reported by the different countries are compared in *Table 3*. We conclude that the uncertainty in the total GHG emissions in the Netherlands are at a similar level as the uncertainties in Flanders, Finland and the random uncertainty reported by Austria. The uncertainties in the total GHG emissions in the United Kingdom, Finland

with LUCF, Norway and Austria (including the systematic uncertainties) are much larger than the values found for the Netherlands.

Table 3: Comparison of uncertainties in Tier 2 analyses

	NL with LUCF 2004			UK with LUCF 2003			Austria with LUCF 1997, incl sys unc*			Flanders with LUCF 2001			Finland with LUCF 1997		
	Tg CO_2 eq	level	uncertainty (2σ) %	Tg CO_2 eq	level	uncertainty (2σ) %	Tg CO_2 eq	level	uncertainty (2σ) %	Tg CO_2 eq	level	uncertainty (95% interval)	Tg CO_2 eq	level	uncertainty (95% interval)
Total	220	100%	4,1	650	100%	14	78	100%	10,5	92	100%	-3,95..+4,97	86	100%	-14..+15
CO_2	182	83%	2,1	556	86%	2,4	60	77%	4,7	76	83%	±2,75	73	86%	±15
CH_4	17	8%	15,1	41	6%	13	8	11%	47,5	7	7%	-14,6..+17,2	5	6%	±20
N_2O	18	8%	42,0	40	6%	226	9	12%	69,4	9	10%	-28,9..+44.6	7	8%	-40..+100
F	2	1%	28,1	13	2%	17,9							1	1%	-10..+20

	NL without LUCF 2004			Austria without LUCF 1997, only random			Norway without LUCF 2010			Finland without LUCF 1997		
	Tg CO_2 eq	level	uncertainty (2σ) %	Tg CO_2 eq	level	uncertainty (2σ) %	Tg CO_2 eq	level	uncertainty (2σ) %	Tg CO_2 eq	level	uncertainty (95% interval)
Total	217	100%	3,9	80	100%	3,8	63	100%	17	63	100%	-4..+8
CO_2	180	83%	1,5	68	85%	1,0	48	76%	4	50	80%	±2
CH_4	17	8%	15,1	10	12%	28,5	6	10%	20	5	8%	±20
N_2O	18	8%	42,0	2	3%	23,9	6	10%	170	7	11%	-40..+100
F	2	1%	28,1				3	5%		1	1%	-10..+20

The large uncertainty in the total GHG emissions in the United Kingdom stems from the very large uncertainty in the total N_2O emissions, which in turn stems from uncertainties in the sub sectors Nitric Acid production (2σ: 230 %), N_2O emissions from agricultural soils (341 %) and N_2O emissions from wastewater handling (215 %). The large uncertainty in Austria stems from the assumed large systematic uncertainties and a larger share of non-CO2 greenhouse gas emissions. In Finland, the sector LUCF explains a large uncertainty in the total CO_2 emissions. The Norwegian uncertainties for all types of gases are larger; also the share of non-CO_2 greenhouse gas emissions is larger.

We conclude that major differences in the uncertainty of the total greenhouse gas emissions of the countries studied stem from the differences in magnitude of the uncertainty in the total N_2O emissions, which vary between around 40 and 230 %. Also the relative share of non-CO_2 gases in the total GHG emission, especially N_2O is key to the explanation.

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Uncertainties in the Estimates of Carbon in Harvested Wood Products for Portugal

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Abstract

This study compares the uncertainty levels in the estimates of carbon accumulation in harvested wood products (HWP) for Portugal using two different methods suggested by the Intergovernmental Panel on Climate Change Good Practice Guidance for Land Use, Land-Use Change and Forestry, namely a simplified method that most countries could use (GPG tier 2 method) and a method requiring country-specific data (GPG tier 3 method). The later method produced more reliable results, leading to a reduction up to 50% in the uncertainty of the estimates of carbon accumulation in HWP when compared to the GPG tier 2 method. This study has also identified the input parameters contributing more to the uncertainty in the estimates of carbon accumulation in HWP.

Keywords: atmospheric-flow approach, carbon, greenhouse gas inventories, harvested wood products, Monte Carlo simulation, Portugal, production approach, stock-change approach, uncertainty

1. Introduction

Harvested wood products (HWP) are globally estimated to accumulate carbon at rates ranging from 26 to 139 Tg year^{-1} (IPCC, 1996; Winjum et al., 1998), depending either on the method or on the inherent assumptions used in the estimations.

The Intergovernmental Panel on Climate Change (IPCC) Good Practice Guidance for Land Use, Land-Use Change and Forestry (GPG LULUCF) (IPCC, 2003) provides a tiered structure of methods for carbon estimation in HWP to be used in national greenhouse gas (GHG) inventories. These methods have varying degrees of complexity and data demand. The tier 1 method is the default method of the IPCC Guidelines (IPCC, 1997), which ignores carbon accumulation in HWP. The tier 2 method (hereafter referred to as GPG tier 2 method) is a simplified method that most countries could use and relies on default input data. Tier 3 methods require country-specific data.

According to the GPG LULUCF, the use of the tier 2 method is unlikely to produce estimates with an uncertainty level less than ±50%. The uncertainty level is expected to be decreased when country-specific data are employed.

The main objective of this study was to compare the uncertainty levels in the estimates of carbon accumulation in HWP for Portugal using two different methods, being one the GPG tier 2 method and the other a method consistent with the GPG LULUCF tier 3 - method B

(hereafter referred to as GPG tier 3 method). Another objective of this study was to identify the input parameters that contribute more to the uncertainty in the estimates.

2. Methodology

Carbon accumulation in HWP was estimated using three alternative approaches that are currently being discussed and evaluated under the United Nations Framework Convention on Climate Change in order to select the approach to be used in future national GHG emission inventories: the stock-change approach (SCA), the production approach (PA) and the atmospheric-flow approach (AFA). These approaches differ on the way the changes in carbon stocks (or emissions) are allocated to countries that consume and produce HWP. The SCA accounts for the net change in carbon stocks of HWP within national boundaries, whereas the PA considers the net change in carbon stocks of HWP produced from domestically-grown wood. With the AFA, the carbon accumulation in HWP is equal to that estimated by the SCA plus the net export of carbon in HWP.

GPG tier 2 and tier 3 methods used in this study are both inflow-outflow methods based on a lifetime analysis, in which the changes in carbon stocks were estimated as the difference between the input of carbon into the pool of HWP and the output of carbon from that pool. The input of carbon into the pool of HWP was estimated on the basis of statistical data on production and trade of HWP and the output of carbon from the pool of HWP was calculated by considering exponential decay rates for the HWP. Carbon accumulation was determined separately for HWP in use and for HWP in solid waste disposal sites (SWDS), which comprise sanitary landfills and open dumps. The change in carbon stocks was calculated for semi-finished products, which consist on sawnwood, wood-based panels, paper and paperboard, and other industrial wood. The later product was not considered by the GPG tier 2 method. *Table 1* summarizes the main differences between the two methods regarding their characteristics and input data. Dias et al. (2007) provide a detailed description of the GPG tier 3 method and of the corresponding input data. The detailed procedure used to calculate carbon in HWP in use and in HWP in landfills with the GPG tier 2 method is described in IPCC (2003) and in Skog et al. (2004), respectively.

Monte Carlo simulation was applied to quantify the uncertainty associated with the estimates of carbon accumulation in HWP. This method selects random values of each input parameter from within their individual probability density functions (PDFs) and the corresponding results are calculated. This procedure is repeated several times. In this study, 5000 iterations were performed. The 2.5^{th} and 97.5^{th} percentiles of the results differed by less than 0.5% after approximately 3500 iterations were carried out. The PDFs of the input parameters were established based on measured data, literature data and expert judgment (*Tables 2 and 3*). Three types of PDFs were adopted in this study, namely uniform, normal and triangular. Uniform distribution was employed when the probability of occurrence was the same for all values of the input parameter falling in a given range. Normal distribution was applied when the uncertainty around the input parameter was expected to be symmetrical, being expressed by the limits of the 95% confidence interval of the PDF. The triangular distribution was used in all other situations. For both triangular and uniform distributions, the uncertainty was defined in relation to the upper and lower limits of the PDF.

Table 1. Main differences between the GPG tier 2 and tier 3 methods

Topic	GPG tier 2 method	GPG tier 3 method
HWP included in the net export term of the AFA	- Sawnwood - Wood-based panels - Paper and paperboard - Roundwood - Chips and particles - Wood residues - Recovered paper - Wood pulp - Recovered fiber pulp	- Sawnwood - Wood-based panels - Paper and paperboard - Roundwood - Chips and particles - Wood residues - Recovered paper - Wood pulp - Recovered fiber pulp - Other industrial wood - Finished solidwood products - Finished paper products
Longevity categories of HWP in use	- Solidwood products - Paper products	- Solidwood products for packaging - Solidwood products for construction - Solidwood products for furniture - Solidwood products for other uses - Printing and writing paper - Other paper and paperboard
Source of the statistical data on production and trade of HWP	Food and Agriculture Organization (FAO)	Data selected from several sources
Growth rate of the input to the pool of HWP in use for the period not covered by statistical data	Default data of the GPG LULUCF	Estimated based on the trend shown by the input to the pool of HWP in use in the period covered by statistical data
Conversion factors for converting to dry weight either the volumes of solidwood and the weights of pulp and paper reported in the statistics	Default data of the GPG LULUCF	Country-specific data
Fraction of bark in roundwood and fraction of roundwood traded with bark	Not considered	Country-specific data
Decay rates of HWP in use and in SWDS	Default data of the GPG LULUCF	Data based on a literature review

The relative contribution of each input parameter to the total uncertainty in the estimates of carbon accumulation in HWP (RC_i, expressed as %) was determined according to Equation 1.

$$RC_i = 100\, CI_i \Big/ \sum CI_i \quad (1)$$

where CI_i is the relative amplitude of the 95% confidence interval obtained for carbon accumulation (difference between the 2.5th and 97.5th percentiles in relation to the result obtained for carbon accumulation) when only the input parameter *i* is affected by uncertainty.

Table 2. Uncertainty associated with the input parameters used in the GPG tier 2 method

Input parameter	PDF type	Uncertainty (%)
Statistical data on production and trade	Normal	±15
Growth rate of the input to the pool of HWP in use	Triangular	-50 to +400
Conversion factor to dry weight of roundwood, solidwood products, chips and particles and wood residues	Triangular	-47 to +98
Conversion factor to dry weight of pulp and paper	Triangular	0 to +6
Fraction of carbon in roundwood, solidwood products, chips and particles and wood residues	Triangular	-20 to +10
Fraction of carbon in pulp and paper	Triangular	-40 to 0
Decay rate of HWP in use	Triangular	-33 to +100
Decay rate of HWP in SWDS	Triangular	-40 to +300
Fraction of solidwood products going to SWDS	Normal	±100
Fraction of paper products going to SWDS, from 1900 to 1969	Normal	±100
Fraction of paper products going to SWDS, from 1970 to 1992	Normal	±50
Fraction of paper products going to SWDS, from 1993 to 2004	Normal	±30
% of anaerobic decay in sanitary landfills	Triangular	-10 to +0
% of anaerobic decay in open dumps	Triangular	-50 to +60
Fraction of carbon in solidwood that effectively decays in anaerobic conditions in SWDS	Triangular	-95 to +40
Fraction of carbon in paper that effectively decays in anaerobic conditions in SWDS	Triangular	-53 to +40

3. Results

The results presented in this study refer to the year 2004. The two methods analyzed provided similar estimates of carbon accumulation in HWP, which varied from 407 to 1295 Gg C year^{-1} for the GPG tier 2 method and from 348 to 1344 Gg C year^{-1} for the GPG tier 3 method (*Figure. 1*). However, the uncertainty levels in the estimates obtained with the GPG tier 3 method were smaller than the uncertainty levels in the estimates obtained with the GPG tier 2 method (*Figure 1*). In fact, the relative amplitude of the 95% confidence interval obtained with the GPG tier 3 method ranged from 26% (uncertainty of -14% and +12%) for the AFA to 72% (uncertainty of -37% and +35%) for the SCA, whilst for the GPG tier 2 method the uncertainty level varied from 52% (uncertainty of -30% and +22%) for the AFA to 89% (uncertainty of -56% and +33%) for the SCA.

Table 3. Uncertainty associated with the input parameters used in the GPG tier 3 method

Input parameter	PDF type	Uncertainty (%)
Statistical data on production and trade	Normal	±15
Growth rate of the input to the pool of sawnwood in use	Triangular	-98 to +50
Growth rate of the input to the pool of other industrial wood in use	Triangular	-95 to +50
Growth rate of the input to the pool of paper in use	Triangular	-99 to +50
Conversion factor to dry weight		
Coniferous roundwood, sawnwood and other industrial wood - produced in Portugal	Triangular	-16 to +18
Deciduous roundwood, sawnwood and other industrial wood - produced in Portugal	Triangular	-15 to +18
Coniferous roundwood, sawnwood and other industrial wood - imported	Triangular	-22 to +56
Deciduous roundwood, sawnwood and other industrial wood - imported	Triangular	-27 to +45
Chips and particles, wood residues, veneer sheets and plywood	Triangular	-30 to +60
Particle board and fiberboard	Normal	±15
Finished solidwood products - produced in Portugal	Triangular	-24 to +30
Finished solidwood products - imported	Triangular	-30 to +60
Pulp and paper	Normal	±3
Fraction of bark in coniferous roundwood	Normal	±40
Fraction of bark in deciduous roundwood	Normal	±44
Fraction of roundwood traded with bark	Uniform	±100
Fraction of carbon in solidwood	Normal	±10
Fraction of carbon in pulp	Normal	±10
Fraction of carbon in paper	Normal	±12
% of coniferous sawnwood consumed in Portugal for packaging	Triangular	-80 to +100
% of coniferous sawnwood consumed in Portugal for construction	Triangular	-11 to +9
% of coniferous sawnwood consumed in Portugal for furniture	Triangular	-80 to +100
% of deciduous sawnwood consumed in Portugal for packaging	Triangular	-80 to +100
% of deciduous sawnwood consumed in Portugal for construction	Triangular	-14 to +13
% of deciduous sawnwood consumed in Portugal for furniture	Normal	±20
% of coniferous sawnwood produced from domestically-grown wood for packaging	Normal	±22
% of coniferous sawnwood produced from domestically-grown wood for construction	Normal	±14
% of coniferous sawnwood produced from domestically-grown wood for furniture	Normal	±25
% of deciduous sawnwood produced from domestically-grown wood for packaging	Triangular	Maximum = 5
% of deciduous sawnwood produced from domestically-grown wood for construction	Triangular	-10 to +0
% of deciduous sawnwood produced from domestically-grown wood for furniture	Triangular	Maximum = 5
% of veneer sheets and plywood for construction	Normal	±40
% of veneer sheets and plywood for furniture	Normal	±13
% of particle board for construction	Normal	±50
% of particle board for furniture	Normal	±12
% of hardboard for packaging	Triangular	-38 to +25
% of hardboard for construction	Triangular	-23 to +25
% of hardboard for furniture	Normal	±25
% of MDF for construction	Triangular	-80 to +100
% of MDF for furniture	Triangular	-5 to +4
Decay rate of HWP in use	Triangular	-33 to +100
Decay rate of HWP in SWDS	Triangular	-40 to +300
Fraction of solidwood products going to SWDS	Normal	±100
Fraction of paper products going to SWDS, from 1900 to 1969	Normal	±100
Fraction of paper products going to SWDS, from 1970 to 1992	Normal	±50
Fraction of paper products going to SWDS, from 1993 to 2000	Normal	±30
% of anaerobic decay in sanitary landfills	Triangular	-10 to +0
% of anaerobic decay in open dumps	Triangular	-50 to +60
Fraction of carbon in solidwood that effectively decays in anaerobic conditions in SWDS	Triangular	-95 to +40
Fraction of carbon in paper that effectively decays in anaerobic conditions in SWDS	Triangular	-53 to +40

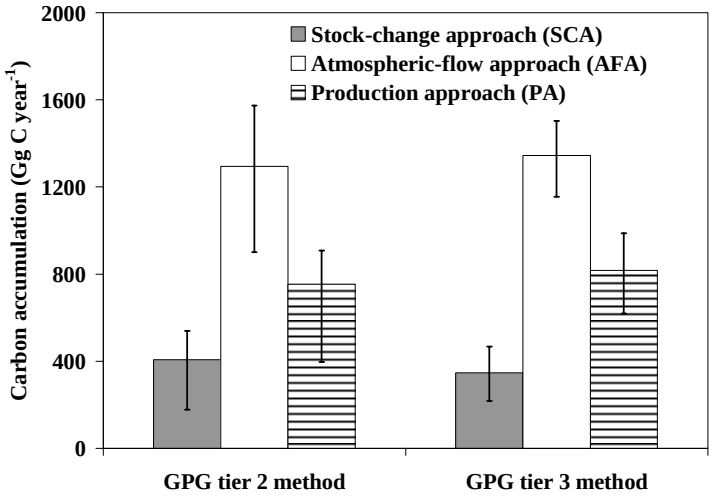

Figure 1. Carbon accumulation in HWP for Portugal in year 2004. The error bars represent the 95% confidence interval of the estimates

Table 4 presents the relative contribution of each input parameter to the uncertainty associated with carbon accumulation in HWP estimated with the two methods, under the three approaches. The largest contributor to the total uncertainty in the estimates obtained with the GPG tier 3 method were the statistical data on production and trade of HWP for the three approaches analyzed. Other important contributions to the uncertainty in these estimates include the decay rate of HWP in use, the fraction of HWP going to SWDS and the conversion factor of solid wood volume to dry weight.

Regarding the GPG tier 2 method, the statistical data on production and trade of HWP were also the major source of uncertainty for the SCA. They were also important for both the PA and the AFA, but for these approaches the more significant contributions to the global uncertainty were respectively the fraction of HWP going to SWDS and the conversion factor of solidwood volume to dry weight. The fraction of carbon in pulp and paper had also an important contribution to the total uncertainty, particularly for the AFA.

4. Conclusions

The GPG tier 3 method originated the more accurate results and, therefore, proved to be the most adequate method for using in national GHG emission inventories. A reduction up to 50% in the uncertainty of the estimates of carbon accumulation in HWP was achieved with the GPG tier 3 method when compared to the GPG tier 2 method.

The parameters that contributed more to the uncertainty in the two methods were the statistical data on production and trade of HWP, the fraction of HWP going to SWDS and the conversion factor of solid wood volume to dry weight. The decay rate of HWP in use and the fraction of carbon in pulp and paper played also an important role respectively in the GPG tier 3 method and the GPG tier 2 method. Efforts should therefore be made to reduce the uncertainty in these input parameters, in order to decrease the uncertainty of the estimates.

Table 4. Relative contribution of the input parameters to the uncertainty associated with the carbon accumulation in HWP estimates

Parameter	Contribution to uncertainty (%)					
	GPG tier 2 method			GPG tier 3 method		
	SCA	PA	AFA	SCA	PA	AFA
Statistical data on production and trade of HWP	30	19	18	31	23	24
Growth rate of the input to the pool of HWP in use	3	2	2	3	2	2
Bark related parameters	-	-	-	-	-	7
Conversion factor to dry weight for solidwood	13	14	31	7	7	16
Conversion factor to dry weight for pulp and paper	1	2	2	2	2	2
Carbon fraction in solidwood	3	3	7	4	5	9
Carbon fraction in pulp and paper	11	13	18	9	10	10
Allocation of solidwood products to final application	-	-	-	1	1	1
Decay rate of HWP in use	11	11	6	18	18	12
Decay rate of HWP in SWDS	5	6	3	4	5	3
Fraction of HWP going to SWDS	16	20	9	15	19	10
% of anaerobic decay in SWDS	4	4	2	3	4	2
Fraction of carbon in HWP decaying under anaerobic conditions in SWDS	3	6	2	3	4	2

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The Difference between Deterministic and Probabilistic Detection of Emission Changes: Toward the Use of the Probabilistic Verification Time Concept

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The assessment of greenhouse gases (GHGs) emitted to and removed from the atmosphere is high on both political and scientific agendas internationally. The Kyoto Protocol to the UN Framework Convention on Climate Change, due in 2008–2012, contains the first legally binding commitments to limit or reduce the emissions of six GHGs or groups of gases (CO_2, CH_4, N_2O, HFCs, PFCs, and SF_6). For Annex I Parties, the targets agreed upon under the Protocol add up to a decrease in GHG emissions of 5.2% below 1990 levels in terms of CO_2 equivalents.

We see two major problems that require a scientific solution before the Kyoto Protocol is extended beyond 2012. Firstly, under the Protocol each government calculates how much CO_2, CH_4, N_2O, etc., its country emits by adding together estimated emissions from individual sources. These so-called "bottom-up" estimates have long been accepted by atmospheric scientists, even though they have never been independently verified. However, in the meantime, scientists have convincing evidence that the emission figures reported by many countries are wrong (House *et al*., 2003; Nilsson *et al.*, 2003; Rödenbeck *et al.*, 2003).

Secondly, a technique that allows detecting highly uncertain emission changes (also called emission signals) that are reported since and with reference to 1990 is not in place. For almost all countries the emission changes agreed upon under the Protocol are smaller than the uncertainty that underlies their combined (CO_2 equivalent) emissions. Clearly, such a technique would be the key to determine the "make or break" of compliance, especially in cases when countries claim the fulfillment of their reduction commitments.

The focus of our study is on the second problem. Jonas *et al.* (2004) distinguish between preparatory signal detection (SD), midway SD, and SD in retrospect, of which the first is most advanced. Preparatory SD allows generating useful information beforehand as to how great uncertainties can be depending on the level of confidence of the emission signal, or the signal one wishes to detect and the risk one is willing to tolerate in not meeting an agreed-upon emission limitation or reduction commitment. We are aware of at least six different preparatory SD techniques, some of which have been presented at the 1st Workshop on Uncertainty on GHG Inventories (Gillenwater *et al.*, 2007; Jonas and Nilsson, 2007; Nahorski *et al.*, 2007). These techniques need to be scrutinized further before a discussion on which of them to select can take place.

The aim of our study is to support a future selection by advancing our insights on the robustness (validity) of these techniques. With the exception of two, these techniques are formulated (in a first step) deterministically. Here, we revisit one of them, the so-called verification time (VT) concept,[1] which has been put on a probabilistic basis by Hudz (2002) to address the detection of net carbon emission changes at the global scale. The VT concept permits assessing emission changes, which are characterized by uncertainty distributions, in terms of their verification times. The VT (more correctly: detection time) is the time until an emission signal outstrips its underlying uncertainty.

To fully explore the pros and cons of this technique, we investigate emission systems under a range of dynamics-versus-uncertainty conditions on a multi-year time scale. For emission systems that exhibit small dynamics and great uncertainties (e.g., comparable to emission signals, as is typical for many 'land use/change and forestry systems'), the probabilistic VT technique should be given preference over the deterministic one as probabilistic and deterministic VTs can differ considerably.

For emission systems that exhibit strong dynamics and small uncertainties (as is typical for many fossil fuel emissions), the difference between the probabilistic and deterministic VTs is small and appears irrelevant in comparison with a base year-to- commitment year/period time span. However, proceeding deterministically and characterizing emission changes by equal-sided (symmetric) uncertainties (as practiced by the IPCC) can leave valuable information unutilized.

For emission systems of any dynamics, if subjected to commitment conditions, the uncertainty becomes paramount if agreed-upon emission limitation or reduction commitments are too small (as is the case under the Protocol). This situation is also typical for many emission reduction projects. Probabilistic and deterministic VTs can differ markedly.

We illustrate the 'economic value' of using the probabilistic VT concept for pricing and trading emission credits. With the help of the sequential bilateral trading scheme proposed by Ermoliev *et al.* (2000) and Godal (2000), we show that in order to achieve detectable emission reductions under commitment conditions, Parties to the Protocol are better off investing in the reduction of uncertainty in addition to striving for an emission target that undershoots the committed target. The application of the probabilistic VT concept can be shown to be cost-effective. In practical situations, the estimation of the probabilistic VT may be complicated by scarce or missing data. To overcome this problem, we discuss methodological challenges related to combining scarce information with expert opinion and simulation models.

1. Introduction

The Kyoto Protocol contains the first legally binding commitments to limit or reduce the emissions of six GHGs or groups of gases (CO_2, CH_4, N_2O, HFCs, PFCs, and SF_6). For Annex I Parties, the targets agreed upon under the Protocol by the first commitment period

[1] The term 'verification time' was first used by Jonas *et al.* (1999) and by other authors since then. Actually, a more correct term is 'detection time'. The detection of emission changes does not imply the verification of emissions. The implicit thinking behind the continued use of 'verification time' is that signal detection should, in the long-term, go hand-in-hand with bottom-up/top-down verification (see Jonas *et al.*, 2004: Section 2.3).

(2008 to 2012) add up to a decrease in GHG emissions of 5.2% below 1990 levels in terms of CO_2 equivalents.[2] Non-Annex I Parties are not required to take on specific commitments for emission reductions.

Among the problems that require a scientific solution is the development of techniques that allow detection and verification of highly uncertain emission changes (also called emission signals). Such a technique would be the key to determine the conditions for extending the Kyoto Protocol beyond 2012. Jonas *et al.* (2004) distinguish between preparatory signal detection (SD), midway SD, and SD in retrospect. We are aware of at least six different preparatory SD techniques (Gillenwater *et al.*, 2007; Jonas and Nilsson, 2007; Nahorski *et al.*, 2007).

The aim of our study is to support a future selection by advancing our insights on the robustness (validity) of these techniques. The robustness is required, in particular, to determine the rules of emission trading schemes endorsed by the Kyoto Protocol (Article 17) as well as joint fulfillment and implementation between Annex I Parties (Articles 4 and 6), and a clean development mechanism (Article 12) that allows Annex I and non-Annex I Parties to act together to reduce emissions (FCCC, 1998; see also WBGU, 1998: Chapter 3; IISD, 2002: 1–3).

With the exception of two, the preparatory SD techniques are formulated (in a first step) deterministically. Here, we revisit one of them, the so-called deterministic verification time (VT) concept. The VT (more correctly: detection time) is the time until an emission signal outstrips its underlying uncertainty. In Hudz (2003), this technique was put on a stochastic basis. The stochastic VT concept permits assessing emission changes, which are characterized by uncertainty distributions, in terms of their verification times.

2. Deterministic VT Concept

The deterministic VT concept was formulated by Jonas *et al.* (1999) (see also Jonas and Nilsson, 2001: Section 3.1.2). Their condition for favorable verification requests that the absolute change in the net emissions of carbon (or any other greenhouse gas) at time t_2, $\left|\Delta F_{net}(t_2)\right|$, with reference to time t_1 ($t_1 < t_2$), is greater than the uncertainty in the reported net carbon emissions at time t_2, $\frac{1}{2}\varepsilon(t_2)$. Mathematically, this condition is expressed as:

$$\left|\Delta F_{net}(t_2)\right| > \frac{\varepsilon(t_2)}{2} \ . \tag{2.1}$$

Under the non-restrictive assumption that first-order (i.e., linear) approximations are applicable, w Jonas, M. and S. Nilsson (2007): e obtain:

$$\left|\frac{dF_{net}}{dt}\right|_{t_1} \Delta t > \frac{1}{2}\left\{\varepsilon(t_1) + \left(\frac{d\varepsilon}{dt}\right)_{t_1} \Delta t\right\}. \tag{2.2}$$

[2] For some Annex I Parties the base year is different from 1990.

This VT concept is visualized in *Figure 1*, where F_{net} describes the net carbon emissions and $\pm\frac{\varepsilon}{2}$ (defined via F^+ and F^-, the upper and lower uncertainty limits of the net carbon emissions) the symmetric uncertainty in F_{net}.

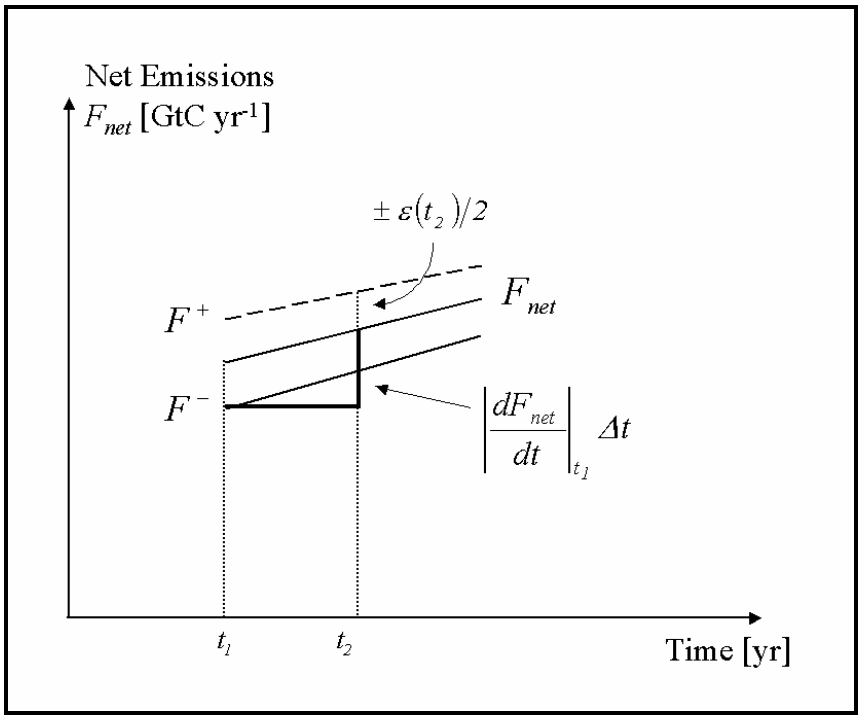

Figure 1. Favorable verification: Simplified linear graphical representation of Equation (2.1) for increasing net carbon emissions (F_{net}) and a decrease in their uncertainty ($\pm\frac{\varepsilon}{2}$). Source: Jonas *et al.* (1999), modified.

We consider Equation (2.2) for the case $\left|\frac{dF_{net}}{dt}\right|_{t_1} > \frac{1}{2}\left(\frac{d\varepsilon}{dt}\right)_{t_1}$. The time Δt is the VT for the dynamical system considered under Equations (2.1) and (2.2). It is the time, which is required for the emission change to outstrip its underlying uncertainty. For the given system, the VT is given by the inequality

$$\Delta t > \frac{\varepsilon(t_1)}{2\left|\frac{dF_{net}}{dt}\right|_{t_1} - \left(\frac{d\varepsilon}{dt}\right)_{t_1}} \quad . \tag{2.3}$$

The important detail that should be borne in mind from the aforementioned is that the deterministic VT concept assumes that uncertainty can be represented by symmetric intervals.

3. Stochastic (Risk-based) VT Concept

Elaboration of a probabilistic (risk-based) VT concept is the subject of Hudz (2002) and Hudz *et al*. (2003). Here, the term *risk* refers to the degree of probability, with which the VT of a GHG emitting or absorbing system can be specified, while its (linear) dynamical behavior is

assumed not to change. As explained in Section 1.1.2, investigations focus on the global scale, where decade-resolved signal changes can be considered to be sufficiently linear. However, temporal verification is not impaired; it is carried out as on sub-global scales.

To facilitate easy understanding and use of the Excel file, we recall the three major steps of Hudz's research:

Step 1 (Data Analysis): Two global net carbon fluxes, the change in atmospheric CO_2 and the CO_2 emissions from fossil fuel burning, cement manufacture and gas flaring, were investigated for different decades. It could be shown that their uncertainties are not normally and symmetrically distributed but take on different shapes.

Step 2 (Methodology): A probabilistic (risk-based) approach is introduced, which considers all probable (linear) signals—as indicated in *Figure 2*—in terms of their VTs and which permits to calculate the minimal time VT^* in compliance with $P(VT^* > VT) = 0.95$.

Step 3 (Applications): The comparison of probabilistically and deterministically determined VTs shows that they can differ (with the probabilistic VT being greater than the deterministic VT) and that the probabilistically determined VT proves more informative (e.g., in regard to the commitment periods underlying the Kyoto Protocol).

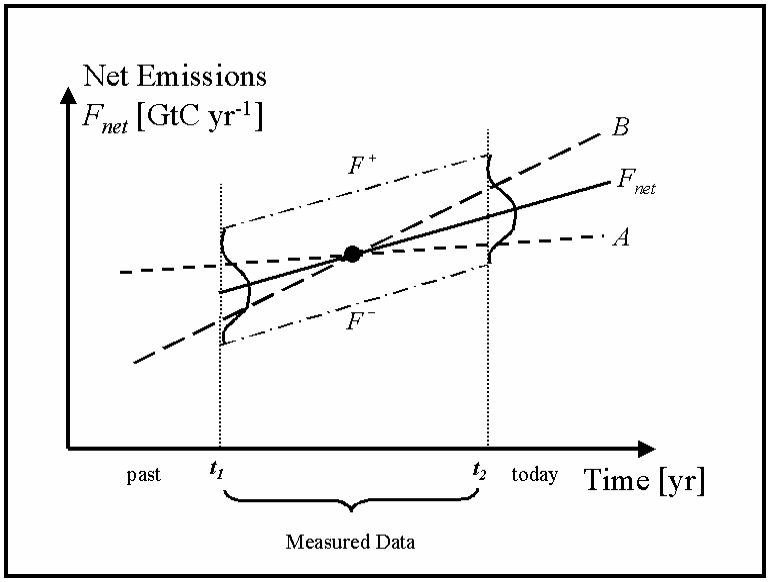

Figure 2. Simplified illustration of the probabilistic (risk-based) approach, for which it is assumed that net carbon emissions (F_{net}) change linearly: A and B are two possible realizations of F_{net} (which is also used here to indicate the mean trend); they are consistent with the probability distributions of F_{net} at t_1 and t_2. However, the VTs for A and B are different: For A it is greater, while for B it is smaller than for F_{net}. F^+ and F^- serve as linear boundary conditions for the uncertainty intervals at t_1 and t_2. Source: Hudz (2002; modified).

4. Simulation of Emissions Trading Markets

Emissions trading is considered as an economic, incentive-based alternative to command-and-control regulations. When applied properly, emissions trading is believed to be an economic incentive that can reduce the aggregate costs of meeting local or regional air quality standards.

It is also believed to provide greater flexibility in meeting both production goals and emission reduction requirements. So far, various emission trading schemes have been designed and implemented by the Parties to the Protocol and on the level of legal entities (e.g., EC, 2003; EEA, 2006; IETA, 2005). Widely discussed in the political arena, they pose scientifically challenging questions: Is the particular program able to ensure the least cost solution for reaching the emission targets? Are the prices of the emission permits fairly and efficiently designed under the implemented schemes? What if the sources underreport emissions, or the emissions are uncertain?

In 1972, Montgomery demonstrated that the least cost solution of reaching the aggregate target of pollution reduction agreements can be realized through trading of emission permits (Montgomery, 1972). The cost-effective solution can be computed and implemented if the abatement cost functions for all countries are known. However, if a permit buyer reveals its abatement cost function, the seller can use this information when bargaining on a permit price such that the buyer is worse off than he/she otherwise would be. Hence, Parties have incentives to keep this information private and the specific costs of emission reductions remain unknown.

Acknowledging this information problem, Ermoliev *et al*. (2000) analyzed a scheme of sequential bilateral trade. The basic feature of this scheme is that two Parties (e.g. picked at random) meet and, if possible, exchange emission permits in a mutually beneficial way. A new pair is picked and the procedure is repeated. Ermoliev *et al.* (2000) proved that this dynamic process will lead the Parties to the least-cost solution when the information of each Party's emission abatement cost function is private. In other words, the feasibility of bilateral trades to deal with incomplete (asymmetric) information was demonstrated.

As emissions of GHGs cannot be observed perfectly, we may assume that Parties can underreport emissions either on purpose or because of uncertainty. The term unreported emissions refers to the fact that activity data are "flexible", in the sense that GHG emitters within each Party can release carbon dioxide that is not included in the emissions reported by the regulatory agency to the Convention Secretariat. Conversion factors can also be manipulated, as many of them do not apply globally. Hence the uncertainty in emission levels can be exploited strategically giving rise to unreported emissions. When there is uncertainty involved in the activity data or conversion factors, the Kyoto Protocol may require that the reported emissions plus the estimated unreported carbon emissions must be below the Kyoto target of that Party. Therefore, in bilateral trades the emission reduction must overshoot the level of uncertainty that provides incentives to reduce uncertainty before trading.

5. Methodology

To go beyond these studies, our primary goal is to combine and integrate the stochastic VT technique with emission trading schemes to study the impact of uncertainty on the performance of emission trading markets. The geographical focus will be (but not necessarily exclusively) on Europe; requirements on emissions data will be satisfied by the GHG database of the UNFCCC (see http://unfccc.int/ghg_emissions_data/items/3800.php); temporal resolution will be annual, otherwise as determined by preparatory SD and our economic modeling.

An effort is currently made by the emissions inventory community to compare existing preparatory SD techniques under standardized conditions and to compile their underlying pros

and cons. This has not yet happened on the economic side. To do this, there are some steps to address the integration of stochastic signal detection and sequential bilateral trade. Building upon the work of Ermoliev *et al.* (1996; 2000), Obersteiner *et al.* (2000), Godal (2000), and Godal *et al*. (2003), we will design a model which will be based upon stochastic optimization allowing for sequential adjustment of emission prices and which shall lead market participants (Parties) to the least cost solution (while considering alternative ways of going about uncertainty under SD). The process will allow permit prices to be adjusted to equilibrium levels. This will ensure that the total costs of emissions control will be minimized. We will define the gap between actual emissions and target emissions as excess emissions. To begin with, a 'monitoring agency' will start with setting emission prices arbitrarily. In our approach, it will follow a two-phase approach: a learning phase and a price implementation phase. After initial prices have been announced, emitters will investigate their own emission levels. Applying a selected SD technique, the agency will be able to state whether actual emissions are in accordance with committed targets. At this point in time, it can be expected that emitters will seek to realize an emissions level that, given the initially announced emission prices, will minimize their total costs (emission reduction plus prices). Based on the emissions reported by the emitters, the agency will derive the total excess emissions. It will then revise old prices and announce new ones that will be used as a basis for the next round of emissions trading.

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Natural versus Anthropogenic Control of Ecosystem Carbon Stocks

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Abstract

Large-scale carbon budgets are dynamic on a wide range of time scales, as a consequence of a diverse set of mechanisms. The mechanisms driving changes in carbon inventories reflect both direct and indirect effects of human actions and ecosystem processes. The tools for quantifying impacts of the direct effects of humans and of some kinds of ecosystem processes are quite mature. But the tools for quantifying and attributing a wide range of indirect responses are still primitive. Progress in attributing and projecting changes in large-scale carbon balance will require fundamental advances in understanding and modeling the interactions between human and ecosystem processes.

Inventory techniques for quantifying ecosystem carbon stocks are improving, developing from a foundation for assessing harvestable forest resources toward a set of general tools for supporting carbon accounting. The challenges, however, in moving from the timber industry to carbon accounting are daunting and far from completely resolved. Required advances include not only quantifying the carbon in soils and non-marketable components of the vegetation but also extending the analysis to ecosystem types not covered in traditional inventories. Assessing leakage and additionality becomes even more challenging when the domain of interest includes multiple types of ecosystems, with different dominant life forms. Remote sensing with LIDAR and RADAR are among the most promising techniques for efficiently extending inventories to poorly characterized ecosystems, including tropical forests, savannas, shrublands, and tundra.

Attributing changes in ecosystem carbon stocks to particular mechanisms is complicated by the diversity of possible mechanisms and by the range of possible interactions among mechanisms. In the past, it was often sufficient to work with three basic groups of mechanisms: (1) direct effects of human actions (e.g. harvesting, planting, or genetic improvement), (2) direct effects of natural processes (e.g. fire, storms, or insect outbreaks), and (3) indirect effects of changes in climate or the composition of the atmosphere (e.g. warming, altered precipitation, or elevated CO2). Increasingly, this list of possible mechanisms must be expanded to include additional indirect of human actions. Some of these are unexpected consequences of climate change (e.g. altered wildfire frequency). Others result from human actions not necessarily related to climate change. Potentially important processes in this category include changes in the deposition of biologically available nitrogen, effects of atmospheric pollutants, and changes in the abundance of invasive species. Finally, we are beginning to see evidence of processes driven through interactions among some of these indirect anthropogenic drivers and ecosystem processes. For example, warming temperatures are, in some locations, altering the life cycle of forest insect pests in a way that is leading to increased forest damage.

In general, neither inventory techniques nor simulation models are well positioned to provide powerful tools for unraveling this multi-process attribution problem. For a few specific mechanisms (e.g. effects of climate change on wildfires), simulation models are increasingly sophisticated and powerful. For most of the mechanisms that involve invasives or other kinds of biotic interactions, specific examples have been analyzed with a largely informal process based on observation and intuition. Progress in the analysis and forecasting of these biotically mediated, indirect effects will require both a new class of observations and a new generation of models.

In the United States, an ambitious new program, the National Ecological Observatory Network NEON), will address many of these needs. NEON will combine long term observations at core sites, studies along gradients, and manipulative experiments to address questions of ecosystem responses to global change, at the continental scale. Although carbon budgets are not the sole focus of NEON, its multi-process approach hold the promise of providing key insights necessary to interpret changes as they occur and to help with the development of models designed to forecast changes before they occur.

Outside the economically developed countries, the challenges of quantifying carbon stocks are severe, and the challenges of attributing changes to particular mechanisms are profound. Recent improvements in techniques for remote sensing of selective logging have the potential to help address one group of important challenges. But, just as increased needs for inventories will likely stimulate increased investments in obtaining them, increased motivation for attributing changes in carbon balance may also stimulate further investments.

The broadening suite of processes and interactions leading to changes in ecosystem carbon stocks creates diverse challenges for carbon accounting. Some of these are biogeochemical, but others are political or ethical. While the carbon accounting community is not in a position to resolve the non-biogeochemical aspects of these questions, the clearest, most comprehensive analyses can make a real contribution to supporting good solutions.

Uncertainty Analysis as Basis for Improving the Quality of Inventory Data in the Land-Use, Land Use Change and Forestry Sector: Case Study of Benin

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Abstract

The uncertainty assessment is increasingly considered as a completeness issue so that an inventory of greenhouse gases (GHG) established or submitted without uncertainty could be treated as incomplete. Even though, the uncertainty information is not intended to dispute the validity of the results, it gives ideas on where and how much effort is needed to improve the inventory in future.

In developing countries where resources and data are limited, estimating the uncertainty associated with GHG inventory becomes a concern and a challenge. This situation is unlikely to change in a near future since currently there is no decision from the Conference of the Parties or the Subsidiaries Bodies of the United Nations Framework Convention on Climate Change (UNFCCC) asking developing countries to report the inventory on a regular basis.
In the case of a study[3] conducted on the Land-Use, Land Use Change and Forestry (LULUCF) sector for Benin, the uncertainties, estimated as 95% confidence interval, based on the Monte Carlo simulation, using @RISK Professional v4.5, are high. This is typical for countries in West Africa where LULUCF, for which the uncertainty in data is high, is a large contributor to the total greenhouse gas inventory.

To estimate the uncertainty in each land use category, the uncertainty in emission factors and activity data has been described, using the probability distribution function (PDF) based on available data and expert judgement.

The sensitivity analysis, as part of the simulation, provided information on the relevant parameters that need to be reviewed to improve the inventory.

1. Introduction

The international community has made a great deal of effort to facilitate and encourage the establishment of high quality inventories i.e. inventories that are transparent, accurate, consistent, complete, and comparable, by providing approved methodological guidance such as those published by the Intergovernmental Panel on Climate Change (IPCC), the UNFCCC and some relevant meetings and conferences.

[3] Guendehou, G.H.S. (2006). *Land-Use Changes and Greenhouse Gas Fluxes: Scientific Understanding and Contribution to Improving Methodologies for Greenhouse Gas Inventory in BENIN.* IGES, Hayama, Japan, 112 pp.

However, the uncertainty sources including, among others, the data acquisition and generation techniques, the data usage, the scientific understanding of emission and removal processes, the functioning of the national system in place and the procedures set up for the elaboration of inventories are not well quantified and affect the quality of the inventory.
The current paper addresses the uncertainty related to data and shows how the uncertainty analysis can be used to identify the parameters that need to be improved.

2. Methodology

The analysis considers, on the one hand forest land, cropland and grassland and on the other hand CO_2 as well as non-CO_2 gases (CH_4, CO, N_2O, and NOx).

To perform the Monte Carlo simulation, the following steps have been applied:

- The spreadsheets model describing the equations, in the IPCC Good Practice Guidance (GPG) for LULUCF, to be used for the calculation of the GHG emission and removal has been developed;
- The probability distribution functions (PDF) have been defined to describe the uncertainty in data (activity data, emission factors) in the spreadsheets. The choice of the distributions has been based on available data and expert judgement: for instance, for the basic wood density which is expected to be a positive value, the use of a distribution that can take negative values will certainly give skewed results, unless the distribution is truncated and supported with robust arguments;
- The defined outputs for the simulation are emissions and removals of GHG;
- The simulation including the sampling and the iteration has been performed;
- The uncertainty in the outputs has been calculated as 95% confidence interval using the distribution describing the outputs;
- A sensitivity analysis: how the input variables affect the output values has been conducted.

3. Results

- An example of spreadsheets model is given in *Table 1* for forest land remaining forest land;
- An example of simulation result is provided in *Figure 1* for CO_2 emissions from forest land remaining forest land;
- *Table 2* gives the uncertainty associated with the estimates for a five year period used for the calculation;
- The results of the sensitivity analysis are presented in *Table 3*.

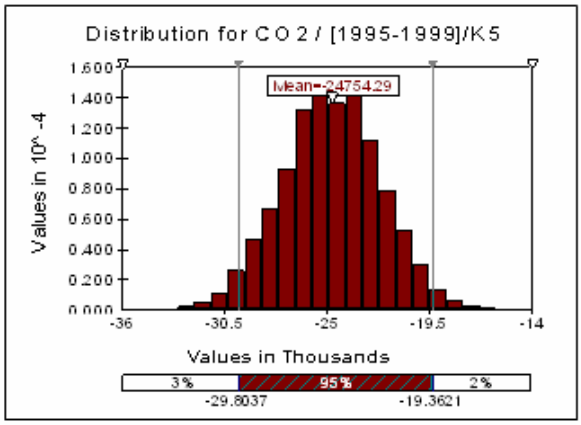
Table 1: Spreadsheets model: example for forest land remaining forest land. Calculation is made for three time periods.

Time period	**[1985-1989]**				**[1990-1994]**			**[1995-1999]**		
Forest land remaining forest land		μ	σ as % of μ		μ	σ as % of μ		μ	σ as % of μ	
Emissions(-)/removals(+) of GHG, (000 t or Gg)	**CO_2**			**-13413.22**			**-19522.74**			**-24761.69**
	CH_4			**-126.10**			**-123.53**			**-122.38**
	CO			**-1103.41**			**-1080.85**			**-1070.83**
	N_2O			**-0.87**			**-0.85**			**-0.84**
	NOx			**-31.53**			**-30.88**			**-30.60**
Land area (ha)		2248314	4%	**2248314**	1968830	4%	**1968830**	1730490	4%	**1730490**
Change in carbon stocks in living biomass, 000 tC				**-14760.34**			**-15338.87**			**-15864.88**
Increase in carbon stocks (biomass increment), 000 tC				1832.38			1604.60			1410.35
Average increment in total biomass (tdm/ha/yr)		1.63	5%	**1.63**	1.63	5%	**1.63**	1.63	5%	**1.63**
Carbon fraction of dry matter (tC/tdm)		0.5	1%	**0.5**	0.5	1%	**0.5**	0.5	1%	**0.5**
Decrease in carbon stocks (biomass loss), 000 tC				-16592.72			-16943.47			-17275.23
Carbon loss due to commercial fellings ($L_{fellings}$), 000 tC				-430.01			-491.05			-539.50
Extracted volume roundwood, 000 m^3		1246.2	3%	**1246.2**	1423.1	3%	**1423.1**	1563.5	3%	**1563.5**
Basic wood density		0.71	2%	**0.71**	0.71	2%	**0.71**	0.71	2%	**0.71**
Biomass expansion factor		1.62	4%	**1.62**	1.62	4%	**1.62**	1.62	4%	**1.62**
Fraction biomass burned offsite from commercial fellings		0.3	5%	**0.3**	0.3	5%	**0.3**	0.3	5%	**0.3**
Fraction biomass left to decay		0.1	5%	**0.1**	0.1	5%	**0.1**	0.1	5%	**0.1**
Carbon loss due to fuelwood gathering ($L_{fuelwood}$), 000 tC				-8281.18			-8732.03			-9086.95
Volume of fuelwood gathering, 000 m^3		14399.55	3%	**14399.55**	15183.5	3%	**15183.5**	15800.65	3%	**15800.65**
Carbon loss due to fire (L_{fire}), 000 t				-7666.52			-7474.85			-7379.02
Areas affected by fire, ha		611511.20	3%	**611511.2**	596223.40	3%	**596223.4**	588579.50	3%	**588579.5**
Average aboveground biomass stocks, tdm/ha		41.79	5%	**41.79**	41.79	5%	**41.79**	41.79	5%	**41.79**
Fraction of biomass transferred to dead organic matter from fires		0.4	5%	**0.4**	0.4	5%	**0.4**	0.4	5%	**0.4**
Carbon loss due to biomass burned offsite				**-215.01**			**-245.53**			**-269.75**
Total carbon loss: fuelwood, burning offsite				**-7881.52**			**-7720.38**			**-7648.77**
Change in carbon stocks in dead organic matter, 000 tC				**10315.28**			**9325.40**			**8506.02**

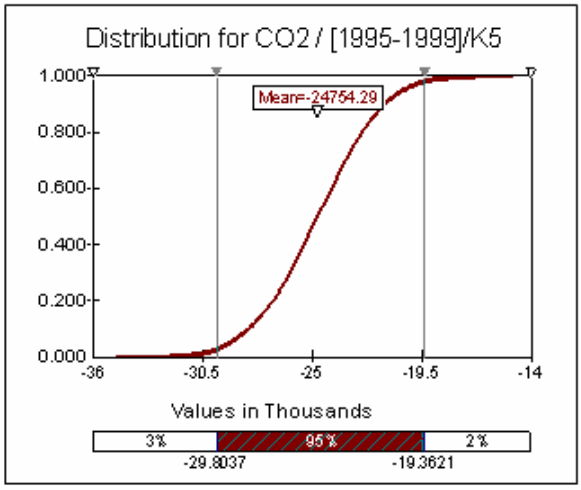
Time period	**[1985-1989]**				**[1990-1994]**			**[1995-1999]**		
Forest land remaining forest land		μ	σ **as % of** μ		μ	σ **as % of** μ		μ	σ **as % of** μ	
Change in carbon stocks in dead wood, 000 tC				5593.78			5190.90			4872.02
Transfer into the dead wood pool (B_{into}), 000 tC				10072.76			9347.28			8773.08
Transfer rate into dead wood, natural mortality tdm/ha/yr		4.35	5%	**4.35**	4.35	5%	**4.35**	4.35	5%	**4.35**
Decay rate constant, $year^{-1}$		0.19	7%	**0.19**	0.19	7%	**0.19**	0.19	7%	**0.19**
1-decay rate constant				0.81			0.81			0.81
Change in carbon stocks in litter, 000 tC		4721.5	10%	**4721.5**	4134.5	10%	**4134.5**	3634	10%	**3634**
Change in carbon stocks in soils, 000 tC				**786.91**			**689.09**			**605.67**
Soil organic carbon accumulation (SOC), tC/ha/yr		0.35	5%	**0.35**	0.35	5%	**0.35**	0.35	5%	**0.35**
Non-CO_2 Greenhouse gas emissions										
N_2O emissions from N fertilization of forest				0			0			0
N_2O emissions from drainage and rewetting of forest				0			0			0
CH_4 emissions from biomass burning, 000 t				**-126.10**			**-123.53**			**-122.38**
Emission factor for CH_4 from biomass burning, t/tC burned		0.016	13%	**0.016**	0.016	13%	**0.016**	0.016	13%	**0.016**
CO emissions from biomass burning, 000 t				**-1103.41**			**-1080.85**			**-1070.83**
Emission factor for CO from biomass burning, t/tC burned		0.14	17%	**0.14**	0.14	17%	**0.14**	0.14	17%	**0.14**
N_2O emissions from biomass burning, 000 t				**-0.87**			**-0.85**			**-0.84**
Emission factor for N_2O from biomass burning, t/tC burned		0.00011	14%	**0.00011**	0.00011	14%	**0.00011**	0.00011	14%	**0.00011**
NOx emissions from biomass burning, 000 t				**-31.53**			**-30.88**			**-30.60**
Emission factor for NOx from biomass burning, t/tC burned		0.004	11%	**0.004**	0.004	11%	**0.004**	0.004	11%	**0.004**

σ is the standard deviation and μ the mean

Figure 1: Simulation result: e.g. for CO_2 emissions from forest land remaining forest land.



Summary Information	
Workbook Name	Spreadsheets_for_@Risk_Sabin_exos_uncert.xls
Number of Simulations	1
Number of Iterations	10000
Number of Inputs	126
Number of Outputs	79
Sampling Type	Monte Carlo
Simulation Start Time	11/30/2005 10:08
Simulation Stop Time	11/30/2005 10:09
Simulation Duration	00:00:57
Random Seed	28879631



Summary Statistics			
Statistic	**Value**	**%tile**	**Value**
Minimum	-34848.91	5%	-29186.41
Maximum	-14949.48	10%	-28230.43
Mean	-24754.29	15%	-27548.86
Std Dev	2666.29	20%	-26976.27
Variance	7109091.233	25%	-26547.53
Skewness	-0.026771877	30%	-26141.09
Kurtosis	2.938471936	35%	-25784.19
Median	-24750.73	40%	-25439.45
Mode	-27871.02	45%	-25110.53
Left X	-29803.69	50%	-24750.73
Left P	3%	55%	-24371.21
Right X	-19362.13	60%	-24023.14
Right P	98%	65%	-23690.45
Diff X	10441.56	70%	-23333.53
Diff P	95%	75%	-22925.90
#Errors	0	80%	-22518.08
Filter Min		85%	-21996.89
Filter Max		90%	-21355.46
#Filtered	0	95%	-20430.13

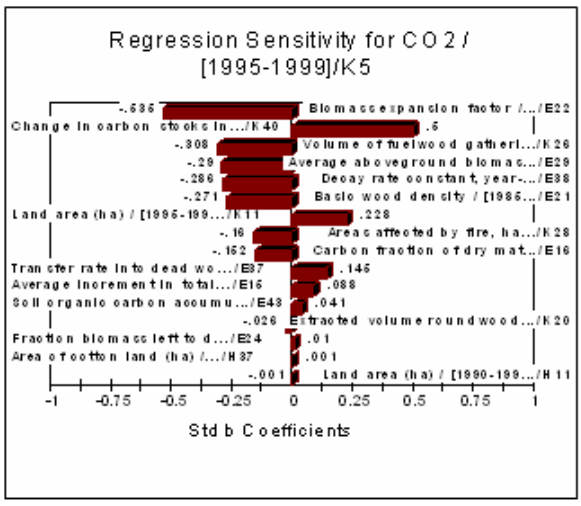


Table 2: Uncertainty associated with the estimates in [1995-1999]. Five years period is used for the calculation of emissions and removals.

Land-use category	Gas	Emission(-)/removals(+) Gg	Uncertainty as 95% confidence interval
Forest land remaining forest land	CO_2	-24761.4	21%
	CH_4	-122.38	27%
	N_2O	-0.84	29%
	CO	-1070.83	34%
	NOx	-30.60	24%
Land converted to forest land	CO_2	-9037.56	14%
	CH_4	-35.27	25%
	N_2O	-0.24	27%
	CO	-308.58	33%
	NOx	-8.82	21%
Cropland remaining cropland	CO_2	-1850.31	40%
Land converted to cropland	CO_2	-64408.6	13%
	CH_4	-198.69	31%
	N_2O	-4.3	36%
	CO	-1738.52	37%
	NOx	-49.67	28%
Grassland remaining grassland	CO_2	-2627.17	81%
	CH_4	-2.87	28%
	N_2O	-0.02	28%
	CO	-25.14	35%
	NOx	-0.72	24%
Land converted to grassland	CO_2	+5540.88	64%
	CH_4	-57.72	30%
	N_2O	-0.40	32%
	CO	-505.09	37%
	NOx	-14.43	27%

The uncertainty has been calculated using the following equation:

$$\%Uncertainty = \frac{1/2\,(95\%\,confidence\ interval\ width)}{\mu} \times 100$$

Table 3: Results of the sensitivity analysis

Key category	**Significant subcategories** (accounting for 25-30% of emissions or removals for the overall category)	**Information from the sensitivity analysis: main input variables that cause large changes in the model outputs**
Forest land remaining forest land – CO_2	- Changes in C stocks in living biomass - Changes in C stocks in dead organic matter	Biomass expansion factor, volume of fuelwood gathering, aboveground biomass stocks, decay rate constant, basic wood density, land area.
Land converted to forest land – CO_2	- Changes in C stocks in living biomass	Land area, increment in living biomass in natural regeneration, transfer rate into dead wood pool due natural mortality in forest regeneration, increment in living biomass in plantation, soil organic carbon accumulation.
Cropland remaining cropland – CO_2	- Changes in C stocks in living biomass - Changes in C stocks in dead organic matter - Changes in C stocks in soils	Increment in total biomass in perennial crops, area of perennial and annual cropland, transfer rate into dead wood due to natural mortality, decay rate constant, annual per ha change in soil organic carbon ($SOCR_{REF}$, stock change factors).
Land converted to cropland – CO_2	- Changes in C stocks in living biomass: forest conversion contributes 81%, grassland conversion contributes 19%.	Carbon before and after conversion during conversion of forest, area of forest converted, carbon before conversion during conversion of grassland, area of grassland converted, annual per ha change in carbon stocks in soil during conversion of forest and grassland.
Land converted to cropland – CH_4	- Biomass burning: forest conversion is more important.	CH_4 emission factor for biomass burning, carbon before and after conversion during conversion of forest, area of forest land converted, fraction of biomass that oxidizes when burned, carbon before conversion during conversion of grassland, fraction of biomass burned onsite and offsite.
Grassland remaining grassland – CO_2	- Changes in C stocks in living biomass - Changes in C stocks in dead organic matter	Carbon loss due to fuelwood gathering, land area, transfer rate into dead wood due to natural mortality, decay rate constant, average increment in total biomass, annual per ha change in C stocks in soil, fraction of biomass left to decay.
Land converted to grassland – CO_2	- Changes in C stocks in soils: cropland conversion is more important.	Area of cropland converted, carbon after conversion during conversion of forest, area of forest land converted, carbon before conversion during conversion of forest and cropland, annual per ha change in C stocks in soil during conversion cropland

The table shows the subcategories and parameters that should be considered in order to improve the overall quality of the inventory.

4. Conclusions

The uncertainty analysis is a useful tool for the decision making in the process of improvement of the GHG inventories quality.

As the paper clearly shows, a practical application of the uncertainty analysis is that it helps to identify where improvements are required.

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IIASA'S Terrestrial Full Carbon Account for Russia: Revised Uncertainty Estimates and its Role in a Bottom-up/Top-down Accounting Exercise

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Abstract

We revised uncertainties in estimates of CO_2 fluxes for 1988-1992 in full carbon account for Russia published in 2000, taking into account recent studies. Much attention is paid to NPP and HR as these two big fluxes determine the uncertainty of the atmospheric CO_2 budget. All fluxes are estimated by bioclimatic zones for comparison with results of atmospheric inverse modeling as well as usage of the fluxes as prior information for the inverse modeling. Found systematic errors were corrected while remainder uncertainties were estimated from conservative point of view. The revised Russia's net atmospheric balance embraces respective top-down estimate, its uncertainty is about 100% (90% C.I.), as a consequence of the increases in both the uncertainty underlying HR and the uncertainty underlying NPP.

Key words: Russia, terrestrial carbon emissions, full carbon accounting, dual-constrained verification, bottom-up top-down, CO_2 accounting gap, uncertainties

1. Introduction

Our research addresses the need to close the gap between bottom-up and top-down accounting of net atmospheric carbon emissions to support the (dual-constrained) verification of CO_2 emissions. House et al. (2003), Nilsson et al. (2003a, b) and Rödenbeck et al. (2003) pinpointed at a 'CO_2 accounting gap' across subglobal scales already in 2003. The geographical focus of our study is on Russia, which is sufficiently large to be resolved in a bottom-up/top-down accounting exercise, in addition to being a signatory state of the Kyoto Protocol. An initial, uncertainty-focused cyclo-stationary atmospheric inversion experiment carried out at LSCE (France) indicated that a potential exists to improve atmospheric top-down estimates if bottom-up accounting is complete ('full') and uncertainties are reliable and better known.

As a base for bottom-up estimate of the atmospheric CO_2 budget (only CO_2 fluxes of the terrestrial biosphere) we use Full Carbon Account for Russia (FCA 2000, Nilsson et al., 2000). In new studies (since the time of publishing FCA 2000) it was found that some processes were not known and thus not taken into account when estimating forest and crop net primary productions (NPP) and heterotrophic soil respiration (HR). But the uncertainty of Russia's atmospheric CO_2 balance is determined by these two big fluxes and their uncertainties.

The objective of the study was to revise uncertainties of the FCA 2000, taking into account recent studies, compose revised bottom-up atmospheric CO_2 budget for Russian bioclimatic zones (BCZs: Polar Desert, Tundra, Pre-Tundra and Northern Taiga, Middle Taiga, Southern Taiga, Temperate, Forest, Steppe, Semi-Desert and Desert) for usage as prior information in the atmospheric inversion experiments, and upscale it to Eurasia and Extratropical Northern Hemisphere for comparison with top-down estimates.

2. Methodology

General methodology overview

We revised uncertainties in estimates of CO_2 fluxes for 1988-1992 in FCA 2000, taking into account recent studies. Much attention was paid to NPP and HR as they determine the uncertainty of the atmospheric CO_2 budget. All fluxes were estimated by BCZ for comparison with results of atmospheric inverse modeling as well as usage of the fluxes as prior information for the inverse modeling. Also it was found that breakdown of the fluxes to the BCZs still provides reasonable level of uncertainties of the estimates.

Found systematic errors were corrected while remainder uncertainties were estimated from conservative point of view (i.e., comprehensive estimation to the level possible, lack of knowledge assimilates to increasing of uncertainty). The uncertainties are estimated for 90% confidence interval (C.I.).

Net atmospheric CO_2 flux (a difference between NPP and all fluxes to the atmosphere, i.e., HR, disturbance and consumption) is upscaled to Eurasia and Extratropical Northern Hemisphere by applying Russian area specific flux to vegetated areas of Eurasia and Extratropical Northern Hemisphere, respectively. The upscaled bottom-up estimate is compared to the top-down estimate by House et al. (2003) for 1980-1989.

2.1. NPP

Forest

It was found that the FCA 2000 estimate of forest NPP is biased because a few processes of organic matter production (fine roots life span and root exudates) were not grasped by the methods for NPP estimation on the plot level (Shvidenko, 2007, personal communication). Thus for further analysis we use the new estimate of forest NPP by Shvidenko et al. (2006) and Shvidenko (2007, personal communication), which is on average 36% higher than the FCA 2000 estimate. Shvidenko et al. (2006) and Shvidenko (2007, personal communication) do not provide forest NPP for bioclimatic zones. We distribute the national total by the BCZ using additional information, namely, the forest NPP estimates by BCZ for the Siberia-II region (Schmullius et al., 2005), FCA 2000 estimate and a composition of model estimates (Cramer et al., 1999). In relation to this information we also estimate uncertainty of the NPP distribution.

To distribute the national total we construct an optimisation problem, i.e., require that the new estimates for the bioclimatic zones, NPP^i_{new} (i=1 corresponds to polar deserts BCZ, ... i=8 corresponds to semi-deserts and deserts BCZ) be as close as possible to corresponding old estimates, NPP^i_{old} (estimates by Nilsson et al., 2000), weighted by its relative uncertainty estimated against Siberia-II data – 0.61 (including bias; Jonas and Gusti, 2007; Schmullius et

al., 2005); and the area specific NPP ($^{*}NPP^{i}_{new}$) to be close as much as possible to the forest NPP estimated for the Siberia-II region, $^{*}NPP^{i}_{Sib2}$, weighted by their representativeness for forests on country scale for that particular BCZ and uncertainty (forest NPP uncertainty (relative) estimated for bioclimatic zones in the Siberia-II region – 0.18 (Shvidenko, 2007, personal communication))

$$\left\{ \sum_{i=1}^{8} \frac{\left(NPP^{i}_{old} - NPP^{i}_{new}\right)^{2}}{S_i^{2}} * \left(1-0.61\right)^{2} + \sum_{i=1}^{7} \left(^{*}NPP^{i}_{Sib2} - {}^{*}NPP^{i}_{new}\right)^{2} * r_i^{2} * \left(1-0.18\right)^{2} \right\} \rightarrow \min$$

With additional constraints on the new NPP estimates: Sum of the new estimates equals to the national total estimated by Shvidenko (2007, personal communication), new estimates for the bioclimatic zones do not exceed corresponding estimates by the mathematical models, because the models tend to overestimate real NPP (Jonas and Gusti, 2007), and at last we assume that the model estimate for semi-deserts and deserts BCZ is highly overestimated thus we require the new estimate to be smaller or equal than the old estimate.

To estimate uncertainty of the distributed NPP we estimated relative distance of the new NPP to the respective BCZ NPP from the Siberia-II region, FCA 2000 (old) and models and choose the largest of them. We assume that probability the uncertainty intervals contain true NPP is 90%.

Agriculture

Russia's arable land (one of the considered land-cover class (LC)) is resolved at the national level in terms of 1) cropland comprising grain crops and crops other than grains (for which annual and perennial grass is used as a surrogate) and 2) pastures. The overall basic assumption underlying all NPP calculations is that the agricultural life cycle is one year, i.e., production equals phytomass.

NPP at the national scale. The sources listing the statistical data (areas, yield, dry matter-to-carbon conversion factors, etc.) that were employed by Nilsson et al. (2000: p. 38) for their FCA 2000 study were found appropriate. Additional knowledge with respect to relative uncertainties and their ranges could be derived from the Austrian Carbon Database that was made available by Jonas and Nilsson (2002) after completion of the FCA 2000 study. The regression equations suggested by Rodin and Krylatov (1998: Tab. 7) allow estimating, using yield as input, the remaining parts of the plants, i.e., their above and belowground contributions. Our recalculations based on the original data and a revision of Russian harvest conditions as of 1990 featured three things: (i) dry matter of annual grass was overestimated by a factor of 10; (ii) spring wheat indeed serves as a good surrogate for grains and a combination of "60% perennial plus 40% annual grass" as a very good surrogate for crops other than grains; and (iii) harvest losses that were considerable at that time (grains: 10–50%; crops other than grains: 15–45%; pastures: 0%) were not taken into account.

NPP at the scale of BCZs. Disaggregating the recalculated, national-scale NPP value, and its uncertainty, across BCZs involved three main steps: (i) an "oblast–LC–BCZ" map overlay ('oblast' is the administrative unit to which harvest statistics refer) to determine NPP for individual BCZs; (ii) deriving the linear regression NPP = f(yield) on the basis of all oblasts and assuming that it also holds for BCZs, which allows establishing the mathematical framework to calculate consistent NPP uncertainties at that scale; and (iii) applying the

assumption that yield uncertainties are equal across BCZs in relative terms, an important but still missing input for this mathematical framework.

Wetlands, Grasslands & Shrubs

Russia's wetlands comprise swamps and bogs, while grasslands & shrubs are not further disaggregated. For reasons of insufficient data, our NPP calculations followed the same simplified structure that had already been applied by Nilsson et al. (2000): NPP density times area times carbon conversion factor. However, we considered additional results that had become available concomitant to and after the FCA 2000 study, notably those from a 17-model global intercomparison experiment with the focus on NPP and its uncertainty (Cramer et al., 1999). (The modeled NPP and uncertainty data underwent a "model grid–BCZ–LC" map overlay to derive the corresponding values for Russia and its eight BCZs.) The comparison with the FCA 2000 NPP values on the national scale shows that the model-derived NPP value is as great for swamps, greater for bogs and smaller for grasslands & shrubs. The spread of NPP values (and uncertainties) for both Russia and its BCZs allowed us to derive uncertainties at these scales and achieve consistency.

2.2. Soil Heterotrophic Respiration

Two independent estimates of heterotrophic soil respiration (HR) and its components (total soil respiration (SR) and root contribution (RC), $HR = SR * \left(1 - \frac{RC}{100}\right)$) were available – by V.Stolbovoi (Nilsson et al. 2000 and Stolbovoi 2003) and I.Kurganova (2002). Since the two estimates of HR differ by 13% in total (difference for the BCZs varies from 8% to 62%) we made an analysis of the HR components. We started with analysis of RC. We found considerable differences as in principal approach as well as in obtained values. V.Stolbovoi comes from mostly theoretical considerations and limited Russian publications data and finds different values for different soil divisions. In contrast, I.Kurganova uses more published data and distinguishes between different vegetation covers. In average Stolbovoi's RC values is 2.6 times less than Kurganova's values. To solve the problem we collected recent published data from which one could estimate RC and its uncertainties. We analyzed SR measurement data provided by Kurganova (2002) and determined bias due to measurement method, uncertainties caused by spatially sparse data and time of measurements. After that we composed matrices of SR, RC and their uncertainties by BCZ, vegetation type and soil division. From these two matrices we calculated matrices of HR, its uncertainties as well as correlations within and across BCZs. At the end we found average HR from our estimate and estimates by Stolbovoi (2003) and Kurganova (2002) for the BCZs and account for additional uncertainty arisen from the estimates variability because we cannot discriminate which of the three estimates is the "best estimate".

We estimated RC from published data for vegetation types: temperate forest; south taiga forest; forest of middle taiga, forest tundra and tundra; wetland; grassland; and cropland. We calculated precision of the estimated RC (90% confidence interval, denoted as *U90p*) as an area-weighted average of the vegetation specific values using formula

$$U90\,p^2 = \frac{\sum_{i=1}^{L} U90p_i^2 * S_i^2}{\left(\sum_{i=1}^{L} S_i\right)^2} + \frac{\sum_{i=1}^{L}\left(\sum_{\substack{j=1 \\ j\neq i}}^{L}(RC_i - RC_j) * S_j\right)^2 * U90_{Si}^2}{\left(\sum_{i=1}^{L} S_i\right)^4},$$

where $U90_{Si}$ is the uncertainty of the *i*-th vegetation type area. In fact the second term in the formula is at least one order smaller than the first one and is not taken into account.

We studied the soil respiration measurement data, used by Kurganova (2002, p.36, Table A1) for estimation of respiration of Russian soils, on possible uncertainties that can occur when using the measurements.

We analyse spatial coverage of the measurements. The measurements are very limited for the territory of Russia. There are about 370 measurement records in the database, 20 of which are outliers. Most of the measurements are located in the European part of Russia and the same time there are not measurements in vast territory in the middle of Russia. Some measurements are adopted from outside of Russian territory (Byelorussia, Ukraine and Kazakhstan). In case if in a BCZ a soil-vegetation class occupies more than 1% of the country area but no valid measurements exist we used the measurements from similar soil-vegetation class in a neighbour BCZ or similar soil division and increased the uncertainty by 20% (90% C.I.). In case if only one measurement is available for a BCZ-soil-vegetation class a 90%[4] uncertainty is assumed.

The estimated soil respiration using those measurements should be attributed to 1955-1975, when most of the measurements were taken, but not to the 1990 because Kurganova (2002) didn't apply any climate corrections. Moreover it looks inappropriate to apply any climate corrections to the measurements because exact years of the measurements are not known in most cases. Nevertheless Stolbovoi (2003) made an attempt to apply some kind of climate corrections based on deviation of monthly mean temperatures in 1990 from last 30-year average (probably, the last 30 years before 1990).

According to Kurganova (2002) the soil respiration measurement data stored in the database and used for the soil respiration estimations were carried out in the field. In fact we don't know the measurement methods applied, but at time when most of the measurements were taken (1955-1975) the most usable method was a closed chamber with a chemical CO_2 absorber (also called non-flow-through steady-state chamber or absorption chamber) (Hutchinson and Rochette, 2003; Shpakivska, 2004). Published comparative studies of different measurement techniques show that the absorption chamber method overestimates the soil respiration for small fluxes (less than about 100 mgC/(m^2h) by about 10% and underestimates big fluxes by about 20-30% (Jensen et al., 1996; Yim et al., 2000). Hutchinson and Rochette (2003) show that the bias strongly depends on exposure time (which typically was 12 or 24 hours), exposure surface of the chemical CO_2 trap etc. Thus we can assume that fluxes smaller than 100 mgC/(m^2h) presented in the database, which were published before 1993, are overestimated by 10% but bigger fluxes – underestimated by 20%.

[4] The assumption of 90% uncertainty for single measurements is arbitrary to a certain extent. But it is a trade-off between higher uncertainty (e.g. in nine cases when more than one measurement is available or neighbor value is adopted the estimated relative uncertainty is larger than 100%) and inclusion of close-to-zero or negative values into the uncertainty interval.

Some of the measurements were made using a closed chamber and the air samples were taken with a syringe, transported to a laboratory and analyzed using a gas chromatograph. According to Pumpanen et al. (2004) such a method underestimates the fluxes up to 35%. Thus we assume that if such a method was used the measurements are underestimated by 30%.

If a closed chamber is used but the measurements are made in-situ with an infrared CO_2 analyzer the underestimation is about 4-14% (Pumpanen et al., 2004). In that case we assume 10% underestimation.

The biases were determined for all measurements in the database and averaged for the BCZ-soil-vegetation classes.

The uncertainty of the average SR for 90% confidence interval for each BCZ-soil-vegetation class is estimated using t-statistics:

$$U90p = \frac{STD * t_{0.9}(N - 1)}{\sqrt{N}},$$

where *STD* is standard deviation, $t_{0.9}(N - 1)$ is a t-value of the Student's t-distribution for 90% probability and N-1 degrees of freedom (N is number of the measurements). The relative uncertainty is estimated using the following expression

$$R\_U90p = \frac{U90p}{M} * 100\%,$$

where M is average of the soil respiration.

The absolute uncertainties were recalculated after the correction of the relative uncertainties from respective average values, and the relative uncertainties and new area weighted uncertainties for the aggregates were calculated. In its turn, the relative uncertainties for the aggregates were calculated from the aggregated average values and absolute uncertainties.

Using information on vegetation type and bioclimatic zone respective RC value was assigned and heterotrophic soil respiration was calculated.

In fact the aggregated values represent only the BCZ-soil-vegetation classes, for which the soil respiration measurements are available but not the whole territory. This leads to additional uncertainty, when the area weighted values are used for estimation of the total flux from the Russian territory.

The uncertainties in the heterotrophic soil respiration (which we can estimate) arise from the uncertainties in soil respiration, uncertainties in root contribution and the area uncertainties in the aggregated values. The area uncertainties are not taken into account because they are very little in case of area weighting (for details see Jonas and Gusti, 2007).

Relative uncertainties of heterotrophic soil respiration for individual BCZ-soil-vegetation classes are estimated using formula

$$R\_U90_{HR_{ijk}} = \sqrt{R\_U90^2_{SR_{ijk}} + R\_U90^2_{RC_{ijk}}},$$

where *i* runs through all vegetation types, *j* – all soil divisions and *k* – all bioclimatic zones.

The uncertainties of heterotrophic soil respiration for the bioclimatic zones are determined using formula

$$U90_{HR_k} = \sqrt{\sum_{i=1}^{L}\left[\left(\sum_{j=1}^{J} U90^2_{SR_{ijk}} * S^2_{ijk}\right) * \left(1 - \frac{RC_{ik}}{100}\right)^2 + \left(\sum_{j=1}^{J} SR_{ijk} * S_{ijk}\right)^2 * \left(\frac{U90_{RC_{ik}}}{100}\right)^2\right]} * \frac{1}{\sum_{i,j=1}^{L,J} S_{ijk}}.$$

Corresponding relative uncertainties are calculated by dividing the absolute uncertainties on average heterotrophic respiration values and multiplying by 100 (%).

For some BCZ-soil-vegetation classes, soil divisions in bioclimatic zones and soil divisions the estimated uncertainties are larger than 100%. It happened in cases of little number of measurements (one or two) or absence of the measurements in large area BCZ-soil-vegetation classes and consequent substitution of the soil respiration values with the ones from similar classes and increment of the uncertainty. Since further we consider the heterotrophic respiration on BCZ scale (for which the uncertainties do not exceed 60%) we do not interpret the uncertainties greater than 100% physically.

Correlation between the heterotrophic soil respiration fluxes from individual BCZ-soil-vegetation classes within one bioclimatic zone and one vegetation type caused by using similar root contribution rate can be estimated by subtracting the uncertainty estimated from the uncertainties of individual BCZ-soil-vegetation class fluxes (as they are independent) from the uncertainties estimated taking into account the dependences.

Common RC factor is used for HR estimations in some vegetation types across the bioclimatic zones, which causes the correlation between the estimated HR in the bioclimatic zones. Particularly, the common RC factor was used for croplands and bogs across all considered bioclimatic zones; for grasslands ('normal') – across Southern Taiga, Temperate, Steppe, Semi-deserts and Deserts bioclimatic zones; for grasslands (tundra) – across Tundra, Forest Tundra and Northern Taiga, and Middle Taiga bioclimatic zones; for northern forests – across Tundra, Forest Tundra and Northern Taiga, and Middle Taiga bioclimatic zones; and for temperate forests – across Temperate, Steppe, Semi-deserts and Deserts bioclimatic zones. The correlation coefficient between two bioclimatic zones *A* and *B* can be calculated using the formula

$$Corr_{AB} = \frac{\sum_{i=1}^{4} U90^2_{RC_i} SR_i}{U90_{HR_A} U90_{HR_B}},$$

where *i* defines the vegetation class for which the autotrophic soil respiration rate is common across the bioclimatic zones *A* and *B*.

The aggregated heterotrophic soil respiration (for the bioclimatic zones or the entire territory) depends on the way of calculation of the aggregated fluxes because of the incomplete spatial coverage of the measurements. The authors of the considered estimates of heterotrophic soil respiration (Nilsson et al. 2000, Kurganova 2002, and Jonas and Gusti, 2007) used mostly similar soil respiration measurement data but applied different approaches, which led to slightly different results. Since we cannot judge whose approach is better we combine all the estimates on the level of the bioclimatic zones (because such values are reported by all the authors), including also different aggregation techniques.

We determined the accuracy (90% C.I.; the uncertainty caused by the usage of different estimation methods) as

$$U90a = \frac{STD * t_{0.9}(N - 1)}{\sqrt{N}},$$

where *STD* is standard deviation, $t_{0.9}(N - 1)$ is a t-value of the Student's t-distribution for 90% probability and *N*-1 degrees of freedom (*N* is number of the groups).

To get more complete uncertainty estimation (*U*90 and respective relative uncertainty *R_U*90) we combined the accuracy with the internal uncertainty of the heterotrophic soil respiration for the bioclimatic zones (*R_U*90*p*) as two independent components

$$U90 = \sqrt{U90a^2 + U90p^2}\ .$$

2.3. Consumption

The estimation of agricultural consumption and its uncertainty was part of our NPP calculations at the national scale. We distributed CO_2 fluxes from consumption of agricultural products, forest products, peat, and grasslands and shrubs by domestic animals, national totals and uncertainties of which are given in Nilsson et al. (2000), proportionally to population in respective BCZ. CO_2 fluxes from consumption of grasslands and shrubs by wild animals is distributed proportionally to areas of grasslands and shrubs in respective BCZ. Uncertainty of the flux caused by consumption of grasslands and shrubs by wild animals is assumed to be 50% in each BCZ. Uncertainty of the flux caused by consumption of grasslands and shrubs by domestic animals and usage of peat is assumed 50% for national totals, the squared uncertainty of distribution of the fluxes by BCZ is estimated as sum of squares of the national total uncertainty and uncertainty of the population in respective BCZ. The uncertainty of population of BCZ is estimated as difference between the BCZ population estimated by two methods – overlaying of BCZ and population grids or overlaying of polygons (all maps are from Russia CD-ROM, Stolbovoi and McCallum, 2002), multiplied by 1.65 (for details see Jonas and Gusti, 2007).

2.4. Disturbances

Nilsson et al. (2000) estimated C-CO_2 fluxes and their uncertainties at national scale for the following disturbances: direct fire (DFCE) and post fire emissions (PFCE), industrial transformation of grasslands and shrubs, insect invasion, forest abiotic disturbances, disturbances of forests by harvesting. We distributed the national totals by bioclimatic zones and estimated uncertainties of the distributions.

We estimated fire emissions by BCZ using data on fire types and areas of different fire types in BCZs by Shvidenko and Nilsson (2000a,b).

For estimating the uncertainty of the DFCE we used the result of the uncertainty study by French et al. (2004), which was done for boreal forests (Alaska) using similar fire emission model. For the four year average carbon flux French et al. (2004) finds 24% CV, which corresponds to 40% for 90% confidence interval uncertainty.

For estimating the uncertainty of the PFCE we used a simplified model of PFCE by Shvidenko and Nilsson (2000b) and applied a Monte-Carlo technique (10000 solutions) to propagate the parameter uncertainties (for details see Jonas and Gusti, 2007). The model simplification consists in using only one decaying pool with average decomposition constant α=0.043. The parameters are modeled using normal distribution with the mean values from Shvidenko and Nilsson (2000b). The following parameter uncertainties (CV) are applied: Area burnt – 0.15 (French et al., 2004), Decomposition constant (α) – 0.12 (sensitivity of the resulting uncertainty to this parameter is very little), Fraction of carbon of decomposed organic matter that is released to the atmosphere (χ) – 0.05 (we assumed that half of the range, reported in the literature (0.77–0.92) (Shvidenko and Nilsson, 2000b), corresponds to standard deviation of the parameter, Amount of organic matter (O) – 0.20, Changes in organic soil (CSOC) – 0.06 (we assumed that half of the range, reported in the literature (0.02–0.11) (Shvidenko and Nilsson, 2000b), corresponds to standard deviation of the parameter. We also take into account that such parameters as O and CSOC depend on the same burnt area.

The resulting uncertainty of the PFCE for 1990 is 40% (90% C.I.). We do not make difference between 1990 uncertainty and five year average uncertainty because the same model (and most of parameters) is used fore each year thus the estimates are not independent.
Uncertainty of the total carbon flux (FCE=DFCE+PFCE) is estimated to be 40% (90% C.I.), taking into account that both DFCE and PFCE depend on the same burnt area. Emissions resulting from burning of organic matter compose mostly of a few gases containing carbon (CO_2, CO and CH_4). Using estimations of French et al. (2004) we found that the CO_2 emissions make up about 85% of direct fire carbon emissions.

We distributed emissions caused by ‘industrial transformation of grasslands and shrubs’, and ‘forest abiotic disturbances’ proportionally to population of the bioclimatic zones. The uncertainty of the distributed flux is estimated similarly as in case of consumption flux.

Flux from disturbances of forests by harvesting is distributed proportionally to actual harvest by forest enterprises (we overlaid BCZ map and Forestry DB from the Russia CD-ROM, Stolbovoi and McCallum, 2002). Square uncertainty of the distribution is estimated by summing squares of total national uncertainty reported by Nilsson et al. (2000) and uncertainty of the harvest distribution by BCZ, which is estimated as misclassified harvest divided by harvest in each BCZ and multiplied by 1.65. We distributed flux caused by forests insect invasion proportionally to 'Insect index' – an index incorporating total forest area in a BCZ and severity of insect damage (compiled from ‘insect’ map from the Russia CD-ROM). For details see Jonas and Gusti (2007).

2.5. Total bottom-up fluxes of CO_2 by BCZ

To estimate total bottom-up fluxes of CO_2 by BCZ we found an arithmetic sum of all fluxes mentioned above for each BCZ. For estimating the uncertainties we assumed correlation between the disturbance and consumption fluxes equals one within each BCZ and the correlation between other fluxes is negligible.

2.6. Bottom-up – Top-down

We upscaled the national total net CO_2 flux for Russia to Eurasia and Extratropical Northern Hemisphere for comparison with the top-down estimate by House et al. (2003). For upscaling we found area-specific flux for vegetated Russian territory (16 Tm^2) and multiplied it by vegetated areas of Eurasia (36 Tm^2) and Extratropical Northern Hemisphere (56 Tm^2; Nilsson et al., 2003a), respectively.

3. Results and Discussion

Results of estimation of other terrestrial ecosystem CO_2 fluxes into and out of the atmosphere, net atmospheric CO_2 flux and their uncertainties are presented in *Tables 2-4*.

The 1988–1992 NPP estimate for Russia's arable land as specified by Nilsson et al. (2000: Tab. 30 and 68) and Nilsson et al. (2003a, c: background data to Fig. 1) was about 957 TgC/yr with an uncertainty ranging from ~ 5 to 18%. The new NPP estimate is smaller by 23% but exhibits a greater uncertainty: 739 TgC/yr ± 25%. In the BCZs the changes are different – from 14% increase in the Semi-Desert & Desert BCZ to 50% decrease in the Tundra BCZ. Major reasons of the bias and increased uncertainty are uncertain yield (at oblast level) and yield losses.

New estimate of forest NPP is greater than the previous one by 36% in total. Major reason for that is the following. FCA 2000 forest NPP estimate was based on usage of field measurements of tree NPP, which did not consider fine roots and root exudates properly (state of the art at the time of measurements). Difference between the NPP estimates for the BCZs varies from -21% in the Steppe BCZ to more than 40% in the Middle Taiga and Pre-Tundra & Northern Taiga BCZs. Uncertainty of the national total is approximately on the same level. Uncertainties of the NPP for BCZs represent our knowledge about distribution of the total NPP between the bioclimatic zones and have different nature than the uncertainty of national NPP estimate.

The 1988–1992 NPP estimates for Russia's wetlands as specified by Nilsson et al. (2000: Tab. 30 and 68) and Nilsson et al. (2003a, c: background data to Fig. 1) were about 487 with an uncertainty ranging from < 5 to 27%. The corresponding values for grasslands & shrubs are 1202 TgC/yr with an uncertainty range from < 5 to 18%. The re-derived NPP estimates are 539 TgC/yr ± 53% for wetlands and 1055 TgC/yr ± 40% for grasslands & shrubs.

New estimate of the soil heterotrophic respiration is 9% smaller than the FCA 2000 estimate and the uncertainty increased from 16% to 24%, in total. Decrease of the HR in BCZs ranges from 7% in the Steppe to 50% in Polar Desert. Major reason of high uncertainty is lack of spatial and temporal coverage of SR and RC measurements. Accounting for inside-BCZ and inter-BCZ correlation increases the uncertainty on 4% in total.

Table 1. NPP and uncertainties for BCZ and LC, TgC/year

BCZ	Arable land			Forest			Wetlands + Grasslands & Shrubs*		
	NPP	U90	R_U90	NPP	U90	R_U90	NPP	U90	R_U90
Polar Desert	0.0	0.0	0	0.0	0.0	0	0.0	0 .. 0.1	-100 .. +112
Tundra	2.3	1.8	80	7.7	1.3	17	340.8	142.5	42
Pre-Tundra & Northern Taiga	2.9	2.0	69	333.6	102.0	31	196.4	61.1	31
Middle Taiga	34.6	18.0	52	1439.8	435.5	30	626.2	242.6	39
Southern Taiga	119.4	53.6	45	411.4	156.0	38	205.9	95.7	47
Temperate Forest	107.5	43.7	41	97.6	39.5	41	27.5	13.8	50
Steppe	392.5	156.4	40	35.3	9.3	26	164.7	115.3	70
Semi-Desert & Desert	79.6	50.6	64	3.2	1.8	58	33.0	12.6	38
Total	738.8	186.8	25	2328.7	349.3	15	1594.4	512.6	32

* In case of the Polar Desert BCZ we provide 90% confidence intervals to avoid negative NPP

Uncertainty of national total of disturbance fluxes increased slightly because of re-estimated uncertainty of fire emissions (fire emissions uncertainty increased from 23% to 40%). Uncertainty of national total of consumption fluxes increased mainly because of re-estimated consumption of agriculture products. Uncertainties of the fluxes estimates for the BCZs rise because of imperfect spatial data on BCZ population, insect invasion and forest harvest (uncertainty of the assumptions on the flux distributions by BCZ are not taken into account). But since the disturbance and consumption fluxes in general are much smaller than the HR and NPP fluxes (except the Temperate forest BCZ where consumption is two times greater than the HR) their uncertainties do not influence the uncertainties of the net atmospheric fluxes of the bioclimatic zones.

Table 2. Majour CO_2 fluxes from and to the atmosphere and atmospheric CO_2 budget, TgC/year (minus = net out of the atmosphere)

BCZ	NPP	HR	Disturbunces	Consumption	Total
Polar Desert	0.05	0.10	0.00	0.00	0.05
Tundra	350.71	235.63	9.62	9.80	-95.66
Pre-Tundra & Northern Taiga	532.88	252.29	49.17	16.05	-215.37
Middle Taiga	2 100.62	1 062.91	75.31	69.58	-892.82
Southern Taiga	736.74	611.06	62.20	190.88	127.41
Temperate Forest	232.59	187.57	23.06	89.70	67.74
Steppe	592.48	522.89	18.88	157.18	106.46
Semi-Desert & Desert	115.80	47.51	1.49	11.76	-55.04
Total	4 661.86	2 919.97	239.80	545.00	-957.09

Table 3. Uncertainty (U90) of major CO_2 fluxes from and to the atmosphere and atmospheric CO_2 budget (assuming correlation between Disturbance and Consumption = 1), TgC/year

BCZ	NPP*	HR*	Disturbunces	Consumption	Total
Polar Desert	0 .. 0.1	0 .. 0.25	0.00	0.00	0.16
Tundra	142.51	139.53	3.76	3.55	199.57
Pre-Tundra & Northern Taiga	118.92	149.20	17.97	7.23	192.45
Middle Taiga	498.84	577.31	15.43	20.15	763.80
Southern Taiga	190.70	135.81	9.89	38.86	239.14
Temperate Forest	60.53	37.66	4.12	43.66	85.82
Steppe	194.58	113.60	2.46	30.30	227.69
Semi-Desert & Desert	52.20	28.50	0.29	3.52	59.59
Total	647.80	686.97	49.21	100.73	956.06

* In case of the Polar Desert BCZ we provide 90% confidence intervals to avoid negative NPP and HR

Table 4. Relative uncertainty (R_U90) of majour CO_2 fluxes from and to the atmosphere and atmospheric CO_2 budget (assuming correlation between Disturbance and Consumption = 1),%

BCZ	NPP*	HR*	Disturbunces	Consumption	Total
Polar Desert	-100 .. +112	-100 .. +153	0	0	316
Tundra	41	59	39	36	209
Pre-Tundra & Northern Taiga	22	59	37	45	89
Middle Taiga	24	54	20	29	86
Southern Taiga	26	22	16	20	188
Temperate Forest	26	20	18	49	127
Steppe	33	22	13	19	214
Semi-Desert & Desert	45	60	19	30	108
Total	14	24	21	18	100

* In case of the Polar Desert BCZ we provide 90% confidence intervals to avoid negative NPP and HR

The new atmospheric net CO_2 flux for entire Russia scaled-up to Eurasia and Extratropical Northern Hemisphere are about two times smaller than the top-down estimate by House et al. (2003) and scaled-up bottom-up estimate by Nilsson et al. (2003a) (*Table 5*). But respective new scaled-up uncertainty interval contains averages of the estimates by House et al. (2003) and Nilsson et al. (2003a) and their uncertainty intervals (excluding top-down Eurasia flux where higher interval value exceeds our higher value).

Table 5. Comparison of net atmospheric CO_2 flux derived from top-down and bottom-up estimates, Pg C/yr (minus = net flux out of the atmosphere)

Atmospheric inversion – 1980-1989 (House et. al, 2003)		FCA 2000 – 1988-1992 Scaled-up (Nilsson et al., 2003a)		Current study – 1988-1992 Scaled-up	
Eurasia	Extratropical Northern Hemisphere	Eurasia	Extratropical Northern Hemisphere	Eurasia	Extratropical Northern Hemisphere
-0.94	-1.45	-0.77	-1.22	-2.1	-3.3
[-2.3 .. 0.72]	[-2.3 .. -0.6]	[-1.16 .. -1.38]	[-1.83 .. -0.61]	[-4.2 .. 0.0]	[-6.6 .. 0.0]

4. Conclusions

We revised uncertainties in estimates of CO_2 fluxes for 1988-1992 in FCA 2000, taking into account recent studies. Much attention was paid to NPP and HR as they determine the uncertainty of the atmospheric CO_2 budget. All fluxes were estimated by BCZ for comparison with results of atmospheric inverse modeling as well as usage of the fluxes as prior information for the inverse modeling. Found systematic errors were corrected while remainder uncertainties were estimated from conservative point of view.

Our revision of the FCA 2000 lead to HR and NPP uncertainties that are greater than those derived previously. It was also found that uncertainties determined at the spatial scale of BCZs are still robust, while HR and NPP uncertainties typically exceed 100% (90% C.I.) at finer resolutions.

New NPP estimate for Russia's arable land is smaller by 23% (957 vs. 739 TgC/yr) but exhibits a greater uncertainty – 25% versus 18% in the FCA 2000. Major reasons of the bias and increased uncertainty are uncertain yield (at oblast level) and yield losses.

New estimate of forest NPP is greater than the previous one by 36% in total (2329 vs. 1707 TgC/yr). Major reason for that is lack of knowledge of fine root NPP (state of the art at the time of measurements). Uncertainty of the national total (15%) is approximately on the same level.

The 1988–1992 NPP estimates for Russia's wetlands as specified by Nilsson et al. (2000) and Nilsson *et al.* (2003a,c) were about 487 with an uncertainty ranging from < 5 to 27%. The corresponding values for grasslands & shrubs are 1202 TgC/yr with an uncertainty range from < 5 to 18%. The re-derived NPP estimates for Russia's wetlands and grasslands & shrubs are 539 TgC/yr ± 53% and 1055 TgC/yr ± 40%, respectively.

New estimate of the soil heterotrophic respiration is 9% smaller than the FCA 2000 estimate (2920 vs. 3197 TgC/yr) and the uncertainty increased from 16% to 24%, in total. Major reason of high uncertainty is lack of spatial and temporal coverage of SR and RC measurements.

Net atmospheric CO_2 flux (a difference between NPP and all fluxes to the atmosphere, i.e., HR, disturbance and consumption – -1.0 TgC/yr) is upscaled to Eurasia (-2.1 PgC/yr) and Extratropical Northern Hemisphere (-3.3 PgC/yr). The re-estimated net fluxes are about two times smaller than the top-down estimate by House et al. (2003) (-0.94 and -1.45 PgC/yr for Eurasia and Extratropical Northern Hemisphere, respectively) and upscaled bottom-up estimate by Nilsson et al. (2003a) (-0.77 and -1.22 PgC/yr). But respective new upscaled uncertainty interval contains averages of the estimates by House et al. (2003) and Nilsson et al. (2003a) and their uncertainty intervals (excluding top-down Eurasia flux where higher interval value exceeds our higher value).

The uncertainty of Russia's net atmospheric balance is approximately 100% (90% C.I.), as a consequence of the increases in both the uncertainty underlying HR and the uncertainty underlying NPP. At this stage of our research we only know that the potential for coupling bottom-up and top-down full carbon accounts is reduced. But we cannot anticipate whether or not the remaining potential for getting benefit out of a coupling can still be considered sufficient. A top-down atmospheric inversion experiment using bottom-up estimates, obtained in this study, as prior information is foreseen in the second part of 2007.

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Interactive Resource Planning Processes and International Experiments within Uncertain Emission Trading Markets

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Abstract

Interactive resource planning becomes more and more important within future emission trading markets. The conferences of Rio de Janeiro 1992 and Kyoto 1997 demand for such new economic instruments which focussed originally on environmental protection in both macro and micro economy. An important economic tool in that area is Joint-Implementation (JI) which is defined in Art. 6 of the Kyoto Protocol. A sustainable development can only be guaranteed if the instrument is embedded in an optimal energy management. In this contribution we describe an international procedure within uncertain markets which helps to establish such an optimal energy management and interactive resource planning processes within uncertain emission trading markets.

1. Introduction

The Kyoto Protocol is an agreement made under the *United Nations Framework Convention on Climate Change (UNFCCC)*. Countries that ratify this protocol commit to reduce their emissions of carbon dioxide and five other greenhouse gases, or engage in emissions trading if they maintain or increase emissions of these gases. The objective is the "*stabilization of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system*" (Weber, 2008) within a uncertain market behavior.

The treaty was negotiated in Kyoto, Japan, in December 1997, opened for signature on March 16, 1998, and closed on March 15, 1999. The agreement came into force on February 16, 2005, following the ratification by Russia on November 18, 2004. As of April 2006, a total of 163 countries have ratified the agreement. Notable exceptions include the United States and Australia. Other countries, like India and China, which have ratified the protocol, are not required to reduce carbon emissions under the present agreement.

Since the Industrial Revolution, around 1800, the burning of fossil fuels has caused a dramatic increase of CO_2 in the atmosphere, reaching levels unprecedented in the last 400 thousand years. This increase has been implicated as a primary cause of global warming (Kyoto, 1997a). The protocol also reaffirms the principle that developed countries have to pay, and supply technology to other countries for climate-related studies and projects. This was originally agreed in the UNFCCC. Economists have been trying to investigate the overall net benefit of Kyoto Protocol through a cost-benefit analysis. Just as in the case of climatology, there is disagreement due to large *uncertainties* in economic variables.

Still, the estimates so far generally indicate either that observing the Kyoto Protocol is more expensive than the not observing the Kyoto Protocol or that the Kyoto Protocol has a marginal net benefit which exceeds the cost of simply adjusting to global warming. The Copenhagen consensus project found that the Kyoto Protocol would slow down the process of global warming, but has a superficial overall benefit (Kyoto, 1997a).

The *Convention on Climate Change* sets an overall framework for intergovernmental efforts to tackle the challenge posed by climate change. It recognizes that the climate system is a shared resource whose stability can be affected by industrial and other emissions of carbon dioxide and other greenhouse gases. This convention enjoys near universal membership, with 189 countries having ratified. Under the convention, governments (Kyoto, 1997b):

- gather and share information on greenhouse gas emissions, national policies and best practices,
- launch national strategies for addressing greenhouse gas emissions and adapting to expected impacts, including the provision of financial and technological support to developing countries,
- cooperate in preparing for adaptation to the impacts of climate change.

2. Climate Change

The climate change refers to the variation in the earth's global climate or regional climates over time. It describes changes in the variability or average state of the atmosphere -or average weather-over time scales ranging from decades to millions of years. These changes may come from internal processes, be driven by external forces or, most recently, be caused by human activities (Kyoto, 1997a). Greenhouse gases, primarily carbon dioxide CO_2, methane and water vapour contribute to global warming (Kyoto, 1997b). In recent usage, especially in the context of environmental policy, the term *climate change* is often used to refer only to the ongoing changes in today's climate, including the average rise in surface temperature known as global warming. Sometimes, the term is also used with a presumption of human causation, e.g., in UNFCCC, which uses *climate variability* for non-human caused variations (Kyoto, 1997a).

2.1 The Kyoto Protocol

The conferences of Rio de Janeiro (1992) and Kyoto (1997) demand for new and important economic instruments which have a focus on environmental protection in the macro and micro economy. An important economic tool being part of Kyoto treaty in that area is a Joint Implementation (JI) program, explicitly mentioned in Kyoto Protocol. This is an international program which intends to strengthen international cooperations between enterprises in order to reduce CO_2 and further greenhouse gas emissions.

A sustainable development can only be guaranteed if the instrument is embedded into an optimal energy management. According to JI this means that it must work on the micro level with minimal costs and it should be protected against misuse on the macro level. For that reason, the Technology-Emissions-Means model, in short: *TEM model*, was developed by the author, giving the possibility to simulate such an extraordinary market situation and behaviour. The case of a cooperative economic behaviour including co-funding in joint international projects is considered, and the mathematical analysis of several trend scenarios

as well. This leads to new results in the area of cooperative time-discrete dynamic games using discrete optimization techniques and exploiting the underlying combinatorial structure. The realization of JI is subject to technical and financial constraints. Specifically, the concept of JI involves a bilateral or multilateral deal in which countries are facing a high pollution abatement in countries with lower costs, and receive credit for the resulting reduction in greenhouse gas emissions. The reductions in emissions resulting from technical cooperations are recorded at the *Clearing House* whose establishment is also a demand of Kyoto Protocol. The TEM model was developed to capture these constraints in an empirically practicable way. The kernel of the TEM model represents an underlying cost game. It can be used to determine feasible sets. The TEM model bases only on empirical parameters; we can compare them with real-world phenomena. The associated cost reductions should then be allocated in an optimal way. This approach is as well integrated in the TEM model as the possibility to regard the influence of several cost allocations on the feasible set of control parameters. In the played cost game, a special solution called the τ value which stands for a rational allocation process is examined (Branzei 2005, Tijs 2003); it was introduced into CO_2 emission control in (Pickl 1999). The main question is: In which situations can the τ value be equivalent to the control parameters needed to reach the regions mentioned in Kyoto Protocol.

2.2 Predictability

The Framework Convention on Climate Change (FCCC) of Kyoto Protocol demands for reductions in greenhouse gas emissions by the industrialized countries. On the other hand, developing countries are expanding their energy consumption, which leads to increased levels of greenhouse gas emissions. The preparation of an optimal management tool in that field requires the possibility to identify, assess and compare several technological options.

For that reason, the mathematical TEM model presented was elaborated. According to FCCC, control parameters were incorporated which have to be determined iteratively, according to the negotiation process. It is a model which integrates economical and technical investments in a coupled time-discrete nonlinear (quadratic) system of equations. The iterative solution of the TEM model with time-discrete control variables implied is an approach to successfully overcome the occurrence of chaos in the TEM model and, by this, to help decision makers for a better predictable, more secure future and for a sustainable development (Pickl, 2002).

Environmental problems belong to the main challenging problems of the 21st century. There is a lack of new allocation principles for investments. Several approaches from game theory concerning this topic may be found. Additionally to these approaches, the improvement of technical *effectivity* through cooperation JI is the center of interest. Therefore, the TEM model was developed giving the possibility to combine both intentions.

2.3 Review of the Model

To provide a view of the behaviour of the key elements of the Kyoto process the presented TEM model describes the economic interaction between several players (sometimes we say equivalently actors) which intends to maximize their reduction of emissions E_i caused by technologies T_i, by expenditures of money or by financial means M_i. The index stands for the i-th player. The players are linked by technical cooperations and by the market. The effectivity measure parameter em_{ij} describes the effect on the emissions of the i-th player if the j-th actor invests money for his technologies. We can say that it expresses how effective technology cooperations are (like an innovation factor), which is the central element of a JI

Program (and which will be the focus of our *uncertainty* approach). The variable φ can be regarded as a memory parameter of the financial investigations, whereas the value λ acts as a growth parameter. For a deeper insight see (Pickl, 1999). The TEM model is represented by the following two equations:

$$E_i(t+1) = E_i(t) + \sum_{j=1}^{n} em_{ij}(t) M_j(t), \tag{1}$$

$$M_i(t+1) = M_i(t) - \lambda_i M_i(t)\left[M_i^* - M_i(t)\right]\left\{E_i(t) + \varphi_i \Delta E_i(t)\right\} \tag{2}$$

Furthermore, we force that

$$0 \le M_i(t) \le M_i^*, \; i = 1,..., \; n \text{ and } t = 0,..., \; N .$$

Additionally we assume

$$-\lambda_i M_i(t)\left[M_i^* - M_i(t)\right] \le 0 \quad \text{for } i = 1,..., \; n \text{ and } t = 0,..., \; N .$$

Then we have guaranteed that $M_i(t+1)$ increases if $E_i(t) + \varphi_i \Delta E_i(t) \le 0$ and decreases if the term is positive. In the following part it is explained why this is necessary from a practical point of view. A detailed description is contained in Pickl (1999).

3. Empirical Foundation – Certainty versus Uncertainty

In the centre of the TEM model is the so called em-matrix. It is a great advantage of the TEM model, that we are able to determine the em_{ij}-parameter empirically. The parameters offer a quantitative measure of climate risk under a range of potential outcomes. This will be explained in the following in detail (This is a summary of the TEM model):

In the first equation of the TEM model, the level of the reduced emissions at the t+1-th time-step depends on the previous value plus a market effect. This effect is represented by the additive terms which might be negative or positive. In general, $E_i>0$ implies that the actors have yet reached the demanded value $E_i=0$ (normalized *Kyoto-level*). A value $E_i<0$ expresses that the emissions are less than the requirements of the treaty. In the second equation we see that for such a situation the financial means will increase, whereas $E_i>0$ leads to a reduction of $M_i(t+1)$. The second equation contains the logistic functional dependence and the memory parameter φ which describes the effect of the preceding investment of financial means.
The dynamics does not guarantee, that the parameter $M_i(t)$ lies in the interval, which can be regarded as a budget for the i-th actor. For that reason we have additionally to impose the following restrictions to the dynamical representation:

$$0 \le M_i(t) \le M_i^*, \; i = 1,..., \; n \text{ and } t = 0,..., \; N .$$

These restrictions ensure that the financial investigations can neither be negative nor exceed the budget of each actor. Now, it is easy to show that

$$-\lambda_i M_i(t)\left[M_i^* - M_i(t)\right] \le 0 \text{ for } \quad i = 1,\ldots, n \text{ and } t = 0,\ldots, N .$$

We have guaranteed that $M_i(t+1)$ increases if $E_i(t) + \varphi_i \Delta E_i(t) \le 0$ and it decreases if the term is positive. Applying the memory parameter φ, we have developed a reasonable model for the money expenditure - emission - interaction, where the influence of the technologies is integrated in the em-matrix of the system. We can use the TEM model as a time-discrete model where we start with a special parameter set and observe the resulting trajectories. Usually, the actors start with a negative value, i.e., they lie under the baseline mentioned in Kyoto Protocol. They try to reach a positive value of E_i. By adding control parameters, we enforce this development by an additive financial term. For that reason the control parameters are added only to the second equation of our model:

$$M_i(t+1) = M_i(t) - \lambda_i M_i(t)\left[M_i^* - M_i(t)\right]\left\{E_i(t) + \varphi_i \Delta E_i(t)\right\} + u_i(t).$$

The introduction of the control parameter $u_i(t)$ implies that each actor makes an additional investigation at each time-step. In the sense of environmental protection, the aim is to reach a state, mentioned in the treaty of Kyoto, by choosing the control parameters such that the emissions of each player become minimized. For details and the treatment as an approximation problem see Krabs (2004). The focus is the realization of the necessary optimal control parameters via a played cost game, which is determined by the way of actors cooperation. First of all it shall be discussed where and how this aspect can be integrated in the TEM model. For analysts it might be necessary to integrate a qualitative measure under a range of potential outcomes. If the em_{ij}-parameters will vary this approach considers the fact that analysts can use this model to simulate the potential financial behaviour and the risk of different policies on the electricity sector. Numerical examples are contained in Pickl (1999).

3.1 Uncertainty and Chaotic Behaviour

The numerical examinations which show that chaotic behaviour can occur,underline the necessity of a control theoretic approach which is implied by an additional control term in the second equation of the TEM model. In the sense of environmental protection, the aim is to reach a state mentioned in the treaty of Kyoto by choosing the control parameters such that the emissions of each player become minimized. The focal point lies in the realization of the necessary optimal control parameters via a played cost game, determined by the way of cooperation between the actors (Pickl, 2002). According to Kyoto Protocol, this approach means that each actor invests additional financial means. There are several possibilities to solve the problem of controllability.

3.2 An Analytic Approach

The TEM model presented in subsection 2.3 is a time-discrete system. Aiming at the time-discrete dynamics it can firstly be structured in the following way:

$$\begin{pmatrix} E \\ M \end{pmatrix}^{(k+1)} = M^{(k)}\left(\begin{pmatrix} E \\ M \end{pmatrix}^{(k)}\right)\begin{pmatrix} E \\ M \end{pmatrix}^{(k)}.$$

Having added the control parameter, we obtain the time-discrete dynamics

$$\begin{pmatrix} E \\ M \end{pmatrix}^{(k+1)} = M^{(k)}\left(\begin{pmatrix} E \\ M \end{pmatrix}^{(k)}\right)\begin{pmatrix} E \\ M \end{pmatrix}^{(k)} + \begin{pmatrix} 0 \\ u^k \end{pmatrix},$$

which we can represented by

$$(D\varepsilon) \quad \mathrm{E}^{(k+1)} = \mathrm{M}^{(k)}\mathrm{E}^{(k)}.$$

Here, the matrices $\mathrm{M}^{(k)}$ incorporate the control variables.

3.3 An Interval-Valued Model Approach

In this extended space notations, the variable E and entire dynamics $(D\varepsilon)$ could be enriched by further environmental and, in particular, genetical items and relations. The shift vector $\left(0^T, \left(u^{(k)}\right)^T\right)^T$ can be regarded as parametric and as a realization of $V\left(E, \overset{\vee}{E}^{v}\right)$; then stability and unstability regions can be determined by a very elegant approach. According to how those matrices are adjusted –and these matrices express the uncertainty behaviour-, we arrive at different behaviours of stability or instability of $(D\varepsilon)$, in the sense of dynamical systems or of parameter estimation. As a dual alternative to that feedback-like realization by the vector $V\left(E, \overset{\vee}{E}^{v}\right)$ which becomes incorporated into the matrix $\mathrm{M}^{(k)}$, the control vectors $u^{(k)}$ could also become integrated into $\mathrm{E}^{(k)}$. The time-dependent parameters $em_{ij}^{(k)}$ can then be treated in similar ways as the controls. Each $\mathrm{M}^{(k)}$ is an element of a finite set of interval matrices and the optimized outcome of a time-discretization. Partially, the parameters are estimated by means of a (generalized) Chebychev approximation and GSIP (Weber, 2007). With the remaining set of parameters, we represent and study different economical and decision scenarios. The aim of the TEM model is to reduce the CO_2 emission of the countries according to the Kyoto Protocol. This refers to real-world processes with all their uncertainties, but until now research with for the TEM model has been done with exact data (see for example the software TEMPI).:

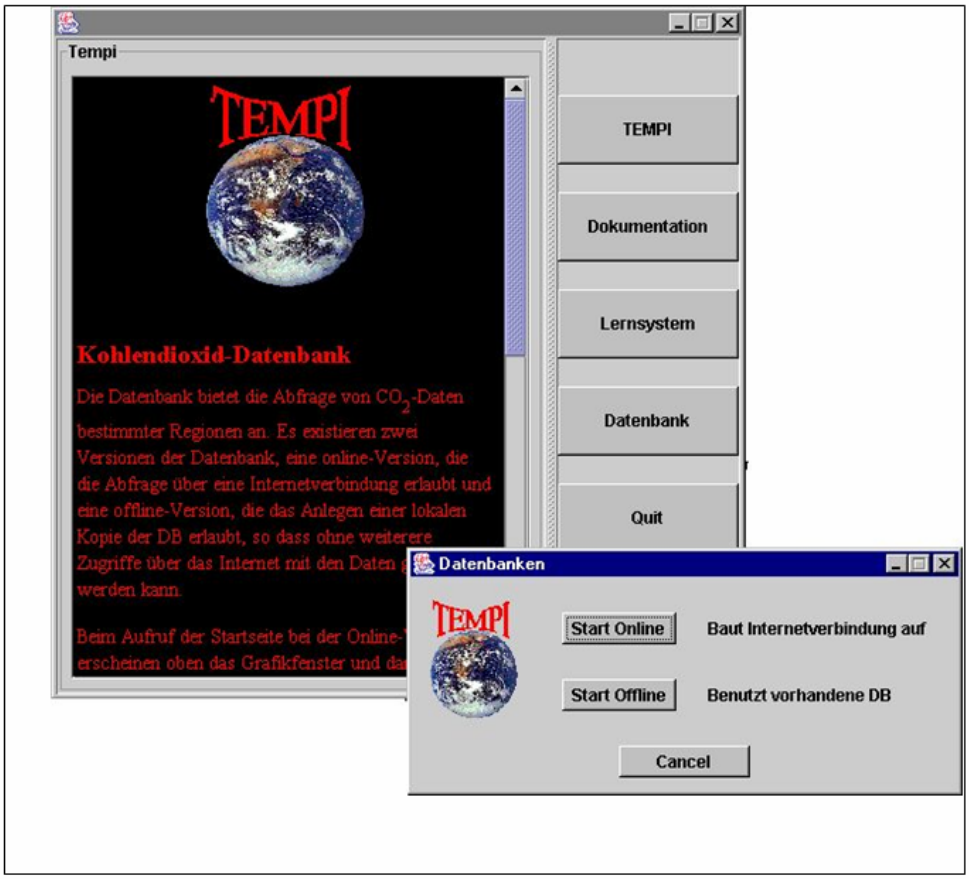

Figure 1: Interactive Software TEMPI – Technology Emissions Means Process Identification

The software initiates that the parameters can be reconsidered as intervals. This leads to a very elegant way to model and simulate
uncertainty aspects within the Kyoto Protocol. In the following paragraph uncertainty in general transaction relationships is discussed.

5. Coping with Uncertainty in General Transaction Relationships

In the following, we will analyze the problem of uncertainty that is inherent to many transaction relationships. Looking at it from a very general perspective, the problem arises because of the division of labor. As it was already shown by Adam Smith, we all gain by specializing on what we can do best. But we also depend on the outcome of other peoples' work, i.e. there is a need for technical and economic coordination for producing a joint outcome. The transition from one production stage to another produces friction and the interfaces between the different stages need to be managed therefore. From the perspective of neoclassical theory as the dominant theoretical position of economic theory, there is no real coordination problem in the first place because there is no uncertainty, or if, it is of a very certain kind. Referring to a distinction elaborated in Knight's dissertation , there might be either risk or uncertainty about the outcome of some event that has an (known) influence on the value of an economic activity like an investment. In the first case of risk, we are dealing with the problem of randomness in the outcome but we do know the probabilities. In the letter case (uncertainty), we are faced with the problem that we have no knowledge about the

probabilities of the outcome. For normal neoclassical analysis, we are dealing either with deterministic outcomes or with risk and not with uncertainty.
Even though a decision situation under uncertainty might be already a difficult starting point for neoclassical analysis, it is by far not the worst case. In a general and rather critical discussion of the treatment of uncertainty in neoclassical economic analysis, Langlois discussed two distinct kinds of uncertainty, i.e., parametric and structural uncertainty . In the case parametric uncertainty, we do know all the parameters of the decision problem though not their probabilities. However, in the case of structural uncertainty we are faced with the more fundamental problem that we do not know the structure of the decision problem in the first place.

Many parameters that might have a decisive influence on the outcome may only show up in later stages as the future unfolds but may be completely unknown and unknowable at the outset. Going back to the problem of the coordination of different economic agents, economic theory knows several coordination mechanisms of which markets or hierarchies are the extremes with cooperative and network organizations being some intermediate forms. Every form has its advantage but also preconditions for being appropriate for certain situations. Derived from the analysis of contract law by MacNeil that also influenced Williamson's version of transaction cost economics, we can apply three criteria for analyzing the "marketness" of transaction relationships: presentiation, i.e., completeness of ex-ante coordination, discreteness of transactions, and (the possibility of) anonymity of the partners to a transaction.

The first criterion of presentiation considers the possibility to realize the contract at present. That means that the contract can be comprehensively specified and if the contract should fail to materialize, remedies are easily found and sanction mechanisms enforced. The second criterion of discreteness refers to the interdependence between different transactions, i.e. if the different transactions are undertaken one by one, or if the first transaction already determines future transactions. The last criterion of anonymity analyses the relevance of the identity of the partners to a transaction. For market transaction, the identity is of little importance because of the exchangeability of the service or product provider given the criteria for the specification of the product are fulfilled.

Table 1: Characteristics of market and non-market transactions

Criteria	Market	Non-Market
Presentiation	-Comprehensive specification tools -Enforceable sanction mechanism	-Specification after the signing of the contract -Iterative specification
Discreteness	-Independent purchases -No binding effect because of past transactions	-Carry-over effects Lock-in because of past transactions -"Power asymmetry"
Anonymity of market participants	-No relevance who offers service/products -Trust in the institutional setting of the market place, e.g. sanction mechanism	-Product/service provider differ in terms of competence/quality -Trust in the relationship

It is therefore, in a sense, only a consequence of the first criterion. *Table* 1*1* compares the characteristics of market and non-market relationships as described by the three criteria. For non-market we face the situation that the criteria are not meet and what is described in the table is either the effect or reaction to the uncertainty that arises or that is the cause of it.

Taking the first criteria as a case in point, a lack of comprehensive specification tools makes a comprehensive specification impossible to reach. The hypothetical market for a potential product exchanged in it is, in a sense lacking the necessary specification infrastructure made up of a body of shared standards. For being able to communicate with the seller, the firm that wants to buy a product needs to know (1) what the specification provided with the product offered in a market means and (2) what kind of specification requirements the product, e.g. a high value component for a larger system has to meet given the specific demands of the firm. Hence, the customer needs to translate his or her needs into a specification language and compare it with the information that is provided along with the components. This information has to be specified or codified in the same specification language or at least in one the buyer is able to understand. Furthermore, the specification language must cover all the information that is important for that customer. Otherwise, an alternative medium (e.g. intensive business and long lasting learning relationships or the use of system integrators) for transmitting this information is necessary which raises information and transaction costs for assessing qualities others than those covered by, for example, a specification standard. The less structured the technological dialogue in a special domain is, the more likely is also a 'semantic mismatch' and uncertainty because of possible incompatibility arises. However, such specification languages (i.e. comprehensive standardization schemes) can be considered as the shared contractual infrastructure of the market place and has to be provided by the market place or as a public good by the commercial community who uses such markets.

However, before firms can agree on shared concepts underlying the specification language, they must be able to make their knowledge explicit and translate and codify it into such a specification language which allows them to communicate all relevant aspects with their business partners. The codification for such a structured exchange to reduce the friction between different vendors to increase the division of labor is often difficult to reach and there is a lively debate about the drivers and inhibitors of 'knowledge codification' (c.f. and for different views on the codification debate).

From the perspective of institutional economics, the main antecedents condition for market-like transactions is an institutional framework in which the transactions are embedded. Institutions can be defined as "the humanly devised constraints that structure human interaction. They are made up of formal constraints (e.g., rules, laws, standards) and informal constraints (e.g., norms of behavior, conventions, self imposed codes-of-conduct), and their enforcement characteristics" .

The economic 'raison d'etre' of institutions is therefore the reduction of uncertainty by providing a more structured interaction between economic agents so that some stable expectations about the economic outcome and the behavior of the transaction partners can be formed. As Coase points out, coordination situations that come closest to the ideal of perfect markets, e.g. commodity and stock exchanges, are in fact highly regulated by the underlying institutional framework in which the transactions are embedded .

6. Decision Processes within Uncertain Markets

From the perspective of institutional economics, we can derive a decision process which starts at the bottom with the determinants of the transaction uncertainty which might be defined by the nature of the products, or the competence and experience of the buyer, for example. These factors lead to certain 'uncertainty position' inherent in the transaction. There are two main instruments that can be used for the reduction of this uncertainty to a level that is acceptable (and cost effective). These are formal institutions, especially standards and legally enforceable measures and informal instruments like business relationships or any other socially sanctioned trust mechanism.

Given the remaining uncertainty, the coordination mechanism will be chosen, either market transaction, cooperative arrangements or even the acquisition of the firms that offers the good or the decision to start production if the firm has the competence and the importance of the products justifies such a make instead of buy decision.

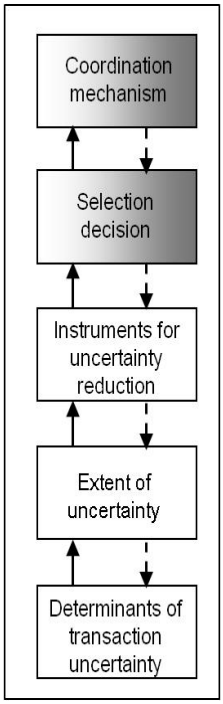

Figure 2. Decision Process for the Coordination and Reduction of Uncertainty

7. Outlook

In this short discussion about the problem of uncertainty in transaction relationships, we have presented different understandings of uncertainty and related concepts (risk, parametric, and structural uncertainty) and the relationship with the coordination problem that arises because of the division of labor. We have then discussed markets as coordination mechanism. Markets however presuppose a very structured and well defined exchange process. To reach such a state of maturity, a body of standards as 'contract infrastructure' is necessary. We briefly discussed the knowledge codification aspect of establishing such an infrastructure and finished the discussion with presenting a decision process about the appropriate coordination mechanism based on the ability of the institutional infrastructure to reduce the uncertainty to an acceptable level. The less uncertainty remains, the more likely is a market transaction. High levels of uncertainty instead favor more cooperative transaction relationships. The

decision to rather control the production process might be another option if justified by the relevance of the products and the costs involved. In a future contribution the application of such an decision procedure to a emission trading market will be discussed.

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Resolution of Stochastic Issues in Estimating Forest Biomass Carbon Stock Changes Using Non-linear Mixed Models

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Abstract

Under the agreed terms of the Kyoto protocol, Ireland is committed to reduce green house gas (GHG) emissions by 13 % above the 1990-base year level. This poses a tremendous challenge, given the rapid growth of the Irish economy in the past decade, since current green house gas (GHG) emission levels are 23 % above the 1990 level. Assuming a business as usual scenario, it is estimated that the contribution of national forests, under Article 3.3, may offset ca. 16 % of the required GHG emissions for the first commitment period (2008 to 2012). However, estimation of the extent to which forests sequester carbon in the mid to long-term is hindered is by a high degree of uncertainty due to spatial heterogeneity and temporal variability. Sensitivity analysis on the national forest sink model (CARBWARE) suggests that the largest degree of uncertainty (ca 30%) was associated with the estimation of vegetation carbon sink. Uncertainty of the vegetation sink was affected most by assumptions on forest management (i.e. forest stocking input data) and biomass algorithm errors. CARBWARE was re-parameterised and improved using permanent plot data to better reflect changes in stand structure over the entire rotation in the Irish forest estate. This implies that stand management assumptions used in the model can significantly influence the uncertainty associated with the estimation of national forest sink capacity.

Introduction

Under the agreed terms of the Kyoto protocol, Ireland is committed to reduce green house gas (GHG) emissions by 13 % above the 1990-base year level. Forest Carbon Sequestration (FCS) is one possible method whereby countries may attempt to offset their emissions of greenhouse gases. In FCS, atmospheric carbon is fixed into organic compounds by forest vegetation, and the net emission of CO_2 is thereby reduced. Increasing forest production so as to increase carbon sequestration takes place in many industrialised countries (Thompson and Matthews, 1989). Globally forests and forest soils represent large carbon reservoirs. Although FCS offers no long term way of reducing atmospheric CO_2 concentrations if humans continue to use fossil fuels, forests can make a significant contribution to the stabilisation of atmospheric CO_2 levels until alternatives to existing energy sources are developed (Kilbride et al., 1999). The present work presents an insight into the ongoing development of the Irish national forest carbon sink model (CARBWARE). CARBWARE estimates the carbon stock

changes in the biomass, litter and dead-wood carbon pools over time. In the present work, particular emphasis is placed on the estimation of the biomass pool.

There have been few studies on the Carbon sink capacity of Irish forests. Using a single biomass expansion factor (BEF) of 1.3 t t^{-1} for all species, ages and yield classes, Kilbride et al. (1999) estimated that the average rate of carbon sequestration by Irish forests is approximately 3.36 t C ha^{-1} yr^{-1}. Black et al. (2004) later developed allometric regressions for estimating forest biomass which they used to predict changes in biomass expansion factors for a Sitka spruce chronosequence. They developed these models using a USDA inventory database and cross-validated them with an Irish biomass data set. They found that the BEF used by Kilbride et al. (1999) caused carbon stocks to be underestimated by between 2- and 4-fold for sites afforested since 1990. They noted the importance of forests of that age as determined by Article 3.3 of the Kyoto protocol, which states that only that carbon sequestered at sites afforested since 1990 is eligible for the issuance of RMU's (removal units.

Models of the carbon stock of Irish forests are important tools for the estimation of the national forest carbon stock. In this context, Gallagher et al. (2004) noted that accurate and up-to-date information is essential for realistic carbon stock estimates and predictions. They noted that carbon stock models can be constantly updated and improved by including the most up-to-date planting and felling data, age and species distributions, volumes, increments and stocking levels, all of which data may be obtained from a national inventory of the forest estate. Due to various constraints, such inventories are typically carried out intermittently, and so models are important tools to estimate the change in carbon stocks over time when inventory information is not up-to-date. The level of uncertainty attached to such model estimates is therefore of interest to scientists and policy-makers.

In order to update Carbon stock models using up-to-date inventory data it is first necessary to correctly parameterise the model from sample data relating to forest stands or individual trees measured over time. It is necessary to allow for serial correlation in the data when carrying out such an exercise. The dependent variable of interest in these inventories is also typically non-normally distributed and bounded in some way, e.g. cumulative gross primary production is non-negative. The models themselves are typically made up of non-linear growth functions. Modelling frameworks that can address all of these issues include the state-space approach (Garcia, 1994) and mixed-models methodology (McCulloch and Searle, 2001). Models that build on the latter methodology have been applied in a variety of modelling studies of the growth of forest stands, including additive generalized linear mixed models (Candy, 1997) and generalized nonlinear mixed effects models (Atsushi & Marušak, 2007).

The potential of a given forest to sequester carbon at different ages can be determined by natural or disturbance-related perturbations in gross primary productivity, net primary productivity and respiration. Disturbance-related changes include various management practices, such as planting, thinning and harvesting. One aim of the present work is to incorporate data on thinning and harvesting events into the parameterisation of CARBWARE for the major forest type in Ireland, Sitka Spruce. This is achieved by parametrising the model using a database of Irish forest stand records developed by The Irish Forestry Board Limited (Coillte) over a period of 60 years. The Coillte database contains records of many descriptive statistics for forest stands, including tree diameter at breast height, top height, basal area, stocking density and volume. Records in the database cover a time period from the early 1960's to the present. Plots on which these measurements were taken were managed in a variety of ways, including selective thinning, systematic thinning, and no thinning.

Updating CARBWARE Using Panel Data

Prior to the present work, the biomass growth curves in CARBWARE were based on tree-level allometric functions obtained from recent research (Monteith, 2000) and stand attributes according to the British Forestry Commission yield models (Edwards & Christy, 1981; Black & Farrell, 2006). This approach was taken due to the lack of inventory information when the model was developed. In the present work we describe the re-parameterisation and improvement of the model using panel data obtained from repeated measurements of stand characteristics over a period of 60 years. CARBWARE estimates stand biomass using as an input the stand mean tree diameter at breast height. For each stand in the Coillte database, the DBH of each tree in the plot is measured at various times over the rotation of the stand. This gives a longitudinal dataset from which makes it possible to use CARBWARE to estimate the stand biomass at any particular time over the stand rotation. CARBWARE can be written as follows:

$$B(t) = (\frac{Cm}{Rm}) * \ln[1 + (\frac{C0}{Cm})e^{Rm*t}] * [\frac{1 - e^{(-k_s(k_t - t))}}{1 - e^{-k_s(k_t * t)}}] \quad (1)$$

Where *Cm*, *Rm*, *C0* are defined as the maximum growth rate, the initial relative growth rate, and the initial absolute growth rate, respectively. k_s and k_t are parameters influencing the form of the estimated growth curve, and *t* is a time variable (years). B(t) is the cumulative stand biomass at time *t* which is estimated using an allometric relationship between DBH and biomass (Black et al., 2004).

In the present work we analyse the Coillte panel data using non-linear mixed effects models to allow for the particular features of the response data noted in the Introduction. Mixed-effects models provide an enormous variety of modelling options and our work in selecting the optimal model formulation is ongoing. However, we present here an example of a preliminary model formulation: Using the Coillte database of panel data we estimated the following non-linear mixed effects model of stand biomass for the *i*th forest stand:

$$E(\ln(B_i(t)) \mid p_i) = \ln[(\frac{Cm}{Rm}) * \ln[1 + (\frac{C0}{Cm})e^{Rm*t}] * [\frac{1 - e^{(-k_s(k_t - t))}}{1 - e^{-k_s(k_t * t)}}]] + p_i \quad (2)$$

Where E(.) is the expectation and p_i is a zero-mean Gaussian random variable with variance σ^2_u that models between-plot variability. An implicit assumption in model (2) is that each series of plot measurements in the Coillte database represent random samples from a hypothetical population of plots. Based on equation (2) the model estimate of the expected stand Biomass for that hypothetical population is given by:

$$B(t) = (\frac{Cm}{Rm}) * \ln[1 + (\frac{C0}{Cm})e^{Rm*t}] * [\frac{1 - e^{(-k_s(k_t - t))}}{1 - e^{-k_s(k_t * t)}}] * e^{(\frac{\sigma_u^2 + \sigma^2}{2})} \quad (3)$$

where σ^2_u and σ^2 are the estimated between-plot and and within-plot variance parameters, respectively. The last factor on the RHS of equation (3) is a bias-correction factor that evolves as a result of assuming that observations on the same plot share a common but unobservable effect (p_i in equation 2). Although it may be possible to specify a marginal model for the expectation of stand biomass, that approach would require separate models for the within-

subject associations and for the effects of model parameters on the marginal expectation (Diggle et al., 2002). By contrast, the conditional formulation described by equation (2) allows us to model the covariate effects and the within-plot associations through a single equation. The model described by equation (2) also allows for serial correlation between successive measurements on a given plot. Estimating CARBWARE in this way provides a platform for an uncertainty analysis of the model estimates which we discuss in our presentation.

Concluding Summary

This short paper presents an introduction into some of the topics that we will discuss in our presentation. Previously, CARBWARE was parametrised using data that was derived under a strong assumption of a marginal thinning intensity management scheme for a variety of yield classes (Black and Farrell, 2006). This approach was taken because of an absence of forest inventory data. The present work parametrises the model using inventory data and evaluates the uncertainty associated with CARBWARE estimates of cumulative stand biomass, and hence of the national forest carbon sink.

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Statistical Spatial Modeling of Gridded Air Pollution Data

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Abstract

This paper aims to contribute to comparing gridded top-down and bottom-up inventories of atmospheric emissions. We propose a statistical (hierarchical Bayesian) model in which bottom-up emission assessments are treated as dependent variable and spatially explicit activity data are treated as covariates. The results of our illustrative example suggest excluding from further analysis two initially considered covariates, and indicate existence of another spatially correlated factor.

1. Introduction

Our contribution is focused on the spatial aspect of inventories for atmospheric pollutant emissions. This perspective is motivated with situations when top-down and bottom-up inventories for the same area and for the same pollutant are available. While all inventories have features of a bottom-up, and of a top-down; the difference is the following. The bottom-up inventory contains detailed information on source types, locations and their emissions. A top-down inventory generally has low spatial resolution. When activity data (e.g. land use, vehicle or other) are available, a top-down inventory is spatially distributed, using these statistics and appropriate emission factors. The idea is then to compare this map with a reference bottom-up inventory, and try to conclude on the relevance of activity data used.

This kind of analysis has been already performed in some studies (Winiwarter *et.al.*, 2003). We apply statistical spatial model (Banerjee *et.al.*, 2004) to compare bottom-up inventory with spatially available activity data, which we treat as covariate information.

2. Statistical model for spatial data

Since the data from inventories are aggregated for each grid cell and they are available on a discrete space, we make use of a model based on Markov random fields. Consider random variables associated with the observations (bottom-up inventory data, in our case) defined at n spatial locations (the lattice areas) and denoted $Y^T = (Y_1, \ldots, Y_n)$. Let the random variables Y_i follow a normal distribution

$$Y_i \sim N(\mu_i, \sigma^2) \quad i=1,\ldots,n \tag{1}$$

with mean μ_i and variance σ^2. Conditionally on the parameters, it is assumed that the components of Y are independent. Let μ_i represent the true underlying emission process. The model of this process is formulated as a conditionally autoregressive (CAR) model, i.e. by

specifying full conditional probability density functions of a Gaussian (normal) form (Banerjee *et.al.*, 2004; Cressie, 1993):

$$\mu_i | \mu_j,\ i \neq j \sim N\left(x_i^T\beta + \Sigma_{j \in Ni}\, w_{ij}(\mu_j - x_j^T\beta)/\, w_{i+},\ \tau^2/\, w_{i+}\right) \qquad i = 1,\ldots,n \tag{2}$$

where $x_i^T = (1, x_{i,1}, x_{i,2}, x_{i,3})$ are explanatory spatial covariates (in the sequel we will use three available covariates) with parameter coefficients $\beta^T = (\beta_0, \beta_1, \beta_2, \beta_3)$, N_i is the set of neighbors of area i defined by the lattice structure, w_{ij} are adjacency weights ($w_{ij}=1$ if j is a neighbor of i, and 0 otherwise, also $w_{ii}=0$), w_{i+} is the number of neighbors of area i and τ^2 is the variance parameter. In our case two areas are considered as neighbors if they share common border. The sum in the mean of conditional distribution (2) expresses that we expect available spatial covariates to explain part of the spatial pattern, and the remaining part is captured through a regional clustering. Conditional variance of μ_i is inversely proportional to the number of neighbors of area i, which means that the more neighbors is assigned to the area, the lower the variance it has. It should also be stressed that we model spatially the mean μ_i, and not the observations Y_i themselves. It introduces the hierarchical structure, but allows for greater flexibility.

The above full conditionals (2) lead to a joint distribution of $\mu^T = (\mu_1, \ldots, \mu_n)$ (Cressie, 1993):

$$\mu \sim \mathrm{N}\,(\mathrm{t},\ (D\text{-}W)^{-1}M) \tag{3}$$

where $\mathrm{t} = [x_i^T\beta]_{n*1}$, $D = \mathrm{diag}[w_{i+}]_{n*n}$, $W = [w_{ij}]_{n*n}$, $M = \mathrm{diag}[\tau^2]_{n*n}$. It is a multivariate normal distribution with the mean specified by covariates, and a diagonal matrix of variance τ^2 which is appropriately modified by the neighborhood structure.

Estimation of unknown parameters β, τ^2 and σ^2 is done with the Bayesian approach. The joint posterior distribution of unknown parameters given the data $p(\beta, \tau^2, \sigma^2 | Y, X)$ is proportional to the likelihood of data given the parameters $L(Y | \mu, \sigma^2)$ times prior distributions of parameters:

$$p(\beta, \tau^2, \sigma^2 | Y, X) \propto L(Y | \mu, \sigma^2)\, p(\mu | \beta, \tau^2)\, p(\beta)\, p(\tau^2)\, p(\sigma^2) \tag{4}$$

where $X = [x_i]_{4*n}$. Symbol '$\propto$' means equal up to a constant. To establish the likelihood function $L(Y | \mu, \sigma^2)$ we recall that elements of vector Y were assumed independent, normally distributed given the mean vector μ and variance σ^2. It gives us a multiplication of normal distributions:

$$L(Y | \mu, \sigma^2) = (\sigma\sqrt{2\pi})^{-n} \exp\left[-(2\sigma^2)^{-1}\, \Sigma_i (y_i - \mu_i)^2\right] \qquad i = 1,\ldots,n \tag{5}$$

The joint prior distribution for mean vector $p(\mu | \beta, \tau^2)$ is defined in (3). For the remaining distributions we used the following non-informative priors (suggested in the literature). Normal distributions were assumed for parameter coefficients $\beta_k \sim N\ (0,\ 10^{-5})$, $k = 1,2,3$ except for the intercept which was assigned improper uniform distribution $p(\beta_0) \propto 1$. Both variances were assumed independent, inverted gamma priors $\sigma^2 \sim IG\ (1,\ 0.1)$, $\tau^2 \sim IG\ (0.5,\ 0.0005)$.

The posterior distribution of parameters is obtained using numerical integration based on Markov Chain Monte Carlo methods (Gamerman and Lopes, 2006). The model was estimated using the WinBUGS software (Lunn *et.al.*, 2000).

3. Data and Results

The data set consists of data on CO emissions (in tones) reported in municipalities of southern Norway (*Figure 1*). We use a log transformation on the emission data to ensure a constant variance. The map comprises 259 municipalities. The data come from StatBank in Statistics Norway (available at http://www.ssb.no). For each municipality three kinds of covariate information are available (*Figure 2*). Covariates are also log transformed for further analysis. Let us then denote for each area i ($i = 1,\ldots,n$):

y_i - (log) CO emissions (in tones)
$x_{i,1}$ - (log) total area (in km^2)
$x_{i,2}$ - (log) population
$x_{i,3}$ - (log) area covered by roads (in km^2)

An initial linear regression model

$$y_i = \beta_0 + \beta_1 x_{i,1} + \beta_2 x_{i,2} + \beta_3 x_{i,3} + \varepsilon_i \qquad i = 1,\ldots,n$$

showed that each covariate is significant (for each parameter coefficient p-value was lower than 2E(-10)), additionally coefficient of determination was calculated: $R^2 = 0.87$.
Residuals of the linear regression were checked for spatial correlation using Moran's I statistic:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(\varepsilon_i - \bar{\varepsilon})(\varepsilon_j - \bar{\varepsilon})}{\sum_i (\varepsilon_i - \bar{\varepsilon})^2} \qquad i, j = 1,\ldots,n$$

where ε_i - residual of linear regression in area i, $\bar{\varepsilon}$ - mean of residuals. Moran's I can be recognized as a modification of correlation coefficient. It accounts for correlation between residuals in area i and residuals in nearby locations. The purpose of the first fraction on the right hand side is to standardize the statistic. Under a null hypothesis where ε_i are independent and identically distributed (i.i.d.), I is asymptotically normally distributed, with the mean and variance defined e.g. in Banerjee *et.al.*, 2004, see also Kopczewska, 2006. In our case the test statistic (standardized Moran's I) is equal $z = 4.65$ ($z_{cr} = 2.33$ at the significance level $\alpha = 0.01$), which suggests evidence against a null hypothesis of no spatial correlation of errors. Moran's I is, however, recommended just as an exploratory information on spatial association, rather than a measure of spatial significance.

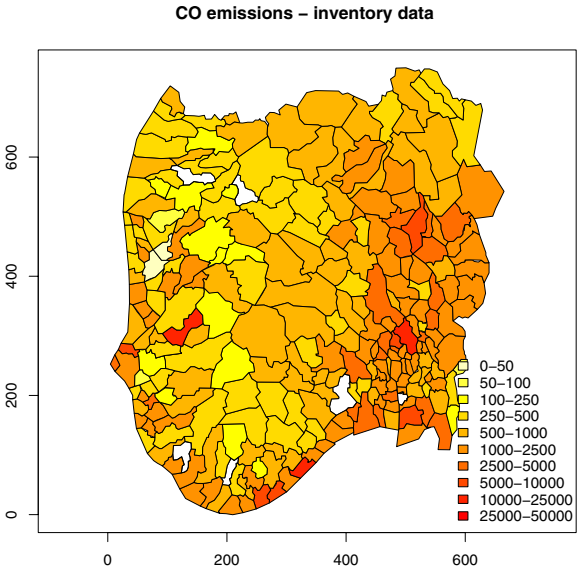

Figure 1. CO emission data (y_i) in tones

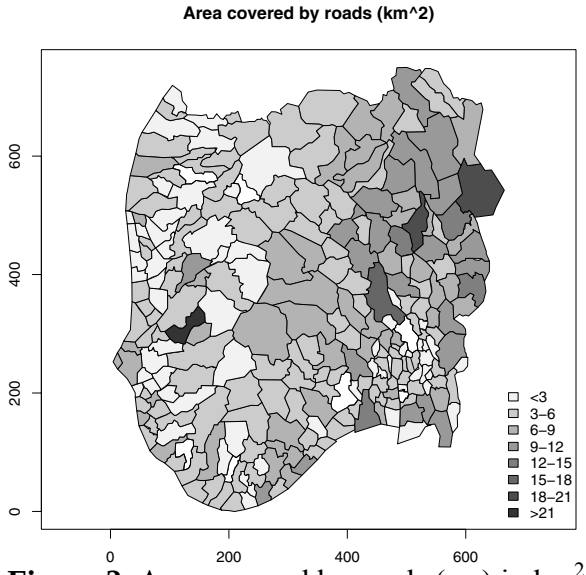

Figure 2. Area covered by roads ($x_{i,3}$) in km^2

Spatial CAR models have been applied to the Norway emission data. Using DIC statistics we compare various combinations of covariate data between the spatial and linear regression models (*Table 1*):

$$\overline{D} + p_D = DIC$$

$\overline{D}$ - posterior deviance (a measure of fit)

p_D - effective number of parameters (a measure of complexity)

Table 1. Model comparison using DIC statistics

model	$\overline{D}$	p_D	DIC
CAR (x_1, x_2, x_3)	217	108	325
CAR (x_1, x_2)	790	60	850
CAR (x_3)	-377	317	-60
linear regression (x_1, x_2, x_3)	415	5	420
linear regression (x_3)	588	3	591

We note that the best result (the lowest DIC) is obtained for spatial CAR model with only one ancillary data on roads (x_3), outperforming among others the CAR model with all the covariates. In case of a simple linear regression the situation was the opposite. It indicates that there exists missing, spatially correlated variable contributing to overall emissions much better than the initial variables x_1, x_2. Just for a comparison there are shown also results for CAR (x_1, x_2) model. Here the situation is quite typical. We have less parameters compared with the case of three covariates and thus lower complexity, on the other hand the model fit is much worse.

Parameter estimates are shown in *Table 2*. Comparing results for model CAR (x_1, x_2, x_3) with results for linear regression, we see that although the 95% credible intervals for β_1 and β_2 does not include zero, their values moved towards zero considerably. On the other hand, estimate of β_3 remained almost the same. It generally confirms our previous conclusion.

Table 2. Parameter estimates (for spatial CAR models 95% credible limits are given in brackets)

variable	linear regression	model CAR (x_1, x_2, x_3)	model CAR (x_3)
β_0	4.027	4.169 (3.91, 4.46)	4.794 (4.72, 4.87)
β_1	-0.308	-0.198 (-0.26, -0.13)	-
β_2	0.266	0.182 (0.13, 0.23)	-
β_3	1.497	1.462 (1.38, 1.53)	1.322 (1.27, 1.38)

Maps of posterior mean for the models are shown on *Figure 3* and *Figure 4*. It can be noticed that model CAR (x_3) maps the original data (*Figire 1*) much better.

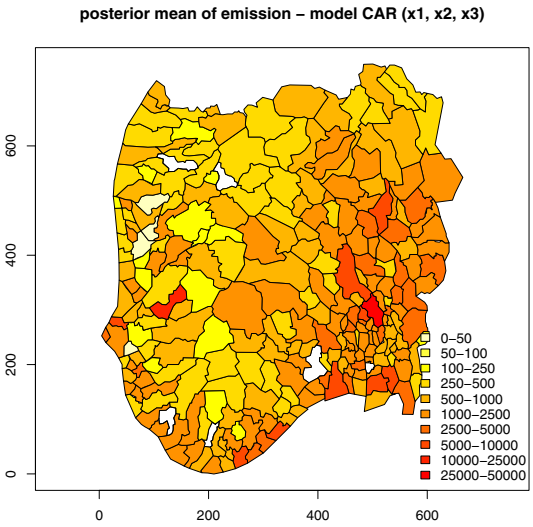

Figure 3. Posterior mean of emission in tones for model CAR (x_1, x_2, x_3)

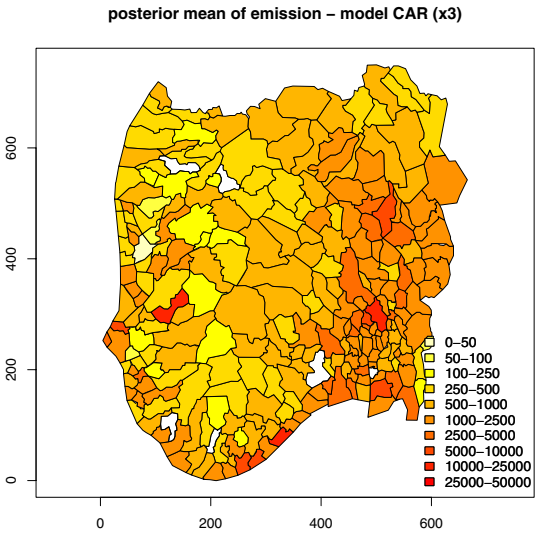

Figure 4. Posterior mean of emission in tones for model CAR (x_3)

4. Conclusions

We have shown the application of spatial conditionally autoregressive model to examine influence of activity data towards independent, bottom-up inventory. While better or poorer appropriateness of covariates can be judged visually from the maps beforehand, the proposed model gives a quantitative result.

Our results suggest excluding from further analysis two initially considered covariates, and indicate existence of another, spatially correlated factor. Generally, such situation - that we get better results just for a subset of covariates plus a spatial component - is not unusual. The point of this contribution was to make use of this approach for comparison of inventory data.
It should be noted that our exercise is to some extend illustrative and in a more realistic application more informative results could be obtained. For example, a potentially problematic part of inventory are emission point sources (plants), which are correctly reported in a bottom-up approach but are missing in ancillary datasets (Winiwarter, 2007). The proposed method seems to be capable to identify such cases.

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Comparison of Preparatory Signal Detection Techniques for Consideration in the (Post-)Kyoto Policy Process

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Key words: Kyoto Protocol, greenhouse gas emissions, emission limitation and reduction commitments, uncertainty, compliance, detection of emission changes

Abstract

Knowledge provided so far of how to go about uncertain emissions and emission changes under the Kyoto Protocol is believed to be appropriate for putting the (post-) Kyoto policy process on a sound basis. Unfortunately, this is not the case. Here we compare six techniques to deal with uncertain emissions and emission changes from a pure technical point of view. Adding the philosophical dimensions underlying these techniques allows us to generate indispensable knowledge for deciding on how to go about uncertainty, and the Protocol from a more general point of view, in the (post-) Kyoto policy process.

1. Introduction

As a consequence of the Kyoto policy process running ahead of science, decision-makers are confronted with a number of severe problems that require careful consideration such as: closing the gaps in the accounting of greenhouse gas (GHG) emissions bottom-up and top-down; the trading of verifiability (bottom-up/top-down) for allowing parts of the biosphere to enter the Kyoto Protocol; linking long-term concentration targets with short-term emission commitments; and learning how to handle uncertainty in the context of reported emissions and emission changes.

The focus on our study is on the latter. It aims at providing a preparatory guide for considering uncertainty in the (post-) Kyoto policy process. We compare available techniques to detect uncertain emission changes (also called emission signals) that countries agree to realize by a specified point in time. Although highly needed, no such technique is in place. From the Kyoto Protocol we know that for almost all countries the emission changes agreed upon under the Protocol are in the same order of magnitude as, if not smaller than, the uncertainty that underlies their combined (CO_2 equivalent) emissions. Clearly, such a technique, if implemented, would be the key to determine the "make or break" of compliance, especially in cases when countries claim the fulfillment of their reduction commitments.

Jonas *et al.* (2004a) distinguish between preparatory signal detection (SD), midway SD, and SD in retrospect, of which the first is most advanced. Preparatory SD allows generating useful information beforehand as to how great uncertainties can be depending on the level of confidence of the emission signal, or the signal one wishes to detect and the risk one is willing to tolerate in not meeting an agreed-upon emission limitation or reduction commitment. Here

we quantitatively compare six different preparatory SD techniques, some of which have been presented at the 1st Workshop on Uncertainty on GHG Inventories (Gillenwater *et al.*, 2007; Jonas *et al.*, 2007; Nahorski *et al.*, 2007). These techniques all agree that uncertainty analysis is a key component of GHG emission analyses. However, they all have their pros and cons and can have a major impact on the design and execution of emission control policies. Providing this comparative basis encompassing six preparatory SD techniques is new. It is this basis which is needed to generate indispensable knowledge for deciding on how to go about uncertainty, and the Protocol from a more general point of view, in the (post-) Kyoto policy process.

2. Definitions and Agreements (abridged)

Signal detection: In our study this term is used in a more general context which goes beyond the strict definition of signal detection (which asks for the time of when an emission change outstrips uncertainty). It also encompasses the notion of significance as used in classical statistics.

Grouping of countries: See T*able 1*.

3. Overview of the Techniques and Their Characteristics (abridged)

Comparison of the major characteristics of the six preparatory SD techniques: See *Table 2*.

4. Preparatory SD Techniques

4.1. Critical Relative Uncertainty Concept

Starting Point:

Annex I countries comply with their emission limitation or reduction commitments under the Kyoto Protocol.

Assumptions:

(1) The relative uncertainty (ρ) of a country's net emissions (x) shall be symmetrical and not change over time, i.e., $r_1 = r_2 (= r)$.

(2) The absolute change in net emissions shall outstrip absolute uncertainty (ε) at t_2, i.e., $|x_1 - x_2| > e_2$.[5]

Systems View:

Intra-systems view suited to support inter-systems (e.g., top-down) view: Only our real diagnostic capabilities of grasping emissions at any point in time—reflected by absolute uncertainty $\varepsilon(t)$—are of interest, i.e.: the uncertainty we encountered in the past, the uncertainty that underlies current estimates, and the uncertainty that we have to cope with in reality at some time in the future. Correlation over time between uncertainties is of no concern for this physically based approach.

[5] The critical relative uncertainty (CRU) concept only considers uncertainty in the commitment year/period, not in the base year (i.e., formally $\varepsilon_1 = 0$). However, for reasons of comparability, we continue to abide by the condition of constant relative uncertainty.

Question:

What are the critical (or maximal) relative uncertainties (CRUs; ρ_{crit}) that can be reported by Annex I countries so as to ensure favorable detection in the commitment year?

Approach:

Deterministic (see *Figure 1*)

Answer:

The answer is given by

$$r_{crit} := \frac{|d_{KP}|}{(1 - d_{KP})}, \qquad \text{(A-6)}$$

where ρ_{crit} is the CRU and d_{KP} the normalized emissions change committed under the Kyoto Protocol (KP) between t_1 and t_2 ($d_{KP} > 0$: emission reduction; $d_{KP} \leq 0$: emission limitation).

Result:

See last column in *Table 3*. The CRU concept cannot remedy the nonscientific shortcomings of the Kyoto Protocol.

4.2. Verification Time Concept

Starting Point:

Annex I countries comply with their emission limitation or reduction commitments under the Kyoto Protocol.

Assumptions:

(1) The relative uncertainty (ρ) of a country's net emissions (x) shall be symmetrical and not change over time, i.e., $r_1 = r_2 (:= r)$.

(2) The absolute change in net emissions shall outstrip uncertainty at time t (which can be $\leq$ or $> t_2$), i.e., $|\Delta x(t)| > e(t)$.

Systems View:

Intra-systems view suited to support inter-systems (e.g., top-down) view: Only our real diagnostic capabilities of grasping emissions at any point in time—reflected by absolute uncertainty $\varepsilon(t)$—are of interest, i.e.: the uncertainty we encountered in the past, the uncertainty that underlies current estimates, and the uncertainty that we have to cope with in reality at some time in the future. Correlation over time between uncertainties is of no concern for this physically based approach.

Question:

What are the times (also called verification times; VTs) when the countries' emission signals outstrip uncertainty?[6]

Approach:

Deterministic (see *Figure 2*)

Answer:

The answer is given by

$$\frac{\Delta t}{t_2 - t_1} > \frac{r}{|d_{KP}| + d_{KP} r} \quad , \tag{B-7a}$$

where Δt is the VT and $t_2 - t_1$ the time between base year and commitment year/period, upon which the VT is normalized.

Result:

See last column in *Table 4*. The VT concept cannot remedy the nonscientific shortcomings of the Kyoto Protocol.

4.3. Undershooting Concept

Starting Point:

Annex I countries comply with their emission limitation or reduction commitments under the Kyoto Protocol.

Assumptions:

(1) Uncertainties at t_1 and t_2 are given in the form of intervals, which take into account that a difference (ε) might exist between the true (t) but unknown net emissions (x_t) and their best estimates (x).

(2) The relative uncertainty (ρ) of a country's net emissions is symmetrical and does not change over time, i.e., $r_1 = r_2 (= r)$.

Systems View:

Intra-systems view: Correlation of uncertainty over time matters.

Question:

Taking into account the combined uncertainty at t_2 and considering that the true emissions are not known, how much undershooting (Und) is required to limit the risk α that countries overshoot their true emission limitation or reduction commitments?

[6] The term "verification time" was first used by Jonas *et al.* (1999) and by other authors since then. A more correct term is "detection time" as signal detection does not imply verification. However, we continue to use the original term as we do not consider it inappropriate given that signal detection must, in the long-term, go hand-in-hand with bottom-up/top-down verification of emissions (see Jonas and Nilsson, 2007: Section 4).

Approach:

Quasi-statistical, based on interval calculus (see *Figure 3*)

Answer:

The answer is given by

$x_{t,2} \geq (1 - d_{KP}) x_{t,1}$ with risk $\alpha \Leftrightarrow$

$$\frac{x_2}{x_1} \leq (1 - d_{KP}) \frac{1 - (1 - 2a)(1 - n)r}{1 + (1 - 2a)(1 - n)r} = 1 - d_{mod}, \qquad \text{(C-13a,c)}$$

where ν approximates (first-order approach) the net (effective) correlation between ε_1 and ε_2; and d_{mod} is the countries' modified (mod) emission limitation or reduction targets defined via

$$d_{mod} = d_{KP} + U \qquad \text{(C-15)}$$

and the undershooting U via

$$U = 2(1 - d_{KP}) \frac{(1 - 2a)(1 - n)r}{1 + (1 - 2a)(1 - n)r} . \qquad \text{(C-18)}$$

Result:

See last column in *Table 5*. The Und concept cannot remedy the nonscientific shortcomings of the Kyoto Protocol.

4.4 Undershooting and Verification Time Concepts Combined

Starting Point:

Annex I countries comply with their emission limitation or reduction commitments under the Kyoto Protocol.

Assumptions:

(1) Uncertainties at t_1 and t_2 are given in the form of intervals, which take into account that a difference (ε) might exist between the true (t) but unknown net emissions (x_t) and their best estimates (x).

(2) The relative uncertainty (ρ) of a country's net emissions is symmetrical and does not change over time, i.e., $r_1 = r_2 (:= r)$.[7]

[7] The combined undershooting and verification time concept (Und&VT) only considers uncertainty in the commitment year/period, not in the base year. However, for reasons of comparability, we continue to abide by the condition of constant relative uncertainty.

(3) The absolute change in net emissions shall outstrip uncertainty at time $t \le t_2$, i.e., the VT shall be equal to or smaller than the maximal allowable VT ($\Delta t \le t_2 - t_1$).

Systems View:

Intra-systems view suited to support inter-systems (e.g., top-down) view: Only our real diagnostic capabilities of grasping emissions at any point in time—reflected by absolute uncertainty $\varepsilon(t)$—are of interest, i.e.: the uncertainty we encountered in the past, the uncertainty that underlies current estimates, and the uncertainty that we have to cope with in reality at some time in the future. Correlation over time between uncertainties is of no concern for this physically based approach.

Question:

Referring to risk as the strength of the Und concept and to time in detecting an emission signal as the strength of the VT concept, can these concepts be combined (Und&VT) so as to take advantage of the two?

Approach:

Quasi-statistical, based on interval calculus (see *Figure 4*)

Answer:

Depending on how δ_{crit}, the critical (crit) emission limitation or reduction, and δ_{KP} relate to each other, the answer comprises four cases (see *Figure 4*). δ_{crit} allows distinguishing between detectable and nondetectable emission changes.[8] The complete answer is given by

$x_{t,2} \geq (1 - d_{KP}) x_{t,1}$ with risk $\alpha \Leftrightarrow$

Case 1: $\delta_{KP} > 0$: $\delta_{crit} \le \delta_{KP}$:

$$\frac{x_2}{x_1} \leq (1 - d_{KP}) \frac{1}{1 + (1 - 2a) r} = 1 - d_{mod} , \qquad \text{(D-3), (C-13c)}$$

where d_{mod} is defined as before (see Equation (C-15)) and U via

$$U = (1 - d_{KP}) \frac{(1 - 2a) r}{1 + (1 - 2a) r} . \qquad \text{(D-5)}$$

Case 2: $\delta_{KP} > 0$: $\delta_{crit} > \delta_{KP}$:

$$\frac{x_2}{x_1} \leq (1 - d_{crit}) \frac{1}{1 + (1 - 2a) r} = 1 - d_{mod} , \qquad \text{(D-6), (C-13c)}$$

[8] δ_{crit} is given by $\rho/(1+\rho)$ in the case $\delta_{KP} > 0$ (emission reduction) and by $-\rho/(1+\rho)$ in the case $\delta_{KP} \le 0$ (emission limitation).

where d_{mod} is defined as before (see Equation (C-15)) and U via

$$U = U_{Gap} + (1 - d_{crit})\frac{(1 - 2a)r}{1 + (1 - 2a)r} \quad . \tag{D-8}$$

$$U_{Gap} = d_{crit} - d_{KP} \quad . \tag{D-9}$$

Case 3: $\delta_{KP} \leq 0$: $\delta_{crit} < \delta_{KP}$:

$$\frac{x_2}{x_1} \leq (1 + d_{crit})\frac{1}{1 + (1 - 2a)r} = 1 - d_{mod} \quad , \tag{D-10), (C-13c}$$

where d_{mod} is defined for all cases as before (see Equation (C-15)) and U via

$$U = U_{Gap} + (1 + d_{crit})\frac{(1 - 2a)r}{1 + (1 - 2a)r} \tag{D-12}$$

$$U_{Gap} = -(d_{KP} + d_{crit}) \quad . \tag{D-13}$$

Case 4: $\delta_{KP} \leq 0$: $\delta_{crit} \geq \delta_{KP}$:

$$\frac{x_2}{x_1} \leq (1 + d'_{crit})\frac{1}{1 + (1 - 2a)r} = 1 - d_{mod} \quad , \tag{D-14), (C-13c}$$

where d_{mod} is defined for all cases as before (see Equation (C-15)) and U via

$$U = U_{Gap} + (1 + d'_{crit})\frac{(1 - 2a)r}{1 + (1 - 2a)r} \tag{D-16}$$

$$U_{Gap} = -2d_{crit} \tag{D-17}$$

$$-d'_{crit} = d_{KP} - 2d_{crit} \quad . \tag{D-18}$$

U_{Gap} in Cases 2–4 is an initial obligatory undershooting which is introduced to ensure that detectability is given before Annex I countries are permitted to make economic use of potential excess emission reductions.

Result:

See last column in *Table 6*. The Und&VT concept cannot remedy the nonscientific shortcomings of the Kyoto Protocol.

4.5. Adjustment of Emissions Concept (GSC #1)

Starting Point:

Annex I countries comply with their emission limitation or reduction commitments under the Kyoto Protocol.[9]

Assumptions:

(1) It is accepted *a priori* that the true but unknown net emissions at t_2 ($x_{t,2}$) can exceed (overshoot) the target emissions commitment (x_2) by some fractional or percentage amount (p or p%, respectively).

(2) The relative uncertainty (ρ) of a country's net emissions is symmetrical and does not change over time, i.e., $r_1 = r_2 (= r)$.[10]

(3) The probability distributions for estimated emissions are normal and the shape of the probability distribution of emissions for each country does not change significantly as emissions change.

Systems View:

Intra-systems view suited to support inter-systems (e.g., top-down) view: Only our real diagnostic capabilities of grasping emissions at any point in time—reflected by absolute uncertainty $\varepsilon(t)$—are of interest, i.e.: the uncertainty we encountered in the past, the uncertainty that underlies current estimates, and the uncertainty that we have to cope with in reality at some time in the future. Correlation over time between uncertainties is of no concern for this physically based approach.

Question:

Can we attain a reasonable level of confidence that countries will have actually achieved the target emissions levels stated in their commitments under the Kyoto Protocol and are in compliance? That is: 1) Would we consider it acceptable if true emissions will exceed (overshoot) the target emissions commitment by some fractional or percentage amount? 2) How much is that amount? 3) How confident do we want to be in our result?

Approach:

Statistical (see *Figure 5*)

[9] The first emissions adjustment method presented by Gillenwater, Sussman and Cohen (GSC #1) was meant to be applied in retrospect (Gillenwater *et al.*, 2007: Section 2.1). However, their method can also be used to generate information that one would like to discuss beforehand; that is, it can also be perceived as a preparatory SD technique and thus be compared with the other techniques discussed so far.

[10] The GSC #1 concept only considers uncertainty in the commitment year/period, not in the base year. However, for reasons of comparability, we continue to abide by the condition of constant relative uncertainty.

Answer:

Depending on whether or not excess emissions are accepted and favorable compliance conditions exist, the answer comprises three cases (see *Figure 5*). The complete answer is given by

Cases 1 and 2: $\delta_{KP} > 0$: $p = \delta_{crit}$:

$$\text{Adj} = \begin{cases} 1 & 1 + z_{u,2}\left(F_N\right)\frac{\rho}{1.96} \le 1 + \rho_{crit} \\ & \left(\text{excess emissions accepted}\right) \\ & \text{for} \\ \dfrac{1 + z_{u,2}\left(F_N\right)\frac{\rho}{1.96}}{1 + \rho_{crit}} & 1 + z_{u,2}\left(F_N\right)\frac{\rho}{1.96} > 1 + \rho_{crit} \\ & \left(\text{excess emissions accepted}\right) \end{cases} \qquad \text{(E-7,8)}$$

Case 3: $\delta_{KP} \le 0$: $p = 0$:

$$\text{Adj} = 1 + z_{u,2}\left(F_N\right)\frac{\rho}{1.96} \qquad \text{(excess emissions not accepted),} \qquad \text{(E-9)}$$

where $\rho/1.96$ is the standard deviation, F_N the standardized cumulative normal distribution, $z_{u,2}$ the standardized accepted upper (u) emissions limit at t_2, and ρ_{crit} the CRU introduced in Section 4.1.

Result:

See last column in *Table 7*. The GSC #1 concept cannot remedy the nonscientific shortcomings of the Kyoto Protocol.

4.6. Adjustment of Emission Reductions Concept (GSC #2)

Starting Point:

Annex I countries comply with their emission limitation or reduction commitments under the Kyoto Protocol.[11]

Assumptions:

(1) It is accepted *a priori* that true emission reductions (increases) fall below (above) the committed level of reductions (increases) by some fractional or percentage amount (p or p%, respectively).

[11] The second emissions adjustment method presented by Gillenwater, Sussman and Cohen (GSC #2) was meant to be applied in retrospect (Gillenwater *et al.*, 2007: Section 2.1). However, their method can also be used to generate information that one would like to discuss beforehand; that is, it can also be perceived as a preparatory SD technique and thus be compared with the other techniques discussed so far.

(2) The relative uncertainty (ρ) of a country's net emissions is symmetrical and does not change over time, i.e., $r_1 = r_2 (= r)$.

(3) The probability distributions for estimated emissions and emission changes are normal and the shape of the probability distribution of emissions and emission changes for each country does not change significantly as emissions change.

Systems View:

Intra-systems view: Correlation of uncertainty over time matters.

Question:

Can we attain a reasonable level of confidence that countries will have actually achieved the emission changes, measured relative to base-year emissions, stated in their commitments under the Kyoto Protocol and are in compliance? That is: 1) Would we consider it acceptable if true emission reductions (increases) will fall below (above) the committed level of reductions (increases) by some fractional or percentage amount? 2) How much is that amount? 3) How confident do we want to be in our result?

Approach:

Statistical (see *Figure 6*)

Answer:

Depending on whether or not diminished reductions (additional increases) are accepted and favorable compliance conditions exist, the answer comprises four cases (see *Figure 5*). The complete answer is given by

Cases 1 and 2: $\delta_{KP} > 0$: $p = 0.1$:

$$\text{Adj} = \begin{cases} 1 & 2(1-\nu)\dfrac{z_{u,2}(F_N)\rho}{1.96\rho_{crit}} \le 0.1 \\ & \text{diminished reduction} \\ & \text{accepted} \\ \dfrac{1-\left(1-2(1-\nu)\dfrac{z_{u,2}(F_N)\rho}{1.96\rho_{crit}}\right)\delta_{KP}}{1-0.9\delta_{KP}} & 2(1-\nu)\dfrac{z_{u,2}(F_N)\rho}{1.96\rho_{crit}} > 0.1 \\ & \text{diminished reduction} \\ & \text{accepted} \end{cases} \quad \text{for} \qquad \text{(F-7,8)}$$

Case 3: $\delta_{KP} = 0$: $p = 0$:

$$\text{Adj} = 1 \qquad \begin{pmatrix} \text{additional increase} \\ \text{not accepted} \end{pmatrix} \qquad \text{(F-9)}$$

Case 4: $\delta_{KP} < 0$: $p = 0$:

$$\mathrm{Adj} = \frac{1 - \left(1 + 2(1-\nu)\frac{z_{u,2}(F_N)\rho}{1.96\rho_{crit}}\right)\delta_{KP}}{1-\delta_{KP}} \qquad \begin{pmatrix}\text{additional increase}\\ \text{not accepted}\end{pmatrix}, \qquad \text{(F-10)}$$

where $\rho/1.96$ is the standard deviation, ν approximates (first-order approach) the net (effective) correlation between the absolute uncertainties ε_1 and ε_2, F_N is the standardized cumulative normal distribution, $z_{u,2}$ the standardized accepted smaller (upper) limit of reduction (increase) at t_2, and ρ_{crit} the CRU introduced in Section 4.1.

Result:

See last column in *Table 8*. The GSC #2 concept cannot remedy the nonscientific shortcomings of the Kyoto Protocol.

5. Discussion (abridged)

The authors of this study might favor specific techniques on how to go about emissions and emission changes under the (post-) Kyoto Protocol and even see the need for further research. However, the authors all agree that uncertainty matters. So far, they disagree for what to actually use uncertainty. Their perceptions range from using an investigation-focused approach to uncertainty analysis to only improve inventory quality to actually apply a technique or combination of techniques under 'favorable' conditions to check compliance. The authors also agree that a single best technique does not—and will, most likely, not—exist, the main reason for this being that the techniques suffer from weaknesses that are not scientific but are related to the way the Kyoto Protocol is designed (as shown in Section 4 above). Whatever decision policy-makers will take at the end of the day on how go about uncertainty under a post-Kyoto treaty, they will find themselves in a deadlock situation. As a consequence of the Kyoto policy process running ahead of science, they will have to cope with serious consequences (which we will discuss at the workshop and in length in our long-paper version).

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Acronyms and Nomenclature

Adj	adjustment
C&C	contraction and convergence
CRU	critical relative uncertainty
GHG	greenhouse gas
GSC	Gillenwater, Sussman and Cohen
KP	Kyoto Protocol
KT	Kyoto target
LULUCF	land-use change and forestry
P	probability
RelDiff	relative difference
SD	signal detection
U	undershooting
Und&VT	undershooting and verification time
VT	verification time

adj	adjusted
corr	correlation
crit	critical
mod	modified
t	true
u	upper

ISO Country Code

AT	Austria	FR	France	NL	Netherlands
AU	Australia	GR	Greece	NO	Norway
BE	Belgium	HR	Croatia	NZ	New Zealand
BG	Bulgaria	HU	Hungary	PL	Poland
CA	Canada	IE	Ireland	PT	Portugal
CH	Switzerland	IS	Iceland	RO	Romania
CZ	Czech Republic	IT	Italy	RU	Russian Federation
DE	Germany	JP	Japan	SE	Sweden
DK	Denmark	LI	Liechtenstein	SI	Slovenia
EC	European Community	LT	Lithuania	SK	Sloval Republic
EE	Estonia	LU	Luxembourg	UA	Ukraine
ES	Spain	LV	Latvia	UK	United Kingdom
FI	Finland	MC	Monaco	US	United States

Appendix: Tables and Figures

Table 1: Emission limitation and reduction commitments of Annex I countries under the Kyoto Protocol (KP). See ISO Country Code for country abbreviations. Sources: FCCC (1996: Annex B, Decision 9/CP.2; 1998: Article 3.8; 1999: Decision 11/CP.4).

Country Group	Annex I Country	Base Year(s) for CO_2, CH_4, N_2O (for HFCs, PFCs, SF_6)	Commitment Period	KP Commitment %
1a	See note below	1990 (1995)	2008–12	92
1b	BG	1988 (1995)	2008–12	
1c	RO	1989 (1995)	2008–12	
1d	SI	1986 (1995)	2008–12	
2	US	1990 (1995)	2008–12	93
3a	CA, JP	1990 (1995)	2008–12	94
3b	HU	1985–87 (1995)	2008–12	
3c	PL	1988 (1995)	2008–12	
4	HR	1990 (1995)	2008–12	95
5	NZ, RU, UA	1990 (1995)	2008–12	100
6	NO	1990 (1995)	2008–12	101
7	AU	1990 (1995)	2008–12	108
8	IS	1990 (1995)	2008–12	110

Note: 1a: AT, BE, CH, CZ, DE, DK, EC, EE, ES, FI, FR, GR, IE, IT, LI, LT, LU, LV, MC, NL, PT, SE, SK, UK.

Table 2: Major characteristics of preparatory signal detection techniques compared in this study. 1: critical relative uncertainty (CRU) concept; 2: verification time (VT) concept; 3: undershooting (Und) concept; 4: undershooting and VT (Und&VT) concepts combined; 5: adjustment of emissions (GSC #1) concept; 6: adjustment of emission reductions (GSC #2) concept. Sources: Jonas *et al.* (2004a: Tab. 3.1), Bun (2007: Tab. 2); modified.

Taken into account by the technique	Preparatory SD Technique					
	1	2	3	4	5	6
Trend uncertainty			√			√
Total uncertainty	√	√		√	√	
Intra-systems view			√			√
Intra-systems view but suited to support inter-systems (e.g., top-down) view	√	√		√	√	
Emissions gradient between t_1 and t_2		√		√		
Detectability of when an emission signal outstrips total uncertainty	√	√				
Undershooting			√	√		
Upward adjustment of reported emissions					√	√
Risk with reference to the concept of significance			√		√	√
Risk with reference to the concept of detectability				√		

Table 3: The CRU concept (Equation (A-6)) applied to Annex I countries. In the last column, we assess the hypothetical situation that the CRU concept had been applied prior to/in negotiating the Kyoto Protocol. Note the over-/undershooting dissimilarity between countries committed to emission reduction ($d_{KP} > 0$) and emission limitation ($d_{KP} \leq 0$).

Country Group	KP Commitment δ_{KP}[a] %	CRU ρ_{crit} %	If the CRU Concept had been applied
1a 1b 1c 1d	8.0	8.7	a) Compliance with the target: It must be expected that Annex I countries exhibit relative uncertainties in the range of 5–10% and above rather than below (excluding emissions/removals due to LUCF and Kyoto mechanisms). Thus, it is impossible for a number of countries in groups 1–4 to meet the condition that their overall relative uncertainty is smaller than their CRU ($\rho < \rho_{crit}$). b) Overshooting the target: To unambiguously attest a decrease in emissions, Annex I countries would have to fulfill an even smaller CRU (as the one given to the left/for their respective country group). c) Undershooting the target: CRUs increase and could be met more easily.
2	7.0	7.5	
3a 3b 3c	6.0	6.4	
4	5.0	5.3	
--	4.0	4.2	
--	3.0	3.1	
--	2.0	2.0	
--	1.0	1.0	
5	0.0	0.0	a) Compliance with the target: Same conclusion for countries in groups 5–8 as for countries committed to emission reduction (see a) above). b) Overshooting the target: CRUs increase and could be met more easily. c) Undershooting the target: To unambiguously attest a decrease in emissions, Annex I countries would have to fulfill an even smaller CRU (as the one given to the left/for their respective country group).
6	-1.0	1.0	
--	-2.0	2.0	
--	-3.0	2.9	
--	-4.0	3.8	
--	-5.0	4.8	
--	-6.0	5.7	
--	-7.0	6.5	
7	-8.0	7.4	
--	-9.0	8.3	
8	-10.0	9.1	

[a] The countries' emission limitation and reduction commitments under the Kyoto Protocol are expressed with the help of d_{KP}, the normalized change in emissions between t_1 and t_2: $d_{KP} > 0$ — emission reduction; $d_{KP} \leq 0$ — emission limitation.

Table 4: The VT concept (Inequality (B-7a)) applied to Annex I countries. The table is to be read as follows: The maximal allowable VT ($t_2 - t_1$) for an Annex 1 country is given for $r = r_{crit}$ (see second column). For a country of group 1a the maximal allowable VT is 20 years or 1, if normalized. Normalized VTs equal to or smaller than 1 (see green fields for emission reduction and orange fields for emission limitation) are compatible with the Kyoto Protocol, i.e., countries report with $r \leq r_{crit}$; normalized VTs greater than 1 (see red fields) are not, i.e., countries report with $r > r_{crit}$. In the last column, we assess the hypothetical situation that the VT concept had been applied prior to/in negotiating the Kyoto Protocol. Note the over/undershooting dissimilarity between countries committed to emission reduction ($d_{KP} > 0$) and emission limitation ($d_{KP} \leq 0$).

Country Group	Max. Allow. VT[a] $t_2 - t_1$ yr	KP Commit. δ_{KP}[b] %	Normalized VTs if countries report with ρ = 2.5 %	7.5 %	15 %	30 %	If the VT Concept had been applied
1a	20	8.0	0.3	0.9	1.6	2.9	a) Compliance with the target: It must be expected that Annex I countries exhibit relative uncertainties in the range of 5–10% and above rather than below (excluding emissions/ removals due to LUCF and Kyoto mechanisms). Thus, it is impossible for a number of countries in groups 1–4 to meet the condition $\rho < \rho_{crit}$ or, equivalently, achieve a normalized VT ≤ 1. b) Overshooting the target: To unambiguously attest a decrease in emissions, Annex I countries would have to fulfill an even smaller CRU (as the one given to the left/for their respective country group) or, equivalently, find it more difficult complying with a normalized VT ≤ 1. c) Undershooting the target: CRUs increase and could be met more easily or, equivalently, compliance with a VT ≤ 1 becomes less difficult.
1b	22						
1c	21						
1d	24						
2	20	7.0	0.3	< 1.0	1.9	3.3	
3a 3b 3c	20 24 22	6.0	0.4	1.2	2.2	3.8	
4	20	5.0	0.5	1.4	2.6	4.6	
--	--	4.0	0.6	1.7	3.3	5.8	
--	--	3.0	0.8	2.3	4.3	7.7	
--	--	2.0	1.2	3.5	6.5	11.5	
--	--	1.0	2.4	7.0	13.0	23.1	
5	20	0.0	infinite				a) Compliance with the target: Same conclusion for countries in groups 5–8 as for countries committed to emission reduction (see a) above). b) Overshooting the target: CRUs increase and could be met more easily or, equivalently, compliance with a VT ≤ 1 becomes less difficult. c) Undershooting the target: To unambiguously attest a decrease in emissions, Annex I countries would have to fulfill an even smaller CRU (as the one given to the left/for their respective country group) or, equivalently, find it more difficult complying with a normalized VT ≤ 1.
6	20	-1.0	2.6	8.1	17.6	42.9	
--	--	-2.0	1.3	4.1	8.8	21.4	
--	--	-3.0	0.9	2.7	5.9	14.3	
--	--	-4.0	0.6	2.0	4.4	10.7	
--	--	-5.0	0.5	1.6	3.5	8.6	
--	--	-6.0	0.4	1.4	2.9	7.1	
--	--	-7.0	0.4	1.2	2.5	6.1	
7	20	-8.0	0.3	> 1.0	2.2	5.4	
--	--	-9.0	0.3	0.9	2.0	4.8	
8	20	-10.0	0.3	0.8	1.8	4.3	

[a] The maximal allowable VT is calculated for each country group as the difference between 2010 (as the temporal mean over the commitment period 2008–2012) and its base year or mean base year, respectively (as specified in Table 1).

[b] The countries' emission limitation and reduction commitments under the Kyoto Protocol are expressed with the help of d_{KP}, the normalized change in emissions between t_1 and t_2: $d_{KP} > 0$ — emission reduction; $d_{KP} \leq 0$ — emission limitation.

Table 5: The Und concept (Equation (C-15) in combination with Equation (C-18) and a correlation of $\nu = 0.75$ typical for currently reported uncertainties; see EEA 2006: Tab. 1.15) applied to Annex I countries. The table lists modified emission limitation or reduction targets δ_{mod} for all Annex 1 countries, where the "$x_{t,2}$-greater-than-$(1- d_{KP})x_{t,1}$" risk a is specified to be 0, 0.1, 0.3 and 0.5. If an Annex I country complies with its emission limitation or reduction commitment ($x_2 = (1- d_{KP})x_1$), the risk that its true but unknown emissions $x_{t,2}$ are equal to or greater than its true but unknown target $(1- d_{KP})x_{t,1}$ is 50%. Undershooting decreases this risk. For instance, a country of group 1 has committed itself to reduce its net emissions by 8%. Reporting with a 7.5% relative uncertainty, it needs to reduce its emissions by 11.4% to decrease the risk from 50% to 0%. In the last column, we assess the hypothetical situation that the Und concept had been applied prior to/in negotiating the Kyoto Protocol. Note the politically unfavorable situation, which arises when d_{KP} varies while ρ and α are kept constant.

Country Group	KP Commit. δ_{KP}[a] %	Modified Emission Limitation or Reduction Target δ_{mod} in % for α =	ρ = 2.5 %	7.5 %	15 %	30 %	If the Und Concept had been applied
1a–d	8.0	0.0	9.1	11.4	14.7	20.8	a) For given δ_{KP} and α: The greater ρ, the greater the modified emission reduction target d_{mod} must be to keep the "$x_{t,2}$-greater-than-$(1- d_{KP})x_{t,1}$" risk α at a constant level (see, e.g., country group 1: third line: d_{mod} values for $\alpha = 0.3$). b) For given ρ and α: The smaller d_{KP}, the smaller the modified emission reduction target d_{mod} can be to keep the "$x_{t,2}$-greater-than-$(1- d_{KP})x_{t,1}$" risk α at a constant level (see, e.g., d_{mod} values for $\rho = 7.5\%$ and $\alpha = 0.3$). As a consequence, countries complying with a smaller d_{KP} (they exhibit a small d_{mod}) are better off than countries that must comply with a greater d_{KP} (they exhibit a great d_{mod}).
		0.1	8.9	10.7	13.4	18.4	
		0.3	8.5	9.4	10.7	13.4	
		0.5	8.0	8.0	8.0	8.0	
2	7.0	0.0	8.2	10.4	13.7	20.0	
		0.1	7.9	9.7	12.4	17.5	
		0.3	7.5	8.4	9.7	12.4	
		0.5	7.0	7.0	7.0	7.0	
3a–c	6.0	0.0	7.2	9.5	12.8	19.1	
		0.1	6.9	8.8	11.5	16.6	
		0.3	6.5	7.4	8.8	11.5	
		0.5	6.0	6.0	6.0	6.0	
4	5.0	0.0	6.2	8.5	11.9	18.3	
		0.1	5.9	7.8	10.5	15.8	
		0.3	5.5	6.4	7.8	10.5	
		0.5	5.0	5.0	5.0	5.0	
---	4.0	0.0	5.2	7.5	10.9	17.4	
		0.1	5.0	6.8	9.6	14.9	
		0.3	4.5	5.4	6.8	9.6	
		0.5	4.0	4.0	4.0	4.0	
---	3.0	0.0	4.2	6.6	10.0	16.5	
		0.1	4.0	5.9	8.7	14.0	
		0.3	3.5	4.4	5.9	8.7	
		0.5	3.0	3.0	3.0	3.0	
---	2.0	0.0	3.2	5.6	9.1	15.7	
		0.1	3.0	4.9	7.7	13.1	
		0.3	2.5	3.5	4.9	7.7	
		0.5	2.0	2.0	2.0	2.0	
---	1.0	0.0	2.2	4.6	8.2	14.8	
		0.1	2.0	3.9	6.8	12.2	
		0.3	1.5	2.5	3.9	6.8	
		0.5	1.0	1.0	1.0	1.0	

Table 5 continued:

5	0.0	0.0	1.2	3.7	7.2	14.0	a) For given δ_{KP} and α:
		0.1	1.0	3.0	5.8	11.3	
		0.3	0.5	1.5	3.0	5.8	Same conclusion for country groups 5–8 as for countries committed to emission reduction (see a) above).
		0.5	0.0	0.0	0.0	0.0	
6	-1.0	0.0	0.3	2.7	6.3	13.1	b) For given ρ and α:
		0.1	0.0	2.0	4.9	10.4	Same conclusion for country groups 5–8 as for countries committed to emission reduction (see b) above).
		0.3	-0.5	0.5	2.0	4.9	
		0.5	-1.0	-1.0	-1.0	-1.0	
---	-2.0	0.0	-0.7	1.8	5.4	12.2	
		0.1	-1.0	1.0	3.9	9.5	
		0.3	-1.5	-0.5	1.0	3.9	
		0.5	-2.0	-2.0	-2.0	-2.0	
---	-3.0	0.0	-1.7	0.8	4.4	11.4	
		0.1	-2.0	0.0	3.0	8.7	
		0.3	-2.5	-1.5	0.0	3.0	
		0.5	-3.0	-3.0	-3.0	-3.0	
---	-4.0	0.0	-2.7	-0.2	3.5	10.5	
		0.1	-3.0	-0.9	2.1	7.8	
		0.3	-3.5	-2.5	-0.9	2.1	
		0.5	-4.0	-4.0	-4.0	-4.0	
---	-5.0	0.0	-3.7	-1.1	2.6	9.7	
		0.1	-4.0	-1.9	1.1	6.9	
		0.3	-4.5	-3.4	-1.9	1.1	
		0.5	-5.0	-5.0	-5.0	-5.0	
---	-6.0	0.0	-4.7	-2.1	1.7	8.8	
		0.1	-4.9	-2.9	0.2	6.0	
		0.3	-5.5	-4.4	-2.9	0.2	
		0.5	-6.0	-6.0	-6.0	-6.0	
---	-7.0	0.0	-5.7	-3.1	0.7	7.9	
		0.1	-5.9	-3.8	-0.8	5.1	
		0.3	-6.5	-5.4	-3.8	-0.8	
		0.5	-7.0	-7.0	-7.0	-7.0	
7	-8.0	0.0	-6.7	-4.0	-0.2	7.1	
		0.1	-6.9	-4.8	-1.7	4.2	
		0.3	-7.5	-6.4	-4.8	-1.7	
		0.5	-8.0	-8.0	-8.0	-8.0	
---	-9.0	0.0	-7.6	-5.0	-1.1	6.2	
		0.1	-7.9	-5.8	-2.7	3.3	
		0.3	-8.5	-7.4	-5.8	-2.7	
		0.5	-9.0	-9.0	-9.0	-9.0	
8	-10.0	0.0	-8.6	-6.0	-2.0	5.3	
		0.1	-8.9	-6.7	-3.6	2.5	
		0.3	-9.5	-8.4	-6.7	-3.6	
		0.5	-10.0	-10.0	-10.0	-10.0	

[a] The countries' emission limitation and reduction commitments under the Kyoto Protocol are expressed with the help of d_{KP}, the normalized change in emissions between t_1 and t_2: $d_{KP} > 0$ — emission reduction; $d_{KP} \leq 0$ — emission limitation.

Table 6: The Und&VT concept (Equation (C-15) in combination with Equations (D-5) [Case 1: green fields]; (D-8) and (D-9) [Case 2: red fields]; (D-12) and (D-13) [Case 3: red fields]; and (D-16) to (D-18) [Case 4: orange fields]) applied to Annex I countries. The table lists modified emission limitation or reduction targets d_{mod} for all Annex I countries, where the "$x_{t,2}$ -greater-than-$(1-\delta_{KP})x_{t,1}$" risk α (Case 1), the "$x_{t,2}$ -greater-than-$(1-|\delta_{crit}|)x_{t,1}$" risk α (Cases 2, 3) and the "$x_{t,2}$ -greater-than-$(1-(\delta_{KP}-2\delta_{crit}))x_{t,1}$" risk α (Case 4), respectively, are specified to be 0, 0.1, 0.3 and 0.5. In the last column, we assess the hypothetical situation that the Und&VT concept had been applied prior to/in negotiating the Kyoto Protocol. The Und&VT concept only partially rectifies (i.e., in Cases 2 and 3, the cases of nondetectability before correction) the politically unfavourable situation under the Und concept, where countries complying with a smaller δ_{KP} exhibit a small δ_{mod} while countries complying with a greater δ_{KP} exhibit a great δ_{mod} (cf. Section 4.3).

Country Group	KP Commit.	Modified Emission Limitation or Reduction Target δ_{mod} in % for					If the Und&VT Concept had been applied
		α =	ρ =				
	δ_{KP}[a]		2.5	7.5	15	30	
	%	1	%	%	%	%	
1a–d	8.0	0.0	10.2	14.4	24.4	40.8	Case 1 (green-colored area): $\delta_{crit} \leq \delta_{KP}$: No necessity for introducing U_{Gap}, i.e., the d_{mod} values from Table 5 continue to stay valid. Case 2 (red-colored area): $\delta_{crit} > \delta_{KP}$: Increase of d_{KP} by U_{Gap} to reach d_{crit}, the relevant reference for undershooting which only depends on ρ and α and not anymore on d_{KP} (see Equations (D-8) and (D-9) in combination with Equation (C-15)). This explains why d_{mod} appears uniform for a given ρ and α. Thus, the Und&VT concept rectifies the Und concept (cf. Table 5), where countries complying with a smaller d_{KP} exhibit a small d_{mod} while countries complying with a greater d_{KP} exhibit a great d_{mod}.
		0.1	9.8	13.2	22.4	38.0	
		0.3	8.9	10.7	18.0	31.3	
		0.5	8.0	8.0	13.0	23.1	
2	7.0	0.0	9.3	13.5	24.4	40.8	
		0.1	8.8	12.3	22.4	38.0	
		0.3	7.9	9.7	18.0	31.3	
		0.5	7.0	7.0	13.0	23.1	
3a–c	6.0	0.0	8.3	13.5	24.4	40.8	
		0.1	7.8	12.2	22.4	38.0	
		0.3	6.9	9.7	18.0	31.3	
		0.5	6.0	7.0	13.0	23.1	
4	5.0	0.0	7.3	13.5	24.4	40.8	
		0.1	6.9	12.2	22.4	38.0	
		0.3	5.9	9.7	18.0	31.3	
		0.5	5.0	7.0	13.0	23.1	
---	4.0	0.0	6.3	13.5	24.4	40.8	
		0.1	5.9	12.2	22.4	38.0	
		0.3	5.0	9.7	18.0	31.3	
		0.5	4.0	7.0	13.0	23.1	
---	3.0	0.0	5.4	13.5	24.4	40.8	
		0.1	4.9	12.2	22.4	38.0	
		0.3	4.0	9.7	18.0	31.3	
		0.5	3.0	7.0	13.0	23.1	
---	2.0	0.0	4.8	13.5	24.4	40.8	
		0.1	4.4	12.2	22.4	38.0	
		0.3	3.4	9.7	18.0	31.3	
		0.5	2.4	7.0	13.0	23.1	
---	1.0	0.0	4.8	13.5	24.4	40.8	
		0.1	4.4	12.2	22.4	38.0	
		0.3	3.4	9.7	18.0	31.3	
		0.5	2.4	7.0	13.0	23.1	

Table 6 continued:

5	0.0	0.0	4.8	13.5	24.4	40.8	Case 3 (red-colored area): $\delta_{crit} < \delta_{KP}$:
		0.1	4.4	12.2	22.4	38.0	
		0.3	3.4	9.7	18.0	31.3	Increase of d_{KP} by U_{Gap} to reach - d_{crit}, the relevant reference for undershooting which only depends on ρ and α and not anymore on d_{KP} (see Equations (D-12) and (D-13) in combination with Equation (C-15)). This explains why d_{mod} appears uniform for a given ρ and α. Thus, the Und&VT concept rectifies the Und concept (cf. Table 5), where countries complying with a smaller d_{KP} exhibit a small d_{mod} while countries complying with a greater d_{KP} exhibit a great d_{mod}.
		0.5	2.4	7.0	13.0	23.1	
6	-1.0	0.0	4.8	13.5	24.4	40.8	
		0.1	4.4	12.2	22.4	38.0	
		0.3	3.4	9.7	18.0	31.3	
		0.5	2.4	7.0	13.0	23.1	
---	-2.0	0.0	4.8	13.5	24.4	40.8	
		0.1	4.4	12.2	22.4	38.0	
		0.3	3.4	9.7	18.0	31.3	
		0.5	2.4	7.0	13.0	23.1	
---	-3.0	0.0	4.3	13.5	24.4	40.8	
		0.1	3.8	12.2	22.4	38.0	
		0.3	2.8	9.7	18.0	31.3	
		0.5	1.9	7.0	13.0	23.1	
---	-4.0	0.0	3.3	13.5	24.4	40.8	Case 4 (orange-colored area): $\delta_{crit} \geq \delta_{KP}$:
		0.1	2.8	12.2	22.4	38.0	
		0.3	1.9	9.7	18.0	31.3	Increase of d_{KP} by U_{Gap} to reach d_{KP} - $2d_{crit}$, the relevant reference for undershooting which, in contrast to the Case 3 ($d_{crit} < d_{KP}$) above, still depends on d_{KP} (see Equations (D-16) to (D-18) in combination with Equation (C-15)). This is a consequence of how the undershooting is realized (detectable reductions are only considered after initial obligatory undershooting).
		0.5	0.9	7.0	13.0	23.1	
---	-5.0	0.0	2.3	13.5	24.4	40.8	
		0.1	1.8	12.2	22.4	38.0	
		0.3	0.9	9.7	18.0	31.3	
		0.5	-0.1	7.0	13.0	23.1	
---	-6.0	0.0	1.3	13.5	24.4	40.8	
		0.1	0.9	12.2	22.4	38.0	
		0.3	-0.1	9.7	18.0	31.3	
		0.5	-1.1	7.0	13.0	23.1	
---	-7.0	0.0	0.4	13.4	24.4	40.8	
		0.1	-0.1	12.2	22.4	38.0	
		0.3	-1.1	9.7	18.0	31.3	
		0.5	-2.1	7.0	13.0	23.1	
7	-8.0	0.0	-0.6	12.5	24.4	40.8	
		0.1	-1.1	11.3	22.4	38.0	
		0.3	-2.1	8.7	18.0	31.3	
		0.5	-3.1	6.0	13.0	23.1	
---	-9.0	0.0	-1.6	11.6	24.4	40.8	
		0.1	-2.1	10.3	22.4	38.0	
		0.3	-3.1	7.7	18.0	31.3	
		0.5	-4.1	5.0	13.0	23.1	
8	-10.0	0.0	-2.6	10.7	24.4	40.8	
		0.1	-3.1	9.4	22.4	38.0	
		0.3	-4.1	6.8	18.0	31.3	
		0.5	-5.1	4.0	13.0	23.1	

[a] The countries' emission limitation and reduction commitments under the Kyoto Protocol are expressed with the help of d_{KP}, the normalized change in emissions between t_1 and t_2: $d_{KP} > 0$ — emission reduction; d_{KP} £ 0 — emission limitation.

Table 7: The GSC #1 concept (Equations (E-7) [Case 1: green fields; here, the $Adj < 1$ values have not been set equal to 1]; (E-8) [Case 2: orange fields]; and (E-9) [Case 3: red fields]) applied to Annex I countries. The table lists the required adjustments Adj for all Annex I countries, where the confidence $1-\alpha$ that true emissions do not exceed (overshoot) target emissions by more than $p = \delta_{crit}$ (Cases 1 and 2) and $p = 0$ (Case 3) is specified to be 0.9, 0.7 and 0.5. In the last column, we assess the hypothetical situation that the GSC #1 concept had been applied prior to/in negotiating the Kyoto Protocol. Note the politically unfavorable situation in Case 2, which arises when d_{KP} varies while ρ and $1-\alpha$ are kept constant.

Country Group	KP Commit. $\square_{KP}$[a] %	CRU $\square_{crit}$ %	Adjustment Factor Adj (absolute) for $1-\alpha$ = 1	ρ = 2.5 %	7.5 %	15 %	30 %	If the GSC #1 Concept had been applied
1a–d	8.0	8.7	1.0					Case 1 (green-colored area): $p = \delta_{crit}$, Adj ≤ 1: favorable compliance conditions; no need for an adjustment (Adj can be set equal to 1). Case 2 (orange-colored area): $p = \delta_{crit}$, Adj > 1: The higher ρ, the level of uncertainty surrounding the emissions inventory estimate, or the greater $(1-\alpha)$, the degree of confidence that is required, the greater the adjustment Adj. However, the smaller d_{KP}, the greater the adjustment Adj to keep the confidence $1-\alpha$ at a constant level (see, e.g., Adj values for $\rho = 15\%$ and $1-\alpha = 0.9$). As a consequence, countries complying with a greater d_{KP} (they exhibit a small Adj) are better off than countries that must comply with a smaller d_{KP} (they exhibit a great Adj).
			0.9	0.935	0.965	1.010	1.100	
			0.7	0.926	0.938	0.957	0.994	
			0.5	0.920	0.920	0.920	0.920	
2	7.0	7.5	1.0					
			0.9	0.945	0.976	1.021	1.112	
			0.7	0.936	0.949	0.967	1.005	
			0.5	0.930	0.930	0.930	0.930	
3a–c	6.0	6.4	1.0					
			0.9	0.955	0.986	1.032	1.124	
			0.7	0.946	0.959	0.978	1.015	
			0.5	0.940	0.940	0.940	0.940	
4	5.0	5.3	1.0					
			0.9	0.966	0.997	1.043	1.136	
			0.7	0.956	0.969	0.988	1.026	
			0.5	0.950	0.950	0.950	0.950	
---	4.0	4.2	1.0					
			0.9	0.976	1.007	1.054	1.148	
			0.7	0.966	0.979	0.999	1.037	
			0.5	0.960	0.960	0.960	0.960	
---	3.0	3.1	1.0					
			0.9	0.986	1.018	1.065	1.160	
			0.7	0.976	0.989	1.009	1.048	
			0.5	0.970	0.970	0.970	0.970	
---	2.0	2.0	1.0					
			0.9	0.996	1.028	1.076	1.172	
			0.7	0.987	1.000	1.019	1.059	
			0.5	0.980	0.980	0.980	0.980	
---	1.0	1.0	1.0					
			0.9	1.006	1.039	1.087	1.184	
			0.7	0.997	1.010	1.030	1.069	
			0.5	0.990	0.990	0.990	0.990	

Table 7 continued:

5	0.0	0.0	1.0					Case 3 (red-colored area): p = 0, Adj ≥ 1: The fractional excess emissions factor p is unconditionally set equal to 0. No excess emissions, i.e., additional emission increases, are accepted. As a consequence, all countries exhibit identical adjustments Adj.
			0.9	1.016	1.049	1.098	1.196	
			0.7	1.007	1.020	1.040	1.080	
			0.5	1.000	1.000	1.000	1.000	
6	-1.0	1.0	1.0					
			0.9	1.016	1.049	1.098	1.196	
			0.7	1.007	1.020	1.040	1.080	
			0.5	1.000	1.000	1.000	1.000	
---	-2.0	2.0	1.0					
			0.9	1.016	1.049	1.098	1.196	
			0.7	1.007	1.020	1.040	1.080	
			0.5	1.000	1.000	1.000	1.000	
---	-3.0	2.9	1.0					
			0.9	1.016	1.049	1.098	1.196	
			0.7	1.007	1.020	1.040	1.080	
			0.5	1.000	1.000	1.000	1.000	
---	-4.0	3.8	1.0					
			0.9	1.016	1.049	1.098	1.196	
			0.7	1.007	1.020	1.040	1.080	
			0.5	1.000	1.000	1.000	1.000	
---	-5.0	4.8	1.0					
			0.9	1.016	1.049	1.098	1.196	
			0.7	1.007	1.020	1.040	1.080	
			0.5	1.000	1.000	1.000	1.000	
---	-6.0	5.7	1.0					
			0.9	1.016	1.049	1.098	1.196	
			0.7	1.007	1.020	1.040	1.080	
			0.5	1.000	1.000	1.000	1.000	
---	-7.0	6.5	1.0					
			0.9	1.016	1.049	1.098	1.196	
			0.7	1.007	1.020	1.040	1.080	
			0.5	1.000	1.000	1.000	1.000	
7	-8.0	7.4	1.0					
			0.9	1.016	1.049	1.098	1.196	
			0.7	1.007	1.020	1.040	1.080	
			0.5	1.000	1.000	1.000	1.000	
---	-9.0	8.3	1.0					
			0.9	1.016	1.049	1.098	1.196	
			0.7	1.007	1.020	1.040	1.080	
			0.5	1.000	1.000	1.000	1.000	
8	-10.0	9.1	1.0					
			0.9	1.016	1.049	1.098	1.196	
			0.7	1.007	1.020	1.040	1.080	
			0.5	1.000	1.000	1.000	1.000	

[a] The countries' emission limitation and reduction commitments under the Kyoto Protocol are expressed with the help of d_{KP}, the normalized change in emissions between t_1 and t_2: $d_{KP} > 0$ — emission reduction; $d_{KP} \leq 0$ — emission limitation.

Table 8: The GSC #2 concept (Equations (F-7) [Case 1: green fields; here, the $Adj < 1$ values have not been set equal to 1]; (F-8) [Case 2: orange fields]; and (F-9) and (F-10) [Cases 3 and 4: red fields]) applied to Annex I countries. The table lists the required adjustments Adj for all Annex I countries, where the confidence $1-\alpha$ that true emission reductions (increases) will not fall below (above) the committed level of reductions (increases) by more than $p = 0.1$ (Cases 1 and 2) and $p = 0$ (Cases 3 and 4) is specified to be 0.9, 0.7 and 0.5. In the last column, we assess the hypothetical situation that the GSC #2 concept had been applied prior to/in negotiating the Kyoto Protocol. Note the politically c unfavorable situation in Case 2, which arises when d_{KP} varies while ρ and $1-\alpha$ are kept constant. However, for the given set of parameters (notably, $p = 0.1$ and $\nu = 0.75$) the span between the smallest and greatest Adj values is negligible.

Country Group	KP Commit.	CRU	Adjustment Factor Adj (absolute) for					If the GSC #2 Concept had been applied
			1 - α =	ρ =				
	□KP[a]	□crit		2.5	7.5	15	3o	
	%	%	1	%	%	%	%	
1a–d	8.0	8.7	1.0					Case 1 (green-colored area): p = 0.1, Adj ≤ 1: Favorable compliance conditions; no need for an adjustment (Adj can be set equal to 1). Case 2 (orange-colored area): p = δ_{crit}, Adj > 1: The higher ρ, the level of uncertainty surrounding the emissions inventory estimate, or the greater ($1-\alpha$), the degree of confidence that is required, the greater the adjustment Adj. However, the smaller d_{KP}, the greater the adjustment Adj to keep the confidence $1-\alpha$ at a constant level (see, e.g., Adj values for $\rho = 15\%$ and $1-\alpha = 0.9$). As a consequence, countries complying with a greater d_{KP} (they exhibit a small Adj) are better off than countries that must comply with a smaller d_{KP} (they exhibit a great Adj). However, for the given set of parameters (notably, $p = 0.1$ and $\nu = 0.75$) the span between the smallest and greatest Adj values is negligible.
			0.9	0.999	1.016	1.040	1.089	
			0.7	0.995	1.001	1.011	1.031	
			0.5	0.991	0.991	0.991	0.991	
2	7.0	7.5	1.0					
			0.9	1.001	1.017	1.041	1.090	
			0.7	0.996	1.002	1.012	1.032	
			0.5	0.993	0.993	0.993	0.993	
3a–c	6.0	6.4	1.0					
			0.9	1.002	1.018	1.042	1.091	
			0.7	0.997	1.004	1.014	1.034	
			0.5	0.994	0.994	0.994	0.994	
4	5.0	5.3	1.0					
			0.9	1.003	1.019	1.044	1.092	
			0.7	0.998	1.005	1.015	1.035	
			0.5	0.995	0.995	0.995	0.995	
---	4.0	4.2	1.0					
			0.9	1.004	1.020	1.045	1.094	
			0.7	0.999	1.006	1.016	1.036	
			0.5	0.996	0.996	0.996	0.996	
---	3.0	3.1	1.0					
			0.9	1.005	1.021	1.046	1.095	
			0.7	1.000	1.007	1.017	1.037	
			0.5	0.997	0.997	0.997	0.997	
---	2.0	2.0	1.0					
			0.9	1.006	1.022	1.047	1.096	
			0.7	1.001	1.008	1.018	1.038	
			0.5	0.998	0.998	0.998	0.998	
---	1.0	1.0	1.0					
			0.9	1.007	1.023	1.048	1.097	
			0.7	1.002	1.009	1.019	1.039	
			0.5	0.999	0.999	0.999	0.999	

Table 8 continued:

5	0.0	0.0	1.0					Cases 3 and 4 (red-colored area): p = 0, Adj ≥ 1: The fractional factor p to allow additional emission changes is unconditionally set equal to 0. No excess emissions, i.e., additional emission increases, are accepted. As a consequence, all countries *de facto* exhibit identical adjustments Adj.
			0.9	1.000	1.000	1.000	1.000	
			0.7	1.000	1.000	1.000	1.000	
			0.5	1.000	1.000	1.000	1.000	
6	-1.0	1.0	1.0					
			0.9	1.008	1.025	1.049	1.098	
			0.7	1.003	1.010	1.020	1.040	
			0.5	1.000	1.000	1.000	1.000	
---	-2.0	2.0	1.0					
			0.9	1.008	1.025	1.049	1.098	
			0.7	1.003	1.010	1.020	1.040	
			0.5	1.000	1.000	1.000	1.000	
---	-3.0	2.9	1.0					
			0.9	1.008	1.025	1.049	1.098	
			0.7	1.003	1.010	1.020	1.040	
			0.5	1.000	1.000	1.000	1.000	
---	-4.0	3.8	1.0					
			0.9	1.008	1.025	1.049	1.098	
			0.7	1.003	1.010	1.020	1.040	
			0.5	1.000	1.000	1.000	1.000	
---	-5.0	4.8	1.0					
			0.9	1.008	1.025	1.049	1.098	
			0.7	1.003	1.010	1.020	1.040	
			0.5	1.000	1.000	1.000	1.000	
---	-6.0	5.7	1.0					
			0.9	1.008	1.025	1.049	1.098	
			0.7	1.003	1.010	1.020	1.040	
			0.5	1.000	1.000	1.000	1.000	
---	-7.0	6.5	1.0					
			0.9	1.008	1.025	1.049	1.098	
			0.7	1.003	1.010	1.020	1.040	
			0.5	1.000	1.000	1.000	1.000	
7	-8.0	7.4	1.0					
			0.9	1.008	1.025	1.049	1.098	
			0.7	1.003	1.010	1.020	1.040	
			0.5	1.000	1.000	1.000	1.000	
---	-9.0	8.3	1.0					
			0.9	1.008	1.025	1.049	1.098	
			0.7	1.003	1.010	1.020	1.040	
			0.5	1.000	1.000	1.000	1.000	
8	-10.0	9.1	1.0					
			0.9	1.008	1.025	1.049	1.098	
			0.7	1.003	1.010	1.020	1.040	
			0.5	1.000	1.000	1.000	1.000	

[a] The countries' emission limitation and reduction commitments under the Kyoto Protocol are expressed with the help of d_{KP}, the normalized change in emissions between t_1 and t_2: $d_{KP} > 0$ — emission reduction; $d_{KP} \leq 0$ — emission limitation.

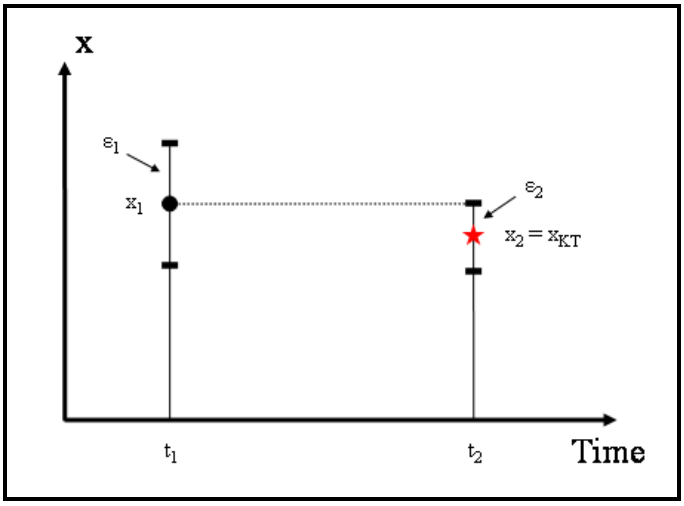

Figure 1: Illustration of the CRU concept ($\rho_1 = \rho_2$): The absolute change in emissions ($|x_1 - x_2| = |d_{KP}|x_1$) outstrips uncertainty at t_2. KT: Kyoto target. Source: Jonas *et al.* (2004a: Fig. 8).

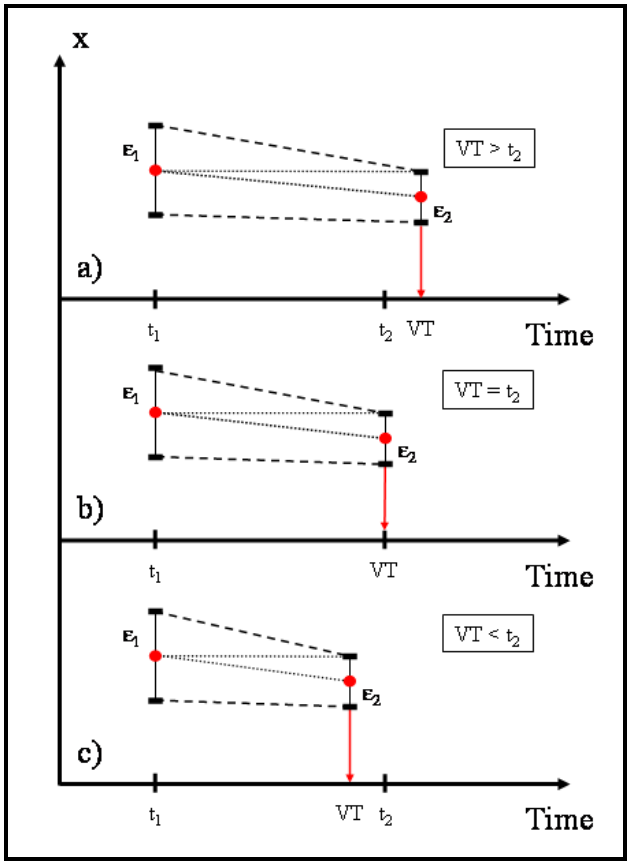

Figure 2: Illustration of the VT concept ($\rho_1 = \rho_2$): The absolute change in emissions ($|\Delta x(t)|$) outstrips uncertainty at a) $VT > t_2$, b) $VT = t_2$ and c) $VT < t_2$. Source: Jonas *et al.* (2004a: Fig. 10; 2007: Fig. 7).

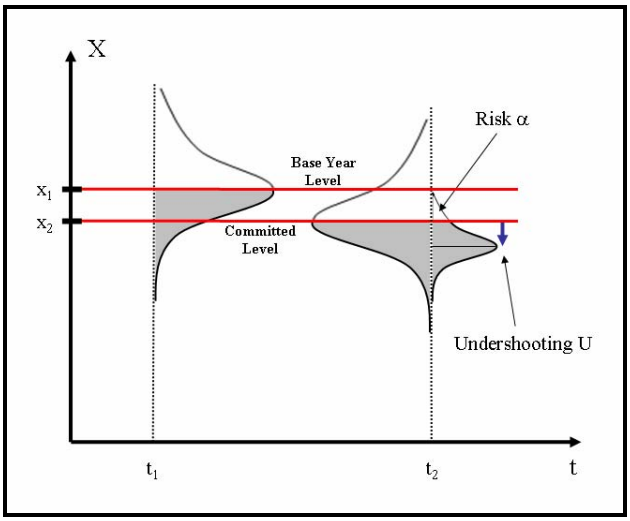

Figure 3: Illustration of the Und concept ($\rho_1 = \rho_2$) with the help of normal probability density functions: Undershooting helps to limit the risk α that countries overshoot their true emission limitation or reduction commitments. Source: Jonas *et al.* (2007: Fig. 11); modified.

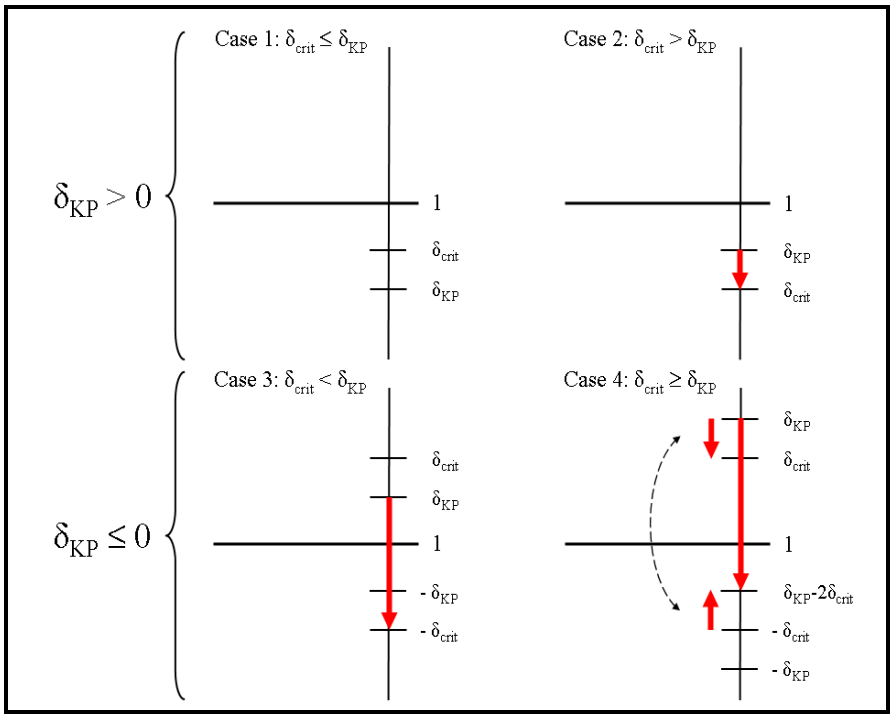

Figure 4: Illustration of the Und&VT concept ($\rho_1 = \rho_2$): It preserves risk as the strength of the Und concept and detectability as the strength of the VT concept. Depending on how δ_{crit} (see text) and δ_{KP} relate to each other, four cases need to be distinguished. These differ in terms of detectability (Cases 1 and 4) versus nondetectability (Cases 2 and 3) and an initial obligatory undershooting U_{Gap} that is introduced (Cases 2–4) to ensure that detectability is given before Annex I countries are permitted to make economic use of potential excess emission reductions. Emission reduction: $\delta_{KP} > 0$; emission limitation: $\delta_{KP} \leq 0$. Source: Bun (2006: Fig. 4).

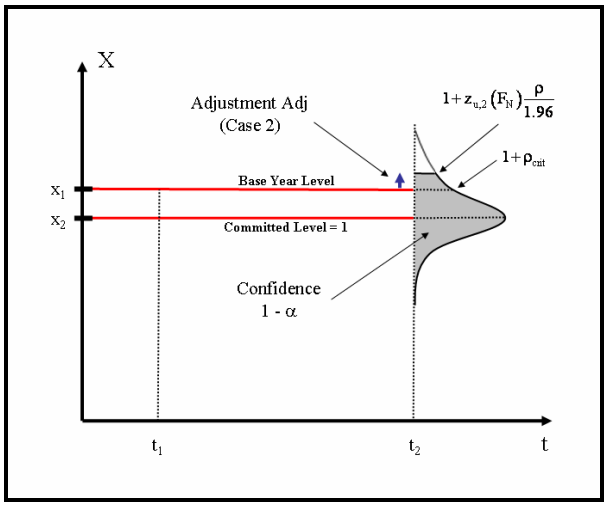

Figure 5: Illustration of the GSC #1 concept ($\rho_1 = \rho_2$) with the help of the standard normal probability density function: It allows specifying the confidence $1-\alpha$ that a country's true but unknown emissions comply with emission targets. Depending on whether or not excess emissions are accepted and favorable compliance conditions exist, three cases need to be distinguished. Here, Case 2 is shown: Given an uncertainty of ρ%, this case requires adjusting a country's emissions estimate at t_2 upward if we want to be $(1-\alpha)$% confident its true emissions do not exceed its emissions target (here referred to as 1) by more than ρ_{crit}%. Emission reduction: $\delta_{KP} > 0$; emission limitation: $\delta_{KP} \leq 0$.

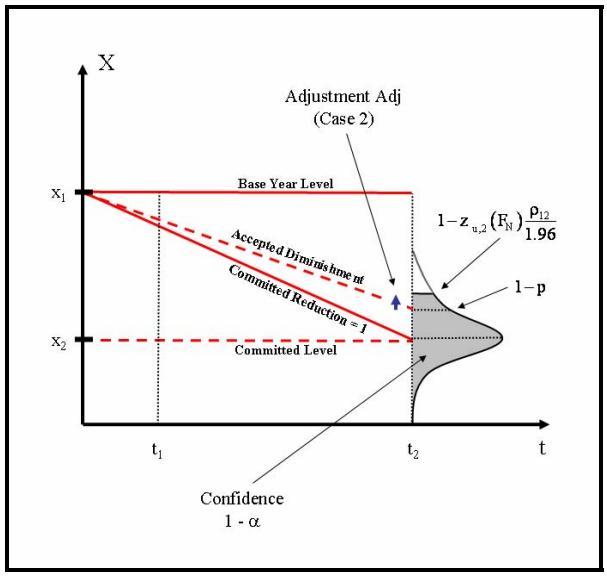

Figure 6: Illustration of the GSC #2 concept ($\rho_1 = \rho_2$) with the help of the standard normal probability density function: It allows specifying the confidence $1-\alpha$ that a country's true but unknown emission changes comply with committed changes. Depending on whether or not diminished reductions (additional increases) are accepted and favorable compliance conditions exist, four cases need to be distinguished. Here, Case 2 is shown: Given an uncertainty of ρ%, this case requires adjusting a country's emissions estimate at t_2 upward if we want to be $(1-\alpha)$% confident its true emission reduction equals at least (100 – p)% of the committed reduction (here referred to as 1). Emission reduction: $\delta_{KP} > 0$; emission limitation: $\delta_{KP} \leq 0$.

The Price of Emissions Permits under Market and Regulatory Uncertainty

Odin K. Knudsen and Pasquale L. Scandizzo

Abstract

In this paper, we explore the effects of uncertainty on pricing of pollution permits. We consider two major sources of uncertainty – that arising from the volatility of demand for the underlying resource (e.g. electricity) and that coming from the regulatory environment. Both sources of uncertainty are common in pollution permit trading as not only does the market respond to the volatility of fundamentals but also to the vagaries of the institutional structure, created by public policy and enforced through regulation. The paper shows that even in the presence of strategic behavior on the part of the agents involved, the trading of permits effectively reduces emissions, and pricing does reflect opportunity costs and environmental objectives. Firms that are more efficient in reducing their emissions gain greater market share. Furthermore, and somewhat paradoxically, the higher uncertainty, the greater the impact of regulation.

Introduction

Pollution permits and trading are becoming increasing important as a market friendly instrument to control pollution at lower costs. Although such schemes have had their birth with sulfur dioxide trading in the United States, they really did not hit international prominence until the Kyoto Protocol came into force. By building into Protocol carbon emission trading and with the emergence of the European Trading System (ETS), pollution trading became a multi-billion dollar market. Despite their growth, the economics underlying these pollution markets are not well understood. Although it is assumed that these markets promote least cost means of meeting targets on carbon emissions, the economics of pricing of permits and penalties are not well understood, along with a host of other issues associated with important policy decisions, including regulatory uncertainty. Because the markets for an externality such as pollution are essentially artificial markets, created by legislation, an additional form of uncertainty is added to the normal randomness of prices: the vagaries of regulatory enforcement. This regulatory uncertainty is quite evident in the carbon emissions trading of the Clean Development Mechanism (CDM) of the Kyoto Protocol and under the ETS where over 12,000 installations must be monitored and comply under the threat of fines and ultimately enforcement is by a combination of fines and litigation against a sovereign nation.

Policies to achieve environmental quality have particular importance as the challenge of mitigating climate change and reducing emissions has taken on currency. Two instruments have received particular support from economists: marketable permits and emission taxes or charges (Pigou, 1920 and 1932; Crocker, 1966; Dales, 1968; Montgomery,1972;Kneese and Schultze, 1975). In theory, pollution taxes or tradeable permits will minimize the costs of achieving a targeted level of pollution (Baumol and Oates, 1988). It will also provide incentives for adoption and diffusion of new and cheaper technologies (Milliman and Prince, 1989).

Analysis of these regulatory instruments under uncertainty has invoked the use of real options analysis where volatility and decision making are collapsed into a option value. This real options approach has been used to determine the value of flexibility or exit and the timing of capital investments of a regulated firm under uncertainty (Teisberg, 1994), finding that investments of utilities will be delayed when there is asymmetry between profits and losses due to regulation. Using real options valuation, it has been also found that a major reason US electrical utilities delay the decision to invest is to gather more information on regulatory restructuring (Ishii and Yan, 2004).

In this paper, we use a real options approach to examine strategic behavior under two sources of dynamic uncertainty: market or demand uncertainty and regulatory uncertainty. These uncertainties have particular relevance to the design of emissions trading permits under cap and trade systems as is currently in operation for carbon in the EU Emissions Trading System (ETS) and potentially for a United States's system under policy discussion by states and the federal government.

Under the Kyoto Protocol and the Marrakesh Accords, three forms of emissions trading were permitted:

1. The trading of Certified Emission Reductions (CERs) under the CDM;
2. The trading of Emission Reduction Units ERUs) under the Joint Implementation mechanism; and
3. The trading of Assigned Amount Units (AAUs) under International Emissions Trading.

Each one of these mechanisms for carbon trading face high regulatory uncertainty. The CDM as the regulations are enforced by a semi-political CDM Executive Board which has made inconsistent decisions and later reversed others. With each change the market has responded with a major variation in prices. Furthermore the Executive Board has relied on Designated Operating Entities (DOEs) to enforce the regulations and standards set by the EB. Since the DOEs are private, standards of validation and verification differ between DOEs. A project developer may find that depending on the particular DOE, even though certified by the EB, a different intensity of enforcement.

The other two markets face similar regulatory uncertainty but of different forms. The ERUs in JI market depends on a supervisory body similar to the EB of yet unknown dimensions and rigor. The market for AAUs while in theory the simplest, depending only on governments to trade a relatively known instrument, has the uncertainty of not only how many AAUs does a country actually possess but also on the political demand by buying countries that the AAUs be greened, that is associated with some other environmental investment scheme of unknown dimensions and rules. These regulatory uncertainties are coupled with the normal market drivers of carbon, e.g. energy prices, industrial activity, economic growth etc.

All these uncertainties are focused on the ETS market which accepts for compliance purposes EUAs, CERs, ERUs and indirectly AAUs. The rules of this market are administered by the European Commission (EC) and depend on the allocation of EUAs to the market and which industries will fall under the ETS and which will not. Furthermore, when there is a miscalculation as with the May 2006 collapse of price of EUAs of 2006 vintage because of an overallocation of EUAs, politics quickly emerges to try and adjust enforcement or standards.

Enforcement mechanisms on industries which receive the EUAs also are uncertain. The EC has the weapon to enforce compliance but only at the national level through the European Court of Justice where fines can be imposed on member states for non-compliance with EC regulations. However the process is laborious, usually taking many years and with uncertain results both on rulings and penalties. At the national level, each EU government finds its own means of enforcement at the industry or entity level. This uncertainty creates a gamesmanship between the EC, the EU states and the industries that eventually have to face the imposition of regulation and possible fines. Furthermore the EC must pursue its enforcement in a political environment and sometimes without the complete capacity to deal with all the legal filings, documentation and defenses.

Finally, the master stroke of uncertainty is no one knows for sure if the markets will continue and if they do, what form they are likely to take. The Kyoto Protocol expires in 2012 and the EC has not announced the 2008 allocations or coverage. Meanwhile trading of all these carbon emissions is taking place at a frenzy pace, and with a great deal of fluctuations in prices. The World Bank reports that trading of all Kyoto instruments has exceeded $20 billion in 2006.

To model such a market in any detail would create such a black box that analytic light is unlikely to emerge. Instead our purpose in the paper is to explore in simple abstract models how regulatory uncertainty could affect the market and prices of permits. Even though several authors have offered a basic treatment (Field 1997, Kahn 1998 Tietenberg 2000, Weber 2002), economic and regulatory issues behind the properties and use of these innovative market instruments still need to be explored, particularly when markets are dynamic and the fundamental drivers are themselves uncertain.

In order to approach the problem gradually, we present a model that focuses on the link between pollution abatement penalties and demand and supply of permits when market demand is stochastic and regulation is uncertain. Trading permits under uncertainty allows firms to behave strategically, by optimally deciding when to exercise opportunities and managing threats of penalties from regulators. From the policy perspective, this approach to pollution trading under uncertainty brings forth the effect of a pollution penalty on the market for permits and on the price of output, how the transaction costs of the regulator affect the price of permits, and how increased level of uncertainty in general affects the market.

In doing this, we are not attempting to model exactly the complexity of any single market such as the ETS but to build an approximation of permit trading markets under regulation that yields insight into the effect of various policy parameters on the market for permits and output. In this respect, we abstract from some of the regulatory complexities, including quantitative restrictions on the importing from secondary markets such as the CDM while giving the regulator more flexibility in the timing of the imposition of the fine. We model the behavior of the regulator as an agent that extracts penalties on firms that exceed their allowances supplemented by market purchased permits but does so only when it is able to cover the transaction costs of enforcement and when the violation is not caused by a transitory increase in output demand of the firm. On the industry side, the firm knows that the regulator will not attack at any violation but only when they suspect that the violation is more permanent, in a sense, imbedded into the fundamentals of the firm and market. But the firm does not know how the demand for output will emerge over the future and may find itself in the position of polluting beyond its allowances and be forced into the market for permits when their prices are high to avoid the imposition by the regulator of penalties. On the other

hand, it may find that demand for its output has fallen and that it is in a position to sell to the market excess allowance. In a dynamic market and regulatory regime, the firm has to decide whether to be short or long in permits and by how much to buffer against the uncertainty of the market and the behavior of the regulator. In turn, the policymaker has to decide what penalties to impose on violations and how overall allocation of permits will affect the industry and the price of output.

Results of Paper

The dynamic uncertainty inherent in pollution permit markets and the strategic decision-making that is demanded of participants in the market both on the part of firms and the regulator create market behavior that is not evident from simple static models of supply and demand. As we have shown in the paper using a real options model operating under dynamic uncertainty, the effect of regulation on permit pricing is not straightforward. The regulator operating also under uncertainty has two instruments at its disposal: the rate of the fine and the timing of the imposition of the fine. The firm on the other hand has several instruments: the amount of output or market share, the amount of pollution permits it secures from the market and the efficiency by which it uses technology to reduce polluting emissions.

We have found that under uncertainty the combination of the threat of the sanction and the market for permits may be effective in reducing the emission levels by shifting the competitive advantage in favor of less polluting firms. This will occur both because of the reduction of firm value to the potential imposition of the sanctions and because less polluting firms will be able to sell part or all of their allowances to the more polluting ones. Uncertainty, however, tends to reduce the value of the market price of permits, since in equilibrium this is simply equal to the expected present value of the fine. Thus, higher uncertainty will require, for the regulation to be effective, comparatively higher fines.

Even under uncertainty of regulation and demand for output, the effect of pollution permit trading is positive to achieving a cleaner industrial base. Firms that are more technologically efficient in reducing pollution will tend to acquire larger market shares, with the exact effect depending on the uncertainty of demand for output and the severity of the fine.

Using this type of real options approach, we believe that avenues of research are open. For example, through relatively simple analytic models other issues with respect to permit trading can be explored, for example, the effect on new entry into the market – when will new firms with cleaner technologies enter the market when demand is uncertain and the behavior of the regulator uncertain. We will explore this issues and others in later papers.

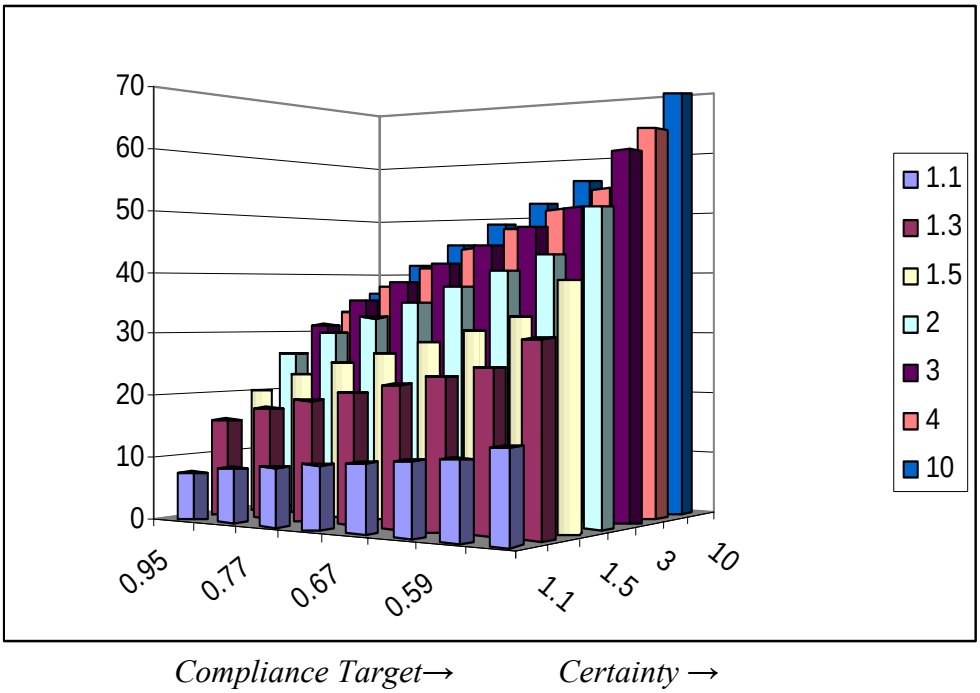

Figure 1. Equilibrium price (Euro/ton) of Permitsunder alternative hypotheses on uncertainty and Compliance targets (fine value $\gamma = 100 Euro / ton$).

The Challenge of Estimating the Uncertainty for GHG Emission Estimates at a Continental Scale on the Example of Agriculture

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Abstract

The estimation of quality level and uncertainty of a greenhouse gas inventory that is build from 15 individual and independent greenhouse gas inventories, as this is the case for the inventory of the European Communities, presents a particular challenge. It is possible only if homogeneous information is available for all Member States, if the approach to estimate the quality level is put on a more quantitative basis, and if a proper evaluation of correlation between Member States is performed. We present a methodology that estimates the quality level and the uncertainty for the categories in the agriculture sector. The method differs from the approach suggested in the IPCC guidelines as quantitative information from the lowest available level – if possible the individual parameters used in the inventory calculations – is used to come up with an – also quantitative – estimate for the quality level and finally the uncertainty estimate. Not surprisingly, N_2O emissions from agricultural soils are found to be dominating the uncertainty of not only the agricultural sector, but also the overall GHG inventory for many countries.

Keywords: uncertainty calculation – agriculture – agricultural soils – European Communities

1. Introduction

The fact that both the European Union and its Member States have joined the United Nations Framework Convention on Climate Change (UNFCCC) poses a particular challenge on the compilation of the European Community (EC) greenhouse gas inventory. On one hand, the emission estimates must be identical to the sum of the emission estimates of the Member States that are part of the 'European bubble', but on the other hand the numbers in itself must be defendable and derived with the best available data and approaches. This calls for continuous interactions between national and 'European' sectoral experts.

For the EC inventory, uncorrelated emission estimates of the individual countries reduce the level uncertainty. To estimate the uncertainty at EC level, it is thus important to make assumptions on the level of correlation between Member States emission estimates. The following approach has been followed in the National Greenhouse Gas Inventory of the European Communities (EEA, 2007): all emission estimates that have been derived using a Tier 1 methodology were assumed to be correlated, while those estimates that are based on a Tier 2 or higher approach are assumed to be uncorrelated. However, in case of a strong dependence of environmental factors (or activities which are not reflected in the inventory approach) also default factors might be uncorrelated. On the other hand, Tier 2 estimates are correlated as much as a common parameter is biased. In order to allow the inclusion of these considerations to some extent in the assessment of the uncertainty of such a "composite"-

inventory, the introduction of additional elements compared to what is reported to the UNFCCC secretariat is proposed.

2. Assessing the Level of Quality

The IPCC methodology estimates emissions *E*s from a certain source category s as

$$E_s = IEF_s \cdot AD_s \quad (1)$$

where AD_s are the activity data for the source category *s* and IEF_s is the implied emission factor for this category. There are three levels for estimating the emissions, called Tier 1, Tier 2, and Tier 3, moving from the use of default values only over the inclusion of national information to the application of modeling approaches. In order to define an EU-wide quality level per source category and sector, two criteria must be met:

1) For each source category and Member State a quality level must be assigned.
2) In order to allow the summation of emission estimated of different quality, the quality level must be measured on an interval scale, allowing 'intermediate' quality levels.

To do so, we developed standard procedures for each source category. These are based on the following principles:

i) An appropriate estimation of the activity data is regarded as basic requirement for the estimation of the source strength. Therefore, even though the methodology used to estimate the activity level influences the *uncertainty* of the emission estimate, it does not impact on the *quality level*. Only if a highly dis-aggregated characterization of the activity data is accompanied with an appropriate parameterization, it is regarded as improving the quality level.

ii) However, the flow of nutrients in agriculture implies that the emission in one category can serve as activity level in another. For example, nitrogen excretion can be regarded as an emission of nitrogen in livestock production systems, but according to the IPCC the amount of nitrogen excreted is an activity data for estimating N_2O emissions from manure management. Thus, in contrast to the IPCC definitions, we define as *activity data* only this information that must be obtained using statistical surveys (e.g., population data, distribution of animal manure systems etc.) and regard everything else as *parameters* (emission factors and other parameters).

iii) A quality level is assessed for each parameter by comparing the IPCC default value with the value used by the countries. If the default IPCC value is used, the quality level is set to Tier 1 and otherwise the quality level is set to Tier 2. Caution must be taken if country-specific data are identical to the default values.

iv) Quality levels are aggregated applying different aggregation rules.

(a) The MEDIAN-rule should be applied where the quality level $Q_{\prod_i P_i}$ of a product of different parameters P_i is to be evaluated. For example the emission factor for CH_4 emissions from manure management is calculated from the CH_4 production potential, the methane conversion factor, and the volatile solid excretion. The aggregation of the quality level of these parameters to estimate the level of quality of the emission factor should follow the following principles. (i) if parameters with very different quality are multiplied, the higher quality should get more weight; (ii) if parameters with different uncertainty are multiplied, it should be good practice to estimate the parameter which is

associated with the higher uncertainty at a higher quality level. Thus, the aggregation rule should reward if efforts have been made to estimate uncertain parameters. However, with the lack of a comprehensive set of relative uncertainty estimates for the individual parameters, in the following equation an arbitrary weighting factor $w_{r,j}$ has been introduced, based on expert judgment.

$$Q_{\prod_i P_i} = 3 - \prod_i \left[(3 - Q_i)^{\frac{w_{r,i}}{\sum_j \{w_{r,j}\}}} \right] \quad (2)$$

with i and j indicating the individual parameters to be multiplied. The term $(3\text{-}Q_i)$ assures that a higher weight is given to the parameter estimated with the higher Tier.

(b) The MAX-rule is a simplification of the median-rule, due to the some times difficult task to assign appropriate weighting factors to the multiplicative parameters. Simplification is justified under certain conditions, i. e., if it is to be expected that the quality level is dominated by one of the multiplicative parameters; if the quality level of the dominating parameters is correlated; or if the methodology to derive the resulting emission factor is very divers, often also based on direct measurements. Under these conditions it is sufficient if one of the main parameters is estimated with a high quality level in order that also the product can obtain the high quality stamp. This rule has been applied to estimate the quality level of CH_4 emissions from enteric fermentation.

$$Q_{A \cdot B} = \max\{Q_A, Q_B\} \quad (3)$$

(c) The MEAN-rule if an emission estimate is based on the estimates of two or more sub-categories. In this case, the quality levels of the individual estimates are aggregated using an emission-weighted average. E.g., the quality level of indirect N_2O emissions from agriculture Q_{4D3} is calculated from the quality levels calculated for indirect emissions through volatilization of nitrogen gases Q_{4D3a} and leaching/run-off of nitrate Q_{4Db} according to:

$$Q_{A+B} = \frac{Q_A \cdot E_A + Q_B \cdot E_B}{E_{A+B}} \quad (4)$$

3. Assessing the Uncertainty

Generally, uncertainties in input data are needed to be derived from indirect sources or from expert judgments. A comparison of the uncertainty estimates of five inventories in the late 1990s (Rypdal and Winiwarter, 2001), showed that the main reason for the difference in estimated uncertainty is the differences in the assessment of N_2O emissions from agricultural soils. (Monni et al., 2004) also stress that differences in reported uncertainties are to a large part due to different ways of assessing the uncertainty. (Rypdal and Flugsrud, 2001) describe two ways to handle correlations. One way is to aggregate the input data set in such a way that the dependencies are eliminated and the other solution is to explicitly model the dependencies in the analysis, if this is allowed by the method used. (Penman et al., 2000) note that correlations, even if they exist, may not be important for the uncertainty assessment of a GHG inventory if the dependency is not sufficiently strong or the inventory is not sensitive to the

dependent inputs. Statistically, if no Monte Carlo model or similar is available, dependencies are dealt with the following equation:

$$\sigma^2{}_{X\pm Y} = \sigma^2{}_X + \sigma^2{}_Y \pm 2 \cdot COV_{X,Y} \quad (5)$$

$$\mathrm{COV}_{X,Y} = \rho_{X,Y} \cdot \sigma_X \cdot \sigma_Y \quad (6)$$

if $\sigma^2{}_X$ is the variance of the parameter X, $\mathrm{COV}_{X,Y}$ is the covariance between the parameters X and Y, $\rho_{X,Y}$ is the coefficient of correlation.

The information on the uncertainty estimates for agricultural sources differs significantly across the 15 Member States for which the EC inventory has to be compiled. Some countries report uncertainties at the level of categories, other give detailed information, for example by main animal types. To allow a comparison at EU level and further processing, the numbers had to be aggregated to the level of the category. As a rule, uncertainties that had to be aggregated to a sub-category (e.g., dairy and non-dairy cattle to cattle or different direct N_2O sources from agricultural soils) were considered to be correlated, and for the aggregation of sub-categories to categories (different animal types, direct and indirect N_2O emissions), the uncertainties are considered to be uncorrelated. Both assumptions are sometimes debatable, but as will be shown below, the degree of correlation below the sub-category level does not have much repercussion on the EC-uncertainty estimate for the categories, and the correlation of sub-categories is important for agricultural soils only, but for this source category it is considered as appropriate. The uncertainties of the categories within agriculture are as well considered to be uncorrelated. This is mainly due to the fact that the largest contribution of the uncertainties stems from the emission factors, so that the uncertainty of the activity data, which might be partly identical across categories, becomes less important. 'Gap filling' as described above is done for the combined uncertainty (AD*EF) only.

To aggregate the uncertainty estimates from the countries to the EU-15, it is important to assess the level of correlation between the estimates of the individual countries. As introduced above, the EC National Inventory Report assumes that for a certain category, countries that use the Tier 1 approach are likely to either over- or underestimate the emissions depending on the quality of the default values. The uncertainty of these countries is assumed to be correlated. On the other hand, if a Tier 2 approach was followed, the error made is more likely to be independent of the error made in other countries (both those using Tier1 and those using Tier 2) and the uncertainty is assumed to be uncorrelated. This approach is not satisfactory, as is neglects that most calculations are done with several parameters so that the degree of 'independence' varies with the amount of effort that has been put into the development of country-specific parameters.

The quantitative assessment of the quality-level outlined in section 0 is proposed to be used as a proxy for the degree of correlation between the uncertainty estimates of different countries. The quality level is transformed to the correlation coefficient on the basis of the following equation:

$$\rho_{X,Y} = \sqrt{(2 - Q_X) \cdot (2 - Q_Y)} \quad (7)$$

where *X* and *Y* stand for two different countries with the level of quality Q_X and Q_Y.

Equation (7) leads to the situation of no correlation $(\rho_{X,Y} = 0)$ for two countries with a Tier 2 approach and full correlation $(\rho_{X,Y} = 1)$ if both countries used a Tier 1 approach. A correlation coefficient can be calculated for any intermediate situation.

The IPCC Good Practice Guidance also suggests that for estimating trend uncertainty, correlation in time exists for the emission factor and no correlation for the activity data. The trend uncertainty is estimated with the help of the so-called "Type A" and "Type B" sensitivity (IPCC, 2000). However, this approach can not be followed here because it would require that the uncertainties for the activity-data and emission factors would be gap-filled. Instead, the data calculated so far allow calculating trend uncertainty on the basis of equation (8) assuming – simplified – that there is full correlation between the years (see EEA, 2007). The correlation between the Member States is the same that was used for the level uncertainty estimate. To estimate the impact of agriculture on the overall GHG inventory's trend uncertainty, the trend uncertainty $u_{t\text{-}p}$ in percent-points is calculated from the relative trend uncertainty $u_{t\text{-}r}$ and the absolute trend according to (EEA, 2007):

$$u_{t-p} = 100 \cdot \left(\frac{\Delta E + \Delta E \cdot \frac{u_{t-r}}{100}}{E_0} - \frac{\Delta E}{E_0} \right) \tag{8}$$

4. Results

Table 1 summarizes the level of quality calculated for EU-15 countries and the EU-15 for the main source categories in agriculture. Enteric fermentation and manure management emissions are in most cases based on a characterization of the animal performance of the most important animal categories. For N_2O emissions from agricultural soils, only few countries have developed national emission factors, even though national information for other parameter, particularly volatilization and leaching fractions, make the quality better than one. *Table 2* summarizes the result of the uncertainty assessment for agriculture. For the EC uncertainty, five scenarios are calculated to give an idea for the range of possible uncertainty values. The first scenario calculates the uncertainty using the 'most probable' correlation level as defined above. However, particularly for N_2O emissions from agricultural soils, the dependence on other exogenous factors, that are not part of the inventory system, has been considered as influencing strongly the uncertainty distribution, so that the 'most probable' level of correlation does not necessarily reflect the reality.

Therefore, a second scenario assumes no correlation between the uncertainty estimates of the individual countries, while the third scenario assumes full correlation. Obviously, this scenario leads to the highest overall uncertainty estimates of 85.4% for agriculture. Two additional scenarios calculate the bounds for the uncertainty estimate assuming that the MS estimate for agricultural soils is un-correlated, but the estimates of all other sub-categories is correlated (lower bound) and finally that only agricultural soil-estimates are correlated (upper bound). The table shows that both bounds are shifted only slightly, the lower from 40.5% to 41.8% and the upper from 85.4% to 84.8%. This highlights again the importance of the estimate of N_2O emissions from agricultural soils. This importance is further translated into the overall greenhouse gas inventory, as shown in *Table 3***Table** *,* giving the uncertainty values as percentage of the total greenhouse gas emissions, where it induces a range of the total uncertainty from 4% to 8%. If agriculture were not part of the greenhouse gas inventory,

the uncertainty would be at a level of 1.4%! The analysis of the trend analysis yield similar results as calculated in (EEA, 2007), as shown in *Table 4*.

Table 1. Summary table for the quality assessment

Member State	TOTAL	Enteric Fermentation	Manure Management	Manure Management	Rice Cultivation	Agricultural soils	Agricultural soils
	ALL	CH4	CH4	N2O	CH4	CH4	N2O
Austria	Tier 1.4	Tier 1.4	Tier 2.0	Tier 2.0	Tier 0.0	Tier 2.0	Tier 1.2
Belgium	Tier 1.3	Tier 1.4	Tier 1.0	Tier 2.0	Tier 0.0	Tier 2.0	Tier 1.4
Denmark	Tier 1.6	Tier 2.0	Tier 2.0	Tier 2.0	Tier 0.0		Tier 1.3
Finland	Tier 1.7	Tier 1.9	Tier 2.0	Tier 2.0	Tier 0.0		Tier 1.6
France	Tier 1.5	Tier 1.9	Tier 1.9	Tier 1.6	Tier 1.0		Tier 1.1
Germany	Tier 1.8	Tier 2.0	Tier 2.0	Tier 2.0	Tier 0.0	Tier 2.0	Tier 1.6
Greece	Tier 1.2	Tier 1.5	Tier 1.7	Tier 1.2	Tier 1.0		Tier 1.1
Ireland	Tier 1.7	Tier 2.0	Tier 1.9	Tier 2.0	Tier 0.0		Tier 1.3
Italy	Tier 1.5	Tier 1.8	Tier 1.9	Tier 1.9	Tier 2.0		Tier 1.2
Luxembourg	Tier 1.6	Tier 2.0	Tier 2.0				Tier 1.0
Netherlands	Tier 1.9	Tier 1.9	Tier 1.6	Tier 2.0	Tier 0.0		Tier 1.9
Portugal	Tier 1.6	Tier 2.0	Tier 2.0	Tier 2.0	Tier 1.0		Tier 1.2
Spain	Tier 1.8	Tier 1.9	Tier 2.0	Tier 2.0	Tier 1.0		Tier 1.5
Sweden	Tier 1.9	Tier 1.9	Tier 2.0	Tier 1.8	Tier 0.0		Tier 1.9
United Kingdom	Tier 1.5	Tier 2.0	Tier 2.0	Tier 1.9	Tier 0.0		Tier 1.1
EU-15	Tier 1.6	Tier 1.9	Tier 1.9	Tier 1.9	Tier 1.7	Tier 2.0	Tier 1.3

Table 2. Summary table for the uncertainty assessment. Relative uncertainties.

Member State	TOTAL	Enteric Fermen-tation	Manure Manage-ment	Manure Manage-ment	Rice Culti-vation	Agri-cultural soils	Agri-cultural soils
	ALL	CH4	CH4	N2O	CH4	CH4	N2O
Austria	39.3	22.4	50.1	100.5	0.0	0.0	100
Belgium	91.6	40.3	41.2	90.6	0.0	46.1	252
Denmark	17.2	12.8	100.5	100.5	0.0	0.0	21
Finland	67.2	16.6	15.7	81.3	0.0	0.0	115
France	103.2	40.3	50.2	50.2	0.0	0.0	200
Germany	70.2	18.6	28.9	75.3	0.0	106.1	120
Greece	70.0	30.4	50.2	111.8	40.0	0.0	104
Ireland	24.2	22.6	11.1	100.6	0.0	0.0	58
Italy	36.0	28.3	102.0	102.0	20.2	0.0	67
Luxembourg	54.8	25.0	50.0	114.4	0.0	0.0	139
Netherlands	41.4	19.6	70.4	100.5	0.0	0.0	83
Portugal	95.3	38.4	82.0	106.8	55.5	0.0	234
Spain	35.3	11.4	11.4	101.3	0.0	0.0	80
Sweden	40.4	25.5	53.9	53.9	0.0	0.0	71
United Kingdom	244.5	22.4	31.6	425.9	0.0	0.0	436
EU-15*	66.8	17.5	28.3	58.9	20.1	105.5	120.3
No correlation	40.5	10.8	18.0	37.5	18.1	105.5	79.5
Full correlation	85.4	26.0	43.1	100.9	24.7	105.7	167.3
Only 4D uncorrelated	41.8	26.0	43.1	100.9	24.7	105.5	79.5
Only 4D correlated	84.8	10.8	18.0	37.5	18.1	105.5	167.3

Table 3. Member State's contribution of uncertainty in agriculture to the overall uncertainty estimate. Emission data from (EEA, 2007)

Member State	Total uncertainty of GHG inventory	Share agriculture in total GHG inventory	Total agriculture	Enteric ferment. (4A)	Manure Managem. (4B)		Agricultural soils (4D)			
							total	direct	indirect	animal prod.
				CH4	CH4	N2O	N2O	N2O	N2O	N2O
	% of total emissions	% of total emissions	uncertainties expressed as % of total GHG emissions							
Austria	3.7	10.3	4.0	0.9	0.6	1.2	3.7	3.0	2.1	0.4
Belgium	7.5	7.7	7.0	1.1	0.7	0.5	6.9		0.0	
Denmark	5.4	15.8	2.7	0.5	1.6	0.9	1.9		0.0	
Finland	58.8	14.6	9.8	0.7	0.1	1.1	9.7	9.0	3.6	0.5
France	21.3	19.4	20.1	2.3	1.3	0.6	19.9		0.0	
Germany	5.6	6.6	4.6	0.4	0.1	0.2	4.7	4.1	2.2	0.1
Greece	12.1	8.6	6.0	0.7	0.2	0.3	6.0	5.2	1.1	2.7
Ireland	6.2	26.6	6.4	3.0	0.4	0.6	5.7	3.9	1.0	4.0
Italy	3.2	7.9	2.8	0.7	0.7	0.8	2.6	1.9	1.6	0.3
Luxembourg	0.0	3.0	1.6	0.0	0.0		0.0	0.0		
Netherlands	4.2	8.5	3.5	0.6	0.8	0.4	3.3	1.4	3.0	0.3
Portugal	9.3	9.3	8.9	1.3	1.1	0.7	8.7	7.6	1.5	3.9
Spain	8.4	11.4	4.0	0.4	0.3	0.8	3.9	0.8	3.8	0.1
Sweden	6.0	13.6	5.5	1.1	0.4	0.4	5.3		0.0	
United Kingdom	16.5	6.8	16.7	0.5	0.1	0.8	16.7		0.0	
EU-15	6.3	9.8	6.6	0.5	0.3	0.3	6.0	0.0	0.0	0.0
No correlation	3.9	9.8	4.0	0.3	0.2	0.2	4.0	0.0	0.0	0.0
Full correlation	8.0	9.8	8.4	0.8	0.5	0.6	8.3	0.0	0.0	0.0

Uncertainty of total inventory given in NIR; sectoral uncertainties calculated from relative uncertainties and emission data.

Table 4. Trend uncertainty in percent-points of the overall EC GHG inventory

	TOTAL	Enteric Fermen-tation	Manure Manage-ment	Manure Manage-ment	Rice Cultiva-tion	Agri-cultural soils	Agri-cultural soils
	ALL	CH4	CH4	N2O	CH4	CH4	N2O
EU-15	7.8	1.7	0.2	5.8	1.2	6.2	17.4
No correlation	6.5	1.0	0.1	4.2	1.1	6.2	12.5
Full correlation	12.6	2.5	0.3	10.3	1.6	6.2	24.1
Only 4D uncorrelated	12.5	1.0	0.1	4.2	1.1	6.2	24.1
Only 4D correlated	6.6	2.5	0.3	10.3	1.6	6.2	12.5

5. Conclusion and Outlook

We present a methodology that estimates the quality level and the uncertainty for the categories in the agriculture sector. The method differs from the approach suggested in the IPCC guidelines as quantitative information from the lowest available level – if possible the individual parameters used in the inventory calculations – is used to come up with a – also quantitative – estimate for the quality level and finally the uncertainty estimate. The methodology proposed is based on standard error propagation rules and additional rules for "quality-level-propagation". It considers possible correlation between source categories

without the need of the aid of Monte Carlo calculations. Not surprisingly, N_2O emissions from agricultural soils are found to be dominating the uncertainty of not only the agricultural sector, but also the overall GHG inventory for many countries. This suggests that further improvements should focus on programmes to reduce the uncertainty of this source category. The analysis of the trend uncertainty neglects that the error of the activity data usually is assumed to be correlated. Thus the next steps must be – besides an improved estimation of the weighting factors to assess the quality level – a more detailed analysis of the trend analysis including the effect of activity data correlation.

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Compliance and Emission Trading Rules for Uncertain Estimates of Inventory Uncertainty

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Abstract.

National inventories of greenhouse gases emissions are computed with rather low precision. Their uncertainty estimates are, however, calculated in a similar way and, therefore, have similar low precision. This should be accounted for in the compliance and trading rules. In this paper we model the uncertain inventories using fuzzy numbers, which allows us to shape both their uncertainties and ignorance of precise uncertainty parameters. Derived this way compliance and emission trading rules generalize those for the interval uncertainty approach, which were considered in the earlier papers. The final conclusion is, however, that the interval uncertainty rules can be still applied, but the noncompliance risk used in them should take much higher values.

Keywords: national inventories of greenhouse gases emission, uncertainty, compliance, emission permit trading.

1. Introduction

Greenhouse gases inventories estimates are far to be exact. Estimation of its uncertainty done for several countries showed that they usually exceed the reductions agreed upon in the Kyoto Protocol. Presented up-to-now ideas to change the compliance checking and emission trading rules to include the uncertainty of inventories assume that the uncertainty estimates are known exactly, see Jonas et al. (2004a, 2004b) and Jonas & Nisson (2007) for a review of techniques and specifically Gillenwater et al. (2007) and Nahorski et al. (2007) for solutions in spirit of the present paper. However, this is far from being true. The uncertainty estimates are calculated in a similar way as the inventories and it may be expected that uncertainty of them is of the similar order as that of inventory itself.

It was shown in Nahorski et al. (2007) that although the stochastic approach may be useful for the determination of the compliance rule, it provides a too complicated and practically useless formula for the emission trading rule. Thus, in this paper a fuzzy approach is used, which can be considered as a generalization of the interval one. The fuzzy set calculus basically inherits the rules from the interval calculus, and this way provides linear dependencies in the resulting formulas. But at the same time the fuzzy variables may be shaped to have more concentrated distributions than the interval ones, and this way can better approximate the real distributions.

The fuzzy approach solves also the problem of imprecise knowledge of the uncertainty interval length by considering the whole family of intervals of different length and this way modeling uncertainty of their knowledge. Coming out from this point of view in this paper the uncertainty of the inventory uncertainty estimate is taken into account and new rules for checking compliance and emission trading rules are proposed. They are generalizations of the

rules presented in Nahorski et al. (2003) and reduce to them when the uncertainty interval estimate is exact. The results of application of these rules are compared to those obtained earlier, for the assumed exact knowledge of uncertainty estimate. The result is that a convenient interval uncertainty approach may be used, but with much higher noncompliance risk.

In section 2 we formulate the problem and introduce some basic notation. Then, in section 3, we recall conditions for checking compliance and formulas for so called efficient emissions, which can be directly traded, without taking account for the emission uncertainty, for the interval type of uncertainty. In section 4 a family of fuzzy numbers is introduced. They are used to model the full inventory uncertainty and form the basis for derivations of generalized compliance and emission trading rules. These rules are compared with the interval approach rules. Section 5 concludes.

2. Notation and Problem Formulation

Basically, the total emission by a party is calculated by summing up emissions from every type of contributing activity and subtracting the gases absorbed by sinks. On the national scale these values are unsure, giving rise to uncertainty. The nature of the uncertainty is a complicated one. It originates from a lack of exact knowledge of some variables and a need for an imperfect modeling of often poorly known processes. *Table 1* gives a few examples of the uncertainty estimates, in percentages of the emissions. Full details can be found in Jonas et al. (2004a, 2004b).

Table 1. Examples of Kyoto reduction commitments and published uncertainty estimates of national emissions, in per cents.

Country	Kyoto reduction	Uncertainty
Austria	8	12
The Netherlands	8	5
Norway	-1	21
Poland	6	6
Russia	0	17
United Kingdom	8	19

In the sequel by $x(t)$ we denote the real, unknown emission of a party in the year t and by $\hat{x}(t)$ its best available estimate. To simplify notation the time argument will be dropped in the sequel.

The Kyoto Protocol declaration requires that each participating country should reduce a prespecified percent of its basic year emission within the given period (around 20 years), although some countries are granted a possibility of stabilizing the emission at the basic year level or even of a limited increase of its emission.

Let us denote by δ the fraction of the party emission that is to be reduced in the commitment period according to its obligation. The value of δ may be negative for parties, which were allotted limitation of the emission increase. Denoting by t_b the basic year and by t_c the commitment year, and by x_b and x_c, respectively, the emissions, the following inequality should be satisfied

$$x_c - (1-\delta)x_b \le 0 \tag{1}$$

As neither x_c nor x_b are known precisely enough, only the difference of estimates can be calculated

$$\hat{x}_c - (1-\delta)\hat{x}_b \tag{2}$$

where both $\hat{x}_c$ and $\hat{x}_b$ are known with an intolerable low accuracy.

3. Interval Type Uncertainty

Compliance. Assuming that the uncertainty intervals at the basic and the commitment years are $2d_b$ and $2d_c$, respectively, we have

$$x_b \in [\hat{x}_b - d_b, \hat{x}_b + d_b], \qquad x_c \in [\hat{x}_c - d_c, \hat{x}_c + d_c]$$

from which, using the interval calculus rules, we get

$$x_c - (1-\delta)x_b \in [D\hat{x} - d_{bc}, D\hat{x} + d_{bc}]$$

where

$$D\hat{x} = \hat{x}_c - (1-\delta)\hat{x}_b \tag{3}$$

and

$$d_{bc} = d_c + (1-\delta)d_b \tag{4}$$

To be fully credible, that is to be sure that (1) is satisfied, the party should prove that $D\hat{x} + d_{bc} \le 0$. We say that the party is *compliant with risk* α, if $D\hat{x} + d_{bc} \le 2\alpha d_{bc}$, that is, not bigger part of its distribution than α lies above zero, see *Figure 1* for the geometrical interpretation. After simple algebraic manipulations this gives the condition

$$\hat{x}_c + (1-2\alpha)d_{bc} \le (1-\delta)\hat{x}_b \tag{5}$$

Thus, to prove the compliance with risk α the party has to satisfy its obligation with the inventory emission estimate increased by the value $(1-2\alpha)d_{bc}$, dependent on its uncertainty measure expressed by d_{bc}. The condition (5) can be also rewritten as

$$\hat{r} = \hat{x}_c / \hat{x}_b \le 1 - \delta - (1-2\alpha)R_{bc}$$

where $\hat{r}$ is the estimated reduction factor and $R_{bc} = d_{bc} / \hat{x}_b$ is the half relative uncertainty interval. Thus, the compliance with risk α can be formally reduced to the form (2) by redefinition of the reduction factor

$$\delta \quad \rightarrow \quad \delta_U = \delta + (1-2\alpha)R_{bc} \tag{6}$$

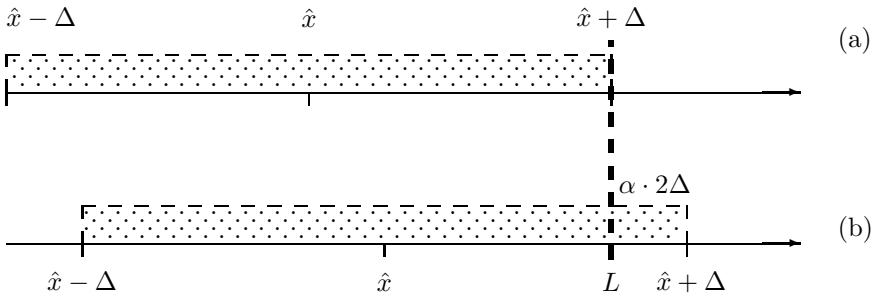

Figure 1. Full compliance (a) and the compliance with risk α (b) in the interval uncertainty approach.

For the sake of simplicity we do not consider here dependence of inventories $\hat{x}_b$ and $\hat{x}_c$. An idea how to include this dependence was presented by Nahorski et al. (2007) and eventually was reduced to introducing a variable $0 \le \varsigma \le 1$, which was used to modify the uncertainty interval, represented by d_{bc} in (4), in the following way

$$d_{bc} = (1-\zeta)(d_c + (1-\delta)d_b)$$

This idea can be easily elaborated for the case considered here.

Emission trading. Admitting the above compliance proving policy it is possible to consider uncertainty in the emission trading. The main idea of this proposition consists in transferring the uncertainty to the buyer together with the traded quota of emission and then including it in the buyer's emission balance.

Let us denote by R_c^S the relative uncertainty of the seller and by $\hat{E}^S$ the unit of the traded estimated emission. Due to the partial cancellation of the subtracted estimated emission and its uncertainty in the buyer's emission balance *the effective traded emission* is, see Nahorski et al. (2007)

$$\hat{E}_{eff} = \hat{E}^S[1-(1-2\alpha)]R_c^S \tag{7}$$

Thus, the bigger seller's uncertainty is, the less purchased unit is accounted for the buyer. Expression (7) reduces emissions estimated with an arbitrary precision to globally comparable values, which can be directly subtracted from any country estimated emission. This way it is possible to construct a market for the effective emissions, see Nahorski et al. (2007).

4. A Fuzzy Type Uncertainty

Although the interval approach provides a very simple and convenient solution, its criticism is sometimes aimed at low precision of defining the uncertainty intervals. Similarly to inventory calculation, also calculation of the uncertainty intervals is inexact and its accuracy may be of the same order as that of the inventory calculation.

The uncertainty of the interval ends can be modeled using fuzzy set approach, see Appendix for a short introduction of some basic notions. A common way for this is to use so called fuzzy interval with the trapezoidal membership function. The uncertainty of the interval ends is modeled there by linear change of the membership function from 0 to 1 at the interval ends.

In this paper the fuzzy numbers are used to model imperfect knowledge of the uncertainty. A fuzzy number is a particular case of a fuzzy interval and may be also considered as a straight generalization of an ordinary number, whose value is unsure. This is the situation, which we spot in the greenhouse gas inventories.

A usual problem with the fuzzy set approach is to determine the membership function. Here, we introduce a membership function dependent on a parameter. Fixing the parameter, the function best fitting the experimenter expectation can be obtained. Moreover, this function can well fit the distribution obtained from Monte Carlo inventory simulations, as shown in the sequel.

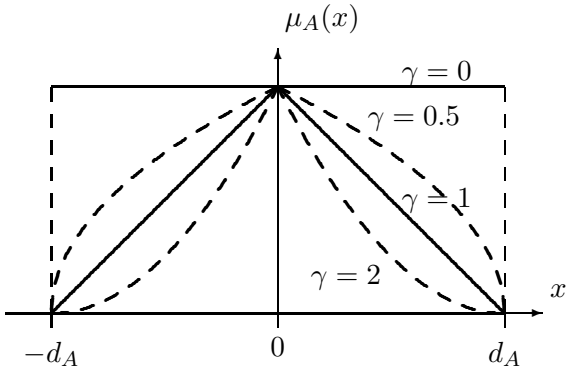

Figure 2. Membership functions for $\gamma =$ 0, 0.5, 1 and 2.

Let us consider a family Φ of fuzzy numbers $A^\gamma = \left\{\left(x, \mu_A^\gamma(x)\right) \mid x \in \text{ supp } A^\gamma\right\}$ indexed by a variable $\gamma \in C^+ = \{\gamma \in C \mid \gamma \geq 0\}$, with the support supp $A^\gamma = \left[d_A^l, d_A^r\right]$. *Figure 2* depicts examples of μ_A^γ representing a fuzzy number 0, for few values of γ. The membership function is chosen there as

$$\mu_A^\gamma(x) = \left(1 - \frac{|x|}{d_A}\right)^\gamma$$

with $d_A^l = -d_A$ and $d_A^r = d_A$. This is a special LR type fuzzy number introduced in Appendix, with $L = R$ and $p_l = p_r$. As can be seen, the introduced family can model wide arrays of fuzzy uncertainties. It can be even more generalized, if two branches, left and right, with different values of γ and d_A, are used.

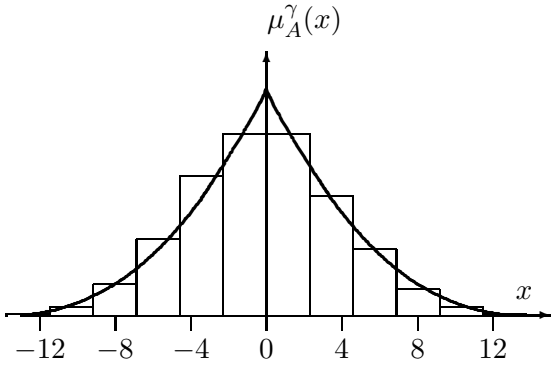

Figure 3. Fit of a membership function $\mu_A^\gamma(x)$ for $\gamma = 2.43$ and $d_A = 14.46$ to the histogram from Vreuls (2004), centered and normalized.

It was suggested on the basis of Monte Carlo simulations (Winiwarter, 2007) that distribution of the inventory error is close to the Gaussian one. Yet, stochastic approach introduces nonlinearities in derivation of the effective traded emission formulas. As seen in Fig. 3, a membership function from the proposed family can also give good fit to Monte Carlo simulation data, as presented originally in Vreuls (2004).

Compliance. Let us assume now that the uncertainty of $\hat{x}_b$ and $\hat{x}_c$ are of the fuzzy type with the membership functions from the family Φ, that is they are fuzzy numbers $\hat{x}_b^\gamma$ and $\hat{x}_c^\gamma$ where

$$\hat{x}_b^\gamma = \left\{\left(x, \mu_{\hat{x}_b}^\gamma(x)\right) \middle| \, x \in \operatorname{supp} \hat{x}_b^\gamma\right\}$$

$$\operatorname{supp} \hat{x}_b^\gamma = \left[\hat{x}_b - d_b, \hat{x}_b + d_b\right]$$

$$\mu_{\hat{x}_b}^\gamma(x) = \left(1 - \frac{\left|x - \hat{x}_b\right|}{d_b}\right)^\gamma$$

and similar for $\hat{x}_c^\gamma$. Then, calculating the difference in analogy to (2) a fuzzy number $D\hat{x}^\gamma$ is obtained

$$D\hat{x}^\gamma = \hat{x}_c^\gamma - (1-\delta)\hat{x}_b^\gamma = \left\{\left(x, \mu_{D\hat{x}^\gamma}^\gamma(x)\right) \middle| \, x \in \operatorname{supp} D\hat{x}^\gamma\right\} \tag{8}$$

with the support

$$\operatorname{supp} D\hat{x}^\gamma = \left[D\hat{x} - d_{bc}, D\hat{x} + d_{bc}\right] \tag{9}$$

and the membership function

$$\mu_{D\hat{x}^\gamma}^\gamma(x) = \left(1 - \frac{\left|x - D\hat{x}_b\right|}{d_{bc}}\right)^\gamma \tag{10}$$

where $D\hat{x}$ and d_{bc} are given by (3) and (4), respectively. The proof of expressions (8) to (10) may be done easily using addition and multiplication rules on fuzzy numbers given in the Appendix. It may be also found in Nahorski et al. (2005).

For this case we say that a party is *compliant with risk* α when not bigger than the α th part of the area under the membership function (10) lies above zero. Simple calculations show that this area is placed within the distance $y = (2\alpha)^{\frac{1}{\gamma+1}} d_{bc}$ from the right end of the interval $[D\hat{x} - d_{bc}, D\hat{x} + d_{bc}]$, see *Figure 4*. Thus we get the following condition

$$D\hat{x} + d_{bc} \le (2\alpha)^{\frac{1}{\gamma+1}} d_{bc}$$

or in a more explicit form

$$\hat{x}_c + \left[1 - (2\alpha)^{\frac{1}{\gamma+1}}\right] d_{bc} \le (1-\delta)\hat{x}_b \tag{11}$$

As before, it can be also transformed to the form

$$\hat{r} = \hat{x}_c / \hat{x}_b \le 1 - \delta - \left[1 - (2\alpha)^{\frac{1}{\gamma+1}}\right] R_{bc}$$

where $R_{bc} = d_{bc} / R_{bc}$, giving rise to redefinition of the reduction factor

$$\delta \quad \rightarrow \quad \delta_U = \delta + \left[1 - (2\alpha)^{\frac{1}{\gamma+1}}\right] R_{bc} \tag{12}$$

This formula can be interpreted as an extension of the formula (6), as it reduces to (6) when $\gamma = 0$.

With a given α the formula (12) shows the dependence of the reduction factor on γ.

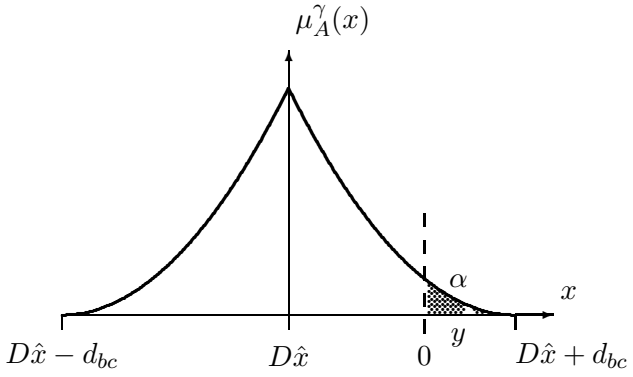

Figure 4. Graphical interpretation of the α th part of the area under the membership function.

Table 2. Comparison of ratios $E_{eff} / \hat{E}^S$ for the interval and fuzzy approaches with $\alpha = 0.3$ and data from *Table 1*.

Country	Uncertainty [%]	Interval	Fuzzy				
			$\gamma = 0.5$	$\gamma = 1$	$\gamma = 1.5$	$\gamma = 2$	$\gamma = 2.5$
Austria	12	0.904	0.965	0.973	0.978	0.981	0.984
The Netherlands	5	0.960	0.986	0.989	0.991	0.992	0.993
Norway	21	0.832	0.939	0.953	0.961	0.967	0.971
Poland	6	0.952	0.983	0.986	0.989	0.991	0.992
Russia	17	0.864	0.951	0.962	0.969	0.973	0.977
United Kingdom	19	0.848	0.945	0.957	0.965	0.970	0.974

Emission trading. After derivations analogous to the interval case we end with the effective reduction for the fuzzy type uncertainty

$$E_{eff} = \hat{E}^S \left\{ 1 - \left[1 - (2\alpha)^{\frac{1}{\gamma+1}} \right] R_c^S \right. \tag{13}$$

It is again an extension of the formula (7) for the interval case. In comparison with the interval case it provides smaller differences between E_{eff} and $\hat{E}^S$, see *Table 2*.

Equivalence of approaches. Let us notice that actually the fuzzy approach formulas (11) and (12) can be considered equivalent to the interval approach ones (6) and (7), provided appropriate values of α is chosen for both cases. Denoting by the subscript $_I$ the interval and by $_F$ the fuzzy case the equalities of the reduction factors or the effective reductions

$$\delta_{U,I} = \delta_{U,F} \quad \text{or} \quad E_{eff,I} = E_{eff,F}$$

after simple algebra provide the same condition

$$(2\alpha_I)^{1+\gamma} = 2\alpha_F$$

For the adopted assumptions $0 \le \alpha_I, \alpha_F \le 0.5$ and $\gamma \ge 0$ we have

$$\alpha_I \ge \alpha_F$$

with strong inequality for internal points of the assumption set. Dependence of α_I on α_F and γ is shown in *Table 3*. The results show that α_I rises quickly when rises γ. In two cases considered in our calculations estimates of γ close to 2 and 2.5 were obtained. Then, practically it seems that $0.2 \le \alpha_I \le 0.3$ should be taken even for small values of α_F.

Table 3. Dependence of α_I on α_F and γ.

α↓ γ→	0.1	0.5	1	1.5	2	2.5
0.05	0.06	0.11	0.16	0.20	0.23	0.26
0.10	0.12	0.17	0.22	0.26	0.29	0.32
0.15	0.17	0.22	0.27	0.31	0.33	0.35
0.20	0.22	0.27	0.32	0.35	0.37	0.38
0.25	0.27	0.32	0.35	0.38	0.40	0.41
0.30	0.31	0.36	0.39	0.41	0.42	0.43
0.35	0.36	0.39	0.42	0.43	0.44	0.45
0.40	0.41	0.43	0.45	0.46	0.46	0.47
0.45	0.45	0.47	0.47	0.48	0.48	0.49

The interpretation of these results is quite straightforward. Ignorance of the exact interval ends knowledge introduces additional uncertainty, which sums up to the uncertainty of the inventory itself. Thus, to obtain the same reduction factor or the same effective reductions a a bigger risk should be adopted in the interval approach. An important practical observation is that bigger values of α_I, like 0.2 to 0.3, should be taken in the interval approach to compensate for ignorance of the exact knowledge of the uncertainty interval length, even if smaller noncompliance risk is actually meant.

Conclusions

The paper deals with the problem of checking compliance of pollutant emission with a given limit in the case when the observed emission values are known with high uncertainty, which is the case of national inventories of emissions of the greenhouse gases. High uncertainty must influence trading in emission permits, which is frequently used to minimize the emission abatement cost (Montgomery 1972).

Not only the inventory itself, but also its uncertainty is calculated with relatively low accuracy. This should be taken into account when deriving the compliance and emission trading rules. The idea proposed in this paper lies in basing the derivations on the fuzzy set approach. A family of fuzzy numbers depending on a free parameter is introduced. This parameter can be chosen to appropriately shape the distribution of uncertainty. The approach provides the linear formulas, which can be used for designing a market for the efficient emission permits.

The results obtained are generalizations of the results derived for the interval type of uncertainty. It was, however, shown that the rules for the interval case can be still used instead of the generalized ones, provided the appropriately higher value of the risk of noncompliance is used.

Appendix: Fuzzy sets and fuzzy numbers

To introduce the notion of a fuzzy set let first us consider a classical set A from an universe U. It can be conveniently described by the characteristic function χ_A defined as

$$\chi_A = \begin{cases} 1 & \text{if} \quad u \in A \\ 0 & \text{if} \quad u \notin A \end{cases}$$

which say that a point $u \in U$ belongs to the set A, if $\chi_A(u) = 1$, or does not belong, if $\chi_A(u) = 0$, see *Figure 5*.

In a fuzzy set the characteristic function χ_A is generalized to take any value from the interval [0,1]. It is then called a *membership function* and is denoted μ_A. The value of a membership function μ_A reflects the degree of acceptance of the point u to the set. Thus, a *fuzzy set* is characterized by the set A and the membership function μ_A. Then, a usual set is a special fuzzy set with the membership function being the characteristic function. A comparison of a membership function and a characteristic function of a set is shown in *Figure 5*. A fuzzy set can be also fully characterized by a family of so called η-cuts[12] denoted by A_η, i. e. points of U, for which the value $\mu_A(u)$ assumes at least the value η, see *Figure 5*, where an example of a η-cut for η=0.5 is depicted.

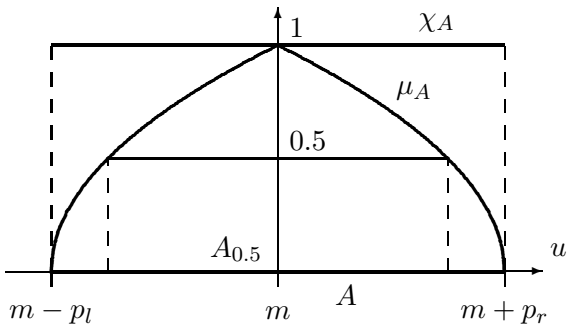

Figure 5. The characteristic function and a membership functions of the set A.

Two additional notions connected with a fuzzy set are worth to mention. One is the *support*, denoted supp A, which is the set of points u, for which the membership function is positive, i. e.:

$$\text{supp } A = \{u \in U \mid \mu_A(u) > 0\}$$

Another definition of the support may be formulated using η-cuts, as

$$\text{supp } A = \lim_{\eta \to 0} A_\eta$$

The second notion is the *core* of the fuzzy set, called core A, which is the set of points, for which the membership function is equal 1, i. e.:

$$\text{core } A = \{u \in U \mid \mu_A(u) = 1\}$$

Using the notion of the η-cuts we may also write

[12] Here we call as the η-cut of a fuzzy set A the notion usually called the α-cut, i.e. the set $A_\eta = \{x \in \text{supp } A \mid \mu_A(u) \geq \eta\}$, for $\eta \in [0,1]$.

$$\text{core } A = A_1$$

A special case of a fuzzy set A is called a *fuzzy number*, if it satisfies three additional conditions:

1. core A consists of only one point.
2. The membership function does not increase starting from the core point towards both sides.
3. Every η-cut is a (connected) close interval

The η-cuts for a fuzzy number form a family of intervals. Each interval can be interpreted as our conviction in precision of knowledge of the core value. Values of the level η close to 1 mean that we are well convinced that the core value is precise. Small values of η, close to 0, mean that our conviction is small. See also Dubois & Prade (2005) for more formal discussion of this subject. Calculations performed on fuzzy numbers allow us to process whole this knowledge in common.

Technically, two functions defined for nonnegative arguments may be introduced, L and R, (Bandemer, 2006), such that they have the unique value 1 at 0, $L(0) = R(0) = 1$, and equal zero for arguments greater or equal 1, $L(u) = R(u) = 0$ for $u > 1$, and are not increasing. Then, given the core $A = \{m\}$, the membership function of a fuzzy number may be constructed using the above functions as its left and right branches

$$\mu_A^l(u) = L\left(\frac{m-u}{p_l}\right) \quad \text{for} \quad u \le m \tag{14}$$

$$\mu_A^r(u) = R\left(\frac{u-m}{p_r}\right) \quad \text{for} \quad u \ge m \tag{15}$$

where p_l and p_r are scale parameters, see *Figure 6*. Let us denote the fuzzy number constructed this way as $A(m, p_l, p_r)_{LR}$.

Although operations on fuzzy sets or fuzzy numbers can be defined in a more general context, they will be restricted here only to fuzzy numbers described in the above LR form. For two fuzzy numbers $A(m, p_l, p_r)_{LR}$ and $B(m, q_l, q_r)_{LR}$ the following operations are defined, see Dubois and Prade (1978):

1. Addition

$$A + B = (m + n,\ p_l + q_l,\ p_r + q_r)_{LR}$$

2. Multiplication by a positive real number c

$$cA = (cm,\ cp_l,\ cp_r)_{LR}$$

3. Multiplication by a negative real number c

$$cA = \left(cm, |c|p_r, |c|p_l\right)_{LR}$$

with interchange of the function L and R in (14) and (15)

$$\mu_{cA}^{l}(u) = R\left(\frac{cm-u}{|c|p_r}\right) \quad \text{for} \quad u \geq cm$$

$$\mu_{cA}^{r}(u) = L\left(\frac{u-cm}{|c|p_l}\right) \quad \textit{for} \quad u \leq cm$$

In this paper we restrict attention to $L = R = M$ and $p_r = p_l = p$. In this case

$$\mu_{cA}(u) = M\left(\frac{|u-cm|}{|c|p}\right)$$

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Development of Emission Factors for GHGs and Associated Uncertainties

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Abstract

Reservoirs and hydroelectric dams need a closer analysis of the impacts due to dams, both in terms of GHG-emissions and the uncertainties associated with estimation. Which emissions to count as net emissions and how to deal with the emissions of CO_2 and CH_4 when they occur at different periods are some of the pertinent issues. The net emissions are the emissions which take into account all the sources as well as sinks of GHGs in the watershed. These emissions may differ significantly from one geographical region to another and depend, inter alia, on temperature, wind speed, solar radiation, physico-chemical water quality parameters, adjacent biospheric composition and several dam operating conditions as well as the age of the reservoir. In addition, there may be diurnal, seasonal and annual variations too. Moreover, the main scientific debate at the moment is centered around the uncertainties associated with extrapolating emissions measured at selected parts and selected intervals of time, there is a strong need for developing region-specific spatio-temporal emission-factors (functions). This will not only reduce the spatial uncertainties but also the uncertainties associated with diurnal, seasonal and annual variations. This paper presents and analyses development of one such predictive tool as emission factors for vegetated and un-vegetated zones. The models are different for running (river) and stagnant (lake) waters and have wider applications in estimating region-specific methane emissions, which is an important requirement under IPCC guidelines.

Introduction

Wetlands are one of the major sources of methane emissions with their annual release in the range of 100 to 200 Tg/yr (Singh et al., 2000; Cicerone and Oremland, 1988; Lelieveld and Crutzen, 1993). In the anoxic sediments of wetlands, methanogenesis occurs in the presence of high concentrations of organic material. Wetland plants provide substrates for methanogenesis in the form of root exudates and associated litter decomposition. Moreover, they also serve as a conduit for methane transport from the sediment to the atmosphere. Production and oxidation of methane in the waterlogged sediments depend on various bio-chemical and bio-physical factors (Williams and Crawford, 1984).

Many studies have indicated that methane emissions from vegetated surfaces are widely different from those which are un-vegetated. These studies clearly indicate that vegetation has a very important role to play especially in methane-emissions from sediment and the rhizosphere. Sediment-rooted plants (macrophytes) subsequently release methane through aerenchyma. Aquatic plants not only transport methane to the atmosphere through aerenchyma, but also provide root exudates or root autolysis products required by the anaerobic food chain and ultimately to methanogenic bacteria for methane production. On the

other hand, in case of un-vegetated portions of the water body, methane has only two transportation routes: one through molecular diffusion across the sediment-water interface and the second one is through ebullition. These processes result in very low fluxes of methane from the un-vegetated portions of the water bodies (Singh et al., 2000).

In general, it has been observed that compared to man-made wetlands, methane emission is much higher in natural wetlands. Even the range of variation has been found to be quite wide in natural wetlands (between 7.3 and 67.72 $mg/m^2/h$) as compared to man-made wetlands (1.53 to 3.07 $mg/m^2/h$). However, in both these types of wetlands, methane emission has been found to be much higher in the vegetated portion of the water body. Climate too plays a vital role in terms of regulating overall methane emissions. When one makes a comparative analysis, it has generally been found that the emission is much higher in summer season and quite low in winter. Hence, in a given region, methane has got a spatial distribution as well as a seasonal (temporal) variation. This necessitates development of region-specific spatio-temporal emission-factors for methane as well as for other GHG gases. As an attempt in this direction, the present paper shows a methodology for developing such emission factors for vegetated and non-vegetated water zones of running (river) and static (lake) water bodies.

Model and Methodology Development: Observations, Assumptions and Uncertainties

The present modeling exercise essentially uses data from one of the Indian studies (Singh et al. 2000) carried out on ten water bodies (Nawabganj lake, Suraj kund, Budha park pond, Motijhil, Bakshi ka Talab, Chinhat lake, NBRI pond, Gomti river, Husainabad tank and Butler palace pond) of Lucknow city in India. Five of these water bodies are natural and five man-made. For data analysis and modeling purposes, four regions were selected : (a) vegetated zone in river water; b) unvegetated zone in river water; c) vegetated zone in lake water and d) unvegetated zone in lake water. The present exercise focused on developing empirical models for vegetated and non-vegetated zones of running (river) and static (lake) water bodies.

There are spatial as well as seasonal variations in methane emissions. Methane emission, *inter alia*, depends on the following parameters :

- Temperature;
- Soil (sediment)-pH;
- Organic carbon;
- Redox-potential;
- Wind-speed;
- Solar-radiation;
- Physico-chemical water quality parameters; and
- Adjacent bio-spheric composition.

Some pertinent observations which have helped in developing the emission factors presented in this paper can be summarized as follows :

- For almost all the water bodies, methane emissions are highest in summer months and lowest in winter months. In rainy season, they lie somewhere in-between.

- The vegetated region of the running water (Gomti river) shows wide variations in emissions ranging from 18 mg m^{-2} h^{-1} in winter to nearly 80 mg m^{-2} h^{-1} in summer. In rainy season the value is around 32 mg m^{-2} h^{-1}.
- The range of variation, however, is quite small in case of non-vegetated zone. For instance, this range is 4.5-8 mg m^{-2} h^{-1} in case of running water and 0.5-2.5 mg m^{-2} h^{-1} in case of standing water (lake).
- In regard to non-vegetated zones, there is one more interesting observation. For both running (river) as well as standing (lake) water, methane emissions are higher in winter and lower in summer. Whereas for vegetated zone the situation is exactly opposite.

The seasonal variation is mainly attributable to the dependence of microbial activity (which is the main regulating factor behind methane emission) on temperature. In fact, a closer look at the data (Singh et al., 2000) clearly indicates that temperature-dependence is far more overriding (Conrad, 1989; Khalil et al., 1991) than dependence on any other parameter, viz. soil pH, organic carbon and redox potential etc. Role of pH is limited to providing the optimum range (from 6 to 8) for methanogenesis to occur (Williams and Crawford, 1984; Worakit et al. 1986). There are some variations in methane emissions due to changes in redox-potential. However, the variations do not follow any discernible or systematic trend (Singh et al. 2000).

Amount and composition (kind) of organic carbon load coming to a water body also plays a significant role. However, assuming that there is a constant amount of organic carbon load continuously flowing into the water-body almost every day (quite a valid assumption for Indian cities), it (organic carbon) can not be used as a determinant for predicting variations dependent on it. Therefore, the main factor which will ultimately determine the rate of methanogenesis and methane–emission is going to be the sediment or soil temperature. A thorough and systematic analysis of data clearly points towards a direct link between methane emission and temperature.

Results and Discussion

The emission factors as functions of temperature for four different types of zones are presented below (equations 1 through 4) :

***Running Water (River)*:**

Vegetated Zone

Emission Factor = $0.3963\ (Temp)^2 - 18.021\ (Temp) + 209.83$ -(1)

Non-Vegetated Zone

Emission Factor = $0.0128\ (Temp)^2 - 0.8654\ (Temp) + 19.006$ -(2)

***Stagnant Water (Lake)*:**

Vegetated Zone

Emission Factor = $0.4169\ (Temp)^2 - 20.860\ (Temp) + 256.29$ -(3)

Non-Vegetated Zone

Emission Factor = $0.0241\ (Temp)^2 - 1.266\ (Temp) + 16.545$ -(4)

These models can be used as emission factors for the similar region and provide an important step forward in the area of developing region-specific emission factors (*Figures 1* through *4*).

Figure 1 : Running Water (River) : Vegetated Zone

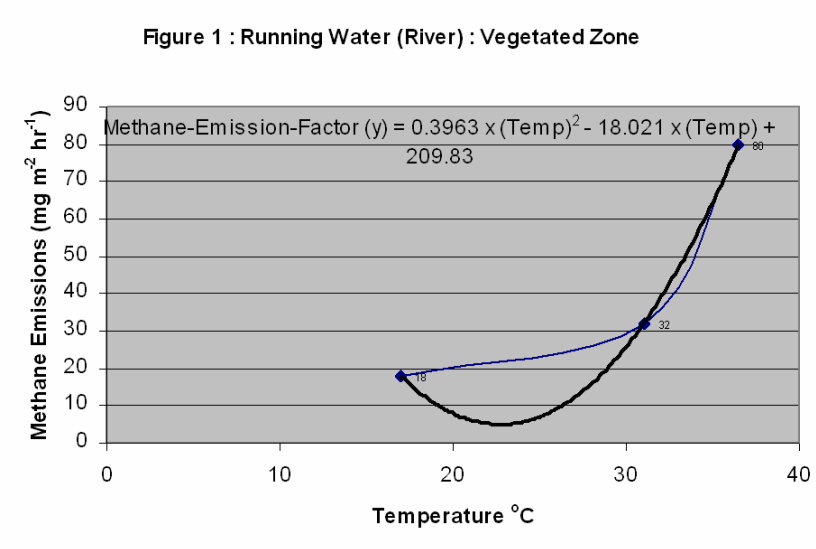


Figure 2 : Running Water : Non-Vegetated Zone

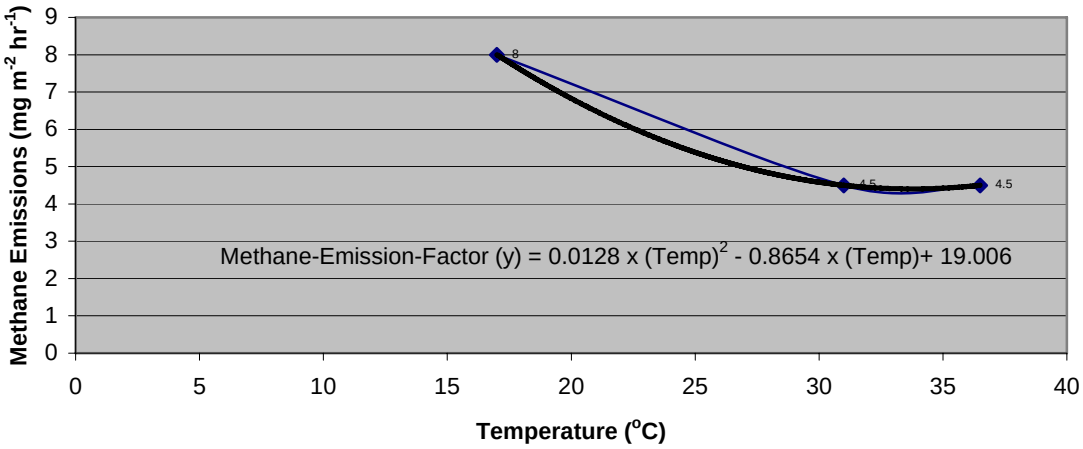


Figure 3 : Stagnant Water (Lake) : Vegetated Surface

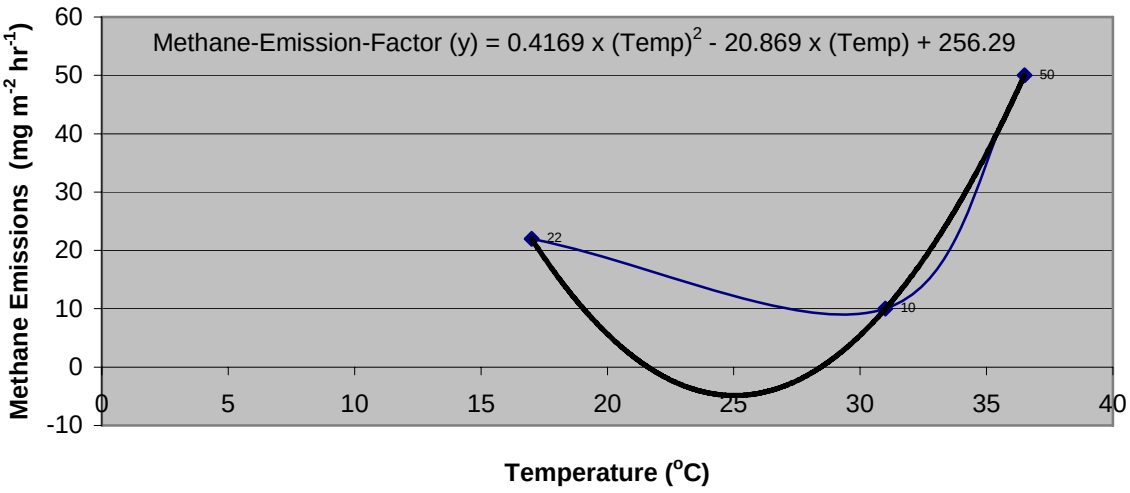
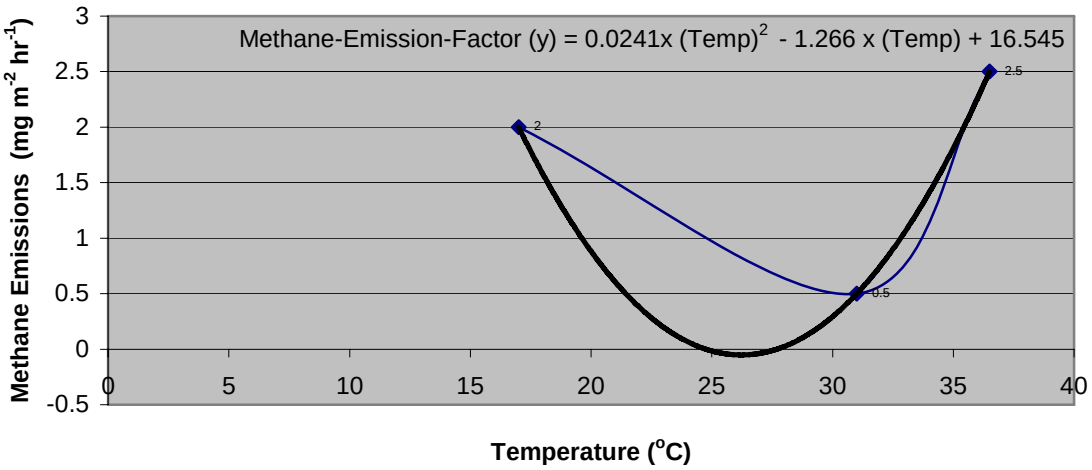


Figure 4 : Stagnant Water (Lake) : Non-vegetated Surface



In India, some studies have been very recently initiated by dividing the whole watershed into various smaller grids depending on their ecological characteristics. Each of these grids would be monitored and studied under the following subcategories: (a) open water; (b) flooded forest; and (c) aquatic macrophyte zone. These emissions would then be summed up for every grid and then appropriately integrated over all the grids so as to estimate the emission for the whole watershed area.

Since the main scientific debate at the moment is centered around the uncertainties associated with extrapolating emissions measured at selected parts at selected intervals of time, monitoring would have to be extended over widely different ecological zones and over longer time frames in order to obtain region-specific spatio-temporal emission-factors (functions). This will not only reduce the spatial uncertainties but also the uncertainties associated with diurnal, seasonal and annual variations. There is a growing consensus amongst scientists world-over that these emissions should be estimated both before and after construction of each dam so as to understand, analyze and quantify the net global warming/GHG-emission potential of various hydroelectric dams. The focus of these field studies should be on developing region-specific emission factors in accordance with recent IPCC guidelines.

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Monte Carlo Analysis of Uncertainties in the Netherlands Greenhouse Gas Emission Inventory for 1990-2004

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Goal

The Netherlands annually report uncertainties in its National Inventory Report (NIR), using IPCC's Tier 1 method. The IPCC guidelines have, however, recommended that a more detailed analysis should be performed when possible. In this context, the goal of the research is two-fold. Firstly, to assess whether a Monte Carlo analysis of the uncertainties in the Dutch NIR would result in different levels of uncertainties compared to those provided by the Tier 1 analysis. Secondly, to assess which parameters contribute the most to the total uncertainty in the emissions, in order to identify areas of high priority for the further improvement of the overall accuracy of the inventory.

Methodology

A Monte Carlo analysis has been applied to the calculations used to estimate greenhouse gas emissions in the Netherlands. The analysis is performed for the Kyoto base year (1990/1995) and for 2004. Basic data for the emission calculations have been extracted from the detailed background information of the Dutch NIR as provided by the Netherlands Environmental Assessment Agency (in Dutch, Milieu-en Natuurplanbureau MNP). The level of sector aggregation at which results are calculated was determined by the level of aggregation used in the Tier 1 analysis (since it is a main goal of this project to compare results between Tier 1 and a Monte Carlo analysis). Depending on data availability, our model works with the most detailed level of information available and regroup it to arrive to the Tier 1 level of aggregation. The software package @Risk was used to assess the propagation of uncertainties in the emission model for the greenhouse gas emissions of each sub sector, sector and the country by greenhouse gas type. In general terms, emissions are calculated by applying an emission factor to an appropriate activity statistic. Hence, the uncertainty in the emission of a gas *i* derives from the uncertainties in both, the emission factors and the activity rate. The probability density functions (PDF) assumed for the emission factors and activity data were based on the uncertainty ranges used in the existing Tier 1 analysis, complemented with expert judgment by experts from the MNP. We accounted for all known correlations in the inventory and took into account non-Gaussian probability distribution functions where appropriate. A detailed overview of the PDFs, uncertainties and assumptions taken into account is reported in Ramirez et al., 2006

The expert judgments and assumptions taken into account in this research have been compared to the uncertainty assumptions (and their underpinnings) used in Tier 2 studies by

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other European countries[14]. Following the IPCC Tier 2 method (IPCC, 2000), uncertainties in the trend emissions were calculated in absolute and in relative terms, and a key source analysis was undertaken. Finally, a pedigree assessment has been carried out for the most sensitive emission factors and activity data to systematically assess strengths and weaknesses in their knowledge base. Pedigree analysis is a part of the NUSAP system (Funtowicz and Ravetz, 1990; Van der Sluijs et al. 2005a). NUSAP conveys an evaluative account of the production process of a quantity and indicates different aspects of the underpinning of the numbers and scientific status of the knowledge base where it stems from. Pedigree is expressed by means of a set of pedigree criteria to assess these different aspects (see *Table 1*). We carried out a quick and dirty pedigree scoring for the 15 inputs of the emission model that have the highest contribution to the uncertainty in the output , both for the total GHG emission in 2004 and for the trend uncertainty. Results from the pedigree analysis and the Monte Carlo sensitivity analysis were combined in a so called Diagnostic Diagram (Van der Sluijs et al., 2005) mapping pedigree and sensitivity of key uncertain inputs, revealing the weakest critical links in the knowledge base of the emission monitoring system with respect to the overall emissions, and helps in the setting of priorities for improvement of the monitoring.

Table 1. Pedigree matrix for emission monitoring. Note that the columns are independent (Risbey et al, 2001).

Scale value	Proxy	Empirical basis	Methodological rigour	Validation
4	Exact measure	Large sample of direct measurements	Best available practice	Compared with independent measurements of same variable
3	Good fit or measure	Small sample of direct measurements	Reliable method commonly accepted	Compared with independent measurements of closely related variable
2	Well correlated	Modelled/derived data	Acceptable method limited consensus on reliability	Compared with measurements not independent
1	Weak correlation	Educated guesses / rule of thumb estimates	Preliminary methods, unknown reliability	Weak / indirect validation
0	Not clearly related	Crude speculation	No discernable rigour	No validation

Results

Table 2 shows a comparison of the results of the Montecarlo analysis for the total and for each type of greenhouse gas. The comparison of the Tier 1 and the Monte Carlo results shows that there is a slight change for the mean emissions which is the result of the asymmetrical PDF's attributed to some variables in the model.

[14] de Keizer *et a.l* (2007), Comparison of uncertainty ranges and correlations assumed in TIER-2 studies of several European countries, abstract also submitted to this conference.

Table 2. Comparison of the results of Monte Carlo analyses and the TIER 1 analysis for the total emissions in the Netherlands, by type of greenhouse gas.

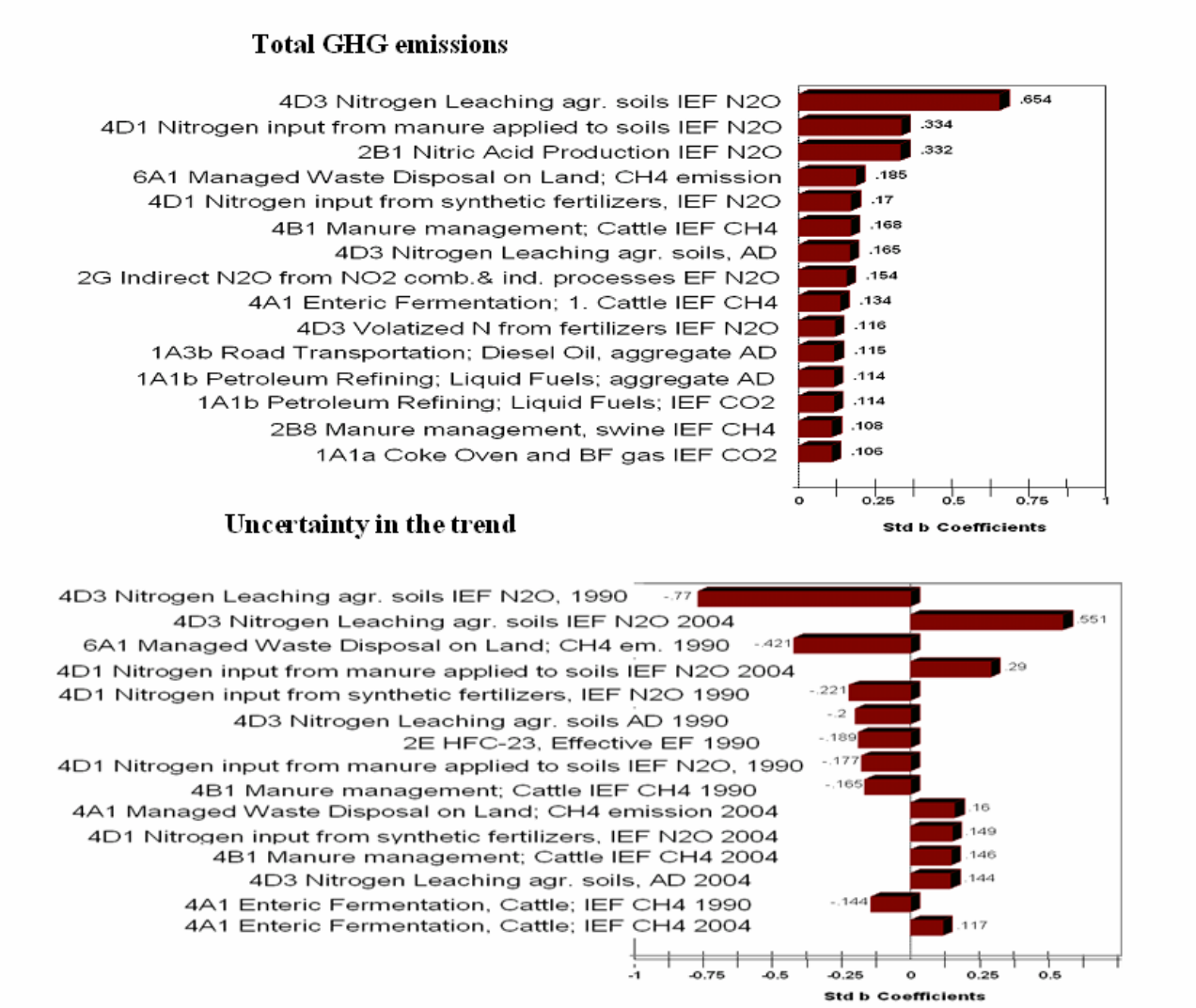
	With LUCF[a]			Without LUCF[a]		
	1990	2004	Trend	1990	2004	Trend
total GHG emissions						
Emissions (mean) [Gg CO_2 eq.]-Monte Carlo	217322	219969	2647 (1.3)*	214434	217211	2777 (1.3)*
2σ [%]- Monte Carlo	5.4	4.1	379 (4.5)**	5.3	3.9	355 (4.5)**
Emissions (mean) [Gg CO_2 eq.]-Tier 1	216394	219845	3451	213493	217077	3584
2σ [%]-Tier 1	4.5 (6.0)***		(3.3)**	4.5 (6.0)***		(3.3)**
total CO_2 emissions						
Emissions (mean) [Gg CO_2 eq.]-Monte Carlo	161892	182291	20399 (9.4)*	158975	179516	20541.5 (9.6)*
2σ [%]- Monte Carlo	2.2	2.1	16 (1.6)**	1.5	1.5	15.1 (1.6)**
Emissions (mean) [Gg CO_2 eq.]-Tier 1	161482	182158	20676	158587	179397	20810
2σ [%]-Tier 1	2.5 (5.0)***		(2.1)**	2.5 (5.0)***		(2.1)**
total CH_4 emissions[b]						
Emissions (mean) [Gg CO_2 eq.]-Monte Carlo				25464	17445	-8019 (-3.7)*
2σ [%]- Monte Carlo				18.7	15.1	61.2 (2.2)**
Emissions (mean) [Gg CO_2 eq.]-Tier 1				25437	17453	-7984
2σ [%]-Tier 1				18 (25)***		(1.4)**
Total N_2O emissions						
Emissions (mean) [Gg CO_2 eq.]-Monte Carlo	23231	17986	-3245 (-1.5)*	21262	17999	-3263 (-1.5)*
2σ [%]- Monte Carlo	46.7	42.0	240.3 (3.4)**	46.2	42.0	235.3 (3.4)**
Emissions (mean) [Gg CO_2 eq.]-Tier 1	21226	17992	-3234	21219	17985	-3234
2σ [%]-Tier 1	45 (50)***		(2.1)**	45 (50)***		(2.0)**
Total F emissions[b,c]						
Emissions (mean) [Gg CO_2 eq.]-Monte Carlo				8734	2252	-6483 (-3.0)*
2σ [%]- Monte Carlo				21.1	28.1	30 (0.9)**
Emissions (mean) [Gg CO_2 eq.]-Tier 1				8250	2242	-6278
2σ [%]-Tier 1				28 (50)***		(0.4)**

[a]: Please note that the numbers presented in this table are hyper precise: not all digits are significant. Because the inputs we received from various sources were hyper precise as well, we were not able to determine the proper number of significant digits. [b]: LUCF does not contribute to emissions in this category therefore results are only presented in the columns corresponding to "Without LCFL"; [c]: the base year for this category is 1995.*: the value outside the brackets is the absolute difference between the emissions in the base year and 2004, while the value inside the brackets is the relative change compared to the 1990 emission and is a percentage. **: the value outside the brackets reflects the uncertainty (2σ) in the absolute difference between the emissions in the base year and 2004, while the value inside the brackets is the trend uncertainty (2σ) relative to the emissions in the base year. ***: the value in brackets is suggested in the TIER-1 if dependencies among the variables were taken into account.

Main conclusions can be summarized as follows:

- The resulting uncertainties of the Monte Carlo analysis for the total emissions and for each type of greenhouse gas are in the same order of magnitude as those obtained by the Tier 1 analysis, although a somewhat higher trend uncertainty was found.

- For the Netherlands inventory, accounting for correlations has a larger impact on the uncertainty in the trend than on the uncertainty in the total greenhouse gas emission.
- In the Tier 1 analysis as presented in the Dutch NIR, the calculated uncertainties for the total emissions of the different greenhouse gases are increased with a correction factor to account for uncertainties not captured in the Tier 1 (see *Table 2*). The argumentation for this correction factor has been that Tier 1 does not account for correlations and asymmetrical distributions and that there are gaps in knowledge which increase the uncertainty in the calculated emission figures. The present Monte Carlo analysis has shown that accounting for correlations and asymmetrical distribution functions does not necessarily lead to a significant increase in uncertainty in total greenhouse gas emissions.
- Uncertainty assumptions in the Netherlands are well in the range of European studies. This point is further developed in de Keyzer et al (2007).
- Resulting uncertainty in total Netherlands greenhouse gas emissions is in the lower range compared to other European countries. This can be explained by the fact that the Netherlands has a higher share of CO_2 emissions compared to most other countries. Since CO_2 emissions factors are relatively well understood and monitored, their uncertainty is quite low and hence the significance of emissions with larger uncertainties (e.g. CH_4 and N_2O) is in the Netherlands smaller than in other countries. Furthermore, some countries (e.g. Norway and the United Kingdom) report very large uncertainty in the total N_2O emissions (respectively 170 and 226 %). These high values influence significantly their uncertainty in the total greenhouse gas emissions.
- A ranking of uncertain inputs of the emission model according to their contribution to variance (*Figure 1*) reveals that the main contributors to overall uncertainty are related to N_2O emissions from agricultural soils (especially indirect N_2O emissions), the N_2O implied emission factors of Nitric Acid Production, CH_4 from managed solid waste disposal on land, and the implied emission factor of CH_4 from manure management from cattle. These results are well in agreement with the top sources contributing most to total annual uncertainty reported in the NIR 2006. The added value of the Monte Carlo analysis is that while the NIR can only rank the contributing sources in terms of the combined uncertainty, by performing a Monte Carlo analysis it is possible to distinguish whether the most important contributing sources to total uncertainty are found in the activity data or the emission factor of the different sectors. Monte Carlo, hence, provides a more detailed picture that can be used in a later stage to define specific areas where further research can help to decrease uncertainties in the total emissions.
- The diagnostic diagram reveals that for the uncertainty in total GHG emission improvements in our knowledge of the emission factors for the IPCC categories 4D3 (indirect N_2O emissions from agricultural soils), 4D1 (direct N_2O emissions from agricultural soils), 2G (indirect N_2O from NO_2 from combustion and industrial processes) and 4B1 (Emissions from manure management: cattle) might be given the highest priority. Inspection of the pedigree analysis shows that the main problem in the knowledge base of these categories is in validation and empirical basis. For the trend uncertainty the ranking does not alter substantially from the one provided by the pedigree analysis.



Note: AD stands for activity data; IEF for emission factor. The number preceding each category corresponds to the IPCC category used in the National Inventory Report. The Standard B coefficient indicates how sensitive the model output is to a change in the input. A standard B coefficient of for example +0.17 means that a +1 standard deviation (of the input) increase in that input causes a +0.17 standard deviation (of the out-put) increase in the output.

Figure 1. Regression sensitivity for total GHG emissions and uncertainty in the trend for the Netherlands 2004

- Despite decreasing the uncertainty in the categories named above the Dutch Tier 1 assessment could be improved to emulate the Tier 2 results by adjusting the Tier 1 uncertainty inputs for 6A landfills; adjusting the Tier 1 uncertainty of activity data for 1A4a commercials and by reconsidering the Tier 1 uncertainty inputs for 4D indirect N_2O emissions from agricultural sources and discuss with other European countries the reasons for the differences in uncertainty assumptions across countries for this category.
- For future years, as long as the emission model does not change substantially and the share of CO_2 and non-CO_2 gases is not substantially different from 2004, it seems justified to use Tier 1 as main method for uncertainty analysis in the NIR. However, because of ongoing emission reduction efforts and changes over time in the fuel mix as well as in the shares of non-CO_2 greenhouse gases, we recommend repeating the Monte Carlo analysis regularly (every 4 years) as part of the QA/QC procedures.

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Addressing Uncertainty and Accuracy in Greenhouse Gas Emission Estimation and Inventories by the Global Oil & Gas Industry

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Abstract

The uncertainty of oil & natural gas Company's greenhouse gas emissions inventory, or of its quantified emission reductions assessment, is determined by the uncertainties of the estimates of the key (largest) contributing sources. In turn, this depends on availability of sufficient data to estimate emissions and properly account for their variability. The emergence of emissions trading systems and new reporting and disclosure schemes has created a need for industry to better understand and address the uncertainties inherent in the data used for emission inventories, or emissions reductions calculations.

This paper provides an overview of activities being undertaken by a collaboration of oil and natural gas industry associations to solicit varied perspectives on priority areas for reducing emissions inventory uncertainties at the entity level, and to develop industry relevant tools to address them.

Key words*:* greenhouse gases, emissions inventory, uncertainty, accuracy, entity emissions

Introduction

The assessment of greenhouse gases GHG emissions and emission reductions are high on both political and scientific agendas in many countries. The global oil & natural gas (O&G) industry has been an active contributor to the development of sectoral guidance for accounting and reporting of GHG emissions, such as IPIECA (2003) *Petroleum Industry Guidelines for Reporting GHG Emissions*, and compiling emissions estimation methods, such as API (2004, 2005) *Compendium of GHG Emissions Methodologies for the Oil and Gas Industry.* This guidance has been recently augmented by API/IPIECA (2007) by its *Guidelines to Account for Reductions Associated with Greenhouse Gas Projects.* All these efforts were centered on common approaches that were adapted for use by the industry sector and are reflective of emission sources and compounds emitted by operations. Sector members have also participated with multiple stakeholders in the development of several international and national guidelines and reporting standards.

The uncertainties inherent in the data used for emission inventories may impact their credibility and the acceptability of assertions of GHG emission reductions. The uncertainty of an O&G company's GHG emission inventory, or of its quantified emission reductions, is determined by the uncertainties of the estimates of their key (largest) contributing sources. In

turn, each of these uncertainties depends on the quality and availability of sufficient data to estimate emissions, or on our ability to measure emissions and properly account for their variability. With the emergence of emissions trading systems, and new reporting and disclosure schemes, data robustness is getting increased attention as a prerequisite for accurate determinations of GHG emissions and emission reductions.

Uncertainty of National Inventories

The Intergovernmental Panel on Climate Change (IPCC, 2000) has initially addressed these issues in the context of national GHG emission inventories. According to their guidance, uncertainty analysis is intended to help "...improve the accuracy of inventories in the future and guide decisions on methodological choice..." Currently, many countries are adopting this methodology to augment their national emission inventories. The First International Workshop on GHG Inventory Uncertainty convened by the International Institute for Applied Systems Analysis (IIASA, 2004) focused on different attempts to improve national inventories; to provide a basis for emissions inventory standardization; and the use of detailed uncertainty analyses in enforcing compliance in emissions trading systems. For example, the U.S. Environmental Protection Agency (EPA, 2007) is now including the expected uncertainty ranges in the details provided in the calculations of national GHG emissions inventory report for each sector of the economy.

While IPCC clearly stresses the value of conducting uncertainty analyses and offers guidance on executing them, the conclusions from ongoing work at the national level indicates that the suggestions made by IPCC, and discussed at the IIASA Workshop, are applicable to emission inventories of complex multinational entities as well as to national inventories. Some of the key benefits identified are applicable both to national and entity inventories, such as:

i. Uncertainty analyses provide a standard measure that can facilitate the process of comparing inventories to one another;
ii. Uncertainty analysis helps identify the most prudent opportunities for improvement in the methods and estimates of GHG emissions and emissions changes;
iii. Uncertainties play a role in determining whether or not commitments have been credibly met.

Most countries performing uncertainty analyses also investigate their impact on the overall national emissions inventory in order to target key areas for improving future estimates. The same rationale is generally valid at the corporate – or entity - level. In either case, estimating uncertainty helps to prioritize resources and to take precautions against undesirable consequences, such as basing strategies on questionable data.

Industry Sector Workshop

As a first step to addressing this issue IPIECA, API and CONCAWE convened an international workshop in Brussels on 16 January 2007. The workshop was organized to gather information from all stakeholders about these concerns and consider methodological aspects from the point of view of academia, regulators and industry. Approximately 70 delegates attended the workshop that consisted of several thematic panels. It afforded the panelists the opportunity to deliver brief remarks followed by extensive discussions of the issues by all participants.

The specific goals for the workshop were:

1. Develop an understanding of the relative importance of the key factors that contribute to uncertainty,
2. Review and discuss emerging techniques for quantitative assessment of the uncertainty and accuracy of GHG emission estimates,
3. Identify emission sources and methods where O&G industry efforts are needed to improve accuracy and reduce uncertainty to acceptable levels, and
4. Create a prioritized list of topics to be addressed by the O&G industry to minimize uncertainty in emission estimates and improve data accuracy.

A complete record of the workshop agenda, presentations, and the upcoming workshop summary report are available on the IPIECA website:
(http://www.ipieca.org/activities/climate_change/climate_publications.php)

Highlights of Workshop Discussions

Confidence in the quality of inventories is key to the successful operation of GHG markets as well as other GHG reduction and mitigation programs. There is therefore a need to improve the robustness of the data used in designing and tracking trading schemes performance. Market participants need confidence in the accuracy of the data used for establishing baselines and the initial allocation process as well as in the validity of the yearly emission reports which determine the market position of individual players. Regulators need the confidence that the methods used for monitoring, reporting, and verifying GHG emissions have a high degree of certainty to demonstrate compliance. Society at large needs confidence that real emission reductions have been attained. As a consequence there is a recognized need to improve data accuracy and reduce uncertainty in order to meet all expectations.

The workshop set out to address the need to ascertain the quality of GHG emission inventories at the entity level and to ensure that company strategies and actions are based on robust data. At the national level, policies and strategies such as the EU Emissions Trading System (EU-ETS) must be able to demonstrate that estimates regarding emissions changes are not only measurable, but are permanent and verifiable. While uncertainty estimates are not intended to dispute the validity of data presented in GHG emission inventories, the variability that they communicate underscores our current limited ability to characterize many sources and sinks and helps to prioritize existing data gaps that should be the focus of future activities.

Emissions Trading Systems are typically developed to allow ‘economically efficient’ reductions of GHG emissions and encourage new low-carbon technologies. System design should make it attractive to reduce emissions while also recognizing the importance of reduced data uncertainty. In the US, Emissions Trading Systems that have been operational since the 1990s have embedded in their design financial rewards for the availability of high quality data. The measurement and tracking system used for these programs was designed to ensure quantifiable, permanent and real emissions reductions, which in turn has led to compliance costs that are 25% of those estimated originally. This approach has also led to a range of improvements in monitoring methods and measurement accuracy assessment techniques.

It is essential that regulations strike a balance between the cost and effort associated with potential reduction of uncertainty of certain sources for which only sparse and/or inaccurate

data is available, and the relative contribution of such sources to the total inventory and its uncertainty.

Summary of Priority Issues

The workshop did not aim to achieve a consensus on all the issues. It merely acted as an initial step of dialogue between Industry, regulators and other stakeholders on GHG data quality expectations. It also provided industry participants with the necessary input to start developing a list of priority actions that are needed in order to reduce uncertainty, improve accuracy and ensure that reported data meets key stakeholders expectations for both voluntary and mandatory GHG reporting schemes.

Companies that are part of the industry sector are quite cognizant of their need to manage risks and develop improved tools that will facilitate compliance with diverse GHG regimes. This is vital both to companies' financial performance and to the protection of their reputation. It was noted by all industry participants that harmonization of measurement, monitoring, and uncertainty assessment methods would assist companies in meeting their various mandates. Hence, guidelines that are tailored specifically to the industry sectors would facilitate improved performance by ensuring that generic guidance is operationalized and made compatible with industry operating and maintenance practices.

Table 1 provides a preliminary list of priority issues that should be addressed by the O&G industry sector. These can be divided into three categories of priority subject areas, including, (a) measurement methods; (b) computational methods; and (c) internal and external communication. To address these issues further will require expanding current industry emission estimation methodology to include considerations of data accuracy and uncertainty. It will also necessitate a continuation of the dialogue between all stakeholders in order to broadly communicate recommended approaches and to ensure that expectations are being met.

Table 1. List of Priority Issues Identified during Industry Workshop

Subject Area	Potential activities
Measurement Methods	– Sampling and analysis issues – Meters & analyzers maintenance and calibration – Temperature & Pressure corrections – Flow measurement devices – Flaring, venting & fugitive emissions – Process emissions
Computational Methods	– Relative contribution of individual sources to overall inventory – Mass based emission factors vs. heating value based factors – Error propagation from individual measurements to annual inventories – Frequency of sampling, analysis, and calibration – Application of Monte-Carlo techniques
External Communication	– Accuracy of direct measurements vs. measurements of indicative parameters – Role of Monitoring and Inventory Management Plans – Carbon balance vs. energy balance

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Can the Level of Uncertainties of a Regional Terrestrial Biota Full Carbon Account be Made Acceptable for Policy Makers?

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Abstract

Based on the idea that only full account of major greenhouse gases corresponds to the eventual goals of the UN Framework Convention on Climate Change and the Kyoto Protocol, the paper considers achieved and expected in future uncertainties of the regional terrestrial biota Full Carbon Account (FCA). The analysis deals with results of assessing a FCA of forest ecosystems of a large boreal region in Central Siberia. It is shown that system integration of available information sources and models of different nature provides estimating the major carbon fluxes (Net Primary Production, NPP, and heterotrophic respiration, HR) for the region for an individual year at the level of 5-8% (here and below confidential interval, CI, 0.9), Net Ecosystem Production (NEP) – 35-40% and Net Biome Production (NBP) – 60-80%. Regionalization of process-based models, introduction of climatic data in empirical models, using the appropriate length of time period for reporting, harmonization and multiple constraints of estimates received by different independent methods allow to decrease the above uncertainties of NEP and NBP by about half that makes relevant the use results of the FCA in the post Kyoto international negotiation process.

Key words: UNFCCC, Kyoto Protocol, regional Full Carbon Account, uncertainties, fuzzy approach.

Introduction

The ten-year period after the Kyoto Protocol was signed clearly demonstrated that the partial accounting schemes introduced by the Protocol have a number of principal gaps that substantially hinder the possibility of reaching the eventual goals of the UN FCCC. The major gaps are: (1) a distortion of the real picture of the role of individual countries in climate change mitigation efforts because a substantial part of emissions and removals of greenhouse gases are not included in the accounting regime; for large regions of the Earth (e.g., the boreal biome) the omitted part can provide emissions that exceed those from industry and "managed" part of the biosphere; (2) the exclusion of "climate friendly" investments in perspective fields of the biosphere [or–using the language of the Kyoto Protocol–in the LULUCF (Land Use Land Cover Change and Forestry) sector]; (3) a threat to the protection of some categories of "unmanaged" ecosystems, e.g. old growth forests; (4) an unsatisfactory consideration of large sources of emissions (e.g., wild fires); and (5) the restriction of opportunities for developing countries to participate in the international processes of climate change mitigation. Substantial problems also arise from the large difficulties (and often – impossibility) of strict definitions of some key terms of the post Kyoto language like managed

land, anthropogenic impacts, base-lines and additionality, etc., that give rise to the doubt of some incentives and results.

Such a situation leads to the relevance of transition to a terrestrial biota full carbon account (FCA), as a principal part of a full greenhouse gases account, independently of future political decisions, e.g., for the second commitment period, how these estimates should be used – either for "accounting" in the Kyoto Protocol's sense or only for an "estimate" as auxiliary information for policy makers. However, a number of studies illustrate a high level of uncertainties of carbon accounting from regional to global scale (Houghton, 2003; Nilsson *et al.*, 2007). Thus, some questions become crucially important: (1) what is an acceptable level of uncertainties which would allow the introduction of FCA's results in the international accounting regime, and (2) is there a methodology of the account which would be scientifically solid, practically applicable and which would deliver a reliable assessment of uncertainties? One relevant solution to the first question is elaborating and quantifying functions of losses due to an uncertain account. Development and parametrization of such a function is a special and complicated task that requires a separate consideration. Analysis of a very few available publications supported by generalized calculations for averaged conditions of Northern Eurasia allows to conclude that the relative uncertainty of Net Biome Production (NBP) at 20-40% (CI=0.9 and assuming that the mean NBP substantially differs from 0) satisfies the average carbon prices and major tendencies of the current post Kyoto market.

With respect to the 2nd question, appropriate methodologies should take into account a fuzzy character of the FCA (Nilsson *et al.*, 2007). Technically, the major idea behind such considerations is a transition to a verified FCA. The latter meaning that the FCA should be provided in a way that presents a comprehensive and reliable assessment of uncertainties at all stages and for all modules of the account. It puts a number of obligatory systems requirements to scientific background, structure and methodology of the accounting schemes. Currently, the following four major approaches are used for terrestrial carbon account: (1) inventory-based landscape-ecosystem approaches; (2) measurements of carbon fluxes *in situ* (eddy covariance method); (3) process-based terrestrial biosphere models; and (4) inverse modeling. Experience proves that – individually applied – none of these basic approaches is able to provide sufficient information to assess uncertainties of the accounting schemes. An acceptable solution is in a system integration of different methods and information sources. General features of such an approach are discussed in our previous paper (Nilsson *et al.*, 2007). As a case-study, here we present an analysis of uncertainties recognized for major components of the FCA for forests of a large boreal region (Central Siberia), following the results received by a number of recent projects fulfilled by IIASA's Forestry Program.

Major Features of the Landscape-Ecosystem Approach

A semi-empirical landscape-ecosystem approach was used as an overall basis of the account (Nilsson *et al.*, 2007). The study's region of the total area of 307 million ha (including 177.6 million ha of closed forests) has been divided in 25 ecological regions (Schmullius, 2005) and about 35,000 polygons. All components of the FCA were estimated by polygons. The polygons have been developed based on application of multi-sensor remote sensing concept (12 instruments from 8 satellites were used) that allowed to provide a 2-level classification of land cover. Major classes of land cover have been delineated at the 1st level of the classification including unproductive areas, agricultural land, forest land, natural grassland, shrubs and wetlands. At the 2nd level, forest land has been divided into closed forests, burn areas, dead stands and (unregenerated) harvested areas. A more detailed classification of

forests was done based on all available information, mostly using updated forest inventory data. Finally, comprehensive parametrization of forest polygons included species composition, age, average height and diameter by species, site index, relative stocking, and growing stock volume. Characteristics of soil were extracted from a soil map at scale 1:1,000,000, which has been produced for the region and overlapped with the polygon map.

The accounting scheme consists of a combination of flux-based and pool-based approaches. The flux-based method was applied as a recurrent chain $NEP = NPP - HSR - DEC - FLIT - FHYD$, $NBP = NEP - DC$, where *NBP, NEP, NPP* are, respectively, Net Biome Production, Net Ecosystem Production and Net Primary Production, *HSR* - heterotrophic soil respiration, *DEC*-flux due to the decomposition of coarse woody debris, and *DC* - fluxes caused by disturbances including consumption of forest products, and the pool-based approach as $\Delta(C) = C_{syst,\ t+\Delta t} - C_{syst,t}$, where $\Delta(C)$ is the change of carbon pools and $C_{syst,\ t+\Delta t}$ and $C_{syst,t}$ are carbon pools at the end and beginning of the period Δt, respectively.

Live biomass of forest ecosystems has been estimated by 7 fractions (stem wood over bark, bark, wood of branches, foliage, roots, understory and green forest floor) using a set of multidimensional models developed by tree species and included age, site index and relative stocking of stands (Shvidenko *et al*., 2007a). The stock of dead wood (snags, logs and dead branches of live trees) was estimated based on sets of available measurements on sample plots in taiga regions of Northern Eurasia and on estimates of forest inventory aggregated by forest enterprises. A special method has been developed for assessing NPP of forest ecosystems (Shvidenko *et al*., 2007a). The rest of major fluxes (HR, D, FLIT, FHYD) were estimated using data of different inventories, surveys and empirical models. Detailed description of the methodology can be found in Shvidenko *et al*. (2007b).

Assessment of Uncertainties

Major prerequisites

Assessment of uncertainties is based on understanding the FCA as a large dynamic fuzzy system that comprises a sophisticated interplay of many stochastic elements/ processes (Nilsson *et al*., 2007). In any practical implementation, systems of such a type cannot be directly validated or verified in any strict formal way. It defines specifics of assessment of uncertainties that includes a number of obligatory prerequisites and requirements to the approaches. (1) A strict-system design of the FCA is a mandatory prerequisite. Explicit structuring of the accounting schemes and delineation of the intra-system and outer boundaries of different nature (spatial, temporal, processes that should be considered, etc.) allow developments of strict algorithms, provide possibility for applying error propagation theory and generate a basis for considering the structural uncertainty of models (accounting systems) used. (2) Need of a comprehensive analysis of completeness of the FCA. This problem includes two interconnected aspects which both impact the results and uncertainties' estimation. The first one deals with the selection of processes and modules should be included in the account. This is closely tied with recognizing of structural uncertainties of the FCA and – in essence – is basically limited by heuristic approaches and expert estimates. The second one defines a "working area" of the FCA, e.g., wheather consumption of plant products or carbon budget of inner waters should be included in the consideration or not. (3) All input information should be presented in a quantitative way; this requirement also supposes the formal use of personal probabilities and corresponding confidential intervals for different assumptions and expert estimates. (4) Need of preliminary harmonizing of major terms and

definitions, in particular, taking into account the multidisciplinary character of the FCA. (5) Assessing uncertainties of initial data based on an analysis of the entire chain of measurements, collection and upscaling of data. While this is a very time consuming stage, it is very difficult to get reliable quantitative conclusions on the topic. (6) Control of temporal and spatial trends of data sets used in the account. (7) Use of a methodology of uncertainty's assessment which would take into account the fuzzy character of the FCA.

Within the landscape-ecosystem approach, the following way of uncertainty's estimation was used: (1) assessment of precision "inside" of individual approaches, methods and models using the error propagation theory according to the algorithms developed; (2) providing a standard sensitivity analysis by applying either Monte-Carlo method or systems of numerical differentiation; (3) transition from precision to uncertainties by expert modification of formal results; and (4) comparative analysis, harmonizing and multiple constraints of results received by independent methods. In general, such an approach should be applied to all components and all stages of the FCA, at least for those where complete formalizing of uncertainties' assessment is difficult or impossible. All estimations below have been done under an assumption that models and methods that were used have no unrecognized biases. Evidently, such an assumption should be used with a precaution: uncertainties of much input data consist of unknown combinations of random and systematic errors.

Uncertainties of carbon pools

Uncertainties of carbon pools' assessment are pool specific and mostly depends on availability and spatial distribution of measurements, as well as on reliability of other information sources (remote sensing imagery, different maps, etc.).

Vegetation pools. Uncertainties of inventory-based estimates of forest live biomass depend upon (1) reliability of delineation of polygon boundaries; (2) accuracy of biometric indicators of forest ecosystems within polygons; (3) accuracy and adequacy of models used for assessing live biomass; (4) variability of models' parameters such as amount of carbon in plant tissues (Mitrofanov, 1977), and (4) assumptions and simplifications were made in the accounting systems. In this study, the latter included: (1) a two-fold increase of random errors of biometric characteristics of polygons comparatively to the requirements of the forest inventory manual (FFSR, 1995) to individual stands, and (2) an assumption about mutual compensation of different impacts on systematic errors on growing stock volume estimated by polygons. The average total forest live biomass is estimated for 2003 at 56.5±2.2 Mg C ha^{-1}, i.e. with the relative uncertainty of 3.9% (here and below CI=0.9). Note, that such a result has been received under the availability of (1) long-term spatially distributed forest inventory data at the level of individual forest stands – primary units of forest inventory; (b) remote sensing information for updating obsolete forest inventory data; (c) statistically valid and regionally distributed multidimensional nonlinear regression equations for transition from indicators, which are measured by forest inventory, to live biomass' estimates by fractions; and (d) accounting methodology for recognized temporal trends in allometric interdependences in forest ecosystems. An assessment of two other biomass pools (coarse woody debris, CWD and dead roots, DR) is more uncertain (estimates for the study's region were 16 and 24%, respectively). Thus, taking into account that the live biomass, CWD and DR in forests of the study's region comprise 81, 8 and 11% of the total forest biomass, the uncertainty of the total biomass stock (for a specific year of the account) is estimated at ~±3%. It allows the detection of change in biomass stock between two inventory periods with an average uncertainty of ~±4-5%. Results delivered by other methods (use of radar and optical satellite instruments,

and dynamic global vegetation models, DGVMs) are more uncertain, and there are large methodological problems with a formal defining uncertainties of these latter methods.

Soil organic carbon pool. Formal assessment of the uncertainty of the soil carbon pool for the region (as well as for entire Russia) is difficult due to the lack of data, which would be satisfactory temporally and spatially distributed, particularly over vast remote territories. A soil map of Russia (1990) at scale of 1:2.5 million with a dataset of average characteristics by soil types still remains a major source of soil information for the country and its large parts. For the study's region, the soil map has been modified to the scale 1:1 million using additional information from different sources. However, original sheets of the soil map at 1:1 million scale were developed during a long period of time, up to 50 years ago. This inevitably makes mandatory the use of expert assumptions that substantially affects the conclusions. Our calculations show that uncertainties of assessment of soil carbon pool are at the level 15-20%. Under the estimate of the soil carbon pool for the region at 31 Pg C, it gives the uncertainties about ±5 Pg C with unknown systematic errors, and the signal of the change can be detected if the change between two consequent estimates exceeds 7 Pg C. Evidently, that this results has no practical meaning within a verified FCA. Another possibility to detect changing the soil carbon stock is the use of appropriate process-based models. However, it has been shown that the uncertainty of the latter approach cannot be properly quantified. Another way to introduce a pool-based account is an assumption on equilibrium state of soil organic carbon. However, this assumption can generates a substantial bias of an unknown value, and attempts to quantify such a bias lead to very approximate conclusions (Shvidenko and Nilsson, 2003). Thus, under currently available information, the pool-based method allows getting useful results but is not able to completely satisfy the major requirements to a verified FCA. Note, that it makes doubtful any application in the post Kyoto world of the "Average Carbon Stock" method that is recommended by some publications (e.g., Kirshbaum and Cowie, 2004), at least for vast boreal regions.

Uncertainties of major fluxes

Net Primary Production. In theory, NPP is defined as difference between gross photosynthesis and autotrophic respiration of ecosystems. However, practically all historically used numerous methods of field measurements of NPP in Northern Eurasian forests measured only a part of NPP allocated in tissues of plants. A substantial part of NPP (root exudates, volatile organic compounds, some others), which comprises up to 20-25% of the total NPP (Vogt et al., 1986; Isidorov and Povarov, 2000), was not measured. Other hardly quantified uncertainties are inherent for these data (Usoltsev, 2007). Thus, the use of available datasets of NPP measurements in Russian forests, which include about 1,000 sample plots, cannot give positive results within the verified FCA. Attempting to get the unbiased estimates, we developed a new semi-empirical method for assessing forest NPP that is based on a spatially distributed system of models of biological productivity of forest ecosystems by dominant major forest forming species (Shvidenko *et al*., 2007a). Uncertainty of the method is defined by (1) spatial and parametric structure of the modeling system that is used for NPP simulation (regional representation of models by regions, tree species and forest types; reliability of forest inventory data; etc.); (2) accuracy of ecological indicators (e.g., life span of fine roots and needles; share of disturbed part of NPP; etc.); and difference of seasonal weather from the many year average climatic indicators. The method is rather resilient to variation of input information; the most sensitive parameters are life span of fine roots and needles. The application of the above system to the land cover of 2003 at the polygon level and aggregation of the results by ecoregion and the region as a whole gave the following results: total forest NPP 3.06±0.14 (here and below – in Mg C $ha^{-1}yr^{-1}$), or 4.6%, including 0.550±0.032;

1.293±0.106; and 1.222±0.130 for aboveground wood, green parts and below ground live biomass, respectively). It means that for an individual year forest NPP is defined rather reliably, at the level of ±6% for above ground and ±11% for below ground live biomass. However, it should be pointed out that all the models were parametrized based on many year average data of measurements.

Heterotrophic respiration. Heterotrophic respiration of forest ecosystems includes two components: soil HR (SHR) and the flux caused by decomposition of coarse woody debris (DEC). Average values of SHR were calculated by soil type, dominant species and ecoregion. Substantial part of the study's region has not been covered by measurements, and we used all available measurements from the forest zone of Russia (Kurganova, 2002; Mukhortova, 2004; etc.). For corrections of SHR for each forest polygon, the regression between NPP and HSR was used. Uncertainty of estimation of SHR depends on (1) amount, seasonal and parametric completeness and spatial distribution of field measurements, (2) understanding of processes which control SR and its separation into autotrophic and heterotrophic parts (where substantial uncertainties exist, see, e.g., Bond-Lamberty *et al*., 2004), and (3) reliability of spatial delineation of basic units of calculation (soil polygons) and their compatibility with vegetation polygons. The overall average forest SHR for the region was estimated to be 2.16±0.17 Mg C $ha^{-1}yr^{-1}$ (~8%) under the assumptions that the variation of the SHR fluxes measured outside of the region and used in the calculation is 30% higher than the variability of the fluxes measured within the region.

Uncertainty of *the decomposition flux* was estimated based on a simple model $DEC = M_{CWD} \bullet \delta_{ji}$, where M_{CWD} is storage of CWD in a polygon and δ_{ij} *(i=1, ..., 9; j=1,2)* is a coefficient of decomposition by bioclimatic zone and class of CWD. Uncertainties of these two components were estimated at 16% and 14% based on results of measurements and different auxiliary sources, that gave the estimate of DEC at 0.219±0.047 Mg C $ha^{-1}yr^{-1}$, i.e. the relative uncertainty is ~22%.

The assessment of *the fluxes to the hydrosphere* (FHYD) has been done by combining two ways: based on measurements of amount of dissolved and particulate organic carbon in rivers and other water reservoirs, and by using measurements of carbon concentration in the soil solution. The average estimate was 0.049±0.011 Mg C $ha^{-1}yr^{-1}$ (23%). Direct empirical data for assessing *the fluxes to the lithosphere* (FLIT) were scarce, and the assessment of this indicator was mostly done in a heuristic way based on all available data from the boreal biome. The estimated uncertainty of FLIT (0.017±0.005 Mg C $ha^{-1}yr^{-1}$ or ~30%) contains substantial assumptions and expert components.

Disturbances. Major types of disturbances (D) included in the analysis were fire, insect and disease outbreaks, harvest and consumption of wood products. Carbon emissions due to disturbance and corresponding uncertainties were estimated by the method described in Shvidenko and Nilsson (2000), Kaiji et al. (2003) and French *et al*. (2004). Major factors, which affect uncertainties of the emissions caused by disturbances, include area by type of D; severity of D and its impact on amount of consumed organic matter; reliability of estimation of gas composition, particularly, after fire; and way of estimation of post-disturbance fluxes (if any). The impacts of these factors are different for different types of D. Estimated uncertainties were: direct emissions due to fire 37.3±8.6 Tg C yr^{-1} (23%); harvest (including impacts of logging, wood removal and decomposition of previously produced wood products) 20.6±5.0 Tg C yr^{-1} (24%); and direct emissions due to insect and diseases outbreaks 2.2±0.8 Tg C yr^{-1} (36%). It means that uncertainty of the total flux due to all accounted D is estimated

to be 59.8±10.1 Tg C yr^{-1}. The average value of the flux caused by D for all forest area in 2003 is estimated to be 0.337 ± 0.057 Mg C yr^{-1} ha^{-1}, or 17%. Note, that the extent and severity of fire for the considered year was about three time higher than the many year average for the region.

Discussion

Uncertainty of aggregated fluxes

As it follows from the above results, Net Ecosystem Production (NEP) of forest ecosystems of the region is estimated to be 0.62±0.23 Mg C $ha^{-1}yr^{-1}$ (the relative uncertainty ~37%) and Net Biome Production (NBP) – 0.28±0.26 Mg C $ha^{-1}yr^{-1}$ (84%). The forest NBP comprises two-thirds of the total NBP for all vegetation of the region: the latter is estimated at 75 Tg C yr^{-1}, and without the consumption of plant products (that is usual in ecological estimations) - 110 Tg C yr^{-1}. All these estimates are calculated for an individual year, while the parametrization of the models used was provided using measurements over a long period of time (sometimes – for several decades). For an individual year, it eliminates an unaccounted part of variability of NEP and NBP, that depends on differences between weather conditions during this year and average indicators for the past period, for which the measurements were provided. Responses of plant and ecosystem physiology to weather are indicated in many studies and used in numerous models of different type. Most interactive vegetation-climate models usually represent respiration as a strongly increasing function of temperature, with photosynthesis assumed a function of light, subject to limitation due to temperature, lengths of growing season (LGS), and availability of water and nutrients. For instance, it was shown that variability in temperature explains almost all the variability of NPP in the boreal zone (Lucht *et al*., 2002); variation of coefficient of decomposition of fresh pine litter in Europe litter is explained for 70 to 90% by a temperature variable combined with a summer drought indicator (precipitation minus potential evapotranspiration between May and September) (Liski *et al*., 2003). This promotes an idea to use seasonal climatic indicators for corrections of major components of the FCA, primarily NPP and HR.

We provided statistical analysis of dependences of NPP and HR of Siberian forests on different climatic indicators. About 20 indicators, such as average annual temperature and precipitation; LGS with daily temperature >0, >5 and >10^{o}C; sum of temperature, precipitation and hydro-thermal coefficient by Seljaninov for the above 3 periods; temperature of the warmest month, etc., was examined. As a general conclusion, such an approach allows to calculate statistically significant regressions, but the accuracy of thelatter was not high. For example, the multiple correlation coefficient for total soil respiration was in limits of 0.45-0.6 (Mukhortova, 2004). One of probable explanations of this result may stem from the incompleteness of usually used simplified functional representations, particularly for the boreal biome. For instance, as it has been recognized from long period measurements of Net Ecosystem Exchange (NEE) by eddy covariance methods, climatic variation is directly responsible for short- but not long-term variation in forest-atmosphere carbon exchange (Richardson *et al*., 2007). Factors acting over long time scales, e.g., water moisture regime and water table depth, substantially control the carbon budget on annual time scales in boreal forests and peatlands. In particular, elevated soil moisture causes decreasing in overall respiration that leads to decreasing NEE; the long-term ecosystem water balance, and particularly, the water table depth may explain much of the observed interannual variability and trend (Dunn *et al*., 2007). Our analysis shows that introduction of seasonal weather corrections of major carbon fluxes explains the interannual variability of NEP by ecoregion in

range of 15-20%, and for the entire region 8-12%, as well as decreases the corresponding uncertainty by about one third. Variability of NBP strongly depends on level of natural disturbances, particularly fire, of which extent has a weak correlation with seasonal climatic characteristics. However, it should be pointed out that these conclusions are preliminary, and the approach requires further investigations in a number of important ramifications (use of monthly and weakly weather data; selection of more relevant analytical expressions for the regressions; etc.).

A reasonable length of the period for reporting of results of the FCA should also be discussed. Delivering the information that is required for an annual FCA for large regions on yearly basis is expensive and resource consuming. Operational supply of some data (e.g., changes in land use – land cover) is difficult and would be possible after development and implementation of integrated systems of observations. Such systems still do not exist in Northern Eurasia. From other side, in order to be used in different climate change negotiations and decisions, FCA's results are required rather for some periods (e.g., 5 years) than annually because the latter would contain additional noise and seasonal variation caused by weather and other specific features of individual years. As it follows from the above assessment, the improved estimate for a period of 5 years have uncertainties at the level of 15% for NEP and 30% for NBP of forest ecosystems of the study's region.

We would like to point out that all above relative uncertainties (expressed in percents to estimated means) are used as a simple illustrative indicator. In essence, they have a limited meaning as a measure of reliability of the account because they have sense only for fluxes that differ substantially from 0 and are highly sensitive to ratio between uncertainty (variability) and the mean values of estimated fluxes.

Comparative analysis with other approaches

The above results of the FCA received by the landscape-ecosystem approach are impacted by a number of assumptions and expert estimates that hinder a strict statistical validation of uncertainties. Thus, an independent control of the results is a relevant procedure of the uncertainty's assessment. One way for this is a non-contradictory closing the balance. The second way is providing comparative analysis with estimates received independently. Unfortunately, there are a very few independent results for the study's region. In order to illustrate the attitude of variations of the results, below we partially use some comparisons for forests of entire Russia.

Dynamic Global Vegetation Models (DGVMs) explicitly describe major physiological processes in ecosystems. Practically, DGVMs or other process-based models are only a tool for predictions of interaction of vegetation and environment. However, oversimplification of description of the land cover (most of models have a very limited number of plant functional types to be properly adequate at a regional level); orientation on a potential but not the actual vegetation cover in major part of the models; lack or incomplete description of disturbances and "artificial" (e.g. agricultural) systems; and some other specific features of DGVMs result in an impossibility of formal assessing the models' uncertainties and do not allow the direct use of this class of the models as a tool of a regional verified FCA. Nevertheless, recent developments show a substantial progress and promising possibilities for future. One of the most uncertain indicators used in DGVMs is the light use efficiency. Recent results in application of hyperspectral remote sensing open interesting new ways (Grace *et al.*, 2007). Application of 17 global models of terrestrial NPP previously analyzed by by Cramer *et al*. (1999) to Russian forests showed that the average NPP for the contry's forests was estimated

at 338 g C $ha^{-1}yr^{-1}$ while an inventory-based estimate was 306 g C ha^{-1} yr^{-1} (Shvidenko *et al.*, 2006), i.e. only ~10% lower. However, the variability of estimates given by the individual models were very high – from 20 to 50% (Gusti, 2007, personal communication). Beer *et al*. (2006) used a "regionalized" LPJ model (including actual land cover, fire and a new permafrost-hydrological model) and received estimates of important components of the carbon budget, which are very close to data from forest inventory (Shvidenko and Nilsson, 2003).

The eddy covariance method presents a unique possibility to directly measure Net Ecosystem Productivity (i.e., accumulated Net Ecosystem Exchange), fluxes of water and energy in response to variability in environmental conditions. Although the method has a clear strength in the uncertainty's estimation (the net flux is the sum of individual half-hourly or hourly flux measurements but not a small difference of several large fluxes), the results are impacted by a sophisticated interconnections of random and systematic errors (Goulden et al. 1996; Moncrieff *et al*., 1996; Falge *et al.*, 2001; Papale *et al*., 2006). The eddy covariance method is accurate when atmospheric conditions are steady, the underlying vegetation is homogeneous and it is situated on flat terrain for an extended distance upwind; under such an ideal conditions the error of the annual NEE of CO2 is less than ± 50 g C m^{-2} yr^{-1} (Baldocchi, 2003). Some elements of field measurement techniques (e.g., night-time fluxes in dense canopies, flow distortion over heterogeneous terrain, filling in gaps of measurements) require future advances in order to have possibility for a reliable estimation of uncertainties. Complete model validation, particularly over the full annual cycle, requires additional information on the balance between assimilation and decomposition processes (Friend *et al*., 2007). The method does not measure NPP directly, and rather complicated calculation schemes which use unjustified assumptions are used (e.g., Schwalm *et al*., 2007). Probably, the most difficult methodological problem of use of eddy covariance measurements in assessing carbon budget of large territories deals with the upscaling the results to large areas (because of a footprint is typically 1 km x 1km) although a number of methods have been suggested (Papale and Valentini, 2003). That is why the major value of eddy covariance methodology is considered in supplying data for global cycle modeling and evaluation process representation, rather than in providing unbiased estimates of NEP for large territories (Friend *et al*., 2007).

Inverse modeling of atmospheric concentration is a sole approach that presents a possibility for a top-down assessing carbon exchange between land and the atmosphere. The CO_2 fluxes estimates include mainly the land use change and net ecosystem uptake for land regions. Uncertainties of the approach are basically defined by amount and distribution of stations for measurements and by imperfection of transport models used. The errors for observation made over the land are generally larger than those over the oceanic territories (Patra *et al*., 2006). The amount of measurements in boreal Asia is very small that substantially impacts assessed uncertainties at the regional level. Recently, a number of results received by inverse modeling have been reported for boreal Asia, meaning the area of the continent to the north from 50^{o} n.l. (*Table 1*). Gurney *et al.* (2003) used an ensemble of 17 and Patra et al., (2006) – of 16 different transport models. The results from Table 1 are rather consistent – in range from – 0.29 to – 0.63 Pg C yr^{-1}, with the overall average ~ -0.45 Pg C yr^{-1}, while the uncertainties - both, "within-model" (the multi-model RMS of the flux uncertainties) and "between-model" uncertainties (1 SD of the estimated fluxes by different transport models) remain high. Assuming the approximate area of boreal Asia of 1.1 x 10^{9} ha and taking into account the area of the study's region, we get the very close results to our estimate for the first years of the 21th centure.

Table 1. Assessment of fluxes for boreal Asia by inverse modeling

Source	Flux (Pg C yr^{-1})	Period	Comments
Maksytov et al., 2003	-0.63±0.36	1992-1996	Included observations in Siberia
Gurney et al., 2003	-0.58±0.53	1992-1996	Average flux from 17 models, uncertainty-"between" models
Baker et al., 2006	-0.37±0.24	1988-2003	
Patra et al., 2006	-0.33	1999-2001	All sites; uncertainties ±0.78-"within", ±0.45-"between" models
Patra et al., 2006	-0.29	1999-2001	Ocean sites only; uncertainties-as above

Overall, it could be concluded that a comparison of the above results with published data for the region received by flux measurements, some global vegetation models and by inverse modeling showed a general consistency in terms of the sign and magnitude of NBP. Evidently the comparison is approximate for a number of reasons (incompatible regions and period of assessments compared; lack of explicit gradients for upscaling of flux measurements in situ; incompatible definitions of some important terms etc.). Uncertainties of the above approaches attributed to large regions are higher than those of the examined landscape-ecosystem approach and, as a rule, cannot be assessed in a strict formal way. Nevertheless, there is a convergence in the results derived from process-based models, remote-sensing-based observations, and inversion of atmospheric data (Friend et al., 2007). In addition, they present important information that helps to eliminate some shortcomings of inventory-based methodologies.

Conclusion

An overall practical conclusion of this study is that a verified FCA for large boreal regions is possible although it requires a systems approach and substantial efforts. However, some precautions should be taken and a number of questions need to be resolved. Existing information for large regions is, as a rule, not satisfactory for an accurate assessment of the final results (NBP, to some extent NEP) for individual years, and the reported period should be compatible with the practical possibilities to detect changes in land use and the distribution of natural and human-induced disturbances. Some empirical and semi-empirical models are based on multi-year sets of measurements and do not take into account temporal trends of a changing world.

The process of multiple constraints requires a mutual "convergence" of different methodologies: proper regionalization of dynamic process-based vegetation models; search of common gradients for upscaling of flux measurements; advances in most important field measurement techniques, etc. Results of the study and recent developments in methodologies of terrestrial biota carbon accountings present evidences of a substantial potential for future improvements. There is an evident convergence of empirical (e.g., landscape-ecosystem) approaches and process-based models. However, strengths and weaknesses of the major approaches that are relevant as components of a verified FCA are of a different nature. While a landscape-ecosystem approach seems appropriate to serve a nuclei of carbon account in past and current periods, only process-based models are able to provide any satisfactory predictions. Georeferenced and quantitative description of land cover classes, an obligatory component of the landscape-ecosystem approach, could serve as a spatial gradient for upscaling the "point" flux measurements. These and other specifics should be taken into account for optimization of the accounting schemes and mutual constraints of the results.

An idea of a verified FCA and understanding of fuzzy essence of any FCA for large territories substantially impact the general philosophy and major methodological decisions of carbon account. The impossibility to avoid heuristic methods and expert estimates within a FCA is principal. It defines a need of modification of approaches for assessment of uncertainties. Analysis of "uncertainties of uncertainties" becomes not less important than assessing uncertainties of major components of a FCA. The estimations of uncertainties by "conventional" methods of mathematical statistics (e.g., recommended by IPCC) could provide conclusions that are very far from reality. This problem will become even more important at a transition to a terrestrial biota full greenhouse gas account with its more complicated structures and sophisticated interactions of major biophilic elements (carbon and nitrogen).

There are needs for some theoretical improvements and developments. We enumerate some important examples. Harmonizing and mutual constraints of independent results delivered by different methods should be provided by formal methods, and such an approach and a corresponding model should be developed, e.g., applying approaches of multi-criteria stochastic optimization. Methodology of development of functions of losses due to different level of uncertainties of the FCA is extremely important for understanding the required levels of FCA's reliability (including consideration of errors of different type). Limits for relevant use of standard normal theory for assessing not homogeneous and "contaminated" data sets should be regulated. Some "conventional" statistical agreements should be reconsidered. For instance, typically used high confidential intervals (0.95 or 0.9) seem excessive for such a problem, and can generate an impression to the public about an unsatisfactory level of the account.

This paper considered uncertainties of a forest carbon budget. Including other greenhouse gases and other land classes in the account leads to some specifics and additional problems (especially for land classes for which long-term series of biometric inventories do not exist) A principal solution of the transition to a verified account of terrestrial budgets of carbon and other major greenhouse gases would be in developing integrated observing systems combined with existing national systems for accounting natural resources (land, forest, wetlands etc.).

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Uncertainty Analysis for Estimation of Landfill Emissions and Data Sensitivity for Input Variation

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Abstract

The results of the research and practical experience confirm that stabilisation of GHG concentrations will require tremendous effort. One of the sectors identified as significant source of methane is disposal of waste to solid waste disposal sites (SWDSs). Methane emissions from the solid waste disposal sites are the key source and concerning to the actual emission factors there are estimated with the high uncertainty level. The emission uncertainty calculation of landfills by using the more sophisticated Tier 2 - Monte Carlo method is evaluated in this article. For this reasons the software package, which works with probabilistic distribution and their combination, was developed. The results, sensitivity analysis and computational methodology of methane emissions from solid waste disposal sites are presented.

Key words: Monte Carlo method, methane emissions, sensitivity analyses

1. Introduction

The results of the research and practical experience confirm that stabilisation of GHG concentrations will require tremendous effort. Without emission limitation, the atmospheric concentrations of CO_2 would grow from 374 ppm in 2002 to 490 – 1 260 ppm in 2100. This would represent 75 – 350 % increase from the year 1750. In order to stabilize the concentrations at the level of 450 ppm, the GHG emissions should drop below the level of the reference year 1990 in the next decade.

The concentration of methane in the atmosphere has increased two and half times in the period of the industrial era. Methane concentration contributes to 20 % of the anthropogenic emissions of GHGs. A rapid growth in methane concentration is caused by intensive farming, livestock production, coal mining, transport and utilization of natural gas and solid waste disposal sites. The life span of methane in the atmosphere is 10 – 12 years. Total annual emission is about 0.4 bill. tons of CH_4 and represents a stable annual increment.

More complex method for estimating methane emissions from solid waste disposal sites (SWDSs) acknowledges the fact that methane is emitted over a long period of time rather than instantaneously. A kinetic approach therefore needs to take into account the various factors, which influence the rate and extent of methane generation and release from SWDSs. The equations presented in IPCC manuals form the base for first order decay (FOD) method

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kinetics and are quoted from the Revised 1996 IPCC Guidelines for National Inventories: Reference Manual IPCC (1996). IPCC Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories IPCC (2000) provide further details on the FOD method, mainly in defining FOD model parameters in terms familiar to users of the default method Tier 1.

Waste sector is about greenhouses gases emissions from three main categories as follows :

- Solid waste disposal (methane),
- Waste waters purification,
- Waste incineration in the combustion plants and non controlled waste incineration (CO_2).

Solid waste disposal is an important emissions source of methane, which is generated during the organic materials decomposition, these are present in the waste and this is enacted under the anaerobic conditions. Waste disposal is the main method of waste treatment in SR, more than 80 % of municipal wastes is put on the land-fills. From the individual greenhouse gases inventory point of view is the waste disposal one category. For the purpose of calculation there is the need to differentiate, if it concerns:

- mixed municipal waste (methodology Tier 2 – formula of first order decomposition),
- industrial wastes and other wastes flows (methodology Tier 1 – simple balance),
- municipal waste waters purification and release,
- industrial waste waters purification and release.

This approach can be used to model landfill gas generation rate curves for individual landfill. It can also be used to model gas generation for a set of SWDSs to develop country emissions estimates or can be applied in a more general way to entire regions.

Emissions of methane from landfill were estimated with methodology First Order Decay (FOD) method Tier 2 according advises of the expert review team of UNFCCC secretariat and European Commission. All time series were recalculated until 1960 and the complete methodology approach was changed. Three versions of FOD method, which are presented in article Farkaš (2006), were considered for the use of Tier 2 method for estimation of methane emissions from SWDS in the SR. Comparing the situation abroad with the situation in country, several differences can be identified:

- Most countries are using site-specific data. The methane emissions are calculated for each SWDS (or group of SWDS) separately and then the results are summed to obtain national methane emissions estimations. This approach is not yet possible in the SR, because collected data on municipal solid waste (MSW) do not include the needed characterization of SWDS,
- Historical data on MSW management and disposal are more detailed that data available in the Slovak Republic,
- Data on MSW fractions are collected in more systematic and regular way that is the practice in the Slovak Republic,
- As the most appropriate approach was selected the Second version of FOD method, as it is defined in the IPCC Good Practice Guidance. This decision is supported by following reasons,

- Parameters used are better defined and allow direct comparison with the Tier 1 method,
- Some of the parameters used are defined as time-variables. This allows modeling of the waste sector transformation in the Slovak Republic in the period 1992-2000.

Structure of required input data better corresponds with MSW data available for the Slovak Republic (data for the use of multiphase method are not available). The uncertainty of estimation of CH_4 emissions is mainly caused by uncertainty of statistical data on consumption. Another source of uncertainty is the applied default emission factors (EF). An additional error in calculation of the other greenhouse gas emissions may occur as a result of less exact methods and it cannot be estimated. The calculation emission uncertainty of landfill by using the more sophisticated Tier 2 - Monte Carlo method is evaluated in this article.

2. Monte Carlo Method

In the some cases the pure analytic solution of investigated problem is difficult to find. For events where significant inaccuracy of mentioned data is presented, the statistical approach is accepting and it help us to include uncertainty to the final assumption. To know the final margin of uncertainty is necessary for estimation of eventual fluctuation of analyzed variable. When to the process evaluation the combination of data with different uncertainty are entered to the result, with using a classical statistical approach it can be difficult in then some cases to obtain reasonable final information.

One method, which allows us to implement all uncertainty to the final analyses, is Monte Carlo method. In many applications of Monte Carlo method, the investigated process is simulated directly. There is no need to describe the behavior of the investigated system, which can be advantages in some complicated systems. The only important requirement is that this system could be described by probability density functions (PDF). We will assume that the properties of a system can be described by PDF's. Once the PDF's are known, the Monte Carlo simulation can proceed by random sampling technique from the PDF's. This approach works with random number generator of random numbers, which have properties of desirable PDF. Many trials are then performed and the expected result is obtained as an average over the number of values. In this case, it can be predicted the statistical structure as are variance, kurtosis and some other higher statistical moments of this simulated result. From these characteristics the estimation of the number of Monte Carlo trials can be achieved to obtain a result with an expected error.

The Monte Carlo method is based on the generation of multiple trials to determine the expected value of a random value. In our case it can be said that this method is uncertainties combination of probability distribution functions for activity data (AD) and EFs. Total emissions are then computed as combination of random numbers for appropriate distribution function for assigned greenhouses gases. The advantage of this method is asymmetry allowance to the statistical distribution (Tier 1 method do not allow asymmetry). This advanced method is useful for data manipulation, in the case, when proper input data quality is provided.

3. Landfill Methane Emissions

For Monte Carlo simulation of CH_4 it was chosen second variant of FOD method. Details one can see in the publication Farkaš (2006). There is important information that from solid waste disposal sites emissions of CH_4 are mainly dependent on the factors from inventory year (amount of waste storage, meteorological conditions, population growth, composition...) and from previous years (managing style of sites...). It is visible that total emissions are dependent to the many factors, which have time dependence. The formulas, which describe these emissions, have form:

$$
\begin{aligned}
L_0(x) &= \frac{16}{12} MCF(x)DOC(x)DOCF(x)F(x), \\
Fk(x) &= (1-e^{-k})e^{-k(t-x)}, \\
MSWL(x) &= MSWT(x)MSWF(x), \\
Q_t(x,t) &= Fk(x,t)MSWL(x)L_0(x), \qquad (1)
\end{aligned}
$$

$$
Q_T(x) = \sum_x (Q_t - R(x))(1-OX(x)). \qquad (2)
$$

The meaning of abbreviation it can be seen bellow.

- Qt methane generated in the year t (Gg/yr)
- t year of the inventory
- x years for which input data should be added
- Fk normalization factor which corrects the summation
- k methane generation rate constant (1/yr)
- MSWT(x) total municipal solid waste (MSW) (Gg/yr)
- MSWF(x) fraction of MSW disposed in the year x
- L0(x) methane generation potential (Gg CH4/Gg waste)
- MCF(x) methane correction factor in the year x (fraction)
- DOC(x) degradable organic carbon in the year x (Gg C/Gg waste)
- DOCF fraction of DOC dissimilated
- F fraction by volume of the methane in the landfill gas
- 16/12 conversion factor from C to CH4
- R(x) recovered methane in the inventory year t (Gg/yr)
- OX(x) oxidation factor (fraction)

These formulas (1) and (2) one can interpreted that formula (1) and terms Q_t represent the contribution of emission from the waste layer imposed in the year 'x' to the year of inventory 't'. It means that result for inventory year 't' is computed by formula (2), which performs the summation of methane submission from different layer stored in different years.

To estimate the total emission for chosen year one can use our presented formulas. The situation starts to be complicated when people begin to assume input data uncertainty. The formulas (1) and (2) show relative complicated relation among the terms in these functions. The interaction of uncertainties starts to be hardly computed.

One can suppose that our emissions production is expressed by function $F(X_i)$, where X_i are factors, which affect the sequential result of emissions (i=1…N, N represents number for

factors). Every factor has own uncertainty, which depend to the many sources. In some situation it is impossible to express variation of these sources to the function value. It is possible only express the interval of eventual values and their statistical behavior. In this case the values X_i can be interpreted as data set. For example factor X_1 will be represented with random values from expected range of values. The function value and their uncertainties it can be expressed:

$$F(X_i)=F(\overline{X}_i+\delta(X_i)), \tag{3}$$

where $\overline{X}_i$ could represent mean (expected value) or special chosen value from possible range of X_i values. It depends on solving algorithm. Our question is how the uncertainties of X_i values will affect the function value $F(X_i)$. The interest is focused to find expression for $\delta(F(X_i))$.

It is visible that direct computation of $\delta(F(X_i))$ is possible only in the special cases. To estimate the properties of $\delta(F(X_i))$ it is possible to analyze the error propagation by linearized theory. Consider term groped with first derivative of Taylor's series for $F(X_i)$. It can be written:

$$|F(X_i)-F(\overline{X}_i)|\leq\sum_i|X_i-\overline{X}_i|\left|\frac{\partial F(\overline{X}_i)}{\partial X_i}\right|, \tag{4}$$

With utilization the same approach it is possible to take the formula for variance:

$$\mathrm{Var}[\delta F(X_i)]\cong\sum_j\sum_i\mathrm{Cov}[\delta(X_i),\delta(X_j)]\left|\frac{\partial F(\overline{X}_i)}{\partial X_i}\right|\left|\frac{\partial F(\overline{X}_j)}{\partial X_j}\right| \tag{5}$$

This simplified approach allows us refuse complicated behavior of function $F(X_i)$ and compute their uncertainty as linear combination of their variables uncertainty, see formula (4). For variance, there is no linear relation, but when correlations among factors X_i are suppressed and $X_i \sim N(\mu_i, \sigma_i)$ then for $\delta(F(X_i))$ a noncentral chi-square distribution can be assumed.

This simple approach has limitation of applicability. It shows error spreading and it forms scheme of uncertainty interactions. Without the generality lose the formula (4) can be prescribed to the applicable form:

$$\delta F(X_i)\cong\sum_i\frac{\delta(X_i)}{\overline{X}_i}\left|G(\overline{X}_i)\right| \tag{6}$$

where $G(\overline{X}_i)=\overline{X}_i F'(\overline{X}_i)$, prime means derivative. This expression shows linearized form of uncertainty combination. When $\delta(X_i)$ is substituted with value, which represents 95% confidence interval, ratio $\delta(X_i)/\overline{X}_i$ represents percentual contribution to the total uncertainty.

The result is linear combination of these percentual submissions. In the linear dependence of $F(\overline{X}_i)$, the solution is modified to the form:

$$\delta F(X_i) \cong \sum_i \frac{\delta(X_i)}{\overline{X}_i} \left| F(\overline{X}_i) \right| \tag{7}$$

In this case the total error of formula above is an addition of particular terms, which are occurred in function defined by expression (1) or (2), except $\overline{X}_i = F_k$ (normalization factor), where dependence is nonlinear. The linear part of $F(\overline{X}_i)$ in the case for example, when $\delta(X_i)$=±50% of $\overline{X}_i \in \{F, MSWL, DOCF, DOCX, MCFN\}$ contribute to the final error by amount of 5/2 $F(\overline{X}_i)$. From this is visible that linearized approach is effective to use only in the case when $|G(\overline{X}_i)|<<1$. On the other hand it shows us that PDF's of $\delta(X_i)$ can play important role within process of uncertainty combination. From this knowledge it is clear that one can not take simply errors from $\delta(X_i)$ and sum then together without to investigation of probability distribution function of $\delta(X_i)$. Initialization records application from our applied values to our FOD model confirm apprehension from linear theory limitations. Uncertainty result for total emissions exceeds about two times mean value. This result, as we will see after application more sophistical method, does not represent reality in our case, when uncertainty $\delta(X_i) \sim \overline{X}_i$. But it helps us to estimate uncertainty propagation in our formula.

The method Monte Carlo is convenient to use for uncertainty problem solving. One requirement is to know distribution function of uncertainties. This approach allows us, with using a power of computer machine, simulate the complete properties of the final probability distribution function $\delta(F(X_i))$ and obtain required statistical characteristics. In this point one should be attentive, how uncertainties are specified. In the case when measurement of data is available the situation is well solvable. In the case of data absence the special estimation is provided. There are special recommendation in the literature IPCC (1996), how to proceed adequate results.

For this reasons the software package, which works with probabilistic distribution and their combination, was developed. With help of AuvTool software, they create useful tools for uncertainties estimation. In developed packages the next statistical distributions are supported: Gumbel, Exponential, Weibull, Lognormal, Uniform, Triangular, Beta, Binomial, Negative binomial, Chi-squre, Noncentral chi-square, F, Noncentral F, Gamma, T, Noncentral T, Normal and Poisson.

To solve equations (1 and 2) with Monte Carlo method it is necessary to specify uncertainty of parameters, which have entry to our formulas. The profiles of PDF's function are obtained after expert consultation and IPCC Guidelines suggestions. After application of Monte Carlo method to the FOD model the final probability distributions are obtained for every spotted year. This approach allows us to see detailed variation and combination of input parameters and their distribution functions. As was shown interaction of PDF's are not simple.

To see the influence of PDF's change to the total emissions, we try to modify PDF's profiles for every input parameter. Every profile in beginning of our analysis was changed to the normal or uniform distribution. The mean values were retained. Uncertainties were changed, the symmetrical uncertainties were setting in the first step of analysis for input parameters.

Result for PDF's exchange was analyzed. After Monte Carlo simulation with 20 000 trials the interested results are obtained. The mean value and average for total emissions are not change significantly. Whereas other statistic characteristics are changed significantly. This result shows dependence to the sort of PDF's and it calls for tidy approach in PDF's selection. Results for sensitivity of input parameters are verified. As was expected, the data accuracy play important role to the total uncertainty. PDFs selection in the case of symmetry uncertainty has less significant influence to the total uncertainty. Increasing of partial uncertainties for input factors multiple total uncertainties in the symmetrical cases. In the case of asymmetry, total uncertainty could be smaller than uncertainties of single input parameters.

On the next we try to analyze parameter influence to the total emissions. It can be seen that variation of parameter "K" and parameter "MSVL" have not significant influence to the total emission. This result was obtained with uniform PDF setting for all parameters and with change of uncertainty level from ±50% to ±5% for given parameter. Other parameters show similar dependence to the uncertainty of total emission. This approach shows that more important feature which has strongest influence to the total uncertainty in our formula is asymmetry allowance. The normal distribution does not allow asymmetry and for this reason one can see disadvantage of Tier 1 method which works with symmetric uncertainty. For this reason it seems that better choice of uncertainty specification is using simple PDF in the case of absence of measured data. For example triangular PDF, which allow asymmetry, has features, which help us to better compute total uncertainty.

4. Conclusion

The main topic of this article was to eliminate uncertainty of methane emissions produced by solid waste disposal sites. From our analyses seems that uncertainty of emissions are strongly dependent to the PDF's setting. These features were identified by simplest linear analyses of uncertainty of total emissions and in the second case with changing PDF's setting. The data accuracy play important role to the computation of the total uncertainty. PDFs selection in the case of symmetry uncertainty has no significant influence to the total uncertainty. Increasing of partial uncertainties for input factors multiple total uncertainties in the symmetrical cases. In the case of asymmetry, total uncertainty could be smaller than uncertainties of single input parameters. It can be seen that variation of parameter "K" and parameter "MSVL" have not significant influence to the total emission. This result was obtained with uniform PDF setting for all parameters and with change of uncertainty level from ±50% to ±5% for given parameter. Other parameters show similar dependence to the uncertainty of total emission. This approach shows that more important feature which has strongest influence to the total uncertainty is asymmetry allowance. The essential result from our study is fact that total uncertainty was reduced comparable to IPCC default recommended value. This value is 50% for total methane emissions from SWDS. This default uncertainty is applicable to the Tier 1 default method. From this value in the Tier 1, the key sources are identified by categories magnitude, which adds up to over 95% of the total emissions or emission trend. In Tier 2 the 90% of the level or trend uncertainties are also taken for the key sources specification. Specification and identification of the key sources are important for economy and government institutions to obtain overview of emissions unload. During the uncertainty computation, the emitting of CH_4 from underlayer and many other factors as meteorological condition, managing of sites is included. These dependences are expressed in FOD model, which was solved by Monte Carlo simulation. Spreading of emission uncertainty during the analyzed period was obtained. From the computed result precision increasing of emissions are

observed. In spite of high inaccuracy on the input data in the beginning of the examined period (this uncertainty has influence to the current uncertainty) the relative valuable result are obtained.

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Development of a Methodology for Temporal and Spatial Resolution of Greenhouse Gas Emission Inventories for Validation

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Introduction

Greenhouse gas (GHG) emission data sets, which are reported to the United Nations Framework Convention on Climate Change (UNFCCC) are available as annual country totals without further temporal and spatial differentiation. To validate such data, measurements of GHG concentrations can be used. However as these measurement data are point measurements in space and time, they have to be compared with concentrations calculated by atmospheric models that need emission data with high temporal and spatial resolution. Thus a methodology is needed that converts annual country data into data with high temporal (e.g. hourly) and spatial resolution. In this paper such a methodology is described. Basically the methods developed for classic air pollutants (like PM10, SO_2, NO_x, NH_3) are used and adjusted, so that then can be applied to GHG emissions. For the spatial resolution, available statistical and land use data are used to allocate activities to the grids in a country. For the temporal resolution, statistical and meteorological data and information about typical daily activity patterns are used to split annual values into hourly values. Furthermore for emissions of different sectors different release heights – e.g. different typical stack heights – are estimated.

Model Description

Our emission allocation model is able to provide input data for macro- and meso-scale modelling according to the requirements of the atmospheric models. On European scale, hourly emissions down to a grid cell size of about 10 km x 10 km are provided. The data base contains annual emissions of more than 250 source groups and we distinguish between point, area and line sources. The integrated meso-scale German emission model provides hourly emission data down to 1 km x 1 km grid cell size and includes more than 48,000 industrial point sources, 83,000 line sources/road segments and more than 500 source groups. The temporal resolution is realised through more than 300 source specific temporal profiles. For a high spatial resolution of area source emissions, statistical data for administrative units and land cover data are used.

Input for the emission model are annual emissions disaggregated into point, area and line sources using different geographic data for spatial allocation of these source types. Point sources are intersected with the model grid by geographic coordinates applying a geographic information system (GIS).

Height of Release of Emissions

If single source information is not available or not suitable for the calculation of effective emission heights, generalized information might be used for the vertical emission allocation. A distribution of the effective emission height is given for SNAP source groups level 1. This information is for instance used by the EMEP atmospheric model.

Spatial Distribution of National Emission Data

Area and line source emission data are spatially distributed to administrative units using statistical information as described in *Table 1*.

Table 1: Spatial resolution: used indicators – data bases describing spatial activity variation of significant emission sources

Sector	**Indicator for spatial resolution**
Line Sources	
Road Traffic	
Highways and national roads	Digital road map, traffic count data
Regional roads	Road map based on road network coordinates
Railways	digital railway network
Area sources	
Road Traffic	
Inner urban streets	Land use-urban area
Major urban streets	land use-urban area and partly geographical information about urban road network
Other Mobile Sources:	Land use data:
Forestry	forest area
Agriculture	agricultural area
Building machinery	urban area
Shipping Traffic	rivers and lakes
Households, small facilities, services	Land use-urban area, industrial area
Industrial area sources	Land use- industrial area
Agriculture / livestock farming	Land use-agricultural area
Point sources	
Air traffic	coordinates of the main airports
Industrial facilities and power plants	Coordinates of the point sources based on emission declaration data bases

In a second step, emissions from area sources are allocated to grid cells within an administrative unit using 1 km x 1 km or 3 km x 3 km land use maps, which distinguish between residential area, industrial area, agriculture, forest, water surface and other area. The land cover information was derived from CORINE for Western countries (EEA 1997) and USGS for Eastern countries (RIVM-NOAA 1996). For the allocation of non-urban road traffic to line segments in Germany, traffic counts that are available for all major road segments, are used (Wickert 2001). For countries, where traffic counts are not available, total

highway emissions per administrative units were allocated to road sections according to the length of the section.

Temporal Resolution of Emission Data

A high number of source specific temporal profiles were developed at IER within different studies (e.g. Müller et al. 1990, Adolph 1997, Seier 1998, Wickert 2001, John 1999, Schwarz 2002). Currently more than 300 temporal profiles are used, stored as hour factors of a complete year (8,760 resp. 8,784 values) in a profile table. Calculated hourly emission data are usually lumped across all detailed sectors to total hourly emission maps or emission maps for different SNAP level 1 source groups. In *Table 2* the indicators used are described for different temporal resolutions distinguished by main sectors.

Table 2: Temporal resolution: used indicators - socio-economic data describing temporal activity variation of significant emission sources

Sector	**Indicator data for monthly resolution**	**Indicator data for daily resolution**	**Indicator data for hourly resolution**
Power Plants	Fuel use	Load curves	Load curves
Industrial combustion plants	Fuel use, degree days (temperature), production	Working times, holidays	Working times
Small combustion plants	Fuel use, degree days (temperature)	User behaviour	User behaviour
Refineries	Oil throughput, fuel use	Working times, holidays	Working times, shift times
Industrial processes	Production	Working times, holidays	Working times, shift times
Road transport	Traffic counts	Traffic counts	Hourly traffic counts
Air transport	Landing-Take-Off (LTO)cycles, passenger and freight numbers	LTO cycles, passenger and freight numbers	LTO cycles, passenger and freight numbers

For most of the source categories, temporal profiles depend on the activity and the emissions follow a process specific activity profile. Temperature dependence was taken into account for small combustion plants as well as vehicle cold starts and gasoline evaporation based on the work of Wickert, 2001. With this approach the seasonal variation of the weekly and diurnal profile can be taken into account and thus accuracy can be improved.

Application of the Emission Model to GHG Emissions

Within the CarboEurope projects officially reported GHG emission data from the UNFCCC database have been temporally and spatially distributed using the Emission Allocation Model EAM. Figure 1 shows an exemplary result for spatially resolved emissions of CO2 and CO for Germany for the year 2000.

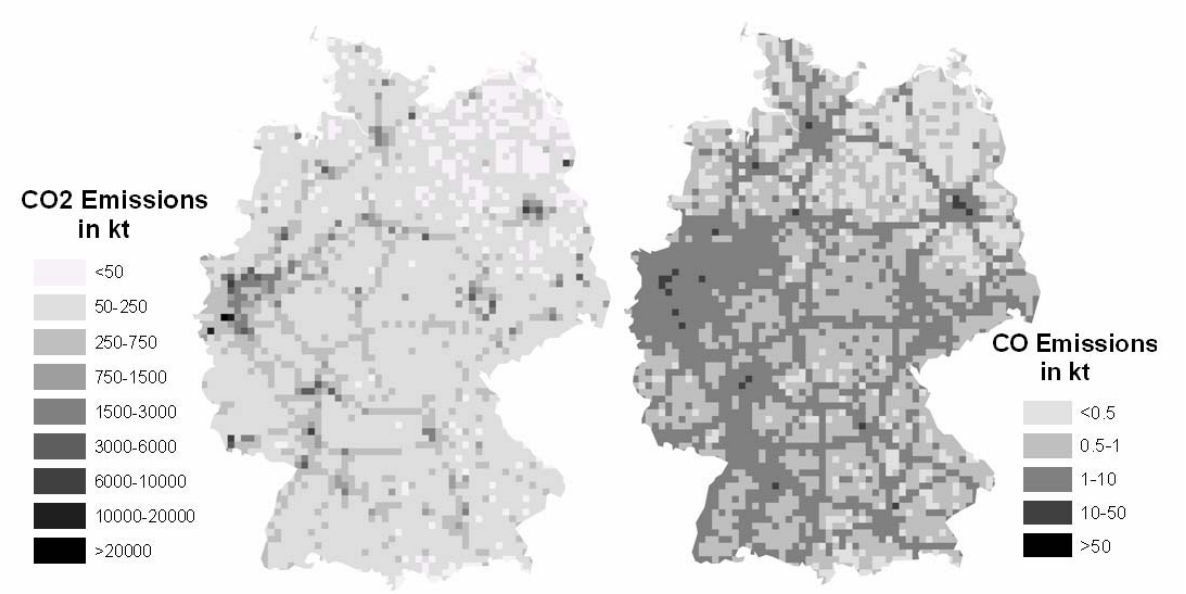

Figure 1: Spatially resolved emissions of CO_2 and CO for Germany for the year 2000 using the IER Emission Model.

Discussion of Uncertainties and Future Improvements

Annual GHG country total emission data officially reviewed and reported to UNFCCC are commonly associated with uncertainty estimations of 10 % up to 50 % depending on pollutant and statistical/methodological level of the national reporting. Uncertainty of CO_2 emissions are estimated to be usually only 10 % up to 30 %, as emission factors are mostly depending on the fuel use.

An in depth uncertainty analysis of emission data needs to address not only the total magnitude of emissions but as well uncertainty in spatial allocation and temporal resolution. As bottom-up emissions can not be calculated for a whole regional modelling domain and a comparison with measured true/real spatial emission information is not possible, an uncertainty quantification can not be done for the complete emission dataset. Therefore, a validation of emission data requires a scientific approach considering model application/uncertainty, parameter sensitivities and the comparison of modelled and measured concentrations/source contributions for selected grid cells/locations. *Table 3* contains an example for a statistical error analysis of non-methane volatile organic compounds (NMVOC) and NO_x emissions from mobile sources for different activity patterns. This may be used as a first rough estimate for the upper bound of the uncertainty of spatially and temporally resolved CO_2 emission data for transport.

To verify temporally and spatially resolved GHG emission data, measured concentrations should be compared with results of atmospheric models that use the emission data sets to be verified as input. This of course makes it necessary to distinguish between uncertainties resulting from the emission data and uncertainties coming from the atmospheric dispersion model used. In addition, the generation of monitoring data has uncertainties and measured concentrations might have an insufficient representativeness for the spatially averaged value of the grid area obtained by the model, which means that measurements at remote sites, which might be representative for a larger area around the site, should be used.

Table 3: Results from a statistical error analysis of NMVOC and NOx emissions from mobile source activities (Kühlwein, J. 2004)

Emission relevant activity	**NMVOC**	**NO_x**
	Variation Coefficients (68.3%-Confidence Interval) of modelled emissions	
Specific road sections	21 to 26 %	16-22%
Urban traffic:		
Hot engine	37%	35%
Cold start	>37%	>35%
Evaporation	30 to 40%	---
Areas (10^3 to 10^5 km^2)	19%	14%
Hourly resolution	10% to 100%, depending on traffic volume	

Generating hourly emission data by applying sector specific temporal profiles may entail additional uncertainties that can lead to a discrepancy between the variation of modelled and measured concentrations. A validation of the temporal emission variation can be done by comparing - as far as possible - representative hourly monitoring data with modelled hourly concentrations using inverse modelling techniques.

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Towards Bayesian Uncertainty Quantification for Forestry Models Used in the U.K. GHG Inventory for LULUCF

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Abstract

The GHG Inventory for the U.K. currently uses a simple carbon-flow model, CFLOW, to calculate the emissions and removals associated with forest planting since 1920. Here we aim to determine whether a more complex process-based model, BASFOR, could be used instead of CFLOW. The use of a more complex approach allows accounting for spatial heterogeneity in soils and weather, but places extra demands on uncertainty quantification. We show how Bayesian methods can be used to address this problem.

Introduction

Quantifying a GHG Inventory is a problem of incomplete information. No amount of data collection will provide us with a full inventory, so additional calculations and assumptions are required. In the case of LULUCF in the U.K., process-based models are used to quantify net CO_2 emissions associated with afforestation, reforestation and deforestation, based on forestry data and soil type information. The model currently used for forests planted after 1920 is CFLOW. This is a simple compartmental flow model for the carbon cycle which uses measured wood productivity as input and calculates the flows of carbon to tree parts and soil, with different turnover rates for the various compartments. We are investigating the scope for replacing CFLOW with a more complex process-based model, BASFOR, that can better take into account the spatial distribution of climate and soil properties across the U.K. However, the use of the models is hampered by incomplete knowledge of input variables as well as model parameters. This causes uncertainty in the model outputs which needs to be quantified and reported in the Inventory. A highly effective means of quantifying uncertainty in inputs, parameters and outputs of process-based models is Bayesian Calibration (BC; Van Oijen et. al. 2005). The key strength of the method is that it not only propagates uncertainty in inputs and parameters to model outputs, but also uses data on output variables to reduce the uncertainty in inputs and parameters. Here we shall demonstrate the application of BC to BASFOR, and show predictions of carbon sequestration including their uncertainty.

Methods

Model BASFOR

The BASic FORest simulator, BASFOR, is a process-based forest model that simulates carbon and nitrogen cycling in trees, soil organic matter and litter (Van Oijen *et al*., 2005). It simulates the response of trees and soil to radiation, temperature, precipitation, humidity, wind speed, atmospheric CO_2 and N-deposition, and thinning regime. The model has 11 state variables, representing carbon and nitrogen pools in trees and soil, and 32 parameters

controlling the rate of physiological processes and morphological characteristics. The model is deterministic and is solved by Euler integration with a time step of one day.

Weather data

Weather data were taken from the UKCIP climate scenarios (Hulme & Jenkins, 1998). For future weather, only the "Medium-high" scenario was used. The data are given for a regular spatial grid of 655 cells of 20 by 20 km each. Current spatial gradients for temperature and precipitation are dominated by latitudinal and longitudinal effects, respectively. Future warming is expected to show a decreasing pattern from the South-East to the North-West.

Atmospheric CO_2

Atmospheric CO_2 concentration has increased from 300 ppm in 1920 to current levels of around 380 ppm, with an average for the period 1920-2000 of 325 ppm. For the average CO_2 level in the period 2000-2080, the Bern model (Joos et al., 1996) predicts a value of 480 ppm.

N-deposition

Early 20th century levels of N-deposition were low across Europe (< 3 kg N ha^{-1} yr^{-1}) (Galloway, 1985). Data and calculations by the Co-operative Programme for Monitoring and Evaluation of the Long-Range Transmission of Air Pollutants in Europe (EMEP) show increasing N-deposition values during most of the 20th century with maxima reached around 1990. The 1999 Gothenburg Protocol to Abate Acidification, Eutrophication and Ground-level Ozone sets emission ceilings for 2010 for NOx, ammonia and other pollutants. Hence we assumed continued reductions of N-deposition until the year 2010, with deposition remaining constant thereafter. These temporal patterns were spatially disaggregated using the 2004 UK deposition map (R.I. Smith, pers. comm.).

Soils

Data on soil nitrogen, carbon and plant available water content were taken from the global soils database produced by the Data and Information Services of the International Geosphere-Biosphere Programme (IGBP-DIS, Global Soil Data Task 2000).

Tree data from sites Dodd Wood and Rheola

Forest Research U.K. provided data on tree growth and soil characteristics from two Sitka spruce stands, for use in model calibration (R. Matthews & P. Taylor, pers. comm.). The sites were Dodd Wood (54.64 °N, 3.17 °W, alt. 381 m., indurated brown earth sandy soil) and Rheola (51.74 °N, 3.68 °W, alt. 220 m., brown earth soil). Trees were planted in 1927 and 1935, respectively, and management followed a 5-year thinning cycle on both sites.

Bayesian calibration and uncertainty quantification

The parameters of the BASFOR model were quantified by means of Bayesian calibration, using the Forest Research data for Dodd Wood and Rheola. The procedure began with quantifying the uncertainty about the parameter values in the form of a prior probability distribution, based on literature data on conifer growth. The Forest Research data on model output variables were used to update the parameter distribution by application of Bayes' Theorem [$p(\theta|D) \propto p(D|\theta)\ p(\theta)$, where θ is the parameter vector and D is the data]. This yielded a posterior, calibrated probability distribution for the parameters. The predictive uncertainty of the model was then quantified by running the model with different parameter settings, sampled from the posterior distribution (n=5), using Markov Chain Monte Carlo (MCMC) simulation (Van Oijen et al. (2005)). One limitation of the present study was that

only the uncertainty in model parameters was quantified. Uncertainty in model drivers (climate, soils) was not quantified, nor was the uncertainty relating to the structure of the BASFOR model itself assessed.

Results

Bayesian calibration and uncertainty quantification

Table 1 lists the major parameters of BASFOR, with their prior uncertainty before application of data from UK forests, and their posterior uncertainty after Bayesian Calibration. For most parameters, prior uncertainty was large, i.e. lower and upper limits were far apart. *Figure 1* (black dotted lines) shows for four model output variables (tree and soil carbon, height and total produced wood volume) how the prior parameter uncertainty effected uncertainty in model outputs at the Dodd Wood site. For example, the uncertainty interval (2 standard deviations wide) for tree carbon at the end of the eighty-year rotation ranged from below 40 to above 80 ton carbon ha^{-1}. *Table 1* and *Figure 1* also show to what extent uncertainties were reduced by the Bayesian calibration using the data from the Dodd Wood and Rheola sites, described above. The marginal posterior probability distributions were much narrower than the prior distributions, as can be seen from the small coefficients of variation. The data from Dodd Wood were not equally informative for all parameters, with CVs for three parameters – initial leaf and stem carbon content and N/C ratio of wood – exceeding 20%. However, Figure 1, red unbroken lines, shows that overall parameter uncertainty had been reduced enough to significantly reduce output uncertainty for the four selected variables.

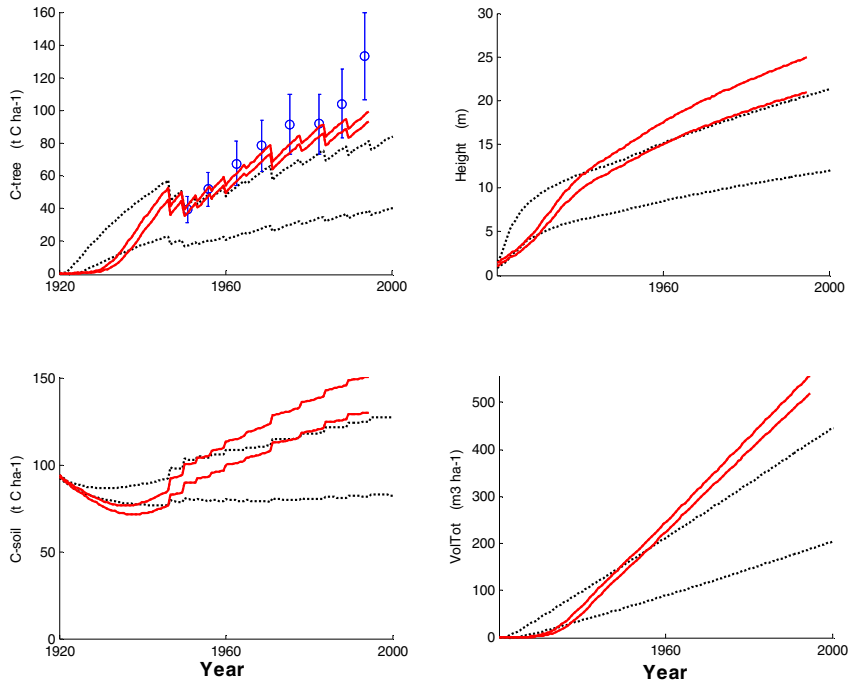

Figure 1. Prior (black,dotted lines) and posterior (red, unbroken lines) model output uncertainty for Dodd Wood. Output variables are tree and soil carbon content, tree height and cumulative wood volume production. Blue circles and vertical lines: data with estimated measurement error

Table 1. Prior and posterior probability distributions for parameters of BASFOR. The prior is beta-distributed between specified lower and upper limits. The posterior, derived using data from Dodd Wood and Rheola, is not analytical and is characterized here by the mean values of the marginal parameter probability distribution and the coefficients of variation (CV = standard deviation / mean) (posterior correlation matrix not shown).

Parameter vector			Prior probability distribution		Posterior probability distribution	
Symbol	Unit	Meaning	Lower limit	Upper limit	Mean	CV
$C_{B,0}$	(kg m^{-2})	Initial value branch C	0.00005	0.005	0.0010	0.18
$C_{L,0}$	(kg m^{-2})	Initial value leaf C	0.0001	0.01	0.0015	0.38
$C_{R,0}$	(kg m^{-2})	Initial value root C	0.0001	0.01	0.0017	0.16
$C_{S,0}$	(kg m^{-2})	Initial value stem C	0.00005	0.005	0.00090	0.34
B	(-)	CO_2-response factor	0.4	0.6	0.52	0.06
$CO_{2,0}$	(ppm)	CO_2-response base level	320	380	362	0.02
f_B	(-)	Allocation to branches	0.25	0.30	0.29	0.02
$f_{L,max}$	(-)	Maximum allocation to leaves	0.27	0.37	0.29	0.03
f_S	(-)	Allocation to stem	0.25	0.3	0.28	0.01
Γ	(-)	Respiration fraction	0.4	0.6	0.48	0.06
k_{CA}	(m^2)	Crown area allometric normalisation constant	5	15	11	0.12
$k_{CA,exp}$	(-)	Crown area allometric exponent	0.3	0.45	0.36	0.07
k_h	(m)	Tree height allometric normalisation constant	4	12	7.5	0.07
$k_{h,exp}$	(-)	Tree height allometric exponent	0.2	0.3	0.26	0.04
LAI_{max}	(m^2 m^{-2} mm^{-1})	Maximum LAI	4	10	6.3	0.06
LUE_0	(kg MJ^{-1})	Light-Use Efficiency	0.001	0.003	0.0014	0.10
$NC_{L,max}$	(kg kg^{-1})	Maximum C/N ratio leaves	0.02	0.05	0.028	0.12
$NC_{R,con}$	(kg kg^{-1})	C/N ratio roots	0.02	0.04	0.023	0.06
$NC_{W,con}$	(kg kg^{-1})	C/N ratio woody parts	0.0005	0.002	0.00080	0.23
SLA	(m^2 kg^{-1})	Specific Leaf Area	5	40	6.0	0.05
T_{opt}	(◦C)	Temperature optimum	12	28	19	0.12
$TC_{L,max}$	(d)	Maximum survival time coefficient leaves	365	1460	1048	0.09
δ	(kg C m^{-3})	Wood density	150	250	182	0.04

C-sequestration 1920-2000

The calibrated model was applied to calculate UK-wide C-sequestration between 1920 and 2000 for a standardized conifer rotation with a 5-yearly thinning interval (*Figure 2*). C-sequestration was defined as the average annual total accumulation of carbon in soil, standing biomass and wood removed at thinnings. Calculated sequestration rates were highest in the South-West of the country, which combines moderately high temperature and precipitation. The far North is identified by the model as an area of net C-source rather than a sink (*Figure 2*). The spatial pattern of C-sequestration was not closely related to the spatial distribution of atmospheric N-deposition and soil nitrogen. The propagation of parameter uncertainty to uncertainty about C-sequestration rates was calculated by taking five samples from the posterior parameter probability distribution (*Table 1*) and calculating the standard deviation for the five different results. *Figure 3* shows the resulting map of sequestration uncertainty. The spatial pattern of sequestration uncertainty differs strongly from that of sequestration

itself (Figure 2), indicating that the coefficient of variation varies between different growing conditions.

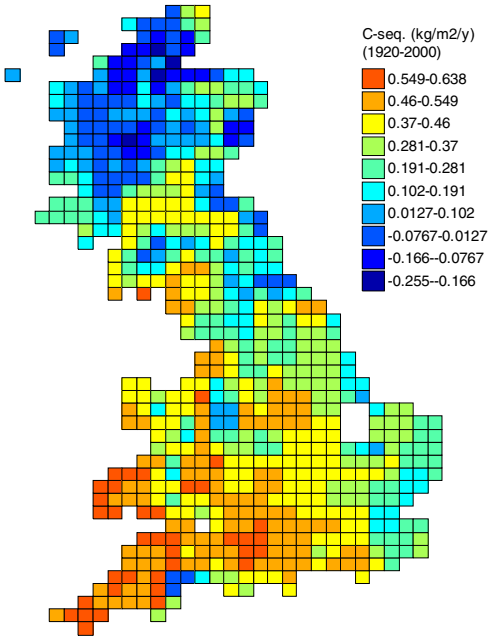

Figure 2. Simulated average annual C-sequestration (in soil, living trees and wood products) for 1920-2000. Results from model BASFOR

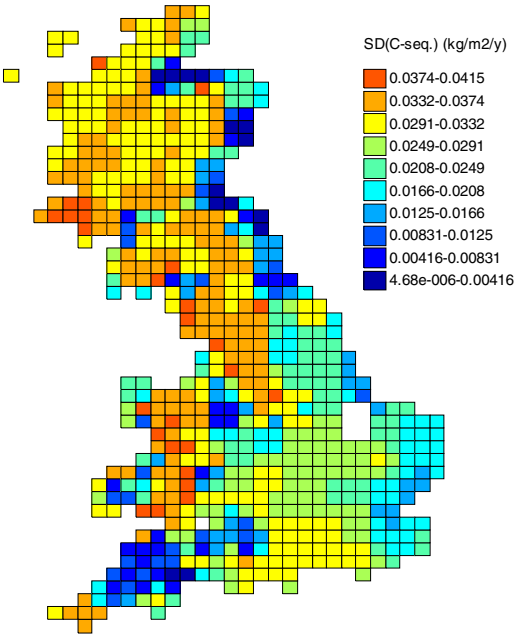

Figure 3. Uncertainty in simulated average annual C-sequestration (in soil, living trees and wood products) for 1920-2000. Results from model BASFOR

C-sequestration 2000-2080

The same calculations of C-sequestration were repeated for the environmental conditions expected for the period 2000-2080. *Figure 4* shows the spatial distribution of expected changes in sequestration, relative to 1920-2000. The changes are not closely related to the magnitude of expected changes in temperature, as the spatial patterns differ. However, some degree of warming is expected across the whole country, causing C-sequestration to change mainly in the higher, colder regions of Wales, North-England and Scotland.

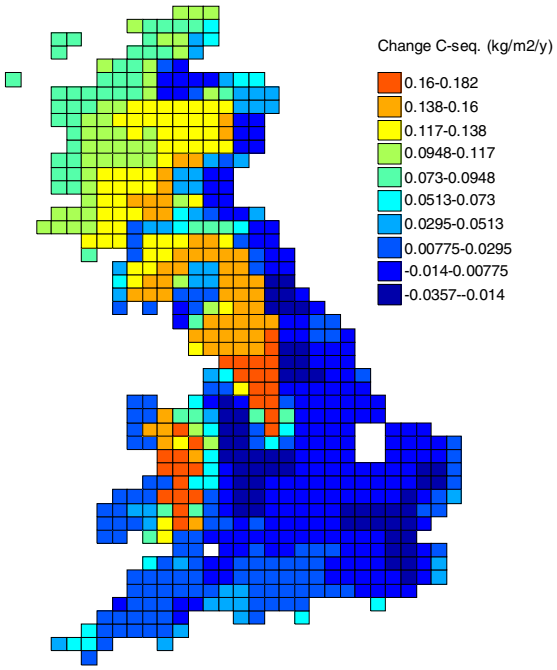

Figure 4. Simulated change in average annual C-sequestration (in soil, living trees and wood products) from 1920-2000 to 2000-2080. Results from model BASFOR

Analysis in terms of environmental change factors: climate, CO_2, N-deposition

The preceding UK-wide assessments of the effects of environmental change on expected C-sequestration rates in conifer forests did not separate out the effects of the different environmental factors subject to change. For the purpose of such analysis, we ran additional simulations for the Dodd Wood site with a range of temperatures, atmospheric CO_2 concentrations and N-deposition rates, in a full-factorial set-up. Average temperature was varied from 6.8 to 9.9 °C (which amounts to expanding the UKCIP-estimates for the site for 1920-2000 and 2000-2080 with one degree on either side of the range), atmospheric CO_2 was varied from 320 to 480 ppm (corresponding to changes estimated by the Bern model using the IS92a emissions scenario for 1920-2000 and 2000-2080), and N-deposition was varied from 0 to double the 1920-2000 average value of 8.0 kg N ha^{-1} y^{-1}. *Table 2* summarizes the results of application of the model for these environmental conditions. The first data column of the table lists the average values of yield class and annual C-sequestration rate across the considered set of environmental conditions, with standard deviations indicating the uncertainty arising from both the variation in environmental conditions as well as the parametric uncertainty determined before. The final three data columns of *Table 2* give the average effect on yield

class and sequestration of changes in temperature, CO_2 and N-deposition, with uncertainties. On the examined site, Dodd Wood, changes in each of the three environmental factors has an effect on the output variables, but with the strongest effect (relative to its expected degree of change) for CO_2. The analysis further suggests that C-sequestration rates are likely to increase to similar extent in soils and in tree biomass.

Table 2. Simulated change in average yield class and annual C-sequestration at the Dodd Wood site due to changes in temperature, CO2 and N-deposition. The standard deviations are due to uncertainty in parameterisation and to variation in interacting environmental factors, but not including soil characteristics

		Impact of environmental change		
Ecosystem variable	Dodd Wood value	Effect of temperature (per °C)	Effect of [CO_2] (per 100 ppm)	Effect of N-deposition (per 10 kg N ha^{-1} y^{-1})
Yield class (m^3 ha^{-1} y^{-1})	7.91 ± 1.11	0.18 ± 0.05	1.32 ± 0.38	0.74 ± 0.26
C-sequestration (t C ha^{-1} y^{-1})	3.99 ± 0.64	0.10 ± 0.03	0.76 ± 0.21	0.41 ± 0.14
C-sequestration, soil (t C ha^{-1} y^{-1})	1.58 ± 0.31	0.05 ± 0.01	0.36 ± 0.10	0.18 ± 0.07
C-sequestration, trees and products (t C ha^{-1} y^{-1})	2.41 ± 0.34	0.05 ± 0.02	0.40 ± 0.12	0.23 ± 0.07

Discussion and Conclusions

This study has tried out methods that may be used to improve the construction of the UK GHG inventory. The process-based forest model BASFOR was parameterised efficiently using Bayesian calibration, allowing for uncertainty quantification when using the model to calculate UK-wide conifer forest C-sequestration and yield class. However, the procedure likely suffered from low quality of some data, in particular those on soils.

Uncertainties

Throughout our study we found relatively little sensitivity of UK forest C-sequestration rates and yield class to soil nitrogen content and atmospheric N-deposition, as opposed to the calculated sensitivities to changes in temperature and atmospheric CO_2 concentration. This finding may be an artefact from the use of the IGBP-DIS dataset with its possibly overestimated values of nitrogen contents of UK soils, leading to apparent nitrogen saturation (Van Oijen & Jandl, 2004).

The impacts of changes in environmental factors

The use of a process-based model for calculating C-sequestration, rather than the semi-empirical model CFLOW currently used in the U.K. GHG Inventory, allowed us to analyse the contributions of changes in temperature, CO_2 and N-deposition to changes in sequestration. However, this analysis should be seen as a proof of concept for the methodology rather than as a high-probability identification of a key environmental variable – given the likely poor quality of the soils data and because the factor analysis should first be repeated for the whole of the UK. The spatial pattern of uncertainties, both expressed in absolute terms and as coefficients of variation showed distinct spatial trends across the country, so not only the calculation of main effects, but also uncertainty quantification needs to be calculated country-wide.

The use of process-based models

The presence of nonlinear individual and interactive effects limits the usefulness of response factors as calculated in *Table 2*. For example, the yield class temperature response factor of 0.18 ± 0.05 (m^3 ha^{-1} y^{-1}) ($°C)^{-1}$ does not necessarily apply outside the Dodd Wood area. This has implications for the way in which we can use results from the process-based modelling to derive modifiers for the yield class values that are used as input for the carbon inventory calculations using CFLOW. The yield class modifiers likely need to be complex multivariate functions of the set of different environmental factors. However, we can calculate such functions if we redo the current factor analysis at a UK-wide scale and with improved input information. This needs to be accompanied by quantification of the uncertainties from incomplete knowledge of parameters, environmental drivers and model structure.

Acknowledgments

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Impact Assessment of Remotely Sensed Soil Moisture on Ecosystem Carbon Fluxes across Europe

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Abstract

While remote sensing stands alone in being able to provide spatially explicit datasets at regional to global scales, it has so far found only few applications in reporting and verifying ecosystem carbon fluxes within the context of the Kyoto Protocol. One of the problems is that new remote sensing datasets can only be used with new or adapted models and data assimilation schemes. In this study remotely sensed soil moisture data derived from ERS scatterometer measurements are used for the first time to model the carbon balance of Europe. By comparing the model results obtained with and without the use of the remotely sensed soil moisture data, the strong impact of soil moisture on the European carbon balance is demonstrated. For many parts of Europe, modeled net ecosystem productivity decreases when soil moisture is taken into account. A comparison with anthropogenic carbon emissions demonstrates that this effect is quite strong. Several European countries shift from being a carbon sink into a carbon source.

Keywords: Carbon sequestration, water limitation, net ecosystem productivity, soil water index, anthropogenic carbon emissions, coarse resolution satellite imagery

1. Introduction

The measurement of carbon stocks in soils and vegetation as a means for reporting and verifying greenhouse gas emissions and removals is a challenging task and is subject to high uncertainties. Nilsson et al. (2001) expressed their concern that the high uncertainties in the estimation of greenhouse gas removals in the forest and agricultural sectors will veil emission reductions to which the signatory countries of the Kyoto Protocol have committed themselves.

Since the early stages of the Kyoto-process, remote sensing has been considered as an important technique that may provide basic input data for inventorying and verifying ecosystem carbon fluxes. However, while remote sensing stands alone in being able to provide regional to global scale data sets, it cannot yet be considered operational in more than a handful of applications related to the Kyoto Protocol (Rosenqvist et al., 2003). This finds e.g. its expression in the *Good Practice Guidance for Land Use, Land Use Change and Forestry* adopted by the Intergovernmental Panel on Climate Change (IPCC) in 2003: This report repeatedly points out the potential of remote sensing to help parties for fulfilling their inventory requirements, but it neither provides concrete advice of how to use remote sensing nor does it provide incentives for doing so (Wagner et al., 2005).

The slow adoption of remote sensing for inventorying and verifying greenhouse gas emissions and removals by the forest and agricultural sectors is due to many reasons, including technological and economic reasons. From a methodological point of view one of the major problems is that the integration of remotely sensed geophysical products (land cover, forest biomass, soil moisture, etc.) into carbon models is a complex process. Typically, it is not possible to simply exchange one type of input data with a remotely sensed data set. Rather, it is necessary to develop new models and data assimilation systems.

In this study a method for estimating ecosystem carbon fluxes across Europe has been developed which is capable of using remotely sensed soil moisture data. Remotely sensed soil moisture data have only become recently available (Wagner et al., 2007) and can be expected to shed new light on the coupling between carbon assimilation and water availability. Their impact is evaluated by comparing modeled ecosystem carbon fluxes with and without the use of remotely sensed soil moisture data. The two model scenarios are also compared with anthropogenic carbon emissions on a national level for assessing the significance of soil moisture effects in the context of the Kyoto Protocol.

2. Theory and Method

The carbon balance of a terrestrial ecosystem is determined by differences in carbon sequestration of plants and soils and carbon release induced by ecosystem respiration. Valentini et al. (2000) demonstrated that ecosystem respiration varies with latitude and is the most important component of the European net carbon balance. Grace and Rayment (2000) suggest that in moist soils, microbial flora adapts to low temperature regimes and therefore stays active over long periods during the growing season as long as soil moisture content does not constrain soil organic matter decomposition. Ciais et al. (2005) show that pronounced soil moisture deficits counteract the effect of high temperatures by a reduction of soil respiration. Clearly, carbon fixation is mainly driven by plant water availability, apart from solar radiation and ambient temperature. Despite this, global carbon budget studies are often dominated by the analysis of temperature effects only (Nemani et al., 2002).

The model used in this study is the production efficiency model C-Fix which has already been used for simulating carbon mass fluxes on a daily basis from local (Veroustraete et al., 2004), over regional (Veroustraete et al., 2002; Chhabra and Dhadwal, 2004; Lu et al., 2005) to global scales. Radiation absorption efficiency is calculated from satellite derived Fraction of Absorbed Photosynthetically Active Radiation (*f*APAR) data and radiation use efficiency, which is the integrated efficiency of photosynthetic metabolism to convert radiation into assimilated carbon. Stratification of radiation use efficiency is obtained using the land cover map described by Bartholomé and Belward (2005). Daily net ecosystem productivity is

estimated from the daily gross carbon uptake by photosynthesis reduced with autotrophic respiration and reduced by a soil dependent respiratory flux originating from the decomposition of soil organic matter and root respiration (Maisongrande et al., 1995). Soil moisture limitation of uptake and release of carbon by ecosystems is accounted for at the photosynthesis (evapotranspiration) and at the soil respiration level (Verstraeten et al., 2006b).

Soil moisture data for Europe have been derived from ERS scatterometer observations using the retrieval method developed by Wagner et al. (1999). The ERS scatterometer is an active microwave sensor operating at a frequency of 5.3 GHz (C-band) with a spatial resolution of 50 km. Radar waves only penetrate a few centimeters into the soil which means that the instrument only collects information about the soil moisture content in the soil surface layer (2-5 cm). However, due to the frequent temporal coverage of the ERS scatterometer, the temporal evolution of the surface wetness conditions is known which allows estimating the soil moisture content in the soil profile (Ceballos et al., 2005). Validation studies over different climatic regions have shown that the soil moisture retrieval error is in the range from 0.03 to 0.06 m^3 m^{-3} (Ceballos et al., 2005; Pellarin et al., 2006; Verstraeten et al., 2006a; Wagner et al., 1999, 2003).

Daily Net Ecosystem Productivity (NEP) was calculated with C-Fix for the year 1997 with and without the use of the ERS scatterometer derived profile soil moisture data. *f*APAR is derived from NOAA-AVHRR Normalized Difference Vegetation Index (NDVI) data according to Myneni and Williams (1994). Meteorological data stem from the World Meteorological Organization (Veroustraete et al., 2002), and antrophogenic carbon emission data from a United Nations Framework Convention on Climate Change (UNFCC) report (UNFCC, 2005).

3. Results and Discussions

When C-Fix is run using remotely sensed *f*APAR data as input it indirectly accounts for the effects of long term water stress in vegetation. However, when remotely sensed *f*APAR and soil moisture data are used as input data, both short and long term impacts of water limitation on carbon fluxes are accounted for. The two models run modes are therefore denoted by Partially Water Limited (PWL) and Fully Water Limited (FWL) modes.

Spatially explicit NEP estimates at the European scale are shown in *Figure 1*. *Figure 1a* shows the results of the partially water limited run mode (NEP_{PWL}), *Figure 1b* the fully water limited run mode (NEP_{FWL}), and *Figure 1c* the difference between the two run modes (NEP_{PWL} - NEP_{FWL}). It can be observed that the effect of soil moisture on NEP simulations varies strongly with location. In most parts of Europe, soil moisture reduces NEP, but still keeps a positive value. In other areas, soil moisture increases NEP. *Figure. 2* illustrates where NEP_{FWL} keeps its negative value, where NEP_{FWL} keeps its positive value, where NEP_{FWL} switches from positive to negative values and finally where NEP_{FWL} switches from negative to positive values.

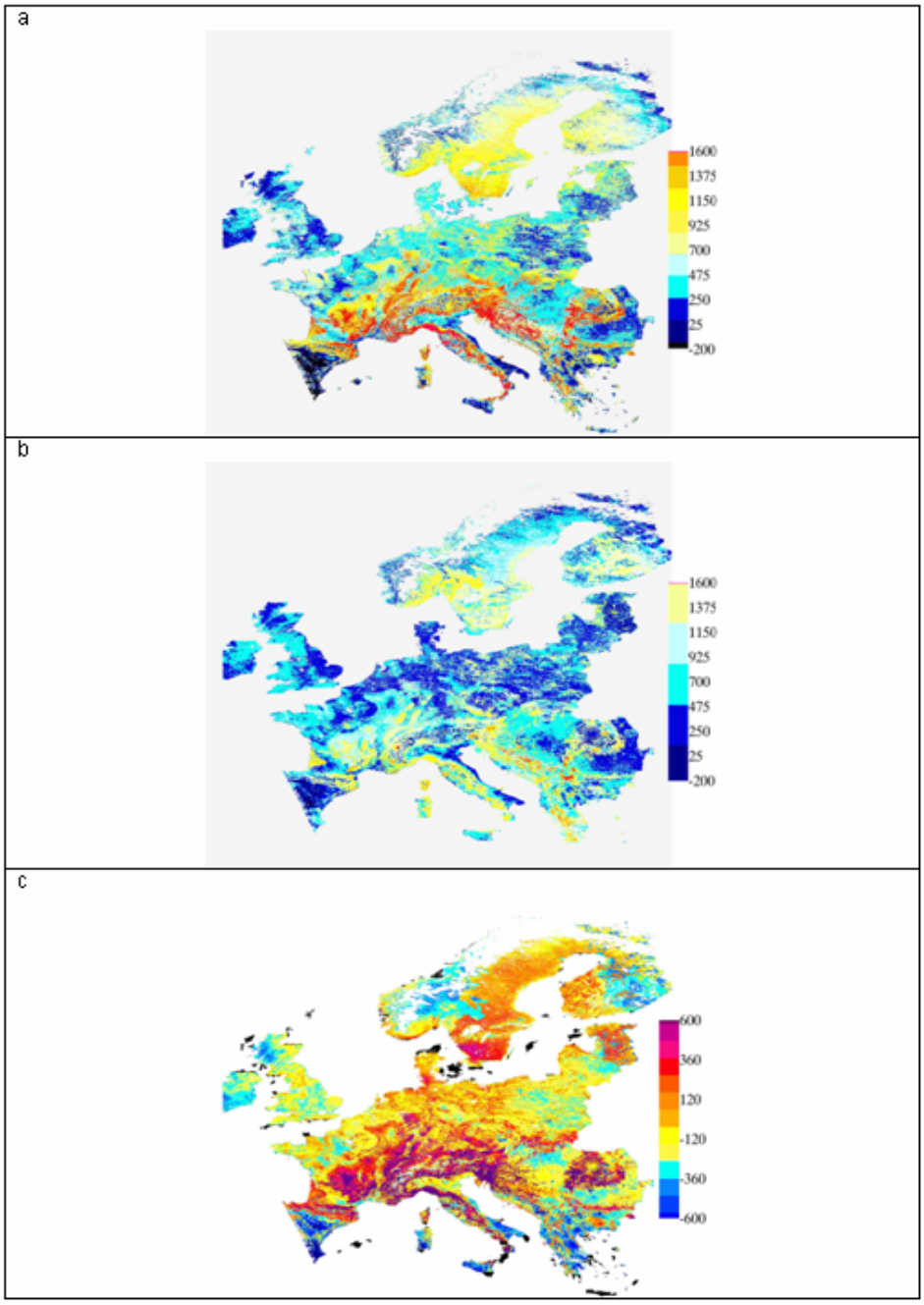

Figure 1. Estimated average daily net ecosystem productivity (in 10^1 g C m^{-2} d^{-1}; thus divide by 10 to get the real value) for 1997 for Europe using the production efficiency model C-Fix. Panel a, partially water limited model run (NEP_{PWL}) and Panel b, fully water limited model run (NEP_{FWL}). Panel c illustrates the difference between the NEP of Panel a and b ($NEP_{PWL} - NEP_{FWL}$).

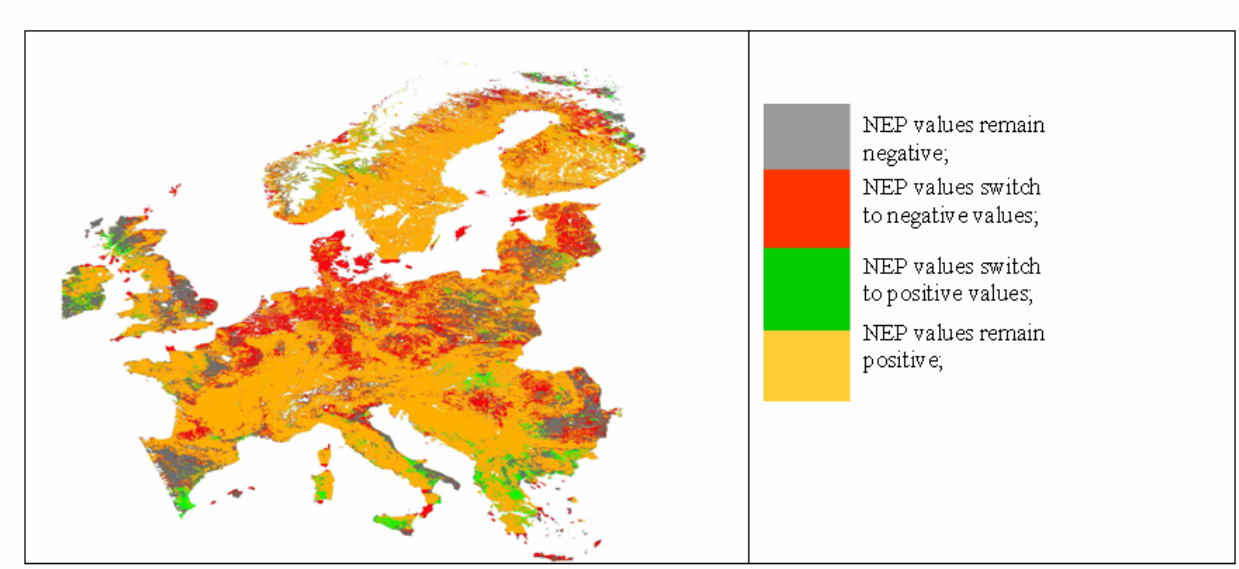

Figure 2. Sign switch of net ecosystem productivity (NEP) from partially water limited to fully water limited mode (Europe, 1997). Orange indicates the areas where NEP stays positive. Grey indicates the areas where NEP stays negative. Red indicates the areas where NEP switches from positive to negative values. Green indicates the areas where NEP switches from negative to positive values.

The spatial patterns of *Figure 1b* are related to high or low soil moisture relative to soil texture properties. Very low soil moisture values reduce and ultimately fully inhibit soil micro-organism activity so that soil respiration is decreased or respectively brought to a standstill. On the other hand, in water depleted soils, the decrease of gross primary productivity can be sharper than that of soil respiration. In that case a decrease in NEP will be the result. Opposite to very dry soils, high soil moisture values can lead to soil anaerobiosis and a significant inhibition of soil micro-organism activity. Very wet conditions inhibit photosynthesis as well.

To put the magnitude of the soil moisture effects into context of the Kyoto Protocol, the difference between NEP and antrophogentic carbon emissions (ACE) is shown in *Table 1* for 26 European countries. Since ACE values are collected at the country level, the analysis of the balance of NEP and ACE is limited to the different European national levels as well. When NEP_{PWL} is selected, 14 out of 26 countries representing 47.5 % of the European continental surface area (approximately 4,300,000 km²), elicit a negative carbon budget. When NEP_{FWL} is selected, the number of countries with a negative carbon budget increase to 26 and the area to 73.2 %. This demonstrates the significant impact of soil moisture on the carbon balance.

Table 1. The difference between net ecosystem productivity (NEP) and anthropogenic carbon emissions (ACE) at European country national level for 1997 (in Tg C a^{-1}). Standard deviations are listed in Italic font.

Country	ACE (Tg C a^{-1})	NEP_{PWL}-ACE (Tg C a^{-1})		NEP_{FWL}-ACE (Tg C a^{-1})	
Austria	66.5	61.7	*90.4*	-15.4	*51.8*
Belgium	122.2	-105.0	*15.9*	-118.3	*7.6*
Bulgaria	61.6	10.2	*100.9*	-23.7	*52.9*
Czech/Slovakia	137.4	-77.7	*60.9*	-114.9	*33.0*
Denmark	65.7	-49.3	*16.4*	-43.6	*10.1*
Estonia	20.2	11.6	*24.7*	-14.7	*23.1*
Finland	62.3	125.7	*149.0*	56.7	*145.5*
France	403.1	206.5	*590.4*	-161.9	*293.5*
Germany	893.5	-548.0	*279.5*	-813.4	*139.0*
Greece	94.3	-18.2	*131.9*	2.2	*90.1*
Hungary	60.5	-12.2	*75.5*	-37.0	*34.1*
Ireland	38.3	-42.6	*16.7*	-37.6	*10.1*
Italy/San Marino	443.1	-103.3	*424.7*	-283.7	*195.7*
Latvia	8.7	30.5	*36.6*	1.4	*35.8*
Lithuania	16.2	1.1	*29.0*	-6.9	*21.8*
Luxembourg	9.5	-9.1	*0.8*	-9.5	*0.3*
Monaco	44.7	-44.7	*0.0*	-44.7	*0.0*
the Netherlands	170.2	-149.7	*19.1*	-167.1	*10.0*
Norway	40.6	219.5	*257.4*	199.7	*220.4*
Poland	361.6	-222.0	*180.2*	-300.2	*120.1*
Romania	123.8	76.4	*278.2*	-63.5	*137.4*
Slovenia	16.1	32.6	*21.9*	1.7	*9.9*
Spain/Andorra*	262.6	-198.4	*583.2*	-217.4	*286.3*
Sweden	56.8	390.1	*251.5*	152.0	*178.7*
Switzerland	43.2	13.9	*42.7*	-26.0	*20.6*
United Kingdom	548.4	-511.7	*77.7*	-533.2	*41.5*

Zero or positive difference (NEP-ACE): the country's ecosystems can recapture anthropogenic carbon emissions.

Negative difference: Anthropogenic carbon emissions are higher than what terrestrial ecosystems can recapture; *For Spain NEP estimates are only representative for the NE-Spain (28.6 % of the total country area); Standard deviations are based on ecosystem carbon fluxes, not on errors on anthropogenic emission estimates.

Net Biome Productivity (NBP) must be used as an indicator for carbon recapturing when in addition to ecosystem respiration other processes like forest clearing, logging, forest fires, crop harvesting or in general land use/land cover changes, are to be accounted for in the carbon balance. To estimate NBP, a NBP/NEP conversion factor was applied. The NBP/NEP factor is estimated to be 0.10 to 0.20 for the global terrestrial carbon cycle (Steffen et al., 1998), 0.47 for European forests ecosystems (Janssens et al., 2003) and 0.23 for European grasslands (Soussana et al., 2004). For all European ecosystems (considering the percentages of land cover) a NBP/NEP factor of 0.15 was used. This results in an annual European NBP of 229±109 Tg C which is 5.5% of European ACE with an error of 38% on the applied NBP/NEP factor. This estimate is quite similar of the estimate of Janssens et al. (2003). The 1997 NBP for forest ecosystems of 227±101 Tg C a^{-1} obtained with C-Fix, is slightly lower than the land-based NBP estimate of 363±159 Tg C a^{-1} as reported by Janssens et al. (2005). In contrast to land information based approaches, remote sensing based estimates of carbon mass fluxes are spatially explicit.

4. Conclusions

Even though in recent years the use of remote sensing for assessing and verifying ecosystem carbon fluxes has grown, the technique is still not used to its full extent within the context of the Kyoto Protocol Process. One of the reasons is that, typically, new models and data assimilation schemes have to be developed that allow the use of remotely sensed data sets. This was the first study which used remotely sensed soil moisture data derived from ERS scatterometer data for assessing the impact of water limitation on the carbon balance of Europe. The analysis demonstrates that soil moisture has an important impact on the spatial patterns of carbon sequestration and that the carbon uptake and anthropogenic emissions in Europe is fundamentally different when water limitation is fully accounted for. Most importantly, the results suggest that Net Ecosystem Productivity (NEP) decreases in many areas when soil moisture is considered. The effect is so strong that some European countries shift from being a sink into a source according to the model.

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Statistical Dependences in Input Data of National GHG Emission Inventories: Effects on the Overall GHG Uncertainty and Related Policy Issues

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The uncertainty of the national Austrian greenhouse gas inventory was assessed for a second time after 7 years. Repeating the exercise allowed to collect further knowledge on the inherent principles of uncertainty combination as applied to emission inventories. As has been discussed in several previous studies, the advantages of the more complex "Monte-Carlo" approach to the simpler "error propagation" method are the possibility to consider virtually any potential probability density distribution, and the option to cover partial as well as total statistical dependence of input parameters. The present study focused on the extent to which input parameters could be considered independent. For several cases it could be shown that both activity as well as emission factor inputs of groups of IPCC source categories depend of each other. This is the case when information obtained at less detail is to be considered more precise than on very detailed information, typical for situation where budgets are assessed (like an energy balance). Also, when emission factors may be traced to a small number of original data (N_2O), or uncertainty derives from few, connected assumptions on the available sets of measurements (CH_4), parameters should not be considered independent. As soon as statistical dependence concerns more than one source category, the IPCC default approach to assess and combine uncertainties is not able to cover this dependence, and will underestimate overall uncertainty. In the case of Austria, an underestimation of almost a factor of 2 (3.6% uncertainty instead of 6.1% derived from the Monte-Carlo approach) occurred for the inventory of the year 2005. It can be shown that such a difference is not necessarily limited to the approach taken, but can likewise occur when statistical dependence is being interpreted in a different way also in the Monte-Carlo approach. Understanding that dependence exists necessarily means to also accept that uncertainty figures for individual source categories can not be used to be combined to a total uncertainty – or, in other words, these sectoral uncertainties may appear too low when considered (or compared) individually. This has consequences on the policy aspects of inventory uncertainties, in terms of prioritization of work as well as assigning responsibilities of inventory improvement.