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IMPROVING EFFICIENCY OF UNCERTAINTY ANALYSIS IN COMPLEX INTEGRATED ASSESSMENT MODELS: THE CASE OF THE RAINS EMISSION MODULE

SILKE GABBERT
Department of Environmental Sciences, Environmental Systems Analysis Group, Wageningen University, The Netherlands
(e-mail: silke.gabbert@wur.nl)

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Abstract. Ever since the Regional Acidification Information and Simulation model (RAINS) has been constructed, the treatment of uncertainty has remained an issue of major interest. In a recent review of the model performed for the Clean Air for Europe (CAFE) programme of the European Commission, a more systematic and structured uncertainty analysis has been recommended. This paper aims at contributing to the scientific debate how this can be achieved. Because of its complex structure on the one hand and limited research resources (time, computational capacities) on the other hand a full-blown uncertainty analysis in RAINS is hardly feasible. Therefore, all types of uncertainty require more efficient ways for uncertainty analysis. With respect to parameter uncertainty, we propose to focus research efforts for uncertainty analysis on key parameters. Among different approaches to select key parameters that have been discussed in the literature screening methods seem to be particularly appropriate for complex, deterministic Integrated Assessment models such as RAINS. Surprisingly, in Integrated Assessment modelling for air pollution problems of screening design have not been taken up so far. As a case study we consider the emission module of RAINS. We show that its structure allows for a straightforward and effective screening procedure.

Keywords: air pollution modelling, parameter uncertainty, RAINS, screening methods

1. Introduction

In the field of long-range transboundary air pollution, the Regional Acidification Information and Simulation model (RAINS) is the most prominent and a widely used Integrated Assessment Model (IAM) (Alcamo *et al.*, 1990; Amann *et al.*, 2004). Developed at the International Institute for Applied Systems Analysis (IIASA, Laxenburg, Austria), the RAINS model has repeatedly been used within political negotiation processes to provide scientific information on cost efficient emission reduction strategies.[1] Currently it is used within the Clean Air for Europe (CAFE) programm of the European Commission to develop long-term policy strategies for the abatement of air pollutants (European Commission, 2001a).

The RAINS model combines data on economic and energy developments, current and future emissions of different air pollutants, costs of the abatement technologies, the atmospheric dispersion, and the environmental effects of pollutants

for a large number of countries. Thus, the structure of the RAINS model is fairly complex, consisting of different modules using several hundreds of parameters. Therefore, RAINS is burdened with various uncertainties due to, for example, variability of parameters, inaccuracy of model specification or lack of knowledge with regard to the processes under study.

Ever since the RAINS model has been in use, the treatment of uncertainties remained an issue of major interest (Alcamo and Bartnicki, 1987, 1990; Amann, 2002; IIASA, 2002). Model developers tried to account for uncertainties by adopting a number of control measures in model design (Amann, 2005). Additionally, they tried to minimise the effects of uncertainties on model outcome at all phases of model development through, for instance, the definition of explicit confidence intervals for several model compartments in order to ensure that model results lie within a range of sufficient accuracy (Amann *et al.*, 2004). Different types of uncertainty analyses have been performed in order to make uncertainties with respect to model parameters transparent and to improve model confidence (Suutari *et al.*, 2001, 2004). However, these studies either addressed very specific aspects of the model (for example atmospheric source-receptor relationships for sulfur within Europe, Alcamo and Bartnicki, 1990) or presented results on a highly aggregated level (for example confidence intervals of country emission estimates, Suutari *et al.*, 2001). Furthermore, because of their technical complexity results of uncertainty analyses have often been difficult to communicate to public decision-makers (Amann, 2005, personal communication).

In a recent review of the RAINS model conducted for the CAFE programme, a review team recommended the development of an uncertainty management system, which allows to take different types of uncertainties[2] into account and to address uncertainties in a more structured way. Furthermore, they concluded that uncertainty analysis should be performed in relation to the end use of model results (European Commission, 2004). However, it is currently an open question how this should be done.

The need for a more systematic and comprehensive uncertainty analysis in IAMs has already been recognised some years ago. Frameworks have been suggested for uncertainty management and for addressing uncertainties in IAMs due to model structure and model quality (van der Sluijs, 1997; van Asselt, 2000; Fisher *et al.*, 2002). These studies are based on the assumption that uncertainty analysis should become an integral part of the IA modelling process instead of being an exogenous element that is added to it. As discussed in Gabbert and Kroeze (2003), a shortcoming of these frameworks is that practical application is very demanding with respect to research resources. As only limited time and computational resources are available, a full-blown uncertainty analysis is hardly feasible. This holds not only for the case where different types of uncertainties should be assessed simultaneously. Even if we address a single type of uncertainty, for example, parameter uncertainty, we see a relationship between information gains and research efforts. Thus, uncertainty analysis in IAMs has clear economic implications: Since both scientists and

public decision-makers usually face constraints (for example in the form of limited budgets, time, and computational capacities), the benefits of uncertainty analysis have to be weighed against the costs, arising mainly through increased research time needed. This holds generally for any IAM, but particularly for those models, which are used as tools for developing policy strategies such as RAINS. Such models are continuously updated and expanded, causing data sets to increase and the model structure to become increasingly complex. Thus, in addition to more systematic concepts we stress the need for more efficient ways of uncertainty analysis and uncertainty management in order to improve and maintain model confidence while taking research budget constraints into account.

Tackling uncertainty due to lack of understanding and due to lack of knowledge of socio-economic development requires search for better information, which can be very expensive and time-consuming. Therefore, these two uncertainties can only be managed through long-term strategies for model improvement. However, for the daily use of IAMs, especially those used to support political negotiations on reducing air pollution, tools for a more efficient management of parameter and model structure uncertainty are required. Currently, the only way to tackle structural uncertainty is probably model comparison (Fisher *et al.*, 2002). In this paper we remain within the RAINS model as a case study and focus on parameter uncertainty. If resources for analysing parameter uncertainty are constrained, the problem is to identify those parameters contributing most to model performance and to concentrate resources on this selection of key parameters first.

Different suggestions how uncertainty analysis could be performed more efficiently have been discussed in the literature on IA modelling, but these suggestions have not been taken up so far. The first aim of this paper, therefore, is to review these approaches and to evaluate their applicability to RAINS (Section 2). Among the methods discussed, screening techniques seem particularly useful for complex IAMs such as RAINS. Thus, the second aim of the paper is to contribute to the scientific debate about better structuring uncertainty analysis within RAINS by applying a screening procedure to the emission module of the model. We identify key parameters of the emission function for the UK to illustrate a more general method (Section 3). In Section 4 of the paper, we discuss the results of our analysis. Section 5 concludes.

2. Structuring Uncertainty Analysis in IAMs More Efficiently: The Concept of Key Parameters

Analysing parameter uncertainty as completely as possible, i.e. taking each parameter into account, can be very informative. However, under resource constraints and based on the experience that in large computational models most of the output variation is often due to only a few parameters (Saltelli *et al.*, 2000), prioritising research resources to these "key" parameters will be much more efficient. In the

recent literature on environmental modelling, different suggestions have been made how to identify key parameters.

ApSimon *et al.* (2002), for example, proposed to apply methods for hazard identification and risk management in order to identify those parts in an IAM where variations of initial model inputs can have "significant consequences". Such hazard and operability studies (HAZOP) have originally been used in chemical and industrial operations. Their objective is to identify possible hazards by dividing the whole operation process of an industrial plant into several components. For each component it can then be assessed whether or not deviations from its defined function occur. This is guided by specific keywords denoting the direction and intensity of the deviation (for example "not", "less", "more", "reverse"). Depending on the severity of the consequences of such deviations, further assessments can follow, including for example data refinements, statistical uncertainty analysis or modifications of the process structure.

As an illustrative example, ApSimon *et al.* (2002) have illustrated how the concept of HAZOP could be applied to some components of the Abatement Strategy Assessment Model (ASAM), an IAM for acidification in Europe developed at the Imperial College in the UK (ApSimon *et al.*, 1994). Their objective was to identify potential consequences of deviations from initial model inputs (e.g. modifications of input data or equations used). This should help to select those parts of the model where improvements might be most urgent. However, for particularly selecting key model parameters HAZOP does not seem to be directly applicable unless some elements are specified more clearly. For example, thresholds have to be defined to decide which deviation from initial model specification leads to "harmful" consequences. Furthermore, we have to consider the case where, within a certain model component, deviations from original functions lead to more than one "harmful consequence." This can easily happen because any component of an IAM usually consists of more than one complex sub-model where numerous deviations can occur. In such a case it has to be decided how to rank harmful consequences in order to see where further analysis might be most important.

Rypdal and Flugsrud (2001) have discussed different quantitative methods, which were applied to the Norwegian greenhouse gas (GHG) inventory. They examined a standardised threshold approach (i.e. ranking emitting sources with respect to their contribution to overall emissions and selecting key sources with respect to a defined emission threshold), simple aggregated sensitivity analysis (where parameters are varied locally), sensitivity analysis based on elasticities, sensitivity analysis based on uncertainty importance (indicating each parameter's contribution to overall uncertainty) and probabilistic analysis (where the correlation between an input parameter and its reported level and trend is calculated). Comparing the different methods, they found to a large extent consistent results with regard to which parameters were identified as key parameters. However, results obtained from the sensitivity analysis based on elasticities and on uncertainty importance as well as results obtained from probabilistic analysis provide more detailed

information with respect to the type of parameter (activity data, emission factor) contributing to model output variability than those from the standardised threshold approach or the simple aggregated sensitivity analysis. Rypdal and Flugsrud are concluding that sensitivity analysis provides a useful tool for the identification and the ranking of key parameters, but it generally is less precise than probabilistic modelling tools. The latter require modelling of uncertainty estimates and interactions of parameters, which in many cases may not be possible due to lack of knowledge.

Even if parameter interactions are known, it might be too time consuming in complex deterministic IAMs to conduct the necessary simulation runs to identify the subset of parameters that controls most of the output variability. For such cases Bettonvil and Kleijnen (1996) have proposed to use screening designs. These are preliminary numerical experiments, which aim at selecting those factors (this can be a parameter, an input variable or a module of a model) having the greatest impact on model performance (Campolongo *et al.*, 2000; Kleijnen *et al.*, 2003). For this purpose different techniques have been developed (Saltelli *et al.*, 2000; Trocine and Malone, 2001). Per definition, screening is a sub-category of sensitivity analysis, but in contrast to the methods mentioned above, usually screening methods provide only qualitative sensitivity measures.[3] Such measures allow for a ranking of key factors without quantifying how much a certain input factor is more important than another. Since screening requires fewer simulations than "conventional" methods of sensitivity analysis it can be conducted with relatively low computational effort. Screening techniques are thus considered to be much more efficient than methods of sensitivity analysis like, for example, those suggested by Rypdal and Flugsrud (2001). Consequently, they are of particular advantage in cases where a first overview of key parameters is needed, which in a later phase can then be used as input information for further uncertainty analysis. The more it is surprising that parameter screening has not been applied to IAMs for air pollution problems so far.

Bettonvil and Kleijnen (1996) have presented a novel technique for screening called Sequential Bifurcation (SB). The objective of SB is to come up with a short-list of "most important parameters".[4] A parameter is called important if its main effect is positive and significant. A parameter's main effect is generally defined as the change in model output when switching that parameter from a low to a high value. These parameter bounds can either be determined through expert consultation or, if available, by using information on parameter variability. Thus, although methodologically SB belongs to sensitivity analysis methods, information about parameter uncertainty is incorporated. In contrast to other screening designs, SB reveals quantitative measures of a parameters' impact on model output.

Compared to other screening methods available (for example the classic group screening techniques, see Saltelli *et al.*, 2000; Trocine and Malone, 2001) SB is assumed to have comparative advantages since fewer simulation runs are required to identify important parameters. This was demonstrated in an application of SB to the "Integrated Model to Assess the Greenhouse Effect" (IMAGE) developed by the

Dutch National Institute of Public Health and Environmental Protection (RIVM) (Bettonvil and Kleijnen, 1996).

3. Identifying Key Parameters within the RAINS Emission Module

3.1. Structure of the RAINS model

The RAINS model provides a multi-pollutant/multi-effects tool for the analysis of cost-effective emission reduction scenarios for sulfur dioxide (SO_2), nitrogen oxides (NO_x), ammonia (NH_3), non-methane volatile organic compounds (VOC) and particulate matter (PM). The model can simultaneously address different environmental problems such as acidification, eutrophication, health effects caused by ozone and particulate matter and vegetation damages through ozone. RAINS can be run in the "scenario analysis" mode for estimating emissions and environmental impacts of pollutants for given energy pathways. In addition to computing historic emissions, RAINS currently allows for projections until 2030. Furthermore, model users can generate information on regional costs and environmental effects for specified emission control strategies. Alternatively, the RAINS model can be operated in an "optimisation mode", analysing cost-effective emission reduction strategies in order to achieve specified deposition and concentration targets (Amann *et al.*, 2004).

Like many environmental IAMs, RAINS has a modular structure. It includes modules for emission generation, emission control options and costs, atmospheric dispersion of pollutants, and sensitivities of ecosystems and humans to air pollutants (Amann *et al.*, 1999). Emission scenarios and control options can be analysed for the sectors "Agriculture", "Energy", "Mobile", "Process" and "VOC sources", which are further disaggregated into more than 170 sub-sectors. International emission inventories and national information provide data for more than 40 different energy production and consumption activities. Furthermore, data on a large number of control technologies have been generated.[5] For each sector, unit and marginal costs of emission reduction are evaluated for specific fuel types and abatement technologies. The necessary data have been compiled from national and international studies (Cofala and Syri, 1998). The emission estimates obtained serve as inputs for assessing environmental damage. Within the deposition module, RAINS computes regional acid deposition loads which are compared with maps of environmental sensitivities ("critical loads" maps) (IIASA, 2004). Databases on critical loads and critical levels are performed by the Coordination Center for Effects (CCE) at the National Institute for Public Health and the Environment (RIVM) in the Netherlands (Cofala and Syri, 1998).

3.2. Searching for key parameters within RAINS

Given the comprehensive databases within RAINS, uncertainties can arise through measurement, approximation or aggregation errors. Additional uncertainties are

introduced through the ageing process of the data. Thus, to control best for parameter uncertainty it is necessary to persistently revise and update databases. It has also been recommended to develop more resolved emission inventories, to make uncertainties of activity data within emission inventories more explicit and to get deeper insight in parameter correlations (Amann *et al.*, 2004). Obviously, the informational needs and research costs for such improvements are immense. Therefore, instead of a full-blown analysis of uncertain parameters focusing research resources on key parameters as defined in the previous section would be much more efficient.

To select key parameters in RAINS we require information on parameters' impact on model output. Classic sensitivity analysis as performed by Rypdal and Flugsrud (2001, see Section 2) would not be an adequate methodology for that purpose: Whereas probabilistic methods and sensitivity analysis based on compiling elasticities require considerable computational effort, the standardised threshold approach and the simple aggregated sensitivity analysis are much less systematic. In addition, the latter two approaches neither make use of available information about a parameter's range of variation nor do they account for parameter interactions. Comparing the approaches discussed in the preceding section screening techniques and in particular SB seem to be most appropriate.

To apply SB to a model, Bettonvil and Kleijnen (1996) assume the simulation model to be a black box. They approximate the "real" model by defining a "metamodel" with which they further operate. Such "metamodel" can, for example, be a first- or second-order polynomial (Kleijnen, 2005). For any chosen metamodel it is assumed that it gives "negligible approximation errors" (Bettonvil and Kleijnen, 1996). However, because of its clear modular structure and the clearly defined relations between the modules this would not be adequate for RAINS. Defining a metamodel would simply complicate things and would introduce additional uncertainties. For identifying key parameters we therefore suggest to use an approach which is motivated by SB but works more straightforward. In the following, this approach will be introduced. To make the differences to SB very clear, we first briefly explain how SB would proceed at a given stage of the screening.

According to the SB method, for identifying a parameter's main effect the analyst first has to define for each parameter of the simulation model a high and a low value. Once parameter bounds have been defined, the next step of the SB procedure would be to calculate model output for the two extreme parameter combinations, i.e. where all factors are set to their high and to their low level, respectively. This generates information about the sum of main effects, which is the maximum range of individual main effects. To avoid that main effects can cancel each other out a basic assumption of SB is that the direction of influence of any parameter on model output is known and the same for all parameters. If the difference between model outputs when all parameters are "on" (at their high level) and "off" (at their low level) is positive, then some of the parameters must be important.

At the time of our analysis information about parameter variability (which is used to define high and low parameter levels) was only available for parameters of the emission module (Suutari *et al.*, 2004), which is the core module of RAINS. Our analysis of key parameters is therefore focusing on the emission module of RAINS as a case study.

Country emissions are estimated as follows:

For a pollutant p, emissions in country i, $em_{p,i}$, are the sum of emissions of individual sectors j. For each sector j, emissions result from an energy consumption activity level $act_{p,i,j}$ (e.g. consumption of hard coal), augmented by an application factor $af_{p,i,j,l}$ (indicating the percentage to which a control technology l is applied to that activity) and a controlled emission factor $cef_{p,i,j,l}$ (representing a percentage of emission reduction if control technology l is applied):

$$em_{p,i} = \sum_j act_{p,i,j} \sum_l af_{p,i,j,l}\, cef_{p,i,j,l} \tag{1}$$

The controlled emission factor can be computed from an uncontrolled emission factor (denoting theoretical emissions when no emission control measures are applied) by subtracting the removal efficiency (indicating the percentage of emission reduction when applying a certain control technology) (Suutari *et al.*, 2004). We concentrate our analysis on SO_2 and NO_x. For these pollutants (Suutari *et al.* 2004) have estimated coefficients of variation for activity data, uncontrolled emission factors and removal efficiencies. Since they assume the application rate to be given (i.e. no political uncertainty), no coefficients of variation have been specified for this parameter. Thus, we defined high and low parameter levels exclusively for the activity levels and the controlled emission factors. Parameter boundaries were determined by adding to (subtracting from) each parameter the standard deviation σ derived from the CV, assuming a normal distribution of parameters. Denoting $act_{p,i,j}$ to be μ_{act} and $cef_{p,i,l}$ to be μ_{cef}, the upper and lower bounds of these parameters are obtained by

$$act^H_{p,i,j} = \mu^{act}_{p,i,j} + \sigma^{act}_{p,i,j}; \quad act^L_{p,i,j} = \mu^{act}_{p,i,j} - \sigma^{act}_{p,i,j} \tag{2}$$

and

$$cef^H_{p,i,j,l} = \mu^{cef}_{p,j,i,l} + \sigma^{cef}_{p,j,i,l}; \quad cef^L_{p,i,j,l} = \mu^{cef}_{p,j,i,l} - \sigma^{cef}_{p,j,i,l}. \tag{3}$$

In order to examine the robustness of our approach with regard to the size of the parameter range, we additionally consider the case where two standard deviations are added (subtracted).

For our empirical analysis we distinguish two cases:

(i) No parameter interactions. This holds if the simulation model has a strict additive structure. In this case the main effect of a parameter is independent of the values other parameters take. Such conditions can be assumed if our interest is to identify key polluting sectors of a country. SB would proceed by calculating model output for systematic combinations of high and low parameter values. SB would finally select those parameters with the largest impact on model output (most important parameters). Where to stop the SB procedure depends on the subjective judgement of the investigator. Thus, the analyst can iteratively define the number of important parameters.

For the emission module of RAINS, however, a SB design would not be efficient. Instead, because of the simple additive structure of the emission module it is sufficient to calculate for each sector j model output only for the two extreme parameter combinations ($act_{p,i}$ and $cef_{p,i,l}$ high, $act_{p,i}$ and $cef_{p,i,l}$ low). The main effect of an individual sector, β_j, can then easily be obtained as follows:

$$\beta_j = em^H_{p,j} - em^L_{p,j} \tag{4}$$

Ranking results obtained for β_j reveals information about which sectors of a country contribute most to overall emissions. With respect to improving model confidence such a procedure might be reasonable if one would like to get a quick insight which sectors should receive prior attention with regard to data improvements.

(ii) Parameter interactions. Because of the multiplicative connection of parameters within sectors (see Equation (1)), parameter interactions have to be taken into account for the identification of key parameters. In case of parameter interactions the standard literature on design of experiments (DOE) and analysis of variance (ANOVA) defines the main effect of a parameter as the difference between (i) the average output when that parameter is at its high level, averaging over all possible combinations of the remaining parameters, and (ii) the average output when that parameter is at its low level. Furthermore, assuming the model to be a black box for the analyst and parameter interactions to be unknown, Bettonvil and Kleijnen (1996) suggest applying a "foldover design", where in addition to calculating model output for a certain combination of high and low parameter values also the mirror observations have to be computed in each step of the SB procedure.[6]

In our case, however, since the emission module can be treated as a separate sub-model within RAINS, parameter interactions are well known for the analyst. Therefore, again, the SB method would be unnecessary. Instead, it is much more efficient to directly compute main effects of activity levels and controlled emission

factors. Using the definition of main effects for the case of factor interactions (see above), the main effect of, for example, the activity level $act_{p,i,j}$, is calculated as follows (Bettonvil and Kleijnen, 1996):

$$\beta^{act}_{p,i,j} = \left[\frac{\left(act^{H}_{p,i,j} * af_{p,i,j,l} * cef^{H}_{p,i,j,l}\right) + \left(act^{H}_{p,i,j} * af_{p,i,j,l} * cef^{L}_{p,i,j,l}\right)}{2}\right] - \left[\frac{\left(act^{L}_{p,i,j} * af_{p,i,j,l} * cef^{H}_{p,i,j,l}\right) + \left(act^{L}_{p,i,j} * af_{p,i,j,l} * cef^{L}_{p,i,j,l}\right)}{2}\right] \quad (5)$$

Inserting Equations (2) and (3) into (5) gives

$$\beta^{act}_{p,i,j} = 2af_{p,i,j,l}\,\sigma^{act}_{p,i,j}\,\mu^{cef}_{cef_{p,i,j,l}} \quad (6)$$

Similarly, for the controlled emission factor, the main effect is

$$\beta^{cef}_{p,i,j,l} = 2af_{p,i,j,l}\,\sigma^{cef}_{p,i,j,l}\,\mu^{act}_{p,i,j} \quad (7)$$

Ranking parameters according to their main effects provides information about which of the parameters are of highest impact for a country's emission and should therefore considered as key parameters.

As an illustrative case study, we have applied our approach to the UK (for the year 2000), which is both for SO_2 and NO_x one of the largest emitting countries within the European Union.[7] With respect to SO_2, combustion and conversion of heavy fuel oil contributes most to overall emissions of the country, followed by the use of medium distillates (diesel oil in the commercial residential sector) and the combustion of medium quality brown and hard coal in power and district heat plants. Emissions of NO_x result to a large extent from medium distillates and gasoline used for road transport. Additionally, the combustion of medium quality brown coal in power plants and the use of gas in the commercial residential sector are of major importance.

For the empirical analysis we used RAINS 8.0 (in the version of January 2003). For all emission scenarios we assumed a successful implementation of current legislation.

4. Discussion of Results

Compared to SB as suggested by Bettonvil and Kleijnen (1996) the screening approach chosen in this paper reveals a complete ranking of sectors and parameters. We only present the first ten positions of the rankings obtained. A complete ranking is straightforward to obtain. Table I presents key sectors, where each sector is characterised by a sector name, the corresponding activity level and an abatement

TABLE I
Key emitting sectors of the UK (sector/activity/abatement technology)

SO_2		NO_x	
Sector	Size of main effect (kt SO_2)	Sector	Size of main effect (kt NO_x)
1. Energy (power and district heat plants)/hard coal (high quality)/no control	221.45	1. Road transport/medium distillates/EURO II (1996) for heavy duty vehicles	109.00
2. Energy (power and district heat plants)/hard coal (high quality)/power plant wet flue gas desulfurisation (already retrofitted)	30.41	2. Road transport/gasoline/no control	62.74
3. Industrial processes (petroleum refineries)/no fuel use/stage 1 control of process emissions	16.31	3. Road transport/medium distillates/EURO I (1992) for heavy duty vehicles	52.95
4. Other transport/medium distillates/(ships)/no control	14.07	4. Energy (power and district heat plants)/hard coal (high quality/no control	52.76
5. Energy (fuel combustion and conversion)/heavy fuel oil/use of low sulfur fuel oil	12.79	5. Energy (power and district heat plants)/hard coal (high quality)/PHCCM	51.65
6. Energy (combustion in residential-commercial sector)/hard coal (high quality)/no control	12.70	6. Road transport/ gasoline/EURO I light duty, spark ignition engines	45.05
7. Industrial processes (coke oven)/no fuel use/stage 1 control of process emissions	11.06	7. Road transport/medium distillates/no control	42.07
8. Industrial processes (sinter agglomeration plant)/no fuel use/stage 1 control of process emissions	9.86	8. Energy (combustion in residential-commercial sector)/gas/no control	41.04
9. Industry (other combustion)/heavy fuel oil/use of low sulfur fuel oil	9.44	9. Other transport (ships, large vessels)/medium distillates/no control	26.55
10. Industry (combustion in boilers)/hard coal (high quality)/no control	5.47	10. Other transport (inland waterways)/medium distillates/no control	24.91

technology. The additive structure of the emission module rules out interactions between parameters across sectors. The ranking of sectors is insensitive with respect to an equal change of parameter ranges. Therefore, results are only presented for the parameter range $\mu \pm \sigma$. Results show a clear dominance of main effects of the sectors at the first position. When going down the ranking, main effects continuously

decrease. For SO_2 the sectors at position 5 and 6, and for NO_x the sectors at position 3, 4 and 5 have quite close main effects.

At a first glance, one might expect those sectors where no control technology has been applied to be the most polluting ones and therefore to dominate the first positions of the ranking. However, Equations (1) and (4) clearly indicate that the absence of an abatement technology in a certain sector need not necessarily have to result in high sector emissions and in a high main effect of this sector. Accordingly, both for SO_2 and NO_x the first ten positions of the sector ranking include several sectors where abatement technologies have been implemented (Table I). However, for both pollutants the sectors without control technology are in fact distributed across the whole range of the ranking. For NO_x, 101 sectors have been analysed. Of these 97 sectors were included into the screening process (for the remaining 4 sectors the dataset was incomplete). In 60 sectors no control technology has been applied, of which 33 are found in the first half of the sector ranking. For SO_2, 71 sectors have been analysed, of which 55 sectors entered the screening process. In 29 sectors of these no abatement technology has been implemented, of which only 12 sectors take positions in the first half of the ranking. Comparing the two pollutants, we find for NO_x more sectors without control technology taking positions within the first ten positions of the ranking. However, whether or not this is a systematic and pollutant specific effect is beyond the scope of this case study; for such purpose a comparison of different countries and years would have been necessary.

For identifying key parameters we have to account for parameter interactions. This case is much more relevant because it provides a more detailed insight into the most sensitive parts of the RAINS emission module. The overall main effect of an individual sector is split into a main effect of an activity level and a main effect of a controlled emission factor. Table II shows results of the parameter screening for SO_2 and NO_x. The ranking of sectors in Table II differs from each other and from that of Table I. Furthermore, the distribution of sectors with and without abatement technology changes across the ranking positions. Looking at main effects of individual *sectors* can therefore lead to different conclusions with respect to the allocation of research resources for model improvements than when examining *key parameters*, which provides more detailed information about which specific elements of sector emissions contribute most to overall country emissions.

Again, the ranking of parameters is robust with respect to the chosen parameter boundaries. At a first glance, this is surprising because in case of factor interactions the main effect of a certain parameter (e.g. an activity level) is calculated as the *average* main effect, averaging over *all possible combinations* of other parameters (here only the controlled emission factor) for which a high and a low level has been defined (see Equation (5)). Thus, one might expect the range of other parameters to be of influence for the position of the parameter of concern within the overall ranking. However, since a change of parameter bounds affects all uncertain parameters equally, it can be easily calculated from Equations (2), (3) and (5) that

TABLE II
Key parameters within the emission module of the UK

SO_2			NO_x		
Sector/activity/abatement technology	Type of key parameter	Size of main effect (kt SO_2)	Sector/activity/ abatement technology	Type of key parameter	Size of main effect (kt NO_x)
1. Energy (power and district heat plants)/hard coal (high quality)/no control	Activity level	150.74	1. Road transport/medium distillates/EURO II (1996) for heavy duty vehicles	Controlled emission factor	70.88
2. Energy (power and district heat plants)/hard coal (high quality)/no control	Controlled emission factor	70.71	2. Road transport/medium distillates/EURO II (1996) for heavy duty vehicles	Activity level	38.12
3. Energy (power and district heat plants)/hard coal (high quality)/power plant wet flue gas desulfurisation (retrofitted)	Activity level	15.69	3. Road transport/gasoline/EURO II for light duty, spark ignition engines	Controlled emission factor	37.39
4. Energy (power and district heat plants)/hard coal (high quality)/power plant wet flue gas desulfurisation (retrofitted)	Controlled emission factor	14.72	4. Road transport/gasoline/no control	Controlled emission factor	34.85
5. Other transport (ships)/medium distillates/no control	Activity level	9.58	5. Road transport/medium distillates/EURO I for heavy duty vehicles	Controlled emission factor	32.99
6. Industrial processes (petroleum refineries)/no fuel use/stage 1 control process emissions	Controlled emission factor	9.51	6. Road transport/gasoline/EURO I for light duty, spark ignition engines	Controlled emission factor	32.96

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TABLE II
(*Continued*)

SO_2			NO_x		
Sector/activity/ abatement technology	Type of key parameter	Size of main effect [kt SO_2]	Sector/activity/ abatement technology	Type of key parameter	Size of main effect (kt NO_x)
7. Energy (combustion in residential-commercial sector)/hard coal (high quality)/no control	Activity level	8.63	7. Energy (power and district heat plants)/hard coal (high quality)/PHCCM	Controlled emission factor	29.98
8. Energy (fuel production and conversion)/heavy fuel oil/use of low sulfur fuel oil	Controlled emission factor	8.01	8. Energy (power and district heat plants)/hard coal (high quality)/no control	Activity level	28.78
9. Industrial processes (coke oven)/no fuel use/stage 1 control process emissions	Activity level	6.79	9. Road transport/gasoline/no control	Activity level	27.88
10. Industrial processes (agglomeration plant)/no fuel use/stage 1 control process emissions	Controlled emission factor	6.45	10. Energy (power and district heat plants)/hard coal (high quality)/no control	Controlled emission factor	23.98

switching from one to two standard deviations will simply double the main effects $\beta^{act}_{p,i,j}$ and $\beta^{cef}_{p,i,j,l}$ while the ranking of parameters remains unchanged.

For SO_2, results indicate that the use of hard coal in power and district heat plants where no control measures have been implemented has the highest impact on overall emissions of the UK. For NO_x we observe the controlled emission factor and the activity level of using medium distillates in heavy-duty vehicles to be of major importance for country emissions. Furthermore, controlled emission factors dominate the first ten positions of the ranking.

For improving model confidence key parameters should receive prior attention. The ranking obtained for SO_2 and NO_x by applying the screening procedure indicates where an investment of research efforts for further uncertainty analysis would be most efficient. Together with information on key parameters probability distribution this allows for a systematic improvement of emission estimates. How many key parameters finally to include in the shortlist of key parameters depends on the amount of research resources available and has to be decided by the analyst and by those responsible for budget allocation.

5. Conclusions and Further Implications

Since research resources are often constrained, efficiency should be an integral element of frameworks for systematic uncertainty analysis. Focusing on parameter uncertainty, this paper suggests to concentrate research efforts on key parameters which have the highest impact on overall model output. To identify key parameters within IAMs different approaches are reviewed, among which Sequential Bifurcation developed by Bettonvil (1990) and Bettonvil and Kleijnen (1996) seems to be most appropriate. However, if the underlying equations of an IAM have an additive structure and parameter interactions are known, we demonstrate that a simple screening procedure works much more efficiently. The screening procedure suggested in this paper is as effective and even more straightforward than SB because the definition of a metamodel (which presupposes assumptions about the functional form of the metamodel and can therefore introduce additional uncertainties) as well as repeated simulation runs of the model of concern are unnecessary for identifying main effects. We show that the screening procedure is robust against changes in parameter bounds if the bounds of all parameters are changed in the same way.

Applied to the RAINS emission module as a case study, the screening procedure points out which parameters are most important for further investigation. This is an important step for systematically improving emission estimates. However, because of its modular structure, the emission module interacts with other modules of RAINS such as the analysis of ecosystem impacts (in this case acidification and eutrophication) and the RAINS optimisation approach. Thus, efficiently improving emission estimates also contributes to improving overall model

confidence. For developing an effective uncertainty management system, as it has been recommended in the CAFE review report of the RAINS model, an extension of the screening to other modules (for example the cost calculation module) would be highly desirable in order to complete the picture about key parameters within RAINS. This would help to take steps for improving model utility in particular with respect to the end use of model results, i.e. comparing different abatement scenarios and providing policy advice on cost-effective pollution reduction strategies. Unfortunately, no information about cost parameter variability, which is necessary to define parameter bounds, is available at present. The establishment of a systematic uncertainty management system is therefore connected with several informational and methodological requirements. This, again, underlines the necessity to organise uncertainty management as efficient as possible.

Focusing uncertainty analysis on key parameters can improve the credibility of complex Integrated Assessment models in many different ways: For stakeholders, for example country representatives, the rankings obtained from the screening procedure indicate to which sectors and parameters prior attention should be paid when generating and maintaining input data. Since the screening can easily be performed for any of the countries included in the model, for the analyst the resulting rankings provide guidance where to start applying techniques for further uncertainty analysis, either in a quantitative, statistical way (by performing, for example, a standard Monte Carlo analysis, see for example van Aardenne *et al.*, 2000) or by using alternative, more qualitative approaches as suggested by van der Sluijs (1997), who proposed to use the notational scheme NUSAP (Numeral, Unit, Spread, Assessment, Pedigree) for assessing the scientific quality of model parameters.[8] This helps to achieve the desired level of confidence for model outcomes and supports an efficient improvement of complex Integrated Assessment models. Finally, focusing on key parameters can facilitate the policy dialogue between analysts and decision makers because the complex problem of analysing parameter uncertainties becomes clearly structured.

Like the RAINS model, many other IAMs for air pollution problems have a modular structure, where at least parts of the model are based on linear equations. Examples are the Coordinated Abatement Strategy Model (CASM) developed by the Stockholm Environment Institute (Gough *et al.*, 1994) and ASAM model mentioned in Section 2 of the paper (ApSimon *et al.*, 1994; Warren and ApSimon, 1999). Therefore the approach presented in this paper is not restricted to RAINS but applies to a larger class of models.

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Notes

1. For the first time, RAINS was chosen by the Executive Body of the Convention on Long-Range Transboundary Air Pollution (CLRTAP) to perform most of the analyses on which the negotiations about the second sulfur protocol were based (United Nations Economic Commission for Europe, 1999). RAINS also provided emission scenarios for preparing the UNECE Gothenburg Protocol "to Abate Acidification, Eutrophication and Ground-level Ozone" (UNECE, 1999) and the "EU National Emission Ceilings Directive for Acidification and Eutrophication" (European Commission, 2001b).
2. The CAFE review team distinguished between (i) uncertainties due to lack of understanding, (ii) uncertainties due to assumptions, simplifications and handling of data, (iii) uncertainties due to statistical variance and (iv) uncertainties related to socio-economic and technological development. In the literature, several other typologies of uncertainties have been proposed (Beck, 1987; Alcamo and Bartnicki, 1990; Lam *et al.*, 1996; Casman *et al.*, 1999; Kann and Weyant, 2000; Aaheim and Bretteville, 2001; see also Gabbert and Kroeze, 2003 for a survey).
3. In the literature, many definitions of sensitivity analysis can be found. Here, we follow Saltelli (2000), who defines "sensitivity analysis" as the "study of how the variation in the output of a model can be apportioned, qualitatively or quantitatively, to different sources of variation". Thus, sensitivity analysis is not an approach to uncertainty analysis, which aims at investigating the probability distributions of these source variations. For a categorisation of techniques for sensitivity analysis see, for example, Kleijnen (1995), Saltelli (2000), Greenland (2001) and Frey and Patil (2002).
4. It can therefore be thought as a generalisation of classical binary search, which aims to find the single most important factor. For further details of SB designs see Bettonvil (1990), Bettonvil and Kleijnen (1996) and Kleijnen *et al.* (2003).
5. For a complete list of sectors, activities and control technologies incorporated into RAINS see the RAINS Europe online webpage, http://www.iiasa.ac.at/web-apps/tap/RainsWeb/.
6. To obtain a mirror observation of model output is calculated for the opposite combination of high and low parameter values of an initial observation. Taking mirror observations into account will double the number of simulation runs of the SB procedure. For details see Bettonvil (1990) and Bettonvil and Kleijnen (1996).
7. For SO_2, only Spain had higher emissions in 2000.
8. NUSAP has been developed by Funtowicz and Ravetz (1990). See also Ravetz and Funtowicz (2002).

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