A Protocol for Assessment of Uncertainty and Strength of Emissions Data

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Contents

1 Introduction

This method is intended to assist in characterizing uncertainties in emissions data for the Mileubalans and to identify critical issues related to uncertainty. The method assesses both quantitative and qualitative dimensions of uncertainty. Quantitative uncertainties are expressed by assigning probability distributions to the main emissions parameters and propagating those uncertainties via Monte Carlo simulations. Qualitative dimensions of uncertainty are expressed by use of a pedigree method, which provides rankings on a variety of qualitative attributes of emissions parameters.

The general features of the method are described below as a series of steps. The first steps attempt to make explicit the structure of the system in which the emissions data is collected by disaggregating the data. A series of steps follow that which are designed to identify the main assumptions employed and key sources of error. These steps help to calibrate the analyst in providing qualitative and quantitative uncertainty estimates in sections 9 and 10. The final sections cover the use of sensitivity analyses and communication of results. Much of the data generated with the method is organized via a Monte Carlo / Pedigree spreadsheet, which is implemented with the '@RISK' software package.

Note that the method is designed to provide a fairly rapid overview and diagnosis of uncertainty so that it can be adapated and used as a standard in a range of emissions studies. It should help structure uncertainty analysis on sets of data where this has not yet been done, or provide a convenient form to represent uncertainties where more detailed analysis on uncertainties has already been completed. The method also adds features that are not normally included in conventional uncertainty analyses. It is intended to convey the most salient uncertainties, and to provide guidance on where to put effort to improve the quality of emissions estimates. The method encourages a consistent characterization of uncertainty, avoiding the use of more precision than is justified by available knowledge. Finally, the method does not attempt to be exhaustive in characterizing all possible uncertainties. In particular, it does not provide a lot of focus on 'structural' uncertainties, which are assumed to play a more modest role in the assessment of emissions data than they do in other domains.

2 Problem Context

The emissions data in the Mileubalans is sometimes geared to specific national legislation. For example, regulations may specify that emissions should not exceed a certain level or that the trend in emissions with time should be reduced. In this regard it is pertinent to ask whether the right quantities are being monitored, whether the emissions can be determined with sufficient accuracy to match the requirements of the standards, and whether the accuracy is sufficient to permit reliable assessment of trends.

- Describe the emissions data being assessed. Include an assessment of the error bars in past emissions estimates.
- Identify any national standards that pertain to the emissions data and outline any requirements set explicitly or implicitly for the accuracy of the data. When explicit requirements are not set, try to determine what level of accuracy in the data would be needed to meet the goals set forth in the regulations.
- Make an assessment of the match between the properties of the data and the requirements of the regulations, identifying problems, challenges, and goals for the emissions monitoring analysis.

3 Identification and classification

The first step in the analysis is to identify the relevant variables that are used in making an assessment of emissions. Identify the set of variables involved in the emissions estimate and sort them as to whether they are input variables (which must be measured or estimated in some way) or derived variables (which are computed from input variables).

4 Disassembly and Aggregation

The next step is to identify relationships between variables and the major assumptions underlying the representation of those relationships. This step reveals the structure of the system of study and it will usually be necessary to provide more detail on the processes and components underlying each of the input variables. The goal of this step is to reveal where all of the input data comes from and what assumptions or aggregations underly it. By disaggregating the input variables in this way the factors underlying the qualitative and quantitative assessments of uncertainty are made explicit. After disaggregation one may choose to add new input variables or derived variables to the set already identified if it helps in structuring the problem or identifying implicit assumptions. Some level of aggegation is usually maintained however in order to keep the number of variables at a manageable level. The steps involved in this process are as follows:

Diagram. Start with the list of variables identified in section 3. Construct an 'influence diagram' or 'tree diagram' showing how the variables relate to one another in calculating the final emissions estimate. Disaggregate variables into components where appropriate. Identify the sources of estimate or measurement for each group of variables and note key assumptions on the diagram.

Aggregate. Now you will probably want to reaggregate the data back to a more manageable level by drawing boundaries on the influence diagram at your desired level of aggregation. Some guidelines for this exercise are given below.

Select. Identify the final set of input variables at your chosen level of aggregation. These are the variables for which you will construct pdf's and pedigrees in the following sections. Enter the list of variables into the @RISK spreadsheet (table 1).

Document. Make a separate list of the main assumptions underlying the list of aggregate variables that you have produced.

The choice of level of aggregation in the second step above entails a degree of subjective judgement. While the choice of aggregation level is best done by the analyst, some elementary guidelines may nevertheless be useful in this regard:

Realism. The level of aggregation should not be so coarse as to overly constrain your view of the complexity of the system.

Tractability. The level of aggregation should not be so fine as to be cognitively unmanageable or intractable.

Data availability. Try to keep the level of aggregation such that you have data on the resolved variables at the resolved scales.

Physical meaning. The level of aggregation should yield variables that have some physical meaning in your understanding of the problem.

Physical relationship. The level of aggregation should yield variables whose physical relationships accord with your views of the underlying processes.

Parsimony. If your influence diagram still has more connections after aggregating than the Tokyo subway map it is probably too complicated. One reason for this is described below.

The error in a model typically decreases with the complexity of the model (as measured by the number of variables for example), but the error in the data required typically increases as complexity increases (ERL, 1985). This tradeoff yields an optimum in reduction of total error which is at an intermediate level of model complexity. Thus, it does not necessarily help to work with the most complex imagineable form of your emissions 'model'.

variable name	lower bound	upper bound	mode	units	proxy	empirical	method	validation	grade
inp_var_1	0.8	1.8	1.6	kton	3	3	2	2	0.6
inp_var_2	8.0	10.0	9.4	kton	4	2	3	3	0.8
inp_var_3	5.0	5.5	5.1	kton	2	3	4	1	0.6
inp_var_4	20	40	28	%	3	1	3	0	0.4
inp_var_5	15	25	20	%	2	3	3	3	0.7
der_var_1									
der_var_2									
der_var_3									
der_var_4									

Table 1: Monte Carlo and Pedigree spreadsheet. The variables and values given in the table are for example only. The variables with the prefix "inp" must have values supplied for the pdf and pedigree matrix. The values of derived variables ("der") are calculated by the spreadsheet program. The value of the final emissions estimate is represented by "der_var_4" here. The pedigree scores for this variable are used to generate the "kite plot" (figure 3).

5 Covariance

The set of variables entered into table 1 will not usually all be independent. Some variables may be related through common processes and may 'covary' with one another as a result. This is important for the Monte Carlo uncertainty analysis, since if we sample one variable at one extreme of its distribution, this may require that we sample other variables from a specific part of their distribution in order to preserve the relationship between the variables. That is, we are not free to sample independently when the variables are not independent.

First, examine the datasets used and identify potential sources of covariance. On that basis, identify any pairings of variables from your list in table 1 that you think are particularly likely to be dependent on one another. Note that there is a trade-off here in that if you identify too few pairings you will possibly be making too generous an assumption about the independence of variables. On the other hand, if you identify all possible pairings, the number of combinations will usually be too large for practical manipulation and assessment. Thus, you should attempt to identify the dependent pairings that are most likely to be critical in their interaction. Unless you have opportunity to assess this systematically in a large data set you will probably have to make this judgement subjectively. Bear in mind that this is an additional source of uncertainty.

Once you have chosen pairings of dependent variables, make an estimate of the correlations between them and enter these into the appropriate places in the spreadsheet (table 1 in the entry for the pdf). Note that you can always go back and redo the Monte Carlo analyses later on with different values for the correlations (or enter more/fewer correlations between variables) to assess the effect this has on the final emissions results. In fact, it is a good idea to do this to get some indication of the importance of the assumptions made in assessing the dependence structure among your chosen variables. To be sure however, these additional runs should be conducted as sensitivity analyses, *not* as a means to 'tune' the results to fit expectations! If the results are sensitive to the covariance structure employed, be sure to note that in communicating results (section 14).

6 Assessment of assumptions

For each of the assumptions identified in the disaggregation step (section 4) and covariance step (section 5) above, provide a brief summary statement on the validity and robustness of the assumption. Try to project what the possible consequences for the final emissions results might be in cases where the assumption is (hypothetically) found to be invalid. These responses can be completed in table 2.

Assumption Describe the assumption	Validity and Robustness What is the domain of validity of the assumption? Under what conditions is it robust or not robust?	Consequences Describe the possible consequences for (hypothetical) cases where the assumption is found to be invalid
paint sales are a good surrogate for VOC emissions	Assumes all VOC released from paint and the unused amount of paint each year is the same. Reasonable assumption unless a big shift in use to different paint types changes stock levels.	paint sales and VOC could be out of sync for some period if big change in buying patterns, but likely corrected over time
overall VOC content in imported paint same as for the NL.	valid so long as imports from countries with similar production standards	if imports favour countries with higher VOC content then undercounting VOC amount.
imported VOC split across sectors as per NL	valid so long as imports not favour specific domestic sectors	if imports going preferentially into high VOC sector (e.g. auto) then undercounting VOC. this seems to be the case.
non-respondents and non-members have similar sales patterns as similar size responding member firms	valid so long as non-members engaged in similar operations as members.	could lead to under or over estimates depending on non-member activities. worst case would be an unknown big producer among non-members, which seems unlikely

Table 2: Assessment of Assumptions.

7 Sources of error

The description of sources of error may have some overlap with the assessment of assumptions. However, there may be sources of error that do not relate specifically to the assumptions described above. The description of error sources will depend on what sources and methods have been used to generate the emissions data. Typical sources of emissions data include instrumental observations, surveys, and models. Some of the errors characteristic of each type of source are as follows:

Instrumental data. There will be some random and systematic errors associated with calibration, operation, and maintainance of instruments. Sources of systematic error include drift of instrument response characteristics with time, and changes in the type or location of the instruments used. Missing data may also be a problem, as well as artefacts caused by changes in the immediate environment of the instrument (e.g. urbanization).

Survey data. Sources of error in survey data include definitional inconsistency across respondents, or changes in definitions of quantities through time, miscategorization of data, misreporting due to confusion over the units used, deliberate misreporting because of incentives to misreport, miscoding of responses, and non-response.

Model data. In some cases, data is generated from models, or may have been augmented in some manner via use of models. Some sources of error related to use of models include the lack of correspondence between the model and the real world, discrepancies in temporal or spatial scale between modelled variables and those of interest, biases toward more or less extreme behaviour in the statistics of the modelled variable, omission of important processes, and inconsistent definitions between model variables and those of interest.

Identify the type of data used to characterize emissions and generate a list of the main sources of error. For each source of error you need provide only a qualitative description. However, you should indicate whether the error is primarily random or systematic in nature. If systematic, indicate the likely direction of bias. These responses can be provided in table 3.

8 Identification of expertise

In preparation for making assessments of the uncertainties, the domains of expertise and experts pertinent to the different input variables must be identified. Where feasible, interviews may need to be conducted with outside experts in order to make some of the necessary judgements on the uncertainty of input variables. When expert

Name of error e.g. instrument drift	Qualitative Description A brief description of the characteristics of the error	Bias classify the error as random or systematic if systematic, indicate the likely direction of bias
definitional inconsistency	different definitions of paint at CBS and VVVF. VVVF estimate to correct for overlap.	systematic, leading to some overcounting and some undercounting if not corrected
definitional vagueness	boundary between paint and raw materials not always clear	unknown
paint dynamics	CBS list from 1950s. now have new paints on market. sometimes not reported as paint	systematic, leading to underestimate
misreporting units confusion	typically using kg instead of tonnes	overestimate by factor 1000, but usually caught and corrected
deliberate misreporting	conceal true level of imports or sales to reduce tax burden	unknown
miscoding survey responses	mistakes in survey data from CBS or VVVF	random and typically caught by cross-checking with past responses
non-response to surveys	sales must be estimated for non-respondents	random
not counting small firms	firms with less than 500K in annual imports not counted by CBS	systematic, leading to underestimate of imports, but likely small because market dominated by larger firms
unofficial imports	cross-border paint purchases. paint cheaper in DE than NL.	systematic, leading to some underestimate
code errors	errors in computer code used to track imports at CBS and sales at VVVF.	could lead to systematic errors, but the direction of such errors is unknown
firm dynamics	firms bought, sold, merge, split. financial reconciliations in such cases may span months and short term CBS data may undercount or doublecount firms as a result. usually corrected in longer term CBS data.	random
imported VOC allocated to sectors per NL	described under ‘assumptions’	possible underestimate due to suspected underallocation to high VOC auto sector
imported paint same VOC as NL	described under ‘assumptions’	bias small if importers have similar standards to NL reasonable as major imports are from EU.

Table 3: Sources of error.

interviews are conducted to complete the qualitative and quantitative uncertainty assessments in sections 9 and 10, some care must be taken in 'debiasing' the experts. Some of the common pitfalls in expert elicitation are as follows:

Over confidence. Experts tend to over-estimate their ability to make quantitative judgements. This is difficult for an individual to guard against; but a general awareness of the tendency can be important.

Anchoring. Assessments are often unduly weighted toward the conventional value or first value given in making the assessment.

Availability. This bias refers to the tendency to give too much weight to readily available data or recent experience (which may not be representative of the required data) in making assessments.

Representativeness. This is the tendency to place more confidence in a single piece of information that is considered representative of a process than in a larger body of more generalized information.

Satisficing. This refers to the tendency to search through a limited number of solution options and to pick from among them. Comprehensiveness is sacrificed for expediency in this case.

Interests. Experts may have political, personal, or other reasons to favour one outcome for the analysis over another. Awareness of this problem can be increased by identifying sources of motivation and interests.

Unstated assumptions. A subjects responses are typically conditional on various unstated assumptions. The affect of these assumptions is often to constrain the degree of uncertainty reflected in the resulting probability distribution. Stating assumptions explicitly can help reflect more of a subject's total uncertainty.

Coherence. Events are considered more likely when many scenarios can be created that lead to the event, or if some scenarios are particularly coherent. Conversely, events are considered unlikely when scenarios can not be imagined. Thus, probabilities are assigned more on the basis of ones ability to tell coherent stories than on the basis of intrinsic probability of occurence.

A fuller description of sources of cognitive bias in expert and lay elicitation processes is available in Dawes (1988). For more detailed instructions on conducting expert elicitations, see Frey (1998).

9 Qualitative assessment

For each of the input variables complete the assessment of pedigree scores. The four dimensions of the emissions monitoring pedigree are given in table 4. The pedigree scores should be entered into the appropriate columns in the spreadsheet (table 1). Scores are entered on a scale from 0 to 4 according to the guidelines given in table 4.

The four pedigree criteria are as follows:

Proxy. Sometimes it is not possible to obtain direct measurements of the emissions quantities reported in the Mileubalans and so some form of proxy measure is used. The proxy pedigree element refers to how good or close a measure the quantity which we measure is to the actual quantity about which we seek information. An exact measure of the quantity would score four. If the measured quantity is not clearly related to the desired quantity the score would be zero.

Empirical. Empirical quality typically refers to the degree to which direct observations are used to estimate the variable. When good quality observational data are used the pedigree score will be high. Sometimes directly observed data are not available and the variable is measured by survey data, generated by models, or using simple rules. Data that is determined by such indirect methods is lower in empirical content and will generally score lower than directly observed data.

Method. Some method will be used to collect, check, and revise the data used for making emissions estimates. Methodological quality refers to the norms for methodological rigour in this process applied by peers in the relevant disciplines. Well established and respected methods for measuring and processing the data would score high on this metric, while untested or unreliable methods would tend to score lower.

Validation. This metric refers to the degree to which one has been able to cross-check the data against independent sources. When the data has been compared with appropriate sets of independent data to assess its reliability it will score high on this metric. In many cases, independent data for the same variable over the same time period are not available and other datasets must be used for validation. This may require a compromise in the length or overlap of the datasets, or may require use of a related, but different, proxy variable, or perhaps use of data that has been aggregated on different scales. The more indirect or incomplete the validation, the lower it will score on this metric.

Score	Proxy	Empirical	Method	Validation
4	An exact measure of the desired quantity	Controlled experiments and large sample direct mmts	Best available practice in well established discipline	Compared with independent mmts of the same variable over long domain
3	Good fit or measure	Historical/field data, uncontrolled experiments, small sample direct mmts	Reliable method common within est. discipline Best available practice in immature discipline	Compared with independent mmts of closely related variable over shorter period
2	Well correlated but not measuring the same thing	Modeled/derived data Indirect mmts	Acceptable method but limited consensus on reliability	Measurements not independent proxy variable limited domain
1	Weak correlation but commonalities in measure	Educated guesses indirect approx. rule of thumb est.	Preliminary methods unknown reliability	Weak and very indirect validation
0	Not correlated and not clearly related	crude speculation	No discernible rigour	No validation performed

Table 4: Pedigree matrix. The pedigree matrix is based on Funtowicz and Ravetz, 1990 and adapted from Ellis et al., 2000.

10 Quantitative assessment

For each of the input variables in the spreadsheet a pdf expressing the uncertainty in true value of the variable must be assessed. The steps involved in assessing the pdf's are as follows:

Structuring. Choose a unit and scale that is familiar to the respondent in order to characterize the selected variable.

Extremes. State the extreme minimum and maximum plausible values for the variable.

Extreme assessment. Try to envision ways or situations in which the extremes might be broader than you have stated. Describe such a situation if you can think of one, and revise the extreme values accordingly in that event. Enter the extreme values into the appropriate columns in the spreadsheet (table 1).

Assessment of knowledge level and selection of distribution. Before specifying more detailed information about the distribution it is important that this be done in a way that is consistent with your level of knowledge about the variable. In particular, we seek to avoid specifying more about the distribution shape than is actually known. The following heuristic is used to guide selection of distribution type: If the pedigree grade for the final emissions estimate is less than 0.3, use a uniform distribution. If it is between 0.3 and 0.7, use a triangular distribution. If it is greater than 0.7, use a normal distribution or other distribution as appropriate.

Specification of distribution. If you selected a uniform distribution you do not need to specify any further values. If you selected a triangular distribution, specify the mode. If you choose another distribution (e.g. normal), you now need to specify what that distribution is, along with values for the 5th, 50th, and 95th percentile values. Refer to the '@RISK' menu for a list of distributions. Briefly justify your choice of distribution if other than uniform or triangular.

Data entry. Enter the results obtained for the distributions for each variable into the appropriate columns in the spreadsheet (table 1).

Check. Now use the spreadsheet software to plot the distribution. If the resulting distribution does not conform to your expectations, revise it until it represents your subjective judgement satisfactorily.

11 Uncaptured assumptions

At this point you may feel that there are still some dimensions of uncertainty in the emissions estimation process that have not been captured in the above method. Describe any such issues here. If it is possible to revise the above to include the effects of such issues (by adding additional variables for example), please do so. If that is not possible, state what effects you think these issues have on the net emissions assessment.

12 Calculation of Monte Carlo and Pedigree results

Having entered all of the appropriate data into the Monte Carlo / Pedigree spreadsheet, run the spreadsheet to produce distributions of the derived variables. Refer to the @RISK report. This summarizes the sensitivity results and provides statistics and distributions for each of the variables. Check the results for general consistency with your expectations to make sure that they seem plausible.

The next step is to combine the quantitative sensitivity results and qualitative pedigree results. This is done by use of the NUSAP diagnostic diagram. Generate a NUSAP diagnostic diagram from the spreadsheet program. An example NUSAP diagnostic diagram is shown in figure 1. Variables that score high on spread and low on strength lie in the top right corner of the diagram (e.g. VOC percent in imported paint on the example in figure 1). Such variables are important contributors to the emissions estimate but are probably not very reliable. Identify the most critical variables in this regard and list them. At this stage you may wish to go back and reassess the assumptions underlying these variables, along with the distributions used to characterize them. Redo the Monte Carlo analysis if necessary. You may also wish to carry out sets of sensitivity runs for the covariance structure among variables discussed in section 5.

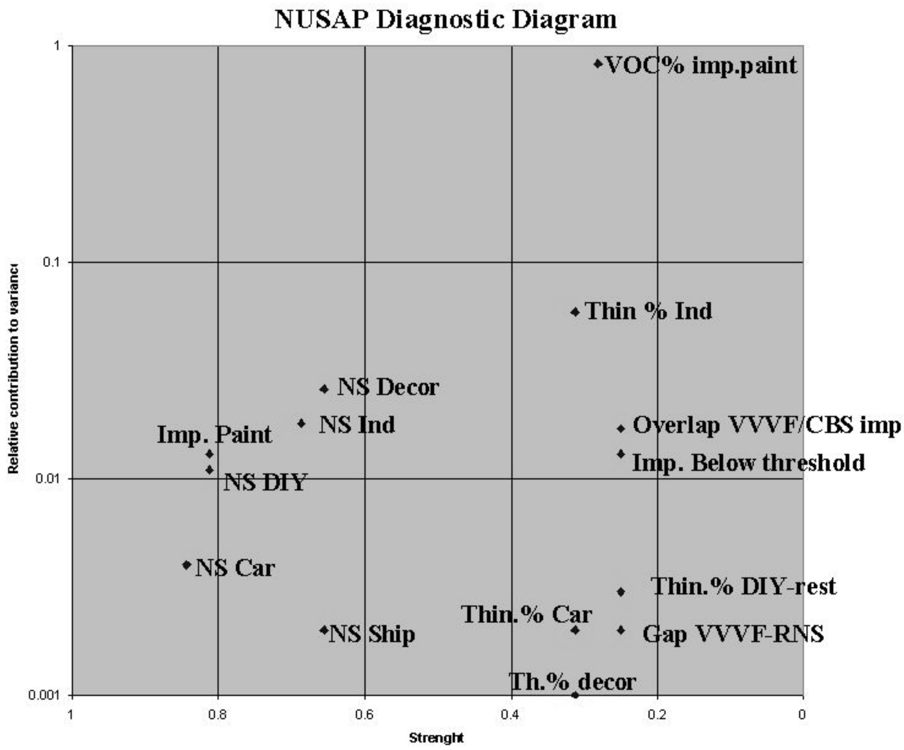

Figure 1: Example NUSAP diagnostic diagram for a case on VOC emissions from paint. The vertical axis is the log of relative contribution to variance in the final output variable as determined from the Monte Carlo sensitivity runs. The horizontal axis is the pedigree grade plotted from 1 to 0 for each variable.

As a final sensitivity experiment, redo the monte carlo analysis with all the pdfs converted to uniform distributions and compare the results with the original. The difference in spread provides some indication of the reduction in uncertainty that is gained by using more specific information in specifying the distributions.

13 Multiple Experts

In the case where multiple experts have completed assessments for pdfs in the spreadsheet the issue arises of how to combine them in calculating and presenting results. This is a difficult issue and there is no single best way to do this in all cases. The difficulty arises in part because different experts may have different (valid) ways to view the problem and it is not clear that one can then average or weight their distributions in a meaningful way. We recommend running the Monte Carlo simulations separately for all the experts and comparing the set of resulting pdfs.

If there is a large spread across experts then this will need to be noted in communicating results. A conservative choice in this case would be to select the broadest distribution obtained from among the different experts and use that — unless there are good reasons to justify rejecting that distribution. One would then note in presenting results that there is expert disagreement, but that the choice of distribution is indicative of the upper range of spread from among the disparate experts.

If there is a relatively small spread among the resulting expert distributions then the selection of distribution is less critical. In this case one can simply select a typical distribution and note that it is indeed typical of the different expert results.

14 Communication of results

The resulting emissions estimate is given by a pdf from the Monte Carlo spreadsheet run. To simplify the pdf (and to make the level of precision conveyed by it more consistent with available knowledge) it can be converted to a whisker plot for communication with users, which summarizes the distribution in the form shown in figure 2. This simplified representation shows only the extremes and mode of the distribution.

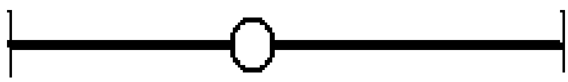

Figure 2: Whisker plot of emissions pdf.

The pedigree results can be displayed as a four corner 'kite' plot (figure 3). The corners of the outer box correspond to a pedigree score of four for each pedigree criterion and the center of the box corresponds to scores of zero. The inner box marks the actual scores obtained on each criterion.

The whisker plot provides a representation of the probability distribution of the final emission result. It represents the quantitative uncertainty of the result. The kite diagram summarizes information on qualitative dimensions of uncertainty in the

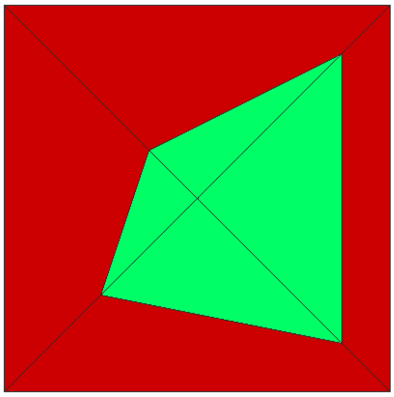

Figure 3: Kite diagram of emissions pedigree.

result. The colors of the kite diagram correspond metaphorically to those of a traffic light. If strength is high in each of the pedigree elements the box will be largely green, indicating that the final result is well underpinned. If strength is lower in some pedigree elements the box will then be redder in color, indicating that the result is not so well underpinned. The whisker plot and kite diagram thus provide complementary information on the uncertainty and quality of the result. The whisker plot expresses uncertainty in the emissions estimate, but that respresentation of uncertainty is itself uncertain. The kite diagram provides one estimate of the reliability of the whisker plot.

Even though you have provided a measure of uncertainty (whisker plot) and a measure of the reliability of the uncertainty estimate (kite plot), there will still be some uncertainties that have not been captured in the whisker and kite plots. These may relate to uncertainties that you know about and identified in section 11, but which you were unable to represent in the formats utilized here. There will also be some uncertainties that simply haven't been identified yet (ignorance). The latter may manifest themselves as surprises. For those uncertainties that have been identified, but not well represented in the above, provide a short written description of the uncertainties and their possible influence on your final estimate of emissions. This may entail simply repeating some of the information supplied in section 11, but it is important to provide this information to users also.

At this point you may wish to modify the whisker plot expressing uncertainty on the emission result on the basis of the uncaptured assumptions outlined. Further, your sensitivity analyses on the covariance structure may indicate that the Monte-Carlo pdf of emissions does not sufficiently capture uncertainty related to covariance structure. If you think you can modify the whisker plot to take these additional uncertainties into account, do so. If not, try to provide a qualitative description of their potential impact.

Finally, bear in mind that the whisker plot distribution for net emissions may or may not encompass the unknown true value of emissions. The distribution is only as robust as the data, assumptions, model, and pedigree underlying it.

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