United Nations Framework Convention on Climate Change

Uncertainty analysis in National Greenhouse Gas Inventories from developing countries

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Diego M. Ezcurra

GHG Support Unit, Transparency Division

Typical problems in developing countries

1. Limited or no technical capacity. Priority is always on GHG accounting
2. Limited staff with statistical background and experience in uncertainty assessment
3. Lack of data collection on uncertainty (institutional arrangements for data collection)
4. Data reported without associated uncertainty
5. Use of default uncertainty data from the 2006 IPCC GLs may not represent national circumstances or level of aggregation
6. Limited/lack of knowledge of 2006 IPCC GLs, tools/software

MONDAY

2. Overview of Uncertainty Analysis in National GHG Inventories
3. Causes of uncertainties associated with input data used in National GHG Inventories
4. How to reduce the uncertainty associated with input data used in National GHG Inventories

TUESDAY

5. Uncertainty associated with the use of national statistics, surveys, censuses and sampling
6. Uncertainty associated with the Use of Empirical Data

WEDNESDAY

7. Methods to combine uncertainties: Approach 1

Propagation of errors

THURSDAY

8. Methods to combine uncertainties: Approach 2

Monte Carlo simulation

FRIDAY

9. Methods to combine uncertainties: Hybrid combinations of Approaches 1 and 2
10. Application of uncertainty estimates to identify areas for improvement – Approach 2 to identify key categories
11. Uncertainty associated with the use of proxy, splicing techniques and expert judgment to fill data gaps

Hands-on exercises!

Energy, IPPU, AFOLU and Waste

2

Session 2. Overview of Uncertainty Analysis in National GHG Inventories

By the end of this session, you will:

1. Know where to find more details
2. Understand the terminology
3. Differentiate accuracy and precision

Learning objectives

Uncertainty overview [1]

2006 IPCC Guidelines for

National Greenhouse Gas Inventories

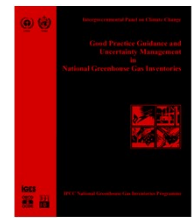
Guidelines Energy IPPU AFOLU Waste

Vol. 1 - Ch. 3: uncertainty

Vol. 1 - Ch. 4: KCA based on uncertainty

Vol. 1 - Ch. 5: Splicing techniques

Good Practice Guidance and Uncertainty Management
in National Greenhouse Gas Inventories



Uncertainty overview [2]

General approach

Uncertainty

Lack of knowledge of the true value of a variable that can be described as a probability density function (PDF). Uncertainty depends on the analyst's state of knowledge, which in turn depends on the quality and quantity of applicable data as well as knowledge of underlying processes and inference methods.

Uncertainty analysis

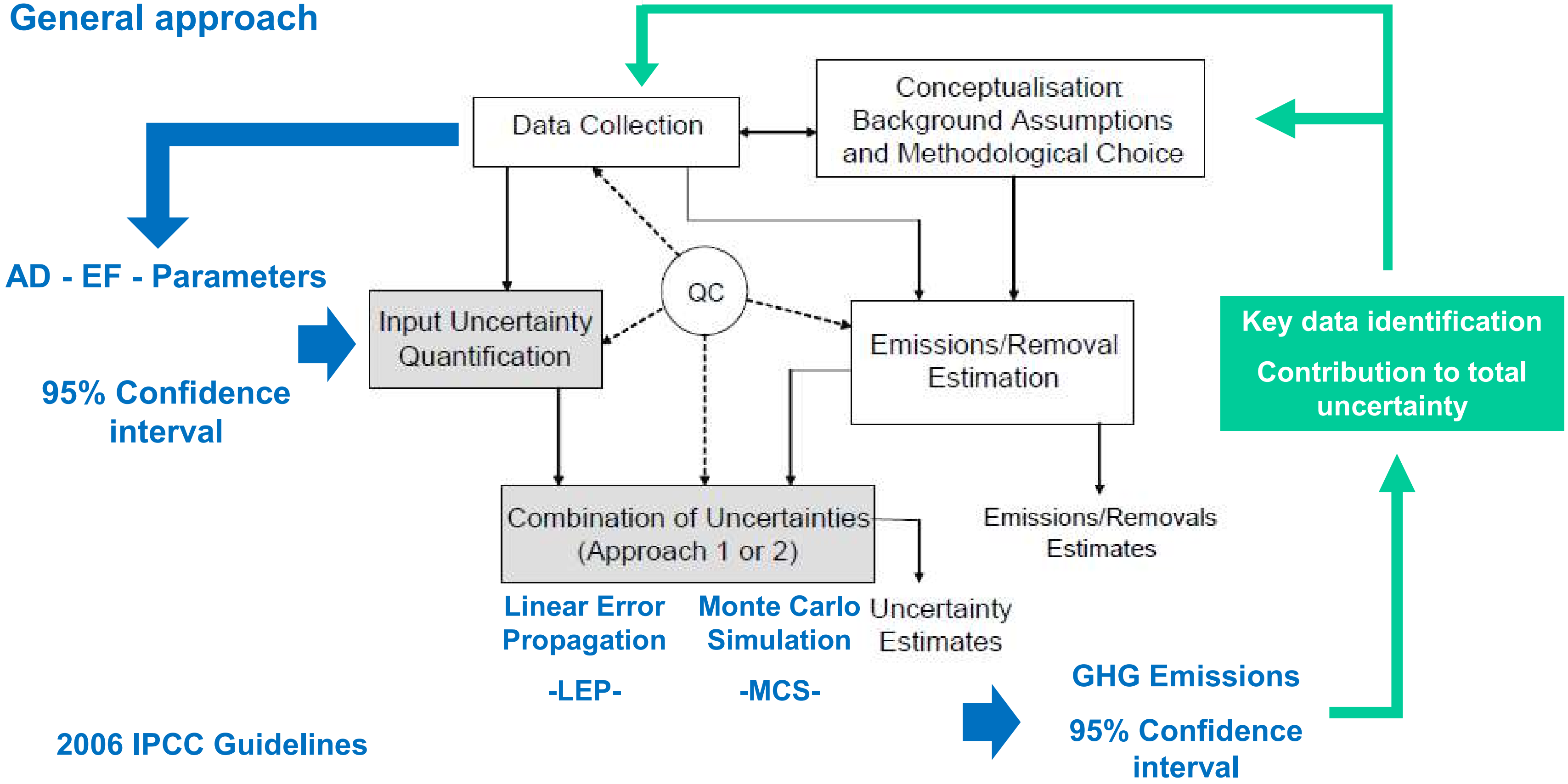
An uncertainty analysis should be seen, first and foremost, as a means to help prioritise national efforts to reduce the uncertainty of inventories in the future, and guide decisions on methodological choice.
Quantitative uncertainty analysis is performed by estimating the 95 percent confidence interval of the emissions and removals estimates for individual categories and for the total inventory

Uncertainty assessment

The term "ASSESSMENT" is intended to convey an exercise that includes the investigation of quantitative and qualitative aspects. In the glossary to the Guidelines, "uncertainty analysis" is defined as only a quantitative exercise.

Uncertainty overview [3]

General approach



2006 IPCC Guidelines

Uncertainty overview [4]

Key concepts

***Confidence interval*:** range that encloses the true, but unknown value, with a determined confidence (probability). Typically, a 95 percent confidence interval is used in greenhouse gas inventories.
Alternative interpretation: Range that may safely be declared to be consistent with observed data or information

***Probability Density Function (PDF)*:** describes the range and relative likelihood of possible values.
For emission inventory, it is used to describe uncertainty in the estimate of a quantity that is a fixed constant whose value is not exactly known.

***Sensitivity analysis*:** method to determine which of the input uncertainties to an inventory contributes most substantially to the overall uncertainty.

Uncertainty overview [5]

Key concepts

Accuracy: *Agreement between the true value and the average of repeated measured observations or estimates of* a variable.
An accurate measurement or prediction lacks bias or, equivalently, systematic error.

Bias / Systematic error: *Lack of accuracy. Bias (systematic error), can occur because of failure to capture all relevant processes involved or because the available data are not representative of all real-world situations, or because of instrument error.*

Precision: *Agreement among repeated measurements of the same variable.*
Better precision means less random error. Precision is independent of accuracy.

Random errors: *Random variation above or below a mean value. Random error is inversely proportional to* precision. Usually, the random error is quantified with respect to a mean value, but the mean could be biased or unbiased. Thus, random error is a distinct concept compared to systematic error.

Uncertainty overview [6]

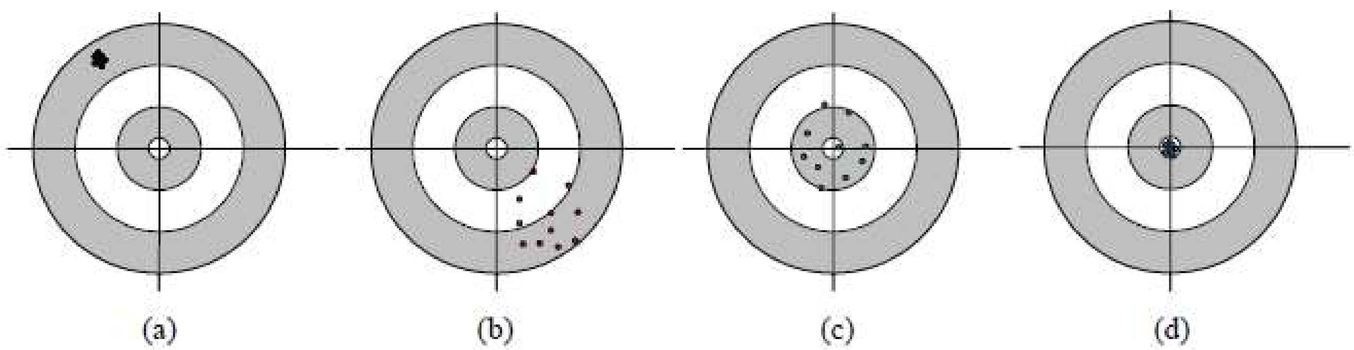
Key concepts

Lack of knowledge of the true value

How far is the true value from the value used?

Accuracy (systematic errors or bias) vs. Precision (random errors)

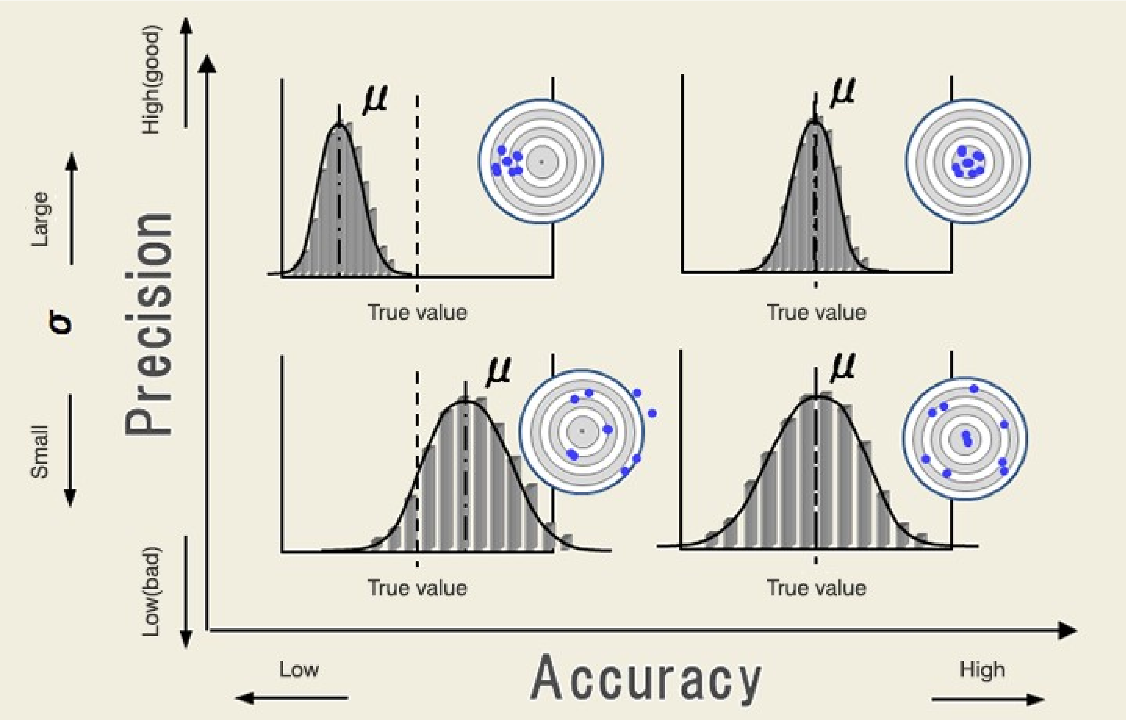
(a) inaccurate but precise; (b) inaccurate and imprecise; (c) accurate but imprecise; and (d) precise and accurate



Uncertainty overview [7]

Key concepts

Accuracy (systematic errors or bias) vs. Precision (random errors)



Source: Hitachi, 3. Semiconductor - Accuracy and Precision, Fig.3-5

Uncertainty overview [8]

Key concepts

The **quantitative uncertainty analysis** tends to deal primarily with **random errors** based on the **inherent variability** of a system and the **finite sample size** of available data, **random components of measurement error**, or **inferences** regarding the random component of uncertainty obtained from **expert judgment**

→ **PRECISION**

It is important to recognize that **some uncertainties that are not addressed by statistical means may exist**, including those arising from **omissions or double counting**, or other **conceptual errors**, or from **incomplete understanding** of the processes that may lead to inaccuracies in estimates developed from models.
Bias or systematic errors

→ **ACCURACY**

Uncertainty overview [9]

Terminology

i) **Confidence interval**: range that encloses the true value with a determined confidence (probability)

95 % CI → 2.5 th [……………………..] 97.5 th

Absolute | Relative

Symmetric: 80 (64-96) — 80 ± 16 — 80 $\boxed{\pm 20\%}$

64 [--------80--------] 96

$\underbrace{\quad}_{16}$ $\underbrace{\quad}_{16}$

16/80 = 0.2

Uncertainty

$\boxed{U_i}$

Asymmetric: 80 (72-104) — 80 -8/+24 — 80 $\boxed{-10\%/+30\%}$

72 [-----80---------------] 104

Large uncertainty:

100 (50-200) — 100 -50/+100 — 100 -50%/+100% — 100 $\boxed{\pm \text{ factor of } 2}$ (half or double)

Factor of "n" — (mean/n) and (mean x n)

Uncertainty overview [10]

Terminology

TABLE 2.2 DEFAULT EMISSION FACTORS FOR STATIONARY COMBUSTION IN THE ENERGY INDUSTRIES (kg of greenhouse gas per TJ on a Net Calorific Basis)										
Fuel		CO_2			CH_4			N_2O		
		Default Emission Factor	Lower	Upper	Default Emission Factor	Lower	Upper	Default Emission Factor	Lower	Upper
Crude Oil		73 300	71 100	75 500	r 3	1	10	0.6	0.2	2
Orimulsion		r 77 000	69 300	85 400	r 3	1	10	0.6	0.2	2
Natural Gas Liquids		r 64 200	58 300	70 400	r 3	1	10	0.6	0.2	2
Gasoline	Motor Gasoline	r 69 300	67 500	73 000	r 3	1	10	0.6	0.2	2
	Aviation Gasoline	r 70 000	67 500	73 000	r 3	1	10	0.6	0.2	2
	Jet Gasoline	r 70 000	67 500	73 000	r 3	1	10	0.6	0.2	2
Jet Kerosene		r 71 500	69 700	74 400	r 3	1	10	0.6	0.2	2
Other Kerosene		71 900	70 800	73 700	r 3	1	10	0.6	0.2	2
Shale Oil		73 300	67 800	79 200	r 3	1	10	0.6	0.2	2
Gas/Diesel Oil		74 100	72 600	74 800	r 3	1	10	0.6	0.2	2
Residual Fuel Oil		77 400	75 500	78 800	r 3	1	10	0.6	0.2	2

75.5 [---77.4---] 78.8 77.4 (-2.5% ; +1.8%) 1 (---3-----------) 10 3 -67% / +233%

Approx. 77.4 ± 2% **Approx. 3 ± factor of 3**

Uncertainty overview [11]

Terminology

Emission factor uncertainties

These will be the same as the uncertainties associated with estimation of the litter and dead organic matter stocks per unit area on the previous land use. Uncertainties need not be estimated where zero carbon density in litter and dead organic matter pools is assumed for Cropland. Where this is not the case, uncertainties should be assessed by analysis of local data and should both exceed a factor of about 2.

Uncertainties associated with carbon stocks and other parameter values are likely to be at least a factor of three unless country-specific data are available from well designed surveys.

Solid storage[b]	The storage of manure, typically for a period of several months, in unconfined piles or stacks. Manure is able to be stacked due to the presence of a sufficient amount of bedding material or loss of moisture by evaporation.	0.005	Factor of 2	Judgement of IPCC Expert Group in combination with Amon *et al.* (2001), which shows emissions ranging from 0.0027 to 0.01 kg N_2O-N (kg N)$^{-1}$.

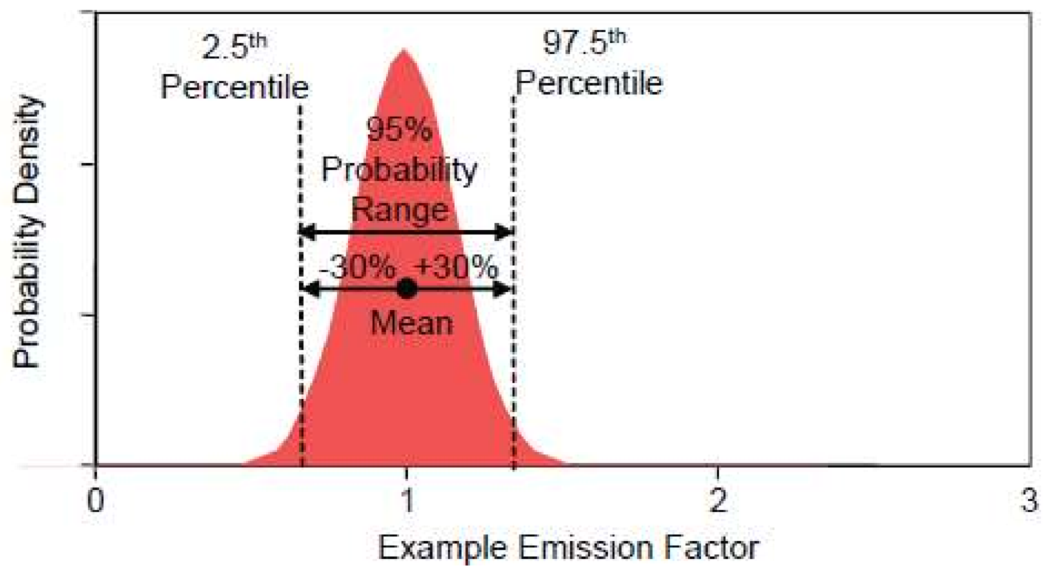
(see Annex 10A.1). Table 10.11 presents the enteric fermentation emission factors for cattle. A range of emission factors is shown for typical regional conditions. As shown in the table, the emission factors vary by over a factor of four on a per head basis.

Uncertainty overview [12]

Terminology

ii) Probability Density Function: range and relative likelihood of possible values

Symmetric (normal distribution)

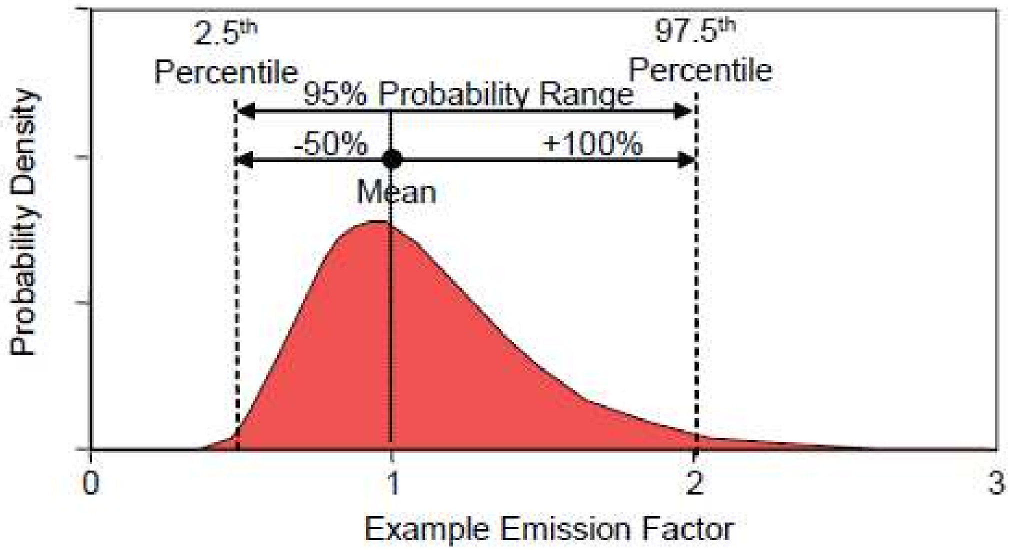


Uncertainty overview [13]

Terminology

ii) Probability Density Function: range and relative likelihood of possible values

Asymmetric (Skewed)



3

Session 3. Causes of uncertainties associated with input data used in National GHG Inventories

By the end of this session, you will:

1. Understand why data is uncertain
2. Identify the causes and implications

Learning objectives

Causes of uncertainty [1]

Causes of uncertainty: Animal population? Age? Livestock characterization? Diet?

Causes of uncertainty [2]

Causes of uncertainty: Land representation? Stand volume? Carbon stock? Below ground biomass?

Causes of uncertainty [3]

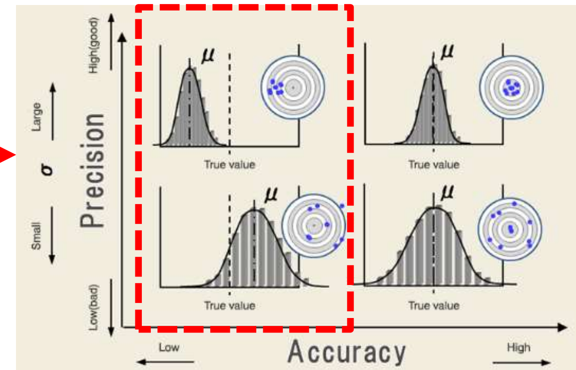
Causes of uncertainty: Pipe length? No. of fittings? Gas composition? Maintenance? Venting?

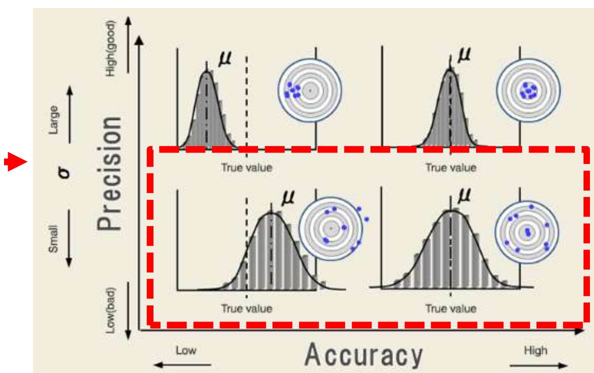
Causes of uncertainty [4]

Causes of uncertainty: Waste generation? Composition? Climate? Treatment? Management type?

Causes of uncertainty [5]

Causes of uncertainty	
Lack of completeness	-Bias
Model	-Bias and Random errors
Lack of data	-Bias and Random errors
Representativeness of data	-Bias
Random sampling error	-Random errors
Measurement errors	-Bias and Random errors
Misreporting	-Bias
Data gaps	-Bias and Random errors





Causes of uncertainty [6]

Causes of uncertainty & examples

Lack of completeness **-Bias**

e.g. sources/sink categories not included in the inventories

Energy: emissions from coke production

IPPU: fluorinated gases not reported

AFOLU: methane emissions from enteric fermentation for dairy cows.

Waste: industrial wastewater for some products not included

Causes of uncertainty [7]

Causes of uncertainty & examples

Lack of data **-Bias and Random errors**

e.g. activity data obtained by interpolation or other methods for missing year

Energy: provisional information in National Energy Balance for recent year

IPPU: cement production missing in national statistics

AFOLU: population for some animal category not informed in the statistics

Waste: amount of MSW surrogated from population, extrapolated from census

Causes of uncertainty [8]

Causes of uncertainty & examples

Representativeness of data -Bias

e.g. emission factor based on particular conditions

Energy: N_2O from internal combustion engines from laboratory test instead of real driving conditions

IPPU: CO_2 emissions form steel production based on full load capacity plant

AFOLU: biomass growth rate based on sampling that do not cover all relevant regions

Waste: wastewater treatment efficiency based on newly built plants data

Causes of uncertainty [9]

Causes of uncertainty & examples

Random sampling error **-Bias and Random errors**

e.g. activity data or emission factors based on limited sampling

- Energy: limited reporting in census of liquid fuels used in transport
- IPPU: amount of glass recovered (by type) based on surveys
- AFOLU: C stored in forest based on limited sampling capacity (few trees)
- Waste: MSW treatment distribution based on information from few cities in the country

4

Session 4. How to reduce the uncertainty associated with input data used in National GHG Inventories

By the end of this session, you will:

1. Learn strategies to deal with uncertainty
2. Understand how to set priorities

Learning objectives

Reducing uncertainty [1]

Causes of uncertainty & strategies

Lack of completeness	Bias	Concept, QA/QC
Model	Bias and Random errors	Concept, QA/QC
Lack of data	Bias and Random errors	Experts, QA/QC
Representativeness of data	Bias	QA/QC, verification
Random sampling error	Random errors	Statistics sizes
Measurement errors	Bias and Random errors	QA/QC, verification
Misreporting	Bias	QA/QC
Data gaps	Bias and Random errors	Statistics, experts

Reducing uncertainty [2]

Improving accounting

Improving conceptualization	Structural assumptions
Improving models	Structure and parameterization
Improving representativeness	Sampling strategies
Using + precise measurement methods	Measurement technologies
Collecting more measured data	Sample size
Eliminating known risk of bias	Following decision trees
Improving state of knowledge	Understanding of the categories

Reducing uncertainty [3]

Improving accounting

Improving conceptualization | **Structural assumptions**

Improving models | **Structure and parameterization**

e.g. better treatment of seasonality effects leading to more accurate annual estimates of emissions or removals in AFOLU.

e.g. moving to higher Tiers in steel production to account for local data at plant level.

Reducing uncertainty [4]

Improving accounting

Improving representativeness **Sampling strategies**

Collecting more measured data **Sample size**

e.g. including emissions data for situations involving start-up or load changes, if frequent, instead of only full load operations.

e.g. perform stratified sampling in forest to account for different characteristics, climate and species

e.g. increasing the sample size for determination of soil organic carbon.

Reducing uncertainty [5]

Improving accounting

Using more precise measurement methods | **Measurement technologies**

e.g. collecting data using standardized measurement methods (i.e. ISO)

e.g. using measured parameters instead of simplified assumptions (density, temperature, mass vs. volume)

Eliminating known risk of bias | **Following decision trees, expert knowledge**

Improving state of knowledge | **Understanding of the categories**

e.g. Verifying the correct positioning and calibration of instruments in gas measurement.

e.g. moving to higher tiers to account for national conditions

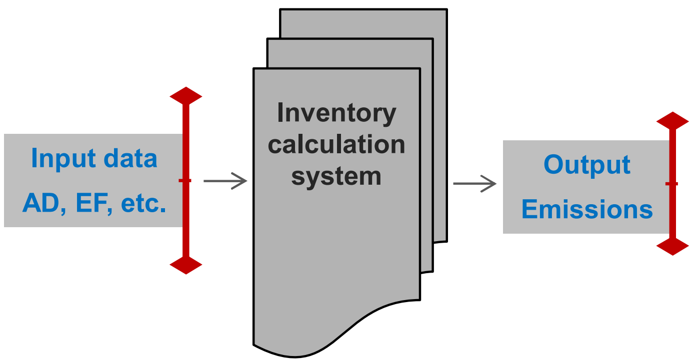
e.g. Involving producers to better understand the details and appropriateness of assumptions.

Reducing uncertainty [6]

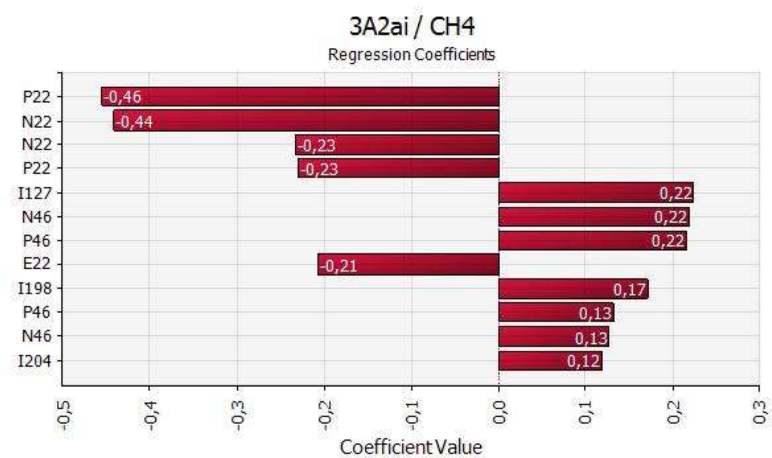
Sensitivity analysis

Purpose: Identify categories, and key variables used that contribute the most to overall uncertainty of the inventory. → **ALLOCATE RESOURCES**

How: Introduce a perturbation to one variable, of the magnitude of its uncertainty, and assess the variation in the result, one at a time (ceteris paribus).



e.g. Sensitivity in CH_4 emission from manure



Conclusions

Uncertainty assessment

- It is a means to help prioritise national efforts to reduce the uncertainty of inventories in the future
- It guides decisions on methodological choice
- It helps understand the quality of the information use
- It is a requirement of GHG Inventories

Assessment of uncertainty in the input parameters should be part of the data collection !

End of day 1

Thank you!

Diego M. Ezcurra

MONDAY

2. Overview of Uncertainty Analysis in National GHG Inventories

3. Causes of uncertainties associated with input data used in National GHG Inventories

4. How to reduce the uncertainty associated with input data used in National GHG Inventories

TUESDAY

5. Uncertainty associated with the use of national statistics, surveys, censuses and sampling

6. Uncertainty associated with the Use of Empirical Data

20%

5

Session 5. Uncertainty associated with the use of national statistics, surveys, censuses and sampling

By the end of this session, you will:

1. Differentiate census and survey
2. Learn when to use std deviation or std error
3. Derive uncertainty based on available data

Learning objectives

Uncertainty associated with activity data [1]

National statistics: census, survey

- Activity data are closely linked to economic activity
- well established price incentives and fiscal requirements for accurate accounting

National statistics

Censuses

V1_Ch2. - Annex 2A.2
2006 IPCC Guidelines
General guidance on performing surveys

Surveys

Counting every instance of a particular activity.
Typically includes both systematic and random errors.

Random errors are typically normally distributed and uncorrelated

Counting a portion of a particular activity.
Typically includes both systematic and random errors.

Random errors are typically normally distributed and uncorrelated

Contact the statistical agencies directly

Uncertainty associated with activity data [2]

National statistics: census

National statistics

Censuses | Surveys

- Check for the size of random errors, look for fluctuations over time, and differential fluctuations in series that ought to be highly correlated with the data of interest
- To check for bias errors, cross-check the data of interest with other, related information. (look up and down the supply chain for fuels, or highly correlated activities with the data of interest, for instance reported fuel input vs. electricity output).
- Interpretation of statistical differences, within, for instance, national energy data are an example of cross checking (e.g. reference approach)..

Often ‘precise but inaccurate’

Uncertainty associated with activity data [3]

National statistics: census

National statistics

- Censuses
- Surveys

Hands-on exercises

Uncertainty associated with activity data [4]

National statistics: census

Periodic publications
ENERGY: liquid fuels commercialization. Fuel consumption statistics are published by the Ministry of Energy every year for gasoil and gasoline. The statistics contains the most updated information for the current and previous years.
Evaluate consistency and identify fluctuations over time in series to derive the uncertainty of the data

Year	Gasoil	Gasoline
2016	**659.034**	**479.291**
2017	**662.157**	**504.563**
2018	**666.065**	**533.358**
2019	**770.377**	**599.242**
2020	**866.303**	**554.953**
2021		
2022		

Source: commercialization tables, 12 July 2021

Year	Gasoil	Gasoline
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2021	**847.566**	**498.429**
2022		

Source: commercialization tables, 18 June 2022

Year	Gasoil	Gasoline
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2021	**847.566**	**480.723**
2022	**884.250**	**426.849**

Source: commercialization tables, 23 June 2023

Uncertainty associated with activity data [4]

National statistics: census

4,5%

U ≈ 5%

3,7%

Periodic publications
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Source: commercialization tables, 23 June 2023

Uncertainty associated with activity data [5]

National statistics: census

Highly correlated activities
ENERGY: fuel consumption vs electricity generation. Fuel consumption and electricity generation are reported every year by the electricity grid administrator.
Evaluate the reported data, calculate the efficiency to identify any inconsistency and assess uncertainty.

	Total
Gas Turbine Generation (MWh)	**59.757.516**
Natural Gas Consumption (10^3 m^3)	**14.975.637**

42%

NCV: 48 TJ/Gg

Density: 0,714 kg/m^3

efficiency ?

Uncertainty associated with activity data [6]

National statistics: census

Highly correlated activities
ENERGY: fuel consumption vs electricity generation. Fuel consumption and electricity generation are reported every year by the electricity grid administrator.
Evaluate the reported data, calculate the efficiency to identify any inconsistency and assess uncertainty

	January	February	March	April	May	June	July	August	September	October	November	December	Total
GT (MWh)	5.155.358	4.554.661	5.010.912	4.657.051	4.714.604	5.288.447	5.432.010	5.592.661	5.316.355	4.290.471	4.512.174	5.232.812	59.757.516
NG (10^3 m^3)	1.711.896	1.375.323	1.480.325	1.331.261	1.345.921	1.572.943	157.041	1.674.304	1.632.617	1.376.352	1.323.954	1.622.381	14.975.637
	0,33	0,30	0,30	0,29	0,29	0,30	0,03	0,30	0,31	0,32	0,29	0,31	0,25

NCV: 48 TJ/Gg

Density: 0,714 kg/m^3

Monthly efficiency ?

	January	February	March	April	May	June	July	August	September	October	November	December	Total
Generation (TJ)	18.559	16.397	18.039	16.765	16.973	19.038	19.555	20.134	19.139	15.446	16.244	18.838	**215.127**
Consumption (TJ)	58.670	47.135	50.734	45.625	46.127	53.908	5.382	57.382	55.953	47.170	45.375	55.602	**513.245**
Efficiency	32%	35%	36%	37%	37%	35%	363%	35%	34%	33%	36%	34%	**42%**

Uncertainty associated with activity data [7]

National statistics: census

≈ 20%

Highly correlated activities
ENERGY: fuel consumption vs electricity generation. Fuel consumption and electricity generation are reported every year by the electricity grid administrator.
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NG (10^3 m^3)	1.711.896	1.375.323	1.480.325	1.331.261	1.345.921	1.572.943	157.041	1.674.304	1.632.617	1.376.352	1.323.954	1.622.381	14.975.637
							1.570.410						18.017.687

NCV: 48 TJ/Gg

Density: 0,714 kg/m^3

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NG (10^3 m^3)	1.711.896	1.375.323	1.480.325	1.331.261	1.345.921	1.572.943	1.570.410	1.674.304	1.632.617	1.376.352	1.323.954	1.622.381	**18.017.687**
	32%	35%	36%	37%	37%	35%	36%	35%	34%	33%	36%	34%	35%

Uncertainty associated with activity data [8]

National statistics: survey

National statistics

Censuses

Surveys

- Sample size and inter-individual variability
- Typical cases: consumer surveys, home expenses survey, land use surveys or forest cover surveys
- The agency conducting the sample will normally be able to advise on sampling error.
- If there is no information available, it may be possible to identify, or infer, the sample and population sizes and calculate sampling error directly.

precision depends on sample size, accuracy depends on sampling design

Uncertainty associated with activity data [9]

National statistics: survey

Heterogeneity (standard deviation) vs. uncertainty in sample mean (standard error)

$$Uncertainty = \pm\left(\frac{1.96 \cdot \sigma}{\mu}\right) \cdot 100\%$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2}$$

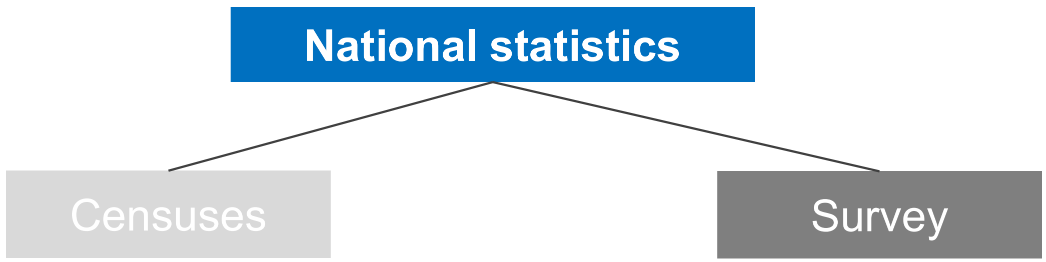
$$Uncertainty = \pm\left(\frac{1.96 \cdot SE}{\mu}\right) \cdot 100\%$$

$$SE = \frac{\sigma}{\sqrt{n}}$$

Standard deviation	Standard error
Variability <u>within</u> the sample	Variability <u>of the mean</u> of the sample
Applicable for individual value	Applicable for country average
Standard deviation tends to remain constant	Standard error falls as sample size grows

Uncertainty associated with activity data [10]

National statistics: survey



Hands-on exercises

Uncertainty associated with activity data [11]

National statistics: survey

AFOLU: Carbon stock in forest from surveys

a) Given a sample with 80 individual values, calculate the mean, standard deviation and standard error.
b) If the sampling is repeated ten times, calculate the mean for each sample and the standard deviation of the sampling distribution of the mean and compare with a).

	Samp. 1	Samp. 2	Samp. 3	Samp. 4	Samp. 5	Samp. 6	Samp. 7	Samp. 8	Samp. 9	Samp. 10
Mean	102	99	101	100	97	100	100	101	102	96
STD	18	21	18	22	20	19	19	20	20	21
SE	2,0	2,4	2,0	2,5	2,3	2,2	2,1	2,2	2,2	2,4

Mean	STD
101	2,1

Uncertainty associated with activity data [12]

National statistics: survey

AFOLU: Carbon stock in forest from surveys

Calculate the uncertainty of the carbon stock obtained from the sampling to be used in the GHG inventory. The emissions from land use change will be calculated for the entire country in the year in which the survey was carried out.

Sample size: 30

Average C stock: 93.7 tC/ha

Standard deviation: 10.2 tC/ha

σ or SE ?

$$Uncertainty = \pm\left(\frac{1.96 \cdot SE}{\mu}\right) \cdot 100\%$$

$$SE = \frac{\sigma}{\sqrt{n}}$$

SE: 1.9 tC/ha

U: 4 %

What if the carbon stock is applied to account for emissions in one deforested area?

Uncertainty associated with activity data [13]

National statistics: survey

WASTE: Municipal solid waste amount and composition

1) The amount per capita is obtained from a sample that covers vehicles collecting in a wide range of areas: urban and rural, wealthy and poor, with and without gardens, etc. and covering several periods throughout the year.

Uncertainty for the entire MSW category? σ or SE ?

Uncertainty for the emissions from managed landfills? σ or SE ?

2) The composition of the MSW was done through a survey at different landfills. A national waste composition was calculated based on the results and is used to calculate the methane emissions in each individual landfill.

Uncertainty for the composition based on amount from each landfill? σ or SE ?

6

Session 6. Uncertainty associated with the Use of Empirical Data

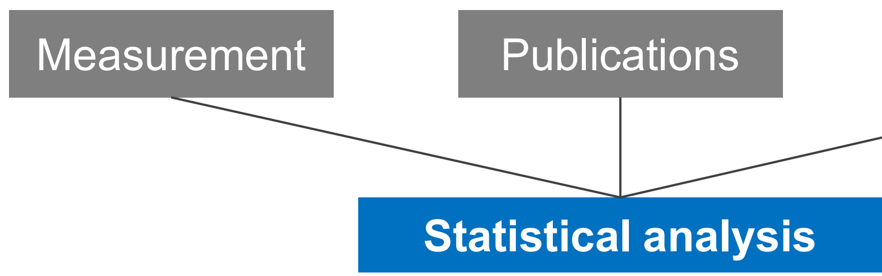
By the end of this session, you will:

1. Learn how to apply statistical analysis
2. Derive uncertainty based on available data

Learning objectives

Uncertainty associated with empirical data [1]

Techniques for quantifying uncertainties



V1_Ch.3 – 3.2.2.2
2006 IPCC Guidelines

- Approach to quantify uncertainty in inventories, mainly associated to emission factors and other estimation parameters
- 6 steps approach to apply systematically

Uncertainty associated with empirical data [2]

Techniques for quantifying uncertainties

Statistical analysis

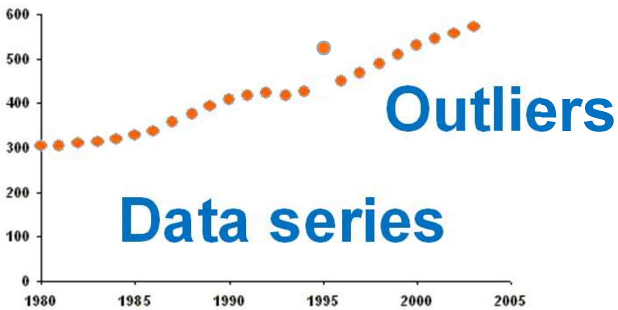
1. Compilation and evaluation of a database
2. Visualisation of data by developing empirical distribution functions
3. Fitting, evaluation, and selection of alternative PDF
4. Characterisation of uncertainty in the mean of the distributions for variability
5. Input to a probabilistic analysis to estimate uncertainty in total emissions
6. Sensitivity analysis

Uncertainty associated with empirical data [3]

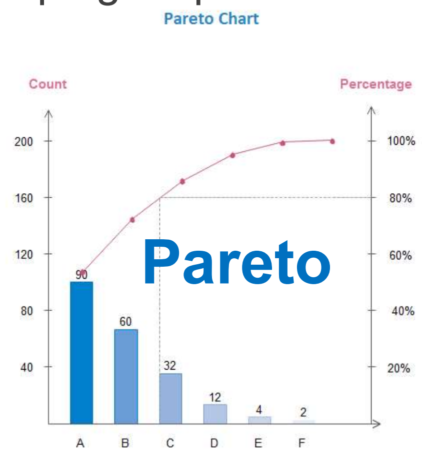
Techniques for quantifying uncertainties

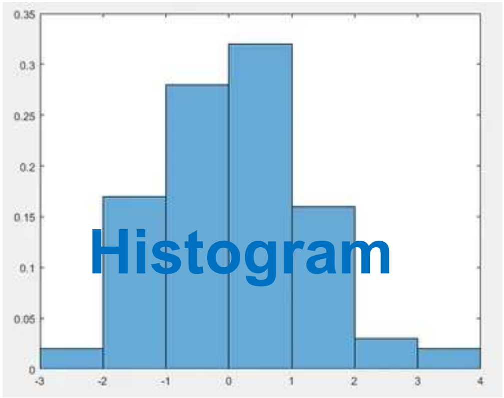
Statistical analysis

1. Compilation and evaluation of a database
2. Visualisation of data by developing empirical distribution functions



Consistency





Uncertainty associated with empirical data [4]

Techniques for quantifying uncertainties

Statistical analysis

3. Fitting, evaluation, and selection of alternative PDF

Possible PDF

Physical process

Expert judgement

Variability

Goodness of fit test

Uncertainty associated with empirical data [5]

Techniques for quantifying uncertainties

Statistical analysis

4. Characterisation of uncertainty in the mean of the distributions for variability
5. Input to a probabilistic analysis to estimate uncertainty in total emissions
6. Sensitivity analysis

$\boldsymbol{\sigma}$ **or SE ?** **95% CI** $\rightarrow$ U_i

$U_i \rightarrow U_{Total}$

$U_{Total} \rightarrow X_i$

Uncertainty associated with empirical data [6]

Techniques for quantifying uncertainties

Measurement

Publications

Statistics

Statistical analysis

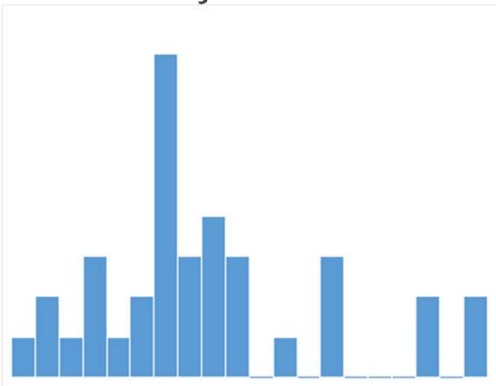
Hands-on exercises

Uncertainty associated with empirical data [7]

Statistical analysis

IPPU: Emission factor for aluminum production

A monitoring system was set to detect the anode effect. Average monthly EF were calculated for CF_4 and recorded for three years.
Perform statistical analysis to identify PDF candidates, calculate the mean, standard deviation, standard error and uncertainty.



μ: 64.3 g CF_4/tAl

σ: 13.8 g CF_4/tAl

SE: 2.3 g CF_4/tAl

U: 7 %

Uncertainty associated with empirical data [8]

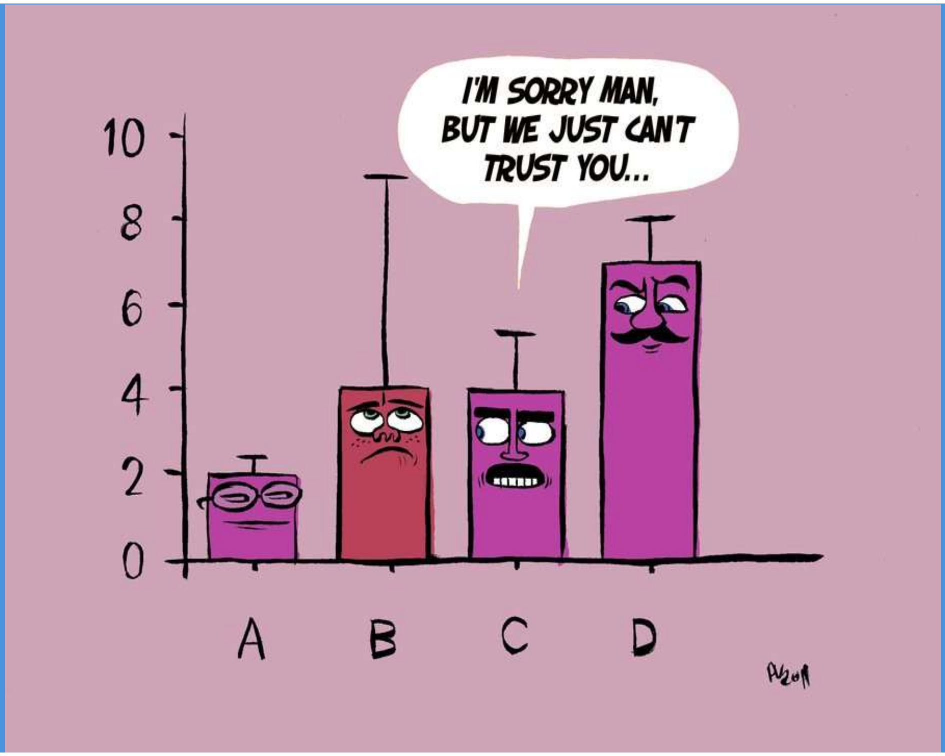
Statistical analysis

Attention!

Measurements taken for another purpose may not be representative.

For example, methane measurements made for safety reasons at coal mines and landfills may not necessarily reflect total emissions because they may have been made only when methane emissions were suspected of being high, as a compliance check.

In such cases, the ratio between the measured data and total emissions should be estimated for the uncertainty analysis.



End of day 2
Thank you!

Diego M. Ezcurra

MONDAY

2. Overview of Uncertainty Analysis in National GHG Inventories

3. Causes of uncertainties associated with input data used in National GHG Inventories

4. How to reduce the uncertainty associated with input data used in National GHG Inventories

TUESDAY

5. Uncertainty associated with the use of national statistics, surveys, censuses and sampling

6. Uncertainty associated with the Use of Empirical Data

WEDNESDAY

7. Methods to combine uncertainties: Approach 1

Propagation of errors

40%

7

Session 7. Methods to combine uncertainties: Approach 1 Propagation of errors

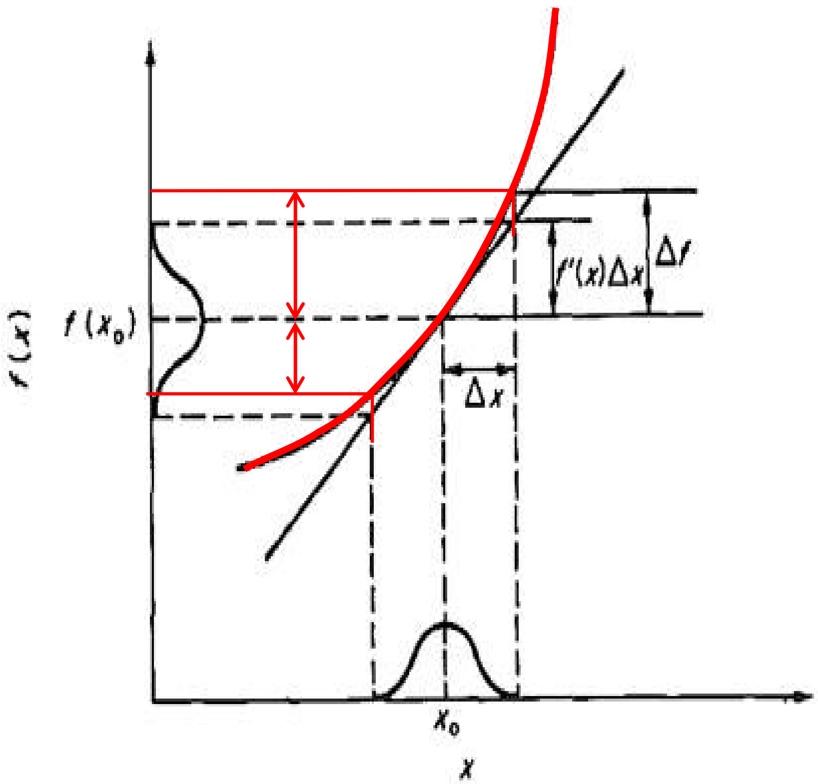
By the end of this session, you will:

1. Understand the basics and assumptions
2. Learn how to apply it to several cases
3. Identify key variables and avoid pitfalls
4. Learn how to deal with asymmetric cases

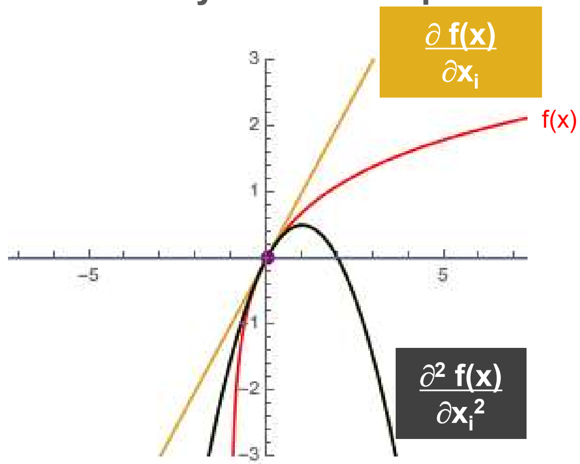
Learning objectives

Combining uncertainty: Approach 1 [1]

Linear Error Propagation (LEP)



First order Taylor series expansion



Assumptions:

- **Small std. Deviation (~30% from the mean)**
- **Symmetric (not skewed)**
- **Normal distribution**
- Uncorrelated variables
- Multiplication or addition

Equations 3.1 and 3.2

Combining uncertainty: Approach 1 [2]

Linear Error Propagation (LEP) **Theory behind it – Don't panic! Bear with me :)**

Taylor 1st order: $f = f(a;b) + \frac{\partial f}{\partial a}\delta a + \frac{\partial f}{\partial b}\delta b + \cdots$ ➡ $f - f(a;b) = \frac{\partial f}{\partial a}\delta a + \frac{\partial f}{\partial b}\delta b$ ➡ $\delta f = \frac{\partial f}{\partial a}\delta a + \frac{\partial f}{\partial b}\delta b$

Variance of a summation: $\boxed{\sigma_f^2 = \left|\frac{\partial f}{\partial a}\right|^2 \sigma_a^2 + \left|\frac{\partial f}{\partial b}\right|^2 \sigma_b^2 + 2\frac{\partial f}{\partial a}\frac{\partial f}{\partial b}\sigma_{ab}}$

Case f = a x b: $\sigma_f^2 = b^2\,\sigma_a^2 + a^2\,\sigma_b^2 + 2\,a\,b\,\sigma_{ab}$

Or, in relative terms

$$\left(\frac{\sigma_f}{f}\right)^2 = \left(\frac{b\,\sigma_a}{a\,b}\right)^2 + \left(\frac{a\,\sigma_b}{a\,b}\right)^2 + \frac{2\,a\,b\,\sigma_{ab}}{(a\,b)^2}$$

$u_f^2 = u_a^2 + u_b^2$ ➡ $u_f = \sqrt{u_a^2 + u_b^2}$ ➡ $U_{total} = \sqrt{U_1^2 + U_2^2 + \ldots + U_n^2}$

Equations 3.1

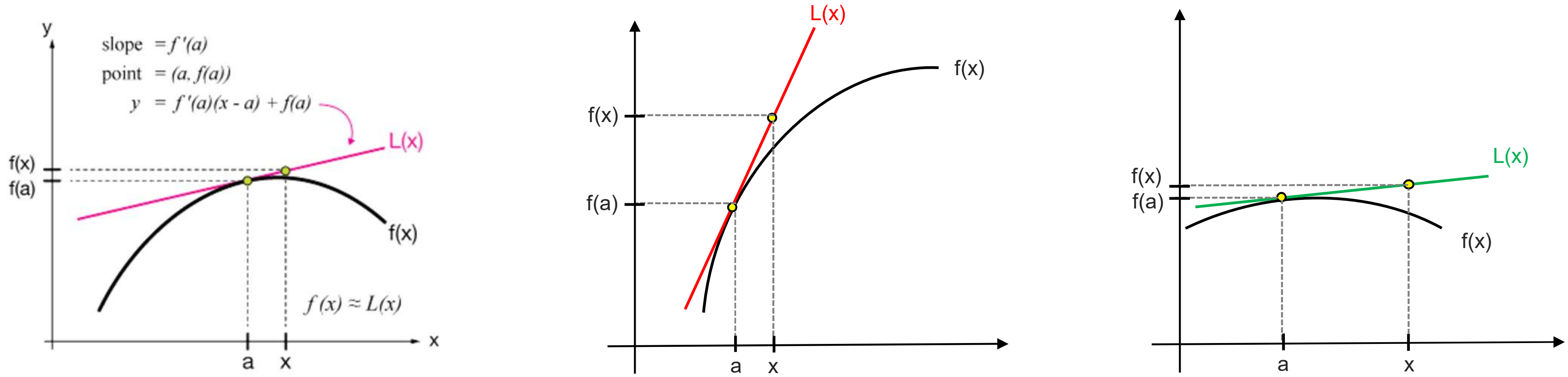
Assumptions:

1) Small std. Deviation (~30%)
2) Symmetric (not skewed)
   Normal distribution
3) Uncorrelated variables
4) Multiplication or addition

Combining uncertainty: Approach 1 [3]

Linear Error Propagation (LEP)

$$\sigma_f^2 = \left|\frac{\partial f}{\partial a}\right|^2 \sigma_a^2 + \left|\frac{\partial f}{\partial b}\right|^2 \sigma_b^2$$



The most important is how the uncertainty of the data affects the result. **!**

Combining uncertainty: Approach 1 [4]

Linear Error Propagation (LEP)

AD x EF

EQUATION 3.1

COMBINING UNCERTAINTIES – APPROACH 1 – MULTIPLICATION

$$U_{total} = \sqrt{U_1^2 + U_2^2 + \ldots + U_n^2}$$

***U_i*: relative**

E1 + E2 + … + En

EQUATION 3.2

COMBINING UNCERTAINTIES – APPROACH 1 – ADDITION AND SUBTRACTION

$$U_{total} = \frac{\sqrt{(U_1 \bullet x_1)^2 + (U_2 \bullet x_2)^2 + \ldots + (U_n \bullet x_n)^2}}{|x_1 + x_2 + \ldots + x_n|}$$

***x_i*: CO_2e**

Combining uncertainty: Approach 1 [4]

Linear Error Propagation (LEP)

Hands-on exercises

Combining uncertainty: Approach 1 [5]

Linear Error Propagation (LEP)

AD x EF

EQUATION 3.1
COMBINING UNCERTAINTIES – APPROACH 1 – MULTIPLICATION

$$U_{total} = \sqrt{U_1^2 + U_2^2 + \ldots + U_n^2}$$

U_i: relative

Example: CO_2 emissions due to fuel consumption

$E = C \times EF$

Gasoil consumption = 18 710 GJ

$E = 18\,710\ [GJ] \times 0.0741\ [\frac{t}{GJ}] = 1\,386\ tCO_2$

Uncertainty in activity data: 10%

Uncertainty in emission factor: 2%

(kg of greenhouse gas per TJ on a Net Calorific Basis)

Fuel	CO_2		
	Default Emission Factor	Lower	Upper
Gas/Diesel Oil	74 100	72 600	74 800

$\frac{[72\,600 - 74\,100]}{74\,100}$ $\frac{[74\,800 - 74\,100]}{74\,100}$

2%   **1%**

Uncertainty in emissions = $\sqrt{10^2 + 2^2} = 10.2\% \sim 10\%$

U = $\sqrt{0.1^2 + 0.02^2} = 0.102 = 10.2\% \sim 10\%$

Combining uncertainty: Approach 1 [6]

Linear Error Propagation (LEP)

AD x EF

EQUATION 3.1
COMBINING UNCERTAINTIES – APPROACH 1 – MULTIPLICATION

$$U_{total} = \sqrt{U_1^2 + U_2^2 + \ldots + U_n^2}$$

U_i: relative

Example: CO_2 emissions due to fuel consumption

$E = C \times \delta \times NCV \times EF$

C: Gasoil consumption = 500 m^3

δ: Density = 0.87 t/m^3

$E = 500 \times 0.87 \times 43.0 \times 0.0741 = 1\ 386\ tCO_2$

Uncertainty in activity data: 5%

Uncertainty in density: 5%

Uncertainty in emission factor: 2%

Uncertainty in NCV: 4%

(kg of greenhouse gas per TJ on a Net Calorific Basis)

Fuel	CO_2 Default Emission Factor	CO_2 Lower	CO_2 Upper
Gas/Diesel Oil	74 100	72 600	74 800
		2%	1%

TABLE 1.2
DEFAULT NET CALORIFIC VALUES (NCVS) AND LOWER AND UPPER LIMITS OF THE 95% CONFIDENCE INTERVALS [1]

Fuel type English description	Net calorific value (TJ/Gg)	Lower	Upper
Gas/Diesel Oil	43.0	41.4	43.3
		$\frac{[41.4 - 43.0]}{43.0}$	$\frac{[41.4 - 43.0]}{43.0}$
		4%	1%

Uncertainty in emissions= $\sqrt{5^2 + 5^2 + 4^2 + 2^2} = 8\%$

Combining uncertainty: Approach 1 [7]

Linear Error Propagation (LEP)

AD x EF

EQUATION 3.1
COMBINING UNCERTAINTIES – APPROACH 1 – MULTIPLICATION

$$U_{total} = \sqrt{U_1^2 + U_2^2 + \ldots + U_n^2}$$

U_i: relative

$$\sigma_f^2 = \left|\frac{\partial f}{\partial a}\right|^2 \sigma_a^2 + \left|\frac{\partial f}{\partial b}\right|^2 \sigma_b^2 \qquad \mathbf{U} = \sqrt{4u_b^2 + u_{EF}^2}$$

Examples: enteric fermentation, transportation, waste treatment

$$E = DE^2 \times EF \;\rightarrow\; E = DE \times DE \times EF \;\rightarrow\; \mathbf{U} = \sqrt{u_b^2 + u_b^2 + u_{EF}^2}$$

$$E = \frac{D \times EF}{\eta} \;\rightarrow\; E = D \times EF \times SC \;\rightarrow\; \mathbf{U} = \sqrt{u_B^2 + u_{EF}^2 + u_{SC}^2}$$

$$E = DDOC \times e^{-k} \;\rightarrow\; \sigma_f^2 = \left|\frac{\partial f}{\partial a}\right|^2 \sigma_a^2 + \left|\frac{\partial f}{\partial b}\right|^2 \sigma_b^2 \;\rightarrow\; \mathbf{U} = \sqrt{u_{DDOC}^2 + (u_k \times k)^2}$$

WOW! It was useful! :)

Combining uncertainty: Approach 1 [8]

Linear Error Propagation (LEP)

E1 + E2 + … + En

EQUATION 3.2

COMBINING UNCERTAINTIES – APPROACH 1 – ADDITION AND SUBTRACTION

$$U_{total} = \frac{\sqrt{(U_1 \bullet x_1)^2 + (U_2 \bullet x_2)^2 + \ldots + (U_n \bullet x_n)^2}}{|x_1 + x_2 + \ldots + x_n|}$$

x_i: CO_2e

Example: CO_2 emissions due to vent and flare

$E = E_{vent} + E_{flare}$

E_{vent} = 7 310 tCO_2e

E_{flare} = 5 282 tCO_2e

$E = 7\,310 + 5\,282 = 12\,592\ tCO_2e$

Uncertainty in vent emissions: 40% ($\pm$ 2 924)

Uncertainty in flare emissions: 10% ($\pm$ 528)

Uncertainty in emissions = $\frac{\sqrt{(0.4 \times 7\,310)^2 + (0.1 \times 5\,282)^2}}{|12\,592|}$

Uncertainty in emissions = $\frac{\sqrt{(2\,924)^2 + (528)^2}}{|12\,592|}$ **= 24%**

Combining uncertainty: Approach 1 [9]

Linear Error Propagation (LEP)

E1 + E2 + … + En

EQUATION 3.2

COMBINING UNCERTAINTIES – APPROACH 1 – ADDITION AND SUBTRACTION

$$U_{total} = \frac{\sqrt{(U_1 \bullet x_1)^2 + (U_2 \bullet x_2)^2 + \ldots + (U_n \bullet x_n)^2}}{|x_1 + x_2 + \ldots + x_n|}$$

x_i: CO_2e

Example: adding multiple emission sources

$$E = E_1 + E_2 + E_3 + E_4 + E_5$$

$$U_E = \frac{\sqrt{(0.4\times200)^2+(0.3\times500)^2+(0.1\times300)^2+(0.8\times100)^2+(0.2\times800)^2}}{|19\ 000|} = 13\%$$

E_1 = 200 tCO_2e ± 40%
E_2 = 500 tCO_2e ± 30%
E_3 = 300 tCO_2e ± 10%
E_4 = 100 tCO_2e ± 80%
E_5 = 800 tCO_2e ± 20%

E = 1 900 tCO_2e

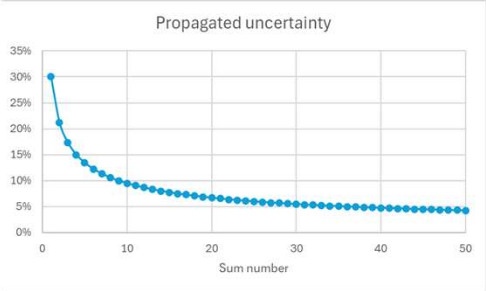
Contribution to uncertainty

$$\frac{(U_i \times E_i)^2}{\sum(U_i \times E_i)^2}$$

=> 10%
=> 36%
=> 1%
=> 10%
=> 41%

Contribution to variance

$$\frac{(U_i \times E_i)^2}{(\sum E_i)^2}$$



Addition reduces overall uncertainty

Combining uncertainty: Approach 1 [10]

Linear Error Propagation (LEP)

E1 + E2 + … + En

EQUATION 3.2

COMBINING UNCERTAINTIES – APPROACH 1 – ADDITION AND SUBTRACTION

$$U_{total} = \frac{\sqrt{(U_1 \bullet x_1)^2 + (U_2 \bullet x_2)^2 + \ldots + (U_n \bullet x_n)^2}}{|x_1 + x_2 + \ldots + x_n|}$$

x_i: CO_2e

Example: subtracting

$E = E_1 - E_2$

E_1 = 500 tCO_2e ± 30%
E_2 = 100 tCO_2e ± 20%

$$U_E = \frac{\sqrt{(0.3\times500)^2+(0.2\times100)^2}}{|400|} = 38\%$$

Subtraction increases overall uncertainty!

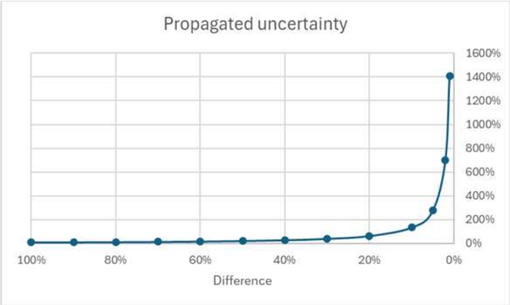
E = 400 tCO_2e

IF
E_1 = 500 tCO_2e ± 30%
E_2 = 400 tCO_2e ± 20%

$$U_E = \frac{\sqrt{(0.3\times500)^2+(0.2\times400)^2}}{|100|} = 170\%$$

E = 100 tCO_2e

Careful if similar values!



Combining uncertainty: Approach 1 [11]

Linear Error Propagation (LEP)

AD x EF

EQUATION 3.1

COMBINING UNCERTAINTIES – APPROACH 1 – MULTIPLICATION

$$U_{total} = \sqrt{U_1^2 + U_2^2 + \ldots + U_n^2}$$

U_i: relative

E1 + E2 + … + En

EQUATION 3.2

COMBINING UNCERTAINTIES – APPROACH 1 – ADDITION AND SUBTRACTION

$$U_{total} = \frac{\sqrt{(U_1 \bullet x_1)^2 + (U_2 \bullet x_2)^2 + \ldots + (U_n \bullet x_n)^2}}{|x_1 + x_2 + \ldots + x_n|}$$

x_i: CO_2e

Example: combining Eq 3.1 and 3.2

Source	Emission (tCO_2e)	Uncertainty in AD U_{AD}	Uncertainty in EF U_{EF}	Combined uncertainty Ui $\sqrt{(U_{AD}^2+U_{EF}^2)}$	Contribution to variance $\frac{(Ui \times Ei)^2}{(\sum Ei)^2}$
a	100	3%	5%	5.8%	0.14%
b	5	3%	75%	75.1%	0.06%
c	28	3%	45%	45.1%	0.65%
d	3.2	3%	100%	100.0%	0.04%
e	21	3%	10%	10.4%	0.02%
	157.2				0.90%
					9%

Combining uncertainty: Approach 1 [12]

Linear Error Propagation (LEP)

Enter Emissions Data

Data Calculated using simple equations

TABLE 3.2 APPROACH 1 UNCERTAINTY CALCULATION												
A	B	C	D	E	F	G	H	I	J	K	L	M
IPCC category	Gas	Base year emissions or removals	Year *t* emissions or removals	Activity data uncertainty	Emission factor / estimation parameter uncertainty	Combined uncertainty	Contribution to Variance by Category in Year *t*	Type A sensitivity	Type B sensitivity	Uncertainty in trend in national emissions introduced by emission factor / estimation parameter uncertainty	Uncertainty in trend in national emissions introduced by activity data uncertainty	Uncertainty introduced into the trend in total national emissions
		Input data	Input data	Input data Note A	Input data Note A	$\sqrt{E^2+F^2}$	$\frac{(G \bullet D)^2}{(\sum D)^2}$	Note B	$\left\lvert\frac{D}{\sum C}\right\rvert$	$I \bullet F$ Note C	$J \bullet E \bullet \sqrt{2}$ Note D	K^2+L^2
		Gg CO_2 equivalent	Gg CO_2 equivalent	%	%	%		%	%	%	%	%
E.g., 1.A.1. Energy Industries Fuel 1	CO_2											
E.g., 1.A.1. Energy Industries Fuel 2	CO_2											
Etc...	…											
Total		$\sum C$	$\sum D$				$\sum H$					$\sum M$
					Percentage uncertainty in total inventory:		$\sqrt{\sum H}$				Trend uncertainty:	$\sqrt{\sum M}$

Enter Uncertainties

AD uncertainties based on source of data

EF uncertainties based on data used

List of source/sinks

Approach 1 uncertainty calculation

A	B	C	D	E	F	G	H	I	J	K	L	M
IPCC category	Gas	Base year emissions or removals	Year *t* emissions or removals	Activity data uncertainty	Emission factor / estimation parameter uncertainty	Combined uncertainty	Contribution to Variance by Category in	Type A sensitivity	Type B sensitivity	Uncertainty in trend in national	Uncertainty in trend in national	Uncertainty introduced into the trend in total national emissions
		Input data	Input data	Input data	Input data	$\sqrt{E^2+F^2}$	$\frac{(G\bullet D)^2}{(\sum D)^2}$	Note B	$\frac{D}{\sum C}$	$I\bullet F$	$J\bullet E\bullet\sqrt{2}$	K^2+L^2
		Gg CO_2 equivalent	Gg CO_2 equivalent	%	%	%		%	%	%	%	%
1.A.1. Energy Industries	CH4	35.5346662	32.9951217	5	25	25.50	0.0	3.20506E-05	0.00010495	0.000801264	0.000742109	1.19275E-06
1.A.2. Manufacturing Industries and Constructior	CH4	57.0302899	51.8776096	5	25	25.50	0.0	4.80131E-05	0.000165011	0.001200328	0.001166804	2.80222E-06
1.A.3. Transport	CH4	81.7067834	37.1466612	5	25	25.50	0.0	-4.94664E-05	0.000118155	-0.00123666	0.000835483	2.22736E-06
1.A.4. Other Sectors	CH4	1041.24025	428.554682	5	25	25.50	0.0	-0.000772946	0.001363136	-0.019323647	0.009638828	0.00046631
1.A.5. Other	CH4	330.338228	97.5658895	5	25	25.50	0.0	-0.000367351	0.000310335	-0.009183772	0.002194401	8.91571E-05
1.B.1. Solid Fuels	CH4	24867.6834	12364.38	10	25	26.93	2.7	-0.011678579	0.039328314	-0.291964463	0.556186352	0.394586505
1.B.2. Oil and Natural Gas	CH4	12570.348	4022.34735	10	25	26.93	0.3	-0.012988732	0.012794183	-0.324718297	0.180937071	0.138180196
2.B. Chemical Industry .	CH4	40.53	37.5018	10	25	26.93	0.0	3.61373E-05	0.000119285	0.000903433	0.001686942	3.66196E-06
4.A. Enteric Fermentation.	CH4	14054.9863	7346.85	15	30	33.54	1.5	-0.005462727	0.023368679	-0.163881819	0.495724537	0.272600067
4.B. Manure Management.	CH4	1903.28061	1199.63088	15	30	33.54	0.0	-8.88245E-05	0.003815756	-0.002664735	0.080944413	0.006559099
4.C. Rice Cultivation.	CH4	522.9	338.94	10	30	31.62	0.0	5.3609E-06	0.001078092	0.000160827	0.015246523	0.000232482
4.F. Field Burning of Agricultural Residues.	CH4	64.3314	[illegible]	[illegible]	[illegible]	[illegible]	0.0	-1.24107E-05	0.000119565	-0.000372321	0.003381819	1.15753E-05
6.A. Solid Waste Disposal on Land.	CH4	1959.72	[illegible]	[illegible]	[illegible]	[illegible]	0.4	0.00787088	0.011891742	0.236126385	0.252261939	0.119391756
6.B. Wastewater Handling.	CH4	787.08	[illegible]	[illegible]	[illegible]	[illegible]	0.0	0.000761896	0.002376612	0.022856865	0.050415547	0.003064164
1.A.1. Energy Industries	CO2	102607.31	[illegible]	[illegible]	[illegible]	[illegible]	11.2	0.094441853	0.305249301	0.472209267	2.158438506	4.881838378
1.A.2. Manufacturing Industries and Constructior	CO2	33991.06	[illegible]	[illegible]	5	7.07	1.1	0.02618491	0.095945987	0.130924551	0.678440577	0.477422855
1.A.3. Transport	CO2	23987.07	[illegible]	5	5	7.07	0.1	-0.022453294	0.026739124	-0.11226647	0.189074157	0.048352797
1.A.4. Other Sectors	CO2	47532.52	11784.04	5	5	7.07	0.2	-0.053800014	0.037482383	-0.269000072	0.265040472	0.14260749
1.A.5. Other	CO2	8370.16	4124.19	5	5	7.07	0.0	-0.004052209	0.013118122	-0.020261045	0.092759127	0.009014766
1.B.2. Oil and Natural Gas	CO2	3408.21	5171.49583	10	15	18.03	0.2	0.009456387	0.016449366	0.141845811	0.232629165	0.074236563
2.A. Mineral Products.	CO2	5744.63	2507.20146	10	15	18.03	0.0	-0.003809586	0.007974844	-0.057143788	0.112781331	0.015985041
2.B. Chemical Industry .	CO2	1355.56	171.93456	10	15	18.03	0.0	-0.002233954	0.000546885	-0.033509311	0.007734125	0.001182691
2.C. Metal Production.	CO2	12932.6799	10507.4715	10	15	18.03	0.9	0.006887639	0.033421905	0.103314586	0.47265712	0.234078657
5.A. Changes in Forest and Other Woody Bioma	CO2	97.19		50	80	94.34	0.0	-0.000199385	0	-0.015950798	0	0.000254428
5.A. Changes in Forest and Other Woody Bioma	CO2	-7810.79	-7721.7341	50	80	94.34	12.9	-0.008539362	0.024561101	-0.683148991	1.736732102	3.482930938
5.B. Forest and Grassland Conversion.	CO2	6.26	280.43888	25	75	79.06	0.0	0.00087917	0.000892013	0.065937785	0.031537424	0.005342401
1.A.1. Energy Industries	N2O	388.516902	328.741673	5	50	50.25	0.0	0.000248607	0.001045653	0.012430334	0.007393886	0.000209183
1.A.2. Manufacturing Industries and Constructior	N2O	112.709781	114.844426	5	50	50.25	0.0	0.000134069	0.000365294	0.006703468	0.002583021	5.16085E-05
1.A.3. Transport	N2O	57.3319301	21.6195922	5	50	50.25	0.0	-4.88495E-05	6.87671E-05	-0.002442474	0.000486257	6.20212E-06
1.A.4. Other Sectors	N2O	194.497577	46.1816455	5	50	50.25	0.0	-0.000252117	0.000146893	-0.01260587	0.001038693	0.000159987
1.A.5. Other	N2O	27.4386549	13.5195061	5	50	50.25	0.0	-1.3288E-05	4.30025E-05	-0.000664398	0.000304074	5.33886E-07
4.B. Manure Management.	N2O	375.1	198.4	15	30	33.54	0.0	-0.000138451	0.000631066	-0.004153541	0.013386927	0.000196462
4.D. Agricultural Soils(2).	N2O	25217.694	9798.17	20	30	36.06	3.0	-0.020551916	0.031165777	-0.616557485	0.881501284	1.157187646
4.F. Field Burning of Agricultural Residues.	N2O	24.304	21.297	20	30	36.06	0.0	1.78812E-05	6.7741E-05	0.000536437	0.001916004	3.95884E-06
6.B. Wastewater Handling.	N2O	452.6	384.4	15	30	33.54	0.0	0.000294175	0.00122269	0.008825264	0.025937172	0.000750622
Keep Blank!	…									0		
Total		314388.7626	202771.1719			$\sum H$	34.6				$\sum M$	11.4670044
					Percentage uncertainty in total inventory:		5.880740472				Trend uncertainty:	3.386296561

Combining uncertainty: Approach 1 [14]

Linear Error Propagation (LEP)

AD x EF

EQUATION 3.1
COMBINING UNCERTAINTIES – APPROACH 1 – MULTIPLICATION

$$U_{total} = \sqrt{U_1^2 + U_2^2 + \ldots + U_n^2}$$

***U_i*: relative**

E1 + E2 + … + En

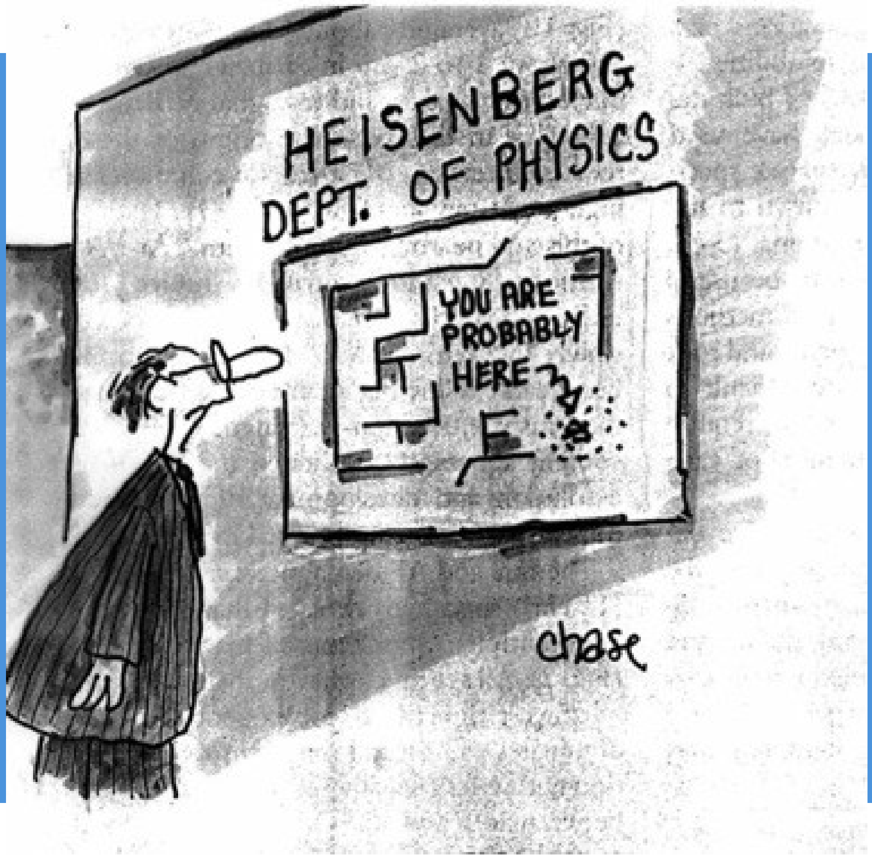
EQUATION 3.2
COMBINING UNCERTAINTIES – APPROACH 1 – ADDITION AND SUBTRACTION

$$U_{total} = \frac{\sqrt{(U_1 \bullet x_1)^2 + (U_2 \bullet x_2)^2 + \ldots + (U_n \bullet x_n)^2}}{|x_1 + x_2 + \ldots + x_n|}$$

***x_i*: CO_2e**

Bonus track!: one way of dealing with asymmetric uncertainties

Source	Emission (tCO_2e)	Uncertainty in AD U_{AD}	Uncertainty in EF (-) U_{EF}	Uncertainty in EF (+)	Combined uncertainty Ui (-) $\sqrt{(U_{AD}^2+U_{EF}^2)}$	Combined uncertainty Ui (+)	Contribution to variance (-) $\frac{(Ui \times Ei)^2}{(\Sigma Ei)^2}$	Contribution to variance (+)
a	100	3%	-5%	5%	6%	6%	0.1%	0.1%
b	5	3%	-50%	100%	50%	100%	0.0%	0.1%
c	28	3%	-30%	60%	30%	60%	0.3%	1.1%
d	3.2	3%	-100%	900%	100%	900%	0.0%	3.4%
e	21	3%	-10%	10%	10%	10%	0.0%	0.0%
	157.2						**0.5%**	**4.8%**
							-7%	**22%**



End of day 3

Thank you!

Diego M. Ezcurra

MONDAY

2. Overview of Uncertainty Analysis in National GHG Inventories
3. Causes of uncertainties associated with input data used in National GHG Inventories
4. How to reduce the uncertainty associated with input data used in National GHG Inventories

TUESDAY

5. Uncertainty associated with the use of national statistics, surveys, censuses and sampling
6. Uncertainty associated with the Use of Empirical Data

WEDNESDAY

7. Methods to combine uncertainties: Approach 1

Propagation of errors

THURSDAY

8. Methods to combine uncertainties: Approach 2

Monte Carlo simulation

60%

8

Session 8. Methods to combine uncertainties: Approach 2 Monte Carlo simulation

By the end of this session, you will:

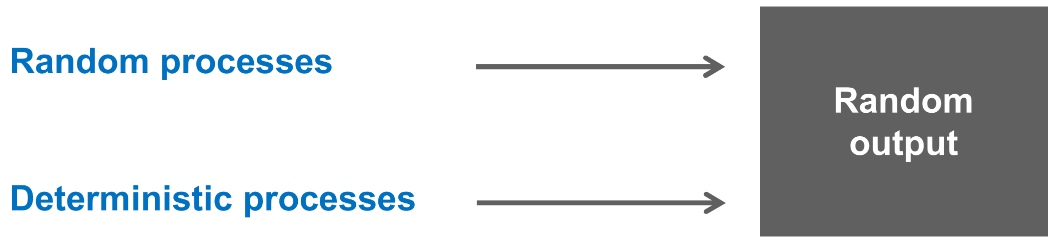
1. Understand the basics of the simulation
2. Learn how to select probability density functions
3. Identify typical problems and avoid misinterpretation
4. Understand how to deal with correlation

Learning objectives

Combining uncertainty: Approach 2 [1]

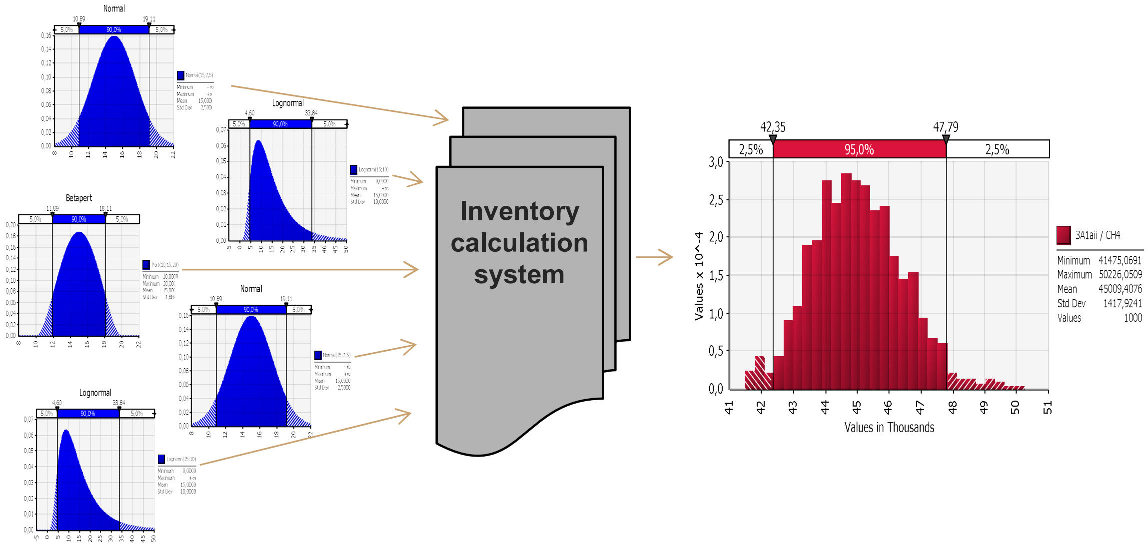
Monte Carlo Simulation (MCS)

Numerical simulation method, nondeterministic, which simulates the behavior of a random static system where input parameters are defined by a known Probability Density Function.



Combining uncertainty: Approach 2 [2]

Monte Carlo Simulation (MCS)



Applicable even if:

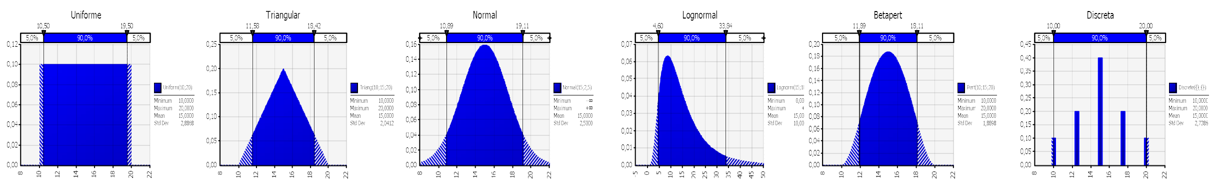
- **Large std. dev.**
- **Skewed distributions**
- **Correlated variables**
- **Complex equations**

Combining uncertainty: Approach 2 [3]

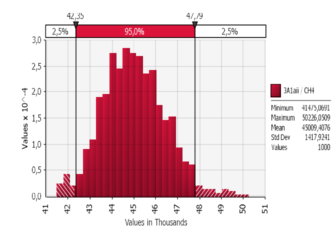
Monte Carlo Simulation (MCS)

Steps

1. Build the calculation model in which uncertainty needs to be evaluated
2. Identify relevant key variables ⟶ Sensitivity
3. Establish the **Probability Distribution Functions** for each of the inputs identified and obtain the parameters to define them



4. Run the simulation
5. Obtain the PDF of the result and determine uncertainty as the 95% CI.



Mean = 100

Standard deviation = 15

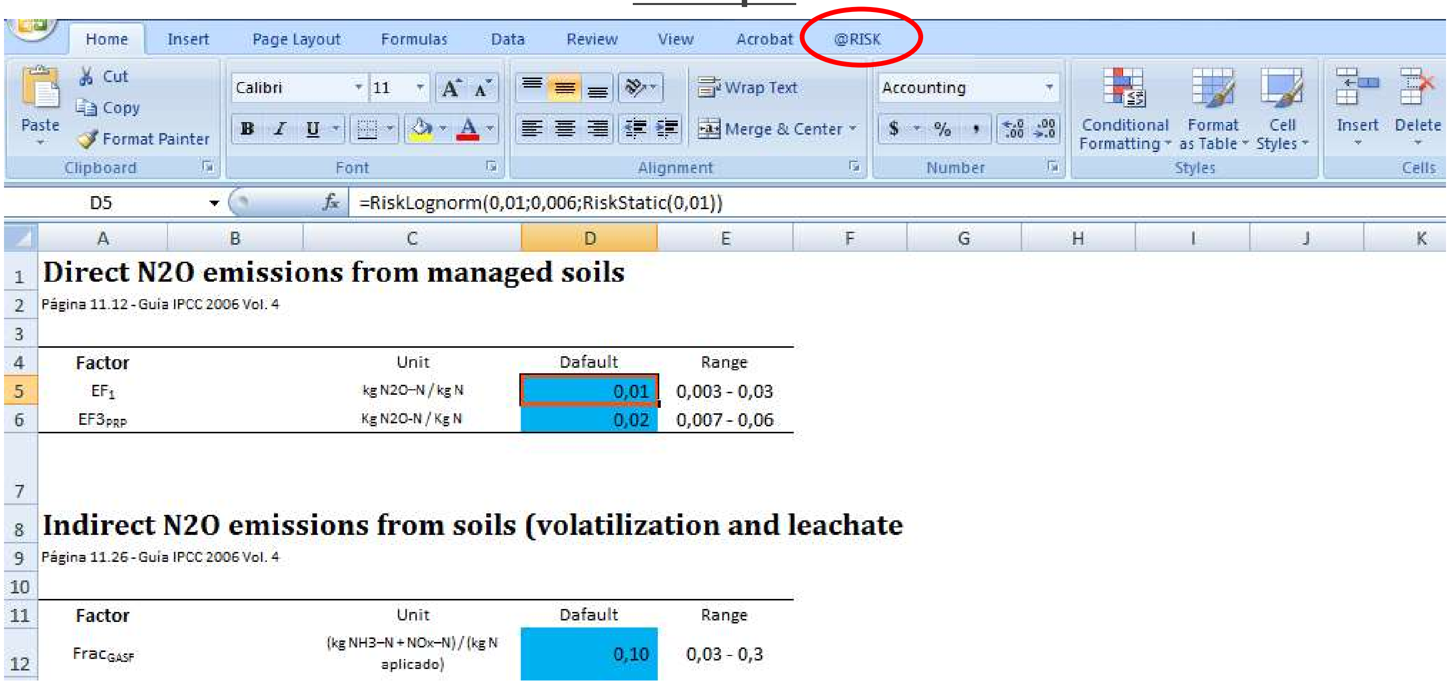
Uncertainty = 30%

CI = [70 ; 130]

Combining uncertainty: Approach 2 [4]

Monte Carlo Simulation (MCS)

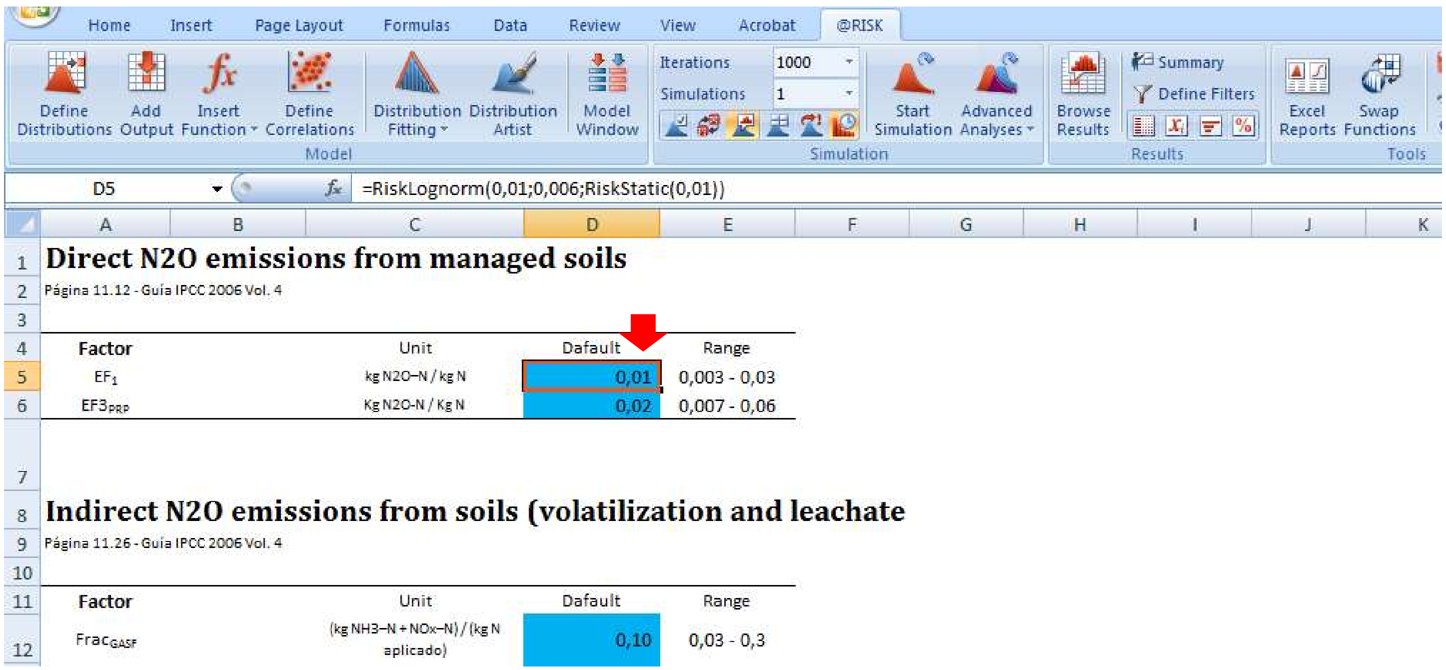
Example



Combining uncertainty: Approach 2 [5]

Monte Carlo Simulation (MCS)

Example



Direct N2O emissions from managed soils

Página 11.12 - Guía IPCC 2006 Vol. 4

Factor	Unit	Dafault	Range
EF_1	kg N2O–N / kg N	0,01	0,003 - 0,03
$EF3_{PRP}$	Kg N2O-N / Kg N	0,02	0,007 - 0,06

Indirect N2O emissions from soils (volatilization and leachate

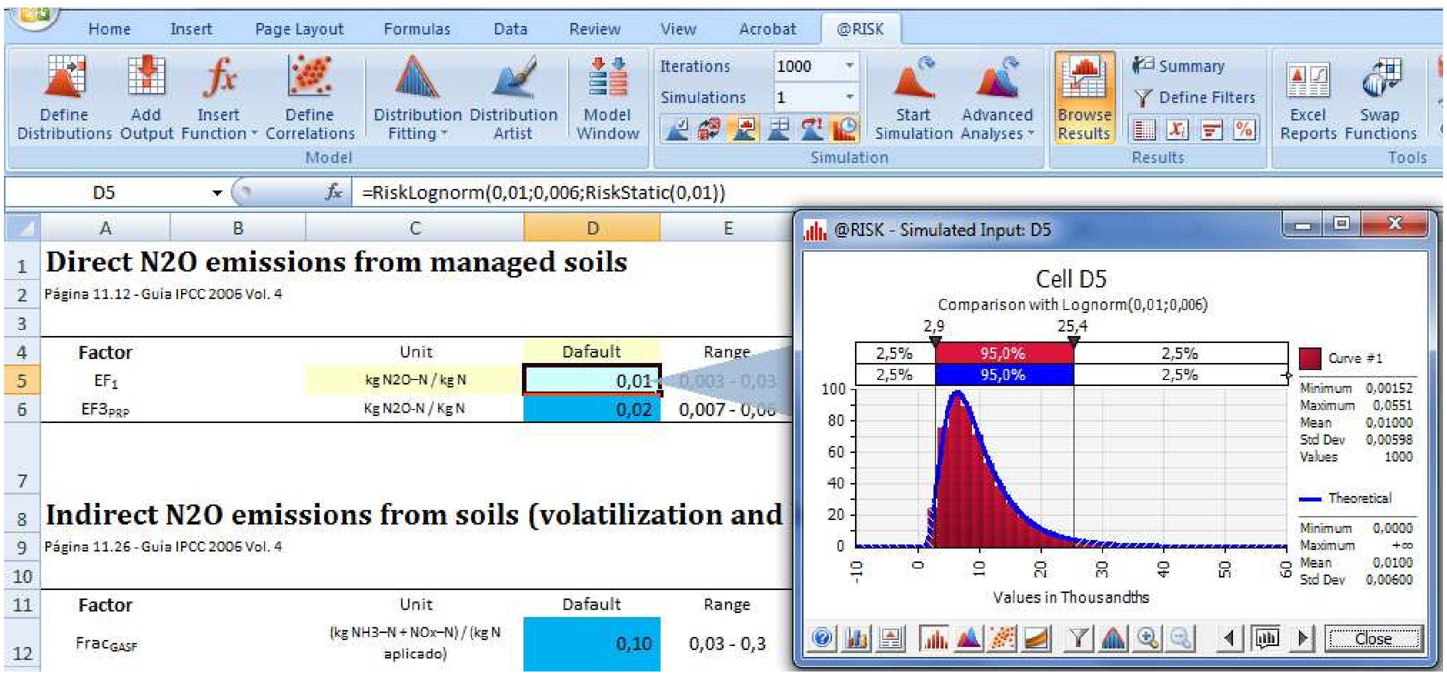
Página 11.26 - Guía IPCC 2006 Vol. 4

Factor	Unit	Dafault	Range
$Frac_{GASF}$	(kg NH3–N + NOx–N) / (kg N aplicado)	0,10	0,03 - 0,3

Combining uncertainty: Approach 2 [6]

Monte Carlo Simulation (MCS)

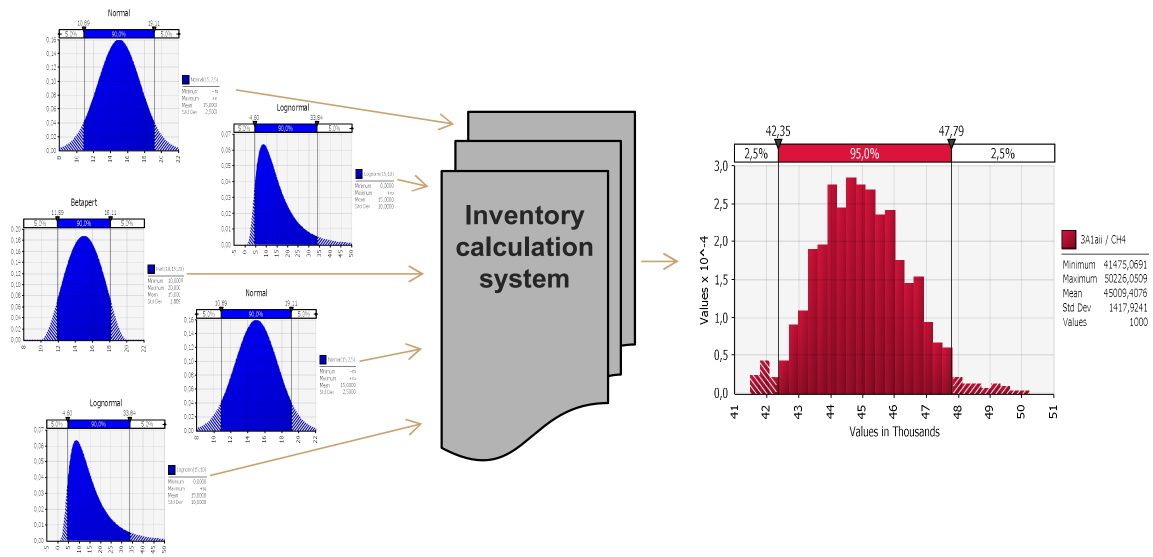
Example



Combining uncertainty: Approach 2 [7]

Monte Carlo Simulation (MCS)

Example



Combining uncertainty: Approach 2 [8]

Monte Carlo Simulation (MCS)

GOOD PRACTICE GUIDANCE FOR SELECTING PROBABILITY DENSITY FUNCTIONS

V1_Ch3. 3.2.2.4

2006 IPCC Guidelines

Recommendations for different cases and commonly applied criteria to follow

Combining uncertainty: Approach 2 [9]

Monte Carlo Simulation (MCS)

Domain (+, -, ∞)

Range (narrow or broad)

Shape (symmetry)

Underlying process (+, x)

Others

Combining uncertainty: Approach 2 [10]

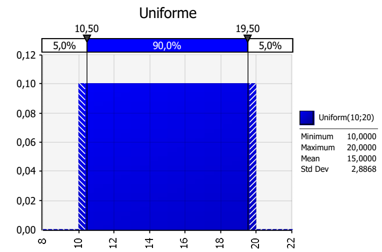
Selecting PDF

Most used PDF

Combining uncertainty: Approach 2 [11]

Selecting PDF

Uniform



All values with same probability

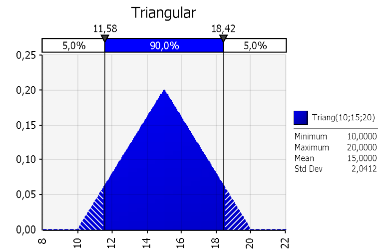
Parameters: Uniform (**min**, **max**)

Application to inventories: large uncertainty and lack of information

Combining uncertainty: Approach 2 [12]

Selecting PDF

Triangular



Intuitive and flexible.

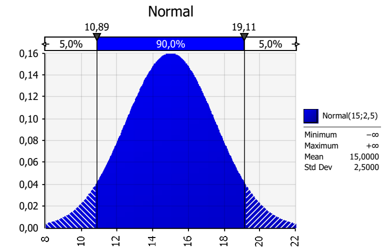
Parameters: Triang (***min, mean, max***)

Application to inventories: expert judgment, knowledge from experience. Limited information.

Combining uncertainty: Approach 2 [13]

Selecting PDF

Normal



Distribution around a most likely central value.

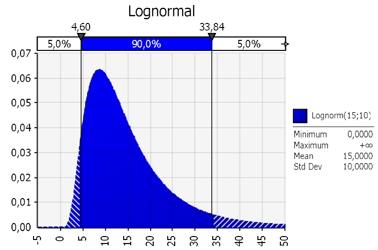
Parameters: Normal (***mean [μ], std. Dev. [σ]***)

Application to inventories: most of situations (central limit). Additive processes.

The interval +/- 2*σ (1.96) accounts for approx. 95% of the values.
σ may be estimated as: (max - mean) / 2

Combining uncertainty: Approach 2 [14]

Selecting PDF



Lognormal

The natural logarithm of the variable adjusts to a Normal distribution

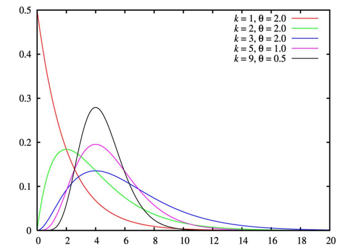
Parameters: Lognormal (***mean [μ], std. Dev. [σ]***)

Application to inventories: Generally good representation for skewed non-negative values (emission factors for N_2O). Multiplicative processes.

Combining uncertainty: Approach 2 [15]

Selecting PDF

Gamma



Similar to lognormal but with not so heavy tails

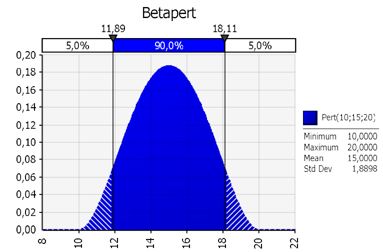
Parameters: Gamma (***shape [k], scale [θ]***)

Application to inventories: Good representation for skewed values. Very flexible depending on its parameters. Mean value: $k.\theta$

Combining uncertainty: Approach 2 [16]

Selecting PDF

Beta pert



Version of the Beta using PERT (Program Evaluation and Review Technique).

Parameters: BetaPert (***min, mean, max***)

Application to inventories: similar to triangular but with lower standard deviation.

Combining uncertainty: Approach 2 [17]

Selecting PDF - Good practice guidance

- The minimum number of probability functions are used
- These probability functions are well known and well based (theoretical or empirical)
- Where empirical data are available, the first choice should be to assume a normal distribution
- If the variable must be non-negative and a normal distribution is assumed, the standard deviation should not exceed 30%
- Truncation of the negative tail of the normal distribution should be avoided (use instead lognormal, Weibull, or Gamma).

Combining uncertainty: Approach 2 [18]

Selecting PDF - Good practice guidance

- Where expert judgment is used, the distribution function adopted might be normal or lognormal, supplemented by uniform or triangular distributions
- If only the interval is known (upper and a lower value), assume that the probability density function is uniform and that the range corresponds to the 95% confidence interval
- If the distribution observed based on data does not seem correct, the data may be the problem (not representative, not random, small sample size, different timing, etc.)

Combining uncertainty: Approach 2 [19]

Selecting PDF - Good practice guidance

- When selecting the PDF from Goodness-of-Fit test, several functions will fit the data satisfactorily within a given probability limit
- Different functions can have radically different distributions at the extremes (few or no data to constrain them), and the choice of one function over another can systematically change the outcome of an uncertainty analysis.

"it must be knowledge of the underlying physical processes that governs the choice of a probability function"

Combining uncertainty: Approach 2 [20]

DEPENDENCE AND CORRELATION AMONG INPUTS

Dependence / Correlation

Relationship between two variables that make them not independent

One variable is determined (partially or totally) by another one

Combining uncertainty: Approach 2 [21]

DEPENDENCE AND CORRELATION AMONG INPUTS

Dependence / Correlation

Negative

Reduces uncertainty range when included

If not included: overestimation of uncertainty

Positive

Increases uncertainty range when included

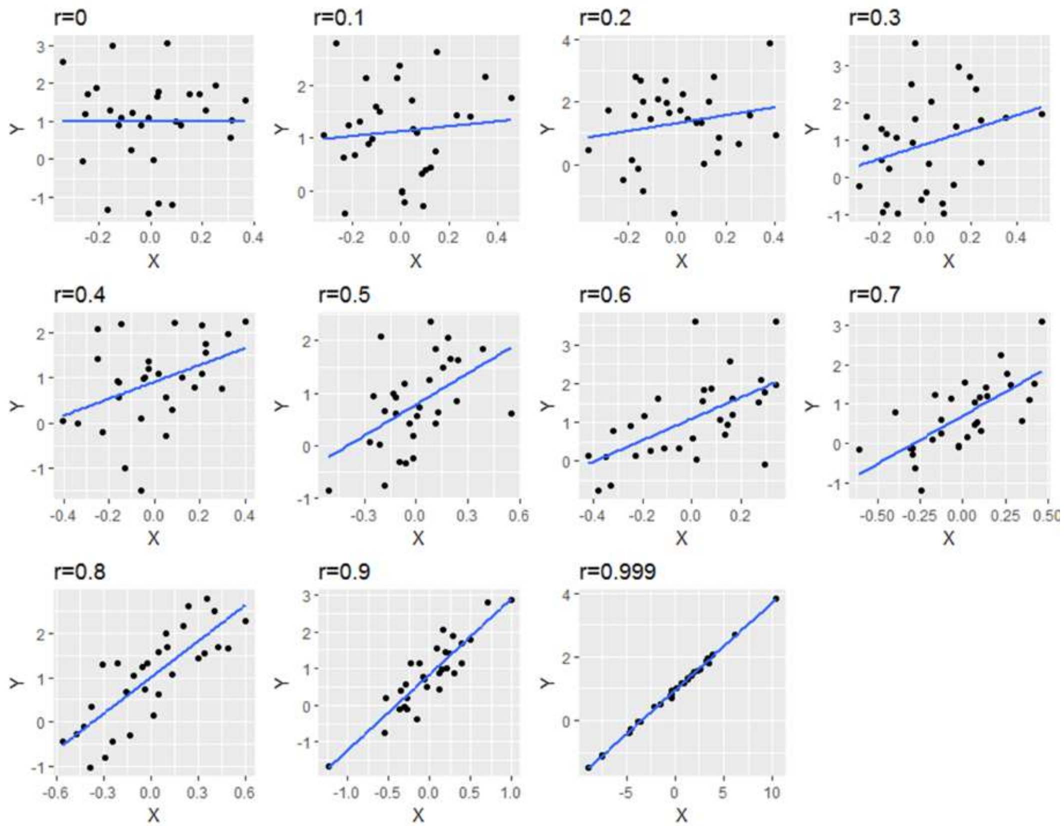
If not included: underestimation of uncertainty

Combining uncertainty: Approach 2 [22]

DEPENDENCE AND CORRELATION AMONG INPUTS

Combining uncertainty: Approach 2 [23]

DEPENDENCE AND CORRELATION AMONG INPUTS



Correlation degree

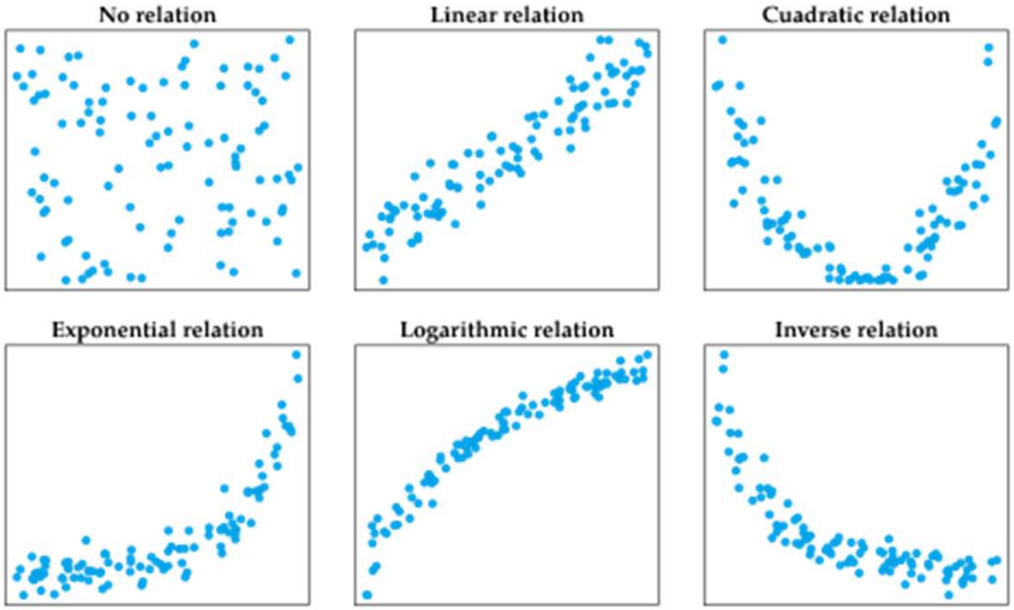
< 0.2	**Very low**
0.2 – 0.4	**Low**
0.4 – 0.6	**Moderate**
0.6 – 0.8	**High**
> 0.8	**Very high**

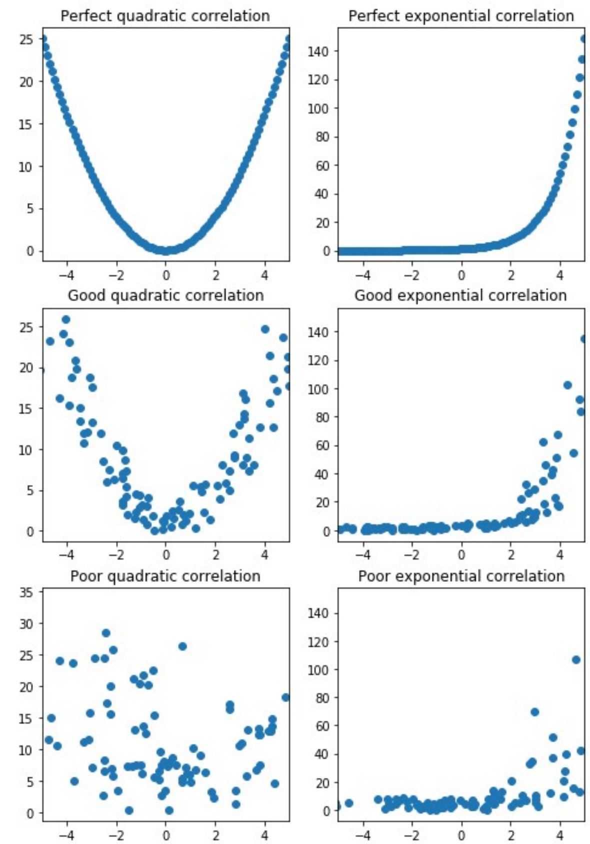
* Indicative ranges

Combining uncertainty: Approach 2 [24]

DEPENDENCE AND CORRELATION AMONG INPUTS

Attention! Non-linear correlation also exists





Combining uncertainty: Approach 2 [25]

DEPENDENCE AND CORRELATION AMONG INPUTS

$$E = \overbrace{FC \times NCV}^{\text{FC (GJ)}} \times EF$$

Are FC (GJ) and EF independent?

FC: Fuel consumption (tonnes)
NCV: Net calorific value (GJ/t)
EF: Emission factor (tCO_2/GJ)

$$EF = \frac{\%C}{NCV} x \frac{44}{12}$$

Are NCV and EF independent?

Combining uncertainty: Approach 2 [26]

DEPENDENCE AND CORRELATION AMONG INPUTS

Dependencies / Correlations

Are always important to uncertainty assessment?

Degree: strong or weak correlation (i.e. 0.8 or 0.2)

Sensitivity: impact to the overall uncertainty

Combining uncertainty: Approach 2 [27]

DEPENDENCE AND CORRELATION AMONG INPUTS

Exists between 2 variables to which uncertainty is NOT sensitive to and dependency is strong	Exists between 2 variables to which uncertainty is sensitive to and dependency is strong
Exists between 2 variables to which uncertainty is NOT sensitive to and dependency is weak	Exists between 2 variables to which uncertainty is sensitive to and dependency is weak

Combining uncertainty: Approach 2 [28]

DEPENDENCE AND CORRELATION AMONG INPUTS

Dependence / Correlation

Strategies

- Define the model so that the inputs are as statistically independent as possible
- Stratify or aggregate the category to minimise the dependency effect
- Model dependency explicitly
- Use sensitivity cases (independent, fully positive and fully negative correlated)

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End of day 4

Thank you!

Diego M. Ezcurra

MONDAY

2. Overview of Uncertainty Analysis in National GHG Inventories

3. Causes of uncertainties associated with input data used in National GHG Inventories

4. How to reduce the uncertainty associated with input data used in National GHG Inventories

TUESDAY

5. Uncertainty associated with the use of national statistics, surveys, censuses and sampling

6. Uncertainty associated with the Use of Empirical Data

WEDNESDAY

7. Methods to combine uncertainties: Approach 1

Propagation of errors

THURSDAY

8. Methods to combine uncertainties: Approach 2

Monte Carlo simulation

FRIDAY

9. Methods to combine uncertainties: Hybrid combinations of Approaches 1 and 2

10. Application of uncertainty estimates to identify areas for improvement – Approach 2 to identify key categories

11. Uncertainty associated with the use of proxy, splicing techniques and expert judgment to fill data gaps

80%

9

Session 9. Methods to combine uncertainties: Hybrid combinations of Approaches 1 and 2

By the end of this session, you will:

1. Understand how to combine approaches
2. Understand why it can efficiently improve results

Learning objectives

Combining uncertainty: Hybrid approach 1 and 2 [1]

Methods to combine uncertainties

Approach 1:

Linear Error Propagation

Approach 2:

Monte Carlo Simulation

Hybrid approach:

Linear Error Propagation with Monte Carlo Simulation

Identify categories that require more complex calculations, have high uncertainty ranges or where dependency is not negligible. Those cases can be propagated using Monte Carlo Simulations and the remaining categories can apply Linear Error Propagation.

Combining uncertainty: Hybrid approach 1 and 2 [2]

Linear Error Propagation (LEP)

1A1 - Energy industries		(2%)	1A: 1%	1 Energy: 2%
1A2 - Manufacturing industries		(3%)		
1A3 - Transport		(2%)		
1A4 - Other sectors		(2%)		
1B1 - Solid fuels	EF: Monte Carlo	(36%)	1B: 29%	
1B2 - Oil and natural gas		(30%)		

Combining uncertainty: Hybrid approach 1 and 2 [3]

Linear Error Propagation (LEP)

Category		Uncertainty	Subsector	Total
2A1 - Cement	EF: Monte Carlo	(3%)	2A - 9%	2 IPPU: 11%
2A2 - Lime		(30%)		
2A4 - Carbonates use		(10%)		
2B1 - Ammonia		(9%)	2B - 14%	
2B2 - Nitric acid		(40%)		
2B5 - Carbide		(11%)		
2B7 - Carbonates		(21%)		
2B8 - Petrochemical		(18%)		
2B9 - Fluorochemical		(50%)		
2C1 - Iron and steel	EF Monte Carlo	(33%)	2C - 28%	
2C2 - Ferrous allay		(56%)		
2C3 - Aluminum	EF: Monte Carlo	(10%)		
2C6 - Zinc		(56%)		
2D1 - Lubricant use		(52%)	2D - 50%	
2D2 - Paraffin wax use		(52%)		
2F4 - Aerosols		(50%)	2F - 50%	

Combining uncertainty: Hybrid approach 1 and 2 [4]

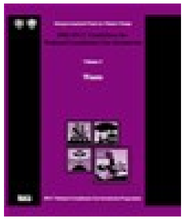
Linear Error Propagation (LEP)

Cattle and dairy cattle: Monte Carlo

3A1 - Enteric fermentation	(6%)	**3A - 5%**	**3 AFOLU: 18%**
3A2 - Manure management	(16%)		
3B1 - Forest land	(219%)	**3B - 57%**	
3B2 - Cropland	(89%)		
3B3 - Grassland	(20%)		
3B7 - Soil organic matter content	(93%)		
3C1 - Biomass burning	(12%)	**3C - 32%**	
3C3 - Urea application	(5%)		
3C4 - Direct N_2O emissions from managed soils	(43%)		
3C5 - Indirect N_2O emissions from managed soils	(62%)		
3C6 - Indirect N_2O emissions	(77%)		
3C7 - Rice cultivation	(115%)		

Combining uncertainty: Hybrid approach 1 and 2 [5]

Linear Error Propagation (LEP)



Monte Carlo Simulation

4A1 - Managed solid waste disposal (32%)
4A3 - Uncategorized solid waste disposal (50%)
4B - Solid waste biological treatment (79%)
4C1 - Waste incineration (64%)
4D1 - Domestic wastewater treatment (19%)
4D2 - Industrial wastewater treatment (76%)

4A - 29%
4B - 79%
4C - 64%
4D - 31%

4 Waste: 21%

Combining uncertainty: Hybrid approach 1 and 2 [6]

Linear Error Propagation (LEP)

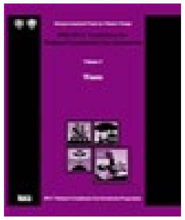
1 Energy: 2%

2 IPPU: 11%

National GHG Inventory

10%

3 AFOLU: 18%



4 Waste: 21%

10

Session 10. Application of uncertainty estimates to identify areas for improvement: Approach 2 to identify key categories

By the end of this session, you will:

1. Learn how to identify key categories
2. Understand why uncertainty can help with efficiency

Learning objectives

Key category analysis [1]

Key categories

Approach 1 Level	V1_Ch4 2006 IPCC Guidelines	Approach 2 Uncertainty

$$L_{x,t} = \frac{|E_{x,t}|}{\sum_y |E_{y,t}|}$$

Objective: to identify those categories that contribute the most to total inventory value.

“Hot spots” can be used to assign resources for improvement and identify mitigation alternatives.

$$LU_{x,t} = \frac{(L_{x,t} \times U_{x,t})}{\sum_y (L_{y,t} \times U_{y,t})}$$

Objective: to identify those categories that contribute the most to total inventory uncertainty.

“Hot spots” can be used to assign resources for improvement in data collection

Key category analysis [2]

Key categories

Approach 1
Level

V1_Ch4
2006 IPCC Guidelines

Approach 2
Uncertainty

$$L_{x,t} = \frac{|E_{x,t}|}{\sum_y |E_{y,t}|}$$

$$LU_{x,t} = \frac{(L_{x,t} \times U_{x,t})}{\sum_y (L_{y,t} \times U_{y,t})}$$

$$LU_{x,t} = \frac{(|E_{x,t}| \times U_{x,t})}{\sum_y (|E_{y,t}| \times U_{y,t})}$$

$$LU_{x,t} = \frac{|\Delta E_{x,t}|}{\sum_y |\Delta E_{y,t}|}$$

Key category analysis [3]

Key categories

Approach 1
Level

V1_Ch4

2006 IPCC Guidelines

Approach 2
Uncertainty

Emission Source	Emission (tCO_2e)	Absolute value of Emission (tCO_2e)	Level Li	Uncertainty Ui	Li x Ui	LUi $\frac{(Li \times Ui)}{\sum(Li \times Ui)}$	Cumulative LUi
E3	28	28	11%	50%	5.3%	28%	28%
E6	8	8	3%	100%	3.0%	16%	44%
E1	80	80	30%	8%	2.4%	13%	56%
E5	37	37	14%	15%	2.1%	11%	67%
E10	19	19	7%	25%	1.8%	9%	77%
E2	5	5	2%	75%	1.4%	7%	84%
E4	-15	15	6%	20%	1.1%	6%	90%
E9	3	3	1%	80%	0.9%	5%	95%
E7	21	21	8%	8%	0.6%	3%	98%
E8	49	49	18%	2%	0.4%	2%	100%
	235	**265**			**0.19**		

Sort high to low

90% cumulative

Key categories based on Level

11

Session 11. Uncertainty associated with the use of proxy, splicing techniques and expert judgment to fill data gaps

By the end of this session, you will:

1. Learn to solve data gaps with splicing techniques
2. Understand how to derive uncertainty for missing data
3. Learn how to derive uncertainty from expert judgement

Learning objectives

Proxy: Splicing techniques and Expert Judgement [1]

Splicing techniques for Data gaps

Data gaps

Periodic data	V1_Ch5 . 5.3 Resolving Data Gaps 2006 IPCC Guidelines	Changes and gaps in data availability

Data are available less frequently than annual or may not cover the entire country.
Estimates need to be updated each time new data becomes available.
New estimates should be extrapolated and then recalculated when new data become available

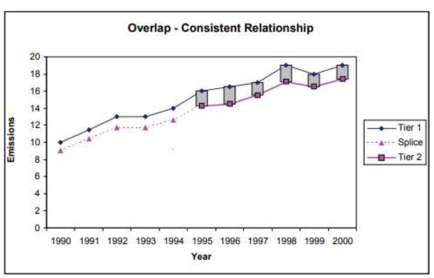
Changes in data collection systems or methodologies (improve or decrease or gaps)
Higher tier methods can be applied for recent years, but not for earlier years
Discontinuation of data sets or different definitions, classifications and levels of aggregation

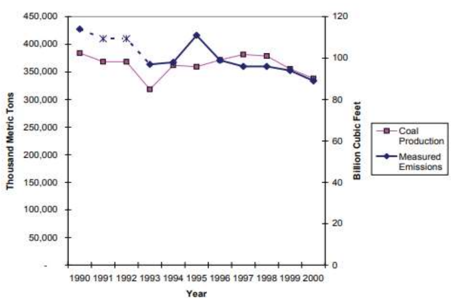
Splicing techniques

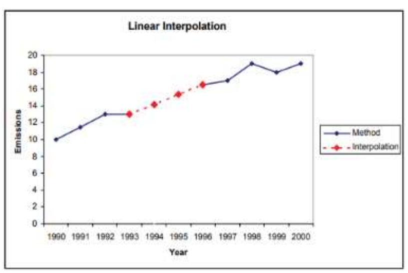
Proxy: Splicing techniques and Expert Judgement [2]

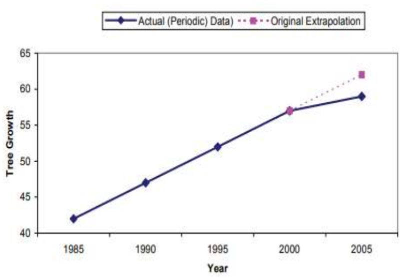
Splicing techniques for Data gaps

Overlap	Surrogate	Interpolation	Extrapolation
New method implemented not available before (or after)	No data for the category but other related available Ratios or regression	Data gap for some years or outliers identified	Data unavailable for last or first year





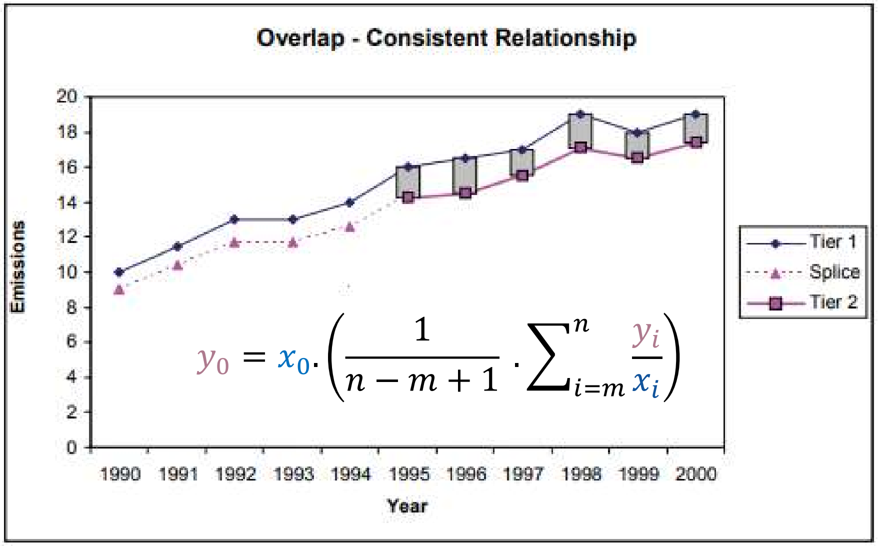




Proxy: Splicing techniques and Expert Judgement [3]

Splicing techniques for Data gaps

Overlap | Surrogate | Interpolation | Extrapolation



$$y_0 = x_0 \cdot \left(\frac{1}{n-m+1} \cdot \sum_{i=m}^{n} \frac{y_i}{x_i} \right)$$

New method implemented not available before (or after)

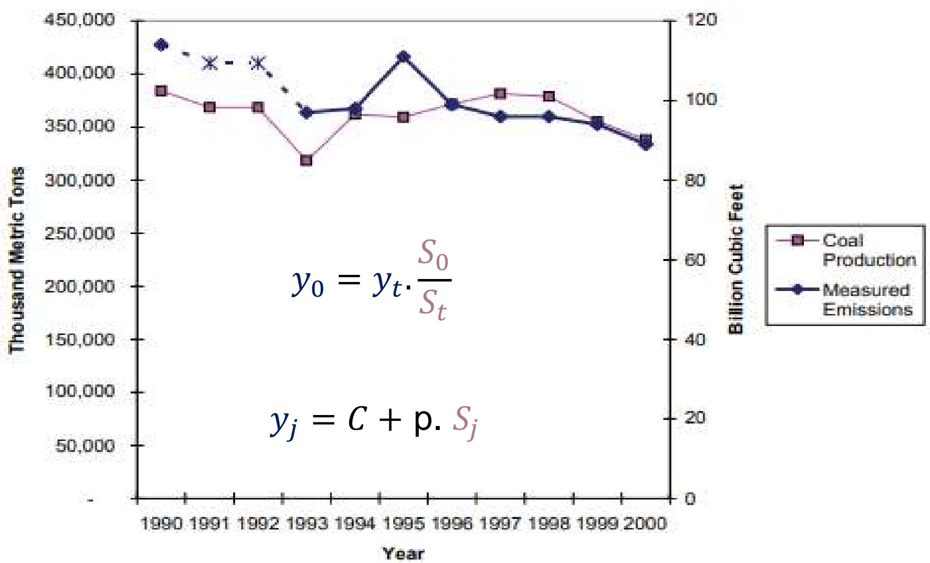
Requires consistent relationship between the two methods

Variability in ratios can be used to assess consistency and uncertainty

Proxy: Splicing techniques and Expert Judgement [4]

Splicing techniques for Data gaps

Overlap	Surrogate	Interpolation	Extrapolation



$$y_0 = y_t . \frac{S_0}{S_t}$$

$$y_j = C + \text{p}. S_j$$

No data for the category but other related available

Ratios or regression analysis (simple, multiple, linear, non-linear)

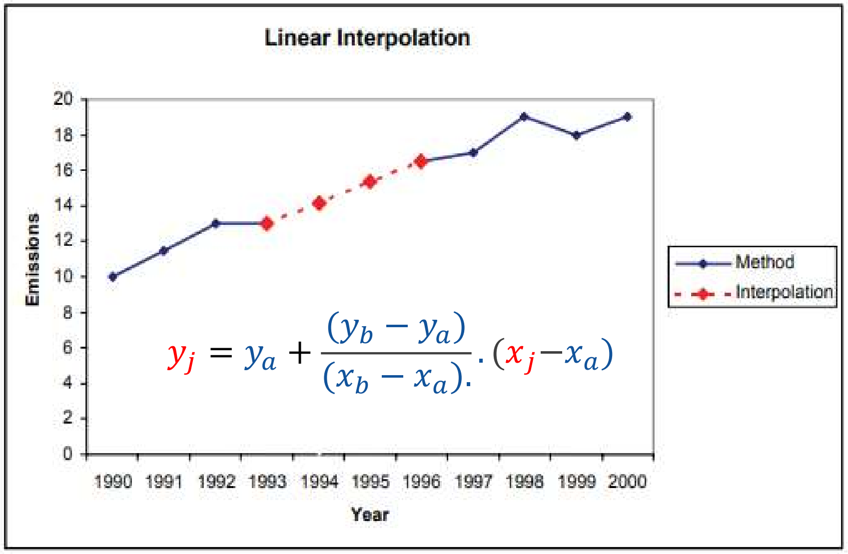
Requires identifying the dependent and independent variable/s and the dependency (correlation)

Standard error for the regression can be used to assess uncertainty (other criteria also possible)

Proxy: Splicing techniques and Expert Judgement [5]

Splicing techniques for Data gaps

Overlap	Surrogate	Interpolation	Extrapolation



$$y_j = y_a + \frac{(y_b - y_a)}{(x_b - x_a)} . (x_j - x_a)$$

Data gap for some years or outliers identified.

Linear models are commonly used but others may apply (quadratic)

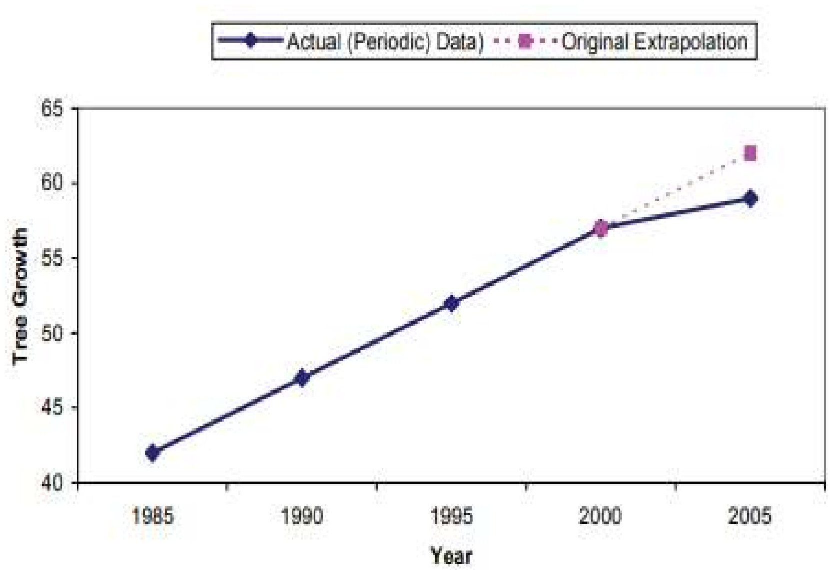
It can be applied intermittently as necessary. Requires smooth or stable trend (low variability). If not, surrogate is a better practice.

Variability in available data can be used to assess uncertainty

Proxy: Splicing techniques and Expert Judgement [6]

Splicing techniques for Data gaps

Overlap	Surrogate	Interpolation	Extrapolation



Data unavailable for last or first year/s

Continuation of the trend, if stable, or surrogate, if higher variability, beyond data´s period.

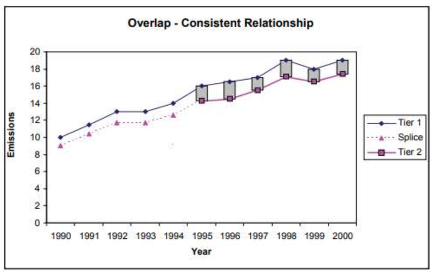
Not recommended for estimations over long periods of time

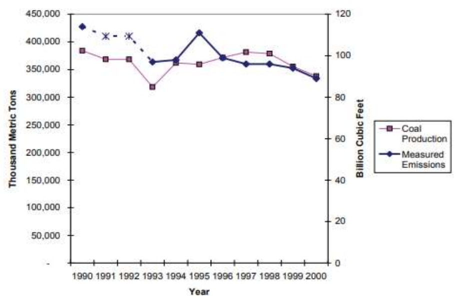
Uncertainty depending on the extrapolation method (trend or surrogate). Could be evaluated ex post if data becomes available.

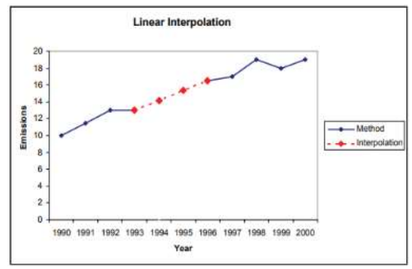
Proxy: Splicing techniques and Expert Judgement [7]

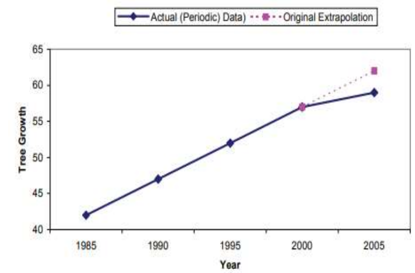
Splicing techniques for Data gaps

Overlap	Surrogate	Interpolation	Extrapolation









Hands-on exercises

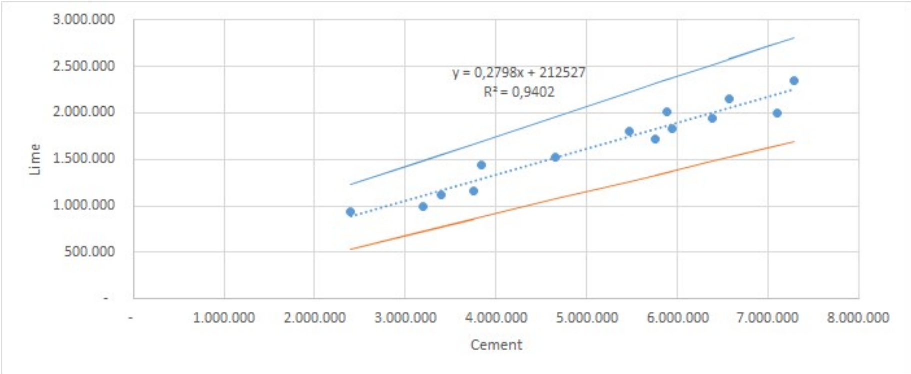
Proxy: Splicing techniques and Expert Judgement [8]

Splicing techniques for Data gaps

Overlap | **Surrogate** | Interpolation | Extrapolation

IPPU: Lime production statistics were not available for the last two years.
Investigate the relationship with the production of cement, surrogate lime production and determine the uncertainty of the estimation used.

Year	Lime	Cement
1	1.167.701	3.751.759
2	1.119.942	3.398.621
3	943.108	2.396.907
4	988.285	3.197.714
5	1.444.813	3.833.116
6	1.527.389	4.654.673
7	1.808.855	5.472.815
8	2.016.509	5.885.219
9	1.834.096	5.947.131
10	1.717.285	5.752.006
11	1.949.142	6.388.311
12	2.000.257	7.104.927
13	2.154.948	6.567.993
14	2.348.841	7.288.507
15		6.992.203
16		7.172.822



U: 15 %

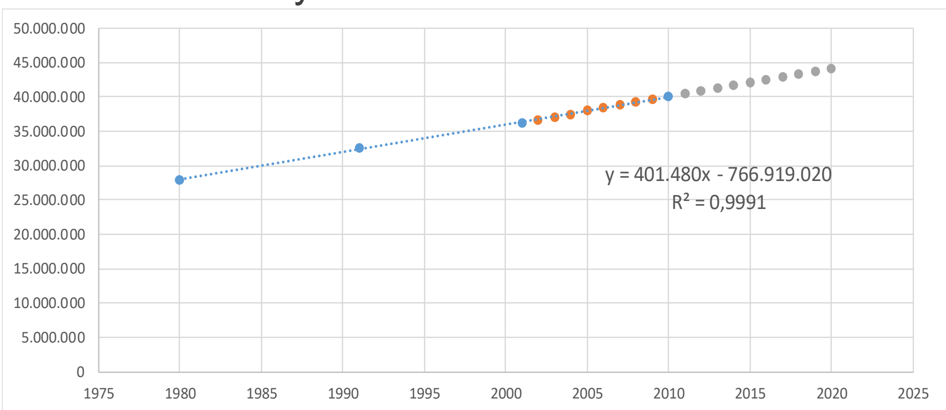
Proxy: Splicing techniques and Expert Judgement [9]

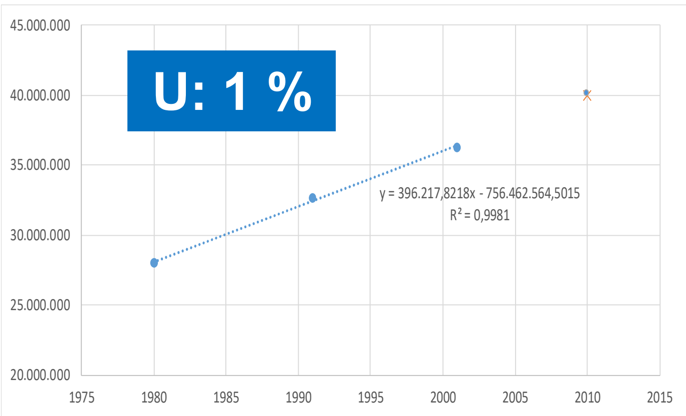
Splicing techniques for Data gaps

Overlap | Surrogate | **Interpolation** | **Extrapolation**

Waste: municipal solid waste generation per capita is used to calculate the amount of waste to be treated in a landfill that serves a specific region. Obtain the yearly population for the region using data from the census and asses the uncertainty. Extrapolate the data from the census to calculate the population in 2020 and asses the uncertainty.

Year	Population
1980	27.949.480
1991	32.615.528
2001	36.260.130
2010	40.117.096

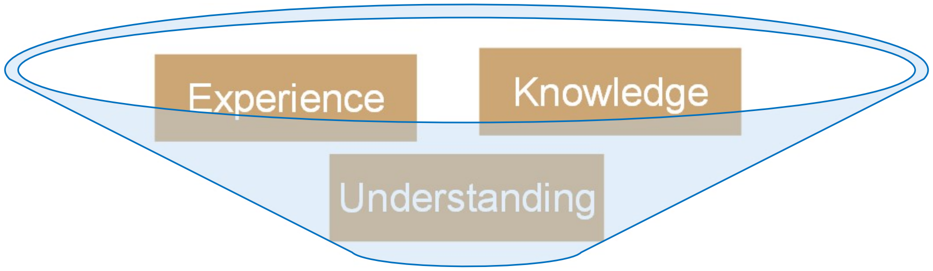




ENCODING EXPERT JUDGEMENT

Proxy: Splicing techniques and Expert Judgement [11]

ENCODING EXPERT JUDGEMENT



Key goal is to characterise the state of knowledge regarding possible values of a particular variable and to develop a PDF

Full range of values

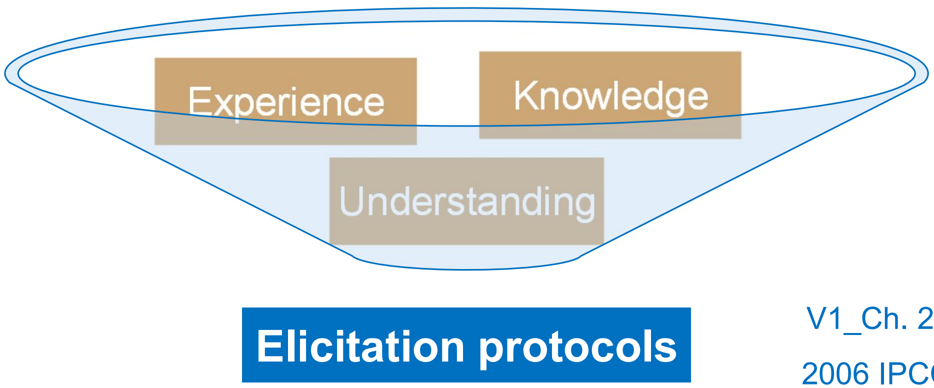
- When no relevant empirical data is available
- Well informed judgements from domain experts
- Formal expert elicitation protocols

IMPORTANT!

Document all the process!

Proxy: Splicing techniques and Expert Judgement [12]

ENCODING EXPERT JUDGEMENT



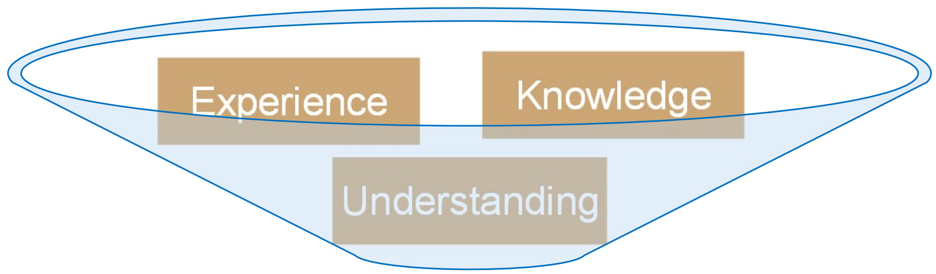
V1_Ch. 2 Annex 2A.1

2006 IPCC Guidelines

- **Motivation:** explaining the problem and purpose
- **Structuring:** defining the specifics of the protocol and problem
- **Conditioning:** previous experiences, models, theory and results
- **Encoding/Elicitation:** obtaining the data and information
- **Verification:** confirmation of outputs, bias testing and feeling of outliers

Proxy: Splicing techniques and Expert Judgement [13]

Elicitation protocols- EXPERT JUDGEMENT



Elicitation protocols

V1_Ch. 2 Annex 2A.1

2006 IPCC Guidelines

Key concern with expert elicitation is to overcome the typical heuristic biases of *availability*, *representativeness*, and *anchoring and adjustment*

⊗ ***Overconfident estimate (narrow interval)***

- Fixed Value → Probability?
- Fixed Probability → Value?
- Interval Methods → Median and quartiles?
- Graphing → Drawing PDF

Proxy: Splicing techniques and Expert Judgement [14]

Elicitation protocols- EXPERT JUDGEMENT

Fixed Value: Estimate the probability of being higher (or lower) than an arbitrary value and repeat, typically three or five times.

e.g. what is the probability that an emission factor would be less than 100?

Fixed Probability: Estimate the value associated with a specified probability of being higher (or lower).

e.g. what is the emission factor such that there is only a 2.5 percent probability (or 1 in 40 chance) that the emission factor could be lower (or higher) than that value?

Interval Methods: It focuses on identifying the median and the quartiles.

e.g. Choose a value of the emission factor such that it is equally likely that the true emission factor would be higher or lower than that value (this yields the median).

Divide the lower range into two bins such that you feel it to be equally likely (25 percent probability) that the emission factor could be in either bin. Repeat for the other end.

Extreme values could be judged by either fixed probability or fixed value methods.

Graphing: The expert draws his/her own distributions.

e.g. Draw a distribution you feel is representative of the emission factor.

This should be used cautiously since some experts may be overconfident about their knowledge of PDFs

MONDAY

2. Overview of Uncertainty Analysis in National GHG Inventories

3. Causes of uncertainties associated with input data used in National GHG Inventories

4. How to reduce the uncertainty associated with input data used in National GHG Inventories

TUESDAY

5. Uncertainty associated with the use of national statistics, surveys, censuses and sampling

6. Uncertainty associated with the Use of Empirical Data

WEDNESDAY

7. Methods to combine uncertainties: Approach 1

Propagation of errors

THURSDAY

8. Methods to combine uncertainties: Approach 2

Monte Carlo simulation

FRIDAY

9. Methods to combine uncertainties: Hybrid combinations of Approaches 1 and 2

10. Application of uncertainty estimates to identify areas for improvement – Approach 2 to identify key categories

11. Uncertainty associated with the use of proxy, splicing techniques and expert judgment to fill data gaps

100%

End of webinar!

Thank you

Diego M. Ezcurra