

Uncertainty analysis in National Greenhouse Gas Inventories from developing countries

19-23 February 2024



GHG Support Unit, Transparency Division

Uncertainty analysis in National Greenhouse Gas Inventories

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

WEDNESDAY

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

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

TUESDAY

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

THURSDAY

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

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



- Chapter 1 Introduction
- Chapter 2 Energy
- Chapter 3 Industrial Processes
- Chapter 4 Agriculture
- Chapter 5 Waste
- Chapter 6 Quantifying Uncertainties in Practice
- Chapter 7 Methodological Choice and Recalculation
- Chapter 8 Quality Assurance and Quality Control



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

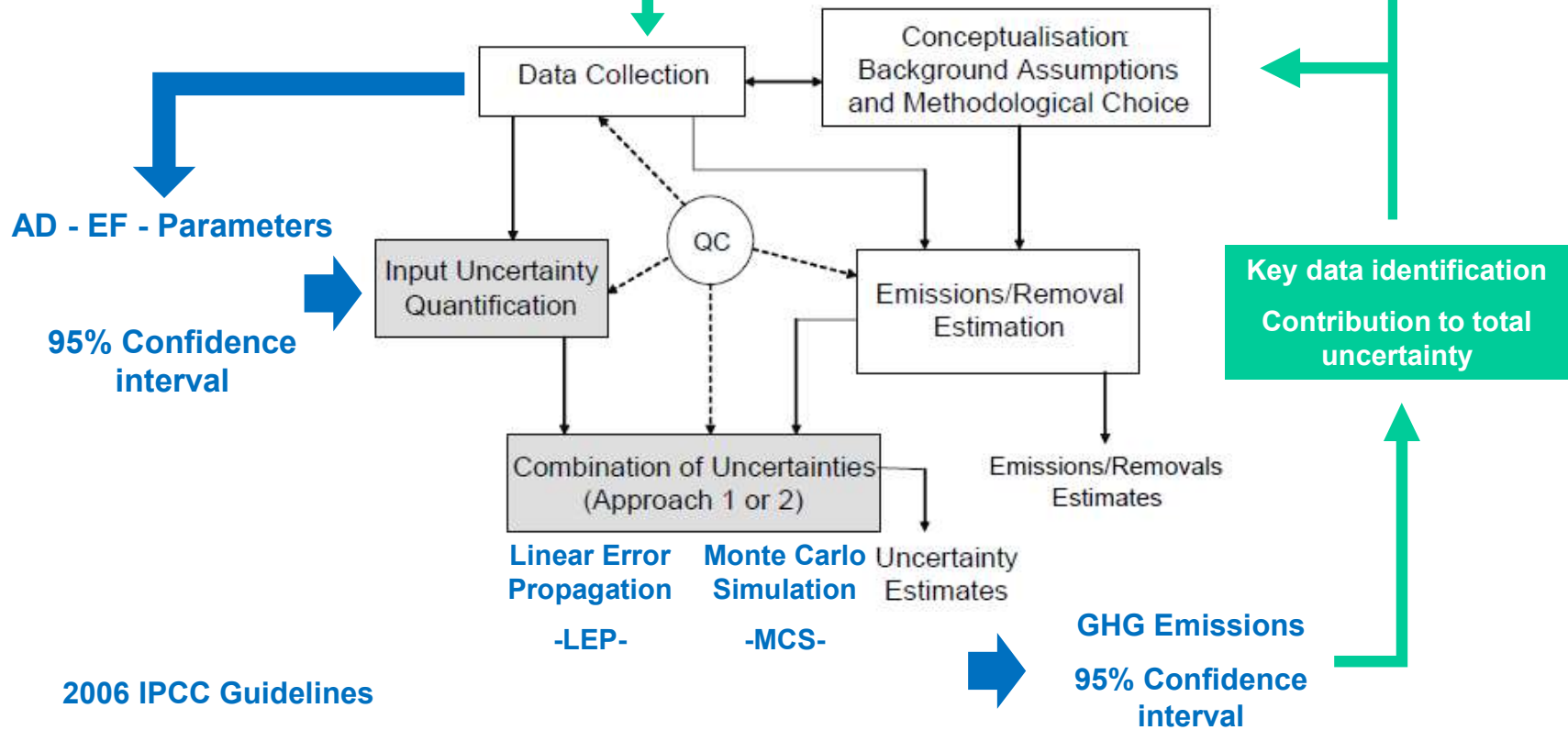
Uncertainty assessment

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



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]

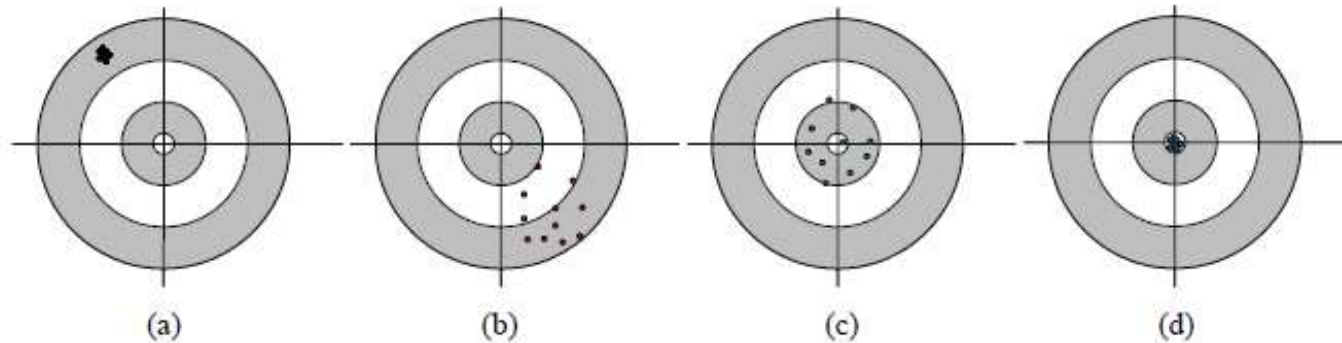
Key concepts

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)

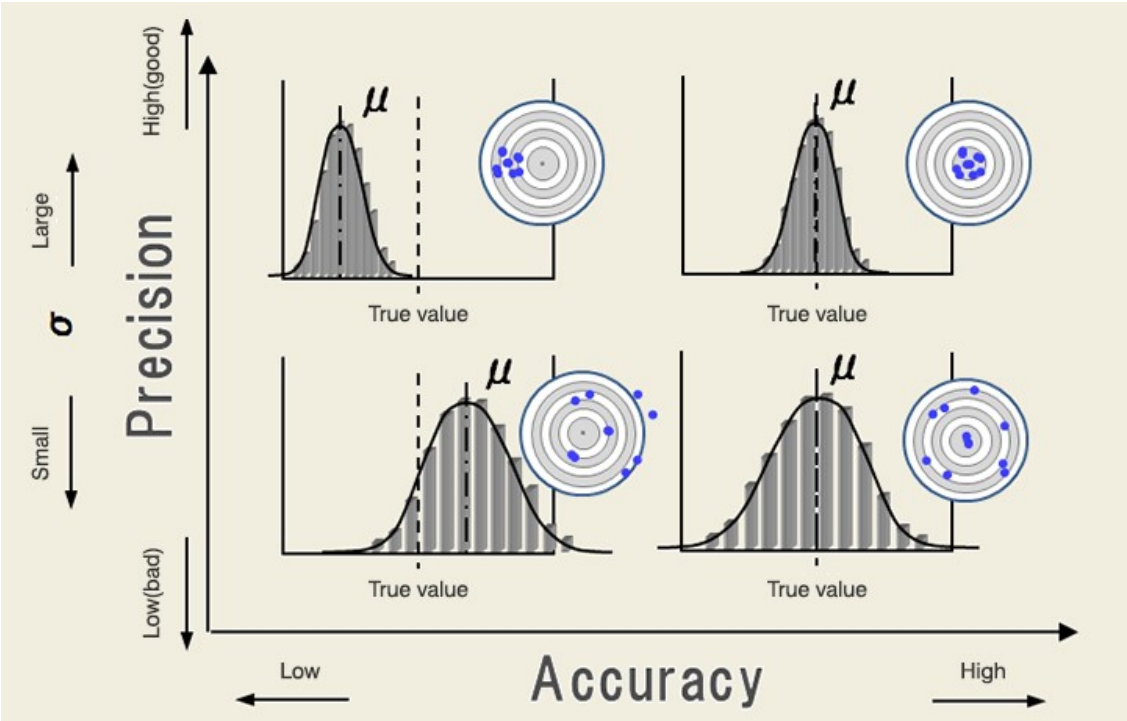
(a) inaccurate but precise; (b) inaccurate and imprecise; (c) accurate but imprecise; and (d) precise and accurate



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 [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 ₂ O			
	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 <i>et al.</i> (2001), which shows emissions ranging from 0.0027 to 0.01 kg N ₂ O-N (kg N) ⁻¹ .
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(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.

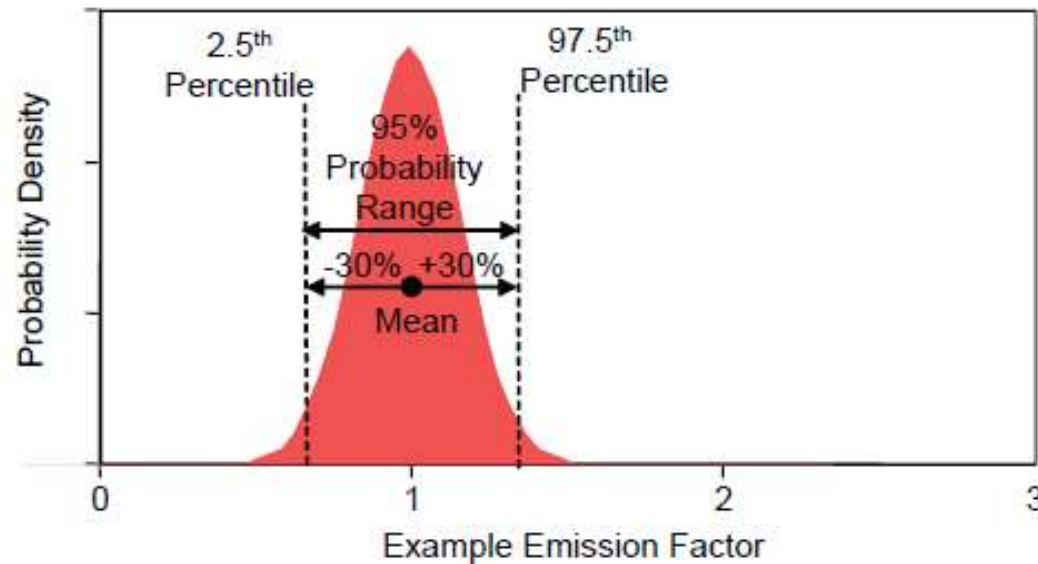


Uncertainty overview [12]

Terminology

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

Symmetric (normal distribution)

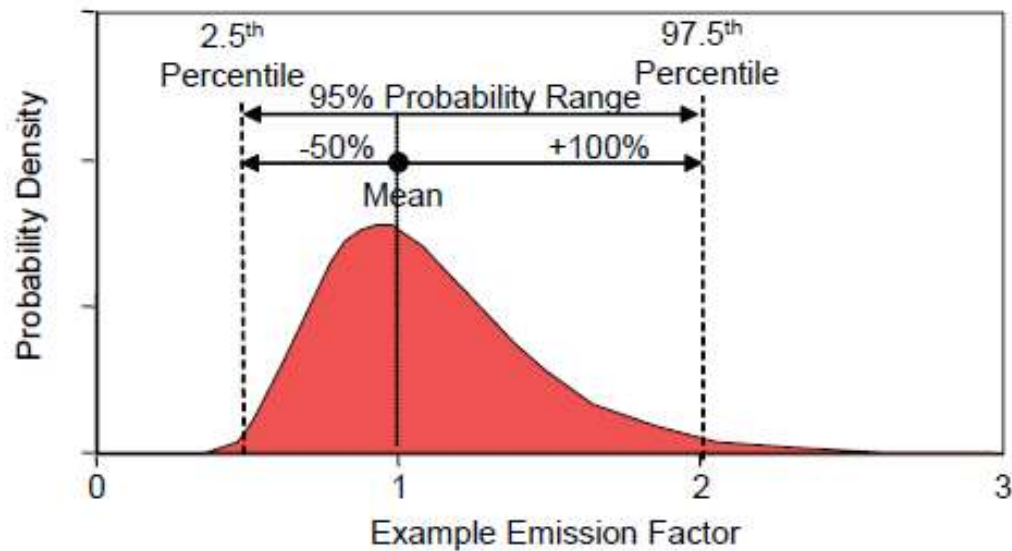


Uncertainty overview [13]

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?



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Causes of uncertainty [2]

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



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Causes of uncertainty [3]

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



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Causes of uncertainty [4]

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



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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

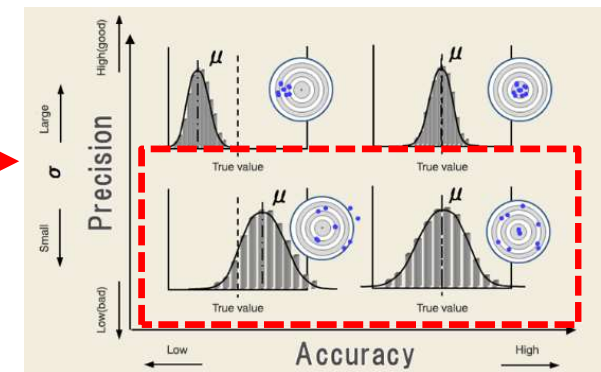
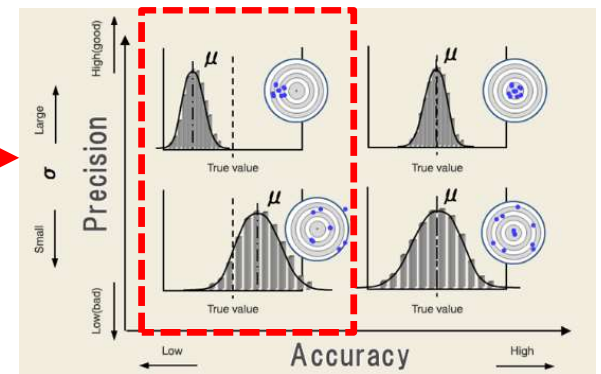
-Bias and Random errors

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: N₂O from internal combustion engines from laboratory test instead of real driving conditions

IPPU: CO₂ emissions from 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

Improving models

Improving representativeness

Using + precise measurement methods

Collecting more measured data

Eliminating known risk of bias

Improving state of knowledge

Structural assumptions

Structure and parameterization

Sampling strategies

Measurement technologies

Sample size

Following decision trees

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.

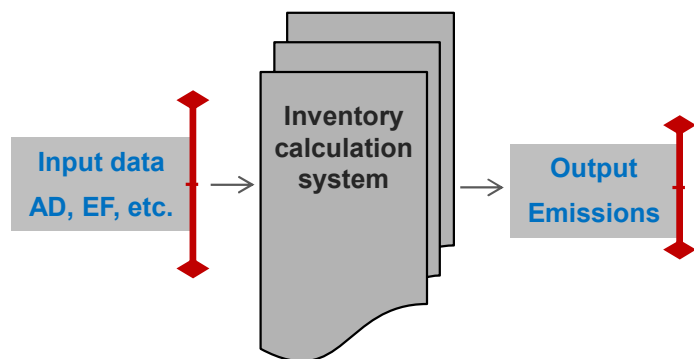


Reducing uncertainty [6]

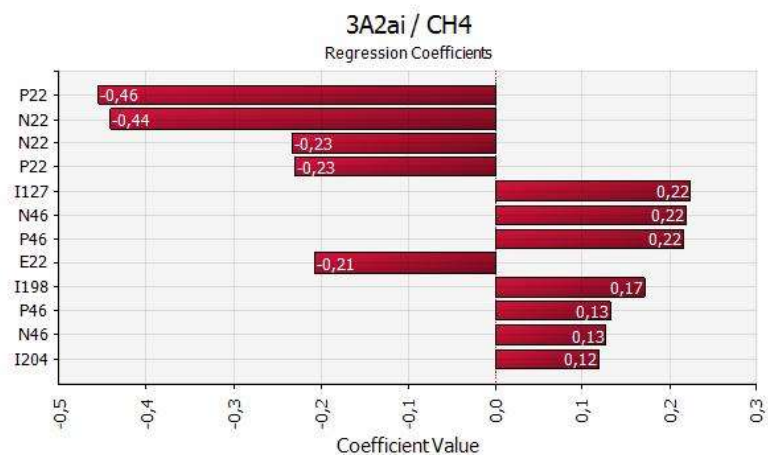
Sensitivity analysis

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 CH₄ 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



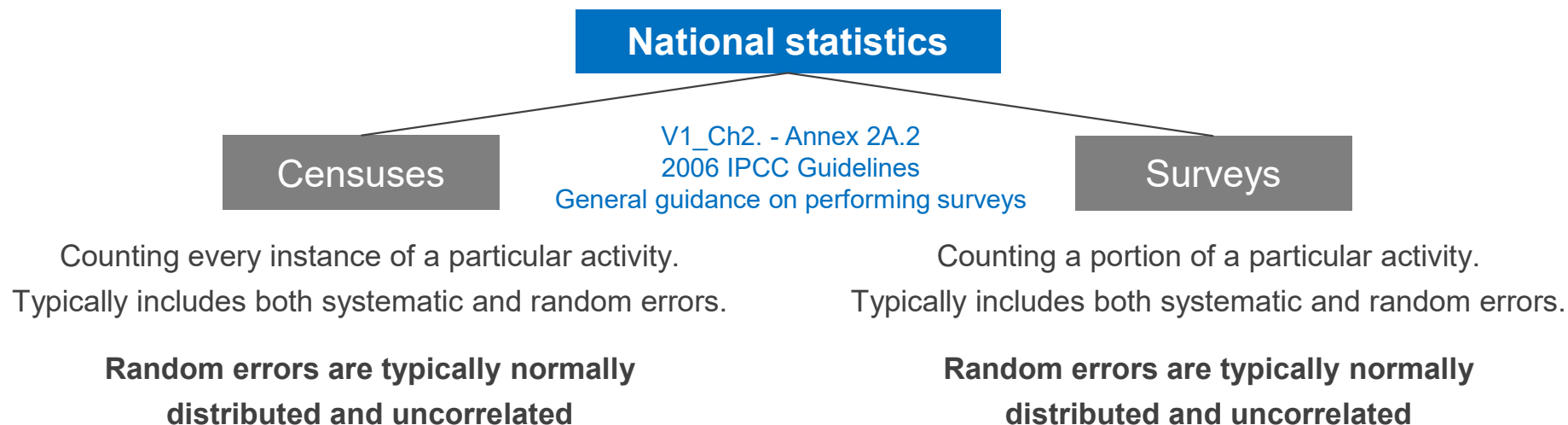
Learning objectives



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

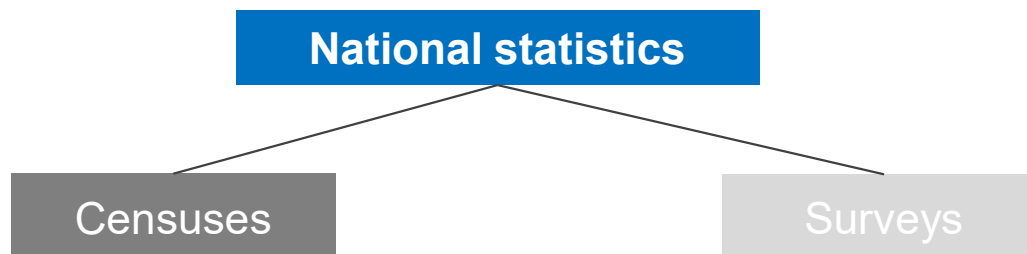


Contact the statistical agencies directly



Uncertainty associated with activity data [2]

National statistics: census



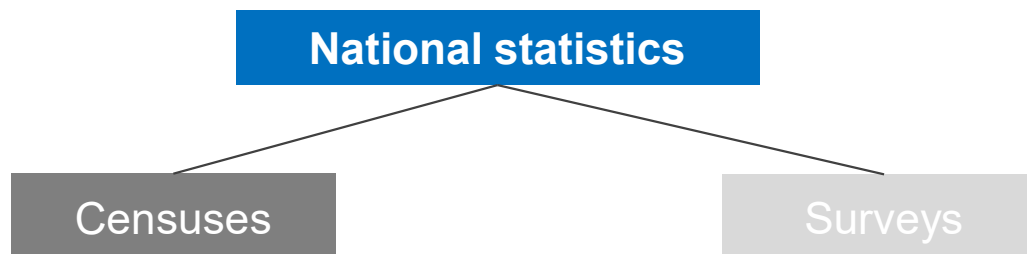
- Check for the size of random errors, look for fluctuations over time, and differential fluctuations in series that ought to be highly correlated with the data of interest
- To check for bias errors, cross-check the data of interest with other, related information. (look up and down the supply chain 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



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
2016	659.034	479.291
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2019	770.377	599.242
2020	866.303	554.953
2021	847.566	498.429
2022		

Source: commercialization tables, 18 June 2022

Year	Gasoil	Gasoline
2016	659.034	479.291
2017	662.157	504.563
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2019	770.377	599.242
2020	866.303	554.953
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

Periodic publications

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Evaluate consistency and identify fluctuations over time in series to derive the uncertainty of the data

4,5%

U ≈ 5%

3,7%

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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/m³

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/m³

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

Highly correlated activities

≈ 20%

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NCV: 48 TJ/Gg

Density: 0,714 kg/m³

1.570.410

18.017.687

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32%

35%

36%

37%

37%

35%

36%

35%

34%

33%

36%

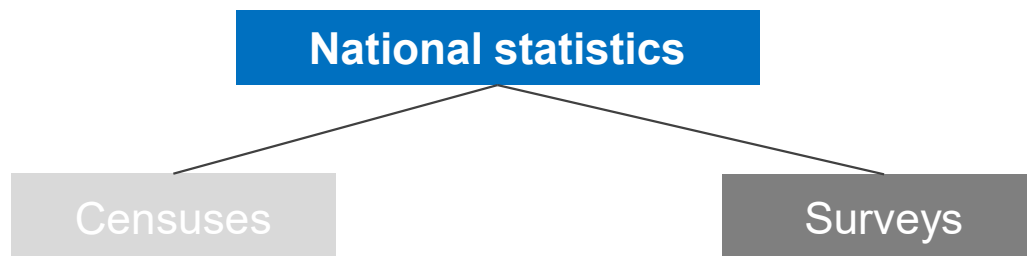
34%

35%



Uncertainty associated with activity data [8]

National statistics: survey



- 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)

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

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

Variability within the sample

Applicable for individual value

Standard deviation tends to remain constant

vs.

uncertainty in sample mean (standard error)

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

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

Variability of the mean of the sample

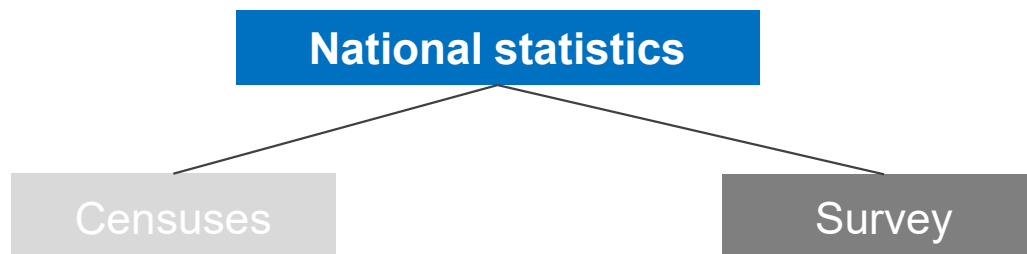
Applicable for country average

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

- Given a sample with 80 individual values, calculate the mean, standard deviation and standard error.
- 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 101
STD 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

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

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

SE: 1.9 tC/ha

U: 4 %

σ or SE ?

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

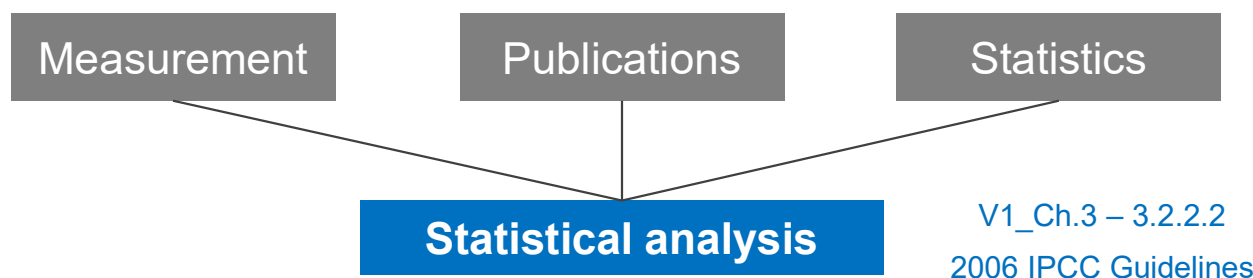


Learning objectives



Uncertainty associated with empirical data [1]

Techniques for quantifying uncertainties



- 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

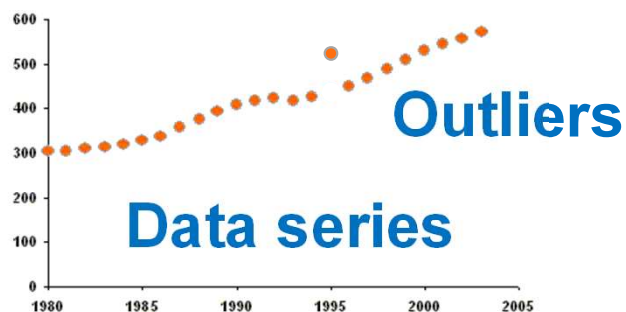


Uncertainty associated with empirical data [3]

Techniques for quantifying uncertainties

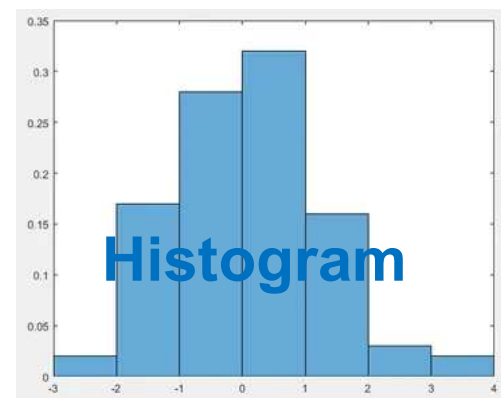
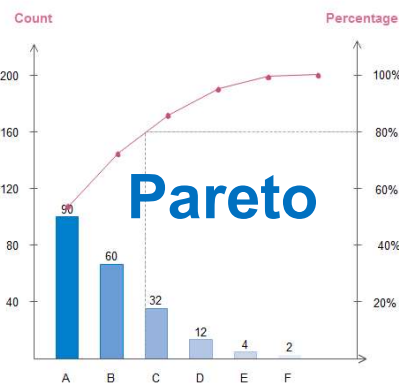
Statistical analysis

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



Consistency

Pareto Chart



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**

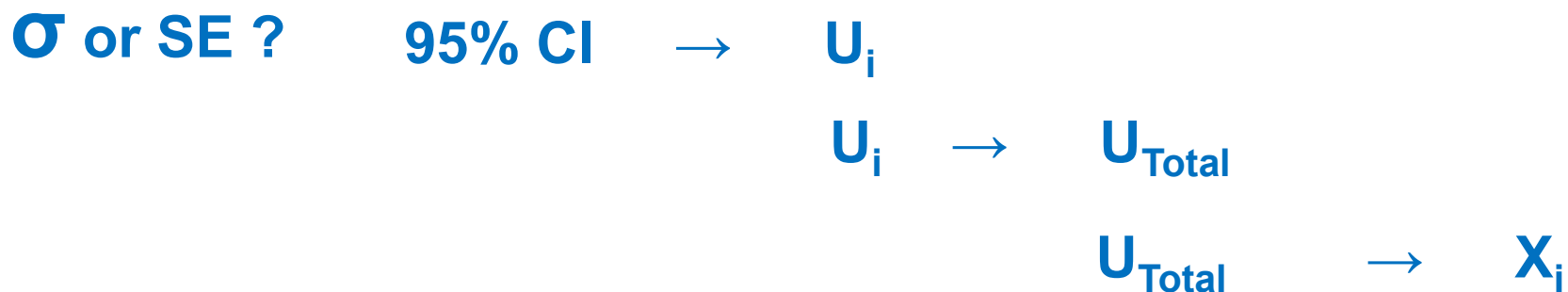


Uncertainty associated with empirical data [5]

Techniques for quantifying uncertainties

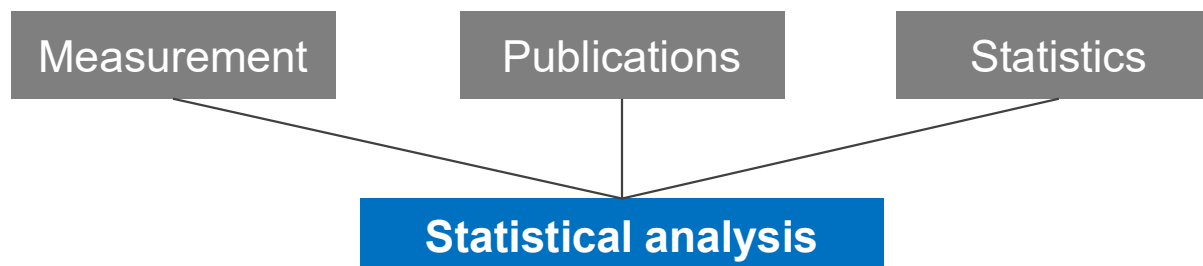
Statistical analysis

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



Uncertainty associated with empirical data [6]

Techniques for quantifying uncertainties



Hands-on exercises



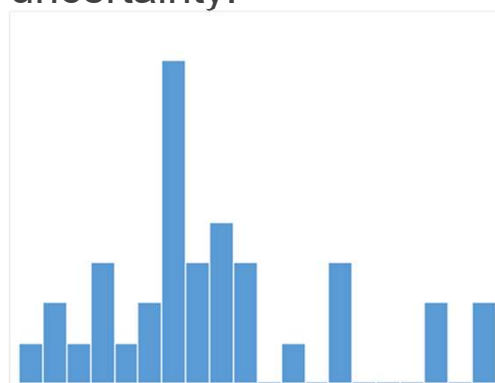
Uncertainty associated with empirical data [7]

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: 5 %



Uncertainty associated with empirical data [8]

Statistical analysis

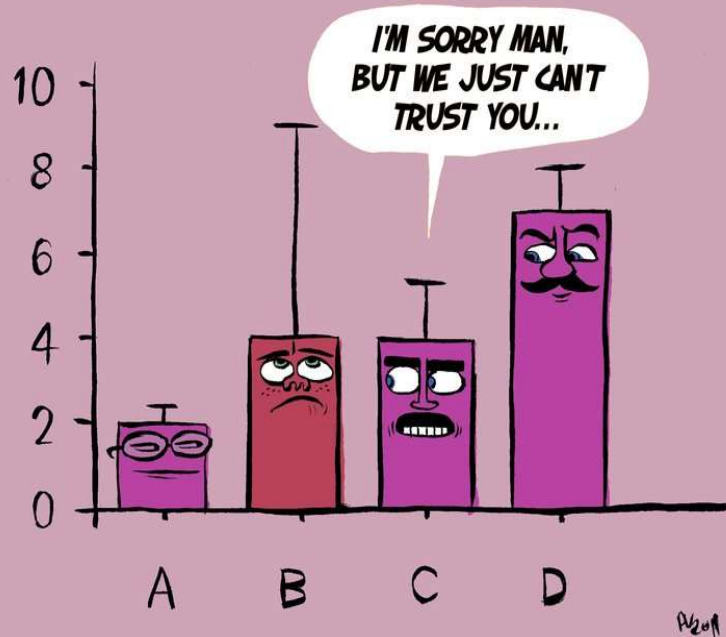
Attention!

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

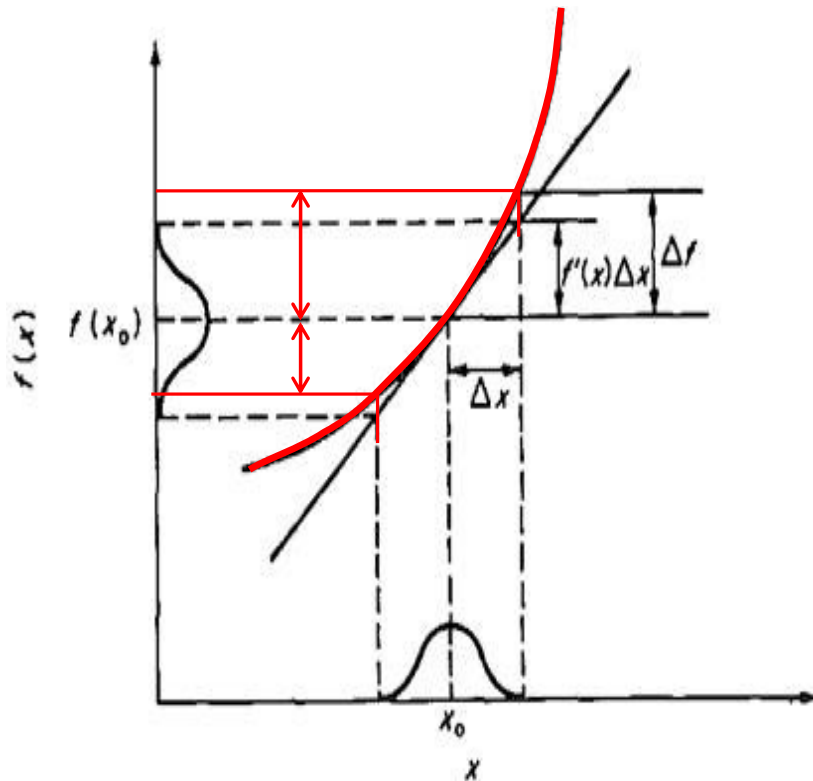


Learning
objectives

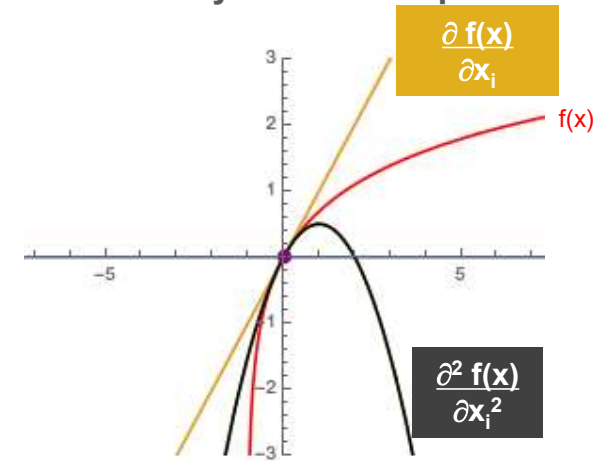


Combining uncertainty: Approach 1 [1]

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: $f = f(a; b) + \frac{\partial f}{\partial a} \delta a + \frac{\partial f}{\partial b} \delta b + \dots \Rightarrow f - f(a; b) = \frac{\partial f}{\partial a} \delta a + \frac{\partial f}{\partial b} \delta b \Rightarrow \delta f = \frac{\partial f}{\partial a} \delta a + \frac{\partial f}{\partial b} \delta b$

Variance of a summation:

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

Case $f = a \times b$:

$$\sigma_f^2 = b^2 \sigma_a^2 + a^2 \sigma_b^2 + 2 a b \sigma_{ab}$$

Or, in relative terms

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

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

Equations 3.1

Assumptions:

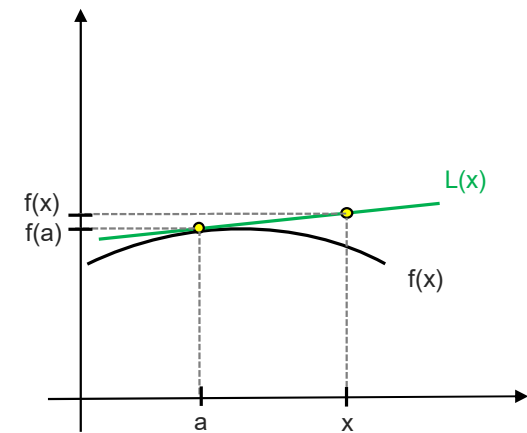
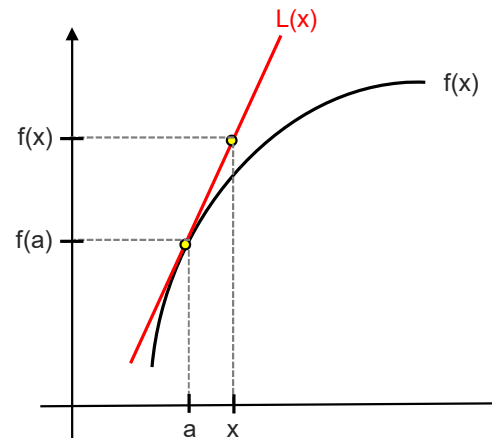
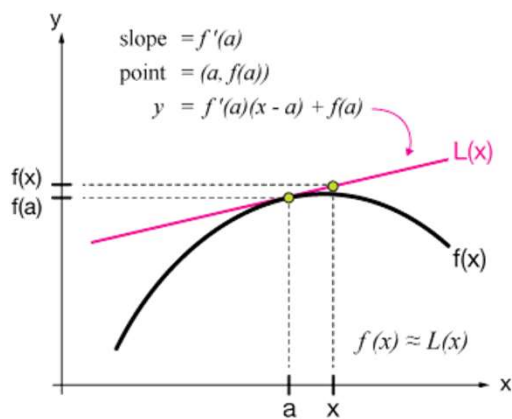
- 1) Small std. Deviation (~30%)
- 2) Symmetric (not skewed)
Normal distribution
- 3) Uncorrelated variables
- 4) Multiplication or addition



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

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

U_j : relative

E1 + E2 + ... + En

EQUATION 3.2

COMBINING UNCERTAINTIES – APPROACH 1 – ADDITION AND SUBTRACTION

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

x_j : CO₂e



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

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

U_i : relative

Example: CO₂ emissions due to fuel consumption

$$E = C \times EF$$

Gasoil consumption = 18 710 GJ

$$E = 18\,710 \text{ [GJ]} \times 0.0741 \left[\frac{t}{GJ}\right] = 1\,386 \text{ tCO}_2$$

Uncertainty in activity data: 10%

Uncertainty in emission factor: 2%

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

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

(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

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

2% 1%



Combining uncertainty: Approach 1 [6]

Linear Error Propagation (LEP)

AD x EF

EQUATION 3.1

COMBINING UNCERTAINTIES – APPROACH 1 – MULTIPLICATION

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

U_i : relative

Example: CO₂ emissions due to fuel consumption

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

C: Gasoil consumption = 500 m³

δ : Density = 0.87 t/m³

$$E = 500 \times 0.87 \times 43.0 \times 0.0741 = 1\,386 \text{ tCO}_2$$

Uncertainty in activity data: 5%

Uncertainty in density: 5%

Uncertainty in emission factor: 2%

Uncertainty in NCV: 4%

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

(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
		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

[41.4 – 43.0] [41.4 – 43.0]

43.0 43.0

4% 1%



Combining uncertainty: Approach 1 [7]

Linear Error Propagation (LEP)

AD x EF

EQUATION 3.1

COMBINING UNCERTAINTIES – APPROACH 1 – MULTIPLICATION

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

U_i : relative

Examples: enteric fermentation, transportation, waste treatment

$$E = DE^2 \times EF$$



$$E = DE \times DE \times EF$$



$$U = \sqrt{u_b^2 + u_b^2 + u_{EF}^2}$$

$$E = \frac{D \times EF}{\eta}$$



$$E = D \times EF \times SC$$



$$U = \sqrt{u_B^2 + u_{EF}^2 + u_{SC}^2}$$

$$E = DDOC \times e^{-k}$$



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



$$U = \sqrt{u_{DDOC}^2 + (u_k \times k)^2}$$

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

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

x_j : CO₂e

Example: CO₂ emissions due to vent and flare

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

$$E_{vent} = 7\,310 \text{ tCO}_2\text{e}$$

$$E_{flare} = 5\,282 \text{ tCO}_2\text{e}$$

$$E = 7\,310 + 5\,282 = 12\,592 \text{ tCO}_2\text{e}$$

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

Uncertainty in flare emissions: 10% (± 528)

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

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



Combining uncertainty: Approach 1 [9]

Linear Error Propagation (LEP)

$E_1 + E_2 + \dots + E_n$

EQUATION 3.2

COMBINING UNCERTAINTIES – APPROACH 1 – ADDITION AND SUBTRACTION

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

x_i : CO₂e

Example: adding multiple emission sources

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

$$U_E = \frac{\sqrt{(0.4 \times 200)^2 + (0.3 \times 500)^2 + (0.1 \times 300)^2 + (0.8 \times 100)^2 + (0.2 \times 800)^2}}{|19\,000|} = 13\%$$

$$E_1 = 200 \text{ tCO}_2\text{e} \pm 40\%$$

$$E_2 = 500 \text{ tCO}_2\text{e} \pm 30\%$$

$$E_3 = 300 \text{ tCO}_2\text{e} \pm 10\%$$

$$E_4 = 100 \text{ tCO}_2\text{e} \pm 80\%$$

$$E_5 = 800 \text{ tCO}_2\text{e} \pm 20\%$$

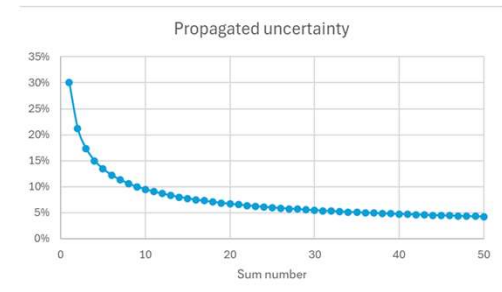
Contribution to uncertainty
=> 10%
=> 36%=> 1%

$$\frac{(U_i \times E_i)^2}{\sum (U_i \times E_i)^2} \Rightarrow 10\% \Rightarrow 41\%$$

Contribution to variance

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

$$E = 1\,900 \text{ tCO}_2\text{e}$$



Addition reduces overall uncertainty



Combining uncertainty: Approach 1 [10]

Linear Error Propagation (LEP)

$E_1 + E_2 + \dots + E_n$

EQUATION 3.2

COMBINING UNCERTAINTIES – APPROACH 1 – ADDITION AND SUBTRACTION

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

x_i : CO₂e

Example: subtracting

$$E = E_1 - E_2$$

$$E_1 = 500 \text{ tCO}_2\text{e} \pm 30\%$$

$$E_2 = 100 \text{ tCO}_2\text{e} \pm 20\%$$

$$E = 400 \text{ tCO}_2\text{e}$$

IF

$$E_1 = 500 \text{ tCO}_2\text{e} \pm 30\%$$

$$E_2 = 400 \text{ tCO}_2\text{e} \pm 20\%$$

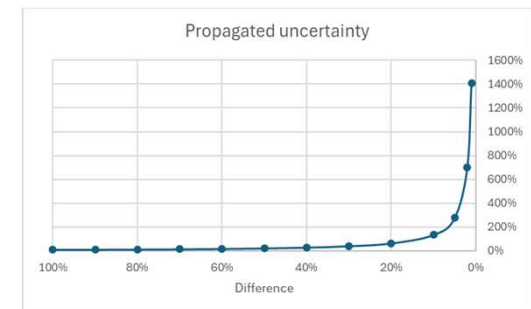
$$E = 100 \text{ tCO}_2\text{e}$$

$$U_E = \frac{\sqrt{(0.3 \times 500)^2 + (0.2 \times 100)^2}}{|400|} = 38\%$$

$$U_E = \frac{\sqrt{(0.3 \times 500)^2 + (0.2 \times 400)^2}}{|100|} = 170\%$$

Careful if similar values!

Subtraction increases overall uncertainty!



Combining uncertainty: Approach 1 [11]

Linear Error Propagation (LEP)

AD x EF

EQUATION 3.1

COMBINING UNCERTAINTIES – APPROACH 1 – MULTIPLICATION

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

U_i : relative

E1 + E2 + ... + En

EQUATION 3.2

COMBINING UNCERTAINTIES – APPROACH 1 – ADDITION AND SUBTRACTION

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

x_i : CO₂e

Example: combining Eq 3.1 and 3.2

Source	Emission (tCO ₂ e)	Uncertainty in AD	Uncertainty in EF	Combined uncertainty U _i	Contribution to variance
		U _{AD}	U _{EF}	$\sqrt{(U_{AD}^2 + U_{EF}^2)}$	$\frac{(U_i \times E)^2}{(\sum E)^2}$
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)

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 <i>t</i> emissions or removals	Activity data uncertainty	Emission factor / estimation parameter uncertainty	Combined uncertainty	Contribution to Variance by Category in Year <i>t</i>	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	$\sqrt{E^2 + F^2}$	$\frac{(G \cdot D)^2}{(\sum D)^2}$	Note B	$\left \frac{D}{\sum C} \right $	$I \cdot F$ Note C	$J \cdot E \cdot \sqrt{2}$ 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 Emissions Data

Data Calculated using simple equations

Enter Uncertainties



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 r 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	Input data	$\sqrt{E^2 + F^2}$	$\frac{(G \cdot D)^2}{(\sum D)^2}$	Note B	$\frac{D}{\sum C}$	I • F	$J \cdot E \cdot \sqrt{2}$	$K^2 + L^2$
	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 Construction	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	-9.49664E-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	0.006559099	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		5	30	36.60	0.0	-1.24107E-05	0.000119565	-0.000372321	0.003381819	1.15753E-05
6.A. Solid Waste Disposal on Land	CH4	1959.72	370.0	5	30	36.60	0.4	0.007870888	0.011891742	0.236126385	0.252261939	0.119391756
6.B. Wastewater Handling	CH4	787.08	74.0	5	30	36.60	0.0	0.000761896	0.002376612	0.022856865	0.050415547	0.003064164
1.A.1. Energy Industries	CO2	102607.31	95900.0	5	5	7.07	11.2	0.094441853	0.305249301	0.472209267	2.158438506	4.881838378
1.A.2. Manufacturing Industries and Construction	CO2	33991.06	30164.0	5	5	7.07	1.1	0.02618491	0.095945987	0.130924551	0.678440577	0.477422855
1.A.3. Transport	CO2	23987.07	8406.48	5	5	7.07	0.1	-0.022453294	0.026739124	-0.11226647	0.189074157	0.048352797
1.A.4. Other Sectors	CO2	47032.52	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 Construction	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

AD uncertainties based on source of data

EF uncertainties based on data used

List of source/sinks



Combining uncertainty: Approach 1 [14]

Linear Error Propagation (LEP)

AD x EF

EQUATION 3.1

COMBINING UNCERTAINTIES – APPROACH 1 – MULTIPLICATION

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

U_i : relative

E1 + E2 + ... + En

EQUATION 3.2

COMBINING UNCERTAINTIES – APPROACH 1 – ADDITION AND SUBTRACTION

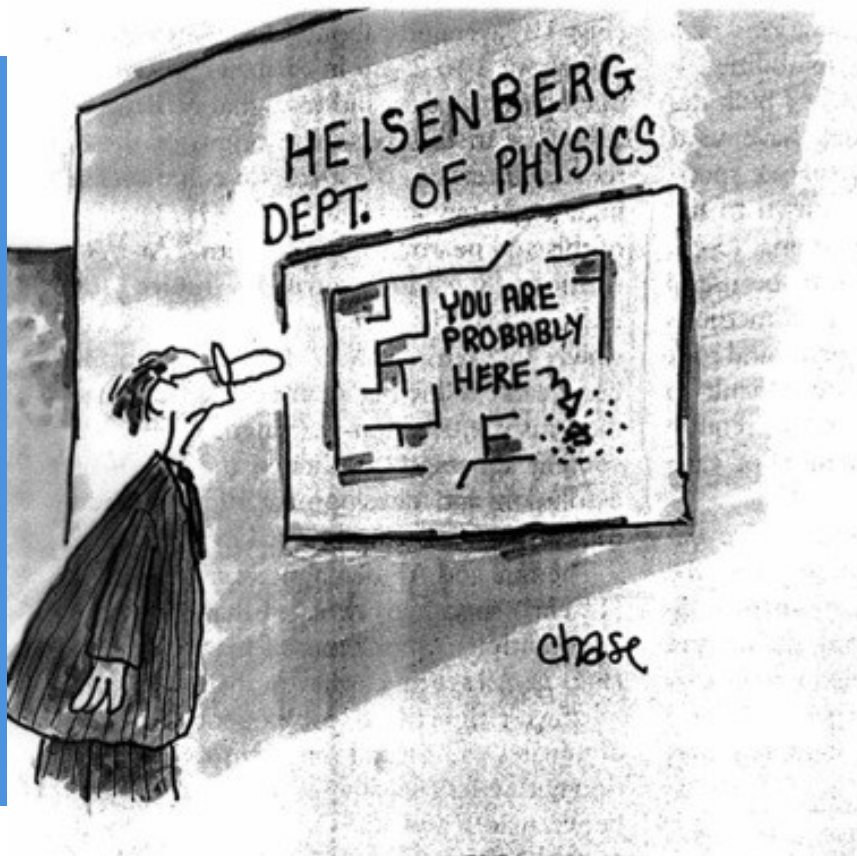
$$U_{total} = \frac{\sqrt{(U_1 \cdot x_1)^2 + (U_2 \cdot x_2)^2 + \dots + (U_n \cdot x_n)^2}}{|x_1 + x_2 + \dots + x_n|}$$

x_i : CO₂e

Bonus track!: one way of dealing with asymmetric uncertainties

Source	Emission (tCO ₂ e)	Uncertainty in AD	Uncertainty in EF (-)	Uncertainty in EF (+)	Combined uncertainty Ui (-)	Combined uncertainty Ui (+)	Contribution to variance (-)	Contribution to variance (+)
		U _{AD}		U _{EF}	$\sqrt{(U_{AD}^2 + U_{EF}^2)}$		$\frac{(U_i \times E_i)^2}{(\sum E_i)^2}$	
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

WEDNESDAY

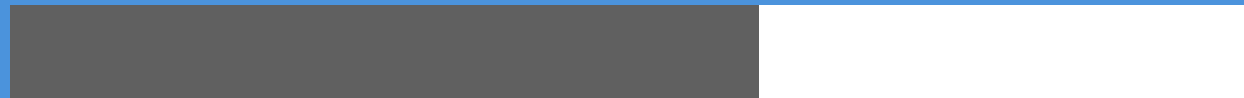
7. Methods to combine uncertainties: Approach 1
Propagation of errors

TUESDAY

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

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]

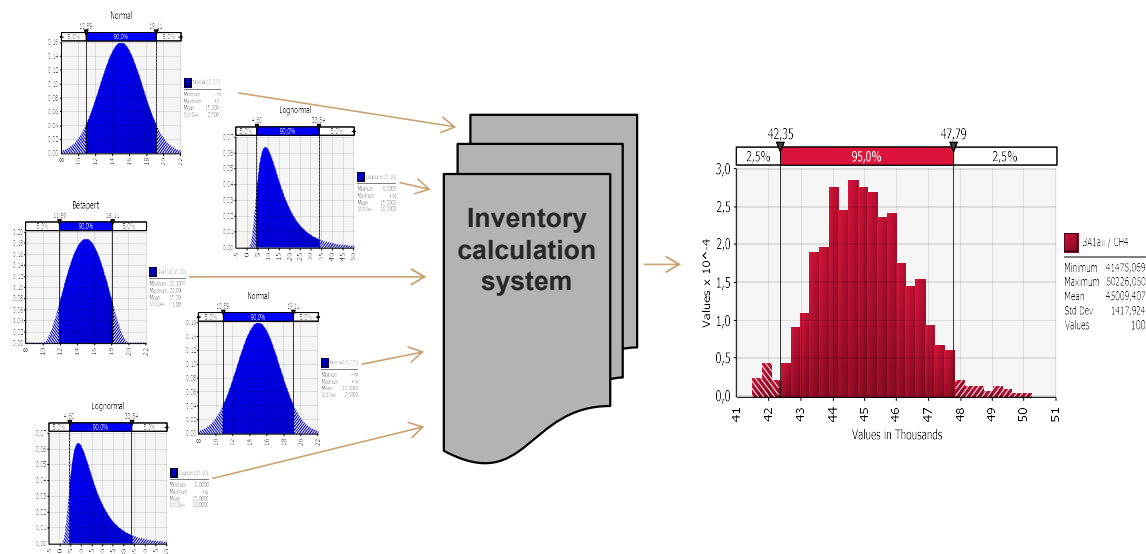
Monte Carlo Simulation (MCS)

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

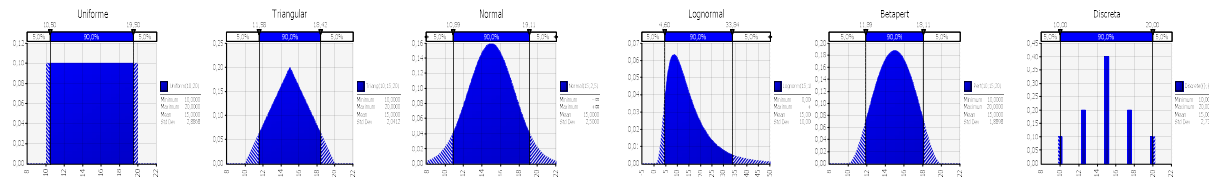
1. Build the calculation model in which uncertainty needs to be evaluated

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

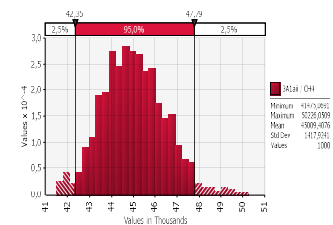
5. Obtain the PDF of the result and determine uncertainty as the 95% CI.

Mean = 100

Standard deviation = 15

Uncertainty = 30%

CI = [70 ; 130]



Combining uncertainty: Approach 2 [4]

Monte Carlo Simulation (MCS)

Example



Excel ribbon showing the @RISK tab highlighted in red. The formula bar displays: `=RiskLognorm(0,01;0,006;RiskStatic(0,01))`

Worksheet content:

1 **Direct N2O emissions from managed soils**
2 *Página 11.12 - Guía IPCC 2006 Vol. 4*

Factor	Unit	Default	Range
EF ₁	kg N2O-N / kg N	0,01	0,003 - 0,03
EF _{3PRP}	kg N2O-N / kg N	0,02	0,007 - 0,06

7

8 **Indirect N2O emissions from soils (volatilization and leachate)**
9 *Página 11.26 - Guía IPCC 2006 Vol. 4*

Factor	Unit	Default	Range
Frac _{GASF}	(kg NH ₃ -N + NO _x -N) / (kg N aplicado)	0,10	0,03 - 0,3



Combining uncertainty: Approach 2 [5]

Monte Carlo Simulation (MCS)

Example



Iterations: 1000
Simulations: 1

Start Simulation Analyses

Browse Results

Summary

Define Filters

Excel Reports Functions

Swap Functions

Model Window

Model

Simulation

Results

Tools

D5 fx =RiskLognorm(0,01;0,006;RiskStatic(0,01))

Factor	Unit	Default	Range
EF ₁	kg N ₂ O-N / kg N	0,01	0,003 - 0,03
EF _{3PRP}	Kg N ₂ O-N / Kg N	0,02	0,007 - 0,06

Direct N₂O emissions from managed soils

Página 11.12 - Guía IPCC 2006 Vol. 4

Factor	Unit	Default	Range
Frac _{GASF}	(kg NH ₃ -N + NO _x -N) / (kg N aplicado)	0,10	0,03 - 0,3

Indirect N₂O emissions from soils (volatilization and leachate)

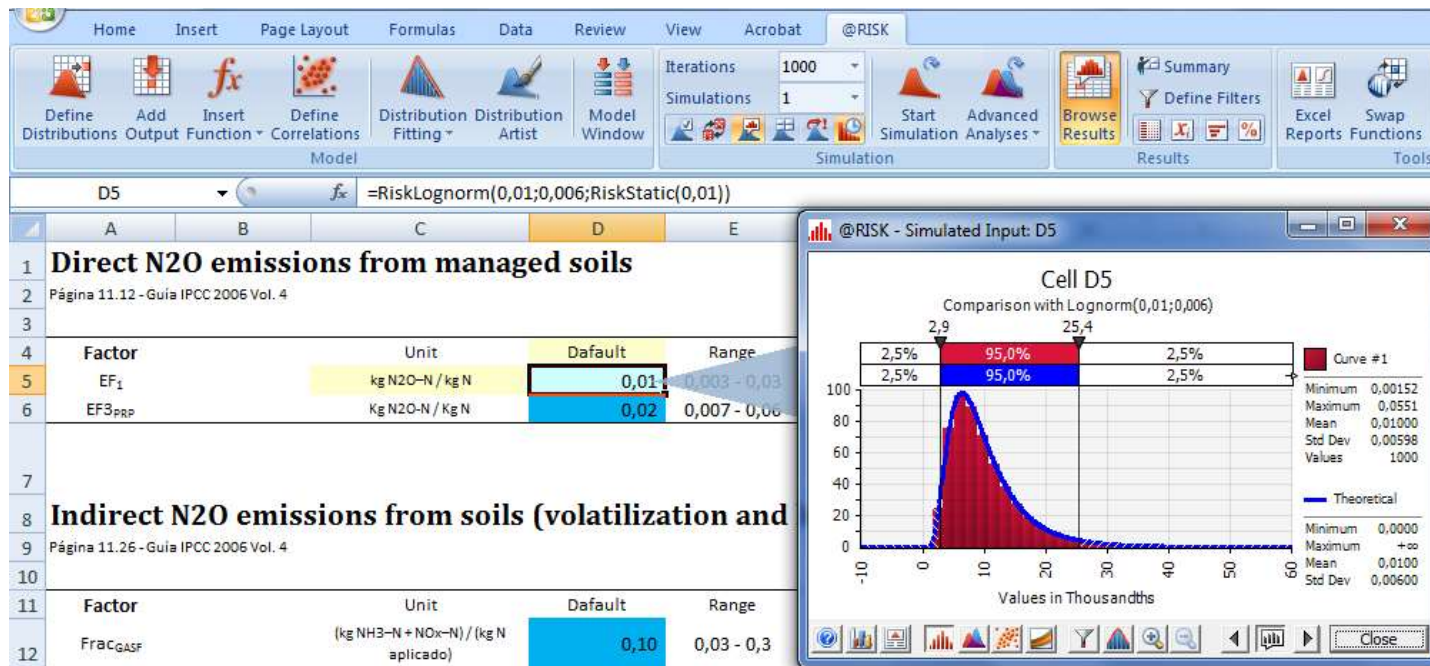
Página 11.26 - Guía IPCC 2006 Vol. 4



Combining uncertainty: Approach 2 [6]

Monte Carlo Simulation (MCS)

Example

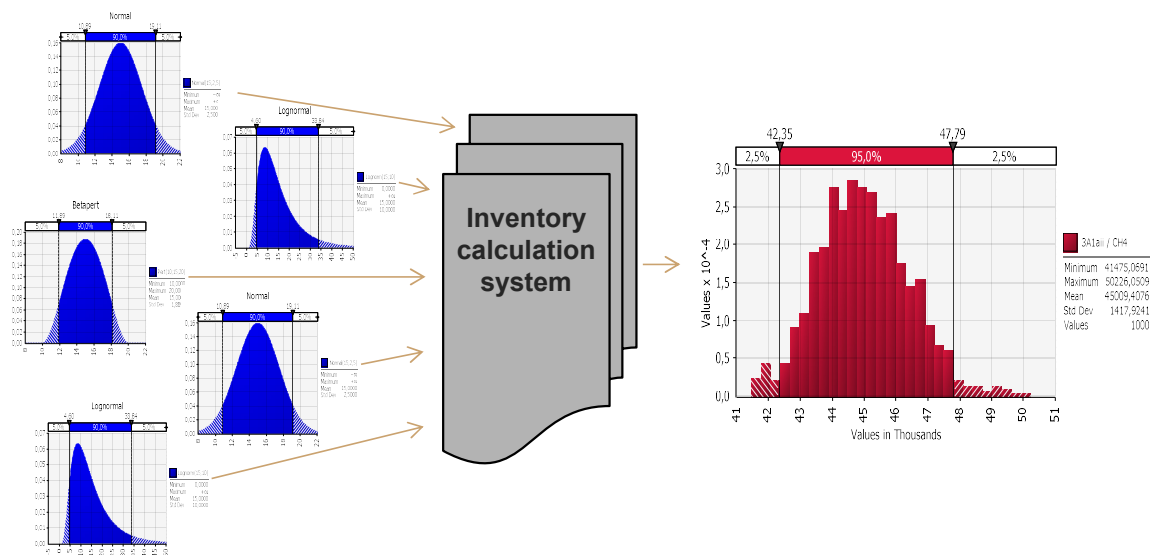


Combining uncertainty: Approach 2 [7]

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



GHG Support Unit, Transparency Division

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

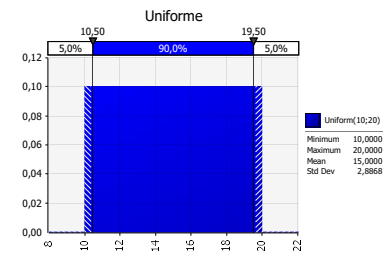
Most used PDF



Combining uncertainty: Approach 2 [11]

Selecting PDF

Uniform



All values with same probability

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

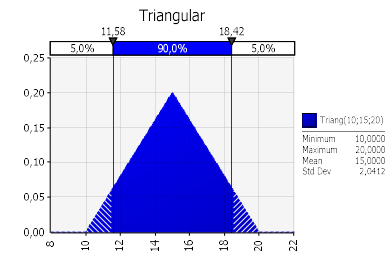
Application to inventories: large uncertainty and lack of information



Combining uncertainty: Approach 2 [12]

Selecting PDF

Triangular



Intuitive and flexible.

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

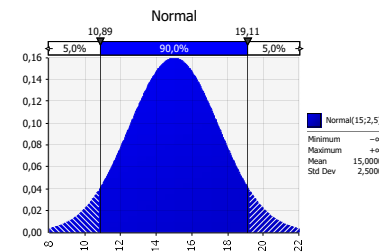
Application to inventories: expert judgment, knowledge from experience.
Limited information.



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 $\pm 2\sigma$ (1.96) accounts for approx. 95% of the values.

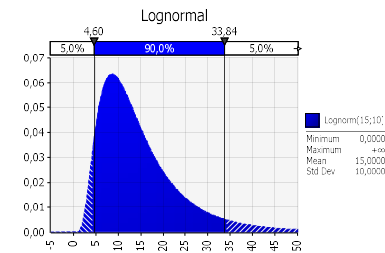
σ may be estimated as: $(\text{max} - \text{mean}) / 2$



Combining uncertainty: Approach 2 [14]

Selecting PDF

Lognormal



The natural logarithm of the variable adjusts to a Normal distribution

Parameters: Lognormal (*mean* $[\mu]$, *std. Dev.* $[\sigma]$)

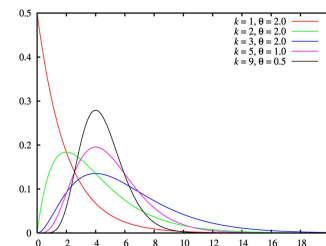
Application to inventories: Generally good representation for skewed non-negative values (emission factors for N₂O). Multiplicative processes.



Combining uncertainty: Approach 2 [15]

Selecting PDF

Gamma



Similar to lognormal but with not so heavy tails

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

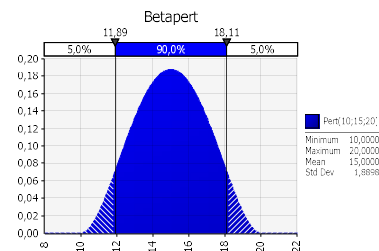
Application to inventories: Good representation for skewed values. Very flexible depending on its parameters. Mean value: $k \cdot \theta$



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

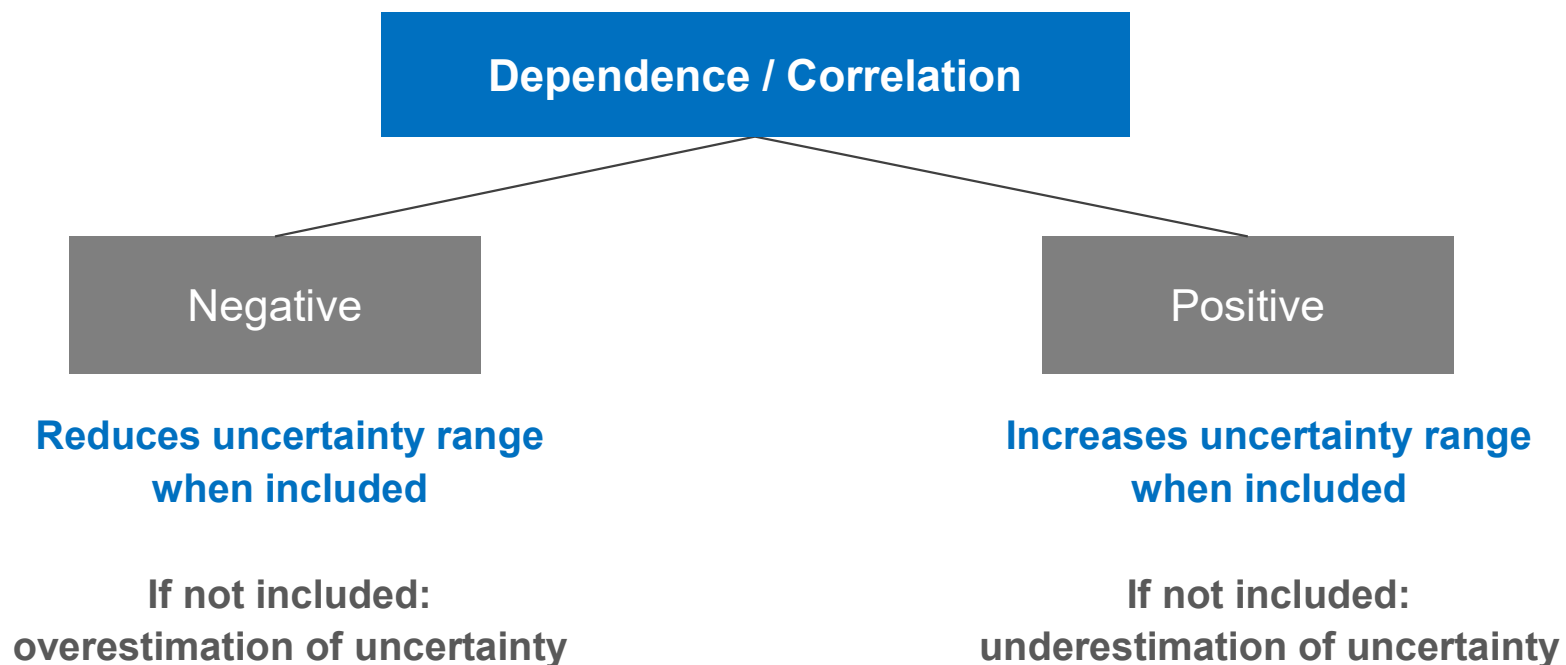
Relationship between two variables that make them not independent

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



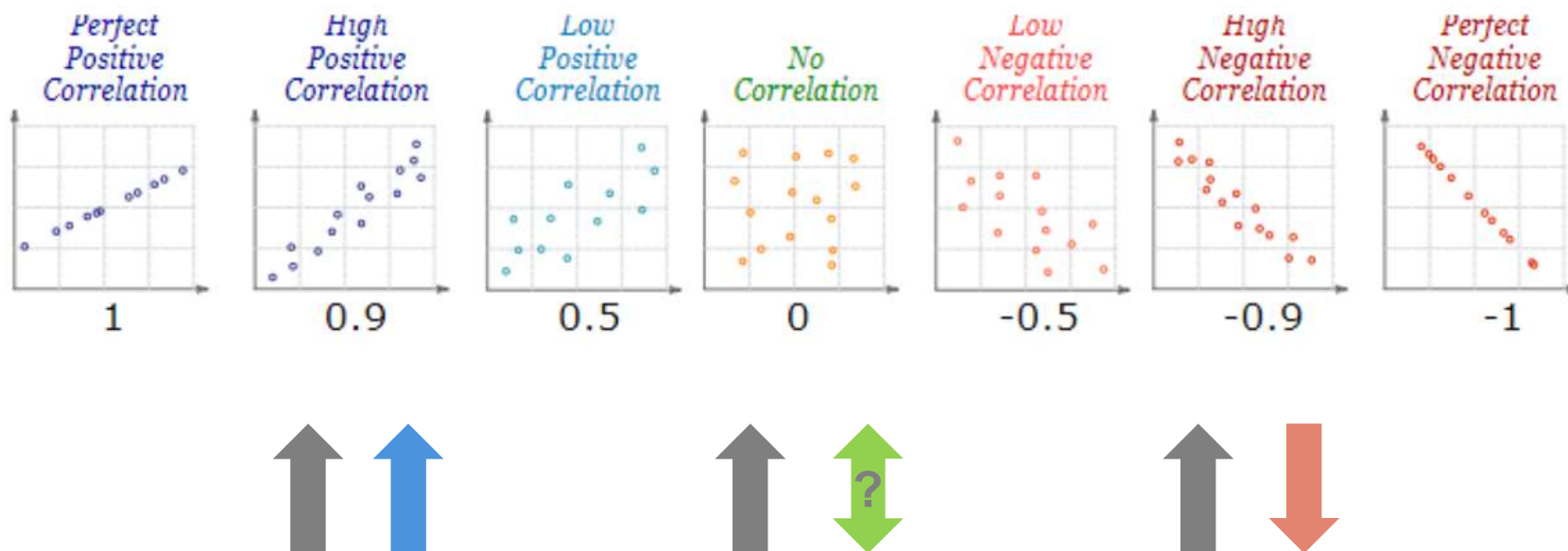
Combining uncertainty: Approach 2 [21]

DEPENDENCE AND CORRELATION AMONG INPUTS



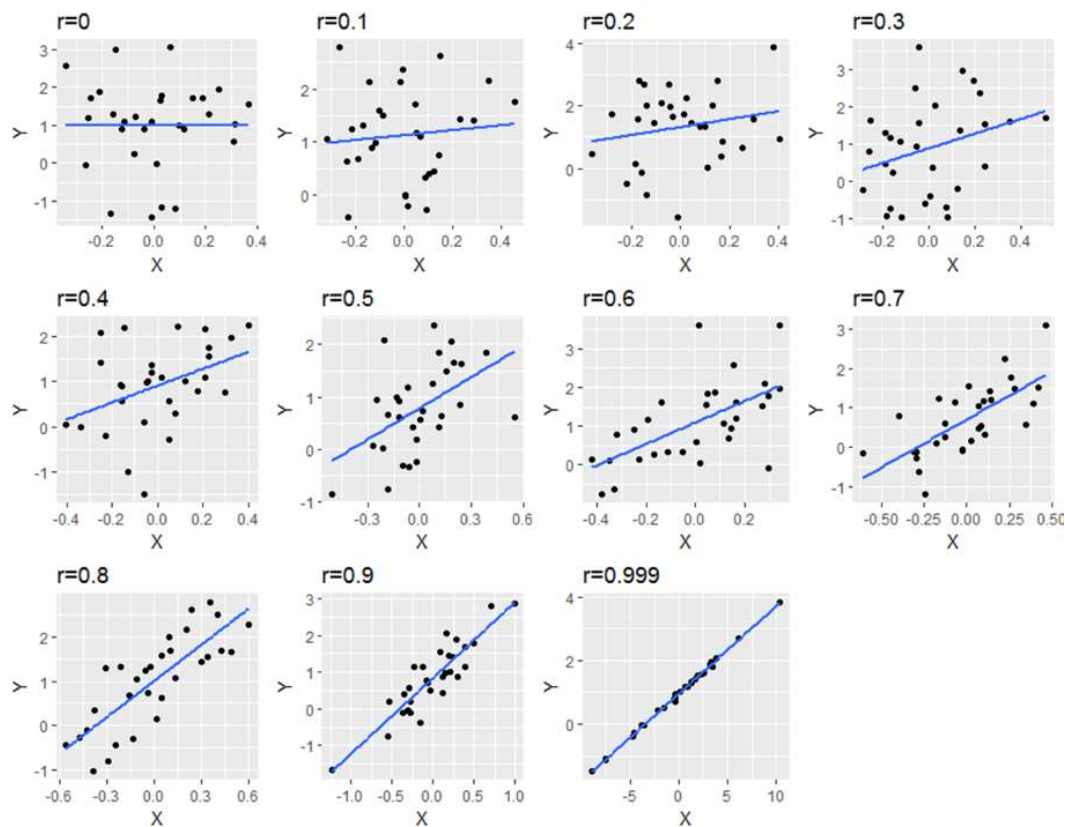
Combining uncertainty: Approach 2 [22]

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

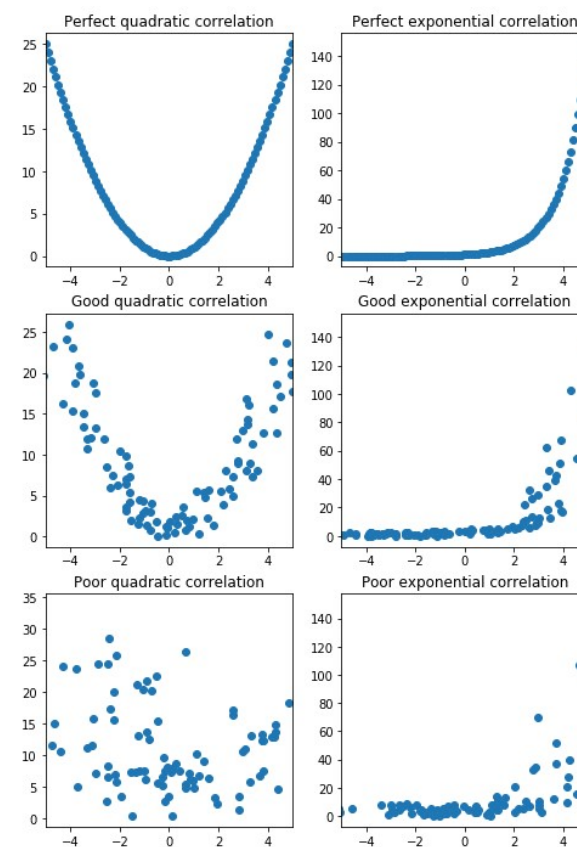
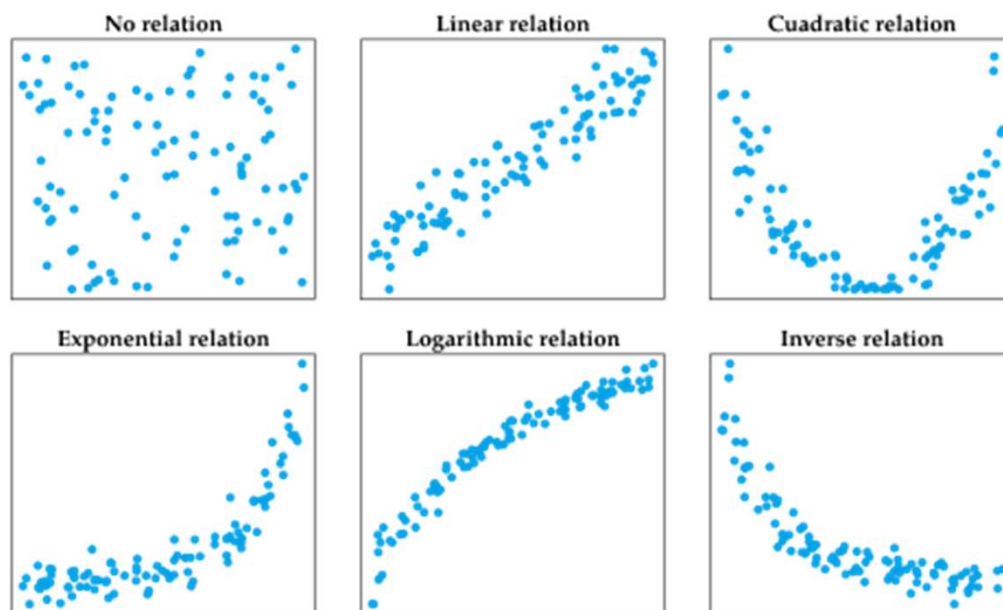
* Indicative ranges



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

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

Are FC (GJ) and EF independent?

FC: Fuel consumption (tonnes)

NCV: Net calorific value (GJ/t)

EF: Emission factor (tCO₂/GJ)

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

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)





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

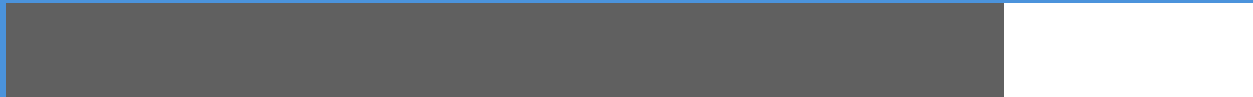
- 7. Methods to combine uncertainties: Approach 1
Propagation of errors

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

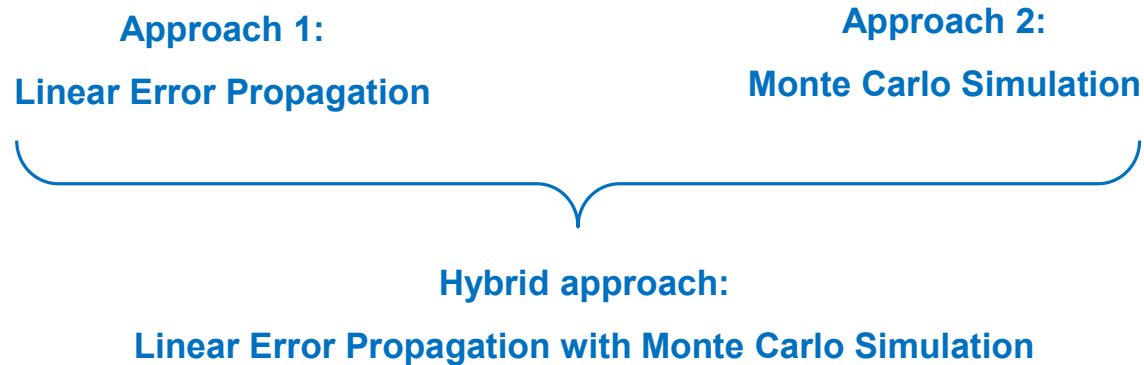


Learning
objectives



Combining uncertainty: Hybrid approach 1 and 2 [1]

Methods to combine uncertainties

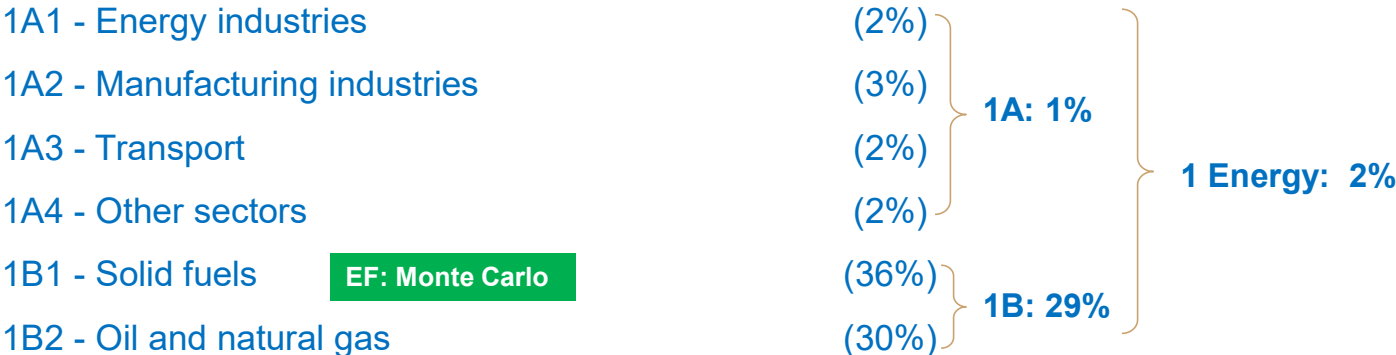


Identify categories that require more complex calculations, have high uncertainty ranges or where dependency is not negligible. Those cases can be propagated using Monte Carlo Simulations and the remaining categories can apply Linear Error Propagation.



Combining uncertainty: Hybrid approach 1 and 2 [2]

Linear Error Propagation (LEP)



Combining uncertainty: Hybrid approach 1 and 2 [3]

Linear Error Propagation (LEP)

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%)	}	2C - 28%		
2B9 - Fluorochemical		(50%)				
2C1 - Iron and steel	EF Monte Carlo	(33%)				
2C2 - Ferrous alloy		(56%)	}	2D - 50%		
2C3 - Aluminium	EF: Monte Carlo	(10%)				
2C6 - Zinc		(56%)				
2D1 - Lubricant use		(52%)	}	2F - 50%		
2D2 - Paraffin wax use		(52%)				
2F4 - Aerosols		(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 ₂ O emissions from managed soils	(43%)		
3C5 - Indirect N ₂ O emissions from managed soils	(62%)		
3C6 - Indirect N ₂ O emissions	(77%)		
3C7 - Rice cultivation	(115%)		



Combining uncertainty: Hybrid approach 1 and 2 [5]

Linear Error Propagation (LEP)

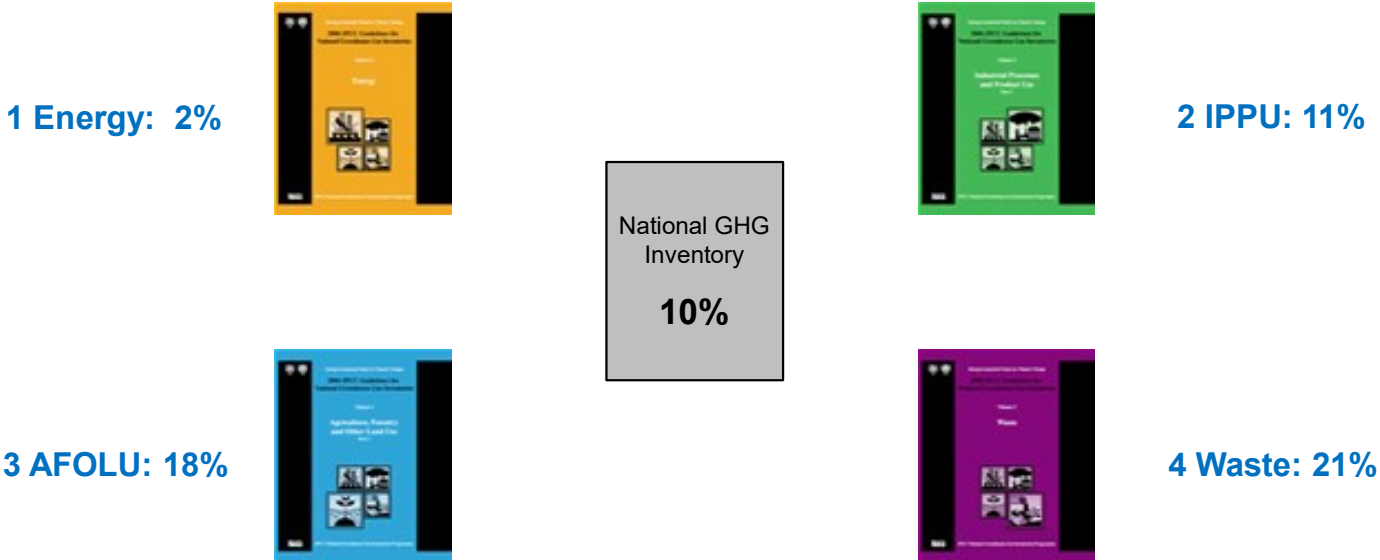
Monte Carlo Simulation

4A1 - Managed solid waste disposal	(32%)	}	4A - 29%	}	4 Waste: 21%
4A3 - Uncategorized solid waste disposal	(50%)				
4B - Solid waste biological treatment	(79%)	4B - 79%			
4C1 - Waste incineration	(64%)	4C - 64%			
4D1 - Domestic wastewater treatment	(19%)	}	4D - 31%		
4D2 - Industrial wastewater treatment	(76%)				



Combining uncertainty: Hybrid approach 1 and 2 [6]

Linear Error Propagation (LEP)



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:

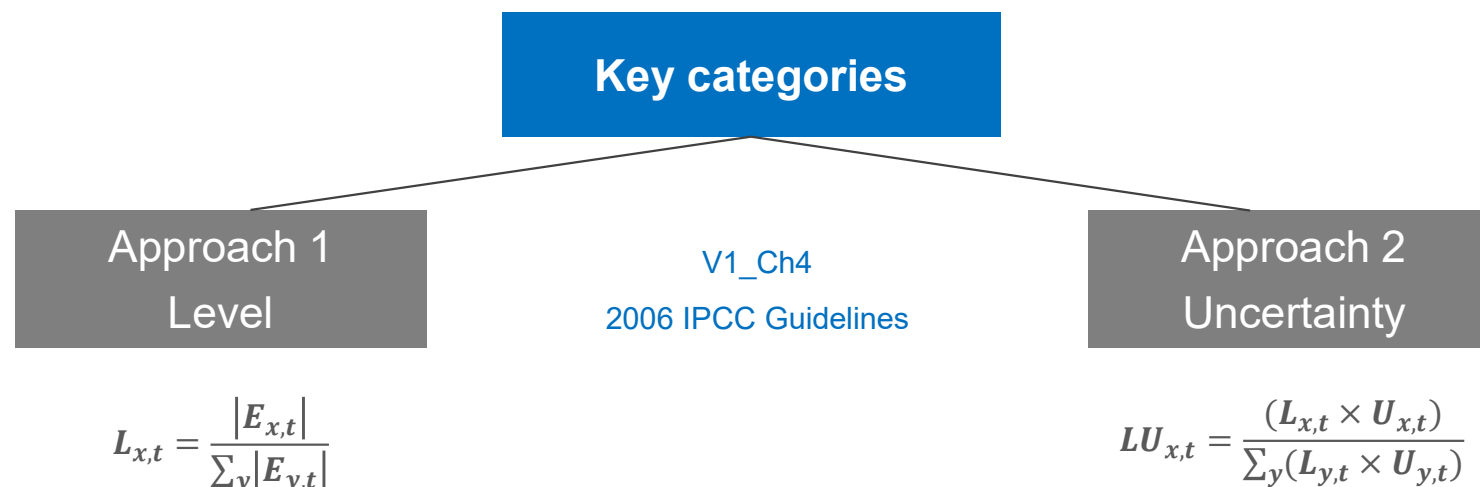
1. Learn how to identify key categories
2. Understand why uncertainty can help with efficiency



Learning objectives



Key category analysis [1]



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

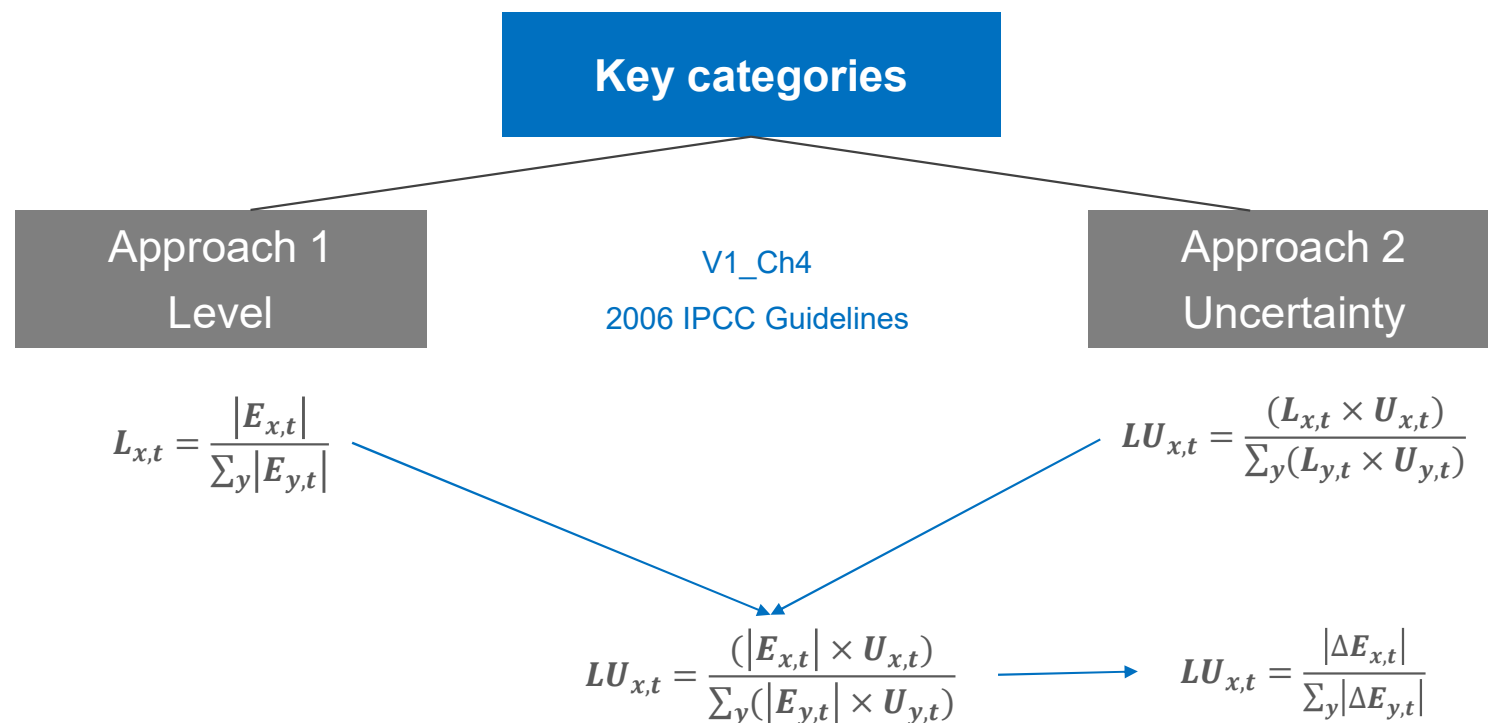
“Hot spots” can be used to assign resources for improvement and identify mitigation alternatives.

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

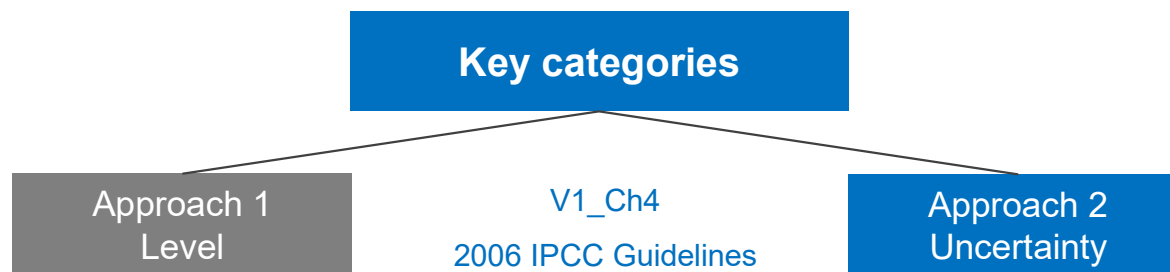
“Hot spots” can be used to assign resources for improvement in data collection



Key category analysis [2]



Key category analysis [3]



Emission Source	Emission (tCO ₂ e)	Absolute value of Emission (tCO ₂ e)	Level Li	Uncertainty Ui	Li x Ui	LUi (Li x Ui) / Σ(Li x 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		

Key categories based on Level

Sort high to low

90% cumulative



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

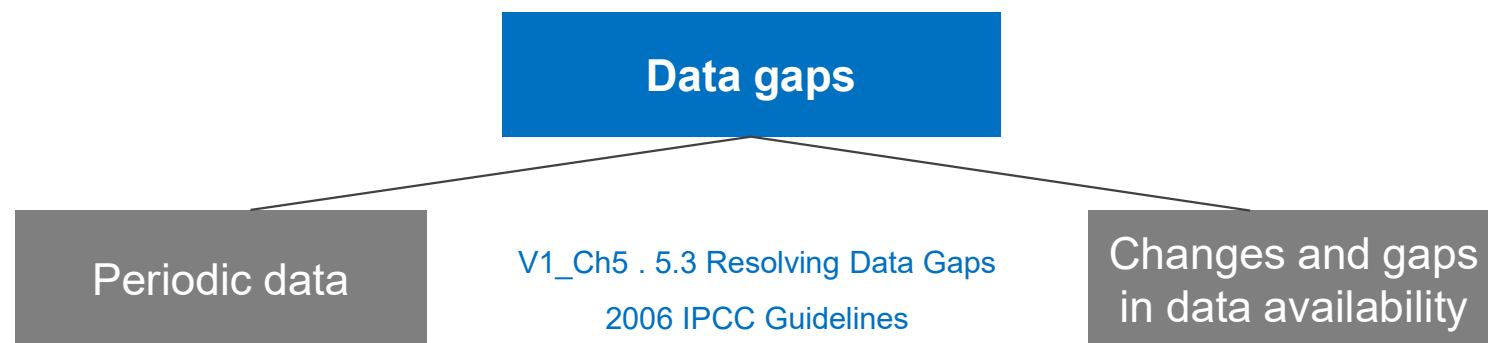


Learning objectives



Proxy: Splicing techniques and Expert Judgement [1]

Splicing techniques for Data gaps



Data 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

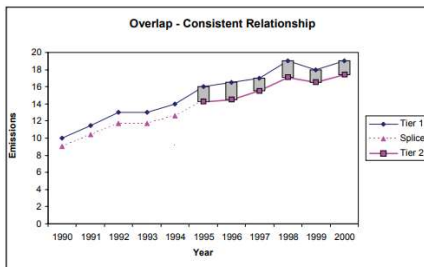


Proxy: Splicing techniques and Expert Judgement [2]

Splicing techniques for Data gaps

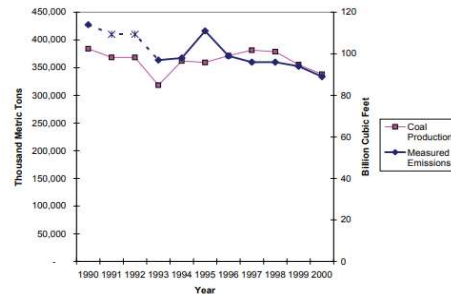
Overlap

New method implemented not available before (or after)



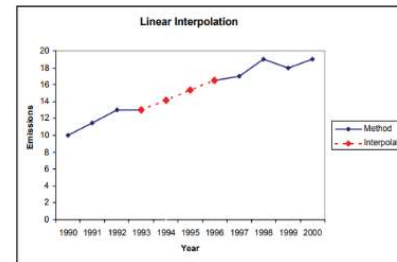
Surrogate

No data for the category but other related available
Ratios or regression



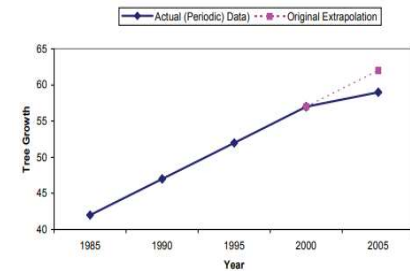
Interpolation

Data gap for some years or outliers identified



Extrapolation

Data unavailable for last or first year



Proxy: Splicing techniques and Expert Judgement [3]

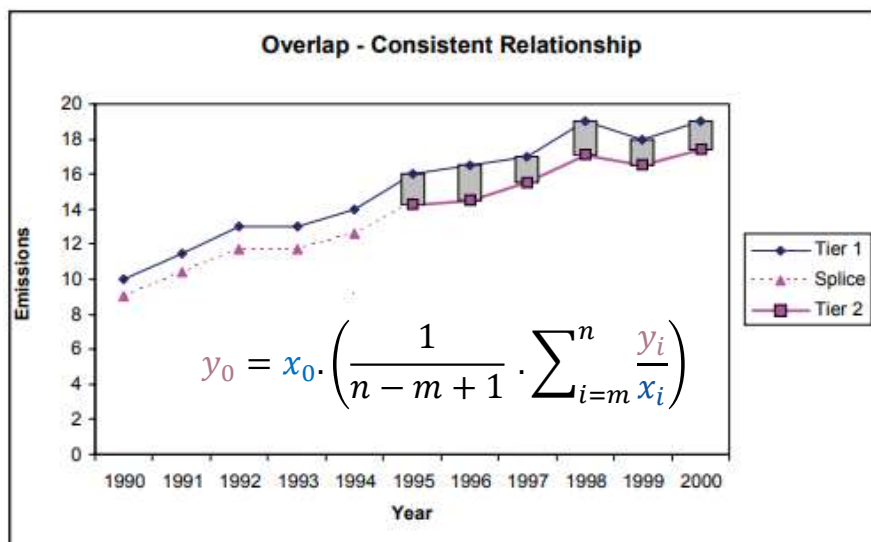
Splicing techniques for Data gaps

Overlap

Surrogate

Interpolation

Extrapolation



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]

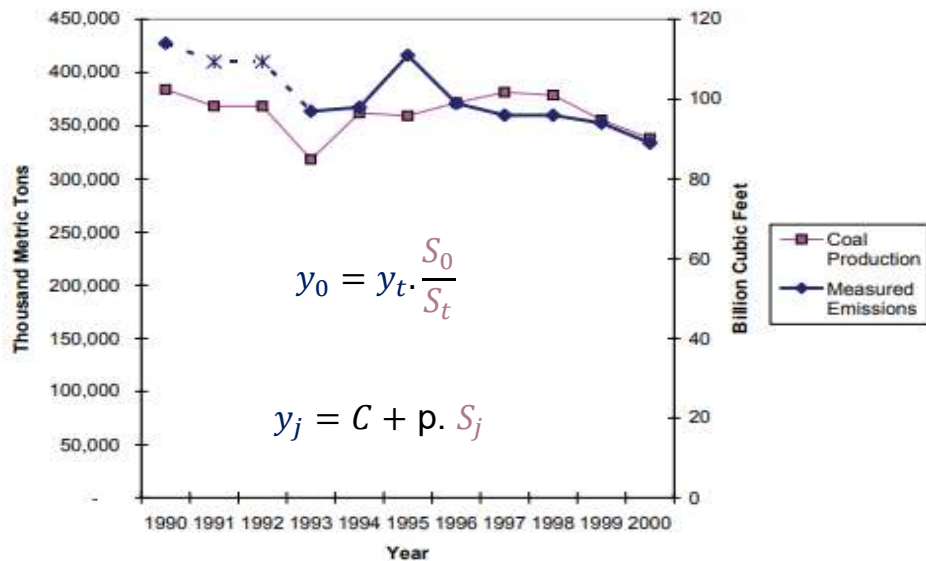
Splicing techniques for Data gaps

Overlap

Surrogate

Interpolation

Extrapolation



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)

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



Proxy: Splicing techniques and Expert Judgement [5]

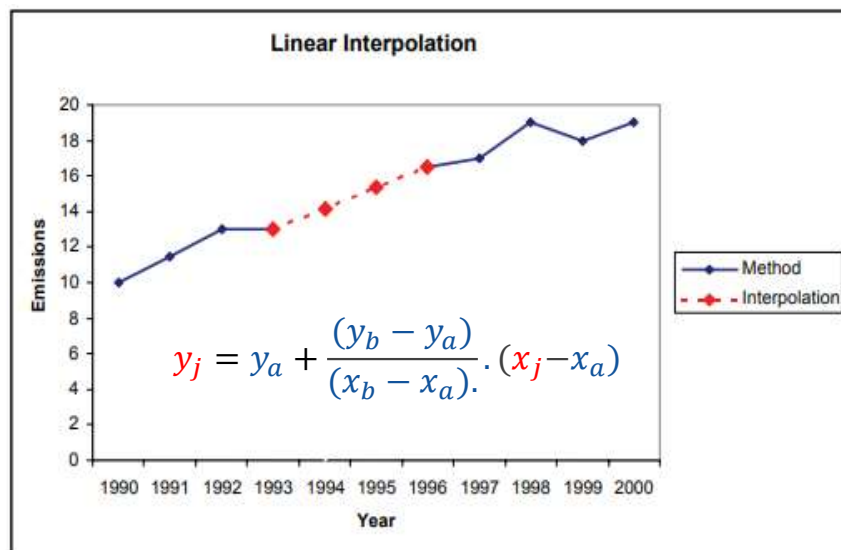
Splicing techniques for Data gaps

Overlap

Surrogate

Interpolation

Extrapolation



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]

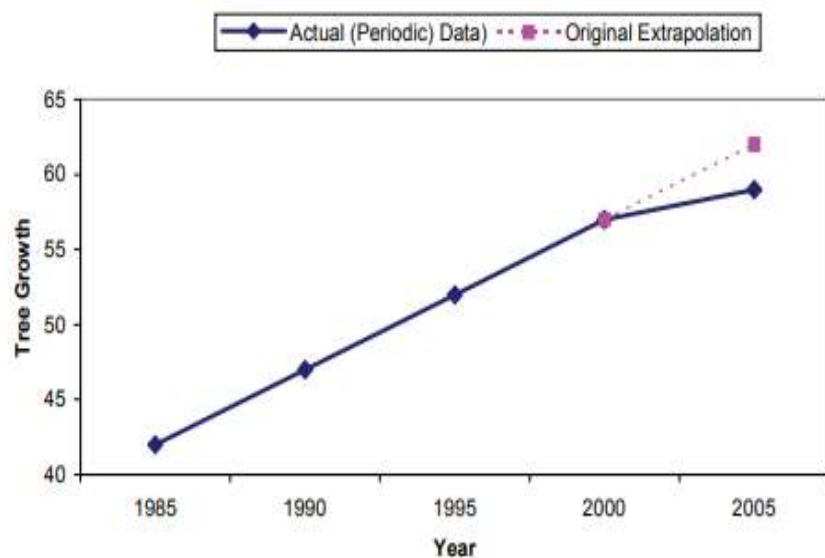
Splicing techniques for Data gaps

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

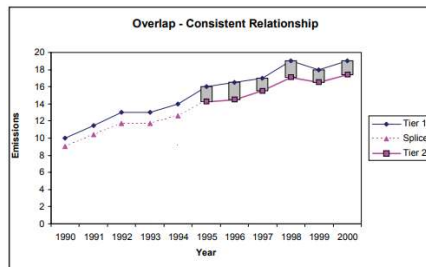
Uncertainty depending on the extrapolation method (trend or surrogate). Could be evaluated ex post if data becomes available.



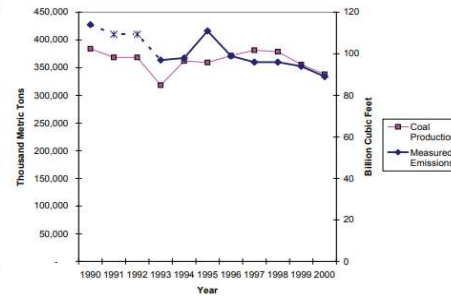
Proxy: Splicing techniques and Expert Judgement [7]

Splicing techniques for Data gaps

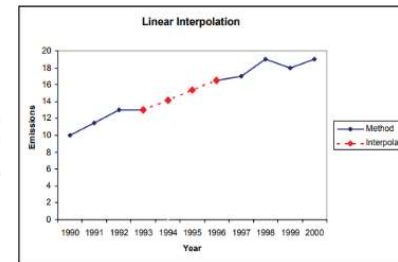
Overlap



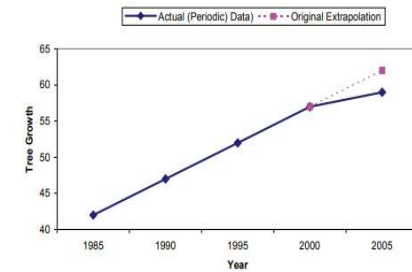
Surrogate



Interpolation



Extrapolation



Hands-on exercises



GHG Support Unit, Transparency Division

Proxy: Splicing techniques and Expert Judgement [8]

Splicing techniques for Data gaps

Overlap

Surrogate

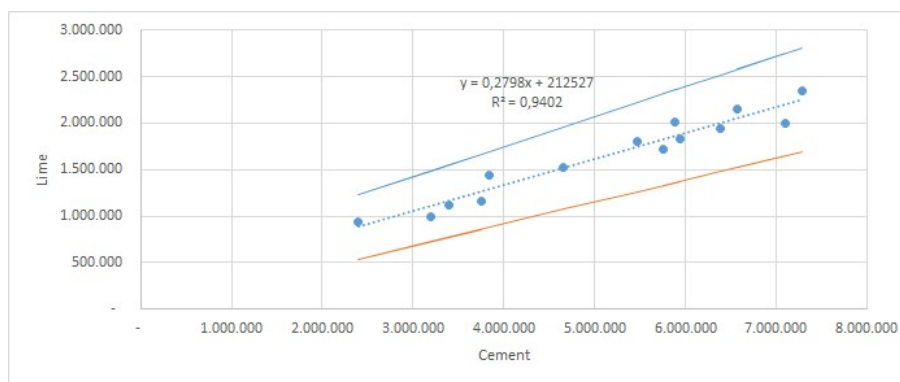
Interpolation

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

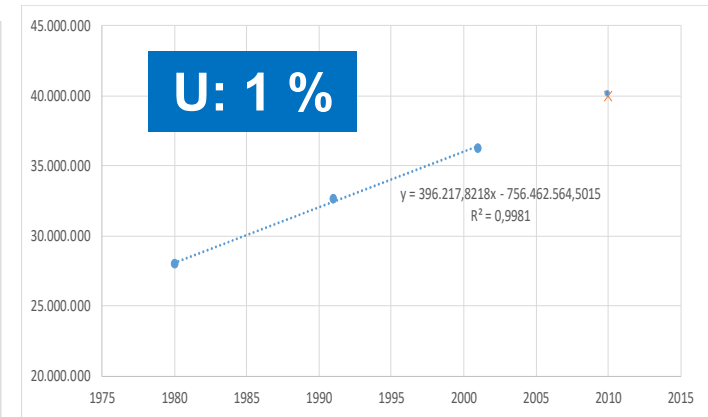
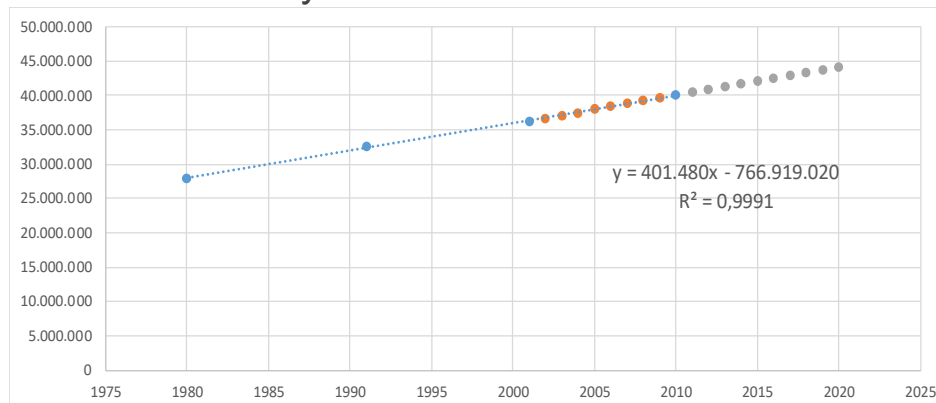
Interpolation

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 assess the uncertainty. Extrapolate the data from the census to calculate the population in 2020 and assess the uncertainty.



Year	Population
1980	27.949.480
1991	32.615.528
2001	36.260.130
2010	40.117.096



Proxy: Splicing techniques and Expert Judgement [10]

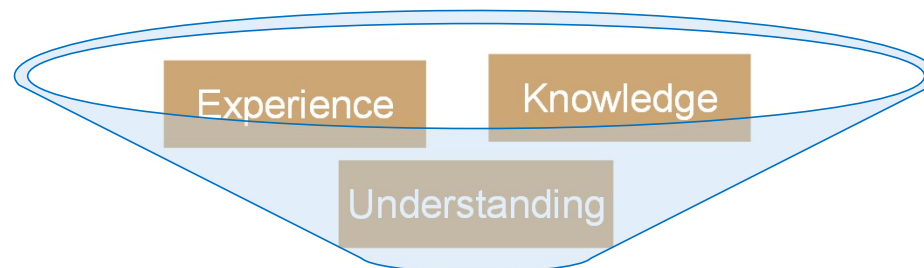
ENCODING EXPERT JUDGEMENT



GHG Support Unit, Transparency Division

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



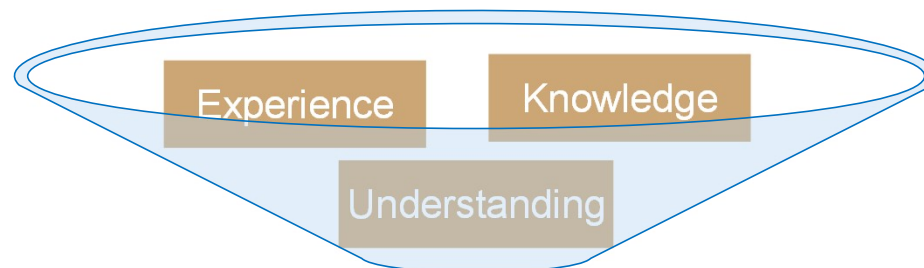
- When no relevant empirical data is available
- Well informed judgements from domain experts
- Formal expert elicitation protocols

IMPORTANT!
Document all the process!



Proxy: Splicing techniques and Expert Judgement [12]

ENCODING EXPERT JUDGEMENT



Elicitation protocols

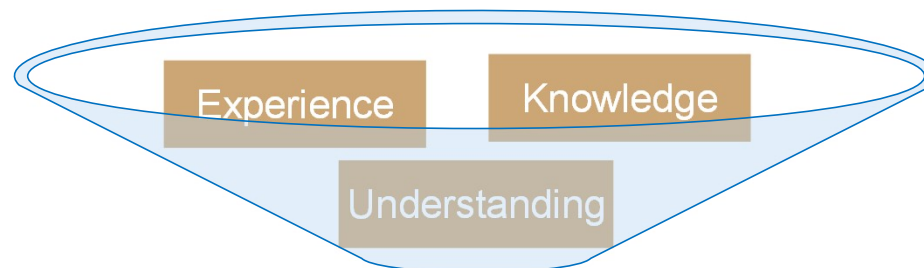
V1_Ch. 2 Annex 2A.1
2006 IPCC Guidelines

- **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*

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

⊗ **Overconfident estimate
(narrow interval)**



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

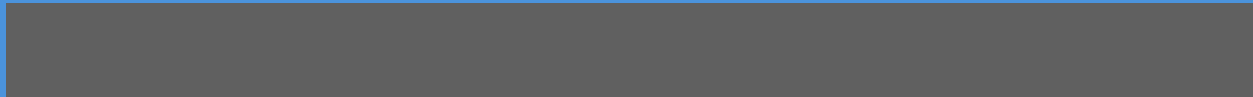
- 5. Uncertainty associated with the use of national statistics, surveys, censuses and sampling
- 6. Uncertainty associated with the Use of Empirical Data

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

