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MinFuture

Compilation of uncertainty approaches and recommendations for reporting data uncertainty

Deliverable 3.3

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List of abbreviations

CA	Consortium Agreement
CC	Consortium Committee
DOA	Description of Action
GA	Grant Agreement
LCA	Life Cycle Assessment
MFA	Material Flow Analysis
MFAs	Material Flow Analyses
MMFA	Mathematical material flow analysis
MSC	Monte Caro Simulation
PCG	Project Coordination Group
PMFA	Probabilistic material flow analysis
PO	Project Office
SPBTT	Science-Policy-Business Think Tank
WP	Work Package

1 Executive Summary

Material flow analysis (MFA) in general, is a term used to summarize a wide range of approaches to describe material stocks and flows in systems defined in space and time. In MFA, the consideration of uncertainty should enable the use of all available information about the system, reflecting the purpose of the MFA and the data quality. The uncertainty of the basic data and the accuracy of the results are fundamental pieces of information for the evaluation process. As MFA concerns gathering, harmonizing and analysing data from various different sources with varying quality, limitations of data are unavoidable in material flow studies. The majority of data in MFA are empirical quantities with uncertainty arising from different sources:

NATURE OF UNCERTAINTY	Causes of uncertainty	*Non-deterministic behaviour of a system* *Uncertainty of model parameter values* *Uncertainty of model structure* *Uncertainty due to external influence factors* *Uncertainty due to numerical solutions of model equations*
	Sources of uncertainty	*Statistical variation* *Variability* *Inherent randomness and unpredictability* *Subjective judgment* *Disagreement* *Linguistic imprecision* *Approximation*
	Types of Uncertainty	*Parameter Uncertainty* *Scenario Uncertainty* *Model Uncertainty* *Output Variable*

If sufficient data are available, unknown flows including their uncertainties can be determined by mass balancing and error propagation. It is also important to convince data providers to include data uncertainty in their publications. In some situations, however, problems will occur with statistical methods, if only limited data are available. Therefore, different approaches to quantify and treat uncertain data are available:

APPROACHES TO DEAL WITH UNCERTAITNY	Data classification	*Asymmetric uncertainty intervals* *Symmetric intervals* *PEDIGREE Matrix* *Information defects*
	Uncertainty analysis	*Gauss's law of error propagation* *Data reconciliation* *STAN Software* *Mathematical material flow analysis* *Probabilistic material flow analysis* *Monte Carlo simulation* *Fuzzy set theory*
	Sensitivity analysis	
	Comparison of model structures	

Based on Laner et al. (2014) a step-wise iterative procedure for handling uncertainty in MFA is suggested. This schematic framework for considering uncertainty in MFA facilitates transparent uncertainty analysis in MFA and is suitable to accommodate any of the approaches presented here. Some studies may not warrant full uncertainty analysis because of different foci of the MFAs. Therefore, only parts of the scheme can be applied. In addition to providing a systematic way to consider uncertainty in MFA, the suggested procedure forms a basis for consistently communicating the approach used to consider uncertainty in a specific MFA study.

In conclusion, it can be said that there are a handful of applicable approaches to consider data uncertainty in MFA. The employment of MFA software would facilitate the implementation of these approaches and reduce the additional workload because of automation to acceptable levels. However, such software support is not yet on the market (with the exemption of STAN[1], which is limited to normally distributed values) and there is a strong necessity to fund such software development. Only then, MFA could enter into an era where reporting uncertainty ranges of stocks and flows is mandatory and state-of-the-art. This would help to judge or gauge the reliability of MFA studies and also allow comparative studies for different regions with respect to quality and quantity of data generation.

[1] STAN is a freeware, produced by TU Wien: www.stan2web.net

2 Introduction

Global demand for minerals is growing rapidly, driven by rapid population growth, urbanisation and an increasingly diverse range of technical applications. Global material supply chains linking the extraction, transport and processing stages of raw materials have become increasingly complex and today involve multiple players and product components. An interactive platform that provides transparency about existing approaches and information gaps concerning global material flows is needed to understand these global supply chains; developing this capability is critical for maintaining competitiveness in the European economy.

MinFuture brings together 16 international partners from across universities, public organisations and companies, to deliver new insight, strategic intelligence and a clear roadmap for enabling effective access to global material information.

Data classification approaches typically focus on the evaluation of input data quality, but do not include mathematically rigorous procedures for propagating uncertainties through the model, whereas statistical approaches also propagate uncertainty through the material flow model to derive consequent uncertainty estimates for the model results. In MFA, the consideration of uncertainty should enable the use of all available information about the system, reflecting the purpose of the MFA and the data quality. Previously, ignoring uncertainty aspects in material flow studies has raised doubts about the reliability of MFA results (Laner et al. 2014). Though different ways of dealing with data uncertainties in MFA and related disciplines have been proposed (Hedbrant and Sörme 2001; Laner et al. 2014; Refsgaard et al. 2007; Weidema and Wesnæs 1996), a sound understanding of the nature of MFA data remains a subject for research.

This report compiles the findings of the task 3 of work package 3. WP3 investigates the state-of-the-art of methods and approaches to analyse, evaluate, and design anthropogenic material systems with the focus on the temporal scale. Task 3.3 deals with model uncertainty analysis. Model uncertainty stems from different problem areas, e.g.: (1) incomplete understanding of the investigated system (real world), which may result in inadequate model outline/structure (e.g. missing material flows and/or processes), (2) aleatory and epistemic data uncertainty. This report will examine the nature of uncertainty that is behind mineral raw materials data. The goal is to provide a compilation of uncertainty approaches and recommendations for reporting data uncertainty.

MFA models can be used to serve different purposes in material management, such as monitoring systems, forecasting changes, or evaluating alternative strategies. Depending on the purpose, MFAs need to include different components. These components are structured hierarchically (see Figure 1): the robustness of the components at higher levels depends on the robustness of the ones at lower levels. Combining these components adds new information and robustness and supports material strategies.

Figure 1: The hierarchical pyramid of MFA components.

Systems represent the totality of the stocks and flows within boundaries defined in space and time at a chosen level of (dis-)aggregation. They include observed and unobserved stocks and flows. Adding a system definition to observed data adds information: Systems define the context of observed flows and they allow for calculation of unobserved flows using mass balance.

Data form the foundation of MFAs. They represent observations of either stocks (at a given point in time) or flows (over a given time period).

Models in this context are mathematical representations of material cycles. They reflect the system definition and the drivers of cycles such as population growth or technologies used. They are used to simulate MFA-based trends and developments

Scenarios here are assumptions of plausible future cycles that are consistent with the mass balance principles and the assumed drivers. They can be used to make forecasts or to evaluate the effectiveness of alternative strategies.

Uncertainty is inherent in all MFAs of historical or future cycles due to errors in system definitions and the data used. Approaches to uncertainty analysis aim at making uncertainties transparent and reducing them. They enable the modeller to make more robust assumptions and become aware of the model's strengths and limitations.

Indicators stands for quantitative measures that aim to reflect the status of complex systems. They are used to analyse and compare performance of businesses, sectors or economies across countries and to determine policy priorities.

Visualisations here are different maps of complex systems. They can inform decision making in industry and government, by visualizing current status and historical trends, and potential future developments under different conditions. Visualization tools are developed to support the recording (monitoring), exploration (analysis), and explanation (interpretation) of information.

Strategy support here has two aspects; (1) Supporting political strategies for raw materials that aim at reaching different goals, such as those of the Strategic Implementation Plan (SIP) of the European Innovation Partnership on Raw Materials, the Circular Economy Action Plan or the SDG's. (2) Supporting strategies for improving and expanding the use of MFA in academia, governments and industry.

1. is addressed in exemplary ways through undertaking case studies on the material use in low-carbon technologies.
2. is addressed through developing a roadmap

As uncertainty is one component of the hierarchy, this report will serve as a guidance for requirements to survey and report uncertainties, and propose methods how to consider epistemic uncertainty in data generation and communication. Existing approaches for data classification and implementation of data uncertainty into modelling will be assessed to derive requirements for consideration and reporting of data uncertainty. Regardless of the MFA and uncertainty method used, MFAs need to include the components depicted in Figure 1. Hence, the uncertainty aspect will be discussed related to the different components of the 'MinFuture Pyramid'.

3 Data Uncertainty in Material Flow Analysis

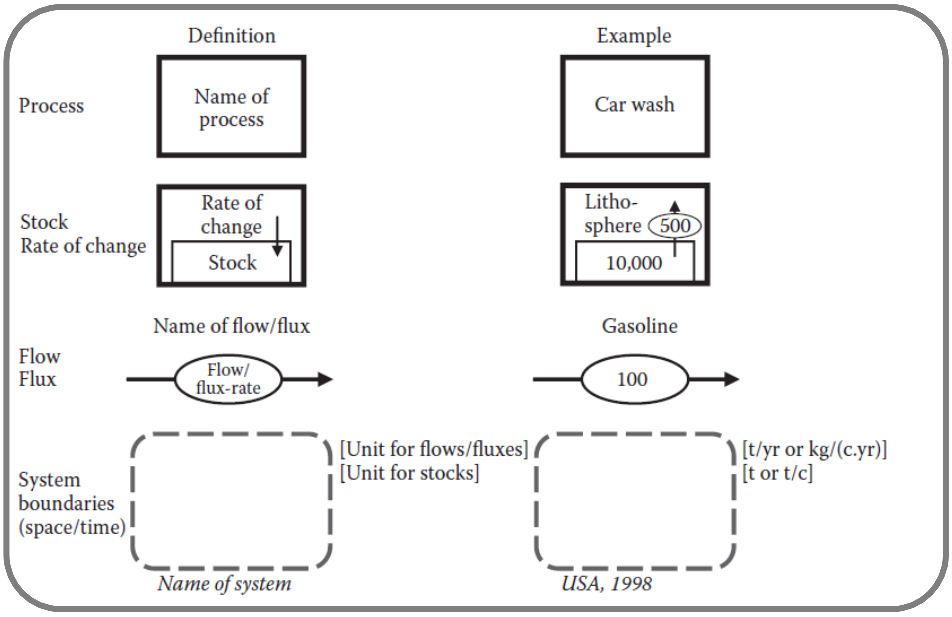
3.1 Material Flow Analysis

Material flow analysis (MFA), in general is a term used to summarize a wide range of approaches to describe material and energy stocks and flows in systems defined in space and time.

MFA is helpful in identifying the accumulation and depletion of materials in natural and anthropogenic stocks, such as buildings, or soil and sediments. Without it, it is impossible to identify the shift of material stocks from natural reserves to anthropogenic accumulations. MFA, sometimes referred to as substance flow analysis (SFA) if a specific substance is the focus, is a systematic assessment of the state and changes of flows and stocks of materials within a system defined in space and time. MFA connects the sources, the pathways, and the intermediate and final sinks of a material. Because of the law of conservation of matter, the results of an MFA can be controlled by a simple mass balance comparing all inputs, stocks, and outputs of a process. It is this distinct characteristic of MFA that makes the method attractive as a decision-support tool in resource management, waste management, environmental management, and policy assessment (Brunner and Rechberger 2016).

By balancing inputs and outputs, the flows of wastes and environmental loadings become visible and their sources can be identified (Brunner and Rechberger 2016). The MFA terms based on the Handbook of Material Flow Analysis: For Environmental, Resource, and Waste Engineers (Second Edition) (Brunner and Rechberger 2016) are described in Figure 2.

MFA has experienced considerable development over the past three decades. A large and still growing community is using this method to analyse the anthropogenic metabolism (Rechberger et al. 2014). MFA is a method for modelling, understanding and optimizing material flow systems. MFAs incorporate databases of increasing size and quality and reveal more and more details about material flows into, within and out of given systems. As a consequence, MFAs are of increasing size and system structures are of increasing complexity (Schwab 2016).



Terms	Descriptions
Substance	Substances are any (chemical) element or compound that is composed of uniform units (atoms, molecules).
Good	Goods are any economic entities of matter with a positive or negative economic value and are made up of one or several substances.
Material	Material serves as an umbrella term for both substances and goods.
Process	Processes are defined as the transformation, transport or storage of materials.
Flow	Flows are defined as a mass flow rate with the ratio of mass per time.
Transfer coefficient	Transfer coefficients describe the partitioning of materials in a process.
Stock	The total amount of materials stored in a process is designated as the stock of materials. Both the mass of the stock as well as the rate of change of the stock per unit time (accumulation or depletion of materials) are important parameters for describing a process.
System	The system is the actual object of an MFA investigation. A system is defined by a group of MFA elements, the interaction between these elements, and the boundaries between these and other elements in space and time.

Figure 2: Terminology and main symbols of MFA based on Brunner and Rechberger (2016) (Allesch 2017).

3.2 Data Uncertainty

A model can never perfectly represent a real system. Because of that, model predictions are always uncertain. Besides MFA concerns gathering, harmonizing, and analysing data about physical flows and stocks from different sources with varying qualities, data limitations are unavoidable in material flow studies (Laner et al. 2014). Although studies of material flow systems can provide information, they also depend on information and a lack of useful information can be a limiting factor. More than that, the results are typically inherently limited in terms of accuracy and, thus, in their reliability in subsequent decision-making processes. Clearly, if MFA is seen as a way of compiling data to create information about material stocks and flows and to aggregate this information to create knowledge about material flow systems, the quality of its fundamental components, data, is substantial (Schwab 2016).

Almost all data used for MFA will be subject to a certain degree of uncertainty. Assessment of data reliability and crosschecking of information and estimates are of great importance, as all data will be more or less uncertain (Lassen et al. 2000). The reason is that MFAs are often based on cross-disciplinary, highly heterogenic data. Often the data are unstructured and can have different formats and qualities due to heterogeneous sources, such as official trade statistics, scientific literature, consumer behaviour studies, and expert estimates. In some cases, extensive statistical data, such as lab data on substance concentrations, might be available, but MFA modeler usually have to cope with isolated values (Schwab 2016).

In many cases, MFA data are not based on empirically well-founded datasets, but on isolated values which are not always provided in consistent formats (Schwab 2016).Therefore, the validity of MFAs depends on the quality and quantity of available data (Dzubur 2017). Data quality and data quantity are constitutive for environmental modelling, also in MFA, which is often based on cross-disciplinary data. Additionally, relevant data may be confidential, lost, highly aggregated, or outdated, or derived in indirect ways. The background of data is not always transparent because of missing meta-information. Besides the data can be inaccurate owing to measurement and collection errors or biased du to the interests of the data producers (Schwab 2016).

Recognizing the shortcomings of MFA data in combination with the mentioned variety of sources and the various ways collected data are applied in the analysis process, the databases of studies are not always comprehensible for agents other than the producer, and the systematic evaluation of data quality is limited. All measured, estimated, or literature-based values should at least random deviations (Brunner and Rechberger 2016). Therefore, MFA should now enter into an era where reporting uncertainty ranges of stocks and flows is mandatory. This would help to judge or gauge the reliability of MFA studies and also allow comparative studies for different regions with respect to data quality. Such analysis of MFA data is a requirement for progress in MFA to produce reliable results (Rechberger et al. 2014).

To develop a robust MFA, modelers usually need to have a good understanding about the reliability of a data source and are able to assign practical and useful estimates on the uncertainty range of the input data (Rechberger et al. 2014). Essentially, there is no collective understanding about what data or, more generally, information in MFA is and how it can be characterized (Schwab 2016). Based on the analysis of data uncertainty by Danius and Burström (2001) it is concluded that to use MFA as a tool for priority setting and follow-up is associated with considerable difficulties.

The data availability generally decreased from the country to the regional level, and even further to the metropolitan areas. In particular, the regional-/urban-scale MFA indicators have higher uncertainty owing to: (1) data being spread between several institutions deploying different collection protocols and uncertainty assessment methods; (2) confidential values; (3) MFA at urban level aggregates uncertainties from more sets of data; and (4) MFA at urban levels is more dependent on imputation methods (Patrício et al. 2015)

Uncertain data may indicate a condition that could be detrimental to environment or public health. Either the data can be used despite the high uncertainty, with a risk for confusion and speculation. Or the data can be ignored, with a risk for also ignoring an important detrimental condition (Hedbrant and Sörme 2001). However, MFA is still a useful tool for screening in order to identify areas for further and more detailed investigation (Danius and Burström 2001).

4 Nature of Uncertainty

Given that material flow data originate from different sources and vary in quality, MFA is naturally confronted with uncertainty (Laner et al. 2015a). Collecting data is an important part of each modelling procedure. If only the point estimators of observations are considered, known constraints such as the conservation laws of mass and energy are frequently violated (Cencic 2018).

4.1 Aleatory variability and epistemic uncertainty

Uncertainty in science may relate to context definition, model structure, model inputs, parameter values, and others (Walker et al. 2003). As a general concept, it is proposed to distinguish epistemic uncertainty and aleatory (also stochastic, or natural) variability (Schwab 2016; Morgan et al. 1992). Therefore, data uncertainties can be grouped into these two categories (Brunner and Rechberger 2016) (see Figure 3).

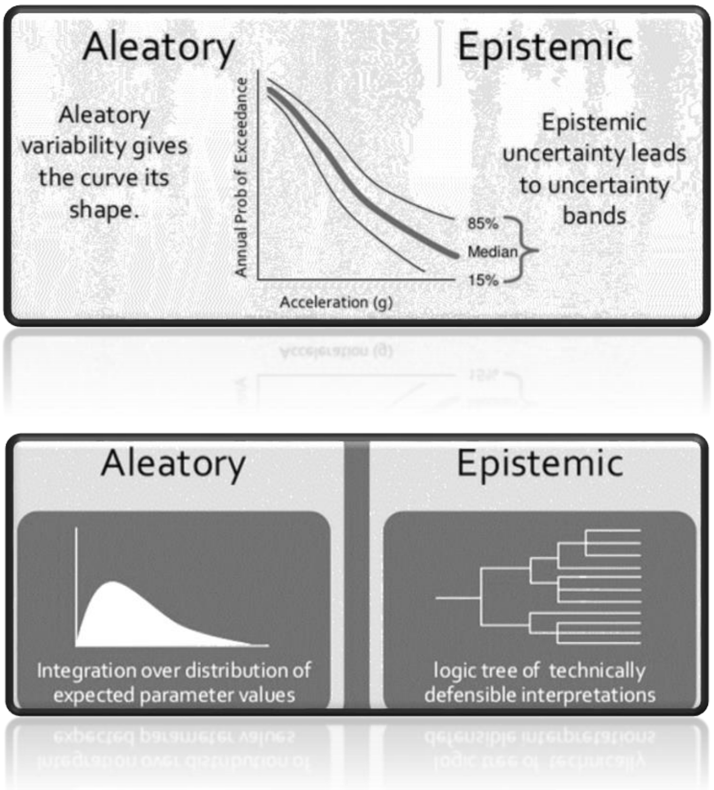


Figure 3: Aleatory and epistemic Uncertainty (Kammerer 2013)

Aleatory variability

> *The word aleatory derives from the Latin alea, which means the rolling of dice. Thus, an aleatoric uncertainty is one that is presumed to be the intrinsic randomness of a phenomenon (Der Kiureghian and Ditlevsen 2009).*

Aleatory uncertainty is often also referred to as variability. It is caused by randomness and cannot be reduced by knowledge (Dzubur 2017) and arises due to inherent variability, natural stochasticity, environmental or structural variation across space or through time, manufacturing or genetic heterogeneity among components or individuals, and a variety of others sources of randomness. Aleatory variability cannot be reduced but only better understood (Brunner and Rechberger 2016). Uncertainties are categorized as aleatory if the modeller does not foresee the possibility of reducing them (Der Kiureghian and Ditlevsen 2009).

Aleatory uncertainty can be appropriately handled with concepts used for describing observed frequencies of random events (frequentist approach) while epistemic uncertainty requires concepts for dealing with the degree of belief in data or reasonable assumptions reflecting available data. These two types of uncertainty are typically confused in MFA, making it difficult to distinguish what is known from what is assumed. (Dzubur 2017).

Epistemic uncertainty

> *The word epistemic derives from the Greek $\varepsilon\pi\iota\sigma\tau\eta\mu\eta$ (episteme), which means knowledge. Thus, an epistemic uncertainty is one that is presumed as being caused by lack of knowledge (or data) (Der Kiureghian and Ditlevsen 2009).*

Epistemic uncertainty is caused by a lack of knowledge and can be minimized through further examination (Dzubur 2017). Uncertainties are characterised as epistemic, if the modeller sees a possibility to reduce them by gathering more data or by refining models (Der Kiureghian and Ditlevsen 2009). Epistemic uncertainty arises due to insufficient knowledge about the world, which includes small sample sizes, detection limits, imperfections in scientific understanding, etc. Epistemic uncertainty is understood as uncertainty due to limited or imperfect knowledge, which could be reduced by further investigation (Schwab 2016).

Table 1: Aleatory variability and epistemic uncertainty (Kammerer 2013)

Aleatory	Epistemic
Natural variability	Modelling or knowledge uncertainty
Not reducible	Reducible with more information
Addressed through integration over parameter distributing	Addressed through use of a logic tree

While epistemic uncertainty relates to knowledge shortcomings, aleatory uncertainty refers to the impossibility of reducing certain entities (or objects, phenomena) to simple empirical quantities such as one precise value. In that sense, variability is an intrinsic property of any entity that has more than one realization. It is thus also an intrinsic part of a complete piece of information. Not knowing about the extent of variability, in return, is a knowledge shortcoming and thus epistemic uncertainty (Schwab 2016). The distinction between aleatory and epistemic uncertainties is determined by modelling choices. The distinction is useful for identifying sources of uncertainty that can be reduced in near-term, i.e., without waiting for major advances to occur in scientific knowledge, and in developing sound risk and reliability models. The distinction is also important from the viewpoint of transparency in decision-making, since it then becomes clear as to which reducible uncertainties have been left unreduced by our decisions (Der Kiureghian and Ditlevsen 2009).

4.2 Causes of uncertainty

As MFA concerns gathering, harmonizing and analysing data about physical stocks and flows from various sources with varying quality, limitations of data are unavoidable in material flow studies (Chen and Graedel 2012; Dzubur 2017). The majority of data in MFA are empirical quantities with uncertainty arising from different sources (Laner et al. 2014). Based on Dzubur (2017) the causes of uncertainty can be assigned as follows:

a) non-deterministic behaviour of a system
b) uncertainty of model parameter values
c) uncertainty of model structure
d) uncertainty due to external influence factors
e) uncertainty due to numerical solutions of model equations

Non-deterministic behaviour of a system

Non-deterministic behaviour of a system is usually due to chaotic behaviour rather than due to true randomness at a macroscopic level. Chaotic behaviour denotes deterministic systems, which are very sensitive to initial conditions. As the initial state of a system can never be reproduced in full, this leads to observed non-deterministic behaviour. Besides, there are also other causes of non-deterministic behaviour which can be well described by random model elements, such as aggregation errors. As chaotic behaviour, this is due to epistemic uncertainty as there is a lack of spatial resolution. Another reason of non-deterministic behaviour can be influence factors, which cannot be measured and therefore, cannot be considered in a model.

Uncertainty of model parameter values

The usage of model parameters can specify the essential structure of dependence in the model. Still, there might remain unknown model variables that must be adapted empirically. Parameter estimation should not only provide the best estimates of model parameters, but also of their uncertainty, which can be propagated in the results.

Uncertainty of model structure

Structural model errors may consist of an inadequate selection of model variables and processes, an inadequate selection of process formulations, or an inadequate formulation of spatial and temporal resolution of a model. Such errors are not easily quantifiable.

Uncertainty due to external influence factors

External influence factors describe the influence of the environment on the considered system.

Uncertainty due to numerical solutions of model equations

Usually, model equations must be solved numerically. The accuracy of these numerical solutions is usually much higher than uncertainty due to other sources, and can often be neglected. An exception is the usage of Monte Carlo simulation techniques to calculate probability distributions, the use of which can lead to significant errors in the results if the number of runs is too low. Other potential causes of uncertainty can be the use of poor numerical techniques.

4.3 Sources of uncertainty

An uncertainty type of central interest in this work is data uncertainty. Ideally, data uncertainty can be understood as a problem of variability and can, if sufficiently large datasets are given, be quantified by statistical methods. These possibilities may, however, be limited as given data may not always be sufficient for proper application of statistical methods. Moreover, data uncertainty is not always a unidimensional phenomenon but may also, in addition to variability, include elements of epistemic uncertainty such as disagreement, linguistic imprecision, systematic error or subjective judgement, and others (Morgan et al. 1992) (Schwab 2016).

The majority of data in MFA are empirical quantities with uncertainty arising from different sources which are summarized by Laner et al. (2014).

Table 2: Sources of uncertainty in material flow data (Laner et al. 2014)

Sources of uncertainty	Description	Examples
Statistical variation	Statistical variation arises from random error in direct measurements of the quantity of interest	Measurements of copper (Cu) content in the same type of cell phone
Variability	Quantities are variable in space and time, which causes values to fluctuate	Cu content in cell phones from the period 2000–2010
Inherent randomness and unpredictability	Uncertainty is irreducible in principle because of indeterminacy (i.e., practical unpredictability)	Cu recovery efficiency in future treatment of waste cell phones
Subjective judgment	Estimating the difference between the quantity being measured and the quantity of interest resulting from systematic error is essentially based on subjective judgment. Systematic error derives from sources of uncertainty, which are unknown (otherwise they should be adjusted for), and is therefore irreducible	Using the Cu content in one type of cell phone to estimate the Cu content in another type
Disagreement	There is no consensus among scientists (opposing views), typically because of a lack of data	Long-term mobilization of Cu from landfilled waste
Linguistic imprecision	Imprecise language causes uncertainty about a quantity	"Nonferrous metal (mainly Cu) content in a cell phone" is an ill-specified quantity
Approximation	Because the model is only a simplified version of the real system, model parameters approximate the real properties of the system	Linear relationship (transfer coefficient) between Cu content of a cell phone and Cu recovered during mechanical treatment is an oversimplified assumption.

4.4 Types of uncertainty

Most uncertainty studies quantify only one type of uncertainty, i.e., uncertainty due to input data (parameter uncertainty). However, outcomes can also be uncertain due to normative choices (scenario uncertainty) and the mathematical models involved (model uncertainty) (Huijbregts et al. 2003). Huijbregts et al. (2003) evaluate uncertainty in environmental LCA studies and the following description is based on that. Although it is about LCA many aspects related to the types of uncertainty can be shifted to MFA.

Parameter Uncertainty

Parameter uncertainty reflects our incomplete knowledge about the true value of a parameter, e.g., due to imprecise measurements, (expert) estimations, and assumptions. Monte Carlo simulation is a technique to quantify parameter uncertainty. It propagates known parameter uncertainties into an uncertainty distribution of the output variable.

Scenario Uncertainty

Normative choices are unavoidable in LCA and MFA studies. These normative choices lead to uncertainty because different choices may generate different outcomes. Quantification of this scenario uncertainty involves two steps.

First, an overview has to be made of the normative choices involved in the LCA study. Second, a procedure has to be developed to quantify the consequences of normative choices in terms of output uncertainty. Figure 4 provides an overview of the scenario uncertainties generally encountered in LCA studies.

- Important normative choices in the inventory analysis are the choice of the procedure to allocate environmental impacts for multi-output processes, multi-waste processes, and open-loop recycling, and the choice of how to assess future situations, such as the disposal of long-life products.
- In the impact assessment, the choice of a particular environmental endpoint should be made explicit. For instance, inclusion or exclusion of "below threshold" impact changes may result in considerably different characterization factors.
- The choice for a particular time horizon should also be considered. For instance, the toxic impact of metals may differ more than six orders of magnitude depending on the time horizon chosen.
- Finally, a potentially important choice is the decision whether to include potential impacts linked to pollutants exported from the emitting region. Exposure that occurs outside this region may fully dominate the potential impacts, obscuring those in the emitting region itself.

LCA phase	Scenario uncertainty	Model uncertainty
goal and scope	functional unit system boundaries	
inventory analysis	allocation waste handling of long-life products	ignoring nonlinear processes complete lack of process data no spatial details on emissions no temporal details on emissions sum emissions
impact assessment	number of impact categories impact definition time horizon of impacts spatial horizon of impacts	ignoring nonlinear processes no information on substance properties no interactions with other pollutants no modeling of metabolites no information on the sensitivity of the receiving environment steady-state assumption uniform mixing of compartments

Figure 4: List of Scenario and Model Uncertainties in Environmental Life-Cycle Assessment (Huijbregts et al. 2003)

Model Uncertainty

Many aspects of the real world cannot be modelled within the present LCA structure. Assumptions and simplifications are made that lead to uncertainty regarding the validity of the model predictions for the real world situation. Quantification of this model uncertainty is comparable with that of scenario uncertainty.

First, an overview has to be made of the relevant assumptions made. Second, a procedure has to be developed to quantify the consequences of model choices in terms of output uncertainty. Figure 4 provides an overview of the model uncertainties generally encountered in LCA studies.

- Important model uncertainties are that spatial and temporal characteristics are generally lost by the aggregation of emissions in the inventory analysis.
- Characterization factors are computed with the help of simplified environmental models that suffer from model uncertainties. For instance, the sensitivity of the receiving environment is not taken into account in the computation of characterization factors for pollutants causing aquatic eutrophication.
- Finally, the lack of characterization factors for toxicologically important substances, such as PCBs, or important sum emissions, such as metals, may cause substantial model uncertainty in LCA outcomes.

5 Dealing with Data Uncertainty: Existing approaches

New challenges emerge when the qualitative discussions of political science meet the quantitative approach of environmental science. There seem today to be little support for how few, subjectively estimated data with large uncertainties should be taken into account. Still, there is a need to consider and calculate results from uncertain data. (Hedbrant and Sörme 2001). Due to differences in data quality, it is not always clear how reliable MFA results are (Schwab 2016). Often, even the basic uncertainty is unknown. If samples of measurement results are available, it is possible to calculate the basic uncertainty of the data, but most often only one number is available (Weidema and Wesnæs 1996).

Measured data always contain uncertainties! Because of that it is possible to encounter contradictions in data when only looking at the mean values. Imagine a process without a stock with one input and one output flow, both measured. Because of random measurement errors their mean values are likely to be not exactly the same, but should be. If those measured values are assumed to be normally distributed given by a mean value and a standard deviation the method of data reconciliation can be applied to adjust the data in order to resolve the contradiction. This is prerequisite for calculating the values of unknown variables and their corresponding uncertainties (Cencic and Rechberger 2008).

Statistics is the way to use several inaccurate data samples to get as decent as possible knowledge of one entity. If there is enough data available it is possible to use statistics (median, standard deviation). In some situations, however, problems will occur with statistical methods (Hedbrant and Sörme 2001).

- If there are only one or few data available
- If data rely on subjective estimations from interview persons
- If available data are not independent
- If data are uncertain

Therefore, different approaches to treat uncertain data have been developed. Methods to deal with uncertainty in MFA range from qualitative discussions to sophisticated statistical approaches. This chapter is mainly based on Dzubur (2017) and Laner et al. (2014) showing methods, which deal with uncertainty in MFA. The majority of methods can be classified into four groups: (1) Data classification methods, (2) Uncertainty analysis approaches, (3) Sensitivity analysis approaches and (4) Comparisons of model structures

5.1 Approaches based on Data classification

In approaches based on data classification, the focus lies on formal concepts to characterize data quality and uncertainty, typically in combination with simple mathematical methods (Dzubur 2017).

1) Asymmetric uncertainty intervals by Hedbrant and Sörme (2001)
2) Symmetric intervals by Lassen and Hansen (2000)
3) PEDIGREE Matrix by Weidma and Wesnaes (1996)
4) Information defects by Schwab et al. (2016).

5.1.1 Asymmetric intervals

Asymmetric intervals are calculated by assigning uncertainty factors to each uncertainty level. Depending on the data source (e.g., recognized authorities vs. informal estimate) and the specificity (e.g., data related to the specific region vs. data on a general level), MFA input data are categorized into groups with predefined uncertainty levels Laner et al. (2014).

Table 3: Asymmetric intervals (Laner et al. 2014)

Data uncertainty characterization	Mathematical treatment	Model output evaluation	Typical application
Data source- and specificity-based concept to derive asymmetric intervals	The uncertainty intervals have qualities similar to the standard deviation of normal distributions	Results are expressed as asymmetric intervals defined by multiplication and division with an uncertainty factor	Descriptive MFA

Asymmetric intervals by Hedbrant and Sörme (2001)

An approach to harmonize societal data where uncertainty intervals are determined is given by Hedbrant and Sörme (2001). Traditionally an uncertainty interval may be written as X ± Y. At decently low uncertainties, for example 100 ± 30 kg, this works fine. However, the larger the uncertainty, the less natural would it be to express it in terms of symmetrical intervals. Small uncertainties have symmetrical intervals (‘numbers’). Large uncertainties have asymmetrical intervals (‘magnitudes’). For large uncertainties people seem to think in terms of magnitudes. Therefore, Hedbrant and Sörme (2001) presented a method based on uncertainty intervals to consider the uncertainties (see Table 4). The intervals are derived through multiplication and division of the data with the respective uncertainty factor (Laner et al. 2014).

Table 4: Asymmetric intervals (Hedbrant and Sörme 2001): Levels, factors and interval sizes of uncertain data

Level	Factor	Interval
1	1.10	*/1.10
2	1.33	*/1.33
3	2	*/2
4	4	*/4
5	10	*/10

The uncertainty levels of different sources of information are defined based on the “source of information” (see Table 5). Especially, when only few sources of specific official statistics are available different sources need to be taken into account.

Table 5: Uncertainty levels with sources of information and with examples, used in the Stockholm study

Level	Source of information	Example
1 (interval ∗/1.1)	Official statistics on local level.	Number of households, cars, Cr content in steel for a specific application apartments, small houses.
2 (interval ∗/1.33)	Information from authorities/ construction/production. Official statistics on (local), regional and national levels. Information from authorities/ construction/ production.	Percentage of leather shoes among shoes. Amount of Pb and Cu in power cables. Cr content in leather Thickness of Ni and Cr layer on plating. Paint per area. Share of Volvo cars among all cars.
3 3 (interval ∗/2)	Official statistics on national level downscaled to local level. Information on request from authorities/ construction/ production.	Annual use of stainless steel on roofs and fronts.
4 (interval ∗/4)	Information on request from authorities/ construction/ production.	Weight of catalytic converters
5 (interval ∗/10)		Cd content in Zn in a type of good, e.g. galvanised goods.

However, though data were characterized by asymmetric uncertainty intervals, Hedbrant and Sörme (2001) assumed that the uncertainty interval had similar qualities as the standard deviation of a normal distribution (upper uncertainty limit is used to define the standard deviation) to perform calculations in the material flow model (Laner et al. 2014).

The mathematical strategy should be simple, to avoid giving an impression of ‘false scientific quality’. Advanced mathematics or the use of advanced mathematical tools may give a ‘quality bias’ that can influence policy formulation. In reality, calculations based on few uncertain data would be a weak foundation for decisions, especially if several uncertain data are used in one calculation. The uncertainty intervals in the results should indicate the decision power, not the use of our methods itself. The final evaluation of the decision power in data has to be made in each individual discussion of the issue where the data is used. Different studies used this method to consider uncertainties within MFA. (Danius and Burström 2001; Cooper and Carliell-Marquet 2013; Egle et al. 2014; Klinglmair et al. 2015).

5.1.2 Symmetric intervals

Symmetric intervals use probability distributions to represent uncertain values and indicate the uncertainty. For example, the 5% percentile would represent the lower and the 95% percentile the upper value of an interval (=90 % confidence interval).

Table 6: Symmetric Interval (Laner et al. 2014)

Data uncertainty characterization	Mathematical treatment	Model output evaluation	Typical application
Intervals are defined to contain the true value with a certain level of confidence	Interval arithmetic (addition of lower and upper bounds)	Uncertainty intervals of results have higher confidence levels than inputs	Descriptive MFA

Symmetric intervals by Lassen et al. (2000)

Lassen et al. (2000) use probability distributions to represent uncertain values and indicate the uncertainty with symmetric intervals. They recommend, that uncertainty should be specified for all figures using probability distributions and indicate the uncertainty by intervals; e.g. 200-250 tonnes. For most figures, there will be a 'true value'; e.g. the actual consumption of the substance within the reference year. But the researcher conducting the SFA does not know this value. When a number of monitoring data exist, it may be possible to use standard statistics to estimate a confidence interval assuming the data are normal distributed, but for most figures in the analysis the uncertainty has to be determined by 'expert judgements'.

In order for the intervals not to be unreasonably wide, it is recommended to use intervals representing a 90% (or 80%) certainty level. In other words: the figures are represented by the interval within which the author estimates the 'true value' with 90% certainty can be found. In addition it can be assumed that the probability is normal distributed with the mean value as the most probable and a symmetric distribution around the mean. This means that the width of the interval directly indicates the uncertainty on the results. It makes no sense to state: 'The consumption is roughly estimated at 100-110 tonnes'. A rough estimate will inherently be quite uncertain and if the estimate is rough it will be more correct to state: 'The consumption is roughly estimated at 20-200 tonnes'.

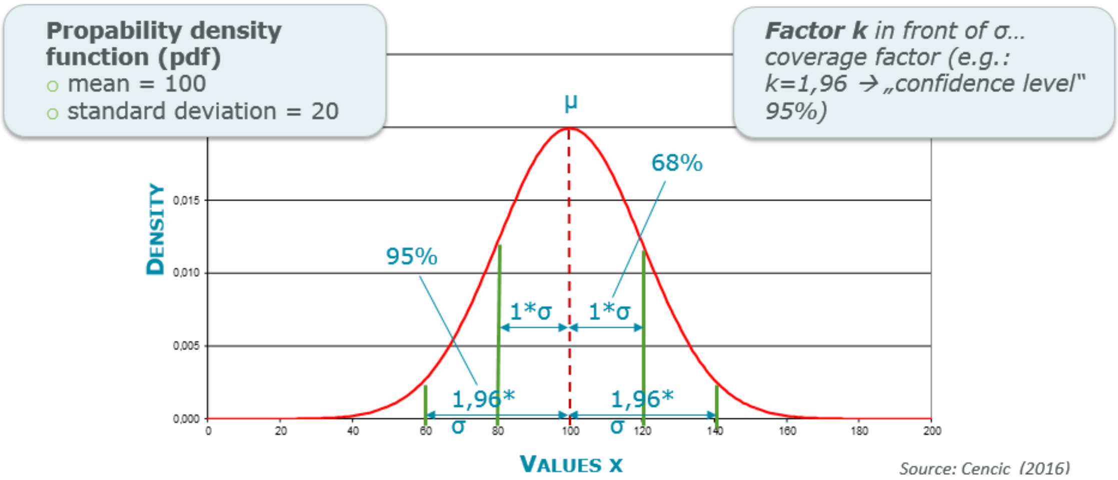


Figure 5: Symmetric intervals based on Cencic (2016) (e.g.: the 2.5% percentile would represent the lower and the 97.5% percentile the upper value of an interval)

5.1.3 Data quality – Data quality indicators

Data quality is the specific characteristic of data as expressed through information about the data (metadata), such as information on its uncertainty (spread and pattern of distribution), its reliability (depending on the methods used for measurements, calculations, assumptions and quality control of data), its completeness (number of data collection points and periods and their representativeness of the total population), its age (year of the original measurement), the geographical area for which the data is representative and the process technology or technological level for which the data is representative (Weidema and Wesnæs 1996).

Data quality indicators were often used to describe different aspects of data quality in LCA (Lloyd and Ries 2007). They may be directly transferred into probability distributions or used to identify possible sources of uncertainty and improve data quality management (Laner et al. 2014).

Table 7: Data quality indicators (Laner et al. 2014)

Data uncertainty characterization	Mathematical treatment	Model output evaluation	Typical application
Basic uncertainty and imperfect data quality are evaluated to calculate data uncertainty	All uncertainties are given as coefficients of variation (standard deviation/mean value)	Confidence intervals cannot be directly constructed from coefficients of variation	No explicit applications in MFA

PEDIGREE Matrix (Weidema and Wesnæs 1996)

Formal data quality management starts with the definition of data quality goals and a data collection strategy as part of the definition of the goal and scope. The quality of the individual data may subsequently be related to the data quality goals through a number of data quality indicators which specify the data quality. Weidema and Wesnæs (1996) introduce the use of a 'pedigree matrix' giving a semi-quantitative indication of:

- Reliability of the data (independent of the data quality goals) including an assessment of the sampling methods and verification procedures.
- Completeness of the data (independent of the data quality goals), including the statistical representativeness of the data, number of measurements in the sample and time periods for data collection.
- Temporal, geographical and further technological correlations (between the data and the data quality goals).

These data quality indicators may subsequently be used

- to revise the data collection strategy to improve the quality of the collected data.
- in combination with uncertainty estimates to give a better assessment of the reliability of the result.

Weidema and Wesnæs (1996) suggest five independent data quality indicators (Pedigree Matrix) which are necessary and sufficient to describe those aspects of data quality which influence the reliability of the result. The matrix is used to communicate data limitations, to assess data quality and associated uncertainty (see Table 8).

Table 8: Pedigree matrix with 5 data quality indicators

Indicator Score	1	2	3	4	5
Reliability	Verified data based on measure-ment	Verified data partly based on assumptions or non-verified data based on measurement	Non-verified data partly based on assumptions	Qualified estimate (e.g. by industrial expert)	Non-qualified estimate
Completeness	Representati ve data from a sufficient sample of sites over an adequate period to even out normal fluctuations	Representativ e data from a smaller number of sites but for adequate periods	Representati ve data from an adequate number of sites but from shorter periods	Representative data but from a smaller number of sites and shorter periods or incomplete data from an adequate number of sites and periods	Representativ-eness unknown or incomplete data from a smaller number of sites and/or from shorter periods
Temporal correlation	Less than three years of difference to year of study	Less than six years difference	Less than 10 years difference	Less than 15 years difference	Age of data unknown or more than 15 years of difference
Geographical correlation	Data from area under study	Average data from larger area in which the area under study is included	Data from area with similar production conditions	Data from area with slightly similar production conditions	Data from unknown area or area with very different production conditions
Further technological correlation	Data from enterprises, processes and materials under study	Data from processes and materials under study but from different enterprises	Data from processes and materials under study but from different technology	Data on related processes or materials but same technology	Data on related processes or materials but different technology

The pedigree matrix, in particular, represents a formalized procedure to communicate data limitations and create a basis for improving the data collection strategy of LCA studies. Because harmonizing data from different sources in LCIs is similar to the challenge of data characterization in MFA, the pedigree matrix may also be useful to express the additional uncertainty resulting from the data limitations in MFA studies.

5.1.4 Combination

To characterize uncertainty of MFA input data in an appropriate way, often the combination of different approaches is required.

Characterizing of uncertainty with data quality and asymmetric intervals (Laner et al. 2015b)

This method builds on the data quality assessment scheme proposed by Weidema and Wesnæs (1996), and the assessment of material flow data uncertainty using data classification presented by Hedbrant and Sörme (2001). The so-called pedigree matrix consists of five independent data quality indicators (reliability, completeness, temporal correlation, geographical correlation, and further technological correlation) and was developed by by Weidema and Wesnæs (1996) to characterize uncertainties of LCI data. The general advantage of this approach is that data quality can be directly used to estimate the quantitative uncertainty of the respective inventory data and the effect of these uncertainties on the results. The approach for estimating uncertainty ranges by Hedbrant and Sörme (2001) as developed to study heavy metal flows in urban systems

The developed approach consists of data quality assessment as a basis for estimating the uncertainty of input data. Four different implementations of the approach with respect to the translation of indicator scores to uncertainty ranges (linear- vs. exponential-type functions) and underlying probability distributions (normal vs. log-normal) are examined.

The approach consists of several steps, which can be summarized as follows:

1) Evaluation of data quality with respect to reliability, completeness, temporal and geographical correlation, and other correlations using indicator scores. For the evaluation of expert estimates, only one data quality dimension is used.
2) Translation of each indicator score into specific uncertainties, taking into account the sensitivity of the quantity of interest with respect to data quality imperfection.
3) Aggregation of the uncertainties associated with the individual scores to the overall uncertainty estimate for the material flow.

5.1.5 Information and information defects

Scientific activity has always been undertaken with the aim of revealing or creating information, be it by observing and describing phenomena such as nature in its immediate surroundings, the relation of objects in space or the behaviour of individuals, among many others. One of the most widely applied formal concepts of information is information theory, as coined by Shannon (1948). Information can be understood as opposed to uncertainty, in that additional information reduces uncertainty, and vice versa (Schwab 2016). While information theory provides useful approaches to technical aspects of information (such as communication and transmission), it is limited regarding the semantic content of information, that is, its meaning.

Information defects (Schwab 2016)

Schwab 2016 presents a quantitative method based on quality indicators and information theory ("information defects").

Four levels of information in MFA can be distinguished (Figure 6). The first information level is "data element" and a data element plus meaning forms "information". "Information background" represents the origination and forming process of the piece of information. Placed in context, it forms "MFA information".

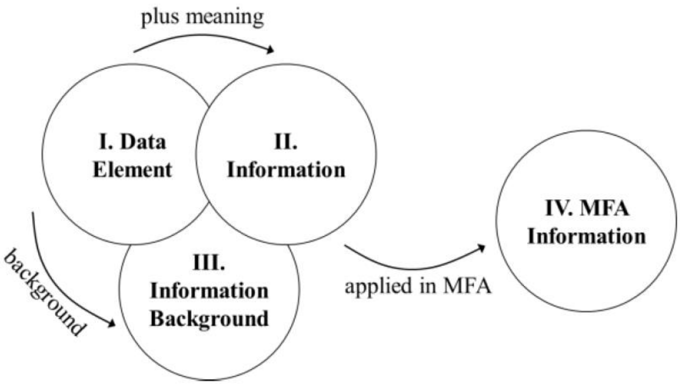


Figure 6: MFA information is information in MFA context: A data element plus meaning forms information, this information has a background and in the context of an MFA study it forms MFA information.

Data attributes are data-associated annotations concerning statistical properties, meaning, origination and application of the data. These data attributes are systematically documented and evaluated in a data characterization matrix, which forms the basis for automated estimation of data quality and subsequent quantification of information content.

The MFA data characterization matrix is structured according to the four information levels and related attributes are grouped in attribute groups (see Table 9). The data characterization matrix facilitates the systematic documentation of MFA data and designated attributes.

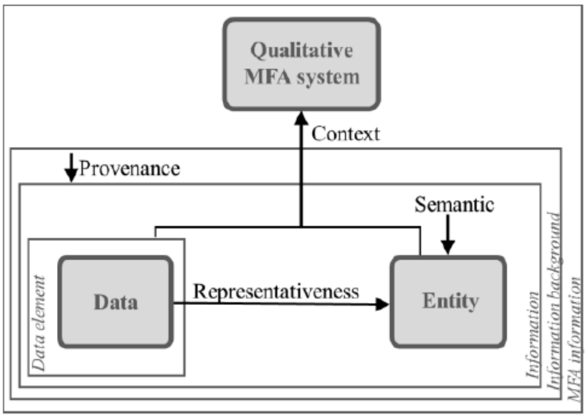


Figure 7: Concept of MFA information defects and their position in the data characterization framework "Data" are numerical values, "entity" is a real-world object or phenomenon described by an information element, "qualitative MFA system" is a system to be quantified by introduction of quantitative information.

Table 9: Structure of the data characterization matrix by information levels and attribute groups

Info. level	Attribute group	Description (no. of attributes)	Attributes
Data element	Statistical characteristics	Documentation of statistical information on a data element (10).	Data element form, location parameter, value (numeric), n, min, max, distribution (form), distribution (paramet.), dispersion (measure), dispersion (numeric)
Information	Semantics	Specification of the meaning of a data element (2).	Description of meaning, semantic precision
	Scale	Specification of the format of an entity (8).	Entity category, entity class, unit, sphere, property type, mathematical form, min (potential), max (potential)
	Complexity	Description of the complexity of an entity (2).	Variety, disparity
Information background	Availability	Distinction if wanted information does exist and is accessible or not (3).	Existence, accessibility, access restriction
	Communication	Documentation of how a piece of information is communicated (3).	Communication type, access type, frequency
	Producer	Documentation of the agent that produced the piece of information, for example an authority (3).	Producer category, producer type, reference
	Origination	Documentation of the data collection method, for example counting or industrial monitoring (3).	Origination category, origination type, origination type quality
MFA information	Application in MFA	Description of how a piece of information is applied in the MFA study (4).	Application type, autonomy, layer, type of good
	System relation	Description of the relation between a piece of information and the studied system (6).	Primary determination, temporal variability, trend, spatial variability, further relation, variability by further relation
	System adequacy	Description of a piece of information's adequacy to (resp. divergence from) the studied system (5).	Temporal divergence, spatial divergence, further divergence, adaptation (type), adaptation (quality)

Uncertainty in regional MFA is rather an epistemic than an aleatory phenomenon, i.e not a consequence of natural variability but of imperfect knowledge. Knowledge shortcomings are here expressed as "defects of information". Information defects are belief indicators that reflect the deviation of given information from a desired state of perfect knowledge. They are expressed on an ordinal scale from 0 (no information defect) to 1 (maximum information defect). The four information defects "semantic", "representativeness", "provenance" and "context" (IDS, IDR, IDP, IDC) appear to be relevant for MFAs (Schwab 2016).

- IDS refers to the semantic precision or resp. imprecision of the meaning of data (Does the specification "smart phones" also refer to mobile phones from before the technological leap, which are still "out there"?).
- IDR indicates how well a given data element represents the entity of interest (Is the complex entity "Pd concentration of mobile phones" quantified based on one or more measurements or independent references?).
- IDP considers the origination and collection method of a data element (How reliable are the information producer and the data collection method?).
- IDC designates how well a given data element fits the context of a study (Is the data element timely and does it refer to the geographical area studied?).

The information defect per flow IDF is quantified in three steps. First, the quality of each data element is described by a set of four defects ID_i (ID_S, ID_R, ID_P and ID_C). Second, each information element is described by one total information defect (ID_{tot}), which is an aggregation of the ID_i of the respective data element. Third, the data quality of each flow is described as IDF, which is a combination of the ID_{tot} of the respective information elements (according to Figure 7).

5.2 Uncertainty analysis

5.2.1 Gauss's law of uncertainty propagation

The propagation of uncertainties can be evaluated by applying Gauss's law of error propagation to a function of interest (Brunner and Rechberger 2016):

$$Y = f(X_1, X_2, \ldots, X_n)$$

The expectation of the result Y and the variance of the result can be estimated from the following two equations. The latter is called Gauss's law of error propagation.

$$E(Y) \approx f(E(X_1), E(X_2), \ldots, E(X_n)) = f(\mu_1, \mu_2, \ldots, \mu_n)$$

$$var(Y) \approx \sum_{i=1}^{n}\left(var(X_i)\cdot\left[\frac{\partial Y}{\partial X_i}\right]^2_{X=\mu}\right) + 2\cdot\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\left(cov(X_i, X_j)\cdot\left[\frac{\partial Y}{\partial X_i}\right]_{X=\mu}\cdot\left[\frac{\partial Y}{\partial X_j}\right]_{X=\mu}\right)$$

If the variables X_i are independent or uncorrelated the above named equation can be reduced to the following equation.

$$var(Y) \approx \sum_{i=1}^{n}\left(var(X_i)\cdot\left[\frac{\partial Y}{\partial X_i}\right]^2_{X=\mu}\right)$$

with

μ_i = $E(X_i)$ = mean of X_i

σ_i = $std(X_i)$ = standard deviation of X_i

σ_i^2 = $var(X_i)$ = variance of X_i

σ_{ij} = $cov(X_i,X_j)$ = covariance of X_i and X_j

5.2.2 Data reconciliation

Because measurements and estimates are subject to measurement or estimation errors, they virtually always violate model constraints (e.g., the law of mass conservation). The idea of data reconciliation is to statistically adjust the measurements and estimates in order to resolve contradictions and find the values that fit the model the best. Data reconciliation is feasible only if the given system of equations (i.e., constraints) can be transformed in such a way that at least one equation without unknown variables can be found. All measured and estimated variables appearing in such equations can be adjusted. Equations containing only constant variables cannot be used for data reconciliation (there are no measured or estimated variables to be reconciled) but can be exploited to perform plausibility checks on constant input data (Brunner and Rechberger 2016). By data reconciliation, the mean values of measured and estimated data are adjusted in such a way that contradictions in model constraints disappear. The best solution is found when the sum of squares of the necessary adjustments weighted by the inverse of the measurement or estimation variances reaches a minimum:

$$F = \sum_{i=1}^{n} \frac{(\tilde{x}_i - x_i)^2}{var(\tilde{x}_i)}$$

This procedure is known as the method of weighted least squares, with F being the objective function to be minimized.

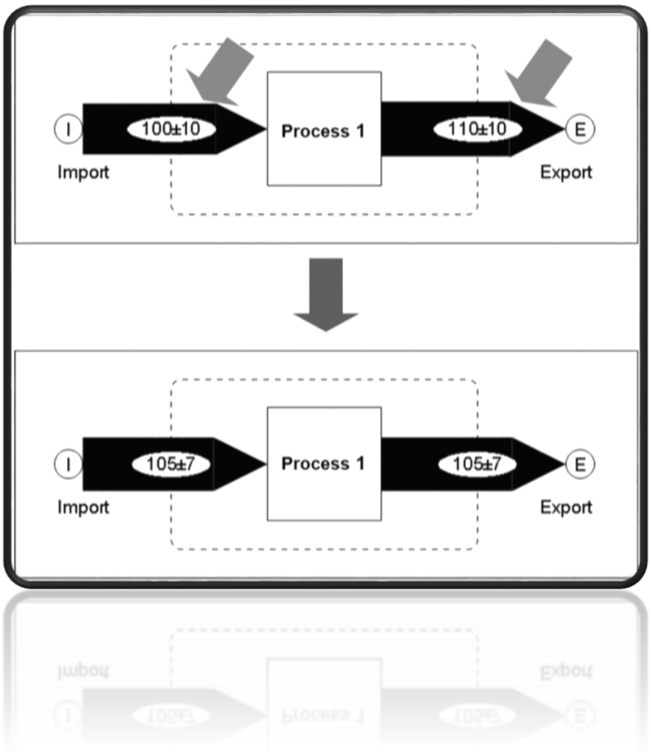


Figure 8: Data reconciliation with the software STAN

Cencic and Frühwirth (2015) and (Cencic 2018) present a new method, based on Bayesian reasoning, for the reconciliation of data from arbitrary probability distributions. The main idea is to restrict the joint prior probability distribution of the involved variables with model constraints to get a joint posterior probability distribution. The procedure is demonstrated with the help of simple graphical examples. Because in general the posterior probability density function cannot be calculated analytically, it is sampled with a Markov chain Monte Carlo (MCMC) method. From this sample the density and its moments can be estimated, along with the marginal densities, moments and quantiles. The method is tested on several artificial examples from material flow analysis, using an independence Metropolis–Hastings sampler.

The advantages of the Bayesian approach are: First, arbitrary continuous pdfs can be used to describe the uncertainty of the observations. Second, even nonparametric estimators of the pdf are allowed, provided that it is possible to draw a random sample from them. Third, not only means, variances and co-variances of observed and unobserved variables can be computed a posteriori, but also various other characteristics of the marginal posteriors, such as the mode, skewness, quantiles, and HPD intervals (Cencic 2018).

5.2.3 STAN Software

The use of a software to support MFA has many advantages: graphical modelling with automatic translation into a mathematical model; database of collected data including source documentation; consideration of data uncertainties; reconciliation of contradicting data; computation of unknown quantities of mass flows and stocks; computerized display of resulting flows as Sankey-style diagrams, and others.

STAN (short for subSTance flow ANalysis) is a free software that supports performing material flow analysis (MFA) according to an Austrian standard. STAN is a ready-to-use tool for doing MFA while taking into account uncertainty (Cencic and Rechberger 2008).

Table 10: STAN Software (Laner et al. 2014)

Data uncertainty characterization	Mathematical treatment	Model output evaluation	Typical application
Uncertain data are specified as the mean and standard deviation of a normal distribution	Analytical calculation of data reconciliation (for overdetermined systems) and error propagation	Resulting uncertainty and, potentially, the extent of data reconciliation to balance the system are used to evaluate the model output	Mainly descriptive, but also exploratory MFA

The calculation algorithm uses mathematical statistical tools such as nonlinear data reconciliation (to adjust conflicting measurements or estimates) and error propagation (to compute the uncertainty of unknown quantities that can be calculated), and performs basic statistical tests to detect gross errors. All uncertain data and parameters (e.g., mass fractions, mass flows, and transfer coefficients) are described by normally distributed independent random variables. Uncertain quantities are expressed by the mean and a measure of variance (Brunner and Rechberger 2016). Based on these assumptions, it is possible to use Gaussian error propagation and data reconciliation to calculate the uncertainty of model outputs.

5.2.4 Mathematical material flow analysis (MMFA)

Mathematical material flow analysis (MMFA) is the combination of conventional material flow analysis (MFA) with state-of-the-art mathematical modelling concepts (Bader et al. 2011). An MMFA describes and quantifies the material flows through a system (Schaffner et al. 2009). Because the assumption of normally distributed quantities is not always compatible with existing knowledge, generalized statistical approaches allowing for assigning various probability distributions to uncertain quantities needs to be suggested (Laner et al. 2014).

Table 11: Mathematical material flow analysis (Laner et al. 2014)

Data uncertainty characterization	Mathematical treatment	Model output evaluation	Typical application
Uncertain model parameters are specified using various probability density functions	Mathematical functions (parameters) are fitted to available data. MCS is used to estimate model outputs and calibrate the model	Sensitivity analysis for identifying critical model parameters and to check plausibility of results	Mainly exploratory, but also descriptive MFA

Often, log-normal distributions are chosen to characterize uncertain quantities because they exclude negative values and allow skewed distributions which are particularly common for low mean values and large variances. In MFA, uniform distributions are typically chosen when it is possible only to specify a range of probable values. The probability distributions of the model parameters and input data are consequently used to estimate the probability distribution of the model outputs by applying Monte Carlo simulations (MCSs). Procedures to handle uncertainty in MFA were introduced by Baccini and Bader (1996) within the framework of mathematical material flow analysis (MMFA).

MMFA is performed following a step-wise, iterative approach consisting of system analysis, establishing the mathematical model, model calibration, and model simulation (including sensitivity and uncertainty analysis) (Laner et al. 2014). Based on Schaffner et al. (2009) an MMFA is carried out in six iterative steps:

1) The system analysis defines the temporal and spatial boundaries and the indicator substances. The relevant balance volumes and flows in the system are identified on the basis of an acquired understanding of the system.
2) The relationships within the system are formulated as mathematical equations (model approach), in which the variables describe the flows and stock change rates of the system. A set of parameters is used to quantify these variables.
3) The input data for these parameters is acquired from all available sources. These include measurement results as well as literature data and estimations. The model is calibrated in discussions with experts.
4) With the compiled dataset, the current state (status quo) of the nutrient flows within the system is simulated, including the uncertainties. The plausibility of

the simulations is checked by comparing these with data from primary measurements and other studies.

5) The critical parameters of the system, i.e. the key parameters driving forces which influence the nutrient flows, can be identified with the aid of a sensitivity analysis.
6) On the basis of this sensitivity analysis, possible mitigation measures (scenarios) are simulated and evaluated for their effectiveness.

MMFA has similarities with a Bayesian approach. Uncertain model parameters are specified using different kinds of probability density functions. In contrast to a Bayesian setting, in this approach, the mathematical functions are fitted to the available data. Therefore, it is also an approach on fitting the model structure. The probability density functions of the model parameters are estimated using different sources and techniques, ranging from formal elicitation of expert to basic (and very general) estimation principles, for example, plausibility reasoning. In MFA, uniform distributions are typically chosen when it is possible only to specify a range of probable values (Dzubur 2017).

5.2.5 Probabilistic material flow analysis (PMFA)

The probabilistic material flow analysis (PMFA) aims at calculating from a whole life cycle perspective concentrations of potential contaminants in complex systems, covering all environmental compartments and life stages of these contaminants. The method of substance/material flow analysis is used to determine flows to and amounts of compounds within the studied environmental compartments and is extended to a PMFA (Gottschalk et al. 2010).

PMFA (similar to MMFA) is a modelling approach for probabilistic MFA. Their step-wise procedure is used to calculate model outputs based on theoretical or data-driven descriptions of model parameters and inputs without any necessity to calibrate the model. Nevertheless, the approach contains elements adapted from Bayesian statistics because prior distributions are defined for all model parameters and posterior distributions are derived using Markov chain Monte Carlo (MCMC) modelling (Laner et al. 2014).

Table 12: Probabilistic material flow analysis (Laner et al. 2014)

Data uncertainty characterization	Mathematical treatment	Model output evaluation	Typical application
Prior probability distributions are defined using the knowledge about the model parameters	Based on observed data, posteriors are derived using Markov chain Monte Carlo (MCMC) modelling and the uncertainty of flows is estimated	Sensitivity analysis for identifying critical model parameters and for scenario development	Exploratory MFA

Gottschalk et al. (2010) define six main steps to develop a modelling approach combining sensitivity and uncertainty analysis, Monte Carlo simulation, Bayesian and Markov Chain modelling to propose a PEC modelling approach for cases characterized by a distinct lack of data.

1) Step 1: Goal definition, including system boundaries constituted by the studied compounds, time and space
2) Step 2: System modelling, definition of goods, products, processes and functions/relations (transfer coefficients)
3) Step 3: Stochastic/probabilistic modelling of the input parameters using distributions
4) Step 4: Calculation/computation
    - Deterministically with point values (e.g. for model validation), (MFA standard)
    - Monte Carlo simulation with the modelled distributions
        - Bayesian optimization
        - Markov Chain Monte Carlo modelling
5) Step 5: Sensitivity analysis
6) Step 6: Interpretation, assessment of pollution potential (PEC)

Bornhöft et al. (2016) presented a new "Dynamic Probabilistic Material Flow Analysis (DPMFA)" method, combining dynamic material flow modelling with probabilistic modelling. Material transfers that lead to particular environmental stocks are represented as systems of mass-balanced flows. The time-dynamic behaviour of the system is calculated by adding up the flows over several consecutive periods, considering changes in the inflow to the system and intermediate delays in local stocks. Incomplete parameter knowledge is represented and propagated using Bayesian modelling.

5.2.6 Monte Carlo simulation

The Monte Carlo simulation method has been applied to measurement system uncertainties with many claimed advantages. Monte Carlo simulation was devised as an experimental probabilistic method to solve difficult deterministic problems since computers can easily simulate a large number of experimental trials that have random outcomes. When applied to uncertainty estimation, random numbers are used to randomly sample parameters' uncertainty space instead of point calculation carried out by conventional methods. Such an analysis is closer with the underlying physics of actual measurement processes that are probabilistic in nature. Monte Carlo method has many advantages over conventional methods in the estimation of uncertainty especially that of complex measurement systems' outputs. The method, superficially, is relatively simple to implement (Papadopoulos and Yeung 2001). To perform Monte Carlo simulation, each uncertain input parameter has to be specified as an uncertainty distribution.

However, often an enormous amount of parameters is used and it is unfeasible to characterize the uncertainty ranges for all of these parameters in detail. This problem can be overcome with the stratified procedure. First, all uncertain input parameters are assigned a distribution with the widest range that can be regarded as realistic, as based on measured data or expert judgment. Next, a sensitivity analysis (e.g., Monte Carlo simulation in combination with Spearman Rank correlation) is performed to identify the parameters that contribute most to the output uncertainty. These important parameters are specified in more detail and their importance is confirmed in a second sensitivity analysis. This second analysis is necessary because defining parameters in more detail may affect their uncertainty importance. Finally, when all important input parameters have been specified in detail, a Monte Carlo simulation can be performed to quantify the output uncertainty (Huijbregts et al. 2003).

5.2.7 Fuzzy set theory

Recent work has demonstrated that fuzzy mathematics provides a computationally efficient alternative to probabilistic methods for representing data uncertainty (Tan et al. 2007). So far, in an MFA context, fuzzy reconciliation approaches have been compared to the standard least squares approach to quantify material flows of resource and recycling systems (Dzubur 2017).

When performing uncertainty propagation, most practitioners choose to represent uncertainties by single probability distributions and to propagate those using stochastic methods. However, the selection of single probability distributions appears often arbitrary when faced with scarce information or expert judgement (epistemic uncertainty). The possibility theory has been developed over the last decades to address this problem (Clavreul et al. 2013).

The concept of fuzzy set theory was introduced by Zadeh (1965) to handle imprecision and uncertainty (Laner et al. 2014). Basic knowledge on the probability theory is first recalled, followed by a detailed description of epistemic uncertainty representation using fuzzy intervals. The propagation methods used are the Monte Carlo analysis for probability distribution and an optimisation on alpha-cuts for fuzzy intervals. The proposed method generalizes the process of random sampling to probability distributions as well as fuzzy intervals, thus making the simultaneous use of both representations possible (Clavreul et al. 2013). A special case of a fuzzy set is an interval where the membership function only takes values 0 or 1 (an element either belongs or does not belong to the set). For example, for the interval [0, 0.35], the value of the membership function of all values between 0 and 0.35 is one (Laner et al. 2014)

Table 13: Fuzzy set theory (Laner et al. 2014)

Data uncertainty characterization	Mathematical treatment	Model output evaluation	Typical application
Model parameters are fuzzy quantities defined by membership function	Mathematical operations for fuzzy quantities allow for propagating data characteristics through the model	Actual state of knowledge is better reflected by the model results in the case of scarce information	Conceptual suggestions for MFA, but not yet case studies

There is a fundamental difference between true random variability, as depicted by a single probability distribution, and epistemic uncertainty, due to incomplete or imprecise information (Clavreul et al. 2013). Alternative representations of epistemic uncertain quantities (which typically applies to most parameters and data in MFA), using interval concepts, possibility theory or fuzzy set theory, have been suggested for environmental assessment tools. The concept of fuzzy set theory was introduced to handle imprecision and uncertainty.

The method used to propagate fuzzy intervals in the general case is very analogous to the Monte Carlo method using single probability distributions, except that in the case of parameters represented by fuzzy intervals, intervals are randomly sampled instead of single values, based on α-cuts.

An example of α-cut is presented in Figure 9 for alpha=0.6 the α-cut is the interval [16.4; 20.9]. If the model is relatively simple and monotonous, propagation of the fuzzy intervals through the model can be performed simply using interval calculus on alpha-cuts. For alpha=0 to 1 with, e.g. step=0.1, the min and max values of the model are determined for all values of the alpha-cuts. However, if the model is not monotonous, it may not be possible to determine the min and max values of the model based solely on the min and max values of the alpha-cuts. In this case it is necessary to use an optimization algorithm to find the min and max values of the model for all parameter values within the alpha-cuts.

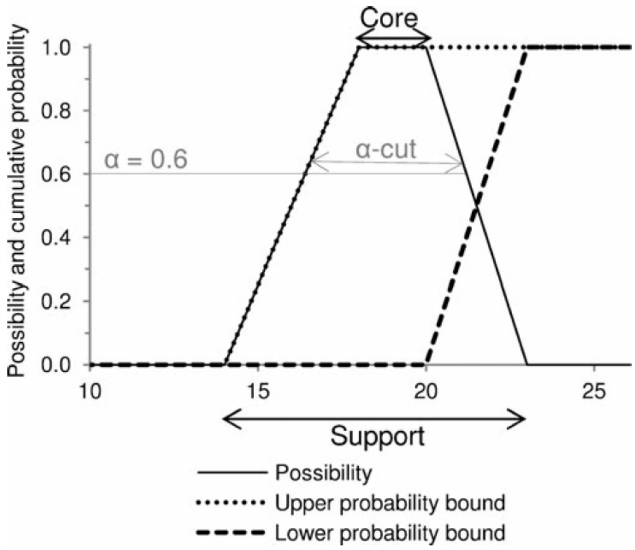


Figure 9: Example of a possibility distribution (Clavreul et al. 2013)

Data reconciliation consists in modifying noisy or unreliable data in order to make them consistent with a mathematical model (herein a material flow network). The conventional approach relies on least squares minimization (Dubois et al. 2013). Dubois et al. (2014) use a fuzzy set-based approach, replacing Gaussian likelihood functions by fuzzy intervals, and a leximin criterion. The setting of fuzzy sets provides a generalized approach to the choice of estimated values that is more flexible and less dependent on oftentimes debatable probabilistic justifications. It potentially encompasses interval-based formulations and the least squares method, by choosing appropriate membership functions and aggregation operations.

Dzubur (2017) presents a fuzzy set-based approach to data reconciliation in material flow modelling. As various MFA studies rely on data about flows and stocks from different sources with varying quality, in the first study, an uncertainty analysis method, which expresses the belief that the available data are representative for the value of interest via fuzzy sets, is presented, specifying the possible range of values of the data. A possibilistic framework for data reconciliation in MFA was developed and applied to a case study on wood flows in Austria. The framework consists of a data characterization and a reconciliation step. Membership functions are defined based on the collected data and data quality assessment. Possible ranges and consistency levels (quantifying the agreement between input data and balance constraints) are determined. The framework allows for identifying problematic data and model weaknesses, and can be used to illustrate the trade-off between confidence in the data and the consistency levels of resulting material flows.

5.3 Sensitivity analysis

Different methods for the treatment of different types of uncertainty are available: Uncertainty analysis is performed in order to quantify the range of possible output outcomes (e.g. indicators), given a set of uncertain inputs. A related practice is sensitivity analysis, which is the study of how uncertainty in the output can be apportioned to different sources of uncertainty in the model input.

In contrast to uncertainty analysis, approaches focusing on sensitivity analysis analyse the effects of parameter uncertainty or variations on the model results relatively, without trying to capture the true range of variation (Dzubur 2017).

Table 14: Sensitivity analysis (Laner et al. 2014)

Data uncertainty characterization	Mathematical treatment	Model output evaluation	Typical application
Define variation ranges for selected parameters using various probability density functions	MCS is used to estimate the variation of model outputs.	Evaluation of the effect of parameter variation on the model results to identify critical model element	Exploratory MFA (typically dynamic models)

Because this facilitates the definition of parameter uncertainties (i.e., the range within they may vary) and puts the focus on evaluating the robustness of the material flow model, this type of approach has been frequently applied to dynamic material flow models (Laner et al. 2014).

Dzubur (2017) summarized that sensitivity analysis is carried out to investigate the effect of individual assumptions and parameter specifications on the model output by exploring the effects of the changes of input parameters on the model output. Whereas local sensitivity analysis methods focus on testing different perturbations of constant or uncertain input parameters and analyse the specific consequences in the output, global sensitivity analysis focuses on the uncertainty in the output and how it can be apportioned to different sources of uncertainty in the inputs (Saltelli et al. 2008). The process of recalculating outcomes under alternative assumptions to determine the impact of variables using global sensitivity analysis can be useful to identify model inputs that cause significant uncertainty in the output in order to increase robustness of the model and understanding of the relationships between input and output variables (Pannell 1997).

Analytical local methods using partial derivatives are usually not useful in dynamic MFA systems, given that the model input parameters are uncertain and the model is of unknown linearity (Dzubur 2017). The common way to treat dynamic MFA in previous literature is local sensitivity analysis, using one-at-a-time (OAT) analysis, where one input variable is changed while the others remain fixed in order to see what effect this produces on the output. Whereas local sensitivity analysis methods focus on testing different perturbations of (constant or uncertain) input parameters and analyse the specific consequences in the output, global sensitivity analysis focuses on the uncertainty in the output and how it can be apportioned to different sources of uncertainty in the inputs (Dzubur 2017).

5.4 Comparison of model structures

Comparisons of model structures are rare in MFA. It is possible to compare the model structure like Klinglmair et al. (2016) with the model structures of the Austrian and Danish phosphorus balance systems. The differences in system boundaries and definition of flows and processes are highlighted and data reconciliation is used to define a measure of model quality (Dzubur 2017). Another comparison was done by Pauliuk et al. (2013). They compared three different approaches of material balance equation systems to quantify the global steel cycle. The comparisons in both studies are done qualitatively (Dzubur 2017).

A comparison of a leaching stock approach and delay approach for dynamic SFA is given in (Kleijn et al. 2000) to identify and estimate future waste flows from societal stocks. The study shows that stock modelling appears to be a useful approach for environmental policy making. The approach of combining the inflow distribution with a delay and a life-span distribution to arrive at an estimate for the outflow distribution certainly works, although very little can be concluded about how realistic the results may be. The approach must be tested with empirical data to obtain more insight.

The analytical calculation of the steady state between the mentioned two modelling approaches is given by (Van der Voet et al. 2002). This study presents analytical conditions under which the calculations of the leaching approach will produce acceptable solutions for dynamic models which should typically be solved using the delay approach (Dzubur 2017).

6 Uncertainty in MFA - Review

In the following an overview of different MFA studies is given which include in one way or another uncertainty in their case studies. The details of the literature review can be found in the annex (Table 18 and Table 19). Many studies have been reviewed and in total 40 studies are included in the following summary.

Table 15: Uncertainty in MFA - Reviewed studies (n=39)

No.	Author	No.	Author
1	(Allegrini et al. 2014)	21	Hoenderdaal et al. 2012)
2	(Allesch et al. 2016)	22	(Klinglmair et al. 2015)
3	(Andersen et al. 2010)	23	(Kovanda et al. 2017)
4	(Andersen et al. 2011)	24	(Kral et al. 2014)
5	(Bader et al. 2011)	25	(Laner et al. 2015)
6	(Bajzelj et al. 2013)	26	(Morf et al. 2007)
7	(Buchner et al. 2014)	27	(Morf et al. 2013)
8	(Buchner et al. 2015)	28	(Ott et al. 2012)
9	(Buchner et al. 2015)	29	(Rechberger et al. 2002)
10	(Chancerel et al. 2009)	30	(Reck et al. 2010)
11	(Cooper et al. 2013)	31	(Schulze et al. 2016)
12	(Cullen et al. 2010a)	32	(Spatari et al. 2002)
13	(Cullen et al. 2013a)	33	(Spatari et al. 2003)
14	(Cullen et al. 2013b)	34	(Stanisavljevic et al. 2014)
15	(Danius et al. 2001)	35	(Tonini et al. 2014)
16	(Dubois et al. 2014)	36	(Van Beers et al. 2005)
17	(Egle et al. 2014)	37	(Van Eygen et al. 2017)
18	(Glöser et al. 2013	38	(Vyzinkarova et al. 2013)
19	(Gradel et al. 2004)	39	(Zhang et al. 2008)
20	(Guyonnet et al. 2015)	40	(Zoboli et al. 2016)

Most of the reviewed studies provide an MFA focusing on the whole economy of one substances (e.g. P Flows) including the processes mining, production, consumption and waste management. About one third assess the waste management either including all processes or only focussing on one waste stream (e.g. WEEE) or on one technology (e.g. composting). The input data for the MFA comes from heterogeneous sources.

- Literature: (industrial and official reports, scientific papers, sales forecasts, statistical data)
- Expert opinions and personal communications
- Measurement: Sampling and analysis

Depending on the data source and the goal of the studies uncertainty was calculated, estimated or described. About 85 % have calculated or estimated an uncertainty (Figure 10).

- Calculated: The uncertainty is calculated based on a mathematical/statistical approach (e.g. standard deviation)
- Estimated: The uncertainty is estimated based on knowledge about the date sources and experiences.
- Described: No method to assess the uncertainties is applied but the uncertainty is described in detail.
-

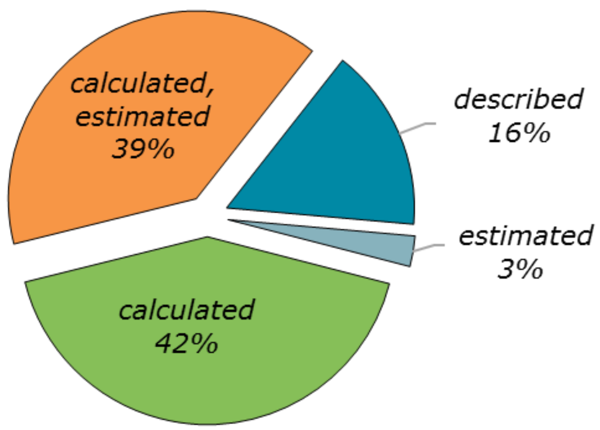


Figure 10: Uncertainty applied in the reviewed studies (n=40)

Different approaches to deal with uncertain data have been developed and were applied in the reviewed studies. The methods deal with uncertainty in MFA range from qualitative discussions to sophisticated statistical approaches. The different methods are explained in detail in chapter 4 .

Table 16: Uncertainty approaches applied in the reviewed studies (n=40)

Data uncertainty - Approach	No.
Asymmetric (Hedbrant and Sörme)	1
Asymmetric (Hedbrant and Sörme), STAN	2
Asymmetric (Hedbrant and Sörme), STAN, Combination (Laner)	1
Asymmetric (Hedbrant and Sörme), symmetric (standard deviation), STAN	2
Combination (Laner)	3
Data reconciliation (Dubois)	1
Detailed description of uncertainty	3
Fuzzy method	1
Gauss's Law of error propagation, STAN	2
Monte Carlo Simulation	1
Monte Carlo Simulation, Global sensitivity analysis,	1
Sensitivity analysis	1
Sensitivity analysis, Gauss's Law of error propagation	1
Set probability (Kovand)	1
STAN and fuzzy model	1
Symmetric (standard deviation)	1
Symmetric (standard deviation), Gauss's Law of error propagation,	3
Symmetric (standard deviation), Monte Carlo Analysis	1
Symmetric (standard deviation), STAN	6
Uncertainty mentioned but not calculated	4
-	3

Most of the studies used a symmetric approach to deal with uncertainty using standard statistics to estimate standard deviations and using Gauss's Law of error propagation. Some additionally include Monte Carlo Simulation and STAN for their analysis. Six studies used the approach developed by Hedbrant and Sörme (2001).

These studies only focus on one substances and mainly evaluate the whole economy with a static MFA. Further sensitivity analysis is applied to quantify the range of possible output outcomes (e.g. indicators), given a set of uncertain inputs. Some studies didn't calculate the uncertainty but described the quality of the data. For example little mass flows are not shown due to uncertainty reasons. Three studies used the combined approach based on Laner et al. (2015b)

The geographic system boundaries of the reviewed MFA include municipalities, cities, countries, continents or the whole world (global). The reviews shows that on the level of cities and countries uncertainty is more often calculated based on mathematical/statistical method. On the global or continent level estimations or descriptions of the uncertainty are more common. Hence, the review indicates that (as expected) the smaller the geographical boundary the easier it is to actual calculate uncertainties.

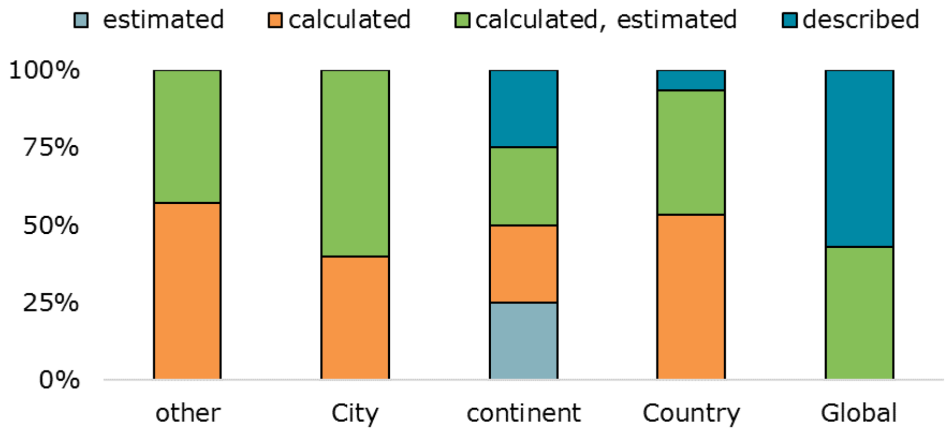


Figure 11: Uncertaitny applied in the reviewed studies related to the geographical system boundary (n=40)

Material flow analysis has been conducted to various extents. Most of the reviewed studies used a static model to describe the material flows. Static models are available on global and national scales. While a static MFA is rather concerned with generating a better understanding of a material system based on simple accounting principles (i.e., mass-balance equations), a dynamic MFA is primarily used to investigate the stock build-up of materials in society (i.e., secondary resources) and in the environment (i.e., dissipative losses) based on the investigation of material flows over time (Brunner and Rechberger 2016). Based on (Laner and Rechberger 2016) static and dynamic MFA methods are:

- Static MFA are established for a certain balancing period in time, for instance, for 1 year. They provide a snapshot of a system in time and are done at different levels of sophistication to investigate the patterns of material use and material losses in the system. Static MFA is typically used to generate a quantitative understanding of material systems and develop alternative management scenarios.
- Dynamic MFA describe the behaviour of a system over several time increments. Thus, dynamic MFA provides information about material usage over time and consequent changes in stocks and flows within the system. While material flows in a static MFA are time independent (i.e., they are not related to material flows at another point in time), material flows in a dynamic model at the time T can potentially depend on all previous states of the system.

The reviewed studies vary greatly in scope and depth and shows that there is a need for development of a standardized methodology to account uncertainties in MFA studies and to ensure high quality within the decision making process (Patrício et al. 2015). A systematic evaluation of uncertainty in MFA is important to understand the robustness of material flow estimates, independent of the approach used for expressing uncertainty (Laner et al. 2015a).

7 Requirements to survey and report uncertainty

7.1 General requirements

Uncertainty is often characterized without the use of formal procedures, which impairs statements about the reliability of the MFA results based on uncertainty analysis. Therefore, consistent and transparent procedures for uncertainty characterization are imperative for uncertainty analysis in MFA. In addition, different uncertainty types need to be addressed by different concepts used to express and propagate uncertainty.

Apart from the existing applications of probability theory, fuzzy set theory may be well suited for dealing with epistemic uncertainty in MFA. (Laner et al. 2014). Uncertainty evaluation of data collected by different institutions should become a standard procedure, given that no general benchmark can be assumed and the data may have a major impact on the result, which is the case with the regional transport statistics (Patrício et al. 2015). There is a need for development of a standardized methodology to account for the uncertainty in MFA studies to ensure high quality of the decision support information and allow or proper comparison between studies conducted by different authors in different countries, regions, and metropolitan areas. In addition, further development of imputation methods for data requiring imputations should be pursued (Patrício et al. 2015). This means that it is often not possible to directly compare the measurement errors of similar data sets from different institutions. However, standardization of international data collection contributes to bridging this gap (Patrício et al. 2015).

The choice of what to include and what to leave out is one of the most fundamental and difficult problems in quantitative analysis. Some system and problems involve tight coupling between a handful of factors and rather loose coupling to the broader world. But more typically systems are interconnected with the broader world in what appears as seamless web of associations and dependencies. Carful study may help but professional taste and judgment must play a significant role in most cases. Clear communication of what was done, why it was done and that the analyst believes are the consequences, are probably as important as anything (Morgan et al. 1992).

As described in chapter5 , there exists an almost overwhelming variety of different methods for representing, propagating and analysing uncertainties. Morgan et al. (1992) define criteria that may be relevant to choice of method, these criteria may be organized into the following four groups:

Uncertainty about the model form:

What is the relative importance of uncertainty about the form of the model versus the contributions of parameter uncertainty? If model structure and relationships are disputed or poorly known, extensive evaluation of parameter uncertainty within a specific model may be pointless and misleading, if the model structure is well characterized, parameter uncertainty analysis is typically appropriate.

The nature of the model:

How large is it, in terms of the number on uncertain input and the computational cost of a single run? How large are the uncertainties? Is its response surface smooth, monotonic in its inputs, and is it reasonably approximated by simple functional forms? Or does it show complex, nonmonotonic or discontinuous behaviour.

The requirements of the analysis:

What is the main purpose of the analysis? Are significant actions to be based directly on its results? Is the uncertainty analysis intended to guide refinement on the model and/or decisions about what additional information to collect? Is the central tendency (mean or median) of the outputs the main interest, or is a solid characterization of the uncertainty also important? How precise an estimate of the full distribution is necessary? Are extreme tails of the output of importance? How much precision is needed in the identification and ranking the main contributors to the uncertainty?

Resources available:

How much time (calendar time and staff time) is available to conduct the analysis? What kind of skills and experience to the analysts have? What kind of computing resources, and, in particular, what kind of software is available?

7.2 Uncertainty: Framework for a step-wise procedure

Laner et al. (2014) presented a step-wise iterative procedure for handling uncertainty in MFA. The full procedure relates to MFA with a focus on understanding mechanisms relevant for material flows in the system (i.e., exploratory MFA). However, apart from step 5, the scheme in Figure 12 also applies to descriptive MFA; the differences are that the focus is on the consistent characterization of MFA data and that simpler mathematical concepts are typically used to propagate uncertainty.

Depending on the specific application, only parts of the scheme in Figure 12 may be completed. Some studies may not warrant full uncertainty analysis because of different foci of the MFAs. If the MFA is mainly used to quantify material balances to improve the database, steps 1 to 3 are of major importance and step 4 resembles the result of the MFA. If the goal of the MFA does not require describing the inherent uncertainty of model outputs resulting from the actual data situation, the characterization of data uncertainty (step 2) is less important than in descriptive MFA, but sensitivity analysis and/or scenario modelling (step 5) are central elements of such approaches. Therefore, in consideration of the problems related to capturing the actual uncertainty of MFA data and parameters, approaches focusing on sensitivity analysis provide an elegant way of exploring the robustness of MFA models and their results.

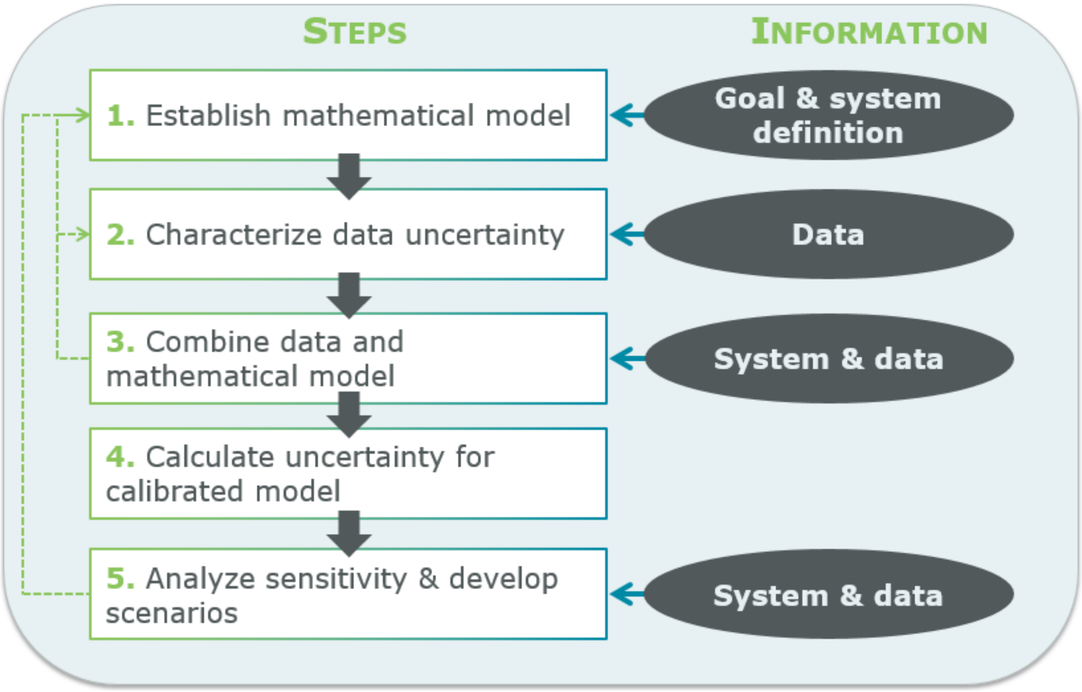


Figure 12: Schematic illustration of the step-wise procedure to consider uncertainty in material flow analysis (MFA) (based on Laner et al. 2014)

1.) Establish mathematical model

- *Define system elements and relationships between these elements*
- *Define equations based on mass balance principle*

The first step for handling uncertainty in MFA, according to Figure 12, is to define the elements of the system and the mathematical relationships between them in consideration of the mass balance principle. This step forms a part of the system definition step and ultimately depends on the goal and scope of the analysis.

2.) Characterize data uncertainty

- *Evaluate information about MFA data (model parameters, inputs and outputs)*
- *Define characterising functions (uncertainty)*

In the second step, uncertain data are characterized by appropriate functions. Basic scientific knowledge (e.g., atomic weight of elements), past data, or expert beliefs can be used to describe the intersubjective knowledge (i.e., expressing current scientific knowledge) of a specific quantity. If sufficient empirical evidence is available, statistical parameter estimation techniques or goodness-of-fit tests can be applied. However, because data uncertainty characterization is often inhibited by scarce information in MFA, formal expert elicitation techniques (Morgan et al. 1992) may be used to express the current scientific knowledge of a quantity. In the case of very poor knowledge or imprecision, this needs to be reflected by the uncertainty characterization (e.g., large spread of probability density functions or use of fuzzy data). Data characterization should also account for logic constraints, for example, the non-negativity of certain variables (e.g., substance concentration of a certain good). In the case of stochastic simulations, normal or log-normal (good data situation), triangular (the most probable value can be derived from expert estimates), and uniform distributions (only vague knowledge about the range containing the true value) are suggested to express information quality. In fuzzy set theory, the amount of available information should be reflected in the shape and range of the membership function (e.g., simple interval vs. trapezoidal function).

3.) Combine data and mathematical model

- *Balance model and cross-check data*
- *Evaluate plausibility and reconcile data iterative*
- *Produce a calibrated model using all available data*

In the third step, the material flow model is balanced using all available information about model parameters, inputs, and outputs. The distinction of model parameters, model inputs, and model outputs enables statements regarding the ability of the model to produce results compatible with observations on the output flows (e.g., application of plausibility criteria). Because the focus of descriptive MFA is to use all data consistently in a snapshot (for a certain time period) model of the system, discriminating between parameters, inputs, and outputs is particularly important for exploratory MFA, where one of the goals is to evaluate the effect of different measures on system behaviour using the material flow model. Based on the comparison of model results with model output information (or desired output qualities), the quality of data for estimating parameter uncertainty may have to be improved. In the case of substantial deviations between observed and modelled flows or implausible results, additional system information is needed. Consequently, the entire procedure of combining data and the mathematical model is iterative and may result in several loops of improving the database to arrive at satisfying or plausible model results. The procedures for evaluating model outputs include the comparison of values before and after data reconciliation, the application of plausibility criteria to model outputs, and formal updating of the model using concepts from Bayesian inference.

4.) Calculate uncertainty for calibrated model

- *Propagate uncertainty through the model and calculate uncertainty of flows*
- *Interpret uncertainty estimates for the resulting flows*

In the fourth step, the calibrated model (satisfying agreement between data and model results has been achieved) is used to calculate the final result (material flows and associated uncertainty). Uncertainty is typically propagated through the model either analytically or using MCS with more than 10,000 simulation runs. This is typically the last step for descriptive MFA, where the main effort lies in iteratively developing the final model based on the available data and the mass balance principle.

5.) Analyse sensitivity & develop scenarios

- *Identify critical model parameters*
- *Change parameters to perform scenario analysis*

For exploratory MFA, sensitivity analysis is used in the fifth and final step to evaluate the effects of parameter variation on the model outputs. It forms the basis to identify critical model parameters, which may be in the focus of measures addressing the material flows in the system. The effect of varying these parameters on the system behaviour (i.e., material flows) can finally be investigated by scenario analysis.

The schematic framework for considering uncertainty in MFA presented in this work should facilitate transparent uncertainty analysis in MFA and is suitable to accommodate any of the approaches presented here. In addition to providing a systematic way to consider uncertainty in MFA, the suggested procedure forms a basis for consistently communicating the approach used to consider uncertainty in a specific MFA study (Laner et al. 2014). Laner et al. (2015a) demonstrate the use of this framework to consider uncertainty and its implementation using two fundamentally different concepts to express uncertainty. Subsequently, the Austrian Pd flow model is used to establish the material flow model and the concept to produce the uncertainty estimates.

8 Uncertainty: MinFuture Pyramid

As already indicated in the previous chapters, a model can never perfectly represent a natural system, because of that, model predictions are always uncertain (Dzubur 2017). MFA relies on data about flows and stocks from different sources with varying quality and can be used to serve different purposes in material management, such as monitoring systems, forecasting changes, or evaluating alternative strategies.

Although studies of material flow systems can provide information, they also depend on information and a lack of useful information can be a limiting factor. If MFA is seen as a way of compiling data to create information about material stocks and flows and to aggregate this information to create knowledge about material flow systems, the quality of its fundamental components is substantial (Schwab 2016). Within the MinFuture project the components are described through the 'MinFuture Pyramid' where the components are structured hierarchically (see Figure 1 = Figure 13). As uncertainty is one component of the hierarchy this report mainly focuses on the uncertainty component. But regardless of the MFA approach used; on the different levels (components) of the pyramid uncertainty plays an important role. As the robustness of the components at higher levels depends on the robustness of the ones at lower levels - also the uncertainty is linked to the different components.

Figure 13: The hierarchical pyramid of MFA components.

Table 17 links the different natures of uncertainty (see chapter 4) and approaches to deal with uncertainty (see chapter 5) with the single components of the 'MinFuture Pyramid'. Although sometimes the clear delimitation of the nature of uncertainty to the 'MinFuture Pyramid' components is difficult, it shows that mainly the data component is in focus of the different uncertainty descriptions. But also the system and models and scenarios components have been taken into account. Parameter uncertainty is distinguished from model uncertainty. Parameter uncertainty is caused by incomplete knowledge about the real value of certain parameters, whereas the model uncertainty originates from an imperfect or neglected consideration of real world effects in the model (Buchner et al. 2015a).

Table 17: Nature of Uncertainty related to the MinFuture Pyramid

Description			Pyramid							
			System	*Data*	*Models*	*Scenarios*	*Uncertainty*	*Indicators*	*Visualisation*	*Strategy support*
Nature of uncertainty	**Causes of uncertainty**	*Non-deterministic behaviour of a system*	■				■	□	□	□
		Uncertainty of model parameter values		■	■	■	■	□	□	□
		Uncertainty of model structure	■	■	■	■	■	□	□	□
		Uncertainty due to external influence factors	■				■	□	□	□
		Uncertainty due to numerical solutions of model equations	■	■	■	■	■	□	□	□
	Sources of uncertainty	*Statistical variation*		■			■	□	□	□
		Variability		■			■	□	□	□
		Inherent randomness and unpredictability		■	■	■	■	□	□	□
		Subjective judgment		■			■	□	□	□
		Disagreement		■			■	□	□	□
		Linguistic imprecision		■			■	□	□	□
		Approximation	■		■	■	■	□	□	□
	Types of Uncertainty	*Parameter Uncertainty*		■	■		■	□	□	□
		Scenario Uncertainty	■		■	■	■	□	□	□
		Model Uncertainty			■		■	□	□	□
		Output Variable			■	■	■	□	□	□
Approaches to deal with uncertainty	**Data classification**	*Asymmetric uncertainty intervals*		■			■	□	□	□
		Symmetric intervals		■			■	□	□	□
		PEDIGREE Matrix		■			■	□	□	□
		Information defects	■	■			■	□	□	□
	Uncertainty analysis	*Gauss's law of error propagation*	■	□	■	■	■	□	□	□
		Data reconciliation	■	□	■	■	■	□	□	□
		STAN Software	■	□	■	■	■	□	□	□
		Mathematical material flow analysis	■	□	■	■	■	□	□	□
		Probabilistic material flow analysis	■	□	■	■	■	□	□	□
		Monte Carlo simulation		□	■	■	■	□	□	□
		Fuzzy set theory	■	■	■	■	■	□	□	□
	Sensitivity analysis		■	■	■	■	■	□	□	□
	Comparison of model structures		■	■	■	■	■	□	□	□

■ The nature of uncertainty or the approaches to deal with uncertainty can be linked to the component of the 'MinFuture Pyramid'.
□ The nature of uncertainty or the approaches to deal with uncertainty cannot be linked directly to the component of the 'MinFuture Pyramid' but potential relations are possible.

Also the delimitation of approaches to deal with uncertainty to the 'MinFuture Pyramid' is difficult. But it shows that data classification models focus on formal concepts to characterize data quality and data uncertainty typically in combination with simple mathematical methods. Data classification methods focus generally on input data. Contrary to uncertainty analysis (statistical approaches), the classification approaches do not include specific methods for propagating uncertainty through the material flow model. In uncertainty analysis (statistical approaches), input data are described by characterizing functions (i.e., probability density functions or membership functions) and rigorous mathematical methods are applied to evaluate the sensitivity and/or uncertainty of model outputs (Laner et al. 2014).

Uncertainty analysis methods focus more on model calculations than in data uncertainty itself although these approaches are using data uncertainty as a base for further calculations. As already mentioned, MFA models can be used to serve different purposes in material management, such as monitoring systems, forecasting changes, or evaluating alternative strategies. Depending on the purpose, MFAs need to include different components.

The following sections describe the relation of the nature of uncertainty and approaches to deal with uncertainty with the components of the 'MinFuture Pyramid'.

System

Systems represent the totality of the stocks and flows within boundaries defined in space and time at a chosen level of (dis-) aggregation. They include observed and unobserved stocks and flows. Adding a system definition to observed data adds information: Systems define the context of observed flows and they allow for calculation of unobserved flows using mass balance.

Nature of Uncertainty

Because a model is only a simplified version of the real system, model parameters approximate the real properties of the system. A system can never be reproduced in full, this leads to observed non-deterministic behaviour.

Approaches to deal with uncertainty

In MFA, the consideration of uncertainty should enable the use of all available information about the system, reflecting the purpose of the MFA and the data quality. The first step for handling uncertainty in MFA is to define the elements of the system and the mathematical relationships between them in consideration of the mass balance principle. Especially uncertainty analysis methods focus on the system component. Data reconciliation is used to balance the system or Gauss's law of error propagation is used to calculate uncertainties with mathematical operations.

Data

Data form the foundation of MFAs. They represent observations of either stocks (at a given point in time) or flows (over a given time period).

Nature of Uncertainty:

Due to the fact that information often originates from different sources, collected data is unavoidably of varying quality. Statistical variations or estimates can lead to data uncertainty. Further data uncertainty reflects the incomplete knowledge about the true value of a parameter, e.g., due to imprecise measurements, (expert) estimations, and assumptions.

Approaches to deal with uncertainty

Data uncertainty is directly related to the nature of uncertainty. To deal with uncertain data appropriate functions need to be characterized. If sufficient empirical evidence is available, statistical parameter estimation techniques or goodness-of-fit tests can be applied. It is also important to convince data providers to include data uncertainty in their publications

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Models and Scenarios

Models in this context are mathematical representations of material cycles. They reflect the system definition and the drivers of cycles such as population growth or technologies used. They are used to simulate MFA-based trends and developments Scenarios here are assumptions of plausible future cycles that are consistent with the mass balance principals and the assumed drivers. They can be used to make forecasts or to evaluate the effectiveness of alternative strategies.

Nature of Uncertainty

Assumptions and simplifications are made that lead to uncertainty regarding the validity of the model predictions for the real world situation. Usually, model equations must be solved numerically. The accuracy of these numerical solutions is usually much higher than uncertainty due to other sources, and can often be neglected.

Approaches to deal with uncertainty

Model predictions are always uncertain. MFA is a method for modelling, understanding and optimizing material flow systems. The material flow model should be balanced using all available information about model parameters, inputs, and outputs. The distinction of model parameters, model inputs, and model outputs enables statements regarding the ability of the model to produce results compatible with observations on the output flows (e.g., application of plausibility criteria). For exploratory MFA, sensitivity analysis is used to evaluate the effects of parameter variation on the model outputs. It forms the basis to identify critical model parameters, which may be in the focus of measures addressing the material flows in the system.

Uncertainty

Uncertainty is inherent in all MFAs of historical or future cycles due to errors in system definitions and the data used. Approaches to uncertainty analysis aim at making uncertainties transparent and reducing them. They enable the modeller to make more robust assumptions and become aware of the model's strengths and limitations.

Indicators

Indicators stands for quantitative measures that aim to reflect the status of complex systems. They are used to analyse and compare performance of businesses, sectors or economies across countries and to determine policy priorities.

Uncertainty

Indicators stand for quantitative measures that aim to reflect the status of complex systems (see MinFuture deliverable 3.2). They are used to analyse and compare performance of businesses, sectors or economies across countries and to determine policy priorities. Indicators are often quantified as possible output outcomes based on a set of uncertain input sensitivity analysis is applied to quantify the range of possible output outcomes (e.g. indicators), given a set of uncertain inputs. Data for the material flow outputs are less readily available and are more aggregated than the material flow input data.

The calibrated model (satisfying agreement between data and model results has been achieved) is used to calculate the final result (material flows and associated uncertainty). Therefore indicators with an associated uncertainty can be calculated and it is possible to interpret uncertainty estimates for the resulting flows.

Visualisation

Visualisations here are different maps of complex systems. They can inform decision making in industry and government, by visualizing current status and historical trends, and potential future developments under different conditions. Visualization tools are developed to support the recording (monitoring), exploration (analysis), and explanation (interpretation) of information.

Uncertainty

Visualisation of uncertainty is possible on different ways. On the one hand it depends on the kind of visualisation of the MFA and the related results (e.g. Sankey, Pie, paired bar, maps, stacked column) and depends on the available data. Details about visualisation can be found in the MinFuture deliverable 3.4.

Strategy and Decision support

Strategy support here has two aspects; (1) Supporting political strategies for raw materials that aim at reaching different goals, such as those of the Strategic Implementation Plan (SIP) of the European Innovation Partnership on Raw Materials, the Circular Economy Action Plan or the SDG's. (2) Supporting strategies for improving and expanding the use of MFA in academia, governments and industry.

Uncertainty

Although studies of material flow systems can provide information, they also depend on information in their production process, and a lack of useful information can be a limiting factor to the level of detail provided in an analysis. More than that, the results are typically inherently limited in terms of accuracy and, thus, in their reliability in subsequent decision-making processes.

9 Conclusion

Sources of uncertainty and approaches to deal with uncertainty are presented with the aim to assist material flow analysis in resources management. The systematic investigation of material flows and stock of anthropogenic systems through MFA allows a new view on the anthroposphere. MFA can link anthropogenic activities with resource consumption and environmental loadings, and is a powerful tool for policy decision support in the fields of resource efficiency, urban planning and environmental protection (Brunner and Rechberger 2016). As the problems addressed by MFA gain in importance now and will become even more important in the future, a rigorous consideration of uncertainty in material flow models is needed (Dzubur 2017). Given that material flow data originate from different sources and vary in quality, MFA is naturally confronted with uncertainty (Laner et al. 2015a).

In MFA, the consideration of uncertainty should enable the use of all available information about the system, reflecting the purpose of the MFA and the data quality (Laner et al. 2014). The uncertainty of the data and the accuracy of the results are fundamental pieces of information for the evaluation process (Brunner and Rechberger 2016). As MFA concerns gathering, harmonizing and analysing data about physical stocks and flows from various different sources with varying quality, limitations of data are unavoidable in material flow studies (Chen and Graedel 2012; Dzubur 2017). The majority of data in MFA are empirical quantities with uncertainty arising from different sources (Laner et al. 2014). Uncertainty in science may relate to context definition, model structure, model inputs, parameter values, and others. In the following the various causes, source and types of uncertainty are summarized (details see chapter 4).

Causes of uncertainty	Non-deterministic behaviour of a system
	Uncertainty of model parameter values
	Uncertainty of model structure
	Uncertainty due to external influence factors
	Uncertainty due to numerical solutions of model equations
Sources of uncertainty	Statistical variation
	Variability
	Inherent randomness and unpredictability
	Subjective judgment
	Disagreement
	Linguistic imprecision
	Approximation
Types of Uncertainty	Parameter Uncertainty
	Scenario Uncertainty
	Model Uncertainty
	Output Variable

If sufficient data are available, unknown flows including their uncertainties can be determined by error propagation. In some situations, however, problems will occur with statistical methods, if there are only one or few data available. Therefore, different approaches to treat uncertain data have been developed. The application of MFA software facilitates the implementation of these approaches and makes the additional workload negligible because of automation (Hedbrant and Sörme 2001). Numerous methods that deal with uncertainty exist. In conclusion, it can be said that there are a handful of simple and sophisticated approaches to include data uncertainty in MFA (Rechberger et al. 2014) – starting from data classification (e.g. asymmetric intervals) to uncertainty analysis (e.g. fuzzy set theory). Different approaches to deal with uncertainty are listed below (details see chapter 5).

Data classification	*Asymmetric uncertainty intervals* *Symmetric intervals* *PEDIGREE Matrix* *Information defects*
Uncertainty analysis	*Gauss's law of error propagation* *Data reconciliation* *STAN Software* *Mathematical material flow analysis* *Probabilistic material flow analysis* *Monte Carlo simulation* *Fuzzy set theory*
Sensitivity analysis	
Comparison of model structures	

The application of MFA software facilitates the implementation of some approaches and makes the additional workload negligible because of automation (Rechberger et al. 2014). Uncertainty is often characterized without the use of formal procedures, which impairs statements about the reliability of the MFA results based on uncertainty analysis. Therefore, consistent and transparent procedures for uncertainty characterization are imperative for uncertainty analysis in MFA. The systematic evaluation of uncertainty in MFA is important to understand the robustness of material flow estimates, independent of the approach used for expressing uncertainty. A crucial step in uncertainty analysis is the characterization of the data uncertainty because this step often lacks a sound empirical basis and is therefore partly dependent on expert estimates and assumptions (Laner et al. 2015a).

MFA models can be used to serve different purposes in material management, such as monitoring systems, forecasting changes, or evaluating alternative strategies. Independent on the purpose, MFAs should include the different components of the 'MinFuture Pyramid' (see Figure 1). These components are structured hierarchically; the robustness of the components at higher levels depends on the robustness of the ones at lower levels. As the robustness of the components at higher levels depends on the robustness of the ones at lower levels - also the uncertainty is linked to the different components. One key conclusion of the analysis in this report is that uncertainty assessment is not just something to be added after the completion of the modelling work. Instead uncertainty should be seen as a red thread throughout the modelling study starting from the very beginning (Refsgaard et al. 2007). Therefore and based on Laner et al. (2014) a step-wise iterative procedure for handling uncertainty in MFA is presented. The full procedure relates to MFA with a focus on understanding mechanisms relevant for material flows in the system (details see chapter 1 and 7).

MFA should now enter into an era where reporting uncertainty ranges of stocks and flows is mandatory. This would help to judge or gauge the reliability of MFA studies and also allow comparative studies for different regions with respect to data quality. Such analysis of MFA data is a requirement for progress in MFA, because we have to assess the level of data quality we need to produce reliable results (Rechberger et al. 2014).

In conclusion, it can be said that there are a handful of applicable approaches to consider data uncertainty in MFA. The employment of MFA software would facilitate the implementation of these approaches and reduce the additional workload because of automation to acceptable levels. However, such software support is not yet on the market (with the exemption of STAN[2], which is limited to normally distributed values) and there is a strong necessity to fund such software development. Only then, MFA could enter into an era where reporting uncertainty ranges of stocks and flows is mandatory and state-of-the-art. This would help to judge or gauge the reliability of MFA studies and also allow comparative studies for different regions with respect to quality and quantity of data generation.

[2] STAN is a freeware, produced by TU Wien: www.stan2web.net

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11 Annex

Table 18: Literature Review: Uncertainty in MFA (1/2)

No.	Author	Publication Title	System Boundary			Materials		Goal	Uncertainty		Mo-dell
			Geo.	*Thematic**	*Time*	*goods*	*substances*		*assigned*	*method(s)*	
1	(Allegrini et al. 2014)	Quantification of the resource recovery potential of municipal solid waste incineration bottom ashes	-	Bottom ash recovery facility	-	bottom ash	Fe, NFe	To quantify recovery efficiencies, resource potential and optimisation potential; To offer a platform for future environmental assessments of incineration	calculated	Symmetric (standard deviation), STAN	static
2	(Allesch and Brunner 2016)	Material Flow Analysis as a Tool to improve Waste Management Systems: The Case of Austria	Austria	Waste management	2012	waste	Cd, C, Cr, Cu, Ni, Hg, N, P, Fe, Zn,	To demonstrate how MFA can be used as tool to design WM-systems; To point out how MFA can be applied as a base for assessment	calculated, estimated	Combination (Laner)	Static
3	(Andersen et al. 2010)	Mass balances and life-cycle inventory for a garden waste windrow composting plant (Aarhus, Denmark)	-	Composting plant (garden waste)	2007	garden waste	C, N, P, Cr, Cd	To offer a detailed LCI of the garden waste composting plant in Aarhus, Denmark	calculated, estimated	Symmetric (standard deviation), STAN	static
4	(Andersen et al. 2011)	Mass balances and life cycle inventory of home composting of organic waste	-	Home composting (Food and garden waste)	two-month	food and garden waste	C, VS, N, K, P, Cd, Cr, Cu and Pb	To provide a LCI as a starting point for making environmental assessment; To present the composition and assess the quality of the final compost product	calculated, estimated	Symmetric (standard deviation), STAN	static
5	(Bader et al. 2011)	Copper flows in buildings, infrastructures and mobiles: a dynamic model and its application to Switzerland	Switzerland	Whole economy	2000	-	Cu	To determine the Cu flows and stocks; To evaluate which stocks have accumulated	calculated, estimated	Sensitivity analysis, Gauss's Law of error propagation	Dynamic
6	(Bajželj et al. 2013)	Designing Climate Change Mitigation Plans That Add Up	Global	Whole economy	2010	GHG		To map the global green house gas emissions, and allocation to human activity	calculated, estimated	-	Static

No.	Author	Publication Title	System Boundary			Materials		Goal	Uncertainty		Mo-dell
			Geo.	*Thematic**	*Time*	*goods*	*substances*		*assigned*	*method(s)*	
7	(Buchner et al. 2014)	In-depth analysis of aluminium flows in Austria as a basis to increase resource efficiency	Austria	Whole economy	2010	-	Al	To establish the Austrian Al budget for the year 2010 as a basis for anthropogenic resource management.	calculated	Asymmetric (Hedbrant and Sörme), STAN	Static
8	(Buchner et al. 2015a)	Dynamic Material Flow Modelling: An Effort to Calibrate and Validate Aluminium Stocks and Flows in Austria	Austria	Whole economy	1964-2012	-	Al	To develop a calibrated dynamic model of Austrian Al flows from 1964 to 2012 for determining in-use stocks and scrap flows	calculated	Monte Carlo Simulation, Global sensitivity analysis,	Dyna mic
9	(Buchner et al. 2015b)	Future raw material supply: Opportunities and limits of aluminium recycling in Austria	Austria	Whole economy	1964-2050	-	Al	To promote sustainable production by using secondary raw material from existing material stocks	calculated	Monte Carlo Simulation	Dyna mic
10	(Chancerel et al. 2009)	Assessment of Precious Metal Flows During Preprocessing of Waste Electrical and Electronic Equipment	-	preprocessing of 1,000 kg of input WEEE	-	WEEE	Ag, Au, Pd, Co, Al, Fe	To quantify the flows of precious metals in and out of a pre-processing facility for WEEE; To determine implications for process optimization	calculated, estimated	Gauss's Law of error propagation, Symmetric (standard deviation)	Static
11	(Cooper and Carliell-Marquet 2013)	A substance flow analysis of phosphorus in the UK food production and consumption system	UK	food production and consumption	2009	-	P	To determine the UK's reliance on imported phosphorus; To identify areas of inefficient use and quantify losses within potentially recoverable waste streams	calculated, estimated	Asymmetric (Hedbrant and Sörme), symmetric (standard deviation), STAN	Static
12	(Cullen and Allwood 2010)	The efficient use of energy: tracing the global flow of energy from fuel to service	Global	Whole economy	2005	Energy	-	To calculate the improvement potential using an absolute physical basis, which is independent of drivers in today's market	calculated, estimated	Absence of any specific uncertainty analysis the values report are rounded	Static

No.	Author	Publication Title	System Boundary			Materials		Goal	Uncertainty		Mo-dell
			Geo.	*Thematic**	*Time*	*goods*	*substances*		*assigned*	*method(s)*	
13	(Cullen et al. 2012)	Mapping the global flow of steel: from steelmaking to end-use goods	Global	Whole economy	2008	Steel	-	To collate the best available data for steel and trace the flow from liquid steel to final products, in an accessible visual form	described	Uncertainty mentioned but not calculated	Static
14	(Cullen and Allwood 2013)	Mapping the global flow of aluminium: from liquid aluminium to end-use goods	Global	Whole economy	2007	-	Al	To understand the potential for future recycling which is complex due to the problems of balancing the alloy mix	described	Uncertainty mentioned but not calculated, mass flows <0.1Mt not shown	Static
15	(Danius and Burström 2001)	Regional material flow analysis and data uncertainties: can the results be trusted	Västerås municipality	Whole economy	1995/ 1998	-	N	To discuss data uncertainties in MFA and analyse how these uncertainties affect the results and the possibilities to draw conclusions	calculated	Asymmetric (Hedbrant and Sörme)	Static
16	(Egle et al. 2014)	The Austrian P budget as a basis for resource optimization	Austria	Whole economy	2004-2008	-	P	To develop a national P balance	calculated	Asymmetric (Hedbrant and Sörme), STAN	Static
17	(Glöser et al. 2013)	Dynamic Analysis of Global Copper Flows. Global Stocks, Postconsumer Material Flows, Recycling Indicators, and Uncertainty Evaluation	Global	Whole economy	1910-2010	-	Cu	To provide such estimates through the development and use of a dynamic model of global copper flows which simulates mass flows over time	calculated, estimated	Symmetric (standard deviation), life time distribution, Stochastic (Monte Carlo) analysis	Dyna mic
18	(Graedel et al. 2004))	Multilevel cycle of anthropogenic copper	Regions/cou ntries	Whole economy	1994	-	Cu	To capture at least 80% of the magnitude of each flow stream by evaluating countries which extract, fabricate, and/or use significant quantities of Cu	described	Detailed description of uncertainty	Static

No.	Author	Publication Title	System Boundary			Materials		Goal	Uncertainty		Mo-dell
			Geo.	*Thematic**	*Time*	*goods*	*substances*		*assigned*	*method(s)*	
19	(Guyonnet et al. 2015)	Material flow analysis applied to rare earth elements in Europe	European Union	Whole economy	2010	-	Pr, Nd, Eu, Tb, Dy and Y	To provide a systemic view of flows and stocks of certain REE along the value chain in the EU, taking into account both primary and secondary sources	calculated	Data reconciliation (Dubois)	Static
20	(Hoenderdaal et al. 2013)	Can a dysprosium shortage threaten green energy technologies?	Global	Green energy technology	2010-2050	-	Dy	To look at current Dy use, future trends and dysprosium supply; To determine if Dy availability may hamper the growth of electric vehicles and wind mills	described	Detailed description of uncertainty	Dynamic
21	(Klinglmair et al. 2015)	Phosphorus in Denmark: national and regional anthropogenic flows	Denmark	Whole economy	2011	-	P	To assess anthropogenic P flows for Denmark, both at the scale of the entire country and its economy, and on a smaller, regional level	calculated	Asymmetric (Hedbrant and Sörme), STAN, Combination (Laner)	Static
22	(Kovanda 2017)	Total residual output flows of the economy: Methodology and application in the case of the Czech Republic	Czech Republic	Whole economy	1990-2014	Total residual output	-	To provide information on used data sources, analysing the total residual output flows compiled	calculated, estimated	Based on Kovanda, set probability	EW-MFA
23	(Kral et al. 2014)	The Copper Balance of Cities Exploratory Insights into a European and an Asian City	Vienna and Taiwan	Whole economy	2008 and 2009	-	Cu	To develop a methodology to analyse and evaluate the Cu flows and stocks for two cities; To discuss the differences between on the basis of selected indicators	calculated, estimated	Asymmetric (Hedbrant and Sörme), symmetric (standard deviation), STAN	Static
24	(Laner et al. 2015a)	Applying fuzzy and probabilistic uncertainty concepts to the material flow analysis of palladium in Austria	Austria	Whole economy	2011	-	Pd	To investigate the effect of a rigorous uncertainty analysis on the evaluation of the Austrian Pd resource system	calculated	STAN and fuzzy model	Static

No.	Author	Publication Title	System Boundary			Materials		Goal	Uncertainty		Mo-dell
			Geo.	*Thematic**	*Time*	*goods*	*substances*		*assigned*	*method(s)*	
25	(Morf et al. 2007)	Metals, non-metals and PCB in electrical and electronic waste – Actual levels in Switzerland	-	WEEE treatment plant	3-day operati on period	-	Al, Sb, Pb, Cd, Cr, Fe, Cu, Ni, Hg, Zn, Sn, Cl, P, PCB sum	To characterize the actual chemical composition and contents of specific pollutants of WEEE	calculated	Gauss's Law of error propagation, Symmetric (standard deviation)	Static
26	(Morf et al. 2013)	Precious metals and rare earth elements in municipal solid waste – Sources and fate in a Swiss incineration plant	-	MSW incinerator	2010	-	Ag, Au, Ba, Be, Bi, Co, Ga, Gd, Ge, Hf, In, Li, Mo, Nb, Nd, Pb, Pr, Pt, Rb, Rh, Ru, Sc, Se, Sr, Ta, Te, Tl, V, W, Y, Zr	To characterize of the elemental composition of MSW and the transfer into the outputs of the MSWI	calculated	Gauss's Law of error propagation, Symmetric (standard deviation)	Static
27	(Ott and Rechberg er 2012)	The European phosphorus balance	EU	Whole economy	1 year	-	P	To develop an SFA model for the EU15 and adopt it to the special requirements for an EU15 wide analysis	calculated, estimated	Symmetric (standard deviation), STAN	Static
28	(Rechberg er and Graedel 2002)	The contemporary European copper cycle: statistical entropy analysis	Europe	Whole economy	1994	-	Cu	To introduce an alternative and useful method for evaluating material flows only.	described	Detailed description of uncertainty	Static
29	(Reck et al. 2010)	Global stainless steel cycle exemplifies China's rise to metal dominance	China	Whole economy	2000 and 2005	stainle ss steel	-	To characterize at the global level the cycle for stainless steel (or any alloy); To analyse the dynamics of a metal market during the early 20th century	calculated, estimated	Gauss's Law of error propagation, STAN	Static
30	(Schulze and Buchert 2016)	Estimates of global REE recycling potentials from NdFeB magnet material	Global	Green energy technology	2020-2030	-	NdFeB	To give an estimate of global annual REE recycling potentials from pre-and post-consumer magnet material in years 2020-30	described	Reflection of data uncertainty	Dyna mic

No.	Author	Publication Title	System Boundary			Materials		Goal	Uncertainty		Mo-dell
			Geo.	*Thematic**	*Time*	*goods*	*substances*		*assigned*	*method(s)*	
31	(Spatari et al. 2002)	The contemporary European copper cycle: 1 year stocks and flows	Europe	Whole economy	1994	-	Cu	To examine the quantity of Cu used in the 1990s; To estimate the amount leaving the economy as discarded waste, the amount recovered or stored	no	no	Static
32	(Spatari et al. 2003)	The contemporary European zinc cycle: 1 year stocks and flows	Europe	Whole economy	1994	-	Zn	To examine the quantity of Zn used in the 1990s; To estimate the amount leaving the economy as discarded waste, the amount recovered or stored	no	no	Static
33	(Stanisavljevic and Brunner 2014)	Combination of material flow analysis and substance flow analysis: A powerful approach for decision support in waste management	Novi Sad	MSW Management	1 year	MSW	C, Cd	To demonstrate how a combination of MFA, SFA and scenario modelling can be used as a base for goal-oriented evaluation	calculated, estimated	STAN	Static
34	(Tonini et al. 2014)	Bioenergy, material, and nutrients recovery from household waste: Advanced material, substance, energy, and cost flow analysis of a waste refinery process	-	MSW Management (1,000 kg)	-	MSW	C, Cfoss, N, P, K, Fe, and Al	To characterize the outputs of a pilotscale waste refinery process; To development a mathematical optimization model to evaluate the potential for recovery	calculated	Symmetric (standard deviation), STAN	Static
35	(Van Beers et al. 2005)	The application of material flow analysis for the evaluation of the recovery potential of secondary metals in Australia	Australia	Whole economy	one year	-	Cu, Zn	To discuss the potential and availability of secondary metals for recovery in Australia; To illustrate research results and case-study examples for Cu and Zn	estimated	Sensitivity analysis	Static

No.	Author	Publication Title	System Boundary			Materials		Goal	Uncertainty		Mo-dell
			Geo.	*Thematic**	*Time*	*goods*	*substances*		*assigned*	*method(s)*	
36	(Van Eygen et al. 2017)	Comprehensive analysis and quantification of national plastic flows: The case of Austria	Austria	Whole economy	2010	plastic	-	To connect the sources (e.g. imports), the pathways (e.g. transfer coefficients) and intermediate (e.g. consumption) and final sinks of materials	calculated	Combination (Laner)	Static
37	(Vyzinkarova and Brunner 2013)	Substance Flow Analysis of Wastes Containing Polybrominated Diphenyl Ethers	Vienna	Whole economy	2010	-	cPentaBDE, cOctaBDE	To identify sources, pathways, and sinks; To determine the fractions of cPentaBDE and cOctaBDE that reach final sinks	calculated, estimated	Symmetric (standard deviation), STAN	Static
38	(Zhang et al. 2008)	Implication of heavy metals distribution for a municipal solid waste management system — a case study in Shanghai	Shanghai	MSW Management	Sampling (October 2004 to September 2005)	-	Pa, Wo, Pu, Gl, Pl, Te, Me, Cd	To analyse the occurrence and distribution of heavy metals in MSW and to discuss their implications for integrated MSW management system in mega-cities	calculated	Symmetric (standard deviation),	Static
39	(Zoboli et al. 2016)	Added Values of Time Series in Material Flow Analysis: The Austrian Phosphorus Budget from 1990 to 2011	Austria	Whole economy	1990-2011	-	P	To identify and assess the extent of the temporal changes that occurred in the system during the last two decades	calculated	Combination (Laner)	Static

Table 19: Literature Review: Uncertainty in MFA (2/2)

No.	Author(s)	Publication Summary
1	(Allegrini et al. 2014)	Municipal solid waste incineration (MSWI) plays an important role in many European waste management systems. However, increasing focus on resource criticality has raised concern regarding the possible loss of critical resources through MSWI. The primary form of solid output from waste incinerators is bottom ashes (BAs), which also have important resource potential. Based on a full-scale Danish recovery facility, detailed material and substance flow analyses (MFA and SFA) were carried out, in order to characterise the resource recovery potential of Danish BA: (i) based on historical and experimental data, all individual flows (representing different grain size fractions) within the recovery facility were quantified, (ii) the resource potential of ferrous (Fe) and non-ferrous (NFe) metals as well as rare earth elements (REE) was determined, (iii) recovery efficiencies were quantified for scrap metal and (iv) resource potential variability and recovery efficiencies were quantified based on a range of ashes from different incinerators. Recovery efficiencies for Fe and NFe reached 85% and 61%, respectively, with the resource potential of metals in BA before recovery being 7.2%ww for Fe and 2.2%ww for NFe. Considerable no recovered resource potential was found in fine fraction (below 2 mm), where approximately 12% of the total NFe potential in the BA were left. REEs were detected in the ashes, but the levels were two or three orders of magnitude lower than typical ore concentrations. The lack of REE enrichment in BAs indicated that the post-incineration recovery of these resources may not be a likely option with current technology. Based on these results, it is recommended to focus on limiting REE-containing products in waste for incineration and improving pre-incineration sorting initiatives for these elements.
2	(Allesch et al. 2016)	This article reviews, categorizes, and evaluates the objectives, means, and results of the application of material flow analysis (MFA) in waste management. It identifies those areas where MFA methodologies are most successful in supporting waste management decisions. The focus of this review is on the distinction between MFA on the level of goods and on the level of substances. Based on 83 reviewed studies, potentials, strengths, and weaknesses are investigated for the two levels of MFA when applied for analysis, evaluation, and improvement of waste management systems. The differences are discussed in view of effectiveness, applicability, and data availability. The results show that MFA on the level of goods are instrumental for understanding how waste management systems function, facilitating the connections of stakeholders, authorities, and waste management companies. The substance level is essential to assess qualitative aspects regarding resources and environment. Knowledge about the transformation, transport, and storage of valuable and hazardous substances forms the base for identifying both resource potentials and risks for human health and the environment. The results of this review encourage the application of MFA on both levels of goods and substances for decision making in waste management. Because of the mass balance principle, this combination has proven to be a powerful tool for comprehensively assessing if a chosen system reaches designated waste management goals.
3	(Andersen et al. 2010)	A comprehensive life-cycle inventory of all consumptions and emissions of environmental relevance was made for the windrow composting plant treating garden waste in Aarhus (Denmark). The flows of materials and substances within the facility were balanced using the mass-balance model STAN. The overall fuel and electricity use at the facility (3.04 L diesel Mg 1 wet waste (ww) and 0.2kWh Mg 1 ww) was low whereas the emissions of CH4 and N2O from the windrows (2.4 0.5 kg CH4–C Mg 1ww and 0.06 0.03 kg N2O–N Mg 1 ww) were relatively high compared to data reported in similar studies. The loss of carbon during the 14-month-long composting was 56%. CH4 made up 2.1% of the C lost. Loss of nitrogen-containing compounds was identified as the most sensible and uncertain parameter and could be relevant for global warming (N2O emissions), acidification (NH3 emissions), and eutrophication (NH3 and NO3 emissions). The compost produced had a very low content of heavy metals and was suitable for use in gardens and/or agriculture.

No.	Author(s)	Publication Summary
4	(Andersen et al. 2011)	A comprehensive experimental setup with six single-family home composting units was monitore+U11d during 1 year. The composting units were fed with 2.6–3.5 kg organic household waste (OHW) per unit per week. All relevant consumptions and emissions of environmental relevance were addressed and a full life-cycle inventory (LCI) was established for the six home composting units. No water, electricity or fuel was used during composting, so the major environmental burdens were gaseous emissions to air and emissions via leachate. The loss of carbon (C) during composting was 63–77% in the six composting units. The carbon dioxide (CO2) and methane (CH4) emissions made up 51–95% and 0.3–3.9% respectively of the lost C. The total loss of nitrogen (N) during composting was 51–68% and the nitrous oxide (N2O) made up 2.8–6.3% of this loss. The NH3 losses were very uncertain but small. The amount of leachate was 130 L Mg 1 wet waste (ww) and the composition was similar to other leachate compositions from home composting (and centralised composting) reported in literature. The loss of heavy metals via leachate was negligible and the loss of C and N via leachate was very low (0.3–0.6% of the total loss of C and 1.3–3.0% of the total emitted N). Also the compost composition was within the typical ranges reported previously for home composting. The level of heavy metals in the compost produced was below all threshold values and the compost was thus suitable for use in private gardens.
5	(Bader et al. 2011)	During the last century, the consumption of materials for human needs increased by several orders of magnitude, even for non-renewable materials such as metals. Some data on annual consumption (input) and recycling/waste (output) can often be found in the federal statistics, but a clear picture of the main flows is missing. A dynamic material flow model is developed for the example of copper in Switzerland in order to simulate the relevant copper flows and stocks over the last 150 years. The model is calibrated using data from statistical and published sources as well as from interviews and measurements. A simulation of the current state (2000) is compared with data from other studies. The results show that Swiss consumption and losses are both high, at a level of about 8 and 2 kg/ (cap year), respectively, or about three times higher than the world average. The model gives an understanding of the flows and stocks and their interdependencies as a function of time. This is crucial for materials whose consumption dynamics are characterised by long lifetimes and hence for relating the current output to the input of the whole past. The model allows a comprehensive discussion of possible measures to reduce resource use and losses to the environment. While increasing the recycling reduces losses to landfill, only copper substitution can reduce the different losses to the environment, although with a time delay of the order of a lifetime.
6	(Bajzelj et al. 2013)	Mitigation plans to combat climate change depend on the combined implementation of many abatement options, but the options interact. Published anthropogenic emissions inventories are disaggregated by gas, sector, country, or final energy form. This allows the assessment of novel energy supply options, but is insufficient for understanding how options for efficiency and demand reduction interact. A consistent framework for understanding the drivers of emissions is therefore developed, with a set of seven complete inventories reflecting all technical options for mitigation connected through lossless allocation matrices. The required data set is compiled and calculated from a wide range of industry, government, and academic reports. The framework is used to create a global Sankey diagram to relate human demand for services to anthropogenic emissions. The application of this framework is demonstrated through a prediction of per-capita emissions based on service demand in different countries, and through an example showing how the "technical potentials" of a set of separate mitigation options should be combined.
7	(Buchner et al. 2014)	Based on the method of material flow analysis (MFA), a static model of Austrian aluminium (Al) flows in 2010 was developed. Extensive data research on Al production, consumption, trade and waste management was conducted and resulted in a detailed model of national Al resources. Data uncertainty was considered in the model based on the application of a rigorous concept for data quality assessment. The model results indicated that the growth of the Austrian "in-use" Al stock amounts to 11 ± 3.1 kg yr−1 cap−1. The total "in-use" Al stock was determined using a Bottom-Up approach, which produced an estimate of 260 kg Al cap−1. Approximately 7 ± 1 kg of Al yr−1 cap−1 of old scrap was generated in 2010, of which 20% was not recovered because of losses in waste management processes. Quantitatively, approximately 40% of the total scrap input to secondary Al production originated from net imports, highlighting the import dependency of Austrian Al refiners and remelters. Uncertainties in the calculation of recycling indicators for the Austrian Al system with high shares of foreign scrap trade were exemplarily illustrated for the old scrap ratio (OSR) in secondary Al production, resulting in a possible range of OSRs

No.	Author(s)	Publication Summary
		between 0 and 66%. Overall, the detailed MFA in this study provides a basis to identify resource potentials as well as resource losses in the national Al system, and it will serve as a starting point for a dynamic Al model to be developed in the future.
8	(Buchner et al. 2015)	A calibrated and validated dynamic material flow model of Austrian aluminium (Al) stocks and flows between 1964 and 2012 was developed. Calibration and extensive plausibility testing was performed to illustrate how the quality of dynamic material flow analysis can be improved on the basis of the consideration of independent Bottom-Up estimates. According to the model, total Austrian in-use Al stocks reached a level of 360 kg/capita in 2012, with buildings (45%) and transport applications (32%) being the major in-use stocks. Old scrap generation (including export of end-of-life vehicles) amounted to 12.5 kg/capita in 2012, still being on the increase, while Al final demand has remained rather constant at around 25 kg/capita in the past few years. The application of global sensitivity analysis showed that only small parts of the total variance of old scrap generation could be explained by the variation of single parameters, emphasizing the need for comprehensive sensitivity analysis tools accounting for interaction between parameters and time-delay effects in dynamic material flow models. Overall, it was possible to generate a detailed understanding of the evolution of Al stocks and flows in Austria, including plausibility evaluations of the results. Such models constitute a reliable basis for evaluating future recycling potentials, in particular with respect to application-specific qualities of current and future national Al scrap generation and utilization.
9	(Buchner et al. 2015)	In order to promote sustainable production by using secondary raw material from existing material stocks, complementary to primary raw material, information about the future availability of secondary resources constitutes a prerequisite. In this study, a dynamic material flow model of historic aluminium (Al) flows in Austria is combined with forecasts on future Al consumption to estimate the development of old scrap generation and in-use stocks until 2050. In-use stocks are estimated to increase by 60 % to 515 kg/cap. by 2050 assuming a scenario of moderate economic growth. Old scrap generation in 2050 would thereby more than double (up to 30 kg/cap.) in comparison to the 2010 amounts. Despite this substantial increase in old scrap generation, industrial self-supply from old scrap will probably not exceed 20 %, and final consumption self-supply of Al will not exceed 40 % given present conditions. Opportunities and limits of increasing self-supply through higher collection rates and lower scrap export levels are investigated in this study as the European Raw Material Initiative considers enhanced recycling to be a key measure to ensure future resource supply. Based on these analyses, a self-sustaining Al supply from post-consumer Al is not expected if current trends of Al usage continue. Therefore, comprehensive resource policy should be based on a profound understanding of the availability of primary and secondary resources potentials and their dynamics.
10	(Chancerel et al. 2009)	The manufacturing of electronic and electrical equipment (EEE) is a major demand sector for precious and special metals with a strong growth potential. Both precious and special metals are contained in complex components with only small concentrations per unit. After the use-phase, waste electronic and electrical equipment (WEEE) is an important source of these “trace elements.” Their recycling requires appropriate processes in order to cope with the hazardous substances contained pinweed and to recover efficiently the valuable materials. Although state-of-the-art pre-processing facilities are optimized for recovering mass-relevant materials such as iron and copper, trace elements are often lost. The objective of this article is to show how a substance flow analysis (SFA) on a process level can be used for a holistic approach, covering technical improvement at process scale, optimization of product life cycles, and contributing to knowledge on economy-wide material cycles. An SFA in a full-scale pre-processing facility shows that only 11.5 wt.% of the silver and 25.6 wt.% of the gold and of the palladium reach output fractions from which they may potentially be recovered. For copper this percentage is 60. Considering the environmental rucksack of precious metals, an improvement of the recycling chain would significantly contribute to the optimization of the product life cycle impact of EEE and to ensuring the long-term supply of precious metals.

No.	Author(s)	Publication Summary
11	(Cooper et al. 2013)	Phosphorus (P) is both an essential resource, required for plant growth and food production, and a costly pollutant, capable of causing eutrophication in water courses. The possibility of future phosphorus scarcity and the requirement to improve the quality of UK waters necessitates the development of a UK phosphorus management system, which increases use efficiency, reduces losses and recycles wastes more effectively. A vital first step towards creating such a system is to conduct a substance flow analysis (SFA), which maps and quantifies the relevant stocks and flows, allowing specific measures to be implemented that target identified losses and areas of inefficient resource use. This paper presents the results of a SFA for phosphorus in the UK, focussing in particular on the food production and consumption system for the year 2009. The SFA results suggest that the UK population consumed around 31.0 kt P in 2009, which was largely achieved by importing food, feed and fertilisers, with net imports totalling 113.5 kt P. Imported fertilisers accounted for 56% of the total imports, containing 77.5 kt P. The largest losses within the systems were those to water, estimated at around 41.5 kt P/yr, and soil accumulations are estimated at 37.5 kt P/yr. The efficiency of UK crop production is estimated at 81%, whereas the efficiency of producing animal products is only 16.5%. Wastewater treatment works (WwTW) received around 55.0 kt P within wastewater, with 57% being removed in sewage sludge. The 23.5 kt P discharged within final effluent represented the largest loss to UK waters. Around 71% of the sludge was recycled to land, containing 22.5 kt P, although the rate of application was around 5× higher than the uptake rate for crops, demonstrating the challenges of effectively recycling bulky wastes. Existing measures aimed at tackling water pollution and climate change have acted to improve P management in the UK, although additional measures focussing particularly on P as a resource are required. The results from this analysis suggest focussing on P removal and recovery at WwTW, as well as developing more effective methods for recycling bulky wastes such as animal manure, food waste and sewage sludge in order to reduce soil accumulations and replace imported fertilisers. Conducting additional SFAs at smaller scales may be necessary in order to develop more specific measures, such as regional recycling strategies.
12	(Cullen et al. 2010a)	The efficient use of energy is a key component of current efforts to reduce carbon emissions. There are two factors which are important when assessing the potential gains from energy efficiency technologies: the scale of energy flow and the technical potential for improvement. However, most efficiency analyses consider only the potential gains from known efficiency technologies, while ignoring the complex flow of energy through the chains of conversion devices. In response, this paper traces the global flow of energy, from fuels through to the final services, and focuses on the technical conversion devices and passive systems in each energy chain. By mapping the scale and complexity of global energy flow, the technical areas which are likely to deliver the largest efficiency gains can be identified. The result is a more consistent basis for directing future research and policy decisions in the area of energy efficiency.
13	(Cullen et al. 2013a)	Our society is addicted to steel. Global demand for steel has risen to 1.4 billion tonnes a year and is set to at least double by 2050, while the steel industry generates nearly a 10th of the world's energy related CO2 emissions. Meeting our 2050 climate change targets would require a 75% reduction in CO2 emissions for every tonne of steel produced and finding credible solutions is proving a challenge. The starting point for understanding the environmental impacts of steel production is to accurately map the global steel supply chain and identify the biggest steel flows where actions can be directed to deliver the largest impact. In this paper we present a map of global steel, which for the first time traces steel flows from steelmaking, through casting, forming, and rolling, to the fabrication of final goods. The diagram reveals the relative scale of steel flows and shows where efforts to improve energy and material efficiency should be focused.
14	(Cullen et al. 2013b)	Demand for aluminium in final products has increased 30-fold since 1950 to 45 million tonnes per year, with forecasts predicting this exceptional growth to continue so that demand will reach 2−3 times today's levels by 2050. Aluminium production uses 3.5% of global electricity and causes 1% of global CO2 emissions, while meeting a 50% cut in emissions by 2050 against growing demand would require at least a 75% reduction in CO2 emissions per tonne of aluminium producede a challenging prospect. In this paper we trace the global flows of aluminium from liquid metal to final products, revealing for the first time a complete map of the aluminium system and providing a basis for future study of the emissions abatement potential of material efficiency. The resulting Sankey diagram also draws attention to two key issues. First, around half of all liquid aluminium (~39 Mt) produced each year never reaches a final product, and a detailed discussion of these high yield losses shows significant opportunities for improvement. Second, aluminium recycling, which avoids the high energy costs and emissions

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		of electrolysis, requires signification "dilution" (~ 8 Mt) and "cascade" (~ 6 Mt) flows of higher aluminium grades to make up for the shortfall in scrap supply and to obtain the desired alloy mix, increasing the energy required for recycling.
15	(Danius et al. 2001)	Regional material flow analysis (MFA) has been proposed to be a useful tool for priority setting and follow-up in environmental management. However, data that are used in regional MFA are usually connected to varying degrees of uncertainties. This paper analyses and discusses how data uncertainties affect the results from a regional MFA study of nitrogen flows in a Swedish municipality. It is argued that the intended use of MFA is associated with considerable difficulties.
16	(Egle et al. 2014)	Phosphorus (P) is a finite and non-substitutable resource that is essential to sustaining high levels of agricultural productivity but is also responsible for environmental problems, e.g., eutrophication. Based on the methodology of Material Flow Analysis, this study attempts to quantify all relevant flows and stocks of phosphorus (P) in Austria, with a special focus on waste and wastewater management. The system is modelled with the software STAN, which considers data uncertainty and applies data reconciliation and error propagation. The main novelty of this work lies in the high level of detail at which flows and stocks have been quantified to achieve a deeper understanding of the system and to provide a sound basis for the evaluation of various management options. The budget confirms on the one hand the dependence of mineral P fertilizer application (2 kg cap−1 yr−1), but it highlights on the other hand considerable unexploited potential for improvement. For example, municipal sewage sludge (0.75 kg cap−1 yr−1) and meat and bone meal (0.65 kg cap−1 yr−1) could potentially substitute 70% of the total applied mineral P fertilizers. However, recycling rates are low for several P flows (e.g., 27% of municipal sewage sludge; 3% of meat and bone meal). Therefore, Austria is building up a remarkable P stock (2.1 kg P cap−1 yr−1), mainly due to accumulation in landfills (1.1 kg P cap−1 yr−1) and agricultural soils (0.48 kg P cap−1 yr−1).
17	(Glöser et al. 2013	We present a dynamic model of global copper stocks and flows which allows a detailed analysis of recycling efficiencies, copper stocks in use, and dissipated and landfilled copper. The model is based on historical mining and refined copper production data (1910−2010) enhanced by a unique data set of recent global semi finished goods production and copper end-use sectors provided by the copper industry. To enable the consistency of the simulated copper life cycle in terms of a closed mass balance, particularly the matching of recycled metal flows to reported historical annual production data, a method was developed to estimate the yearly global collection rates of end-of-life (postconsumer) scrap. Based on this method, we provide estimates of 8 different recycling indicators over time. The main indicator for the efficiency of global copper recycling from end-of-life (EoL) scrap the EoL recycling rate☐ was estimated to be 45% on average, ± 5% (one standard deviation) due to uncertainty and variability over time in the period 2000−2010. As uncertainties of specific input data mainly concerning assumptions on end-use lifetimes and their distribution are high, a sensitivity analysis with regard to the effect of uncertainties in the input data on the calculated recycling indicators was performed. The sensitivity analysis included a stochastic (Monte Carlo) uncertainty evaluation with 105 simulation runs.
18	(Gradel et al. 2004)	A comprehensive contemporary cycle for stocks and flows of copper is characterized and presented, incorporating information on extraction, processing, fabrication and manufacturing, use, discard, recycling, final disposal, and dissipation. The analysis is performed on an annual basis, ca. 1994, at three discrete governmental unit levels−56 countries or country groups that together comprise essentially all global anthropogenic copper stocks and flows, nine world regions, and the planet as a whole. Cycles for all of these are presented and discussed, and a "best estimate" global copper cycle is constructed to resolve aggregation discrepancies. Among the most interesting results are (1) transformation rates and recycling rates in apparently similar national economies differ by factors of two or more (country level); (2) the discard flows that have the greatest potential for copper recycling are those with low magnitude flows but high copper concentrations electronics, electrical equipment, and vehicles (regional level); (3) worldwide, about 53% of the copper that was discarded in various forms was recovered and reused or recycled (global level); (4) the highest rate of transfer of discarded copper to repositories is into landfills, but the annual amount of copper deposited in mine tailings is nearly as high (global level); and (5) nearly 30% of copper mining occurred merely to replace copper that was discarded. The results provide a framework for similar studies of other anthropogenic resource cycles as well as a

No.	Author(s)	Publication Summary
		basis for supplementary studies in resource stocks, industrial resource utilization, waste management, industrial economics, and environmental impacts.
19	(Guyonnet et al. 2015)	This paper explores flows and stocks, at the scale of the European Union, of certain rare earth elements (REEs; Pr, Nd, Eu, Tb, Dy and Y) which are associated with products that are important for the decarbonisation of the energy sector and that also have strong recycling potential. Material flow analyses were performed considering the various steps along the value chain (separation of rare earth oxides, manufacture of products, etc.) and including the lithosphere as a potential stock (potential geological resources). Results provide estimates of flows of rare earths into use, in-use stocks and waste streams. Flows into use of, e.g., Tb in fluorescent lamp phosphors, Nd and Dy in permanent magnets and Nd in battery applications were estimated, for selected reference year 2010, as 35, 1230, 230 and 120 tons respectively. The proposed Sankey diagrams illustrate the strong imbalance of flows of permanent magnet REEs along the value chain, with Europe relying largely on the import of finished products (magnets and applications). It is estimated that around 2020, the amounts of Tb in fluorescent lamps and Nd in permanent magnets recycled each year in Europe, could be on the order of 10 tons for Tb and between 170 and 230 tons for Nd.
20	(Hoenderdaal et al. 2012)	Dysprosium, one of the various rare earth elements, is currently for more than 99% mined in China. As China is reducing its exports, new mining projects outside of China are needed to sustain supply and meet future demands. Dysprosium is mainly used in permanent magnets to retain the magnet's strength at elevated temperatures. Therefore, the use of dysprosium doped permanent magnets is preferred in electric vehicles and direct-drive wind turbines. Based on four scenarios it could be shown that dysprosium demand will probably outstrip supply in the short term (up to 2020). Although new mines are being developed, it takes several years for them to become productive. For the long term it is expected that enough dysprosium oxide is available in the earth crust (which is economically feasible to mine with current dysprosium prices) to fulfil the projected demand of dysprosium up to 2050. Recycling of dysprosium can further secure dysprosium supply in the long term by reducing primary dysprosium use by 35% in 2050. Electric vehicles are likely to play a dominant role in future increases in dysprosium demand. Even with the limited market share in 2011, electric vehicles already contribute to 20% of dysprosium use.
21	(Klinglmair et al. 2015)	Substance flow analyses (SFA) of phosphorus (P) have been examined on a national or supra-national level in various recent studies. SFA studies of P on the country scale or larger can have limited informative value; large differences between P budgets exist within countries and are easily obscured by country-wide average values. To quantify and evaluate these imbalances we integrated a country-scale and regional-scale model of the Danish anthropogenic P flows and stocks. We examine three spatial regions with regard to agriculture, as the main driver for P use, and waste management, the crucial sector for P recovery. The regions are characterised by their differences in agricultural practice, population and industrial density. We show considerable variation in P flows within the country. First, these are driven by agriculture, with mineral fertiliser inputs varying between 3 and 5 kg ha^{-1} yr^{-1}, and animal feedstuff inputs between 5 and 19 kg ha^{-1} yr^{-1}. We identified surpluses especially in areas with a larger proportion of animal husbandry, owing to additional application of manure in excess of crop P demand. However, redistribution of the large amounts of P in manure is not feasible owing to transport limitations. Second, waste management, closely linked to population and industrial density is the driver behind differences in recoverable P flows. Current amounts of potentially recoverable P cannot change the reliance on primary P. The most immediate P re-use potential exists in the areas around the eastern urban agglomerations, from more complete recovery of sewage sludge (with unrecovered P amounts of up to 33% of P in current mineral fertiliser imports) and the biowaste fraction in municipal solid waste currently not collected separately (24% of P in current mineral fertiliser imports), since this region shows both the highest proportion of crop production and fertiliser use and lowest soil P budget.

No.	Author(s)	Publication Summary
22	(Kovanda et al. 2017)	The article goes beyond standard emission and waste statistics and elaborates upon total residual output flows of economies based on economy-wide material flow accounting and analysis (EW-MFA). This concept allows for evaluation of total environmental pressures related to material output flows and assessing the potential trade-offs if environmental policies are more successful in some fields than in others. We provide basic information on EW-MFA and its output accounts and indicators and describe in detail the methodology of their compilation. The methodology is then applied to the Czech Republic for the period 1990–2014. All major components of residual output flows, i.e. emission and waste flow, dissipative use flow and unused domestic extraction accounts, as well as domestic processed output (DPO) and total domestic output (TDO) indicators, went down in the monitored period. We identified a few major driving forces behind this decrease, including changes in the structure of the economy, changes in the structure of TPES, technological change, advances in waste management, and changes in the agricultural system of the Czech Republic. The results further indicate that another decrease in DPO and TDO indicators is at stake, as Czech economic policies are aimed at maintaining the current relatively high proportion of manufacturing industries in the economy.
23	(Kral et al. 2014)	Material management faces a dual challenge: on the one hand satisfying large and increasing demands for goods and on the other hand accommodating wastes and emissions in sinks. Hence, the characterization of material flows and stocks is relevant for both improving resource efficiency and environmental protection. This article focuses on the urban scale, a dimension rarely investigated in past metal flow studies. We compare the copper (Cu) metabolism of two cities in different economic states, namely, Vienna (Europe) and Taipei (Asia). Substance flow analysis is used to calculate urban Cu balances in a comprehensive and transparent form. The main difference between Cu in the two cities appears to be the stock: Vienna seems close to saturation with 180 kilograms per capita (kg/cap) and a growth rate of 2% per year. In contrast, the Taipei stock of 30 kg/cap grows rapidly by 26% per year. Even though most Cu is recycled in both cities, bottom ash from municipal solid waste incineration represents an unused Cu potential accounting for 1% to 5% of annual demand. Nonpoint emissions are predominant; up to 50% of the loadings into the sewer system are from nonpoint sources. The results of this research are instrumental for the design of the Cu metabolism in each city. The outcomes serve as a base for identification and recovery of recyclables as well as for directing no recyclables to appropriate sinks, avoiding sensitive environmental pathways. The methodology applied is well suited for city benchmarking if sufficient data are available.
24	(Laner et al. 2015)	Material flow analysis (MFA) is a widely applied tool to investigate resource and recycling systems of metals and minerals. Owing to data limitations and restricted system understanding, MFA results are inherently uncertain. To demonstrate the systematic implementation of uncertainty analysis in MFA, two mathematical concepts for the quantification of uncertainties were applied to Austrian palladium (Pd) resource flows and evaluated: (1) uncertainty ranges expressed by fuzzy sets and (2) uncertainty ranges defined by normal distributions given as mean values and standard deviations. Whereas normal distributions represent the traditional approach for quantifying uncertainties in MFA, fuzzy sets may offer additional benefits in relation to uncertainty quantification in cases of scarce information. With respect to the Pd case study, the fuzzy representation of uncertain quantities is more consistent with the actual data availability in cases of incomplete databases, and fuzzy sets serve to highlight the effect of uncertainty on resource efficiency indicators derived from the MFA results. For both approaches, data reconciliation procedures offer the potential to reduce uncertainty and evaluate the plausibility of the model results. With respect to Pd resource management, improved formal collection of end-of-life (EOL) consumer products is identified as a key factor in increasing the recycling efficiency. In particular, the partial export of EOL vehicles represents a substantial loss of Pd from the Austrian resource system, whereas approximately 70% of the Pd in the EOL consumer products is recovered in waste management. In conclusion, systematic uncertainty analysis is an integral part of MFA required to provide robust decision support in resource management.

No.	Author(s)	Publication Summary
25	(Morf et al. 2007)	The chemical composition of waste of small electrical and electronic equipment (s-WEEE), a rapidly growing waste stream, was determined for selected metals (Cu, Sb, Hg etc.) and non-metals (Cl, Br, P) and PCBs. During a 3-day experiment, all output products and the s-WEEE input mass flows in a WEEE recycling plant were measured. Only output products were sampled and analysed. Material balances were established, applying substance flow analysis (SFA). Transfer coefficients for the selected substances were also determined. The results demonstrate the capability of SFA to determine the composition of the highly heterogeneous WEEE for most substances with rather low uncertainty (2r 6 ± 30%). The results confirm the growing importance of s-WEEE regarding secondary resource metals and potential toxic substances. Nowadays, the thirty times smaller s-WEEE turns over larger flows for many substances, compared to municipal solid waste. Transfer coefficient results serve to evaluate the separation efficiency of the recycling process and confirm – with the exception of PCB and Hg – the limitation of hand-sorting and mechanical processing to separate pollutants (Cd, Pb, etc.) out of reusable fractions. Regularly applied SFA would serve to assess the efficacy of legislative, organizational and technical measures on the WEEE.
26	(Morf et al. 2013)	In Switzerland many kinds of waste, e.g. paper, metals, electrical and electronic equipment are separately collected and recycled to a large extent. The residual amount of municipal solid waste (MSW) has to be thermally treated before final disposal. Efforts to recover valuable metals from incineration residues have recently increased. However, the resource potential of critical elements in the waste input (sources) and their partitioning into recyclable fractions and residues (fate) is unknown. Therefore, a substance flow analysis (SFA) for 31 elements including precious metals (Au, Ag), platinum metal group elements (Pt, Rh) and rare earth elements (La, Ce, etc.) has been conducted in a solid waste incinerator (SWI) with a state-of-the-art bottom ash treatment according to the Thermo-Re concept. The SFA allowed the determination of the element partitioning in the SWI, as well as the elemental composition of the MSW by indirect analysis. The results show that the waste-input contains substantial quantities of precious metals, such as 0.4 ± 0.2 mg/kg Au and 5.3 ± 0.7 mg/kg Ag. Many of the valuable substances, such as Au and Ag are enriched in specific outputs (e.g. non-ferrous metal fractions) and are therefore recoverable. As the precious metal content in MSW is expected to rise due to its increasing application in complex consumer products, the results of this study are essential for the improvement of resource recovery in the Thermo- Re process.
27	(Ott et al. 2012)	Phosphorus (P) is considered a potentially critical resource because reserves are limited; it is required by all creatures, and it cannot be substituted. In this paper a substance flow analysis of phosphorus for the former 15 member states of the European Community (EU15) is presented. In order to consider the heterogeneity of the database with regard to quantity and quality all data are considered with uncertainty ranges. Error propagation and data reconciliation are performed applying the software STAN. Comparing basic and reconciled data shows that the result is reliable enough to allow the following conclusions: the system of the EU15 is largely dependent on imports of phosphorus. Net per capita consumption in the EU15 is 4.7 kgP/yr of which only 1.2 kgP/yr reach the consumer. The main losses are a net accumulation in agricultural soils (2.9 kgP/yr), followed by losses to landfills (1.4 kgP/yr) and to the hydrosphere (0.55 kgP/yr). Only 0.77 kgP/yr are recycled. Optimizing phosphorus fertilization, collecting and recycling of phosphorus-rich wastes, increasing the connection of households to sewer systems, and implementing tertiary wastewater treatment comprehensively could reduce Europe’s import dependence on phosphorus significantly.

No.	Author(s)	Publication Summary
28	(Rechberger et al. 2002)	The copper flows and stocks of the European economy are investigated and evaluated over a 1-year period in the early 1990s. The method applied is statistical entropy, which quantifies the distribution pattern of a substance (e.g. copper) caused by a system (e.g. political economy). Contemporary copper management can be defined as a simple chain of four processes: production of refined copper from ore; manufacture and fabrication of products and goods; consumption, utilization and storage (infrastructure) of goods; and separation of copper from waste for recycling and finally, landfilling (waste management). Relevant recycling streams (new and old scrap) within or between production, manufacture, and waste management processes also characterize the system. Throughout the life cycle of copper the statistical entropy varies considerably among the above-mentioned processes and covers about 50% of the possible range between total dissipation and maximal concentration of the total throughput of copper. Nevertheless, present copper management does not show a clear entropy trend across its life cycle. The system as a whole neither dissipates nor concentrates copper significantly with regard to the original ore. Even a more optimized waste management system with higher recycling efficiency could not significantly change this finding since today's copper flows into waste management are small compared to the consumption of copper. The relatively limited impact on the entropy trend of contemporary waste management may increase in the future because the infrastructure, which has been established over the last few decades, will be continuously renewed and replaced. As a result of these larger waste streams, decreasing overall entropy trends will be realizable, provided efficient recycling technologies are applied. This indicates the possibility for long-term feasible (perhaps sustainable) copper management. The entropy approach improves our understanding of industrial metabolism and is a useful decision support and design tool, since complex systems can thereby be quantified by a single metric per substance.
29	(Reck et al. 2010)	The use of stainless steel, a metal employed in a wide range of technology applications, has been characterized for 51 countries and the world for the years 2000 and 2005. We find that the global stainless steel flow-into-use increased by more than 30% in that 5 year period, as did additions to in-use stocks. This growth was mainly driven by China, which accounted for almost half of the global growth in stainless steel crude production and which tripled its flow into use between 2000 and 2005. The global stainless steel-specific end-of-life recycling rate increased from 66% (2000) to 70% (2005); the landfilling rate was 22% for both years, and 9% (2000) to 12% (2005) was lost into recycled carbon and alloy steels. Within just 5 years, China passed such traditionally strong stainless steel producers and users as Japan, USA, Germany, and South Korea to become the dominant player of the stainless steel industry. However, Chinadid not produce any significant stainless steel end of- life flows in 2000 or 2005 because its products-in-use are still too new to require replacements. Major Chinese discard flows are expected to begin between 2015 and 2020.
30	(Schulze et al. 2016)	Rare earth element (REE) containing neodymium-iron-boron (NdFeB) magnets play a major role in green technologies, including motor and generator applications. Recycling of REE from NdFeB magnets is expected to be beneficial from an environmental point of view compared to the production of magnets using primary REE currently practiced. This study gives a broad overview of global recycling potentials from end-of-life magnets from eleven different application groups and industrial scrap, quantified through dynamic material flow analysis. Data was obtained through a review of the literature, complemented by expert estimations. Recycling potentials achievable for REEs used in NdFeB magnets, namely neodymium (Nd), praseodymium (Pr), terbium (Tb) and dysprosium (Dy), were calculated for years 2020–2030, derived from two demand scenarios to reflect uncertainties in historic NdFeB demand figures and future demand development, taking into account the recent success in heavy REE reduction efforts. The most important NdFeB application groups in terms of recycling potentials are identified. The modelled scenarios show that between 18 and 22 percent of global light REE (Nd and Pr) and 20–23 percent of heavy (Dy and Tb) REE demand for use in NdFeB magnet production can be met by supply from secondary sources from end-of-life magnets and industrial scrap in years 2020, 25 and 30 (ranges of values for individual years and scenarios).

No.	Author(s)	Publication Summary
31	(Spatari et al. 2002)	Substance flow cycles can provide a picture of resource uses and losses through a geographic region, allowing us to evaluate regional resource management and estimate gross environmental impacts. This paper traces the flow of copper as it enters and leaves the European economy over 1 year and provides the numerical accounting of copper flows that are further analysed in a companion paper in this issue. We examine the major flows of copper from ore, as it is extracted from the earth, transformed into products, and discarded or recycled. A regional material flow model was developed to estimate patterns of copper use in the early 1990s in select European countries. Successive mass balance calculations were used to determine copper flows, including the amount of metal that enters use in society and is deposited in waste repositories. A database that records temporal and spatial boundary conditions and data quality was developed for continental substance flow analysis. The majority of copper is mined, smelted, and refined outside of Europe. Across the life cycle, a net total of 1900 Gg/year of copper is imported into Europe. About 40% of cathode copper produced within the system is made from old and new scrap. It is estimated that approximately 8 kg of copper per person enters use in society, largely in infrastructure, buildings, industry, and private households. The majority of copper in finished products is contained in pure form (70%), the remainder in alloy form. The waste management system in Europe recycles about 60% of the copper from waste. The copper discard flow from post-consumer waste is roughly five times higher than that from copper production waste. This ratio would decrease if we consider production wastes generated outside of the European system boundary. The net addition of copper to the stock in society in the system is about 6 kg/person. Given the in-service lifetime of the applications of copper identified in this model, most of the copper processed during the last few decades still resides in society, mostly in non-dissipative uses.
32	(Spatari et al. 2003)	A regional material stock and flow (STAF) model was constructed to track the pathway of zinc in the early 1990s in selected western European countries. This paper traces the major flows of zinc from ore, to product, to potential secondary resource as it moves through the European economy over 1 year. Successive mass balance estimations were used to determine zinc flows, including the amount of metal that enters stocks in waste reservoirs and products. A resource-specific model and database were used to allocate zinc flows and record temporal and spatial boundary data and data quality criteria. The model shows that for primary zinc, as for other non-ferrous metals, most is imported as concentrate from North and South America and Oceania, and is smelted in Europe to refined metal. It is estimated that 5 kg zinc per person enters use annually in the European economy; this is partly balanced by a flow to waste management of about 2 kg per capita. The largest flows of zinc in discard streams are in construction and demolition debris and in end-of-life vehicles. Only about 34% of the discarded zinc is recycled. While zinc's residence time can be high for many of its applications in the building and construction sector, since the majority of zinc is used as an anti-corrosion coating, there are dissipative losses occurring during the lifetime of products and infrastructure containing zinc. This study and others suggest that zinc losses to the environment are significant in magnitude, and their impacts should be evaluated over time and at various spatial scales.
33	(Stanisavljevic et al. 2014)	The novelty of this paper is the demonstration of the effectiveness of combining material flow analysis (MFA) with substance flow analysis (SFA) for decision making in waste management. Both MFA and SFA are based on the mass balance principle. While MFA alone has been applied often for analysing material flows quantitatively and hence to determine the capacities of waste treatment processes, SFA is more demanding but instrumental in evaluating the performance of a waste management system regarding the goals "resource conservation" and "environmental protection". SFA focuses on the transformations of wastes during waste treatment: valuable as well as hazardous substances and their transformations are followed through the entire waste management system. A substance-based approach is required because the economic and environmental properties of the products of waste management – recycling goods, residues and emissions – are primarily determined by the content of specific precious or harmful substances. To support the case that MFA and SFA should be combined, a case study of waste management scenarios is presented. For three scenarios, total material flows are quantified by MFA, and the mass flows of six indicator substances (C, N, Cl, Cd, Pb, Hg) are determined by SFA. The combined results are compared to the status quo in view of fulfilling the goals of waste management. They clearly point out specific differences between the chosen scenarios, demonstrating potentials for improvement and the value of the combination of MFA/SFA for decision making in waste management.

No.	Author(s)	Publication Summary
34	(Tonini et al. 2014)	Energy, materials, and resource recovery from mixed household waste may contribute to reductions in fossil fuel and resource consumption. For this purpose, legislation has been enforced to promote energy recovery and recycling. Potential solutions for separating biogenic and recyclable materials are offered by waste refineries where a bioliquid is produced from enzymatic treatment of mixed waste. In this study, potential flows of materials, energy, and substances within a waste refinery were investigated by combining sampling, analyses, and modelling. Existing material, substance, and energy flow analysis was further advanced by development of a mathematical optimization model for determination of the theoretical recovery potential. The results highlighted that the waste refinery may recover ca. 56% of the dry matter input as bioliquid, yielding 6.2 GJ biogas-energy. The potential for nitrogen, phosphorous, potassium, and biogenic carbon recovery was estimated to be between 81% and 89% of the input. Biogenic and fossil carbon in the mixed household waste input was determined to 63% and 37% of total carbon based on 14C analyses. Additional recovery of metals and plastic was possible based on further process optimization. A challenge for the process may be digestate quality, as digestate may represent an emission pathway when applied on land. Considering the potential variability of local revenues for energy outputs, the costs for the waste refinery solution appeared comparable with alternatives such as direct incineration.
35	(Van Beers et al. 2005)	The rate of metal use has risen rapidly in recent decades resulting in increasing amounts of landfilled mining wastes and produced metals being stockpiled as in-use products. These two reservoirs will become important for their metal content recovery over the next decades as a result of population growth, increasing per capita resource use, and anticipated metal price increases due to supply limitations. This paper discusses the potential and availability of secondary metals for recovery in Australia, illustrated by research results and case-study examples for copper and zinc. Barriers and enabling mechanisms for enhanced utilisation of secondary (non-virgin) resources are evaluated against the mining of virgin resources with the aim to present decision support guidelines to industry and government for resource policies and practices, and technology innovations.
36	(Van Eygen et al. 2017)	Plastics have been increasingly used in a wide range of applications, generating important waste streams, but overall information on their flows through society is generally not available. Therefore, the national plastic flows in Austria were analysed and quantified from the production stage up to the waste management stage, for the reference year of 2010. To achieve this, material flow analysis was used to set up a model quantitatively describing the Austrian plastics budget, and the quality of the data sources was assessed using uncertainty characterization. The results show that about 1.1 million tonnes (132 kg/cap·a ± 2%) of primary plastics were produced in Austria, whereas about 1.3 million tonnes (156 kg/cap·a ± 5%) of plastics products were consumed. Roughly one third of the consumed amount contributed to net stock increase in all consumption sectors, and about half of this increase occurred in building and construction, whereas packaging waste constituted approximately half of total post-consumer wastes (70 kg/cap·a ± 4%). Of the total waste amount (including traded and production waste, 91 kg/cap·a ± 3%), the majority was incinerated in waste-to-energy plants or in the cement industry (46% and 21% respectively), whereas the rest was mainly recycled mechanically or chemically (21% and 10% respectively). The results identify the major national flows and processes of plastics, and evaluate the overall data availability for quantifying these flows. Furthermore, the increasing amounts of plastic wastes, due to large stocks having been built up in sectors with long product lifetimes, necessitate assessing which processing capacities are needed and which treatment priorities are to be set in waste management.

No.	Author(s)	Publication Summary
37	(Vyzinkarova et al. 2013)	The present article examines flows and stocks of Stockholm Convention regulated pollutants, commercial penta- and octabrominated diphenyl ether (cPentaBDE, cOctaBDE), on a city level. The goals are to (1) identify sources, pathways, and sinks of these compounds in the city of Vienna, (2) determine the fractions that reach final sinks, and (3) develop recommendations for waste management to ensure their minimum recycling and maximum transfer to appropriate final sinks. By means of substance flow analysis (SFA) and scenario analysis, it was found that the key flows of cPentaBDE stem from construction materials. Therefore, end-of-life (EOL) plastic materials used for construction must be separated and properly treated, for example, in a state-of-the-art municipal solid waste (MSW) incinerator. In the case of cOctaBDE, the main flows are waste electrical and electronic equipment (WEEE) and, possibly, vehicles. Most EOL vehicles are exported from Vienna and pose a continental, rather than a local, problem. According to the modelling, approximately 73% of cOctaBDE reached the final sink MSW incinerator, and 17% returned back to consumption by recycling. Secondary plastics, made from WEEE, may thus contain significant amounts of cOctaBDE; however, uncertainties are high. According to uncertainty analysis, the major cause is the lack of reliable values regarding cOctaBDE concentrations in European WEEE categories 3 and 4, including cathode ray tube monitors for computers and televisions. We recommend establishing a new, goal-oriented data set by additional analyses of waste constituents and plastic recycling samples, as well as establishing reliable mass balances of polybrominated diphenyl ethers' flows and stocks by means of SFA.
38	(Zhang et al. 2008)	Heavy metal contamination in municipal solid waste (MSW) is of increasing concern. The occurrence and distribution of heavy metals in MSW and their implications for the integrated MSW management system in mega-cities have been investigated by means of material flow analysis based on a case study of Shanghai in China. A good statistical basis was provided through a one-year monitoring program on the mass and metals composition of the waste from three MSW treatment facilities. The results showed that the main heavy metals in the MSW were Zn, Cr, Cu, and Pb (on average N100 mg kg^{-1}), followed by Ni, Cd, and Hg. The MSW contained higher levels of Cu and Ni in metals, Cr and Pb in plastics, and Pb and Zn in the inorganic fractions. Regardless of the sources, the statistically similar heavy metal contents in the organic fractions indicated that effective blending and diffusion of heavy metals had taken place throughout the MSW collection, transfer, transportation, and storage, leading to cross-contamination of the waste fractions. PU (composed of putrescible waste and miscellaneous indistinguishable particles) contributed the majority of the heavy metals to the MSW, followed by plastics, as a result of the predominance in the overall composition of PU and plastics rather than from differences in their heavy metal contents. Therefore, manual or mechanical separation of some significantly heavy metal-rich fractions alone is not sufficient to reduce the heavy metal contents in the MSW. Source separation of organic waste and the diversion of tailored inorganic waste such as hazardous components, construction and demolition waste, etc., are proposed to control the heavy metal contamination in MSW. For the mixed MSW management system, physicochemical fractionation to exclude particles containing high levels of heavy metals can be conducted.
39	(Zoboli et al. 2016)	Material flow analysis is a tool that is increasingly used as a foundation for resource management and environmental protection. This tool is primarily applied in a static manner to individual years, ignoring the impact of time on the material budgets. In this study, a detailed multiyear model of the Austrian phosphorus budget covering the period 1990–2011 was built to investigate its behaviour over time and test the hypothesis that a multiyear approach can also contribute to the improvement of static budgets. Further, a novel method was applied to investigate the quality and characteristics of the data and quantify the uncertainty. The degree of change between the budgets was assessed and showed that approximately half of the flows have changed significantly and, at times, abruptly since 1990, but it is not possible to distinguish unequivocally between constant and moderately changing flows given their uncertainty. The study reveals that the phosphorus transported in waste flows has increased more rapidly than its recovery, which accounted for 55% to 60% of the total waste phosphorus in 1990 and only 40% in 2011. The loss ratio in landfills and cement kilns has oscillated in the range of 40% to 50%. From a methodological point of view, the multiyear approach has broadened the conceptual model of the budget, making it more suitable as a basis for material accounting and monitoring. Moreover, the analysis of the data reconciliation process over a long period of time proved to be a useful tool for identifying systematic errors in the model.