LEVERAGING LCA TO STRENGTHEN GHG PROTOCOL CORPORATE ACCOUNTING

Technical Report 2: Life Cycle Data and its Use for Corporate GHG Accounting

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ABBREVIATIONS AND ACRONYMS

CO_2e	CO_2 equivalent
DESNZ	Department for Energy Security and Net Zero
EEIO	Environmentally Extended Input-Output
EF	Emission factor
GHG	Greenhouse gas
GTAP	Global Trade Analysis Project
GWP	Global warming potential
IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
LCA	Life cycle assessment
LCI	Life cycle inventory
LULUC	Land use and land use change
U.S. EPA	United States Environmental Protection Agency
USLCI	U.S. Life Cycle Inventory
USEEIO	US Environmentally-Extended Input-Output
VAT	Value-Added Tax
WFLDB	World Food LCA Database
WIOD	World Input-Output Database

GLOSSARY

Activity data	Quantitative measure of an activity that generates GHG emissions.
Aggregated emission factors	Emission factors that do not provide access to the detailed model underlying them, and therefore generally provide a single aggregated value in CO_2e.
Biogenic carbon	Carbon in, or derived from, living organisms or biological processes, but not including fossilized materials or those from fossil sources (GHG Protocol, 2026).
Bottom-up approach	A modelling approach that estimates emissions through detailed process-level modelling by representing the specific processes, and their associated input and output flows, required to deliver a product or service (e.g., life cycle assessment)
Cradle-to-gate	An assessment that includes part of the product's life cycle, including material acquisition through the production of the studied product and excluding the distribution, use and end-of-life stages (Life Cycle Initiative, n. d.).
Cradle-to-grave	A cradle-to-grave assessment considers impacts at each stage of a product's life cycle, from the time natural resources are extracted from the ground and processed through each subsequent stage of manufacturing, transportation, product use, recycling, and ultimately, disposal (Life Cycle Initiative, n. d.).
Direct emissions	Emissions from sources that are owned or controlled by the reporting organization (GHG Protocol, 2022).
Disaggregated emission factors	Emission factors that provide access to the underlying model (i.e., a chain of interconnected processes), the different GHGs included, and may allow an adaptation.
Emission factor	A calculated ratio relating GHG emissions to a given measure of activity.
Environmentally Extended Input-Output emission factors	Emission factors that reflect the average emission intensity of commodities (i.e., products and services) and/or sectors. They are derived by combining national input-output tables, which describe economic exchanges between various sectors of an economy, with environmental tables, which quantify emissions (or other environmental flows) attributable to each economic sector. These emission factors are developed using a top-down approach.
Gate-to-gate	An assessment that includes a single activity (e.g., a production stage) or a group of activities within the life cycle (i.e., a part of the life cycle).
Global Warming Potential	A metric measuring the radiative forcing potential of a gas emitted into the atmosphere from the time of emission over a certain period, relative to that of CO_2. It is therefore an integrative measure, assessing the impact over a defined time frame instead of a specific time (IPCC, 1990).
Hybrid data	Secondary data adapted by using primary data.
Indirect emissions	Emissions that are a consequence of the activities of the reporting organization, but occur at sources owned or controlled by another organization (GHG Protocol, 2022).

Land use	Use of a specific area of land for a particular purpose with a certain level of intensity that reflects land management practices.
Land use change	A transition from one land use category to another, such as from forest to grassland or cropland (GHG Protocol, 2022).
Life cycle inventory (LCI) data	A dataset that represents interconnected unit processes and their associated intermediate and elementary flows, capturing the full supply chain required to deliver a given function (e.g., producing a good).
Minimum boundaries	Boundaries provided by the GHG Protocol to indicate the minimum emissions sources to be included for each of the scope 3 categories.
Physical data	Data expressed with a physical unit (e.g., mass, volume, number of units)
Primary data	Data collected directly from the reporting organization's own operations or from partners within its value chain.
Process-based emission factor	Emission factors derived from a detailed modelling of the underlying model (i.e., a chain of interconnected processes). Inputs (e.g., energy, materials, resources) and outputs (e.g., waste, direct emissions) of a given process or activity is visible to the user. They are constructed using a bottom-up approach.
Proxy data	Data used to replace another data that is missing. Proxy data is more generic or based on the modeling of a similar activity, typically from the literature.
Scope 1	A reporting organization's direct GHG emissions (GHG Protocol, 2015a).
Scope 2	A reporting organization's emissions associated with the generation of electricity, heating/ cooling, or steam purchased for own consumption (GHG Protocol, 2015a).
Scope 3	A reporting organization's indirect emissions other than those covered in scope 2 (GHG Protocol, 2015a).
Secondary data	Data that does not come from the specific activities of the organization or its value chain (e.g., sourced from literature or databases).
Semi-aggregated emission factors	Emission factors that do not provide access to the full underlying modelling details, but that provide GHG emissions broken down by scope, scope 3 category, emission source, or GHG.
Financial (or spend-based) data	Data expressed with a monetary unit (e.g., expenditure)
Supplier-specific emission factors	Emission factors that are provided by the reporting organization's suppliers or partners within its value chain and inform about the emissions of their specific products or services.
Top-down approach	A modelling approach that estimates emissions by allocating high-level emission data, usually at the level of entire sectors, industries, or regions, to a specific unit of product or service. For instance, this approach is used in environmentally extended input-output (EEIO) models.

INTRODUCTION

The development of organizational greenhouse gas (GHG) inventories has experienced remarkable growth in recent years. The GHG Protocol has established itself as the primary reference framework guiding organizations in conducting such assessments. However, despite its widespread adoption, the GHG Protocol presents certain limitations, and several operational challenges arise when implementing GHG inventories in accordance with its standards and guidelines.

The main objective of this work is to identify how life cycle assessment (LCA) practices and tools can support the process of quantifying GHG emissions at the organizational level and strengthen its methodological robustness.

This work is structured into four documents, each with the specific objectives:

- *Technical Report 1: Comparison of the GHG Protocol and LCA frameworks*. This report aims to compare the GHG Protocol and LCA frameworks across a wide range of methodological aspects, highlighting their differences, similarities, and potential inconsistencies.
- *Technical Report 2: Life Cycle Data and its Use for Corporate GHG Accounting*. This report aims to present and describe the different types of data (i.e., emission factors) typically used to develop organizational GHG inventories, outlining their respective strengths and limitations.
- *Technical Report 3: Guidelines for Improved Corporate GHG Accounting*. This report aims to provide guidelines for improving the consistency, transparency, and robustness of organizational GHG inventories, drawing on life cycle thinking and practices.
- *Summary Report*. This report summarizes the main aspects of the three technical reports.

This document constitutes *Technical Report 2*. It aims to describe the main advantages and limitations of the different types of emission factors typically used in corporate GHG accounting. These types of data are examined across several characteristics (e.g., modelling approach, level of aggregation, reference unit, representativeness, accessibility).

This document is structured into several subsections, specifically describing process-based emission factors (including Life Cycle Inventory, supplier-specific, and sectoral or regulatory emission factors) and spend-based emission factors (with a focus on Environmentally Extended Input-Output [EEIO] emission factors).

The previous document of this work focuses on the differences between organizational carbon accounting – as applied under the GHG Protocol – and life cycle assessment (LCA), both product and organizational LCA. Then, the subsequent document provides guidance to support practitioners in improving the robustness of GHG inventories, particularly from the perspective of LCA best practices. These documents frequently refer to the content of this present *Technical Report 2*; reading it separately is therefore recommended.

The GHG Protocol is currently updating its suite of corporate standards and guidance. While most of the information discussed in *Technical Report 2* is expected not to be affected by the updates, some aspects related to the GHG Protocol's standards and guidance may change. Once published, revised standards and guidance will take precedence if any differences arise.

1. OVERVIEW OF THE DIFFERENT DATA TYPES

1.1 GHG emissions calculation

Different approaches can be used to quantify GHG emissions. The most accurate method to account for emissions from a process is to measure them directly. The GHG Protocol's standards and guidelines define *direct measurement* as including direct monitoring (e.g., GHG sensor at a smokestack exit), as well as mass balance and stoichiometric calculations (e.g., estimating CO_2 emissions from fuel combustion based on its carbon content). In practice, direct measurements are most often applied to scope 1 emissions, where the organization can access the physical emission source. For scope 2 and 3 emissions, as well as for scope 1 emissions that cannot be measured directly, the organization will need to perform calculations, by multiplying *activity data* and *emission factors* to estimate the amount of emissions generated by a specific activity[1] (hereinafter also referred to as "emission source"). This approach is illustrated in Figure 1-1.

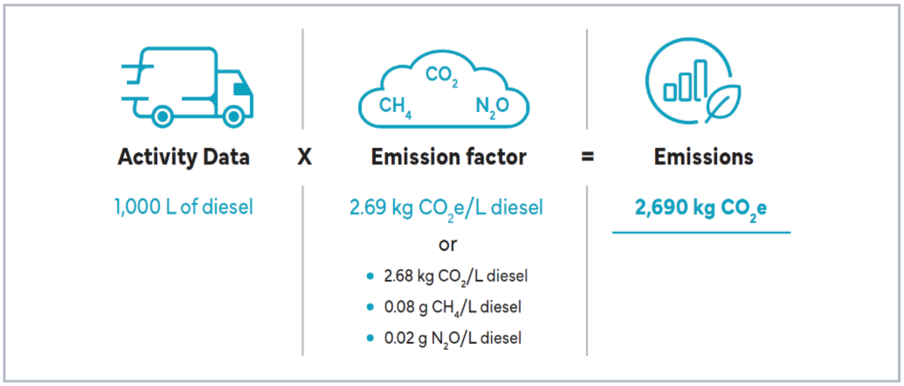


Figure 1-1: General GHG emission calculation approach

An **activity data** is a quantitative measure of an activity that generates GHG emissions. For instance, to calculate a truck's emissions, the activity data can be the amount of fuel consumed by the truck (litres) or the distance travelled by the truck (km).

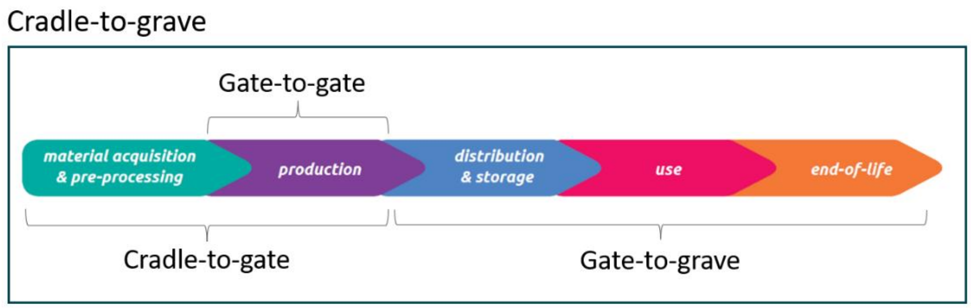
An **emission factor** (EF) is a calculated ratio that indicates GHG emissions per unit of activity data. It can be expressed either in terms of the mass of GHGs or in CO_2 equivalent (CO_2e). In the example of the truck, the EF can either be expressed as the amount of each GHG emitted during fuel combustion per litre of fuel consumed (e.g., kg N_2O/litre), or per kilometer travelled (e.g., kg N_2O/km), or as an aggregate value of all emitted GHGs and expressed in kilograms of CO_2e (e.g., kg CO_2e/litre or kg CO_2e/km) calculated using the *Global Warming Potential* (GWP) values of GHGs.

The activities included within the boundaries of EFs vary. As illustrated in Box 1-1, EFs can cover the upstream activities of a product life cycle, from material acquisition through the production of the studied product: this is called *cradle-to-gate*. Other EFs can include the downstream activities of a product life cycle, after its production (e.g., distribution, use and end-of-life of the product): this is called *gate-to-grave*. *Cradle-to-grave* EFs include all activities along the product life cycle, even if they occur at different time frames. An EF can also cover one or several activities taking place within a specific site (e.g., organization,

[1] See section 7.2 of the Scope 3 Standard (GHG Protocol, 2011a)

plant), which is referred to as *gate-to-gate* (e.g., fuel combustion in a furnace, or a specific production process within the life cycle). It is important to understand which activities are included in an EF to ensure it aligns with the study boundaries, scopes, and scope 3 categories for which the EF is applied. Further information on boundaries is provided in section 3 of *Technical Report 1*.

Box 1-1: System boundaries in product LCA



Note: Reproduced and adapted from the *Product Standard* (Figure 7.5, p.41), by GHG Protocol, 2011b. https://ghgprotocol.org/sites/default/files/standards/Product-Life-Cycle-Accounting-Reporting-Standard_041613.pdf. System boundaries used in product LCA have been added to the original figure.

This figure shows the main stages of a product's life cycle. Here, the gate-to-gate boundary is illustrated by the production stage (i.e., a single activity), but it can refer to any activity or group of activities within the life cycle.

1.2 Data characteristics

The robustness and usability of greenhouse gas (GHG) inventories rely heavily on the **quality of the data** used to estimate emissions. Several characteristics can help define data quality.

First, ***representativeness*** indicates how closely data reflects the actual activity and real-world conditions over time (*temporal representativeness*), across locations (*geographical representativeness*), and within the relevant technological context (*technological representativeness*). To model an activity occurring in 2025, data from 2024 is more temporally representative than data from 2015. To estimate emissions taking place in Madrid, Portuguese data is more representative than Chinese data. Similarly, data from the same plant better reflects the specific characteristics of its products compared to average data from the entire industrial sector. Technological representativeness is often regarded as the most sensitive parameter when assessing data quality, because the technological characteristics of activities may vary significantly and have an important influence on GHG emissions. Some sectors and activities can be particularly sensitive to a specific dimension of representativeness (e.g., time representativeness is very important for the digital sector due to the rapid evolution of technologies involved).

Representativeness can be linked with ***specificity,*** which expresses the granularity level of data: data that represents an activity with very specific characteristics (e.g., performances of a product, precise location or time where and when the activity occurs, etc.) is more specific than an average or a default value (e.g., industry or country average). Data aiming to represent a single product, from a specific plant and a given year, is very specific, but if it is modelled using average or outdated data, or with data from another region or technology, it is not representative.

Completeness represents the extent to which all necessary data for modelling an activity is actually included in the activity's modelling. For instance, excluding infrastructure and machinery production, packaging, and supply chain losses reduces the completeness of the data in representing the production of a specific product.

Consistency between two datasets indicates how similar they are in terms of their methodological choices, assumptions, or data used to calculate each one.

Additionally, data can be defined by its ***accessibility*** (e.g., whether it is openly available or requires a specific tool), its ***affordability*** (i.e., the cost to access the data), its ***adaptability*** (e.g., whether the underlying model can be refined to improve its representativeness), and its ***transparency*** (e.g., whether the methodology, data, assumptions, and modelling choices are clearly documented and easily accessible).

Finally, data can be characterized by its ***coverage*,** which indicates the extent to which the sectors of an entire economy, the technologies, the regions, or the temporalities are represented by EFs within a given data source (e.g. database).

The next sections assess these characteristics for the most frequently used data types in GHG accounting.

1.3 Overview of the different types of emission factors

Chapter 7 (p. 64-85) of the *Corporate Value Chain (Scope 3) Standard* (GHG Protocol, 2011a) and the *Scope 3 Calculation Guidance* (GHG Protocol, 2013a) provide different calculation methods linked to specific types of data to use, and include decision trees to help select the most relevant method, but they do not explicitly mandate or prohibit any type of data, as long as they respect the general principles of the *Corporate Accounting and Reporting Standard*[2] (GHG Protocol, 2015):

- **Relevance**: Ensure that the GHG inventory appropriately represents the emissions and is useful for decision-making.
- **Completeness**: Include all emission sources within the inventory boundaries.
- **Consistency**: Use consistent methodologies across the different data calculation aspects and between the data and the rest of the model.
- **Transparency**: Disclose all assumptions, methodological choices and data sources used.
- **Accuracy**: Reduce uncertainty as far as possible so that results enable robust conclusions.

The *Scope 3 Calculation Guidance* provides specific guidance and examples on how to use various types of secondary data for most scope 3 categories.

[2] See Chapter 4 of the Scope 3 Standard (GHG Protocol, 2011a).

As explained in section 1.1, the most commonly used approach for organizations to estimate GHG emissions associated with an activity is to multiply *activity data* by *emission factors*. However, since activity data is typically sourced directly from the reporting organization's records, and the choice of GWP values is prescribed by standards or limited to a small number of options, the main methodological decision for organizations is usually the selection of appropriate EFs. Therefore, the rest of this document focuses on EFs.

EFs used for GHG accounting can be categorized into several types based on **four characteristics**: the data origin (linked to specificity), the modelling approach used for their calculation, the level of disaggregation, and the type of reference unit. These characteristics describe practical attributes of an EF, while those described in section 1.2 relate to the quality of the EF, either intrinsically or in how well it matches the activity for which emissions are quantified.

1.3.1 Data origin

The **data origin** describes the **level of specificity of the EF** and can be viewed along a spectrum. EFs that are specific to the reporting organization or directly provided by another organization within its value chain (i.e., supplier-specific EFs) are called *primary data*. Although activity data should usually be primary data (e.g., amount of purchased product, distance travelled, amount of waste treated), EFs are often not primary data. Indeed, obtaining primary data for emission factors is more challenging because it often requires conducting lengthy and costly studies. For instance, a supplier can perform an LCA to calculate a specific EF associated with the production of one of the goods purchased by the reporting organization, but it is not feasible to conduct such analyses for each of the EFs needed for an organizational GHG inventory.

Therefore, *secondary data* are typically used as proxies to assess those EFs. A *proxy* is a substitute value used to estimate emissions from an activity when precise data is unavailable, either by replacing the missing EF with a more generic one or by using one derived from a comparable activity providing the same product or service. However, the proxy must be carefully chosen and well documented to optimize the representativeness of the process and ensure the accuracy of the selected EF.

A third type of EF, called *hybrid EFs*, consists of adapting secondary data to better represent an organization's value chain using primary data. For instance, a generic dataset representing metal production could be adapted by using the specific energy consumption required by an organization's supplier to produce the same metal. This would improve the technological representativeness of the EF. Hybridizing EFs is only feasible with disaggregated secondary data because it requires access to the detailed EF model to modify it.

1.3.2 Modelling approach

The **modelling approach** describes the **analytical method used to develop an EF and estimate the emissions associated with a given activity**. Two modelling approaches can be used: *bottom-up* and *top-down*. Bottom-up modelling builds the EF from a detailed representation of the processes involved in delivering the activity or product. This typically includes modelling each step of an industrial process, such as its material and energy inputs, the emissions and wastes generated, the equipment used or the downstream treatments of residues. By modelling each stage of the supply chain this way and connecting processes, the bottom-up approach captures all direct and indirect emissions occurring within the defined boundaries. LCA is the most common example of a bottom-up approach (see Box 2-1 for more details).

Top-down modelling takes the opposite approach. It works by taking high-level emission data, usually at the level of entire sectors, industries, or regions, and allocating it to a specific unit of product or service, rather than modelling individual processes. For example, estimating industrial-sector emissions from national statistics and then allocating them per dollar of output is a top-down approach.

1.3.3 Disaggregation level

The **level of disaggregation** describes the **level of data that an EF makes visible to the user**. The level of disaggregation of available EFs varies, ranging from *disaggregated* to *aggregated*. Disaggregated EFs provide detailed access to the model they are based on (e.g., life cycle inventory [LCI] data providing details of the modelling for various activities involved in the production of a product) and to the different GHGs included. They thus enable greater transparency in their modelling, the possibility to adapt or refine the EFs to better represent the activity they aim to depict, and to determine which GHGs are included (e.g., CH_4, N_2O emissions, etc.).

Conversely, aggregated EFs typically provide only a single value (e.g., an EF expressed in kg CO_2e/kg) or a few GHG emission values, without access to the underlying modelling structure or assumptions, making it harder to identify the activities and emission sources incorporated in the EF calculation and impossible to adapt those calculations.

Between these two levels lies a broad range of *semi-aggregated* EFs. The latter do not provide access to the full underlying modelling details, but they may provide GHG emissions broken down by scope, scope 3 category, emission source, or GHG.

By nature, a top-down modelling approach provides aggregated or semi-aggregated EFs because it is not developed with thorough knowledge of the activities and phenomena involved in the process that the EF represents, but rather on a limited set of high-level data.

Providing aggregated EFs also enables organizations to safeguard proprietary information and enhance confidentiality by withholding detailed information about their activities. In practice, no EF is fully disaggregated. Instead, EFs have varying levels of detail depending on their modelling approach and their intended purpose.

1.3.4 Reference unit

The **reference unit** corresponds to the **denominator of the EF**. It can be expressed in two types: either *physical* or *financial*.

On the one hand, physical EFs use measurable physical quantities as reference units, such as mass, volume, energy, distance, or time. Because they describe tangible and observable flows, they are generally more robust and less affected by economic phenomena. Physical EFs are often conflated with *process-based* (or *activity-based)* EFs, although these concepts differ. These differences are further explained in section 2.

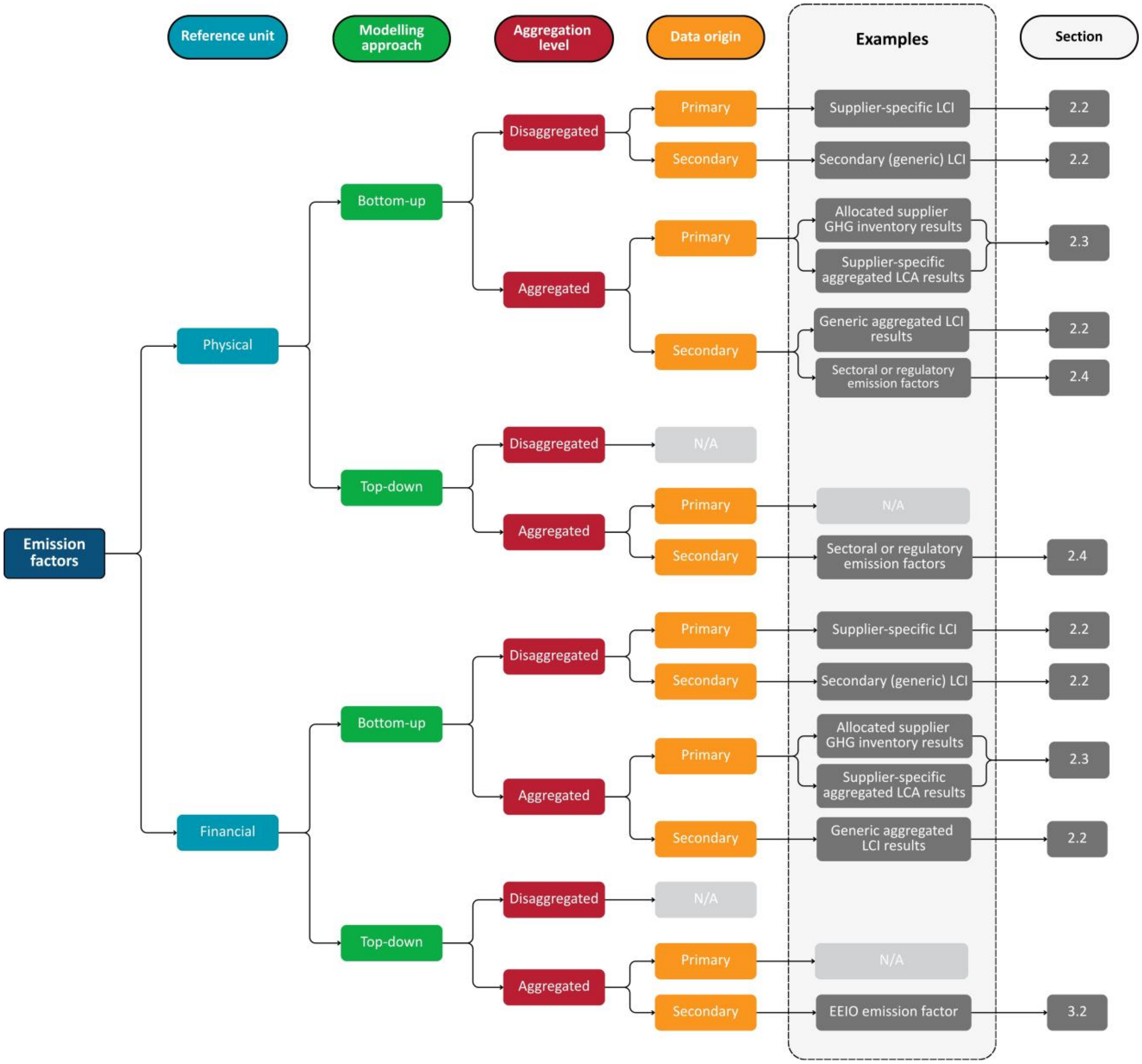
On the other hand, *financial* EFs are expressed with a monetary reference unit, typically one unit of currency (e.g., per dollar or per euro). They are also called *spend-based* EFs and are further explained in section 3. Financial EFs naturally align with the activity data most readily available to organizations, such as procurement or financial records, and provide a practical way to aggregate emissions from various activities, for example, by representing the average emissions intensity of an entire industrial sector.

1.3.5 Overview

Figure 1-2 presents the different types of EFs according to the characteristics defined in the previous sections and provides specific examples of EFs. Figure 1-3 provides a schematic overview of the different types of EFs that can be used in corporate accounting and shows how they overlap. It presents the same information as Figure 1-2 regarding reference unit, level of disaggregation, and data origin, but does not include the modelling approach.

The following sections describe the different types of EFs in detail, highlighting the main advantages and drawbacks of each and providing examples. For the reader's convenience, each section refers to the relevant parts of Figure 1-3.

Section 2 focuses on process-based EFs, including generic LCI, supplier-specific LCI, supplier-specific aggregated and sectoral or regulatory default EFs. Financial (or spend-based) EFs are further discussed in section 3.



Emission factors associated with a "physical" reference unit have a physical denominator (e.g., one unit of mass, volume, energy, etc.). In contrast, emission factors associated with a "financial" reference unit have a monetary denominator (i.e., one unit of currency).

Figure 1-2: Classification of emission factors based on four characteristics

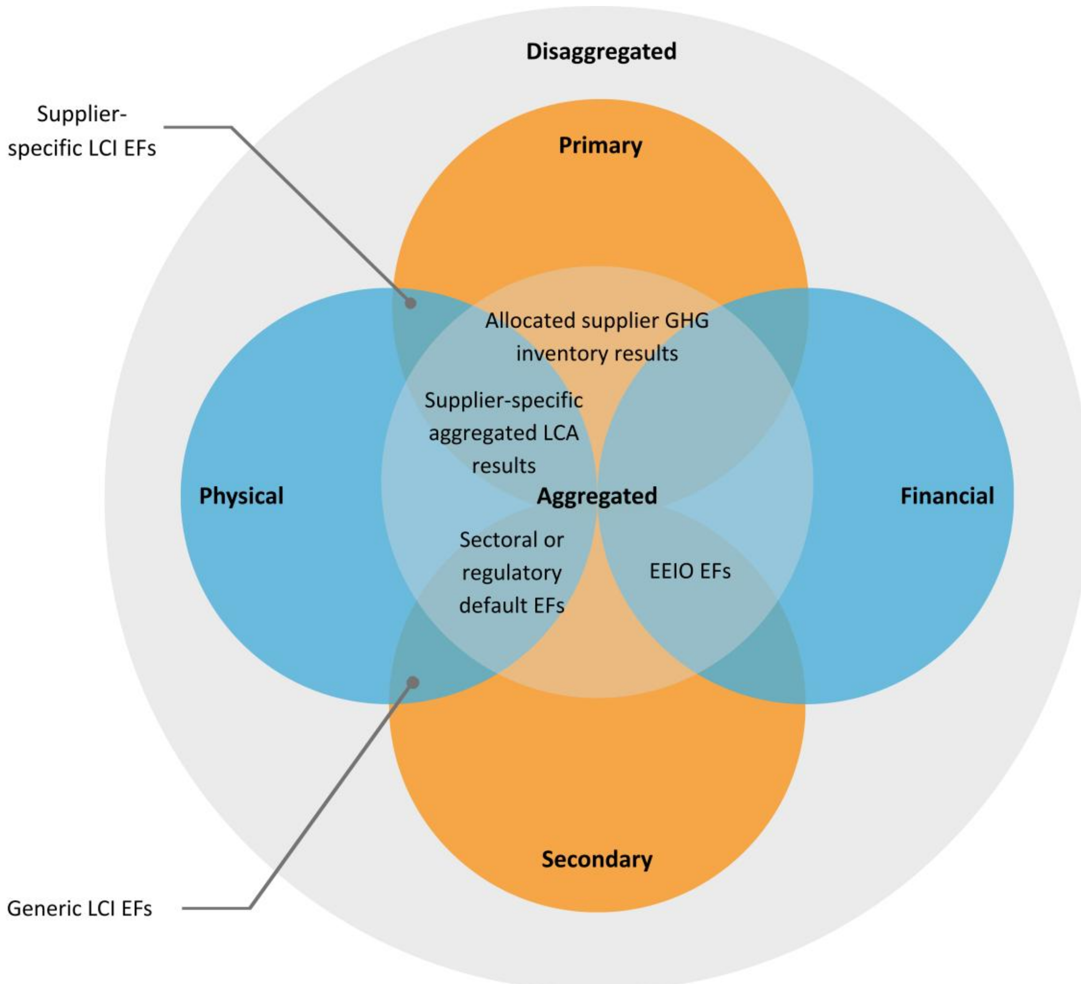


Figure 1-3: Mapping of the main emission factors across three characteristics

2. PROCESS-BASED EMISSION FACTORS

2.1 Definition

Process-based (or **activity-based**) **EFs** are derived **from a detailed modelling of the underlying processes involved**. As such, they are developed following a bottom-up approach. Most of the time, process-based EFs are **based on a physical reference unit** (e.g., per kilogram of material, per kWh consumed, per kilometre travelled). Thus, the terms “process-based” and “physical” EFs are typically used interchangeably. When physical process-based EFs are used, activity data should also be expressed in physical units (e.g., kilos of a material, number of products, kWh of energy). However, a process-based EF could also be calculated and reported using **a financial reference unit** (e.g., an organization’s GHG inventory results allocated per dollar of product sold by this organization), making it a financial (or spend-based) EF.

Section 2 focuses on physical process-based EFs, as they are the most widely used. Nevertheless, financial process-based EFs exhibit mainly the same characteristics and advantages as physical process-based EFs described in section 2. They also share the same limitations as spend-based EFs discussed in section 3 regarding sensitivity to price effects.

Process-based EFs can be derived from **various data sources**:

- For direct emissions (i.e., scope 1), EFs are generally derived from publicly available data sources (e.g., government guides).
- For indirect emissions related to energy production (i.e., scope 2), EFs can also be obtained from these public data sources, as well as from energy suppliers, or LCI data.
- For other indirect emissions (i.e., scope 3), EFs should ideally be quantified by collecting data directly from a supplier or a partner within the value chain whenever possible, in order to improve the accuracy and representativeness of the quantified emissions, though secondary data from other sources are often used (e.g., from databases, literature, sectoral or regulatory standards).

The different types of process-based EFs are discussed in the following sub-sections.

2.2 Life Cycle Inventory emission factors

LCI EFs quantify the resource inputs (e.g., raw materials, land use) and emissions to air, water, and soil from each unit process in a product or service’s life cycle. These EFs are developed using a **bottom-up approach** and are often used to quantify scope 3 emissions. Box 2-1 further describes LCI data.

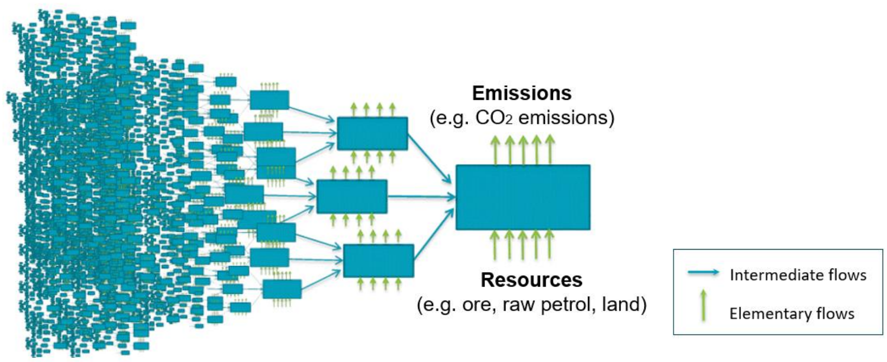
As illustrated in Figure 2-1, LCI EFs can be based on either **primary** or **secondary data**. Indeed, they can be developed using data from a partner within the reporting organization’s value chain, and therefore be *supplier-specific LCI* EFs (i.e., primary data). They can also be developed using secondary data sources (e.g., LCI databases, literature) and therefore be *generic LCI* EFs (i.e., secondary data). These emission factors are generally **disaggregated**, providing access to the underlying network of processes. Section 2.2 only addresses disaggregated EFs. For limitations related to aggregated EFs, including aggregated LCI EFs, refer to section 2.3.

LCI EFs can cover any stage or combination of stages in the life cycle (e.g., raw materials extraction, production, use, etc.), depending on the defined boundaries. Most of them have cradle-to-gate boundaries, but some may have other boundaries, such as gate-to-gate or gate-to-grave boundaries.

Box 2-1: Life Cycle Inventory

Life Cycle Inventory (LCI) is a step of Life Cycle Assessment (LCA) that identifies and quantifies all the **physical inputs and outputs** of a product system. It describes the resources extracted from the environment (e.g., minerals, biomass, fuels), the energy used, and the emissions released into the air, water, and soil.

An LCI model is structured as a network of **unit processes**, each representing an individual activity (e.g., electricity generation, steel production, transportation, waste treatment). These processes exchange two main types of flows: *intermediate flows*, which represent exchanges between processes within the technosphere (e.g., electricity, chemicals) and *elementary flows*, which represent exchanges with the environment (e.g., CO_2 emissions, ore extraction). By connecting these flows, the LCI depicts the entire supply chain needed to deliver a product or service.



To develop these models, organizations can use primary data from their own activities or supply chain, or secondary data from literature to model the *foreground* of their system, which refers to the activities they have influence upon. They can also rely on **LCI databases** for the *background* of their system, which refers to the activities they have little influence over or little information about (e.g., primary materials extraction, electricity generation, waste treatment). LCI databases provide pre-modelled processes for many sectors and regions. The most widely used databases include ecoinvent (Wernet et al., 2016), Sphera Managed LCA Content Database (formerly GaBi) (Sphera, 2026) and the U.S. Life Cycle Inventory (USLCI) Database (National Laboratory of the Rockies, 2012), which are generalist databases covering many different sectors. Other LCI databases are more specialized in specific sectors of the economy (e.g., Agribalyse (Cornelus et al., 2024) for agriculture and food systems, Athena (Athena Sustainable Materials Institute, n. d.) for building materials and products, etc.).

LCI models are typically developed and calculated using specialized **LCA software** tools (e.g., SimaPro (Pré Sustainability, 2026), openLCA (GreenDelta, 2026), etc.), which allow users to assemble process networks, manage databases, and compute the final inventory.

The results of the LCI serve as inputs to the Life Cycle Impact Assessment (LCIA) phase, where the inventory of all the elementary flows is translated into environmental impact indicators using established methods (ReCiPe (Huijbregts et al., 2017), TRACI (Bare J., 2011), IMPACT World+ (Bulle et al., 2019), etc.). In this way, the LCI provides specific, detailed and transparent emission factors that can then be used in corporate GHG accounting.

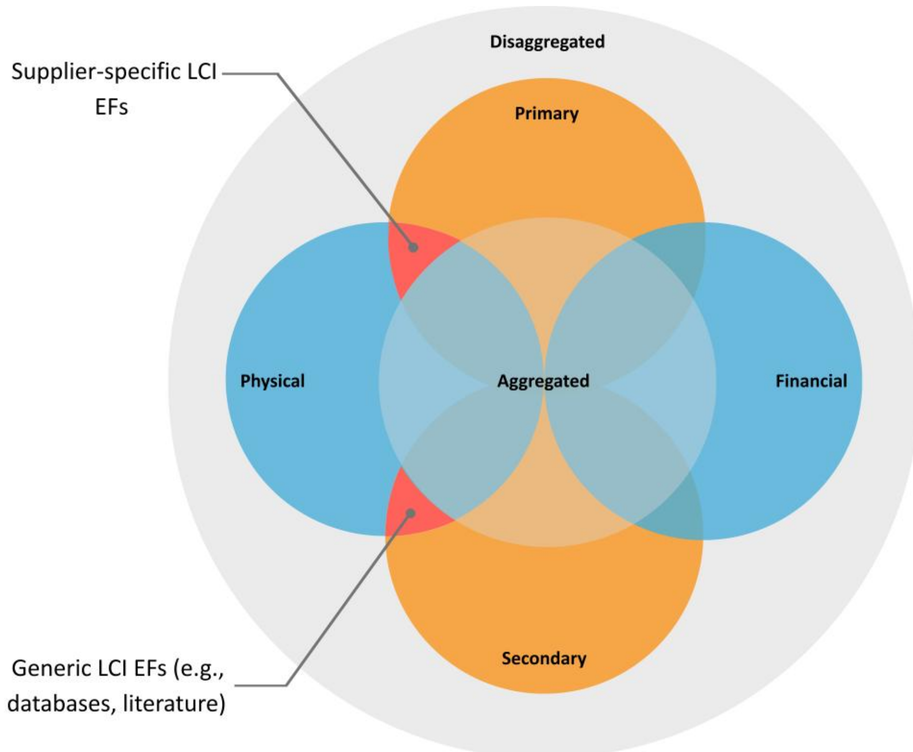


Figure 2-1: Illustration of Life Cycle Inventory emission factors

2.2.1 Main advantages of supplier-specific LCI emission factors

Supplier-specific LCI EFs are developed using a bottom-up modelling approach and are generally disaggregated. They typically represent one or more life cycle stages of a product or service (e.g., cradle-to-gate), while capturing the full value chains associated with those stages. For this reason, they are relatively **comprehensive** in coverage and particularly useful for quantifying indirect emissions.

Because these EFs generally provide a detailed inventory, they enable **specific** and **adaptable** modelling of the product or activity, allowing representative primary data to be used. With this type of data, the modelling of an activity (e.g., yield, type and amount of energy or material used, waste-treatment technology, direct emissions, region of operation) or of a product (e.g., energy consumption, life expectancy, maintenance needs) can be refined so that the EF is more **representative** of the reporting organization's context. This adaptability also allows the organization to continuously update the EFs to reflect changes in its operations or to improve their quality as new data becomes available. Detailed access to the underlying model further enhances **transparency**.

Additionally, disaggregated EFs help target specific parts of the reporting organization’s activities and its supply chain that may be GHG-intensive, thereby identifying more precise emissions reduction pathways. To enhance the **representativeness** of the EF in terms of temporality, geography and technology, the reporting organization can collaborate closely with its suppliers to gather their activity data, and thus strengthen the value chain’s engagement in the decarbonization process.

2.2.2 Main advantages of generic LCI emission factors

Like supplier-specific LCI emission factors, generic LCI EFs are developed using a bottom-up approach and generally provide a **transparent,** detailed, and therefore **adaptable**, inventory.

Their main advantage is that they are relatively **accessible** compared to supplier-specific EFs, thanks to the existence of multiple LCI databases.

Although generic LCI EFs are not specific, their representativeness and specificity can be improved by adjusting them using primary data (i.e., activity data) from suppliers, resulting in a hybrid approach. When improved in this way, they offer the same advantages as the supplier-specific LCI EFs described in section 2.2.1.

2.2.3 Main limitations of supplier-specific LCI emission factors

Supplier-specific LCI EFs can be **resource-intensive to develop** and model, as they require access to extensive data, time, and expertise in LCA modelling. As a result, they are often **limited in availability** and they are **infrequently updated**. Therefore, organizations frequently use generic LCI databases that provide pre-modelled EFs to serve as proxies for their activities.

Additionally, most LCI EFs are **developed using the LCA methodology rather than the GHG Protocol**. Therefore, they typically take into account the complete life cycle emissions of a product or service, from production through to its consumption, transformation, or even end-of-life. This can raise the following challenges when applying them in the context of the GHG Protocol:

- First, it may be necessary to adapt EFs to align with the definitions of the GHG Protocol's scopes and scope 3 categories, and to avoid the double-counting of emissions. For example, an EF might include cradle-to-gate emissions of a product, along with its end-of-life. However, according to the *Scope 3 Standard*, cradle-to-gate emissions are accounted for in scope 3, category 1 (purchased goods and services), while the end-of-life must be accounted for in another scope 3, category 12 (end-of-life treatment of sold products) (see section 3.1.2 of *Technical Report 1* for more information). Similarly, life cycle emissions from electricity production must be divided between scope 2 and 3 emissions. *Technical Report 3* provides practical guidance to adapt EFs.
- Second, they often extend beyond the minimum boundaries specified for each scope 3 category (see section 3.1.4 of *Technical Report 1* for more information). If the reporting organization follows specific reporting standards based on the GHG Protocol (e.g., the Science Based Target initiative) that require including only the emission sources that fall within the minimum boundary requirements, then optional emission sources must not be included, or emission sources that are outside the minimum boundaries must be reported separately. In the latter case, the process-based EFs must be adapted. For instance, the minimum boundaries of the scope 3, category 4 (upstream transportation and distribution) only account for scope 1 and 2 emissions from transportation providers. All the other life cycle emissions (e.g., from the production of fuels, infrastructures, etc.) extend beyond the minimum boundaries and must therefore be excluded from the EFs to align with the GHG Protocol's minimum boundary requirements. *Technical Report 3* provides practical guidance for adapting LCI EFs for each emissions category, ensuring alignment with the GHG Protocol's minimum boundary requirements.

In addition, *Technical Report 1* highlights methodological differences between LCA and GHG Protocol frameworks that could lead to inconsistencies when LCI data are used in inventories conducted following the GHG Protocol standards (e.g., allocation, biogenic carbon accounting, electricity accounting).

Finally, even when supplier-specific LCI EFs are developed from primary data, they are usually partly based on generic data from LCI databases. For example, a reporting organization purchasing a product from a supplier may collect primary data from its supplier (e.g., quantity of raw materials, amount of electricity consumed) to calculate a cradle-to-gate EF for scope 3, category 1, but the background unit processes used for the modelling may be derived from generic LCI databases. Therefore, the limitations mentioned in section 2.2.4 also apply to the background data used by partners along the supply chain to develop supplier-specific LCI EFs.

2.2.4 Main limitations of generic LCI emission factors

Existing LCI databases **lack comprehensive coverage**. Because EFs are costly to develop, databases do not provide emission factors for all sectors, technologies, or regions. Box 2-2 provides examples of the main LCI databases and their characteristics. When an EF is not available within an existing database, the organization can develop one based on data from scientific literature, which requires time and specialized skills to collect the data and model the processes.

The significant resources required to produce these datasets often result in **infrequent updates**, which particularly limits the robustness of data in sectors for which time representativeness is crucial (e.g., the digital sector which undergoes rapid technological development).

Because EFs in databases come from various data providers, they may have different boundary assumptions, geographical coverage, technological specifics, and time periods, which can affect their **comparability**. Additionally, limited transparency about the assumptions and methods used to compute these EFs can lower the quality of the modelled emission factors.

Finally, generic LCI EFs are often developed according to LCA approaches. As a result, they may present greater consistency issues with GHG Protocol requirements than supplier-specific LCI EFs, due to limited traceability of the data source and the inability to collaborate with data providers to adapt the EF.

Box 2-2: Examples of LCI databases and their main characteristics

Characteristic	Agri-footprint	Carbon Minds	ecoinvent	Sphera Managed LCA content (formerly GaBi)	World Food LCA Database (WFLDB)
Geography	Global	Global	Global	Europe, US	150+ countries
Main sectors	Agriculture and Food	Chemicals and plastics	Wide coverage	Wide coverage	Agriculture and Food
Number of datasets	4800+	1500+	26 000+	20 000+	3800+
Life cycle stages	Cradle-to-Gate	Cradle-to-Gate	Various	Various	Cradle-to-Gate
Aggregation level	Disaggregated	Disaggregated	Disaggrega ted	Aggregated	Disaggregated
Licence	Licenced	Licenced	Licenced	Partly	Licenced
Reference	(Blonk et al., 2025)	(Stellner et al., 2024)	(Wernet et al., 2016),	(Sphera, 2026)	(Bayart et al., 2025)

2.3 Supplier-specific aggregated emission factors

Another type of process-based EFs is **supplier-specific EFs**. These can be provided by the reporting organization's suppliers or partners within its value chain, and inform about the emissions of their specific products or services.

Supplier-specific EFs are derived from **primary data**. Some of these EFs are **disaggregated** and thus correspond to supplier-specific LCI EFs, which are presented in section 2.2. Other supplier-specific EFs are **aggregated** and are presented in section 2.3. The latter refers to:

- Supplier-specific EF derived from an **allocation of the supplier's GHG inventory results**. This type of EF is either **semi-aggregated** (i.e., by scope, scope 3 categories, emission source, or GHG), which enhances transparency and adaptability, or **aggregated** as a single value (e.g., kg CO_2e per kWh from a specific electricity provider, per parcel shipped by a logistics company, etc.).
- Supplier-specific **aggregated LCA results** (e.g., kg CO_2e per unit of product), which are available when the supplier conducts an LCA of a specific product or service, and then provides the results to the reporting organization.

These two types of supplier-specific aggregated EFs are illustrated in Figure 2-2.

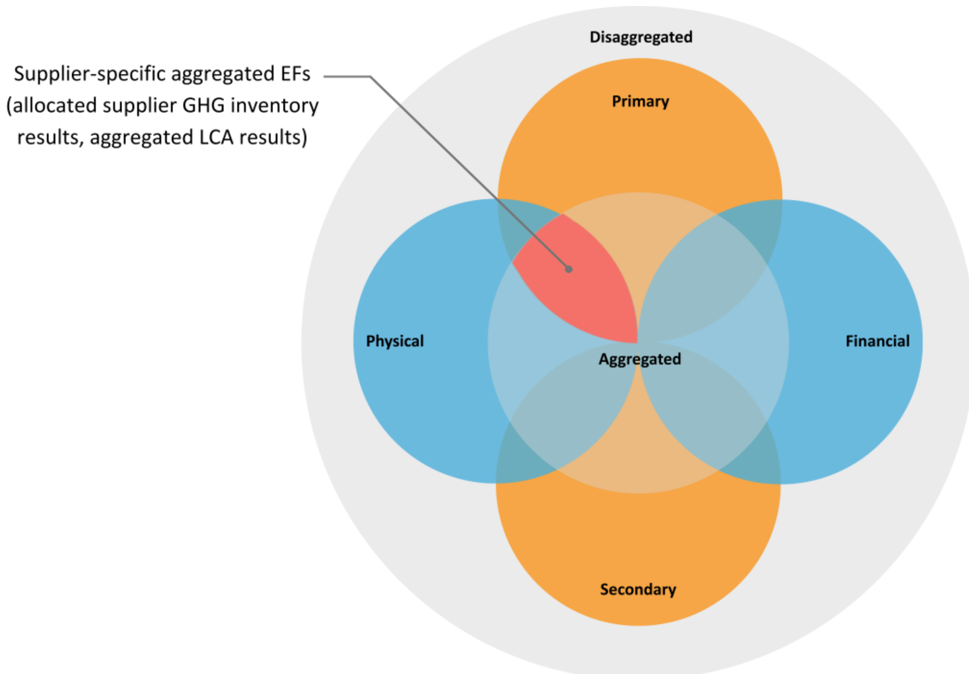


Figure 2-2: Illustration of supplier-specific emission factors

Although supplier-specific EFs are more commonly used to calculate the emissions of purchased goods and services (scope 3, category 1), they can also be used for any emission source along the value chain.

EFs derived from an allocation of the supplier's GHG inventory results, also referred to as "allocated supplier GHG inventory results", can be calculated through two types of approaches:

- The **first type of allocation** simply consists of dividing the **total supplier's GHG inventory results by the total amount of output units produced**. The outputs can be expressed either in a physical unit (e.g., the number of sold products, total mass produced) or a financial unit (e.g., revenue generated by sold products). This approach results in an emissions intensity (e.g., kg CO_2e per sold product, kg CO_2e per dollar of revenue, etc.), but it does not address multifunctionality; the emissions intensity's value is the same for all outputs.
- The **second type of allocation** addresses multifunctionality (see section 9 of *Technical Report* 1 for further information on multifunctional systems). It consists of partitioning the supplier's GHG inventory results between its multiple outputs produced, by applying an **allocation procedure** outlined in the GHG Protocol guidance[3] (e.g., physical allocation, economic allocation). The allocated values can be expressed in a physical or financial unit.

Box 2-3 illustrates the two approaches. Allocation can be performed either by the reporting organization using its supplier's GHG inventory results or, more commonly, by the supplier, who provides the reporting organization with an already allocated EF.

[3] See section 8 of the *Scope 3 Standard* (GHG Protocol, 2011a).

Box 2-3: Example of allocated supplier GHG inventory results

In this example, the reporting organization purchases gold from a supplier that operates a mine. The supplier provides the reporting organization with its GHG inventory results, which are **500 tCO_2e annually** (including scope 1, 2, and relevant upstream scope 3 emissions). The mine is a multifunctional system, producing and selling both **gold** and **aggregates**, so the results relate to both outputs. Specifically, the mine produces **2 tons of gold** per year, sold at **$100,000/kg**, and **1,000 tons of aggregates** per year, sold at **$0.5/kg**. In order to calculate an EF for gold production only, and thus the emissions associated with its gold purchases (scope 3, category 1), the reporting organization must partition the mine's GHG inventory results between the gold and aggregates produced.

The first type of allocation may consist of dividing the mine's GHG inventory results by the total mass of outputs produced by the mine. This results in an EF expressed in a physical unit:

$$EF_{gold} = \frac{Total\ mine\ emissions}{Total\ mass\ of\ all\ outputs} = \frac{500\ tCO2e}{2\ t + 1000\ t} = 499\ kg\ CO2e/t$$

This type of allocation assigns gold and aggregates equal GHG emissions responsibility (**499 kg CO_2e per ton of output)**. However, it does not reflect that the mine's emissions are primarily driven by gold production, and it does not address multifunctionality.

To address multifunctionality, the organization should partition the mine's emissions among its outputs using an allocation procedure that best reflects the causal relationship between the production of the outputs and their resulting emissions. In this example, **economic allocation** (based on the revenue of sold products) is most appropriate. The allocation would therefore be performed as follows:

$$Economic\ allocation = \frac{Revenue\ from\ gold}{Total\ revenue\ from\ all\ products} \times Total\ mine\ emissions$$
$$= \frac{2\ t\ \times 100\ \$/t}{(2\ t \times 100\ \$/t) + (1{,}000t \times 0.0005\ \$/t)} \times 500\ tCO2e = 499\ tCO2e$$

Gold accounts for 99.5% of the mine's revenue, thus 99.5% of the mine's emissions are allocated to gold production. 499 tCO_2e are allocated to gold production, resulting in an EF of **249.5 tCO_2e per ton of gold**. This value is about 1000 times higher than the one obtained with the first type of allocation, but it is more accurate because it properly addresses multifunctionality.

2.3.1 Main advantages

Supplier-specific EFs that are aggregated enhance the provider's data confidentiality and are easy for the reporting organization to use when estimating emissions.

Since these EFs are supplier-specific, they have the same advantages as supplier-specific LCI EFs, which are described in section 2.2.1. Their main advantage is their **high level of specificity**, which significantly enhances the accuracy of the results and enables the reporting organization to identify the exact contribution of each product or service purchased from suppliers to its GHG inventory results. It helps pinpoint the most GHG-intensive suppliers and provides insight for the supplier selection process. They also favour engagement of the reporting organization's value chain partners, which can be helpful when the former attempts to reduce its emissions.

2.3.2 Main limitations

Aggregated or semi-aggregated supplier-specific EFs can **lack transparency** regarding what is included (e.g., activities, GHGs) and their underlying methodological choices (e.g., modelling assumptions, allocation methods). This hinders **compliance with some of the GHG Protocol's requirements**, especially regarding system boundaries, included GHGs reporting requirements, and consideration of biogenic and land use and land use change (LULUC) emissions. The quality of such EFs heavily depends on methodological choices. However, suppliers often have varying levels of expertise in GHG accounting principles and methodologies.

Data collected from the supplier must be verified to ensure both **comprehensive coverage** and the **avoidance of double counting of emissions**. In the former case, reported data may omit important life cycle stages or emission sources. For instance, a reporting organization can collect supplier-specific EFs to quantify emissions from purchased goods and services (scope 3, category 1). If the supplier reports only its scope 1 and scope 2 emissions, it does not meet the minimum boundary requirements for the category, which mandates cradle-to-gate emissions. In the latter case, the data may include life cycle stages that are outside the expected boundaries. Following the same example as above, the supplier-specific EF may instead include all of its emissions, covering scope 1, 2, and 3. However, downstream scope 3 emissions (e.g., the use phase of the product sold to the reporting organization) must be excluded to comply with the scope 3, category 1 boundaries and avoid overlaps with other scope 3 emissions categories, in order to avoid the double counting of emissions. *Technical Report 3* provides recommendations to share organizational GHG inventory results along the supply chain.

From the reporting organization's perspective, the variability and flexibility in methodological choices (e.g., boundaries, allocation methods, update frequencies) allowed within the main GHG accounting standards like the GHG Protocol, combined with the lack of standardization, may **cause inconsistencies when aggregating data from multiple suppliers** in its own GHG inventory. These inconsistencies may be more important in the case where organizations engage with numerous suppliers. For instance, when suppliers provide the reporting organization with EFs derived from an allocation of their GHG inventory results, the type of allocation highly influences the value of the resulting EFs. However, the approach(es) applied by the suppliers may not be consistent with that used by the reporting organization to calculate other EFs within its GHG inventory.

To enhance transparency and better evaluate the robustness of information provided by suppliers, the reporting organization should request that suppliers provide supporting documentation describing the methodology followed. However, this may cause confidentiality issues, as such information is often proprietary. To address this, organizations should implement **confidentiality agreements** (e.g., nondisclosure agreements) or require that suppliers obtain third-party assurance (GHG Protocol, 2011a).

Technical Report 3 provides guidelines for improving the sharing of emission data (i.e., GHG inventory results) with partners along the value chain.

2.4 Sectoral or regulatory default emission factors

The third type of process-based EFs is **sectoral or regulatory default EFs**. These are proposed by international organizations (e.g., Intergovernmental Panel on Climate Change [IPCC], International Energy Agency [IEA]), government agencies (e.g., Department for Energy Security and Net Zero [DESNZ], United States Environmental Protection Agency [U.S. EPA]), or industry associations (e.g., World Steel Association, Plastics Europe, Clean Cargo Working Group).

As illustrated in Figure 2-3, these EFs are **secondary data**. They are generally **physical** and **aggregated,** reflecting average emissions per unit of activity and per equipment category (e.g., average kg CO_2e per vehicle-kilometre by vehicle type).

Sectoral or regulatory EFs can be developed using either a top-down or a bottom-up approach. These methods are both discussed in section 2.4.

The completeness of their coverage varies: some adopt a **life cycle perspective** (e.g., an LCA-based EF for a specific equipment or activity developed by an industry association), while others focus only on the **direct emissions of an activity**. Indeed, a specific subset of these EFs is *direct emission factors*, which have narrow boundaries and account only for direct emissions associated with a specific activity (e.g., EFs considering only combustion emissions for vehicle use). The latter are often **disaggregated** by individual GHG. They are typically used for calculating scope 1 emissions and may be used for some scope 3 categories (e.g., upstream or downstream leased assets [categories 8 and 13], use of sold products [category 11]).

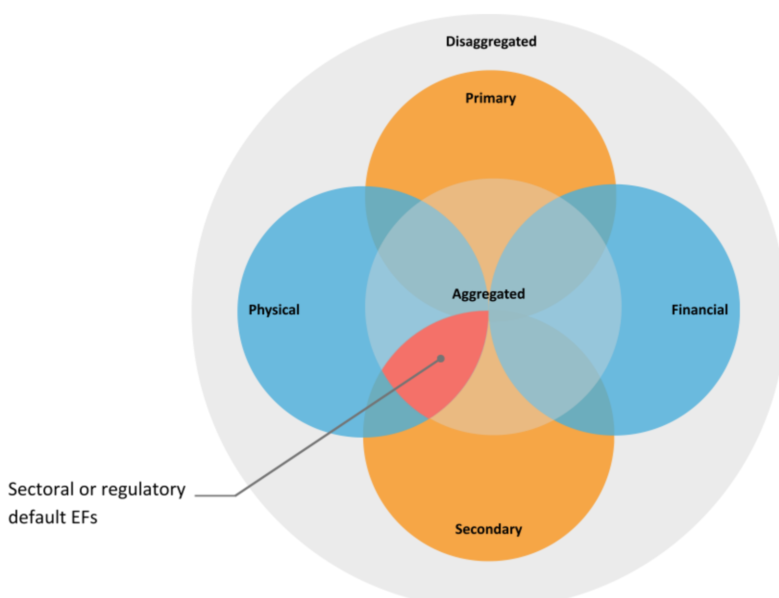


Figure 2-3: Illustration of sectoral or regulatory default emission factors

2.4.1 Main advantages

The main advantage of sectoral or regulatory default EFs is their **sectoral relevance**. They reflect the distinct technologies and practices of specific industries or activities (e.g., construction, transport, agriculture), which enhances the accuracy and credibility of the EF. **EFs accounting only for direct emissions** are typically calculated following internationally recognized methods (e.g., IPCC), thereby providing a **high level of credibility**. The latter are also typically precise due to the relative simplicity of the activity they model (e.g., combustion, chemical process) and the high level of scrutiny they are under.

Supported by large organizations, sectoral or regulatory default EFs tend to be **more robust, methodologically rigorous, and frequently updated**, even though their quality can vary significantly depending on their provider

Additionally, these EFs are widely used in **adopted regulations** across a region or sector, thereby facilitating compliance and comparability of organizations' GHG inventory results.

Finally, many of them are **easy and free to access**, often designed for practical use in common reporting contexts, and are typically accompanied by guidance documentation to support their practical application.

2.4.2 Main limitations

Although they can come with documentation to facilitate their use, it may be complex to identify the scope, assumptions and methodological choices used to calculate sectoral or regulatory default EFs, because they are generally aggregated (i.e., provided as one single value expressed in CO_2e). This hinders **compliance with some of the GHG Protocol's requirements**, especially regarding the separation of GHG emissions, the reporting of biogenic and LULUC emissions, and the selection of GWP values.

Most of these EFs represent regional or sectoral averages, which means they **do not accurately reflect the actual performance** and practices of individual organizations within the sector. These EFs can, for example, misrepresent factors such as geography, scale, or operating conditions of the activity whose emissions are quantified.

Additionally, they **lack sectoral coverage**. Indeed, they are only available for certain **specific sectors or activities** and generally cannot be used to quantify all the reporting organization's activities.

Finally, sectoral and regulatory EFs which account only for the **direct emissions** of an activity may not be appropriate to use for some scope 3 categories (e.g., for purchased goods and services [category 1]) as they include only direct emissions of the supplier, and thus do not comply with the minimum boundaries.

3. SPEND-BASED EMISSION FACTORS

3.1 Definition

Financial (or spend-based) EFs are used to estimate GHG emissions associated with various expenses of the reporting organization. They are **based on a financial reference unit**, expressing emissions per unit of monetary expenditure (e.g., kg CO_2e per dollar spent). When financial EFs are used, the activity data corresponds to the reporting organization's expenses (e.g., dollars spent on raw materials or for a particular service). Using expenses as activity data provides an accessible way to estimate scope 3 emissions, especially for categories lacking supplier-specific data.

Process-based EFs, described in section 2, that are expressed in a financial reference unit can be considered as spend-based EFs. However, the most common spend-based EFs are Environmentally Extended Input-Output (EEIO) EFs. As such, the terms "spend-based" and "EEIO" EFs are typically used interchangeably.

Section 3.2 focuses on EEIO EFs.

3.2 Environmentally Extended Input-Output emission factors

Environmentally Extended Input-Output (EEIO) EFs combine national *input-output* tables, which describe monetary flows between sectors of an economy, with environmental accounts, which quantify emissions (or other environmental flows) attributable to each economic sector. It results in EFs that reflect the **average emission intensities of commodities** (i.e., products and services) and/or sectors, which can then be linked to expenditure categories within an organization's procurement data.

As illustrated in Figure 3-1, EEIO EFs are **secondary data** developed using a **top-down approach** and are **aggregated**.

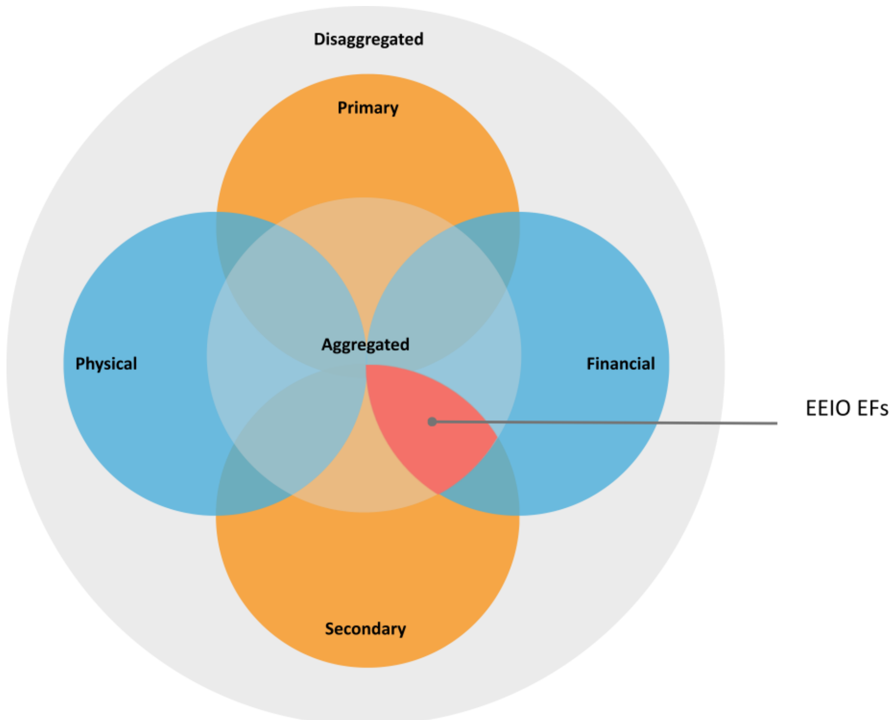


Figure 3-1: Illustration of Environmentally Extended Input-Output emission factors

Input-output tables represent emissions from a specific year because they are built using yearly national inventories. EEIO EFs generally cover a wide range of activities in the life cycle of commodities, including the **production stages of goods and services** (i.e., cradle-to-gate boundaries) but usually excluding downstream stages such as product transformation, use, and end-of-life treatment, unless explicitly modelled.

EEIO EFs **aggregate emissions across all commodities within a sector**, which means that they represent an **average across suppliers, technologies, and, to some extent, geographic locations**. Depending on the database, these EFs may be provided at either the regional level, therefore reflecting the emissions of a region's economic sector (e.g., OpenIO-Canada [Agez, 2026] providing sectoral EFs for each Canadian province and territory), the national level (e.g., the US Environmentally-Extended Input-Output [USEEIO] [Yang et al., 2017] providing EFs for the United States of America), or at the global level (e.g., Exiobase [Stadler et al., 2026] providing EFs for 44 countries and 5 larger regions, covering the whole world). The number of sectors represented and the level of sectoral granularity also vary across databases, as the way countries structure and manage their statistical data can vary significantly (e.g., 163 sectors represented in Exiobase 3.10, and up to 500 for Eora Global Supply Chain Database, depending on the region). Box 3-1 provides examples of EEIO databases and their main characteristics.

The use of spend-based EFs is one of the methods recommended by the *Scope 3 Standard* for estimating scope 3 emissions. Their use is mentioned for purchased goods and services (category 1), capital goods (category 2), upstream transportation and distribution (category 4), business travel (category 6), downstream transportation and distribution (category 9), and investments (category 15). Using EEIO EFs for other scope 3 categories is not mentioned in the *Scope 3 Calculation Guidance*, but their use is implicitly allowed, provided that activity data in the form of expenses is available to estimate the emissions, and that this data represents an expenditure incurred in a sector of the economy. However, some other standards or initiatives based on the GHG Protocol explicitly require the use of one of the methods recommended by the *Scope 3 Calculation Guidance* and therefore do not permit the use of EEIO EFs for categories where this approach is not explicitly mentioned.

Box 3-1: Examples of global EEIO databases and their main characteristics

Characteristic	OpenIO-Canada v2.11	USEEIO v2.5	Exiobase 3.10	Eora2	Global Trade Analysis Project (GTAP) 12	World Input-Output Database (WIOD) 2016	OECD 2025
Geographic granularity (countries and regions)	13 Canadian regions (+ 49 Exiobase regions)	US + 49 Exiobase regions (+ specific tables for 50 US states)	45 (+ 5 regions)	190	145	43 (+ 1 rest of the world region)	80 (+ 1 rest of the world region)
Temporal coverage (years)	2014-2022	2017-2022 (2010-2022 for older versions)	1995-2024	1990-2022	7 reference years / 2023 latest	2000-2014	1995-2022
Commodity coverage (sectors)	490	400	200	500 – 26 (simplified version)	65	56	50
Licence	Free	Free	Free	Licenced	Licenced	Free	Free
Reference	(Agez, 2026)	(Yang et al., 2017)	(Stadler et al., 2026)	(Lenzen et al., 2013; Katafuchi et al., 2025)	(Aguiar et al., 2025)	(Timmer et al., 2015)	(OECD, 2025)

3.2.1 Main advantages

The main advantage of EEIO EFs is their **ease of use**. Most EEIO databases are freely accessible and, as they are expressed in a financial reference unit, they enable direct matching with the reporting organization's expenses, which are generally readily available within organizations.

EEIO EFs also provide **extensive coverage**. On the one hand, EEIO databases are inherently comprehensive, as they represent the **entire economy**. This broad coverage facilitates the inclusion of emissions associated with a wide range of commodities for the reporting organization, including services (e.g., insurance, banking), which are often difficult to assess with process-based EFs. On the other hand, EEIO databases **capture entire value chains** associated with commodities, as all economic exchanges between sectors are inherently included in national input-output tables. As such, EEIO EFs capture all upstream supply chain emissions beyond direct suppliers, and include activities that are usually truncated and excluded from process-based EFs, such as services (e.g., insurance, marketing), or goods and activities not directly related to the product’s life cycle (e.g., office furniture, office heating, etc.). Thus, the background data of EEIO EFs is more complete than that of process-based data.

As they cover a large number of economic commodities and/or sectors, the reporting organization often have access to all the necessary spend-based EFs from a single database. This ensures the **consistency of background data** and the methodological choices behind EFs calculations, unlike process-based EFs that are usually provided from different sources.

3.2.2 Main limitations

Although EEIO EFs are relatively easy to use, they present several limitations. Though some of these limitations can be corrected, it requires specific expertise and access to accurate data.

a) Sectoral aggregation and technological representativeness

The main limitations of EEIO EFs lie in their **high level of sectoral aggregation**:

- On the one hand, since these EFs are aggregated averages across sectors, technologies and regions, they do not accurately represent the actual emissions of individual commodities, suppliers, or activities within a sector. As a result, they **lack technological representativeness**, and results may be highly uncertain and inaccurate for heterogeneous economic sectors or when the purchase corresponds to a niche commodity (see Box 3-2Box 3-2 for more information on sectoral aggregation of EEIO EFs).
- On the other hand, emissions results derived from EEIO EFs are **not always aligned with the physical reality** of the reporting organization because of sectoral aggregation. Changes in sourcing may not be reflected in emissions results if the newly sourced product remains within the same commodity category. For example, a reporting organization may switch its current steel supplier to another supplier operating in the same region, but that has implemented more energy-efficient practices. In EEIO databases, a single EF may be provided for the "Steel products" commodity. Therefore, the organization would apply the same EF for both suppliers, and the emission reductions achieved through the supplier change would not be reflected. Sectoral aggregation prevents capturing improvements that can be made within the supply chain and may discourage organizations from implementing them or from engaging partners in decarbonization strategies.

Aggregation issues may also arise from the activity data if the reporting organization's expenditures are aggregated despite representing very different commodities or activities. For example, an organization may have an expense associated with "business travels" in its procurement data, aggregating expenses from the use of various modes of transportation (e.g., train, plane, car) that have significantly different GHG emission intensities, as well as restaurant and hotel expenditures. In this example, these expenses should be disaggregated in order to match the most representative EEIO EF for each expense.

However, EEIO EFs' lack of specificity may improve technological representativeness when **the specific technology provider is unknown**. Indeed, the values of the EEIO EFs result from the economic weighting of each technology used by suppliers within a sector. Therefore, it can be more representative than another type of EF that is not representative of the specific activity, and for which no proxy data is available. For instance, Exiobase provides an EF for wheat production. If the reporting organization knows the exact technology used by its providers, it should first seek out EFs that reflect that technology. If the organization lacks that information and purchases large amounts of wheat from multiple providers, using an average EEIO EF for wheat production from the region where its main providers are located might statistically provide more accurate results than using the process-based EF of a specific mode of production, which would be unlikely to represent the various technologies used by its providers.

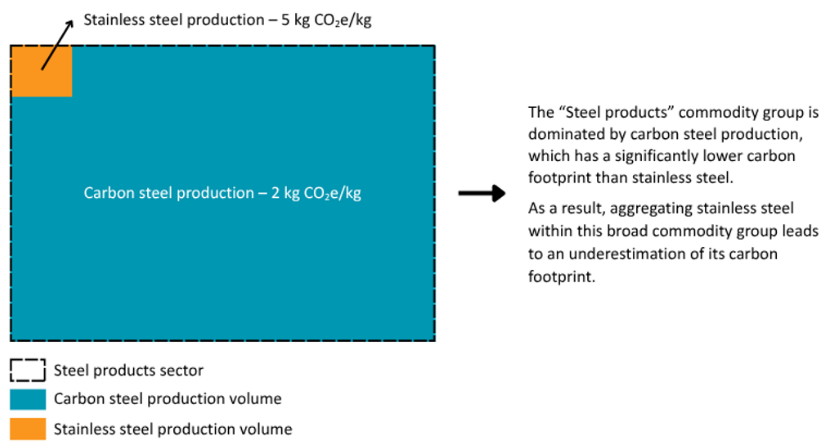
Box 3-2: Example of sectoral aggregation of EEIO emission factors

An EEIO database may provide one emission factor for "Steel products", a group of commodities that includes both **carbon steel** and **stainless steel** products.

According to product-specific studies (e.g., LCA studies), the carbon footprint of stainless steel production is around 2.5 times greater than that of carbon steel, at around 5 kg CO_2e/kg compared to roughly 2 kg CO_2e/kg, respectively.

In Canada, roughly 40 tonnes of carbon steel are produced for every tonne of stainless steel. In a simplified example where this EEIO "Steel products" emission factor covered only these two products and both had the same price[4], the sector-average emission factor would be calculated as a production-weighted average.

Using the carbon footprint values above, this would yield an average emission factor of 2.07 kg CO_2e/kg of steel, as illustrated in the figure below. Applying this aggregated emission factor to stainless steel would therefore underestimate resulting emissions by almost a factor of 2.5.



**Note: In reality, stainless steel is significantly more expensive than carbon steel. This simplification is used to illustrate more clearly the aggregation issue associated with EEIO emission factors.*

b) Sensitivity to price effects

Another limitation of EEIO EFs stems from the fact that spend-based EFs are expressed per unit of monetary expenditure. As a result, the emissions calculated with these EFs are highly sensitive to price effects. More precisely:

- A higher-priced commodity will be assessed as having a greater environmental impact, which may not reflect reality. For instance, if an organization replaces an input with an equal quantity of a lower-carbon alternative that happens to be more expensive, the organization's calculated emissions will increase.

[4] Stainless steel is significantly more expensive than carbon steel. This is a simplification to illustrate the aggregation issue of EEIO emission factors.

- Similarly, fluctuations in prices affect the calculated emissions, rather than reflecting actual emission reductions or better procurement practices. For example, an organization that enters into a new purchasing agreement with a provider will see its GHG inventory results change, even though the provider's practices and emissions remain unchanged.
- Other price effects, such as inflation and price volatility, also influence results while not corresponding to changes in physical activity or emissions. This is particularly important when significant price variations occur over the course of one year.

Due to the latter effect, EEIO EFs from the most recent available year do not always accurately reflect the current-year situation, as they may be biased by macroeconomic factors. For example, an organization conducting its GHG inventory for 2025 should not automatically use 2020 EEIO EFs even if they are the most recent data available, because the COVID-19 crisis disrupted markets for several months in 2020, making that year potentially unrepresentative.

In addition, national input-output tables are built from yearly national accounts and emission inventories, and describe the economy as an annual average. Consequently, production volumes and the associated emissions per unit of expenditure are treated as constant throughout the year. For example, the emissions associated with supplying one dollar of metal are assumed to remain unchanged across the year, whereas in practice this ratio may vary from month to month, particularly due to price changes. This temporal mismatch becomes an important limitation when significant price variations occur within a single year, affecting both the matching of activity data to EFs and the calculation of the EFs themselves through the models underlying the EEIO tables. For instance, if an organization purchases metal at the beginning of the year and its price increases significantly during the year, the emissions associated with an average dollar of metal for that year will underestimate the emissions associated with a dollar of metal actually purchased by the organization. This is because a dollar spent early in the year allows for the purchase of more metal, resulting in higher emissions than an annual average dollar.

c) Reference unit

The **currency in which EEIO EFs are expressed** (i.e., the denominator of the EF) may include different life cycle phases. Indeed, EEIO EFs are generally expressed in *basic price* (producer price) or *purchaser price*:

- The **basic price** is the amount received by the producer, excluding retail margins and taxes on the product. The corresponding EEIO EF therefore includes processes up to the factory gate of the producer, and represents the producer’s perspective.

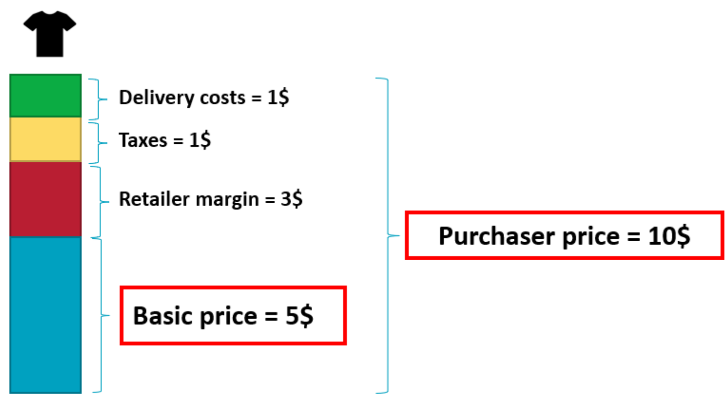
- The **purchaser price** is the amount paid for the purchase of a ready-to-buy product or service. It includes the basic price, downstream distribution costs (including margins), retailing (including margins) and consumption taxes (i.e., Value-Added Tax or similar tax). The corresponding EEIO EF therefore includes processes up to the installations of the reporting organization, and represents the consumer’s perspective.

Box 3-3 illustrates this distinction. The reference unit of the EFs varies between EEIO databases (e.g., the USEEIO are expressed in purchaser price, whereas Exiobase is expressed in basic price). However, most databases report values expressed at the basic price; therefore, they are misaligned with the reporting organization's expenses, as the latter correspond to the purchaser price. Consequently, expenses must be adjusted to align with the EFs. Table 3-4 of *Technical Report 3* indicates the reference unit of the main EEIO databases.

In addition, the EFs may not be expressed in the same currency as the activity data (e.g., the EF expressed in American dollars and the activity data in Canadian dollars), requiring the use of currency conversion factors, thus adding another source of uncertainty to the calculation.

Box 3-3: Example of basic price versus purchaser price

In this simplified example, the reporting organization operates in the apparel sector and purchases t-shirts at 10 dollars each. This amount corresponds to the **purchaser price** (i.e., the consumer's perspective) and includes 5 dollars of basic price (i.e., the amount received by the producer), 1 dollar of transportation costs for delivery, 3 dollars of retailer margin, and 1 dollar of consumption taxes.



d) Temporal representativeness

When using EEIO EFs, their **temporality** should be considered. First, EEIO EFs are expressed in the currency unit of a specific reference year, which may not correspond to the organization's reporting period (i.e., the year of the activity data, for which the GHG inventory is prepared). This temporal mismatch is common, since input-output data (i.e., economic exchanges between sectors) are usually published with **a delay of a few years**. As a result, organizations usually use EEIO EFs from a year prior to the reporting period. However, **inflation or deflation** that has occurred between the reporting year and the EEIO EFs reference year **may distort GHG emissions calculation** (see section 3.2.2 of *Technical Report 3* for practical guidance).

Second, temporal representativeness can be significantly affected by the **price effects** described in section 3.2.2 b), introducing an additional source of distortion into the calculation.

e) Geographical representativeness

The **geographical representativeness** of EEIO EFs can be limited. First, most of the EEIO EFs do not consider each country individually; they often group countries that do not constitute a significant part of the world economy, or for which good-quality data is not accessible, into aggregated regions of the world. For example, Exiobase models Brazil separately, while aggregating all other South American countries into a single region. This can result in a lack of specificity when accounting for emissions from products or services originating from one of these countries.

Secondly, EEIO emission factors are generally *production-based* rather than *consumption-based*. This means that they represent the production of a commodity (i.e. product or service) within a given region, rather than the mix of that commodity consumed in the region, including imports and exports. Selecting an EEIO EF associated with a commodity within a specific country implies that this latter was produced with that country's energy mix, technologies, yields, production systems, industrial structure, supply chain characteristics, and environmental performance representative of that region. However, **omitting to include imported commodities in the calculation of the average EF can misrepresent the reported impacts of such commodities**, especially in the case of commodities or activities that rely heavily on imports.

For example, an EEIO EF for "fruits" in the "Quebec, Canada" geography which is *production-based* represents fruit production in Quebec. It assumes that the fruit was produced using the energy mix and production systems representative of Quebec. However, an EF for "fruits" in the "Quebec, Canada" geography which is *consumption-based* represents a weighted average of the fruits consumed in Quebec, including both local production and imports (e.g., fruits that may come from abroad).

Although it may not be feasible to disaggregate all expenditures by production region, the reporting organization should consider the geography of EEIO emission factors when geographic representativeness may significantly influence the results. As such, section 3.2.4 of *Technical Report 3* provides guidance to help select the geography of EEIO emission factors.

f) Included GHGs

Additionally, even though EEIO EFs cover the entire economy, the **GHGs included are often limited**. They are based on countries' statistical data, which means they mostly account for emissions from the GHGs that are of concern to those specific countries. For EEIO databases covering several countries, the underlying emission values often need to be harmonized and report only the GHGs that are common across all these countries. EEIO tables providers often use additional data and assumptions to address inconsistencies and fill in missing data, but this still results in limited GHG emissions coverage. Although accounting for only a few GHGs (such as CO_2, CH_4, N_2O, and SF_6) provides a good representation of emissions for most economic sectors, this is not always true for sectors with very specific emissions (e.g., the healthcare sector using particular GHGs in its operations).

g) Boundaries

Some emission sources included in EEIO EFs may be double-counted when these EFs are combined with other types of EFs (e.g., supplier-specific or generic LCI EFs).

EEIO EFs are generally expressed in *basic price*, and sometimes in *purchaser price*. Those based on the purchaser price typically include emissions associated with transportation services from the producer's gate to the consumer (i.e., the reporting organization), embedded in the purchaser price EFs.

However, transportation from the producer to the reporting organization is already reported in upstream transportation and distribution (scope 3, category 4). Consequently, organizations that separately account for this transportation segment in category 4 while using EEIO EFs that already include it may **inadvertently double count the associated emissions**, although this issue is generally of very little significance compared to the overall purchased goods emissions.

4. SYNTHESIS

This section synthesizes the characteristics (specificity, disaggregation level, modelling approach, reference unit) of the different EF types, and their performance across several data quality indicators (specificity, representativeness, accessibility, adaptability, transparency, alignment with the GHG Protocol methodology, and affordability). A summary is provided in Table 4-1. Some EF types that were aggregated in previous sections are separated in Table 4-1 when their performance differs significantly (e.g., supplier-specific aggregated LCA results and allocated supplier GHG inventory results, even though they are both supplier-specific EFs). Overall, each EF type possesses distinct advantages and limitations; no single EF performs best in all aspects.

4.1 Specificity and coverage of the data source

Specificity expresses the granularity level of data: data that represents an activity with very specific characteristics (e.g., performances of a product, precise location or time where and when the activity occurs, etc.) is more specific than an average or a default value (e.g., industry or country average). An EF can be *specific* but not *representative* if it describes a specific activity while relying on generic or proxy data. **Coverage** indicates the extent to which the sectors of an entire economy are represented by EFs within a given data source (e.g., database). Overall, a trade-off typically exists between the level of specificity and coverage.

Generic LCI EFs that are disaggregated generally demonstrate the highest specificity because they allow detailed modelling of process parameters, geographic context, and product characteristics. However, the complexity of their modelling and the resources required to calculate these EFs can reduce the number of EFs included in LCI databases and, consequently, the database coverage, even though the main LCI databases still cover many industrial sectors.

Aggregated supplier-specific EFs (i.e., aggregated LCA results or allocated GHG inventory results) generally rate highly in specificity because they depict the supplier's actual operations, although their aggregation may complicate evaluating their level of specificity.

Sectoral or regulatory default EFs are generally less specific because they represent averages across similar technologies, industries, or regions. Sectoral EFs databases typically have limited coverage, as they focus on a particular industrial sector. In contrast, some regulatory EFs databases may offer broader coverage of the main activities within a region.

EEIO EFs are the least specific, representing broad economic sector averages that do not consider technological differences, detailed geographic variations, or supplier performance. Nonetheless, they encompass the entire region's economy, providing very high coverage.

4.2 Geographical, temporal and technological representativeness

Representativeness indicates how closely data reflects the actual activity and real-world conditions over time (temporal representativeness), across locations (geographical representativeness), and within the relevant technological context (technological representativeness).

Supplier-specific EFs and LCI EFs can accurately capture these aspects when developed with high-quality primary data. Generic LCI EFs sometimes lack geographic and technological coverage because they are based on secondary available data. Additionally, the time and resources required to develop these EFs can also result in outdated data that therefore lack temporal representativeness.

Sectoral or regulatory default EFs typically represent broad regional averages (e.g., national energy mixes), making them quite representative. However, they don't enable supplier comparisons or operational decisions, because they are secondary data. These default EFs are generally updated regularly.

EEIO EFs provide regional or country-level coverage and often rely on aggregated emissions across all activities within an industrial sector. Therefore, significant technological or geographical nuances between suppliers in the same economic sector may be hidden. They are typically updated on an annual basis, but with several years' delay, which reduces their temporal representativeness when used to assess the current-year situation.

4.3 Adaptability

Adaptability indicates the extent to which data can be refined or modified to improve its specificity and representativeness.

Disaggregated LCI EFs are the most flexible: they enable modifications to better reflect the context of the modelled process (e.g., technology parameters or geographic specificities). As a result, they generally better align with the reporting organization's methodological choices for its corporate GHG accounting (e.g., boundaries, allocation methods, GHGs included, etc.). They can also be hybridized by adapting a generic dataset with supplier-specific values.

Conversely, aggregated EFs provide limited adaptability unless detailed documentation is provided. However, their specificity can reduce their need for adaptability. Sectoral or regulatory default EFs offer very limited adaptability since they are standardized averages, and EEIO EFs are not adaptable at all because of their aggregated structure, which hinders users from adjusting assumptions or substituting technologies.

4.4 Transparency

Transparency indicates the extent to which the methodology, model, data, and assumptions are well documented and easily accessible.

Disaggregated EFs are the most transparent, allowing users to access underlying assumptions, coverage of the dataset, and the secondary data sources.

Conversely, aggregated EFs lack transparency because they do not provide access to the detailed underlying model. The transparency of these EFs thus largely depends on the level and quality of information and documentation provided by the data provider. Aggregated supplier-specific EFs can also lack transparency when suppliers do not disclose the choices behind their model, and when competitive considerations restrict the sharing of methodological detail. Sectoral or regulatory default EFs generally have transparent methodologies, but they are not as detailed and transparent as disaggregated ones. EEIO EFs, while documented at a high level, often offer limited transparency regarding methodological choices and data sources.

4.5 Consistency with the GHG Protocol and GHGs covered

EFs based on a life cycle assessment approach are typically developed following LCA frameworks rather than the GHG Protocol. Therefore, they often cover more than one scope or category, include emissions outside the minimum boundaries of the scope 3 categories, and/or include more GHGs than the ones required by the GHG Protocol. As such, cradle-to-gate or cradle-to-grave EFs may require adjustments to avoid double-counting, exclude GHGs not mandated by the GHG Protocol, and align more closely with the GHG Protocol. These adjustments can be applied to disaggregated EFs, but not to aggregated ones.

Supplier-specific EFs may also encompass upstream or downstream emissions that fall outside the expected scope 3 category boundaries, depending on the calculation method. However, those derived from an allocation of the supplier's GHG inventory results, calculated based on the GHG Protocol's methodology, better align with the GHG Protocol if they are calculated accurately.

Consistency with the GHG Protocol for sector or regulatory default EFs varies significantly depending on the methodology followed to develop them. For instance, several cradle-to-gate EFs only include the direct emissions (scope 1) of the organizations in the industrial sector, and therefore do not comply with the minimum boundaries requirements.

EEIO EFs may also include life cycle stages that fall outside the expected scope 3 boundaries, thus not being compliant with the GHG Protocol. Moreover, some of these EFs do not account for the seven GHGs required by the GHG Protocol. Finally, inconsistencies can occur if the reference unit in which the EEIO EFs are expressed (basic or purchaser price) does not match the unit of the activity data.

4.6 Accessibility and affordability

Accessibility (i.e. whether it is open-access or requires a specific tool) and **affordability** (the cost to access the data) also vary depending on the EF type.

Supplier-specific EFs, especially those based on LCI, require significant resources for data collection, technical expertise, or database licensing. Although their modelling is typically simpler than a full LCA, because it concentrates solely on climate change and a few GHGs, it requires detailed bottom-up modelling. This approach involves covering many processes and utilizing highly specific data to accurately quantify all underlying activities. As a result, organizations often need to develop internal expertise or outsource consulting services. Moreover, as the data necessary to calculate supplier-specific EFs may be confidential, access to transparent, disaggregated EFs may require confidentiality agreements or third-party assurance between the reporting organization and its suppliers. Generic LCI databases can help address this issue, but they often come with high licensing costs.

EEIO EFs are typically available at no cost and often in accessible formats (e.g., Excel files). This makes them technically usable by any organization at no additional cost. They are thus easy to access, but the underlying methodology can be complex, and proper use may require specialized expertise.

Regulatory EFs are usually free and easily accessible, as they are produced and maintained by public agencies. In contrast, sectoral EFs are typically available only to members of specific industry associations. Because they are intended for broad application, they usually come with detailed documentation and straightforward formats for corporate GHG accounting.

Table 4-1: Summary of the characteristics of the different emission factor types

Characteristic	Generic LCI EFs	Supplier-specific LCI	Supplier-specific aggregated LCA results	Allocated supplier GHG inventory results	Sectoral or regulatory default EFs	EEIO EFs
Data origin	Secondary	Primary	Primary	Primary	Secondary	Secondary
Disaggregation level	Disaggregated or aggregated	Disaggregated	Aggregated	Aggregated	Aggregated	Aggregated
Modelling approach	Bottom-up	Bottom-up	Bottom-up	Bottom-up	Bottom-up or top-down	Top-down
Reference unit	Physical or financial	Physical or financial	Physical or financial	Physical or financial	Physical	Financial
Specificity	Very high to medium	Very high	High	High	Low	Very low
Coverage of the data source	High to medium (when adaptable)	N/A	N/A	N/A	Medium to low	Very high
Geographical representativeness	Medium to low	High	High	High	High to low (depending on availability)	Medium to low
Technological representativeness	Medium to low	High	High	High	Low	Low to very low
Temporal representativeness	Low	High to medium	High to low (depending on update frequency)	High	High to medium	Medium to low
Adaptability	High	Very high	Low	Medium to low	Very low	Very low
Transparency	High	High to medium	High to low	High to low	Medium	Medium
Consistency with GHG Protocol	Potentially low (but often improvable)	Potentially low (but improvable)	Potentially low	High	High to low	Medium to low
Affordability	Medium	Low to very low	Low to very low (for the supplier)	Low to very low (for the supplier)	High	High
Accessibility	Medium to low	Very low	Medium to low	Medium	High	High

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