

Faculté des bioingénieurs

***Assessing the effect of data granularity
on the carbon footprint of an entity
within a complex organization***

A comparative analysis of data granularity across emission categories, effect on the identification of reduction levers, and a methodological framework transferable to other entities

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Abbreviations list

Abbreviation	Definition
ADEME	French Agency for Ecological Transition
ADFI	Administration des Finances (UCLouvain)
ADE	Academic scheduling management software
APPA	Internal facility management platform (UCLouvain)
AR6	Sixth Assessment Report (IPCC)
BSE	Bio Science Engineering (Faculty of Bioscience Engineering, UCLouvain)
CH₄	Methane
CMP	Corporate Mobility Plan (UCLouvain)
CO₂	Carbon dioxide
CO₂e	Carbon dioxide equivalent
DESNZ/DEFRA	Department for Energy Security and Net Zero / Department for Environment, Food and Rural Affairs (Royaume-Uni)
EF	Emission Factor
EPA	Environmental Protection Agency (États-Unis)
EPL	Louvain School of Engineering (UCLouvain)
EPFL	Swiss Federal Institute of Technology Lausanne
ESPO	Faculty of Economic, Social, Political and Communication Sciences (UCLouvain)
EU	European Union
FTE	Full-Time Equivalent
GDPR	General Data Protection Regulation
GHG	Greenhouse Gas
GTPL	Technical Building Management Department, Louvain-la-Neuve (UCLouvain)
GWP	Global Warming Potential

Abbreviation	Definition
GWP₁₀₀	Global Warming Potential over 100 years
HHV	Higher Heating Value
ILC	Institute of Language and Communication Sciences (UCLouvain)
IMMC	Institute of Mechanics, Materials and Civil Engineering (UCLouvain)
IMP	Inventory Management Plan
IPCC	Intergovernmental Panel on Climate Change
ISO	International Organization for Standardization
ISIT	Institute for Sustainable IT
LHV	Lower Heating Value
LLN	Louvain-la-Neuve
N₂O	Nitrous oxide
PB	Petabyte
SEPI	Real Estate and Campus Planning Department (UCLouvain)
SME	Small and Medium-sized Enterprise
UCLouvain	Université catholique de Louvain
UNFCCC	United Nations Framework Convention on Climate Change
UQAM	University of Quebec in Montreal
WBCSD	World Business Council for Sustainable Development
WEEE	Waste Electrical and Electronic Equipment
WRI	World Resources Institute

1 Introduction

Since the onset of industrialization, the accumulation of greenhouse gases (GHG) in the atmosphere has driven a measurable rise in global temperatures, now approximately 1.1 °C above pre-industrial levels (Calvin et al., 2023). Climate change has progressively shifted from a distant environmental concern to an immediate operational risk for governments, businesses, and institutions alike. Addressing it rests on a precondition that is easy to state and hard to meet: an organization cannot reduce emissions it cannot measure. Because these emissions are distributed across every sector of the economy, with no single activity reducible to zero (European Parliament, 2024), acting on them requires quantifying how they are distributed within each organization's own activities.

This need gave rise to organizational carbon accounting, formalized through frameworks such as the GHG Protocol and ISO 14064 (International Organization for Standardization, 2018; World Resources Institute, 2004). Quantifying an organization's carbon footprint under these frameworks can be approached with tools spanning a wide spectrum, from expert-led assessments that demand extensive primary data and technical expertise, to simplified calculators built for non-specialists. A rigorous assessment at the expert end of this spectrum demands a level of expertise, time, and financial resources that most organizations cannot mobilize.

The problem is particularly acute in complex organizations such as universities, where a single institution comprises dozens of semi-autonomous entities (faculties, institutes, and services), each with distinct activities and data collected by non-expert contributors (Ahonen et al., 2024). In these settings, the literature consistently identifies data availability and collection effort, rather than the calculation itself, as the binding constraint on carbon accounting (Woszczek et al., 2025). Each entity must independently locate, format, and transmit heterogeneous data, and the level of detail it collects governs both the burden placed on contributors and the operational usefulness of the result.

It is to serve precisely these entities that simplified carbon footprint tools emerged: by automating the application of emission factors and supplying default values when needed, they allow non-expert contributors to produce an inventory without dedicated sustainability expertise (Birnik, 2013; Padgett et al., 2008). This accessibility comes at a cost. Every simplified tool trades precision for usability, and the reliability of its output is ultimately bounded by the granularity of the data its users can supply.

Yet a basic question remains unanswered: for a given emission category, how much does refining data precision change the result? Recent work has assessed whether existing data meets reporting standards, but none quantifies, category by category, the effect of increasing granularity on the final footprint (Woszczek et al., 2025). Lacking this, organizations have no basis for deciding where to concentrate their limited data collection effort, which categories warrant detailed primary data and which are adequately captured by less detailed indicators,

and they risk spreading that effort uniformly across categories that contribute unequally to the total.

The present work is situated in this gap. As part of its institutional transition plan, UCLouvain has undertaken to measure its carbon footprint by enabling each of its entities to assess its own emissions, so that individual results can be aggregated into a coherent institutional total and, taken separately, can reveal where each entity is able to act concretely. The Faculty of Bioscience Engineering (BSE) serves here as a case study, not only to compute its footprint, but to use it as a test environment for granularity questions. The general objective of this thesis is therefore to determine, for each emission category, the level of data granularity beyond which additional collection effort no longer meaningfully improves the assessment, and to translate these findings into an operational framework that an entity can reproduce autonomously.

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2 State of the art

2.1 The big picture, climate changes a growing concern

What started with a handful of coal-fired mills in Britain evolved into a planetary transformation. Since the 18th century, industrialization, population growth, and the expansion of global consumption have steadily increased greenhouse gas (GHG)² emissions, altering the composition of the atmosphere. Global average temperatures over the period 2011–2020 were approximately 1.1 °C above pre-industrial levels, while carbon dioxide (CO₂) concentrations have grown by almost 50%, reaching their highest level in at least 2 million years (Calvin et al., 2023).

These changes are no longer projections; they are observed realities. Heatwaves, ecosystem disruption, sea-level rise, and the increasing frequency of extreme weather events are converging toward a common conclusion: the climate system has been pushed outside the operating envelope under which modern societies, economies, and food systems were built (Calvin et al., 2023; Rockström et al., 2009). This pressure has progressively reframed climate change from a long-term environmental concern into an immediate operational risk for institutions, governments and businesses.

Mitigating this trajectory requires, as a precondition, the ability to measure anthropogenic emissions in a way that is consistent, comparable and actionable. An organization cannot reduce what it cannot quantify, nor demonstrate progress to regulators, financiers or stakeholders.

At the European scale, emissions are distributed across all major sectors of the economy, with no sector reducible to zero and no single one bearing the full burden (Figure 1). This sectoral distribution motivates an organization-level accounting approach: climate impacts arise from interconnected economic activities, and acting on them requires identifying how those activities are distributed within each entity (European Parliament, 2024). Because these emissions involve several GHG with distinct warming effects and lifetimes, organizations further need a shared currency to make these different sources comparable.

² Greenhouse gases are atmospheric compounds that absorb and re-emit infrared radiation, thereby contributing to global warming (World Resources Institute, 2004).

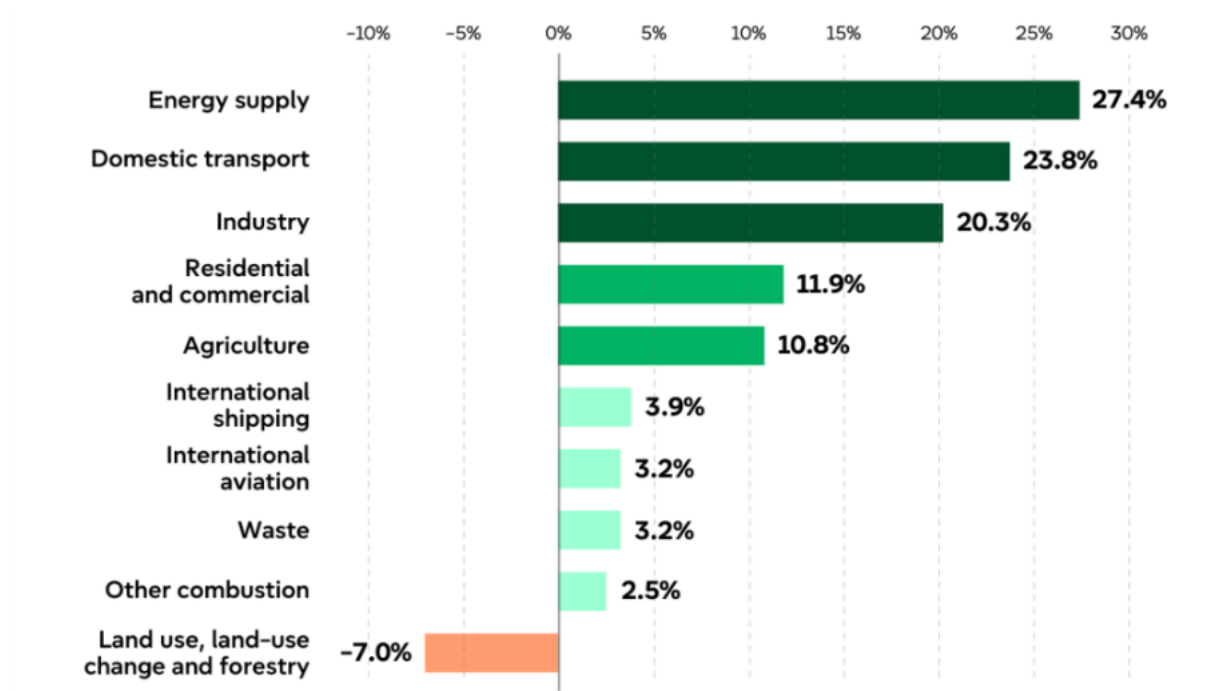


Figure 1 : Share of greenhouse gas emissions by sector in the EU in 2022 (European Parliament, 2024)

2.2 Carbon footprint

2.2.1 Historical evolution

The carbon footprint, broadly defined as the “total amount of GHG emissions directly and indirectly caused by an activity or accumulated over the life stages of a product” (Wiedmann and Minx, 2008), emerged as a formal accounting concept in the early 1990s, but its origins lie in a political rather than a corporate logic.

The United Nations Framework Convention on Climate Change (UNFCCC, 1992) first required countries to report national GHG inventories, establishing a political foundation for systematic emissions measurement, but only at the national scale, with no obligation for individual organizations. The Kyoto Protocol (UNFCCC, 1998) then translated this recognition into binding reduction targets for industrialized nations, which created an immediate practical problem: how do you verify that a country is actually reducing its emissions? Answering this question requires attributing emissions not just to countries but to the economic actors within them such as industries, sectors, and organizations. This demand for verifiable, comparable measurement at a more precise scale than the national inventory drove the development of dedicated accounting frameworks at the organizational level³ (UNFCCC, 1998).

The GHG Protocol was established in 1998 as a collaboration between the World Resources Institute (WRI) and the World Business Council for Sustainable Development (WBCSD). It

³ The term "organization" is used throughout this work in the broad sense defined by ISO 14064-1 (2018): any person or group of people with its own functions, responsibilities and objectives. Encompassing companies, public bodies, research institutions, universities, and their operational sub-units such as faculties or departments.

published its first corporate standard in 2001, introducing two elements that have since become universal: the three-scope structure for classifying emission sources, and CO₂e as a common unit of measurement (World Resources Institute, 2004). ISO 14064 followed in 2006, providing a complementary verification framework built on the same principles, with the specific goal of enabling third-party verification, allowing inventories to become comparable and certifiable across organizations (ISO, 2018).

This evolution from national political commitments to corporate accounting reflects a gradual but decisive shift in how anthropogenic GHG emissions are conceptualized and measured. It also raised a central methodological challenge: these emissions involve a heterogeneous mix of gases, all contributing to global warming yet not climatically equivalent. Reporting them in physical mass units alone is therefore insufficient. The GHG Protocol⁴ and ISO 14064⁵ addressed this by adopting a common unit of measurement capable of aggregating all relevant gases into a single, comparable indicator the CO₂e, grounded in the concept of global warming potential (GWP⁶) developed by the IPCC (Calvin et al., 2023).

2.2.2 Why CO₂e?

Greenhouse gases differ substantially in their atmospheric lifetime and heat-trapping intensity. Reporting emissions in physical mass units alone would combine gases that are not climatically equivalent. One ton of methane and one ton of CO₂ do not produce the same warming effect and adding them directly yields a meaningless figure. To enable meaningful aggregation, all GHGs are converted to carbon dioxide equivalents (CO₂e) using their respective global warming potentials (GWP), typically over a 100-year horizon (GWP₁₀₀). For instance, 1 kg of methane (CH₄) carries approximately 27 times the warming impact of 1 kg of CO₂ over 100 years; for nitrous oxide (N₂O), the factor is approximately 273 (Forster et al., 2021).

While CO₂ accounts for the largest share of emitted mass, other gases contribute disproportionately to observed warming relative to their volume. Methane and nitrous oxide together account for a share of warming that far exceeds their mass fraction (Figure 2).

⁴ Provides the world's most widely used greenhouse gas accounting standards for companies.

⁵ International, three-part standard framework used to quantify, monitor, report, and verify organizational and project-level greenhouse gas (GHG) emissions.

⁶ GWP is a metric measuring each greenhouse gas's heat-trapping ability relative to CO₂ over a defined time horizon.

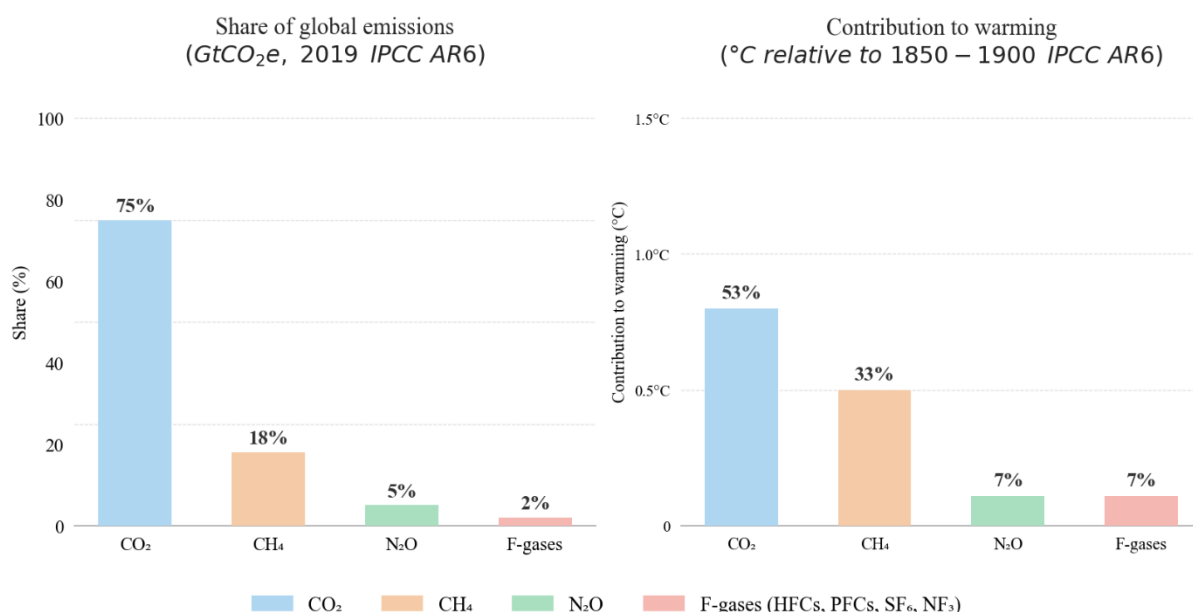


Figure 2 : Share of global GHG emissions (left) and contribution to observed warming (right) by gas (Calvin et al., 2023)

The CO₂e unit reconciles these two views into a single, comparable indicator, expressed through the following equation:

$$Emission (tCO_2e) = GHG(kg) \times \frac{GWP}{1000} \quad (1)$$

Some definitions restrict "carbon footprint" to CO₂ only (Calvin et al., 2023). The GHG Protocol, the de facto standard for organizational accounting, encompasses all seven Kyoto Protocol gases expressed in CO₂e. Table 1 shows the GWP₁₀₀ values for major GHGs, which are the conversion coefficients implicitly applied in every organizational carbon footprint.

Table 1 : Global Warming Potential (GWP₁₀₀) of major Kyoto Protocol greenhouse gases (Forster et al., 2021).

Gas	GWP ₁₀₀ (AR6)
CO ₂	1
CH ₄ (fossil fuel sources)	29.8 ± 11
CH ₄ (biogenic source)	27.0 ± 11
N ₂ O	273 ± 130

The CO₂e unit is thus both the starting point and the output of any carbon footprint calculation. Understanding how it is produced from raw organizational data requires examining the two fundamental inputs: activity data and emission factors.

2.2.3 Conversion process of activity data into CO₂e

Once the organizational and operational boundaries of a carbon footprint have been defined, the calculation rests on a conceptually simple but consequential equation: GHG emissions are

obtained by multiplying activity data by a corresponding emission factor (EF), yielding a result expressed in mass of CO₂e (Gao et al., 2014).

$$Emission(tCO_2e) = activity\ data \times Emission\ factor \quad (2)$$

Although the equation is simple, each input raises quality issues, and their combined uncertainties directly condition the reliability of the result.

Activity data refers to quantitative information describing the scale of an emission-generating activity, for example, liters of fuel consumed, kilowatt-hours of electricity purchased, kilometers traveled, or square meters of heated space. Depending on the scope and source, activity data can be primary, measured directly within the organization (e.g., metered electricity consumption), or secondary, derived from sectoral averages or published databases when direct measurement is impractical (World Resources Institute, 2004). Primary data is more accurate and specific, but collecting it requires significant resources and may require dedicated monitoring infrastructure. Secondary data is more accessible but reflects only the average behavior of a sector or process, obscuring the organization's specific characteristics (World Resources Institute, 2004). In practice, most organizations use a combination of both, prioritizing primary data for high-emission sources and using secondary data to fill gaps where direct measurement is not feasible (Kocabey Çiftçi and Özceylan, 2025).

Emission factors (EFs) are coefficients that convert a unit of activity into an equivalent quantity of GHG emissions, generally expressed in kgCO₂e per unit of activity, for example, kgCO₂e per liter of diesel burned or per kWh of electricity consumed. Selecting an appropriate EF is as important as the quality of the activity data itself: the same activity can produce very different emission estimates depending on the factor applied. The IPCC Guidelines for National GHG Inventories structure emissions calculation methodologies into three tiers of increasing complexity, each reflecting a different level of data specificity (Table 2) (IPCC, 2006).

Table 2 : The three tiers of emission factors as defined by the IPCC Guidelines for National GHG Inventories (IPCC, 2006))

Tier	Description
1	Basic method using default global averages, applicable in the absence of local data
2	Intermediate method using country-specific factors accounting for regional differences in fuel quality, technology or grid composition
3	Most demanding level, based on facility- or process-specific measurements (the most accurate)

Higher-tier factors substantially reduce uncertainty, a consequence of their greater specificity relative to the organization's actual operational context. Some major EF databases include those published by the IPCC, the US Environmental Protection Agency (EPA), the French Agency for Ecological Transition (ADEME, Base Empreinte®), and the UK Department for Energy

Security and Net Zero (DESNZ/DEFRA), each reflecting different geographical and sectoral context.

The result of this calculation is not a definitive figure but an estimate whose reliability depends on the quality and specificity of both inputs. The GHG Protocol formally distinguishes two sources of uncertainty: parameter uncertainty, arising from imprecision in activity data or EFs, and model uncertainty, stemming from assumptions embedded in the calculation methodology (World Resources Institute, 2004). These uncertainties are cumulative and unevenly distributed across an inventory: an activity-data uncertainty of $\pm 10\%$ combined with an EF uncertainty of $\pm 15\%$ inherits both. Well-documented Scope 1 sources typically carry low parametric uncertainty; Scope 2 sources occupy an intermediate position, as grid-average EFs introduce regional variability that direct measurement cannot resolve; while Scope 3 categories relying on expenditure-based EFs can exceed 80% uncertainty per input (Klaaßen and Stoll, 2021). Recognizing this reliability gradient is particularly important in the context of simplified tools, where trade-offs between data accessibility and calculation accuracy are inherent to their design and where the granularity of the data supplied by users directly conditions the quality of the result.

2.2.4 The three scopes of the GHG protocol: defining the perimeter of a carbon footprint

Once an organizational boundary has been established determining which entities and assets fall under the reporting entity's responsibility. The GHG Protocol requires the definition of an operational boundary, specifying which emission sources will be quantified and how they will be categorized. To structure this classification, the GHG Protocol introduced a three-scope framework that has since become the universal reference for organizational carbon footprint (World Resources Institute, 2004). Scope 1 covers direct emissions from sources owned or controlled by the organization, Scope 2 covers indirect emissions from purchased energy, and Scope 3 covers all other indirect emissions along the value chain: upstream and downstream (Figure 3).

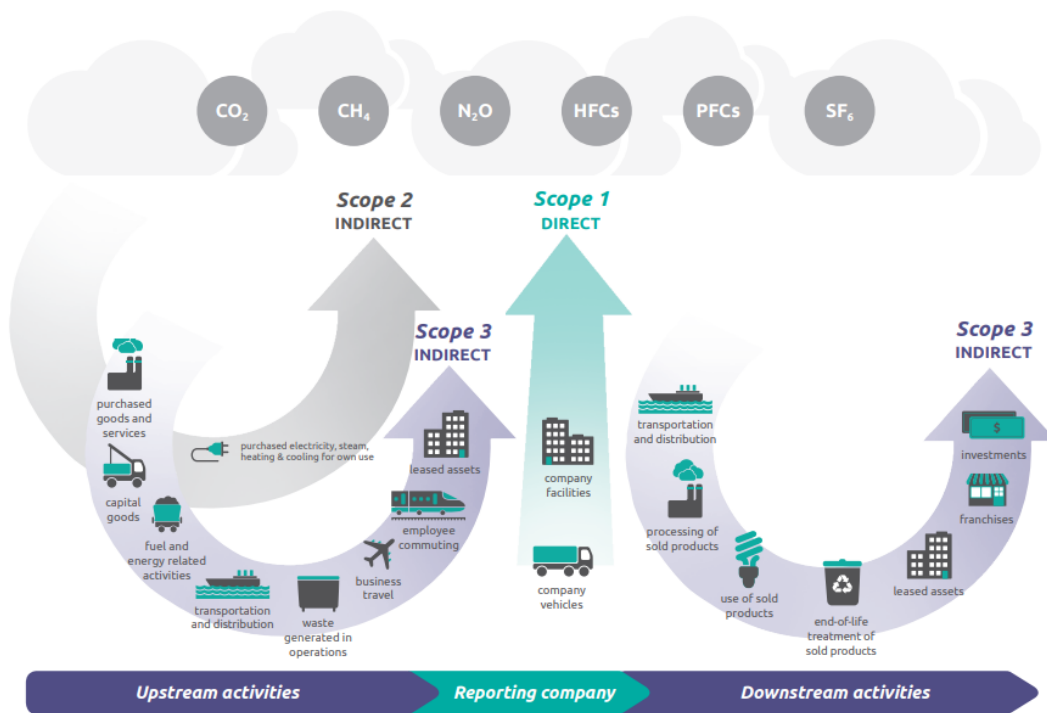


Figure 3 : Three-scope framework introduced by the GHG protocol (WRI and WBCSD, 2011)

Reporting Scopes 1 and 2 is mandatory under the GHG Protocol, but Scope 3 reporting has long been voluntary.

This distinction has significant practical consequences. Research consistently demonstrates that Scope 3 emissions represent the dominant share of organizational carbon footprints, accounting on average for more than 75% of an industry sector's total emissions, with Scopes 1 and 2 combined accounting for only around 26% (Huang et al., 2009). Restricting a footprint to Scopes 1 and 2 therefore risks capturing only a fraction of an organization's actual climate impact, which can lead to misdirected reduction strategies (Hettler and Graf-Vlachy, 2024).

Beyond the question of scopes inclusion, the reliability of the resulting footprint depends heavily on how boundaries are drawn in practice. Klaaßen & Stoll (2021) state that the three primary recurring issues in carbon reporting are (1) inconsistency across reporting years and entities, (2) boundary incompleteness, where only a subset of a Scope 3 category is accounted for, and (3) systematic exclusion of activities. These findings highlight that the conceptual framework, while comprehensive in principle, offers too much flexibility in its application, producing outcomes that vary considerably across organization, even within the same sector. This methodological freedom is a central tension in carbon footprint practice and directly shapes the design choices and limitations of any carbon accounting tool.

The methodological landscape described above encompasses scope definitions, boundary choices, calculation approaches, and data quality gradients, establishes the technical requirements for any carbon footprint assessment. Implementing these requirements in practice, however, requires significant expertise, time, and resources that most organizations cannot mobilize. This gap between methodological rigor and organizational capacity has driven

the development of carbon footprint calculation tools, including software platforms, calculators, and models, designed to lower the barriers to GHG accounting. Before examining how these tools respond to this challenge, it is necessary to understand one structural issue that affects any carbon footprint regardless of the tool used: the relationship between data quality, uncertainty, and granularity.

2.2.5 Data quality, uncertainty, and the granularity question in carbon footprint accounting

The uncertainty of a carbon footprint result is not uniformly distributed across emission categories. Well-documented Scope 1 sources, such as direct fuel combustion measured through utility bills, typically carry low parametric uncertainty, because both the activity data and the associated EFs are precise and directly measured. Scope 2 sources occupy an intermediate position: purchased electricity is generally well-metered, but the associated EF varies with the national grid composition and can shift significantly from year to year as renewable capacity evolves. Scope 3 categories relying on expenditure-based EFs carry substantially higher uncertainties, because monetary factors average across entire economic sectors and cannot capture the specific products, technologies, or geographies of individual suppliers (Klaaßen and Stoll, 2021; World Resources Institute, 2004). This reliability gradient has a direct practical consequence: not all inventory categories benefit equally from additional data collection effort, and investing in greater precision for an already well-constrained category yields negligible improvement to overall inventory quality.

This tension between data collection burden and inventory quality has been identified as a structural challenge in university carbon accounting. Woszczek et al. (2025) demonstrate at LUT University that different Scope 3 categories exhibit fundamentally different data sufficiency situations, with some adequately addressed by existing institutional data and others requiring substantial improvement, and that time constraints within a reporting cycle limit how many such improvements can be implemented simultaneously.

Despite this emerging body of work, these assessments remain qualitative: they identify whether current data meets reporting standards but do not quantify the sensitivity of the final result to data granularity choices. The magnitude of this granularity effect at the category level remains empirically underexplored.

2.3 Carbon footprint tools: from expert assessment to simplified calculators

2.3.1 The accessibility imperative

A rigorous carbon footprint assessment conducted in accordance with ISO 14064 or the GHG Protocol Corporate Standard is a major undertaking. It requires defining organizational and operational boundaries, collecting primary activity data across all relevant emission categories, selecting and justifying appropriate emission factors, documenting assumptions and data gaps,

quantifying uncertainties, and in the case of ISO 14064 the inventory needs to be submitted to third-party verification (International Organization for Standardization, 2018; World Resources Institute, 2004). In practice, this process typically mobilizes a dedicated sustainability expertise team over several weeks to months, depending on the size and complexity of the organization. For most small and medium-sized organizations, and for decentralized entities within larger institutions such as university faculties, these requirements place a full expert assessment out of reach, not because the methodology is unclear, but because the organizational capacity, technical expertise, and financial resources required to execute it are simply not available. These obstacles can be grouped into three fundamental constraints:

- A lack of technical expertise in GHG accounting methodologies
- Insufficient financial resources to hire external consultants or dedicated sustainability staff
- Limited organizational capacity to collect, process, and interpret the detailed data required by standardized frameworks.

Even when an organization's leaders recognize the strategic value of carbon measurement, whether to comply with regulations, ensure transparency for stakeholders, or support a decarbonization plan, the practical requirements of expert-led assessments remain out of reach for most entities. The result is systematic under-reporting. In the UK alone, for example, over 270 carbon reporting solutions exist for SMEs (Icebreaker One, 2024), yet most organizations outside of large corporations remain unable to measure or report their environmental impact, preventing them from accessing sustainable financing, participating in supply chains, and implementing evidence-based reduction strategies.

Simplified carbon footprint calculation tools have emerged as an answer to this accessibility gap. By reducing the burden of data collection, automating the application of emission factors, providing default assumptions for unavailable data, and offering intuitive user interfaces, these tools aim to make carbon accounting accessible to organizations that cannot afford to hire expert consultants or devote full-time staff to sustainability reporting (Padgett et al., 2008; Salo et al., 2019).

2.3.2 Uses for which the tools are particularly effective

Simplified carbon footprint calculation tools offer two capabilities that are genuinely valuable for organizations in the early stages of carbon accounting. First, they standardize calculation logic: when multiple entities apply the same tool and methodology, heterogeneity among users is reduced and comparative analysis becomes possible, even if the absolute accuracy of individual results remains uncertain (Birnik, 2013). Second, they enable longitudinal monitoring: when a single tool is applied consistently across reporting periods, it becomes possible to detect trends and track reduction efforts over time, even when systematic biases affect absolute values (WRI & WBCSD, 2011). These strengths are conditional, however: longitudinal monitoring and inter-entity comparability are only held when the same methodology and the same level of data granularity are applied consistently across reporting

periods and entities. The question of what level of data granularity is sufficient to produce reliable and comparable results is therefore central to any deployment of simplified tools in a decentralized institutional context.

2.3.3 Tool spectrum, from expert assessment to simplified calculators

Carbon footprint calculation tools range from process-based assessments conducted by experts, which require detailed primary data and technical expertise, to simplified calculators that prioritize ease of use over precision. The methodological basis of a tool determines both its data requirements and its sensitivity to systematic errors. Scope 1 and 2 emissions are generally well-documented and traceable through utility bills, fuel receipts, and energy invoices, making their calculation relatively straightforward regardless of the tool used. Scope 3 emissions, by contrast, represent the most data-intensive and uncertain part of any organizational inventory, as they depend on external actors across the value chain over whom the reporting organization has no direct control. It is precisely for this category that the GHG Protocol Technical Guidance identifies four calculation methods arranged along a precision–effort continuum (WRI & WBCSD, 2013) (Figure 4).

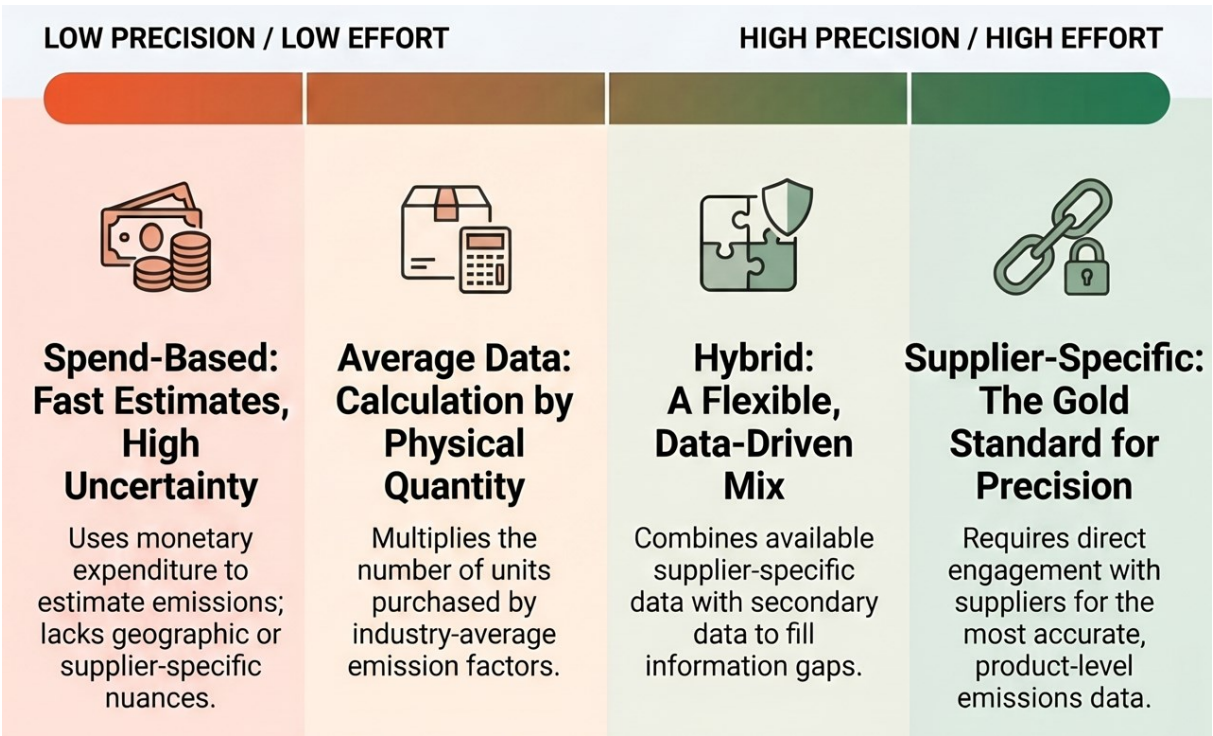


Figure 4 : Four Scope 3 calculation methods ranked by precision and data requirement, from spend-based (low effort, high uncertainty) to supplier-specific (high effort, lowest uncertainty)

In practice, most tools and assessments combine these methods across emission categories, applying more specific approaches where data allows and monetary proxies elsewhere. Simplified tools for non-expert users sit at the accessible end of this spectrum, relying

predominantly on spend-based or average-data methods, this is a design choice that lowers the barrier to entry but bounds the reliability of the results they can produce.

2.3.4 Trade-off between accuracy and accessibility

The development of any carbon footprint calculation tool is subject to an inevitable tension: methodological rigor requires thorough data collection and technical expertise, while practical accessibility requires simplification and the use of default values. No tool can maximize both aspects simultaneously. Simplified tools explicitly prioritize accessibility, accepting a loss of accuracy as the price to pay for democratizing carbon accounting. The crucial question is not whether this trade-off exists because it is inherent to the tools but rather whether the compromises made are compatible with the tool's intended use.

Rigorous assessments and simplified tools make fundamentally different trade-offs between data requirements and accessibility (Figure 5).

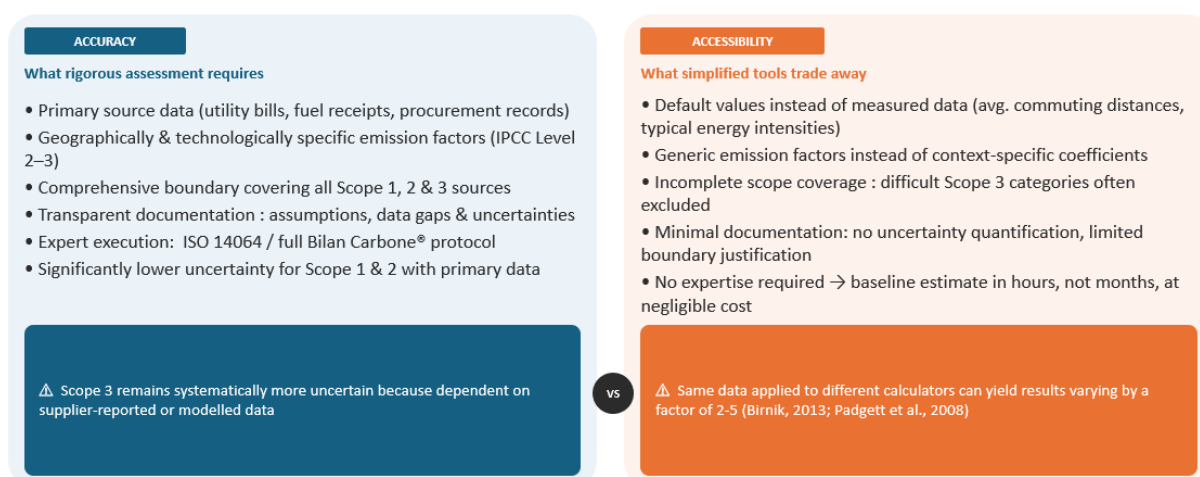


Figure 5 : The accuracy–accessibility trade-off in carbon footprint calculation tools.(Birnik, 2013; International Organization for Standardization, 2018; Padgett et al., 2008; WRI & WBCSD, 2011)

Simplified carbon footprint calculation tools therefore occupy a transitional role. They reduce barriers to the initial adoption of carbon accounting, enabling organizations to establish approximate baselines and identify emissions hotspots, but they cannot replace rigorous assessments when decisions carry financial, legal, or reputational consequences. Recognizing where this trade-off matters most, and where the precision gain from additional data collection is negligible relative to the effort required, is a prerequisite for any entity seeking to produce results that are both reliable and reproducible without dedicated sustainability expertise.

2.3.5 Current simplified tool limitations

Simplified tools carry structural limitations that must be understood before their outputs are used to make important decisions with financial, legal, or reputational consequences.

Carbon footprint calculations are based on emission factors that convert physical activities into equivalent amounts of CO₂. In simplified tools, these factors are often integrated at the time of development and rarely updated. This creates a growing gap between the tool's internal factors and the reality of the user's energy mix, supply chain conditions, or technological context (Birnik, 2013). The problem is particularly acute for electricity-related emissions, where the carbon intensity of the grid varies considerably from country to country and changes from year to year as renewable capacity increases. A tool based on a national average from several years ago may systematically overestimate or underestimate Scope 2 emissions. For institutions operating in multiple countries or undergoing significant energy transitions, static factors introduce a structural bias that compounds over time.

Simplified tools transfer methodological responsibility from trained consultants to end users who may lack the knowledge to interpret ambiguous input categories, assign activities to the correct domain, or recognize when a default value is inappropriate in their context. Moore et al. (Moore et al., 2025) found that user errors in data entry and category assignment were common when developing an improved calculator, and that the trade-off between ease of use and accuracy was inevitable. This is not the fault of individual users, but a structural consequence of the tool's design: simplifications that reduce barriers to entry also reduce safety barriers against classification and interpretation errors. The principle of "garbage in, garbage out" remains a fundamental obstacle to the quality of results, regardless of the sophistication of the calculation tool.

The results generated by simplified tools are appropriate for raising awareness, establishing directional goals, and identifying key sources of emissions where approximate accuracy is sufficient. Their reliability therefore depends not only on the tool itself but on the quality and granularity of the data supplied by users, a dependency that becomes structurally significant when data collection is distributed across non-expert contributors in decentralized institutions (OECD, 2025).

Of these limitations, the dependency on input data quality is the most consequential: static emission factors and user classification errors are both manifestations of the same underlying problem, namely that the reliability of any simplified tool is ultimately bounded by the granularity and accuracy of the data its users can supply. The other limitations such as inter-tool divergence and opacity of calculation logic matter primarily when results are used for external reporting or cross-organizational comparison. A context that requires a level of auditability that simplified tools cannot provide.

2.4 Carbon footprint accounting in complex organizations

Carbon footprint assessments are most effective when the entities responsible for emissions can recognize their own contribution to the results. At the macro scale whether a national inventory, a sector-wide estimate, or a single institutional total, figures are too aggregate for individual actors to identify their role or feel motivated to act. Research on organizational carbon accounting consistently shows that people are more likely to engage in reduction efforts

when they can understand the direct link between their activities and the resulting emissions (Ahonen et al., 2024). This gap between macro-scale measurement and individual engagement is particularly acute in complex organizations, where a single institutional carbon footprint figure masks the heterogeneous emission profiles of dozens of semi-autonomous entities, each with different activities, different data, and different reduction levers.

The term “complex organization” in the context of this thesis refers to decentralized institutions (universities, public bodies, research organizations, etc.) that share a set of structural characteristics that systematically complicate the measurement of greenhouse gases : These institutions comprise several semi-autonomous entities⁷ operating under the same institutional structure, each with heterogeneous emission profiles and non-expert users responsible for data collection (Ahonen et al., 2024; Helmers et al., 2021).

Universities are a typical example: a single institution may comprise dozens of faculties, departments, research institutes, and administrative units, each with a distinct emission profile. For example, energy and equipment-intensive laboratories generate emissions predominantly through purchased goods and infrastructure, while administrative offices are driven primarily by commuting and travel. Each unit may operate under different financial authorities, data systems, and management structures, making the collection of consistent and comparable emissions data challenging both technically and in terms of coordination (Ahonen et al., 2024).

2.4.1 Methodological fragmentation and the need for a unified internal framework

The methodological diversity observed at the interinstitutional level is often even more pronounced within complex organizations themselves. When different entities within the same institution use different calculation methods, boundary definitions, or emission factor databases, the results cannot be aggregated: adding them together produces a result that reflects methodological inconsistency as much as actual emissions. This internal fragmentation is a direct consequence of the lack of a unified institutional framework, encompassing a common methodology, a shared emission factor database on emission factors, and a standardized data collection protocol applied consistently to all reporting entities (Gao et al., 2014; Klaaßen and Stoll, 2021).

Several calculation methods may coexist in practice within a single institution. Activity-based methods applied to energy and travel data can be used alongside expenditure-based approximations for purchase categories, survey estimates for commuting, and default national averages for categories where primary data is not available. Each approach has different uncertainty profiles and is sensitive to different data quality issues. Without explicit documentation indicating which approach was applied to which category and why, the aggregated results are difficult to interpret and impossible to validate (Birnik, 2013; Padgett et al., 2008). The literature consistently identifies the lack of a common institutional framework

⁷ Refers to any operational sub-unit of an organization (service, department, faculty, or geographic site) that manages activities and are data relevant to greenhouse-gas reporting.

as the main obstacle to meaningful long-term monitoring and comparison across entities (Ahonen et al., 2024; Helmers et al., 2021).

In a decentralized context where each entity reports independently, consistency matters more than methodological perfection. Consistent application of the same methodology across entities and over time is essential to produce comparable results: changes in methods, boundaries, or data sources must be transparently documented, as they otherwise make it impossible to distinguish real emission reductions from methodological artifacts (World Resources Institute, 2004). A unified internal framework does not require resolving all methodological debates, but it requires making coherent choices and applying them consistently across entities and over time.

This need for a unified framework raises a practical question: which data are needed, and how can an institution organize it so that the carbon footprint is reproducible from one year to the next without imposing a disproportionate burden?

2.4.2 Data availability and quality: a structural barrier to decentralized accounting

Data availability and quality represent the most consistently cited barrier in the literature on carbon footprint assessment for complex organizations. Time constraints, limited staff resources, and data reliability have been identified as primary obstacles to Scope 3 reporting in Finnish universities (Woszczek et al., 2025), a finding echoed by studies reporting that excessive data collection requirements rank among the main challenges faced by institutions, alongside the absence of a standardized framework and persistent concerns about data reliability (Ahonen et al., 2024). The consequences are significant: insufficiently accurate data prevents organizations from identifying credible emission reduction actions and undermines their capacity to manage emissions effectively. Beyond accuracy, there is a broader allocation problem: as reporting requirements grow, the organizational resources devoted to data collection may reduce the capacity available for concrete efforts to reduce emissions.

In a decentralized context where data collection relies on non-expert contributors distributed in each entity of the organization, this challenge is structurally amplified. Each entity must independently locate, format, and transmit heterogeneous data, often without the information systems or dedicated personnel required to do so efficiently. The granularity of the data collected, being the level of detail required for each emission category directly determines both the burden imposed on contributors and the precision and operational usefulness of the resulting inventory. A highly granular collection protocol may yield more accurate results but at the cost of a collection effort that is not always sustainable for non-expert users. While a low-granularity approach reduces the burden but may produce results too approximate to support entity-level decision-making. This trade-off between data granularity and collection effort has not yet been addressed by an operational framework in the literature, particularly in the context of decentralized institutions with non-expert users (Valls-Val and Bovea, 2021; Woszczek et al., 2025).

2.4.3 Existing frameworks for inventory data management and their limitations for decentralized institutions

An operational guide for structuring data collection in the context of carbon accounting exists but was not designed with the goal of decentralized institutions use in mind. The GHG Protocol Corporate Standard (WRI and WBCSD, 2011) dedicates a full chapter to inventory quality management and recommends that organizations develop an Inventory Management Plan (IMP) an internal document that formalizes data sources, collection procedures, contributor responsibilities, quality controls, and documentation rules. EPA has developed complementary tools in the same spirit, including a simplified IMP template designed for smaller organizations (EPA, 2026). These frameworks establish useful principles: identifying data sources by emission category, documenting estimation methods, defining roles and frequencies, and ensuring year-to-year data traceability.

These guides nonetheless present two structural limitations that are directly relevant to the deployment context examined in this thesis. First, they were designed for centralized organizations with a dedicated sustainability team (capable of coordinating data collection, validating submissions, and ensuring methodological continuity across reporting cycles). They do not address the case where collection depends on dozens of non-expert contributors distributed across semi-autonomous entities, without dedicated time or specific training. Second, these frameworks focus on what must be documented (methods, sources, assumptions) but remain silent on how organizations should structure and store their data upstream of the inventory, in a way that minimizes collection effort in subsequent reporting cycles. Yet it is precisely this preventive and organizational dimension that conditions the long-term viability of a carbon accounting system in a decentralized institution: a contributor who knows exactly what data to retain, in what format, and at what frequency, substantially reduces the burden of each new collection cycle. This operational gap between the generic normative guidance that exists and the concrete needs of decentralized institutions with non-expert users remains unaddressed in the literature (Valls-Val and Bovea, 2021; Woszczek et al., 2025).

2.5 Operational value of entity-level carbon accounting

Producing a carbon footprint is only a first step toward emission reduction. Its operational value depends on whether the results are actionable at the level of the entities responsible for the emissions. Research consistently shows that an aggregated institutional figure, while useful for reporting, has limited practical value for driving targeted reduction efforts: organizations that can identify emission hotspots at the entity level and link them to specific categories of activities are better positioned to develop and monitor concrete reduction actions (Ahonen et al., 2024). This distinction between institutional-level reporting and entity-level decision support is directly relevant to the question of data granularity: a carbon footprint calculated from aggregate proxies may satisfy reporting requirements while remaining too imprecise to identify which activities within an entity are driving emissions and where reduction efforts should be concentrated. The practical usefulness of a carbon footprint therefore depends not only on

how it is calculated, but on whether the data underlying it is specific enough to support the decisions that entities can make.

2.6 Research gap and thesis positioning

The literature reviewed in the preceding sections reveals a consistent pattern: while carbon footprint frameworks are well-developed at the conceptual level, their practical implementation in decentralized institutions faces two unresolved challenges. First, data quality and collection effort have been identified as persistent structural barriers (Woszczek et al., 2025), yet no study quantifies per emission category, the effect of increasing data precision on the resulting carbon footprint estimate, leaving organizations without operational guidance on where to invest their limited data collection resources. Second, existing tools either serve large organizations with dedicated sustainability teams or were designed for individual research use (Birnik, 2013), leaving decentralized institutions such as universities without a methodology that is both rigorous enough to support decision-making and reproducible by non-expert entity-level contributors (Ahonen et al., 2024).

3 Objectives and approach

Carbon footprint assessments at the organizational level face a fundamental tension: increasing data granularity improves precision but also increases the time and expertise required for data collection and processing. This tension raises a practical research question: "What level of data granularity is sufficient to identify actionable emission reduction levers, while keeping the process reproducible by the entity itself, without relying on a dedicated researcher or external expert?"

To investigate this, the BSE Faculty at UCLouvain serves as a case study, with the focus set on teaching activities. The aim is not simply to calculate the faculty's carbon footprint, but to use that assessment as a test environment: a setting in which to evaluate, across all emission categories, where deeper data collection genuinely improves the result and where it yields diminishing returns. Concretely, the university's 2024 carbon footprint serves as a map of emission categories, and the full assessment is replicated at the faculty level. Data are collected directly at that scale for each category, so that more precise emission factors can be matched to more granular, entity-specific data.

The general objective of this thesis is threefold: to determine the effect of data granularity on the results of an entity-level carbon footprint; to assess, for each emission category, the threshold beyond which additional data collection effort no longer meaningfully improves the assessment; and to translate these findings into a transferable operational framework that allows an entity to reproduce the process autonomously for future iteration.

Two sub-objectives structure this work.

The first sub-objective is to conduct a sensitivity analysis across the different emission categories by testing scenarios at different levels of data detail and measuring their effect on the final carbon footprint result. The working hypothesis is that granularity has a significant and non-linear effect in some categories, but a negligible one in others, meaning that uniformly high data precision is neither necessary nor efficient across all categories.

The second sub-objective is to produce an operational guide covering the full process, from data collection to calculation, grounded in the conclusions of the sensitivity analyses. The guide targets two distinct actors: the faculty-level officer missioned to collect and process emission data, and the university's central services responsible for data storage and provision. For the former, it specifies the recommended level of granularity and calculation procedure for each emission category. For the latter, it defines how data should be structured and made available upstream, so that the collection burden for future reporting cycles is substantially reduced.

The underlying hypothesis is that defining the right level of detail per category and embedding it into a structured data collection protocol is what separates a one-off assessment and a process that an entity can own and repeat independently in the future. Although developed and validated for the Faculty of BSE, the framework is designed to transfer to other faculty-level entities with comparable activity profiles; its applicability to broader organizational contexts remains a perspective for future work.

The general approach follows four sequential steps: establishing the full carbon footprint of the faculty using a standard methodology; constructing alternative granularity scenarios for the sensitive categories; comparing results quantitatively to identify sensitivity thresholds; and synthesizing the findings into the operational guide (Figure 6).

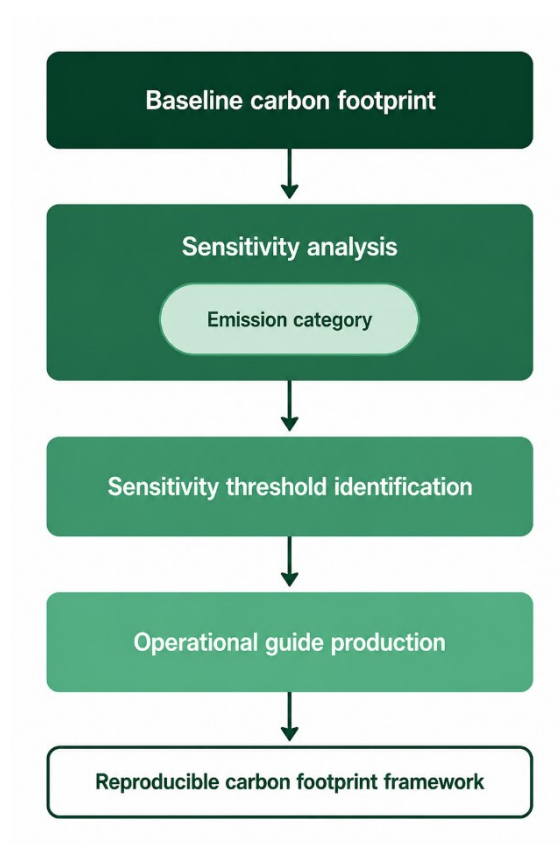


Figure 6 : General research approach for the thesis

4 Material and methods

4.1 System boundaries and scope definition

The Faculty of BSE of the Catholic University of Louvain, located on the Louvain-la-Neuve (LLN) campus, in Belgium, serves as the case study for this investigation. The faculty comprises approximately 1,300 students and 72.5 full-time equivalents (FTE) of academic and administrative staff. Its activities are distributed across several buildings shared with other faculties, a structural characteristic that constitutes the central methodological constraint for allocating energy consumption and waste to the faculty.

The scope is restricted to teaching activities. This boundary reflects both a deliberate choice and a data constraint: teaching is the domain over which the faculty exercises direct operational control, and for which the relevant data are accessible. The population covered includes professors in their academic role, teaching assistants for the teaching component of their work, administrative staff, and students enrolled in the faculty. Research activities and staff exclusively dedicated to research fall outside the scope. Laboratory activities associated with teaching courses are included. In principle, their effective coverage is data-dependent and specified in the relevant subsections. The faculty was selected as one of three pilot entities within UCLouvain's transition plan, under which a carbon accounting firm was mandated to develop a simplified tool enabling small institutional entities to assess their own carbon footprint based on the university's 2024 triennial assessment.

The reference period is the calendar year 2024 for energy and financial data. Room scheduling data, used to derive faculty-level allocation keys for energy consumption, correspond to the academic year 2024–2025, under the assumption that the distribution of room usage across faculties is stable between consecutive academic years.

The inventory follows the three-scope structure defined by the GHG Protocol Corporate Standard (WRI & WBCSD, 2011). Scope 1 covers direct emissions from natural gas combustion for space heating, refrigerant fluid losses are excluded because no annual recharge data are available at the building level, making any estimate reliant on unvalidated default leakage rates. Scope 2 covers indirect emissions from purchased electricity. Scope 3 covers indirect emissions from the procurement of goods and services, staff and student mobility, waste generation, and digital infrastructure. Certain Scope 3 categories are only partially covered due to the unavailability of faculty-level data, these limitations are documented in the corresponding subsections.

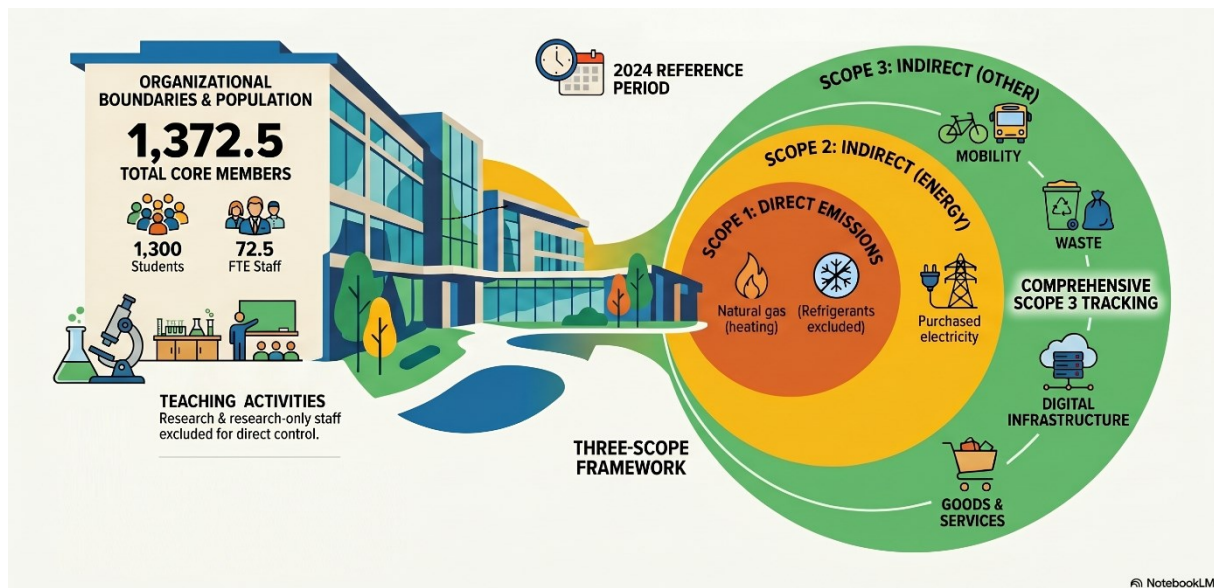


Figure 7 : Organizational network of the BSE faculty

4.2 General methodological framework

The carbon footprint assessment presented in this study follows the activity-based approach defined by the GHG Protocol Corporate Standard (WRI and WBCSD, 2011). Emissions are calculated as follows, with intermediate calculations performed in kg CO₂e:

$$\text{Emission (tCO}_2\text{e)} = \text{Activity data} \times \text{Emission factor} \quad (3)$$

Depending on the emission category and the level of data granularity available, both activity-based and expenditure-based approaches are applied. The activity-based approach uses physical quantities: mass, volume, distance, or energy, multiplied by a material- or process-specific EF. The expenditure-based approach multiplies a monetary value by a sector-average EF expressed in kg CO₂e per monetary unit. The choice between them, and its implications for result precision, are detailed in the corresponding subsections.

EF are sourced primarily from the Base Empreinte® database maintained by ADEME (“Base Empreinte®,” 2026). This database was selected for its methodological transparency, its regular update cycle, and its established use in French-speaking institutional carbon accounting. All factors incorporate a 100-year global warming potential (GWP₁₀₀)⁸ to aggregate non-CO₂ greenhouse gases into a single comparable metric. The selection of input data and the assignment of emission factors were validated by a carbon accounting expert mandated by

⁸ GWP₁₀₀ is a standard, IPCC-adopted metric measuring a greenhouse gas's heat-trapping ability relative to carbon dioxide over a 100-year period (Calvin et al., 2023)

UCLouvain as part of its triennial institutional carbon footprint assessment, conducted under the university's transition plan based on 2024 data.

Since the majority of raw data are available at the university or campus level rather than at the faculty level, an allocation key is systematically applied to derive faculty-level estimates. An allocation key is a ratio that attributes a fraction of the total university-level activity to the faculty, based on a variable assumed to be proportional to the faculty's contribution to that activity. The choice of allocation key is not neutral: different keys applied to the same raw data can yield substantially different emission estimates, and no single key is universally appropriate across all emission categories. The allocation key therefore varies by category and is explicitly justified in each corresponding subsection.

4.3 Data collection and processing

4.3.1 Energy

Electricity and heat consumption data were obtained from UCLouvain's technical building management department as structured Excel files covering all buildings on the Louvain-la-Neuve campus for the calendar year 2024. Electricity consumption is expressed in kWh while heat consumption is expressed in MWh and converted to kWh prior to processing to match the emission factor unit (kgCO₂e per kWh). For buildings supplied by two distinct heat sources (the urban heat network and on-site cogeneration), reported in separate files, figures were aggregated per building before allocation. A cleaning step verified correct building attribution and computed annual totals from monthly records.

Room scheduling data for 2024–2025 were extracted from the ADE Scheduler platform and cross-validated against the official course list provided by the faculty administrative department. Discrepancies in room assignments and missing entries were corrected prior to use. Room surface areas were obtained from APPA (UCLouvain's internal facility management platform) which records floor areas in m² and building codes for all registered teaching spaces. Of the 114 rooms in the BSE faculty scope, 34 had no surface entry in APPA, representing 27.8% of total faculty room hours. The treatment of these rooms is detailed in the allocation subsection. Ten rooms totaling 237 faculty hours (2.4% of the total) could not be linked to any building or surface record and were excluded from the calculation.

The five data sources mobilized (faculty schedules, campus-wide ADE records, APPA surface data, building total surface records) and the two energy consumption files were not designed for combined use and required manual name-mapping across systems before any allocation could be performed.

4.3.2 Purchases

Purchase data were obtained from UCLouvain's Administration des Finances (ADFI) as a structured Excel file listing all faculty expenditures for the calendar year 2024. Each line item

includes a purchase description and a unit price. The assignment of each line item to its corresponding ADEME emission category was performed by the thesis co-supervisor and validated by the carbon accounting firm mandated by UCLouvain under its transition plan.

For 136 out of 698 line items (19.5%), a physical quantity is also recorded: representing a mass, a volume, or a number of units depending on the purchase type. For the remaining 562 line items (80.5%), no physical quantity is available. This distinction between monetary-only and quantity-enriched lines is the basis for the two granularity levels (cf. section 4.6).

4.3.3 Mobility

Mobility-related emissions cover all modes of transport used by the faculty population in the context of their academic activities. Three distinct categories are addressed: staff daily commuting, student commuting, and Erasmus student travel. Survey-based data were gathered and used for each of them. In all cases, survey responses are extrapolated to the full target population under the assumption that respondents are representative of the entire group.

Staff commuting

Staff commuting emissions fall under Scope 3, Category 7 of the GHG Protocol (WRI and WBCSD, 2011), which covers transport between employees' homes and their worksite. Emissions are quantified using the distance-based method: for each respondent, the individual carbon footprint is calculated as:

$$C = \frac{EF \times d \times 2 \times 235 \times (1 - rw\ rate)}{1000} \times FTE \quad (4)$$

Where EF is the mode-specific emission factor (kgCO₂e/km, sourced from the ADEME Base Empreinte®), d is the one-way commuting distance (km), 2 accounts for the return trip, 235 is the number of working days per year for a full-time schedule, rw rate is the individual telework rate, and FTE is the respondent's full-time equivalent. The GHG Protocol explicitly endorses extrapolation from a representative survey sample when full-population data are unavailable (WRI & WBCSD, 2013).

The data source is UCLouvain's corporate mobility plan survey⁹ (CMP), a triennial survey most recently conducted in September 2024. The Louvain-la-Neuve campus dataset contains 1,669 respondents representing 1,498 FTE, out of a total LLN staff population of 4,192.9 FTE, yielding a response rate of 35.7% in FTE terms. The survey records each respondent's primary commuting mode, one-way distance, and telework frequency. Individual emission values were

⁹The CMP is the university's strategic mobility plan aimed at reducing carbon emissions by promoting sustainable, low-carbon transportation for both staff and students (PDE_UCLouvain, 2024).

pre-calculated in the survey file by UCLouvain's external mobility consultant using the formula above.

Students daily commuting

Three data sources are used for student daily mobility. The first is the student component of the UCLouvain corporate mobility plan survey (2024), which collected responses from over 5,300 students across the university, representing a response rate of approximately 17%. It records commuting distance, mode of transport, and student type (daily commuter or resident). It is used here in two ways: as a university-level aggregate scaled to the faculty for the first granularity level, and as the source for the train/bus modal split among public transport users on the LLN campus (55.2% train, 44.8% bus), which informs the weighted EF applied at the faculty level. The second and third are two faculty-specific surveys conducted during the 2024–2025 academic year: one targeting daily commuters and one targeting residents (students living in shared or not student accommodation near campus), both administered within the BSE faculty and achieving a combined response rate of approximately 20% of enrolled students. Because daily commuters and residents exhibit structurally different mobility patterns in terms of frequency, distance, and mode, they are treated as distinct sub-populations and surveyed separately.

Erasmus outgoing mobility

Two data sources are available for Erasmus outgoing students. The first is an administrative file provided by UCLouvain's international relations service listing all 41 outgoing Erasmus students from the faculty for the 2024–2025 academic year, including their destination, but without mode of transport. The second is a dedicated survey designed and distributed by the author to all 41 outgoing students, which collected 24 responses, representing a response rate of 58.5%. The survey recorded departure and arrival locations, mode of transport, and number of return trips per student during the exchange period (with means of transportation for each additional trip).

4.3.4 Wastes

Waste data were collected through UCLouvain's central facilities service in the form of an Excel file covering the Louvain-la-Neuve campus for the calendar year 2024. Data are available at the campus level only, with no disaggregation by faculty or building. They cover seven waste streams: household waste destined for incineration, paper and cardboard for recycling, garden waste for composting, mixed metals for recycling, healthcare waste (category B2 and litter), special industrial waste (chemical), and electronic and IT equipment. For each stream, the total mass collected is recorded in tons. Emission factors from the ADEME Base Empreinte® were applied to each stream individually, with each factor selected to reflect the declared end-of-life treatment pathway, converting waste mass to tCO₂e.

4.3.5 Digital

Data from digital infrastructure were obtained through UCLouvain's central IT services as an Excel file covering the entire university for the calendar year 2024. The data distinguish between incoming network traffic 15.7 petabytes¹⁰ (PB), representing data received by UCLouvain servers from external sources, and outgoing network traffic 8.99 PB, representing data sent from UCLouvain servers to external destinations, yielding a total of 24.69 PB exchanged. This metric captures network traffic on UCLouvain infrastructure only; embodied carbon in devices, on-premises server hardware, and storage energy consumption fall outside the scope of this dataset due to the absence of faculty-level data for these categories. Data consumption generated off campus through personal internet connections is similarly excluded, as it does not transit through UCLouvain infrastructure.

4.4 Allocation keys

Every carbon footprint assessment relies on allocation choices. Because the BSE faculty shares buildings, infrastructure, and university-wide services with other entities, raw consumption data are rarely directly attributable to the faculty. An allocation step is therefore required to translate aggregate or shared measurements into a faculty-level estimate. The allocation keys vary by emission category, reflecting the nature of each source and the available data: each is justified in the corresponding subsection.

4.4.1 Energy

Since BSE does not occupy dedicated buildings but shares facilities with other faculties, energy consumption must be allocated to the faculty level. The allocation operates in two steps. For each room used by the faculty, the fraction of its total scheduled usage attributable to BSE courses is calculated from the scheduling data as a ratio of faculty hours to total room usage hours. This ratio is then multiplied by the room's share of total building floor area (estimated or precise), depending on data availability, to derive the fraction of the building's total energy consumption attributable to that room's faculty usage. Summing these fractions across all rooms within a building yields the building-level allocation factor. This procedure assumes energy consumption is uniformly distributed across the building's floor area, which likely underestimates consumption in laboratory spaces relative to administrative or teaching rooms; the direction and magnitude of this bias are discussed in the results.

For three buildings (De Serres, Carnoy A+B, and Carnoy C), internal floor plans were unavailable, and the faculty's spatial fraction could not be determined from APPA data. For each of these buildings, the fraction was estimated as a fixed proportion of total building area based on

¹⁰ A petabyte (PB) is a unit of digital information equal to 10^{15} bytes, or approximately one million gigabytes. It is the standard unit used to measure large-scale network traffic volumes.

physical layout observation. A campus-wide cogeneration credit was allocated to the faculty using the ratio of BSE scheduled hours to total campus scheduled hours (1.68%), applied to the total avoided emissions computed from the cogeneration plant's reported output and the Belgian electricity grid emission factor.

4.4.2 Purchases

No allocation is required for this category, as purchases data were obtained directly at the faculty level from UCLouvain's ADFI and are entirely attributable to the BSE faculty.

4.4.3 Mobility

The allocation approach varies across the three mobility subcategories depending on the level at which the data were collected. Where data are available at the university level only, a population-based ratio is applied to derive faculty-level estimates. Where data are collected directly at the faculty level, no allocation is required.

Staff commuting

Since the CMP survey covers the entire LLN campus, faculty-level emissions are derived by scaling the campus-wide emission intensity to the BSE faculty headcount according to:

$$E_{BSE} = \frac{E_{CMP}}{FTE_{CMP}} \times FTE_{BSE} \quad (5)$$

where E is total emissions (tCO₂e), FTE is full-time equivalent headcount, and subscripts denote BSE faculty and CMP respondents respectively.

The 72.5 FTE figure corresponds to the net active FTE for 2024, as recorded in UCLouvain HR records. The gross registered headcount of 97.2, which counts all staff formally enrolled in the HR system regardless of whether they were physically present and working during the reporting year, differs from the net figure precisely because it includes individuals on long-term sick leave, sabbatical, or other extended absences. Since these individuals are not generating regular commuting emissions, the gross figure was not retained. Whether externally contracted lecturers are captured in the 72.5 FTE figure is unclear; to the extent they are not, their commuting emissions are absent from this estimate. This exclusion is a structural consequence of the scaling method applied: since they hold no FTE contract, they cannot be incorporated into an FTE-based calculation without a dedicated data collection effort. This scaling approach assumes that BSE staff commute like the average LLN respondent: an assumption that cannot be verified or refined with the current data structure, as the CMP survey contains no faculty identifier. If BSE staff are systematically more car-dependent or live farther from campus than the average LLN employee, this assumption introduces a downward bias; the inverse would produce an upward bias.

Students daily commuting

For the CMP survey, results are scaled to the faculty level using the ratio of enrolled BSE students to total UCLouvain students on the Louvain-la-Neuve campus: 1,300 out of 26,334, giving a scaling factor of 4.74%. No allocation is required for the two faculty-specific surveys, as responses were collected directly from BSE students. Because both surveys cover all five years of the program proportionally, respondents are considered representative of the full student population, and results are scaled to the total enrolled headcount by applying a scaling factor equal to the ratio of total enrolled students to survey respondents, computed separately for daily commuters and residents.

For daily commuter emissions, the public transport category was recorded as a single undifferentiated mode without distinguishing between train and bus at the individual level. A weighted emission factor is therefore applied using the modal split recorded in the CMP survey among Louvain-la-Neuve students using public transport: 55.2% train and 44.8% bus, yielding a composite factor of 0.0921 kgCO₂e/km, computed as $(0.55 \times 0.0484) + (0.45 \times 0.146)$, where 0.0484 kgCO₂e/km is the Belgian rail factor and 0.146 kgCO₂e/km is the urban bus factor, both from the ADEME Base Empreinte®. This modal split is the only available source for this breakdown at the campus level.

Erasmus outgoing mobility

No allocation is required for either data source. The administrative file lists only BSE outgoing students, and the dedicated survey was distributed exclusively to BSE Erasmus.

4.4.4 Waste

Since waste data are available at campus level only, an allocation key is required to derive faculty-level estimates. The ratio of BSE faculty full-time equivalents to total Louvain-la-Neuve campus FTEs is used as the allocation key, drawn from UCLouvain HR records for 2024. An FTE-based key was preferred over a raw headcount key as it better reflects actual presence and activity on campus. This key is applied uniformly across all seven waste streams, which introduces a directional bias for laboratory-driven streams such as hazardous industrial waste and electronic equipment: laboratory-intensive faculties structurally generate disproportionate volumes of these relative to administrative units, meaning the uniform key likely underestimates BSE's contribution to those specific streams.

4.4.5 Digital

Since digital infrastructure data are available at the university level only, an allocation key is required to derive faculty-level estimates. The combined population of BSE faculty (enrolled students and academic and administrative staff expressed in FTE) relative to the total UCLouvain headcount across all campuses is used as the allocation key. In the absence of faculty-level data on server usage, storage consumption, or network traffic, the university-wide population serves as the best available proxy for digital resource use. This approach assumes

equal per-capita data consumption across all user types. Research-intensive staff are likely to generate disproportionately higher traffic through large dataset transfers and computational workloads. Given BSE's research profile, this assumption likely underestimates the faculty's actual digital footprint.

4.5 Emission factors

EFs are sourced from the Base Empreinte® database (version 23.9) maintained by ADEME, except for two categories for which no equivalent entry exists in that database. These two exceptions are the teleworking EF (0.729 kgCO₂e per working day) (Braga Kappler et al., 2026), and the digital infrastructure factor (0.210 kgCO₂e per GB) (ISIT¹¹, 2026). Both were selected as part of UCLouvain's institutional carbon accounting process.

Where physical activity data are available: energy in kWh, distance in km, or mass in kg, a material or process-specific factor is applied directly. Where only monetary data are available, a sector-average factor expressed in kgCO₂e per thousand euros is used. Heat EFs are applied on a higher heating value¹² (HHV) basis, consistent with the reporting convention used in the energy data provided by UCLouvain's technical services. The complete list of EFs, with associated categories, values, units, and sources, is provided in Appendix (9.1).

4.6 Granularity scenario construction

For each emission category, the alternative levels of data granularity available are translated into explicitly defined calculation scenarios. The number of scenarios varies by category depending on how many distinct levels of data detail are operationally available. Where multiple scenarios are compared, all other parameters are held constant such that any difference in the resulting emission estimate is attributable solely to the granularity dimension being tested.

Energy is excluded from the granularity comparison. The allocation method operates at the finest level the available data permit from the outset (the individual room) and no valid alternative on a larger scale exists. A building-level allocation without temporal correction would systematically overattribute consumption to BSE in shared buildings and was therefore rejected on methodological grounds.

¹¹ ISIT (Institute for Sustainable IT): European network of institutes promoting responsible digital practices and publishing emission factors for digital infrastructure, including network traffic.

¹² HHV (higher heating value): total heat released by fuel combustion including condensation of water vapor in fuel gases, as opposed to lower heating value (LHV) which excludes it. (Gillenwater, 2005)

4.6.1 Purchases

Two granularity levels are defined for the purchases category and labelled G1 and G2 consistently throughout the sensitivity analysis.

G1 uses an expenditure-based approach: the monetary value of each purchase line item is multiplied by the sector-average EF for the corresponding ADEME category, expressed in kgCO₂e per thousand euros, drawn from the ADEME Base Empreinte®. This level requires only the financial data provided by ADFI and the ADEME category assignment.

G2 uses a hybrid approach. For the 19.5% of purchased items for which a physical quantity is available, a product-specific or material-specific emission factor from the ADEME Base Empreinte®, expressed in kgCO₂e per unit, mass or volume, replaces the monetary factor. For the remaining 80.5% of line items for which no physical quantity is recorded, the G1 expenditure-based factor is retained as a fallback. G2 is therefore not a pure activity-based approach but a partial refinement applied where the data allow it.

4.6.2 Mobility

Staff commuting

Staff commuting emissions are quantified at a single granularity level: the BSE faculty on the Louvain-la-Neuve campus. Descending to a finer level, such as by department or staff category (academic, administrative, technical), was not possible with the available data. The CMP survey contains no organizational identifier linking individual respondents to a faculty or department, making it impossible to isolate a BSE-specific emission intensity from the campus-wide dataset. The single-level structure of this post is therefore a structural constraint of the data source, not a methodological choice.

Students daily commuting

Two granularity levels are defined for student daily mobility. The first uses the scaled CMP result as a proxy for faculty-level emissions, applying the university-wide student mobility profile to the BSE population via the enrolment ratio (cf. section 4.4.3). The second uses the two faculty-specific surveys (one for daily commuters and one for residents) as the reference estimate, collected directly from BSE students and requiring no population-based scaling. Comparing these two levels quantifies the effect of substituting a university-level survey, scaled by population ratio, with faculty-specific data collection targeting each sub-population separately.

Erasmus outgoing mobility

Two granularity levels are defined based on the method used to assign mode of transport and number of return trips. G1 assigns mode of transport according to the UCLouvain institutional travel rule (*charte de mobilité internationale*, 2021) and assumes one return trip per exchange period for all students. G2 uses the mode of transport and number of return trips declared by survey respondents directly, extrapolated to the full population of 41 students by proportional

scaling under the assumption that respondents are representative of the full cohort at their respective destinations.

4.6.3 Waste

Only one granularity level is available for waste. Data are available at campus level only, with no disaggregation by faculty, building, or activity type within UCLouvain's current tracking infrastructure. The granularity analysis for this category is therefore limited to assessing the adequacy of the allocation proxy and identifying the direction of potential bias, rather than comparing two computed estimates.

4.6.4 Digital

Only one granularity level is available for digital infrastructure. Network traffic data are available exclusively at the university level, with no disaggregation by campus, faculty, or user type. The single scenario reflects total university traffic allocated to BSE via population share, and the absence of more granular data precludes the construction of alternative scenarios.

4.7 Method for comparing granularity levels

For each emission category, the granularity assessment compares emission estimates obtained at diverse levels of data detail and evaluates whether the gain in precision justifies the additional data collection effort. The assessment combines two elements: a quantitative comparison of the estimates obtained at each granularity level, and a qualitative evaluation of what information is invisible at the lower granularity level and becomes accessible at the higher one.

For categories with two discrete granularity levels (purchases, Erasmus outgoing travel, and student commuting), the two estimates are compared directly. The difference is interpreted against three criteria:

- The magnitude relative to the total faculty footprint
- The nature of the information that the lower granularity level fails to capture
- The practical feasibility of collecting higher granularity data in future assessment cycles.

For categories with a single available granularity level (staff commuting, waste, and digital infrastructure) no quantitative comparison is possible. The analysis instead examines the adequacy of the allocation proxy or data source used, identifies the direction and magnitude of residual bias, and specifies the data infrastructure or collection effort that would be required to reduce uncertainty in future iterations.

4.8 Tool and data processing

Data preprocessing and aggregation were performed in Python 3.9.13. The libraries used and their respective purposes are listed in Table 3.

Table 3 : Software libraries used for data preprocessing and aggregation.

Library	Purpose
pandas	Tabular data manipulation
openpyxl	Excel file handling
requests	Web scraping of UCLouvain scheduling platform
BeautifulSoup	HTML parsing for scheduling data extraction
matplotlib	Data visualization
pathlib, datetime, re	File management and text processing

Three scripts were developed for the energy allocation workflow: one to extract room occupancy data from the UCLouvain scheduling platform (monhoraire.uclouvain.be), one to enrich the extracted data with faculty entity codes retrieved from the UCLouvain course catalogue, and one to compute faculty-level allocation keys from the consolidated scheduling dataset. Additional scripts were developed to produce the data visualizations presented in the Results section.

For the purchases category, Windows Copilot was used to process faculty purchase records extracted from UCLouvain's financial system. For each line item, Copilot identified the corresponding ADEME emission category and assigned the associated emission factor from the Base Empreinte® database. All category assignments and EF selections were manually reviewed and validated by the thesis co-supervisor before use. The output is a structured Excel file recording, for each purchase line, the assigned category, emission factor, and calculated emission total.

Claude (claude-sonnet-4-6, Anthropic) was used to support the scheduling data extraction and correction workflow, limited to structured data processing tasks (parsing, deduplication, and format standardization) under direct supervision of the author, with all outputs manually reviewed before use.

Final emission calculations were performed in Microsoft Excel for all categories. The selection of input data sources and the assignment of emission factors were validated by an independent carbon accounting expert mandated by UCLouvain as part of its institutional carbon accounting project.

5 Results

5.1 Global emission picture

The total carbon footprint of the BSE faculty reaches 1,690 tCO₂e for the calendar year 2024 (Figure 8). Student commuting alone accounts for 67.3% of this total, a figure driven by structural patterns in student residential choices and regional transport infrastructure, over which the faculty and central administration exercise limited direct leverage in the short-to-medium term. This post is necessary for a complete inventory, but its dominance compresses the remaining categories and obscures emission sources that are more directly actionable through institutional decisions.

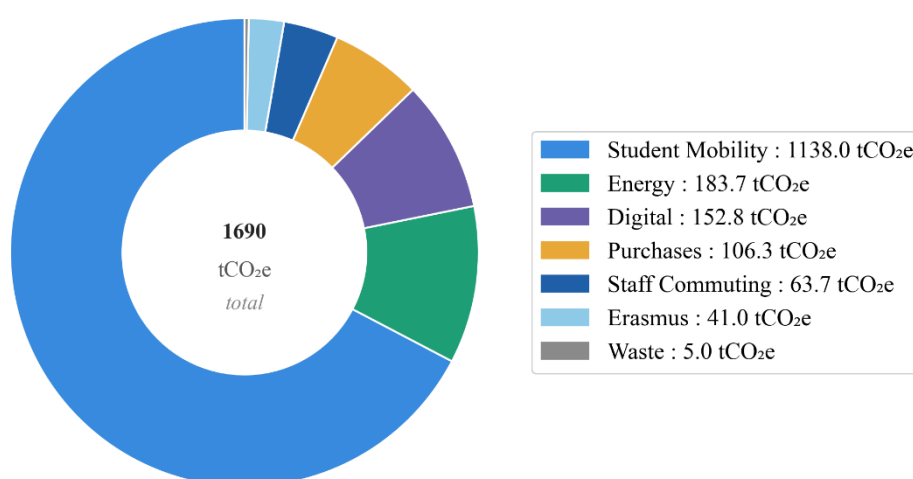


Figure 8 : Carbon footprint of the BSE faculty, UCLouvain (2024), distributed across seven emission categories at the best available granularity level per category

Restricting the analysis to the six categories under the faculty's operational or procurement control shifts the priority structure substantially. Energy becomes the leading post (33.3%), followed by digital infrastructure (27.7%) and purchases (19.3%), for a controllable total of 552 tCO₂e (Figure 9). In these categories, facility management decisions, procurement policies, and travel governance directly determine emission trajectories. Staff commuting is retained in this view because, unlike student mobility, it is partially addressable through telework policy, campus accessibility agreements, and modal shift incentives. Those are levers that fall within the faculty's institutional authority.

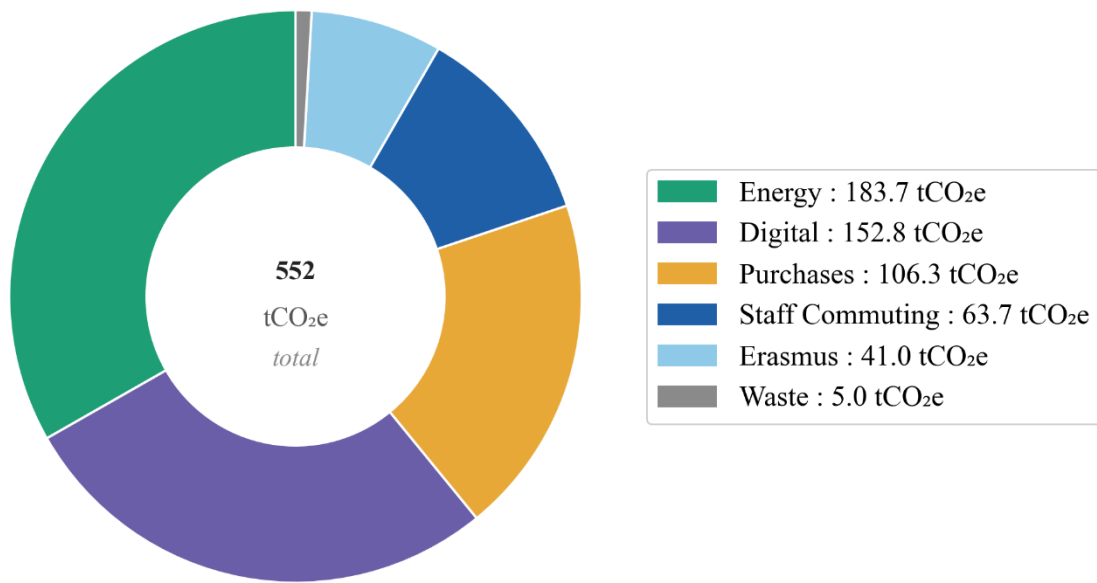


Figure 9 : Carbon footprint of the BSE faculty excluding student mobility, restricted to emission categories within the faculty's operational or procurement control (2024).

The two figures are complementary rather than alternative: the first captures the full scope of the faculty's climate impact, the second identifies where administrative action is most likely to produce measurable reductions.

5.2 Emission results and granularity sensitivity by category

5.2.1 Student daily commuting

Student daily mobility is the dominant emission source, accounting for 67.3% of the faculty's total footprint at its highest granularity level. Scaled to the BSE faculty, the university-level CMP survey yields 666 tCO₂e per year. The two faculty-specific surveys yield 1,138 tCO₂e per year. The gap between the two granularity levels is 71% (Figure 10)

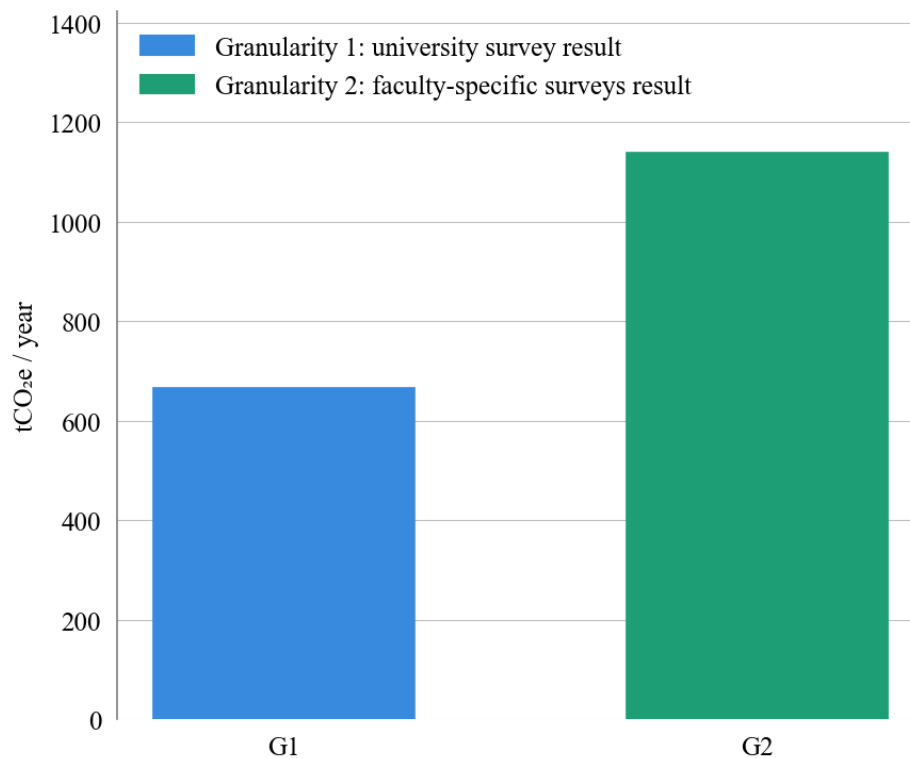


Figure 10 : Comparison of granularity levels for student daily mobility (tCO₂/year)

This gap reflects a structural difference between the university-wide mobility profile captured at G1 and the actual mobility patterns of BSE students. At G1, the CMP survey captures the full LLN student population, including residents who travel very short distances or not at all during the week; this yields an average one-way distance of 13.8 km per student. The faculty-specific surveys treat daily commuters and residents separately, applying a distinct emission profile to each sub-population. Since daily commuters travel an average of 34.2 km one-way and represent 61% of the BSE student population, they account for approximately 86% of total mobility emissions. An asymmetry invisible at G1, which treats all students as equivalent emission sources.

Daily commuters represent 61% of the student population but concentrate 86% of total mobility emissions, while residents account for the remaining 39% of students but only 14% of emissions (Figure 11). A reduction strategy built on the G1 estimate would be working from a baseline 42% below the faculty-specific result, with no basis for identifying daily commuters as the primary lever.

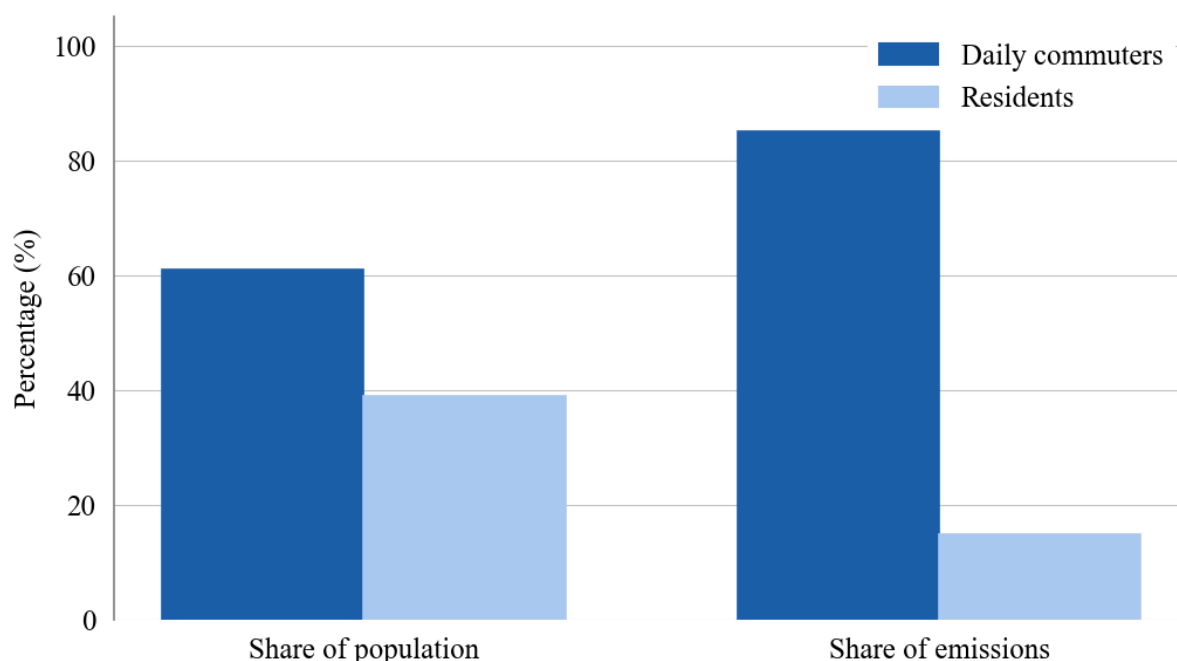


Figure 11 : Share of emissions and share of population by student mobility type

Residual uncertainty on the G2 estimate is limited. A sensitivity analysis on train commercial speed (the principal assumption for daily commuters) produces a range of 1,089 to 1,168 tCO₂e, a spread of less than 8% around the central estimate. This is narrow enough for the G2 figure to be considered robust for planning purposes, and sufficient to ground a targeted strategy on daily commuter behavior rather than on the total student population.

5.2.2 Staff commuting

Staff commuting accounts for 3.8% of the faculty's total footprint, with an estimated 63.7 tCO₂e for 2024. Unlike the other mobility categories in this assessment, no granularity comparison is possible: the CMP survey contains no faculty identifier, making it impossible to isolate a BSE-specific emission intensity from the campus-wide dataset. The estimate is therefore derived by scaling the campus-wide emission intensity of 875.5 kgCO₂e per FTE per year to the BSE faculty's 72.5 FTE.

Solo car drivers represent 26% of respondents yet account for 36.1 tCO₂e, more than half the faculty total. Car-based modes reach 46.7% of respondents once shared rides are included, but the emission weight is concentrated in solo use. Train travel at 22.1% of respondents contributes 9.7 tCO₂e, reflecting the low EF of Belgian rail. Bus travel at 9.2% of respondents produces 9.0 tCO₂e, nearly matching train in absolute emissions despite covering far fewer respondents, a direct consequence of its higher peri-urban EF. Active modes like cycling (11.1%) and walking (10.9%) contribute to zero emissions (Figure 12).

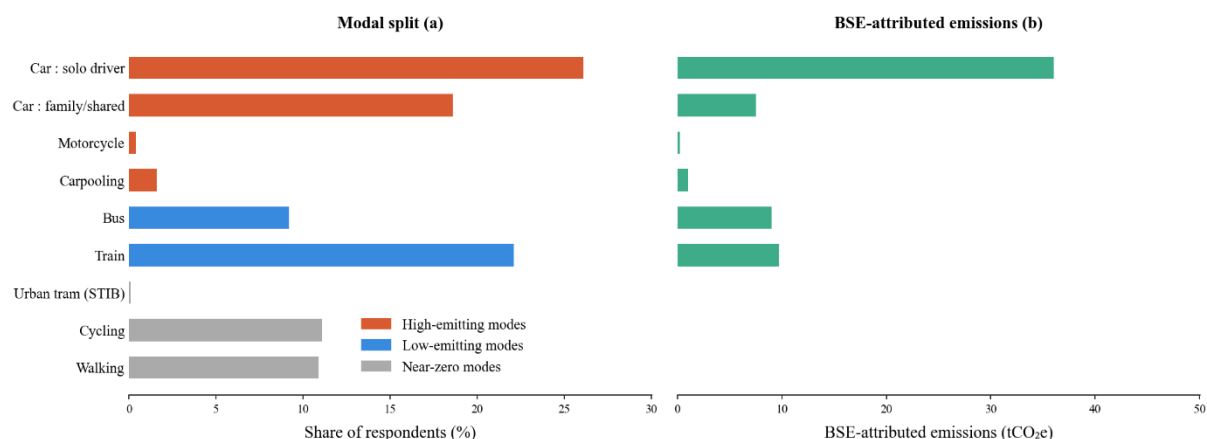


Figure 12 : Modal split (a) and BSE-attributed emissions by commuting mode (b), based on CMP survey (Louvain-la-Neuve campus, 2024)

Modes used by comparable shares of respondents produce radically different emission totals depending on their emission factor: train and solo car each account for roughly one in five respondents, yet their emission totals differ by a factor of nearly four.

The 63.7 tCO₂e estimate rests on one central assumption: that BSE staff commute like the average LLN respondent. This cannot be verified with the current data structure, since the CMP survey contains no faculty identifier. The uncertainty is therefore structural rather than statistical; it cannot be reduced through further analysis of existing data, but only by adding a faculty identifier to future CMP questionnaires.

5.2.3 Erasmus outgoing mobility

Erasmus OUT mobility for the BSE faculty covers 41 outgoing students for the 2024–2025 academic year across 15 destinations in Europe, Canada, and South America. G1, built from the administrative list, assigns transport mode using the UCLouvain institutional rule¹³ (*charte de mobilité internationale*, 2021) and assumes one round trip per student, yielding 38.7 tCO₂e (0.94 tCO₂e per student). G2, based on a survey of 24 students (58.5% response rate) with destination-weighted extrapolation, yields 41.0 tCO₂e (1.00 tCO₂e per student). The gap is +5.9%, with G2 above G1 (Figure 13)

¹³ train below 8 hours of travel, plane above (*charte de mobilité internationale*, 2021)

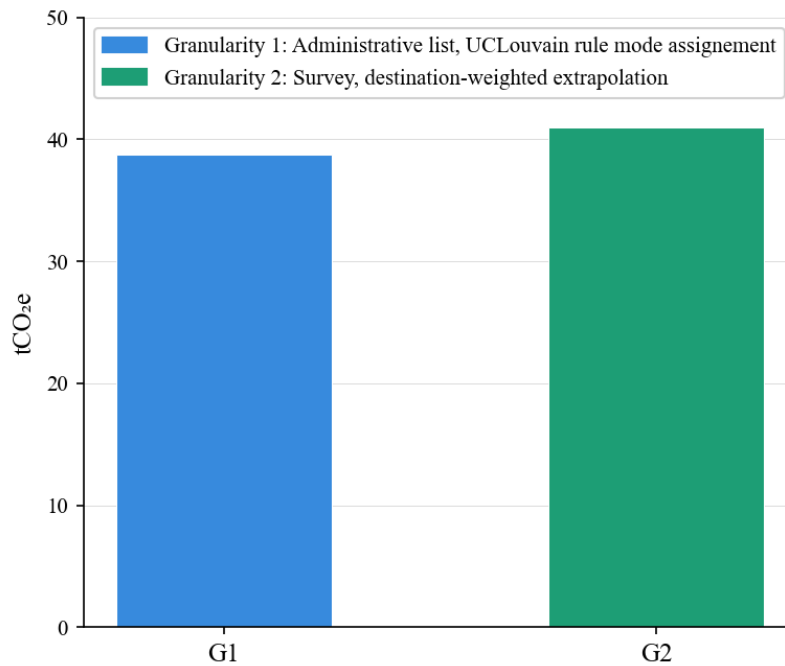


Figure 13 : Erasmus OUT emissions by granularity level

The gap originates from two biases invisible to an administrative-list approach. First, G1 assumes one return trip per student; the survey reveals several students made multiple trips during their exchange, including four round trips for EPFL, three for Torino, and two for Uppsala and Bologna. On long and medium-haul routes, each additional trip carries significant emissions.

Second, G1 applies the UCLouvain travel rule uniformly, a deliberate simplification at this granularity level. G2 reveals where it misfires: students to Italy, Austria, and Denmark predominantly took the train on journeys the rule assigned to plane. This rail preference on medium-haul routes may partly reflect the environmental awareness of a faculty with a strong sustainability curriculum, though cost and convenience cannot be ruled out. These modal divergences partially offset the trip-count underestimation, keeping the G1–G2 gap below 10%, but the directional errors are systematic and destination-specific.

The emission distribution under G2 is concentrated: Argentina (2 students), UQAM Montréal (4 students), and Bologna (4 students) account for 46.2% of total emissions despite representing only 10 of 41 students (Figure 14). Intercontinental destinations dominate through their emission factor, but Bologna's disproportionate share reflects a compounding effect: multiple trips combined with plane use on a corridor where train is a viable alternative. This destination-level breakdown is visible only at G2 and is precisely what makes it actionable: a reduction strategy targeting intercontinental travel and high-frequency corridors cannot be built from an administrative list.

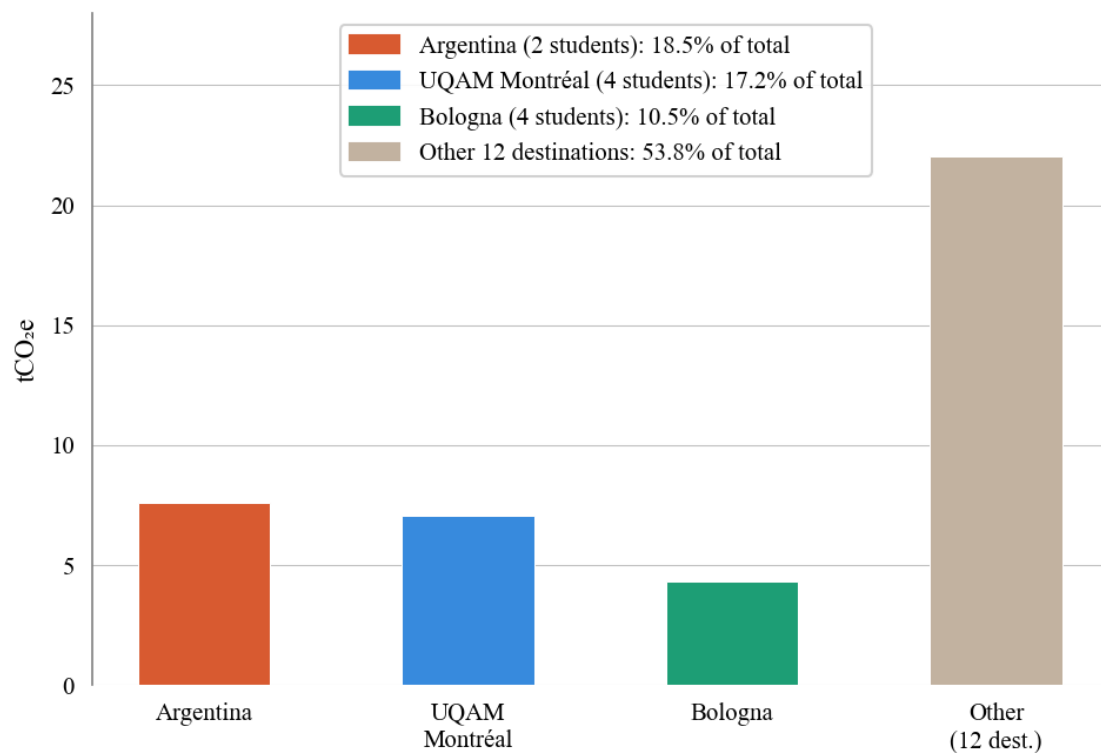


Figure 14 : Erasmus OUT emission distribution by destination (G2)

5.2.4 Energy

Energy consumption for the BSE faculty in 2024 totals 183.7 tCO₂e under the central spatial scenario, with a range of 160.4 to 248.0 tCO₂e across the three hypotheses tested (a spread of -13% to +35%) around the central estimate. The cogeneration credit of 53.3 tCO₂e is constant across all three scenarios, so the entire spread originates from the gross allocation alone. The three spatial scenarios are presented as donuts charts, with buildings of known floor areas fixed across all three and only the fractions of De Serres, Carnoy A+B, and Carnoy C varying (Figure 15).

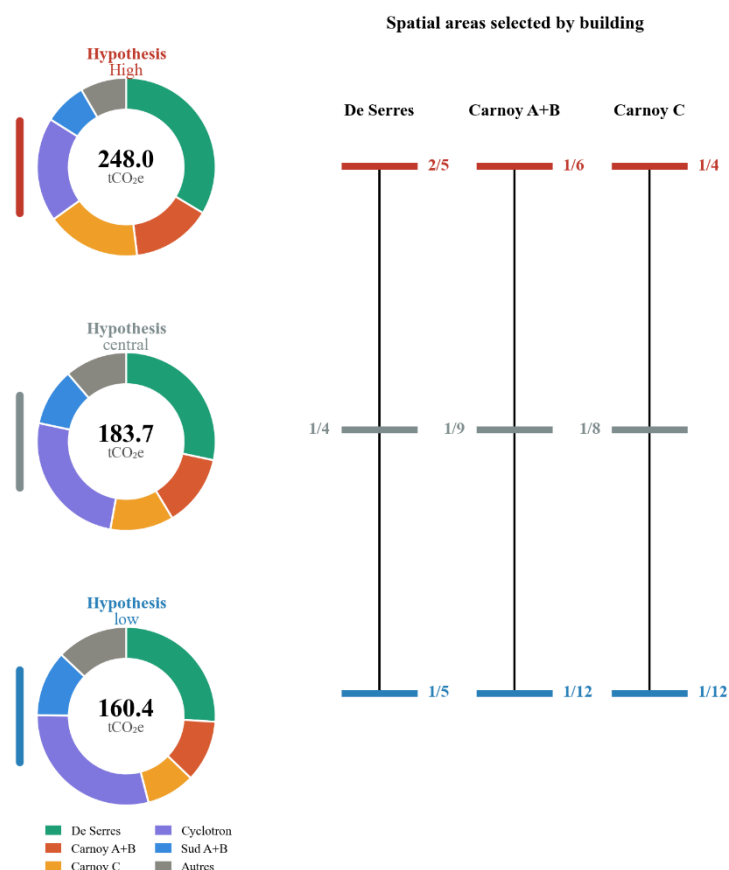


Figure 15 : BSE faculty energy emissions under three spatial allocation scenarios (tCO₂e net of cogeneration credit)

The 55% difference between the lowest and highest net result is driven by three buildings alone. Everything else in the allocation is deterministic: buildings with known floor area contribute a fixed quantity regardless of the hypothesis retained, and the cogeneration credit is constant across all scenarios.

The central scenario is reported as the reference value because its spatial fractions are the most geometrically defensible single-value approximation available, but it carries no greater empirical authority than the low or high. All three are plausible, and none is verifiable without floor-plan access. The width of the range reflects a genuine epistemic limitation that arithmetic cannot resolve. Without floor plans for De Serres, Carnoy A+B, and Carnoy C, the result cannot be narrowed further. The EFs, by contrast, are the most reliable element in the chain: the Belgian electricity mix factor and the district heating factor are drawn from established databases and carry no local assumption. The uncertainty in this post is spatial, not energetic. A secondary source of bias, unquantifiable from the available data, stems from the uniform floor-area distribution assumption: laboratory spaces consume substantially more energy per m² than administrative or teaching rooms, so the allocation likely underestimates BSE's actual consumption to the extent that its rooms include energy-intensive uses. Metered data at the room or zone level would be required to correct this bias.

5.2.5 Digital

Digital infrastructure accounts for 9.0% of the faculty's total footprint, with an estimated 152.8 tCO₂e for 2024. As with staff commuting, no granularity comparison is possible for this post: network traffic data are available at the university level only, with no disaggregation by campus, faculty, or user type. The estimate is derived by applying a population-share allocation key of 2.95% (BSE headcount (1,372.5) relative to total UCLouvain headcount (44,702.3)) to the university's total network traffic of 24.69 PB.

This split reflects the university-level proportion and cannot be attributed to faculty-specific usage patterns, as no disaggregated data are available (Figure 16). Nevertheless, the dominance of incoming traffic at the institutional level suggests that data consumption, rather than data generation, is the primary driver of UCLouvain's digital footprint.

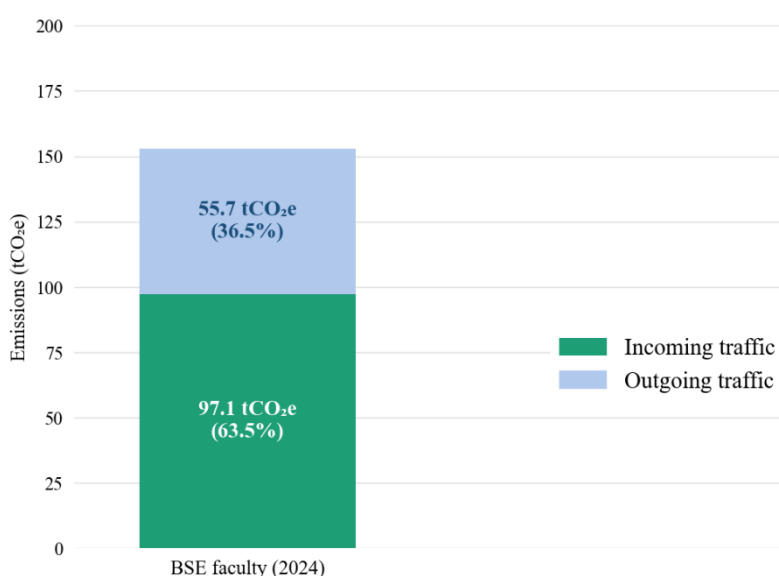


Figure 16 : BSE faculty digital emissions allocated from UCLouvain network traffic, split between incoming and outgoing traffic (2024)

5.2.6 Purchases

Purchases account for 6.3% of the faculty's total footprint. The G1 estimate, based on monetary EFs applied across all 698 purchase lines, gives 109 tCO₂e. G2 yields 106.3 tCO₂e, a reduction of 2.7 tCO₂e (–2.5%). This aggregate gap is modest, but it masks a more substantial effect at the line level: the 136 enriched lines drop from 16.4 tCO₂e at G1 to 13.7 tCO₂e at G2, a reduction of –16.3% on that subset alone. The 562 remaining lines are unchanged across both granularity levels, which dilutes the effect at the portfolio level. The gap is therefore not small in itself; it reflects only the share of lines to which the refinement could be applied (the 136) (Figure 17).

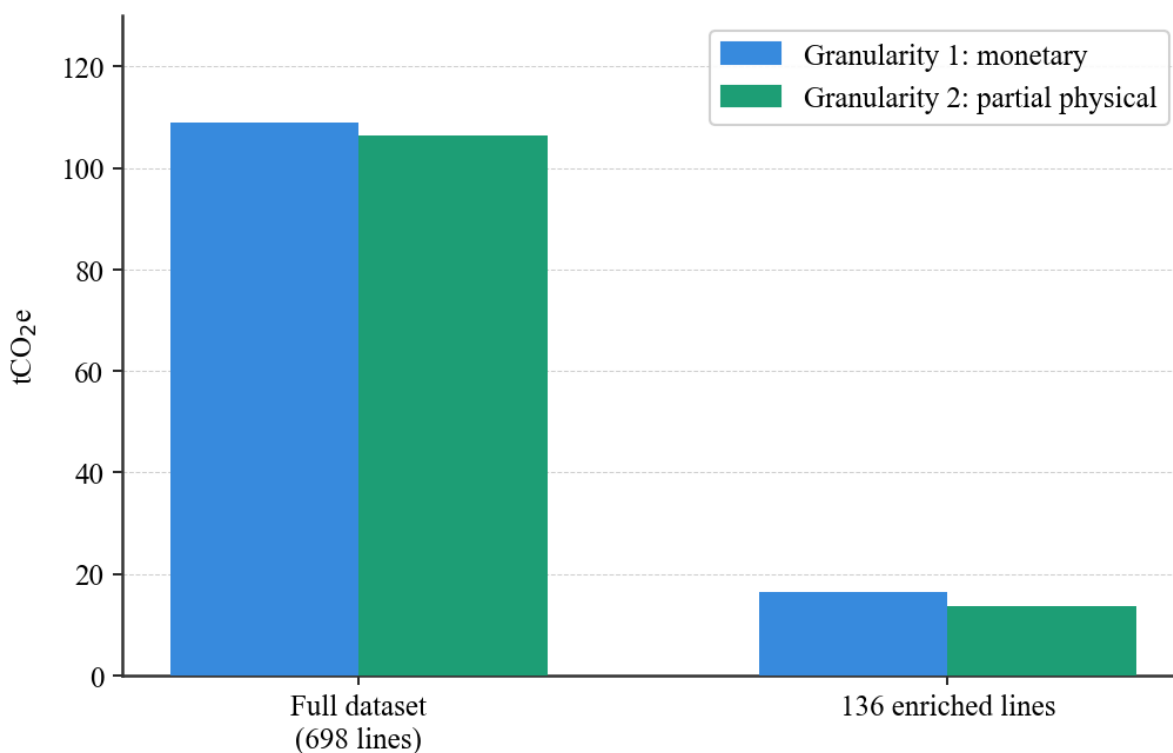


Figure 17 : Purchases emissions at G1 and G2, at two scales. Left: full dataset (698 lines). Right: lines with product-specific data available (136 lines)

Of the 136 lines for which product data were available, only 58 were ultimately assigned a physical or product-specific emission factor. The remaining 78 could not be matched, due to insufficient product descriptions, unit incompatibilities, or the absence of a suitable entry in the Base Empreinte® and were returned to the G1 monetary estimate. The 58 matched lines contribute 2.2 tCO₂e, the 78 unmatched lines 11.5 tCO₂e, and the 562 untouched lines 92.6 tCO₂e (Figure 18). The net reduction at G2 suggests that the monetary approach tends to overestimate high-value, low-mass purchases but this cannot be generalized across the full dataset.

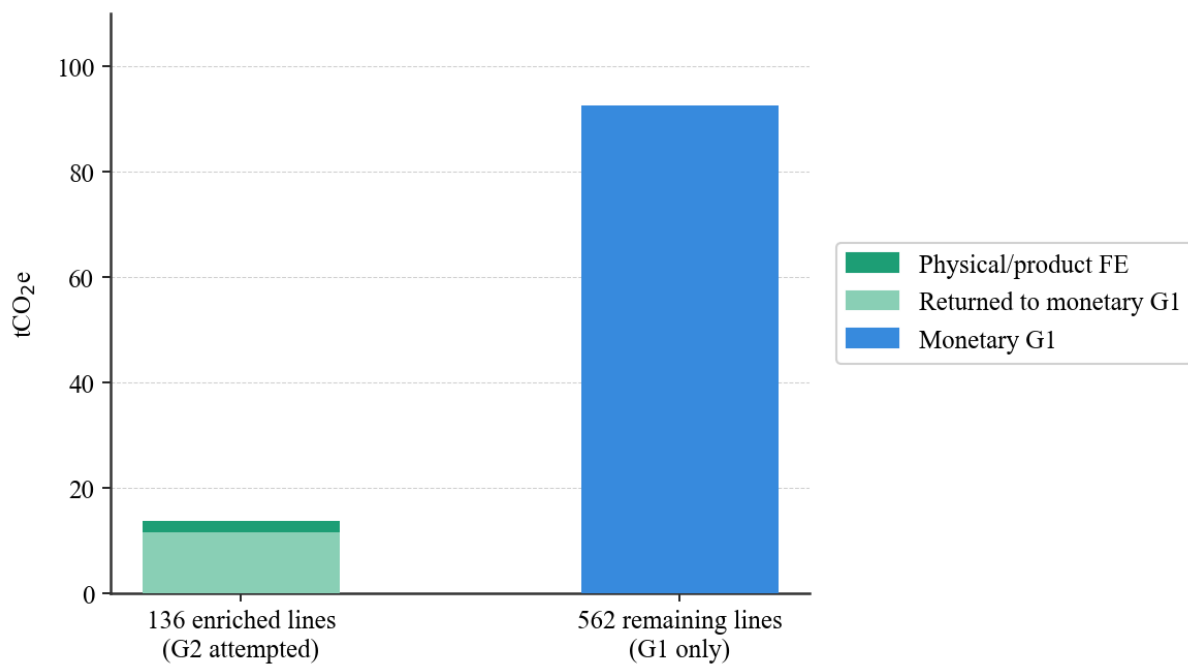


Figure 18 : G1 and G2 emission factor composition across the 698 purchase lines.

The most informative finding is structural: the ceiling on granularity improvement is set not by analytical effort but by the composition of the purchase dataset itself. Of 698 purchase lines, only 58, which represent 8.3% of the dataset and 2.06% of the post total emission, reached a level of product specificity sufficient to replace the monetary estimate. The monetary approach is therefore not a simplification to be corrected but the only defensible method for the vast majority of this post, given current data availability.

5.2.7 Waste

Waste accounts for 0.3% of the faculty's total footprint, with an estimated 4.99 tCO₂e for 2024. As with staff commuting and digital, no granularity comparison is possible: waste data are available at campus level only, with no disaggregation by faculty, building, or activity type possible. The estimate is derived by applying an FTE-based allocation key (72.5 BSE FTE out of 4,192.9 total LLN FTE (1.74%)) over the total LLN campus waste footprint of 287.6 tCO₂e (Figure 19).

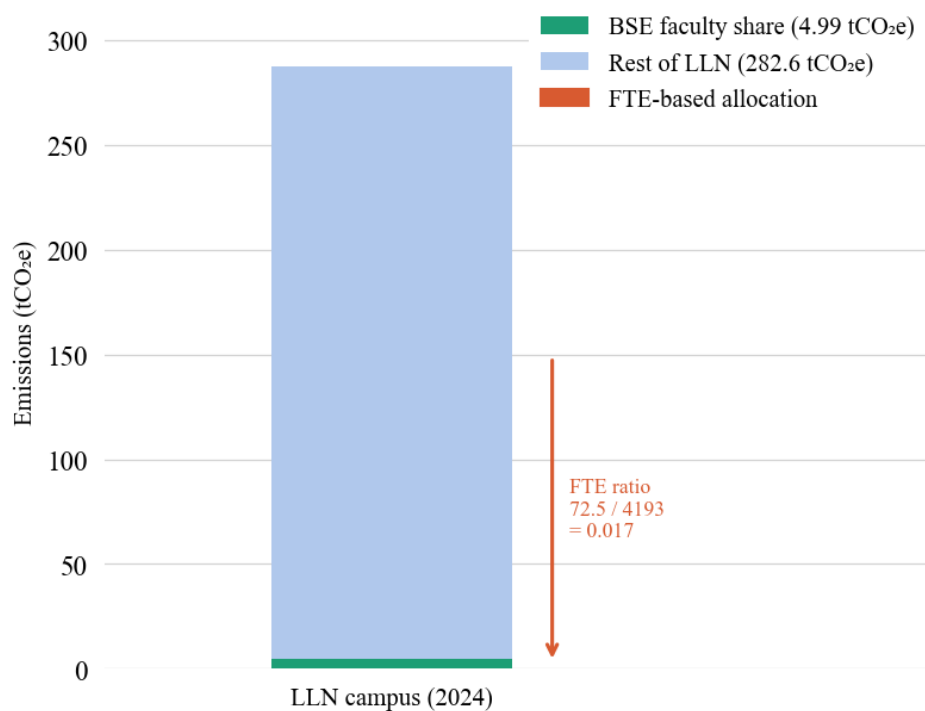


Figure 19 : BSE engineering faculty share of LLN campus waste emissions, by FTE-based allocation (2024).

At 4.99 tCO₂e, this post represents well under 1% of the faculty's total footprint. Even a 50% error in this estimate would be invisible at the scale of the carbon footprint. The allocation-by-proxy approach is therefore proportionate to the post's magnitude. Obtaining entity-level waste data would require a dedicated institutional agreement with UCLouvain's facilities management service; an investment the current order of magnitude does not justify.

6 Discussion

The discussion is structured around four themes. First, drawing on the empirical findings of this assessment, an improved data collection framework is proposed for future BSE faculty carbon assessments. Second, the transposability of the methodology is examined across other entity types within UCLouvain, identifying where it applies directly and where it requires adaptation. Third, the findings are situated in the context of an institutional carbon accounting tool currently being developed at UCLouvain. Finally, the generalizability of the approach and its underlying principles to complex organizations beyond this university is assessed.

6.1 Proposed data collection framework for future BSE faculty carbon assessments

As Woszczek et al. (2025) rightly note, in carbon footprint it is not only the calculation that matters, but getting the right data from the right people.

Normative frameworks such as the GHG Protocol's Inventory Management Plan¹⁴ (IMP) and the EPA¹⁵'s simplified IMP template provide a useful reference for structuring carbon inventory processes. The EPA template defines seven core components¹⁶ that together constitute a comprehensive architecture for institutionalizing GHG reporting (EPA, 2026; World Resources Institute, 2004). However, these frameworks share a structural limitation directly relevant here: they were designed for centralized organizations with a dedicated sustainability team and remain silent on how data should be organized upstream of the inventory in ways that minimize the collection burden across reporting cycles (cf. section 2.4.3).

For a decentralized entity relying on non-expert contributors without dedicated time, this gap is not marginal. It is the difference between a one-off assessment and a reproducible annual process. The following per-category guide therefore constitutes a partial IMP, adapted to the specific constraints of a faculty-level entity within a complex organization. It deliberately covers two of the EPA template's core components: emissions quantification and data management, where the gap between generic normative guidance and operational reality is most consequential for non-expert users. Base-year adjustment and third-party auditing are excluded: the former requires at least two completed inventory cycles to be meaningful, and the latter presupposes a level of methodological maturity and institutional capacity that a first-

¹⁴ GHG Protocol IMP: Is a structured internal document recommended by the GHG Protocol Corporate Standard to formalize data sources, collection procedures, contributor responsibilities, quality controls, and documentation rules for greenhouse gas inventories (World Resources Institute, 2004)

¹⁵ EPA: The U.S. Environmental Protection Agency has developed a simplified IMP template designed for smaller organizations (EPA, 2026)

¹⁶ The seven components are: organization information, boundary conditions, emissions quantification, data management, base year definition, roles and responsibilities, and auditing and verification (EPA, 2026; World Resources Institute, 2004)

iteration assessment cannot yet justify (International Organization for Standardization, 2018; World Resources Institute, 2004).

What distinguishes this guide from existing IMP templates is not its scope but its orientation. Rather than documenting what has been done after the fact, it specifies what data to collect, from whom, in what format, and at what frequency, before the next reporting cycle begins. This preventive and organizational dimension is precisely what conditions the long-term viability of carbon accounting in a decentralized institution: a contributor who knows exactly what data to retain substantially reduces the burden of each subsequent collection cycle, without requiring dedicated sustainability expertise, a point made by both Valls-Val & Bovea (2021) and Woszczek et al. (2025).

Energy: The core problem is not missing data but incompatible data. Building-level consumption figures, room scheduling records, and surface area databases all exist within UCLouvain's infrastructure, but they were not designed to work together (cf. section 4.3.1), and the manual alignment they require is not a one-time cost. Any future assessor will face the same reconstruction from scratch unless the data infrastructure changes.

The uncertainty on this post is spatial, not energetic: EFs for Belgian electricity and district heating are well established and carry no local assumption. Granularity in the G1/G2 sense is therefore not the relevant lever here. The binding constraint is geometric, not analytical, and cannot be reduced by any increase in data collection effort at the activity level. The single most impactful improvement is obtaining architectural floor plans for the three buildings where spatial fractions had to be estimated, which alone would reduce remaining uncertainty to the 2.4% of faculty hours currently excluded for lack of room data.

For future iterations, the following data chain must be in place and maintained annually:

- Annual building energy consumption per energy type from GTPL¹⁷
- Room-level scheduling data extracted from ADE
- Room surface areas from APPA
- Architectural floor plans for total building area including shared spaces

Without it, the allocation remains geometrically ambiguous for any building where the faculty does not occupy a clearly delimited zone. A secondary but tractable improvement concerns the cogeneration credit: a more precise future allocation would require UCLouvain's technical services to disaggregate plant output by end-use category rather than applying a single campus-wide ratio.

Purchases: The -2.45% gap between G1 and G2 confirms that the monetary approach is a reasonable proxy for this post at the current level of data availability. The ceiling on granularity improvement is not set by analytical effort but by the composition of the purchase dataset itself: only 8.3% of lines reached a level of sufficient product specificity to replace the monetary

¹⁷ (Service de gestion technique du patrimoine de Louvain-la-Neuve): UCLouvain's technical building management department for the Louvain-la-Neuve campus, responsible for energy supply and building maintenance.

estimate, because physical quantities and precise product descriptions are absent from the majority of ADFI records.

Granularity therefore does not reduce overall uncertainty for this post; it redistributes it. The 19.5% of lines enriched to G2 carry lower uncertainty individually, but the 80.5% remaining on a monetary approach retain the same high parametric uncertainty as at G1. The net effect on inventory reliability is marginal until the upstream data conditions change.

The fix must be made upstream, not analytically. If ADFI systematically recorded a product description and physical quantity at the point of invoice encoding, the share of lines eligible for a physical EF would increase substantially in future iterations without any additional collection effort from the faculty. A maintained correspondence table between recurring purchase descriptions and their ADEME categories would further reduce the categorization effort currently concentrated on new purchase types each year. Together, these two changes would progressively shift the purchases post from a predominantly monetary estimate toward a hybrid approach, improving precision where it matters most. It should be noted that the limited impact of G2 in this assessment is partly specific to the BSE faculty's purchase profile, which contains relatively few high-volume material purchases; faculties with a different procurement structure may see a substantially larger gain from the same refinement.

Staff and student commute : The 71% increase from the university-scaled estimate (G1) to the faculty-specific survey (G2) for student commuting is the most striking illustration of what granularity choices cost in practice: the university-level CMP is structurally blind to the commuter/resident asymmetry that drives faculty-level emissions, and no analytical refinement of the university level survey can correct for this. The faculty-specific survey is not a refinement; it is a different method entirely, and the only valid one for this post. This shift in method also changes the nature of the uncertainty. At G1, the uncertainty cannot be quantified or reduced by further analysis: there is no way to assess how far the BSE commuting profile diverges from the LLN campus average without collecting BSE-specific data. At G2, the remaining uncertainty is quantifiable and could be eliminated entirely by a faculty-level CMP survey replacing the current university-wide one.

For future iterations, the two-survey design can be consolidated into a single instrument with a branching question separating daily commuters from residents. Two improvements would reduce the main residual uncertainties: asking daily commuters for their one-way distance directly rather than travel time, which eliminates the speed conversion step, and asking all respondents for their actual number of return trips per year rather than deriving commuting frequency from academic calendar assumptions. Annual collection is recommended: the commuter/resident split is sensitive to cohort composition, which renews substantially each year as graduating students are replaced by incoming ones.

For staff, the constraint is different in nature. The CMP provides rich individual data but no faculty identifier, meaning the uncertainty on this post is structural, not statistical and cannot be reduced by better analysis of existing data. Unlike student mobility, where moving to G2 resolves the uncertainty by replacing the university-wide instrument with a faculty-specific one, staff commuting has no equivalent G2 option available: the CMP already operates at the

individual level, and the missing element is not data granularity but data labelling. The only fix is to add a faculty identifier to the CMP questionnaire. Until then, this estimate should be reported with an explicit statement about its representativeness assumption. Staff mobility patterns are structurally more stable than student ones, making the CMP triennial cycle the appropriate collection frequency for this post. Any improvement to the survey instrument requires institutional renegotiation best aligned with that existing rhythm. Replicability depends on two conditions outside the faculty's control: the CMP being renewed on this cycle, and the individual-level data remaining accessible in disaggregated form. If future releases provide only aggregated results, the per-FTE scaling used here would no longer be applicable. Telework rate should be retained in the staff calculation, as it is the one variable that directly adjusts for actual commuting frequency.

Erasmus travel: The 5.9% gap between G1 and G2 is modest, but it reveals what the survey adds beyond aggregate refinement: G2 does not only refine the total, it changes which destinations are identified as priority reduction levers. Destination-specific patterns invisible to G1 emerge clearly: corridors where the UCLouvain travel rule misassigns mode, and corridors where the number of return trips is systematically underestimated. The pattern of multiple return trips is partly consistent with induced mobility: proximity to the home country lowers the perceived cost of returning, making additional personal trips and family visits in both directions more likely, an effect that a single-return assumption structurally cannot capture and that only declared behavioral data can reveal. Bologna is the clearest illustration: G1 assigned plane travel to all students and assumed a single return trip, while the survey revealed a modal split between plane and train users alongside multiple round trips among those flying; a compounding effect that makes Bologna appear as a moderate-emission destination at G1 while it accounts for a disproportionate share of total emissions at G2, and identifies high-frequency plane users on medium-haul corridors as a concrete reduction lever.

While the G2 estimate is methodologically robust for 2024, it should not be treated as a stable annual reference. The cohort size is consistent from year to year (40–50 outgoing students), but the emission total is highly sensitive to the behavioral profile of a small number of destinations. Bologna's disproportionate share in 2024 reflects a specific cohort pattern (multiple round trips by plane) that could equally emerge at any other destination in subsequent years. Year-to-year variability is therefore driven not by changes in student volume but by changes in the modal and frequency choices of a few high-emission corridors, a structural feature of small-cohort Erasmus programs that any single-year estimate must acknowledge.

At G1, the uncertainty is directionally biased rather than random: the single-return assumption and the institutional travel rule both introduce known underestimation errors that partially offset each other without cancelling. At G2, this directional bias is replaced by a sampling uncertainty tied to the representativeness of the 24 survey respondents for the full cohort of 41 students: an uncertainty that shrinks as response rate improves.

For future iterations, the survey effort required to reach G2 is low: 41 students is a fully enumerable population, and a 58.5% response rate was achieved with a single survey. More importantly, the behavioral data needed is partially embedded in an existing administrative process: Erasmus students are already required to declare their transport mode to qualify for UCLouvain's green travel top-up grant. Formalizing that declaration to include departure and arrival points and number of return trips would produce G2-quality data at zero additional respondent burden, through the international mobility office rather than a dedicated survey.

Digital infrastructure is the only post in this assessment where no granularity alternative exists and where improving the allocation requires a change at the institutional IT infrastructure level, beyond anything the faculty can achieve independently. Unlike mobility posts, the uncertainty here is due to allocation logic, not data resolution. The current population-share allocation assumes equal per-capita data consumption across all user types, which likely underestimates usage for research-intensive staff relative to students or teaching-focused staff members.

A more precise approach would be to exploit UCLouvain's eduroam network, through which students and staff authenticate individually. Per-account traffic data, cross-referenced against a faculty membership list (staff + students), would allow faculty-level network consumption to be computed directly without relying on population ratios. Two unresolved issues block this path. First, staff who simultaneously belong to a faculty and a research entity would attribute research-driven data consumption (potentially very high for experiment-intensive work) to the teaching scope, introducing a structural overestimation bias. Second, per-account traffic monitoring raises GDPR compliance questions requiring a formal data governance review before implementation. Until both are addressed, the population-share allocation remains the only defensible method, and its limitations should be explicitly documented in any reporting.

Waste: At 0.3% of the total footprint, waste does not justify investment in more precise data collection at this stage. The FTE-based allocation is proportionate to the post's magnitude; even a 50% error in this estimate would not materially affect the result.

If a more precise allocation were needed in future iterations, the relevant variable is not FTE but activity type: faculties with laboratory-intensive teaching generate disproportionate volumes of chemical and electronic waste relative to their headcount, meaning an FTE key systematically underestimates their contribution. A more defensible allocation for lab-driven waste streams would weight by teaching hours in laboratory settings rather than staff equivalents: a change that would require UCLouvain's facilities management service to tag waste collection by building or organizational unit, and one worth pursuing only if waste becomes a materially larger share of the footprint than it currently is.

A cross-post synthesis of granularity impact on uncertainty is provided in Appendix (9.3).

Table 4 Per-category data requirements.

Category	Data required	Source	Recommended collection frequency	Priority improvement
Energy	Building consumption, room scheduling, surface areas, floor plans	GTPL, ADE, APPA	Annual	Obtain floor plans for buildings with estimated spatial fractions
Purchases	Expenditure file with product descriptions and physical quantities	ADFI	Annual	Systematic encoding of physical quantities at invoice level + more precise description
Student commuting	One-way distance, transport mode, number of return trips, commuter/resident split	Faculty survey	Annual	Single survey with branching question; ask distance directly rather than travel time
Staff commuting	Individual commuting mode, distance, telework rate, entity identifier	Campus mobility survey	Triennial	Add entity identifier to campus mobility survey
Erasmus	Destination, transport mode, number of return trips	International mobility office / dedicated survey	Annual	Formalize travel mode declaration to include return trips
Digital	Entity-level network traffic	Central IT services	Annual	Per-account traffic monitoring pending data governance review
Waste	Campus-level waste by stream	Facilities management	Annual	No improvement justified at current footprint share

6.2 Transposability to other UCLouvain faculties and entities

The methodology developed in this thesis was designed for and validated against a single entity: the BSE teaching faculty. Not every post transfer to every entity type, and not every entity of the same type will face identical constraints, but the methodology provides a structured starting point for any UCLouvain entity attempting a first carbon assessment. The analysis below is organized by entity type rather than by emission post, reflecting the practical question

any entity must answer before a first assessment: given what we are, what from this methodology can we use directly, and where must we adapt?

Teaching faculties

Teaching faculties share the same campus infrastructure and administrative systems as BSE, making this the entity type for which the methodology transfers most directly. The energy allocation chain (building consumption from GTPL, room scheduling from ADE, surface areas from APPA) is identical across all faculties sharing the campus infrastructure. The student and staff mobility methods apply without structural modification, the Erasmus survey logic transfers directly wherever outgoing student mobility exists, and the G1–G2 purchases framework and FTE-based waste allocation are equally applicable.

Significant divergences exist within this category, however. A faculty like EPL¹⁸, with laboratory-intensive teaching across engineering disciplines, will have a substantially different energy and purchases profile than a faculty like ESPO, whose activities are concentrated in lecture halls and seminar rooms with minimal equipment use. For EPL, the energy post will carry greater absolute weight, with greater uncertainty from shared building allocation; the purchases post may also show a larger G1–G2 gap if physical quantities are more systematically recorded for laboratory supplies. For ESPO, by contrast, student mobility is likely to remain the dominant post, as it is for BSE faculty, but the commuter/resident split and average distances will differ depending on the geographic profile of each faculty's student population. So even if the method is the same, the results will not be.

Research institutes

For UCLouvain's 22 research institutes, the methodology requires more substantial adaptation. The dominant emission posts and the value of granularity refinement vary substantially depending on whether an institute's activities are experimentally or theoretically oriented. Student mobility does not apply and can be dropped from the scope entirely. Staff commuting transfers directly via the CMP, with the same structural limitation as for the BSE faculty: the absence of an entity identifier prevents institute-specific emission intensities from being computed directly. International travel for conferences and field research replaces Erasmus as the relevant mobility category, using the same distance-based calculation logic but drawing trip data from research unit travel records rather than the international relations office. Energy allocation simplifies considerably for institutes occupying dedicated buildings: exclusive building occupancy allows direct consumption attribution, removing the room-level scheduling step that is the most complex part of the current procedure.

Within this category, divergence between entity types is substantial enough to require genuinely different assessment strategies. A transfer test conducted on the IMMC research institute (an engineering institute at UCLouvain whose procurement is dominated by specialized scientific equipment) confirms this divergence empirically: while the methodology is procedurally transposable, only 143 of the 1,202 screened purchase items (11.9%) could be

¹⁸ EPL (Louvain School of Engineering) and ESPO (Faculty of Economic, Social and Political Sciences) are two teaching faculties of UCLouvain, representative respectively of engineering and social sciences activity profiles.

assigned a G2 EF, because specialized instrumentation is poorly represented in the ADEME Base Empreinte® (Appendix 9.2). For research-intensive entities, the binding constraint on granularity improvement is therefore not data quality but EF availability; a limitation largely absent for teaching faculties or administrative services. For a humanities institute like ILC¹⁹, where activities are concentrated in offices and seminar rooms and the dominant emission post is likely staff mobility, the G2 gain on purchases is expected to be larger, as standardized consumables are better represented in the ADEME Base Empreinte® than specialized.

Technological platforms

UCLouvain's 45 technological platforms present the most energy and equipment-intensive emission profile of any entity type. For platforms built around analytical chemistry, for example: where materials characterization, large-scale computing infrastructure, and specialized equipment purchases are likely to dominate, energy and purchases will far outweigh the emission posts that drive the BSE faculty footprint. The energy allocation chain applies directly where platforms occupy identifiable spaces within shared buildings, but a floor-area-based allocation may systematically under attribute consumption to the platform relative to its actual usage intensity. A usage-based allocation weighted by equipment operating hours would be more defensible for this entity type but requires data that UCLouvain's current infrastructure does not provide at that resolution.

Within this category, a platform centered on data processing and computational modeling will have a digital infrastructure footprint that far exceeds its physical energy consumption, while a chemistry platform will present the opposite profile (one where energy and specialized equipment purchases dominate). Across both cases, the main constraint on granularity improvement will consistently be the absence of product-level emission factors for specialized scientific instruments in reference databases such as the ADEME Base Empreinte®.

Central administrative services

For central administrative services, the methodology simplifies substantially. Student mobility does not apply. International travel is minimal. Energy attribution is straightforward where a service occupies identifiable office space. Staff commuting via the CMP applies directly and is likely to represent the dominant emission post, given the absence of laboratory activities and the standard nature of most administrative purchases.

The divergence within this category is nevertheless significant. A purely administrative service like ADFI: whose activities consist of financial processing, document management, and internal coordination, presents a profile where staff commuting and standard office purchases dominate, and where the monetary G1 approach is likely sufficient for all purchase lines given the absence of material-intensive procurement. SEPI²⁰, by contrast, manages building renovation and campus infrastructure; its purchases include construction materials, technical equipment, and contractor services whose EFs differ substantially from those of office supplies. For SEPI, the G1 monetary approach may systematically misrepresent procurement emission

¹⁹ ILC (Institute of Language and Communication Sciences) is a humanities research institute at UCLouvain

²⁰ SEPI (*Service des études du patrimoine immobilier*): UCLouvain's real estate and campus planning department.

intensity, and a targeted G2 effort on high-expenditure material lines is more justified than for a purely administrative entity, even though both fall under the same institutional category.

A transversal limitation: entity size

Across all four entity types, one structural constraint applies regardless of activity profile: entity size. Methods that are statistically robust at the BSE scale: a student survey achieving 20% response rate across 1,300 enrolled students, or a purchases dataset of 698 lines, become fragile for smaller entities. A research institute with 30 staff members cannot meaningfully apply campus-wide emission intensity scaling without large representativeness uncertainty; nor can a faculty with 200–300 enrolled students produce a reliable commuting estimate from a 20% survey. For small entities, the appropriate response is either to aggregate results across similar units before reporting, or to accept that certain posts will carry irreducible uncertainty that no methodological refinement can address. The size threshold below, which these methods become unreliable is not formally defined in the literature and remains an open question for future work.

6.3 Towards an institutional tool

The post-by-post findings made throughout this thesis converge towards a structural conclusion that goes beyond any individual emission category: entity-level carbon accounting in a complex organization cannot rely on top-down institutional estimates for its dominant posts, but it also cannot function as a collection of isolated, methodologically inconsistent assessments. The 71% granularity gap in student mobility illustrates the first problem while the purchases and energy posts illustrate the second. The solution is not methodological perfection at the entity level; rather, it is methodological consistency across entities, and that consistency can only be enforced through a shared tool. Applying the same organizational data to different tools or methodologies can produce substantially different estimates, precisely because tools differ in their boundary assumptions, EF databases, and default values (Birnik, 2013; Padgett et al., 2008).

What a unified tool must deliver goes beyond calculation convenience. Four functional requirements emerge from the literature and from the empirical findings of this thesis. First (1), it must enable multi-year repeatability: a tool encoding its methodology, emission factors, and boundary choices explicitly allows the same assessment to be reproduced annually without reconstructing the methodological framework from scratch, making trend detection possible even when absolute estimates carry systematic uncertainty (Mariette et al., 2022). Second (2), it must enable institutional aggregation: when all entities apply the same tool with the same factors and the same perimeter conventions, their results can be summed into a coherent institutional total. Third (3), it must provide entity-level visibility: each entity must be able to see its own carbon footprint independently, not only as a fraction of an institutional aggregate, because entity-level visibility is a necessary condition for entity-level accountability and action (Ahonen et al., 2024). Fourth (4), it must be methodologically transparent: a tool that operates as a black box, accepting inputs and returning a figure without exposing the emission factors,

boundary assumptions, or gap-filling methods applied, prevents users from critically assessing their results and creates a false sense of precision (Spandonidis et al., 2024).

Evaluated against these four requirements, GES 1point5 stands out as the tool most directly aligned with the needs of a decentralized academic institution (Mariette et al., 2022). Its emission categories are calibrated to the academic footprint (energy, mobility, purchases, digital infrastructure, and food) and its open-source structure allows EFs to be adapted to national energy mixes and institutional contexts, enabling comparisons between institutions worldwide. Building on this architecture, a pre-encoding function that allows central services to input shared data while entities complete the remaining categories independently would directly address the data governance problem identified throughout this thesis for decentralized institutions.

UCLouvain is currently moving in this direction. As part of its institutional carbon strategy, the university has initiated a process to adapt GES 1point5 to its own operational context, with a pilot deployment across several entities planned for 2026. The technical specifications developed for this adaptation independently reflect the same structural gaps this thesis identified empirically: the need for Belgian-specific EFs for energy, the ability to encode purchases in physical quantities rather than monetary values alone, the separation of student and staff mobility as distinct calculation modules, and the pre-encoding function described above. This alignment between the empirical findings of this thesis and the institutional tool specification is not coincidental. It reflects the same underlying constraints that any entity-level carbon accounting system at UCLouvain must address, regardless of the methodology used to identify them. If deployed at scale, this tool would do what this thesis achieved manually for a single faculty: produce a complete, entity-level carbon footprint for every entity across the university and aggregate them into a coherent bottom-up institutional total for the first time.

Two limitations of this tool-based approach deserve honest acknowledgment. First, GES 1point5 in its current form was designed for research laboratories, not for the full diversity of entity types found at a university (teaching faculties, administrative services, research institutes, and support units) each type has distinct emission profiles that the tool's default category structure does not fully cover yet. The adaptations requested by UCLouvain are a prerequisite before the tool is deployable at full scale. Second, and more fundamentally, a tool enforces methodological consistency but cannot substitute for data quality. The practical guide (cf. section 6.1) identifies, for each emission category, the upstream process changes that condition certain granularity levels. But that guide was developed and validated for the BSE faculty alone. That transposability assessment (cf. Section 6.2) does not substitute for a dedicated granularity analysis conducted within each entity: the binding data constraint differs across entities, and what constitutes the dominant source of uncertainty for BSE may be negligible for another entity with a different activity profile. Deploying a shared tool without that entity-specific groundwork risks producing results that are methodologically consistent across entities but empirically unreliable within them. Further research replicating the granularity analysis of this thesis for other faculty and entity types within UCLouvain remains a prerequisite for the tool to deliver on its full potential. A top-down institutional assessment already exists at UCLouvain and has been independently validated; whether a bottom-up

aggregation of entity-level assessments would converge toward the same total remains an open empirical question, one that the deployment of a shared tool across entities would be well positioned to answer.

6.4 Transposability to other complex organizations

Two principles emerge from this work that generalize beyond UCLouvain and apply to any complex organization attempting to implement entity-level carbon accounting.

The first is that data precision is not uniformly valuable across emission categories; its effect on result reliability depends entirely on which category is being refined and what data is available. For any complex organization, the implication is the same: uniformly high data precision across all categories is neither necessary nor efficient. Effort should be concentrated where the emission share is large and where granularity demonstrably changes what the results reveal. An inaccurately treated dominant post does not just produce an imprecise number: it makes the primary reduction lever structurally invisible, rendering any subsequent reduction strategy directionless regardless of how well other categories are measured.

The second principle is that any tool deployed across a complex organization must be calibrated to that organization's specific emission profile rather than designed as a generic instrument. A university where mobility represents the dominant emission post requires fundamentally different data collection infrastructure than a manufacturing company where Scope 1 direct emissions dominate, or a research institute where specialized equipment purchases drive the result. Generic tools force a uniform data collection burden across all categories regardless of their relative weight, systematically misallocating effort toward posts that contribute little to the total while underinvesting in those that drive it. The comparison between BSE and IMMC illustrates this even within a single institution: despite sharing the same methodology and the same EF database, the binding constraint on granularity improvement differs entirely between a teaching faculty and a research institute. What remains transferable across all entity types is not the data itself but the calculation framework: EFs, allocation logic, and granularity assessment procedures can be shared and reused once established, meaning the investment in methodology pays off across the entire organization even when data collection must remain entity specific.

These two principles connect to a broader gap documented in the literature on carbon accounting in higher education. Ahonen et al. (2024) report that 97% of Finnish universities track their carbon footprint but only 39% have set reduction targets. The gap between measurement and action is striking. The results of this thesis help explain why. If the dominant emission post of an entity is made invisible by insufficient data granularity or aggregated into an institutional total that no single entity feels responsible for, there is no empirical basis on which to build a reduction strategy. The transition from carbon accounting as a reporting exercise to carbon accounting as a decision-making tool depends less on the sophistication of the calculation engine than on the quality and resolution of the data that feeds it. Precise entity-

level data is not methodological refinement; it is the prerequisite for informed action. That is the central lesson this thesis draws from the BSE faculty case, and the one most likely to hold beyond it.

7 Conclusion and perspectives

7.1 Conclusion

This thesis set out to determine the effect of data granularity on the results of an entity-level carbon footprint; to identify, for each emission category, the threshold beyond which additional data collection effort no longer meaningfully improves the quality of the assessment and to translate those findings into a transferable operational framework that allows an entity to reproduce the process autonomously in future reporting cycles. The Faculty of Bioscience Engineering at UCLouvain served as the case study, with the full assessment conducted for the 2024 reference year across seven emission categories: energy, purchases, student commuting, staff commuting, Erasmus outgoing travel, digital infrastructure, and waste.

The first and most consequential finding is that the sensitivity of the carbon footprint result to data granularity is not uniform across emission categories. It depends first on whether the category's emission share justifies investing in higher-granularity data, and second on whether the lower-granularity level is blind to distinctions that are decision-relevant at the entity level. When those distinctions exist, moving to a higher-granularity level does more than simply refine the estimate: it produces a materially different number that changes both the baseline and where reduction efforts should be concentrated. Student daily mobility illustrates this most clearly: the faculty-specific survey result is 71% higher than the university-wide estimate once scaled to the faculty. Not because of a measurement error but because a university-wide survey cannot capture the specific student origin profile and modal behavior of a single faculty, nor distinguish between sub-populations with structurally different emission profiles. By contrast, Erasmus outgoing travel shows a granularity gap that is sufficient to reveal destination-specific patterns invisible at the lower level but does not materially alter the total at the scale of the faculty. For waste, which represents a negligible share of the total footprint, the emission share alone is sufficient to conclude that further data refinement is unnecessary: even a significant error in the allocation proxy would be invisible at the scale of the overall inventory.

These three cases illustrate a principle that holds across all categories examined: uniformly high data precision is neither necessary nor efficient. Effort invested in refining a well-constrained or structurally minor category yields negligible improvement to the overall inventory quality, whereas the same effort applied to the dominant and granularity-sensitive category changes not only the total but the identity of the primary reduction lever. For some categories, however, the ceiling on granularity improvement is set not by analytical effort but by the structure of the data available upstream. Purchases illustrate this clearly: the limiting factor is not the calculation method but the absence of physical quantities and precise product descriptions in

the procurement records themselves: a constraint that no analytical refinement can resolve, and whose fix is therefore institutional rather than methodological.

The second objective of this thesis was to produce an operational framework covering the full process from data collection to calculation, grounded in the conclusions of the sensitivity analyses. The per-category guide proposed (cf. section 6.1) constitutes a partial inventory management plan, adapted to the specific constraints of the BSE faculty as a teaching entity within a complex organization, in the sense defined by the GHG Protocol Corporate Standard (World Resources Institute, 2004). What distinguishes it from existing normative frameworks is not its scope but its orientation: it is designed to structure data collection before the assessment begins, rather than to document it afterward. It is precisely this preventive dimension that separates a one-off assessment from a process a non-expert contributor can reproduce annually without a dedicated researcher, which is precisely the gap that Valls-Val & Bovea (2021) and Woszczek et al. (2025) identify as unaddressed in the existing literature on carbon accounting in decentralized institutions.

The transferability analysis (cf. section 6.2) confirms that the methodology transfers structurally to other UCLouvain entity types, but that the constraint on granularity improvement varies across entity profiles. For other teaching faculties on the Louvain-la-Neuve campus, the methodology applies without structural modification, though the relative weight of each emission category will differ with the faculty's activity profile. For central administrative services, student mobility drops out of scope entirely and staff commuting becomes the dominant category, simplifying the methodology substantially. For technological platforms, the energy and purchases categories carry disproportionate weight relative to their headcount, and a floor-area-based energy allocation is likely to under-attribute consumption relative to actual equipment-driven usage intensity. For research institutes, the IMMC transfer test demonstrates the limit of this transferability in the purchases category: specialized scientific instrumentation is poorly represented in reference databases such as the ADEME Base Empreinte®, meaning that emission factor availability rather than data quality sets the ceiling on granularity improvement.

The broader implication of this work connects to a pattern documented in the literature on carbon accounting in higher education: Ahonen et al. (2024) report that a large majority of Finnish universities track their carbon footprint but that a much smaller share have set concrete reduction targets. This gap between measurement and action is precisely what entity-level granularity is designed to close: An institutional total tells an organization that it emits, but not where, and not which entity is responsible for which share: these are the preconditions for any concrete reduction target. The results of this thesis suggest that data granularity is part of the explanation: a carbon footprint calculated at insufficient resolution produces a number but not a lever, and without an identifiable lever there is no empirical basis on which to build a reduction strategy, regardless of how sophisticated the calculation engine is.

7.2 Perspectives

Three research directions emerge from this work with sufficient precision to be actionable.

The first research direction concerns the validation of the methodological outputs and recommendations produced in this thesis, through their application to a representative set of UCLouvain entities with contrasting activity profiles. This thesis established granularity thresholds and data collection recommendations for one teaching faculty; whether those thresholds and recommendations hold, shift, or collapse entirely for any other entity type within the institution remains untested. A coordinated replication across structurally contrasted entities would produce the evidence base needed to determine whether a single differentiated data collection protocol can serve the entire institution, or whether the heterogeneity across entity types requires genuinely distinct methodological approaches for each. This replication should also serve as an opportunity to critically assess the limitations of the methodology developed here (the allocation choices, the survey designs, the granularity scenarios) and to refine them based on empirical confrontation with different data environments. This work is beyond the scope of a single master's thesis (the data access negotiations, entity coordination, and methodological adaptation required across multiple institutional actors cannot be compressed into a single research cycle) and could take the form of a cohesive set of master's theses working in parallel toward a common framework, or a broader coordinated research project, with the shared goal of producing a methodology validated across the full diversity of UCLouvain entities. This methodological work is not an end in itself: its primary purpose is to lay the empirical foundation on which the institutional tool described in the second direction can be properly configured, because a tool deployed without entity-specific validated protocols will default to generic assumptions that undermine precisely the granularity that makes entity-level accounting actionable.

The second direction concerns the empirical validation and implementation of the adapted GES 1point5 tool currently under development at UCLouvain. The four functional requirements defined in section 6.3 provide a structured evaluation framework against which the tool's performance can be assessed once deployed. The deployment will serve three sequential purposes: first (1), to test whether a bottom-up aggregation of entity-level assessments converges toward the top-down institutional total produced by UCLouvain's 2024 triennial assessment, or diverges, and if so in which categories and for which entity types. Second (2), to assess whether the tool can produce an emission profile that is specific enough to identify the dominant emission posts within each entity's activity perimeter. Third (3), to evaluate whether, based on those entity-specific profiles, the tool can translate results into concrete reduction levers that fall within the operational authority of the entity itself. The tool is therefore not the starting point, but the destination of the research program described above: it is what transforms a validated methodology into a scalable, institutionally owned process. Achieving this transformation, however, requires one additional condition: the tool must be implemented as a mandatory reporting instrument across the institution rather than an optional resource, because a tool that entities can choose not to use will not produce consistent, comparable, and aggregable results that justify the investment in its conception and deployment.

The third and most fundamental direction concerns the data governance infrastructure that underlies everything described in this thesis. Across every emission category examined, the recurring obstacle was not methodological but structural: most of the data needed to produce a reliable entity-level carbon footprint already exists within UCLouvain's administrative systems, but it was not designed to be used for that purpose. Each emission category relies on data tracked somewhere within UCLouvain's administrative infrastructure, but held in separate systems, with incompatible formats, and without the cross-referencing identifiers that would allow them to work together. The allocation chain for space heating and electricity illustrates this most concretely: the four data sources required to compute a faculty-level energy estimate all exist within UCLouvain's infrastructure, but they were never designed to work together and combining them required manual reconstruction from scratch.

What this points to is a challenge that is not primarily technical but organizational and decisional. For UCLouvain's Sustainability Transition Plan to move from an abstract commitment to an operational reality, the challenge must be addressed at two levels simultaneously: at the institutional level, central services must restructure how data is stored and made accessible, while at the entity level, someone must be assigned explicit responsibility for the carbon accounting process and given the time to carry it out. At each of these levels, a distinct choice is required. The first is to make existing data accessible to entities in a usable form: not merely stored somewhere in a central service, but structured, documented, and retrievable without requiring a dedicated researcher to reconstruct it each time. The second, and more demanding, is to redesign the way certain administrative data is collected at the point of entry: embedding carbon-relevant fields into existing systems, such as a faculty identifier in the mobility survey, physical quantities in purchase records, building-level energy disaggregation, so that the data required for a carbon assessment becomes a byproduct of normal administrative operations rather than a dedicated collection exercise. If both conditions are met, the burden of future assessments shifts from data gathering to data processing, which is precisely what makes the tool described in the second direction viable at scale, transforming entity-level carbon accounting from a one-off research exercise into an institutionally owned and annually reproducible process.

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9 Appendix

9.1 Emission factor used throughout the master thesis

1. "The emission factors used in the assessment were grouped by emission category to improve readability and to clarify the methodological link between each activity data item and its associated source. Product-specific emission factors applied to individual purchase lines at G2 are not listed here due to the volume of entries; they are sourced entirely from the ADEME Base Empreinte® database and accessible via the following reference: ("Base Empreinte®," 2026).

Category	Emission factor	Source
Stationary energy – natural gas	0.185	Base Empreintes – Natural gas kWh PCS – Combustion
Stationary energy – natural gas	0.028	Base Empreintes – Natural gas kWh PCS – Upstream
Fuel combustion – diesel	2.490	Base Empreintes – Diesel B7 – Combustion
Fuel combustion – diesel	0.610	Base Empreintes – Diesel B7 – Upstream
Fuel combustion – petrol	2.200	Base Empreintes – Petrol 95 E10 – Combustion
Fuel combustion – petrol	2.200	Base Empreintes – Petrol 98 – Combustion
Fuel combustion – petrol	0.500	Base Empreintes – Petrol 95 E10 – Upstream
Electricity or energy consumption	0.220	Base Empreinte
Purchases – monetary emission factors	641.947	Base Empreintes – mixed monetary emission factors
Purchases – monetary emission factors	176.512	Base Empreintes – mixed monetary emission factors
Purchases – monetary emission factors	253.389	Base Empreintes – mixed monetary emission factors
Purchases – monetary emission factors	419.905	Base Empreintes – mixed monetary emission factors
Purchases – monetary emission factors	238.550	Base Empreintes – mixed monetary emission factors
Purchases – monetary emission factors	118.878	Base Empreintes – mixed monetary emission factors
Capital goods – buildings	440	Base Empreintes – Educational building / concrete structure
Capital goods – infrastructure	319.000	Base Empreintes – Standard parking facility / reinforced concrete
Capital goods – machinery and equipment	5500	Base Empreintes – Machine weight

Waste – household waste	344.000	Base Empreintes – Waste incineration – Household waste, RER
Waste – cardboard recycling	992.000	Base Empreintes – Packaging / Cardboard / Recycling
Waste – organic waste	140.000	Base Empreintes – Food and green waste / Industrial composting
Waste – ferrous metal waste	54.700	Base Empreintes – Waste incineration – Ferrous metal waste, RER
Waste – healthcare waste	943.000	Base Empreintes – Healthcare waste / Incineration – Impacts
Waste – hazardous industrial waste	844.000	Base Empreintes – Hazardous industrial waste / Incineration – Impacts
Waste – electrical and electronic equipment	2000.000	Base Empreintes – WEEE ²¹ / Average WEEE / Average end-of-life treatment – Impacts
Travel – diesel car	0.190	Base Empreintes – Car / Diesel engine / 2023
Travel – diesel car	0.063	Base Empreintes – Car / Diesel engine / 2023
Travel – train	0.048	Base Empreintes – Passenger train Belgium
Travel – train	0.006	Base Empreintes – Long-distance train / 2019 France
Travel – urban public transport	0.003	Base Empreintes – Metro, tramway, trolleybus / 2018 / Urban area >250,000 inhabitants
Travel – bus	0.146	Base Empreintes – Average bus / Urban area of 100,000 to 250,000 inhabitants
Travel – moped	0.085	Base Empreintes – Moped / Rural or urban / 2023
Travel – air transport	0.331	Base Empreintes – Passenger aircraft / >220 seats, 500–1000 km, 2023 / with contrails
Travel – air transport	0.169	Base Empreintes – Passenger aircraft / >220 seats, 2000–5000 km, 2023 / with contrails
Travel – air transport	0.151	Base Empreintes – Passenger aircraft / >220 seats, >5000 km, 2023 / with contrails
Travel – zero direct emissions	0.000	No source indicated
Specific activity factor	0.729	ADEME study
Specific activity factor	0.210	ISIT and German study

²¹ Waste Electrical and Electronic Equipment

9.2 Transfer test of the purchase granularity methodology to the IMMC research institute

The purchase methodology developed for the BSE faculty was applied to the IMMC research institute as a transfer test, with the objective of assessing whether the G1-to-G2 granularity improvement produces equivalent analytical gains across entity types with different procurement profiles.

The full IMMC purchase footprint under the G1 monetary baseline is 3,131.69 tCO₂e. The G2 test was not applied to this whole footprint but to a detailed purchase file of 1,202 lines, which constituted the operational dataset available for line-level treatment. Under G1, these 1,202 lines accounted for 346.31 tCO₂e which represent 11.1% of the full IMMC purchase footprint. The remaining 2,785.38 tCO₂e (88.9%) corresponds to purchase lines outside this detailed file, to which no G2 treatment was applied, and which therefore remained on the monetary approach throughout.

Each of the 1,202 screened lines was examined to determine whether the purchase could be linked simultaneously to a sufficiently identifiable product, a usable quantity or unit, and a defensible physical or product-specific emission factor from the ADEME Base Empreinte®. Only lines satisfying all three conditions were converted to a G2 estimate; the file itself contained descriptions, monetary values, and quantity information where available or usable, rather than a complete quantity field on every line.

Of the 1,202 screened lines, 143 were replaced by a G2 emission factor and 1,059 were retained under G1. The 143 replaced lines fell from 24.33 tCO₂e under G1 to 17.24 tCO₂e under G2, a reduction of 7.09 tCO₂e, or 29.1% on the replaced subset. The 1,059 non-replaced lines (321.98 tCO₂e) were unchanged. Integrated into the full footprint, this brought the IMMC purchase total from 3,131.69 to 3,124.60 tCO₂e, a reduction of 7.09 tCO₂e, or 0.23% of the full purchase footprint.

These two figures must be read together. The 29.1% reduction confirms that the G2 mechanism works as intended where it can be applied: matching a specialized purchase to a product-specific factor materially changes its estimate. But the 143 lines on which it could actually be applied represent a small fraction of the screened file and a negligible fraction of the total footprint, so the net effect at the entity level is marginal. Why the substitution rate remained low is the central result of this test. Within the screened file, the binding constraint was not the absence of a quantity field but the difficulty of combining all three required elements (product identification, usable quantity, and a robust emission factor) for purchases dominated by

specialized scientific equipment, laboratory components, and technical services. In the first classification, 245 lines were reported as identifiable but not converted to G2 because no defensible physical or product-specific factor could be assigned, indicating that for these lines the limitation lay in the reference database rather than in the purchase records themselves. This first-pass count has not been independently re-verified against the classification file and should be read as an order of magnitude.

The IMMC case therefore illustrates a structural limitation of the granularity approach for research-intensive entities, operating at two levels. First, only a minority of the purchase footprint was available in a detailed, line-level form suitable for G2 treatment at all. Second, even within that subset, the ADEME Base Empreinte®, which was not designed to cover specialized research instrumentation at this level of granularity, could not supply defensible factors for most identifiable items. The methodology is therefore transferable at the workflow level (G1 monetary baseline → line-by-line screening → selective G2 substitution applies without modification), but its quantitative added value depends strongly on the compatibility between purchase descriptions, quantities, and the available emission factor databases. Where purchases are standardized and physically identifiable, the replacement rate and analytical gain are larger; where they are specialized or poorly represented in reference databases, the monetary approach remains the only defensible method for most lines, and additional data collection effort yields diminishing returns regardless of its quality.

9.3 Granularity impact on uncertainty by emission post

Table 6 : Cross-post uncertainty comparison (G1 vs G2)

Post	G2 uncertainty	G1 uncertainty	Nature at G1	Nature at G2	What would reduce it
Student mobility	High	Low	Non-quantifiable: BSE profile unknown vs LLN average	Quantifiable: parametric on speed assumption	Faculty-level CMP replacing university-wide instrument
Erasmus	Medium	Medium	Directional bias: single return + modal rule both underestimate	Sampling uncertainty: 24/41 respondents	Formalized transport declaration via international mobility office

Purchases	High	High	Monetary EF: sector average, no product specificity	Redistributed: 19.5% lines improved, 80.5% still monetary	Systematic encoding of physical quantities at invoice level
Energy	Medium	N/A	Spatial: floor plan fractions estimated (-13% to +35%)	N/A	Architectural floor plans for three buildings
Staff commuting	High	N/A	Structural: no faculty ID in CMP, BSE profile unknown	N/A	Faculty identifier added to CMP questionnaire
Digital	Medium	N/A	Allocation logic: population share proxy unverifiable	N/A	Per-account traffic monitoring pending GDPR review
Waste	High	N/A	FTE-based allocation: proxy not verified at faculty level	N/A	No improvement justified at current footprint share

Assessing the Effect of Data Granularity on the Carbon Footprint of an Entity within a Complex Organization

A comparative analysis of data granularity across emission categories, effect on the identification of reduction levers, and a methodological framework transferable to other entities

Valérian Vermeeren

Organizational carbon accounting frameworks are well established conceptually, yet their practical implementation in decentralized institutions remains constrained by two unresolved challenges: the absence of empirical guidance on where data precision actually matters, and the lack of operational frameworks reproducible by non-expert contributors. This thesis addresses both gaps through a full carbon footprint assessment of the Faculty of Bioscience Engineering at UCLouvain (2024), spanning the three scopes of the GHG Protocol across seven emission categories. Emissions were computed using an activity-based approach with ADEME Base Empreinte® factors. Two objectives are pursued: (1) quantifying, per emission category, the sensitivity of the carbon footprint result to data granularity, and (2) translating these findings into a transferable operational framework for future autonomous entity-level assessments. Granularity sensitivity proves highly heterogeneous: for student mobility the faculty-specific estimate exceeds the scaled university-wide one by 71%, while for purchases the gap is ~2.5%. Where it matters, insufficient resolution renders the dominant reduction lever structurally invisible rather than merely imprecise; for categories that are either minor or institutionally constrained, the residual uncertainty is irreducible by granularity: structural, allocation-based, or sampling-bound, not a matter of finer data. Uniformly high data precision is therefore neither necessary nor efficient: effort concentrated on dominant, granularity-sensitive categories shifts both the total and the identity of the primary reduction lever. A per-category operational guide is proposed as a partial inventory management plan oriented toward preventive data structuring, transferable across UCLouvain entity types. A transfer test on a research institute confirms that the binding constraint on granularity improvement shifts from data quality to emission factor availability for research-intensive procurement profiles. These findings connect to a broader pattern: in complex organizations, the gap between measuring a footprint and acting on it is less a calculation problem than a data-resolution one. Entity-level granularity analysis is thus a prerequisite for moving from carbon reporting to evidence-based reduction.