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Unlocking the LCA recycling modelling dilemma in steelmaking industry through the inclusion of temporal, spatial, and steel grades variability

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ABSTRACT

This study provides recommendations on selecting the most appropriate recycling modelling approach for Life Cycle Assessment (LCA) in the steel sector. To this end, the paper evaluates how different stakeholders (e.g., managers, process engineers, communication experts, and policymakers) may address this issue based on their interpretation of the uncertainty of the results. Using a large dataset including 475 heats (furnace batches), 8 steel families, and 2 production sites, we apply the Circular Footprint Formula to cross-evaluate two widely used recycling modelling approaches: substitution and cut-off. Results show that the substitution approach introduces higher variability due to its sensitivity to scrap composition, while the cut-off approach yields less variable results. These differences have practical implications: the cut-off method may be more suitable for applications that require robust comparisons (e.g. communication, policy-making), whereas uses aiming to extract insights from variability (e.g. process optimization, internal learning) may prefer the substitution method. Although based on a limited number of factories, this study offers valuable insights for LCA practitioners and highlights the importance of accounting for uncertainty when modelling steel recycling.

1. Introduction

The steel sector is extremely relevant to several industries, since steel is widely used across multiple industrial applications, including construction, automotive, machinery, energy, and transportation. Owing to its mechanical strength, durability, versatility, and cost-effectiveness, steel remains a fundamental material for industrial production. Globally, steel demand is closely linked to economic development, urbanization, and industrial growth, making the sector a strategic pillar of industrial economies (World Steel Association, 2023). At the same time, steel production is highly energy-intensive and accounts for a significant share of global energy demand (approximately 8%) and greenhouse gas emissions (around 7%) (International Energy Agency, 2020). For this reason, the environmental sustainability of steelmaking industry is a topic that has attracted increasing attention of policy-makers, industry stakeholders, and the research community (Allwood et al., 2010). Two production routes are currently used for producing steel: the blast furnace/basic oxygen furnace (BF/BOF) route generally exhibits higher environmental impacts because it relies on virgin materials such as iron ore; the electric arc furnace (EAF) route instead mainly uses scrap as an iron source, resulting in lower environmental burdens (Andreotti et al., 2023).

Reducing the environmental impact and increasing the circularity of the steel sector are therefore key priorities for enhancing environmental sustainability across industrial sectors as demonstrated by the numerous international programs and research activities (Andreotti et al., 2023; Blanco Perez et al., 2025). These programs highlight the importance of Life Cycle Assessment (LCA) as a key methodology for quantifying the environmental impact of steelmaking, including primary and secondary steel (Suer et al., 2022). LCA is particularly relevant for the steel sector because it enables the quantitative evaluation of environmental impacts across the entire products' life cycle while explicitly accounting for resource circularity. More specifically, LCA allows the assessment of the environmental impacts and benefits associated with the use of secondary materials in production sites (e.g., scrap), the recycling of waste and co-products generated in manufacturing processes (e.g. slags and dust),

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and the recycling of steel products at their end of life (Rieger et al., 2021). For instance, a life cycle perspective is essential for capturing the differences between the BF/BOF and the EAF routes in terms of environmental performance (Andreotti et al., 2023). According to the ISO 14040 and ISO 14044 standards, an LCA study shall be conducted following four phases: (i) goal and scope definition, (ii) life cycle inventory (LCI), (iii) life cycle impact assessment (LCIA), and (iv) life cycle interpretation (International Organization for Standardization, 2022a, 2022b).

Despite the widespread application of LCA in the steel sector, one of the main challenges encountered by Suer et al. (2022) in reviewing the LCA literature on steelmaking is the uncertainty inherent to the results, which are subject to variation depending on multiple methodological choices and boundary conditions. A large multitude of definitions are available in the literature for the term uncertainty, here we refer to "*the probability or confidence for a certain event to occur*", which embraces everything we do not know (Hauschild et al., 2018, p.275). Uncertainty is indeed a controversial topic in LCA literature. Two types of uncertainty affect the application of the LCA methodology (Igos et al., 2019): aleatory and epistemic uncertainty. Aleatory uncertainty (also called variability) stems from inherent variations in the analysed process; temporal and spatial variability are examples of aleatory uncertainty (Hauschild et al., 2018; Igos et al., 2019). Epistemic uncertainty is related to any type of lack of knowledge in the application of LCA (Barahmand and Eikeland, 2022; Hauschild et al., 2018; Lo Piano and Benini, 2022). For instance, the choice of the recycling modelling approach is a source of epistemic uncertainty in the goal and scope definition phase (Igos et al., 2019). In the LCI phase, epistemic uncertainty is often related to background and foreground data quality (Heijungs, 2020), which is defined as the "*characteristics of data that relate to their ability to satisfy stated requirements*" (International Organization for Standardization, 2022b). Characterization factors are the main sources of epistemic uncertainty in the LCIA phase (Igos et al., 2019). The uncertainty of LCA results thus derives from the cumulative effect of all the above-mentioned uncertainty sources. To address this issue, LCA practitioners can decide to focus specifically on some types of uncertainty (Michiels and Geeraerd, 2020). Several techniques can be used to evaluate the uncertainty of the results: i) *uncertainty analysis* based on statistical evaluation, ii) *scenario analysis* to compare the influence of a set of assumptions in different boundary conditions, and iii) *sensitivity analysis* to evaluate the influence of parameter variations on the results (Igos et al., 2019).

1.1. Epistemic uncertainty in the steel sector

The most debated source of epistemic uncertainty in the application of LCA to the metals sector is the choice of the recycling modelling approach (Atherton, 2007; Rossi et al., 2025). In general, recycling processes are intrinsically affected by multifunctionality issues because their function is both to produce secondary materials and to provide waste management (Husmann et al., 2025). Allocation criteria, including the specific case of end-of-life allocation, remain a highly debated issue because no universally recognized "correct" solution exists (Guinee et al., 2004). More specifically, the methodological debate around end-of-life allocation concerns whether the impacts and benefits of recycling should be allocated to the product systems consuming recovered materials or to the product system generating the waste to be managed (Husmann et al., 2025). Several options exist: cut-off (also called "recycled content") approach and substitution method (also called "system expansion" and "avoided burden") are the two most common (van der Harst et al., 2016), with the Circular Footprint Formula (CFF) emerging as the recommended approach within the Product Environmental Footprint (PEF) recommendation (European Commission, 2021). The cut-off approach assumes that the function of recycling is producing secondary materials, thus allocating the impact of recycling to the product systems consuming recycled resources. On the other hand, the substitution approach considers recycling as a waste management process whose environmental impacts and avoided burdens are allocated to the producer of the waste (Husmann et al., 2025). The CFF instead is defined as a "*formula used to allocate to the system under study the burdens of ingoing virgin and recycled material, outgoing recyclable material, disposal, and energy recovery*" (Damiani et al., 2022, p.30) and it represents a hybrid solution between the substitution and the cut-off approaches (Husmann et al., 2025). In the case of secondary steel life cycle, these approaches differ in the way environmental impacts are allocated to the recycled inputs (i.e. scraps) and outputs (e.g. slags, dusts, and the steel products once they reach the end of their life) (van der Harst et al., 2016). The CFF allows LCA practitioners to easily switch between recycling modelling approaches by changing the value of an allocation factor, namely the parameter A, thus providing the possibility to consider intermediate solutions between the substitution (i.e., $A = 0$) and the cut-off methods (i.e., $A = 1$). The main advantage of applying the CFF lies in enabling a consistent transition between alternative approaches by modifying a single allocation parameter (A), while keeping all other modelling choices unchanged. This framework allows the exploration of a continuous spectrum of hybrid solutions between the cut-off and substitution approaches. For final products, the PEF method – and thus all PEF-based certification schemes – associates specific A values to metals (i.e. A=0.2), but for all intermediate products like steel billets, setting $A = 1$ is recommended (Damiani et al., 2022). On the other hand, the Environmental Product Declaration (EPD) methodology imposes the use of the cut-off approach (Durão et al., 2020). Therefore, despite several methodological harmonization efforts reported in the literature (Santero and Hendry, 2016) and from the European Commission (Damiani et al., 2022), the methodological choices made by LCA practitioners on this topic are still very heterogeneous (Suer et al., 2022). It is important to note that although these approaches differ in the allocation of the environmental impacts of recycling across value chains none of them can be considered wrong in principle (Guinee et al., 2004). Therefore, different actors of a value chain may express different preferences regarding recycling modelling, thus resulting in a multitude of recommendations and hierarchies (Husmann et al., 2025). For this reason, understanding how uncertainty affects the choice of the best recycling modelling approach is relevant for all actors in the steel value chain, including steel producers (i.e., the focus of this study), users (e.g. construction and automotive sectors), and recyclers (e.g. scrap shredding and sorting industry).

1.2. Aleatory uncertainty in the steel sector

Regarding aleatory uncertainty, the main sources of variability investigated for steelmaking are related to the output steel grades (Andersson et al., 2017) and spatial variability (Brogaard et al., 2014). The environmental burdens of steelmaking have been investigated across Europe (Pinto and Diemer, 2020; Weckenborg et al., 2024), China (Gao et al., 2025; Wang et al., 2023), Middle East (Nurdiawati et al., 2025). On the other hand, temporal variability is often neglected, even though time is a significant source of variability (Gauffin et al., 2017), because steel is continuously cast in melt shops. In this context, the term "heat" refers to a single, traceable batch of molten steel that is produced, refined, and cast under controlled conditions, as commonly defined in steelmaking practice (García-Menéndez et al., 2021). All heats are potentially different in terms of materials and energy consumption, since the input scrap is highly heterogeneous (Haupt et al., 2017). Therefore, in every heat, secondary steel producers melt different additions to balance the presence of impurities in scrap (also called tramp elements) (Paeng et al., 2024; Reck and Graedel, 2012) and guarantee the final composition required by the product destination (Astudillo et al., 2024; Haupt et al., 2017). Haupt et al. (2017) used granular heat-by-heat data to create a machine learning regression model predicting the energy that will be consumed to melt the materials. Based on the energy values predicted by the model, Haupt et al. (2017)

adjusted the electricity consumption in the LCI of a representative ecoinvent process for the EAF route (Frischknecht and Rebitzer, 2005), and calculated the related impacts on *Climate change*. Astudillo et al. (2024) used time-variable inventory data to evaluate the optimal scheduling of a steelmaking plant, with the objective of minimizing its environmental impact over a reference time. In these studies, Haupt et al. (2017) and Astudillo et al. (2024) calculated the environmental impact of steel production using the cut-off approach, but it is evident that switching to alternative recycling modelling approaches would substantially change the results. However, we acknowledge that these studies are very data-intensive, and can be conducted only if large industrial datasets with heat-by-heat granularity are available, but this is often a limiting factor (Rovelli et al., 2022).

1.3. Research gap and objectives of the study

Depending on the intended application of the LCA results, uncertainty can be considered in different ways (Bamber et al., 2020). With specific reference to the steel sector, uncertainty can be perceived as a limiting factor that complicates decision-making, especially when comparing alternative solutions under highly uncertain conditions. One example is the comparison between steel- and concrete-based structural elements for constructions (Zhao et al., 2021). In their comparative LCA, Zhao et al. (2021) first presented deterministic results that did not account for uncertainty, and subsequently reported probabilistic results obtained through Monte Carlo simulation. The deterministic results suggested a clear ranking among the analysed alternatives in terms of *Climate Change* impact. However, when uncertainty was considered, the probabilistic results revealed that this hierarchy was no longer well defined, particularly for two of the proposed solutions, due to significant overlaps between the box plots and the probability density functions of the alternatives (Zhao et al., 2021). Conversely, uncertainty can also be considered a useful source of information for optimizing the process based on temporal variability. For instance, high variability in the results may indicate that the use of certain scrap types can reduce energy consumption and the *Climate change* impact of the EAF process compared to other scrap types (Haupt et al., 2017). Moreover, variability may indicate that, at certain hours of the day, the EAF performs better than at others, due to dynamic changes in the carbon intensity of the electricity mix, thereby supporting the optimal planning of operations (Astudillo et al., 2024).

These examples show that, while in some cases LCA practitioners may aim to minimize result uncertainty to support clearer decision-making between alternatives (e.g., different structural element designs), in other applications emphasizing uncertainty may be desirable to address more complex decision contexts such as process optimization. In other words, depending on the intended use of the results, the interpretation of uncertainty may vary, and the preferred modelling approach may change accordingly. Given these premises, the aim of the present study is to provide recommendations on the selection of the most appropriate LCA recycling modelling approach in the steel sector grounding on the interpretation of uncertainty in results. A recycling modelling approach can indeed be selected by LCA practitioners to obtain the uncertainty distribution that aligns most closely with the intended use of the LCA results. To the best of our knowledge, this study represents the first attempt to address the LCA recycling modelling dilemma by means of uncertainty analysis, offering a novel contribution toward reducing ambiguity around this critical methodological choice. This investigation originated within the European project ALCHIMIA ("Data and decentralized Artificial intelligence for a competitive and green European metallurgy industry") (European Commission, 2022), whose objective was to develop a heat-specific process optimization model for the steelmaking process, focused on scrap use, that includes LCA and techno-economic evaluations. The most suitable recycling modelling approach therefore needed to be selected, which prompted more general recommendations on this topic, beyond process optimization.

2. Materials and methods

This section summarizes the methodology followed in this study, which reflects the ISO 14040 and ISO 14044 guidelines for LCA, including goal and scope definition (Section 2.1), LCI (Section 2.2), LCIA (Section 2.3), and life cycle interpretation (Section 2.4) (International Organization for Standardization, 2022a, 2022b).

2.1. Goal and scope definition

The goal of the LCA study is to assess the potential environmental impact of secondary steel produced by CELSA Group, while also quantifying the uncertainty of the LCA results, including both aleatory and epistemic uncertainty. The evaluation of this uncertainty will provide indications about the most suitable recycling modelling approach to adopt, depending on the intended use of the LCA results. The functional unit is the production of 1 kg of steel. The analysed steelmaking processes include the EAF, the Ladle, and the Ladle Furnace (LF), and they are located in two plants owned by CELSA Group:

- EAF: consumes electricity to melt scrap and mix it with minerals and carbon sources;
- Ladle: a large crucible where steelmakers add tapping additions, like ferroalloys;
- LF: homogenizes the material mix by adding argon and consuming electricity to maintain the steel in a liquid state. Further additions are also melted in the LF.

For all these stages, the system boundaries (represented in Fig. 1) include the upstream processes related to the extraction, processing, and supply of raw materials and the electricity consumption. The system boundaries also include the transport and pre-treatment of scrap, which is cleaned before entering the EAF, as well as all the downstream processes associated to waste management. The main waste types are refractories, electrodes, dust, and slag. In terms of their treatment, according to CELSA Group, refractories and electrodes are disposed of, meanwhile slag is reused as aggregate in asphalt production (Saade et al., 2015) and zinc is recovered from dust (Ng et al., 2016). Direct emissions from each step of the steelmaking process are also considered as biosphere flows directly released to the environment. In addition to the EAF, the Ladle, and the LF stages - for which primary data were collected from CELSA Group - the system boundaries have been expanded to include the full life cycle of steel using secondary data. These additional stages are continuous casting, modelled according to Bieda et al. (2018), and the end-of-life stage. Further processing of steel, and the use phase are excluded due to lack of data. For this reason, the system boundaries are also defined as "cradle-to-gate with options", according to (Santero and Hendry, 2016). At end-of-life, the steel produced by CELSA Group plants becomes post-consumer scrap, which is partially landfilled (15%) and partially recycled (85%), according to the Annex C of the PEF method (Damiani et al., 2022). As typical in the metals sector, closed-loop recycling is assumed, which implies that all the recovered steel is newly recycled via the EAF route as a source of iron (Husmann et al., 2025).

In the scope definition phase, the recycling modelling approach must be declared. Due to its versatility, the CFF has been used to model both the use of secondary materials (various types of scrap) and the recycling of waste (dust, slag, and end-of-life steel). By setting the A parameter to 0 or 1, we can indeed switch between two different recycling modelling approaches: the substitution method and the cut-off method (Damiani et al., 2022). A sensitivity analysis is performed to address the epistemic uncertainty related to the choice of the recycling modelling approach. However, as stated in the introduction, the CFF not only allows for comparison between the cut-off and substitution approaches,

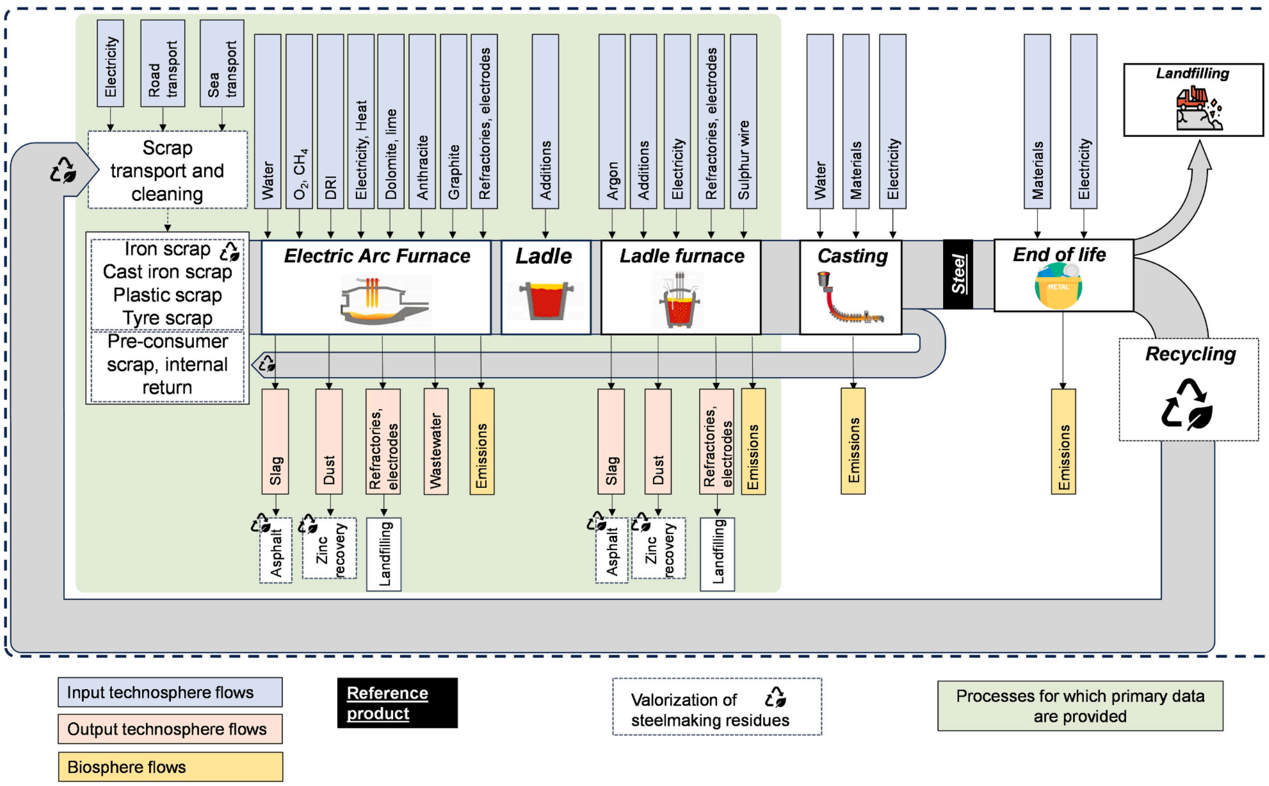

Fig. 1. System boundaries considered in the present study in relation to secondary steel production in two steelmaking plants owned by CELSA Group, with specification of main inputs and output flows. Additions in the Ladle and Ladle furnace include Aluminium, Anthracite, Calcium carbide, Calcium silicide, Deoxidants, Ferroboron, Ferrochromium, Ferrosilicon, Graphite, CaO, Magnesite, Recarburizer, Silicomanganese, Sodium aluminate, Fluorspar, Sulphur wire, Titanium, Vanadium.

but also enables the evaluation of intermediate approaches that consistently allocate environmental credits both to the use of recycled materials and to recycling at end of life. This is the case of the application PEF method for finite products made of steel, which recommends $A=0.2$ (Damiani et al., 2022). Since steel is largely used in finite products, and in light of the relevance of the PEF method, additional results obtained using $A=0.2$ are reported as *Supporting Information,* section *"Additional results"*.

The CFF also allows for modelling of avoided products, meaning that the materials recovery from secondary sources prevents the consumption of primary materials. As shown in Fig. 1, internal pre-consumer scrap is also included within the system boundaries. This scrap is not considered waste, but rather an additional material flow that circulates within the plant without crossing the system boundaries (Durão et al., 2020). Consequently, the environmental burden of the entire process is attributed to pre-consumer scrap that is remelted at the top of the plant as a loop (Durão et al., 2020).

2.2. Life cycle inventory

The LCI includes quantitative data on material and energy consumption, direct pollutant emissions to the environment, and waste generation. The ecoinvent 3.11 cut-off version database (Frischknecht and Rebitzer, 2005) has been used as the background database and the SimaPro software v10.2 has been used to build the LCI model.

The LCI modelling of recycling is based on the CFF, whose parametric equations (Damiani et al., 2022) are implemented in the LCA software, as extensively described in the *Supporting Information,* sections *" Scrap"* and *"Waste"*. Moreover, a comprehensive summary of all model inputs and outputs, including a specification of the background datasets adopted for the LCI modelling, is provided in the *Supporting Information,* section "*Data*". The key modelling assumptions are described in the *Supporting Information,* section "*Assumptions*", and summary of the of the steel families and the corresponding number of heats is provided in the *Supporting Information,* section *"Steel families and heats"* To address data gaps in the background database, literature sources have been used. This applies to zinc recovery (Viklund-White, 1999), vanadium production (Weber et al., 2018), Direct Reduced Iron (DRI) (Nurdiawati et al., 2023), and continuous casting (Bieda et al., 2018).

As underlined in previous paragraphs, the LCI modelling of steelmaking processes depends on multiple factors, such as the specific heat, the characteristics of each factory, and the steel grades that shall be produced. More specifically, the sources of uncertainty affecting the LCI phase are:

- **Temporal variability**: all data vary from heat to heat but cannot be reported for confidentiality reasons, as time-series are proprietary to the CELSA Group. A statistical analysis of uncertainty is conducted based on 475 heats.
- **Spatial variability:** a scenario analysis is conducted to compare two different factories (hereinafter referred to as Factory 1 and Factory 2). The same technologies are deployed in both factories; the main differences lie in the materials mix and the energy mix used at the two production sites.
- **Steel grades variability**: for Factory 1, a scenario analysis is conducted across eight steel families to account for variability in output steel grades. These families are labelled according to the CELSA Group nomenclature (Families A, B, C, D, H, M, S, U). The families group steel grades with similar characteristics in terms of chemical and physical properties, mainly related to alloying levels. Since the characteristics of steel are closely linked to its applications, the steel grade produced is directly determined by customer requirements, which may vary significantly. As a result, different steel grades are

produced in each heat, leading to variations in the material mix charged during steelmaking and in the associated environmental impacts (Haupt et al., 2017). Consequently, steel grade variability represents a distinct source of variability in the assessment.

In addition to the variability sources related to the LCI considered in this study, future research could investigate technological variability. For instance, DRI can be produced using different reducing agents (Ramezani Moziraji et al., 2024), or the BF/BOF route could be considered as an alternative to the EAF route (Andreotti et al., 2023). These alternative technological configurations were not included in the present study due to the lack of primary data. A general and comprehensive overview of the uncertainty sources that could be considered in LCA studies are available in Hauschild et al. (2018).

We underline that, despite uncertainty in background and foreground data quality being the most commonly evaluated type of uncertainty in the LCA literature (Heijungs, 2020), Monte Carlo simulations were not performed in this study. The reason is that, without properly considering correlations between LCI flows, Monte Carlo approaches are purely stochastic and may lead to inconsistent conclusions (Groen and Heijungs, 2017). This theoretical issue has been demonstrated in the cement sector, where many types of materials are mixed to achieve the desired composition (Marsh et al., 2024). A similar mixing of materials occurs in steelmaking, therefore, we decided to exclude Monte Carlo simulations from this study.

2.3. Life cycle impact assessment

Following the PEF recommendations, the LCIA method used in this study is Environmental Footprint (EF) 3.1 (Damiani et al., 2022). Among the impact categories included in the method, we selected the most relevant for the metals sector according to (Santero and Hendry, 2016):

- *Acidification*
- *Climate Change*
- *Eutrophication, freshwater* (chosen as a representative category for all eutrophication-related impacts)
- *Photochemical ozone formation*
- *Ozone depletion*

In the LCIA, all types of uncertainty mentioned in previous sections must be addressed to quantify the range of result variations arising from both epistemic and aleatory sources, as reported in Table 1. Epistemic uncertainty related to A is assessed through sensitivity analysis considering A=0 and A=1. Aleatory uncertainties - including temporal, spatial, and steel grades variability - are respectively addressed using either statistical evaluation of time-series data and scenario-based approaches considering site differences and steel family distinctions.

Table 1
Overview of the uncertainty sources considered in the study, including their type, associated LCA phase, evaluation method, and specific conditions analysed.

Uncertainty source	Uncertainty type	LCA phase	Technique for uncertainty evaluation	Considered uncertainty conditions
CFF allocation parameter A	Epistemic	Goal and scope definition	Sensitivity analysis	$A = 0, 1$
Temporal variability	Aleatory	LCI	Uncertainty analysis based on statistical evaluation	475 data points from time series
Spatial variability	Aleatory	LCI	Scenario analysis	Factory 1, Factory 2
Steel grades variability	Aleatory	LCI	Scenario analysis	8 steel families

To consider all these sources of uncertainty, the LCIA is performed multiple times: the number of runs covers all 475 heats from two factories (i.e., Factory 1 - including all steel families - and Factory 2) for a total of 950 heats. Since the calculations are conducted twice - once with $A = 0$ and once with $A = 1$ - 1900 runs are overall required.

2.4. Life cycle interpretation

This phase aims to explain how uncertainty in LCA results is interpreted in this study to provide recommendations on the most appropriate recycling modelling approach. However, since the perception of uncertainty varies among users of LCA results depending on the intended application, we considered a range of possible application contexts for LCA, drawing inspiration from (Subal et al., 2024):

a) Product development and process optimization;
b) Communication (internal/to the public);
c) Strategic development of organization;
d) Organizations internal learning;
e) Development of regulations/laws.

To support the interpretation of the LCIA results, they are visualized using box plot diagrams, which are commonly employed to summarize key features of statistical distributions. Wider boxes and longer whiskers denote greater uncertainty, thereby reducing the statistical representativeness of the mean impact value (Hollberg et al., 2021). Separate panels are used to display results for $A = 0$ and $A = 1$ across all selected impact categories. To account for the variability of output steel grades, the results are first disaggregated by steel family produced in Factory 1, with each family represented by an individual box. A similar approach is then applied to assess spatial variability between Factory 1 and Factory 2, with each factory associated with one box per condition ($A = 0$ and $A = 1$). In this representation, the width of each box and whisker only reflects the temporal variability of LCIA results. Box plots, also called, box-and-whisker plots, are particularly suitable for data series composed of multiple data points, a condition that applies only to temporal variability among the selected sources of uncertainty.

In addition, a contribution analysis is carried out to identify the main environmental hotspots and to assess how their relative contributions vary over time. The contribution analysis is illustrated using stacked column charts, in which each segment represents the mean impact of each contributor, while the variability of these contributions is estimated using their standard deviation across all heats, which is reported in the *Supporting Information,* section *"Contribution analysis"*.

3. Results

This section presents the influence associated with the CFF allocation parameter A, together withtemporal variability, steel grade variability (Section 3.1) and spatial variability (Section 3.2) on the uncertainty of the LCIA results.

In order to validate the robustness of the results, a verification was carried out to ensure that the impact values reported in this section are in the same order of magnitude as the results obtained using the ecoinvent dataset "*steel production, electric, low-alloyed*" (Frischknecht and Rebitzer, 2005) considering the electricity mix of the countries in which the two factories are located. However, numerical results for this comparison are not presented, since the LCI developed in this study is considerably more detailed than the corresponding ecoinvent dataset; therefore, a direct comparison would not be methodologically consistent.

3.1. LCIA results for Factory 1

The results of the LCIA conducted for Factory 1 are based on 475 data points. Fig. 2 shows the variability in results for $A = 0$ (substitution) and

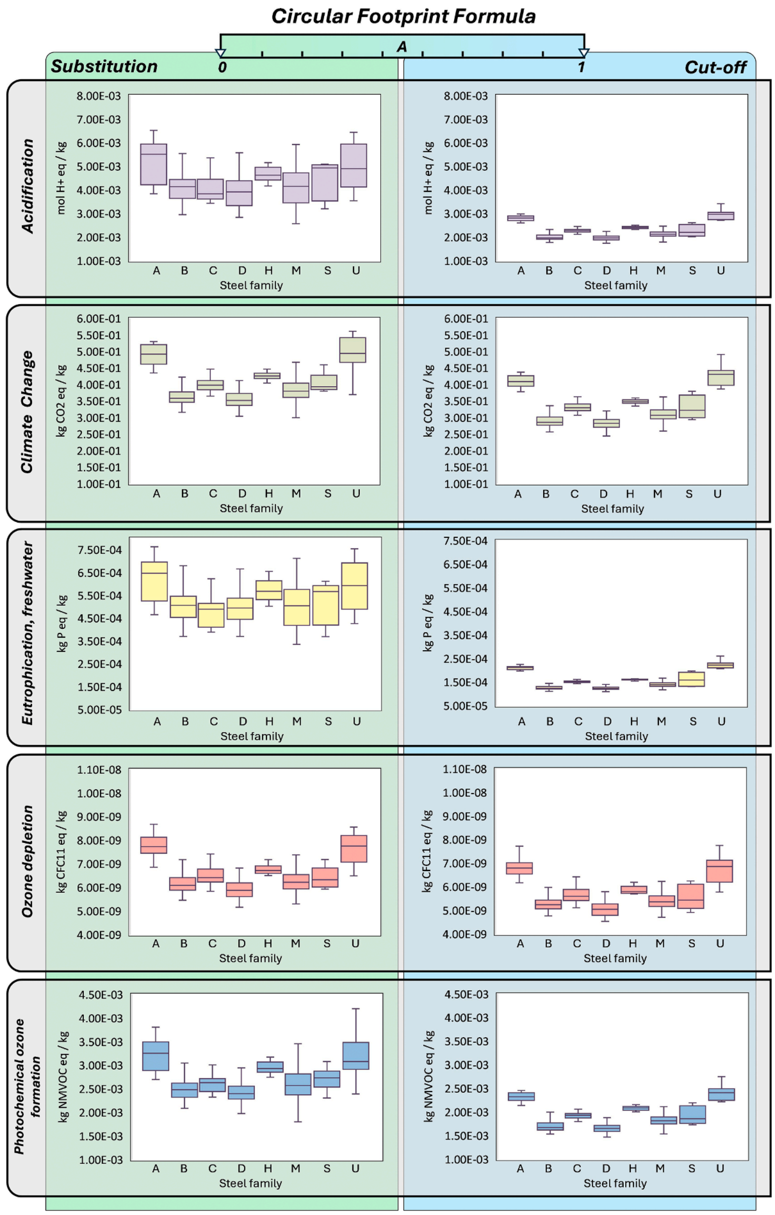

Fig. 2. Comparison of the Life Cycle Impact Assessment (LCIA) results of different steel families (A, B, C, D, H, M, S, U) produced in Factory 1 with the substitution approach ($A = 0$, left) and the cut-off approach ($A = 1$, right).

$A = 1$ (cut-off), across five selected impact categories and eight steel families.

When comparing the results from the two recycling modelling approaches, we observe that - across all impact categories and steel grades - the mean environmental impact is consistently lower for $A = 1$ than for $A = 0$. Additionally, the boxes and whiskers drawn for $A = 0$ are generally wider, indicating greater variability in the LCIA results when using the substitution recycling modelling approach. In contrast, adopting the cut-off approach ($A = 1$) reduces both the mean impact values and the associated variability across all categories.

When comparing the steel families based on the overall trend of their mean environmental impact across the evaluated impact categories, shown in Fig. 2, three clusters can be identified:

- Low-impact steel families (B, D);
- Medium-impact steel families (C, M, S);
- High-impact steel families (A, U).

The clustering approach described above reflects the general trend across the evaluated impact categories and, in particular, is consistent with the pattern observed for the *Climate change* indicator. This is particularly relevant because *Climate change* has already been used as a reference metric in environmental classification schemes for steel (Blanco Perez et al., 2025) and in ongoing initiatives of the European Commission (Blanco Perez et al., 2024).

However, when variability is considered alongside mean values, comparing steel grades becomes much more challenging with the substitution approach. The high variability in the results makes it difficult to confidently state, for example, that a product made from a low-impact steel family (e.g., B) consistently has a lower impact than one made from a high-impact family (e.g., U) for every heat, due to significant overlap in the box plots. In contrast, the cut-off approach allows to more clearly identify the best performing steel family because of the reduced variability. Nevertheless, Fig. 2 also shows that the differences between steel families can vary depending on both the value of A and the specific impact category considered. For instance, when *Climate Change* or *Ozone* *depletion* are used as the reference impact category, the distinctions between steel families are more pronounced, thus improving comparability even with A=0.

Fig. 2 therefore shows that the choice of the A factor has a more pronounced influence on certain impact categories than on others. On the other hand, the box-and-whisker plots indicate that for *Acidification, Eutrophication*, and *Photochemical ozone formation*, both the mean environmental impact and the dispersion around the mean (i.e., the width of the boxes and whiskers) markedly decrease when switching from $A = 0$ to $A = 1$. In contrast, this difference is much less evident for *Climate change* and *Ozone depletion*, where the variability of the results remains relatively similar between $A = 0$ and $A = 1$. This behaviour can be explained by the fact that the A allocation factor primarily affects the modelling of secondary material consumption (i.e. scrap supply) and output waste recycling (i.e. dust and slag). Therefore, the greater the contribution of these material flows to a given impact category, the larger the difference between the results obtained with $A = 0$ and $A = 1$. A contribution analysis representing the contribution of the different life cycles stages to each impact category (shown in Fig. 3) is therefore necessary to fully interpret the patterns observed in Fig. 2.

Fig. 3 presents the contribution analysis for both $A = 0$ and $A = 1$, across the selected impact categories, based on the mean contributions. To represent such contributions as percentage of the total, a stacked column diagram is used, where each segment corresponds to a different contributor. These contributions are subject to temporal variations, estimated calculating their standard deviations (available as *Supporting Information,* section *"Contribution analysis"*). Three steel families are included as representative cases:

- Class D, representing low-impact steel families;
- Class M, representing medium-impact steel families;
- Class U, representing high-impact steel families.

According to Fig. 3, when $A = 0$, iron scrap (represented by the blue segment) constitutes the main contributor to the environmental impact of steel. This pattern holds true across all impact categories and is particularly pronounced for *Acidification, Freshwater Eutrophication*, and *Photochemical Ozone Formation*. Although iron is the primary constituent of scrap, the environmental impact associated with scrap inputs is largely driven by the presence of undesired, high-impact tramp elements

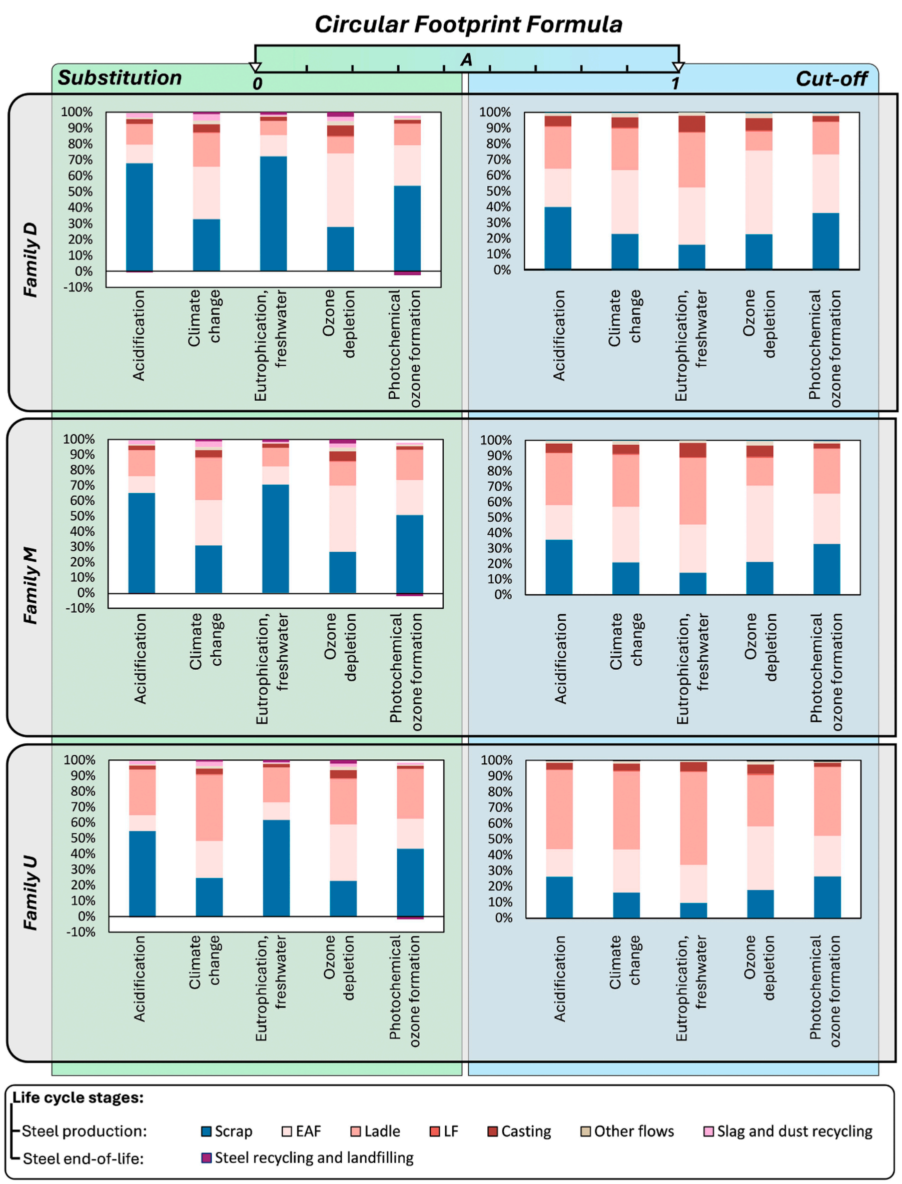

Fig. 3. Contribution analysis of the Life Cycle Impact Assessment (LCIA) results calculated for three steel families (D, M, U) produced in Factory 1, under the substitution approach ($A = 0$, left side) and the cut-off approach ($A = 1$, right side). EAF = Electric Arc Furnace, LF = Ladle Furnace.

– above all copper, zinc, and nickel. Even in small quantities, these elements significantly increase the overall environmental burden of scrap (Paeng et al., 2024). Regarding other impact categories, such as *Climate Change* and *Ozone Depletion*, contributions are more evenly distributed across scrap, EAF, and Ladle. Given that iron scrap is the main contributor with the substitution approach, the analysis focuses on the variability of scrap contributions. It is observed that the standard deviation of the impacts of scrap is significantly higher compared to other contributors, especially for the impact categories that exhibit the highest variability in Fig. 2 (see *Supporting Information,* section *"Contribution analysis"* for more details on standard deviation). This observation clearly indicates that the high variability of impact indicators noted in Fig. 2 is mostly due to the highly aleatory nature of the scrap contributions, especially due to its variable material composition.

Considering the cut-off approach, the environmental burden of embodied materials is not attributed to scrap consumption since it is considered a secondary resource. Therefore, the impact related to scrap is limited to sorting and pressing operations, transport to the melt shop, and pre-treatment.

For this reason, the percentage contribution of scrap use is considerably lower than in the substitution scenario, but anyway significant. Conversely, with the cut-off approach, the main environmental impacts arise from the EAF and the Ladle. The impact of EAF operation is primarily due to electricity consumption and the use of carbon sources such as coal and anthracite. The Ladle's impact is largely linked to the use of tapping additions, including various ferroalloys, minerals, and metals employed to adjust the final steel composition. The LF and casting stages are minor contributors. The standard deviation values obtained with the cut-off approach (available in the *Supporting Information,* section *"Contribution analysis"*) demonstrate that the variability of the impacts of all contributors remains unchanged compared with the substitution approach, except for scrap and all recycling processes. In particular, the standard deviation of the impacts associated with scrap, which was dominant under the substitution approach, is drastically reduced with the cut-off method. This is because the cut-off approach does not consider scrap chemical composition, which is strongly stochastic. This

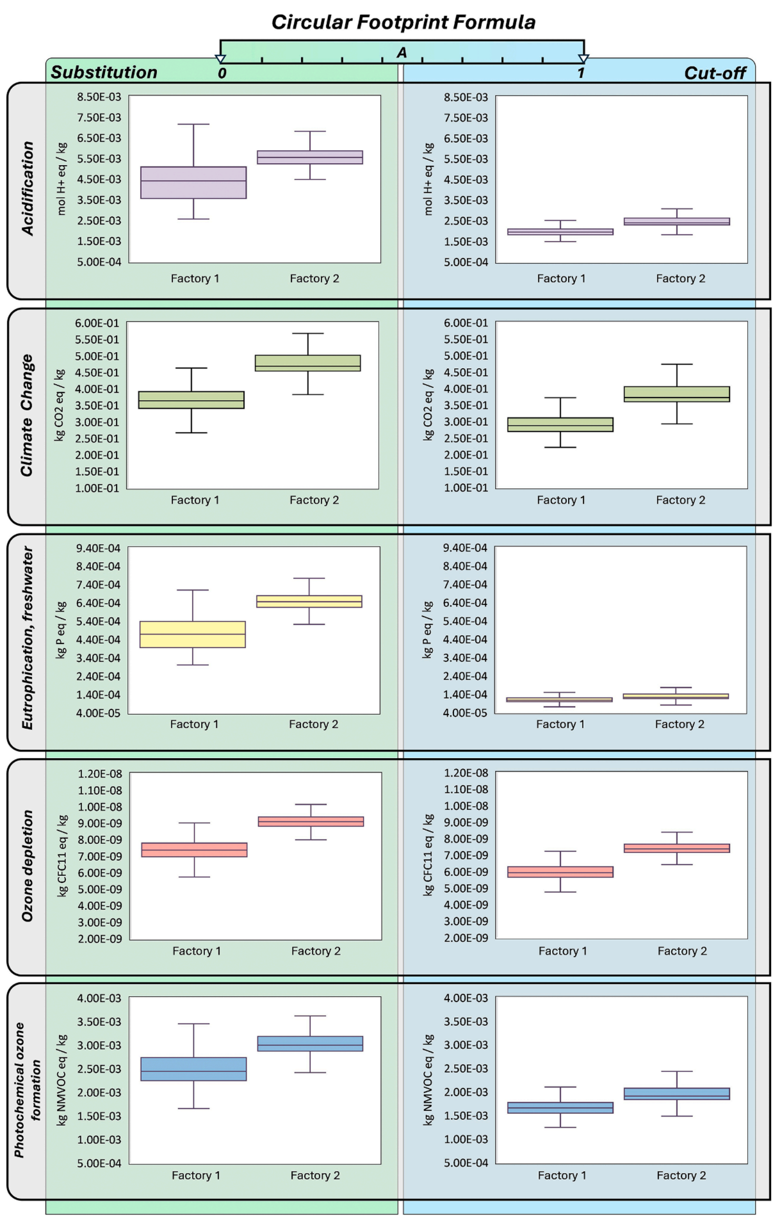

Fig. 4. Comparison of the Life Cycle Impact Assessment (LCIA) results of different Factories (Factory 1, Factory 1) with the substitution approach ($A = 0$, left) and the cut-off approach ($A = 1$, right).

trend explains the reduction in result variability illustrated in Fig. 2 when switching from the substitution to the cut-off approach.

The substitution approach, therefore, combined with a careful characterization of the scrap input composition, captures the environmental burden associated with tramp elements better than the cut-off approach, as it attributes an impact to all elements embodied in the scrap. In metallurgy, tramp elements represent a major challenge for electric steelworks, as impurities contained in scrap may lead to defects in the final steel products. Currently, their concentration is primarily controlled through dilution with high-purity materials such as DRI, since large-scale removal technologies have not yet been deployed at the industrial level due to techno-economic constraints. Nevertheless, the development of effective removal strategies remains an active and promising research area in metallurgy (Paeng et al., 2024). Based on our results, we therefore recommend the substitution approach for LCA studies aimed at assessing the environmental burdens and potential benefits of strategies designed to reduce the presence of tramp elements in scrap melted in EAFs.

The role of scrap in steelmaking process optimization strategies has also been emphasized by Astudillo et al. (2024). Similar to our study, they analysed temporal variability and identified scrap savings as a key strategy for reducing the *Climate Change* impact, along with improving energy and resource efficiency in the EAF and the ladle. These findings, obtained using the cut-off approach, are consistent with the contribution analysis presented in Fig. 3 for A=1. Also Haupt et al. (2017), who conducted a heat-by-heat study, highlighted that a significant share of the energy demand and *Climate Change* impact of the steelmaking process under evaluation is directly or indirectly influenced by the variable characteristics of scrap - particularly including the electricity required to melt different scrap types.

3.2. LCIA results for Factory 1 and Factory 2

Fig. 4 shows that, regardless of the recycling modelling approach adopted, Factory 2 consistently exhibits a higher mean environmental impact compared to Factory 1. This difference arises because Factory 2 uses a different electricity mix and different quantities of ferroalloys and carbon sources, although the same technologies are deployed at both factories.

Regarding the variability of LCIA results in the individual factories, the trends observed previously are confirmed in Fig. 4. Specifically, for both factories, result variability is higher with the substitution approach than the cut-off. However, in both approaches, the box plots for Factory 1 and Factory 2 largely overlap, suggesting that adding data from Factory 2 does not noticeably increase the variability in the environmental impact of the steel overall produced across CELSA Group's facilities. Comparing the two recycling modelling approaches, we observe that Factory 1 exhibits slightly greater variability than Factory 2, but only under the substitution approach. This difference is further explained by the contribution analysis presented in Fig. 5. The contribution analysis shows that, similarly to the results obtained for Factory 1 (Fig. 3) with $A = 0$, iron scraps are the major impact contributor in both factories, while the EAF and ladle become the main hotspots with $A = 1$. A notable difference is observed in the variability of iron scrap's contribution:

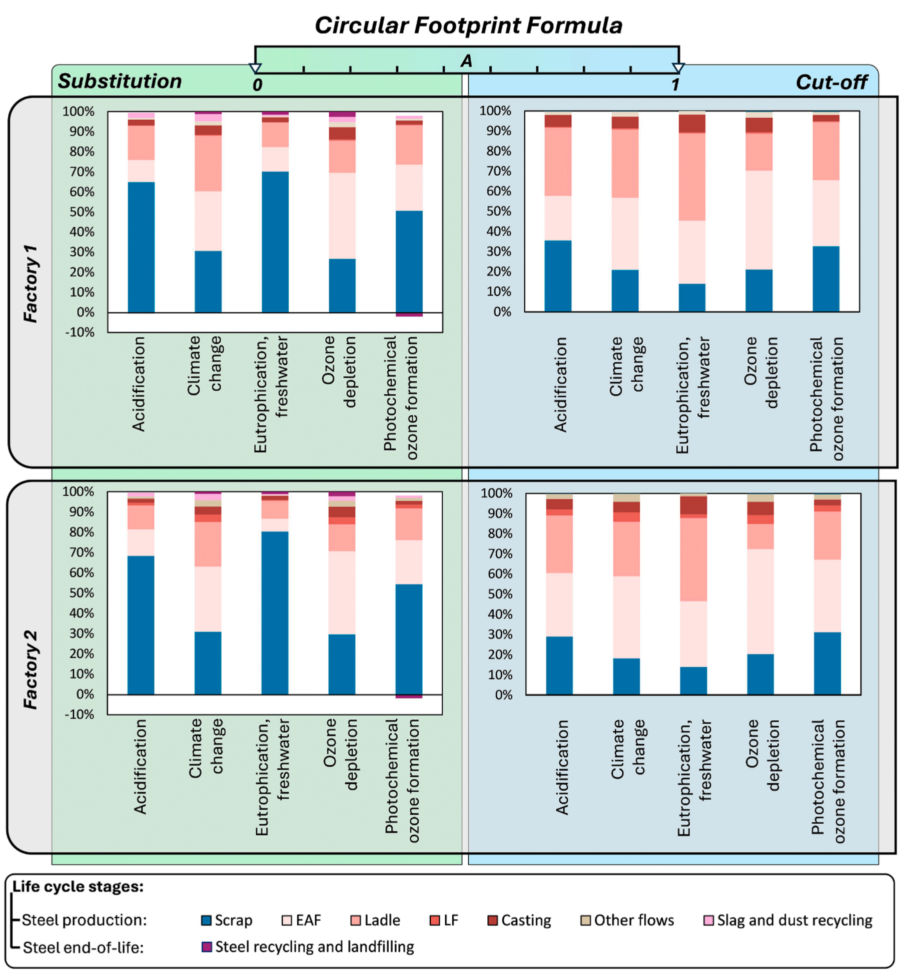

Fig. 5. Contribution analysis of the Life Cycle Impact Assessment (LCIA) results calculated for two steel Factories (Factory 1, Factory 2), with the substitution approach ($A = 0$, left side) and the cut-off approach ($A = 1$, right side). EAF = Electric Arc Furnace, LF = Ladle Furnace.

Factory 2 exhibits less pronounced variability, as indicated by lower standard deviations compared to Factory 1. This evidence suggests that the characteristics of scrap used in Factory 2 are less variable than in Factory 1. Conversely, with the cut-off approach, electricity consumption in the EAF and ferroalloy additions represent the main impact sources. The percentage contributions of these inputs show little variability in both factories. Consequently, the overall variability of the results remains similar between Factory 1 and Factory 2 when $A = 1$.

The same number of heats was selected for Factory 1 and Factory 2 to ensure methodological consistency. Additional calculations (whose results are not included in Fig. 4 and Fig. 5) confirm that using all the over 800 heats available for Factory 2 would not significantly alter the box plots, supporting the robustness of the results based on 475 heats.

4. Discussion

This section discusses the uncertainty of LCA results in relation to each of the potential applications of LCA, as identified by (Subal et al., 2024). This section shows that different stakeholders (e.g., engineers, managers, communication experts, and policy-makers) may interpret result uncertainty differently, leading to preferences for different recycling modelling approaches.

4.1. Products development and process optimization

As presented in the results, the substitution modelling approach amplifies the temporal variability of LCA outcomes. The contribution analysis highlights iron scraps as the main environmental impact contributor, both in terms of average percentage impact and variability. This means that the substitution approach emphasizes the environmental implications of scrap variability, making it easier to distinguish between low-impact and high-impact heats. With the support of LCA practitioners, process engineers could analyse results on a heat-by-heat basis to identify specific scrap characteristics that reduce environmental impacts. For example, in the case of Factory 1, it emerged that using scraps with low copper and zinc contents lowers the overall environmental burden of the output steel, regardless of the steel family. Such detailed differences between heats would be less evident using the cut-off approach, which results in narrower variability. In fact, process optimization engineers involved in the ALCHIMIA project preferred to use LCIA results calculated with the substitution approach, because it captures differences between scrap types, facilitating the development of optimization models aimed at minimizing the environmental impact of scrap use. In this context, process optimization engineers tend to interpret variability as valuable information rather than as an error margin around the mean impact value (Astudillo et al., 2024). On the other hand, product development engineers - intended as engineers that use the steel produced by CELSA Group to make final products - might have a different perspective. When tasked with choosing between two steel grades based on environmental sustainability, the high uncertainty affecting LCIA results with the substitution approach makes comparisons among steel families more challenging. This would likely lead product developers to prefer the cut-off approach, which provides clearer differentiation between steel families due to reduced uncertainty.

4.2. Communication (internal/to the public)

Marketing teams are usually responsible for communicating the environmental performance of their products to consumers, while also emphasizing the credibility of their claims and avoiding greenwashing (Marrucci et al., 2025). Given this objective, we assume that marketing professionals would prefer to communicate simplified metrics - such as the mean environmental impact values - because they are more accessible to non-expert audiences (Iovino et al., 2024). However, communicating uncertainty is also crucial to ensure transparency, as high uncertainty in LCA results may lead the audience to question the reliability of the environmental claims (Herrmann et al., 2014). In this regard, the cut-off approach may facilitate communication in the steelmaking sector because it reduces the variability around mean environmental impact values.

However, it should be emphasized that differences in impact values between the cut-off and substitution approaches arise from the underlying allocation logic and do not reflect intrinsic improvements in environmental performance. Therefore, meaningful comparisons are only possible when a consistent allocation approach is applied (e.g., within EPD schemes), and this comparability constraint should be explicitly communicated. Different considerations apply to internal reporting or communication with expert stakeholders - such as sustainability managers in client companies purchasing intermediate steel products. In these cases, using the cut-off approach may help clearly communicate how steel families rank in terms of environmental impact. However, this choice may also be less straightforward, since, as seen in the process optimization analysis, engineers might view variability as a valuable source of insight. Therefore, depending on the specific purpose of internal communication, either the substitution or the cut-off approach may be appropriate.

4.3. Strategic development of organization

The strategic development of an organization is a complex process in which company management must make decisions that are relevant in the present while also accounting for long-term implications, such as the supply chain management (Sellitto et al., 2019). In addition, methodological choices in LCA represent only one of several sources of uncertainty influencing strategic decision-making. For instance, European policies on steel labelling (Blanco Perez et al., 2025, 2024), actual scrap availability, and price volatility, may substantially influence the strategic development of organizations in the steel sector (Pauliuk et al., 2013). From a technological perspective, the large-scale deployment of hydrogen-based ironmaking and steelmaking technologies could further reshape long-term investment and production strategies (International Energy Agency, 2020). In other words, the strategic development of steelmaking organizations is strongly influenced by several types of contextual uncertainties. For these reasons, unlike the previous use cases, it is more difficult to provide a clear recommendation on the most appropriate recycling modelling approach for strategic decision-making. Nevertheless, abstracting from the broader techno-economic and regulatory context which lies beyond the scope of this study, it is reasonable to assume that decision-making under conditions of high uncertainty can be more challenging. In this respect, based on our results, the lower variability associated with the cut-off approach may facilitate more stable comparisons and support strategic evaluations. This could be the case of selecting suppliers for electricity and raw materials, whose comparison would be more complicated if results have a higher variability. On the other hand, strategic planning also requires an understanding of how risks and opportunities may evolve over time. In this context, the substitution approach offers the advantage of amplifying the effects of temporal variability, potentially helping managers to make more informed decisions in dynamic and evolving environments. Therefore, for strategic development purposes, the choice of the most appropriate recycling modelling approach should depend on the specific nature of the decision being made and the time horizon considered.

4.4. Organizations internal learning

Internal learning is a broad concept that refers to enhancing workers' awareness and understanding of their role in supporting environmental sustainability (Subal et al., 2024). Due to its general nature, it is difficult to provide universally valid recommendations on which recycling modelling approach is most appropriate for all internal learning contexts. In this paper, we examined the case of CELSA Group, a multinational company operating multiple production sites, including Factory 1 and Factory 2. In this context, fostering the exchange of information on LCIA results within the CELSA Group can present a valuable opportunity for internal learning. Comparing the mean environmental impacts between the two sites is likely of limited relevance, as they are part of the same corporate structure and not in competition. Instead, cross evaluating the variability of results can yield meaningful insights, support process improvement and promoting synergies between factories. For instance, analysing the factors that contribute to differences in the variability of scrap-related impacts could inform strategies for enhancing circularity and traceability across the group. Given these considerations, the substitution approach - which amplifies the expression of temporal variability - appears to be the more suitable option in this specific internal learning context. An important internal learning from applying the substitution approach is the crucial role of collecting detailed data on scrap composition. As CELSA Group plans future data collection campaigns in other production sites, prioritizing this information will be essential to better discriminate between low- and high-impact scraps and to improve the overall quality and relevance of LCIA results.

4.5. Development of regulations/laws

Policymakers increasingly rely on LCA results to support decisions regarding green investments, funding allocation, and the development of certification schemes (Blanco Perez et al., 2025). As demonstrated in the previous sections, making consistent comparisons in high-uncertainty conditions is particularly challenging. For instance, LCIA results showed that with the substitution approach, the uncertainty would prevent policymakers from confidently attributing incentives to the most virtuous steel families or factories. Given this, it is likely that policymakers would prefer to base decisions on LCIA results with lower variability using the cut-off approach. Currently, most policies in the steel sector prioritize *Climate Change* as the main indicator for guiding decarbonization strategies, rather than considering the full environmental footprint (Andreotti et al., 2023). In this context, our analysis shows that *Climate Change* is the impact category where differences between the two recycling modelling approaches are least pronounced. Therefore, the choice of modelling approach may have a limited influence on uncertainty for policies focused specifically on decarbonization. Moreover, one key task of policymakers - especially in initiatives like PEF-based labelling - is to benchmark the environmental impact of products manufactured across diverse sites and regions. Since such benchmarks are based on mean environmental impact values, adopting the cut-off approach, which is associated with lower result variability, ensures that the mean values used in benchmarking are more statistically robust and representative.

5. Conclusions

This paper provides recommendations for selecting the most suitable recycling modelling approach in the steelmaking sector, based on the interpretation of LCA results uncertainty. From a methodological perspective, this represents a novel contribution to the scientific literature.

The analysis was conducted within the framework of the ALCHIMIA project, which offered a particularly suitable case study thanks to its extensive and high-quality primary dataset, encompassing 475 heats, 8 steel families, and 2 production sites. Using the CFF - and specifically the parameter A - this study compares the two main recycling modelling approaches used in the LCA community: the substitution approach and the cut-off approach. The results show that the substitution approach leads to greater variability in the LCA outcomes, due to its sensitivity to the chemical composition of scrap, which is highly variable across time and space. In contrast, the cut-off approach reduces result variability, as the embodied material impacts of scrap are not accounted for directly.

While this observation has methodological relevance, it also carries practical implications. Based on our findings, we can conclude that if the intended use of the LCA results involves comparisons between alternatives - as in the case of marketing, communication experts, policymakers, or product developers - then minimizing uncertainty is critical, and the cut-off approach is generally more appropriate. Conversely, if the goal is to extract insights from variability - as in the case of process optimization engineers or, in some instances, strategic managers - then the substitution approach is preferable.

However, some of the applications considered here (e.g. *Strategic development of organization* and *Organizations internal learning*) are too broad and context-dependent to allow for a clear, generically valid recommendation. In addition, we recognize that the interpretation of uncertainty is in any case context-dependent and subjective.

We acknowledge a limitation of this study: deriving general recommendations from a case study involving only two production sites may be debatable. Nevertheless, it is reasonable to assume that the provided recommendations can be realistically extended to all electric steelworks. Despite the results obtained for Factory 1 and Factory 2 showing different levels of variability, both cases demonstrated that the substitution approach amplifies the variability of the results because it captures the material composition of scrap. Since scrap always contains impurities in variable quantities and represents the main contribution to the bill of materials of every EAF (Sandberg et al., 2007), it is reasonable to assume that the same recommendation can be extended to all electric steelworks, although this was not explicitly demonstrated in this study due to the limited number of factories considered in this study.

However, the strength of this work lies in the scale and richness of the dataset, which includes several hundred heats - a level of detail rarely available to most LCA practitioners. As such, we believe the insights presented here can serve as a valuable orientation tool, especially for those without access to sufficiently comprehensive data for assessing uncertainty, when selecting a recycling modelling approach. Nevertheless, this study underscores the importance of explicitly addressing uncertainty and variability when making methodological choices in LCA, particularly regarding recycling modelling in complex industrial systems such as steelmaking.

CRediT authorship contribution statement

Federico Rossi: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Fabio Iraldo:** Writing – review & editing, Funding acquisition. **Monia Niero:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.resconrec.2026.109023.

The *Supporting Information* is an Excel file structured into a Title page and eight subsections. The life cycle modelling of input scrap and the end-of-life of steel based on the CFF is described in the "*1, Scrap*" subsection, while the modelling of output waste using the CFF is reported in the "2. *Waste*" subsection. The "*3. Data*" subsection provides a spreadsheet containing detailed information on all inputs and outputs of the LCA model, including background datasets from the ecoinvent 3.11 cut-off database (Frischknecht and Rebitzer, 2005); the quantities cannot be disclosed for confidentiality reasons. All assumptions adopted for the life cycle modelling of scraps and output waste are summarized in the "*4. Assumptions*" subsection. The "5. *Steel families and heats*" subsection reports the steel classes considered in the study and the corresponding number of heats used in the uncertainty analysis. The "*6. Contribution analysis*" section provides a quantitative overview of the main environmental contributors to the impact of steelmaking processes in term of mean value and standard deviation. The section "*7. Additional results*" contains the same results of the study in Fig. 2 and Fig. 4 calculated assuming A=0.2 as recommended by the PEF guidelines for finite steel products.

Data availability

The authors do not have permission to share data.

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