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Uncertainty in prospective Life Cycle Assessment: A review of current practices and the role of scenario choice

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Abstract: In the context of the ecological crisis, assessing the environmental impacts of products and services can play a crucial role in guiding future development. Prospective Life Cycle Assessments (pLCA) have gained increasing attention in recent years, due to their ability to anticipate future environmental impacts of technologies, even when the technology is at an early stage of development. Besides the inherent uncertainties embedded in any quantification of environmental impacts, the future-oriented outlook of pLCAs introduces additional uncertainties as they depend on assumptions related to the technology's prosperity and broader societal development. A widely suggested approach to address these uncertainties is to apply scenarios to consider multiple potential futures, instead of relying on a single projection. While scenario-based approaches can be a valuable tool for pLCA, addressing uncertainty is still an evolving practice, leading to differing approaches among practitioners. Consequently, a varying approach to account for and interpret uncertainties in pLCA can reduce the transparency and robustness of results, potentially leading to sub-optimal decision support. To address this gap, this study examines how uncertainties are addressed in current literature on pLCA, as well as what the implications of scenario choice are for the uncertainty of LCIA results. To explore how current pLCA practice addresses uncertainty and utilises scenarios, a systematic literature review was conducted using a predefined classification framework. The results show that uncertainties in pLCA are often related to a lack of knowledge and data-related uncertainties. To explore the implications of scenario choices, prospective LCIA results related to the climate change impact category were modelled across different background system activities within four sectors. The findings demonstrate that the choice of scenario affects LCIA results differently, depending on the technological and regional context, thus suggesting that the implications of a specific scenario choice can not be generalised across contexts. Combined with insights from the literature review, which revealed inconsistencies in how uncertainties are addressed, these observations suggest that current pLCA practices may contribute to a reduced transparency and reliability of results. Therefore, this study suggests further research aimed at developing a more standardised practice for addressing and managing uncertainties to increase the reliability and transparency of pLCA studies.

1 Introduction

In the current ecological crisis, the assessment of the environmental impacts of products, services, and technologies can play a crucial role in guiding future development[1]. Life Cycle Assessments (LCA) are a widely used tool to quantify the environmental impacts through all life cycle stages (i.e. from resource extraction to end-of-life stages)[2], making it a useful tool for evidence-based decision making[3,4]. However, the inherent uncertainties in LCA calculations can undermine its effectiveness in decision-making processes[5–7]. If these uncertainties are not accounted for in the interpretation of findings, the use of such models can introduce a risk of overconfidence in results, and thereby lead to sub-optimal decisions[4,8,9]. Addressing uncertainties is thus an important step towards ensuring reliable and transparent decision-support[6].

Traditionally, LCAs have been used to evaluate the environmental impacts of existing technologies, spanning a wide range of products and services, for example, transport infrastructure[10], construction materials[11] and renewable energy (e.g. wind turbines[12] and photovoltaics[13]). The commonly used LCA guidelines and databases, such as the ISO 14040, ISO 14044, and ecoinvent, are well suited for this traditional approach[14–16]. However, assessing the environmental impacts of emerging technologies has gained increased attention as a response to the awareness of their potential role in sustainable development. This has led to the establishment of prospective Life Cycle Assessments (pLCA)[17]. Various typologies and definitions exist for the concept of future-oriented LCA, for instance, ex-ante, dynamic, and anticipatory LCAs. While these are all based on the same fundamental concept, they have minor differences in approach and perspective[18]. Following the definition of Cucurachi *et al.*[19], pLCA refers to situations where the studied technology is at an early stage of development, but is modelled at industrial scale in a future time, allowing the tool to identify potentially avoidable environmental impacts and lock-ins in the early stages of development. This can guide decision-makers in an appropriate direction in advance and prevent them from investing in technologies expected to have a higher environmental impact than other alternatives[20].

While traditional LCA guidelines and databases are well suited for a retrospective LCA approach, they do not fully address or accommodate the challenges when conducting pLCAs[20,21], such as limited knowledge about the future characteristics of a technology, limited data, and scaling issues[17].

To overcome such challenges, models can be used as tools to anticipate future developments and their associated environmental impacts, for example, by presenting an anticipated up-scaling of the emerging technology, or an anticipated development of potential future socioeconomic conditions [5]. However, including models to anticipate future developments increases the complexity and, in turn, the potential for uncertainty, as each additional assumption, parameter, or scenario introduces new sources of variability and unknowns [19].

To navigate the complex landscape of uncertainties, classification frameworks have been developed. For example, Walker *et al.* [22] defines uncertainty as *"any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system"*, and suggests dividing uncertainty into three dimensions; the nature, the location, and the level, with additional sub-divisions [22]. Building on Walker's framework, which categorises uncertainty in a broad model-based decision-making context, several studies have adapted it to emphasise different aspects specific to LCA [5,8,23].

The academic literature on uncertainties in pLCA addresses the issue of uncertainty in a variety of different ways. In numerous cases, uncertainty is not explicitly defined, but rather described as an inherent part of pLCA, or solely by its heightened presence in pLCA compared to traditional LCA [24–26]. This reflects an understanding of the nature of uncertainty, despite a lack of a systematic approach to fully define its characteristics or implications. Some define uncertainties with a focus on lack of case-specific data [24]. Similarly, others argue that the uncertainty of pLCA will decrease with increased data or knowledge [27]. Sander-Titgemeyer *et al.* [28] uses Walker's matrix for uncertainty identification, followed by a classification by relation to the unknown future (scenario dependency) and relation to other elements, such as allocation method (scenario independency). Another topic often addressed concerning uncertainty is the challenges arising when dealing with emerging technologies, where data availability is limited to the Technology Readiness Level (TRL) of the system [29,30]. In such cases, the necessary up-scaling of the technology from laboratory to industrial scale introduces uncertainty due to assumptions about future development [31–33]. While uncertainty in pLCA has gained increasing attention in recent years, the field is highly affected by the novelty of the subject. This is evident from the inconsistency in how uncertainty is addressed.

Regarding the management of uncertainty, traditional uncertainty assessments in LCA, such as uncertainty and sensitivity analyses, often follow a positivist approach, assuming that uncertainties can be reduced through better data or modelling [20]. Uncertainty analysis is often conducted through Monte Carlo simulations [8], allowing probabilistic assessments of uncertainty by generating a distribution of possible outcomes rather than relying on a single deterministic value. For sensitivity analysis, a widely adopted method is global sensitivity analysis [8]. This technique evaluates how different input parameters impact the model's output, helping identify which variables contribute most to uncertainty and should be prioritised for refinement [34].

However, as the increased complexity of pLCAs introduces additional uncertainties [28,34,35] related to the issues of 'unknown unknowns', these are not as easily addressed by common state-of-the-art uncertainty quantifications [20]. Thus, van der Giesen *et al.* [20] argue for a more constructivist perspective, recognising that uncertainty is inherent in complex systems and cannot always be quantified. One of the highly suggested ways to handle uncertainty in pLCA is the use of scenarios to anticipate future development, enabling the consideration of multiple potential futures instead of relying on a single static projection [20,29,36]. Scenarios are especially highlighted as a preferred approach to situations with deep uncertainty, where traditional quantitative methods are insufficient [37]. Moreover, scenarios are argued to increase the transparency and reliability of pLCA results in a decision-making context.

The literature reveals different methods for using scenarios. A common approach is using scenarios to anticipate future technological development and up-scalings [35,38,39], whilst others use scenarios to project pessimistic, moderate and optimistic scenarios for the same technology path [24,26,27]. For example, the scenarios presented by Fouquet *et al.* [26], include two variables expected to change over time; the electricity mix and improvements in manufacturing processes. For each of these variables, three scenarios are set up, respectively, addressing a baseline scenario, as well as an optimistic and a pessimistic scenario. According to Saavedra del Oso *et al.* [29], the key choices regarding scenario development are made during the Goal & Scope definition phase. Moreover, the paper presents another consideration related to scenario development, as a scenario approach can be predictive (*what will happen?*), explorative (*what can happen?*), and/or normative (*how can a specific target be reached?*) [40].

A common characteristic for these approaches is that they take the point of departure in a predicted development, and assume an environmental impact related to this. Contrary to these approaches, Jouannais *et al.* [41] shifts the focus from trying to predict a specific technological development to defining a probability threshold, and defining which circumstances need to be fulfilled for the technological development. This is done through a scenario discovery algorithm, an analysis of requirements on uncertain factors which allows the assessment of whether the overall success probability of the technological concept meets the decision-making threshold [41].

Despite methodological advancements and increased attention on using scenarios to address uncertainties, challenges have been identified, particularly in terms of consistency and transparency, which hinder the reproducibility of scenarios [36].

The scenarios generated for the foreground system are closely related to the specific technology under study. However, for the background system processes, practitioners often rely on the use of large databases, such as ecoinvent. To address the challenges related to consistency and transparency, Mendoza Beltran *et al.*[36] have developed a method to systematically change the background system processes of ecoinvent to align with different scenarios of Integrated Assessment Models[36]. A further development of this approach has led to the creation of the Python library premise, which allows for systematic integration of IAMs across multiple sectors[42]. Premise allows for scenario generation for the years 2005 – 2100 with projections from the IAMs; IMAGE, REMIND, and TIAM-UCL[42]. However, the process of generating scenarios requires a certain technical level and computation time, decreasing its applicability for practitioners lacking these resources. As an alternative, researchers from the Norwegian University of Science and Technology (NTNU) are developing a simulation tool which integrates premise, enabling quicker computational time and more accessible scenario generation. Currently (May 2025), the NTNU tool allows for scenario generation for two IAMs; IMAGE and REMIND. The two IAMs are based on different assumptions, with REMIND having a focus on the energy sector and its implications for climate change[43], and IMAGE having a broader focus on modelling the interaction of human and natural systems[44]. Additionally, the tool allows for specifications of Shared-Socioeconomic-Pathways (SSPs) and policies[45]. The pathways outline three possible global futures, offering more nuanced alternatives to the current baseline development, in which projected global warming will range from 3.1°C to 5.1°C by year 2100[46]. Whilst the pathways are defined by various conditions, they are primarily grouped according to the societal/economic trends under which they are set to exist. SSP1 represents optimistic trends driven by sustainability, whereas the same is applicable to SSP5, however, driven by fossil fuel-focused developments. In contrast, SSP2 more moderately functions under trends extrapolated from historical developments, continuing existing socio-economic trends[45]. The pathways are further divided into four climate policy assumptions: no climate policy (Base scenarios), Paris Agreement Objective (PkBudg scenarios), National Policies Implemented (NPI) and Nationally Determined Contributions (NDC)[45].

While several studies are identified using premise to generate prospective background systems, most do so in isolated cases (e.g. construction materials[47] or wind turbines[48]). No study was identified focusing on a systematic exploration or mapping of how background system scenarios behave across different sectors and regions. This reveals a knowledge gap related to the implications of using tools such as premise for scenario generation.

The pLCA literature reveals a non-systematic practice in how uncertainties are defined, classified and managed which has led to the following research question: *How is uncertainty characterised and managed in current prospective Life Cycle Assessment (pLCA) practices, and how can a scenario-based approach be utilised to increase the reliability and transparency of results?* with the following sub-questions:

- What types of uncertainties are addressed in current prospective pLCA practice?
- How are scenarios typically used in current prospective pLCA practice?
- How are pLCA results affected by the choice of scenario, and what implications does this have for the associated uncertainties?

2 Materials and methods

2.1 Classifications in current pLCA literature

The first part of this study utilised a systematic literature review to map the current practice of uncertainty in pLCA. The search for relevant pLCA studies to include in the literature review was conducted through the database Scopus. The initial search aimed to identify published peer-reviewed papers about future-oriented LCAs and uncertainty. Therefore, the following search string was constructed, using multiple words aimed at identifying pLCA and uncertainty-related aspects: (TITLE-ABS-KEY (”prospective LCA”) OR TITLE-ABS-KEY (plca) OR TITLE-ABS-KEY (”ex-ante LCA”) AND TITLE-ABS-KEY (uncertainty) OR TITLE-ABS-KEY (sensitivity) OR TITLE-ABS-KEY (variability)) AND (LIMIT-TO (DOCTYPE , ”ar”)) AND (LIMIT-TO (LANGUAGE , ”English”)).

The search, carried out in March 2025, yielded 119 studies. Due to the relative novelty of the pLCA methodology, the search was limited to the years 2010 – 2025, reducing the number of results to 109 papers. Firstly, the abstracts were read to exclude irrelevant papers. The exclusion criteria were:

- Papers about listeria containing the same words as defined in the search string, but with a different meaning.
- Papers focusing on LCA, where the technology under assessment was not an emerging technology, or where the assessment method was not future-oriented. For example, a traditional LCA case study of Tiger Puffer, suggesting the use of ex-ante LCA for parameter optimisation[49].

The process resulted in 30 papers, which were read more in-depth in a second round. Finally, the remaining papers underwent a final round of classification, during which they were organised into two primary categories: methodological contributions and applied research studies. While the methodological contributions support the factual ground of this study, the pool of applied research papers made up the final group of 23 analysed papers.

The final list of papers was used as a basis for a literature review aiming to map what types of uncertainties, and methods to manage these, are addressed in the current pLCA literature. A deductive approach was taken, constructing a pre-defined framework from existing classifications deriving from LCA literature, aiming to ensure a systematic and consistent analysis of the contents of the papers[50]. The findings from the analysis were incorporated into an Excel spreadsheet with each row representing a paper and the columns representing the pre-defined criteria of the analytical framework (see Supplementary Information 1).

As an overarching theoretical framework, the three dimensions of Walker *et al.*[22] were applied; nature, location, and level. To classify the nature of uncertainties, it has been estimated whether they are epistemic (i.e. stemming from lack of knowledge) or aleatory (i.e. due to random variability)[22]. The location of the uncertainty has been further defined by the five criteria of the Pedigree Matrix Weidema and Wesnæs[51], a data quality framework, dividing quality indicators according to reliability, completeness, geographical correlation, temporal correlation and technological correlation. The quality indicators of the pedigree matrix are used as a framework to classify uncertainties by their source. During the initial reviews of the chosen papers, it became evident that a significant amount of uncertainties derive from scaling issues and model uncertainties, respectively, leading to the two additional classifications being applied along with the five criteria of the Pedigree Matrix (Figure 1).

In analysing Walker *et al.*[22] dimension of level, i.e. the depth of uncertainties in the reviewed papers, the initial aim was to apply the four levels of uncertainty, as presented by Stirling[52]. However, the complex and often overlapping depth of the uncertainties has led to its exclusion from the analysis.

The literature review was extended with a section focusing on methods applied to address the uncertainties. Two of the 23 papers were excluded from the method analysis, as the premise of these papers deviated from the scope of methods aimed to be documented in this study. A column was dedicated to the general question of what methods were applied in the paper. This served to capture a whole picture of the approach, bringing relevant context to how scenarios otherwise may or may not have been applied. Given that scenarios were applied as a method in a paper, these were addressed directly in two separate columns, asking whether the scenarios are related to the foreground or background system, respectively. The categorisation aims to provide insights into how uncertainties are approached on different system levels, helping to clarify whether scenario assumptions in current practice primarily affect product modelling or the broader system. Additionally, a column was dedicated to potential descriptions of the scenario approach of the paper; the amount of scenarios applied, the time frame of projection, as well as the type of scenarios, if specified.

2.2 Modelling prospective LCIA results

The second part of this study utilised a simulation tool developed by the NTNU to explore how different background system scenarios affect the environmental impacts of activities. The tool allows 19 different scenario combinations, which can be modelled with 10-year intervals between 2030 and 2100. The applied scenarios consist of pre-defined IAM scenarios, which are subdivided into different SSP pathways and policies. The combinations of background systems are visualised in Figure 2.

For this study, the modelling spanned across the 19 scenarios for the years 2030, 2040, and 2050. The applied impact assessment method was ReCiPe, midpoint (H), with the no LT (long-term) option. Results were produced for the impact category Climate Change. Midpoint indicators are chosen (as opposed to endpoint) to avoid the additional uncertainty related to adding an aggregation step to the model[53]. Additionally, the 'no LT' version of the impact assessment method was chosen due to the temporal scope being less than 100 years, which aligns with the period before long-term emissions are modelled to be emitted to the air[54]. The choice of focusing solely on climate change was based on it being a shared focus of the IAMs REMIND and IMAGE[55,56].

Four technologies were chosen as case studies based on a set of criteria. Firstly, it was decided to choose activities from differing sectors to enable analysis of potential sector-related differences. Secondly, the study required each activity to span across two regions to enable analysis of potential regional differences. For continuity and comparability, regions within Europe and Asia were set as criteria for the activity. Lastly, the NTNU tool presented a few limitations, as it could not produce status quo results for all activities in the database. This led to the choice of the following four technologies; electricity, transport, steel, and wheat. The functional units of the case studies are 1 kilowatt hour (electricity), 1 ton kilometer (transport), and 1 kilogram for steel and wheat. This resulted in a total of eight activities; *electricity, production mix* and *transport, freight train, diesel* were analysed across China (CN) and the Netherlands (NL), *steel production* was analysed across India (IN) and Europe without Switzerland and Austria (EwSA), and lastly, *wheat production* was analysed across India (IN) and Germany (DE). As stated, LCIA results were generated for 19 scenarios for each of the eight activities for the years 2030, 2040, and 2050, leading to

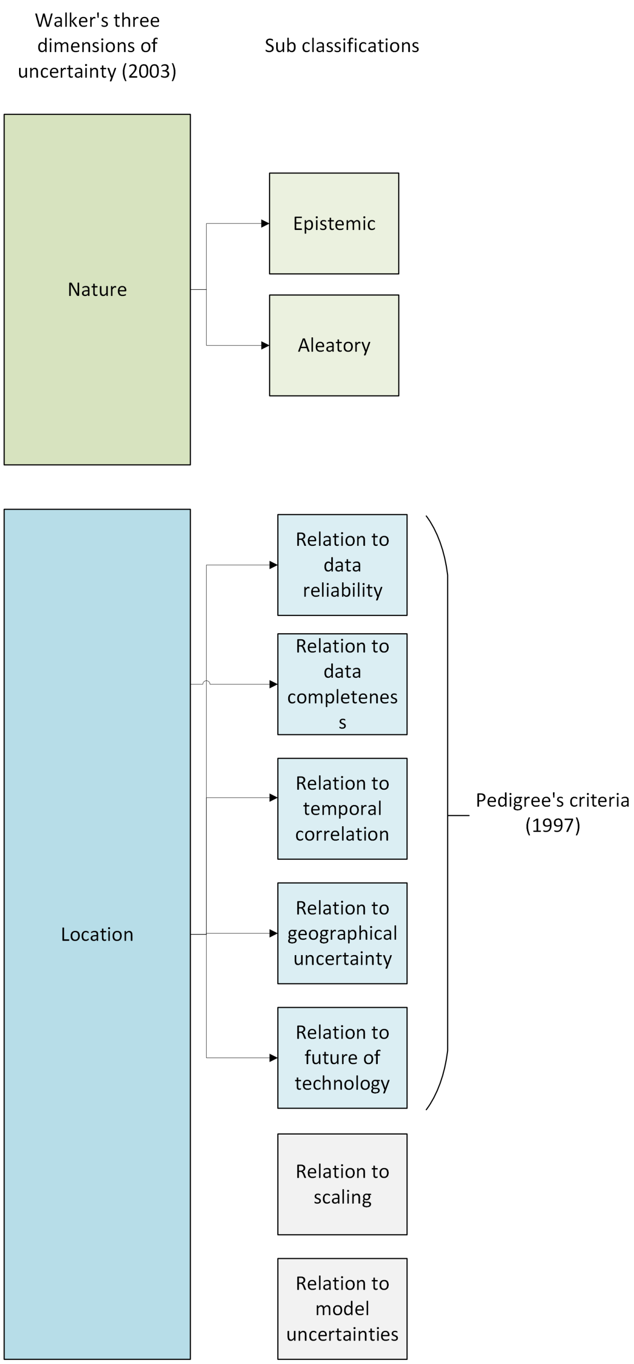

Fig. 1 The content analysis uses pre-defined classifications, based on Walker *et al.*[22] (exl. level), along with sub-classifications based partly on the five criteria of Weidema and Wesnæs[51].

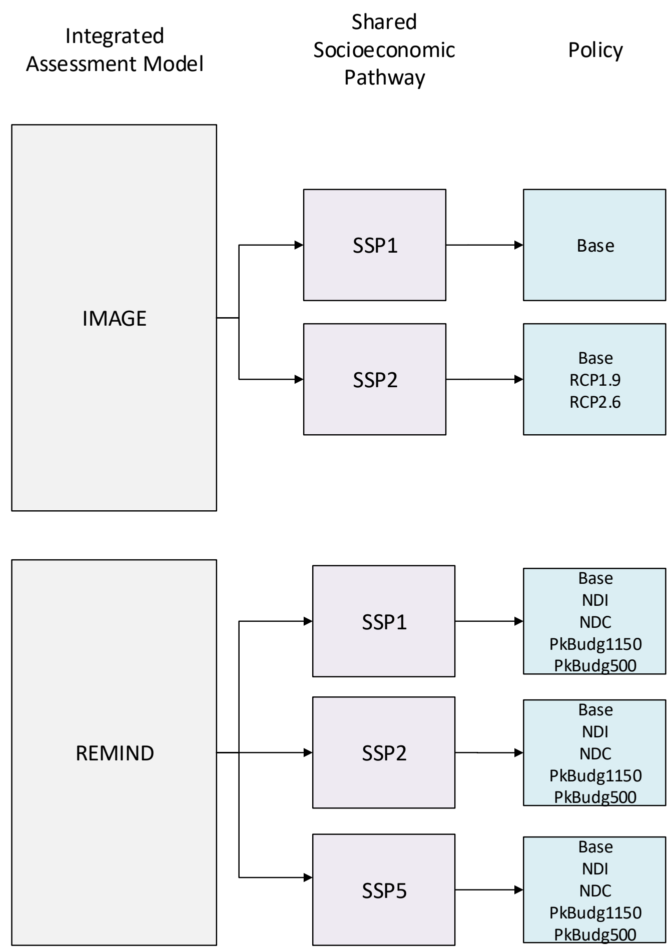

Fig. 2 Construction of each scenario, based firstly on IAM models; IMAGE (Integrated Model to Assess the Global Environment) and REMIND (Regional Model of Investment and Development), secondly on SSPs (Shared Socioeconomic Pathways), and lastly on respective policies; Base, RCP (Representative Concentration Pathways), NPI (National Policies Implemented), NDC (Nationally Determinde Contributions), and PkBudg1150 and 500 (Paris Agreement Objective).

a total of 57 LCIA results for each activity, as visualised by Figure 3.

Analysis of scenario modelling output

The analysis of the eight activities was initiated by analysing the range of LCIA results across scenarios. The range of results was visualised as shaded areas between minimum and maximum values, with a coloured line showing the average result across scenarios. The width of the shaded area was interpreted as uncertainty, meaning that a wide range of results indicated high uncertainty about the future development, whilst a narrow range of results indicated more certainty about the future development. Additionally, status quo values were provided for each activity to compare the assumptions of scenario ranges to an assumed status quo. Visualisations were constructed in PyCharm using Matplotlib[57].

To analyse the distribution of the LCIA results across scenarios, Kernel Density Estimation (KDE) was applied to generate density plots in PyCharm using scipy.stats[58] for KDE computations and Matplotlib for visualisations[57].

A density plot was constructed for each of the four technologies, visualising the distribution of results for each region. The density plots enabled identification of the shape and spread of the underlying data. The interpretation of results was based on analysing overlapping and non-overlapping areas to identify similarities and differences in results. Additionally, the spread of data was interpreted by the width of the distribution, i.e. a narrow distribution suggests similar results, whereas a wide distribution suggests a higher variety in results.

Additionally, density plots were made for the distribution of the difference in results across regions for each technology. The difference was calculated using Equation 1.

$$\text{Difference} = \text{CO}_2\text{-eq}_{\text{RA}} - \text{CO}_2\text{-eq}_{\text{RB}} \tag{1}$$

Where RA refers to one region and RB refers to the other region of the same technology.

To analyse whether the variables *IAM* and *pathway* behave similarly across activities, strip plots have been used to visualise the results for each *IAM* and *SSP*, plotting them comparatively for the years 2030, 2040, and 2050. The strip plots are generated in PyCharm using seaborn.sns[59]. This approach allowed for a clear comparison of variability and trends tied to specific modelling assumptions.

Multiple linear regressions were conducted in PyCharm for the 57 LCIA results for each activity to analyse the statistical relationship between the independent categorical variables *IAM*, *pathway* and *year* to the dependent continuous variable kg CO2-eq/functional unit. The analysis was performed using the statsmodels library for statistical modelling[60]. The model is defined by Equation 2.

$$\text{GWP} = \beta_0 + \beta_1 \cdot IAM + \beta_2 \cdot pathway + \beta_3 \cdot year \tag{2}$$

Where:
B_0 = Intercept, representing the baseline (status quo) level of GWP
IAM = Explanatory variable representing IAM model
pathway = Explanatory variable representing pathway
year = Explanatory variable representing scenario year
B_1, B_2 and B_3 = Coefficients estimating the effect of each explanatory variable on the baseline.

Similarly, multiple linear regressions were conducted for the difference in GWP across regions. The difference was calculated using Equation 1 and the regression model was defined by Equation 3.

$$\text{Difference in GWP} = \beta_0 + \beta_1 \cdot \text{IAM} + \beta_2 \cdot \text{Pathway} + \beta_3 \cdot \text{Year} \tag{3}$$

The results from the multiple linear regressions were used to identify the Coefficient of Determination (R^2) for each model, suggesting how much the independent categorical variables can explain the dependent continuous variable. Additionally, the estimated coefficients were used to identify which independent variables are most influential on the range of results for each activity. Lastly, the number of statistically significant variables for the individual models was analysed. The results between regression models were compared to identify similarities and differences across models.

3 Results and analysis

3.1 Mapping of uncertainty in current pLCA practice

Nature of uncertainty

The first part of the literature review focused on the nature of uncertainties addressed in the pLCA literature. Out of the 23 analysed papers, 12 papers (52%) exclusively addressed the epistemic nature of uncertainty. Some papers use the term ”epistemic” to describe the uncertainty (e.g. Mendoza Beltran *et al.*[36], Fonseca *et al.*[61]), while others relate uncertainty to a lack of knowledge, for example, about the development of the emerging technology or the development of supply-chain related aspects (e.g. Horup *et al.*[47]). In some cases, uncertainty is described as inherent to the future-oriented outlook of pLCA, without specific examples of what this inherent uncertainty entails (e.g. Röder *et al.*[62]). 9 papers (39%) address a combination of the epistemic and aleatory nature of uncertainty. The uncertainties are either addressed in relation to methodological choices (e.g. in relation to goal and scope or LCI) or in relation to the consistency of results (interpretation). For example, Jouannais and Pizzol[63] mention epistemic uncertainty in relation to the unpredictable behaviour of

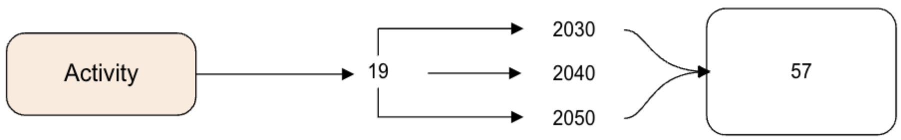

Fig. 3 The scenarios derive from eight activities, each yielding 19 scenarios with varying IAMs, pathways, and policies. These scenarios are projected for three different years; 2030, 2040, and 2050, finally resulting in 57 scenarios per activity.

the technology under study, while certain parts of the technology are modelled as a random draw, thereby introducing aleatory uncertainty to the system. In contrast, Saavedra del Oso *et al.*[29] address the epistemic and aleatory uncertainty by conducting an uncertainty analysis of performance parameters by including a 10% upper and lower bond, supporting the notion that the nature of uncertainty is addressed in different LCA stages. One paper out of the 23 papers (4%) was identified as exclusively addressing the aleatory nature of uncertainty. This is identified through an explicit reference to the uncertainty being aleatory (natural variation)[64].

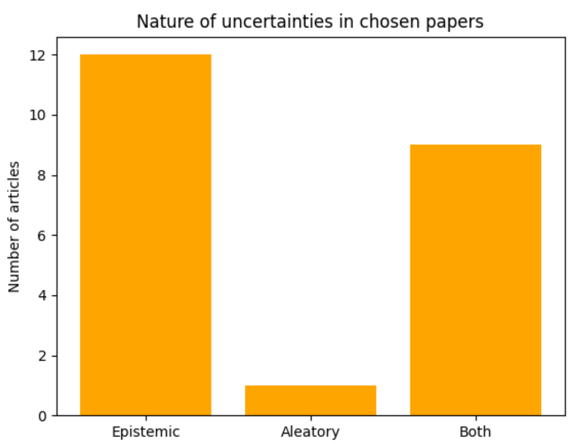

Fig. 4 The bar chart presents distribution of observed uncertainties, categorised by nature; epistemic, aleatory, or both.

These findings indicate a higher tendency in pLCA literature to emphasise the epistemic nature of uncertainty. This aligns with results by Gavankar *et al.*[37], a review in which reducible epistemic uncertainties were found to be acknowledged seven times as often as non-reducible variability (aleatory uncertainty). Despite the 10-year time gap between the findings presented by Gavankar *et al.*[37] and the findings presented in this study, the overarching trend of addressing epistemic uncertainty more often remains consistent. However, the relatively higher representation of aleatory uncertainties in the findings of this study might suggest that the acknowledgement of natural variability among uncertainties has increased in the last decade. Another explanation for the difference in findings can be related to the difference in how uncertainty is conceptualised across papers. While several studies address subjects related to epistemic and aleatory uncertainty, the distinction is often implicit, thus increasing the room for interpretation, which can lead to different conclusions. As suggested by the literature review, results are products of ambiguous definitions and interpretations, leading to a decrease in reproducibility and comparability in pLCA . These findings suggest a need for methodological standardisation and guidance, ensuring consistency and transparent management of different uncertainty types.

Location of uncertainty

Figure 5 shows the observed trends for the location of the uncertainties, which are addressed in the current literature.

Out of the seven categories of the location dimension, *data-related* uncertainties are the most frequently observed source of uncertainty, with 18 out of the 23 papers (78%) addressing this aspect. In general, the uncertainty is related to a lack of process-specific data, leading to the use of secondary data, proxy data and estimations[24,31,61]. As a consequence, varying sources are used with inconsistent data quality, representativeness, and reliability, which also introduces uncertainty[30]. In addition to the specific sources of data-related uncertainties, two distinct scopes are identified. In some papers, the uncertainty is related to specific data inputs, such as the input quantities of pulp and water[28] or energy[27], while others address the data-related uncertainty as a general issue. An example of the latter case is presented by Mendoza Beltran *et al.*[36], describing that inventories in general have large parameter uncertainties, which are expected to be increased for pLCA studies.

Seven papers (30%) address the process of *up-scaling* in relation to uncertainty. In general, the uncertainties are described as being introduced by the precision of the up-scaling process, the ambiguity of future development, and as an amplification of existing uncertainties. When up-scaling a technology from laboratory to industrial scale, several assumptions are required regarding how the technology under study will behave. These assumptions are described as contributing to uncertainty, since the accuracy of the predicted behaviour on an industrial scale relies on the precision of the assumptions[31,62]. Besides the uncertainty regarding how precise the up-scaling assumptions are, some technologies are modelled at such an early stage that there are ambiguous opinions about whether the efficiency of the process will increase or decrease when scaled up to industrial scale. This point is highlighted by Sinke *et al.*[27], for which there are ambiguous opinions about the efficiency of culture medium, an ingredient necessary to produce cultivated meat, thus introducing a high degree of uncertainty about the assumed efficiency for the up-scaled technology. The previous examples highlight aspects of epistemic uncertainties introduced by a lack of knowledge of how the up-scaled system will operate. In contrast, Villares *et al.*[65] highlights uncertainties which are closer related to aleatory uncertainty by stating that up-scaling amplifies the existing imprecision and variability of the modelled system.

4 papers (7%) address *temporal aspects* in relation to uncertainty. Whilst being a frequently addressed topic, two distinct areas of focus are identified; the first topic addresses the uncertainty of results of future projections, and the second topic addresses the data input and the degree to which older data can be considered representative. Regarding the uncertainty of results, indications of uncertainty increasing with the extent of the projection are observed consistently within the analysed papers. This is highlighted by Horup *et al.*[47] and Mendoza Beltran *et al.*[36], modelling future projections through IAM-based scenarios for building materials and vehicles, respectively. In both cases, the papers find that the range of results across scenarios increases over time, concluding that uncertainty increases over time. While there is relative agreement on the uncertainty of future projections, diverging opinions about the temporal representativeness of input data are identified. For example, Horup *et al.*[47] highlights the potential over- and underestimations by using ecoinvent data to predict future environmental impacts, thus concluding that ecoinvent data are already outdated. In contrast, whilst acknowledging the higher uncertainty of pLCA compared to traditional LCA, Villares *et al.*[65] argues that the use of two decades old data is representative for their study of the emerging technology, bioleaching of e-waste. In another study by Villares *et al.*[38], the authors furthermore argue that a 10-year future projection is viable to conduct based on 25-year-old data. These findings indicate a general agreement about the uncertainty increasing with the use of long-term projections. However, different views are identified regarding the temporal representativeness of older data (i.e. ecoinvent database) when conducting pLCAs.

3 papers (13%) address *geographical representativeness* in relation to a lack of knowledge of where the production will take place in the future. For example, Jouannais and Pizzol[63] present a consequential pLCA, highlighting geographical location as an uncertainty. From a consequential approach, an increase in demand will be answered by different producers, and their location will have an effect on the total environmental impact of the technology under study. Similarly, Jouannais *et al.*[41] highlights unknown production location as contributing to uncertainty. In another example, the geographical uncertainty is addressed in relation to input data by conducting a global sensitivity analysis to analyse the models' response to the chosen geography[25].

The examples of uncertainties related to geographical aspects generally address similar topics related to the uncertainty about future production locations and how this will impact results. However, there are diverging ways to address this aspect, for some through qualitative descriptions, whilst others account for them through statistical measures, indicating an inconsistent practice across pLCA papers.

A central element of pLCA is the focus on assessing the environmental impacts of emerging technologies. Due to its future-oriented perspective, naturally, a large part of the uncertainties are related to either the unknown *technological prosperity*, or other influencing factors such as the technological landscape, consumption patterns, and other supply-chain related aspects. 11 out of 23 papers (48%) address uncertainty in relation to the unknown future development.

Regarding the unknown development of the technology, uncertainty is emphasised in relation to the early-stage nature of the technology, for which it is unknown what configuration or combination of the parameters will result in the desired technological property[63]. In other cases, limited data and experience of the early-stage technology contributes to uncertainty about future performance and large-scale feasibility[61,62]. Regarding the uncertainties which indirectly impact the future prosperity of the technology under study, various examples are observed, such as related to the supply chain[26,62], the technological landscape[30], production conditions[62], energy production[26,36] and consumption patterns[26,62].

11 papers (48%) addressed uncertainties which were not captured by the pre-defined categories of the analytical framework, falling into a category of *other/mixed*. An example is Porcelli *et al.*[34] emphasising the modelling complexity in relation to uncertainty. Specifically, there is a trade-off between simplifying assumptions to reduce model complexity along with its ability to predict phenomena, and the uncertainty introduced by additional modelling due to the increase in input factors. Another example, also related to simplicity of the model, is the argument of attributional modelling to keep the model simple and avoid uncertainties[62]. Whilst these uncertainties do not fit into the initial analytical framework, they

show a similar focus on the trade-off between complex modelling to increase the level of detail, along with increased uncertainties.

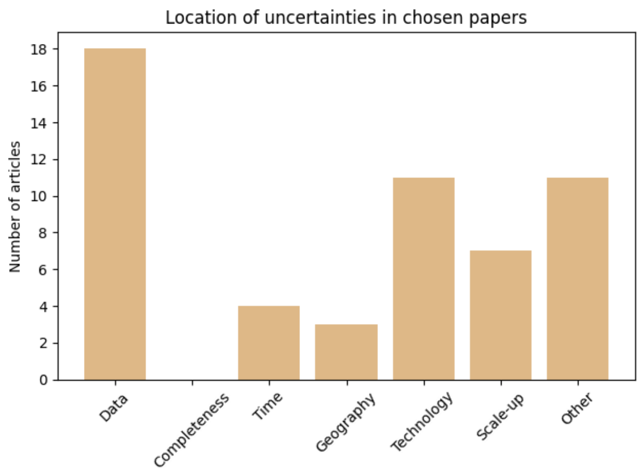

Fig. 5 The bar chart presents distribution of observed uncertainties, categorised by location; data reliability, data completeness, temporal corralation (time), geographical aspects, technological prosperity, scale-up related, and other/mixed.

It is, from the chosen papers, evident that data-related sources are the most frequent from which uncertainties arise. This trend highlights a limitation in prospective modelling, as future-oriented scenarios depend on assumptions and secondary data, making the data input a consistent point of uncertainty. Given the fragility of data reliability in future projections, robust scenario construction becomes essential, not only to predict future developments, but also to communicate the range and implications of data uncertainty in a constructive and transparent manner.

3.2 Application of scenarios in chosen papers

20 out of 21 papers (95%) apply scenarios to some degree, with varying approaches. The exception is Matin and Flanagan [66], in which uncertainty and sensitivity analyses are conducted, however, with no scenario or time frame specified. In some papers, it is explicitly stated that the scenarios are used to address uncertainty, while others apply scenarios without direct reference to uncertainty. While these findings indicate that scenarios are widely applied, an overview of the literature review proves that the approach to scenarios can vary. This variation is reflected in the time frame of their projection, in whether the scenarios are applied to the foreground and/or background system, and in the number of scenarios.

Time projection for scenarios

10 of the papers (48%) defined a time frame for the projection of the scenarios, while 11 of the papers (52%) did not. It can thus be argued that there is a fair variation in how time projection is included in scenario construction. Papers without explicit references to a set time frame have been categorised as having *not defined* a time frame (Figure 6). For the papers with a *defined time frame*, a common observation is scenario projections with ten-year intervals between 2030, 2040, and 2050 [35,36,47,48]. Additionally, some papers are identified with time projections to 2050 and 2060 with 5-year intervals [28,34]. A common characteristic of these papers is a recent publication date, relative to the remaining papers. Moreover, all except one utilise premise to generate background system scenarios. These findings indicate an evolving common practice for time projections. In addition, single examples are identified using other time frames. These include long-term projections, for example, 100-year projections [26], and short-term projections [38,67]. For example, in a paper by Villares *et al.* [38], the time projection does not involve a long-term set of intervals, such as every ten years. Instead, the authors consider a shorter-term time horizon of up to 10 years. This time frame is chosen to reflect a realistic development period for scaling up the technology, while keeping impact assessments relevant to near-future conditions [38].

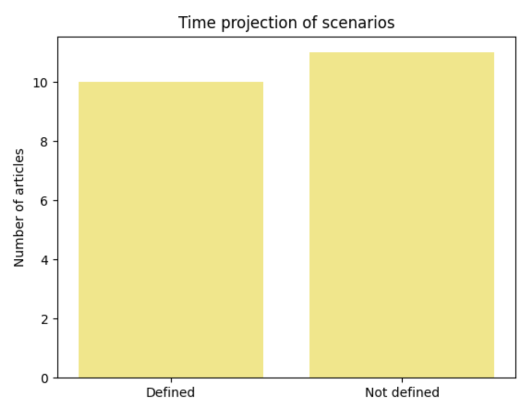

Fig. 6 The bar chart presents the frequency of timeframe application in scenario construction across 21 papers.

Scenario application

Results have been classified by whether the scenarios are related to the *foreground or background systems* (Figure 7). Eight of the 21 papers (40%) analyse both foreground and background systems in their scenarios, eight papers (40%) applied scenarios to the foreground system, while four papers (20%) applied scenarios to the background system only.

For the eight papers applying scenarios to the *foreground system*, some include multiple scenarios for the same technology, while others present the assessed emerging technology as the only scenario. An example presenting multiple scenarios for the technology is observed in a paper by Abbate *et al.* [31]. In this paper, a sensitivity analysis, performed on repairable carbon-fibre-reinforced polymers to address uncertainty, is the basis for six foreground system scenarios being constructed; three for each of two presented composite types. Likewise, in a paper presented by Spreafico and Thonemann [30], the analysed technology itself serves as the variable of the scenarios. In this case, three scenarios are constructed to respectively address the current, future, and patented technology. In other examples, the emerging technology is presented as one scenario, compared with other non-prospective alternatives [62]. These examples highlight a difference in the number of scenarios included.

For the four papers identified as exclusively applying scenarios for the *background system,* this is typically done using premise, either by conducting scenarios for specific activities or for the whole background database. An example is presented by Spreafico [35], where six prospective scenarios, such as SSP2-NPI, SSP2-PkBudg1150, are applied to specific background system activities. Similarly, other studies are identified constructing two scenarios (SSP2-Baseline and SSP2-RCP2.6) [28] and six scenarios (combination of SSP1, SSP2 and SSP5 pathways) [36]. These findings highlight a difference in practice regarding the number of scenarios analysed.

For the seven papers applying scenarios to the *foreground and background systems*, this involves a combination of technology projections and different background system scenarios. One example is presented in a paper by Li *et al.* [24]. The study, focusing on two emerging pretreatment technologies of crumb rubber, initially performs a scale-up analysis of four scenarios. The first is a baseline scenario, followed by three scenarios focusing on, respectively, CO_2 reuse, pressure reduction, and fewer chemical agents. Subsequently, the background system was tested by an allocation scenario analysis, examining the impact on results by adjustments in system expansion, physical allocation, and economic allocation [24]. In another study, three scenarios are conducted named 'Optimistic, 'Moderate ,' and 'Pessimistic', aligning the narrative of the scaled-up technology to varying modified background systems using premise [48]. A simpler scenario structure is identified in a paper by Villares *et al.* [38], describing the performance of a sensitivity analysis based on changes in technology efficiency and energy supply. Adjustments in technology are related to the foreground system, while adjustments in energy supply relate to the background system [38]. These examples highlight an inconsistency in practice when scenarios are constructed for foreground and background systems, both in terms of how the foreground system scenarios are generated as well as the basis for the background systems.

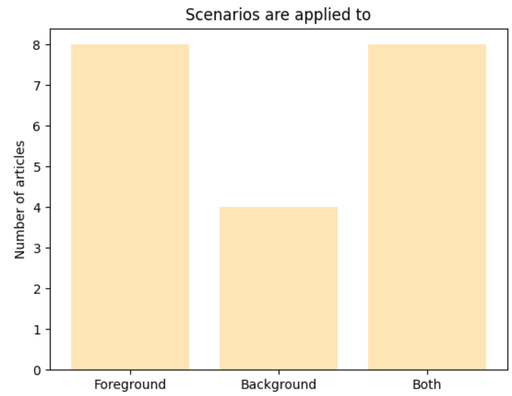

Fig. 7 The bar chart presents the frequency of scenario application to the foreground system, background system, or both, across 21 papers.

In general, the literature review findings indicate that using scenarios for pLCA is a common practice. However, inconsistencies are observed, both in terms of the described aim of using scenarios (i.e. explicit mentioning of uncertainty or not) and their configuration.

Regarding the configuration of scenarios, differences are observed in terms of defined time projection, whether scenarios are applied to the foreground system, background system, or both, and the number of scenarios applied. The findings suggest that the scenario configuration depends on the study approach, which correlates with the level of uncertainty present for the emerging technology under assessment. For cases with higher epistemic uncertainties related to making future projections, multiple variables are involved in the scenario generation (such as technology design, geographical location, electricity input, etc.), which steeply increases the final number of scenarios. Despite the case-dependent scenario approach, recent publications increasingly adopt premise for conducting background system scenarios. This indicates a preference for applying tools that standardise practice. However, even within the papers applying premise in scenario generation, an inconsistency is observed in terms of the number and selection of scenarios. A more standardised scenario approach could, thus, further enhance the transparency of how the choice of scenario influences results, leading to a more robust interpretation of results.

3.3 Range of results from prospective scenario modelling

The LCIA results for the 19 different scenarios analysed for each of the eight activities are visualised in Figures 8 – 11.

Generally, the range of results for the European regions across the activities shows a similar assumed development

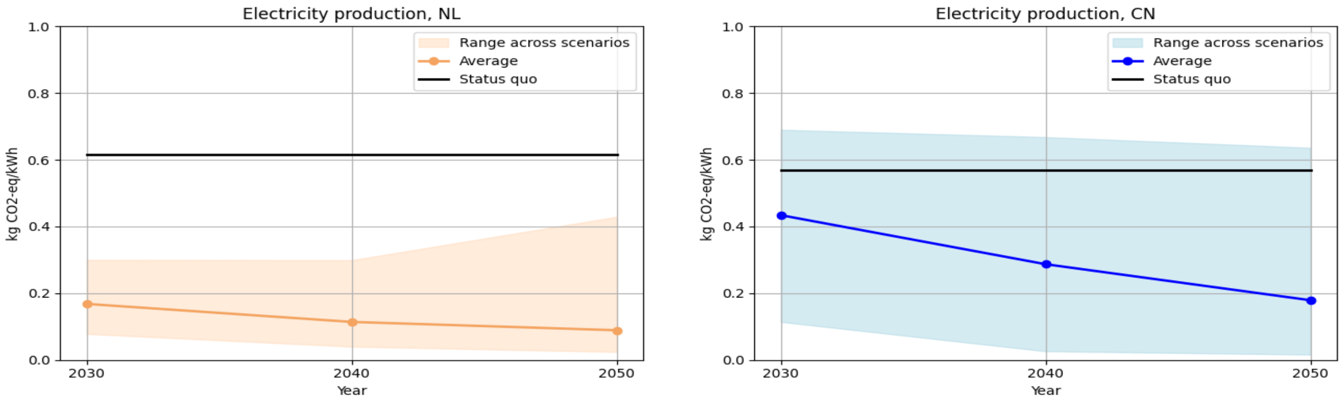

Fig. 8 Predicted development in GWP for *electricity, production mix, NL* on the left side and *electricity, production mix, CN* on the right side. The black lines show status quo, while coloured lines indicate the average value of 19 future scenarios, and the coloured shaded area indicates the range in all 19 scenarios.

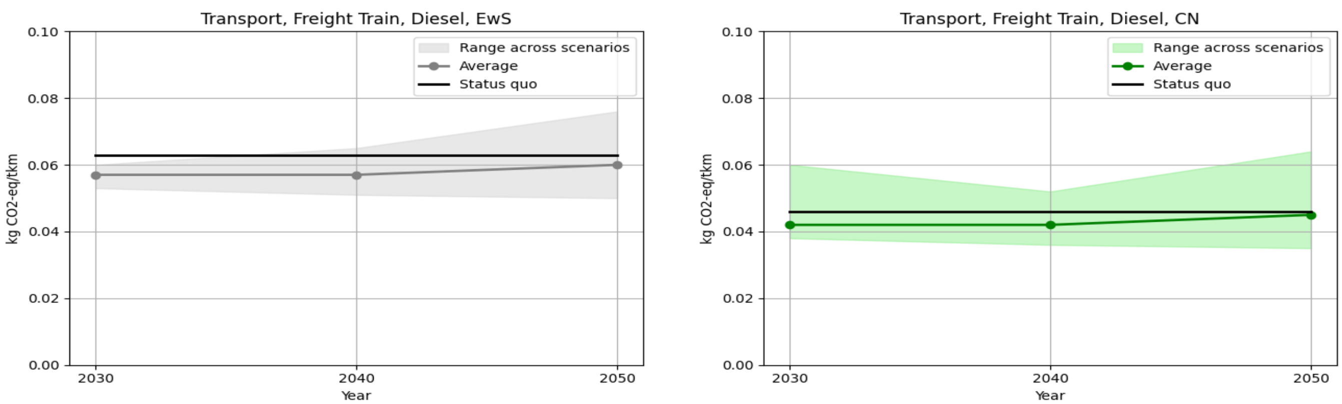

Fig. 9 Predicted development in GWP for *transport, freight train, EwSA* on the left side and *transport, freight train, CN* on the right side. The black lines show status quo, while coloured lines indicate the average value of 19 future scenarios, and the coloured shaded area indicates the range in all 19 scenarios.

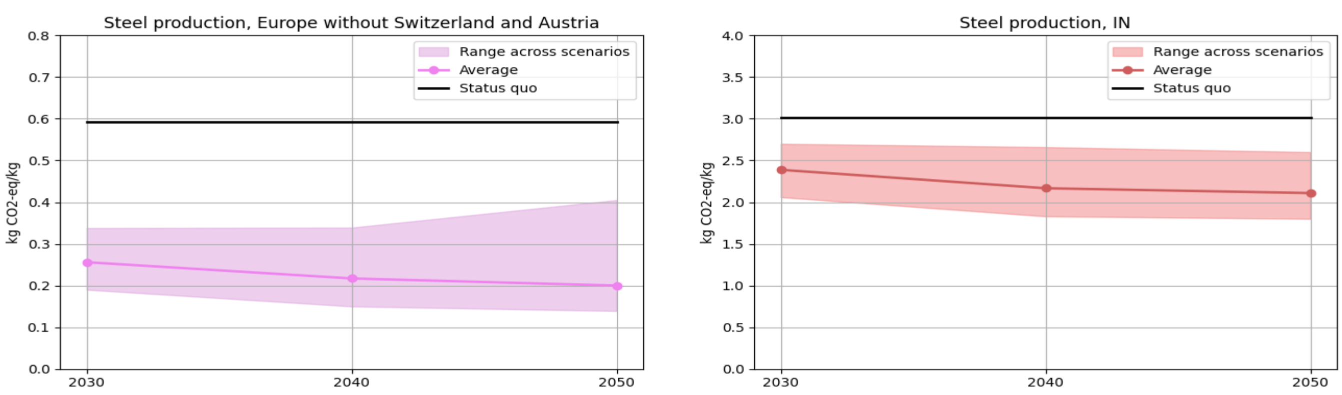

Fig. 10 Predicted development in GWP for *steel production, electric, low-alloyed, EwSA* on the left side and *steel production, electric, low-alloyed, IN* on the right side. The black lines show status quo, while coloured lines indicate the average value of 19 future scenarios, and the coloured shaded area indicates the range in all 19 scenarios.

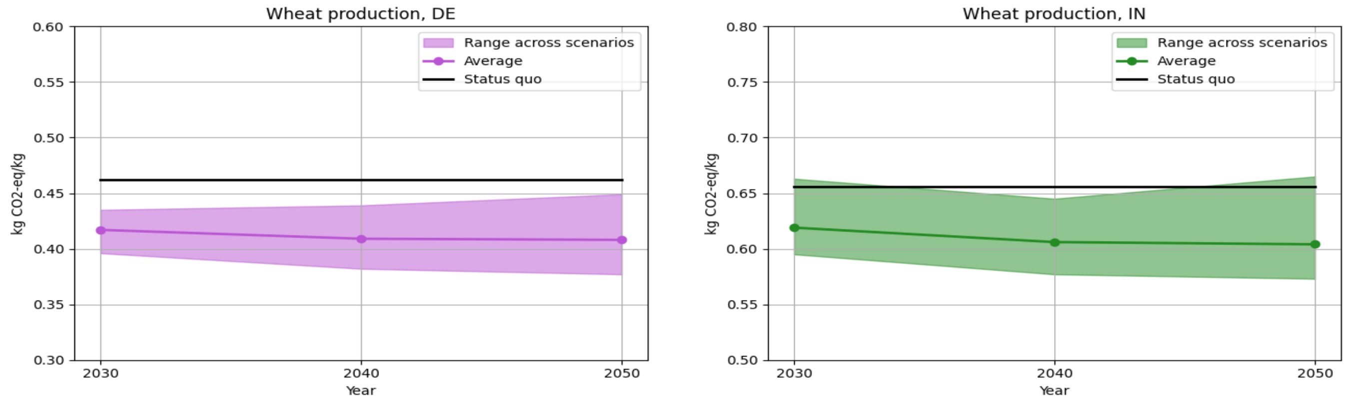

Fig. 11 Predicted development in GWP for *wheat production, DE* on the left side and *wheat production, IN* on the right side. The black lines show status quo, while coloured lines indicate the average value of 19 future scenarios, and the coloured shaded area indicates the range in all 19 scenarios.

trend, with the shaded area having a trumpet shape. The trumpet shape suggests that the possible range of results increases over time, indicating an increase in uncertainty related to the extent of the forecast. In contrast, the comparison of the activities for the non-European regions (i.e. CN and IN) do not show the same consistency in projected developments. For example, *electricity, production mix, CN* in Figure 8 and *steel production, electric, low-alloyed, IN* in Figure 10 show an almost uniform range of results over time, whilst the range of results for *transportation, freight train, diesel, CN* in Figure 9 and *wheat production, IN* in Figure 11 decreases towards 2040 and increases again towards 2050. Since the results show different trends across activities and regions, this indicates that the projected development across IAM based scenarios depends on the context of the analysis, for example, which activities and regions are included.

The black line in Figures 8 – 11 show the results when assuming status quo, i.e. not taking potential background system developments into account. These results are equivalent to using ecoinvent results directly. The results show different trends across technologies and regions, in terms of whether assuming status quo leads to an overestimation or underestimation of results.

For *electricity, production mix, NL* in Figure 8, the range of results of the prospective scenarios are below the line assuming status quo. This indicates that assuming the status quo leads to an overestimation of the GWP/kWh. This is also the case for both regions of *steel production, electric, low-alloyed* (Figure 10). In comparison, the status quo assumption for *electricity, production mix, CN* in Figure 8 is within the range of scenario results, indicating that assuming status quo can lead to under- or overestimation of GWP/kWh. However, the distance between the average value and status quo increases over time, indicating that the risk of overestimation increases when the extent of the projection increases. For *transport, freight train, diesel* (Figure 9), the results are similar across regions and show that assuming status quo provides similar results to the average value for the scenario generation, indicating the potential of both overestimation and underestimation of results. However, the difference between status quo assumption and average result for scenarios decreases towards 2050. For *wheat production*, assuming status quo will lead to overestimations of CO2-equivalents for the DE region, whereas for the IN region, this is only the case for 2040 (Figure 11). For 2030 and 2050 the status quo assumption falls within the scenario ranges.

The different trends observed across technologies can be explained by the difference in how the IAMs project the development of different sectors. For example, premise applies sector-specific transformations and efficiencies for the electricity sector and steel production[42]. This means that efficiency and market adjustments are directly applied to the activities within these sectors, leading to a relatively higher decrease in CO_2-eq compared to the transport and agriculture activities[42]. Since *transport, freight train, diesel* and *wheat production* are not included in the major transformation sectors, the observed changes in GWP can be assumed to derive from the transformation of activities in the supply chain (for example, electricity). A modelled decarbonisation of the electricity sector can, thus, indirectly have a relatively large influence on energy-intensive sectors and processes, whereas such effects might not be observed in less energy-intensive sectors and processes.

These findings highlight two aspects; the first aspect is related to the comparison of assuming status quo in prospective assessments with the range of results for the scenarios. The findings indicate the potential risk of over- or underestimating results. However, the observed inconsistency of trends across regions and technologies indicates that the extent of the potential over- or underestimation depends on the context of the activity under assessment. For the latter aspect, the range of results, the findings indicate a similar inconsistency, suggesting that the projected development depends on the context and region-specific assumptions embedded in the IAMs.

3.4 Distribution of LCIA results

Figures 12 – 15 show the distributions of the 57 LCIA results generated for each activity.

For the *electricity, production mix* (Figure 12), the distributions reveal an overlap between the two regions, indicating similar results. The overlap in results suggests that the relative performance of the regions (meaning which region has higher environmental impact scores) depends on the choice of scenario. The width of the distributions suggests that the results for NL are more narrowly distributed compared to the results for CN. Moreover, the distribution for NL is unimodal and slightly skewed to the right, suggesting that a majority of results are centred around the mean, with a tendency towards higher values. In contrast, the distribution for CN is bimodal, indicating two peaks in the data. One of the peaks is aligned with the one observed for NL, whilst the other is slightly higher. The bimodal distribution indicates the potential presence of a subset of scenarios generating higher GWP results.

Similar to the electricity distributions, the distributions for *transport, freight train, diesel* (Figure 13) overlap. This suggests that the choice of scenario can also be influential for which region has the lowest value of CO_2-eq. In contrast to the electricity, the distributions for the two regions are similar, with a relatively narrow width and unimodal pattern. This indicates a similar spread of results, with EwSA in general producing slightly higher GWP.

A different trend is observed for *steel production, electric, low-alloyed*, which reveals no overlapping areas between the regions, as visualised by Figure 14. This indicates that the choice of scenario will not influence the relative performance of steel production for the regions; IN will generate higher impact scores for all scenario combinations. Both distributions are unimodal, however, the distribution for EwSA is narrower, indicating a higher consistency in results.

Similarly, the distributions for *wheat production* (Figure 15) show no overlap, indicating that under all scenario assumptions, IN will produce higher results for the climate change impact category than DE. As with transportation, both distributions are similar in terms of width and unimodal pattern, indicating similar spread in results with a higher mean for one region.

To further analyse the regional differences across scenarios, density plots showing the distribution of the difference between regional results were generated for each activity (Figure 16). For transport and wheat, the distribution of differences is narrow, indicating a consistent absolute difference between the regional results across the scenarios. The consistent difference of results between the regions was also indicated by the similarity in distribution of results for the regions in Figures 13 and 15. In contrast, the distribution of differences for electricity and steel is wider, indicating an inconsistency in the absolute difference in results across scenarios for the two regions. These results are consistent with the observed differences in distributions in Figures 12 and 14.

These results indicate a sector-specific sensitivity for the climate change impact category, depending on which scenarios are included in the analysis. This sensitivity is highlighted by the examples from the electricity and transportation sectors, where the choice of scenario can shift the ranking of the regional impact scores, which was not present for the steel and agricultural sectors. Consequently, the choice of scenario introduces an additional source of uncertainty, as the results become dependent on the selection of scenarios. In a decision-making context this means that scenario choices could lead to different conclusions.

3.5 Variability of prospective LCIA results across IAM and pathway

Variability across IAM results

Figures 17–20 visualise the variability of GWP across the variable *IAM*. For *electricity, production mix, NL* (Figure 17), the scenarios generated with IMAGE show a wider spread over time, indicating increasing uncertainty. In contrast, the scenarios generated with REMIND show a slight decrease over time. In comparison, both REMIND and IMAGE show a similar trend of slightly decreasing values over time. This suggests that REMIND projects similar development trend over time for both regions. However, a difference is observed for how IMAGE projects development trends across the regions, which can be explained by different assumptions regarding technology efficiency and market adjustments for NL and CN within the IMAGE model. Additionally, the differing development trajectories across *IAMs* for NL suggests that the LCIA results are more sensitive to the choice of IAM for this region compared to CN.

The results for *IAM*s for *transport, freight train, diesel* indicate consistencies across as well as witin the regions. As indicated by Figure 18, the *IAM*s behave similarly across regions, with IMAGE showing more concentrated projections of results, and REMIND showing a higher variation of maximum and minimum results. Within regions, similar trends can especially be observed for EwSA, as both *IAM*s show an in-

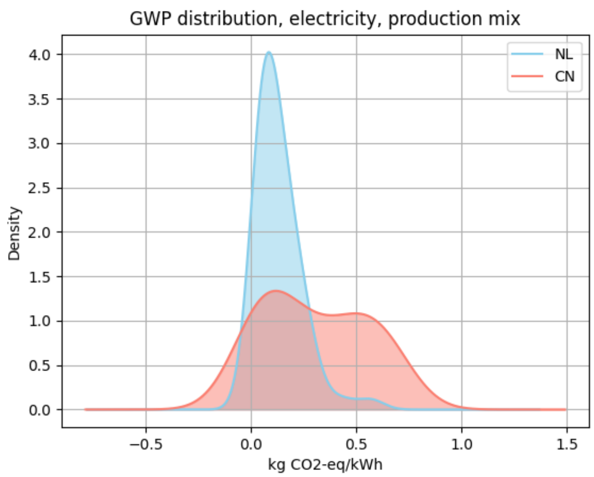

Fig. 12 Density distribution of GWP values for *electricity, production mix, NL*, visualised in blue, and *electricity, production mix, CN*, visualised in red.

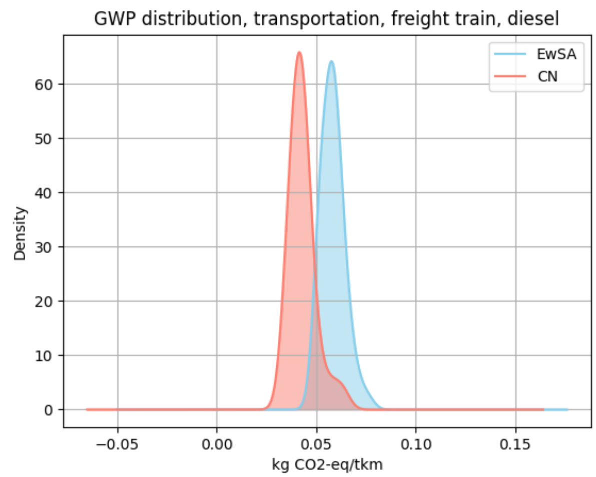

Fig. 13 Density distribution of GWP values for *transportation, freight train, diesel, EwSA*, visualised in blue, and *electricity, production mix, CN*, visualised in red.

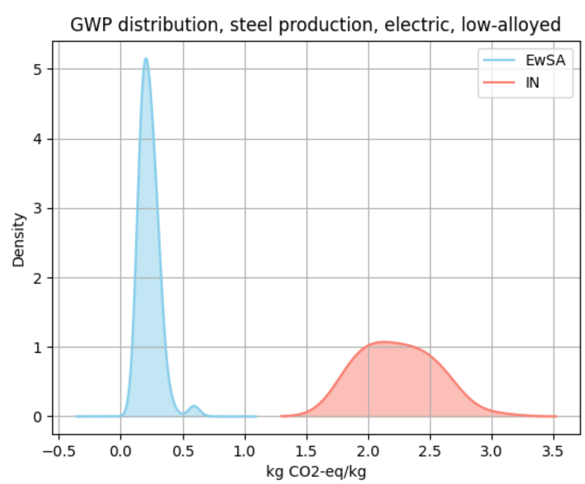

Fig. 14 Density distribution of GWP values for *steel production, electric, low-alloyed, EwSA*, visualised in blue, and *steel production, electric, low-alloyed, IN*, visualised in red.

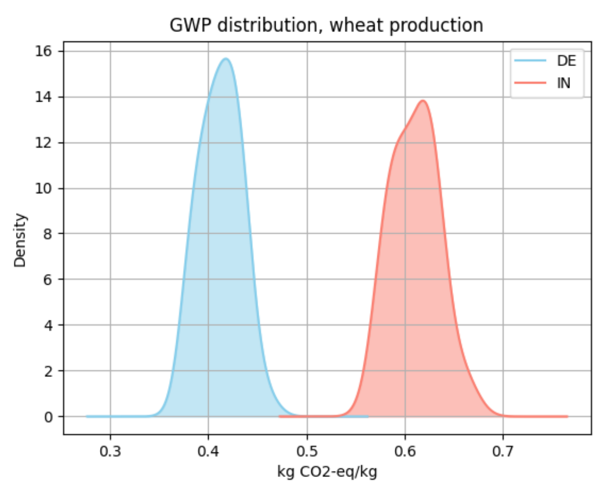

Fig. 15 Density distribution of GWP values for *wheat production, DE*, visualised in blue, and *wheat production, IN*, visualised in red.

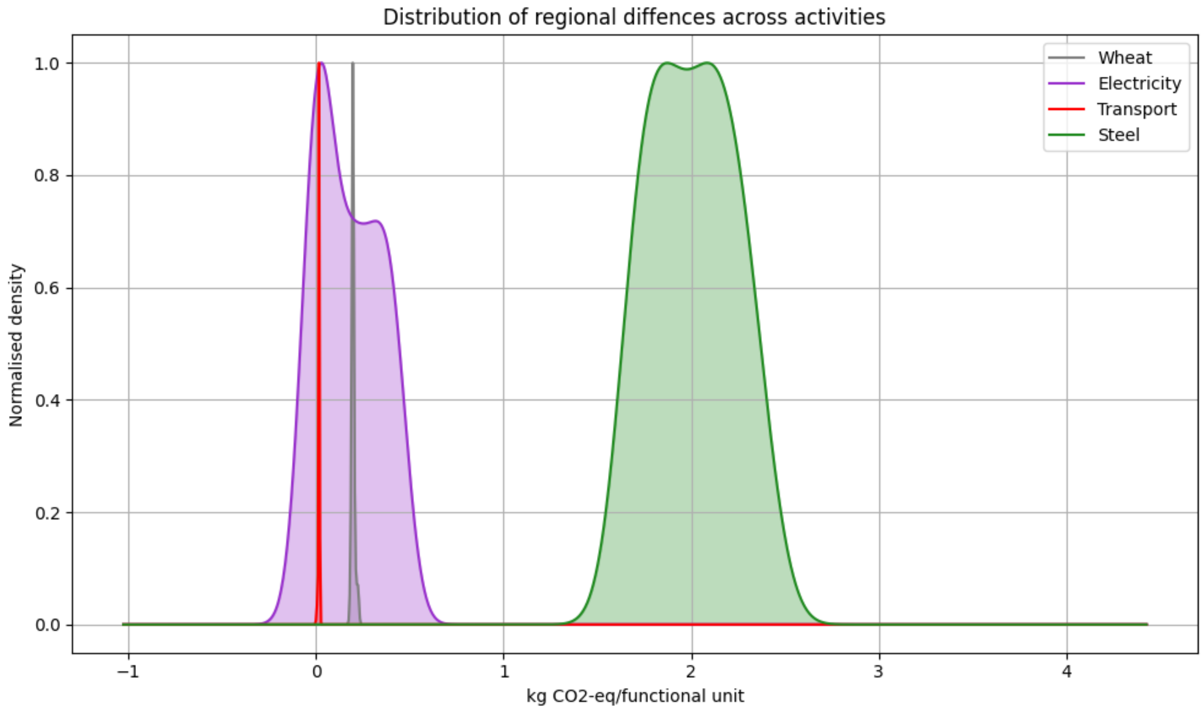

Fig. 16 Density distribution of regional difference in GWP values across activities; *wheat production* visualised in gray, *electricity, production mix*, visualised in purple, *transportation, freight train, diesel*, visualised in red, and *steel production, electric, low-alloyed*, visualised in green.

creasing range of results over time. This is also observed for scenarios of the REMIND model for CN, however, the scenarios generated for IMAGE reflect a stagnating development.

The LCIA results across *IAM* for *steel production, electric, low-alloyed* (Figure 19) show a similar trend as for electricity. For the region of EwSA, REMIND has a consistent range, having a lower impact on GWP over time, whilst IMAGE projects a wider spread. For the region of IN, both *IAM*s project relatively constant results over time.

The LCIA results for *wheat production* (Figure 20) show a similar development for scenarios of the REMIND model, with increasing minimum and maximum values over time. However, the scenarios generated with IMAGE show different trends across the two regions. For DE, the scenarios follow a similar projection as the REMIND models, with increasing minimum and maximum values over time. In contrast, for the IN region, IMAGE projects a decrease in values over time.

The overall trend across all activities and regions demonstrates more ambitious development projections of carbon efficiency for scenarios from REMIND. This is interpreted by REMIND, yielding the lowest results for all activities and regions. In general, both *IAM* produce similar maximum values, with occasional examples where one *IAM* has considerably higher values.

Additionally, these findings uncover variabilities in how the two IAMs, REMIND and IMAGE, project results across technologies and regions. In alignment with the results from the density distributions, presented in Section 3.4, a higher variation was observed in trends across regions for *electricity, production mix* and *steel production, electric, low-alloyed*. These differences highlight the impact of the model's assumptions about technology efficiency and other market-related developments. These variations underscore the importance of considering different *IAM*s for decision-making, especially when considering different geographical contexts, to reduce the risk of overconfidence in results.

Variability across Shared-Socioeconomic-Pathways

In Appendix A–D, similar analyses are visualised for the same set of activities and regions. These plots are based on the same data points as the ones used for the plots in Figures 17 – 20, however, they are centered around scenario *pathways* as variables in the pLCAs. As a result, othe verall tendencies for *pathway* follow similar trajectories as *IAM* . For example, for *electricity, production mix, NL* the spread of data increases over time, while for *electricity, production mix, CN* a consistent spread with incremental decrease in GWP is observed (Appendix A).

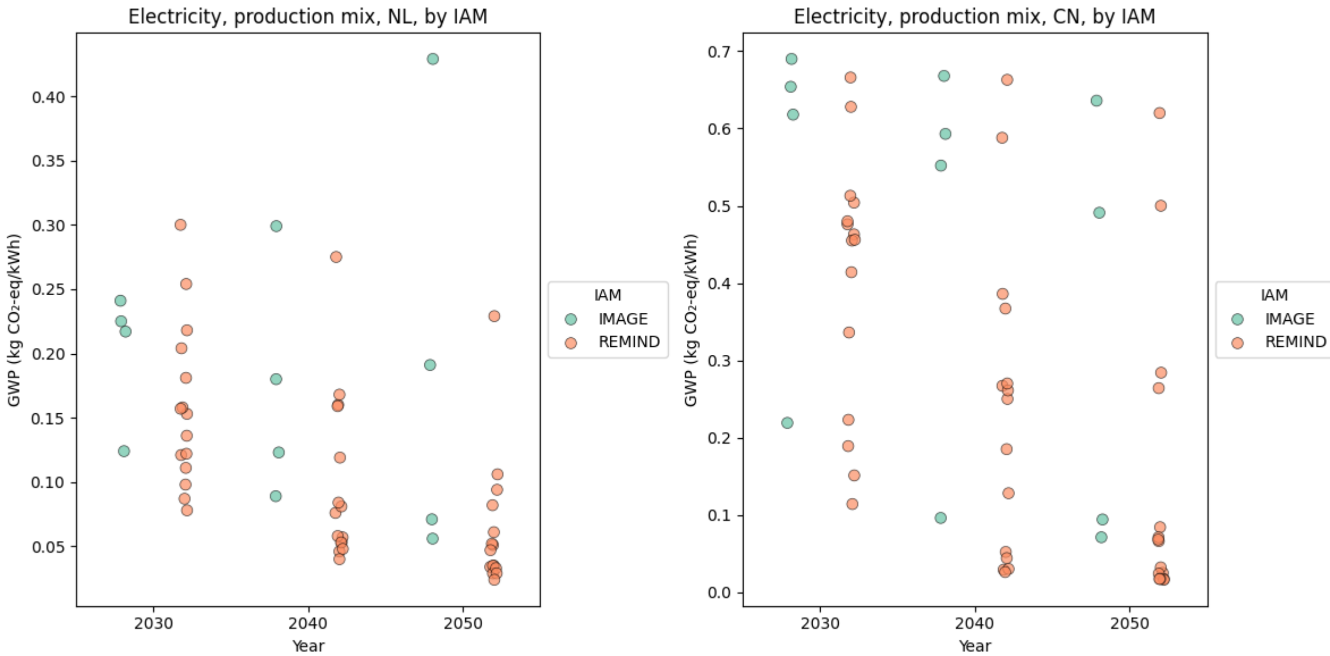

Fig. 17 Strip-plot illustrating the predicted development in GWP for *electricity, production mix*, classified by applied IAM; IMAGE or REMIND, across the years of 2030, 2040, and 2050.

Fig. 18 Strip-plot illustrating the predicted development in GWP for *transport, freight train, diesel*, classified by applied IAM; IMAGE or REMIND, across the years of 2030, 2040, and 2050

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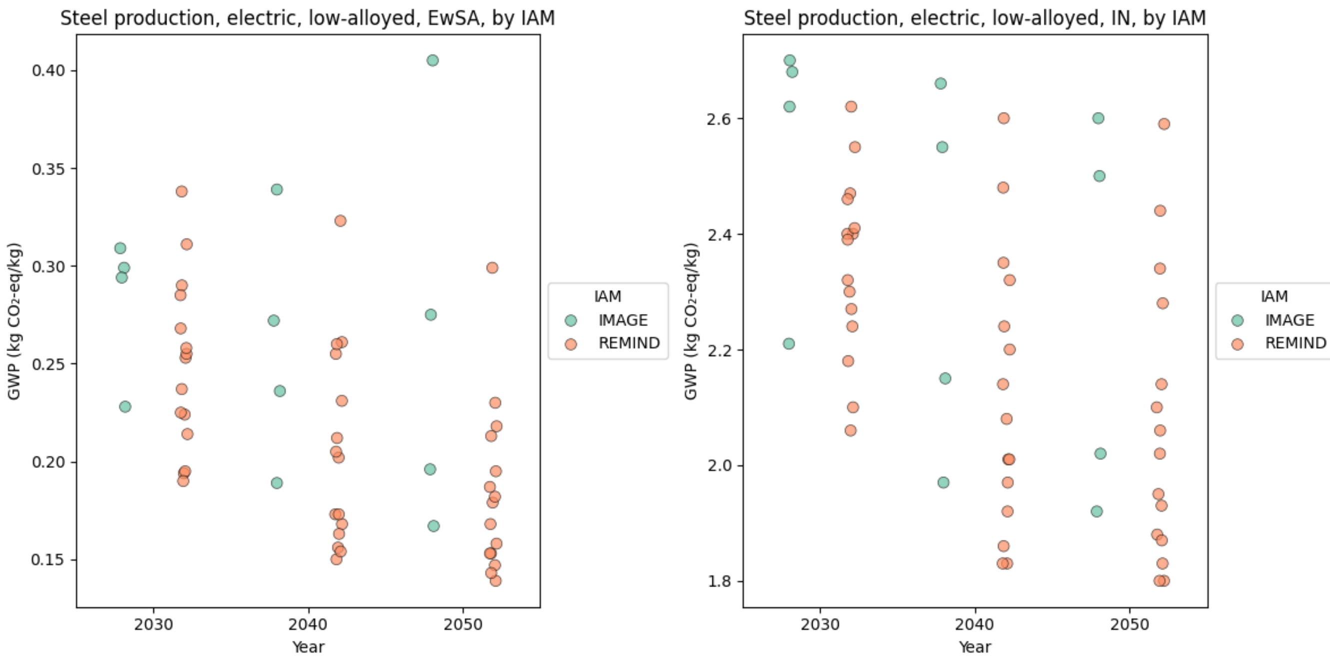

Fig. 19 Strip-plot illustrating the predicted development in GWP for *steel production, electric, low-alloyed*, classified by applied IAM; IMAGE or REMIND, across the years of 2030, 2040, and 2050.

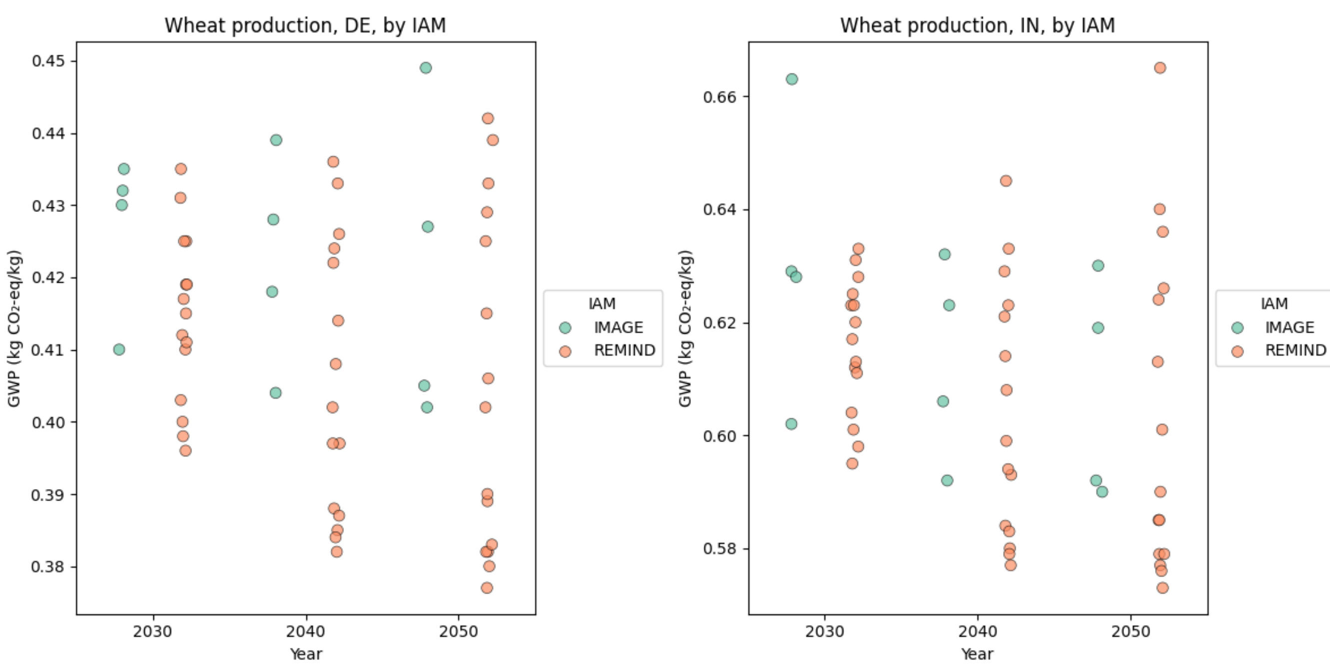

Fig. 20 Strip-plot illustrating the predicted development in GWP for *wheat production*, classified by applied IAM; IMAGE or REMIND, across the years of 2030, 2040, and 2050.

Similar to the analysis of variability for *IAM*, the *pathway* analysis showed that the pathways did not behave similarly across activities and regions. Therefore, it is not possible to determine one pathway as generating the lowest (optimistic) or highest (pessimistic) GWP results overall. In contrast, the *pathway* considered to be either optimistic or pessimistic depends on which sector and region is analysed. This indicates that for some activities, the choice of *pathway* can lead to different conclusions regarding which technology or regions perform best.

In parallel with *IAM*, these findings underline that *pathway* choice significantly influences GWP projections, and that uncertainty can be affected by, or intertwined with, socio-political complexity.

3.6 Multiple linear regression of prospective LCIA results

The multiple linear regression models for the eight activities achieved R^2 values between 0.77 – 0.94, indicating that the independent categorical variables can explain between 77% and 94% of the variance of results for the activities (see Supplementary Information 2). The regression analysis revealed 11 — 16 significant variables for the activities as visualised by Figure 21. The statistically significant variables consist of a mix of the two *IAM*s (REMIND and IMAGE), the *pathways* (SSP1, SSP2 and SSP5) and the *years* (2030, 2040 and 2050).

Comparing the coefficient results from the linear regressions (Figure 21), it becomes evident that there are similarities and differences in how the independent variables contribute to the LCIA results. A general trend is observed between the coefficients and their significance; the independent variables with the highest coefficients are also the ones which are statistically significant. Additionally, the number of statistically significant variables is between 11 – 17, indicating a similarity of amount of significant variables across the activities. However, there is a difference in which of the independent variables are statistically significant for the individual activity. Only four independent variables (SSP5-PkBudg500, SSP2-PkBudg500, SSP2-Base, and SSP1-PkBudg500) are identified as statistically significant variables across all eight activities. Despite the four variables' statistical significance across all activities, a difference is observed concerning the relative contribution of each variable to the results. For example, the independent variable SSP1-PkBudg500 has a relatively high coefficient for the transport activities, whilst having a relatively low coefficient for the steel production. This inconsistency is also observed for other independent variables. For example, the choice of *IAM* is a statistically significant variable for some activities (e.g. *electricity, production mix, NL* and *transport, freight train, diesel, CN*) and not for others (*electricity, production mix, CN* and *transport, freight train, diesel, EwSA*). This variability in results indicates that the sensitivity of the LCIA results to the variables in the IAM-based background systems is highly context-dependent. For example, the choice of IAM can be a dominant factor for the LCIA results in one case, whilst for another case, both IAMs can produce similar results, thus, the choice of IAM is of less importance for the outcome. These results emphasise the potential risk of relying on a single scenario to project a future development, highlighting the potential of added transparency by including a range of scenarios.

3.7 Multiple linear regression of the difference between regions

The multiple linear regression results showed significant differences in the explanatory power of the model. In the case of electricity and steel, the models achieve R^2-values of 0.86 and 0.93, indicating that the model can explain 86% and 93% of the variance in results, respectively. The regression results revealed 11 independent variables as statistically significant for electricity. The 11 parameters are a mix of nine *pathways* (SSP1, SSP2 and SSP5), one *IAM* (IMAGE) and one *year* (2030). For steel production, the amount of statistically significant variables was 15, which are a mix of 11 *pathways* (SSP1, SSP2 and SSP5), two *IAMS* (IMAGE and REMIND) and two *years* (2040 and 2050).

Similar to the multiple linear regressions for the activities, there is variation regarding which of the independent variables has the highest coefficient. A high coefficient means that the individual variable has a high influence on the difference in results across the regions. For example, for electricity, the independent variables with the highest coefficients are the *IAM* IMAGE, or the *pathways* SSP5-NPI, or SSP5-Base. In comparison, the individual variables with the highest coefficients for steel are the *IAM* REMIND, or the *year* 2040, or the *pathways* SSP2-RCP2.9, SSP5-Base, or SSP5-PkBudg500. These findings indicate a technology-dependent influence regarding which of the independent variables of the model drives the difference in results.

In contrast, the multiple linear regression analyses for transport and wheat showed considerably lower explanation power of the model, with R^2-values of 0.59 and 0.58, respectively. These results indicate that there are other factors besides the independent variables which explain the difference in results. For transport, the regression statistics revealed seven significant independent variables, four of which are *pathways* (SSP1, SSP22, and SSP5) and two *IAM*s (IMAGE and REMIND). For wheat, only two independent variables were identified as statistically significant (SSP2-Base and SSP2-NPI).

These findings highlight the difference in projections, based on whether the activity is part of a sector which undergoes major transformation (electricity and steel) in premise

Independent variable	Electricity NL	Electricity CN	Transport EwSA	Transport CN	Steel EwSA	Steel IN	Wheat DE	Wheat IN
C(IAM)[T.IMAGE]	**0.188**	0.033	0.004	**0.008**	**0.171**	**0.716**	**0.027**	**0.030**
C(IAM)[T.REMIND]	**0.286**	**0.263**	0.002	0.001	**0.229**	**0.481**	**0.031**	**0.027**
C(Pathway)[T.SSP1-Base]	0.005	**0.111**	**0.007**	**0.008**	0.009	**0.261**	**0.015**	**0.014**
C(Pathway)[T.SSP1-NDC]	0.030	0.011	0.000	0.004	0.019	**0.122**	0.001	0.000
C(Pathway)[T.SSP1-NPI]	0.003	0.018	**0.006**	**0.005**	0.001	**0.182**	**0.010**	0.004
C(Pathway)[T.SSP1-PkBudg1150]	0.027	0.064	0.001	0.000	0.016	0.085	0.005	0.008
C(Pathway)[T.SSP1-PkBudg500]	**0.062**	**0.175**	**0.006**	**0.008**	**0.065**	**0.122**	**0.023**	**0.024**
C(Pathway)[T.SSP2-Base]	**0.073**	**0.155**	**0.005**	**0.009**	**0.047**	**0.323**	**0.025**	**0.035**
C(Pathway)[T.SSP2-NDC]	**0.053**	0.029	0.004	0.004	**0.045**	0.008	**0.012**	**0.014**
C(Pathway)[T.SSP2-NPI]	0.028	0.017	0.000	0.000	0.011	**0.158**	0.004	**0.020**
C(Pathway)[T.SSP2-PkBudg1150]	**0.047**	**0.116**	**0.005**	**0.007**	**0.044**	0.022	**0.018**	**0.019**
C(Pathway)[T.SSP2-PkBudg500]	**0.070**	**0.188**	**0.007**	**0.008**	**0.069**	**0.168**	**0.026**	**0.056**
C(Pathway)[T.SSP2-RCP19]	**0.132**	**0.354**	0.001	0.005	**0.094**	**0.280**	0.010	0.013
C(Pathway)[T.SSP2-RCP26]	**0.085**	0.050	0.004	**0.006**	**0.047**	0.030	0.003	0.001
C(Pathway)[T.SSP5-Base]	**0.144**	**0.396**	**0.006**	0.002	**0.090**	**0.525**	**0.025**	**0.024**
C(Pathway)[T.SSP5-NDC]	**0.054**	0.011	**0.004**	**0.005**	**0.042**	0.008	**0.012**	**0.014**
C(Pathway)[T.SSP5-NPI]	0.033	**0.319**	0.003	0.001	**0.028**	**0.412**	**0.014**	**0.013**
C(Pathway)[T.SSP5-PkBudg1150]	**0.061**	**0.159**	**0.006**	**0.007**	**0.054**	0.068	**0.021**	**0.022**
C(Pathway)[T.SSP5-PkBudg500]	**0.076**	**0.201**	**0.007**	**0.008**	**0.068**	**0.182**	**0.025**	**0.027**
C(Scenarioyear)[T.2030]	**0.114**	0.035	**0.003**	**0.004**	**0.102**	**0.566**	**0.014**	**0.010**
C(Scenarioyear)[T.2040]	**0.167**	**0.112**	**0.003**	0.003	**0.141**	**0.345**	**0.022**	**0.045**
C(Scenarioyear)[T.2050]	**0.193**	**0.220**	0.000	0.001	**0.157**	**0.287**	**0.023**	**0.024**

Fig. 21 Coefficients for all independent variables across all activities; Electricity NL and CN (*electricity, production mix*), Transport EwSA and CN (*transport, freight train, diesel*), Steel EwSA and IN (*steel production, electric, low-alloyed*), and Wheat DE and IN (*wheat production*). Significant variables are written in bold. Green cells indicate higher coefficients, and red cells indicate lower coefficients.

Independent variable	Electricity	Transport	Steel	Wheat
C(IAM)[T.IMAGE]	**0.158**	**0.004**	**0.134**	0.002
C(IAM)[T.REMIND]	0.027	**0.003**	**0.311**	0.004
C(Pathway)[T.SSP1-Base]	**0.100**	0.001	**0.132**	0.001
C(Pathway)[T.SSP1-NDC]	0.035	**0.004**	0.021	0.001
C(Pathway)[T.SSP1-NPI]	0.016	0.000	0.061	0.006
C(Pathway)[T.SSP1-PkBudg1150]	0.025	0.001	0.019	0.002
C(Pathway)[T.SSP1-PkBudg500]	**0.091**	0.001	**0.177**	0.001
C(Pathway)[T.SSP2-Base]	**0.077**	**0.004**	**0.156**	**0.011**
C(Pathway)[T.SSP2-NDC]	0.019	0.000	0.066	0.002
C(Pathway)[T.SSP2-NPI]	0.039	0.001	0.050	**0.016**
C(Pathway)[T.SSP2-PkBudg1150]	0.063	0.002	**0.097**	0.001
C(Pathway)[T.SSP2-PkBudg500]	**0.104**	0.001	**0.219**	0.002
C(Pathway)[T.SSP2-RCP19]	**0.228**	**0.004**	**0.306**	0.003
C(Pathway)[T.SSP2-RCP26]	0.030	0.003	0.103	0.002
C(Pathway)[T.SSP5-Base]	**0.246**	**0.004**	**0.315**	0.001
C(Pathway)[T.SSP5-NDC]	0.060	0.001	**0.087**	0.002
C(Pathway)[T.SSP5-NPI]	**0.280**	**0.003**	**0.264**	0.001
C(Pathway)[T.SSP5-PkBudg1150]	**0.093**	0.001	**0.135**	0.001
C(Pathway)[T.SSP5-PkBudg500]	**0.116**	0.001	**0.234**	0.002
C(Scenarioyear)[T.2030]	**0.146**	0.000	0.013	0.004
C(Scenarioyear)[T.2040]	0.059	0.000	**0.195**	0.001
C(Scenarioyear)[T.2050]	0.021	0.000	**0.237**	0.002

Fig. 22 Coefficients for all independent variables, showing regional differences for all activities; Electricity (*electricity, production mix*), Transport (*transport, freight train, diesel*), Steel (*steel production, electric, low-alloyed*), and Wheat (*wheat production*). Significant variables are written in bold. Green cells indicate higher coefficients, and red cells indicate lower coefficients.

or if the changes are induced indirectly through other sectors (transportation and wheat). These findings align with the findings of the density distributions, which indicated that the regional difference for electricity and steel results were subject to scenario-specific differences, whilst transportation and wheat were subject to non-scenario specific differences. Therefore, a higher statistical correlation between the independent variables was expected for electricity and steel. The sector-dependency of results introduces a substantial uncertainty, as the results depend on the assumption embedded in the projected sector and region-related developments across scenarios. Additionally, the varying statistical relationships between the conducted multiple linear regressions make it difficult to analyse general trends across the sectors and determine, on a general level, which variables are most important. In a decision-making context, this decreases the robustness of results, as it is difficult to make general assumptions about the behaviour of scenarios. The lack of generalisability across technology and regions requires extensive knowledge about the assumptions for each individual scenario for a practitioner to be able to consider the implications of scenario choice.

4 Discussion

The findings of this study provide insights into how uncertainty is addressed in current pLCA literature, as well as how the choice of background system scenario influences LCA results. However, certain limitations need to be discussed to ensure a nuanced interpretation of results. This section discusses some of this study's key methodological choices and limitations to address their influence on the results. Potential approaches to address the limitations and areas for further research are also suggested.

Literature review on uncertainty in pLCA

Choosing a deductive approach has provided a clear analytical framework, aiding in positioning the study within existing knowledge. Moreover, it allowed a more focused and potentially more efficient literature review. However, such arguments rely on the set framework, especially given that the framework applied in this study is constructed from various typologies. It could furthermore be argued that a predefined framework might limit engagement with literature, as there is a risk of confirmation bias[50].

In contrast, the inductive approach is of an exploratory nature, which covers exploring new phenomena or when existing theories are inadequate[50]. In terms of uncertainties in pLCA, existing theories could be deemed insufficient. True to the methodology's nature, the analysis would have a bottom-up structure, starting with observations in the chosen papers, followed by a subsequent generalisation, thus potentially reflecting a truer representation of the state of the art[50]. Given the limited knowledge existing within pLCA, such an approach could allow a beneficial level of flexibility, holding space for changes in research direction based on emerging data. The ambiguity of the research topic, which an inductive approach could potentially aid in capturing on a higher level, is, however, a double-edged sword. Entirely inductive approaches can lead to subjectivity or inconsistency[50] – a relevant aspect given that the content analysis of the literature review results was developed in collaboration between two researchers. The framework surrounding the analysis was constructed by various sets of typologies, not only to introduce nuance and perspectives to the findings of the chosen papers, but also to ensure clarity and coherence in how the findings should be classified. These are measures meant to, partly, leave minimal room for interpretation when analysing the content, thus strengthening continuity despite the analysis being conducted by more than one researcher. A measure to further combat this aspect could have been to have both researchers analyse all of the papers, including reviewing the findings of the other.

To limit the search, specific search words have been used for sorting throughout the literature, thus leaving out papers in which uncertainty management potentially could have been addressed in a more ambiguous tone. While such an approach is a tangible way of narrowing down material, the immaturity of the subject of uncertainties in pLCAs is relevant to take into consideration. It could be argued that in a research field so relatively unexplored, there can exist a margin of error, in which explicit typologies and terms are not yet widely accepted as set practice. Moreover, the papers have a varying emphasis on uncertainty – for some papers, uncertainty is a central aspect, whilst for others it is a subject included in the discussion section, ultimately creating a challenge in assessing uncertainties on an even level. However, due to limited resources, a wider search demanding interpretation and assumptions of relevance was deemed impractical.

Limitations of pLCA results

The choice of which activities to include for the modelling of prospective scenarios is a key element of the methodological approach. In this study, eight activities were analysed – two regional cases for each of the four technologies, with each technology representing a different sector (electricity, transport, steel, and agriculture). The selection was based on an assumption that the projected development trajectories vary across sectors and regions.

A key limitation of this approach is that only one technology was assessed for each sector. This reduces the generalisability of results, as there is a potential risk of technology-specific conditions affecting results, which are not representative of all technologies within the sector. Addressing this limitation could include the generation of results for multiple technologies within a sector, thus increasing generalisability.

Due to the relative novelty of the subject, few papers have been identified applying a similar approach. However, a study has been identified, where premise was used to generate a range of results across 9 scenarios for different building materials for the Danish building sector[47]. By focusing on multiple materials within a single sector, their findings highlighted potential differences in assumed development trajectories within a sector. Interestingly, their findings indicated similar development trajectories across materials with minor differences (trumpet shape, i.e. increasing range of results over time). This suggests that the sector-specific modifications of the IAMs have a similar impact across the technologies within the sector. Another interesting element to compare is the regional focus. In the study by Horup *et al.*[47], all building materials are representative for Denmark, which is categorised as Europe by the IAMs[68]. Similarly, the range of results for the European regions in Figures 8, 9, 10, and 11 have more similar development trajectories (trumpet shape) compared to the range of results for CN and IN. These results suggest a similar region-specific development across different sectors, besides the ones included in this study.

Moreover, the density distributions presented in Section 3.4 indicated the regionally determined influence of the prospective scenarios. The results highlighted a technology/sector-specific sensitivity, where the choice of scenario can be influential for which region has lower GWP scores. The novelty of pLCA and the relatively recent development of premise limits the number of papers focusing on the regional difference in technology performance. However, an example of this is identified in a study by Spreafico[35], where the author compares the environmental impact of *market group for electricity, medium voltage* for Europe and CN. Different scenarios within the SSP2 pathway are modelled for the European region, and one scenario is modelled for CN (SSP2-NPI). The author concludes that all the scenarios, except the one for CN, reduce emissions compared to the baseline. While this conclusion holds for the specific case presented by Spreafico[35], the findings in the present study suggest that a different combination of scenarios could lead to different outcomes. This highlights the importance of presenting a range of scenarios instead of one to reduce the risk of overconfidence in results in a decision-making process.

The results of the multiple linear regression, presented in Section 3.6, show a high degree of variation in which of the independent variables contributes most to the dependent variable across activities, and when the difference between regions was analysed. One possible explanation is that the validity and reliability of the model varies across predictors, due to the predictor variables (*IAM*, *pathway*, and *scenario year*) having differing amounts of observations. The predictors with sufficient amounts of data (for example, *IAM*) are expected to provide more valid and representative results, and to better reflect the relationship between the predictor and the independent variable. In contrast, for the predictor *pathway*, the low amount of data points may provide misleading results (e.g. for the coefficient and the confidence intervals), since the amount of data points is too low to reflect the relationship between the predictor and the dependent variable. Each of the categories of the categorical variable *pathway* consists of a combination of SSP and policy. In an attempt to increase the amount of data points per category, it could be argued to divide the data into categories according to the pathways, SSP or policy. However, the GWP result (dependent variable) reflects the combined effect of a specific SSP and policy. Thus, treating the SSP or policy as an independent variable could lead to a misrepresentation of the modelled outcomes and lead to wrong conclusions about the influence on GWP.

Given these limitations, the regression results should be interpreted with caution to prevent overconfidence in results. As with all modelling, especially relevant for a subject such as pLCA, which operates within a high degree of epistemic uncertainty, there is a risk of quantification to back-fire. As stated by Saltelli *et al.*[9], an excessive focus on producing precise numbers increases the risk of pushing *"a discipline away from being roughly right towards being precisely wrong"*.

The results of the prospective background activities were presented for the Climate Change impact category. This choice was based on climate change being a shared focus of the IAMs REMIND and IMAGE[55,56]. Despite the exclusion of other impact categories, the results revealed diverging trends in projected developments across technologies and regions, suggesting the importance of transparency in scenario selection. However, the narrowed scope of analysed environmental impacts limits the representativeness of results to the climate change impact category. Including other impact categories would enable a comparison of whether the identified trends in results are limited to the chosen impact category or if the results can be generalised across impact categories.

Despite the methodological limitations, this study provides valuable insights into the field of uncertainty in pLCA. The literature review revealed a predominant focus on the epistemic nature of uncertainty, for which the use of scenarios is considered a viable solution. Additionally, the findings from the modelling of prospective background system activities revealed a potential context-dependency of the IAM-based scenarios. Further research should focus on expanding the analysis of technologies within different sectors, as well as expanding the results to other impact categories to enable more generalisable results. These efforts could enhance the robustness and reliability of using tools such as premise to generate background system scenarios as a way to address the epistemic nature of uncertainty in pLCA.

5 Conclusions

This paper shows a higher tendency in pLCA literature to emphasise the epistemic nature of uncertainty, aligning with findings in other studies. Differences in how uncertainty is conceptualised, often implicitly rather than explicitly, contribute to inconsistent findings across studies, reducing reproducibility and comparability in pLCA. This highlights the need for clearer methodological standards and guidance on managing different types of uncertainty. The reviewed papers moreover show that data is the most common source of uncertainty in prospective modelling, underscoring the need for robust and transparent scenario design to address the uncertainty of future projections. While scenarios are a widely applied method to address uncertainty, there is considerable variation in their configuration, purpose, and level of detail. These findings point to a broader need for methodological consistency to enhance transparency, comparability, and robustness in scenario-based pLCA.

Prospective scenario modelling overall shows that projected developments vary significantly across regions and activities. Comparing scenario results to status quo assumptions reveals that relying on static background data can lead to over- or underestimation, depending on the context. These findings highlight the importance of considering regional and sector-specific dynamics in IAMs, as well as the risks of oversimplifying future developments in pLCA.

Density distributions of GWP suggest that for certain technologies, the choice of scenario can influence the difference between regional scores. Consequently, the choice of scenario introduces an additional source of uncertainty, as the results become dependent on the selection of scenarios. In a decision-making context, this uncertainty is important since different scenario choices could lead to different conclusions. In scenario modelling, the choice of IAM and pathway has an evident influence on GWP projections, additionally suggesting that assumed policy within scenarios has an impact and should be included in a potential expansion of the study. Moreover, variability in multiple linear regression results indicates that the sensitivity of the LCIA results to the variables in the IAM-based background systems is highly context-dependent. This emphasises the potential risk of relying on a single scenario to project a future development.

Along with the previously mentioned factors, varying statistical relationships among the regressions lead to difficulty in making general assumptions about the behaviour of scenarios, ultimately decreasing the robustness of results in a decision-making context. The findings of this study underline how the lack of generalisability across technology and regions requires extensive knowledge about scenario assumptions and associated implications for a practitioner to meaningfully interpret and apply results.

For pLCA practitioners, this study emphasises the importance of documenting and communicating scenario assumptions clearly, using multiple scenarios to explore a range of possible futures, and being cautious of over-relying on default or standardised pathways without context-specific justification. For users of pLCA results, such as policy decision-makers or industry stakeholders, it is essential to be aware that outcomes may vary substantially depending on scenario choices. Decisions supported by pLCA should therefore consider the scenario-dependency of results as a critical dimension of uncertainty that can influence the robustness and relevance of the conclusions drawn.

Further research should focus on expanding the analyses to technologies within different sectors and to other impact categories to enable more generalisable results about the implications of scenario choice. These efforts could enhance the robustness and reliability of using tools such as premise to generate background system scenarios as a way to address the epistemic nature of pLCA.

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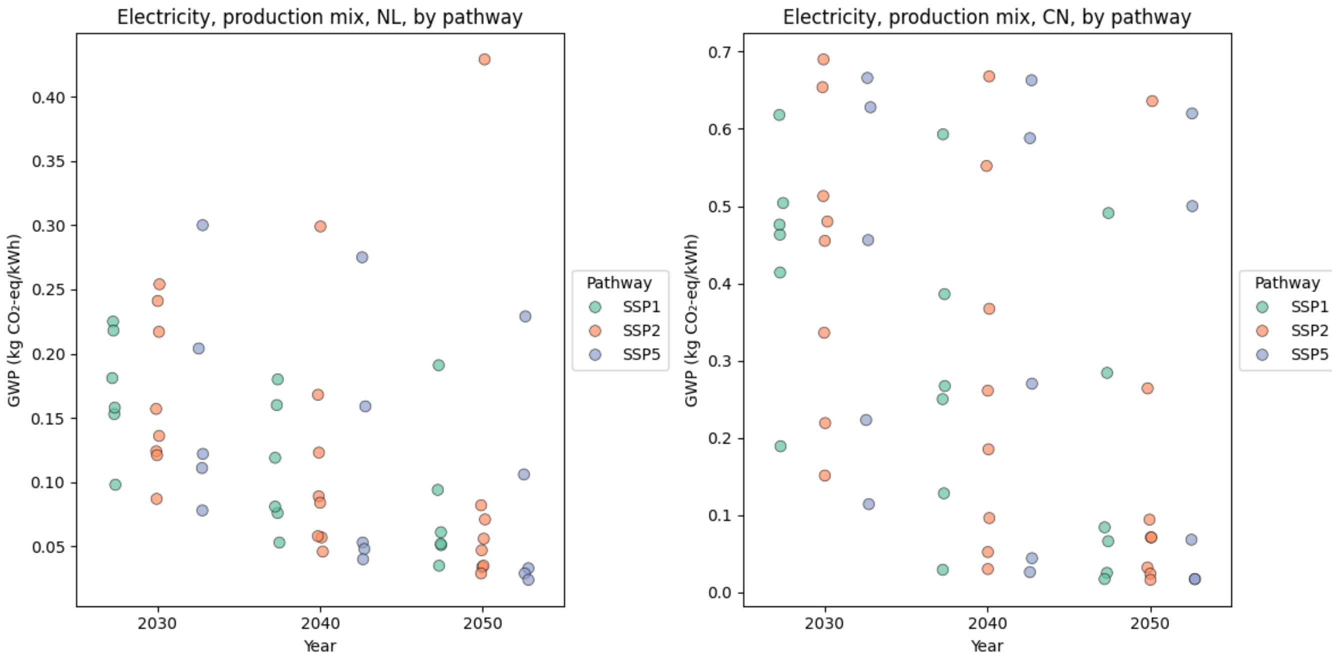
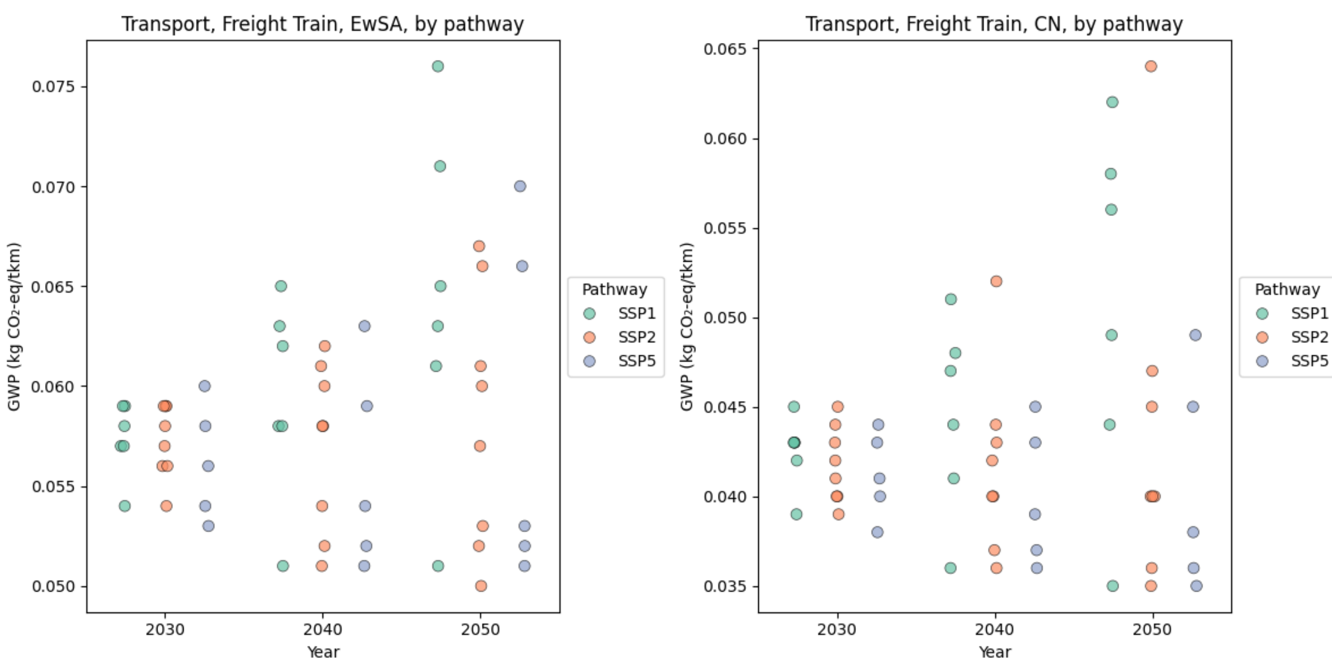
Appendix A

Strip-plot illustrating the predicted development in GWP for *electricity, production mix*, classified by applied pathway; SSP1, SSP2, or SSP5, across the years of 2030, 2040, and 2050.

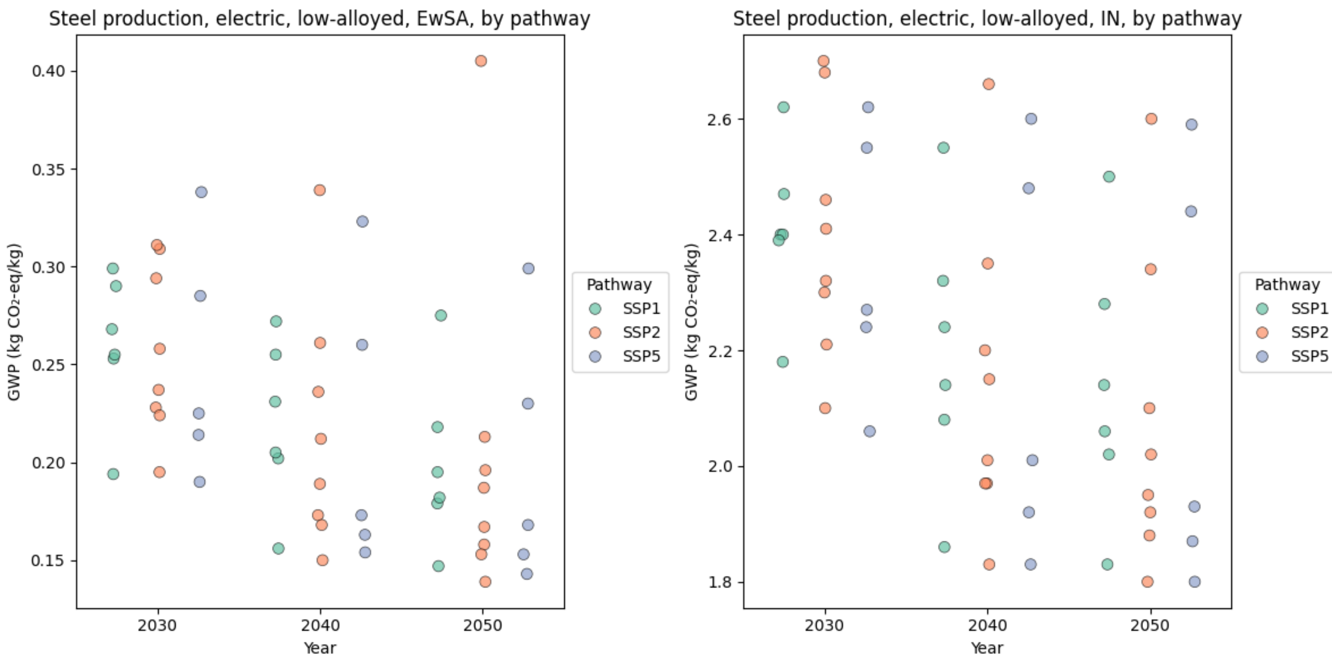


Appendix B

Strip-plot illustrating the predicted development in GWP for *transport, freight train, diesel*, classified by applied pathway; SSP1, SSP2, or SSP5, across the years of 2030, 2040, and 2050.



Appendix C
Strip-plot illustrating the predicted development in GWP for *steel production, electric, low-alloyed*, classified by applied pathway; SSP1, SSP2, or SSP5, across the years of 2030, 2040, and 2050.



Appendix D
Strip-plot illustrating the predicted development in GWP for *wheat production*, classified by applied pathway; SSP1, SSP2, or SSP5, across the years of 2030, 2040, and 2050.