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An Uncertainty-Informed Life-Cycle Assessment Framework for Additive Manufacturing in Aerospace Applications

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Abstract

The rapid expansion of space activities requires manufacturing strategies that align environmental performance with engineering functionality, yet sustainability assessments of additive manufacturing (AM) remain affected by significant data uncertainty. This study presents an uncertainty-informed Life-Cycle Assessment (LCA) framework to evaluate the environmental and performance trade-offs between Laser Powder Bed Fusion (LPBF) and conventional CNC machining for a satellite mounting bracket. The assessment adopts a process-based cradle-to-gate approach and integrates a hybrid uncertainty propagation methodology combining Dempster–Shafer theory for epistemic uncertainty with Monte Carlo simulation for aleatory variability. Environmental impacts are represented as interval-valued outcomes with associated belief–plausibility measures, enabling explicit quantification of epistemic uncertainty. In parallel, a performance-based benefit metric based on stiffness-to-mass ratio is introduced and propagated under uncertainty using a consistent framework. Environmental and performance indicators are normalised and combined into a composite trade-off metric, allowing the evaluation of manufacturing alternatives across a range of environmental weighting scenarios. Decision outcomes are expressed in terms of belief and plausibility, capturing both support and indeterminacy under uncertainty. Results indicate that CNC machining exhibits lower midpoint environmental impacts and narrower uncertainty intervals across key categories, while LPBF shows higher potential impacts and substantially wider epistemic uncertainty, primarily driven by powder production and limited inventory data. However, when performance benefits are considered, LPBF may become preferable under specific trade-off conditions. These findings highlight the importance of explicitly accounting for epistemic uncertainty and performance considerations when evaluating sustainability trade-offs in aerospace manufacturing. The proposed framework supports early-stage eco-design by enabling robust decision-making under incomplete knowledge.

Keywords: space sustainability; additive manufacturing; life-cycle assessment; epistemic uncertainty; aerospace manufacturing

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1. Introduction

The rapid expansion of the global space sector is reshaping both industrial practices and environmental responsibilities. Once dominated by governmental agencies, space activities are increasingly driven by commercial actors, enabling new services ranging

from Earth observation to satellite-based communications and navigation. While these developments offer significant societal and economic benefits, they also introduce pressing sustainability challenges. The concept of the "space sustainability paradox" has emerged to describe this tension: space technologies can support global sustainability objectives, yet their production and deployment generate environmental impacts both on Earth and in the orbital environment [1]. As international attention intensifies around climate targets and responsible resource use, it is essential to ensure that the growth of the space economy aligns with broader environmental goals.

Manufacturing processes play a critical role in this context. The environmental footprint of space missions is not limited to launch emissions or in-orbit debris generation; it also includes material extraction, component manufacturing, and supply-chain activities occurring on Earth. Aerospace manufacturing is typically energy-intensive and material-demanding, involving high-performance alloys and precision machining. Consequently, improving sustainability at the manufacturing stage represents a strategic leverage point for reducing the overall environmental burden of space systems.

Life-Cycle Assessment (LCA) has become a widely adopted methodology for quantifying environmental impacts across product systems. It is formally standardised under ISO 14040 and ISO 14044 [2,3], which define the principles, framework, and methodological requirements for LCA studies. These standards explicitly recognise uncertainty as an inherent aspect of LCA modelling and require that its influence on results be evaluated where relevant. In particular, ISO 14044 highlights the need for sensitivity and uncertainty analyses to assess the robustness of conclusions, especially when results are used for comparative assertions. However, while the standards emphasise the importance of uncertainty characterisation, they do not prescribe specific methods for representing or propagating epistemic uncertainty arising from incomplete knowledge. As a result, most LCA applications rely on probabilistic approaches, which may not fully capture uncertainty in data-scarce or early-stage engineering contexts.

Within the space sector, LCA is increasingly applied to evaluate spacecraft manufacturing and mission-level sustainability performance, notably through efforts led by the European Space Agency (ESA) Clean Space Office and related methodological developments [4,5]. However, its application to emerging manufacturing technologies remains subject to significant methodological and data-related challenges.

Among these technologies, additive manufacturing (AM), and particularly Laser Powder Bed Fusion (LPBF), has gained increasing attention in aerospace engineering [6,7]. LPBF enables the production of geometrically complex metallic components through layer-wise melting of powder feedstock, allowing for part consolidation, weight reduction, and enhanced functional integration. These characteristics are particularly relevant in aerospace applications, where structural mass directly influences launch costs, payload capacity, and mission efficiency. Even modest reductions in component mass can translate into significant system-level benefits, including reduced propellant consumption and improved mission performance.

From a life-cycle perspective, such performance improvements may generate long-term sustainability advantages that extend beyond the manufacturing stage. However, the environmental implications of AM remain contested, particularly when the analysis is restricted to cradle-to-gate manufacturing impacts. Several LCA studies comparing additive and conventional subtractive manufacturing processes report diverging conclusions [8–10]. While AM can reduce material waste and eliminate tooling, metallic powder production and LPBF processing are highly energy-intensive [11,12]. As a result, many studies report higher environmental impacts for LPBF compared to conventional machining when functional equivalence is enforced [9,10]. These discrepancies highlight

the sensitivity of results to modelling assumptions, system boundaries, and data quality, and point to the need for more robust comparative assessment frameworks.

A critical yet often underexplored dimension in this context is uncertainty. Environmental assessments of emerging manufacturing technologies are affected by substantial epistemic uncertainty, arising from incomplete knowledge, immature datasets, and variability in process parameters. Traditional LCA uncertainty analysis typically relies on probabilistic Monte Carlo simulations, which assume that uncertainties can be represented through fully specified probability distributions. However, in early-stage or data-scarce contexts, such assumptions may not be justified and can lead to overconfident results.

To address this limitation, alternative approaches based on interval analysis and evidence theory have been proposed for representing epistemic uncertainty in LCA [13,14]. In particular, Dempster–Shafer theory provides a framework for modelling uncertainty under incomplete knowledge by assigning probability masses to sets of values rather than precise outcomes. Probability boxes (*p-boxes*) and associated belief–plausibility (*Bel–Pl*) measures allow the propagation of bounded uncertainty through system models, producing impact ranges that explicitly reflect epistemic imprecision. Such approaches have been widely applied in space systems engineering to support design under uncertainty and robust decision-making in early phases [15–17] but remain underexplored in comparative LCA studies of manufacturing technologies.

Furthermore, most existing LCA comparisons between additive and subtractive manufacturing focus exclusively on environmental indicators, neglecting performance-related benefits that are central to aerospace applications. In practice, manufacturing choices are not driven solely by environmental considerations but by trade-offs between performance and environmental burden. This requires the integration of environmental impact assessment with performance-based metrics within a unified decision-making framework.

This study addresses these gaps by developing an uncertainty-informed LCA framework that integrates evidence-theory-based modelling of epistemic uncertainty with Monte Carlo propagation of aleatory variability. The framework is applied to a comparative assessment of LPBF and CNC machining for the production of a satellite mounting bracket. Environmental impacts are computed under a hybrid Dempster–Shafer Theory–Monte Carlo (DST–MC) approach, combining epistemic uncertainty representation with stochastic propagation of aleatory variability, yielding interval-valued impact estimates with associated belief measures. In parallel, a performance-based benefit metric based on stiffness-to-mass ratio is introduced and propagated under uncertainty using a consistent modelling approach.

To support decision-making, environmental impacts and performance benefits are normalised and combined into a composite trade-off metric, allowing the evaluation of manufacturing alternatives across a range of preference weights. Decision outcomes are expressed in terms of belief and plausibility measures, enabling the explicit representation of support and indeterminacy under uncertainty.

The objective of this study is therefore twofold: (i) to quantify and compare the environmental impacts of LPBF and CNC manufacturing routes under epistemic and aleatory uncertainty, and (ii) to evaluate the resulting performance–environment trade-offs using an evidence-based decision framework. By explicitly accounting for uncertainty and integrating performance considerations, the proposed methodology provides a more robust basis for sustainability assessment and decision-making in aerospace manufacturing contexts.

While previous studies have explored uncertainty in LCA using probabilistic methods or interval-based approaches, the contribution of this work lies in the integration of multiple elements into a unified decision-oriented framework.

Specifically, this study introduces: (i) the propagation of epistemic uncertainty directly at the life-cycle inventory (LCI) parameter level using Dempster–Shafer theory, (ii) the consistent coupling of environmental impact assessment with a performance-based engineering

model under uncertainty, (iii) the use of belief–plausibility measures to distinguish between robust preference, plausible preference, and decision ignorance, and (iv) a continuous trade-off formulation enabling decision analysis under varying environmental priorities.

This combination provides a structured methodology for decision-making under incomplete knowledge, extending beyond conventional uncertainty-aware LCA approaches.

2. Materials and Methods

2.1. LCA Model Definition

2.1.1. Case Study Definition

The proposed uncertainty-informed LCA framework is demonstrated through a case study comparing additive and subtractive manufacturing routes for structural aerospace components. In particular, the analysis focuses on the production of a satellite mounting bracket manufactured either through LPBF or CNC machining.

The objective of the case study is to evaluate the environmental trade-offs between these two manufacturing technologies while explicitly accounting for epistemic uncertainty in key life-cycle parameters. The case study therefore serves both as a practical validation of the proposed uncertainty quantification methodology and as a decision-support example for manufacturing trade-offs in aerospace applications.

The selected component is intended as a representative demonstrator for methodological development rather than a basis for general conclusions across all aerospace applications. The transferability of results depends on factors such as component complexity, material selection, process parameters, and mission context.

2.1.2. Functional Unit

The functional unit (FU) was defined as the production of one satellite mounting bracket fulfilling identical structural and geometric performance requirements. The mounting bracket is representative of secondary structural elements commonly used in spacecraft subsystems.

This component was selected for several reasons. First, it represented a typical secondary structure element frequently manufactured using both additive and subtractive processes. Second, the relatively simple geometry allowed for transparent modelling of manufacturing processes and material flows. Third, the component provided a realistic case study for analysing environmental trade-offs between manufacturing technologies while ensuring reliable data availability.

The functional unit ensured baseline equivalence in terms of structural and geometric requirements, enabling a consistent comparison of manufacturing routes at the component level.

However, it did not fully capture potential functional enhancements enabled by additive manufacturing, such as mass reduction or design integration. To address this limitation, a separate performance model based on stiffness-to-mass ratio was introduced and evaluated under uncertainty (Table 1). This distinction allowed the analysis to differentiate between baseline functional equivalence and performance-driven advantages.

Table 1. Reference geometry and loading conditions for the benchmark bracket.

Parameter	Value
Length (L)	0.08 m
Width (b)	0.04 m
Thickness (t)	0.006 m
Load (F)	250 N

2.1.3. System Boundaries

The LCA adopts a cradle-to-gate system boundary focusing on manufacturing-related stages. The analysed system included raw material production, material preparation, and component manufacturing processes associated with each production route.

For the LPBF route, the system included aluminium powder production, powder handling, additive manufacturing operations, and associated electricity consumption. For the CNC route, the system included aluminium billet production, machining operations, and material removal processes.

Processes related to transportation, use phase, and end-of-life treatment were excluded from the analysis in order to isolate the environmental performance of the manufacturing stage. This boundary definition enabled a direct comparison of the environmental implications of additive and subtractive production technologies.

The system definition and modelling assumptions were aligned with ESA guidance for the application of LCA to space systems, with the aim of ensuring consistency with emerging space-sector environmental assessment practice [5,18,19].

It is important to note that this boundary excludes use-phase and system-level effects, such as mass-induced launch savings or mission performance improvements. As a result, the conclusions of this study are limited to manufacturing-stage impacts and do not represent full life-cycle sustainability performance.

2.1.4. Process Modelling

The Life-Cycle Inventory (LCI) model was implemented using the openLCA software version 2.3 environment and relied on process data extracted from the Strathclyde Space Systems Database (SSSD v1.0.3), which is structured for space-system applications and built using *Ecoinvent v3.9*-based background datasets.

The manufacturing systems were represented through a process-flow tree linking material inputs, energy consumption, and emissions associated with each process stage. The process models for both manufacturing routes were implemented as interconnected process-flow networks, linking material production, energy use, and emissions across all stages defined within the system boundaries.

Inventory exchanges were expressed per functional unit and include electricity use, material inputs, auxiliary consumables, and waste generation associated with each manufacturing process. Characterisation factors for midpoint impact assessment were derived from the environmental footprint (EF) method and applied to the elementary flows extracted from the SSSD-based inventory model, ensuring consistency with both European LCA practice and ESA guidelines for space-system environmental assessment [18].

2.2. Uncertainty Modelling

Uncertainty treatment in this work was motivated by the recognised importance of both stochastic and epistemic sources of uncertainty in LCA, particularly in engineering contexts where information is limited and process data are partly assumption-driven [13,14,20]. This is especially relevant in the space sector, where design-stage assessments often rely on incomplete knowledge and evolving technical definitions [17,21,22].

The adopted approach is consistent with ISO 14044 [3], which recommends evaluating the influence of uncertainty on LCA results, while extending this requirement by explicitly accounting for epistemic uncertainty in situations where probability distributions cannot be robustly defined.

2.2.1. Selection of Epistemic Variables

Epistemic uncertainty arises from incomplete knowledge regarding process parameters and manufacturing conditions. In this study, epistemic variables were defined directly at the level of process-specific and auxiliary inventory parameters, ensuring consistency with the implemented LCI model and uncertainty propagation framework.

For each manufacturing route, the following parameters were treated as epistemically uncertain:

- Material input scaling factor (m_{in}).
- Particulate-related exchanges (E_{PM}).
- Process-specific electricity consumption:
  - LPBF: build phase (E_{build}) and post-processing (E_{post}).
  - CNC: machining operations (E_{CNC}).
- Scrap or waste fraction (f_w).
- Auxiliary consumables, including process gases (e.g., argon), solvents, and tool wear.

Baseline values for these parameters were defined for both LPBF and CNC manufacturing routes, and plausible intervals were specified to represent epistemic uncertainty. The selected intervals reflected differences in data maturity and process variability, with wider ranges assigned to LPBF parameters to capture the higher epistemic uncertainty associated with additive manufacturing processes.

For example, electricity consumption for LPBF was decomposed into build and post-processing contributions, with ranges of $[120, 190]$ kWh and $[8, 30]$ kWh per functional unit, respectively, while CNC machining electricity was represented by a narrower interval of $[8, 14]$ kWh. Similarly, the material input scaling factor varied between $[1.10, 1.45]$ for LPBF and $[2.25, 2.75]$ for CNC, reflecting differences in buy-to-fly ratios. Waste fractions and auxiliary flows were also parameterised through bounded intervals consistent with the underlying process assumptions.

A summary of the epistemic parameterisation adopted for the LCI model is reported in Table 2. These parameter ranges formed the basis for constructing probability boxes used to represent epistemic uncertainty in the subsequent uncertainty propagation analysis. Additional variability around these intervals was introduced through parameter-specific dispersion factors, enabling the representation of combined epistemic and aleatory uncertainty within the *p-box* formulation.

Table 2. Epistemic uncertainty intervals for key LCI parameters in LPBF and CNC processes.

Parameter	Process	Interval	Unit
Material input (m_{in})	LPBF	[1.10, 1.45]	kg
	CNC	[2.25, 2.75]	kg
Electricity (build)	LPBF	[120, 190]	kWh
Electricity (post)	LPBF	[8, 30]	kWh
Electricity (machining)	CNC	[8, 14]	kWh
Scrap fraction (f_w)	LPBF	[0.03, 0.18]	–
	CNC	[0.52, 0.68]	–
Particulate flows (E_{PM})	LPBF	$[10^{-4}, 1.2 \times 10^{-3}]$	kg
	CNC	$[10^{-4}, 8 \times 10^{-4}]$	kg
Auxiliary flows	LPBF	process-specific ranges	–
	CNC	process-specific ranges	–

The specified parameter intervals were derived from a combination of literature sources, database-informed assumptions based on the SSSD/Ecoinvent framework, and engineering judgement in cases where empirical data were limited. Such an approach is consistent with established LCA practice under data scarcity, where parameterisation relies on structured assumptions and expert knowledge rather than purely measurement-

based evidence [3,23]. As a result, these ranges should be interpreted as representations of epistemic uncertainty arising from incomplete knowledge, rather than stochastic variability [24–27]. The relative width of the parameter intervals, particularly for LPBF, reflects the higher degree of epistemic uncertainty associated with emerging manufacturing processes, where reported values in the literature and databases exhibit larger dispersion [28]. These ranges were defined to encompass plausible operating conditions rather than best-case estimates, ensuring that uncertainty propagation captures the full extent of incomplete knowledge.

2.2.2. Representation of Epistemic Uncertainty

Epistemic uncertainty is represented using probability boxes (*p-boxes*), which define lower and upper bounds on cumulative distribution functions rather than precise probability distributions. For each epistemic parameter X defined by a plausible interval $[\mu_{\min}, \mu_{\max}]$, a *p-box* is constructed to capture bounded uncertainty without assuming a fully specified distribution.

The *p-box* envelope is defined using shifted exponential cumulative distribution functions (CDFs).

A nominal value is introduced as $\mu_{\text{nom}} = (\mu_{\min} + \mu_{\max})/2$, and a dispersion parameter is defined as $\sigma = f|\mu_{\text{nom}}|$, where f is a parameter-specific relative dispersion coefficient. The shifted-exponential CDF is given by:

$$F(x;\mu,\beta) = \begin{cases} 0, & x < \mu, \\ 1 - \exp\left(-\dfrac{x-\mu}{\beta}\right), & x \geq \mu, \end{cases}$$

where $\beta = \sigma$ controls the spread of the distribution. The lower and upper bounds of the p-box are defined as:

$$F_L(x) = F(x;\mu_{\max},\beta), \qquad F_U(x) = F(x;\mu_{\min},\beta).$$

2.2.3. Conversion to Dempster–Shafer Focal Elements

The continuous *p-box* is discretised into a finite set of focal elements using α-cuts on the probability axis. A sequence $0 = \alpha_0 < \alpha_1 < \cdots < \alpha_N = 1$ is defined, and each interval (α_{k-1}, α_k) is assigned a basic probability mass $m_k = \alpha_k - \alpha_{k-1}$.

The bounds of each focal element are obtained from the inverse CDFs:

$$q_L(\alpha) = F_U^{-1}(\alpha), \qquad q_U(\alpha) = F_L^{-1}(\alpha),$$

yielding interval-valued focal elements:

$$FE_k = [q_L(\alpha_{k-1}), q_U(\alpha_k)].$$

This results in a discrete evidence-theory representation of epistemic uncertainty, where focal elements are associated with masses that sum to unity. Epistemic variables were assumed to be independent in this study in order to maintain tractability of the evidence-theory framework, as the explicit modelling of dependencies would require the construction of joint focal elements, leading to a rapid combinatorial increase in the number of epistemic states.

However, in practical manufacturing systems, several parameters are likely to be correlated. In the case of LPBF, for example, material input, scrap rate, process energy consumption, and auxiliary consumables are linked through process efficiency and build conditions. Neglecting these dependencies may influence the resulting uncertainty bounds,

potentially leading to either overestimation or underestimation of interval widths and affecting the shape of the belief–plausibility curves.

In the absence of reliable joint data to characterise these dependencies, an independence assumption was adopted as a first-order approximation. The implications of this assumption are discussed in Section 4, and the incorporation of dependency structures represents an important direction for future work.

In this study, the *p-box* support was discretised using $n_{\text{grid}} = 1500$ points, and a fixed set of α-cuts $(0, 0.2, 0.5, 0.8, 1)$ was adopted to ensure reproducibility.

2.3. Uncertainty Propagation

2.3.1. Propagation of Aleatory Uncertainty

Aleatory uncertainty associated with Life-Cycle Impact Assessment (LCIA) characterisation factors is propagated using a Monte Carlo (MC) simulation. Characterisation factors are sampled around their database mean values using a relative standard deviation fraction f_{CF}. In this study, $f_{\text{CF}} = 0.10$, corresponding to a 10% relative dispersion.

For each Monte Carlo realisation s, characterisation factors are independently sampled using normal distributions centred at their mean values and truncated to non-negative values. Environmental impacts are then computed as:

$$I^{(s)} = \sum_j q_j \cdot CF_j^{(s)},$$

where q_j represents the inventory flow and $CF_j^{(s)}$ the sampled characterisation factor.

2.3.2. Impact Computation Under DST–MC Uncertainty

Each elementary flow in the LCI was associated with a scaling factor linked to one of the epistemic variables defined in Section 2, such that uncertainty propagation was performed through a parameterised modification of inventory exchanges rather than direct perturbation of flows.

Environmental impacts were computed by combining epistemic uncertainty in inventory parameters with aleatory uncertainty in characterisation factors.

The LCI was expressed as a set of elementary flows per functional unit. Characterisation factors were matched to flows using identifiers (e.g., name and CAS number), and unmatched flows were excluded from the analysis.

Inventory flows were linked to epistemic variables through a rule-based mapping based on flow attributes (e.g., name, category, and subcategory). Flows not associated with epistemic variables are treated deterministically.

Epistemic uncertainty was represented through focal elements derived from the *p-box* discretisation. Assuming independence between variables, joint epistemic states were constructed by combining focal elements across all parameters, each associated with a joint mass.

For each epistemic state, inventory flows were scaled according to the corresponding parameter intervals. Aleatory uncertainty in characterisation factors was then propagated using a Monte Carlo simulation. For each state, the minimum and maximum impacts across all realisations were retained, yielding interval-valued outcomes $[I_{\text{min}}, I_{\text{max}}]$.

This resulted in a set of weighted impact intervals associated with the joint epistemic states. In this study, $N_{\text{CF}} = 200$ Monte Carlo samples were used, and a fixed random seed (2026) ensured reproducibility.

To assess the numerical robustness of the uncertainty propagation, a limited convergence analysis was conducted on representative impact categories, focusing on the

sensitivity of results to (i) the discretisation of p-boxes through α-cuts and (ii) the number of Monte Carlo samples used for aleatory uncertainty propagation.

Specifically, the baseline configuration used in the main analysis (5 α-cuts and $N_{CF} = 200$ samples per epistemic state) was compared against (i) a higher-resolution Monte Carlo setting ($N_{CF} = 500$) and (ii) an alternative α-cut discretisation with 7 levels. The evaluation considered the stability of (i) global impact interval widths, (ii) belief–plausibility curves, and (iii) the transition region of the environmental weighting parameter λ in the trade-off analysis.

2.4. Performance Benefit Metric

In addition to environmental impacts, a performance-based benefit metric was introduced to support the comparison between manufacturing routes. In aerospace applications, structural components are typically required to provide high mechanical stiffness while minimising mass, since structural mass directly affects launch cost, payload allocation, and overall mission efficiency.

The mounting bracket was modelled as a representative structural component subjected to a prescribed static load F applied at the free end. The structural response was characterised through the resulting tip displacement δ. The effective bending stiffness was defined as

$$k = \frac{F}{\delta}.$$

The primary performance benefit metric was then defined as the stiffness-to-mass ratio

$$B_0 = \frac{k}{m},$$

where m is the component mass. In the reference configuration, the mass was computed from the material density ρ and the component volume V as

$$m = \rho V.$$

To account for process-related and design-related effects, the performance model introduced a set of uncertain parameters. Young's modulus E and material density ρ were treated as uncertain material properties within ranges representative of aluminium alloys used in LPBF and CNC manufacturing. In addition, a process-dependent correction factor E_{factor} was introduced to account for effective stiffness deviations caused by manufacturing-induced effects such as porosity, anisotropy, residual defects, and geometric imperfections.

In the revised performance model, an explicit geometry factor V_{factor} was also introduced to represent lightweighting and geometric redesign. This factor modified the reference volume according to

$$V = V_{\text{ref}}\, V_{\text{factor}},$$

where V_{ref} denotes the benchmark bracket volume. Values of $V_{\text{factor}} < 1$ represent reduced material usage associated with redesign opportunities enabled by additive manufacturing. In a simplified structural approximation, the second moment of the area was assumed to scale proportionally with the same factor, such that

$$I_{\text{eff}} = I_{\text{ref}}\, V_{\text{factor}}.$$

To account for manufacturing-enabled advantages extending beyond the isolated component, two multiplicative benefit factors were further introduced:

- A long-term performance factor g_{lt}, representing possible system-level benefits such as improved reliability, reduced maintenance, or simplified assembly;

- A design-related factor g_{d}, capturing additional benefits associated with additive manufacturing, such as part consolidation and increased design flexibility.

The overall benefit metric was therefore written as

$$B = g_{\mathrm{d}}\, g_{\mathrm{lt}}\, B_0.$$

The intervals assigned to the long-term benefit factor (g_{lt}) and design factor (g_d) were based on scenario-based engineering assumptions reflecting potential performance improvements enabled by additive manufacturing, such as design integration, weight reduction, and system-level optimisation. Due to the limited availability of empirical data for these effects, the selected ranges represent plausible values derived from engineering judgement and literature-informed expectations rather than directly measured quantities. As such, they should be interpreted as epistemic assumptions within the performance model.

While E and ρ correspond to physically measurable material properties, the parameters E_{factor}, V_{factor}, g_{lt}, and g_{d} are modelling and scenario parameters introduced to represent process-induced effects and manufacturing-enabled functional advantages that are not directly captured by material data alone. These parameters should therefore be interpreted as structured engineering assumptions rather than directly measured quantities.

Epistemic uncertainty in the performance model was represented using Dempster–Shafer focal elements, defined by parameter intervals and associated masses. The epistemic representation adopted for the revised model is summarised in Table 3. For comparison purposes, a simpler baseline configuration without explicit lightweighting benefits was also considered. The differences between the baseline and revised performance models are summarised in Appendix A.

Table 3. Epistemic uncertainty representation of performance model parameters for LPBF and CNC manufacturing routes in the revised performance model. Each parameter is described by Dempster–Shafer focal elements (FEs) defined by intervals and associated probability masses.

Process	Parameter	FE	Interval	Mass
LPBF	E [GPa]	FE1	[67, 69]	0.25
		FE2	[69, 71]	0.50
		FE3	[71, 73]	0.25
	ρ [kg m^{-3}]	FE1	[2550, 2625]	0.25
		FE2	[2625, 2685]	0.50
		FE3	[2685, 2720]	0.25
	E_{factor}	FE1	[0.92, 0.95]	0.25
		FE2	[0.95, 0.98]	0.50
		FE3	[0.98, 1.00]	0.25
	V_{factor}	FE1	[0.72, 0.80]	0.25
		FE2	[0.80, 0.88]	0.50
		FE3	[0.88, 0.95]	0.25
	g_{lt}	FE1	[1.00, 1.03]	0.35
		FE2	[1.03, 1.07]	0.45
		FE3	[1.07, 1.12]	0.20
	g_{d}	FE1	[1.00, 1.04]	0.30
		FE2	[1.04, 1.09]	0.45
		FE3	[1.09, 1.15]	0.25
CNC	E [GPa]	FE1	[68, 69]	0.35
		FE2	[69, 70]	0.45
		FE3	[70, 71]	0.20
	ρ [kg m^{-3}]	FE1	[2690, 2700]	0.35
		FE2	[2700, 2710]	0.45
		FE3	[2710, 2720]	0.20
	E_{factor}	FE1	[0.99, 1.00]	0.50
		FE2	[1.00, 1.00]	0.50
	V_{factor}	FE1	[0.98, 1.00]	0.50
		FE2	[1.00, 1.02]	0.50
	g_{lt}	FE1	[1.00, 1.00]	1.00
	g_{d}	FE1	[1.00, 1.01]	0.70
		FE2	[1.01, 1.03]	0.30

Joint epistemic states were generated through the Cartesian combination of focal elements across all uncertain parameters. Within each epistemic state, conditional variability

was introduced through Monte Carlo sampling using independent normal distributions with parameter-specific coefficients of variation. For each state, lower and upper conditional estimates of the benefit metric, denoted by $B_{\min}$ and $B_{\max}$, were obtained from the sampled realisations.

This procedure yielded a set of weighted benefit intervals associated with the joint epistemic states, consistent with the hybrid DST–MC framework adopted for environmental impacts.

2.5. Belief–Plausibility Curves

The uncertainty on each impact category was summarised using belief and plausibility curves derived from the ensemble of impact bounds. For a threshold t, the belief that the impact did not exceed t was computed as the mass of focal elements whose upper bound lay below the threshold, while plausibility was computed as the mass of focal elements whose lower bound lay below the threshold:

$$\mathrm{Bel}(I \le t) = \sum_{\omega : I_{\max}(\omega) \le t} m(\omega), \qquad \mathrm{Pl}(I \le t) = \sum_{\omega : I_{\min}(\omega) \le t} m(\omega),$$

where ω denotes a joint epistemic state obtained from the combination of focal elements across all epistemic variables, with associated joint mass $m(\omega)$. Belief–plausibility curves were evaluated on a grid of $N_{\mathrm{grid}} = 200$ thresholds spanning the range of computed impact bounds for each category.

2.6. Normalisation of Impact and Benefit Indicators

Prior to trade-off analysis, environmental impacts and performance benefits were normalised to a common dimensionless scale to ensure comparability.

For each impact category, global minimum and maximum values across both manufacturing routes were identified from the full set of conditional bounds obtained across all epistemic states. Environmental impacts were then normalised as

$$I^{\mathrm{norm}} = \frac{I - I_{\min}^{\mathrm{global}}}{I_{\max}^{\mathrm{global}} - I_{\min}^{\mathrm{global}}}.$$

Similarly, the benefit metric was normalised using global bounds across both manufacturing routes:

$$B^{\mathrm{norm}} = \frac{B - B_{\min}^{\mathrm{global}}}{B_{\max}^{\mathrm{global}} - B_{\min}^{\mathrm{global}}}.$$

This global normalisation ensured that the two manufacturing routes were assessed on the same scale and avoided distortions associated with route-specific ranges.

2.7. Trade-Off Formulation Under Uncertainty

To evaluate the trade-off between functional benefit and environmental burden, a composite score was defined as

$$S = B^{\mathrm{norm}} - \lambda I^{\mathrm{norm}},$$

where $\lambda \ge 0$ is a weighting parameter expressing the relative importance assigned to environmental impact.

For each impact category, pairwise comparisons were performed between LPBF and CNC using the corresponding benefit and impact intervals associated with their joint

epistemic states. For each combination of states, best-case and worst-case score bounds were evaluated for both manufacturing routes.

Decision preference was then assessed according to the following interval-dominance rules:

- LPBF was considered preferable if its worst-case score exceeded the best-case score of CNC;
- CNC was considered preferable if its worst-case score exceeded the best-case score of LPBF;
- Otherwise, the comparison was classified as indeterminate (ignorance).

Belief and plausibility measures were subsequently obtained by aggregating the joint masses of the state combinations supporting each decision outcome. In this way, the trade-off analysis distinguished between robust preference, plausible preference, and indeterminate regions.

The analysis was repeated over a range of λ values in order to explore how the decision changed as greater importance was assigned to environmental performance. This formulation is consistent with decision-support approaches for comparing alternatives under epistemic uncertainty, where performance and environmental burden must be balanced under incomplete knowledge.

3. Results

3.1. Environmental Impact Results

3.1.1. Deterministic Midpoint Comparison

Figure 1 presents the deterministic midpoint environmental impacts associated with the LPBF and CNC manufacturing routes across the selected midpoint impact categories. These values correspond to baseline LCA results obtained using nominal parameter values within a cradle-to-gate system boundary, prior to uncertainty propagation.

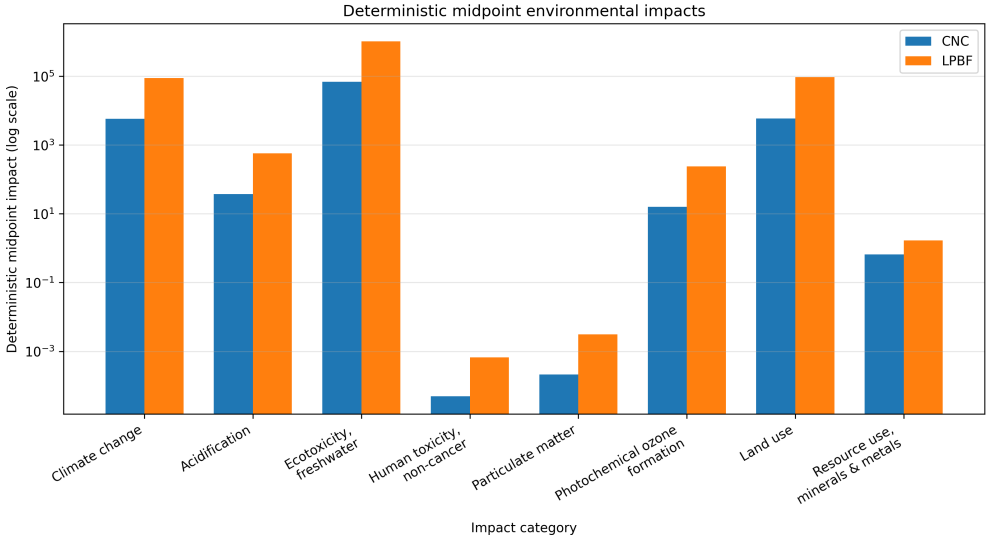

Figure 1. Deterministic midpoint environmental impacts for LPBF and CNC across selected categories (logarithmic scale).

Across all considered midpoint impact categories, CNC machining consistently exhibits lower environmental impacts than LPBF. This trend is observed for Climate Change, Acidification, Ecotoxicity (Freshwater), Human Toxicity (Non-Cancer), Particulate Matter Formation, Photochemical Ozone Formation, Land Use, and Resource Use (Minerals and Metals).

The magnitude of the difference varies substantially across categories. The highest absolute impacts are observed for Ecotoxicity (Freshwater) and Land Use, where LPBF values exceed those of CNC by more than one order of magnitude. Climate Change impacts are also significantly higher for LPBF, reflecting the high energy demand associated with powder production and laser-based processing. In contrast, categories such as Human Toxicity and Particulate Matter exhibit lower absolute values but maintain a consistent relative difference between the two manufacturing routes.

The use of a logarithmic scale in Figure 1 highlights the wide variation in impact magnitudes across categories, spanning several orders of magnitude, while preserving the consistent dominance of CNC over LPBF.

Numerical values corresponding to the deterministic midpoint comparison are reported in Table 4.

Table 4. Deterministic midpoint environmental impacts for the CNC and LPBF manufacturing routes. Relative difference is computed as $(I_{\mathrm{LPBF}} - I_{\mathrm{CNC}})/I_{\mathrm{CNC}} \times 100$.

Impact Category	Unit †	CNC	LPBF	Relative Difference (%)
Climate Change	kg CO_2 eq	5730.72	87,399.39	1425.10
Acidification	mol H^+ eq	37.44	566.71	1413.63
Ecotoxicity, Freshwater	CTUe	69,314.29	1,019,458.07	1370.78
Human Toxicity, Non-Cancer	CTUh	4.93×10^{-5}	6.70×10^{-4}	1259.18
Particulate Matter	disease incidence	2.14×10^{-4}	3.11×10^{-3}	1354.83
Photochemical Ozone Formation	kg NMVOC eq	15.79	238.80	1412.31
Land Use	Pt	5879.29	94,538.51	1507.99
Resource Use, Minerals & metals	kg Sb eq	0.6553	1.6807	156.49

† Units follow the environmental footprint (EF) method as implemented in the LCI database.

3.1.2. Relative Comparison

To quantify the difference between the two manufacturing routes, Figure 2 shows the relative increase in LPBF impacts with respect to CNC.

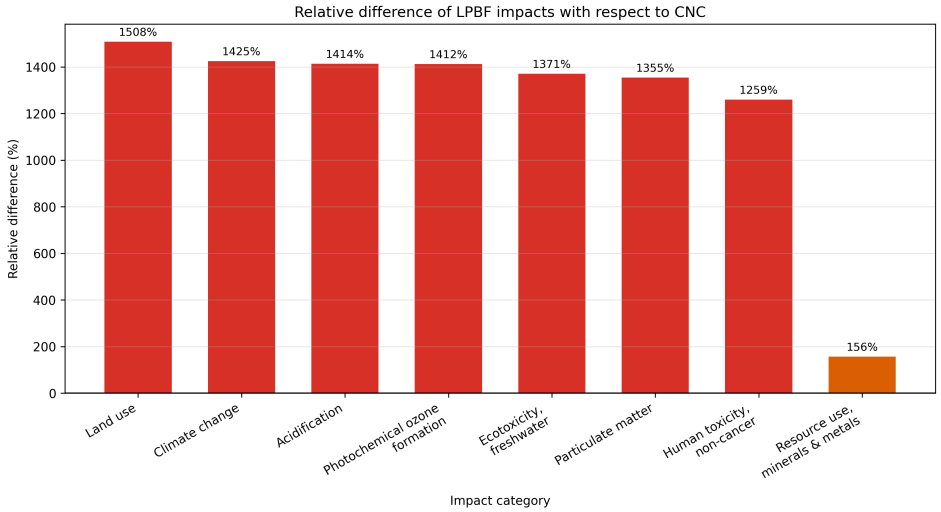

Figure 2. Relative difference of LPBF impacts with respect to CNC, sorted in descending order. Positive values indicate higher impacts for LPBF.

The results indicate that LPBF impacts are systematically higher than CNC ones across all categories, with relative increases ranging from approximately 150% to over 1500%. The largest relative differences are observed for Land Use (approximately 1500%), Climate Change (approximately 1400%), and Acidification and Photochemical Ozone

Formation (both exceeding 1400%). Ecotoxicity (Freshwater) and Particulate Matter also show substantial increases, exceeding 1300%.

Even in categories with comparatively lower relative differences, such as Resource Use (Minerals and Metals), LPBF still exhibits an increase of more than 150% compared to CNC. No category shows a reversal of this trend.

These results establish a clear baseline: under deterministic conditions and for an equivalent functional unit, CNC machining outperforms LPBF across all considered midpoint environmental indicators. The higher environmental burden associated with LPBF is primarily driven by energy-intensive powder production and process-related electricity consumption.

3.1.3. Baseline Interpretation

The deterministic comparison provides a reference point for subsequent uncertainty analysis. It shows that, when uncertainty is not considered, LPBF presents a systematic environmental disadvantage at the manufacturing stage within a cradle-to-gate perspective.

This result indicates that any potential environmental advantage of LPBF cannot be inferred from process-level impacts alone but must arise from additional factors such as functional improvements (e.g., mass reduction, part consolidation) or system-level benefits. The following sections therefore investigate how uncertainty and performance considerations influence this baseline conclusion.

3.2. Uncertainty Characterisation

3.2.1. Epistemic Uncertainty Analysis

Figure 3 presents the overall width of the impact intervals obtained after propagation of epistemic uncertainty using the DST–MC framework. The interval width is defined as the difference between the global maximum and minimum impact values across all epistemic states and Monte Carlo realisations. A complete numerical summary of the uncertainty ranges for all midpoint impact categories is provided in Appendix B.

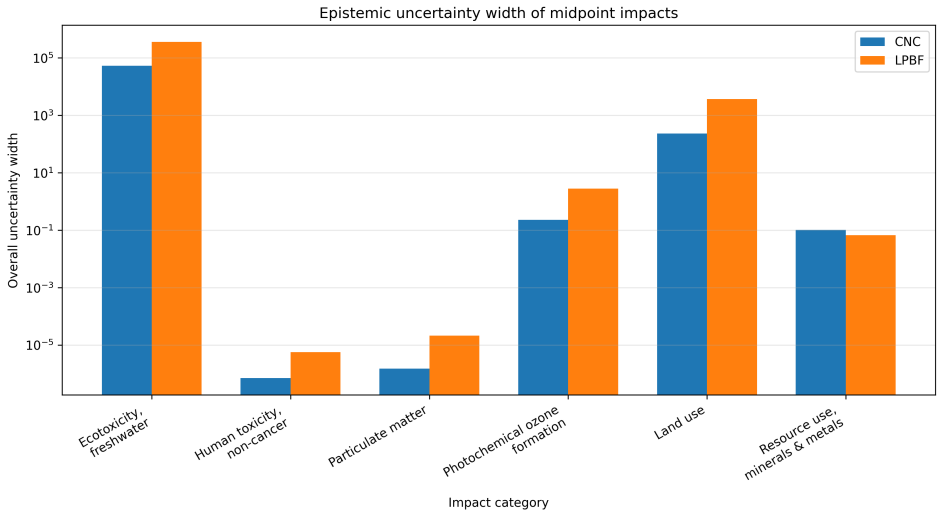

Figure 3. Overall uncertainty width of midpoint environmental impacts for LPBF and CNC across selected categories (logarithmic scale).

Across all midpoint impact categories, LPBF generally exhibits larger uncertainty widths than CNC, indicating a higher degree of epistemic uncertainty associated with additive manufacturing. This behaviour is consistent with the modelling assumptions adopted in this study, where wider parameter intervals were assigned to LPBF inventory variables to reflect the lower maturity and higher variability of AM process data.

The difference in uncertainty magnitude varies across midpoint impact categories. The largest uncertainty widths are observed for Ecotoxicity (Freshwater) and Land Use, where both processes show substantial variability, but LPBF displays significantly broader intervals. This reflects the strong sensitivity of these categories to material-related flows and upstream processes, which are characterised by uncertain input parameters such as material input and energy consumption.

Intermediate levels of uncertainty are observed for Photochemical Ozone Formation, where LPBF again shows a wider interval than CNC. In contrast, categories such as Human Toxicity (Non-Cancer) and Particulate Matter exhibit relatively small absolute uncertainty widths, although LPBF still maintains consistently higher values.

An exception is observed for Resource Use (Minerals and Metals), where CNC shows a slightly larger uncertainty width than LPBF. This behaviour can be attributed to the higher material input and scrap rates associated with subtractive manufacturing, which amplify the sensitivity of this category to uncertainties in material-related parameters.

Overall, these results indicate that epistemic uncertainty is both process-dependent and impact-category-dependent, with LPBF generally characterised by higher uncertainty due to the combined effect of wider parameter intervals and a larger number of influential uncertain variables.

3.2.2. Belief–Plausibility Representation

The structure of epistemic uncertainty was further analysed through belief–plausibility (*Bel–Pl*) curves, which provided a cumulative representation of the impact intervals associated with each manufacturing route.

Figure 4 shows the *Bel–Pl* curves for the Ecotoxicity (Freshwater) category, selected as representative due to its high impact magnitude and pronounced uncertainty. The curves define lower and upper bounds on the probability that the impact does not exceed a given threshold. The gap between the belief and plausibility functions represents the degree of epistemic uncertainty: a wider gap indicates greater imprecision in the knowledge of the system.

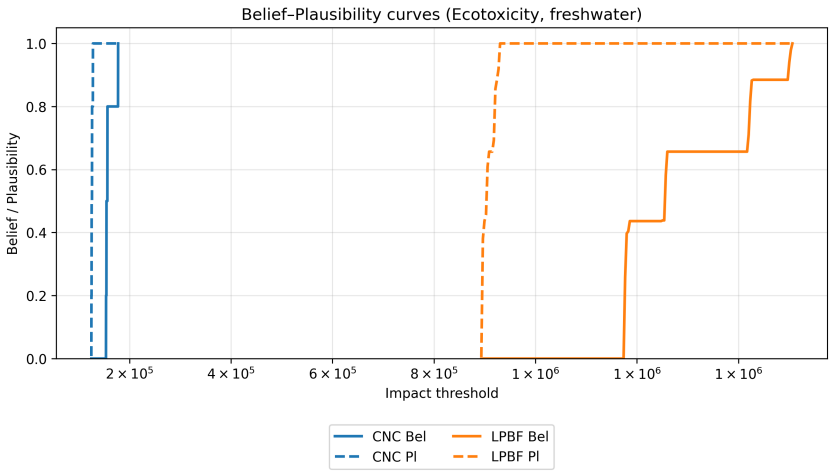

Figure 4. Belief–plausibility curves for the *Ecotoxicity (Freshwater)* impact category for LPBF and CNC. The wider envelope observed for LPBF indicates higher epistemic uncertainty.

For this category, LPBF exhibits a significantly wider *Bel–Pl* envelope than CNC, confirming the higher epistemic uncertainty identified in the interval-width analysis. The broad separation between belief and plausibility indicates that a wide range of impact values is compatible with the available information, reflecting the strong influence of uncertain parameters such as material input and energy consumption.

Conversely, CNC shows a narrower *Bel–Pl* envelope, indicating more constrained and better-defined impact estimates. This is consistent with the more mature and better-characterised nature of conventional machining processes and their associated LCI data.

More generally, the *Bel–Pl* representation shows that the difference between LPBF and CNC is not limited to impact magnitude but also extends to the confidence associated with these estimates. LPBF is characterised by both higher impacts and greater epistemic uncertainty, whereas CNC shows lower impacts with more constrained uncertainty bounds. The numerical bounds underlying these representations are reported in Appendix B.

3.3. Performance and Eco-Efficiency

The performance results presented in this section correspond to the revised performance model, which incorporates manufacturing-enabled benefits such as lightweighting, design integration, and long-term functional improvements.

A baseline performance configuration without these additional factors was also evaluated for sensitivity analysis and is discussed in the trade-off section. The revised model is adopted here as it provides a more realistic representation of the functional advantages associated with additive manufacturing.

3.3.1. Performance Benefit Comparison

Figure 5 compares the overall performance benefit metric obtained for the LPBF and CNC manufacturing routes. The benefit metric is based on the stiffness-to-mass ratio and incorporates both material-related properties and manufacturing-enabled advantage factors.

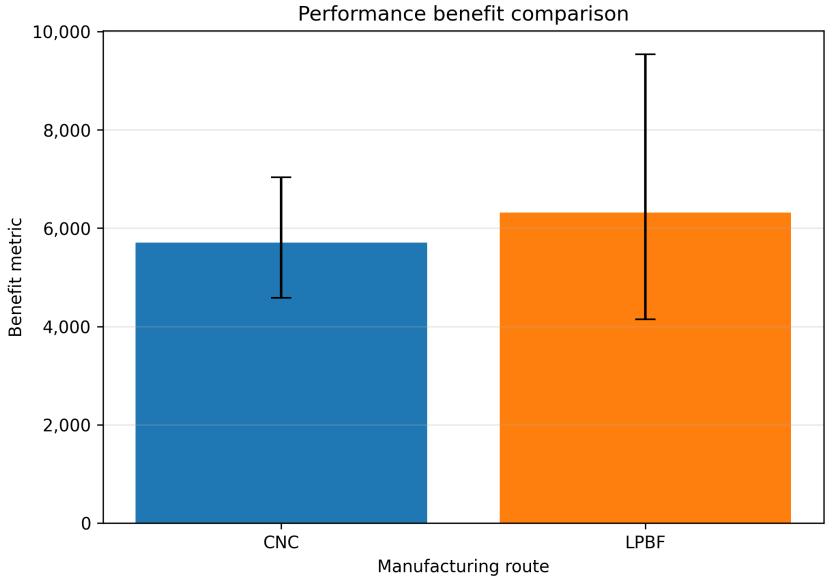

Figure 5. Comparison of the performance benefit metric for CNC and LPBF manufacturing routes. The metric is based on the stiffness-to-mass ratio and includes manufacturing-related correction factors. Error bars represent the range of values obtained from the uncertainty propagation, highlighting the larger variability associated with LPBF compared to CNC.

LPBF exhibits a higher central benefit value than CNC, primarily due to the inclusion of manufacturing-enabled advantage factors such as lightweighting and design integration, which are not captured in conventional subtractive manufacturing.

However, LPBF also shows a substantially wider benefit interval compared to CNC, reflecting greater uncertainty in the estimation of its performance advantage. This wider range is associated with the larger variability assigned to material properties and benefit factors for LPBF, as well as the less mature and more variable nature of additive manufac-

turing processes. In contrast, CNC exhibits a narrower interval, indicating more robust and well-characterised performance estimates.

3.3.2. Eco-Efficiency Comparison

To relate functional performance to environmental burden, an eco-efficiency indicator was defined as the ratio between the mean benefit metric and the deterministic midpoint impact for each category. Figure 6 compares this indicator for LPBF and CNC across selected midpoint impact categories.

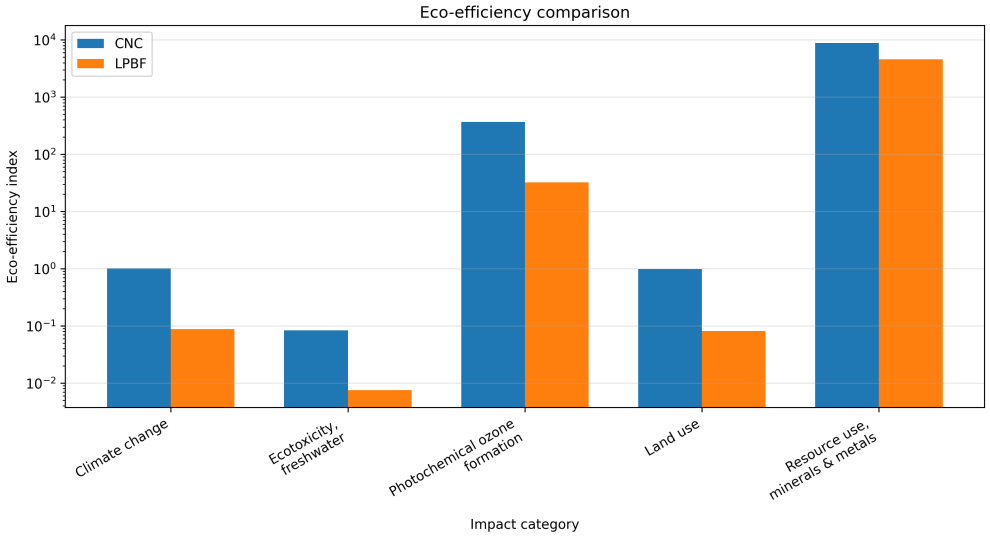

Figure 6. Eco-efficiency comparison between CNC and LPBF across selected midpoint impact categories. Eco-efficiency is defined as the ratio between the mean performance benefit and the deterministic midpoint environmental impact. Results are shown on a logarithmic scale to highlight differences across categories. CNC consistently exhibits higher eco-efficiency, indicating that the performance gains of LPBF do not compensate for its higher environmental impacts at the manufacturing stage.

The results show that CNC consistently exhibits higher eco-efficiency than LPBF across all considered categories. Despite the enhanced performance benefit associated with the revised model, this advantage is insufficient to compensate for its substantially higher environmental impacts at the manufacturing stage.

The difference is particularly pronounced in categories such as Climate Change, Ecotoxicity (Freshwater), and Land Use, where LPBF exhibits significantly lower eco-efficiency values due to the combined effect of high impacts and only moderate performance gains. Even in categories where the gap is smaller, such as Resource Use (Minerals and Metals), CNC maintains a clear advantage.

These findings indicate that, at the process-level and under the adopted functional unit, the performance improvements enabled by LPBF do not offset its environmental burden. The eco-efficiency analysis therefore reinforces the deterministic impact comparison, showing that CNC remains preferable when both performance and environmental impacts are considered simultaneously. At the same time, it highlights the conditions under which LPBF could become competitive, namely through larger functional gains or system-level benefits not captured within a cradle-to-gate assessment.

3.4. Trade-Off and Decision Analysis Under Uncertainty

3.4.1. Belief–Plausibility-Based Decision Analysis

To evaluate the preference between manufacturing routes under uncertainty, the composite score $S = B^{\text{norm}} - \lambda I^{\text{norm}}$ was analysed across a range of environmental weighting

factors λ. For each impact category, belief and plausibility measures were computed to quantify the support for LPBF or CNC being preferable.

Two modelling configurations were considered: (i) a baseline performance model, and (ii) a revised model including explicit manufacturing-enabled benefits such as lightweighting and design-related advantages.

Figures 7 and 8 present representative results for Land Use and Ecotoxicity (Freshwater). For clarity, the figures presented here correspond to the revised model, while the baseline configuration is documented in Appendix A.

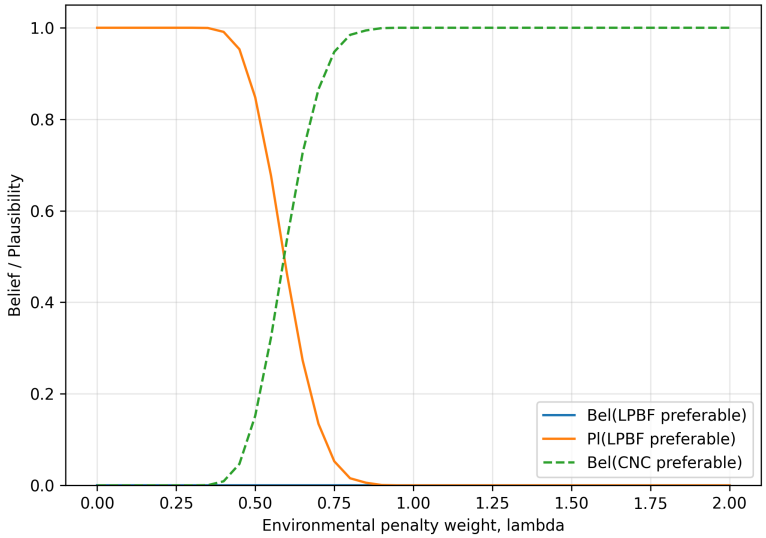

Figure 7. Belief and plausibility of LPBF preference as a function of the environmental weighting parameter λ for the Land Use category under the revised performance model. A smooth transition in plausibility is observed, while CNC remains the only robustly preferable option.

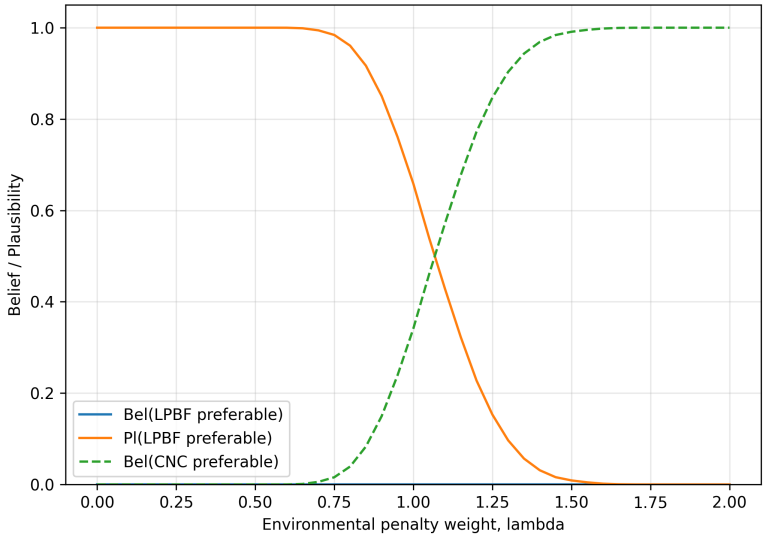

Figure 8. Belief and plausibility of LPBF preference as a function of λ for Ecotoxicity (Freshwater) under the revised performance model, showing a similar transition behaviour.

Under baseline assumptions without performance-related correction factors, the belief supporting LPBF preference remains negligible across the full range of λ, while CNC is consistently supported by belief. This indicates that CNC is the only robustly preferable option when performance advantages are not explicitly considered.

3.4.2. Revised Performance Model

When manufacturing-enabled benefits are incorporated, the trade-off structure becomes significantly more informative. As shown in Figures 7 and 8, LPBF exhibits high plausibility for low values of λ, reflecting its superior performance potential.

As λ increases, a smooth transition occurs in which plausibility shifts from LPBF to CNC. This transition region was found to be stable with respect to the numerical discretisation parameters, including the number of α-cuts and Monte Carlo samples (see Appendix C). Within this region, neither alternative can be considered clearly preferable based solely on plausibility.

At higher values of λ, environmental impacts dominate the composite score, leading to a rapid increase in belief supporting CNC preference, which approaches unity.

Importantly, despite the presence of a clear plausibility transition, the belief supporting LPBF preference remains negligible across all values of λ. This indicates that LPBF is never robustly preferable under worst-case conditions, even when enhanced performance assumptions are considered, and that CNC remains the only option supported by strong belief across the entire range of λ.

These results demonstrate that the revised model introduces a genuine and continuous trade-off between performance and environmental impact, while preserving CNC as the only option supported by strong belief.

3.4.3. Decision Uncertainty and Ignorance

In addition to preference measures, the Dempster–Shafer framework enabled the quantification of decision ambiguity through the ignorance mass.

Figure 9 shows the evolution of ignorance as a function of λ.

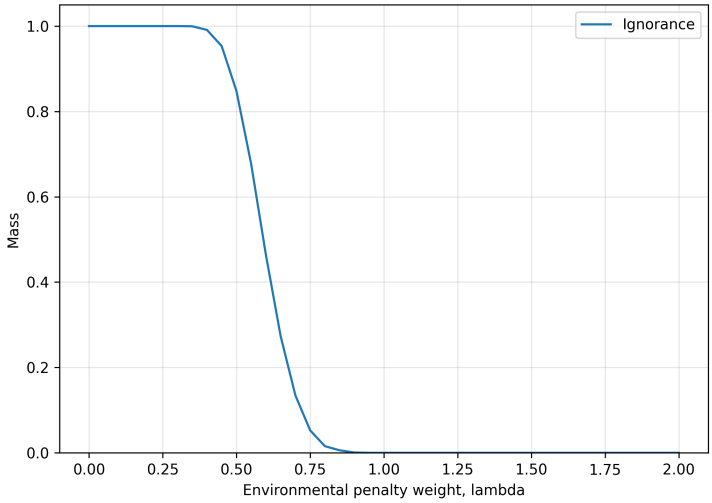

Figure 9. Ignorance associated with the decision between LPBF and CNC as a function of λ under the revised performance model. The region of indeterminacy corresponds to the transition between performance-driven and impact-driven regimes.

Ignorance represents the proportion of epistemic states for which neither LPBF nor CNC can be conclusively identified as preferable, corresponding to overlapping score intervals.

Under the revised performance model, ignorance is concentrated in an intermediate range of λ, approximately aligned with the plausibility transition region. This reflects the increased overlap between alternatives when performance benefits partially compensate for environmental impacts.

At low values of λ, LPBF is highly plausible but not supported by belief, while at high values of λ, ignorance rapidly decreases as CNC becomes clearly dominant.

Compared to the baseline case without performance-related correction factors, the revised model leads to a broader and more gradual region of ignorance, indicating increased decision sensitivity to epistemic uncertainty.

3.4.4. Interpretation of Trade-Off Behaviour

The trade-off analysis highlights the critical role of modelling assumptions in shaping decision outcomes under uncertainty.

While the baseline model leads to a trivial dominance of CNC, the revised model reveals a structured and continuous trade-off between performance and environmental impact. In particular, LPBF becomes a plausible alternative over a substantial range of λ, and a transition region emerges in which the preferred option depends on stakeholder priorities.

However, the absence of significant belief supporting LPBF indicates that its advantages are not sufficient to guarantee robust preference under uncertainty. Instead, the revised model exposes a regime of decision ambiguity rather than a true reversal of preference.

These findings suggest that LPBF competitiveness is highly sensitive to the representation of functional benefits. Although performance improvements can substantially influence plausibility, they do not fully offset environmental burdens within a cradle-to-gate perspective.

A full numerical summary of the uncertainty ranges for LPBF and CNC across all analysed midpoint impact categories is reported in Appendix A (Table A1).

4. Discussion

From a methodological perspective, these findings can be interpreted in light of the ISO 14040 and ISO 14044 standards [2,3], which require that uncertainty be considered in the interpretation of LCA results, particularly in comparative studies. While the standards emphasise the need for uncertainty and sensitivity analyses to support robust conclusions, they do not explicitly address how to represent situations where knowledge is incomplete or where data cannot be reliably described using precise probability distributions.

While ISO 14040 and ISO 14044 require that uncertainty be considered in LCA interpretation, they do not prescribe specific methods for representing epistemic uncertainty, particularly in cases where reliable probability distributions cannot be defined. Conventional probabilistic approaches typically assume well-characterised variability, which may lead to an under-representation of imprecision in data-scarce contexts.

In contrast, the evidence-theory-based framework adopted in this study enables the explicit representation of epistemic uncertainty through bounded intervals and belief–plausibility measures. This allows the distinction between robust preference, plausible preference, and decision ignorance, which is particularly relevant in early-stage design and emerging technology assessments where knowledge is incomplete.

The results of this study highlight that, in such contexts, conventional probabilistic approaches may provide an incomplete representation of uncertainty by under-representing epistemic imprecision. The proposed evidence-theory-based framework complements ISO requirements by enabling a structured distinction between variability, lack of knowledge, and decision ambiguity.

The results provide a consistent picture of the environmental and performance trade-offs between additive (LPBF) and subtractive (CNC) manufacturing under epistemic uncertainty. The deterministic comparison shows a clear dominance of CNC across all midpoint impact categories, consistent with previous studies reporting higher environmental burdens for metal additive manufacturing due to energy-intensive powder production and process electricity consumption [8–10]. This reinforces the view that, when assessed at the process level within a cradle-to-gate boundary, LPBF does not inherently deliver environmental advantages.

However, the contribution of this study lies not in confirming this baseline result, but in demonstrating how uncertainty fundamentally alters its interpretation. The uncertainty analysis shows that LPBF is characterised by significantly wider impact intervals than CNC, reflecting the higher epistemic uncertainty associated with emerging manufacturing technologies. This is consistent with the recognised limitations of LCA in data-scarce contexts, where incomplete knowledge and modelling assumptions dominate the uncertainty structure [13,14,20]. The wider parameter ranges assigned to LPBF at the inventory level directly contribute to the broader impact intervals and wider belief–plausibility envelopes observed in the results. This indicates that the uncertainty in the outputs is primarily driven by epistemic assumptions on process parameters, rather than by stochastic variability alone. As a result, the sensitivity of the results to input ranges is explicitly captured through the propagation of these intervals, without requiring separate one-at-a-time sensitivity analysis.

A key modelling assumption in this study is the independence of epistemic variables. In practical manufacturing systems, however, parameters such as material input, scrap rate, energy consumption, and auxiliary consumables are often interdependent, particularly for LPBF processes where process efficiency and build conditions influence multiple variables simultaneously. The neglect of such dependencies may affect uncertainty propagation, as correlations can either amplify or reduce the resulting interval widths and influence the shape of the belief–plausibility curves. In the present framework, independence was adopted due to the lack of reliable joint data and to maintain computational tractability, as modelling dependencies within an evidence-theory framework would require the construction of joint focal elements, leading to a rapid combinatorial increase in epistemic states. While the qualitative trends observed in the results are expected to remain consistent, this assumption may influence the magnitude of uncertainty bounds and the extent of decision indeterminacy. Future work should investigate the incorporation of dependency structures, for example through copula-based approaches or structured expert elicitation. The belief–plausibility representation highlights that this uncertainty primarily manifests as imprecision rather than variability, indicating that a wide range of impact values remains compatible with the available information.

Crucially, the results demonstrate that epistemic uncertainty does not change the ranking of alternatives, but fundamentally alters the confidence with which decisions can be made. This distinction is particularly relevant in the context of ISO-compliant LCA interpretation, where conclusions must be supported by an understanding of their robustness. Although a deterministic ranking may satisfy basic comparative requirements, the presence of wide epistemic uncertainty intervals challenges the strength of such conclusions and indicates that additional caution is required when interpreting results for decision-making.

In this study, CNC remains the environmentally preferable option in deterministic terms; however, the presence of wide uncertainty bounds for LPBF introduces regions in which its performance cannot be conclusively assessed. This distinction between ranking and decision confidence is not captured by conventional probabilistic LCA approaches and represents a key methodological insight of this work.

The integration of evidence theory provides a structured framework to address this limitation. By distinguishing between belief, plausibility, and ignorance, the proposed approach enables a more nuanced interpretation of decision outcomes under incomplete knowledge. In this study, LPBF emerges as a plausible alternative under performance-driven conditions, but it is never supported by strong belief. This indicates that, even when accounting for manufacturing-enabled benefits, LPBF does not achieve robust preference under worst-case assumptions. Rather than reversing the decision outcome, uncertainty expands the region of indeterminacy, highlighting the limits of current knowledge.

The introduction of performance-related benefits significantly enriches the analysis. The revised performance model reveals a continuous trade-off between environmental impact and functional performance, with a smooth transition in plausibility as the environmental weighting parameter increases. This behaviour reflects a realistic decision-making context in which engineering performance and environmental sustainability must be jointly considered. However, the results also show that the performance gains associated with LPBF remain insufficient to compensate for its environmental burden at the manufacturing stage.

This implies that additive manufacturing can only become environmentally competitive if its benefits extend beyond the component level to system-level effects. In the context of the space sector, such effects include reduced launch mass, improved payload efficiency, and enhanced mission performance, which are not captured within a cradle-to-gate boundary. This finding is consistent with emerging space-sector LCA practice, where early design decisions are recognised as critical leverage points for system-level sustainability [5,19].

From an engineering perspective, these results highlight the importance of integrating uncertainty-aware methods into early-stage design processes. In space applications, decisions are often made under incomplete information, where overconfidence in model outputs can lead to suboptimal or non-robust choices. The proposed framework provides a means to explicitly represent this uncertainty and to distinguish between robust, plausible, and indeterminate decisions, thereby supporting more informed design trade-offs.

A limited convergence analysis was conducted to evaluate the numerical stability of the uncertainty propagation (see Appendix C). The results indicated that increasing the number of Monte Carlo samples from 200 to 500 led to only minor changes in the global impact interval widths, with relative variations remaining small across the tested configurations. Similarly, refining the α-cut discretisation primarily improved the smoothness of the belief–plausibility curves without altering their overall shape or the ordering of alternatives.

Importantly, the location of the decision transition region in the environmental weighting parameter λ remained stable across all tested configurations. These findings suggest that the numerical settings adopted in the main analysis provide sufficient accuracy for the qualitative conclusions of the study, while denser discretisations mainly affect graphical resolution rather than decision outcomes.

Overall, this study shows that the main effect of epistemic uncertainty is not to overturn deterministic conclusions but to reveal where those conclusions are fragile. By combining LCA with evidence theory and performance modelling, the framework provides a more transparent and decision-relevant representation of sustainability trade-offs in aerospace manufacturing. This is particularly relevant for emerging technologies such as additive manufacturing, where uncertainty is intrinsic and must be treated as a central element of the assessment rather than a secondary consideration.

5. Conclusions

This study presented an uncertainty-informed LCA framework integrating Dempster–Shafer Theory (DST) and Monte Carlo (MC) simulations to evaluate environmental and performance trade-offs between LPBF and CNC manufacturing for aerospace applications.

The results show that, under a cradle-to-gate perspective, CNC machining consistently exhibits lower environmental impacts across all midpoint categories. In contrast, LPBF is associated with significantly higher impacts, primarily driven by energy-intensive powder production and process electricity consumption. Moreover, LPBF is characterised by substantially greater epistemic uncertainty, reflecting the lower maturity and higher variability of additive manufacturing data.

When performance is considered, LPBF demonstrates higher potential benefits due to manufacturing-enabled features such as lightweighting and design integration. However,

these advantages are not sufficient to offset its environmental burden within the analysed system boundaries. Eco-efficiency results therefore confirm CNC as the preferable option when both performance and environmental impacts are jointly considered.

The uncertainty-based trade-off analysis provides a more nuanced interpretation. While LPBF emerges as a plausible alternative under performance-driven conditions, it does not achieve belief-supported preference. CNC remains the only robustly preferable option across all environmental weighting scenarios. This distinction highlights the importance of differentiating between plausible and robust decisions when evaluating alternatives under epistemic uncertainty.

More broadly, the results demonstrate that uncertainty does not overturn deterministic conclusions but instead expands the region of decision indeterminacy. This reinforces the need for decision frameworks that explicitly account for incomplete knowledge.

The proposed framework illustrates the value of integrating epistemic and aleatory uncertainty within LCA, particularly for emerging technologies. By combining environmental and performance indicators within an evidence-theory-based structure, it supports more transparent and robust decision-making in early-stage design contexts. In this respect, the approach complements ISO 14040/14044 requirements by providing additional capabilities to represent epistemic uncertainty and decision ambiguity where data limitations are significant.

Future work should prioritise extending the framework beyond the cradle-to-gate perspective to full life-cycle and system-level assessments, including mission-level evaluations in aerospace applications. Such developments are essential to capture downstream benefits of additive manufacturing, such as mass reduction, payload efficiency, and operational performance, which are not addressed in the present study.

In conclusion, while additive manufacturing offers promising performance advantages, its environmental competitiveness remains contingent on both uncertainty reduction and the inclusion of broader system-level effects beyond the manufacturing stage.

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Conflicts of Interest: Author Andrew Ross Wilson was employed by the company Metasat UK Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

LCA	Life-Cycle Assessment
LCI	Life-Cycle Inventory
LCIA	Life-Cycle Impact Assessment
LPBF	Laser Powder Bed Fusion
CNC	Computer Numerical Control
DST	Dempster–Shafer Theory
MC	Monte Carlo
DST–MC	Hybrid Dempster–Shafer and Monte Carlo Framework
Bel	Belief
Pl	Plausibility
FE	Focal Element
p-box	Probability Box
EF	Environmental Footprint
FU	Functional Unit
SSSD	Strathclyde Space Systems Database
AM	Additive Manufacturing
Pt	Points (dimensionless EF indicator unit)
CTUe	Comparative Toxic Unit for Ecosystems
CTUh	Comparative Toxic Unit for Humans
NMVOC	Non-Methane Volatile Organic Compounds

Appendix A. Baseline vs. Revised Performance Model

This appendix provides additional details on the performance modelling assumptions used in the trade-off analysis. In particular, it presents a comparison between the baseline and revised configurations of the performance model.

The baseline model represents a conservative assumption set, in which LPBF benefits are captured only through material-property ranges and moderate scenario-based multipliers. The revised model extends this formulation by explicitly introducing a geometry factor V_{factor} to account for lightweighting and redesign opportunities enabled by additive manufacturing.

Table A1 summarises the main differences between the two modelling configurations.

Table A1. Comparison between baseline and revised performance-model configurations used in the trade-off analysis.

Aspect	Baseline Model	Revised Model
Geometry treatment	Fixed benchmark geometry for both LPBF and CNC.	Explicit geometry factor V_{factor} introduced.
Mass representation	$m = \rho V_{\text{ref}}$.	$m = \rho V_{\text{ref}} V_{\text{factor}}$.
Second moment of area	Fixed reference value.	Approximated as $I_{\text{eff}} = I_{\text{ref}} V_{\text{factor}}$.
Lightweighting effects	Not explicitly represented.	Explicitly modelled through $V_{\text{factor}} < 1$ for LPBF.
Design advantage (g_{d})	Primary additive-manufacturing advantage.	Retained as a moderate bonus.
Long-term benefit (g_{lt})	Moderate scenario factor.	Moderate scenario factor.
LPBF benefit structure	Benefit as multiplicative factors.	Benefit as combined effects of lightweighting, design advantage, and long-term factors.
CNC representation	Reference process.	Reference process.
Interpretation	Conservative scenario with limited physical representation of redesign benefits.	More physically grounded representation of additive-manufacturing advantages.
Effect on trade-off results	Strong dominance of CNC with limited LPBF plausibility.	Emergence of a transition region in plausibility, while CNC remains the only robustly preferable option in terms of belief.

Appendix B. Uncertainty Ranges

This appendix reports the numerical uncertainty ranges obtained from the DST–MC propagation for LPBF and CNC across the analysed midpoint impact categories. For each process and category, Table A2 lists the global lower and upper bounds of the impact interval, I_{min} and I_{max}, together with the relative width, defined as $(I_{max} - I_{min})/I_{det}$, where I_{det} is the deterministic midpoint impact.

Table A2. Summary of uncertainty ranges for LPBF and CNC across selected midpoint impact categories. Relative width is defined as $(I_{max} - I_{min})/I_{det}$.

Category	Process	I_{min}	I_{max}	Relative Width (%)
Acidification	CNC	37.24	37.59	0.9
	LPBF	564.17	570.77	1.2
Air acidification	CNC	30.49	30.90	1.3
	LPBF	461.26	467.25	1.3
Climate change	CNC	5699.81	5760.46	1.1
	LPBF	8.69×10^4	8.80×10^4	1.2
Critical raw materials	CNC	2.49	2.58	3.4
	LPBF	35.12	36.01	2.5
Ecotoxicity (freshwater)	CNC	1.25×10^5	1.78×10^5	76.1
	LPBF	9.96×10^5	1.35×10^6	35.1
Ecotoxicity, marine	CNC	8.77×10^6	9.10×10^6	3.7
	LPBF	1.11×10^8	1.12×10^8	0.9
Eutrophication, freshwater	CNC	2.77	2.81	1.6
	LPBF	42.65	43.38	1.7
Eutrophication, marine	CNC	5.74	5.81	1.2
	LPBF	87.09	88.24	1.3
Eutrophication, terrestrial	CNC	56.39	57.30	1.6
	LPBF	855.28	867.10	1.4
Human toxicity (non-cancer)	CNC	4.90×10^{-5}	4.97×10^{-5}	1.4
	LPBF	6.67×10^{-4}	6.72×10^{-4}	0.8
Human toxicity, cancer	CNC	2.02×10^{-6}	2.05×10^{-6}	1.5
	LPBF	2.79×10^{-5}	2.82×10^{-5}	0.9
Ionising radiation	CNC	1068.05	1092.59	2.3
	LPBF	1.63×10^4	1.66×10^4	2.3
Land use	CNC	1.11×10^4	1.13×10^4	4.0
	LPBF	1.72×10^5	1.75×10^5	4.0
Ozone depletion	CNC	7.89×10^{-4}	8.04×10^{-4}	1.9
	LPBF	0.01	0.01	1.5
Particulate matter	CNC	9.69×10^{-5}	9.84×10^{-5}	0.7
	LPBF	3.09×10^{-3}	3.14×10^{-3}	0.7
Photochemical ozone formation	CNC	15.68	15.91	1.4
	LPBF	237.76	240.57	1.2
Resource use, fossils	CNC	8.69×10^4	8.81×10^4	1.4
	LPBF	1.34×10^6	1.35×10^6	1.2
Resource use, minerals and metals, reserve base	CNC	0.60	0.71	15.5
	LPBF	1.65	1.72	4.0
Resource use, minerals and metals, ultimate reserve	CNC	0.03	0.03	6.5
	LPBF	0.15	0.15	1.5
Total cumulative energy demand	CNC	1.08×10^5	1.10×10^5	1.0
	LPBF	1.67×10^6	1.68×10^6	0.9
Water use	CNC	3.24×10^6	3.35×10^6	13.4
	LPBF	5.13×10^7	5.22×10^7	7.5

Appendix C. Convergence and Numerical Stability Analysis

A convergence analysis was performed to assess the sensitivity of the DST–MC uncertainty propagation to discretisation choices and sampling resolution. The analysis was conducted for the Land Use impact category, which is representative of the trade-off analysis and exhibits non-trivial uncertainty behaviour.

Three configurations were compared: (i) the baseline configuration (five α-cuts, $N_{CF} = 200$), (ii) an increased Monte Carlo sampling density ($N_{CF} = 500$), and (iii) an alternative α-cut discretisation (seven α-cuts).

The comparison was based on three criteria:

- The global interval width of impact results;
- The maximum absolute deviation between belief–plausibility curves;
- The shift in the transition region of the environmental weighting parameter λ.

The results showed that the relative change in interval widths remained small across all configurations (typically below a few percent), indicating stable propagation of epistemic uncertainty. Differences in belief–plausibility curves were limited to minor local variations, primarily reflecting discretisation effects rather than structural changes in the uncertainty representation, with no change in the overall ordering of alternatives. The transition region in λ remained consistent across configurations, confirming that the decision conclusions were not sensitive to the chosen discretisation. A quantitative summary of these results is provided in Table A3.

Table A3. Summary of convergence and numerical stability analysis for the Land Use category. Interval-width changes are reported relative to the higher Monte Carlo sampling configuration ($N_{CF} = 500$).

Test	Quantity	Result	Interpretation
MC sampling, LPBF	Interval-width change	5.86%	Minor variation
MC sampling, CNC	Interval-width change	2.46%	Stable
α-cut refinement	λ transition shift	0.00	Stable transition region
α-cut refinement	Maximum ignorance change	0.00	Stable decision ambiguity

Overall, the convergence analysis demonstrates that the selected numerical settings provide sufficient stability for the purposes of this study.

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