Dissecting uncertainty in life cycle assessment studies for sustainable pavement management

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11. Sustainability

Executive summary

The integration of environmental performance into pavement management (PM) is complicated by uncertainties that often go unaddressed in traditional life cycle assessment (LCA) studies. These uncertainties are particularly acute in the early stages of PM, where data is limited. To address this gap, our study introduces a refined uncertainty analysis methodology focusing on improved sensitivity analysis within LCA, targeting the evaluation of environmental impacts of maintenance and rehabilitation (M&R) measures. Our framework accounts for various types and sources of uncertainty, including the variability of input parameters and the choices made in methodology. We apply three global sensitivity analysis (GSA) methods—Extra Trees, Sobol, and PAWN—to identify key variables and evaluate their influence on uncertainty. Employing a case study of the Dutch main road network, we assess the environmental impacts related to global warming and ozone layer depletion across multiple reclaimed asphalt pavement (RAP) scenarios. Our results underscore the significant role of pavement-vehicle interaction (PVI) in driving environmental impacts and uncertainty while highlighting transportation as a consistent source of uncertainty. Notably, Extra Trees and PAWN emerge as strong, computationally efficient alternatives to the more commonly used Sobol method. Overall, this study offers actionable insights for PM, enabling targeted improvements in environmental performance and providing a nuanced understanding of how different GSA methods can effectively manage uncertainties.

Keywords
life cycle assessment, pavement management, uncertainty analysis, sustainability, global sensitivity analysis

1 INTRODUCTION

The integration of environmental performance into pavement management (PM) has become increasingly important as sustainability gains momentum in transportation agencies worldwide. Road pavements undergo multiple maintenance and rehabilitation (M&R) cycles during their service life, each introducing a new set of environmental impacts. Life cycle assessment (LCA) has proven to be a valuable tool for evaluating these impacts and informing decision-making across various PM stages [1–3]. However, LCA studies in this context are subject to the effects of multiple sources of uncertainty, such as the quality and variability of the input parameters, as well as the methodological choices made by the executioner [4]. This is particularly true at the early PM stages, when M&R is planned at the network-level, access to project-specific data is limited, and many input parameters are either unknown or undetermined [5].

In LCA studies, the presence of uncertainty is an unavoidable factor. However, conventional assessments often rely on single-point estimates and fail to capture the complex uncertainties associated with these evaluations, which can lead to erroneous conclusions and ultimately undermine the credibility of the results. While recognizing the importance of uncertainty analysis in LCA [6,7], limited attention has been paid to its systematic integration and implementation in the analyses [8,9]. This gap is especially pronounced in the pavement domain, where only a small number of LCA studies have comprehensively incorporated uncertainty into their analyses [10–18]. In general, the entire PM process is susceptible to the effects of uncertainty, but the need for robust LCA frameworks that account for these uncertainties and help practitioners understand their influence on the results is most acute during the early stages. During these stages, assessing environmental performance requires making a number of assumptions, which in turn, introduces additional sources of uncertainty to the analysis [5,19].

Uncertainties can be incorporated into LCA in a variety of ways, ranging from simple qualitative evaluations to robust quantitative assessments that also incorporate sensitivity analysis [4]. A robust uncertainty analysis goes beyond mere characterization and propagation of uncertainties, in the sense that it also investigates how fluctuations in input parameters contribute to these uncertainties. Sensitivity analysis serves as a critical tool in this regard, pinpointing the most influential parameters and thereby directing efforts to improve data collection, refine computational models, and fine-tune methodological approaches. Recognizing these key contributors to uncertainty is crucial for informed PM decision-making. It not only deepens our understanding of what contributes the most to the environmental impacts and why, but also opens up avenues for model simplification through factor fixing and prioritization [20].

In the realm of pavement LCA, local sensitivity analysis (LSA) techniques, namely One-At-A-Time (OAT) analyses, have often been the go-to approach for assessing how variations in individual input parameters affect the results [14,21]. While this method is straightforward and relatively easy to implement, its primary limitation is the narrow scope, which focus on one parameter at a time and fails to consider the full spectrum of input variations [22]. In contrast, Global Sensitivity Analysis (GSA) approaches offer a more comprehensive approach to sensitivity analysis [4,22]. Spearman's Rank Correlation Coefficients (SRCCs) are an example of such GSA techniques that has been previously used by the pavement LCA scholarship [11]. This approach quantifies the strength and direction of relationships between inputs and outputs and, and unlike LSA, covers the entire input space [4]. However, the effectiveness of SRCCs is constrained to models that exhibit monotonic relationships and high linearity [23].

When it comes to GSA techniques, the Sobol method is highly regarded for its robustness [20,24]. It provides nuanced insights into both the individual and interactive effects that various parameters have on the uncertainty of the results, albeit at a high computational cost [4,23,25]. Alternative GSA methods, like Extra Trees [26] and PAWN [27], have shown promise in other research areas when compared to Sobol [25,28]. However, their application in the realm of pavement LCA remains at the best limited. While our previous work did feature Extra Trees [18], a comprehensive comparison with other GSA techniques in the context of pavement LCA remains an open avenue for exploration.

This study serves as a natural extension of our previous research work [18], where we introduced an LCA framework that accounts for multiple types and sources of uncertainty in the analysis, and is applicable to the early stages of PM. The present study adds depth to this foundation by evaluating the performance of three GSA techniques—Extra Trees [26], Sobol [24] and PAWN [27]—in discerning the most influential variables affecting the uncertainty in the LCA outcomes. The overarching goal of this research is to improve our methodological understanding of how to strategically account for uncertainties in pavement LCA, thereby advancing the field's capabilities in implementing more robust and reliable uncertainty analysis approaches.

2 METHOD

2.1 Environmental Impacts: LCA framework

The LCA framework employed in this study, as illustrated in Figure 1, covers all relevant processes in the life cycle of a pavement system [18]. These include the extraction and procurement of raw materials, their transportation, and subsequent transformation into asphalt mixtures during the production phase. It also covers on-site construction activities, such as paving and equipment operation, as well as the effects of pavement-vehicle interaction (PVI) during the use phase. Specifically, the framework accounts for additional fuel consumption arising from increased rolling resistance (RR) over time due to pavement deterioration in the use phase [29]. End-of-life (EOL) activities, including the removal, recycling, and transportation of waste materials, are also integrated into the assessment. The framework is in alignment with multiple established LCA guidelines, including the Asphalt Product Category Rules of the Netherlands (NL-PCR) [30] and the Dutch Determination Method for the Environmental Performance of Buildings and Civil Engineering Works [31], which is based on the European standard EN-15804 [32].

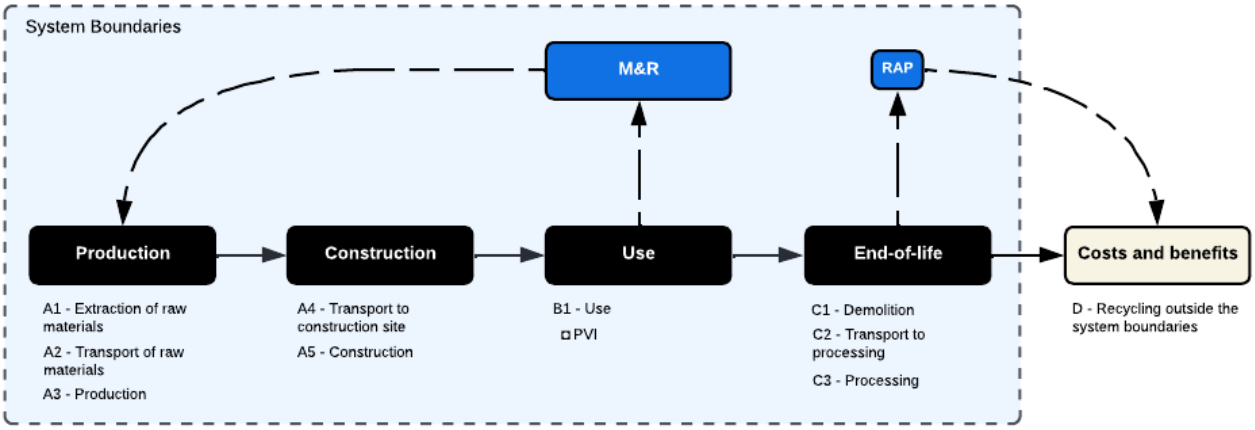

Figure 1. System boundaries of the LCA of pavement M&R measures. Adapted from Vargas Farias et al. [18].

Normative standards advocate for incorporating the environmental costs and benefits of recycling outside the system boundaries (Module D) into the analysis [30–32]. In pavement systems, this involves considering the benefits of recycling materials at EOL into reclaimed asphalt pavement (RAP) for new mixtures or as secondary materials for other civil works (i.e., rubble foundation material), which are quantified by the avoided impacts of using virgin materials. Nonetheless, as the use of RAP as secondary material is common practice, it already enters the system free of burden. In other words, the environmental loads from RAP processing are accounted for in the EOL phase (Module C) of the original system and are not allocated to new systems. Therefore, including Module D in the analysis could risk double counting benefits, already considered in Module A1 of this and other systems [33]. Owing to this and coupled with the lack of reliable avoided impact estimates of substituting virgin materials with RAP, this framework defaults to a cut-off approach, deliberately excluding Module D from the analysis to avoid overestimations and inaccuracies in environmental benefit calculations.

2.2 Uncertainty framework

Expanding upon our previous work [18], this study introduces a refined uncertainty analysis framework that features an advanced sensitivity analysis methodology, outlined in Figure 2. The framework unfolds in the following steps:

1. **Identification:** the first step focuses on identifying uncertain input parameters and methodological choices that could affect environmental impact calculations.
2. **Characterization:** Parameter uncertainty is characterized based on data quality and variability using the ecoinvent method [34]. This approach represents the range and likelihood of values that parameters can take using Probability Density Functions (PDFs). When sufficient empirical data is at hand, variability is directly derived from the data itself. In cases where only single-point estimates are available, default uncertainty values from the ecoinvent method serve as substitutes [35]. Data quality is assessed using the ecoinvent method's pedigree matrix, which evaluates data sources with a score from 1 to 5 (best to worst case scenario) for five different indicators: reliability, completeness, and temporal, geographical, and further technological correlation. Thereafter, the uncertainties due to data quality and variability are combined to provide a comprehensive characterization of parameter uncertainty [34]. Methodological choices, on the other hand, such as variations in system boundaries or different value assumptions, are represented by different scenarios.
3. **Propagation:** After characterizing uncertainties, the next step is to evaluate their impact on the study's outcomes**.** To achieve this, stochastic sampling techniques—specifically, Latin-Hypercube Sampling (LHS), an optimized

version of Monte Carlo sampling, and Sobol sampling—are combined with scenario analysis. This approach yields a variety of input combinations for each predefined scenario, resulting in a corresponding range of environmental impact outcomes.

4. **Sensitivity analysis:** Three GSA techniques— Sobol, Extra Trees, and PAWN—are employed to assess the influence of the parameters on the uncertainty of the results. These GSA techniques work with input-output pairs—which consist of the sets of sampled input combinations and their corresponding output values— that are generated for each scenario during the uncertainty propagation stage.

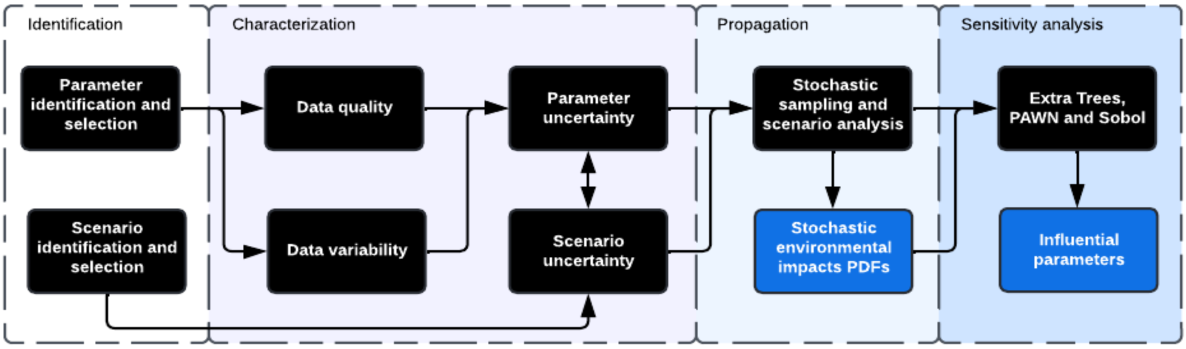

Figure 2. Uncertainty analysis framework. Adapted from Vargas Farias et al. [18].

Global Sensitivity Analysis techniques: Sobol, Extra Trees, and PAWN

Sobol is a well-established GSA technique in the field that employs variance-based metrics to identify influential input variables [4,24,25]. It produces three separate indices: first-order, second-order, and total indices. These indices measure the individual effect of each input variable, capture interactions between pairs of variables, and reveal the overall impact of each variable, respectively [25]. While Sobol is a robust and distinguished GSA method, it comes at a high computational cost, requiring numerous samples for the calculation of sensitivity indices. Specifically, $n(k+2)$ samples are required for first order indices, and $n(2k+2)$ for higher order indices, with n a baseline sample size, and k the number of input parameters. Additionally, it may face convergence issues for non-uniformly distributed parameters [36], and may not perform well when the output distribution is highly skewed and variance is not an adequate proxy of uncertainty [20,37].

Extra Trees, the short terms for Extremely Randomized Trees, is an ensemble machine learning algorithm used for both classification and regression tasks [26]. It creates a set of decision trees, randomizes the features used at each node, and aggregates their predictions to model the relationship between input parameters and model outputs [26,28]. The algorithm determines the significance of input variables using the Mean Decrease Impurity (MDI) metric. A variable is considered important when it is associated with high MDI values [25]. Extra Trees is a computational efficient GSA alternative that offers results comparable to total Sobol indices [28], and has shown promising outcomes in LCA studies at smaller sample sizes [25,28].

Finally, PAWN is a moment-independent, distribution-based GSA method that calculates sensitivity indices for the model input parameters by observing changes in the output's cumulative distribution. To do so, it varies parameter values simultaneously, computing Kolmogorov-Smirnov (KS) statistics for each variation [27,38]. This approach is effective for non-normally distributed LCA outcomes as it denotes the influence of the inputs through distribution changes rather than variance alone [20,25,39]. PAWN sensitivity indexes are defined using a specified statistic of the KS values (e.g., mean, median or maximum) calculated across predefined conditioning intervals [25,27]. Similar to Extra Trees, PAWN has shown similar results to total Sobol indices in the LCA context [25]. Given its applicability regardless of the shape of the output distribution and its relatively low computational cost [27], PAWN is an advantageous GSA alternative worth considering when performing uncertainty analyses.

3 CASE STUDY

We adopted the M&R of the main road network in the Netherlands as a case study to evaluate and compare the performance of the various GSA techniques. Specifically, we quantify the environmental impacts of a mill-and-fill treatment that comprises the removal and application of a 50-mm thick DZOAB surface layer—a durability-enhanced porous asphalt (PA) mixture (equivalent to PA 16) that composes most of the main roads in the Netherlands—in a straight and plan 1km-long carriageway road pavement segment section with 3 lanes, each 3.5m-wide. The analysis period, corresponding to the average lifespan of a DZOAB surface layer, is 14 years.

In early PM, several assumptions concerning the application of treatments must be made. These include factors such as the RAP content in the mixture, the type of bitumen used (either regular or modified), and the construction rate. To examine the impact of RAP content variations, this study delineates two specific scenarios: one featuring a mixture with 0% RAP and another with 30% RAP. Furthermore, to gain a more comprehensive view of environmental impacts, two additional scenarios are defined for the use phase: one that includes PVI effects and another that excludes it. This approach helps to balance the analysis, as PVI-related impacts often drive the environmental impacts of pavements [1,18,29].

The background system was modelled using the ecoinvent 3.3 database. All foreground input parameters for each scenario were included in the uncertainty analysis, including those related to materials production, transportation, additional vehicle fuel consumption due to increased RR over time, and energy consumption for production, construction, and end-of-life (EOL) stages (Table 1). The mean values of most input parameters were sourced from the NL-PCR and existing LCA studies specific to the Netherlands [30,40–42]. Extra fuel consumption values related to RR were calculated using the MIRIAM model and empirical pavement roughness and macrotexture models based on International Roughness Index (IRI) and Mean Profile Depth (MPD) measurements. Our previous work describes in detail how these models were built and how the extra fuel consumption values were obtained [18].

Table 1. Parameter uncertainty characterization values.

Phase	Input parameter	Unit	Uncertainty value	Uncertainty value source	Mean—0% RAP	Mean—30% RAP	Distribution
A1	**Raw materials content**						
	Bitumen	kg	0.0012	[34]	52.00	41.20	lognormal
	Crushed sand	kg	0.0012	[34]	43.00	34.20	lognormal
	Crushed stone 3*	kg	0.0012	[34]	852.00	586.10	lognormal
	Asphalt granulate—RAP	kg	0.0012	[34]	0.00	300.00	lognormal
	Filler (others)	kg	0.0012	[34]	0.00	9.40	lognormal
	Medium filler	kg	0.0012	[34]	51.00	27.00	lognormal
	Drip resistant material	kg	0.0012	[34]	2.00	2.10	lognormal
A2	**Transport to asphalt plant**			[34]			
	Bitumen - truck	km	0.1207	[34]	250.00	250.00	lognormal
	Crushed sand - truck	km	0.1207	[34]	25.00	25.00	lognormal
	Crushed sand - inland vessel	km	0.1207	[34]	660.00	660.00	lognormal
	Crushed stone 3* - truck	km	0.1207	[34]	25.00	25.00	lognormal
	Crushed stone 3* - inland vessel	km	0.1207	[34]	53.00	53.00	lognormal
	Crushed stone 3* - sea vessel	km	0.1207	[34]	933.00	933.00	lognormal
	Own material – truck	km	0.1207	[34]	0.00	25.00	lognormal
	Own material - inland vessel	km	0.1207	[34]	0.00	150.00	lognormal
	Medium filler - truck	km	0.1207	[34]	136.00	136.00	lognormal
	Drip resistant material - truck	km	0.1207	[34]	177.00	177.00	lognormal
A3	**Energy consumption**			[34]			
	Natural gas	m3	0.0012	[34]	7.43	8	lognormal
	Electricity	kWh	0.0012	[34]	6.23	5.61	lognormal
	Diesel	l	0.0012	[34]	0.12	0.12	lognormal
A4	**Transport to construction site**			[34]			
	Distance to construction site	km	0.1207	[34]	44.40	44.4	lognormal
A5	**Energy consumption**			[34]			
	Asphalt set (spreader + roller)	l	0.0014	[34]	0.32	0.32	lognormal
B1	**Extra fuel consumption**						
	Passenger car	l	46736.19	[18]	68967.84	68967.84	normal
	Heavy Duty Vehicle (HDV)	l	10534.82	[18]	17729.00	17729	normal
	HDV + trailer	l	41990.32	[18]	58536.78	58536.78	normal
C1	**Energy consumption**						
	Milling + cleaning + sweeping	l	0.0014	[34]	0.77	0.77	lognormal
C2	**Transport to processing**			[34]			
	Distance to processing	km	0.1207	[34]	44.40	44.4	lognormal
C3	**Diesel consumption**			[34]			
	Crane and shovel	l	0.0014	[34]	0.19	0.185	lognormal
	Breaker	l	0.0014	[34]	0.19	0.185	

Note: Values are given for 1 ton of asphalt and scaled to the FU in the analysis considering an asphalt mixture density of 2000 kg/m^3 [30].
*According to the NL-PCR, crushed stone 3 refers to coarse aggregates obtained from a quarry using explosives rather than from a river/lake obtained via excavation and crushing [30].

The ecoinvent method combines data quality and variability, contingent upon the assumption that parameters follow lognormal distributions. In most cases, due to insufficient empirical data, variability was defined using predetermined uncertainty factors from ecoinvent, which vary in function of the type of exchange [34]. For instance, material quantities, such as those in A1, are assigned a variance of the log-transformed data of $\sigma_b^2 = 0.0006$. Thereafter, data quality may amplify such variance based on data quality scores. For example, the whole material quantities in A1 originate from the same source [30], and except for the data quality indicator 'reliability', that receives a 2, this source receives the highest data quality scores (all equal to 1). Based on the method, this score adds an uncertainty value of $\sigma_n^2 = 0.0006$ to the variability variance [30]. As a result, the total parameter uncertainty value for material quantities in A1 is $\sigma^2 = 0.0012$. Equation 1 shows how the calculation of total parameter uncertainty σ^2 above described is carried out.

Equation 1. Total parameter uncertainty [34].

$$\sigma^2 = \sigma_b^2 + \sum_{n=1}^{5} \sigma_n^2$$

Where all terms are expressed as variance of the log-transformed data, i.e., the underlying normal distribution with σ_n^2 representing total parameter uncertainty; σ_b^2, basic uncertainty or data variability, and $\sum_{n=1}^{5} \sigma_n^2$, additional uncertainty due to each data quality dimension included in the assessment.

The variability of the PVI input values was characterized independently of predetermined values provided by the ecoinvent method, as it was defined by the spread of the values themselves, which are normally distributed. To integrate this with data quality uncertainty—which is always given in lognormal terms—we adopted the procedure provided by Muller et al. [43]. The high uncertainty values for extra fuel consumption are primarily attributed to the error in the IRI and MPD regression models, as well as the variability in other inputs required for the calculations. Notably, traffic data introduces high uncertainty into the extra fuel consumption values due to large fluctuations in traffic intensity at different network locations.

4 RESULTS AND DISCUSSION

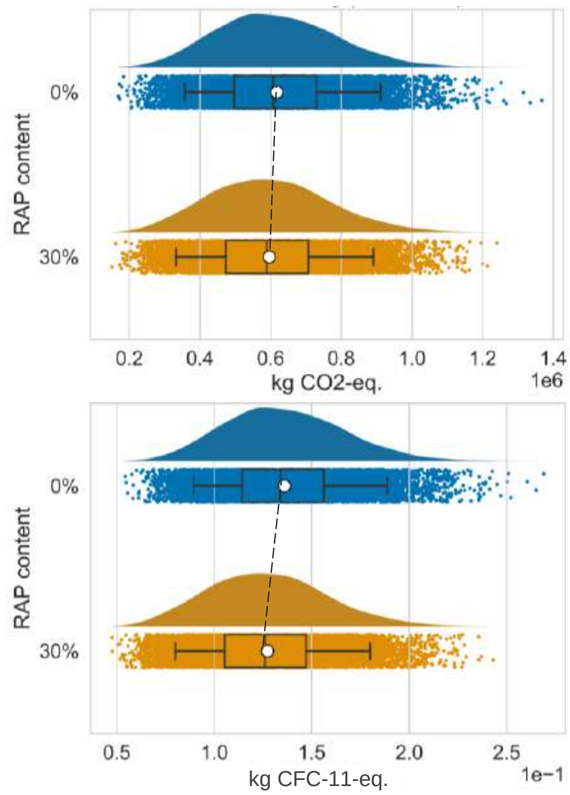

Figure 3a. Environmental impacts including PVI.

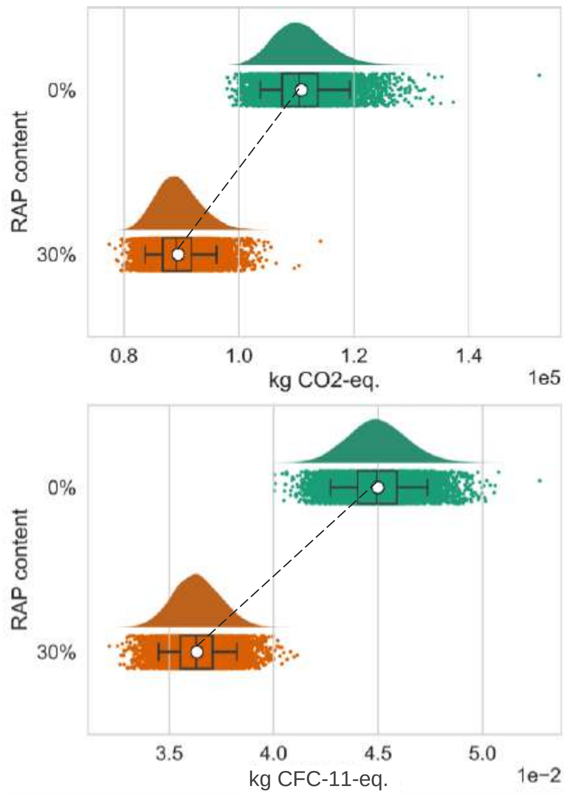

Figure 3b. Environmental impacts excluding PVI.

The proposed LCA framework was implemented in the OpenLCA software with external processing in Python based on the workflow presented in Jaxa-Rozen et al., [44]. The environmental impact results for the case study are depicted in Figure 3a and Figure 3b. The analysis of the figures shows that the 30% RAP scenario outperforms the 0% RAP scenario in both PVI scenarios. However, this advantage becomes almost imperceptible when PVI is considered and the order of magnitude of the impacts increases by one. Even when considering the lower impact bounds—essentially the most favourable cases—our research confirms that the influence of PVI continues to overshadow environmental gains in other life cycle stages[29]. Further, building on our earlier research [18], this study illustrates that the dominant impact of PVI is not limited to CO_2 emissions alone.

The pronounced spread of environmental impact results in PVI scenarios is fundamentally ascribed to the large uncertainty exhibited in the PVI input values. Furthermore, the significant role of PVI in driving the overall environmental impacts implies that the effects of these uncertainties, substantial, are likely to be intensified as they are propagated through the assessment. Given the crucial role of PVI, developing a deeper understanding of how different pavement properties affect RR is essential. This knowledge is key for designing pavement structures and M&R strategies aimed at effectively mitigating environmental impacts. Consequently, gaining clearer insights into the accurate modelling of these mechanisms and their implications on fuel economy is imperative. It is only with this refined knowledge that the reduction of uncertainty and therefore more accurate and dependable results can be attained.

Owing to the widespread uncertainty ranges exhibited in PVI scenarios, the ability of sensitivity analysis to discern the influence of other parameters on result uncertainty is significantly constrained irrespective of the GSA method employed. The overwhelming influence of PVI effectively overshadows the contributions of all other parameters, demanding the use of scenarios that exclude PVI to offer a more nuanced examination of the influence of other inputs. The practical considerations and findings of these more focused analyses are delineated in the subsequent paragraphs.

Each sensitivity analysis method shows distinct application needs, primarily in terms of sample size requirements. The number of samples required to perform sensitivity analysis depends on the GSA method applied. 12,000 LHS samples were generated per each scenario to perform Extra Trees and PAWN [25], as well as to plot the PDFs of the environmental impacts previously shown. For Sobol, *n* was set at 2,500 [25], and *k* at either 22 or 26, depending on the number of parameters of each RAP scenario. As a result, 60,000 Sobol samples for the 0% RAP scenario and 70,000 for the 30% RAP scenario were generated with Sobol sampling. Both LHS and Sobol sampling were implemented using the SALib Python library [45]. First-order (S1) and total Sobol indices (ST) were calculated using the SALib python library [45]. MDI measures for Extra Trees were estimated using the scikit-learn Python library [46], and the model parameter settings defined by Jaxa-Rozen & Kwakkel [28]. Finally, KS-max (PAWN max) and KS-median (PAWN) values were computed using the SAFE toolbox Python library [47].

Figure 4 and Figure 5 illustrate the comparative sensitivity results derived from each GSA method. These results were obtained by evaluating the relative importance of each parameter in contributing to the overall uncertainty of the environmental impact outcomes, with sensitivity values normalized to the largest value in the set of results for each respective method. Across all three GSA methods and RAP scenarios, a consistent pattern in relative importance emerges, pinpointing similar parameter contribution rankings. For the global warming impact category, transportation processes consistently dominate the uncertainty. This is particularly evident in the overseas import of coarse aggregates in A2. This trend may be partially attributed to the high uncertainty values that the ecoinvent database assigns to transportation processes, a resolution that is especially pertinent in the early PM stages where exact distances between locations may not yet be clearly defined. In the production category, natural gas consumption in A3 stands out as the most influential parameter, along with bitumen and coarse aggregates in A1. For ozone layer depletion impact category, bitumen is the leading contributor to uncertainty, followed by transportation processes.

The findings from the sensitivity analysis underscore the need of refining transportation input data, which emerges as a prominent source of uncertainty across impacts. Addressing this can effectively narrow the uncertainty range of the environmental impact results, thereby enabling more accurate and reliable assessments. Conversely, the sensitivity results of bitumen and coarse aggregate quantities yield different insights. Despite having relatively low input uncertainty values, these parameters introduce significant uncertainty into the results, most likely due to their relatively large contribution to environmental impacts. This suggests that even minor changes in their input values can have a significant impact on the results—where slight improvements could lead to significant impact reductions—making them prime candidates for targeted actions. However, validating such a claim requires further and concerted research on the subject.

To gain a better understanding of parameter influence on result uncertainty, we must draw a distinction between the rankings and relative importance values that the GSA methods assign to these parameters. While Sobol and Extra Trees generally align in their relative importance values—a finding supported by existing literature [28]—PAWN often assigns higher relative importance values to the same parameters, a phenomenon previously observed in comparative studies [20,25]. This discrepancy is not merely a matter of different scales or metrics; it reflects fundamental differences in what these indices measure and how they do it [20]. Sobol indices, for instance, measure the expected reduction in output variance if a parameter is fixed, and may not capture the full complexity of a model, its uncertainty, or properly quantify the relative parameter importance on the outputs [20]. PAWN, on the other hand, considers both conditional and unconditional variances, offering a more nuanced view of each parameter's influence [25]. This is especially valuable in models with skewed output distributions or significant variable interactions, where fixing a parameter might counterintuitively increase overall output uncertainty [25]. Therefore, while Sobol remains a standard in GSA, PAWN may provide more comprehensive and nuanced insights from particularly complex or interactive models [25].

While the analytical depth provided by various GSA methods is valuable, practical considerations, such as the computational time required to carry out the analysis preconized by these methods should also be taken into account. On average, processing each sample takes about 3.11 seconds. Consequently, a 12,000-sample analysis would consume roughly 10.4 hours, whereas larger sample sizes of 60,000 and 70,000 would extend the computation time to approximately 51.9 and 60.5 hours, respectively. This computational burden becomes even more pronounced when multiple scenarios are considered. Given these executional factors, Extra Trees and PAWN stand out as efficient alternatives to Sobol for conducting reliable sensitivity analysis in pavement LCA, provided that higher-order Sobol indices are not essential. These methods not only offer results comparable to Sobol but do so with significantly less computational demand. Moreover, PAWN extends the sensitivity analysis to accommodate non-normal distributions. However, it is worth noting that the sensitivity of PAWN indices to tuning parameters has been the subject of attention [48], and given its relatively recent introduction, it cannot simply be considered a superior alternative to the well-established Sobol methodology. Therefore, we recommend employing both Extra Trees and PAWN, the former for its close approximation to Sobol indices and the latter for its ability to handle a variety of distributions as well as to discern the nuanced impact of parameters on the uncertainty in the results. Including both methods as part of the uncertainty analysis facilitates cross-comparison and enhances the understanding of the effects of the uncertainties on the results without incurring additional computational costs.

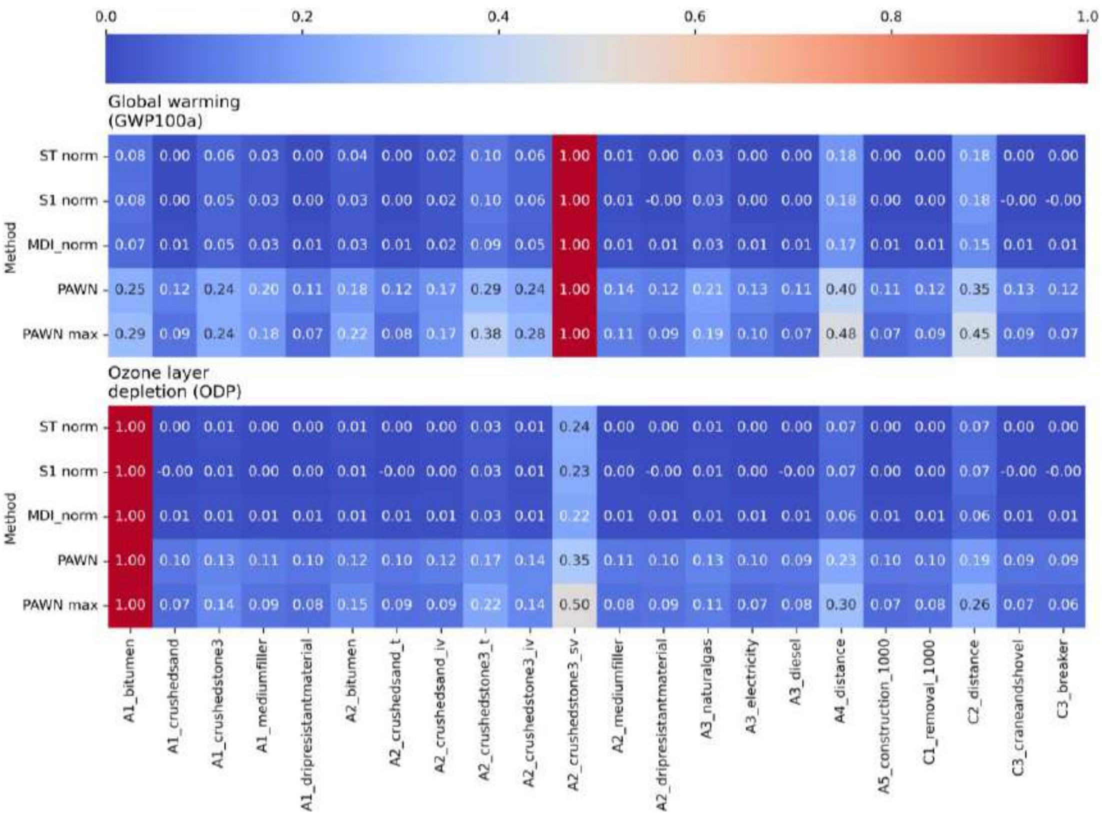

Figure 4. Comparison of parameter relative importance in sensitivity results for 0% RAP scenario. Key: 'T': truck; 'iv': inland vessel; 'sv': sea vessel; 'ST': total Sobol index; 'S1': First order Sobol index; 'MDI': mean decrease impurity (Extra Trees); 'PAWN': PAWN median sensitivity index; 'PAWN max': PAWN max sensitivity index.

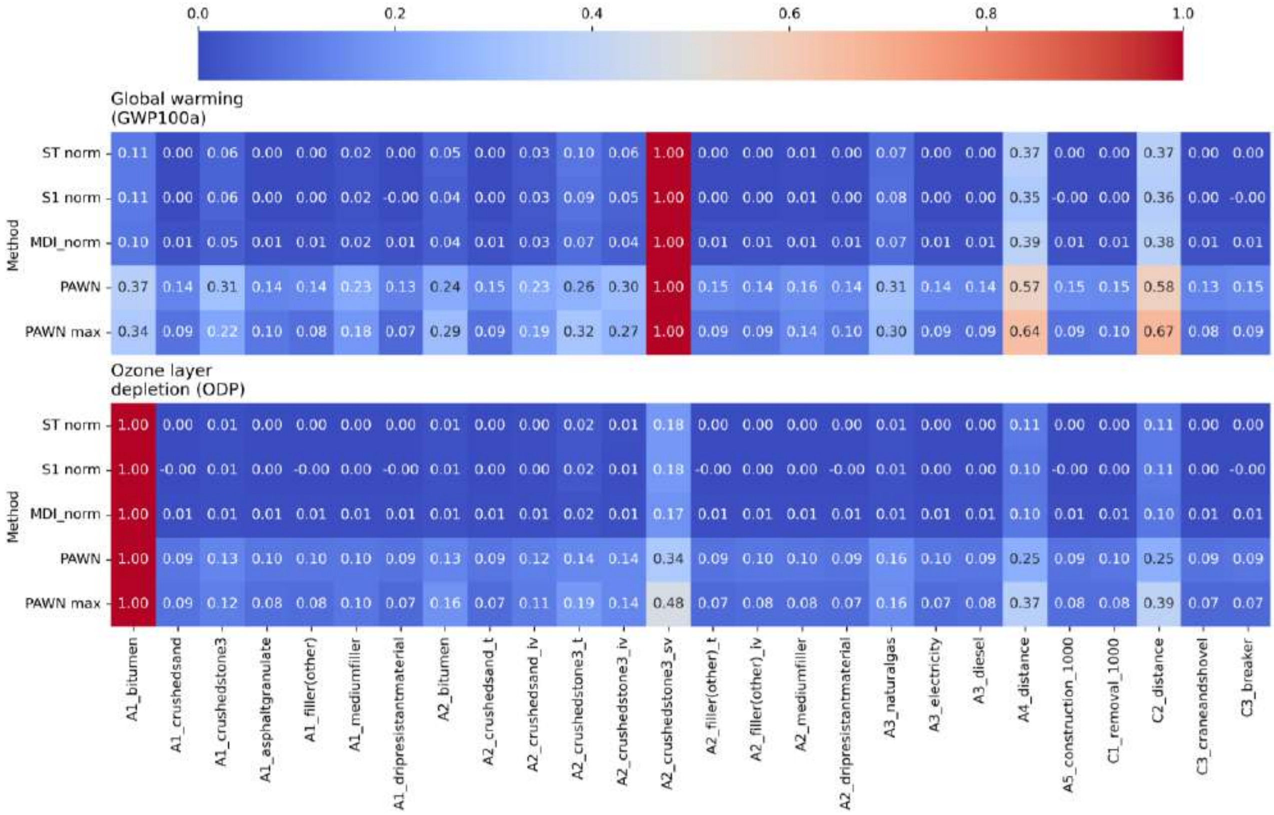

Figure 5. Comparison of parameter relative importance in sensitivity results for 30% RAP scenario. Key: ‘T’: truck; ‘iv’: inland vessel; ‘sv’: sea vessel; ‘ST’: total Sobol index; ‘S1’: First order Sobol index; ‘MDI’: mean decrease impurity (Extra Trees); ‘PAWN’: PAWN median sensitivity index; ‘PAWN max’: PAWN max sensitivity index.

5 CONCLUSIONS

This study builds upon our previous work [18] by enriching the discourse on uncertainty analysis in pavement LCA, with a specific focus on the adequacy of three GSA methods, namely Sobol, Extra Trees, and PAWN. While our earlier framework provided a foundational approach to accounting for multiple types and sources of uncertainty, the present study adds depth by evaluating the performance of these GSA techniques in discerning the most influential parameters affecting the uncertainty in LCA outcomes.

Our findings confirm the dominant role of PVI in environmental impacts, underscoring the need for improved prediction models for more accurate assessments. The study also highlights the remarkable contribution of inputs related to transportation processes and key material quantities like bitumen and coarse aggregates to uncertainty, marking them as prime candidates for both reducing environmental impacts and mitigating uncertainty. Importantly, the study reveals that while Sobol is the most popular GSA method, both PAWN and Extra Trees offer comparable results but at a significantly reduced computational cost. Extra Trees excels at approximating Sobol indices, whereas PAWN stands out for its ability to provide nuanced insights in cases of complex model interactions or skewed output distributions.

In practical terms, the study provides actionable guidance for PM by identifying key areas where refined data could significantly reduce overall uncertainty and by highlighting processes with high potential for environmental performance improvements. The outcomes of the study also underpin the benefits of a multi-method approach to foster a more reliable and comprehensive sensitivity analysis. The computational efficiency of Extra Trees and PAWN makes them particularly suitable for large-scale, network-level analyses where a multitude of alternatives and variables are at play and computational time is a limiting factor. Finally, this study not only elevates the methodological standards in pavement LCA, but also enriches our understanding of the varying roles and effectiveness of different GSA methods in uncertainty management. This sets the stage for more robust, reliable, and sustainable decision-making in PM.

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