The importance of incorporating uncertainty into pavement life cycle cost and environmental impact analyses

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ABSTRACT: We present an approach for conducting probabilistic life cycle cost analyses (LCCA) and life cycle assessments (LCA) and demonstrate its value with case study results. We define uncertainty quantities and methods for characterizing uncertainty for different types of parameters. The approach includes leveraging outputs from Pavement-ME to characterize uncertainty in pavement performance over time. Uncertainty in the input data and scenarios is used in a Monte Carlo analysis to quantify the uncertainty in life cycle costs and environmental impacts. The probabilistic results are then used to calculate several comparative metrics, including the statistical confidence that one alternative has a lower cost or environmental impact than another alternative, and to determine the parameters that contribute most to the variance of the results. The approach enables a wide analysis of the scenario space to determine which scenarios are most relevant to the comparison of alternatives, and iterative analyses that feature refined data selected in the influential parameter analysis. We demonstrate the value of the approach and the benefits of incorporating uncertainty into LCCAs and LCAs via results from cases in the literature.

1 INTRODUCTION

Uncertainty is pervasive in pavement life cycle cost and environmental impact analyses. Sources of uncertainty include inherent variation in data, the pedigree of data, the evolution of pavement performance and maintenance over time, the evolution of data over time, and analysis choices that require a value judgment. Incorporating uncertainty into these analyses is beneficial because it provides a more accurate representation of data and its evolution, enables quantitative risk assessments, and streamlines data collection by quantifying parameters that matter most to the results.

Literature exists on uncertainty in life cycle assessment (LCA) (Gregory et al. 2016; Williams et al. 2009) and life cycle cost analysis (LCCA) (Ilg et al. 2016). However, there has been minimal application of these concepts to pavement LCA and LCCA. The US Federal Highway Administration (FHWA) describes an approach for conducting probabilistic pavement LCCAs (FHWA Pavement Division 1998), but there is limited guidance on how to characterize uncertainty in the inputs for such analyses. Similarly, FHWA guidance on pavement LCA (Harvey et al. 2016) describes sources of uncertainty and generic approaches for analyzing uncertainty from the LCA literature, but there is no detailed information on how to characterize uncertainty for input parameters or conduct a probabilistic pavement LCA.

We have developed approaches for conducting probabilistic LCCAs (Swei et al. 2013) and LCAs (Noshadravan et al. 2013; Gregory et al. 2016). They leverage outputs from Pavement-ME to characterize inputs, particularly the uncertainty in pavement performance over time. In addition, we have developed methods to estimate uncertainty in initial and future costs (Swei et al. 2016) and life cycle inventory data. Uncertainty in the input data is used in a Monte Carlo analysis to quantify the uncertainty in life cycle costs and environmental impacts. The probabilistic results are then used to calculate several comparative metrics, including the statistical confidence that one alternative has a lower cost or environmental impact than another alternative, and to determine the parameters that contribute most to the variance of the results. The approach enables a wide analysis of the scenario space to determine which scenarios are most relevant to the comparison of alternatives, and iterative analyses that feature refined data selected in the influential parameter analysis. In this paper we present a summary of both the probabilistic LCA and LCCA approaches, along with examples of case study results to demonstrate the benefits of incorporating uncertainty into LCCAs and LCAs. We begin with an overview of uncertainty concepts that are the foundation for any probabilistic LCA and LCCA, and then move to concepts that are specific to pavement analyses.

2 UNCERTAINTY QUANTITIES, CHARACTERIZATION, AND ANALYSIS

2.1 *Uncertainty quantities*

The LCA literature (see (Lloyd & Ries 2007) for a summary) has coalesced around three types of uncertainty for both life cycle inventories (LCI) and life cycle impact assessment (LCIA) methods: parameter (uncertainty in input data), scenario (uncertainty in choices), and model (uncertainty in mathematical relationships) uncertainty. Differentiating these types of uncertainty can be challenging because of the overlap among them. All forms of uncertainty are expressed as uncertainty in a parameter value, even if there is an aggregate of multiple types of uncertainty.

We found guidance on uncertainty quantities from the work of Morgan and Henrion (1990), which defines quantities used in uncertainty analyses for risk and policy analysis. They define eight types of uncertainty quantities. The five that are of most relevance to LCA and LCCA are listed in Table 1. There will likely be a single decision variable and only a few outcome criteria for each analysis. However, there will almost certainly be numerous empirical, model domain, and value parameters. Some empirical quantities will be used directly in life cycle inventories, such as quantities of material inputs or emission outputs; these are *inventory parameters*. However, other empirical quantities are actually *model parameters*, such as pavement thickness or vehicle fuel efficiency, which are used to calculate inventory parameters.

Table 1. Summary of types of quantities in LCAs and LCCAs. Content adapted from (Morgan & Henrion 1990).

Quantity	Description	Example
Decision variable	Frame the decision – what is the best outcome?	Which product has lowest cost or environmental impact.
Outcome criterion	Metric for measuring performance.	Metric from a life cycle impact assessment method.
Empirical parameter	Measurable (in principle) with a *true* value.	Electricity consumption, particulate emissions, material cost.
Model domain parameter	Define scope of system with an *appropriate* value.	Temporal or geographic boundaries.
Value parameter	Represent aspects of the preferences of the analyst with an *appropriate* value.	Discount rate, allocation factor, model form.

2.2 *Uncertainty characterization*

Uncertainty characterization for quantities in LCAs and LCCAs depends on the type of quantity, but also the source of uncertainty. There are multiple sources of uncertainty; Morgan and Henrion (1990) define seven such sources. We build off of these and other work in the LCA community in defining types, sources, and methods for characterizing uncertainty in inventory parameters, listed in Table 2. Measurement uncertainty derives from variation and stochastic error in input data. This can be caused by geographic, temporal, and process variation or from inaccuracy in the measurement process itself. Inventory quantities application uncertainty (IQAU) stems from the pedigree, or quality, of the inventory data amounts. The pedigree is related to the appropriateness of the input and output amounts in an inventory from a particular data source. Intermediate flows application uncertainty (IFAU) also deals with data pedigree, but it refers to the appropriateness of other life cycle inventory data sets to represent intermediate flows (i.e., cumulative LCI data for upstream processes) in the inventory under consideration.

The methods listed in Table 2 for characterizing uncertainty are particularly relevant for empirical parameters. Indeed, it is possible to combine estimates of measurement uncertainty, IQAU, and IFAU into a single quantitative uncertainty characterization for a parameter (see section S2 of the supporting information of (Gregory et al. 2016) for details).

Empirical quantities may be represented by a weighted probability distribution (such as a normal or log-normal) because they have a true value. By contrast, model domain and value parameters should be defined as a range of continuous or discrete values with equal likelihood (i.e., an unweighted or uniform distribution) because one cannot state that one quantity is more likely than another.

Table 2. Sources of and methods for characterizing uncertainty in parameters.

Types of Uncertainty	Sources of Uncertainty	Methods for Characterizing Uncertainty
Measurement uncertainty	Variation and stochastic error: geographic, temporal, & process variation; measurement inaccuracy.	Use actual data on variation or use estimates from an expert panel (e.g., ecoinvent estimates).
Inventory quantities application uncertainty	Pedigree of inventory data amounts: appropriateness of input/output amounts from data source applied to inventory.	Pedigree matrix approach: qualitative characterization of data pedigree translated into quantitative distribution.
Intermediate flows application uncertainty	Appropriateness of intermediate flows: appropriateness of other LCIs applied to represent intermediate flows.	Extension of pedigree matrix approach.
Cutoff uncertainty	Incomplete or missing data: exclusion of input or output processes or substances.	Conduct hybrid LCA.
Human error uncertainty	Human errors: mistakes in data entry.	Unknown.

There may be instances where it is not possible to quantify uncertainty in any type of parameter because there is no clear representative value and/or distribution. In these cases, a rough distribution should be defined, erring on the side of overestimating uncertainty. Such a situation may occur for parameters that deal with activities that will occur in the future (e.g., vehicle fuel efficiency or pavement degradation rate). If such a parameter is found to be influential, discrete values may be defined within a uniform distribution in order to enable analysis of specific scenarios.

2.3 *Uncertainty analysis*

The conventional uncertainty analysis approach is to conduct a probabilistic parameter uncertainty analysis for a few selected scenarios. While this approach may be effective for preliminary analyses, we propose a more robust approach that accounts for uncertainty in parameter, scenario, and model uncertainty through the simultaneous analysis of empirical, model domain, and value parameters across a wide range of the scenario space. Details of the approach can be found in (Gregory et al. 2016); a summary is presented here.

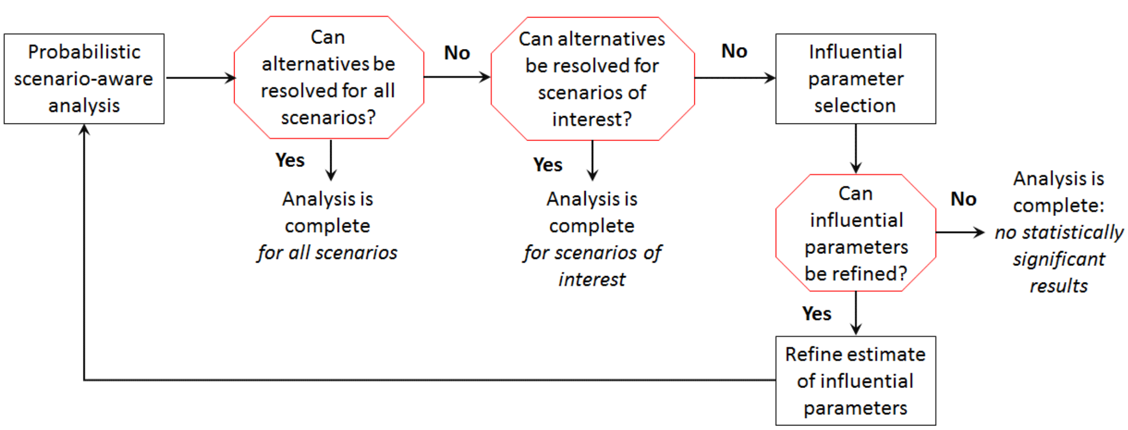

Figure 1. Methodology for evaluating uncertainty in comparative LCAs and LCCAs. Adapted from (Gregory et al. 2016).

The methodology is outlined in Figure 1. It is intended for comparative analyses of two or more alternatives, which is typical for most life cycle cost and environmental impact assessments. The process is for a single set of decision variables and outcome criteria (e.g., impact assessment methods or net present value) and therefore must be repeated for different sets of decisions or criteria. It may be necessary to iterate the process several times before drawing final conclusions.

The methodology begins with an aggregated probabilistic scenario-aware analysis. This is a simultaneous analysis of uncertainty in empirical, model domain, and value parameters using a probabilistic analysis of the relative performance of the alternatives. The probabilistic analysis can be accomplished using any sampling-based method (such as a Monte Carlo or structured sampling). Care must be taken in the analysis to correlate parameters that are common between the two alternatives.

The first question asked in the approach is whether the alternatives can be resolved for all scenarios (i.e., we can statistically resolve the difference in the cost or impact of two alternatives). To do this we calculate the probability that one alternative has a lower impact than another across all of the simulations. This is accomplished using the comparison indicator, CI_L, defined as the ratio of the cost or environmental impact two products:

$$CI_L = \frac{Z_{L,B}}{Z_{L,A}} \qquad \text{Equation 1}$$

where $Z_{L,A}$ and $Z_{L,B}$ are the cost or environmental impact for alternatives *A* and *B*, respectively, using the cost or environmental impact metric L. CI_L is calculated for a single simulation and therefore, can capture correlation in the parameters used in both alternatives in each simulation. We define β as the frequency that alternative *B* has a lower cost or impact than *A* across a set of simulations:

$$\beta = P(CI_L < 1) \qquad \text{Equation 2}$$

We can state that *B* and *A* are resolvable if β or (1- β) is greater than a threshold value, β_{crit}. This threshold, β_{crit}, is a decision parameter that controls the level of confidence in the decision and should be set by the analyst for a given context.

Returning to the first question in the approach (whether the alternatives can be resolved for all scenarios), if β=1, then one alternative clearly has a lower cost or impact than the other and the analysis is complete. If they cannot, the next question is whether the alternatives can be resolved for scenarios of interest. It is unlikely that the two alternatives will be resolvable for all scenarios. By contrast, it is likely that some scenarios are of more interest to a particular set of decision makers (e.g., because they feel that a particular set of framing conditions are likely to be considered valid). If the alternatives can be resolved for the scenarios of interest, then the analysis is complete and the scenarios under which one alternative has a lower impact than another can be identified as statistically significant. This requires an approach to identify scenarios of interest, which can be done by manually analyzing sets of simulation results for given values of model domain and value parameters (i.e., sets of scenarios). This will likely be tedious for large sets of scenarios. Statistical software packages have category and regression tree (CART) algorithms that may be used to analyze results across many scenarios. CART algorithms identify a succinct description of the statistically differentiable subpopulations within the scenario populations by recursively partitioning the space of input data and fitting a simple regression model within each partition.

If the alternatives cannot be resolved for the scenarios of interest, then the influential parameters for all scenarios need to be identified in order to determine the parameters that are worthy of further refinement because of their influence on the result. Influence can be assessed using different methods of sensitivity analysis.

Once influential parameters are identified, an assessment needs to be made as to whether resources are available to improve the fidelity of the analysis (third question in Figure 1). This would manifest in the refinement of uncertainty characterization for influential parameters (e.g., more data collection). If the influential parameters cannot be refined, then the analysis is complete and the outcome is that there are insufficient statistically significant results for the scenarios of interest. If they can be refined, then the entire process should be repeated using the refined uncertainty characterizations. This iterative process of influential parameter identification and refinement represents one of the major benefits of using uncertainty analysis in LCA and LCCA: resource-intensive data collection is only required for parameters influential parameters.

3 UNCERTAINTY CHARACTERIZATION AND ANALYSIS FOR PAVEMENT LCA AND LCCA

The previous section provided guidance on characterizing and analyzing uncertainty that is applicable to all LCAs and LCCAs, but it is worth discussing issues that are relevant specifically to pavement analyses. Following the structure of the previous section, there are three activities required to conduct a comparative analysis: define quantities, characterize uncertainty, and analyze comparative uncertainty.

3.1 *Define uncertainty quantities*

Figure 2 shows the scope of analysis that may be considered in pavement LCAs and LCCAs, although some elements may be excluded in analyses. Inventory data is required for each process in the life cycle and consists of background and foreground data. Although there is no clear differentiation between the two types, foreground data is generally relevant to a specific analysis (e.g., quantities of materials or fuel consumption), whereas background data represents upstream impacts or costs that may be relevant to many analyses (e.g., unit material costs or environmental impacts). Uncertainty quantities and characterization of background data need only be done once, but the process needs to be conducted for foreground data in each analysis.

Empirical, model domain, and value parameters must be defined for inventory parameters that represent collected data (e.g., emission quantities) and model parameters that are used to calculate inventory parameters (e.g., pavement thickness). A complete list of the 82 input parameters for a comparative pavement LCA is listed in Section S6 of the supporting information in (Gregory et al. 2016), but examples of parameters for each uncertainty type are listed in Table 3. Note that the first four empirical parameters are model parameters. That is, they will be used to calculate quantities, such as mass of aggregate or fuel, that will be used in an inventory. This is because it is typically more feasible to characterize uncertainty for model parameters because the sources of uncertainty can be decomposed.

Model domain parameters define the scope of the analysis and are chosen by the analyst – there are no true values, only appropriate values. It is important to note that it is possible to conduct analyses with and without elements of the life cycle if there are questions about data or models (these are the parameters listed with the "scope" prefix). This enables the analyst to determine the influence of the element on the comparative results.

Finally, value parameters represent preferences made by the analyst in conducting the LCA or LCCA where, once again, there are appropriate values, not true values. Allocation factors in LCA are a common example, as are discount rates in LCCA. The use of maintenance strategy as a value parameter is due to the fact that the analyst cannot know what the actual maintenance strategy

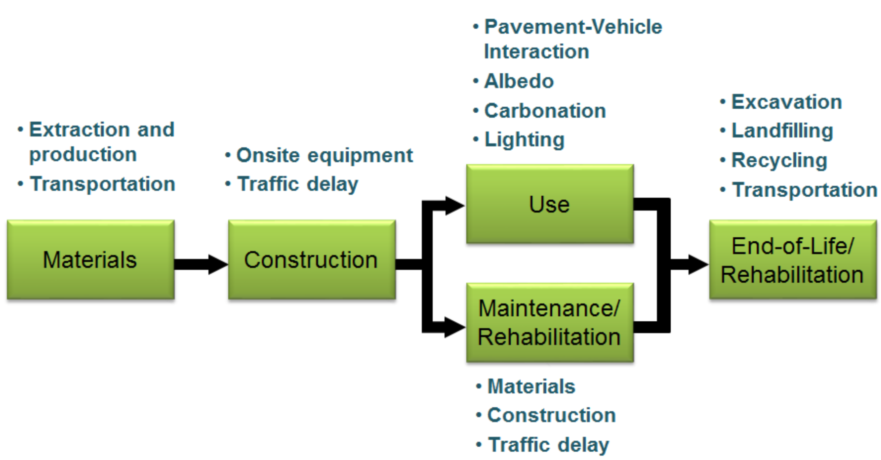

Figure 2. System boundary for pavement LCAs and LCCAs. Analyses may not include all elements.

will be. Rather, there may be several different potential maintenance strategies. This parameter enables the analyst to explore the impact of different strategies on comparative results.

Table 3. Examples of empirical, model domain, and value parameters from a pavement LCA (drawn from (Gregory et al. 2016)).

Empirical parameters	Model domain parameters	Value parameters
Fuel efficiency – cars	Design life	Salvage life allocation
Traffic growth factor	Analysis period	Maintenance strategy
PCC thickness	Scope*: albedo	
AC thickness, layer 1	Scope: PVI-deflection	
AC milling energy	Scope: PVI-roughness	

**Scope* refers to whether or not the phenomenon (albedo or pavement-vehicle interaction, PVI) is included in the analysis.

3.2 *Characterize uncertainty*

Uncertainty for background data is already included in some databases, such as the ecoinvent and USLCI databases. Characterizing uncertainty in empirical parameters for foreground data is decomposed into the first three elements listed in Table 2: measurement uncertainty, inventory quantities application uncertainty (IQAU), and intermediate flows application uncertainty (IFAU). Obtaining primary data on the variation in application uncertainty is preferable, but estimates of measurement uncertainty for different types of quantities are provided by the ecoinvent center (Weidema et al. 2013). They also provide factors that can be used to quantify uncertainty associated with IQAU. We have demonstrated how those same factors can be used to quantify uncertainty associated with IFAU and then combined with a quantitative uncertainty for measurement uncertainty and IQAU (see section S2 of the supporting information of (Gregory et al. 2016)). This results in a weighted probability distribution (e.g., log-normal) for an empirical parameter

Separating assessments of data quality for IQAU and IFAU is important. For IQAU, the pedigree of the data is related to the appropriateness of the input and output amounts in an inventory from a particular data source. For IFAU, the pedigree refers to the appropriateness of other life cycle inventory data sets to represent intermediate flows (i.e., cumulative LCI data for upstream processes) in the inventory under consideration.

As noted in Section 2.2, uncertainty in model domain and value parameters should be defined as a range of continuous or discrete values with equal likelihood (i.e., an unweighted or uniform distribution). The model domain parameters about scope will be binary (i.e., whether to include the activity or not). Model domain parameters about analysis period or design life will likely be uniform discrete because the choice of a different design life results in a different pavement design, and the choice of analysis period results in a different maintenance schedule. However, it is also possible to use uniform continuous distributions for model domain or value parameters, such as discount rate.

There is an opportunity to couple pavement LCA and LCCA with outputs from mechanistic-empirical pavement design software, such as Pavement-ME, as a means of quantifying inputs and characterizing uncertainty. In particular, the software can provide details on pavement mechanical response and deterioration over time, which are important for calculations of excess fuel consumption due to pavement-vehicle interaction. In addition, information is provided on the statistical confidence of the deterioration curves, thereby providing a quantitative characterization of the uncertainty in the curves. Noshadravan et al. (2013) provide details on how to translate the deterioration curves at several levels of reliability into uncertainty characterizations and quantitative assessments of roughness-induced excess fuel consumption emissions over time. Swei et al. (2013) provide details on how to translate the uncertainty in the deterioration curves into uncertainty in the timing of future maintenance activities on the basis of when predicted pavement distress exceeds a performance threshold.

Initial and future material and construction costs used in pavement LCCAs are highly influential and thus, uncertainty characterization for these parameters is particularly important. Swei et al. (2013) describe how to conduct a univariate regression analysis using historical bid data in order to test whether a statistically significant relationship between average unit cost and bid volume exists. Defining this relationship enables more accurate estimates of unit material and construction costs, and it also enables quantification of the uncertainty in the estimate. In addition, forecasting techniques have been used to probabilistically project prices and their uncertainty (Swei et al. 2013; Swei et al. 2016).

3.3 *Analyze comparative uncertainty*

The process for conducting comparative uncertainty analyses for pavement LCAs and LCCAs is outlined in Section 2.3, but it is worth highlighting specific results of interest. We give examples of the format of the results from studies published in the literature. The intent is to demonstrate the type of results that can be drawn from probabilistic studies and the benefits of the approach.

The first result of interest is a probabilistic distribution of results for the complete life cycle along with each life cycle phase. Figure 3 shows an example of results from a comparative pavement LCA. From this result one can gain insight into the relative magnitude and variation in impacts among the alternatives, and the life cycle phases that most influence the results.

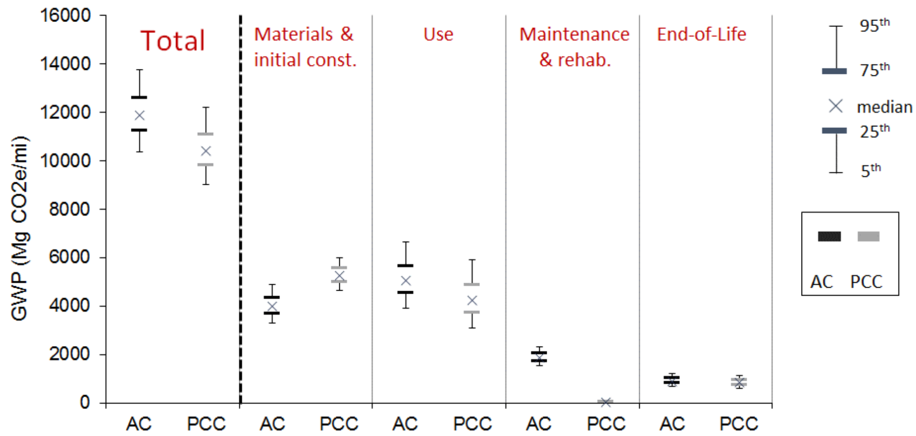

Figure 3. Probabilistic global warming potential (GWP) results of a comparative pavement LCA of an urban interstate pavement in Arizona for the complete life cycle and each life cycle phase. Results from a case presented in (Xu et al. 2014).

The second set of results of interest are intended to assess the statistical significance of the difference among alternatives (determine whether they are resolvable) and quantify differences among alternatives, statistically significant or otherwise. Table 4 shows four metrics that can be used to assess and quantify differences between alternatives. They are depicted graphically in Figure 4. We calculate $\Delta\mu$ because it can be considered as the conventional metric for comparing costs or environmental impacts in deterministic LCAs and LCCAs. We calculate ΔZ_{90} because it can be viewed as the difference between the alternatives from a risk-averse perspective. The cumulative distribution function (CDF) in Figure 4a is useful for viewing the impacts of taking different risk levels in quantifying the differences among alternatives. $\Delta\mu$, α_{90}, and β values for several dozen pavement LCCA cases can be found in (Swei et al. 2015).

Table 4. Metrics for comparative LCAs and LCCAs. Values may be costs or environmental impacts.

Metric	Meaning
$\Delta\mu = \frac{\mu_B - \mu_A}{\mu_A}$	The difference between the mean value of alternative A and the mean value of alternative B.
$\Delta Z_{90} = \frac{Z_{90,B} - Z_{90,A}}{Z_{90,A}}$	The difference between the 90th percentile value of alternative A and the 90th percentile value of alternative B.
$\beta = P(CI_L < 1)$	The frequency that alternative B has a lower cost or impact than alternative A. Values greater than 0.9 (or less than 0.1) indicate alternative A (or alternative B) have a statistically significant lower cost or impact. *CI* is defined in Equation 1.
$CI_* = \begin{cases} CI_{0.1}, & \beta > 0.9 \\ CI_{0.9}, & \beta < 0.1 \end{cases}$	The value of *CI* when β is 0.9 (or 0.1). This represents the maximum statistically significant difference between the two alternatives. It is only meaningful when $\beta > 0.9$ (or $\beta < 0.1$).

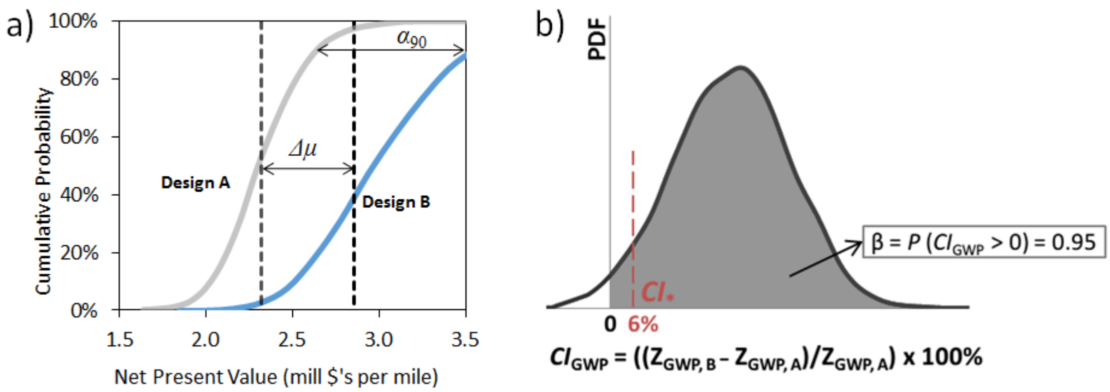

Figure 4. a) Cumulative probability density functions of life cycle cost for two design alternatives showing the $\Delta\mu$ and ΔZ_{90} metrics. b) Probability density function of the comparison indicator for global warming potential impacts of two alternatives. In this case, design A has a statistically significant lower impact than design B, i.e., β = 0.95. CI_* = 6% means the maximum statistically significant difference is 6%.

While it is conventional to use $\Delta\mu$ and α_{90} to calculate differences between alternatives, they do not comment on the statistical significance among alternatives. For this reason we use β to determine whether there is a statistically significant difference among alternatives, and we use CI_* to quantify the maximum statistically significant difference between the two alternatives. The example in Figure 4b shows a case where β=0.95, which indicates that the result is statistically significant (based on a threshold value of 0.9), and the statistically significant difference, CI_*, is 6%. $\Delta\mu$, β, and CI_* values for several dozen pavement LCA cases can be found in (Xu et al. 2014).

There are two additional results that are necessary to support the comparative uncertainty analysis approach described in Section 3.3: a ranking of influential parameters, and a categorization of resolvable scenarios. Table 5 shows the influential parameters in a pavement LCCA case. Influential parameters are listed for each of the two design alternatives and the difference between the two alternatives. These are calculated using sensitivity analysis techniques, such as regression or variance-based methods. These results are important because they inform the selection of parameters for data refinement. Influential parameters for LCCA scenarios have been calculated in (Swei et al. 2015) and for LCA scenarios in (Xu et al. 2014; Gregory et al. 2016).

Results from categorization analyses using CART algorithms show which scenarios have statistically resolvable results and the values of key parameters in those groups of scenarios. Figure 5 shows the results of categorization analyses in a comparative LCA. Meaningful scenario groups are isolated and designated by the parameter listed in the box, which indicates that all scenarios in that group

Table 5. Influential parameters in a pavement LCCA using urban interstate cases in four climates. Cases and data from (Swei et al. 2015). Influential parameters are listed for the hot mix asphalt (HMA) alternative, the jointed plain concrete pavement (JPCP) alternative, and the difference between the two alternatives.

Parameter	LTPP Climate Zone			
	Wet Freeze (Missouri)	Dry No Freeze (Arizona)	Dry Freeze (Colorado)	Wet No Freeze (Florida)
HMA	**HMA**	**HMA**	**HMA**	**HMA**
Pavement-ME Reliabiltity		0.08	0.06	0.10
Aggregate Price	0.16	0.07	0.01	0.00
AC Surface Price	0.25	0.13	0.06	0.31
AC Binder Price	0.38	0.10	0.16	0.11
AC Base Price	0.01	0.43	0.64	0.28
JPCP	**JPCP**	**JPCP**	**JPCP**	**JPCP**
JPCP Layer Price	0.82	0.96	0.95	0.99
Difference	**Difference**	**Difference**	**Difference**	**Difference**
JPCP Layer Price	0.19	0.56	0.32	0.85
Aggregate Price	0.13	0.01	0.01	
AC Surface Price	0.20	0.04	0.03	0.04
AC Binder Price	0.31	0.04	0.11	0.02
AC Base Price	0.02	0.23	0.55	0.04

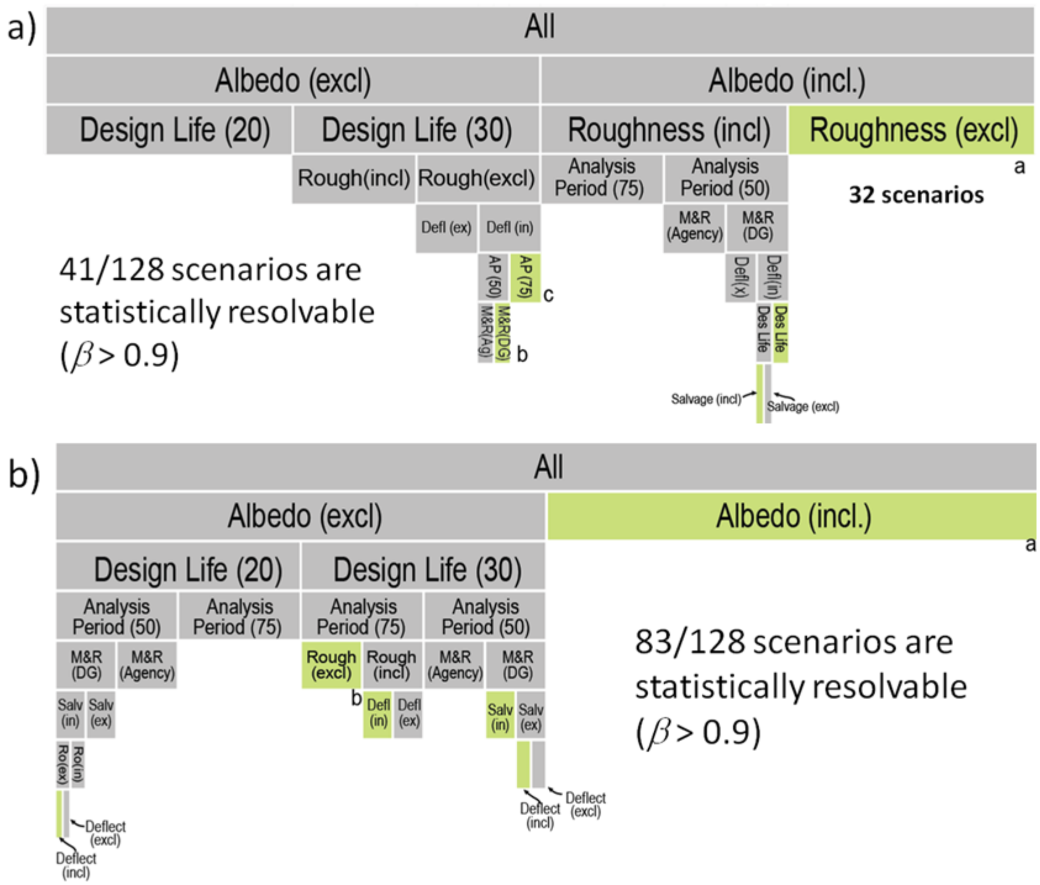

Figure 5. Categorization analysis results of resolvable scenarios from a comparative pavement LCA case in (Gregory et al. 2016). a) Results shown for all empirical quantities are at full range of values (iteration 1). b) Results shown for refined data analysis (iteration 2 – refined rate of roughness evolution and the impact factor for bitumen). Boxes indicate a collection of scenarios that share a fixed value for the parameter listed in the box. Green bars differentiate scenarios that are statistically resolved (β > 0.9). For binary model domain parameters the scope is either included (incl) or excluded (excl). Parenthetical numbers indicate the value of the parameter. Rough or Ro = roughness; AP = Analysis period; Defl = deflection; M&R = maintenance and rehabilitation; Des Life = design life; Salv = salvage.

have a fixed value of that parameter. Green boxes indicate scenarios that are statistically resolved. Figure 5a shows results after the initial probabilistic scenario-aware analysis in which empirical quantities are at their full range of values. Figure 5b shows results after a second iteration that used more refined data for two parameters (rate of roughness evolution and the impact factor for bitumen) that were identified as influential in the sensitivity analysis.

There are 128 total scenarios analyzed (each one includes thousands of simulations) and in the first step 41 scenarios are resolvable, whereas the second iteration after data refinement leads to 83 scenarios that are resolvable. This highlights the effectiveness of the data refinement, but it is also interesting to observe the scenario subpopulations that lead to resolvable results. For example, 32 of the 41 resolvable scenarios in Figure 5a include albedo and exclude the impact of pavement roughness in the analysis scope. The other 9 resolved scenarios are distributed among the states examined, but all share the common feature of including the impact of pavement deflection. The subpopulation of scenarios which exclude albedo effects (the left half of tree), serves as a lesson on the importance of considering and isolating individual scenarios and scenario populations. This subpopulation seems irresolvable because it has a β of 0.6. Within this group, however, one can isolate six specific scenarios (labelled groups b and c in Figure 5a) that are, in fact, resolvable.

The data refinement step successfully produced significant resolution in about 65% (83 of 128) of scenarios, but much of the scenario space remains unresolved. If those scenarios are of particular interest, then the analyst should iterate through the process again, identifying influential parameters and exploring whether resources are available to improve the fidelity of parameter estimates. Although an initial sensitivity analysis provides useful guidance for those iterations, that analysis should be repeated each time more refined information is introduced.

4 OPPORTUNITIES FOR FUTURE RESEARCH

There are several opportunities to improve uncertainty analyses in pavement LCA and LCCA, particularly uncertainty characterization. This includes the data used to quantify measurement uncertainty, which can be accomplished through data collection of the variation in inventory and model parameters used in LCIs. In addition, further research on the factors used to quantify uncertainty due to IQAU and IFAU would be beneficial. Another topic worthy of research is the development of models for how inventory data and environmental impacts will evolve over time and the associated methods to characterize uncertainty. This is particularly important given the long analysis periods used in pavement LCAs and LCCAs. Finally, additional research on uncertainty in impact assessment methods and their evolution over time would be an important contribution to the field of study.

If the pavement LCA and LCCA communities adopt a probabilistic approach in analyses, a body of work will be developed that can be used to establish priorities for data refinement and model improvement. It will also enable decision-makers to have a better understanding of the conditions that are most likely to lead to statistically significant results.

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