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Comparative pavement life cycle assessment with parameter uncertainty

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ABSTRACT

We present a comparative life cycle assessment of pavements considering measurement uncertainty and the data-quality uncertainty. We account for the uncertainty due to the prediction of roughness over pavement lifetime and propagate the consequence into the overall footprint. The uncertainty propagation is conducted using a Monte Carlo simulation. Making use of a comparison indicator, the difference in the environmental impacts of two alternative designs is statistically characterized taking into account the correlation in the input parameters. The contribution of different phases and their associated uncertainty characterized and compared for two pavements.

1. Introduction

There is a growing interest in environmentally conscious design of civil infrastructures and, in particular, pavements. Improving the sustainability of pavements requires a thorough evaluation of environmental impacts within all stages of a pavement's life. There are notable differences, however, across pavement life cycle assessment (LCA) studies stemming from variation in the activities included; a factor often due to resource constraints. A thorough quantification of environmental impacts of pavements, requires information from numerous sources related to stages of its life cycle; information that is not always available. As such, LCA studies are generally subjected to assumptions and simplifications regarding their scope, system boundaries and data inevitably leading to uncertainties in LCA assessments.[1]

There is also often uncertainty associated with the data due to inherent variations, measurement inaccuracies, lack of information, inefficiencies in manufacturing, or simply human error. Moreover, uncertainty can stem from the quality or appropriateness of the data because in many cases there is a limitation in its availability or access to it, and the use of proxies are unavoidable. Over the past decade there has been significant attention paid to the incorporation of uncertainty in LCA. Here we conduct a life cycle assessment of pavements with uncertainty in the input measurement, and data-quality uncertainty using either empirical data or expert estimates.

2. Methodology

The goal of the system boundary of a LCA is to reflect the impacts associated with the construction of a road, given that it will be constructed. The system boundary of the LCA encompasses five main phases (Santero and Horvath, 2009) – material extraction, construction of the pavement, use phase, maintenance and rehabilitation, and finally end-of-life. Each phase

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[1] Santero et al. (2010) surveys some of these issues.

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consists of components (Fig. 1). Here we consider all phases and include nearly all of the recommended subcategories within them. Most of the phases are consistent with standard material extraction and manufacturing or construction processes. The environmental impact of the use phase, however, is modeled as a differential effect, with the burden calculated relative to some appropriate baseline.

Pavement-vehicle interaction (PVI) accounts for the extra fuel consumption in the vehicles on the road caused by the change in the structural and surface properties of pavements. It is important to emphasize that this is not the entire burden of fuel use, but rather the effect of pavement properties on the fuel economy of vehicles. The impact of PVI within the entire life cycle can be significant, especially for high-volume roadways (Akbari et al., 2009). Two major sources of PVI include fuel losses due to changes in roughness and fuel losses due to deflection of the pavement. Our LCA model accounts for both roughness and deflection components. The deflection losses are calculated based on the model developed by Akbarian et al. (2012). The model uses a mechanistic approach to predict the deflection of the road over its lifetime as a function of the structural properties of the pavement. The predicted deflection can then be translated to the associated increase in the fuel loss relative to a fully rigid pavement. Roughness is characterized by the international roughness index (IRI). The prediction of IRI over time is extracted from output of the pavement design software, Pavement-ME, which implements the calculations specified by Mechanistic-Empirical Pavement Design Guide (MEPDG) (American Association of State Highway and Transportation Officials, 2008; National Cooperative Highway Research Program, 2004). The progressive change in the roughness relative to its value at initial construction is calculated and translated to the extra fuel consumption using the empirical model presented by Zaabar and Chatti (2010). Depending on the traffic level and climatic condition of the road, the effect of PVI on global warming potential can be significant and should be sufficiently accounted for in a full LCA analysis of pavements (Akbarian, 2012). There are other sources of PVI-based mechanisms that have not been accounted in this study due to either their negligible effect or lack of information. In particular, the texture may contribute to the additional fuel loss due vehicle operation (Wang et al., 2012).

Albedo accounts for the effect of solar reflectance of a pavement on the global warming potential. Depending on the degree of their reflectivity, pavements can reflect some portion of the incoming solar radiation back into space, which increases the radiative forcing of the earth's surface and in turn affects the global warming potential. The equivalent CO_2e offset attributed to the reflectivity of the pavements can be estimated based on the work of (Akbari et al., 2009). The reflectivity is characterized by a dimensionless number, which varies from zero (fully absorbent) to one (fully reflective). The estimation requires a baseline value of reflectivity with respect to which equivalent carbon dioxide of pavement due to radiative forcing is calculated. In this work we set the baseline value at 0.33, which roughly represents the average reflectivity of the earth.

Concrete carbonation is the process by which a portion of carbon dioxide that was liberated during calcination is sequestrated. The process of carbonation is complex and depends on different factors. In particular, the rate of carbonation is difficult to determine. Lagerblad (2006) uses a simple model for this that relies on Fick's second law of diffusion that we adopt.

Lighting accounts for the associated energy demand affected by the pavement. The electricity required for lighting varies based on the properties of the surface material. The requirements are often specified by the state US Department of Transportation for pavement types. The environmental impact of lighting is calculated using the methodology detailed in (Santero and Horvath, 2009).

The end-of-life activities could encompass anything from complete disposal through landfilling to recycling of the material being removed, depending upon the end of life scenario. Both methods have their complexities, but the rate of recycling is so variable from project to project that it requires far more assumptions by the practitioner. In this work we assume that the pavements are completely landfilled at the end of their lifetime. This may introduce some bias in the comparative assessment of end of life since types of pavement can be subjected to different waste implications.

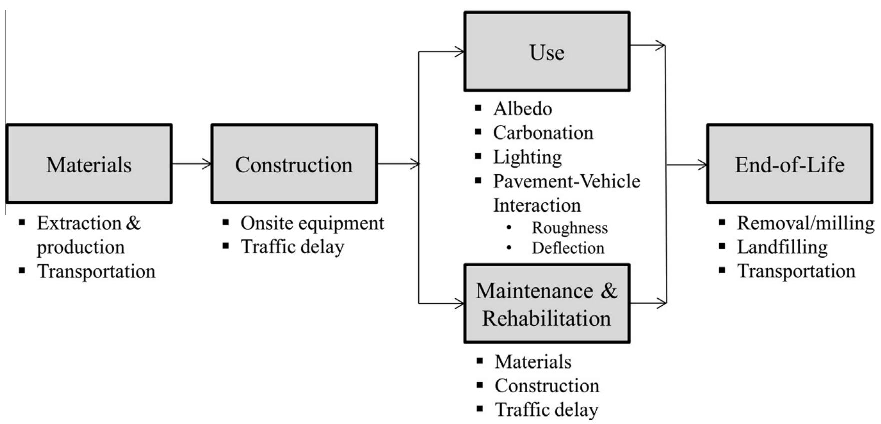

Fig. 1. System boundary for pavement LCA.

Our life cycle inventory has been compiled using available data from various sources. Given the specification of a pavement design, the flow of material and energy consumption can be evaluated. Transportation distances for most materials were obtained from the US Bureau of Transportation Statistics (2007), while cement transportation information was calculated from the Portland Cement Association (2010) environmental surveys. Life cycle inventory data for upstream unit processes were obtained from Swiss Center for Life cycle Inventory (ecoinvent center) (Hischier and Weidema, 2010) and US life cycle inventory (USLCI) databases (National Renewable Energy Laboratory, 2012). Additionally, the environmental impact of cement was calculated using confidential energy and material usage surveys for individual cement plants obtained from the PCA, which enables us to characterize variation in the impacts. The information on the characterization of burden for construction processes, including asphalt and concrete mixing and paving energy, as well as the maintenance energy can be found in (International Grooving and Grinding Association, 2009; Stripple, 2001).

We use global warming potential (GWP) based on Intergovernmental Panel on Climate change (IPCC). GWP characterizes the impacts of greenhouse gas emissions on climate change in terms of carbon dioxide equivalents; GWP is one of the many metrics for comparing emissions and does not encapsulate all aspects related to the environmental impacts.

A computational model to numerically evaluate the life cycle global warming potential has been developed. The model has separate moduli that allow us to compute the impact of each phase and the subcomponent within each phase separately. The overall impact can readily be obtained by adding up the impact of all the subcomponents.

The LCA model for pavements depends on a variety of input parameters. These parameters define characteristics of the model such as pavement design specifications, material and energy flows, environmental impact quantities, etc. The accuracy of LCA results relies heavily on the fidelity of the data used in characterizing these inputs to the models. There is often uncertainty associated with the data and input parameters. The uncertainty can be due to factors such as inherent variation in the physical quantity, inaccurate measurement or implementation of design parameters, lack of information and inability to acquire high quality input data. This source of uncertainty is referred to as parameter uncertainty hereafter. For characterization purposes we categorize the parameter uncertainty in two types that are referred to measurement uncertainty and application uncertainty.

Measurement uncertainty refers to errors due to the inability to precisely measure a value, whether due to human error, improperly calibrated equipment, or inherent variation of the value. Ideally the measurement uncertainty for an input quantity is defined by prescribing its probability distribution. From a statistically sufficient number of samples for a quantity of interest, a probability distribution can be estimated and in turn incorporated in the LCA model using, for instance, a Monte-Carlo simulation. The empirical data required to accomplish this, however, are sometimes not available or in many cases expensive to obtain. In the absence of readily available empirical information, one may use expert estimates to approximate the spread around the deterministic values for uncertain quantities. The ecoinvent guideline (Weidema et al., 2011) provides default quantities for measurement uncertainty categorized by process or material type as well as type of emissions based on expert estimates. The default distributions are assumed to be lognormal and the uncertainty is defined by prescribing the variance of underlying normal distributions. In the absence of empirical data, we make use of these default distributions to characterize the parameter uncertainty whenever it is appropriate. For each uncertain input parameter in the model the measurement uncertainty is approximated by a lognormal distribution. While such a choice introduces some modeling bias, it is a reasonable approximation due to the positivity of these values as well as their multiplicative effects on the overall output. This is consistent with the assumptions in the ecoinvent data quality guidelines.

The second type of parameter uncertainty arises from the appropriateness of the data source used in modeling a quantity of interest. Essentially, it quantifies the stochastic errors due to the use of other relevant data sources to represent the amount or flow of materials and processes in the system that may or may not be an accurate representation of the data; application uncertainty. One approach to account for the uncertainty due to data quality and appropriateness in LCA is the use of data quality indicators (DQIs). Here, we make use of data quality indicators established by ecoinvent to quantify the application uncertainty. In ecoinvent the DQIs are based on using a pedigree matrix approach adapted from Weidema and Wesnas (1996) and Weidema (1998). Based on this uncertainty due to the appropriateness of the data is characterized using five indictors, each one assessing a specific aspect of data quality. These characteristics include "reliability", "completeness", "temporal correlation", "geographical correlation", and "further technological correlation". For characterization purposes the quality of data with respect to each characteristic is divided into five levels (Weidema et al., 2011) and a pedigree score between one and five is assigned accordingly. Pedigree scores for five characteristics are then translated into variances of statistically independent zero-mean normal distributions that characterize the uncertainty attributed to the appropriateness of the data. These variances are referred to as uncertainty factors in ecoinvent. The relationship between the scores and the factors is defined such that if the values are adapted from sources not wholly applicable to the systems being assessed, they will score higher within the pedigree matrix and have a greater uncertainty. If, however, they are directly specified for each of the parameters, the uncertainty is zero. In the quantification of data quality uncertainty in the ecoinvent guideline, the appropriateness is defined with respect to the quantities in the inventory. This addresses the quality of the data source as far as the amount of a given material or process is concerned. Due to data limitations, it is common to use other relevant unit processes to represent intermediate flows within an inventory; i.e. appropriateness can also be discussed with respect to the representation of the intermediate flow. This can introduce another source of application uncertainty not considered in Weidema et al. (2011). This addresses the stochastic error by using a proxy process to represent the environmental impact of the target process of interest.

For a given individual input and output exchange in a data source where its uncertainty is quantified based on the eco-invent guideline, $\{\sigma^2_{\alpha_i}\}_{i=1}^{5}$ is the set of uncertainty factors based on the corresponding pedigree scores that characterize the application uncertainty. Each α_i refers to a specific characteristic of data source quality. Assuming that the inherent measurement uncertainty in the data is characterized by a lognormal distribution and the variance of underlying normal distribution is denoted as σ^2_m, the variance of the underlying normal distribution reads

$$\sigma^2_p = \sigma^2_m + \sum_{i=1}^{n} \sigma^2_{\alpha_i} \tag{1}$$

The overall parameter uncertainty is fully defined by prescribing the mean value and σ^2_p for the uncertain input parameter.

The roughness-induced emissions are an important element of the use phase in the LCA model. There is an underlying probabilistic model associated with the prediction of IRI over time using MEPDG. The procedure for pavement design involves prescribing a level of reliability in the prediction of IRI based on an agency's criteria, and ensuring that the IRI does not exceed a target critical value over pavement lifetime. Although the pavement is designed for a prescribed level of reliability, the uncertainty in the roughness evolution over time can be significant. This uncertainty is propagated into the estimation of roughness-induced emissions in pavement LCA. The amount by which this uncertainty affects the scatter in the estimation of environmental impact can be different by pavement types and depends on how the difference in roughness relative to the initial condition changes over time. In this study we propagate the uncertainty in IRI evolution into the associated environmental impact by generating different realizations for IRI evolution curve at each Monte Carlo run making use of the MEPDG predictive model. Fig. 2 schematically shows the IRI evolution over time for levels of reliability.

Once the statistical distribution of each input parameter is characterized using either empirical data or pedigree matrix approach, the Monte Carlo simulation can be performed to propagate the uncertainty into the life cycle global warming potential. For this purpose numerical values of all the uncertain inputs are sampled based on their corresponding distributions. The set of inputs is fed into the life cycle model and the corresponding realization of modeled GWP for each LCA phase is computed, which can be summed up to obtain the realization of overall GWP. This process is repeated for N_{mc} set of input samples which leads to N_{mc} numerical realizations of GWP. From these samples the probability distribution as well as all the statistics of this quantity, such as median, variance, and percentiles, can be estimated. This is summarized in Fig. 3.

The result of a LCA is usually interpreted in a comparative manner. In this context, uncertainty in the difference between two products drives the decision rather than the overall uncertainty in individual products. As such, the comparison needs to be conducted in a statistical manner. To characterize the uncertainty in the relative impact of two products, we make use of a comparison indicator variable (Huijbregts et al., 2003) defined as the ratio between the environmental impact of two products as follows

$$CI_{GWP} = \frac{Z_{GWP,A}}{Z_{GWP,B}} \tag{2}$$

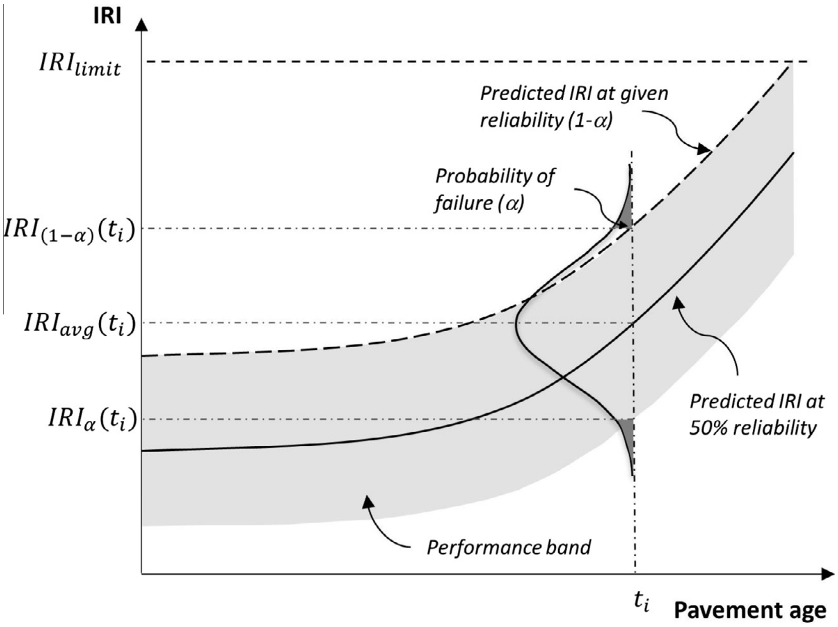

Fig. 2. Schematic representation of IRI prediction over pavement age for 50% (mean), α and $(1-\alpha)$ level of reliability based on MEPDG. Note: The performance band indicates the uncertainty in the prediction, which propagates into the estimation of IRI-induced emissions. Source: American Association of State Highway and Transportation Officials (2008).

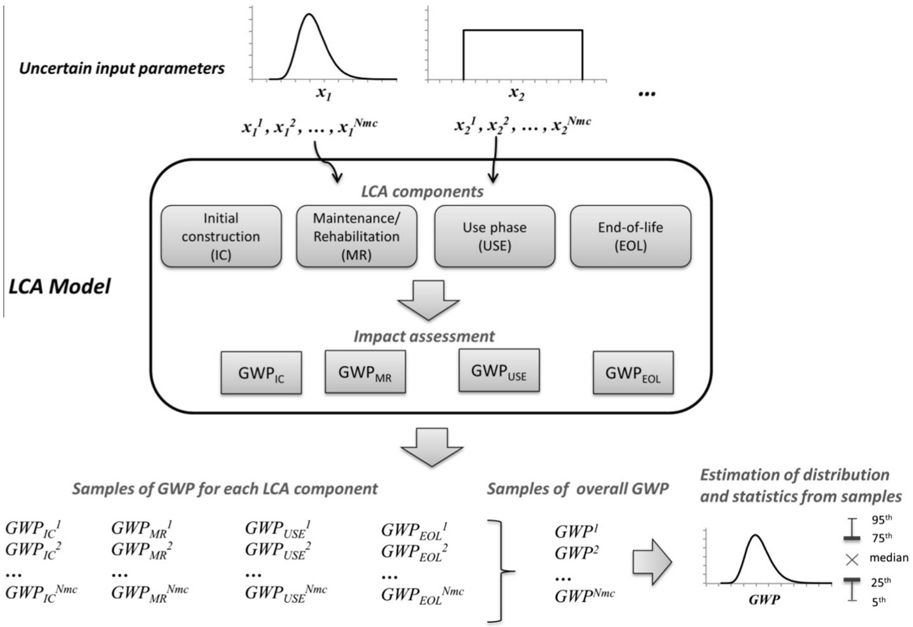

Fig. 3. Monte Carlo simulation is performed to propagate the parameter uncertainty into the global warming potential. Note: The samples of GWP for each LCA components and the samples of overall GWP are obtained and used to estimate the probability distribute.

in which $Z_{GWP,A}$ and $Z_{GWP,B}$ are the global warming impact for products A and B and CI_{GWP} is the resulting comparison indicator.

In a comparative life cycle assessment there is often correlation among model inputs across the competing products. In assessing uncertainty in the difference between two products this correlation must be considered to avoid statistical bias. To that end, the analysis is conducted simultaneously for both products such that for each Monte Carlo run the same sample sets are used for the correlated parameters. The comparison indicator is then computed at each run and stored. The resulting samples of CI_{GWP} are used to estimate the probability distribution and statistics of this quantity. The comparison indicator is defined to characterize the relative difference in the performance of two designs in a statistical sense and it should be interpreted in terms of the probability of event $CI_{GWP} < 1$. As such from the statement $CI_{GWP} = \frac{Z_{GWP,A}}{Z_{GWP,B}} < 1$ in a single Monte Carlo run no conclusion regarding the superiority of design A versus B can be drawn. Instead as a measure of comparison, one can look at the probability that the comparison indicator is less than one, that is $\beta = P(\mathbf{CI}_{GWP} < 1)$, which characterizes the likelihood that design A has lower impact than design B (alternatively one can look at $1 - \beta$ as the likelihood that design B has lower impact than design A). A decision regarding the superiority of design A over design B (respectively design B over design A) can then be made when β (respectively $1 - \beta$) is greater than a prescribed threshold. This threshold is a decision parameter that controls the level of risk that a decision-maker is willing to take and should be set by the decision-maker for a given context.

3. Case study

We compare the life cycle global warming potential of a hot-mix Asphalt Concrete (AC) and a jointed plain Portland Cement Concrete (PCC) designs for an urban interstate highway in Missouri (dry-freeze climatic region). The pavements were designed by an independent firm and are considered equivalent because they have been created and optimized under the same set of contextual conditions. Their effectiveness and future characteristics, such as maintenance and rehabilitations schedule, have been evaluated by the pavement designer using Pavement-ME software, which implements calculations specified by MEPDG (American Association of State Highway and Transportation Officials, 2008; National Cooperative Highway Research Program, 2004). MEPDG is specified by the US Federal Highway Administration as an improvement to the previous design manual, which did not take into account variation in climate, increased truck loads, variation in rehabilitation requirements and material properties, along with other deficiencies. It allows for optimization of the pavement design to reduce material usage and cost. Different distress types were taken into account in evaluating MEPDG-based maintenance schedules, including roughness, rutting, cracking, and faulting. The inventory quantity data was derived from the output of MEPDG, which contains the material type and quantity specifications. The designs are detailed in Tables 1 and 2 shows their associated maintenance schedules. The analysis period is 50 years, thus it includes maintenance necessary for roads to be functional for that time.

Table 1
Specifications of pavement designs.

Specifications for both PCC and AC designs	AADT (vehicle/day)	78,378
	AADTT (trucks/day)	8000
	Number of lanes	6
	Lane width (m)	3.60
	Paved shoulders	2
	Shoulder width (m)	3.60
PCC design	Concrete thickness (mm)	280
	Dowels (mm)	42
	Crushed stone base thickness (mm)	152
AC design	Asphalt thickness (mm)	343
	Crushed stone base thickness (mm)	610

Table 2
Maintenance schedule based on MEPDG.

	Year	Activity
PCC design	30	6 mm diamond grinding and full depth repair, 0.13% slab replacement
AC design	20	50 mm mill, 50 mm AC overlay, patching of 0.13% lane area in the travel lane
	37	50 mm mill, 50 mm AC overlay, patching of 0.18% lane area in the travel lane

3.1. Results

Numerical realizations of modeled GWP for both pavement designs are obtained by performing Monte Carlo simulations with 10,000 trials. Statistical distributions of these quantities are then estimated from these realizations. For each pair of samples of impact quantity for AC and PCC design, the associated realization of comparison indicator is also computed using Eq. (1). These realizations are then used to estimate the probability density function of CI_{GWP}.

Fig. 4 compares the GWP, in megagrams (Mg) CO_2e, as well as the GWP associated with life cycle phases for AC and PCC designs corresponding to the urban interstate highway being assessed. Each data point in the plot depicts the 5th, 25th, 50th (median), 75th, and 95th percentile of the values observed. The estimated probability density functions of GWP are also compared in Fig. 5a. A considerable overlap is seen between the ranges of GWP values. To quantify the difference in GWP impact of two pavements, the probability density functions of comparison indicator, CI_{GWP}, is estimated and shown in Fig. 5b. The value of β is about 0.70, which would generally not be considered statistically significant.

The result presented in Fig. 5a shows a relatively larger variation in the GWP associated with the PCC design. This mainly arises from the use phase component as depicted in Fig. 4. In particular, breaking down the use-phase impacts into its subcomponents shows that the larger scatter in the GWP impact of the PCC design in this case is driven by the uncertainty in IRI-induced emissions. This is linked to the behaviors of pavements in terms of their roughness evolution over time for the scenario under study. Fig. 6 demonstrates the progression of roughness-induced GWP over pavement lifetime based on 50% and

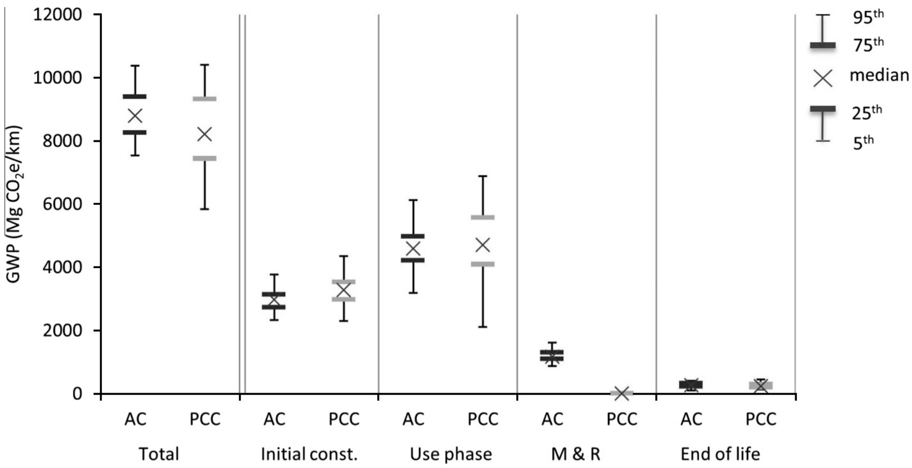

Fig. 4. Comparison of GWP and the contribution of different phases.

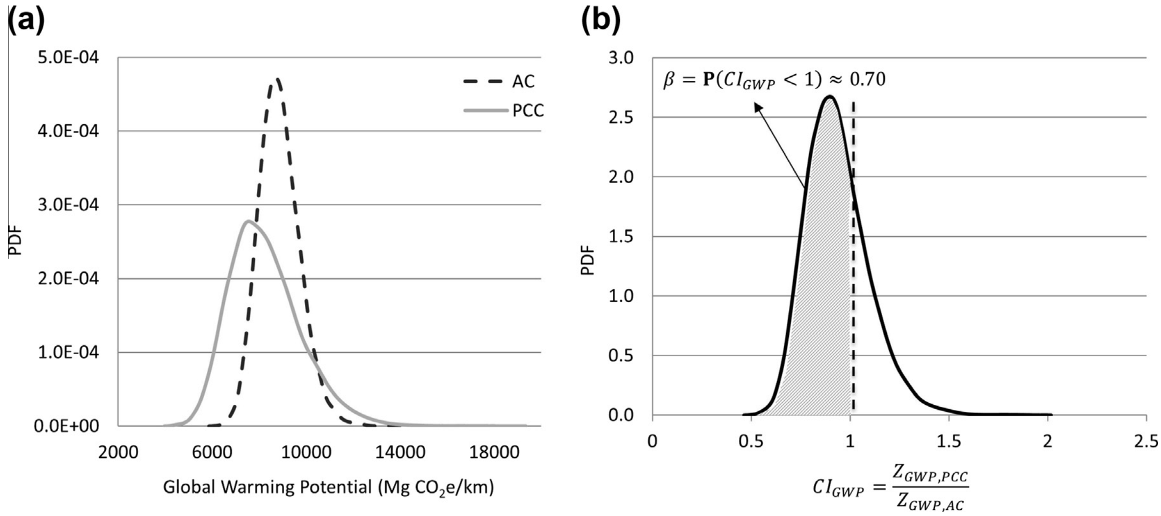

Fig. 5. (a) Estimated probability distribution function of GWP for AC and PCC designs and (b) probability distribution of comparison indicator.

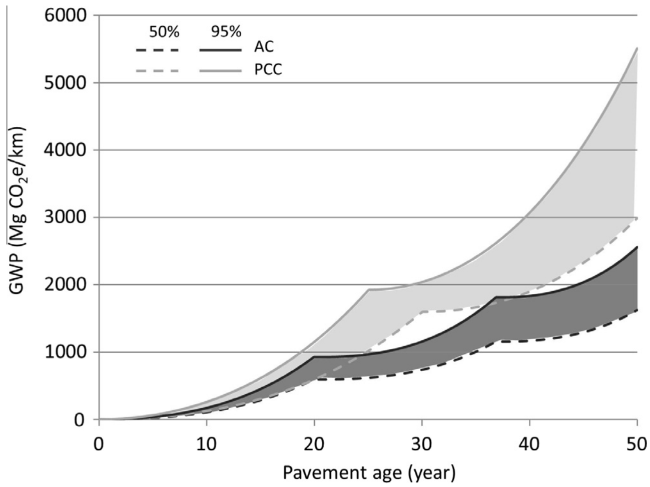

Fig. 6. Progression of IRI-induced emissions over pavement age based on 50% and 95% levels of reliability.

95% levels of reliability for both AC and PCC designs. It is seen that the difference in the predictions is more pronounced for the PCC design, which explains larger variation in the IRI-induced emissions and consequently the use phase.

The performance of pavement types in terms of progression of roughness and other distresses heavily depends on the specific designs under study and, in particular, the climatic condition. Different situations will affect the environmental advantage of alternative pavement types as far as the roughness effect is concerned. This emission scenario dependency is generally the case for many other elements of pavement LCA as well. The results presented in this work compare the environmental implications of two alternative pavement designs under a specific scenario. There is variation in scenarios under which pavements are designed or intended to be used. These scenarios are defined by prescribing pavement specifications or operational context. Material mixes can vary for regions. Use of recycled material can introduce variation in the material production and end-of-life phases. Further, the choice of analysis period and design life can potentially influence the results of comparative assessment (Santero et al., 2011).

4. Conclusion

There is significant uncertainty associated with the input parameters of pavement LCA models. The incorporation of uncertainty into a comparative life cycle assessment is crucial to the credibility of any conclusions drawn regarding the environmental implications of alternative pavement designs. We demonstrate a methodology for conducting a comparative full life cycle assessment of pavements under uncertainty in the input parameters. The uncertainty stemming from the measurement as well as data quality was characterized and propagated into the environmental impact using a Monte Carlo simulation. The level of statistical difference in the performance of two pavements was quantified using a comparison indicator. A case study was presented comparing global warming potential of two alternative pavement designs for an urban interstate highway in Missouri. The contributions of phases and their associated uncertainty were characterized and compared for two pavements. The emissions due to pavement vehicle interaction, in particular roughness, have considerable effect on the overall impact and the associated uncertainty.

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