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Development of Roughness Prediction Models for Life Cycle Assessment Studies of Recycled Pavement Projects

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Abstract

The few existing life cycle assessment studies considering pavement recycling techniques usually omit the stages of maintenance and rehabilitation (M&R) and use. The reason for this omission is the lack of information about how the pavement's performance evolves over time and absence of methods to determine the M&R frequency and service life for completed projects. As a result, the deterioration of pavement recycling projects in the long term is not clearly understood. Few projects have available data, the majority of which are on low volume primary and secondary roads. This paper describes an approach to develop a family of roughness models for recycling projects in Colorado using functional data analysis, and individual models for selected projects in Virginia to support ongoing life cycle assessment (LCA) studies. In the case of Colorado, full depth reclamation (FDR) projects will most likely deteriorate following an average group rate of 1.4 in./mi/year, with an initial international roughness index (IRI) between 52 and 70 in./mi. For the individual roughness models developed for Virginia projects, the initial IRI values and the rate of change for the treatments analyzed were found to range between 49 and 107 in./mi and between 0.7 and 5.2 in./mi/year, respectively, depending on the recycling method and type of stabilization treatment. The results of an LCA case study show that, in addition to recycling, Virginia Department of Transportation can achieve statewide emission reduction goals if focus is placed on achieving smoother roads while measures are taken to keep the annual rates of deterioration low.

Asphalt pavement recycling techniques, including hot in-place recycling, cold in-place recycling (CIR), cold central plant recycling (CCPR), and full depth reclamation (FDR), have proven to be cost-effective rehabilitation strategies that offer many advantages compared with traditional methods, such as milling and filling. Some of these advantages include reduction in virgin material needs, reduced traffic congestion, and lower environmental impacts (*1–3*). Despite many successful experiences, some departments of transportation (DOTs) are still reluctant to use in-place pavement recycling treatments because of concerns about the performance of these treatments compared with more traditional pavement maintenance and rehabilitation (M&R) treatments.

The existence of criteria for selecting the right treatment to apply to the right candidate road section at the right time is one of the most commonly cited bottlenecks impeding the widespread use of asphalt pavement recycling treatments (*1*). The Federal Highway Administration's (FHWA) 2006 Recycled Materials Policy, revised in 2015 (*4*), aims to encourage the use of recycling techniques in pavement rehabilitation projects. An extract from the 2015 policy states, "the determination of the use of recycled materials should include an initial review of engineering and environmental suitability." Several FHWA publications include technical guidelines and checklists providing information to support the review of the engineering suitability aspects of the policy statement, covering initial project level forensic examinations and the identification of the failure mechanism of candidate projects. However, until

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recently, there were no guidelines on how to assess the environmental suitability of these recycled materials.

Life cycle assessment (LCA), a standardized methodology intended to analyze and quantify the potential environmental impacts of a process, product or system, can be used to ascertain the suitability of the FHWA policy from the environmental perspective. Because pavement LCA is an emerging field of study, and few analyses involving recycling projects have been carried out, many important components still need to be developed for the sake of a comprehensive analysis. Key among these are: (i) an inventory database that covers various unit processes related to the recycling of a road pavement using various techniques; (ii) performance prediction model models that predict how these recycled pavements will deteriorate over time; (iii) a tool that conducts an inventory analysis and estimates the associated potential environmental impacts.

Some of the needs listed above are corroborated by National Cooperative Highway Research Program Synthesis 421, which identified the lack of a well-designed experimental approach to assess the progression of pavement distresses and the overall decline in the pavement condition index that can provide information on life cycle cost and service life of in-place recycling techniques (*1*). Among the existing studies that have analyzed and documented the performance of in-place pavement recycling techniques (*5–8*) only a few have provided a time evolution of project performance exceeding five years (*9*, *10*).

A recent survey conducted by Transportation Pooled Fund 5-268 (*11*) to synthesize long-term performance data from states with active in-place recycling projects revealed that only a few states collect/monitor the performance of completed projects. Asked whether performance data was being collected for their recycled projects, 18 out of the 46 participating states answered affirmatively. The Moving Ahead for Progress in the 21st Century (MAP21) and Fixing America's Surface Transportation (FAST) Act (*12*) require state agencies to collect and report performance data for pavements on the national highway system (NHS). However, since most states have only executed pavement recycling projects on low volume roads, the lack of available performance data on NHS routes is not surprising. Data provided by those states collecting performance data showed significant variations from state to state—type of performance indicators measured, number of data collection years—and some missed relevant information such as recycling thickness, stabilizers/recycling additives used, traffic information, and climate information, for instance.

Motivated by the needs discussed above, this paper presents the development of pavement performance prediction models (PPPMs) for recycled asphalt pavements that will not only serve as critical inputs to enhance the comprehensiveness of pavement LCA modeling but also aid DOTs and other decision makers in (i) quantifying the service life of recycling projects and (ii) developing M&R strategies for better planning and allocation of funds in the future.

Objectives

The primary objective of this paper is to present single and family-type performance models to characterize deterioration of pavement recycling projects. Furthermore, it presents a modeling approach to analyze and extract projects with similar deterioration trends where data sufficiency may be a limitation, and introduces the development of individual and family-type roughness prediction models for recycled pavements—in Virginia and Colorado respectively—to be utilized at the M&R and use stages of ongoing LCA studies. Finally, it illustrates the relevance of the models developed when used in the context of an LCA study that aims to quantify the 10-year global warming score associated with the recycled pavement projects completed in Virginia.

Background

Wolters and Zimmerman reviewed state practices on performance modeling and developed three pavement performance modeling options for two groups of models—individual and family-type models—for Pennsylvania DOT (*13*). Deterioration models were developed for Virginia DOT (VDOT) in a study that incorporated the structural capacity of the pavement in the form of a modified structural index along with the pavement age and discussed several model shapes (*14*). However, models for in-place recycling projects were not specifically developed in any of these studies. A literature review identified three recent studies that discussed deterioration models for in-place recycling projects as part of a broader project (*3*, *15–17*). Senhaji (*15*) discussed a two-pronged approach to estimating the performance and lifespan of in-place recycling treatments. Linear models for conventional asphalt concrete overlays, CIR, and FDR were developed for this project.

Cross et al. (*18*) compared the energy, greenhouse gas, and environmental emissions of CIR, traditional mill and fill, and a hot mix asphalt overlay using the pavement life-cycle assessment tool for environmental and economic effects (PaLATE). The study incorporated CIR only as an end-of-life treatment option. The use stage was not considered in the study, and therefore the impact of the progression of roughness was not discussed. Giani et al. (*19*) assessed the environmental sustainability of three pavement types: one with virgin materials using traditional technology, and two others with various combinations of reclaimed asphalt pavement (RAP) and warm mix asphalt (WMA) in the base layer. The service lives of the pavements were estimated from averages derived from experience, while the frequency of maintenance treatments applied at the use stage derived from expert opinion—not from performance models.

Santos et al. (*3*) conducted LCA for an in-place recycling project and compared the results with two other pavement maintenance alternatives: traditional reconstruction and corrective maintenance. The authors developed an LCA model that included the use stage in the system boundaries. To determine the M&R strategies to be implemented in these projects, the authors used a quadratic model that predicted the pavement IRI progression from the treatment age. The IRI prediction was subsequently used to estimate the additional fuel consumption from rolling resistance.

Saboori et al. (*16*) estimated the potential environmental impacts of alternative end-of-life treatments, including pavement recycling treatments, in California. The scope of the study did not include the M&R and use stages because of the lack of information on (i) how pavement roughness evolves over time (affecting vehicle fuel consumption), and (ii) how to determine the M&R frequencies and service life of each alternative treatment. The study concluded by emphasizing the need for PPPMs that can help to explain how pavement recycling-based treatments affect pavement performance.

Several approaches—both deterministic and probabilistic—have been used to develop PPPMs. These include, among others, neural networks, fuzzy logic systems, genetic algorithms, neurofuzzy systems, and regression methods (*20–25*). Despite its simplicity compared with the other methods, the traditional regression analysis approach has the potential to satisfy the model validation criteria. Thus, it was included in this study. Other functions—exponential, sigmoidal, and logistic—that are commonly used outside the pavement domain were also evaluated. The exponential model describes a mathematical function whose growth rate value is proportional to the function's current value. Since the condition of a pavement section each year depends on the condition in the previous year, the inclusion of the exponential model is then justified. Specifically, the *2P* and *3P* (where P stands for parameter, indicating the number of model coefficients) forms were evaluated.

Methodology

Data Collection

Performance data were collected as part of a broad pavement recycling synthesis project using a web-based survey shared with members of the American Association of State Highway and Transportation Officials Research Advisory Committee in 2018. Eighteen states indicated that they monitored the performance of active pavement recycling programs, and eight provided performance data in a response survey. However, based solely on the period over which data were collected, only data from Virginia and Colorado were deemed suitable for modeling performance.

Colorado Data. Performance data from 36 FDR projects received from Colorado DOT were used in this study. The performance data were collected over 0.10 mi sections for each project, and included IRI, rutting, fatigue cracking, transverse cracking, and longitudinal cracking. Information on the construction year, average daily truck traffic, overlay thickness, and recycling cost was also provided for each project. Information about the thickness of the recycling layer and the type and quantity of stabilizing/recycling agents used was not available or not provided.

The average project age, computed from the year of project completion, was 8.3 years with a range of three to 11 years. The rehabilitation history on these projects since completion was not provided with the data. Figure 1 is a scatterplot matrix showing the distribution, correlations, and density eclipse for IRI, annual average daily truck traffic (AADTT), overlay thickness, and project age. A table summarizing project details for Colorado was not included due the manuscript length requirement (available on request from authors).

Virginia Data. VDOT submitted data from 16 FDR, four CIR, and two CCPR projects. The available data include pavement age along with condition descriptors, such as fatigue cracking, rutting, IRI, transverse cracking, longitudinal cracking, patching, and bleeding. Information on the overall condition of the projects in the form of summarized indices (i.e., critical condition index [CCI], load-related distress index, and non-load-related distress index) was also included. Other pertinent information such as the thickness of the recycling layer, the type and quantity of stabilizing/recycling agents, overlay thickness, truck traffic volume, and the rehabilitation history of these projects since completion was provided with the data. A scatterplot matrix of the projects showing distributions, linear fits, and correlation between these variables is presented in Figure 2. The pooled data showed negative correlation between CCI and age, and positive correlation between IRI and age. These trends were expected, as they are characteristic of pavement deterioration with time. The ages of the projects ranged from a minimum of five years to a maximum of nine years. Details of the final selected projects are highlighted in Table 1.

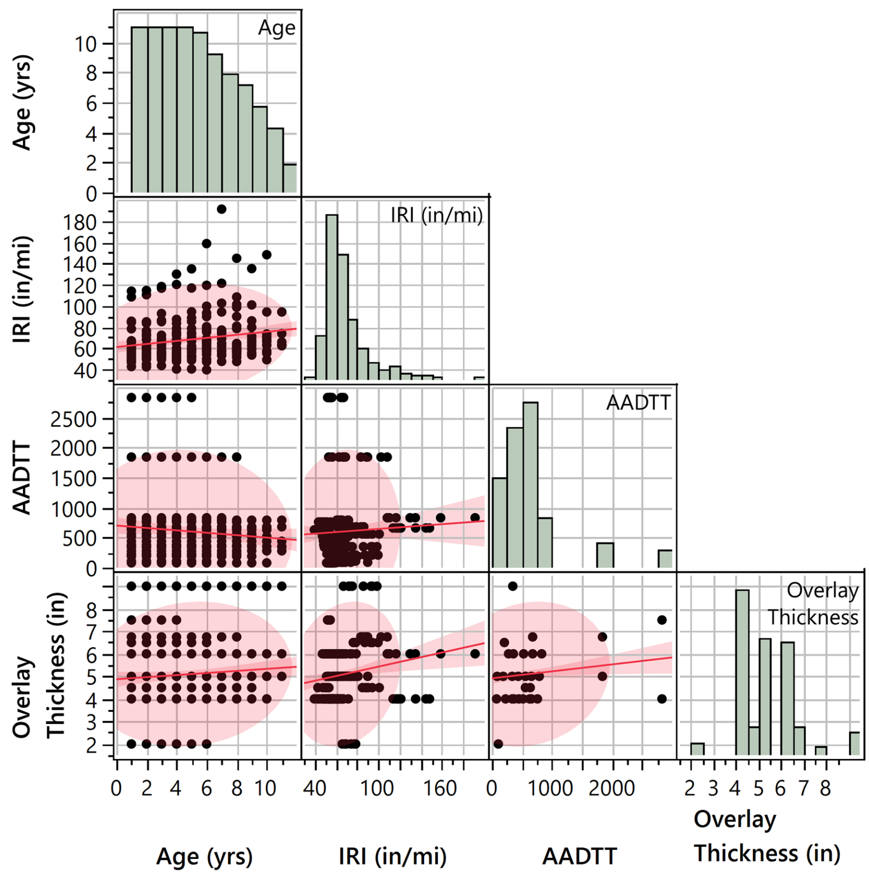

Figure 1. Scatterplot matrices for the data from Colorado Department of Transportation full depth reclamation (FDR) projects.
Note: AADTT = annual average daily truck traffic; IRI = international roughness index.

Data Processing

This section discusses the approach used to analyze the performance data received. Only the roughness data are analyzed in this paper. For one of the datasets, a systematic approach was used to identity projects of similar behavior and develop a model representative of that group. First, projects were grouped by performing an analysis of means (ANOM) test on the parameter estimates (slopes and intercepts) from a regression fit. This was done after the performance data had undergone filtering and cleaning. Then, functional data analysis was conducted with the objective of extracting important features such as shapes and trends from the data analyzed as a group. The resulting functional principal components (FPCs), which carry these trends extracted from the aggregated data, were then classified into the groups identified earlier from the ANOM test, using discriminant analysis. A mixed model design of experiments (DoE) was constructed using IRI as a response variable as a function of pavement age, and AADTT and pavement overlay thickness as treatment factors to select variables for the final deterioration model. The details of these steps are further described in the following paragraphs.

Exploratory Data Analysis. Building on the assessment of the scatterplots, linear fits of IRI versus age were plotted utilizing curve fitting tools in JMP statistical software (*26*). From the visual and interactive functionality in the software, data preparation steps involving the identification and removal of erroneous data (e.g., unreasonably high or low data points, negative values) were carried out to clean the raw data. Utilizing curve fitting tools, the analysis was carried out by “Recycling Method” and “Project” was used as a grouping variable so that separate exponential 2P (two-parameter) models were fitted for each of the projects (R^2 of 0.935) at each level of recycling method. For nonlinear modeling, a requirement of a minimum three time-series data points (*27*) was set to clean the data and projects with less than three years of data were removed from the analysis. Since the M&R history of some projects was not available for analysis, periods where there were more than two consecutive

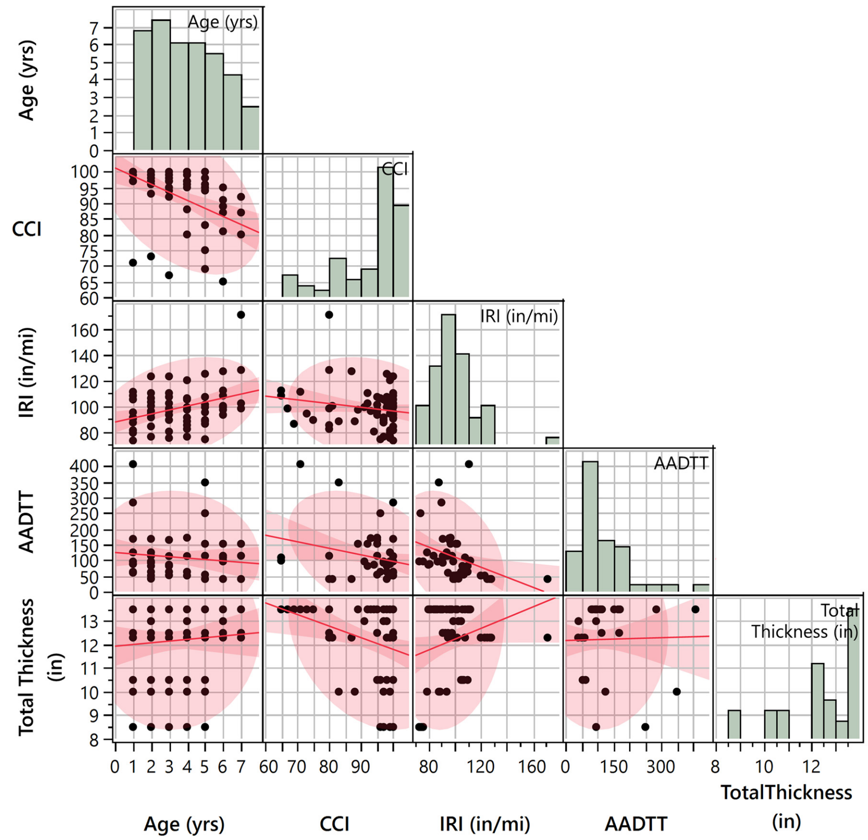

Figure 2. Scatterplot matrices for recycled pavement projects in Virginia.
Note: AADTT = annual average daily truck traffic; CCI = critical condition index; IRI = international roughness index.

Table 1. Details of Virginia Department of Transportation Recycling Projects

Route (length in miles)	Recycling methods	Recycling/ stabilization agent content (%)	AADTT (2017)	Pavement structure (above subgrade)				Total thickness (in.)
				Layer 1	Layer 2	Layer 3	Layer 4	
IS81SB (3.7)	FDR lime + CIR FA + CCPR	*CIR & CCPR (2% FA + 1% lime) FDR (3% cement + LKD)	6943	2.0 in. SMA12.5D	4.0 in IM19.0D	6.0 in CCPR	12.0 in FDR	24.0
SR3EB (3.0)	FDR cement	4% cement	92	2.0 in. SM12.5A	2.0 in. IM19.0A	9.5 in. FDR	-	13.5
SR3WB (3.0)	FDR cement	4% cement	85	2.0 in. SM12.5A	2.0 in. IM19.0A	9.5 in. FDR	-	13.5
SR6EB (3.6)	FDR cement	5% cement	127	1.5-in SM12.5A	2.0-in IM19.0A	9.0-in FDR	-	12.5
SR13EB (3.6)	FDR cement	5% cement	172	1.5-in SM12.5A	2.0-in IM19.0A	9.0-in FDR	-	12.5
SR24EB (2.9)	FDR cement	4% cement	61	1.5-in SM9.5D	9.0-in FDR	-	-	10.5
SR40FA (0.25)	FDR FA	2.7% FA + 1% cement	48	2.5-in SM9.5D	9.8-in FDR	-	-	12.3
SR40EA (0.25)	FDR EA	3.5% EA	48	2.5-in SM9.5D	9.8-in FDR	-	-	12.3
US17NB (9.8)	CIR EA	2.5% EA	127	1.5-in SM12.5A	2.0-in IM19.0A	5.0 in. CIR	-	8.5
US17SB (9.8)	CIR FA	2.5% FA	170	2.0-in SM12.5A	3.0-in IM19.0A	5.0 in. CIR	-	10.0

Note: AADTT = average annual daily truck traffic; CIR = cold in-place recycling; CCPR = cold central plant recycling; EA = emulsified asphalt; FA = foamed asphalt; FDR = full depth reclamation; IM19.0D = intermediate mix with 19.0 mm maximum nominal aggregates, “D” for binder with performance grade 70-22; SMA12.5D = stone matrix asphalt with 12.5 mm maximum nominal aggregates, “D” for binder with performance grade 70-22; SM9.5A = surface mix with 9.5 mm maximum nominal aggregates, “A” for binder with performance grade 64-22; SM9.5D = surface mix with 9.5 mm maximum nominal aggregates, “D” for binder with performance grade 70-22; SM12.5A = surface mix with 12.5 mm maximum nominal aggregates, “A” for binder with performance grade 64-22.; SM19.0A = surface mix with 19.0 mm maximum nominal aggregates, “A” for binder with performance grade 64-22;.
*Thickness of right lane of I-81 is not consistent for the entire 3.7 miles. The initial part is 4 in. asphalt over 8 in. CCPR while the rest is 6 in. asphalt over 6 in. CCPR. The left lane composed of 5 in. CIR with a 4 in. asphalt overlay.

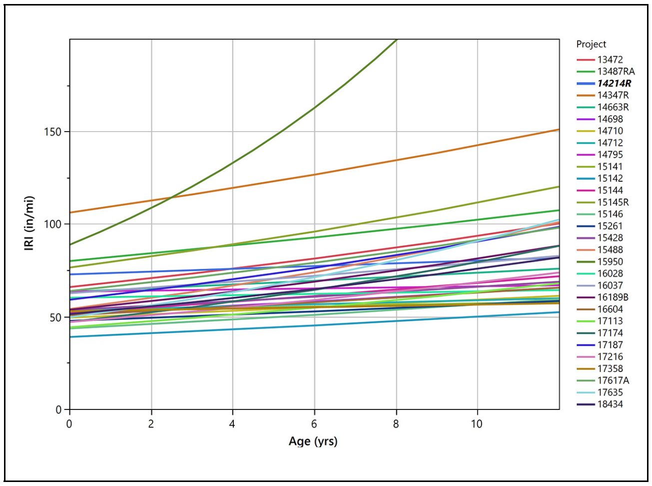

Figure 3. Initial model re-fitting after outlier removal for Colorado Department of Transportation full depth reclamation projects showing irregular slopes and random intercepts.
Note: IRI = international roughness index.

measurements showing an improvement in the pavement condition (roughness or overall condition index) were visually identified and marked as points where some form of M&R activity had been performed. Only the periods before the marked points were considered for subsequent analysis. After the data processing/filtering steps, a total of 30 FDR projects from Colorado DOT, and eight FDR and two CIR projects from VDOT were considered for analysis. The cleaned data for the selected projects were then re-fitted. The result for Colorado DOT is shown in Figure 3.

A consolidation of all the fitted models presented in Figure 3 shows no obvious patterns. They contain only irregular intercepts and random slopes with no clear criteria to group the projects. Consolidating the projects and developing a model based on the average to represent FDR projects was not considered appropriate as it would mean losing many important trends/features in the data. To ensure sample homogeneity the researchers examined how model parameters differ for each project compared with an overall parameter mean. An ANOM test with an alpha level of 0.05 was used to identify which projects had different rates of IRI change (slope) and initial IRI (intercept). The projects were then flagged into three initial groups: statistically different exceeding upper limit of overall project mean (UDL), statistically different exceeding lower limit of overall project mean (LDL), and not enough evidence to support a statistical difference from overall project mean (Avg). The ANOM test was not conducted for the VDOT data, as the interest with this dataset was developing models for each project rather than a family-type model to represent the various recycling methods.

Functional Data Analysis. To validate the results obtained from the ANOM test, a method used in analyzing functional data was employed (*28*). The strength of this approach is that it takes many functional processes and extracts important features to use in further modeling.

The functional data explorer platform fits surrogate functions, in this case B-splines (splines are knotted or jointed polynomials), to the data using a mixed model where the spline coefficients are treated as random effects estimated via best linear unbiased predictors. Data in this analysis are in vector form and the objective is to seek a few scalars that explain as much of the information in the data as possible. The first step to obtaining these information-containing scalars is finding vectors, v_k, that explain the largest amount of variation in the data, Yi, once centered and (usually) scaled.

$$\begin{aligned} &v_k \ \text{ minimizes } \ \sum_i \| \, Y_i - v_k v_k^T Y_i \|^2 \ \text{ subject to} \\ &v_k v_k^T = 1 \ \text{ and } \ v_k^T v_k = 0 \ \text{ if } \ j \neq k \end{aligned} \tag{1}$$

These scalar projections of the data, $S_{k,i} = v_k^T Y_i$, called principal components, are used in place of the complete data vectors:

$$Y_i \approx S_{1,i} v_1 + S_{2,i} v_2 + S_{3,i} v_3 + \ldots \tag{2}$$

A set of orthogonal basis functions $\varphi_k(t)$ that explain the maximal amount of variation in the observed functions is found by going through the analogous process in function space. Each observed function is smoothed and approximated by linear combination of basis vectors:

$$y_i(t) \approx \beta_{1,i} b_1(t) + \beta_{2,i} b_2(t) + \beta_{3,i} b_3(t) + \ldots \tag{3}$$

A similar dimension reduction can be applied to find a small number of functions that explain the variation in the data. This gives us the more compact representation of the function:

$$y_i(t) \approx S_{1,i} \varphi_1(t) \ + \beta_{2,i} \varphi_2(t) \ + \beta_{3,i} \varphi_3(t) \ + \ldots \tag{4}$$

Instead of the basis functions, the functions presented in Equation 4 were decomposed into much smaller linear combinations of eigenfunctions and FPC scores. The eigenfunctions, $\varphi_k(t)$, are orthogonal "natural harmonics" that describe variation in the shape of the data functions. The scores are the most concise derived feature from the data. These scores can be used as inputs and outputs of other statistical models. In this case, the output FPCs, which carry the shapes extracted from the various functions, were save for feature extraction and classification analysis in another modeling platform.

Discriminant Analysis. Fisher (*29*) described the linear discriminant function and its offshoots, the quadratic discriminant function, and multi-class discrimination using Mahalanobis distance (a measure of the distance between a point and a distribution). Discriminant analysis seeks to classify observations described by values on continuous variable into groups. A classification categorical variable is predicted based on known continuous responses, also known as covariates. The quadratic method, which assumes that the within-group covariance matrices differ, was used in the analysis. The FPC scores were used as covariates to classify the projects into the preliminary groups (UDL, LDL, and Avg) identified from the exploratory data analysis. Instead of developing individual deterioration models for 30 FDR projects, there are now three classified groups to work with.

Development of PPPMs

Regression analysis was performed to predict the projects' IRI using project age as the predictor variable. A mixed model DoE analysis with appropriate response variables (IRI) was used and constructed the model effects using the FPCs, AADTT, and overlay thickness as treatment factors. Generalized regression with standard least squares was used, assuming a normal distribution for the IRI response. In pavement LCA modeling, IRI prediction models are used to forecast the progression of surface roughness over time and subsequently to assess the impact of rolling resistance on vehicle fuel consumption. Several model shapes from various functions discussed in Ercisli (*14*) were initially fitted to the data from individual projects to determine which models best fit the trends observed in the scatter plots.

The most plausible models were then selected using the second order Akaike information criterion (AICc) weight (calculated from the AICc). This estimator represents the relative likelihood of a model (where 1.0 is most likely) when comparing several models. Usually, boundary conditions for the response variable are set, and the effects on the resulting models are re-evaluated. No boundary conditions for the maximum IRI value were set, though a pavement with an IRI greater than 500in./mi is generally considered not rideable except at low speeds (*30*).

The models satisfying the boundary conditions with AICc weights closest to 1.0 were then selected. Finally, an inverse prediction of the project age with the IRI threshold values considered by the DOTs was carried out to estimate the service life of the projects.

Results and Discussion

Exploratory Data Analysis

Figure 4 presents the results of the ANOM test. Observations in red are statistically different from the overall project mean. For the FDR projects, 56% of the projects had initial IRIs (intercept) that were not significantly different (Avg group) from the overall project mean, while 26% and 17% were respectively significantly above (UDL group) and significantly below (LDL group) the overall project mean. The IRI growth rate (slopes) were not used for the initial grouping, as 93% of the projects' IRI growth rates were not significantly different from the overall project mean (in which case, one deterioration model would be sufficient to represent the whole group of projects).

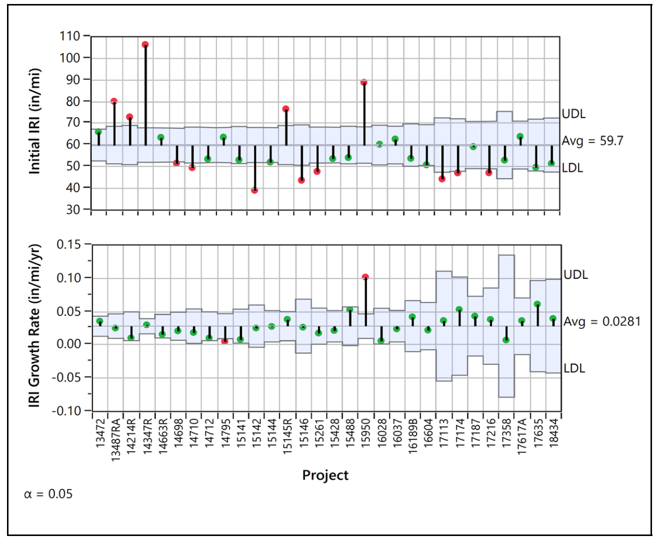

Figure 4. Results of analysis of means (ANOM) test showing projects with significantly different slopes and intercepts above and below the overall project means.
Note: IRI = international roughness index; UDL = statistically different exceeding upper limit of overall project mean; Avg = not enough evidence to support a statistical difference from overall project mean; LDL = statistically different exceeding lower limit of overall project mean.

Functional Data Analysis

Among the B-spline surrogate models (i.e., linear, quadratic, and cubic) fitted to the initial data, a linear model with one knot (indicated by the red dash-line) was selected as the best fit based on the Bayesian information criterion fit statistic (Figure 5*a*) for FDR projects. The curve in the overall IRI prediction plot (left chart of Figure 5*b*) is a prediction of the mean curve while the grid (right chart of Figure 5*b*) shows the individual plots for the projects. The overall IRI prediction plots show the location of the knots/joints (indicated by the vertical blue dashed line). While not a focus of the analysis, the location of the knot is of particular importance, as it indicates a point in the project's service life where there is a significant change in the pavement condition. The knot was situated at age six years for FDR projects in Colorado. Routine maintenance

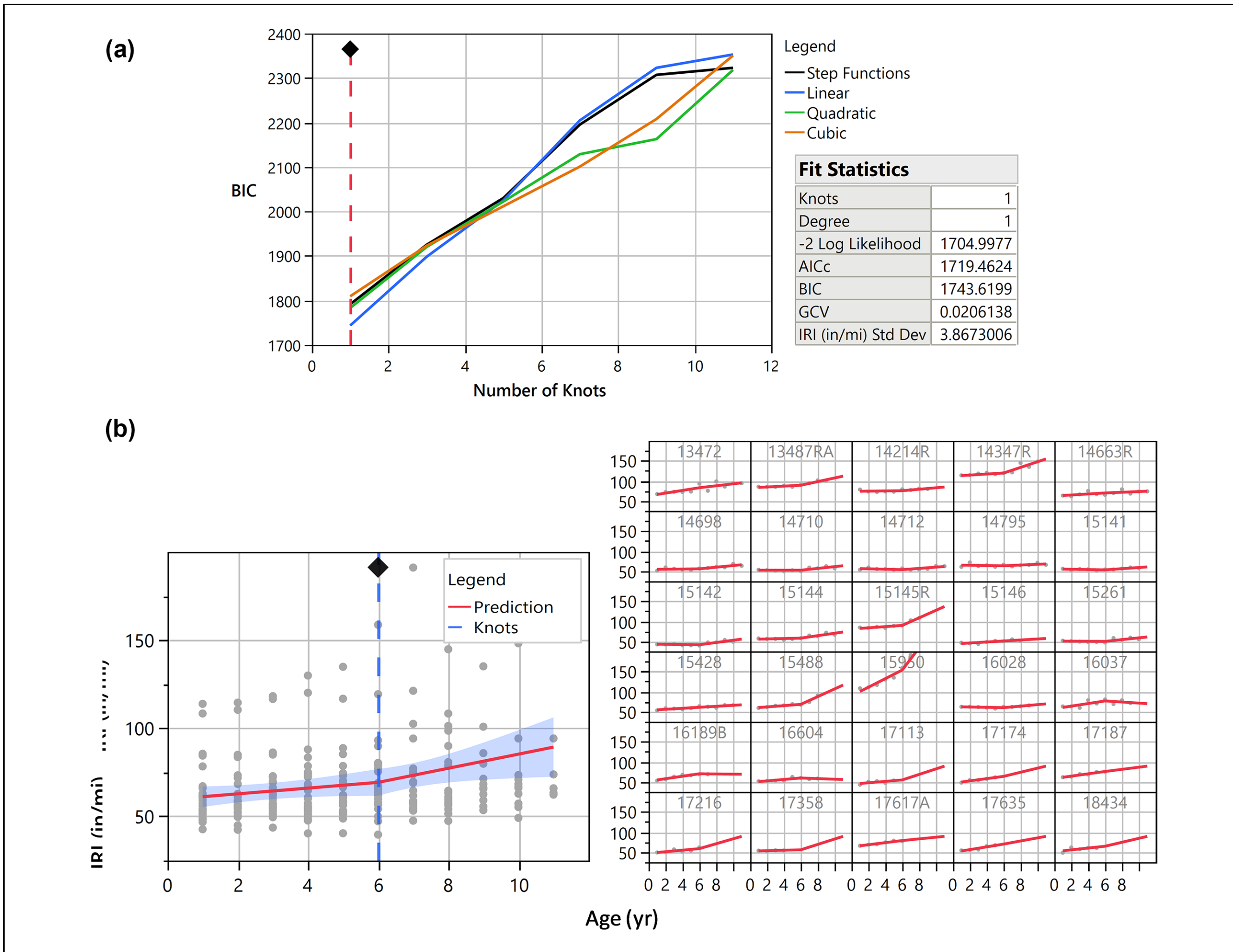

Figure 5. (*a*) Solution path plot with fit statistics; (*b*) B-spline fit on initial data showing the overall international roughness index (IRI) prediction (left plot) and grid of individual project IRI predictions (right plot) for full depth reclamation.

practices would be of primary importance before this point in the pavement's age to delay deterioration and extend the pavement life.

The results from the FPC analysis (FPCA) after the fitting of the surrogate B-spline (linear model with one knot) to the initial data are presented in Figure 6.

The FPCA report lists eigenvalues that correspond to each FPC in order, from largest to smallest. The percent variations accounted for by each FPC and the cumulative percent are indicated in the bar chart. For the FDR projects, while two FPCs explain approximately 99.7% of the variation in the data, the eigenvalue of FPC1 alone explains more than 96% (Figure 6*a*). Projects that may be outliers from other projects, or project grouping, in some cases, can be revealed from an assessment of the score plots (Figure 6*b*). Projects 15950, 13472, 15145, and 14347R in Figure 6*b* are outliers. The prediction profiler highlights the impact of each FPC on the IRI over time (Figure 6*c*). High values of FCP1 result in lower initial IRI values than the mean. FPC2 seems to control the slope of the mean curve; high values show slower deterioration before age six years with deterioration increasing afterwards.

Discriminant Analysis

The discriminant analysis is more suitable to highlight outliers or to identify groups of projects than the visual assessment of the score plots from the FPCA. Figure 7 shows canonical plots from the discriminant analysis. The plots highlight three distinct groups from the classification exercise. A separate report shows projects that were misclassified. Out of 30 FDR projects, three were misclassified.

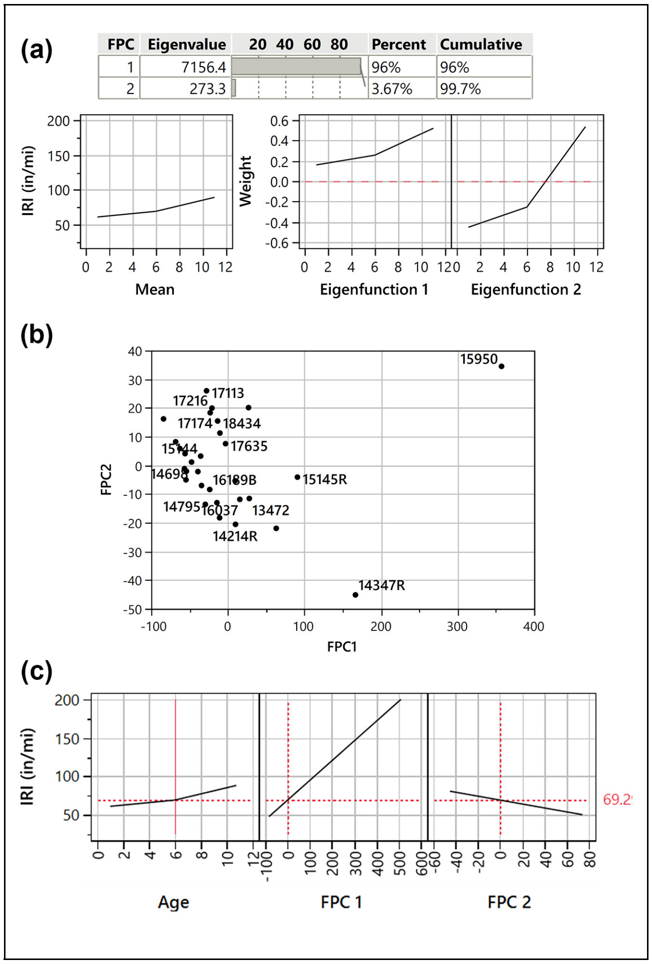

Figure 6. Full depth reclamation results: (*a*) plot of mean international roughness index (IRI) versus age with extracted shapes (eigenfunctions) explaining variations; (*b*) score plot showing potential clustering/grouping of projects; (*c*) functional principal component (FPC) profiler showing correlation between FPCs and IRI as a function of age for FDR projects.

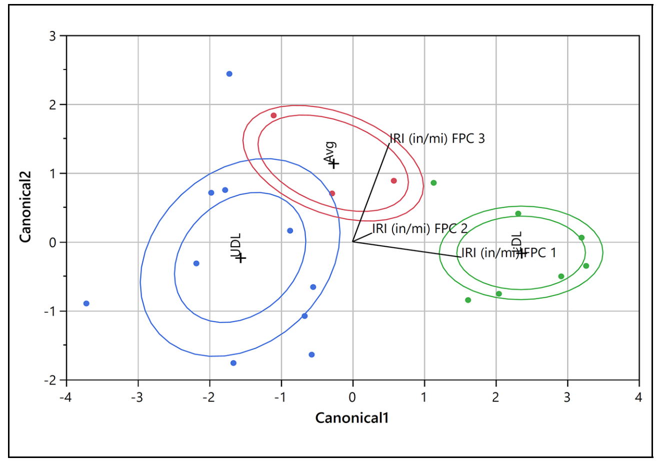

Figure 7. Results of the discriminant analysis showing distinct groups in canonical plot for the full depth reclamation projects in Colorado.

Note: FPC = functional principal component; IRI = international roughness index; UDL = statistically different exceeding upper limit of overall project mean; Avg = not enough evidence to support a statistical difference from overall project mean; LDL = statistically different exceeding lower limit of overall project mean.

Key to Figure 8:
SN = structural number.
IM19.0A = Intermediate mix with 19.0 mm maximum nominal aggregates, "A" for binder with performance grade 64-22.
IM19.0D = Intermediate mix with 19.0 mm maximum nominal aggregates, "D" for binder with performance grade 70-22.
SMA12.5D = Stone matrix asphalt with 12.5 mm maximum nominal aggregates, "D" for binder with performance grade 70-22.
SM9.5D = Surface mix with 9.5 mm maximum nominal aggregates, "D" for binder with performance grade 70-22.
SM12.5A = Surface mix with 12.5 mm maximum nominal aggregates, "A" for binder with performance grade 64-22.
SM19.0A = Surface mix with 19.0 mm maximum nominal aggregates, "A" for binder with performance grade 64-22.
FA = Foamed asphalt.
EA = Emulsified asphalt.
HMA = Hot mix asphalt.
CCPR = Cold central plant recycling.
FDR = Full depth reclamation.
CIR = Cold in-place recycling.

Prediction Models

Individual Models. As stated above, an ongoing LCA study involving the selected VDOT projects requires roughness models for each of these projects. The model functions and corresponding statistics from the regression analysis are presented in Table 2.

Based on the AICc weight values, the exponential 2P model was found to be the model that best predicts IRI from the treatment age compared with the linear model. Table 3 shows the estimates and test statistics for the final IRI model selected. For the sake of simplicity, the growth rate term b in the exponential model is expressed as linear deterioration rates in the discussion. The IS81SB project was found to have a significantly lower initial IRI value (49.4 in./mi) compared with the overall project average of 85.8 in./mi. The SR40EA project was found to have a significantly high rate of IRI deterioration (7 in./mi, *linear approx. of the term, b*) compared with the overall project average of 2 in./mi/year. The average rates of change of IRI for the cement-stabilized and bitumen-stabilized FDR projects were found to be 1.5 and 5.2 in./mi/year, respectively, while the bitumen-treated CIR treatments were found to deteriorate at an average rate value of 0.7 in./mi/year.

Family-Type Models. For the FDR projects, AADTT and overlay thickness were not statistically significant parameters. The parameter estimates for fitted models for each project group by recycling method are presented in Table 3.

Table 2. Model Comparison Report with Fit Statistics

Function	General equation	Akaike information criterion (AICc)	AICc weight	SSE	RMSE
Exponential 2P	$a \times e^{(b \times Age)}$	495.4	73%	2927.9	8.1
Linear	$a + b \times Age$	497.4	27%	3019.0	8.2

Note: SSE = sum of square error; RMSE = root mean square error.

Table 3. Parameter Estimates and Statistics for International Roughness Index Prediction Models

			A			*b*		
State	Recycling method	Project/Group	Estimate	Standard error	*p*-value	Estimate	Standard error	*p*-value
Virginia	FDR lime + CIR FA + CCPR	IS81SB	49.429	6.817	<.0001	0.008	0.031	1.000
	FDR cement	SR3EB	79.201	6.968	<.0001	0.034	0.022	0.111
	FDR cement	SR3WB	89.868	7.181	<.0001	0.021	0.020	0.301
	FDR cement	SR6EB	89.995	5.751	<.0001	0.007	0.012	0.520
	FDR cement	SR13EB	91.914	5.628	<.0001	0.014	0.011	0.191
	FDR cement	SR24EB	107.000	8.460	<.0001	0.004	0.024	1.000
	FDR FA	SR40FA	89.711	6.266	<.0001	0.035	0.015	0.019
	FDR EA	SR40EA	100.774	5.906	<.0001	0.058	0.012	0.000
	CIR EA	US17NB	74.208	8.417	<.0001	0.003	0.034	0.938
	CIR FA	US17SB	84.158	8.247	<.0001	0.013	0.029	0.648
Colorado	FDR	Avg	68.944	1.794	<.0001	0.022	0.004	0.000
		LDL	50.804	1.538	<.0001	0.024	0.004	0.000
		UDL	76.579	1.556	<.0001	0.015	0.004	0.000

Note: A = initial IRI; *b* = growth constant, i.e., the frequency of growing by a factor **e**; CIR = cold in-place recycling; CCPR = cold central plant recycling; EA = emulsified asphalt; FA = foamed asphalt; FDR = full depth reclamation. Avg = not enough evidence to support a statistical difference from overall project mean; LDL = statistically different exceeding lower limit of overall project mean; UDL = statistically different exceeding upper limit of overall project mean.

The same exponential functions used for VDOT's individual models were also used for the family-type models. The deterioration in FDR projects that were completed with an initial IRI between 75 and 105 in./mi were most likely to follow predictions in the UDL group at a growth rate of 4.02 in./mi/year; between 52 and 70 in./mi, the Avg group at a rate of 1.4 in./mi/yr; between 38 and 51 in./mi, the LDL group at a rate of 0.93 in./mi/yr.

LCA Case Study

This section illustrates the relevance and applicability of the roughness prediction models developed in the paper when used in the context of an LCA study.

Goal and Scope

The goal of the study was to quantify and compare the environmental performance of selected recycling projects completed by VDOT utilizing the roughness models developed earlier in this paper. The projects were selected to cover various stabilization types (i.e., cement, foamed asphalt, and emulsion asphalt) for each recycling method (i.e., CIR, FDR), while ensuring variations in the initial roughness and annual deterioration rates. The physical functional unit was one lane-mile of a recycled pavement project with a width of 12 ft. Details about the types of mixtures, thickness of the layers and the structural number of the projects studied are given in Figure 8. The analysis period was 10 years, starting in 2018, and only the use stage was included in the system boundaries. Finally, the environmental impact assessment was limited to the global warming (GW) score for the sake of simplicity.

Inventory and Impact Assessment

Rolling resistance is the vehicle energy loss associated with pavement–vehicle interaction (PVI), as the vehicle moves over a pavement surface. Among other factors, it is affected by pavement surface texture, roughness, and stiffness, and generally, the higher the resistance to the rolling of the tires, the more fuel is consumed. Among the three mechanisms influencing rolling resistance only

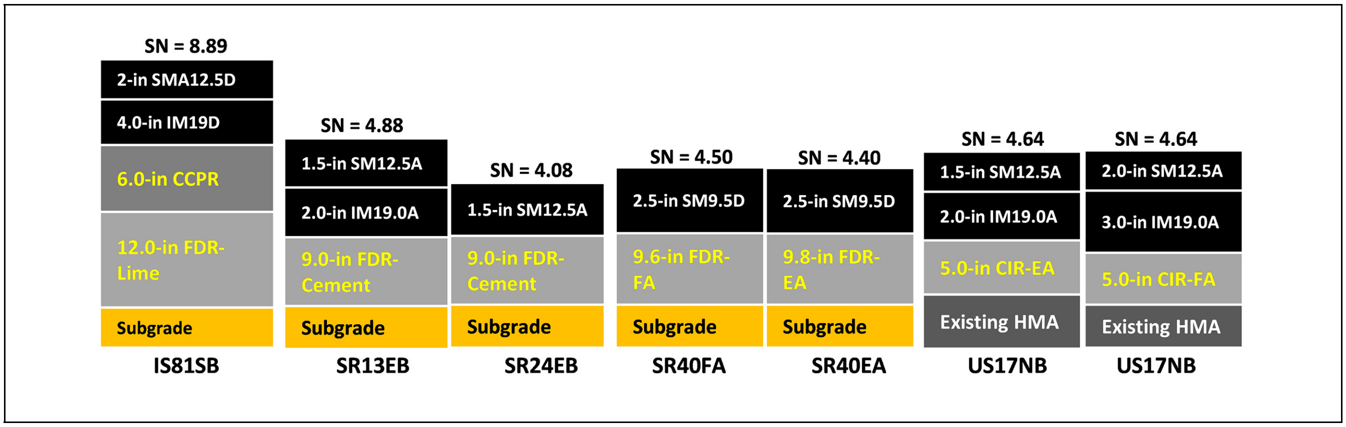

Figure 8. Details of recycled pavement projects considered in the case study.
Key to Figure 8:
SN = structural number.
IM19.0A = Intermediate mix with 19.0 mm maximum nominal aggregates, "A" for binder with performance grade 64-22.
IM19.0D = Intermediate mix with 19.0 mm maximum nominal aggregates, "D" for binder with performance grade 70-22.
SMA12.5D = Stone matrix asphalt with 12.5 mm maximum nominal aggregates, "D" for binder with performance grade 70-22.
SM9.5D = Surface mix with 9.5 mm maximum nominal aggregates, "D" for binder with performance grade 70-22.
SM12.5A = Surface mix with 12.5 mm maximum nominal aggregates, "A" for binder with performance grade 64-22.
SM19.0A = Surface mix with 19.0 mm maximum nominal aggregates, "A" for binder with performance grade 64-22.
FA = Foamed asphalt.
EA = Emulsified asphalt.
HMA = Hot mix asphalt.
CCPR = Cold central plant recycling.
FDR = Full depth reclamation.
CIR = Cold in-place recycling.

roughness was considered. The roughness prediction models developed for the projects under study were used to project the progression of roughness over a 10-year analysis period. The model developed by Ziyadi et al. (*31*) was used to calculate environmental impacts and energy consumption depending on pavement roughness and vehicle speed. The general form of the roughness–speed impact (RSI) model is given by Equation 5.

$$RSI_{t=0}^{Energy} : \hat{E}(v, IRI) = \frac{p}{v} + (k_a.IRI + d_a) + b.v + (k_c.IRI + d_c).v^2 \quad (5)$$

where:
$\hat{E}$ = estimated energy consumption per vehicle distance (kJ/mile)
v = average speed (mph)
IRI = international roughness index (in./mile)
k_a, k_c, d_a, d_c, p, b = model coefficients

The model developed by Ziyadi et al. (*31*) was calibrated with data from a series of MOVES simulations using ordinary least squares fitting method to obtain values for the model coefficients for the four classes of vehicles in the MOVES software (Table 4).

The model was reformulated and expanded to cover the complete list of the U.S. Environmental Protection Agency's Tool for Reduction and Assessment of Chemicals and Other Environmental Impacts (TRACI) (*32*) impact categories resulting from an increment rate of pollutants as a function of vehicle speed and pavement IRI (Equations 6 and 7).

$$\Delta RSI_{t=0}^{Env.} : \Delta\hat{I}(v, \Delta IRI) = [q_v.\Delta IRI/63.36].I_i(v) \quad (6)$$

$$RSI_{t=0}^{Env.} : \hat{I}(v, IRI) = I_i(v) + \Delta\hat{I}(v, \Delta IRI) \quad (7)$$

where:
$\Delta\hat{I}(v, \Delta IRI)$ = estimated additional TRACI impact i per vehicle distance (mile) at a given speed because of change in pavement roughness ΔIRI (in./mile)
q_v = % increase per one unit (63.36 in./mile) change in IRI
$I_i(v)$ = baseline TRACI impact i at a given speed and $IRI = 0$

The baseline IRI value was defined to be equal to 60 in./mi which corresponds to the boundary between an excellent and good condition rating (*33*). Where a project's initial IRI was below this threshold value (as in the case of the IS81 project), the initial IRI of that project was used as a baseline in the estimation of vehicles' energy consumption. The traffic information used as inputs to the RSI model are shown in Table 5.

Table 4. Roughness–Speed Impact Model Regression Coefficients per Vehicle Type (*31*)

Coefficient	Passenger car	Small truck	Medium truck	Large truck
K_a	6.70E−01	7.68E−01	9.18E−01	1.40E + 00
K_c	2.81E−04	1.25E−04	1.33E−04	1.36E−04
D_c	2.1860E−01	3.0769E−01	9.7418E−01	2.3900E + 00
D_a	2.1757E + 03	7.0108E + 03	9.2993E + 03	1.9225E + 04
B	−1.6931E + 01	−7.3026E + 01	−1.3959E + 02	−2.6432E + 02
P	3.3753E + 04	1.1788E + 05	1.0938E + 05	8.2782E + 04

Table 5. Traffic Information Inputs Used in the Roughness–Speed Impact Model

Traffic information (one direction)	I81	SR13	SR24	SR40	US17
Total annual average daily traffic	31,000	2,300	17,000	4,900	29,000
% Passenger cars	74.0	97.1	98.3	93.0	97.0
% Small trucks	2.0	0.9	0.8	0.8	0.4
% Medium trucks	21.0	1.4	0.3	2.2	1.1
% Large trucks	3.0	0.6	0.6	4.0	1.1
% Annual growth	5.0	3.0	3.0	3.0	3.0
Average traffic speed (mph)	70	45	60	45	55

Table 6. Cumulative Global Warming (GW) Score after 10 Years of Service

Project ID	BaselineInternational Roughness Index (IRI) (in./mi)	Initial IRI (in./mi)	IRI change rate (in./mi/year)	2018 Annual average daily traffic		Speed (mph)	GW score (tonne-CO_2-equivalent)
				Passenger cars	Total trucks		
IS81SB	49	49	0.8	22940	8060	70	20.16
SR13EB	60	92	1.4	2233	67	45	6.36
SR24EB	60	107	0.5	16711	289	60	41.40
SR40FA	60	90	3.4	4557	343	45	37.15
SR40EA	60	100	7.1	4557	343	45	51.57
US17NB	60	74	0.2	28130	752	55	35.34
US17SB	60	84	1.2	28130	752	55	70.06

Results and Interpretation

Table 6 reports the resulting 10-year GW score for the projects under consideration. For one lane-mile of pavement project, the cement-stabilized FDR projects (SR13&SR24) yielded the lowest average score at 23.9 tonne-CO_2-equivalent while the asphalt stabilized CIR projects (US17) yielded the highest average score at 52.7 tonne-CO_2-equivalent. The average GW score from the asphalt stabilized FDR projects was 44.4 tonne-CO_2-equivalent.

To understand/explain further the factors influencing the use stage impacts, the 10-year GW scores for each project, along with several input parameters, were analyzed. Generally, the higher the route traffic, the higher the GW score. However, large trucks on low volume roads traveling at low speeds between 45 and 55 mph can yield very large GW scores. For any two projects with the same traffic inputs, the GW score is higher for the project with higher initial IRI, as observed with the asphalt stabilized FDR (SR40) and asphalt stabilized CIR (US17) projects in the GW progression chart (Figure 9). The interstate project with the lowest initial IRI and low deterioration resulted in the lowest GW score even though it had comparable number of passenger cars as the US17 projects. Since the initial roughness after projects are completed and their future deterioration rates can be controlled (to some extent) by VDOT, measures should be taken to keep these factors low by incentivizing contractors to attain low initial roughness even on low volume primary and secondary roads.

Conclusions

Pavement performance prediction models are essential to pavement management programs. These models

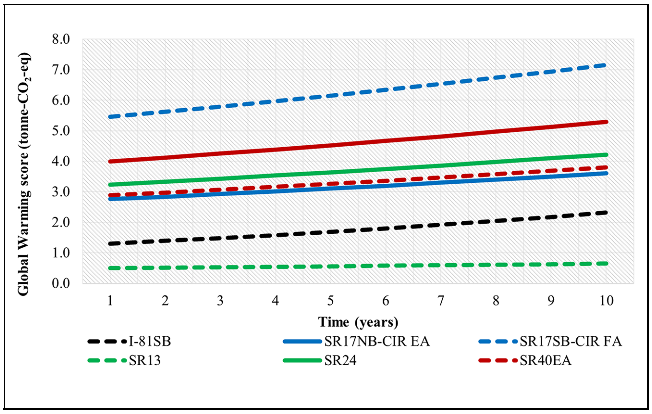

Figure 9. Progression of global warming score for various recycling projects over the analysis period.

facilitate the quantification of pavements' service life for use in LCA studies and life cycle cost analysis (LCCA). The performance data required to model these prediction curves are rarely available for pavement recycling projects. Only a few states collect data for the majority of low volume primary and secondary roads rehabilitated with various recycling methods. To aid the modeling of the M&R and use stages of an ongoing LCA study, performance models to predict IRI using family-type models and individual models were developed.

The following conclusions can be drawn from this study:

1. In the case of Colorado, FDR projects will most likely deteriorate following the "Avg group" trends at a rate of 1.4 in./mi/yr, with an initial IRI between 52 and 70 in./mi.
2. For the individual roughness models developed for Virginia, the initial IRI values and the rate of change for the treatments analyzed were found to range from 49 to 107 in./mi and from 0.7 to 5.2 in./mi/year respectively, depending on the recycling method and type of stabilization treatment.
3. Overall, the average initial IRI measurements for projects in Colorado were lower than for projects in Virginia. One possible explanation is that most of the rehabilitated projects in Colorado are rural highways (AADTT up to 2,800) compared with Virginia, where the majority of such projects are primary roads (AADTT up to 250, the exception being the interstate project with AADTT up to 7,090). Also, it is typically harder to achieve lower roughness on lower volume roads with constrained geometric standards. The rate of IRI deterioration, however, is not significantly different between the two states.
4. In addition to pavement recycling, building smoother roads is an important measure for VDOT and other state agencies to meet MAP21/FAST Act goals. Research has shown that pavements with low initial roughness after construction remain smoother over their life (*34*). Thus, focusing on building smoother roads and ensuring that the annual deterioration rate remains low are important steps to achieve low environmental burdens in the use stage.

Future Work

The few LCA studies that incorporate recycled asphalt pavements usually omit the M&R and use stage because of the lack of information on how the performance of completed projects evolves over time, and how to determine the M&R frequencies and service life of each alternative treatment. Performance models can be used to predict deterioration over time, thereby informing owner agencies on rehabilitation cycles and allowing for better budget allocation during planning. In the near future, this study will be complemented with the following:

1. The roughness prediction models developed in this research will be uploaded to a model library of an LCA tool currently under development. These models will be available for LCA studies where project-specific data is not available.
2. Together with agency rehabilitation decision matrices and trigger values, these models will be used to develop M&R schedules.
3. Models for other pavement condition parameters such as fatigue cracking, longitudinal cracking, and patching will be developed using the same methods. The set of predictors will be expanded to consider other factors, such as material properties, traffic, and climate zones as data become available for these types of pavements.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: all authors; data collection: E. Amarh, G. Flintsch, B. Diefenderfer; analysis and interpretation of results: E. Amarh, J. Santos; draft manuscript preparation: E. Amarh, J. Santos. All authors reviewed the results and approved the final version of the manuscript.

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