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Performance of US Concrete Highway Bridge Decks Characterized by Random Parameters Binary Logistic Regression

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ABSTRACT

This study employs a random parameters binary logistic regression (LR) to characterize the impact of environmental and structural parameters on concrete highway bridge deck deterioration nationwide. Two specific gaps in the literature are addressed: the use of a nationwide dataset for analysis and the implementation of a methodology to account for unobserved heterogeneity. A total of 3,262 bridge deck deterioration observations derived from the authors' Nationwide

Concrete Highway Bridge Deck Performance Inventory (NCBDPI) database were used in this study. Deterioration rate (DR) was computed as the decrease in the concrete bridge deck condition rating (CR) over time. Bridge decks with deterioration rates (DR) below a certain threshold were categorized as the lowest deteriorated bridge decks ("lowest DR") and decks with DR above a certain threshold were considered among the highest deteriorated ("highest DR"). The following variables were found to be significant in the final model: average daily truck traffic (ADTT), climatic region, distance from seawater, bridge deck area, age of bridge, type of design and/or construction, structural material design, deck protection, type of membrane, type of wearing surface, and maintenance responsibility. The results show that bridge decks with a high ADTT, age of bridge, bridge decks located in cold regions, and those that are close to seawater are associated with the "highest DR" group of bridge decks. Furthermore, type of design and/or construction and maintenance responsibility play a role in deck being associated with "highest DR".

Keywords: Highway bridge deck, concrete, performance, deterioration, National Bridge Inventory, database, random parameters binary logistic regression.

INTRODUCTION AND BACKGROUND

Over 600,000 bridges across all states represent critical components of the US transportation system, ensuring network continuity. The highest costs in bridge superstructure repair and rehabilitation are incurred through maintenance, repair, and replacement of concrete bridge decks (Li and Zhang, 2001). Understanding the causes of bridge deck deterioration is therefore central to asset management. Bridge decks, which are exposed to freeze and thaw cycles, deicers, and heavy traffic loads, are a bridge's most susceptible element. Concrete bridge deck deterioration is also a leading cause for structural deficiency (Russell 2004). According to the Federal Highway Administration (FHWA), two billion dollars are spent annually for maintenance and capital costs for concrete bridge decks (ASCE, 2013). As a direct consequence, Departments of Transportation (DOT) and the FHWA are interested to determine the reasons behind concrete bridge deck deterioration.

Previous work has attempted to model bridge condition ratings (CR) by using various deterministic and stochastic models, such as simple regression (Morcous and Hatami, 2011), multiple regression (Reardon, 2015, Tae-Hoon et al., 2006; Bolukbasi et al., 2004), Markov models (Agrawal et al., 2010; Morcous, 2006, Madanat, 1995), and Bayesian models (Attoh-Okine and Bowers, 2006). Although these methods have been used to model bridge CR, the most commonly used and widely accepted method across civil engineering disciplines is logistic regression (LR). In the transportation field, LR has been widely used to model injury severity of crashes (Dissanayake and Lu, 2002; Harb et al., 2008; Donnell and Mason, 2004; Al-Ghamdi, 2002; Mannering and Bhat, 2014; Anderson and Hernandez, 2017; Al-Bdairi et al., 2018) and route/mode choice (Abdel-Aty and Abdalla 2004; Bierlaire et al. 2010; Dalumpines and Scott 2017; Mai et al. 2015; Mishra et al. 2013; Tan et al. 2015; Vidana-Bencomo et al. 2018; Washington et al. 2009). In construction management, LR has been used to model contractors' bids and worker safety (Lowe and Parvar, 2004; Hwang and Kim, 2016; Alomari et al., 2017), disputes (Diekmann and Girard, 1995; Cheung et al., 2010), contractors performance (Wong, 2004), and risk analysis (Ozdemir, 2016; Mwesige et al., 2016; Smith and McCarty, 2009). Lastly, in structural engineering, LR models have been used to study the performance of beam-column connections (Mitra et al., 2011; Kang and Mitra,

2012) and failure mode of reinforced concrete interior beam column joints under seismic loading (Vandana and Bindhu 2017).

More closely related to this study, Ariaratnam et al. (2001) used LR to study the performance of local sewer systems in Edmonton, Canada. Age, diameter, material, waste type, and average depth of cover were modeled as the independent variable. Salman and Salem (2012) applied three different regression models, including multinomial and binary logistic regression to establish deterioration models for wastewater collection lines. Shan and Lewis (2016) used a binary LR to characterize deficient steel bridges with concrete cast-in-place deck and multibeam/girder designs based on the NBI data. The best model consisted of eight independent variables (average daily traffic (ADT), structure length, length of maximum span, bridge roadway width, state code, owner, and age), two of which, owner and state code, were insignificant. In addition to these studies, there have been recent works that use LR to study material behavior. This has included evaluating the splitting tensile strength in plain and steel fiber-reinforced concrete based on compressive strength (Behnood et al. 2015), reproducing the stiffness degradation curve of asphalt specimens during fatigue testing (Mateos et al. 2017), analysis of asphalt fatigue test results (Mateos et al. 2015), and comparing low-temperature crack intensity on pavements with high modulus asphalt concrete and conventional asphalt concrete (Rys et al. 2017).

Directly related to the current study, statistical analysis and modeling of concrete bridge deck condition data has been performed by several researchers. For example, Madanat, et al. (1995) used an ordered probit model to estimate Markovian transition probabilities from deck condition ratings contained in the Indiana Bridge Inventory (IBI), a subset of the NBI. Using the same data set, Mauch and Madanat (2001) introduced a semiparametric hazard rate model and stochastic duration models (Mishalani and Madanat, 2002) to study bridge deck condition transition probabilities. Using NBI data for the State of Wisconsin, Tabatabai, et al. (2011) evaluated different distributions for analysis of condition rating data. More, a number of published studies have specifically investigated the effects of chloride penetration on deck performance (e.g., Williamson, 2007; Lounis, 2000; Wedding et al., 1983).

While some published work has focused on concrete bridge deck CR, no attempts have been made to use a nationwide dataset. Some studies have used subsets of a nationwide dataset, but focus on a disaggregated picture (i.e., state or region). In addition, since these works have been completed, the NBI dataset has substantially grown and provides researchers with more information for analysis. A nationwide model can provide a holistic view of variables that impact bride deck deterioration. More, using region-specific indicators (i.e., climatic characteristics), the nationwide model can potentially help in identifying problematic regions regarding bridge deck deterioration. This, in turn, can lead to more focused analyses based on needs, as well as define regions based on such characteristics. As it pertains to structural and bridge engineering applications, as well as applications to concrete bridge decks, the LR analyses do not address what has become a prevalent issue in today's datasets: unobserved heterogeneity (i.e., unobservables). As such, the current study distinctively fills these gaps in the literature. To the best of the authors' knowledge, this is the first attempt at modeling NBI data on a nationwide scale and the first attempt at overcoming a key limitation within the NBI data by utilizing a random parameters estimation approach to account for unobserved heterogeneity.

Objective and Motivation

The objective of this study was to characterize the effect of various environmental, structural, construction, climatic, and traffic related parameters on concrete bridge deck performance. Specifically, the focus was on two extreme groups: bridges that have experienced the highest and lowest levels of deterioration. A random parameters binary LR framework was developed to quantify the impact of various parameters on the likelihood of a bridge deck being associated with the group of highest and lowest deterioration rates (DR), while also accounting for a key limitation within the data: unobserved heterogeneity. This method uniquely fills a gap in literature with its application to bridge deck deterioration.

DATASET

The authors have created a Nationwide Concrete Bridge Deck Performance Inventory (NCBDPI) database (Ghonima et al., 2018) with the specific goal of adopting a more statistical and data mining approach to understanding concrete highway bridge deck performance. The primary source of information for the NCBDPI database is the National Bridge Inventory (NBI) database (FHWA, 2017). For this research, a number of NBI items were extracted and complemented with additional parameters such as climatic region, distance to seawater, bridge age, and deterioration rate (DR). One of the key performance metrics available in the authors' NCBDPI database is the DR, which is defined as follows (Ghonima et al., 2018):

$$\mathrm{DR} = {}^{(\mathrm{CR}' - \mathrm{CR}'')}\big/_{\mathrm{TICR}} \qquad \text{(Eq. 1)}$$

where CR' and CR" are the bridge deck condition ratings (CR) at the beginning and end of a series of consecutive CR, and TICR (= time-in-condition rating) is the duration in years, as illustrated in Fig. 1. Deterioration is referred to as the observed decrease in CR. Also, maintenance is used to refer to any deck improvement action that increases the CR, similar to many published materials in the past. Note that the DR could only be calculated when CR' > CR'', i.e. when deterioration occurred. For the sample deck shown in Fig. 1, one fully observable cycle of deterioration occurs. DR was employed in this analysis as the independent variable because of its ability to capture the rate of change of CR, which TICR cannot. This emerged from discussions with a number of stakeholders involved in the overall research (Ghonima et al., 2018), in particular from bridge inspectors that have found some bridge decks to deteriorate much faster than others.

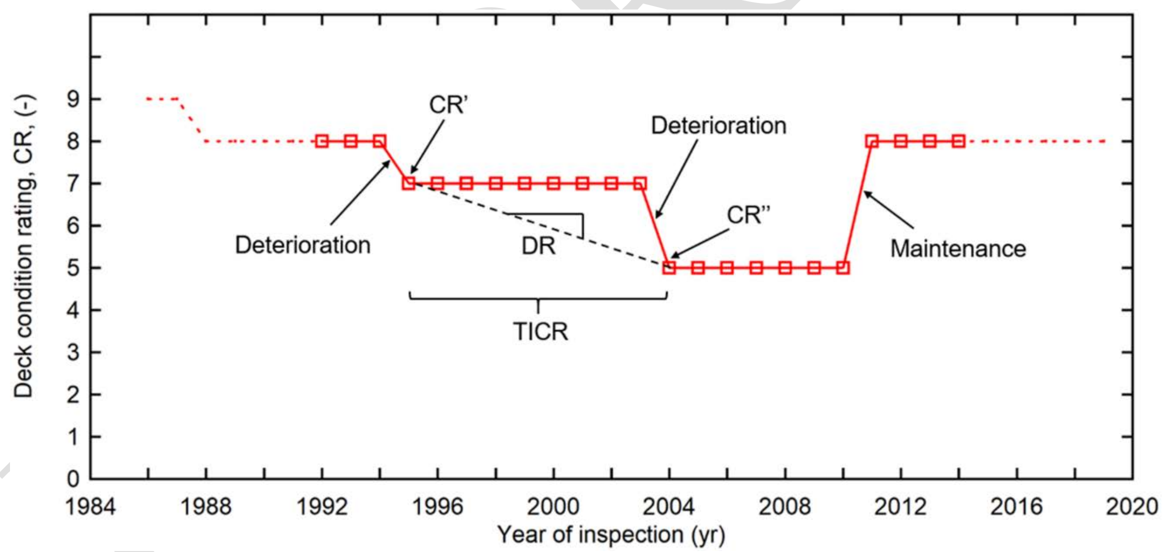

Fig. 1. Sample concrete bridge deck condition rating (CR) with computed independent variables. Note: A decrease and an increase in the assigned CR is considered deterioration and maintenance, respectively. Data considered in this analysis include years 1992 to 2014.

This study regarded concrete bridge decks with DR ≤ 0.056 as the group with the lowest deterioration rate ("lowest DR") with a total of 1,569 observations. DR = 0.056 means that a bridge deck was assigned the same CR for approximately 18 years, i.e. TICR = 18, before experiencing a one-unit CR decrease. Concrete bridge decks assigned a DR ≥ 2 were considered as part of the group associated with the highest deterioration rate ("highest DR") with a total of 1,693 observations. DR = 2 means that the bridge was assigned the same CR for one year, i.e. TICR = 1, before a two-unit CR decrease occurred. The thresholds of 0.056 and 2 were selected after careful analysis and discussing with practitioners, bridge engineers from two state DOTs, and the FHWA what might be a reasonable TICR before a bridge deck is assigned a lower CR. While ideally, a physics-based classification would be applied to select boundaries, this is not possible here given that the CR are based on qualitative visual inspection results that include a number of deterioration mechanisms. As can be observed, using this approach produced two groups with similar numbers of samples.

The lowest and highest DR groups were coded as binary variables and assigned 0 and 1, respectively. The reason behind taking these values was to make a clear distinction between the best and worst performing concrete bridge decks.

Table 1 presents a summary of the variables included in the study and/or their frequencies. Refer to Ghonima, et al. (2018) for more details. Following are some observations: The average ADTT on the bridges in the dataset is nearly 1000. A significant majority of the bridges has cast-in-place decks. In terms of structural material and/or design, close to 80% of the bridge decks are part of either a simple or continuous span concrete or prestressed concrete bridge system. Close to 75%

of the bridges have no deck protection and more than 75% of the bridges have no membrane. A majority of the bridge decks captured in the sample were in rural areas. Finally, a state highway agency was responsible for the maintenance of nearly two-thirds of the bridges.

Table 1. Summary statistics and counts for the bridge deck variables included in this study.

Continuous variables	**Minimum**	**Mean**	**Maximum**
Distance from Seawater (km)	0	5,655	16,619
Deck Area (ft^2) – computed from NBI Items 49 and 51	2370	74,304	4,080,000
Average Daily Truck Traffic (ADTT) – NBI Item 109	0	983	25,432
Bridge Age (years) – computed from NBI Items 27 or 106	0	39.8	122
Number of Lanes (-) – NBI Item 28	1	1.45	11
Categorical variables	**Categories**	**Frequency**	**Percentage**
Deck Structure Type – NBI Item 107	Cast-in-Place	2,899	88.0
	Concrete Precast Panels	397	12.0
Structural Material/Design – NBI Item 43a	Concrete – simple span	764	23.2
	Concrete – continuous	454	13.8
	Prestressed concrete – simple	872	26.5
	Prestressed concrete – continuous	515	15.6
	Steel – simple span	554	16.8
	Steel – continuous	137	4.2
Climatic Region (IECC)	Very Hot	215	6.5
	Hot	919	27.9
	Average	553	16.8
	Cold	1,045	31.7
	Very Cold (VC)	444	13.5
	Extremely Cold (EC)	33	1.0
	Average Marine (AM)	38	1.2
	Hot Marine (HM)	49	1.5
Deck Protection – NBI Item 108c	None	2,421	73.5
	Epoxy-Coated Reinforcing	487	14.8
	Galvanized Reinforcing	16	0.5
	Other Coated Reinforcing	4	0.1
	Cathodic Protection	2	0.1
	Polymer Impregnated	11	0.3
	Internally Sealed	1	0.0
	Unknown	329	10.0
	Other	25	0.8
Type of Membrane – NBI Item 108b	None	2,566	77.9
	Built-up	106	3.2
	Preformed Fabric	99	3.0
	Epoxy	23	0.7
	Unknown	403	12.2
	Other	99	3.0

Table 1. (Continued)

Type of Wearing Surface – NBI Item 108a	None	207	6.3
	Monolithic Concrete	1,239	37.6
	Integral Concrete	248	7.5
	Latex Concrete or Similar Additive	131	4.0
	Low-Slump Concrete	59	1.8
	Epoxy Overlay	36	1.1
	Bituminous	1,160	35.2
	Timber	88	2.7
	Other	128	3.9
Functional Classification of Inventory Route – NBI Item 26	Rural	2,339	71.0
	Urban	957	29.0
Type of Design and/or Construction – NBI Item 43b	Slab	664	20.1
	Stringer/multi-beam or girder (SB)	1,628	49.4
	Girder and floor beam system	60	1.8
	Tee beam (TB)	275	8.3
	Box beam or girders – multiple (BBM)	387	11.7
	Box beam or girders – single or spread (BBS)	36	1.1
	Frame	17	0.5
	Truss – through	60	1.8
	Arch-deck	17	0.5
	Channel beam (CB)	152	4.6
Maintenance Responsibility – NBI Item 21	State Highway Agency	2,134	64.7
	County Highway Agency (CHA)	838	25.4
	Town or Township Highway Agency	139	4.2
	City of Municipal Highway Agency (CMHA)	140	4.2
	State Toll Authority (STA)	45	1.4

ANALYSIS

Logistic Regression

Logistic (or logit) regression (LR), a modeling approach that describes the occurrence probability of an outcome or event, is a method of fitting a regression curve to determine the outcome probability of said outcome or event as a function of covariates (i.e., independent variables). In the case of binary logistic regression, in which the outcomes are binary (i.e., 0 or 1), the probability that the outcome takes on the value 1 is determined through a set, or function, of covariates (Train 2009; Washington et al. 2011; Greene 2018). Covariates can be continuous, categorical, or both.

For the current study, the outcome being modeled is bridge deck deterioration rate (DR), where concrete bridge decks associated with the two groups “lowest DR” and “highest DR” were coded as 0 and 1, respectively. Because some of the independent variables are categorical, several indicator variables were created to differentiate the different categories. But, to avoid multicollinearity issues, only k-1 indicators from the same categorical variable could be included in the final model specifications (Yannis, et al., 2011). For example, the variable category Climatic Region (Table 1) consists of 8 different sub-categories; therefore, at most, seven indicator variables indicating climatic region can be included in final model specifications.

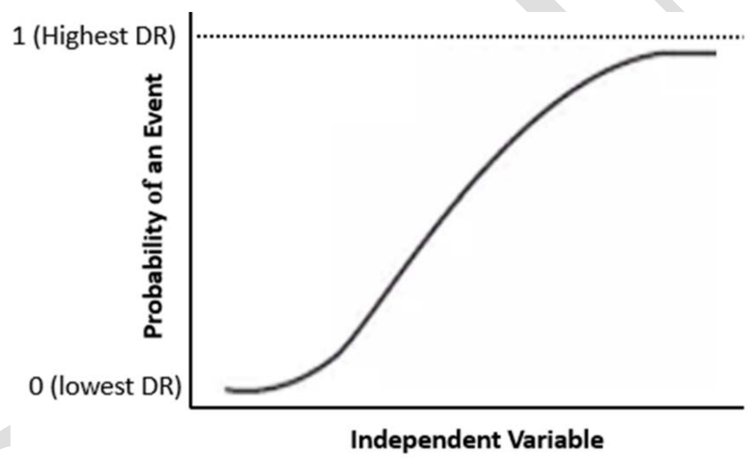

Fig. 2. S-shape probability function used in binary logistic regression (LR).

The probability function of a logit model that describes a dependent variable in terms of independent variables can be represented as an S-shape function (Fig. 2), where the logit probability is represented as (McFadden 1981; Train 2009):

$$P_n(i) = \frac{e^{(\beta_i X_{in})}}{\sum_{\forall i} e^{(\beta_i X_{in})}} \qquad \text{(Eq. 2)}$$

where $P_n(i)$ is the probability of observation n having outcome i, β_i is a vector of estimable parameters indexed by outcome i, and X_{in} is a vector of explanatory variables (e.g., climatic region, wearing surface, etc.) used to determine the outcome probability. Now, by satisfying the alternative-specific-constant rule in logit modeling (see Train (2009) for a full discussion), normalizing one of the outcomes to utilize a binary logit framework for the current study results in the following (Train 2009; Washington et al. 2011; Hensher et al. 2015; Greene 2018):

$$P_n(i) = \frac{e^{(\hat{\beta})}}{1 + e^{(\hat{\beta})}} \text{, where } \hat{\beta} = \beta_0 + \beta_1 X_{1,n} + \cdots + \beta_i X_{i,n} + \varepsilon_{in} \qquad \text{(Eq. 3)}$$

where ε_{in} is a Type I Extreme Value distributed error term and all other terms have been defined previously. The error term attempts to capture unobservables within the data; that is, attributes that are unobserved by the analyst (variables not included or collected in the data). In the case of the current study, each and every variable that contributes to the deterioration of a bridge deck is likely not included in the utilized data. This could be a result of several factors, such as the data is unavailable or the data is not collected. Therefore, these variables not included in the data are considered unobservables. These unobservables can result in unobserved heterogeneity, which if not accounted for, can result in biased estimates, incorrect inferences, and inaccurate recommendations. In addition, unobserved heterogeneity can be a result of variation within an existing variable due to unobserved characteristics. For instance, climatic regions are available, but no information on weather irregularities are included. This unobservable can be “embedded” in climatic region variables; therefore, resulting in unobserved heterogeneity (the reader is referred to Mannering et al. (2016) for a full discussion on methods and implications as it pertains to unobserved heterogeneity in econometric analyses).

As such, the current study attempts to account for these unobservables by estimating a model with random parameters. As opposed to a traditional logit model, in which coefficient estimates are assumed to have the same sign (or effect) across all observations, a random parameters model allows beta estimates to vary across observations based on a distribution defined by the analyst (i.e., beta will be negative for a proportion of observations and positive for the remainder, or vice-versa). To estimate such a model, a mixing distribution is introduced to the binary logit formulation in Eq. (2) (Greene 2016a; McFadden and Train 2000; Train 2003; Washington et al. 2011):

$$P_n(i \mid \phi) = \int_x \frac{e^{(\hat{\beta})}}{1 + e^{(\hat{\beta})}} f\left(\hat{\beta} \mid \phi\right) d\hat{\beta} \qquad \text{(Eq. 4)}$$

where $P_n(i \mid \phi)$ is now the weighted outcome probability of $P_n(i)$ taking on the value 1 conditional on $f\left(\hat{\beta} \mid \phi\right)$. In particular, $f\left(\hat{\beta} \mid \phi\right)$ is the density function of $\hat{\beta}$ with distributional parameter ϕ. The density function, $f\left(\hat{\beta} \mid \phi\right)$, is what allows parameter estimates to vary across observations so as to permit $\hat{\beta}$ to account for observation-specific variations of the effect of X on $P_n(i \mid \phi)$ (Washington et al. 2011). In general, the density function is specified to be normally distributed and is the distribution assigned to $f\left(\hat{\beta} \mid \phi\right)$ in the present study (Greene 2016b; Hensher et al. 2015).

Due to difficulties in computing the probabilities in such a model, a simulation-based approach is applied to estimate parameters. To simulate, previous work has shown that Halton draws provide a preferred alternative to merely random draws; therefore, Halton draws are used in the current study (Bhat 2003; Halton 1960; Train 2000). Using Halton draws, the simulated probabilities are inserted into the log-likelihood function of the logit model, thus providing a simulated log-likelihood (Train 2009; Washington et al. 2011):

$$SLL = \sum_{n=1}^{N} \sum_{i=1}^{I} \delta_{in} \ln[P_n(i \mid \phi)] \qquad \text{(Eq. 5)}$$

where N is the total number of observations, I is the total number of outcomes, δ_{in} is equal to 1 if the observed outcome for observation n is i and zero otherwise, and all other terms have been defined previously. Using Halton draws, $P_n(i \mid \phi)$ are approximated by drawing values of β from the density function (given values of the distribution parameter ϕ) and used to estimate the logit probability shown in Eq. (2). This is done many times and the computed logit probabilities are then summed and averaged to obtained the simulated probability, $P_n(i \mid \phi)$.

LR differs from multiple linear regression with respect to the interpretation of the coefficients of the independent variables. In multiple linear regression, the beta estimates can be interpreted as a marginal effect (i.e., the effect on a dependent variable due to a one-unit increase in explanatory variable, X). However, this is not the case with LR models. In some cases, LR coefficients are interpreted using the log of the odds (i.e., odds ratios). However, odds ratios are most often seen in the statistics literature (Ramsey and Schafer 2012), whereas pure econometrics analyses almost exclusively consist of marginal effects to interpret parameter estimates (Greene 2018; Greene and Hensher 2010; Hensher et al. 2015). Therefore, the current study uses marginal effects to interpret estimates from the LR model.

As described previously, marginal effects measure the impact of an explanatory variable, due to a one-unit increase, on the probability that the outcome takes on the value 1. For continuous explanatory variables, marginal effects are computed as (Greene 2016a, 2018):

$$\frac{\partial P_n(i)}{\partial X_{ink}} = [1 - P_n(i)]P_n(i)\beta_{n(i)} \qquad \text{(Eq. 6)}$$

where $\frac{\partial P_n(i)}{\partial X_{ink}}$ is the derivative of the probability of observation n having deterioration outcome i. However, for indicator variables, marginal effects are computed differently. For indicator variables (the majority of variables used in the present study), marginal effects are defined as the difference of the estimated probabilities when indicator variable X_{ink} changes from zero to one while all other variables remain equal to their means (remain constant) (Greene 2018):

$$M_{X_{ink}}^{P_n(i)} = \Pr\left[P_n(i) = 1 | \mathrm{X}_{(X_{ink})}, X_{ink} = 1\right] - \Pr\left[P_n(i) = 1 | \mathrm{X}_{(X_{ink})}, X_{ink} = 0\right] \qquad \text{(Eq. 6)}$$

where $\mathrm{X}_{(X_{ink})}$ is the mean of all other variables (the variables that are being held constant) while X_{ink} changes from zero to one.

Logistic Regression Coefficients

This study began by generating several indicators from the categorical variables and creating natural logarithm variables from variables that had large values, as this would result in marginal effects of essentially zero (marginal effects are discussed in the coming sections) (i.e., ADTT, deck area, distance from seawater, etc.). Using a stepwise procedure, in which the model was built-up from just the constant, Table 2 shows that 25 variables were found to have a statistically significant impact on bridge deck deterioration. In addition, as anticipated, model estimates show that the data is susceptible to large amounts of heterogeneity (i.e., unobservables). This is observed by the 9 variables with normally distributed estimated random parameters. That is, these 9 variables have heterogeneous effects on bridge deck deterioration.

Table 2. Random parameters binary logit model specifications.

Variable	Coefficient	Std. Error	*t*-statistic	Marginal Effects
Constant	4.660	0.686	6.79	
Natural Logarithm of Deck Area [DA]	-0.472	0.064	-7.42	-0.117
Natural Logarithm of ADTT [ADTT]	0.320	0.025	12.58	0.079
Natural Logarithm of Distance to Seawater [SW]	-0.255	0.028	-9.23	-0.063
Age of Bridge [AGE]	-0.028	0.003	-9.62	-0.007
(Std. Dev. Of Normally Distributed Random Parameter)	*(0.038)*	*(0.002)*	*(17.89)*	
Structural Material Design				
1 if Continuous Concrete, 0 Otherwise [CONCR]	0.545	0.184	2.97	0.135
(Std. Dev. Of Normally Distributed Random Parameter)	*(3.266)*	*(0.269)*	*(12.13)*	
1 if Simple Prestressed Concrete, 0 Otherwise [SMPCR]	1.856	0.164	11.33	0.459
1 if Continuous Prestressed Concrete, 0 Otherwise [CONPCR]	1.045	0.200	5.23	0.258
(Std. Dev. Of Normally Distributed Random Parameter)	*(3.417)*	*(0.268)*	*(12.77)*	
1 if Simple Span Steel, 0 Otherwise [SMSTL]	0.923	0.167	5.54	0.228
(Std. Dev. Of Normally Distributed Random Parameter)	*(1.357)*	*(0.165)*	*(8.25)*	
1 if Continuous Steel, 0 Otherwise [CONSTL]	0.525	0.254	2.07	0.130
Climatic Region				
1 if Very Hot, 0 Otherwise [VH]	-1.694	0.238	-7.13	-0.419
1 if Average, 0 Otherwise [AVG]	-0.778	0.133	-5.84	-0.193
(Std. Dev. Of Normally Distributed Random Parameter)	*(0.886)*	*(0.169)*	*(5.23)*	
1 if Extremely Cold, 0 Otherwise [EXCLD]	4.252	0.571	7.44	1.052
1 if Hot Marine, 0 Otherwise [HMAR]	1.252	0.482	2.60	0.310
Deck Protection				
1 if Epoxy-Coated Reinforcing, 0 Otherwise [EPOX]	2.273	0.254	8.94	0.563
(Std. Dev. Of Normally Distributed Random Parameter)	*(6.187)*	*(0.488)*	*(12.67)*	
1 if Polymer Impregnated, 0 Otherwise [POLY]	3.444	1.213	2.84	0.852

Table 2. (continued)

Type of Membrane				
1 if Built-Up Membrane, 0 Otherwise [BUM]	0.911	0.219	4.16	0.226
Type of Wearing Surface				
1 if No Wearing Surface, 0 Otherwise [NOSUR]	1.735	0.241	7.18	0.429
(Std. Dev. Of Normally Distributed Random Parameter)	*(2.218)*	*(0.345)*	*(6.42)*	
1 if Integral Concrete, 0 Otherwise [ICON]	1.947	0.250	7.79	0.482
1 if Latex Concrete or Similar Additive, 0 Otherwise [LATEX]	0.730	0.232	3.14	0.181
1 if Low-Slump Concrete, 0 Otherwise [LSLMP]	1.866	0.306	6.10	0.462
Type of Design and Construction				
1 if Girder and Floor Beam System, 0 Otherwise [GFBS]	2.307	0.410	5.62	0.571
1 if Tee Beam, 0 Otherwise [TB]	1.346	0.198	6.80	0.333
1 if Truss (Through), 0 Otherwise [TRS]	1.991	0.381	5.22	0.493
Maintenance Responsibility				
1 if County Highway Agency, 0 Otherwise [CNTY]	1.089	0.150	7.26	0.270
(Std. Dev. Of Normally Distributed Random Parameter)	*(3.393)*	*(0.215)*	*(15.76)*	
1 if City of Municipal Highway Agency, 0 Otherwise [CITY]	0.404	0.259	1.56	0.100
(Std. Dev. Of Normally Distributed Random Parameter)	*(2.183)*	*(0.384)*	*(5.68)*	
Model Statistics				
Number of Observations	3,262			
Log-Likelihood at Zero	-1,953.98			
Log-Likelihood at Convergence	-1,484.24			
McFadden Pseudo R-Squared	0.24			

Referring to Table 2, final model specifications show that significant variables were found in the following categories: Maintenance Responsibility, Type of Design and/or Construction, ADTT, Climatic Region, Distance to Seawater, Deck Area, Age of Bridge, Structural Material Design, Deck Protection, Type of Membrane, and Type of Wearing Surface. Those variables were chosen through a stepwise procedure based on (1) their statistical significance and (2) were assumed to play a role in bridge deck performance.

The beta estimates and independent variables from the final model specifications can now be substituted into the right-hand side of Eq. 3 to give:

$$\log\left(\frac{P_n(i)}{1-P_n(i)}\right) = 4.660 - 0.472 \cdot \ln(\mathrm{DA}) + 0.320 \cdot \ln(\mathrm{ADTT}) - 0.255 \cdot \ln(\mathrm{SW}) - 0.028 \cdot \mathrm{AGE} + 0.545 \cdot \mathrm{CONCR} + 1.856 \cdot \mathrm{SMPCR} + 1.045 \cdot \mathrm{CONPCR} + 0.923 \cdot \mathrm{SMSTL} + 0.525 \cdot \mathrm{CONSTL} - 1.694 \cdot \mathrm{VH} - 0.778 \cdot \mathrm{AVG} + 4.252 \cdot \mathrm{EXCLD} + 1.252 \cdot \mathrm{HMAR} + 2.273 \cdot \mathrm{EPOX} + 3.444 \cdot \mathrm{POLY} + 0.911 \cdot \mathrm{BUM} + 1.735 \cdot \mathrm{NOSUR} + 1.947 \cdot \mathrm{ICON} + 0.730 \cdot \mathrm{LATEX} + 1.866 \cdot \mathrm{LSLMP} + 2.307 \cdot \mathrm{GFBS} + 1.346 \cdot \mathrm{TB} + 1.991 \cdot \mathrm{TRS} + 1.089 \cdot \mathrm{CNTY} + 0.404 \cdot \mathrm{CITY} \quad \text{(Eq. 7)}$$

As mentioned previously, the more common way to interpret parameter estimates in an econometric analysis is to look at marginal effects (see Table 2). Taking the natural log of ADTT (continuous variable) as an example, and holding all other variables equal to their means (held constant), increasing the natural logarithm of ADTT by unity significantly increases the probability of high bridge deck deterioration by 7.9%. Interpretation of marginal effects on log-transformed variables follows that of Haleem and Abdel-Aty (2010). While the interpretations are similar for the indicator variables, they are relative to "otherwise." This indicates that inference can be made relative to all other categories, or inference can be made directly on the indicator variable. A full discussion of significant variables and their effects on bridge deck deterioration probability is provided in the discussion of significant variables.

Variable Importance

To assess the relative importance of the individual predictors in the model, the absolute value of the t-statistic for each model variable can be used to obtain variable importance. All measures of importance were scaled to have a maximum value of 100. As can be seen in Fig. 3, ADTT, simple prestressed concrete, age of the bridge, and distance to seawater are the most influential variables.

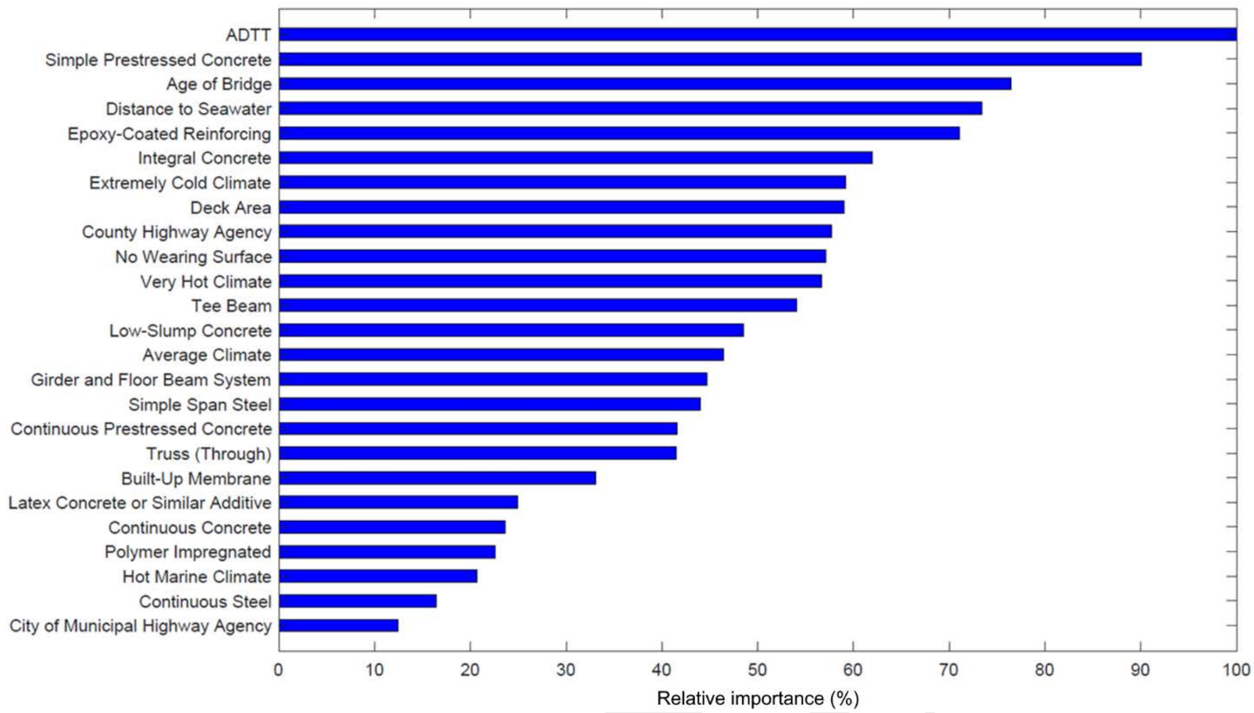

Fig. 3. Relative importance of model parameters based on *t*-statistic (scaled to 100).

Variable Elasticities for Continuous Variables

In addition to interpreting estimates through marginal effects, an alternate method consists of using elasticities to interpret parameter estimates. In cases where the explanatory variables have large values (e.g., ADTT, deck area, distance to seawater), the effect of a 1% increase on the probability of the outcome taking on the value 1 may be more intuitive (Ulfarsson and Mannering, 2004). Consider a one-unit increase in ADTT to a 1% increase in ADTT, for example. Using elasticities can provide a unit-less measure to choice sensitivity to each independent variable (Yannis et al., 2011; Broach, 2012). However, the calculations for elasticities is different. In NLOGIT, elasticities of the probability are computed as (Greene 2016b):

$$\frac{\partial \log E[y \mid X]}{\partial \log X_{ink}} = \frac{X_{ink}}{E[y \mid X]} \times M_{X_{ink}}^{P_n(i)} \quad \text{(Eq. 8)}$$

A naïve pooling method was used where elasticities for each observation were calculated and the mean of all cases was taken as the elasticity (Hensher et al., 2015) (Table 3).

Table 3. Elasticities for continuous variables.

Continuous Variable	Elasticity
Natural Logarithm of ADTT	0.731
Natural Logarithm of Deck Area	-2.724
Natural Logarithm of Distance to Seawater	-1.089

As can be seen in Table 3, following the interpretation from Wooldridge (2010) and Greene (2018), the elasticity of the natural log of ADTT means that a 1% increase in the natural log of ADTT results in an increase of bridge deck deterioration probability by 73.1%. On the other hand, a 1% increase in deck area and a 1% increase in distance to seawater (their natural logarithms) result in a decrease in bridge deck deterioration probability by 272% and 109%, respectively. These results suggest that bridge deck area and distance to seawater have a significant impact on bridge deck deterioration.

Statistical Evaluation of the Final Model

To evaluate the statistical fit of the LR model, a log-likelihood ratio test was performed. In a binary LR, a model having more predictors is expected to provide a better fit to the data than a model having fewer predictors. A log-likelihood ratio test estimates the overall explanatory power of a model to determine if the independent variables chosen for the model improve the overall model fit. In the case of the current study, being that a model with random parameters was estimated, the log-likelihood ratio test determines if the log-likelihood of the random parameters model is of more significance than the log-likelihood with fixed parameters (model not accounting for data unobservables). Therefore, the log-likelihood ratio test is computed as follows (Washington et al. 2011):

$$\chi^2 = -2[LL(\beta_{\text{Fixed}}) - LL(\beta_{\text{Random}})] \qquad \text{(Eq. 9)}$$

where $LL(\beta_{\text{Fixed}})$ is the log-likelihood at convergence of the fixed parameters model, $LL(\beta_{\text{Random}})$ is the log-likelihood at convergence of the random parameters model, and χ^2 is a chi-square statistic with degrees of freedom equal to the number of estimated random parameters in β_{Random}. In the log-likelihood ratio test, the null hypothesis is that the fixed parameters model is true and the alternative hypothesis is that the random parameters model is true. Thus, if the p-value for the log-likelihood ratio test is statistically significant, there is evidence that the random parameters model is preferred and the null hypothesis can be rejected (Washington et al. 2011) (Table 4).

Table 4. Likelihood ratio test results.

Model	Parameters	Log-Likelihood	Degrees of Freedom	χ^2	p-value
Fixed	28	-1,953.98	-	-	-
Random	28	-1,484.24	9 (Estimated Random Parameters)	939.48	0.000

As seen from Table 4, the null hypothesis that the fixed parameters model is preferred is rejected. In particular, the overall model fit of the random parameters model is of more significance with well over 99% confidence. Moreover, when comparing the log-likelihood at zero (estimated with only the constant) to the log-likelihood at convergence of the random parameters model, a McFadden Pseudo R-Squared value of 0.24 is obtained. A model with a McFadden Pseudo R-Squared value of this magnitude is considered to have an "exceptional" fit (McFadden 1973, 1977, 1981).

DISCUSSION OF SIGNIFICANT VARIABLES

To ease discussion, a synthesis of significant variables will be done by variable category as defined in Table 2. To begin, the variables not related to a specific category will be discussed (ADTT, distance to seawater, and deck area have been discussed previously): age of bridge. Both of these variables are significant and have heterogeneous effects (i.e., they have normally distributed random parameters). As it pertains to the age of the bridge, model estimations show an estimated parameter mean of -0.028 and an estimated standard deviation of 0.038. Based on these estimations, the normal distribution curve indicates that the estimated parameter mean is greater than zero for 23.1% of bridge decks and less than zero for 76.9% of bridge decks. In other words, as bridge age increases, 23.1% are more likely to have high deterioration and 76.9% are less likely. The heterogeneous effects here may be attributed to corrosion. In regards to corrosion, it has been proposed that corrosion rate decreases with age (Tabatabai and Lee 2006; Vu and Stewart 2000). Therefore, as age increases, it may be less likely to observe high deterioration. However, some environments are more severe than others and the natural protection from corrosion due to the high alkalinity of cement-based materials can be reduced (Bien et al. 2007; Gucunski et al. 2011). For the latter, this occurs due to chloride ingress, which upon reaching the rebar will destroy the passivity layer. In such a case, corrosion as a result of age can lead to an increase in likelihood of high deterioration.

Structural Material/Design (NBI Item 43A)

Five variables related to structural material/design, which describes the bridge superstructure material and whether it is simple-span or continuous, are found to be significant. The assumption here is that when the bridge is considered continuous, so is the deck, and vice versa. Of these five variables, three have heterogeneous effects on deterioration probability. The first structural material/design variable with heterogeneous effects is: concrete continuous. Referring to model estimations, this parameter has an estimated mean of 0.545 and an estimated standard deviation of 3.266. Using the normal distribution curve, these estimates indicate that 43.4% of concrete continuous decks are less likely to have high deterioration and 56.7% are more likely. Being that cracking can lead to bridge deck deterioration by allowing water and chemicals to penetrate the deck, this random parameter may be attempting to capture unobservables related to cracking (Schmitt and Darwin 1995). Specifically, cracking is greater in continuous span decks due to the negative bending moment regions at the interior supports (Grace et al. 2004). In addition, it has been shown that the severity of cracking is directly correlated with the severity of vibrations (Alampalli et al. 2002). Therefore, the proportion of continuous concrete bridge decks that are less likely to have high deterioration may be experiencing fewer vibrations at a lesser severity, in addition to less cracking (the bridges have shorter spans that result in less cracking). Also with a normally distributed estimated random parameter is the indicator for continuous prestressed concrete. Referring to model estimations, the estimated parameter mean of 1.045 and estimated standard deviation of 3.417 indicate that 38% of bridge decks supported by a continuous prestressed concrete bridge superstructure are less likely to have high deterioration and 62% are more likely. The non-homogenous nature in this variable may also be attributed to cracking. That is, prestressed concrete without longitudinal cracks reduces the likelihood of deterioration due to corrosion and/or freeze-thaw cycles. However, if transverse cracking takes place (i.e., parallel to the transverse prestressing), there is a high likelihood of early deck deterioration, as well as exposed tendons that can be prone to corrosion (Poston et al. 1989). This random parameter may be capturing these differences in cracking among decks supported by prestressed concrete bridge superstructures.

The third variable, also with a normally distributed random parameter, is the indicator for concrete bridge decks supported by simple-span steel bridge superstructures. With an estimated parameter mean of 0.923 and a standard deviation of 1.357, 24.8% of bridge decks supported by simple span steel bridge superstructures are less likely to experience high deterioration and 75.2% are more likely to experience high deterioration relative to decks supported by simple span concrete superstructures. The heterogeneous nature of this variable may be linked to end restraints of steel superstructures and shrinkage (Russell 2004). In addition, concrete deck cracking is observed more in curved bridges than in straight bridges and more cracking is observed as restraint increases, steel configuration, girder depth, or close girder spacing (Russell 2004). These attributes impacting bridge deck deterioration are unobserved in the NBI data; therefore, the randomness in this parameter may be accounting for these unobservables that can result in varying effects across bridge decks.

Deck Protection (NBI Item 108C)

For deck protection variables, two are found to be significant. Of the two variables, the first with a normally distributed random parameter is epoxy-coated reinforcing bars. Therefore, with an estimated parameter mean of 2.273 and a standard deviation of 6.187, 35.7% of decks protected by epoxy-coated reinforcing bars are less likely to experience high deterioration and 64.3% of decks are more likely to experience high deterioration. The heterogeneous nature of this variable is likely related to the location of deck deterioration. For instance, Lawler et al. (2011) found that bridge decks with epoxy-coated reinforcing bars have less than 0.15% corrosion-induced deterioration. However, Lawler et al. (2011) also observed deterioration in bridge decks with epoxy-coated reinforcing bars, specifically at cracks or construction joints. This finding shows that a large proportion of bridge decks with epoxy-coated reinforcing may have considerable deterioration stemming from cracks and/or construction joints, suggesting that these locations be investigated further for such bridge decks.

Type of Membrane (NBI Item 108B)

Of the several variable categories, type of membrane is the only category to have just one significant variable. In particular, bridge decks with a built-up membrane have a 22.6 percentage point increase in probability of suffering from high deterioration, according to marginal effects. This finding may be attributed to this type of membrane being popular in the 1960s and, in nearly all cases, having been discontinued (Manning 1995). For built-up membranes, two layers are used: glass fabric and coats of coal-tar pitch emulsion (Hagenbuch 1971; Manning 1995). However, over time, condition surveys showed that the glass fabric being used in built-up membranes was rotting (Manning 1995). These findings suggest that built-up membranes increase the probability of being associated with high deterioration as a result of built-up membrane characteristics being prone to rotting, specifically the glass fabric.

Type of Wearing Surface (NBI Item 108A)

Four wearing surfaces have significant impacts on high deck deterioration probability, including integral concrete, latex concrete, low-slump concrete, and no wearing surface. Of the four significant wearing surfaces, one is found to have deck-specific variation based on a normal distribution: bridge decks with no wearing surface. Specifically, with a mean of 1.735 and a standard deviation of 2.218, 21.7% of bridge decks with no wearing surface are less likely to be associated with high deterioration and 78.3% of bridge decks with no wearing surface are more likely. A plausible explanation for no wearing surface decreasing the likelihood of deterioration on some decks may be linked to limit states or specific climatic regions. Another plausible reason may by attributed to the use, or non-use, of de-icers on bridge decks with no wearing surface (this would also correspond to climate regions).

Type of Design and/or Construction (NBI Item 43B)

Three variables related to design and/or construction are found to significantly affect the probability of high deck deterioration. For these variables, there are no heterogeneous effects across bridge decks. Although, each of these variables have considerable impacts on deck deterioration according to marginal effects, with one having larger effects on deck deterioration compared to the others. To be specific, based on marginal effects, girder and floor beam systems increase the probability of deck deterioration by 57.1 percentage points. A plausible explanation for the increase in probability may be attributed to the type of bridge. For example, tied arch bridges experience web-gap fatigue in the connections of girder and floor beam systems (National Academies of Sciences, Engineering, and Medicine 2013). Another plausible explanation may be linked to bridges that have not been retrofitted or repaired in regards to web-gap fatigue cracks (Dexter and Ocel 2013).

Maintenance Responsibility (NBI Item 22)

For this category, just two variables are found to be significant, both of which have non-homogenous effects on bridge deck deterioration. The first of these variables is the indicator for county highway agency (i.e., maintenance responsibility is that of a county highway agency). Turning to model estimates, the indicator for county highway agency has an estimated parameter mean of 1.089 and an estimated parameter standard deviation of 3.393. Based on a normal distribution, these estimates indicate that 37.4% of bridge decks under the maintenance responsibility of a county highway agency are less likely to have high deterioration. On the other hand, however, 62.6% of bridge decks under the maintenance responsibility of a county highway agency are more likely to have high deterioration. The second variable, also with a normally distributed random parameter, is city or municipal highway agency being responsible for deck maintenance. With an estimated parameter mean of 0.404 and an estimated standard deviation of 2.183, 42.7% of bridge decks under the maintenance of a city or municipal highway agency are less likely to have high deterioration and 57.3% of bridge decks are more likely to have high deterioration. A plausible explanation for the heterogeneous nature in these two variables may be linked with funding for bridge deck maintenance. For instance, routine maintenance is not eligible for federal funds (FHWA 2018). Therefore, the varying effects of these two variables could be a result of limited or available funding at the county-specific level or the city- and municipal-specific level. With the Highway Bridge Program giving state DOTs discretion in regards to funding bridge rehabilitation, replacement, and several preservation activities (FHWA 2018), Strategic Highway Research Program et al. (2018) suggest that DOTs must design and build new bridges to have the longest potential service life. In doing so, this can free up funds for bridge preservation, bridge maintenance, and repairs (Strategic Highway Research Program et al. 2018).

IECC Climatic Region

The final set of variables found to be significant on the probability of bridge deck deterioration are climatic indicators. In this study, climate regions according to the International Energy Conservation Code (IECC) were adopted (International Code Council 2012). Inherently, these indicators serve as surrogates for region-specific climates and can help guide future work in defining specific regions to be considered for region-specific bridge deterioration models. With that in mind, four climatic indicators are significant, one of which has heterogeneous effects on bridge deck deterioration: average climate. Referring to model estimations, the indicator for average climate has an estimated parameter mean of -0.778 and an estimated standard deviation of 0.886. Therefore, based on the normal distribution curve, 19.0% of bridge decks located in the average climatic region are more likely to be associated with high deterioration and 81.0% of bridge decks in the average climatic region are less likely to be associated with high deterioration. These varying effects may be explained by weather irregularities, such as harsh winters or extreme summers. Specifically, Kesiraju (2017) found some correlation between bridge deck deterioration and climate change, where climate change may be a primary source of weather irregularities (Huybers et al. 2013).

As for the remaining three climatic variables, very hot climates, extremely cold climates, and hot marine climates impact the probability of bridge deck deterioration. First, according to marginal effects, there is a 41.9 percentage point decrease in the probability of bridge deck deterioration for bridge decks in very hot climates. This follows the findings of Ghonima et al. (2018), where as climate becomes colder bridge decks are more likely to be associated with high deterioration, while hotter climates are less likely. The next climatic variable is related to extremely cold climates. Pointedly, marginal effects show that bridge decks in extremely cold climates have a 105.2 percentage point increase in the probability of high deterioration. This finding is in-line with several previous works, as specific aspects in extremely cold climates can lead to bridge deck deterioration. Bridge decks in extremely cold climates will be susceptible to a large number of freeze-thaw cycles that accelerate deterioration (Hema et al. 2004). Specifically, cold climates use de-icing methods, where chlorides from de-icing salts can penetrate the bridge deck and eventually "depassivate" the reinforcing steel initiating corrosion (Gong et al. 2013; Njardardottir et al. 2005). More, de-icers can have negative reactions with the cement paste and/or aggregates in the bridge deck; therefore, increasing the likelihood of deterioration (Xie and Shi 2015). The final climatic indicator is for hot marine climates, in which marginal effects show a 31.0 percentage point increase in the probability of bridge deck deterioration. As it pertains to marine climates, bridge decks can be exposed to sulfate ions from seawater. These sulfate ions can then attack components of the cement paste in the bridge deck inducing deterioration (Hema et al. 2004). In addition, marine climates have other sulfates, such as sodium and magnesium, that can also induce deterioration (Hema et al. 2004).

Table 5. Summary of significant variables and effects on deck deterioration probability.

Category	Variable	Effect on Probability
Continuous Variables	Deck Area	↓
	ADTT	↑
	Distance to Seawater	↓
	Age of Bridge	↑↓
Structural Material Design	Continuous Concrete	↑↓
	Simple Prestressed Concrete	↑
	Continuous Prestressed Concrete	↑↓
	Simple Span Steel	↑↓
	Continuous Steel	↑
Deck Protection	Epoxy-Coated Reinforcing	↑↓
	Polymer Impregnated	↑
Type of Membrane	Built-Up Membrane	↑
Type of Wearing Surface	No Wearing Surface	↑↓
	Integral Concrete	↑
	Latex Concrete or Similar Additive	↑
	Low-Slump Concrete	↑
Type of Design and Construction	Girder and Floor Beam System	↑↓
	Tee Beam	↑
	Truss (Through)	↑
Maintenance Responsibility	County Highway Agency	↑↓
	City or Municipal Highway Agency	↑↓
Climatic Regions	Very Hot	↓
	Average	↑↓
	Extreme Cold	↑
	Hot Marine	↑

↓ = Decrease in Bridge Deck Deterioration Probability
↑ = Increase in Bridge Deck Deterioration Probability
↑↓ = Heterogeneous Effects on Bridge Deck Deterioration Probability

SUMMARY AND CONCLUSIONS

The objective of this study was to examine how environmental and structural parameters affect the performance of concrete bridge decks by means of random parameters binary logistic regression (LR) modeling. The model is used to compute the likelihood for a concrete bridge deck being associated with the "highest deterioration rate (DR)" group, which is the worst performing set of bridge decks, while also accounting for unobservables in the data. The random parameters LR model development is based on 3,262 observations extracted from a nationwide database, which was developed by the authors previously (Ghonima et al., 2018). In the final model, the DR was used as the dependent variable, while ADTT, Climatic Region, Distance from Seawater, Type of Design and/or Construction, Bridge Age, Bridge Deck Area, Structural Material Design, Deck Protection, Type of Membrane, Type of Wearing Surface, and Maintenance Responsibility characteristics were used as independent variables. A log-likelihood test was performed to show that the random parameters model is preferred over the traditional binary model, where results indicated with well over 99% confidence that the random parameters model is statistically preferred (several variables were found to have statistically significant random parameters). Significant bridge deck deterioration variables were ranked in order of their relative importance in the model. Based on marginal effects and elasticities, as presented in Table 5, it was found that bridge decks 1) with higher ADTT, 2) extremely cold climate, 3) hot marine climate, and 4) with no wearing surface are all associated with an increase in “highest DR” group probability. On the other hand, 1) deck area, 2) distance to seawater, 3) age of bridge, and 4) very hot climates are associated with a decrease in “highest DR” group probability. Some of these variables were also found to be heterogeneous across observations, as detailed in the discussion.

In the future, additional variables could be added, such as structural design characteristics (e.g., minimum deck thickness, reinforcement bar size, bar spacing), construction practice (e.g., concrete temperature, placement procedure, curing practice), specifications (e.g., water-to-cement ratio and minimum cementitious material content), and other notable variables (e.g., application of deicers and freeze-thaw cycles). By adding additional data (i.e., potential bridge deck deterioration variables), data-heterogeneity is mitigated by reducing the number of unobservables (i.e., there are more observed characteristics to be used by the analyst). In addition, it is recommended that future studies utilize this methodology to model those additional variables to determine their significance and impacts on bridge deck deterioration.

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