Deterioration and Predictive Condition Modeling of Concrete Bridge Decks Based on Data from Periodic NDE Surveys

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Abstract: A novel approach and program are developed for deterioration and predictive modeling of concrete bridge decks based on nondestructive evaluation (NDE) data. Through an iterative process—combined with data processing, bridge deck segmentation, regression analysis, data integration, and deterioration and predictive modeling—the developed program aids estimates of the remaining service life of bridge decks. Data collected on an actual bridge deck during a period of five and half years are used to illustrate the operation and performance of the developed program. Based on evaluation of condition maps, condition indices, and deterioration curves developed for a range of input parameters, the proposed method quantifies progression of deterioration in bridge deck. By reviewing the predictive models, combined with segmentation of the bridge deck area, a more realistic and practical estimation of the deck's remaining service life can be made. It is anticipated that the proposed method will provide objective and comprehensive evaluation and prediction of bridge deck condition based on data from multiple NDE technologies. **DOI:** **10.1061/(ASCE)IS.1943-555X.0000483.**

Author keywords: Nondestructive evaluation; Bridge decks; Deterioration and predictive modeling; Segmentation; Concrete.

Introduction

According to a recent report (ASCE 2017), nearly 40% of bridges in the United States are 50 years old or older and over 9% are structurally deficient. Moreover, a great number of the nation's bridges are rapidly approaching the end of their design life. As a consequence, the cost of the backlog of bridge rehabilitation projects is estimated at $123 billion (ASCE 2017). Bridge decks are reported to be deteriorating much earlier than other bridge components (Nowak and Szerszen 2003) due to their direct exposure to traffic and environmental loads. Thus, they are by far the largest expenditure in bridge maintenance and repair (Gucunski et al. 2012). For these reasons, it is very important to accurately and objectively assess the condition of bridge decks, and to identify the main causes of deterioration using accurate, rapid, and nondestructive technologies. Periodically collected multiple nondestructive evaluation (NDE) technology data sets present opportunities for prediction of remaining service life which will further provide significant assistance in optimizing bridge maintenance, rehabilitation, and repair strategies.

The dominant practice of bridge deck inspection by US transportation agencies is a visual one accompanied by simple nondestructive procedures such as chain dragging and hammer sounding. Based on such inspections, agencies report National Bridge Inventory (NBI) deck condition ratings defined by FHWA (2004, 2012) and AASHTO (2015). NBI ratings are nationally adopted as bridge condition evaluation and repair guidelines. Generally qualitative and subjective visual inspection data make it challenging to develop models that objectively describe hidden deterioration processes in most cases.

Due to the importance of prediction, significant efforts have been made to develop deterioration models that permit remaining deck service life to be predicted using various methodologies (Melhem and Cheng 2003; Oh et al. 2006; Williamson et al. 2007; Lee 2011; Ghodoosipoor 2013; Zatar 2014; Azari et al. 2016; Saberi et al. 2016; Jeong et al. 2017). Ghodoosipoor (2013) proposed deterioration models for bridge decks through a system reliability analysis based on visual inspection data. Several studies have been conducted to predict remaining service life of bridge decks based on reinforcement corrosion. Melhem and Cheng (2003) suggested prediction of remaining service life through *k*-nearest neighbor learning and inductive learning techniques based on reinforcement corrosion data. Williamson et al. (2007) developed and validated a chloride corrosion model using Monte Carlo resampling of data collected from ten bridge decks in Virginia. Zatar (2014) proposed modeling the remaining service life and service life extension provided by various repair and protection methods based on half-cell potential measurements on highway bridges in West Virginia. Oh et al. (2006) developed a realistic evaluation system for estimating the service life of concrete bridge decks based on deterioration models derived from traffic loads and environmental effects. Lee (2011) presented a time-dependent reliability approach to estimate the remaining service life of a rehabilitated bridge deck considering a number of factors: structure supporting the deck, geometry, material properties, moisture, creep, fatigue, thermal effects, corrosion, and failure modes.

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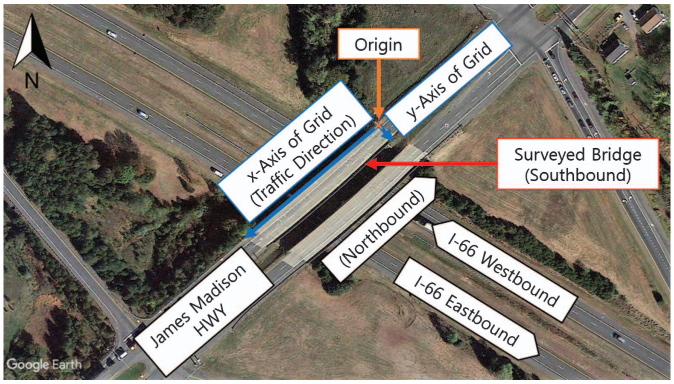

Fig. 1. (Color) Satellite view of the surveyed bridge, James Madison HWY over I-66, southbound—most recent photo (October 2013). (Imagery © 2019 Google.)

Although many researchers have proposed deterioration models for bridge decks and ways to estimate remaining service life, most studies have been performed within a relatively short time period or based on a single inspection method, or they have heavily relied on simulations and calculated data.

This paper presents a program for estimating the remaining service life of a concrete bridge deck based on analysis of data from multiple NDE technologies collected periodically over a period of five and half years. It provides (1) a brief description of NDE surveys of the concrete deck of a bridge in Virginia conducted between 2009 and 2015 (Gucunski et al. 2015; Azari et al. 2016; Gucunski et al. 2017b); (2) a description of the key features and interfaces of the developed NDE data-processing and data analysis program; (3) a discussion of the quantification of condition deterioration progression and bridge deck deterioration and of predictive models based on different mathematical curve models; and (4) an example of estimation of remaining bridge deck service life based on the developed models. The models derived from the developed program will be continuously improved and calibrated as data on other bridges become available.

Background

Description of the Surveyed Bridge

The nondestructive survey was performed on the bridge carrying southbound US Route 15 over Interstate 66 (I-66) in Haymarket, Virginia (Fig. 1). Selected information about the bridge, taken from the NBI, is provided in Table 1. The surveyed bridge deck is a two-lane and shoulder, two-span-bridge approximately 84 m long and 13 m wide. It was built in 1979 with a bare, cast-in-place, 22-cm-thick reinforced concrete deck. According to the latest inspection in 2015, average daily traffic on the bridge was 15,577 vehicles. The bridge deck received a consistent NBI rating of 6 (satisfactory condition) for 25 consecutive years (1991–2015). It has been surveyed four times by the Rutgers NDE team as a part of the FHWA's Long-Term Bridge Performance (LTBP) Program in September 2009, August 2011, October 2014, and May 2015. Temperature and relative humidity data on the surveying days obtained from the nearest weather station are listed in Table 2 with precipitation histories.

NDE Technologies

Five NDE technologies were deployed simultaneously, as shown in Fig. 2, to detect and characterize three main deterioration types in

Table 1. National Bridge Inventory data for the surveyed bridge

Datum	Description
Name	James Madison HWY over I-66
Structure number	000000000014178
Total length	42.1 m
Deck width edge to edge	12.8 m
Year built	1979
Number of main spans	2
Main span material	Steel continuous
Main spans design	Stringer/multibeam or girder
Deck type	Concrete cast in place
Wearing surface	Monolithic concrete
Average daily traffic (latest survey in February 2015)	15,577

Table 2. Temperature, relative humidity, and precipitation history during the survey

Survey date	Temperature (°C)	Relative humidity (%)	Precipitation history
September 18, 2009 (Friday)	19.4	83	24 mm on August
September 19, 2009 (Saturday)	18.9	52	22; dried for
September 20, 2009 (Sunday)	20.0	49	27 days
August 2, 2011 (Tuesday)	29.4	43	9 mm on July 25;
August 3, 2011 (Wednesday)	25.6	71	dried for 8 days
August 4, 2011 (Thursday)	26.1	69	
October 6, 2014 (Monday)	13.9	55	15 mm on
October 7, 2014 (Tuesday)	16.7	72	September 25;
October 8, 2014 (Wednesday)	19.4	65	dried for 11 days
May 26, 2015 (Tuesday)	25.0	60	7 mm on May 21;
May 27, 2015 (Wednesday)	25.6	69	dried for 5 days
May 28, 2015 (Thursday)	26.7	65	

Note: Temperature and relative humidity = average of data measured at nearest weather station during typical survey schedule, 10 a.m.–2 p.m.

Fig. 2. (Color) Nondestructive evaluation data collection on the deck of the studied bridge.

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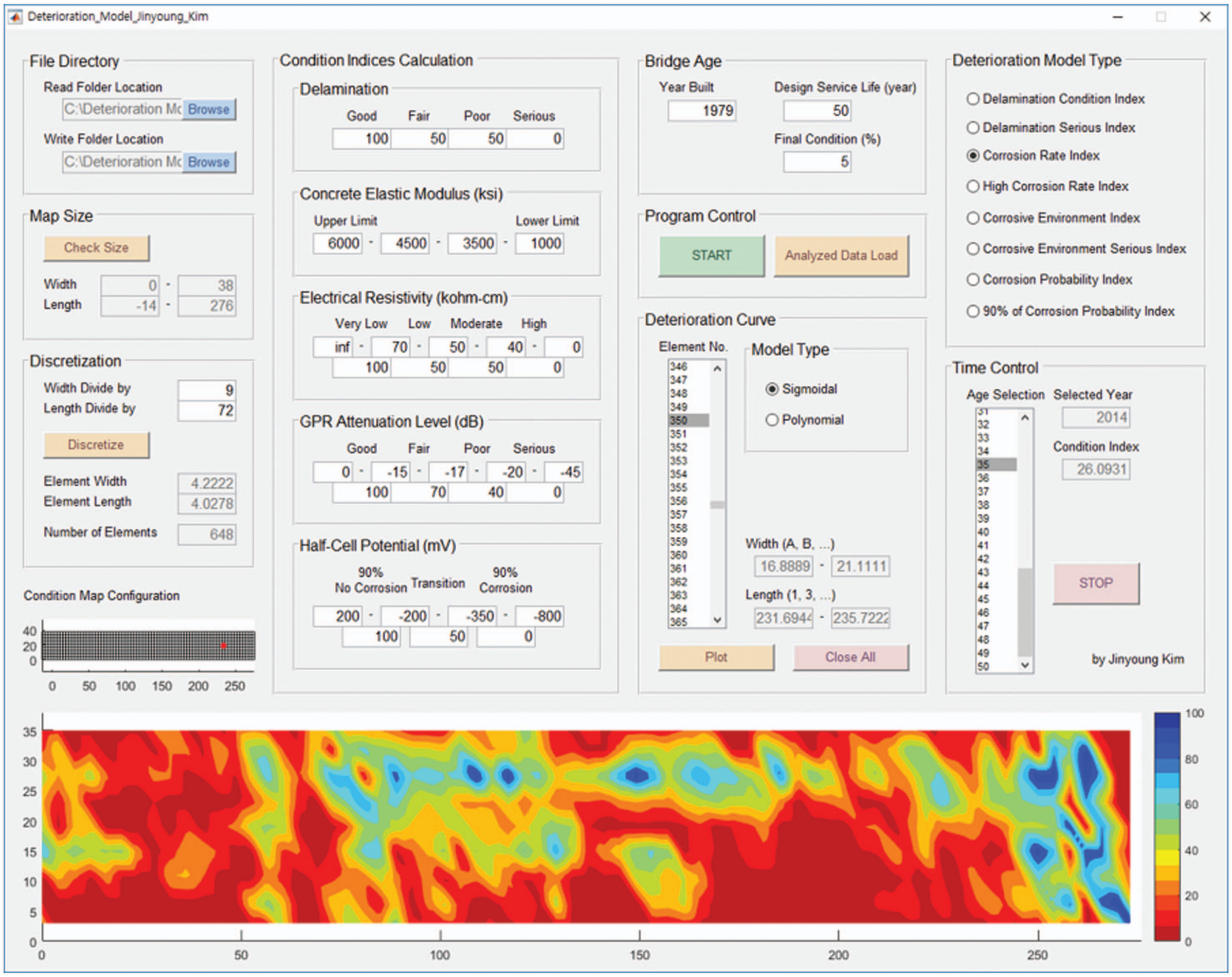

Fig. 3. (Color) Graphical user interface of the developed deterioration-modeling program.

concrete bridge decks: (1) assessment of the corrosive environment and related anticipated corrosion rate via electrical resistivity (ER) as well as assessment of the probability of active reinforcement corrosion via half-cell potential (HCP); (2) assessment of delamination via impact echo (IE); and (3) assessment of concrete quality degradation via ground penetrating radar (GPR) and the ultrasonic surface wave (USW) method. Detailed descriptions of the physical principles of operation and application of each of the five NDE technologies can be found in Gucunski et al. (2012, 2017b). It is significant that variation in environmental conditions, such as pore solution composition, degree of polarization, temperature, and saturation, influence the NDE results, especially those from ER and HCP. Because of practical issues, however, controlling environmental parameters during the survey of an actual bridge deck was not viable. Except when using GPR, the bridge deck was surveyed on a grid measuring 60×60 cm, with the first longitudinal line of the grid offset 30 cm from the parapet. GPR scanning was in the longitudinal direction of the bridge with 60-cm spacing between the survey lines. The origin of the coordinate system was on the northwestern corner of the deck as depicted in Fig. 1, with the x-axis parallel to and the y-axis perpendicular to the direction of traffic. NDE survey results are summarized and presented here as two-dimensional (2D) color-coded condition maps; summary conditions are expressed in terms of condition indices (CIs) (Kim et al. 2015, 2016a, b, 2017).

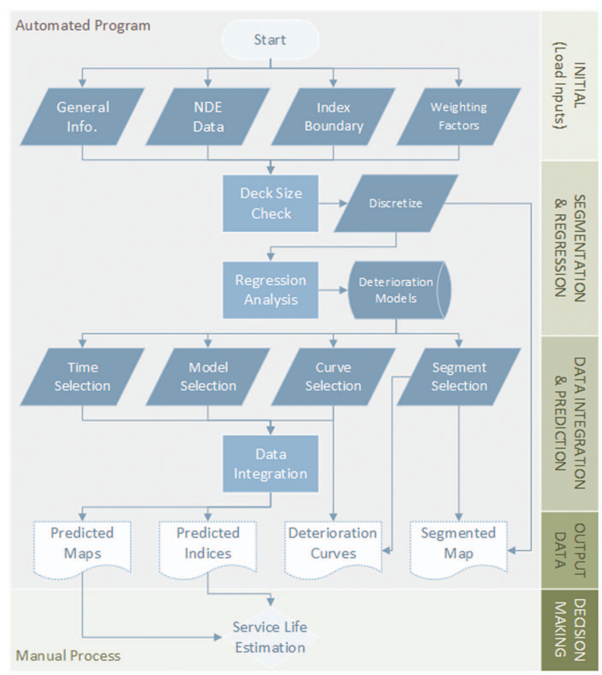

Fig. 4. (Color) Flowchart of the developed deterioration modeling program with processing steps.

Data-Processing and Data Analysis Program

A novel automated NDE data-processing and data analysis program, developed using MATLAB, was designed to (1) create condition maps and compute CIs, (2) develop deterioration models, (3) predict conditions, and, ultimately, and (4) estimate the remaining service life of a bridge deck. The program's graphical user interface (GUI) and a flowchart representing the fundamental algorithm

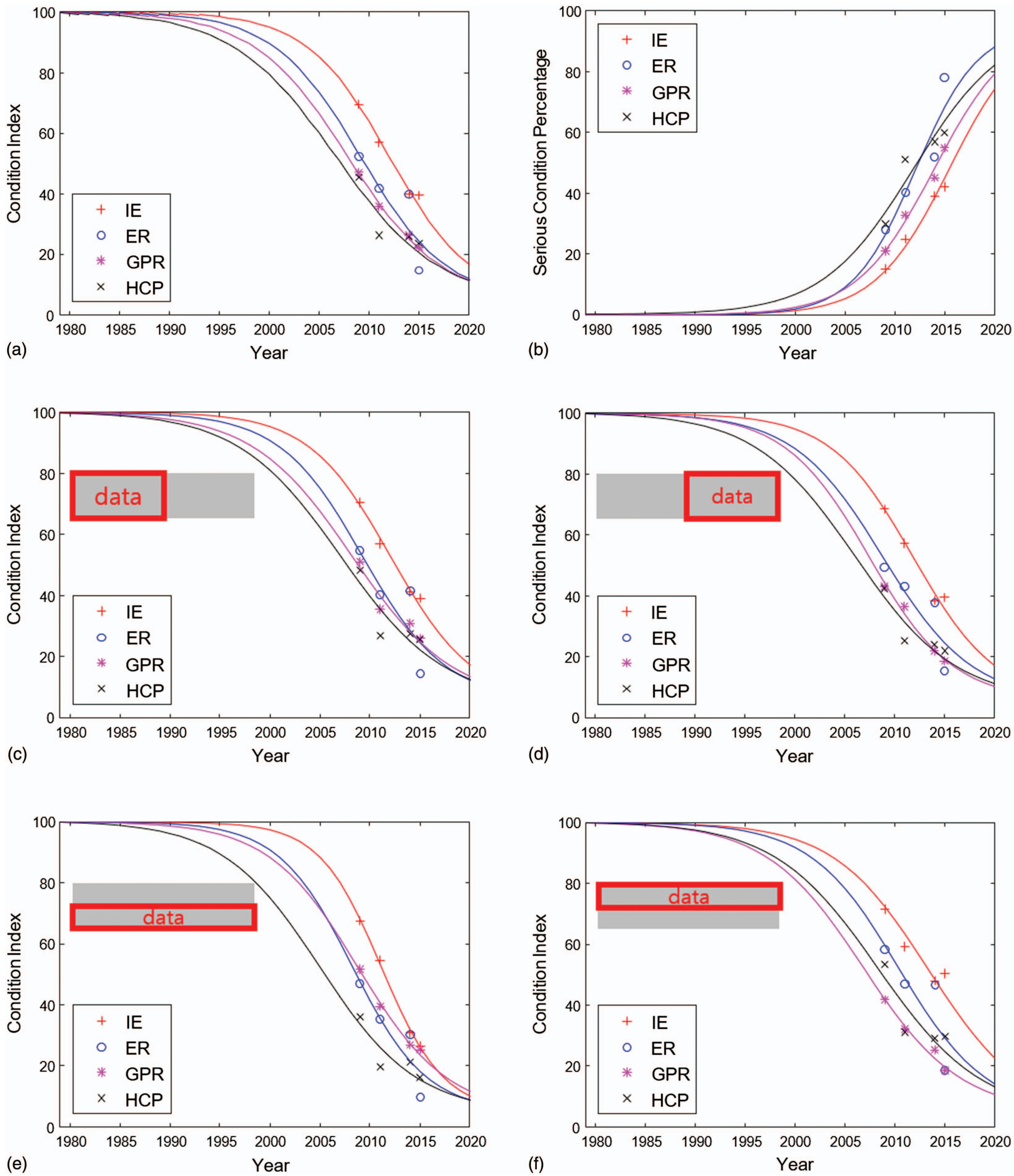

Fig. 5. (Color) Deterioration models based on four NDE technologies: (a) single-segment based on condition indices; (b) single-segment based on serious condition percentages; (c) north span and (d) south span of 1 × 2 segmentation (longitudinal discretization); and (e) western side and (f) eastern side of 2 × 1 segmentation (transverse discretization).

are shown in Figs. 3 and 4, respectively. The main flow of the program can be divided into five processing steps: (1) NDE data input, (2) deck segmentation and data regression, (3) data integration and prediction, (4) data output, and (5) decision making. Initially, the program imports separate text-based input files containing each of the five NDE data types: ER, HCP, IE, GPR, and USW, along with general bridge information. Data boundaries and weighting factors for each NDE technology are input to create condition maps and to quantify the summarized bridge deck conditions as CIs. As a default, the CI for each NDE method is calculated on a scale of 0 (worst) to 100 (best) through a weighted deck area approach using the following equations:

$$CI_{ER} = \frac{A_{\text{Very Low}} \times 100 + A_{\text{Moderate}} \times 50 + A_{\text{High}} \times 0}{A_{\text{Total}}} \tag{1}$$

$$CI_{\text{HCP}} = \frac{A_{90\%\,\text{Sound}} \times 100 + A_{\text{Transition}} \times 50 + A_{90\%\,\text{Corrosion}} \times 0}{A_{\text{Total}}} \tag{2}$$

$$CI_{IE} = \frac{A_{\text{Good}} \times 100 + A_{\text{Fair}} \times 50 + A_{\text{Poor}} \times 50 + A_{\text{Serious}} \times 0}{A_{\text{Total}}} \tag{3}$$

$$CI_{\text{GPR}} = \frac{A_G \times 100 + A_F \times 70 + A_P \times 40 + A_S \times 0}{A_{\text{Total}}} \tag{4}$$

where $A_{\text{Very Low}}$, A_{Moderate}, and A_{High} = deck areas with ER =<40, 40–70, and >70 $\text{k}\Omega \cdot \text{cm}$, respectively (Langford and Broomfield 1987; Dyer 2014); $A_{90\%\text{Sound}}$, $A_{\text{Transition}}$, and $A_{90\%\text{Corrosion}}$ = areas with HCP =>200, −350 to −200, and < -350 mV, respectively (ASTM 2015); A_{Good}, A_{Fair}, A_{Poor}, and A_{Serious} = areas in good, fair, poor, and serious condition, respectively (Gucunski et al. 2017b; Kim et al. 2017; Gucunski et al. 2017a); A_G, A_F, A_P, and A_S = areas with GPR signal attenuation (normalized dB) = > -15, −15 to −17, −17 to −20, and < -20, respectively (Azari et al. 2016); and A_{Total} = total surveyed area.

The weights in Eqs. (1)–(4) are the suggested values resulting from discussions in the FHWA LTBP regarding the presentation of summary condition data. However, it was recognized in those discussions that bridge owners would assign different weights based on their experience of deterioration processes and decision making. For concrete quality based on USW data, on the other hand, CI calculation similar to that in Eqs. (1)–(4) was not applicable due to the inherited variation in concrete modulus of elasticity at the time of construction (Gucunski et al. 2017b; Kim et al. 2017; Gucunski et al. 2017a). Furthermore, compared with other NDE data, less pronounced changes were observed in concrete modulus of elasticity as the deck deteriorated. For these reasons, USW data are not included in subsequent discussions here.

Once input data sets and parameters are loaded into the program, the bridge deck area is discretized into segments for further evaluation. An example of segmentation is shown in Fig. 3, which shows the bridge deck discretized into 648 1.3 × 1.2-m (4.2 × 4.0-ft) segments (9 × 72). Segment size was determined to have at least four data points per segment for each NDE technology, considering the grid size used during the survey. The segmented deck area is plotted and the segment numbers listed in a listbox from which the user can select a segment of interest and review the corresponding deterioration curves. Deterioration modeling combined with segmentation can assist in prioritizing deck areas for intervention. For example, relatively rapid deterioration of a lane (transverse discretization) or severe damage to a span (longitudinal discretization) can be identified intuitively by reviewing condition maps and indices with appropriate segmentation.

Once segmentation is completed, deterioration models for each segment are computed through various multiple regression analyses. The results are stored in a database for later reloading. The duration of analysis depends on the size of the input data set, the number of segments, and computer performance. However, analysis of a typical highway bridge takes up to several minutes on a desktop computer with a Core i5-6400 processor, integrated graphics, and 16-GB memory.

Once analysis results are obtained and saved, deterioration curves for each segment, derived from varying curve models and data types, can be selected and visually reviewed. Based on the selected deterioration models and data types, deterioration curve data for each segment are integrated to reconstruct condition maps and compute CIs (Fig. 3) to predict bridge deck condition at an arbitrarily selected point in time. Detailed descriptions of the deterioration analysis, integration of discretized data, and condition prediction are provided in subsequent sections.

Deterioration Modeling

Several deterministic models of deterioration curves were studied. These included linear (linear, bilinear, and trilinear), nonlinear (polynomial), and sigmoidal (S or reversed-S) regressions (Draper and Smith 1998; Seber and Wild 2003). The sigmoidal curves were almost horizontal (zero slopes) at both ends, representing the deterioration progression of typical bridge decks more realistically than the polynomial curves. In fact, the former were observed to fit the data with higher coefficients of determination (R^2) than the latter. Therefore, although the developed program is equipped with a function for both sigmoidal and polynomial deterioration analyses, polynomial regression is not included in subsequent discussions here.

Table 3. Coefficient values for deterioration models in Fig. 5

Model	NDE data	Coefficient *a*	*b*	*c*	*d*
Condition index (1 × 1)	IE	100.01	4.39	2,012.08	0.10
	ER	100.03	4.59	2,009.18	0.10
	GPR	100.09	4.54	2,007.89	0.09
	HCP	100.21	4.43	2,006.70	0.08
Serious condition percentage (1 × 1)	IE	0.03	95.81	2,015.41	0.12
	ER	0.01	95.15	2,012.05	0.14
	GPR	0.01	95.68	2,013.91	0.11
	HCP	−0.03	95.88	2,011.86	0.10
Condition index (1 × 2, north)	IE	100.01	4.39	2,012.17	0.11
	ER	100.03	4.65	2,009.37	0.10
	GPR	100.13	4.31	2,008.38	0.09
	HCP	100.20	4.36	2,007.20	0.08
Condition index (1 × 2, south)	IE	100.01	4.39	2,011.98	0.10
	ER	100.05	4.53	2,008.94	0.10
	GPR	98.90	5.59	2,010.97	9.85
	HCP	100.22	4.51	2,006.15	0.08
Condition index (2 × 1, west)	IE	100.00	4.91	2,011.12	0.14
	ER	100.01	4.86	2,008.25	0.12
	GPR	100.05	4.59	2,008.79	0.10
	HCP	100.19	4.74	2,004.96	0.09
Condition index (2 × 1, east)	IE	100.01	3.56	2,013.33	0.09
	ER	100.02	4.45	2,010.37	0.10
	GPR	100.13	4.57	2,006.83	0.09
	HCP	100.15	4.25	2,008.29	0.08

The results of sigmoidal regression analyses based on four NDE technologies (IE, ER, GPR, and HCP) without segmentation (single-segment) are plotted in Fig. 5(a). The program searches and reads NDE data in the selected segment for deterioration modeling; in this case, the entire NDE data set was used to build the models because no segmentation was applied. The marks and solid lines in the plots represent actual NDE data surveyed in 2009–2015 and best-fit curves, respectively. A four-parameter logistic model was used for the sigmoidal regression according to the following equation (Seber and Wild 2003):

$$CI = a + \frac{b-a}{1+10^{(c-t)d}} \tag{5}$$

where a and b = lower and upper asymptotes, respectively; c = inflection point in time; d = slope of the sigmoidal curve at its midpoint; and t = time.

Polynomial regression was achieved using least squares to fit quadratic polynomials to the actual data set. Fig. 5(a) is based on the CIs calculated by Eqs. (1)–(4) with an assumed CI of 100 at the time of bridge construction in 1979. Fig. 5(b), on the other hand, is based on the serious condition percentage—that is, the percentages of deck area in serious (worst) condition for each NDE method (areas of A_{High} for ER, $A_{90\%\mathrm{Corrosion}}$ for HCP, A_{Serious} for IE, and A_S for GPR divided by A_{Total}). Therefore, the curves based on the CIs begin with 100 in 1979 whereas the initial values of the curves based on the serious condition percentage are 0. This reflects a common practice of assessing the percentage of deteriorated bridge deck area, such as delamination detected by chain drag and corrosion detected by half-cell potential. The model coefficients a, b, c, and d for the CI [Fig. 5(a)] and the serious condition percentage [Fig. 5(b)] are provided in Table 3.

Deterioration models for segmented bridge deck areas are shown in Figs. 5(c–f), and their model coefficient values are provided in Table 3. Figs. 5(c and d) are the first and second segments of the 1 × 2 segmentation (longitudinal discretization), respectively representing the north and south spans of the bridge deck. Figs. 5(e and f) are the first and second segments of the

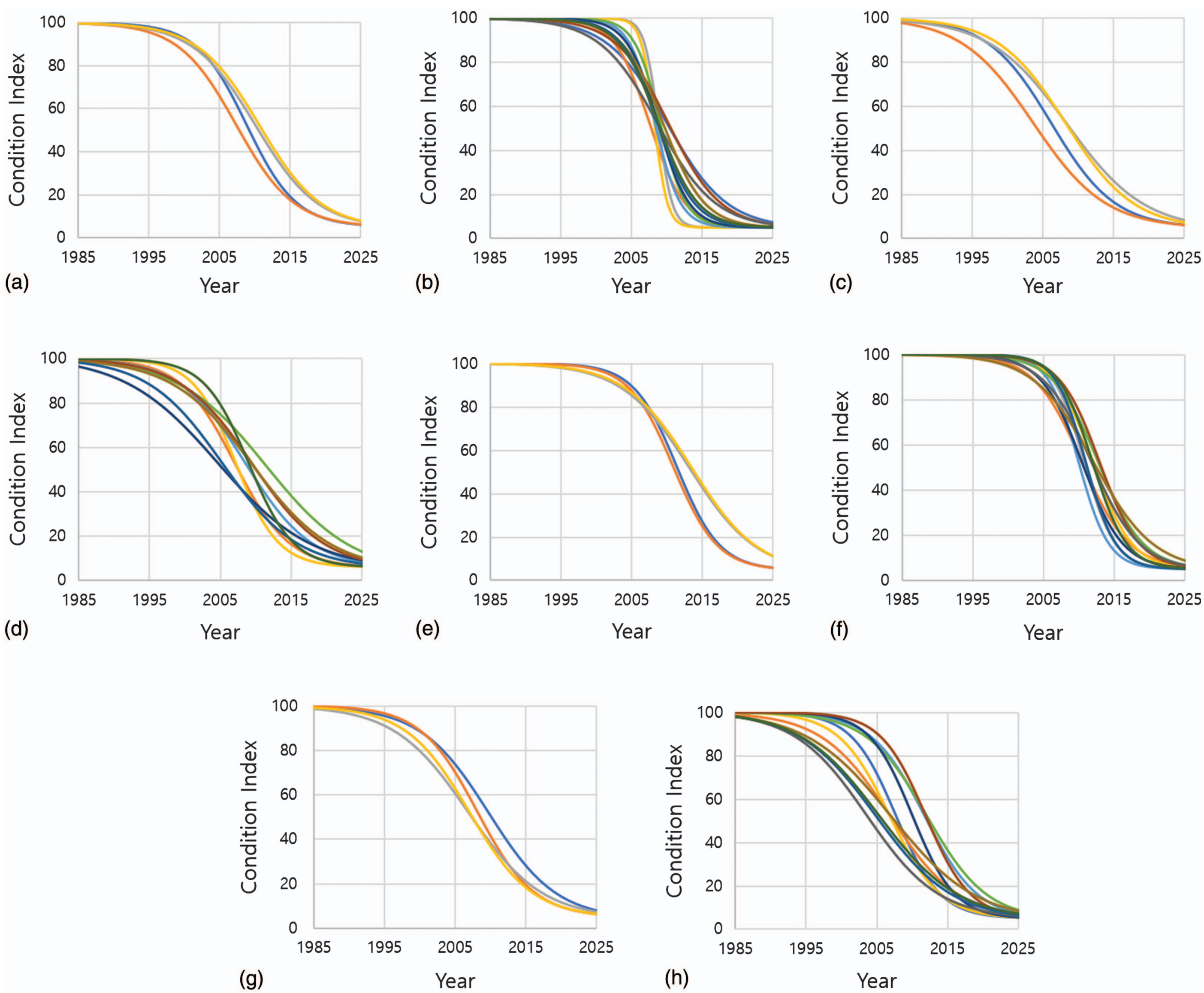

Fig. 6. (Color) Deterioration models of the 2 × 2 segmented and 3 × 4 segmented bridge deck areas based on data from four NDE technologies: (a) ER, 4 segments; (b) ER, 12 segments; (c) HCP, 4 segments; (d) HCP, 12 segments; (e) IE, 4 segments; (f) IE, 12 segments; (g) GPR, 4 segments; and (h) GPR, 12 segments.

Table 4. Coefficient values for deterioration models in Fig. 6

	ER				HCP				IE				GPR			
Model	*a*	*b*	*c*	*d*	*a*	*b*	*c*	*d*	*a*	*b*	*c*	*d*	*a*	*b*	*c*	*d*
2 × 2	100.0	4.89	2009	0.12	100.1	4.77	2006	0.10	100.0	4.91	2011	0.14	100.1	4.28	2010	0.09
	100.0	4.80	2007	0.11	100.3	4.73	2004	0.08	100.0	4.91	2011	0.14	100.0	4.81	2008	0.11
	100.0	4.47	2010	0.10	100.2	4.00	2008	0.08	100.0	3.56	2013	0.09	100.2	4.40	2007	0.08
	100.0	4.43	2011	0.10	100.1	4.49	2008	0.09	100.0	3.57	2013	0.09	100.1	4.72	2007	0.10
3 × 4	100.0	5.06	2009	0.26	99.0	5.81	2011	11.46	100.0	4.96	2011	0.16	100.0	4.98	2008	0.14
	100.0	4.94	2009	0.14	100.0	4.86	2007	0.11	100.0	4.91	2012	0.15	100.1	4.59	2007	0.09
	99.0	5.87	2011	0.21	100.3	4.96	2001	0.10	100.0	4.94	2010	0.15	99.0	5.90	2011	9.28
	100.0	4.86	2009	0.13	100.0	4.99	2007	0.14	100.0	4.89	2011	0.14	100.0	4.94	2007	0.12
	100.0	4.66	2009	0.10	100.1	4.45	2009	0.09	100.0	4.08	2013	0.10	100.0	4.64	2012	0.11
	100.0	3.98	2011	0.09	100.2	2.26	2012	0.07	100.0	4.15	2012	0.10	100.0	4.31	2012	0.10
	100.1	4.72	2008	0.10	101.1	3.67	2005	0.06	100.0	4.54	2012	0.11	100.0	4.94	2010	0.14
	100.1	3.81	2011	0.09	100.1	4.01	2010	0.08	100.0	3.78	2013	0.09	100.0	4.86	2012	0.14
	100.0	4.76	2008	0.11	99.0	5.85	2011	1.12	100.0	4.04	2012	0.09	100.3	4.73	2004	0.08
	100.0	4.11	2012	0.10	100.2	3.55	2010	0.08	100.0	3.32	2014	0.09	100.4	3.81	2007	0.07
	100.0	4.60	2011	0.11	100.3	4.45	2005	0.08	100.0	3.11	2013	0.08	100.4	4.49	2005	0.08
	100.1	3.61	2011	0.08	100.0	4.96	2009	0.13	100.0	4.18	2013	0.11	100.4	4.35	2005	0.08

2 × 1 segmentation (transverse discretization), representing the split between the shoulder and the right and left lanes. The most rapid decrease in the segmental CIs are found in the 2008–2012 period, in which the inflection points of the sigmoidal deterioration curves are located. Slightly higher deterioration rates are observed for the south span [Fig. 5(b)] and the shoulder [Fig. 5(c)] compared with the other segments. This can be identified in the corrosion resistivity (ER) map for 2014, shown in Fig. 3, in which hot colors represent areas with anticipated high or very high corrosion rates and cool colors represent areas with anticipated low or very low corrosion rates. More severe deterioration in the bottom half of the map, presumably from the accumulation of soil, deicing chemicals, and debris in the shoulder area, could have considerably accelerated bridge deck deterioration—that is, chloride-induced corrosion—as a whole. As can be seen, an appropriate segmentation of NDE data in bridge deck condition assessment delivers useful information for more economical and effective maintenance and rehabilitation planning. For this bridge deck, for example, the south span and shoulder would have priority in maintenance and/or repair.

In all plots in Fig. 5, the highest deterioration rate is observed in the HCP and ER curves; the lowest is observed in the IE curves. This explains the general assumption of concrete deterioration stages: (1) development of a corrosive environment by chloride and moisture penetration (ER and GPR), (2) rebar corrosion (HCP and ER), (3) concrete degradation (GPR), and (4) corrosion-induced delamination (IE). It also agrees with Pailes and Gucunski's (2015) study on evaluation of concrete bridge decks based on multimodal NDE data.

Deterioration curves for different numbers of segments for the four NDE methods are compared in Fig. 6, and their model coefficients *a*, *b*, *c*, and *d* are provided in Table 4. Figs. 6(a, c, e, and g) are curves for four segments (2 × 2), and Figs. 6(b, d, f, and h) are curves for 12 segments (3 × 4). SDs of the deterioration curves shown in Fig. 6 are listed in Table 5.

Table 5. Standard deviation of deterioration models of 4- and 12-segment deck areas for ER, HCP, IE, and GPR

	Standard deviation			
Segmentation	ER	HCP	IE	GPR
4 segments (2 × 2)	2.5	3.6	2.5	2.4
12 segments (3 × 4)	3.1	4.7	2.5	6.0

As expected, SD values increased when the number of segments increased from 4 to 12, with the greatest increase for GPR (2.4–6.0); they remained almost constant for IE. Deterioration models for segmented decks showing low SD values had a narrow range of segmental CIs. In contrast, segmental CIs for deterioration models with high SD values ranged widely. Another interesting finding is the close similarity between the ER and HCP deterioration curves for the deck with 4 segments. However, when the number of segments increased to 12, these curves became quite distinct, leading to the conclusion that deterioration curves are unique to each segmented deck area. Thus, as much as the application of multiple NDE methods is important for comprehensive bridge deck evaluation, a proper segmentation of NDE data is essential for effective and objective deterioration modeling.

Condition Prediction

Based on the selected models, deterioration curve data for each segment are integrated to reconstruct condition maps. Corresponding CIs are calculated to predict bridge deck condition with age as well as to estimate CI values from a time when surveys were not conducted. The program creates condition maps based on eight deterioration models, as shown in Fig. 3: two (CI and serious condition percentage) each for ER, HCP, IE, and GPR. MATLAB's filled 2D contour function is based on the reconstructed matrix of the integrated data in x, y, and z format, where x and y are the x- and y-coordinates, respectively, and z is the CI. Initially, isolines are computed and displayed based on the matrix. Then the areas between them are filled with corresponding colors with respect to the x-y plane.

Fig. 7 compares condition maps based on actual NDE data collected in 2014 [Fig. 7(a)] and reconstructed condition maps with 648 segments (9 × 72) based on the deterioration models [Fig. 7(b)] to evaluate map reconstruction for each NDE technology. Note that neither display of reconstructed condition maps to scale nor coverage of skewed areas is as yet supported in the current version of the developed program. Both condition maps are color-coded, 2D, and contoured. The reconstructed maps are plotted via MATLAB's contour function with a 10-level color scale; the actual condition maps are created using commercial surface-mapping software, Surfer by Golden Software, with broader color scales. Although the overall color legends are distinct for the reconstructed and actual maps, nearly identical color (deterioration) patterns can

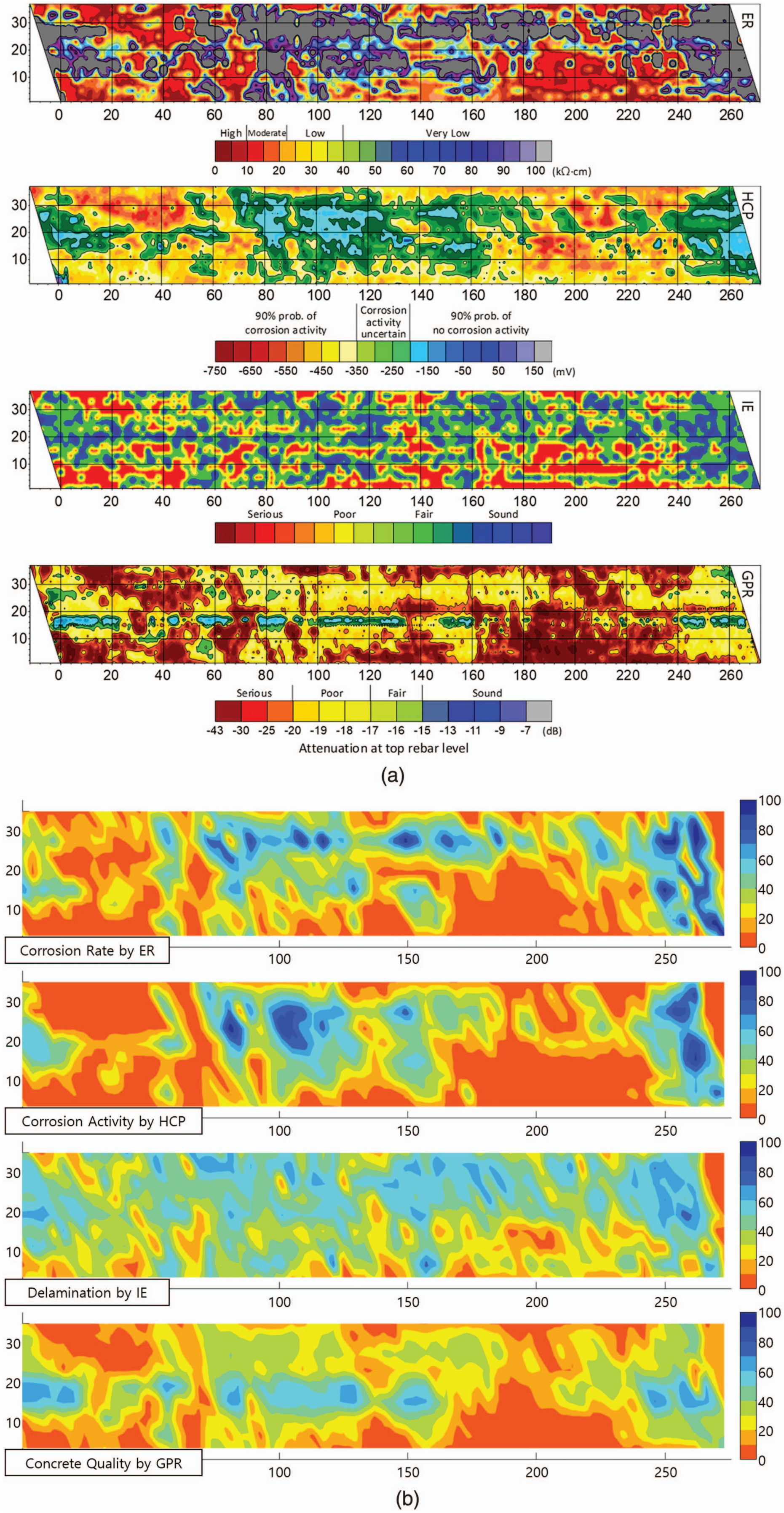

Fig. 7. (Color) Comparisons of ER, HCP, IE, and GPR actual and reconstructed condition maps for 2014: (a) condition maps based on actual NDE data; and (b) reconstructed condition maps based on deterioration models (not to scale). Axes are in feet.

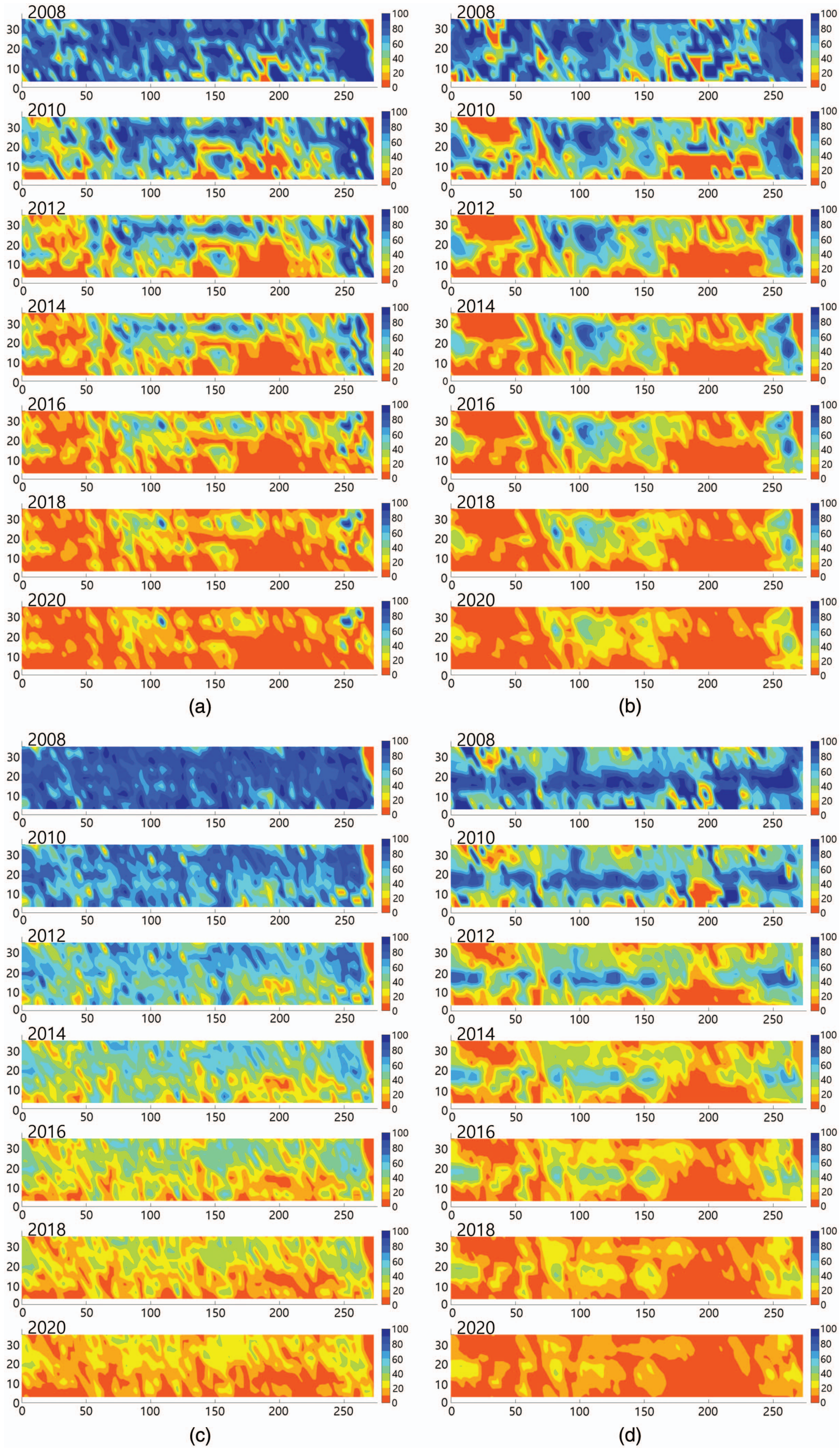

Fig. 8. (Color) Reconstructed two-year CI maps (2008–2020) showing deterioration progression: (a) ER; (b) HCP; (c) IE; and (d) GPR.

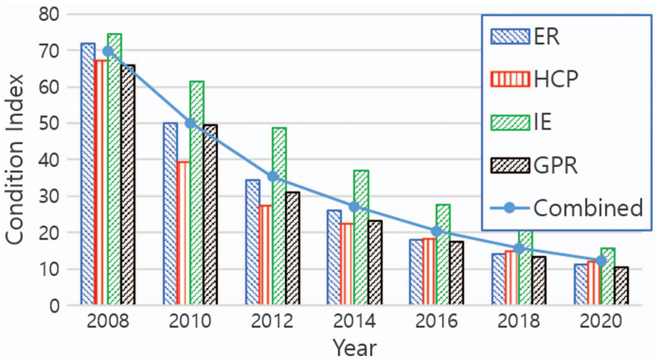

Fig. 9. (Color) Estimated condition indices based on deterioration models for each NDE type and average (combined) indices (2008–2020).

be identified for the NDE technologies except IE. The reason is that map reconstruction through segmentation, regression, deterioration modeling, integration, and contour mapping may not provide high resemblance when deteriorated areas are dispersed and small. This is the nature of segmentation with regression analysis. As the dispersed areas of deterioration combine to form larger areas, more accurate condition prediction becomes possible through map reconstruction. Note that the reconstructed IE map more closely resembles the actual map with more segments. However, excessive segmentation without considering the grid size used during the survey may result in segments without data.

Reconstructed condition maps with 648 segments for each NDE technology, in two-year increments from 2008 to 2020, are shown in Fig. 8. The program supports real-time display and update of maps for a selected deterioration model and year. Thus, the user can review condition maps and indices estimating possible bridge deck conditions in a near future, and check the deterioration models for a specific segment to further analyze deterioration in the areas of interest.

Deterioration progression can be clearly followed in all condition maps presented in Fig. 8, as reflected in an increase in deteriorated area size and deterioration severity with time. The dominant color thus changes with age from blue to red. In addition, the maps identify very similar deterioration patterns for different NDE technologies. It is expected that nearly the entire bridge deck will have seriously deteriorated by the year 2020, except for delamination, and that expected CIs in 2020 will be between 10.5 and 12.0. The delamination CI is estimated to be 15.7 in 2020—31%–50% higher than estimated CIs for the other NDE methods. Still, comparable ranges of CIs point to corrosion as the primary cause of delamination.

Estimated CIs are plotted in Fig. 9. The combined index is an average of CIs for ER, HCP, IE, and GPR, based on which overall bridge deck condition can be simply quantified. Observed for all NDE methods is a gradual decrease in CIs with time since the deterioration is approaching its final stage. According to the predictive model, in the 12 years from 2008 to 2020, the combined CI will have decreased significantly, from 70 to 12.

To evaluate correlations among NDE data for the four technologies, reconstructed condition maps for 2016 for ER, HCP, IE,

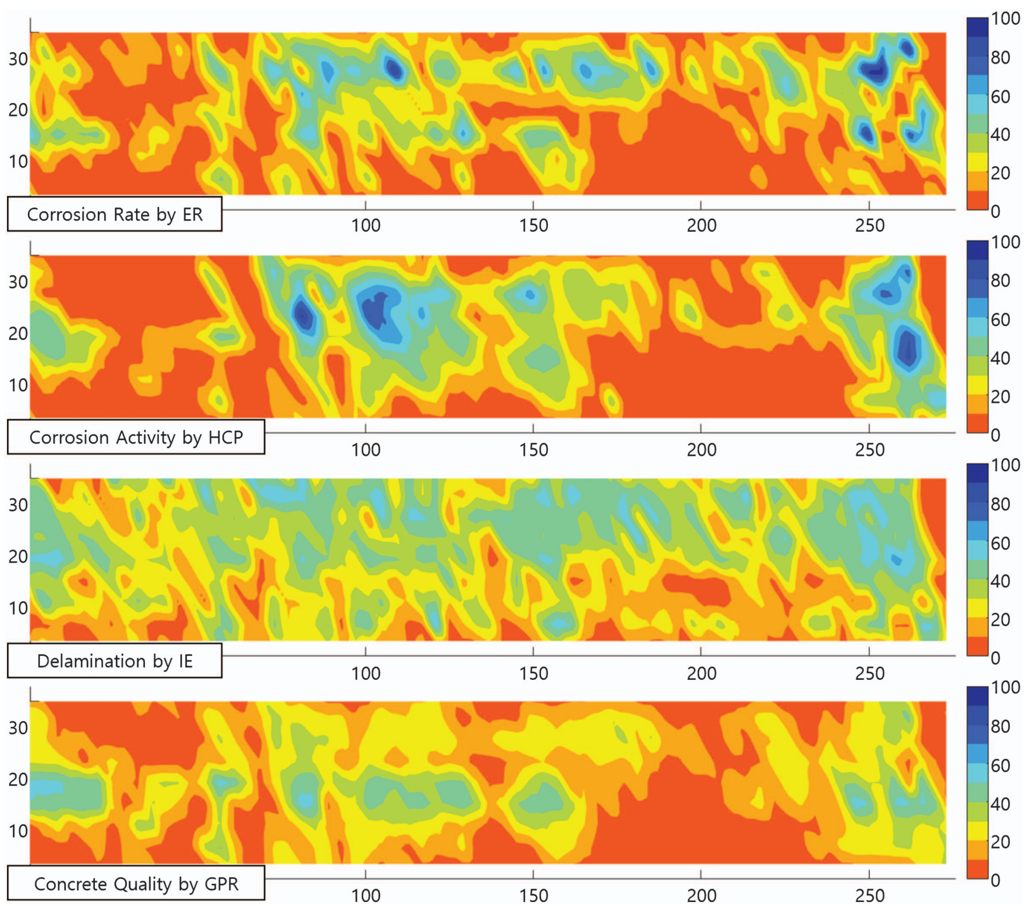

Fig. 10. (Color) Comparison of 2016 reconstructed condition maps: ER, HCP, IE, and GPR. Axes are in feet.

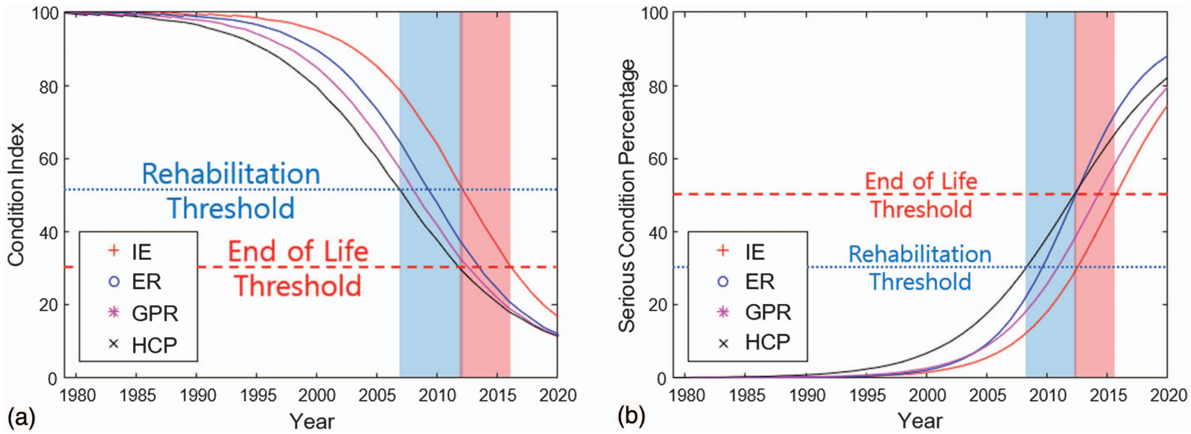

Fig. 11. (Color) Examples of service life predictive models with hypothetical end-of-life and rehabilitation thresholds set to 30 and 50, respectively, based on (a) condition indices; and (b) serious condition percentage.

and GPR are compared in Fig. 10. Overall, very similar deterioration patterns are observed, with correlations among ER, HCP, and GRP especially strong because these technologies are influenced by concrete's electrical properties—primarily electrical conductivity—and processes (Wenner et al. 1915; Maser and Rawson 1993; ASTM 2015). On the other hand, although the dominant delamination location well matches the most severely corrosion-affected areas from other maps, the correlations between IE and these maps are not as strong. It should be noted that the IE condition map for 2016 correlates better with the 2010–2012 condition maps for ER, HCP, and GRP. This may indicate that the deterioration of this bridge deck identified by IE (delamination) is delayed about 5 years compared with the deterioration detected by ER, HCP, and GPR, which again supports the observation that the main cause of delamination of this bridge deck is rebar corrosion.

Remaining Service Life Estimation

Estimation of the remaining service life of the surveyed bridge deck is illustrated in Fig. 11. The models shown are based on deterioration curves from the four NDE technologies without segmentation (single-segment). Fig. 11(a) is based on the CIs [Fig. 5(a)], and Fig. 11(b) is based on the serious condition percentage [Fig. 5(b)]. The model coefficient values a, b, c, and d for the CI and the serious condition percentage are provided in Table 3. Horizontal dashed lines in the plots at the CI and serious condition percentage of 30 and 50, respectively, represent hypothetical end-of-life and rehabilitation thresholds. As an illustration, this bridge deck is assumed to be replaced when its CI falls below 30 or its serious condition percentage rises above 50.

According to the predictive model shown in Fig. 11(a), the bridge deck reached its end-of-life threshold during in 2012–2016. That is, for the given parameters, including data boundaries, weighting factors, segmentation, and curve shape, the life of this bridge deck is about 33–37 years until its CI falls below 30. A similar trend is observed from the serious condition percentage shown in Fig. 11(b). As illustrated, the bridge deck service life estimation can be conducted easier and faster using the developed program through a real-time presentation of CIs, maps, and predictive models. The same curves can be used to define points in time when certain interventions need to take place for optimized bridge deck management. As an example, it is assumed, and illustrated by the dotted lines in Fig. 11, that the thresholds for a certain action are set for the CI to fall to or below 50 or for the serious condition percentage to rise to or above 30.

Summary and Conclusions

An automated, multiple NDE data processing and data analysis program was developed for condition mapping, computation of condition indices, deterioration modeling, and remaining service life estimation for concrete bridge decks. The ultimate objective of the program is to deliver useful information to bridge owners and engineers in support of decision making in bridge management. The program follows the sequence of actions related to NDE data processing, bridge deck segmentation, regression analyses, data integration, deterioration and predictive modeling, and service life estimation. Segmentation and many other input parameters can be easily adjusted so that condition maps, condition indices, and deterioration curves are displayed and updated in real time, reflecting the effects of changes in input parameters. Also, one can review the program condition maps and indices for projected future conditions of a bridge deck, and further evaluate deterioration models of a segmented area of interest.

Multiple NDE data sets collected for the bridge in Haymarket, Virginia, during five and a half years (2009–2015) were used to demonstrate the program's deterioration modeling and remaining-life prediction capabilities. Periodical and long-term bridge deck condition assessment using consistent approaches is vital for the development of realistic and reliable predictive models. Furthermore, it is highly recommended that the bridge deck be evaluated soon after completion of bridge construction to establish baseline conditions.

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