Canadian Science Publishing | Canadian Journal of Civil Engineering

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Journal:	*Canadian Journal of Civil Engineering*
Manuscript ID	cjce-2018-0697.R1
Manuscript Type:	Article
Date Submitted by the Author:	07-Mar-2019
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Keyword:	asphalt, surface distress, IRI, International Roughness Index, pavement
Is the invited manuscript for consideration in a Special Issue? :	Not applicable (regular submission)

Roughness Prediction Models using Pavement Surface Distresses in Different Canadian Climatic Regions

Submission date: March 26, 2019

Word count: 5,180 words, 8 tables, and 3 figures.

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Abstract

The correlation between the International Roughness Index (IRI) and distress is inherent, as roughness is a function of both the changes in elevation of the distress-free pavement surface and the changes in elevation due to existing surface distress. In this way, a relationship between existing surface distress and IRI may be developed. However, the susceptibility of pavement to various types of surface distress is affected by many factors, including climatic conditions. A model that relates pavement surface distress to IRI for Canada needs to account for climatic conditions in different locations. This paper investigates the relationship between pavement surface distresses and IRI for different climatic conditions in Canada using historical data collected at numerous pavement test section locations sourced from the Long-Term Pavement Performance Program (LTPP) database. Developed models were calibrated then validated and found to be statistically significant.

Keywords: asphalt, surface distress, IRI, pavement, roughness

Introduction

The implications of cost savings and increased safety have driven the rise in popularity of Pavement Management Systems (PMS) across North America. It is widely accepted within the pavement management industry, that it is far more cost effective to regularly maintain pavement structures rather than inevitably replace them prematurely as a result of poor maintenance. As such, many transportation agencies are prioritizing the effective maintenance of their pavement assets to ensure both longevity of life of the pavement as well as the safety of users.

Pavement management systems utilize the current conditions of pavement structures to select the adequate future maintenance and rehabilitation treatments (Soliman 2017). Selection of future maintenance and rehabilitation treatments are influenced by the prediction of future pavement conditions on the basis of current pavement conditions along with a host of other influential factors. Investigation into this type of prediction model from historical data collected and stored in the LTPP database is the subject matter explored by Meegoda and Gao (2014). For the purposes of this paper, this type of prediction model is not explored. Instead, the subject matter of this paper consists of the exploration of the relationship between the current pavement condition, as represented by the IRI values, and the current and visually quantifiable surface distresses.

IRI does have limitations in its usefulness, much like the other existing indices used to gauge pavement condition. However, of the existing indices, IRI is one of the most utilized world-wide. Many Canadian territories use the IRI as a tool for pavement evaluation and in some cases for planning and investment purposes as indicated by (Transportation Association of Canada 2006). As a part of its use in pavement evaluation, IRI can serve as the foundation upon which PMSs are built. This means that based upon IRI measurements for pavements, maintenance treatment decisions are made to maximize benefit for the agency and users alike. IRI can also be used to fuel decisions within a PMS that is built around other measures of pavement condition. Through conversations with the Asset Preservation Manager at the City of Saskatoon, it was explained that the City of Saskatoon's PMS is built around Pavement Condition Index (PCI) as the primary pavement evaluation measure; however, IRI was heavily utilized by the same PMS in guiding the decision-making process around the type of treatment to be applied, once maintenance was recommended. In this way, IRI although not the primary pavement evaluation index, plays a very important role in the PMS of the City of Saskatoon and is measured, collected and stored on a regular basis for this reason. It was also explained that in addition to the collection of IRI data, pavement surface distress data was collected and categorized by severity on a far more regular basis.

Obtaining IRI data is often outsourced to private contractors due to the cost and level of expertise required to collect and analyze the necessary data, ultimately resulting in standardized IRI measurements. Furthermore, the cost of maintenance of the equipment used to capture the necessary data would be impractical for road agencies in some cases. For smaller road agencies in Canada, budgetary constraints combined with a smaller road network emphasize the impracticality of commissioning IRI measurement projects much less carrying them out in-house. The benefits associated with knowing and recording IRI values for their managed roads are lost for these reasons.

The LTPP started in 1987 to study the performance of in service pavements (LTPP 2017). The program was aimed at the collection and housing, in a single database, pertinent data from 2,509 pavement road test sections across North America. Although data is not currently being collected at most test sections, the program continues collecting data from more than 700 of these test sections across North America.

Out of the 2,509 test sections, 141 are located across all 10 Canadian Provinces. The breakdown of these 141 test locations per Province are: Alberta (17), British Columbia (4), Manitoba (26), New Brunswick (4), Newfoundland (3), Nova Scotia (1), Ontario (36), Prince Edward Island (3), Quebec (20), and Saskatchewan (27) as shown in Figure 1 below. The data collected from these test locations varying from 1997 to 2015 was used as the foundation of the analysis described in this paper.

Background

Alberta Infrastructure's Transportation and Civil Engineering Division prepared a document in 2002 outlining the comparative uses of IRI across Canada. Although over a decade ago, this document illustrated the wide variety of uses of IRI within the industry, especially as it applies to pavement management. Within the document, it is stated that most Canadian agencies that do not use IRI as part of their business plans convert IRI data to other useful indices which are then utilized (Ashraf and Jurgens 2010).

The prediction of IRI data from pavement distress data is not a new concept. Sandra and Sakar demonstrated the successes of building such a model in their paper, Development of a model for estimating International Roughness Index from pavement distresses (2013). However, this study was carried out in India, which has very different climatic conditions than Canada. It is known that extreme climatic conditions in Canada play a role in surfaces distress of pavements. As such, the relationship between IRI and pavement surface distress would differ from that found by Sandra and Sakar.

Furthermore, the model developed by Sandra and Sakar made use of data that was collected with specific intent to develop such a model. Unfortunately, this meant only a very small section of road was analyzed, resulting in a model that identified and quantified the relationship between IRI and surface distress for that road section only. This means that the resulting model would be limited in its usefulness across India and questionable even for similar roads in similar climatic regions given the width of data used to construct the model. For the purposes of a similar model development for all of Canada, it would be a costly and time-consuming endeavor to collect similar data for multiple road sections across the country. As such, the reliance on historical

Canadian LTPP data, for the sake of building such a model will at the very least yield desired insight into the effects of the different climates on the prediction of IRI values.

One advantage of collecting specific IRI data for the construction of such a model as carried out by Sandra and Sakar, allowed them to isolate the IRI contributed by the distress-free surface from the IRI contributed by surface distresses. In this way, a more accurate measure of IRI caused by distress could be isolated and used in the construction of their model. This was not possible in the research associated with this paper, as the LTPP database does not store IRI data disaggregated into IRI caused by surface distress or IRI caused by distress-free surface. In this way, the technique used by Sandra and Sakar may be superior to using LTPP historical data.

Utilizing LTPP data to construct roughness models is also not a novel idea, as it was carried out by Meegoda and Gao (2014) in their paper, Roughness Progression Model for Asphalt Pavements Using Long-Term Pavement Performance Data. Their research was aimed at the construction of a model that would predict the progression of pavement performance, using roughness as an indicator. Models of this sort are the basis upon which PMSs are built, the prediction of future performance based on current performance. In this way, the need for maintenance can be forecasted and the necessary maintenance plans can be made. Although their research is not directly related to the research being carried out in this paper, they do show that models built for the prediction of roughness from LTPP are useful.

Objectives

The prediction of accurate IRI data would be a useful and powerful tool for Canadian road agencies. Especially if the obtained IRI data was obtained from a model that utilized easily collected surface distress data. A model of this sort would potentially nullify the obstacles associated with cost and loss of time related to the conventional methods of collection and analysis of data to obtain IRI measurements. Road agencies that do not have the necessary resources to obtain IRI measurements through conventional means, would now benefit from being able to better maintain their road networks by utilizing universally accepted methods of pavement evaluation and management based on IRI. The benefits of such a model would also not be confined to agencies that lack resources as the benefits and cost savings would be appreciated by all stakeholders in the pavement evaluation and management industry.

The objective of this paper is to identify a simple linear model that is able to accurately predict useful IRI data for asphalt concrete roads in Canada based on historically collected pavement surface distresses data gathered from the LTPP database.

It is understood that different climatic conditions can have varying effects on pavement surface distresses. Across Canada, there are some common climatic conditions; however, due to the large size of the country, there are also varying ones. Since the objective of such a model for the prediction of IRI is based on surface distresses, the variation in climatic conditions across Canada must also be factored into the analysis. Therefore, this paper will discuss the effects of differing climatic conditions across Canada on the prediction of IRI from surface distress data.

Analysis of LTPP Data

The LTPP InfoPave database was used as the source of all historical pavement distress and regional climatic condition data obtained for the purposes of analysis. The useful data extracted from the database included IRI measurements, various visually quantifiable pavement surface distress data and regional climatic conditions for all of the existing 141 test sections across Canada (LTPP 2017).

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Figure 1 LTPP Infopave map of available Canadian road section data (LTPP 2017).

Because pavement distresses differ by type of pavement surface, and because 137 of the 141 LTPP test locations in Canada were flexible asphalt concrete pavement surfaces, data from rigid pavement surface test locations were eliminated from the analysis. The eliminated test sections consisted of 1 in New Brunswick and 3 in Quebec. This was done to ensure the most accurate prediction model for a uniform pavement surface type could be obtained. Canadian roads within the LTPP are heavily dominated by flexible asphalt pavement. As such, this surface type was chosen as the most suitable as it would yield the most useful data for the analysis.

IRI data for both the left and right wheel paths per test section were available for extraction from the LTPP database. In addition to these measurements, the Mean Roughness Index (MRI) measured in meters per kilometer, is the average of the left and right wheel path IRI's, was presented for each test section. The MRI was preferentially chosen to be used as the most appropriate data for analysis in building these prediction models. This preference for MRI data versus either the left or right wheel path IRI data allowed for a more uniform prediction model from surface distresses, as these distresses do not uniformly occur along either the left or the right wheel path. Thus, an average of the left and right wheel path IRIs (MRI) will take into consideration the effects of a defect that only occurs in 1 wheel path; whereas the effects of a defect occurring in only 1 wheel path would be confined to that wheel path IRI measurement. Should the model have been built around a single wheel path IRI data, the effects of surface distresses occurring in the other wheel path along the same test section, would not have been taken into account in the analysis. This would result in a model that only takes certain pavement defects into consideration, which would limit the usefulness of the model's output.

For each instance of MRI data, 5 runs per test section were available for analysis. For the purpose of creating the most accurate model, the average of the 5 MRI measurements obtained per test section was used as the single MRI value to be used during analysis.

For all the data obtained from the LTPP database, the climatic regions across Canada were heavily dominated by either wet freeze or dry freeze. Climatic conditions at 135 of the filtered 137 test sections in Canada belonged to either of these 2 climatic regions. The remaining 2 locations were categorized as wet non-freeze regions and were both located in British Columbia. Due to the dominance of wet freeze (88) and dry freeze (47), the data from the 2 anomalous test sections in British Columbia were removed from the analysis. As such, only data obtained from the 135 test sections were used. The resulting filtered data was then split according to the 2 dominant climatic regions, wet freeze and dry freeze, to create 2 separate sets of data for analysis.

For each of the 135 filtered test sections available for analysis, there existed 14 categorical and 1 non-categorical pavement surface distress datasets. The total distress data that was available for analysis, including 3 categories of severity for each the 14 categorical distress data, totaled 43 distress data available for analysis per test location.

The 14 categorical distress data were all categorized according to the LTPP Distress Identification Manual definitions. The differences in definition occurred where some distresses were collected by area versus length versus depth etc.

In order to build a model that would predict MRI from pavement surface distress data, the MRI data collected and the pavement surface distress data collected would have to be correlated. This would be to ensure that the MRI data is reflective of the surface distress conditions at the time.

This is difficult to ensure when analyzing historical data. To ensure this correlation of MRI and surface distress data, the obtained LTPP data would again have to be filtered against a suitable criteria. The criteria used to filter this data assumed that no adverse change in pavement surface condition was underwent at any test section within 20 days of collection of either the MRI or surface distress data. As such, only MRI and pavement surface distress data collected within 20 days of each other per test location was found to be suitable for the analysis. All other data was eliminated from the analysis to remove the likelihood of maintenance works being carried out on the pavement surface or any substantial accumulation of distresses to the pavement surface occurred between collections of the data.

Because of the large size of the data due to the categorization of 14 of the surface distress data available, and the objectives of building a simple model, the available data would have to be filtered to capture only the most pertinent data affecting IRI. To achieve this goal and to ensure the filter criteria chosen included the surface distress data be: 1. easily collected via visual inspection, and 2. directly affect IRI measurements. Filtering the available data against these 2 criteria resulted in the identification of 8 pertinent categorical surface distresses, which included: alligator crack area, block crack area, edge crack length, longitudinal crack length (in the wheel path), transverse crack numbers, transverse crack length, patched area, and pothole area. In addition, 1 non-categorical data: raveling area was included in the analysis. Other surface distress data were eliminated because they were believed not to have effect on the collection of IRI data. This belief was based on the assumption that IRI data is measured along the wheel path only. As such, only distresses that affect the wheel path would affect the measurement of IRI. An example of this elimination saw the lengths of longitudinal cracks within the wheel path being included in the dataset for analysis, whereas the number of longitudinal cracks outside the wheel path was eliminated from the dataset.

All 8 categorical distresses were categorized by severity with each category having its own unique definition and unit of measurement as previously outlined. Table 1 below presents all 9 of the distresses that resulted from filtering of the data, of which 8 are categorical, along with their corresponding units of measurement, associated severities and definitions for each category of severity according to the obtained LTPP data.

Table 1 Useful Surface Distress Data from LTPP Infopave (*LTPP 2017*) (Miller and Bellinger 2017)

IRI and thus MRI data can be thought of as a function of existing surface distress for a given pavement; however, these roughness indices are also a function of the actual variations in pavement surface elevation. A road is built with a certain MRI, therefore changes in MRI are more important that the actual MRI. As demonstrated by Sandra and Sarkar (2013), for a prediction model of this type to be developed, IRI measurements had to be split into IRI that results from pavement surface distress and IRI that results from pavement surface roughness. Similarly, in developing a model that can predict MRI from historical pavement distress data, the contribution of pavement surface roughness must first be removed from the MRI values to be useful.

Separating MRI measurements in this way, from historical data, is difficult because no distress-free surface MRI measurements were recorded, i.e. MRI measurements taken on each section prior to any surface distresses being present. To accomplish this goal of isolation of MRI due to surface distress, the data within each of the 2 datasets (separated by climatic region) were sorted and grouped according to common test sections. The distress data for each section was then analyzed to identify instances of little or no surface distress measurements, i.e. instances where measurements for all 25 distresses (8 categorical and 1 non-categorical) were 0 or very low. The corresponding MRI values for these instances were taken as the initial MRI values for their respective test sections. These chosen initial MRI values were then subtracted from the remaining MRI values for their respective sections to yield the MRI values resulting solely from pavement surface distress. This was referred to as the Distress MRI to differentiate it from the total MRI. For test sections where an instance of minimal or zero distress data could not be found, the data for the test sections were removed from the dataset as an initial MRI value and thus a Distress MRI would be impossible to identify.

After filtering the data to ensure usefulness for the objectives of this analysis, the resulting dataset consisted of 1 MRI measurement and 25 correlated pavement surface distress datasets for a total of the 277 datasets scattered across all Canadian Provinces except British Columbia and Nova Scotia. Of the 277 datasets, 110 were in dry freeze and 167 were in wet freeze climatic regions. A sample of the resulting dataset showing average MRI measured along with correlated categorical alligator cracking surface distress measurements for 3 datasets in the dry freeze regions of Alberta is shown in the table below.

Table 2 Sample of Resulting Filtered Dataset

Model Development

Both climatic datasets were analyzed separately for the purposes of drawing comparison between the resulting models. Therefore, 2 separate analyses and hence 2 separate models were built for the prediction of MRI data for dry freeze climatic regions and wet freeze climatic regions within Canada. For the purposes of later validation of the built models, 30% both datasets were removed before analysis and saved. As such, only 70% of each dataset was used for the calibration of the models.

IBM's SPSS computer software was used for the purposes of analysis of the filtered data. To preserve the goal of building a simple model, linear regressions were used to analyze and identify the best-fit equation that utilized all the available pavement surface distress data to predict the associated MRI data per test section for both datasets. By using a linear regression, this ensured that in the future, obtaining MRI values from the model would be a quick and easy process. A backward elimination technique was used to identify distress data that did not contribute significantly to the model predictions. These identified distress data were removed from the dataset and the regressions repeated on the remaining data. This process was repeated recursively until the resulting models contained only significantly contributing distress data. Two differing models for the prediction of MRI values according to each dataset was obtained through this process. The results of regression analysis for each of the datasets are shown in Tables 3-6 below:

Table 3 Resulting Linear Model Coefficients and Statistical Significance for Dry Freeze Canadian Climates

Table 4 Resulting Linear Model Summary and Statistical Significance for Dry Freeze Canadian Climates

Table 5 Resulting Linear Model Coefficients and Statistical Significance for Wet Freeze Canadian Climates

Table 6 Resulting Linear Model Summary and Statistical Significance for Wet Freeze Canadian Climates

Tables 3 and 5 show both the coefficients and variables included in each resulting model developed. Tables 4 and 6 show that both models are statistically significant at both a 95% and 99% confidence level as the significance for both models is 0.000. The R-square value for the dry freeze climate model reflects 76.3%, while that of the wet freeze climate model reflects 43.5%. These R-square values indicate how closely the MRI predicted by the model fits the actual MRI data measured. Analysis of both R-square values show that the dry freeze model is far more accurate than the wet freeze model. This was further illustrated during the model validation process. Table 7 below shows a summary of the coefficients and variables for both models for comparison.

Table 7 Model Comparison between Wet and Dry Freeze Canadian Regions

The resulting equation for each model is as follows:

Dry Freeze Region:

[1] MRI = 0.286 + 0.003*High Severity Alligator Cracking + 0.048*High Severity Transverse Crack Number + 0.019*Low Severity Patch Area + 0.019*Medium Severity Patch Area + 0.633*High Severity Pothole Area

Wet Freeze Region

[2] MRI = 0.533 + 0.011*High Severity Alligator Cracking + 0.002*Low Severity Block Cracking Area + 0.001*Medium Severity Block Cracking Area + 0.618*High Severity Longitudinal Wheel Path Crack

In both models, high severity alligator crack area is a significant contributor to the prediction of Distress MRI values. This was expected due to the frequent occurrence of this distress throughout both sets of data. Also expected, was the dominance of high and medium severity distresses that significantly contributed to the prediction of Distress MRI values in both models. Only 1 low severity distress was included in each of the models. This is suspected to be due to the lack of data in the medium and high severity categories of that surface distress dataset.

The dry freeze model included expected surface distresses with the largest model coefficient and thus most influential distress factor coming from high severity pothole area. Patch area at low and medium severities, high severity alligator crack area and high severity transverse crack number complete the model influences. It is not surprising that these distresses are significant contributors to the predication of Distress MRI.

The wet freeze model also included expected surface distresses but this model shared only alligator cracking at high severity with the model obtained for the dry freeze region. Block crack area at both low and medium severity also played roles. It is peculiar that low and medium severity block cracking were significant contributors to MRI values but high severity block cracking was not. Post-analysis of the block cracking data in the dataset revealed very little non-zero data within the set. This provides a valid reason for its elimination through regression analysis. Therefore, conclusion can be definitively drawn to say that block cracking in wet freeze regions in Canada affect IRI and thus MRI measurements. The largest model coefficient and thus most influential factor came from high severity longitudinal cracking within the wheel path. This surface distress was not a significant contributor in the dry freeze regions.

The variables between the resulting models is testament to the difference in surface distresses and their severities in the 2 different regions across the country. The 2 models also show that there does exist a relationship between MRI values measured and current pavement surface distress in Canada.

Model Validation

Both resulting models were then used to generate predicted Distress MRI values for their respective remaining 30% of data, which was initially removed from the analysis. The predicted MRI values were then compared to the actual Distress MRI values as measured for those 30% of data both graphically and using a Chi-square goodness of fit test. By not including the 30% of the data used for model validation in the regression used to create the models, this ensured that the validation process would yield a true reflection of the accuracy with which the model is able to make predictions. Figures 2 and 3 below show the results of the graphical comparisons or MRI in m/km for the dry freeze and wet freeze models respectively.

Figure 2 Predicted and measured distress MRI (m/km) for Canadian dry freeze regions.

Figure 3 Predicted and measured distress MRI (m/km) for Canadian wet freeze regions.

From Figures 2 and 3 it is noticed that the fry Freeze model Distress MRI predictions are closer to and follow a similar pattern as the measured Distress MRI, versus the wet freeze model. This was expected given the R-squared values for each model, as previously outlined. Both the graphical results and the R-squared values for each model implies that the dry freeze model is superior to the wet freeze model in accuracy of prediction, although both models are statistically significant. This was also the interpretation of the results, shown below in Table 8, of a Chi-squared goodness-of-fit test.

Table 8 Chi-squared goodness-of-fit test values for both models

Both models' Chi-square values are less than their respective critical values, as shown; however, the Chi-square value for the dry freeze model is lower. The chi-squared value and degrees of freedom for the wet freeze model is significantly lower than that of the dry freeze model because of the lower number of usable data points for the wet freeze region. The lower chi-squared value for the wet freeze region does not indicate a stronger model, in fact based on the R-squared values for both models; the dry-freeze model is far stronger.

Summary and Recommendations

PMSs are extremely useful in the cost-effective preservation and rehabilitation of pavement surfaces. These systems are dependent on the current pavement conditions in order to predict future conditions and thus necessary maintenance and rehabilitation works that will be necessary in the future. IRI has proven a very useful index to reflect the measure of current pavement conditions. The usefulness of IRI in the prediction of future pavement conditions is undeniable and has been adopted for this purpose in many PMSs across Canada. However, the process necessary to obtain current IRI measurements is both costly and time-consuming. This paper outlines a means to obtain IRI data for current pavement conditions through a faster and less costly process than conventional methods. This process is possible through the isolation of measured IRI measurements that result from current pavement surface distresses and identifying a relationship between the pavement surface distress and the isolated IRI. There are a number of different external factors that affect pavement surface distress, one such factor is climate. Because Canada was the subject location for this study, the climatic conditions there were factored into the analysis by grouping distress and MRI data from similar climatic conditions. Thus, the resulting models would only be applicable to specified climatic areas.

Both models were developed using the same process for their respective datasets, dry freeze and wet freeze regional data. Seventy percent of each dataset was used to calibrate each model, while the remaining 30% of the data was used to validate each model. Although both models were statistically significant at both 95% and 99%, the resulting models had very different associated accuracies based on their R-squared values. The dry freeze model was superior with a relatively high R-square value of .763 compared to the wet freeze model with a low R-square value of .341.

Although the relationship between MRI and pavement surface distress has been successfully identified for 2 climatic regions across Canada through this study, there are further analyses that could be carried out to refine the resulting models. As Sandra and Sarkar (2013) did in their study, IRI values on distress-free pavement sections can be measured and recorded. The application of this approach would more accurately isolate the IRI that is solely due to pavement surface distress, thus improving the accuracy of the models developed in this study. Furthermore, analysis taking into consideration the traffic distributions at the different test locations could also prove useful in obtaining a more accurate model for the prediction of MRI for both climatic regions tested.

As in the case of the City of Saskatoon, where both surface distress data and IRI measurements are captured, the successful prediction of IRI from the cheaply and hence far more frequently obtained surface distress data could prove financially advantageous to the City’s PMS predictions.

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TABLES

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FIGURES

Figure 1 LTPP Infopave Map of Available Canadian Road Section Data

Figure 2 Predicted and measured distress MRI (m/km) for Canadian dry freeze regions

Figure 3 Predicted and measured distress MRI (m/km) for Canadian wet freeze regions

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Table 1 Useful Surface Distress Data from LTPP Infopave (*LTPP 2017*) (Miller and Bellinger 2017)

Surface Distress	Unit of Measure	Severity	Definition of Severity
Alligator Crack	Area (square meter)	Low	Few or no connecting cracks, not spalled or sealed, no pumping evident.
		Medium	Interconnected cracks possibly slightly spalled, may be sealed, pumping may be evident.
		High	Moderately or severely spalled interconnected cracks, may be sealed, pumping may be evident
Block Crack	Area (square meter)	Low	Cracks of unknown width well sealed or with mean width of 6 mm or less.
		Medium	Mean crack width from 6 to 19 mm or under 19 mm with adjacent low severity random cracking.
		High	Mean crack width greater than 19 mm or under 19 mm with moderate to high severity random cracking.
Edge Crack	Length (meter)	Low	Length of low severity edge cracking.
		Medium	Length of moderate severity edge cracking.
		High	Length of high severity edge cracking.
Longitudinal Crack in Wheel Path	Length (meter)	Low	Cracks of unknown width well sealed or with mean width of 6 mm or less.
		Medium	Mean crack width from 6 to 19 mm or under 19 mm

			with adjacent low severity random cracking.
		High	Mean crack width greater than 19 mm or under 19 mm with adjacent moderate to high severity random cracking.
Transverse Crack	Number (counts)	Low	Cracks of unknown width well sealed or with mean width of 6 mm or less.
		Medium	Mean crack width from 6 to 19 mm or under 19 mm with adjacent low severity random cracking.
		High	Mean crack width greater than 19 mm or under 19 mm with adjacent moderate to high severity random cracking.
Transverse Crack	Length (meter)	Low	Cracks of unknown width well sealed or with mean width of 6 mm or less.
		Medium	Crack mean width from 6 to 19 mm or under 19 mm with adjacent low severity random cracking.
		High	Crack mean width greater than 19 mm or under 19 mm with adjacent moderate to high severity random cracking
Patching	Area (square meter)	Low	Area of patching with low severity distress or patch deterioration.
		Medium	Area of patching with moderate severity distress or patch deterioration.
		High	Area of patching with high severity distress or patch

			deterioration.
Potholes	Area (square meter)	Low	Less than 25 mm deep.
		Medium	From 25 to 50 mm deep.
		High	More than 50 mm deep.
Raveling	Area (square meter)	Non-categorical	

Table 2 Sample of Resulting Filtered Dataset

State_Code_Exp	Date	MRI Avg.	SHRP_ID	Gator_Crack_A_L	Gator_Crack_A_M	Gator_Crack_A_H
Alberta	07/25/2002	2.101	0501	0.0	1.3	0.0
Alberta	07/19/2005	2.943	0501	8.8	1.9	0.7
Alberta	06/04/1998	2.106	0501	0.0	1.8	0.0
Alberta	05/24/1999	1.930	0501	0.5	0.0	0.0
Alberta	06/12/2006	2.592	0501	8.7	1.8	0.7
Alberta	07/17/2000	2.068	0501	0.6	0.0	0.0
Alberta	07/29/2002	1.428	0501	104.5	93.3	15.7

Table 3 Resulting Linear Model Coefficients and Statistical Significance for Dry Freeze Canadian Climates

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.286	.037		7.645	.000
	GATOR_CRACK_A_H	.003	.001	.211	3.612	.001
	TRANS_CRACK_NO_H	.048	.012	.234	4.038	.000
	PATCH_A_L	.019	.007	.157	2.616	.011
	PATCH_A_M	.019	.001	.757	12.619	.000
	POTHOLES_A_H	.633	.183	.200	3.450	.001

Table 4 Resulting Linear Model Summary and Statistical Significance for Dry Freeze Canadian Climates

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Sig.
1	.873	.763	.746	.24756	.000[a]

Table 5 Resulting Linear Model Coefficients and Statistical Significance for Wet Freeze Canadian Climates

Model	Unstandardized Coefficients B	Unstandardized Coefficients Std.	Standardized Coefficients Beta	t	Sig.

		Error			
1 (Constant)	.533	.113		4.714	.000
GATOR_CRACK_A_H	.011	.003	.434	3.191	.003
BLOCK_CRACK_A_M	.001	.001	.360	2.755	.009
LONG_WP_L_H	.618	.180	.438	3.441	.001
BLOCK_CRACK_A_L	.002	.001	.513	3.733	.001

Table 6 Resulting Linear Model Summary and Statistical Significance for Wet Freeze Canadian Climates

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Sig.
1	.660	.435	.373	.43637	.000

Table 7 Model Comparison between Wet and Dry Freeze Canadian Regions

Dry Freeze Region Model		Wet Freeze Region	
Coefficient	Variable (Distress)	Variable (Distress)	Coefficient
+ 0.286	Constant	Constant	+ 0.533
+ 0.003	Alligator Cracking High Severity	Alligator Cracking High Severity	+ 0.011
+ 0.048	Transverse Crack Number High Severity	Block Crack Area Low Severity	+ 0.002

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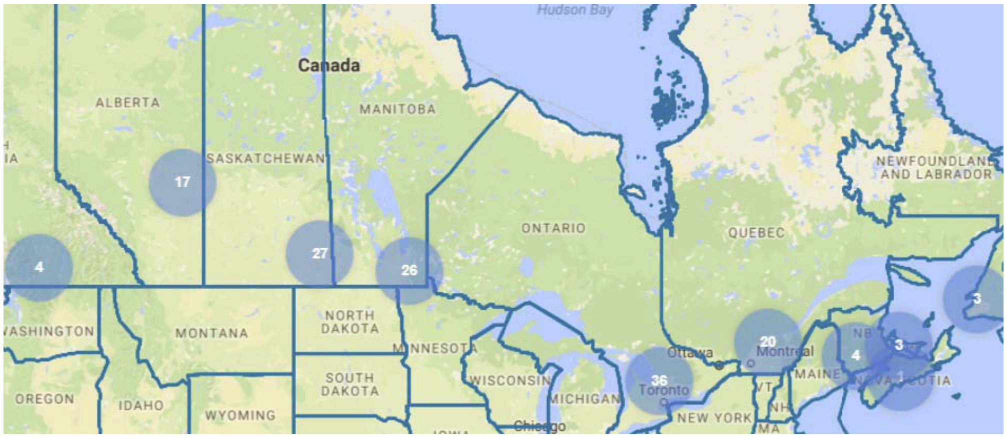
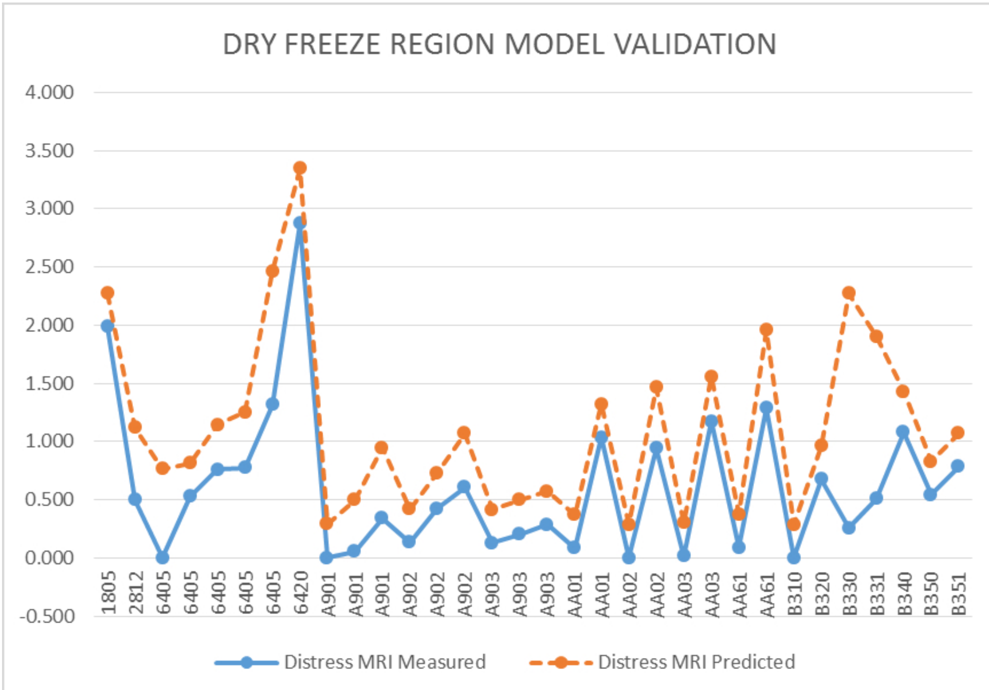
+ 0.019	Patch Area Low Severity	Block Crack Area Medium Severity	+ 0.001
+ 0.019	Patch Area Medium Severity	Longitudinal Wheel Path Crack High Severity	+ 0.618
+ 0.633	Pothole Area High Severity		

Table 8 Chi-squared goodness-of-fit test values for both models

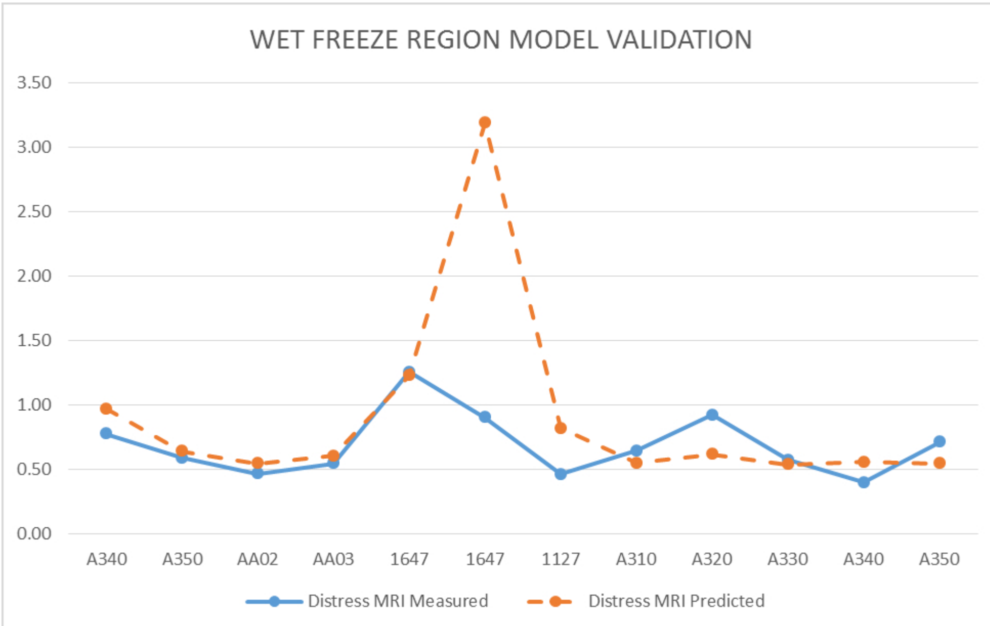
Model	Dry Freeze Model	Wet Freeze Model
Chi-squared value	35.607	2.121
Degrees of freedom	124	33
Critical Value	150.989	20.86



LTPP Infopave map of available Canadian road section data



Predicted and measured distress MRI for Canadian dry freeze regions



Predicted and measured distress MRI for Canadian wet freeze regions