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A MACHINE-LEARNING SOLUTION FOR QUANTIFYING THE IMPACT OF CLIMATE CHANGE ON ROADS

Piryonesi, S. M.[1,2] and El-Diraby, T. E. [1]
[1] University of Toronto, Canada
[2] madeh.piryonesi@mail.utoronto.ca

Abstract: Modeling pavement performance is a must for road asset management. In the age of climate change, pavement performance models need to be able to quantify the impact of climate change on roads. This paper provides a practical decision-support tool for predicting the condition of asphalt roads in the short and long term under a changing climate. Users have the option of running a predictive model under different values of climate stressors. The prediction of deterioration is performed via machine learning. More than a thousand examples of road sections from the Long-Term Pavement Performance (LTPP) database were used in the process of model training. The models can predict future values of pavement condition index (PCI) with an accuracy above 80%. The results were implemented in a web-based platform, which includes a map with an interactive dashboard. Users can query any road, input its data, and get relevant predictions about its deterioration in two, three, five and six years. To show the effectiveness of the solution two sets of examples were presented: two individual roads in Ontario and British Columbia and a group of 44 roads in Ontario. The condition of the latter was predicted under a hypothetical climate change scenario. The results suggested that the roads in Ontario will experience a more relaxed deterioration under this climate change scenario.

1 INTRODUCTION

This paper aims to create a practical decision-support tool for predicting the deterioration of asphalt roads. The platform will also facilitate quantifying the impact of climate change on roads. So, this study has two major facets: predicting road conditions using machine learning and implementing the results in a web-based platform coupled with a map. Users can query different roads and learn about their future conditions under different ranges of climatic stressors and traffic volumes. Such decision-support tools can be highly useful to transportation agencies and decision makers in different levels of government.

In this study, the road condition is measured via the pavement condition index (PCI). The reason behind choosing the PCI was its popularity among municipalities and departments of transportation (DOTs). The authors conducted a survey on 58 municipalities in Ontario and asked about the type of data they collect for representing the level of service of roads. The most popular performance indictor (PI) was the PCI with 84% followed by followed by the surface distress index (SDI) with 23% and the international roughness index (IRI) with 16%. These numbers motivated the authors to conduct the analysis on the PCI. Nevertheless, this study could be generalized to other PIs. Conducting all analysis based on the PCI and using easy-to-collect or free data makes the results reproducible for most municipalities in Ontario.

Furthermore, climate change is another factor that necessitates further research on the impact of climate stressors on roads. Governments recently have become interested in the impact of climate change on infrastructure. In Ontario, Canada, the Province requires all municipalities to include the impact of climate change in the design and maintenance of their infrastructure (Government of Ontario 2016). Accordingly, municipalities must develop relevant tools for understanding this impact. This research could help both industry and academia in this regard.

2 LITERATURE REVIEW

2.1 Pavement Performance Modeling

It is incumbent upon municipalities to model the deterioration of roads. Currently, the main types of deterioration models include deterioration master curves, statistical regression-based models (including mechanistic and mechanistic-empirical methods), Markov models and data analytics models. In practice, deterioration master curves are widely used by the industry (Ford et al. 2012, El-Diraby et al. 2017). Most these deterioration curves are representing the changes in a performance indicator (e.g. PCI) over time using a sigmoidal function (Wu 2015). These curves are deterministic. Furthermore, they cannot take into account factors such as traffic and climate (Wu 2015, Piryonesi and El-Diraby 2018). Mechanistic-empirical (M-E) methods were developed to address the weaknesses of these empirical deterioration curves. Both categories rely on correlation analyses (Archilla and Madanat 2000, Ayed 2016). Over the last two decades, M-E models gained momentum and several DOTs have used this type of analysis for predicting the condition of their roads. Although M-E models are more accurate, but they are criticized for being deterministic, requiring expensive data such as deflection measurement and being unreliable for predicting unseen data (Ens 2012, Chi et al. 2014, Wu 2015). Markov models are a category of probabilistic methods frequently used in the literature of deterioration modeling (Li et al. 1996, Pulugurta et al. 2009). Unlike correlation-based techniques, Markov models define the deterioration of roads as a series of discrete events, and their output is a class of performance indicators in lieu of a real number. These models entertain probabilities. As a result, they are adopted to develop more sophisticated infrastructure deterioration models (Pulugurta et al. 2009, Ens 2012, Ford et al. 2012). However, they disregard the history of deterioration and cannot entail climatic attributes and traffic (Ens 2012, Anyala et al. 2014, Piryonesi and Tavakolan 2017, Piryonesi and El-Diraby 2018). It is worth mentioning that semi-Markov models could address the problem of time homogeneity (Black et al. 2005, Ens 2012).

The most recent method for modeling road performance is using machine learning. According to National Cooperative Research Program (NCHRP), machine-learning techniques have been used to a lesser extent because the results of such analyses are not easy to interpret (Ford et al. 2012). The NCHRP report merely limits machine learning to artificial neural networks (ANNs). Neural networks have been criticized for their lack of interpretability despite their learning capability (Cervantes et al. 2017, Piryonesi and El-Diraby 2018).

The most commonly used algorithm for pavement performance modeling is the ANN. Ferregut et al. (1999) used ANNs in predicting the remaining life of asphalt pavement. They used an array of nine attributes as the input of their model: the thickness of the asphalt concrete; thickness of base layers; and seven readings of an FWD. Another example of using ANNs for predicting pavement performance is available at (Lou et al. 2001). Using the data of Florida DOT, they used predictive attributes such as the age of road and three consecutive values of crack index (CI) to predict the CI in the near future. Kırbaş and Karaşahin (2016) used an ANN to predict the deterioration in the PCI based on the age of road. They reported that the ANN outperformed the deterministic regression. A shortcoming of their work was the small size of their training set, which entailed less than 100 examples. The literature includes other similar studies that have relied on ANNs and a small training set (Terzi 2007, Ford et al. 2012). Most these studies result in overparameterized models. In addition to ANNs, a few other probabilistic prediction studies on pavement are available, which are majorly based on Bayesian models (Ramia and Ali 1997, Anyala et al. 2014).

The black-box nature of ANNs motivated researchers to use other algorithms. Chi et al. (2014) learned four decision trees for predicting structural condition index (SCI) based on the data of Texas DOT. The highest accuracy their models could achieve, in predicting five classes of SCI, was only 62%. The small size of their training set, which included 354 examples, may have adversely affected the accuracy. Among the attributes used by Chi et al. (Chi et al. 2014) were the amount of distress and ride score over five years, which are not free or easy to collect. Another study that is not merely based on neural networks is done by Kargah-Ostadi and Stoffels (2015). This study as well used the LTPP data to predict the roughness of roads. This is a common trend among the researchers who use the LTPP data (Haider et al. 2007, Kargah-

Ostadi et al. 2010, Kargah-Ostadi and Stoffels 2015, Ziari et al. 2016), most probably, because the PCI data is not given in this database, and its preparation requires a lot of effort.

Notwithstanding the availability of different classification algorithms, most researchers relied on regression algorithms. A few studies that used classifiers such as decision trees expressed concern about the low accuracy (Chi et al. 2014, Piryonesi and El-Diraby 2018). In this paper, more advanced classifiers, such as ensemble algorithms or naïve Bayes coupled with kernels, are used for predicting the PCI deterioration. These algorithms have a higher accuracy when compared with their predecessors. Notwithstanding their high learning capabilities, this category of machine learning algorithms is barely used in deterioration modeling. To the best knowledge of authors, the only study that has used an ensemble learning method for performance modeling is a recent research conducted by Gong et al. (2018).

Another distinguishable aspect of this research, that differentiates it from previous studies, is the selection of attributes. As discussed above, most previous studies tend to focus on predicting a single type of distress such as rutting depth, pothole or roughness. These indices cannot comprehensively represent the health of pavement. But, the PCI, which is a more complex index composed of different types of distresses, could reflect the pavement condition more holistically. Furthermore, the predictive attributes of previous studies mostly are not free or easy to collect. It was mentioned that most small municipalities do not have access to updated deflection data collected by the FWD (Chi et al. 2014, El-Diraby et al. 2017).

2.2 Considering Climate Change in Deterioration Modeling

The notion of incorporating climatic attributes in deterioration modeling is gaining traction in the wake of climate change. For instance, a new provincial regulation in Ontario mandates municipalities to consider the impact of climate change on infrastructure, and vice versa (Government of Ontario 2016). Driven by such motives, research has been recently moving towards calculating the impact of climate. Anyala et al. (2014) investigated the impact of different climatic scenarios on asphalt pavement rut progression. They combined M-E models with simulation to create deterioration models for different climate scenarios. Ayed (2016) also considered the impact of climate change in developing M-E models for predicting the condition of roads in Canada. The PIs of interest were riding comfort index (RCI) and the SDI. As mentioned, crude Markov models are incapable of representing climate stressors explicitly, but Osorio-Lird et al. (Osorio-Lird et al. 2018) developed multiple Markov models to consider the impact of climate.

The number and extent of studies that specifically quantify the impact of climate change are limited. Schweikert et al. (2014) developed a software for analyzing the impact of climate change on road infrastructure. Their study brought together quantitative and qualitative methods to quantify the risks and consequences of climate change in the policy level. Neumann et al. (2015) estimated the cost that climate change imposes on the US infrastructure until the end of 21st century. Their study included roads, bridges, coastal development and urban drainage. In a more specific study, Chinowsky et al. (2013) calculated the cost of different types of climate change adaptation on roads in the US. Their study included different climate change scenarios and was studying the impact until year 2100. A limitation of their study was that instead of modeling the impact of climate stressors, they relied on one-number estimates from the literature for quantifying the impact of temperature and precipitation on roads. For climate change scenarios, they relied on Special Report on Emissions Scenarios (SRES).

3 METHODOLOGY

The current study proposes a decision-support tool for predicting the future condition of roads using machine learning. The developed tool has the capability of predicting the deterioration of roads under different values of climate stressors. A few factors distinguish this paper from previous studies. First, this study relies on machine-learning classifiers for predicting the PCI rather than curves or regression models. Second, it facilitates the study of climate change by including different climatic attributes in the predictive model. The models can explicitly represent climatic attributes. Users can input a range for each climate stressor and learn the impact on the road networks. Third, the models are implemented in an online platform with a map for the use of practitioners. Figure 1 is giving a brief overview of the methodology of this work.

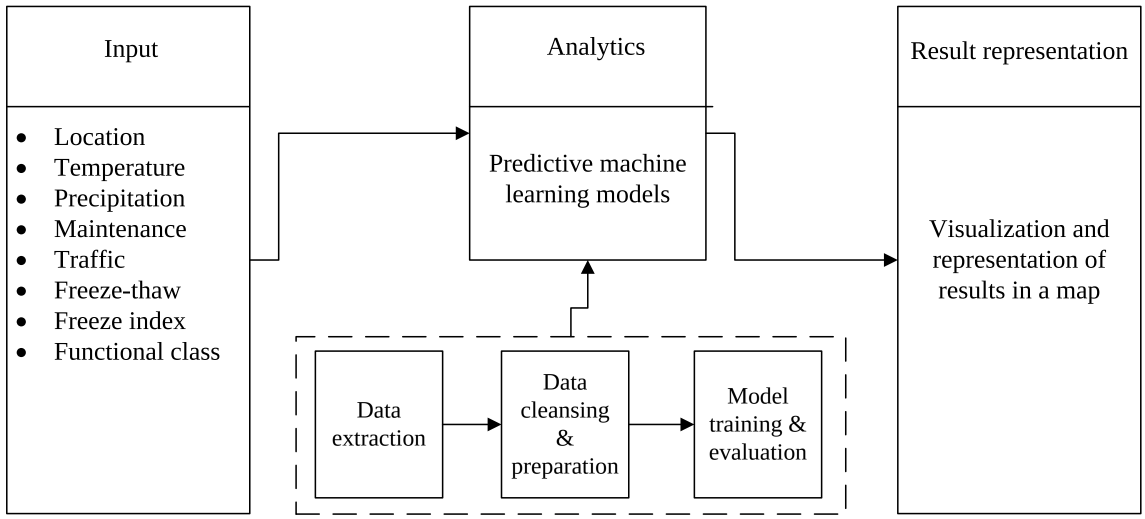

Figure 1. An overview of the methodology and scope

As shown in Figure 1, user can query a road on the map and enter some values for its different current attributes. Each input could be a single value or a range of possible values. The entered data will be fed into a predictive model, which is trained by machine learning. The model will iterate through the input values and print different results for each input. The future PCI will be predicted for two, three, five and six years. The results will be graphically represented on a map. The necessary steps for training the predictive models are shown inside a dashed-line rectangle. These steps include retrieving training data, cleaning and preparing the data, training the models and testing their accuracy.

4 DATA PREPARATION

The data was retrieved from the LTPPP database. This open database contains the information of more than 2500 road sections across the US and Canada (InfoPave 2018). The LTPP database does not entail the PCI, but it includes the necessary data for PCI calculation such as the distresses and their severity levels. For that reason, the first step was to generate PCI values from distresses given that the emphasis of this research was on the PCI. This task was done according to ASTM D 6433–07 guideline (Way et al. 2015). With this aim, the curves presented at ASTM D 6433–07 were digitized and their mathematical formulas were extracted using curve fitting. Given that the training set included 3277 examples, calculating the PCI for the training set manually was impractical. As a result, the extracted formulae were imbedded in a computer program to calculate the PCI from distresses.

The intention was to predict the PCI in the short-term. So, the horizons of prediction were chosen as two, three five and six years. The number of examples for each prediction interval included 1196, 942, 616 and 523 respectively, totalling up to 3277 records. Each example included fifteen possible predictive attributes. A list of these attributes and their description is given in Table 1. The target variable is the future class of PCI based on ASTM's guideline. In this study the last three classes are merged and called Very Poor. Thus, the models have five labels.

Table 1. Predictive attributes and their description

Field name	**Description**
PCI0	The (initial) value of PCI at time of analysis
AGE	Age of road (since construction)

PAVEMENT_TYPE	Type of pavement (as defined by FHWA in LTPP)
FREEZE_INDEX_YR	Calculated freeze index for year (in Celsius days)
MAX_ANN_TEMP_AVG	Average of daily maximum air temperatures for year
MIN_ANN_TEMP_AVG	Average of daily minimum air temperatures for year
TOTAL_ANN_PRECIP	Total precipitation for year (in mm)
FUNC_CLASS	Functional class of road (as defined by FHWA in LTPP)
FREEZE_THAW_YR	Number of freeze-thaw cycles per year
OVERLAY_THICKNESS	Thickness of the placed layer in rehabilitation
AADT_ALL_VEHIC_2WAY	Average annual daily traffic
REMED_TYPE	Type of last remedial action (as defined by FHWA in LTPP)
REMED_ YEARS	Number of years since the last remedial action
CONSTRUCTION_NO	Number of conducted remedial actions
GBE	Granular Base Equivalence
PCI (target variable)	The class of PCI after three years (as categorized by the ASTM)

5 MODEL TRAINING

Several classification models were trained to predict the class of PCI in the future. Some of the models are shown in Table 2. The level of PCI was predicted after two, three, five and six years. The accuracy of the models was tested using a tenfold cross-validation. Table 2 shows the results of the cross-validation accuracy for different models in predicting the PCI in three years. All attributes of Table 1 were simultaneously used in training these models. As a generic observation, the ensemble learning algorithms had a significantly higher performance than their base learner. Note that these two models rely on decision tree I as base learner. Decision trees, on the other hand, did better in comparison to linear classifiers such as naïve Bayes classifier or logistic regression. Coupling the naïve Bayes classifier with kernels increased its accuracy considerably.

Table 2. The accuracy of different models in predicting the PCI in three years

Type of model	**Accuracy (percent)**	**Comments**
Gradient boosted trees	81.05 ± 5.97	50 single learners (trees)
Random forest	70.01 ± 4.48	50 single learners (trees)
Decision tree I	63.37 ± 4.07	Leaf size = 2, confidence = 0.25
Decision tree II (C4.5)	72.70 ± 4.21	Leaf size = 2, confidence = 0.25
Naïve Bayes classifier	57.10 ± 2.08	-
Naïve Bayes classifier with kernel	70.15 ± 5.16	Number of kernels = 10
Logistic regression	54.56 ± 4.25	-
k-NN	64.28 ± 6.03	k = 4

6 MODEL IMPLEMENTATION

The trained models were implemented into an interactive portal coupled with a map. Figure 2 shows an overview of how the online portal functions. It has two major modules: a front-end webpage that is available to the user; and a server that is responsible for analytics, storing data and visualization. The front-end webpage contains the fields that allow users to input data. This part of the interface is created by a static HTML code. In addition to direct input, the platform also has the capability of reading from files, in case a user wants to upload the data collectively. Once the user enters the name and information of a road, the webpage will send a request to the server-end. The server will then response with the map data. A map on the other side of the page will display the result. The process of reading from the map will be briefly explained below.

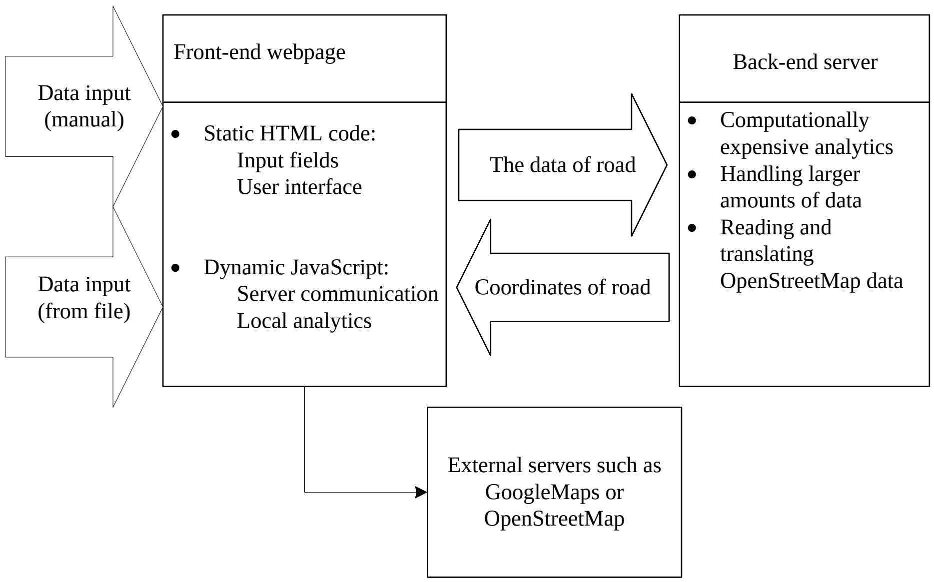

Figure 2. A schematic representation of the information flow between the web page and the server

Each input field could be input either as a single number or a range of possible values. These data will be fed into a dynamic script written in JavaScript. This program can conduct the prediction locally for models that do not include a computationally expensive process. However, more computationally complex models, such as ensemble learning models, could be run on the server side. Another case in which the server conducts the calculation is when the users inputs a range of values rather than a single number for climatic attributes. In this case the model needs to be run multiple times, and this iteration of models needs computational power. The JavaScript program is also responsible for communication with the server or any other external servers such as Google Maps.

Raw map data was fetched from OpenStreetMap (2018), which is an open source editable map. The extracted data was stored in the server waiting for the service program to operate. The OpenStreetMap raw data is in XML format. Service program will have to use an external library to operate the map data. The name of every road is then transferred into an array of longitude and latitude coordinates that could be represented visually. Since JavaScript could support JSON data, every response by the server is be represented in JSON format. Responses from the service program will be transferred into JSON String and then sent to the front-end. The response will be accordingly displayed on a map (see Figure 3).

To demonstrate the functionality of the map two different examples were studied. The first example included predicting the condition of two individual roads, one in Ontario (ON) and one in British Columbia (BC), and the second entailed 44 roads in Ontario. The input data of the two individual roads is given in Table 3. The data was input into the web portal and the result of the condition prediction was recorded in Table 4.

Table 3. Input variables for two different roads

Input	Location	PCI0	AADT	Age	Pavement Type	Freeze Index	Avg. Max Temp	Precipitation	Freeze & Thaw	Last M&R (yr)	GBE
Road #1	ON	58.1	10000	19.2	1	1046	10.2	1226.9	106	6	35.7
Road #2	BC	100	10475	18.3	1	26	15.6	1498	34	0.1	28.4

Table 4. The results of predicting the condition of the roads of Table 3 for different years

Road	PCI (2 Yr)	PCI (3 Yr)	PCI (5 Yr)	PCI (6 Yr)
Road #1	Poor (90%)	Poor (100%)	Poor (94%)	Very Poor (97%)
Road #2	Good (100%)	Good (95%)	Good (100%)	Good (100%)

The results of PCI prediction for the roads of Table 3 is presented in Figure 3. When the user queries a road and inputs its data, the model will predict the condition and color the road accordingly. The predictions of Figure 3 are for five years, but the user can switch between different years of prediction.

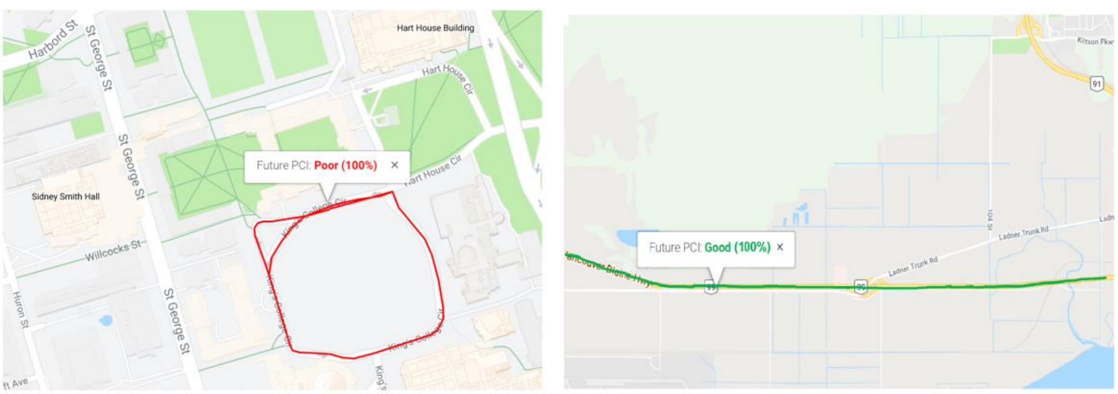

Figure 3. The results of PCI prediction in five years for the roads of Table 4.

For the second example, the data for 44 roads in Ontario was used. These roads are real road sections in different conditions and operating attributes. The attributes of these roads were prepared in a CSV file and uploaded to the web-based platform. The prediction of condition was done under the current climate and a hypothetical climate change scenario. It was assumed that the climate change scenario is affecting the roads at the end of 21st century. The current conditions of roads and the results of predictions under the current climate is given in figures 4. It shows the results of prediction for different years. The model predicted that none of the twenty-two initially Good roads will remain in a Good condition after five or six years, and they will degrade to worse PCI classes. Figures 4 and 5 entail a lot of information. To simplify the results, the mean and standard deviation of PCI values were written below each bin.

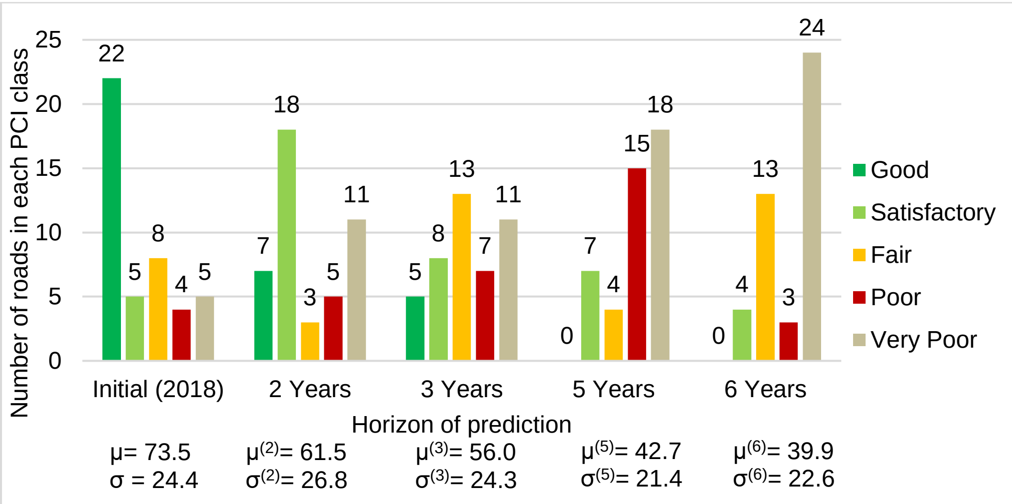

Figure 4. The prediction of condition under the current climate

The same roads of figure 4 were studied under a climate change scenario. Note that detailed modeling of different climate change scenarios for each road section is beyond the scope of this paper. Several assumptions were made for calculating the value of climate stressors. It was assumed that the temperature will increase by 6 degree Celsius, the annual freeze index and number of freeze thaw cycles will decrease proportionally, and the annual precipitation will increase by 10%. Note that all these are within the range of projections of RCP 8.5 scenario for Ontario in year 2098 (IPCC 2014, Deng et al. 2018). Therefore, the range of climatic stressors is justifiable based on the climate change literature.

The result of predictions for roads under this climate change scenario is given in Figure 5. When compared with Figure 4, it could shed some light on the climate change impact on road deterioration. One could easily notice that in **Error! Reference source not found.**, virtually in all cases, the deterioration becomes more relaxed, given that the number of roads in Poor and Very Poor condition is smaller than Figure 4. On the other hand, the number of roads in a Good condition in **Error! Reference source not found.** is larger than Figure 4. An easier way to compare the graphs would be comparing the aggregate results of mean and standard deviation.

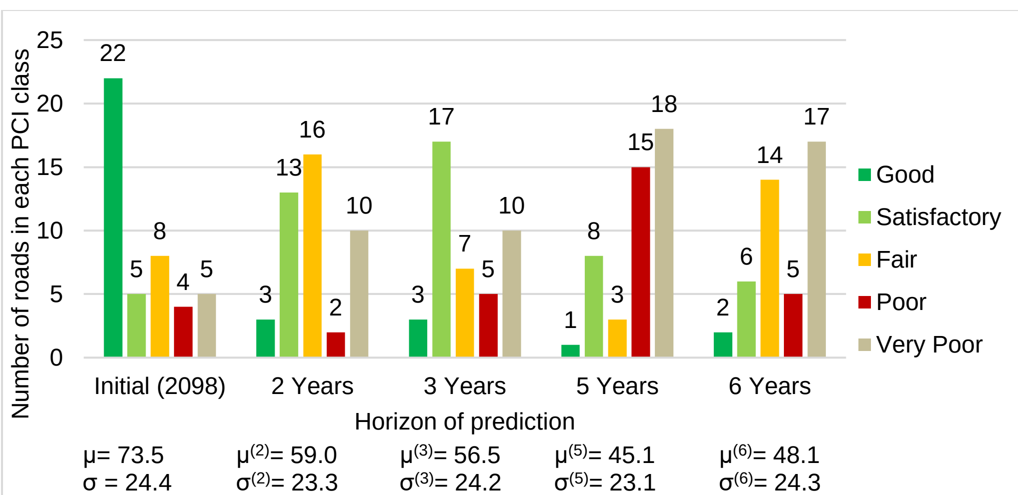

Figure 5. The prediction of condition deterioration under a climate change scenario

7 CONCLUSION

In this paper an interactive online decision-support tool was introduced to help predicting the condition of roads. Since the training data was collected over a large geographic spread, and several relevant climatic stressors were among the predictive attributes, the developed tool could be used in quantifying the impact of climate change on road networks. An immediate conclusion of this study is that climate change affects various regions differently; therefore, its impact on infrastructure is not going to be the same everywhere. While it will alleviate the deterioration of roads in Ontario, it could exacerbate the conditions in another place.

This study had a few limitations in terms of quantifying the impact of climate change, which could be addressed in the future research: insufficient granularity; excluding the impact of climate change on AADT; and excluding the impact of harsh climatic events such as tornados and storms.

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