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Enhanced Prediction of Urban Road Pavement Performance under Climate Change with Machine Learning

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Abstract: In light of climate change, increasing traffic demands, and aging infrastructures, flexible pavements face escalating challenges in terms of resilience and longevity. This paper highlights the potential of Machine Learning (ML) to integrate with Mechanistic-Empirical pavement design, aiming to facilitate proactive maintenance and rehabilitation and ultimately enhanced resilience of urban road pavements. A comprehensive analysis comprising 4800 case studies across 10 major Canadian cities was conducted, encompassing various scenarios reflecting climate change pathways, pavement structures, and traffic levels. The findings indicate an increased risk of failure, particularly rutting, under projected future climate conditions. The study demonstrates that developed artificial neural network models exhibit high accuracy in predicting fatigue cracking (R2: 0.96) and rutting (R2: 0.98). Furthermore, it emphasizes the potential of ML techniques in conducting impact assessments and devising strategies for climate change adaptation, considering the evolving landscape of urban complexities.

Keywords: Flexible pavement; Climate change; Machine learning; Mechanistic-Empirical; Performance prediction.

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1. Introduction

The effects of climate change have the potential to be geographically widespread and diverse, placing impacts and loads on pavement systems beyond their original design levels. Canada is particularly affected, experiencing faster and more intense warming compared to the global average—a trend expected to worsen with the continued emission of large amounts of greenhouse gases (GHGs) into the atmosphere each year [1]. In 2020, Canada had over 1 million kilometers of public road assets, with municipalities owning over two-thirds of these roads [2]. With nearly three in four Canadians residing in large urban centers [3], functionality, safety and resilience of urban road pavements is of utmost importance.

To date, the adoption of Machine Learning (ML) applications represents a promising trend in advancing the precision and comprehensiveness of climate change impact analysis [4-8]. However, a limited number of case studies have thus far embarked upon assessing the structural performance of asphalt concrete (AC) pavements under climate change while leveraging ML-based techniques [9-14], however, even among these few studies, most have mainly relied on traditional multilayered elastic analysis software to predict pavement behavior, overlooking the nuanced and dynamic climate-related factors influencing pavement performance. In an extensive study by Qiao et al. [12], a data-driven methodology was developed to quantify the impacts of climate change on pavement service life in locations where Falling Weight Deflectometer (FWD) data were measured. This methodology involved training supervised models, including Artificial Neural Network (ANN), using historical climate, maintenance, and traffic data to predict layer stiffness. Future climate projections were then utilized to predict layer stiffness and ultimately estimate changes in service lives due to climate change using a traditional multi-layer elastic analysis in KENLAYER computer program [15]. In another study conducted at University of Toronto [13], an ML-based decision-support tool was developed to predict future road conditions under climate change. Instead of undertaking detailed modeling of various climate change scenarios for each road, they opted to utilize historic deterioration trends observed in the Long-Term Pavement Performance (LTPP) database. In a more recent investigation by Elwahsh et al. [14], the utilization of machine learning in intelligent and proactive road maintenance systems was explored as a prospective strategy for climate change adaptation, particularly in developing nations. As part of their study, pavement performance was indirectly forecasted employing models based on data from road surface condition sensors measuring friction and moisture levels, among others.

However, to develop accurate ML models for climate change adaptation, it is essential to utilize advanced and robust climate simulation capabilities, as exemplified by the AASHTOWare® Pavement Mechanistic-Empirical Design (PMED) with its Enhanced Integrated Climatic Model (EICM) [16]. The software considers hourly climate data, enabling the simulation of climatic variations and thus providing insights into the relative impact of climate change on pavement performance. Previously, several studies utilizing the PMED have documented quantifiable changes in pavement performance due to climate change [17-22]. A comprehensive study conducted in the United States utilized data from an ensemble average of 19 different CMIP5 climate models and three individual models (MIROC-ESM, CCSM4, and MRI-CGCM3) for different GHG emission scenarios. The climate projection data was integrated with the PMED software to forecast pavement performance, revealing that the percentage increase in fatigue cracking (2–9%) was observed to be lower compared to AC rutting (9–40%). This suggested that temperature increases in the future will have a greater impact on AC rutting [19].

The wide array of material input properties, traffic conditions, and climate factors, along with the associated computational costs and expertise required for PMED simulation, undoubtedly pose challenges, especially for network-level quantifications and strategic urban planning. Hence, it's crucial to investigate surrogate ML models, especially ANN, known for its reliability and effectiveness in handling large datasets and nonlinear functions. This main objective of this study is to use PMED simulations to effectively train ANN, aiming to obtain rapid and reliable predictions of pavement performance under climate change at large scale.

2. Methodology

Daily climate change data was obtained from the outputs of Coupled Model Intercomparison Project Phase 6 (CMIP6) climate model datasets, which has been downscaled and bias-adjusted using Bias Correction / Constructed Analogues with Quantile Mapping (BCCAQ) method [23]. Daily data were then transformed into an hourly format using the method proposed by Linvill as shown in Equation 1 [24].

$$T(t) = (T_{max} - T_{min}) \times \sin[(\pi \times t)/(DL + 4)] + T_{min} \tag{1}$$

where $T(t)$ is temperature at time t after sunrise; T_{max} is maximum temperature; T_{min} is the minimum temperature in the morning, and DL is daylength (in hours).

First, series of simulations were carried out via the AASHTOWare® PMED with projected climate data for several representative locations across Canada as summarized in Table 1.

Table 1. Ten representative cities across Canada.

City (abbreviation)	Province	Geographical Region
Victoria (VIC)	BC	West Coast
Vancouver (VAN)	BC	
Saskatoon (SAS)	SK	Prairies
Edmonton (EDM)	AB	
Winnipeg (WIN)	MB	
Waterloo (WAT)	ON	Central
Montreal (MON)	QC	
Fredericton (FRE)	NB	Atlantic
Charlottetown (CHA)	NL	
Halifax (HAL)	NS	

Performance projections were conducted for the baseline and additional projected scenarios, by varying both the structure and traffic elements, as outlined in Table 2. The investigation spanned five cycles, each encompassing a 20-year period, from the year 2000 to 2100. This extended timeframe allows for an examination of the evolving climate patterns and their potential implications for pavement infrastructure resilience. Covering 32 scenarios for each city at 3 emission levels, each simulation spanned a 20-year period. The combined scope of scenarios amounted to a total of 480 for each city. Next, input vectors were defined in one matrix and associated target vectors in another for all scenarios.

Two ANN models were constructed using neural network toolbox of MATLAB [25]: one to predict fatigue cracking and the other to predict rutting. For the purpose of designing each ANN model, a two-layer feedforward network architecture with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer was considered as shown in Figure 1. Input variables included several climate factors, such as Mean Annual Air Temperature (MAAT), Mean Monthly Air Temperature (MMAT), and Freeze-Thaw Cycles (FTCYC), for each climate scenario. Additionally, layer thicknesses of asphalt, base, and subbase, as well as the resilient modulus of the subgrade and traffic level, were considered as input variables. With the network architecture defined, the dataset was randomly partitioned using the commonly-used ratios of 70% for training, 15% for validation, and 15% for testing. For the network training purpose, the Levenberg-Marquardt Back-Propagation (LMBP) algorithm, widely recognized as a leading alternative in terms of convergence speed and local minima avoidance, was employed.

Table 2. Different pavement configuration and climate scenarios.

Subgrade Resilient Modulus (MPa)	**Traffic**	**Layer Thickness (mm)**			**Climate**	
	AADTT	**Hot Mix Asphalt**	**Granular Base**	**Granular Subbase**	**Design Period**	**Shared Socio-economic Pathways (SSPs)**
30 and 50	2500 and 7500	150 and 200	150 and 250	250 and 350	[Cycle 1] 2000-2020 [Cycle 2] 2020-2040 [Cycle 3] 2040-2060 [Cycle 4] 2060-2080 [Cycle 5] 2080-2100	SSP 1-2.6 SSP 2-4.5 SSP 5-8.5

With respect to the performance analysis of the ANN, Mean Square Error (mse) metric was checked for the accuracy and effectiveness of ANN models. Mathematically, mse represents the mean sum of squares of errors between the network-predicted outputs (a_i) and the observed target data (t_i), as shown in Equation 2.

$$mse = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \tag{2}$$

The ANN models were subsequently refined and optimized to enhance their predictive accuracy and generalization.

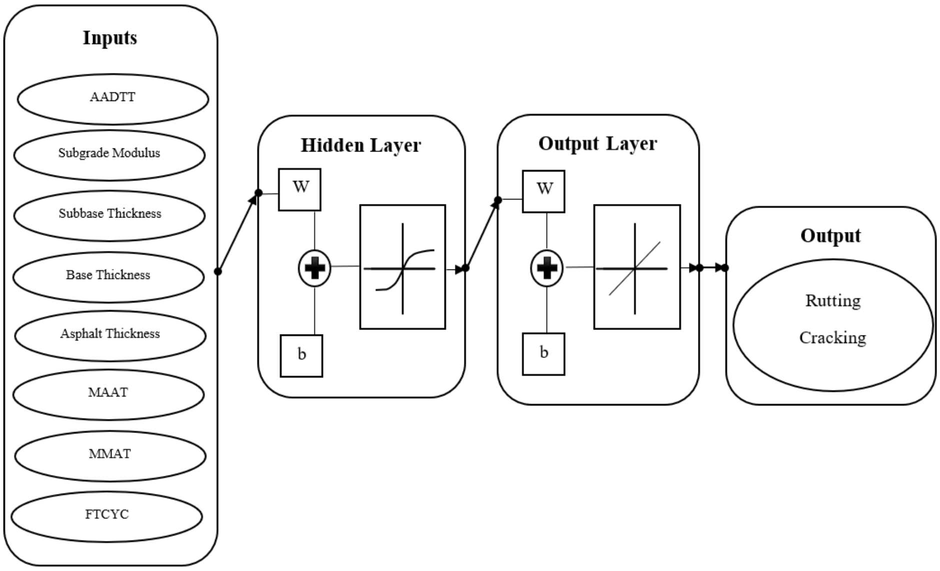


Figure 1. Diagram of the ANN modeling structure

3. Overview of future climate projections

As illustrated in Figure 2, projected climates are anticipated to be generally warmer, with a more pronounced increase expected by the late century (cycles 4 and 5), as reflected by a faster increase in MAAT. The increasing trend aligns with the relevant SSP scenarios, with the highest MAAT values observed under SSP 5-8.5, a high reference scenario with no additional climate policy and fossil fuel intensive development.

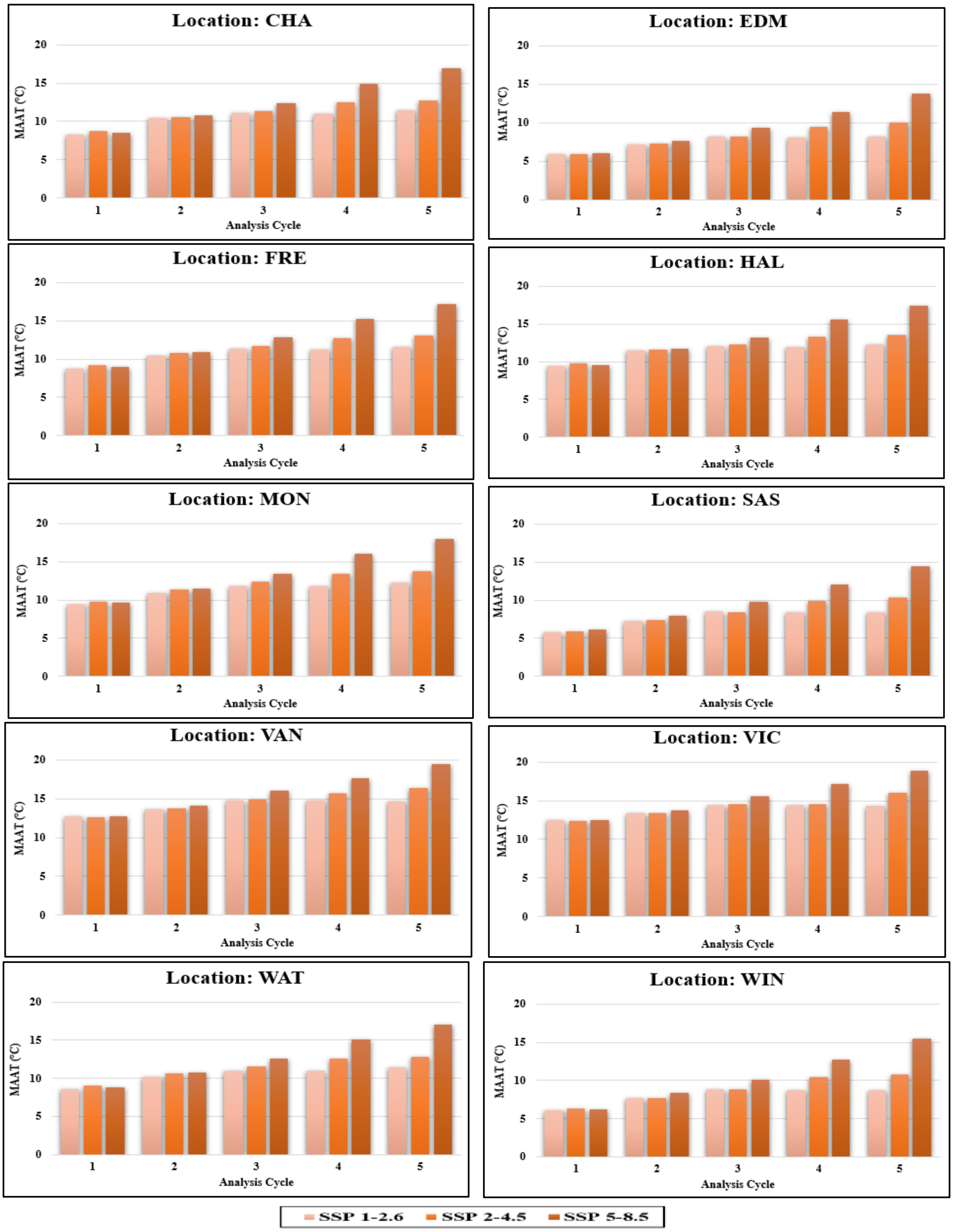
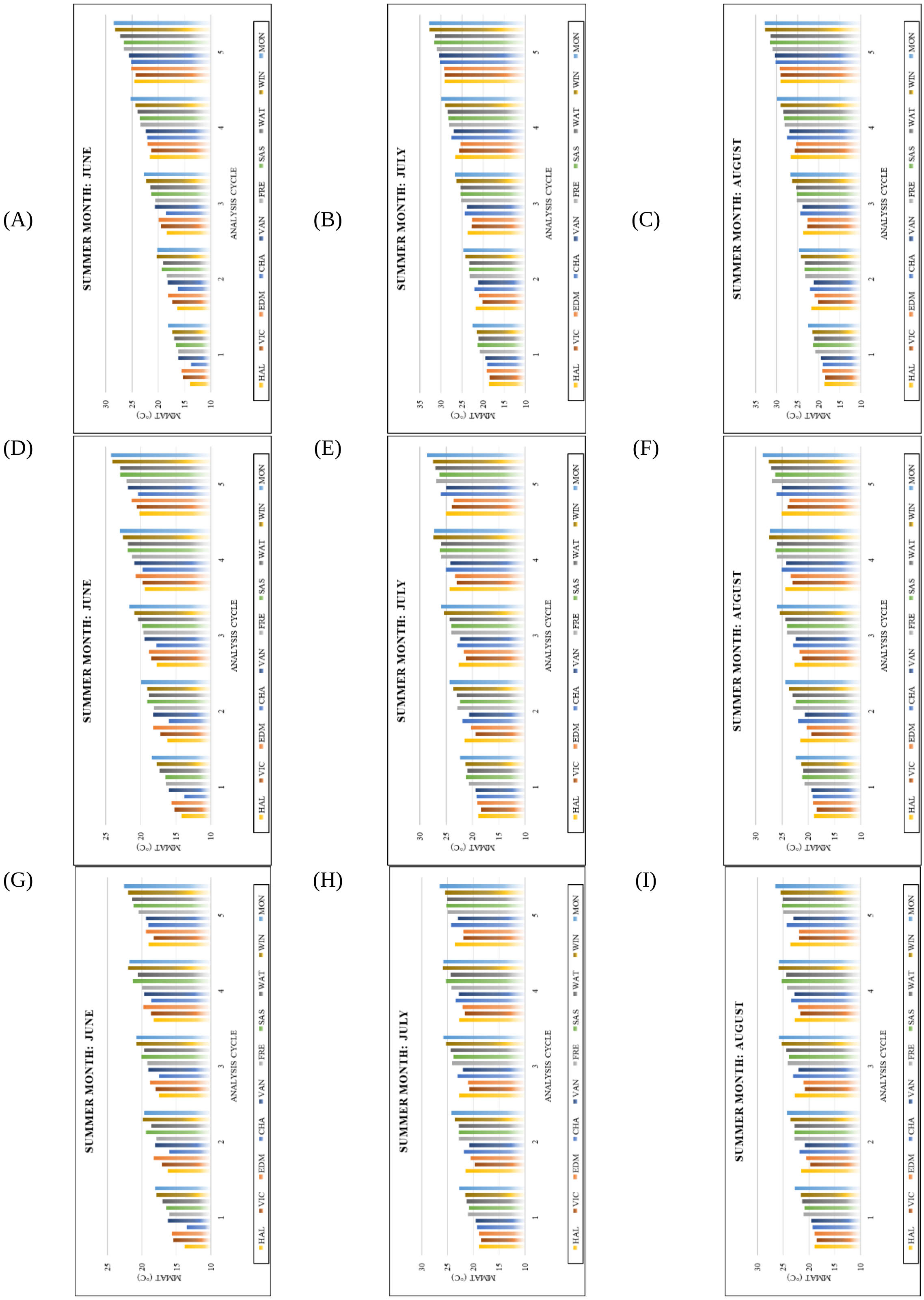


Figure 2. Trends in Mean Annual Air Temperature (MAAT) under Climate Change for Selected Cities

Figure 3 illustrates the variations in MMAT for the months of June, July, and August, which typically represent the warmest months of the year during the summer season. This is particularly pertinent to understanding pavement rutting, as higher temperatures during the summer months can exacerbate the susceptibility of asphalt pavements to rutting. As temperatures increase, the modulus of asphalt mix decreases due to the softening of the asphalt binder, resulting in greater deformation under traffic loads. The permanent deformation, commonly referred to as rutting, has the potential to compromise the structural integrity of the pavement and diminish its overall service life. By comparing MMAT variations across different cities, one can observe that certain colder cities with relatively low MAAT values, such as Winnipeg, Saskatoon, and Montreal, experience some of the highest temperatures during the summer months. This observation implies that solely depending on MAAT may provide an incomplete understanding of the impact of climate change on rutting. In these instances, even some of the coldest cities may experience substantial temperature rises during summer, potentially resulting in asphalt softening and heightened susceptibility to rutting. Therefore, despite their colder MAAT, these cities may still face challenges related to pavement rutting during the warmer seasons. It underscores the importance of considering seasonal temperature variations in assessing the risk of rutting and implementing appropriate pavement design and maintenance strategies to mitigate its effects.



(A) (B) (C)

(D) (E) (F)

(G) (H) (I)

Figure 3. Variation of Summer Season's MMAT under SSP 5-8.5 (A-C), SSP 2-4.5 (D-F) and SSP1-2.6 (G-I)

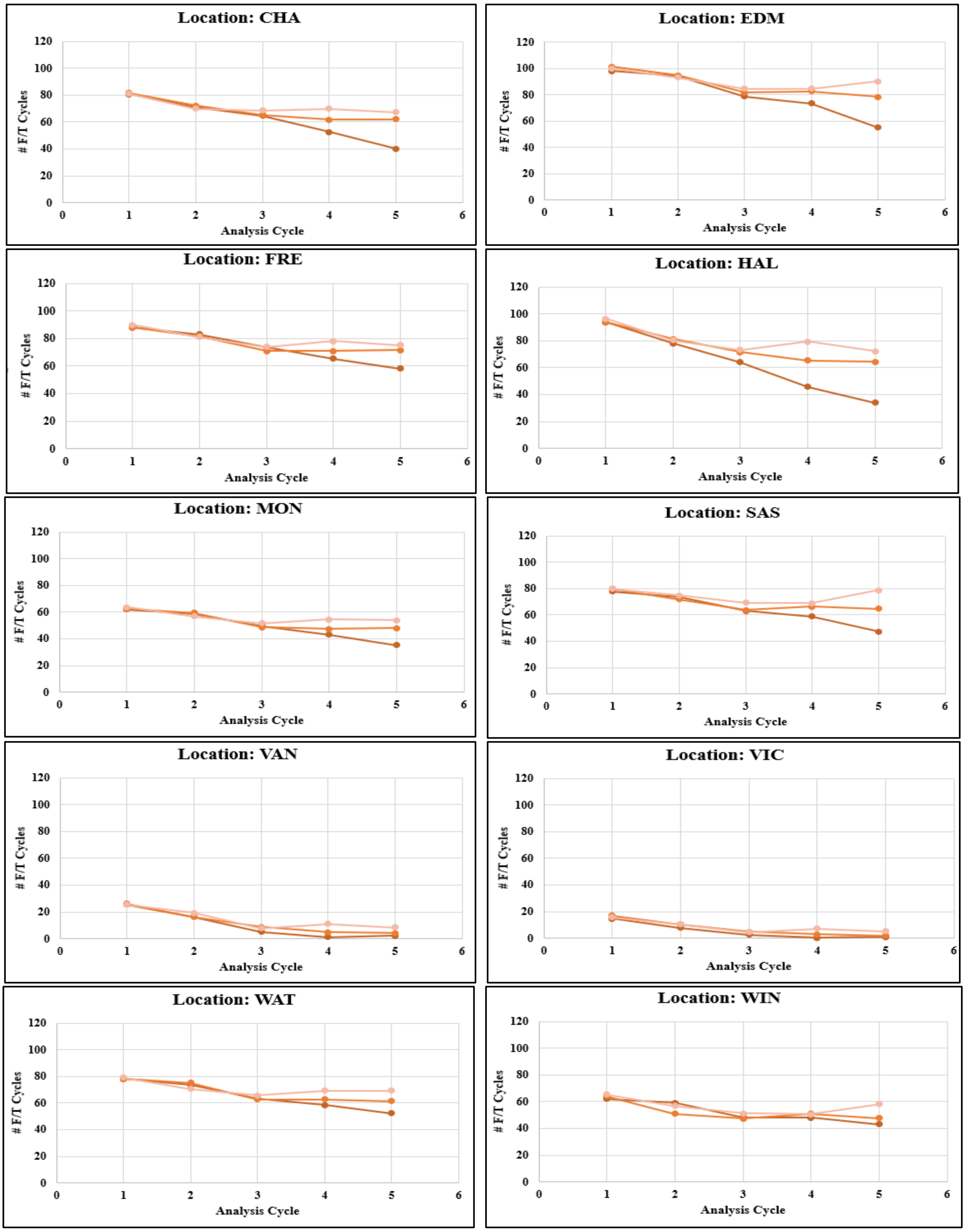


Figure 4. Variation of Average Annual Number of FTCYC for different cities

Figure 4 depicts the average annual number of FTCYC across different cities and their trend over time. With climate change, there is a notable reduction in the FTCYC observed which can be attributed to several factors associated with global warming, including overall increases in temperatures. As temperatures rise, fewer days with temperatures below freezing occur, leading to a decrease in the frequency of freeze-thaw cycles. The figure also highlights the impact of SSP scenarios and their impact on the frequency of FTCYC experienced by pavements in different cities. In most cities under examination, it is projected that FTCYC levels will persist at notably high levels by the end of the century. This persistence poses a continuous risk of thermal damage to asphalt mixes as well as frost heaving in pavement subgrade.

4. PMED performance predictions

Figures 5 illustrates the average predicted pavement rutting for all evaluated scenarios. It is evident that a warmer climate in the future is anticipated to heighten the risk of rutting in the pavement. This phenomenon can be partly attributed to the increased susceptibility of asphalt mixes to permanent deformation under higher temperatures.

To mitigate the potential for rutting distress in the future, several design feature revisions could be contemplated. This includes enhancing the dynamic modulus of the asphalt mix, achieved through the utilization of polymer-modified asphalt binder, especially in surface layers. Additionally, augmenting the quantity of crushed aggregate, substituting natural fines with manufactured fines in asphalt mixes, and ensuring a balanced asphalt binder content in the mix are all viable strategies. It is important to note that altering one parameter may impact another. For instance, reducing asphalt binder content to enhance rutting resistance could potentially lead to an increase in in-place air voids, consequently resulting in more fatigue cracking. Moreover, in order to alleviate rutting in unbound layers and subgrade, actions such as increasing the resilient modulus of the aggregate base, improving the density of the aggregate base, stabilizing the upper foundation layer for weak, frost-susceptible, or swelling soils, employing thicker granular layers, incorporating a layer of select embankment material with sufficient compaction, and increasing the thickness of the asphalt layers could be undertaken [26].

Figure 6 shows the result of climate change impact on fatigue cracking. It was found that the magnitude of predicted changes was relatively lower compared to those of the rutting. This finding corroborates the conclusions drawn by Qiao et al. [27], and Gudipudi et al. [22] highlighting that the expected impacts of warming temperatures on rutting are more pronounced. Similarly, in a separate study by Chowdhury examining climate change effects on PMED -predicted performance in cities of Boise, Denver, and Detroit in the US, the projected temperature increase had less significant effect on bottom-up fatigue cracking for the selected study locations [17]. Similarly, in the analyzed cases, it appears that climate change has lower effects on fatigue cracking compared to the baseline scenario.

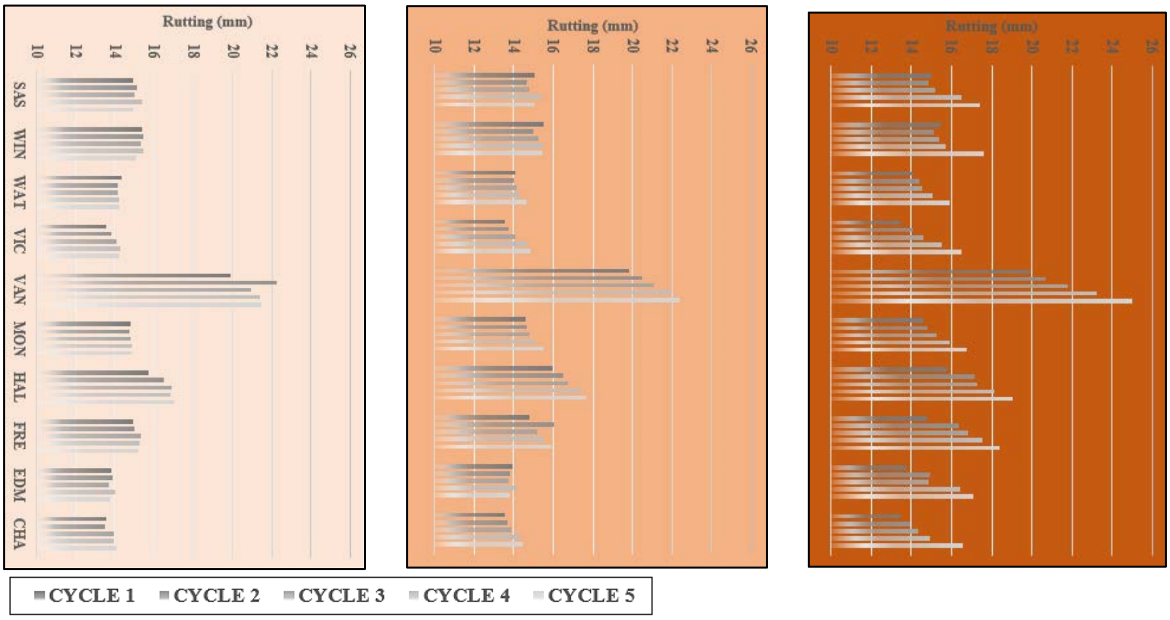

SSP 1-2.6 SSP 2-4.5 SSP 5-8.5

Figure 5. Predicted pavement rutting for different cities under changing climate

5. ANN Modeling Results

Results confirmed that network dimensionality can affect network overfitting or underfitting, leading to a reduction in performance predictions. Conventionally, as the number of features increases, the likelihood of issues such as model being under or over-fitted also increases [28]. Therefore, for better performance of ANN, it was observed that employing a model that is just large enough in size to produce a satisfactory fit was the appropriate answer. It was revealed that a single hidden layer with 10 neurons yielded optimal performance while maintaining computational efficiency. The observations from Table 3 indicate that both the MSE measures and the R-squared metrics confirm reasonably good predictions by the generated models. It should be emphasized that, MSE values close to zero and R-squared values close to one indicate a high level of accuracy, suggesting a strong agreement between predicted and observed values [29].

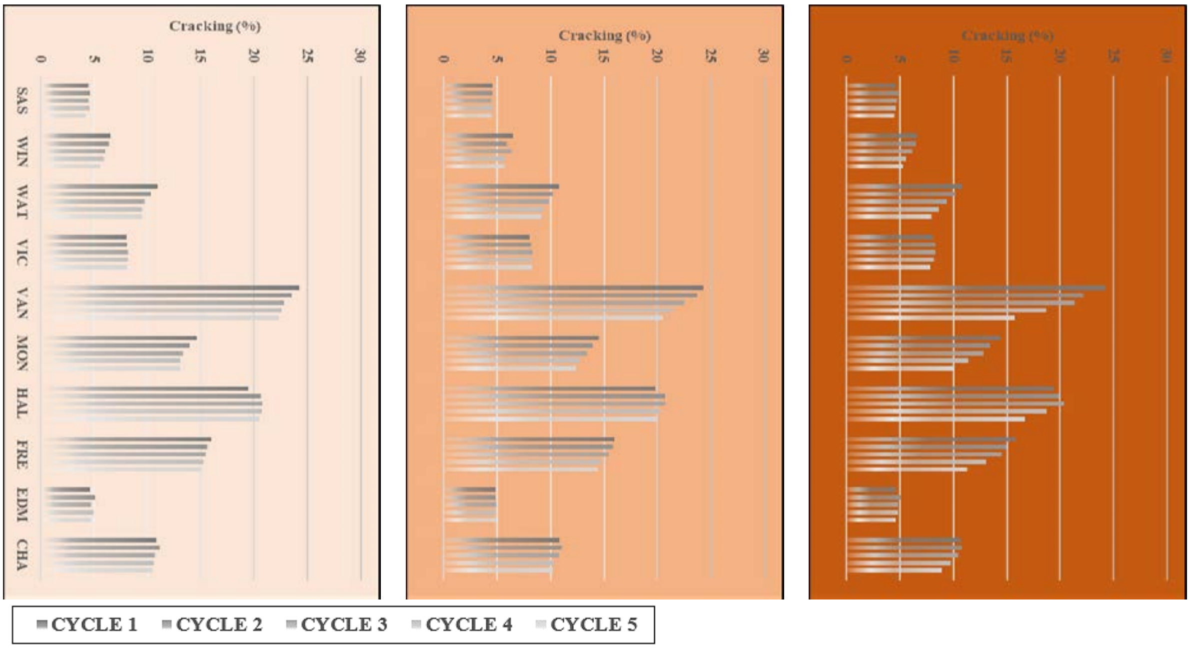

SSP 1-2.6 SSP 2-4.5 SSP 5-8.5

Figure 6. Predicted fatigue cracking for different cities under changing climate

Table 3. Performance measures of developed ANN models

Model Type	Samples	Observations	mse	R^2
Rutting	**Training**	3360	0.6627	0.9672
	Validation	720	1.2167	0.9513
	Testing	720	0.5681	0.9730
Cracking	**Training**	3360	4.9222	0.9846
	Validation	720	6.1878	0.9804
	Testing	720	5.1736	0.9840

The network predictions and the corresponding targets are plotted in Figures 7 and 8. For a perfect match, the data should align along a 45-degree line, where the network outputs and targets are equal. The dashed line in the figures represents the desired 45-degree line fit line, however the solid line indicates the best fit linear regression line between outputs and targets. The results indicated that a strong relationship was established given the complexity of climate change and its impacts on cracking and rutting. This finding proposes that the ANN approach could be particularly convenient and beneficial for potential use by road agencies in future large-scale climate change adaptation studies under different circumstances.

6. Conclusions

In this paper, an ML-based prediction modeling process was considered to analyze pavement performance under climate change scenarios across 10 representative cities over a large geographic spread in Canada. Training dataset included outputs from diverse pavement simulation within AASHTOWare® PMED encompassing 20-year fatigue cracking and rutting distresses. One immediate conclusion from this study is that climate change affects regions differently. Meanwhile, the varying impacts on different distresses remain discernible, with rutting being notably more affected. Furthermore, the study determined that utilizing eight (8) key and straightforward design inputs was sufficient for precisely constructing two-layer feed-forward network ANN models. Finally, the outlined method can expedite decision-making processes related to climate resilience, adapt to evolving pavement condition data for accurate predictions, and cater to diverse analysis needs as required.

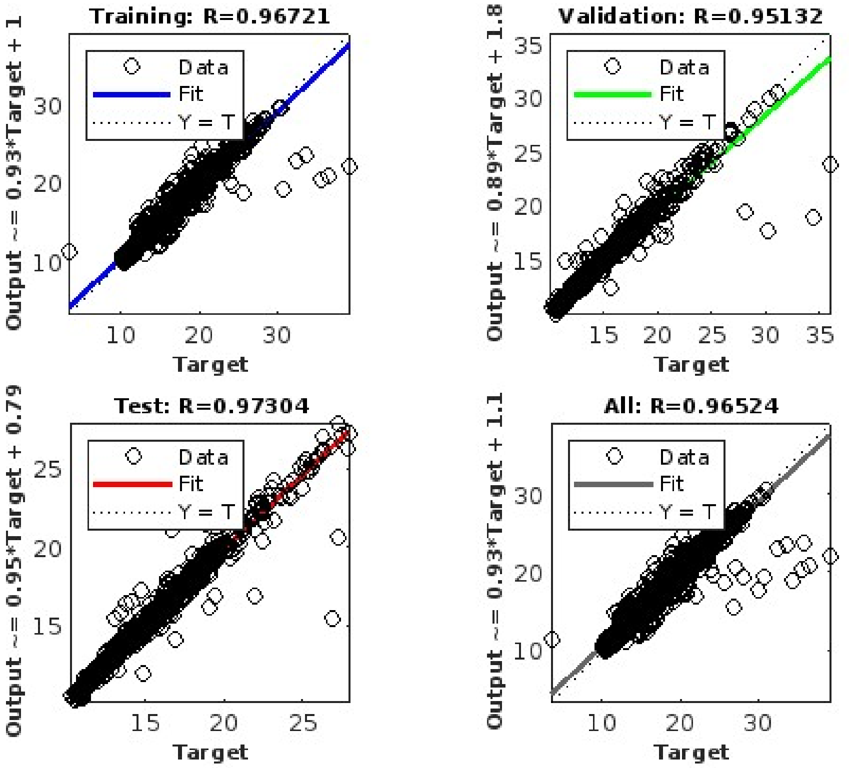


Figure 7. Regression plots of developed ANN fitting model for rutting distress

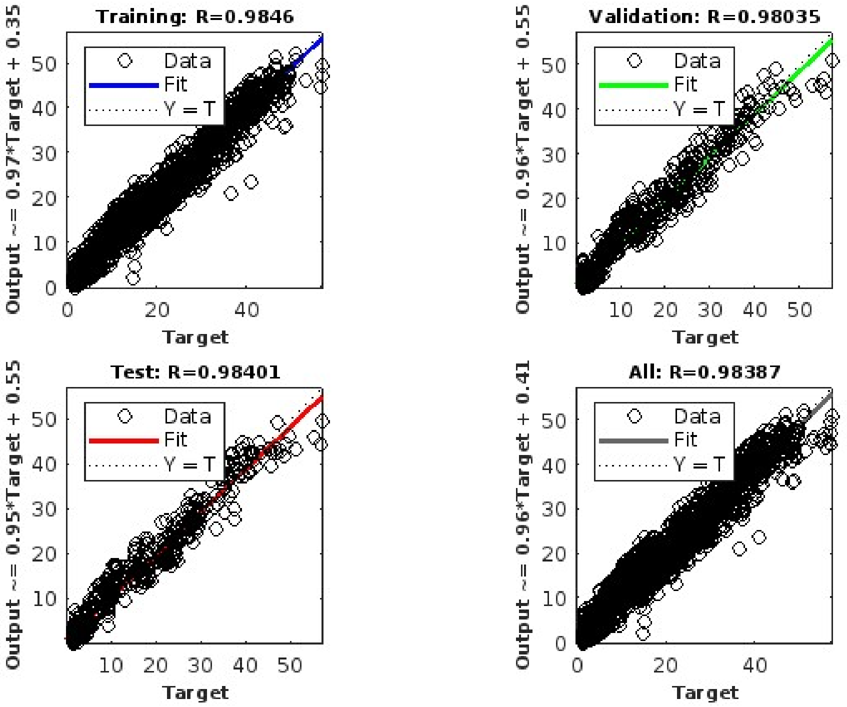


Figure 8. Regression plots of developed ANN fitting model for cracking distress

7. Acknowledgements

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