Planning for Winter Road Maintenance in the Context of Climate Change

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ABSTRACT

Winter weather creates mobility challenges for most northern jurisdictions, leading to significant expenditures on winter road maintenance (WRM) activities. While the science and practice of snow and ice control is continually evolving, climate change presents particular challenges for the strategic planning of WRM. The purpose of this study is 1) to develop a winter severity index (WSI) to better understand how winter weather translates into interannual variations in WRM activities and 2) to apply the WSI to future climate change projections to assist a northern community in preparing for climate change. A new method for creating a WSI model is explored, using readily available data from maintenance records and meteorological stations. The WSI is created by optimizing values for three levels of snowfall as well as potential icing events and is shown to have high predictive accuracy for WRM (coefficient of determination $R^2$ of 0.93). The WSI is then applied to historic and future climate data in a municipality located in central British Columbia, Canada. Findings reveal that much of the variability in WRM can be attributed to weather. The results of the climate change analysis show that winter precipitation in the region is expected to increase by 5.2%–12.3%, and winter average temperatures are projected to increase by 1.5$^\circ$–2.8$^\circ$C in the 2050s, compared to the 1976–2000 baseline based on 65 GCMs. Based on the midrange (25th to 75th percentiles) of the 65 GCM projections, annual demand for WRM activities is estimated to decrease by 13.0%–22.0%.

1. Introduction

Human-induced environmental change is a major challenge facing all levels of government. Anthropogenic greenhouse gas (GHG) forcing is contributing to a variety of changes in the biophysical system, resulting in myriad impacts on communities globally (IPCC 2014). To inform adaptation strategies and measures, there is a need to better understand the impacts of environmental change on affected systems. The transportation sector, while vital to the global economy, has been relatively understudied in the climate change impacts literature (Jacobs et al. 2013; Koetse and Rietveld 2009; Wall et al. 2015). Furthermore, while there is a clear consensus among scientists and political leaders that adaptation (as well as mitigation) actions must take place, the data and analyses necessary to inform adaptations are not readily available for decision-makers in the transportation sector (Wall et al. 2015) and concrete adaptations in this sector remain limited (Koetse and Rietveld 2009; Wall et al. 2015; Wall and Meyer 2013; Picketts et al. 2016).

A variety of factors impede the process of adaptation planning and the investment in planned adaptations in the transportation sector. First, climate change impacts and adaptations studies are not a high priority for transportation agencies in most countries (Picketts et al. 2013; Burch 2010). Second, with an aging infrastructure, many jurisdictions are facing infrastructure deficits. As such, road authorities are cautious to pursue adaptation initiatives that may result in short-term increased expenditures (TAC 2013; Wall and Meyer 2013). Third, climate projections are inherently uncertain, whereas transportation design, construction, and maintenance standards traditionally have relied on data with comparatively higher levels of certainty (Jacobs et al. 2013;
Wall et al. 2015). For these and other reasons, road agencies have experienced challenges amassing the information and resources necessary to incorporate adaptation considerations into transportation infrastructure planning and design.

One aspect of adaptation planning in the context of surface transportation is road maintenance. The design, construction, and maintenance of road infrastructure relies on historical probabilities of weather and climate risks (Hayhoe et al. 2015). Historical temperature, rainfall, and snowfall records, as well as the probabilities of extreme events such as storm surges, are all included in planning for transport infrastructure (Hayhoe et al. 2015).

Changes in mean and extreme temperatures have been recognized as contributing to premature depreciation of transport assets (Hayhoe et al. 2015; Venner and Zamurs 2012; Mills et al. 2007, 2009). Paved infrastructure is constructed with materials that are specific to a particular temperature range. Temperatures outside the design specifications increase the likelihood of cracking, rutting, buckling, or subsidence (Meyer and Weigel 2011). Hot weather also can delay road maintenance work because of health and safety concerns (Venner and Zamurs 2012). Adaptations such as different pavement binders can be used to improve the resiliency and reduce maintenance costs for road surface infrastructure. A recent study by Fletcher et al. (2016) found that for pavement to withstand projected temperature increases into the 2050s, more heat-resistant pavement binders will need to be used across much of Canada.

Drought conditions also affect transportation, both directly and indirectly. For example, more frequent or intense forest fires come with added maintenance costs that have been experienced in Australia, Russia, the United States, and Canada in recent years (Hayhoe et al. 2015; Venner and Zamurs 2012). Furthermore, the Arizona Department of Transportation estimated that the forest fires in 2011 caused the state over $2 million in extra maintenance costs (Venner and Zamurs 2012). Another secondary impact of increasing temperatures is wind storms and dust storms. These storms contribute to increased maintenance costs as road authorities may need to replace signage and signals and incur the costs associated with road closures in these extreme events (Venner and Zamurs 2012).

Extreme precipitation events are particularly costly for road authorities. Intense rainfall can cause washouts and flooding, and heavy snowfall reduces roadway capacity, both leading to regionwide travel disruptions and unpredictable maintenance costs (Jaroszwseski et al. 2010; Suarez et al. 2005). Tens of millions of dollars in maintenance costs have been incurred by departments of transportation across the United States in recent years due to intense precipitation and flooding (Venner and Zamurs 2012), and winter maintenance budgets were exceeded by municipalities across Canada in both 2013/14 and 2014/15 due to heavy snowfalls (Howlett 2014; The Weather Network 2015).

This paper focuses on winter maintenance of roads in the context of a changing climate. Winter road maintenance (WRM) is required to ensure the safety and mobility of road network users, and it is estimated that over $3 billion is spent annually in North America on related activities (Usman et al. 2010; Tsapakis et al. 2013; Ye et al. 2009). The variability and limited predictability of winter weather, especially in light of climate change, is a major challenge for road authorities—one that has only recently begun to receive serious attention (cf. XIVth International Winter Road Congress held in Andorra in 2014).

In the Canadian context, each year approximately CAD $1.3 billion is spent on WRM by road authorities (Suggett et al. 2006), with individual road authorities having control over the methods and practices used for snow and ice control (Nassiri et al. 2015). While our understanding of how climate change may impact transportation operations and infrastructure in Canada is evolving (e.g., Andrey et al. 2014; PIEVC 2008), scant attention has been paid to the issue of winter maintenance of roads. Because of the high costs of WRM, coupled with projections of higher winter precipitation for some jurisdictions, assessing the impacts of climate change on winter maintenance activities is of practical value and also provides an opportunity to illustrate how weather/climate indices can be important translation devices between the climatological modeling community and transport authorities.

This research has two objectives. The first is to develop a winter severity index (WSI) that explains the historical temporal variation in WRM expenditures using weather data as the explanatory variables. The second is to apply this WSI to climate data in order to project changes to WRM expenditures associated with climate change. For objective two, we focus on the case study community of Prince George, British Columbia.

2. Study area: Prince George, British Columbia

Prince George, British Columbia, Canada, is a suitable case study community for exploring the implications of climate change for road maintenance implications because of Prince George’s northerly location, heavy reliance on functioning road networks, and expressed interest in applying the results to improve transportation infrastructure management. Prince George is located at 54°N latitude in interior British Columbia, Canada, and
is a key transportation network node for the province. Prince George, which has a population of 77,000 and encompasses a total land area of 316 km², has an extensive transportation network, including rail, an airport, and 630 km of roads. Climate baseline data [1976–2000; from Adjusted and Homogenized Canadian Climate Data (AHCCD) station 1096450] indicates that average summer (June–August) and winter [December–February (DJF)] temperatures in Prince George are 14.3°C and −8.0°C, respectively. Annual average precipitation is 687 mm, with considerable interannual variability. Figure 1 shows the monthly average temperatures and precipitation over the 1976–2000 time period. Annually, the ratio of rain to snow was approximately 2:1, and Prince George typically experiences snow cover from November to March (Picketts et al. 2012).

Over the past 100 years, there has been a warming trend of 1.3°C in Prince George, and the region is projected to experience further changes in temperature as well as more precipitation, especially in winter (Picketts et al. 2012). These changes have potential implications for the transportation system in and around Prince George. Winter weather is a matter of concern, as Prince George allocates a full 5% of its annual municipal budget to snow and ice control activities, and these resources are collected through a snow control levy that appears on all municipal tax bills. Further, over the past two decades, there has been a steady increase in the WRM budgets, and annual WRM expenditures since 1994 have ranged from CAD $3.60 million to CAD $7.02 million (City of Prince George 2014). Any surplus resources are then held in the Snow Control Reserve to be used for years in which there is a deficit. Since 1994, there have been six years with a recorded surplus and 13 years with a deficit.

A previous study (Picketts et al. 2013) has identified four main areas of concern for transportation in Prince George: pavement surface deterioration (often attributed to increased winter freeze–thaw cycles), unsafe road conditions (particularly ice), increased salt use, and insufficient storage capacity for snow disposal sites. This study builds directly and pragmatically on several years of community-engaged research, including a preliminary assessment of climate change and transportation infrastructure that identified WRM and pavement design as local research priorities (Picketts et al. 2016). Because the current paper emerged as part of a larger adaptation initiative—completed in collaboration with Prince George over a number of years (e.g., Picketts et al. 2013, 2016)—the 1976–2000 baseline period is used to maintain consistency across phases of work.

3. Methods

a. WSI approach

Weather information is crucial for day-to-day WRM activities, and the transport sector has a long history of using observational and forecast weather information as well as transport-specific weather products when making short-term operational decisions (Andrey and Knapper 2003; Hinkka et al. 2016). From a tactical perspective, however, other weather tools are needed to inform budget planning, equipment purchases, and contract planning. These include WSIs that can be used to benchmark and track weather and climate variability and change.
While various methods can be used to document the relationship between weather and WRM [e.g., cluster analysis (Ye et al. 2009) or classification and regression trees (Andrey et al. 2008; Brenning et al. 2011)], one particularly promising approach involves the creation of weather indices (Cornford and Thornes 1996; Venäjäinen and Kangas 2003; Carmichael et al. 2004; Andrey and Matthews 2012). Weather indices have advantages related to ease of use/interpretation, providing that the scoring system adequately reflects the winter weather circumstances that trigger WRM. Previous studies have used different individual, or combinations of, weather variables in creating maintenance-relevant WSI (e.g., cluster analysis (Ye et al. 2009) or classification and regression tree (Andrey et al. 2008; Brenning et al. 2011), one analysis (Ye et al. 2009) or classification and regression on the severity of the weather from a WRM perspective. Because of these data limitations as they pertain to the future and also the past (availability of RWIS data), a simplified WSI was developed.

**b. WSI model development**

The approach taken was to develop a WSI whereby days were assigned scores between zero and one. For the sake of simplicity and to avoid the double counting of weather triggers, each weather condition was considered in turn. As such, each day was assigned to only one weather condition. For example, if both snow and rain with cold temperatures occurred in the same 24-h period, the day would always be assigned to the snowfall category.

To determine the thresholds of the weather triggers and the associated scores, an optimization routine in Microsoft Excel is used. The optimization routine was set to maximize the $R^2$ value between annual expenditures on WRM and annual WSI scores. The routine maximized the $R^2$ value by concurrently defining appropriate threshold values for each of the weather components as well as the daily scores that best reflect the severity of the weather from a WRM perspective.

Previous studies have often used expert opinion and/or physical processes to direct the formation of weather categories; however, an optimization approach closely aligns the weather triggers and thresholds with WRM activity (Matthews et al. 2017a,b).

To demonstrate the threshold concept for snowfall, each day with measurable snowfall (i.e., $\geq 0.4$ cm of snowfall or $\geq 0.4$ mm liquid precipitation equivalent) was identified, and the optimization routine was set to allocate each day to one of three categories: low accumulation, moderate accumulation, or high accumulation. The cutoff values between categories were assigned by the routine so as to optimize the correlation between the resulting WSI and WRM expenditure at the annual level. This process was replicated for the potential icing weather trigger. At the same time, the optimization routine assigned scores between 0.0 and 1.0 for each of the weather triggers, all in a way that maximized the fit, as measured by $R^2$, across the 14 years. Table 1 outlines the explanatory variables that were used in the development of the WSI that was calibrated to annual WRM expenditures in Prince George.

Most WSI use salt/deicing use, snowplow hours, or other materials use (sand, gravel, fracture) as a response variable. For this study, the WSI scores were correlated to expenses associated with snow and ice control, by calendar year from 1994 to 2012 (adjusted for inflation). The decision to use annual WRM expenditures as a
response variable for the WSI development was because of its practical relevance for decision-makers. These expense data were provided by the City of Prince George, and the weather data used to calculate the WSI were obtained from the Environment Canada weather archives for the Prince George sewage treatment plant (STP) station (53°52′N, 122°46′W; climate ID 1096468).

c. WSI model development results

As explained, an optimization algorithm was used to determine the eight constants for the Prince George WSI. Category thresholds and weights were derived simultaneously through this optimization algorithm. The values for these constants are provided in Table 2. After the variable constants were determined, the first step was to categorize each day based on the thresholds in Table 2. All together, there were 6575 days during the 1994–2013 winter study period, 1213 of which met the criteria for one of the conditions considered as potential maintenance triggers. Daily scores were aggregated to the yearly level, with yearly values ranging from 12.25 (2010) to 21.65 (2011). The calendar year 2010 recorded 63 cm of snowfall and average winter temperature of −2.3°C. Conversely, the calendar year 2011 year recorded 260 cm of snowfall with average winter temperature of −2.5°C. For the study period, there was an average of 156 cm of snowfall and mean winter temperature of −5.5°C recorded in Prince George. The average annual WSI score was 17.1 (standard deviation of 2.7) and average annual expenditures on snow and ice control were CAD $5.4 million annually from 1994 to 2012 (adjusted to 2012 dollars).

As shown in Table 2, while relatively few days were categorized as high snowfall days (average 9.7 days yr−1), this component contributes the most to the annual WSI score (average annual score contribution of 7.3). Conversely, low snowfall days were recorded on an average of 20.3 days yr−1 but only contributed an average score of 2.0 per year. This illustrates the importance of relatively extreme snowfall events for WRM expenditures in Prince George. The Prince George WSI has a strong association with the millions of dollars spent on WRM activities ($R^2 = 0.93$). Figure 2 illustrates the annual variation in both WSI and expenditure, and Fig. 3 shows their correlation.

While other factors—such as road network length, population size, changing travel behaviors, cost of materials, and technological innovations—affect absolute expenditures on WRM, this analysis demonstrates that over the 18 years in the study period, weather accounts for 93% of the variability in WRM expenditures. When the expenditures are adjusted for population (Canadian dollars spent on WRM per resident), the fit of the model improves slightly to $R^2 = 0.95$.

One limitation of this method in developing a WSI is that the use of the optimization algorithm has likely led to overfitting of the data. This is especially a concern when working with small datasets. To test the predictive accuracy of the model and the degree of overfitting that may have occurred, the results from a WSI previously developed by Andrey and Matthews (2012) relative to the new calibrated WSI presented were compared. There are two ways to calculate the predictive accuracy of the model. The first method is through the use of test-set cross validation. This is done through the use of training (model calibration) and testing datasets. The second method is through use of the leave-one-out

### Table 1. WSI constants (A–H).

<table>
<thead>
<tr>
<th>Index component</th>
<th>Component variables</th>
<th>Daily score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snowfall (low)</td>
<td>Low amount of snow (0.4 to A cm)</td>
<td>Daily score E</td>
</tr>
<tr>
<td>Snowfall (moderate)</td>
<td>Moderate amount of snow (A to B cm)</td>
<td>Daily score F</td>
</tr>
<tr>
<td>Snowfall (high)</td>
<td>High amount of snow (&gt;B cm)</td>
<td>Daily score G</td>
</tr>
<tr>
<td>Potential icing</td>
<td>&lt;0.4 cm daily snowfall, &gt;C mm of rainfall, ≤D °C minimum daily temperature</td>
<td>Daily score H</td>
</tr>
</tbody>
</table>

### Table 2. Snowfall constants and days meeting criteria for 1994–2013.

<table>
<thead>
<tr>
<th>Index component</th>
<th>Component variables</th>
<th>Daily score</th>
<th>Annual mean No. of days</th>
<th>Annual mean contribution to scores</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snowfall (low)</td>
<td>Low amount of snow (0.4 cm)</td>
<td>0.10</td>
<td>20.3</td>
<td>2.0</td>
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<tr>
<td>Snowfall (moderate)</td>
<td>Moderate amount of snow (2.1 cm)</td>
<td>0.20</td>
<td>13.1</td>
<td>2.6</td>
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<tr>
<td>Snowfall (high)</td>
<td>High amount of snow (&gt;5.2 cm)</td>
<td>0.75</td>
<td>9.7</td>
<td>7.3</td>
</tr>
<tr>
<td>Potential icing</td>
<td>&lt;0.4 cm daily snowfall, rainfall &gt;0.4 cm, ≤0°C minimum daily temperature</td>
<td>0.25</td>
<td>20.7</td>
<td>5.2</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>63.8</td>
<td>17.1</td>
<td></td>
</tr>
</tbody>
</table>
cross-validation method. Both of these methods use the mean squared error (MSE; the sum of squared residuals) as an indicator of predictive accuracy. The model with the lowest MSE has better predictive accuracy. The calibrated WSI developed for this study has the better predictive accuracy (MSE = 0.088) than the model developed by Andrey and Matthews (2012) for Environment Canada (MSE = 0.313).

In future studies, a longer time period or a finer-resolution response variable (e.g., monthly expenditures) would allow for the partitioning of the observations into a training (model calibration) dataset and a testing dataset. This would provide a more realistic assessment of the robustness of the model. However, 18 years of WRM expenditures provides an adequate dataset for the purposes of this study. Because a clear relationship between WRM practices (as a function of expenditures) and weather has been established, it is possible to project the impact of changing climate and weather on WRM.

**d. Climate change analysis of demand for WRM**

To assess the implications of climate change for WRM in Prince George, this study applies the WSI to historical weather observations and future climate simulations...
using the change field method (CFM). By contrast, some climate change studies have used the model output method [daily climate change projection downscaled from Fletcher et al. (2016) and Hambly et al. (2013)]. However, Matthews (2014) compared the use of model output method and the CFM approach in the context of projecting the impacts of WRM in Prince George and found that there was very little difference between the direct model output method and the CFM approach. The CFM approach has the added benefit of being easily computed for a wide range of climate models and thus was chosen for use in this study.

From a climate modeling perspective, future projections of change are calculated based on a climatological baseline period. The climatological baseline period for climate models used in this study is 1976–2000. Projected changes in winter severity are determined by calculating the average annual difference in winter severity scores between the climatological baseline period to the future projections. The observed weather data for this study is obtained from the Prince George STP station (53°52\'N, 122°46\'W; Climate ID: 1096468) for the 1976–2000 observed climate normal period (because of missing data limitations, it was not possible to use 1971–2000).

The CFM approach has a number of advantages over the use of direct model output data or statistical downscaling techniques (Anandhi et al. 2008, 2011). The main advantage is its ease of implementation. Only two kinds of data are needed: 1) complete daily observed data for the research area and 2) access to climate anomalies (or deltas) for the variables of interest. These anomalies can be obtained from model output data by calculating the difference between the twentieth century [20C (1976–2000)] and twenty-first century [21C (2041–70)]. There are a number of readily available products that provide these anomalies for a specified location. Climate anomalies were obtained in 2014 from the Canadian Climate Data and Scenarios site (CCDS 2017), a network that provides a suite of model output data, including climate anomalies, that can then be applied to observed weather data to obtain future climate projections for a given location. Using the CFM approach, it is possible to assess many possible futures.

There are two main methods of applying the CFM approach, additive and multiplicative. Anandhi et al. (2011) assessed various CFM methodologies and found that the additive and multiplicative approaches are most appropriate when exploring projected trends in climate. For the additive approach, the mean difference between 20C and 21C for a given location is computed. This difference (also referred to as delta or climate anomaly) is then added to the observed daily level data. The additive approach is advised for temperature variables. A multiplicative approach, however, is best used for precipitation variables where it is the ratio (or percent) difference between 20C and 21C that is important. The daily observed precipitation data are then multiplied by the percent change in projected precipitation [for more information on the CFM approach, see works by Anandhi et al. (2011) and Hay et al. (2000)]. Anandhi et al. (2011) assessed various additional CFM methodologies, and they found that the use of the additive and multiplicative approach is most appropriate when looking at projected trends in climate impacts.

Given the need to project a range of possible futures, the CFM approach was used to project the percent change in the WSI into the mid-2050s relative to the 1976–2000 baseline period. To do this, climate anomalies were downloaded from the CCDS website for the Prince George region for 65 GCMs, spanning three scenario groups (Table 3 and Fig. 4 provide the projected climate anomalies from the CCDS website). The CFM additive approach was used for the temperature variable, and the multiplicative approach was used for the precipitation variable. Only the mean temperature climate anomaly was available for the majority of the models, and as such this was applied to all temperature variables. For example, if the mean temperature anomaly was 1.9°C, then 1.9°C was added to each of the daily temperature variables (Tmean, Tmin, Tmax). Thus, the analysis is most likely conservative in its estimates of future change, because the daily minimum temperatures are expected to warm more than daily maximum temperatures.

Annual precipitation in Prince George is projected to increase by 3.7%–10.6% for the 2050s based on the mid-range of the ensemble of 65 GCM projections. Annual temperatures are projected to increase by 1.5°–2.4°C for the 2050s based on the midrange. For the winter months (DJF), precipitation in Prince George is projected to increase by 5.2%–12.3% for the 2050s based on the midrange of the ensemble of 65 GCM projections. Winter temperatures are projected to increase by 1.5°–2.8°C for the 2050s, based on the midrange. Nearly all of the 65 projections indicate that winter in Prince George will be warmer and wetter in the 2050s with the winter months warming more than the rest of the year.

The WSI calculator was then applied to both the observed (1976–2000) and the modeled climate data to project changes in expected budget for snow and ice control into the 2050s. WSI scores were calculated for each day in both the observed and future time periods and aggregated to the annual level.

4. Results and discussion

All 65 models project a net decrease in the need for WRM activities relative to the observed historical period.
The average annual WSI score for the 2050s was 16.3, in comparison to 20 for the baseline period. The lowest annual index score for the 2050s was 4.6 and the highest was 32.8. During the observed period, the lowest annual WSI score was 9.1 and the highest annual score was 31.8. Of the 65 models, there was an average of 4 years out of 25 that would have WSI scores higher than 20 in the 2050s. Figures 5 and 6 illustrate the projected changes for the demand for WRM. Each point on these figures represents a 25-yr average change in the demand for WRM.

The empirical estimates of the projected change in demand for WRM expenditures in Prince George addresses the second objective of the research. When the WSI is applied to climate data from the 65 GCMs, there is a consistent projection for a net reduction in future WRM expenditures. Despite increasing precipitation, the projected warmer temperatures result in more

<table>
<thead>
<tr>
<th>Simulation</th>
<th>B1 runs</th>
<th>A2 runs</th>
<th>A1B runs</th>
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<tr>
<td></td>
<td>ΔTmean (°C)</td>
<td>ΔPrecip (%)</td>
<td>ΔTmean (°C)</td>
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<tr>
<td>BCCR-BCM2.0 (Run 1)</td>
<td>-0.33</td>
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<td>CGCM3 T47 (Mean)</td>
<td>2.03</td>
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<td>1.53</td>
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<td>NCAR PCM (Mean)</td>
<td>2.29</td>
<td>11.19</td>
<td>2.81</td>
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</table>

**FIG. 4.** Projected annual changes to temperature and precipitation in Prince George for the 2050s.
precipitation falling as rain rather than snow. This leads to decreased projected costs for Prince George because a substantial portion of WRM expenditures are allocated to snow removal.

Based on the midrange (25th to 75th percentiles) of the 65 GCM projections, it is estimated that annual demand for WRM activities will decrease by between 13.0% and 22.0% by the 2050s. Assuming an average of CAD $5.3 million per year for WRM expenditures (adjusted to 2012 dollars), this translates into an annual average savings of between CAD $689,000 and CAD $1,166,000, assuming that all else remains unchanged. The other anticipated changes are likely to be offsetting; for example, population increase would equate to higher demand for WRM, but continually improving technologies and practices would be expected to offset some of these trends. As well, the projected cost savings do not consider the possibility that the municipality will need to retain a minimum equipment and/or staff complement in order to provide adequate service when heavy snowfalls occur. In this case, the assumed linearity of the relationship between winter severity and winter maintenance costs would be called into question.

One of the limitations of the above analysis relates to the use of the CFM, which does not account for the possibility of more variability and extremes. Extremes have not been assessed as part of this research, and instead annual and overall averages have been used. The development of scenarios that examine climate variability and extremes is a key challenge facing the climate modeling community (Barrow et al. 2004). Extremes occur infrequently, are localized, and often are excluded from climate scenarios.

One method that can be employed to further assess the impacts of more or less variable climatic conditions...
is to compute synthetic data by permuting the variance of the observational time series, as well as the mean. Synthetic data can be created from any permutation of the temperature and precipitation delta that are outside the current intermodal range and then applied to the observed data, in the same way as is done for the CFM (Lehmann et al. 2013). While existing models can guide researchers toward the permutations that are most likely, the models are unable to convey the entire suite of possible futures. While simply computing a wider range of temperature and precipitation delta permutations allows for a broader range of possible outcomes, these data still have the same variance in temperature and precipitation as is seen in the CFM and the model output data.

5. Conclusions

The first objective of this study was to develop a WSI model that explains the temporal variation in WRM expenditures in Prince George using weather data as the explanatory variables. The coefficient of determination ($R^2$) between annual WSI and annual expenditures is 0.93, which represents a very good fit. With an MSE of 0.088, this WSI is considered to have reliable predictive accuracy. As such, this WSI can be seen as an appropriate tool, when combined with modeled climate data, for estimating future WRM expenditures in Prince George.

The second objective looked to apply the WSI to modeled climate data to obtain a wide range of empirical estimates of the projected demand for WRM expenditures in Prince George into the 2050s. Results show that the CFM approach is an effective and efficient method for obtaining a range of estimated changes for WRM expenditure in Prince George for the midcentury. More importantly, the study illustrates how climate modeling information, which is inherently uncertain, may be applied in a way that can inform changes in transportation maintenance programs. This work provides a tangible example of how local practitioners can use observed and projected climate data to anticipate how current practices may need to be revised and how future budgets may be affected. By quantifying the impacts of projected changes in costs, it is made clear that climate change is a local priority that will affect budgets and practices (TAC 2013).

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