Data-driven climate indices as a climate translation service

by

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A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Doctor of Philosophy
in
Geography

Waterloo, Ontario, Canada, 2020

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

Exceptions to sole authorship:

Chapter 2: Matthews, L., Minokhin, I., Andrey, J., Perchanok, M. (2017a). Operational Winter Severity Indices in Canada – From Concept to Practice, *Proceedings of the Transportation Research Board, Standing Committee on Winter Maintenance* (AHD65). Paper #17-03338.

Chapter 3: Matthews, L., Andrey, J., Fletcher, C., Oozeer, Y. (Submitted). Long-term trends in winter weather severity affecting winter road maintenance. *Climate Services.* CLISER-D-20-00027.

Chapter 4: Matthews, L., Scott, D., & Andrey, J. (2019). Development of a data-driven weather index for beach parks tourism. *International Journal of Biometeorology*, 1-14. doi:10.1007/s00484-019-01799-7

Chapter 5: Matthews, L. Scott, D., Andrey, J., Mahon, R. Trotman, A., Burrowes, R., Charles, A. (Accepted). Developing Climate Services for Caribbean Tourism: A Comparative Analysis of Climate Push and Pull Influences Using Climate Indices, *Current Issues in Tourism.* Manuscript ID: CIT-6574.

I hereby declare that as a lead author on all four manuscripts, I was responsible for the conceptualization of the research, and I served as the principal investigator for the research that forms the basis of this PhD. I was responsible for the data analysis and the writing of all four manuscripts. I also was responsible for submitting the manuscripts to each respective journal/conference, addressing the comments from the peer-reviewers and reviewing the article proofs. My supervisors and co-authors, Dr. Jean Andrey and Dr. Daniel Scott, offered intellectual insight, feedback, suggestions, as well as editorial changes. In Chapter two, Ivan Minokhin conducted the data processing of the RWIS weather data and provided assistance in interpreting residuals. Also in Chapter two, Max Perchanok provided insight on winter maintenance in Ontario and feedback on the manuscript. In Chapter three, Dr. Christopher Fletcher and Dr. Yaasiin Oozeer acquired and organized the climate projections data. In Chapter 2 and Chapter 3 I gratefully acknowledge the provision road weather data and road maintenance data from the Ontario Ministry of Transportation. In Chapter 4, I gratefully acknowledge the provision of parks visitation data from the Ontario Ministry of Natural Resources, Parks and Protected Areas. In Chapter 5, the Caribbean Tourism Organization, the Caribbean Institute for Meteorology and Hydrology (Dr. Roché Mahon, Adrian Trotman, and Amanda Charles), and ESSA technologies (Dr. Ravidya Burrowes) provided exclusive access to regional data that was essential to the analysis as well as valuable feedback on regional information priorities and user perspectives. Lastly, each of the four manuscripts makes extensive use of weather observation data from Environment and Climate Change Canada.

Abstract

Weather and climate have a powerful influence on humans and society. The ways in which individuals, organizations, and communities are sensitive to weather and climate varies considerably due to social, economic, institutional, and technological factors (Kirchhoff *et al.* 2013). The complexity and variability across space and time of the human-environment interface motivates the demand for tools and techniques that are able to effectively translate climatic information into usable products and services for decision-making. Furthermore, notwithstanding the extensive availability of weather and climate information, its use in informing both weather risk-management decisions and climate-change adaptation initiatives remains limited. One factor in the underutilization of weather and climate information stems from the difficulty of translating weather and climate data into useable information for decision-makers (Rayner *et al.* 2005, Lemos 2008, Weaver *et al*. 2013, Fellman 2012, Kirchhoff *et al.* 2013, Soares & Dessai 2015).

Organizations have been increasingly seeking tools that can inform decision-making for both short-term weather risk management and long-term climate change adaptation measures (WMO 2016). Regardless of the temporal scope of a decision, there is a need to identify and quantify the climatic sensitivity and associated risks and opportunities of climatic stimuli (Damm *et al.* 2019). The non-linearity of climate-society interactions combined with the highly context-dependent nature of societal sensitivities to climatic stimuli poses a number of practical challenges. This gap in research, and in practice, provides a novel research opportunity to investigate the prospect of developing techniques that can quantify weather sensitivity in a variety of applications.

These context-specific and user-driven climatic information products and services are often referred to as climate *translation* products and services (Damm *et al.* 2019). A core impediment to the development of climate translation services is an incomplete understanding of how individuals, organizations, and sectors are sensitive to climatic stimuli. A number of methods has been used to define this sensitivity but to date and there has been a dominant focus on stated-preference methods to ascertain user needs and sectoral climatic sensitivities. Expert consultations, user interviews, and participant surveys have been used

extensively to define context-specific weather and climate sensitivities. However, a growing literature explores the use of data-driven techniques to explore societal sensitivity to weather and climate. Focusing on the highly climate-sensitive transportation and tourism sectors, this dissertation proposes a conceptualization of climatic sensitivity that is premised on the need for multiple climatic thresholds. This dissertation proposes a framework for data-driven techniques that can be used to develop climatic indices based on the underlying relationships between weather and society and presents the first data-driven approach to define *multiple* climatic thresholds for the climate-society nexus in two climate-sensitive sectors.

The overarching purpose of this dissertation is to further the development of climate services and increase the scholarly understanding of context-specific climatic thresholds that communicate a societal response and can be applied to weather forecasts and climate projections at different temporal scales. The first manuscript uses expert knowledge in combination with mathematical optimization to develop a data-driven winter severity index that works well in predicting winter maintenance activity across 20 road maintenance jurisdictions in Ontario. The second manuscript builds on the first paper through an extension to include climate change projections, and provides greater focus on role of co-production in climate services development. This second manuscript explores the frequency, and intensity of past and future winter weather as it relates to winter road maintenance of provincial highways in Ontario, Canada. The climate change analysis reveals that winter severity, as it relates to snow and ice control, is projected to decrease through to the end of the century. The third manuscript of this dissertation explores the feasibility of transferring the methods developed in the first two manuscripts to develop a data-driven tourism climate index for Ontario Provincial Parks. This third study advances our understanding of beach park-visitor's climatic sensitivity and provides tourism planners, managers, and decision-makers with enhanced information to inform decision-making. The final manuscript of the dissertation examines the intra-annual effect of weather on tourism demand to three Caribbean destinations (Barbados, Antigua and Barbuda, and Saint Lucia) from Ontario, Canada. This study refines the Holiday Climate Index: Beach through optimization to develop two new indices which estimate the climatic pull-factor of the destination, and the climatic push-factor from the source market. Findings reveal that the data-driven indices

have greater predictive accuracy than the extant climate indices for tourism. In conclusion, this dissertation demonstrates the feasibility of developing data-driven indices in the transportation and tourism sectors that can form the foundation of climate service translation tools.

Acknowledgements

First and foremost, I would like to thank my co-adviser and mentor, Jean Andrey, for all of your support, patience, encouragement, and quick wit through this journey. Your scholarly and personal support is deeply cherished. Thank you to Daniel Scott, my co-advisor, for your guidance, brilliant insights, and encouragement. Dan and Jean, you both have my sincerest gratitude and respect as scholars and humans and I will treasure this experience of working with you both.

I would also like to thank the other members of my committee, Christopher Fletcher, Christopher Lemieux, and Jason Thistlethwaite. Your feedback and suggestions have been greatly appreciated. I want to extend my appreciation to my external committee member William Gough (University of Toronto Scarborough) for your enthusiasm and feedback. I would also like to thank Brian Mills and Brent Doberstein for your kind and generous support both personally and professionally.

Thank you to my friends and family for your continued encouragement, laughter, and support. A special thanks to Amber and Michelle for leading the way and to Yue and Xiaomeng for going through this at my side… or from across the room. Extra thanks to all of the staff in EV1 for being such an incredibly kind, funny, and supportive group.

A very special thank you to the *Original 5* for being there from the start.

Lastly, immense gratitude and love to Ivan, Hannah, and Ava for your patience, love, laughter, and support.

Dedication

For my girls.

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List of Abbreviations and Acronyms

3S tourism – Sun-sand-surf tourism
AMC – Area Maintenance Contracts
AMS – American Meteorological Society
CIMH – Caribbean Institute for Meteorology and Hydrology
CCCS – Canadian Centre of Climate Services
CS – Climate Services
CTO – Caribbean Tourism Organization
ECCC – Environment and Climate Change Canada
GFCS – Global Framework for Climate Services
GCM – Global Climate Model
HCI:Beach – Holiday Climate Index: Beach
HCI:Urban – Holiday Climate Index: Urban
MDSS – Maintenance Decision Support Systems
MMIS – Maintenance Management Information System
MTO – Ontario Ministry of Transportation
NA-CORDEX – North American - Coordinated Regional Climate Downscaling Experiment
RCM – Regional Climate Model
RCP – Representative Concentration Pathway
RWIS – Road Weather Information Systems
TCI – Tourism Climate Index (Mieczkowski, 1985)
UNWTO – United Nations World Tourism Organization
USFHA – United States Federal Highways Administration
WMO – World Meteorological Organization
WRM – Winter Road Maintenance
WSI – Winter Severity Index

Chapter 1:

Introduction to Dissertation

1.1 Problem Context

Short-term weather stressors, inter-annual climate variability, and long-term climatic trends all have profound impacts on humans and society (Thomalla *et al.* 2006, IPCC 2014). A number of authors have sought to measure these weather sensitivities and associated risks across sectors such as agriculture (Stockle *et al.* 1992, Rosenzweig *et al.* 2013, Zhao *et al.* 2014), energy (Beccali *et al.* 2008, Pernigotto *et al.* 2014), transportation (Koetse & Rietveld 2009, Venner & Zamurs 2012, Meyer & Weigel 2011, Markolf 2019), tourism (Scott *et al.* 2007, de Freitas 2015, Fisichelli *et al.* 2015, Rutty & Scott 2010, 2013, 2015), and health (Kunkel *et al.* 1999, Anderson & Bell 2009, Gachon *et al.* 2016). Much of the recent interest in weather sensitivities and associated risks has emerged as a by-product of the attention and interest in climate change impacts; because weather sensitivities often are measured as the first step in assessing the potential implications of climatic variability and change for society. However, developing methods that can be used to calculate climatic sensitivity across spatial and temporal scales from near-term episodic events to long-term climatic sensitivities remains challenging (Thomalla *et al.* 2006).

The core challenge that transcends all studies of weather and society is the difficulty of establishing correlated risks across disparate sectors and scales. The specific climatic thresholds that reflect behavioural or societal sensitivities to climatic stimuli fluctuate over space and time because of complex interactions of social, economic, political, technological, institutional, and environmental relationships (Kovats *et al.* 2005, Lorenzoni *et al.* 2005, Renaud *et al.* 2010). The non-linearity of human and societal responses to weather/climatic stimuli also has posed a conceptual and methodological challenge in part due to the difficulty of establishing climatic thresholds that reflect societal sensitivity to climate (Kovats *et al.* 2005, Lorenzoni *et al.* 2005, Eugenio-Martin & Campos-Soria 2010, Fellman 2012). While the biophysical components of a social-ecological system respond in a reactive, and often linear manner, the societal components of a social-ecological system respond in both reactive and proactive ways, and in a non-linear manner (Burton *et al.* 1993, Smithers & Smit 1997). For example, in a controlled setting, a crop will consistently perform well under specific weather conditions. Similarly, a solar panel will produce the same amount of energy for the same amount of incoming radiation. These relationships are predictable and are modelled in such a way as to provide information to enable decision-making (Fellman 2012). The social and economic aspects of a system, however, are sensitive in more complex ways (Renaud *et al.* 2010, Fellman 2012). This complexity presents a barrier for the translation of basic climate services (CS) to special CS intended to meet the needs of specific user groups/decision makers.

It is specifically this complexity of the human-environment nexus that drives the demand for tools and techniques that can efficiently and effectively translate climatic information into salient products and services for decision-making in ways that reflect sensitivities in relevant and interpretable ways. Vaughan *et al*. (2016) found that a key barrier to the production of decision-relevant weather and climate information is a limited understanding of the extent and ways in which individuals, organizations, and sectors are sensitive to climatic stimuli. A persistent gap in the science-policy research arena is the critical need to develop ways to produce decision-relevant information that is highly specific to the unique contexts of each place and sector (Kirchhoff *et al.* 2013). Despite the ever-increasing availability of weather and climate data, its use in informing decision-making in a variety of contexts remains limited, and stems from the challenge of establishing correlated relationships between weather and society (Rayner *et al.* 2005, Lemos 2008, Weaver *et al*. 2013, Fellman 2012, Kirchhoff *et al.* 2013, Soares & Dessai 2015). Regardless of whether an organization is seeking to explore impact-based forecasting for high impact weather, or a company is endeavoring to project the impacts of climate change for their operations and investments, there is a need to identify and quantify the climatic sensitivity and associated risks and opportunities of climatic stimuli and their variability and change across timescales (Damm *et al.* 2019). This gap in the literature, and in practice, provides a unique research avenue to explore the potential for developing a framework and techniques that can quantify weather sensitivity in a variety of contexts. This specific type of information is often referred to as climate *translation* products and services (Damm *et al.* 2019).

The necessity for research in climate translation services is highlighted in a number of high-profile documents and programs. Importantly, the increasing demand for decision-relevant climate information has led to calls for an improved standardization and coordination of the provision, utility, and application of weather and climate information. These calls led to the development of the Global Framework for Climate Services (GFCS) in 2012. The GFCS is funded by the World Meteorological Organization (WMO); its goal to enable informed climate-related decision-making (WMO, 2012). The vision of the GFCS is "to enable better management of the risks of climate variability and change and adaptation to climate change, through the development and incorporation of science-based climate information and prediction into planning, policy and practice on the global, regional and national scale" (WMO, 2017). The GFCS seeks, specifically, to facilitate the contextualization, or translation, of scientific weather and climate information for decision-making (WMO 2017, Vaughan & Dessai 2014).

At the national scale in Canada similar efforts are emerging; specifically, with major investment in the development of the Canadian Centre of Climate Services (CCCS) which is a federal branch of the Environment and Climate Change Canada and was founded in 2018. The CCCS provides access to user-demand driven climate data, tools, and sector-specific information explicitly developed for the Canadian context. The CCCS has a mandate to support the implementation of the Pan-Canadian Framework on Clean Growth and Climate Change - the national equivalent to the GFCS. Both the GFCS and the CCCS promote the development, dissemination, and application of user-driven climate information to improve resiliency to climate variability and change.

These CS providers are positioned at the intersection of climate science, policy, and practice (Vaughan & Dessai 2014) and, as such, CS research and practice is truly an interdisciplinary and transdisciplinary endeavor (McNie 2012, Vaughan & Dessai 2014). CS are envisioned as a way to enable climate change adaptation planning to both mitigate risks and to capitalize on opportunities (Damm *et al.* 2019). As such, CS providers facilitate the translation of observed weather conditions, forecast data, vulnerability assessments, and climate change projections into products and services to inform decision making (Vaughan & Dessai 2014, Vaughan *et al.* 2016). Translation service providers create tailor-made information to bridge the interface between the scientific community and the users. The challenge for these organizations is to facilitate collaboration and information flow between diverse research disciplines and between the research and public policy community (Kirchhoff *et al.* 2013, WMO 2016).

In order to develop CS, there is a requirement for data from the meteorological/climatological communities to be integrated with that from sectors of interest. Traditionally, government weather and CS providers have been concerned primarily with the development of infrastructure and processes for gathering, processing, and disseminating weather and climate observations, forecasts, alerts/warnings, and projections. These are considered basic services by the WMO. Basic services are "those services delivered at public expense to discharge a government's sovereign responsibility for protection of life and property, for the general safety and well-being of the national community and for provision for the essential information needs of future generations" (Anderson *et al.* 2015, p. 19). The top portion of Figure 1-1 depicts the hydro-meteorological value chain that are core to these basic services developed and disseminated by weather service providers internationally (Anderson *et al.* 2015). Special services, however, extend beyond the traditional offerings and are: "those services beyond the basic services aimed at meeting the needs of specific users and user groups and that may include provision of specialized data and publications, their interpretation, distribution and dissemination. Many services, particularly special services, often go well beyond the simple dissemination of information to include consultative advice or scientific investigation into particular meteorological and hydrological phenomena and events or their impacts" (Anderson *et al.* 2015, p. 19).

Translation services would be considered a special service under the WMO and the lower portion of Figure 1-1 depicts a schematic of the CS value chain as it is integrated within the hydro-meteorological production and delivery chain. Both impact-based forecasting and socio-economic projections of climate impacts are considered 'value-added' services or special services (Anderson *et al.* 2015). The areas highlighted in orange and yellow are related to CS translation services, and Figure 1-1 highlights where translation services are situated in the broader landscape hydro-meteorological products and services. These highlighted areas are also where contributions from this dissertation are focused.

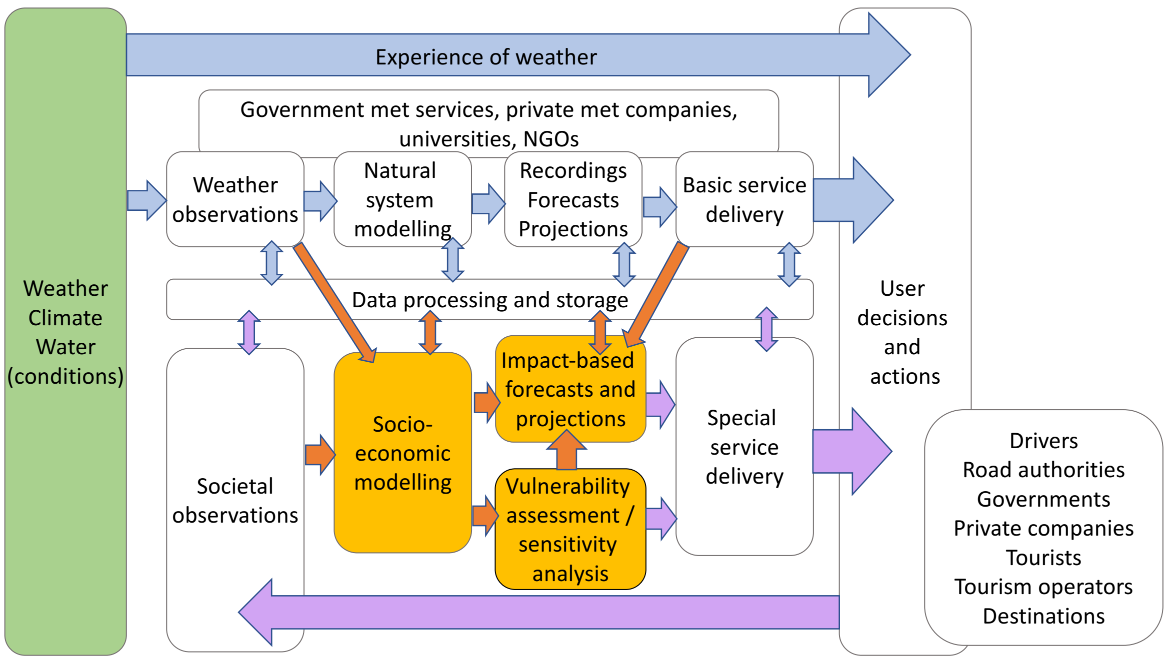


Figure 1-1. Schematic of climate services value chain integrated within the hydro-meteorological production and delivery chain (adapted from Anderson *et al.* 2015, p. 148).

While there has been progress in improving the coordination, development, and delivery of CS through entities such as the GFSC and the CCCS, the challenge of developing *tailored* climate information remains an area of emerging scholarship and praxis (Damm *et al*. 2019). A critical attribute of tailored translation services for climate risk management is their efficacy, *i.e.*, how well the forecasts or projections of impacts reflect the actual impacts and responses. Part of the challenge of identifying correlated sensitivities is the difficulty of identifying and describing societal thresholds to climatic stimuli, *i.e.*, at what point does a weather element result in a stronger or weaker impact on humans and/or society.

The concept of a climatic threshold can be exemplified through the instance of human exposure to extreme cold. A threshold of 0°C is not considered extreme in terms of human health (exposure), but this threshold is acutely important for transportation safety and maintenance as this freezing point results in more dangerous driving conditions (Thornes 1993). Extending this example; there is a biophysical process that can inform the selection of thresholds to communicate a hazardous health event such as an extreme cold warning. For example, while frostbite can occur at temperatures above -10 °C, there is a significant and rapidly increasing risk of developing frostbit at temperatures below -15 °C (Hassi & Makinen 2000). These biophysical responses to cold are not location-specific; regardless of where in the world a person is located, they will experience frostbite at a specific temperature. However, the point at which extreme cold warnings are issued by a weather or health authority actually varies geographically, even within the same jurisdiction. For example, Environment and Climate Change Canada (ECCC), the Canadian national meteorological service provider, issues differential warnings based on the frequency with which different minimum temperatures are reached in a given geographic region; not the biophysical risk of acquiring frostbite. In 2019, David Phillips, a Senior Climatologist at ECCC, rationalized the variable thresholds at which severe cold warnings are issued in different parts of Canada (CBC, 2019). In February 2019 both Toronto and Ottawa experienced temperatures of -32 °C, but only Toronto received an extreme cold warning (CBC, 2019). Phillips highlighted that temperatures need to reach -30 °C in Toronto for an alert to be issued but for Ottawa it needs to reach -35 °C (CBC, 2019). Further north in Northern Ontario temperatures needs to reach -40°C, and in Nunavut -55°C (CBC, 2019). This emphasizes that practitioners already conceptualize weather sensitivity and risk as a context-specific condition rather than a generic condition. Further complicating these matters is that different health authorities within the same geographic region may release health warnings at different temperature thresholds. For example, while ECCC's extreme cold warning is triggered at -30 °C in Toronto, the City of Toronto's health authority releases extreme cold warnings at -15 °C (Gough *et al.* 2014).

The conceptualization and operationalization of extreme heat is similarly complex. The precise definition of extreme heat varies geographically due to a variety of social and geographical considerations. As outlined in Health Canada's report, *Adapting to Extreme Heat Events: Guidelines for Assessing Health Vulnerability,* certain populations are more or less vulnerable to extreme heat because individuals have differential vulnerabilities due to age, income, health, fitness, medication and other community and socio-economic factors (Health Canada 2011). Furthermore, as highlighted by Gachon *et al.* (2016), the standard operating procedures for disseminating heat warnings varies based on the jurisdiction in question. These differential vulnerabilities to extreme heat events, and differential operating procedures, are illustrated by the vast array of thresholds at which heat advisories are disseminated locally and internationally (Casati *et al.* 2013).

While some jurisdictions may use ambient air temperature at a specific threshold to administer an advisory, ECCC issues heat advisories when the humidex, a combination of relative humidity and temperature, are expected to reach or exceed a threshold (Health Canada 2011). However, the specific threshold at which heat advisories are administered varies geographically. For example, in the Windsor–Essex–Chatham–Kent region of Ontario, Canada there needs to be more than two consecutive days with maximum daily temperatures ≥ 31°C and minimum daily temperatures ≥ 21°C *or* a Humidex ≥ 42°C for an advisory to be issued. In Northern Ontario, by contrast, the thresholds are different and there needs to be more than two consecutive days with maximum daily temperatures ≥ 29°C and minimum daily temperatures ≥ 18 °C *or* a Humidex ≥ 36°C (Gachon *et al.* 2016).

Across Canada these thresholds change in both the variable used (*i.e.*, ambient air temperature or humidex), and the temporal aspect of the event (*i.e.*, temperatures for one hour, or for two consecutive days depending on the region). For example, in Nova Scotia, New Brunswick, Prince Edward Island, and Newfoundland and Labrador, warnings are issued when temperatures meet a specific threshold for at least one hour (Gachon *et al.* 2016). Furthermore, other heat indices are used in different jurisdictions such as the simplified Wet Bulb Globe Temperature (WBGT), apparent temperature, or the heat index as used by the National Weather Services in the United States. These thermal indices take into account meteorological elements other than ambient air temperature that are crucial for human vulnerability to heat stress (Gachon *et al.* 2016).

These two examples of extreme cold and extreme heat exemplify the challenge of establishing weather thresholds to single atmospheric parameters in diverse geographic regions. The challenge, however, becomes greater when the societal response is no longer biophysical (*e.g*., frostbite or heatstroke), but is instead a complex interaction of physical, social, technological, economic, political and environmental relationships. This has been a longstanding issue and in the 1993 edition of *Environment as Hazard*, Burton *et al.* (1993) highlighted the importance of thresholds for understanding the impact of weather on society. Using the example of society's sensitivity and risk to snowfall, Burton *et al.* (1993)

underscore that the societal impacts of, and behavioural response to, climatic stimuli are not linear and are clearly context-specific.

> "*The relation between snowfall characteristics and impact is not a simple linear function: it depends upon the ways in which the people of the area commonly cope with the event. Snowfall below a critical threshold value may not cause any significant damage or disruption. Once a critical threshold has been passed, however, damage may mount rapidly. The specification of these relations and the definition of the threshold levels for a given place or society pose significant problems for research not normally approached by physical scientists. A threshold of crippling snowfall for Toronto, for example, is lower than the threshold for Northern Ireland. Indeed, the common units of measurement employed for physical delimitation may be unsuited for assessment of social impact. Where the units are appropriate, an accurate measure of social significance of hazard may be gained only by a specific combination of such measurements and requires research on both physical and social systems.*"
>
> \- (Burton *et al.* 1993, p. 33)

Indeed, in the context of winter road maintenance (WRM) the response to a specific amount of snowfall accumulation will vary geographically for a variety of interacting social, cultural, economic, technological and political reasons. This is complicated even further when individuals or institutions are responding to the integrated or combined effects of multiple weather variables. In the context of WRM there is a sensitivity to a suite of meteorological phenomena including snowfall, but also rain, freezing rain, blowing snow, cold temperatures, freeze-thaw cycles, and combinations of these variables.

While attempts have been made to integrate climatic variables into winter-road maintenance models and indices in an effort to inform decision-making (Rissel & Scott 1985, Boselly *et al*. 1993, Cornford & Thornes, 1996, Venäläinen 2001, Carmichael *et al.* 2004, Suggett *et al.* 2006), there is no universal physical unit of 'winter weather'. Similarly, when this concept is extended to tourism, there is no universal and physical unit of 'beach weather' or ‘camping weather’ in existence despite efforts to develop such indices (Mieczkowski 1985, Rotmans *et al.* 1994, Scott & McBoyle 2001, Scott *et al.* 2004, Hein *et al.* 2009, Scott *et al.* 2016).

These two globally important sectors, transportation and tourism, are the focus of this dissertation as both transportation and tourism are sensitive to weather and climate in a variety of complex ways. Different individuals in different jurisdictions in different sectors respond to climatic stimuli in varied and complex ways and this has led to calls to explore the concept of flexible indices with multiple thresholds that are specific to both the geographic location, and the activity in question.

Not all are convinced that CS can deliver products for all hazards and sectors. Kovats *et al.* (2005) and Lorenzoni *et al.* (2005), for example, argue *against* scientific explorations of climatic thresholds for societal and economic studies in climate adaptation planning. These authors argue that clear thresholds for the socio-economic and health impacts of climate change are impossible to identify because of the complexity in human and social responses to climatic stimuli. Importantly, these scholars have conceptualized thresholds as a single value for a single climatic variable at which point “result in damages that could be considered unacceptable by policy makers” (Lorenzoni *et al.* 2005, p. 1389). Given the non-linearity of the climate-society nexus, exploration of single thresholds that reflect specific sensitivity are likely to fail. With specific respect to road conditions in winter, there is no single definable snowfall threshold at which plows in all jurisdictions undertake road maintenance activities. Instead there are multiple and incremental thresholds that reflect differential sensitivities to climatic stimuli.

As such, investigations of weather and society interactions need to embrace this complexity by exploring *multiple* climatic thresholds for a *combination* of atmospheric events at which an increasing or decreasing number of tourists visit a destination, or at which point increasing or decreasing amounts of road maintenance are administered. An index approach is a promising avenue to explore the notion of multiple thresholds with the potential of advancing CS translation tool development for a multitude of applications and is the focus of this dissertation.

1.2 Methodological Approach

In 1887, Halford Mackinder published "On the Scope and Methods of Geography" in which he strongly advocated that first, geography should be a distinct academic discipline, and secondly, the central role of geographers was to bridge the gaps between the natural and social sciences (Mackinder 1887 as cited in Castree *et al.* 2009). This human-environment remains a central focus for many geographers today (Turner 2002). However, as the discipline of geography has evolved, the field of geography became increasingly segmented between the physical and human divide (Holt-Jensen 1999). A branch of geography that continues to primarily focus on this biophysical and human interaction is known as environmental geography or integrated geography. Environmental geography is often seen as a middle ground between these two ends of the disciplinary continuum. Geographers such as Turner (2002) and Castree *et al.* (2009) advocate that human-environment studies act as the unifying link between physical sciences and social sciences for modern geography.

Investigations of weather and climate translation services are situated in this human-environment nexus.

While there is no unifying epistemology for geography (Holt-Jensen 1999), elements of positivism and post-positivism have dominated physical geography in particular, with a focus on quantitative methods (Philip 1998). However, postmodernism and critical theories have had more prominence in human geographical studies with a focus on qualitative methods (Philip 1998, Castree *et al.* 2009, Holt-Jensen 1999). Environmental geographers, caught in the proverbial middle, may hold either (or both) of these views, and may opt for a multiple-methods approach (Philip 1998, Turner 2002). For example, the pivotal work by Gilbert White (1945) on flood hazards in the United States was instrumental in infusing behavioural geography into what had been a primary focus on engineering solutions. The work of White was formative for the field of hazards geography and geography as a whole. These works gave rise to what has become modern hazards geography and has had a strong influence on work related to global environmental change (Burton *et al.* 1993) and studies of weather and society more broadly. Building on these early works, geographers have continued to research the climate-society interface, and the contributions of geographers to tackling global environmental change in research, policy, and practice remains significant today (Moser 2010, O'Brien 2011, Randalls 2017).

The focus in this dissertation is the climate-society interface, an area of scholarly interest that is connected with two related, yet disparate, research traditions – environmental hazards and global environmental change. While the environmental hazards and climate change fields share similar concepts, the timescales of interest are different. Further, the methods and conceptual frameworks by which researchers approach complex human-environment interactions dictate the types and utility of knowledge that is created. Recently there has been a movement away from the traditional deductive methodologies and more interest in the inductive and abductive approaches to geographical scholarship more generally (Miller & Goodchild, 2015).

This dissertation aligns with the work of Barnett *et al.* (2008) in recognizing the importance of context in approaching human-environment studies. Specifically, the concepts of scale, place, people, economy, society, environment are all relevant and the specific climatic thresholds that induce human- or societal-responses will vary over space and time because of these contextual realities. As such, this dissertation intentionally adopts an inductive and data-driven approach for all four manuscripts. The four manuscripts presented in this dissertation all use a shared method for developing mathematically optimized and context-specific climatic indices that can be tailored to the unique social, cultural, economic, and environmental realities of each place-based decision-making arrangement.

While techniques, such as optimization may limit the generalizability of the results, the trajectory of data-driven geography and data-driven science in general is associated with richer and more complete description of phenomena at smaller scales, albeit with less information about larger scales. As Miller and Goodchild (2015, p. 455) state, data-driven geography will result in "…a shift away from the general and towards the specific—away from attempts to find universal laws that encompass all places and times and towards deeper descriptions of what is happening at particular places and times". This is precisely what this dissertation aims to achieve: a richer and deeper description of the human-environment nexus for specific decision-making contexts. This dissertation does not aim to contribute to a unifying theory about climate and society interactions, but instead seeks to explore a unifying framework for translating climate-society interactions to describe the place-based and specific relationships between weather and society for specific purposes. This dissertation aims to demonstrate a method for developing customized metrics of weather and society interactions that are reproducible in a variety of societal applications, adding important conceptual and methodological insights into the notions of multiple thresholds and multiple timescales of application.

1.3 Research Goal and Objectives

Increasingly, there are calls to develop tools and techniques that can enable the effective translation of weather and climate observations into salient information for decision-making in a variety of contexts (Cash *et al.* 2006, Kirchhoff *et al.* 2013, Vaughan & Dessai 2014, WMO 2017). Weather and climate indices are a category of such tools that simplify weather and climate information in ways that are relevant to societal phenomenon. When integrated within the CS landscape (Figure 1-1), tools such as climate indices can enable the efficient translation of complex climatic phenomena into a societal response through the identification of multiple weather thresholds, and can be applied to decisions across multiple timescales and/or provide insights into behavioural responses to climatic stimuli. Indices can be used for risk management, strategic planning, budgeting, public communications, and performance management in a variety of contexts. This dissertation explores a framework for developing flexible climate indices as a tool that can aid decision-makers in reducing climate risk. A framework for flexible climate index development provides a unique avenue to explore climatic sensitivity and risk across temporal and spatial scales in a way that can be calibrated and adjusted over time. Figure 1-2 illustrates the general framework that is used in developing the climate indices presented throughout this dissertation.

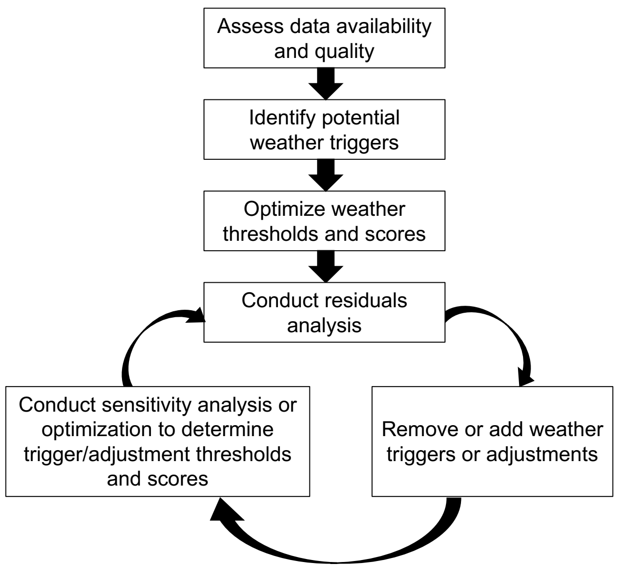


Figure 1-2. Framework for the development of a flexible climate index (reproduced from Matthews *et al.* 2017b)

The complexity and the non-linearity of these sectoral responses to climatic stimuli has posed scientific challenges in identifying climatic thresholds for different interactions. The methodological goal of this dissertation is to explore whether the methods developed for index construction in one sector (transportation) are transferable to a second sector (tourism). These are two sectors that are highly sensitive to climate variability and change and have a long history of using weather information for decision-making. While both sectors are climate-sensitive, the nature and specific thresholds of climate sensitivity are fundamentally different. In the transport sector, the behaviours of individuals (drivers) occur within the context of an institutional arrangement that prescribes strict maintenance standards that are tied to specific weather events. Furthermore, in the context of WRM, climatic stimuli exert a unidirectional force on human responses. The response to winter weather is to perform WRM activities, but the specific quantities and types of maintenance that follow or precede a weather event vary based on the nature of the weather elements in play and the types of infrastructures in need of treatment. In the tourism sector, the relationship is less procedural, as the individual agency afforded to tourists does not have firm protocols of when to respond to climatic stimuli. Tourist behaviours are individual and constrained by non-climatic drivers of tourism demand such as economic growth, travel pricing, geopolitical effects, and socio-cultural factors such as the timing of school holidays (Scott 2019).

Different individuals and organizations, undertaking different activities, respond to diverse climatic stimuli in diverse ways. Identifying exactly at which point(s) weather elements exert either a greater or lesser pull or push factor on human and institutional responses is a core methodological contribution of this dissertation. Thresholds are an element in many weather risk management decisions as well as climate change adaptation strategies. However, how thresholds are set, particularly as they relate to different kinds of sensitivities specific to the contextual realities of the situation in question, is under-explored in the CS literature. This dissertation presents the first data-driven approach to define *multiple* climatic thresholds for the climate-society nexus. It explores the concept of multiple thresholds that can provide insights into both peak/optimal/highest as well as the minimum/worst/least of a societal response in a way that is more illuminating than the other works. This dissertation begins with a fundamentally different approach to exploring the climate-society nexus by acknowledging that, as Kovats *et al.* (2005) and Lorenzoni *et al.* (2005) argue, single climatic thresholds are impossible to determine and instead empirically identifying the multiple thresholds of the climate-society interactions is crucial for furthering the development of CS for both weather risk management and climate change adaptation.

Overall, there are a number of conceptual and methodological considerations that have been highlighted throughout this introduction. The core considerations for furthering the development of CS tool development are the challenges of working at multiple timescales, with multiple climatic thresholds, for diverse user groups with differential agency to make decisions, and doing so in such a way to create salient information for CS users. There is a practical requirement for CS tools to be usable for the users of the climate information. The establishment of correlated risk metrics with a high degree of fit and the overall usability of the resulting indices are also important considerations in the development of CS tools.

This dissertation seeks specifically to overcome these conceptual challenges by exploring a framework that can be used to develop weather and climate indices based on underlying relationships between weather and society. The overall goal of this dissertation is to further the development of CS and increase our understanding of context-specific climatic thresholds, particularly the methodological challenges of simultaneously identifying multiple climatic thresholds that communicate a societal response and can be applied to weather forecasts and climate projections at different temporal scales. The practical benefit of this research is that it is intended to increase the level of climate risk management across sectors and informs decision making by focusing specifically on the issues of snow and ice control in the transport sector, and forecasting tourist flows in the tourism sector. Collectively, the purpose of the four manuscripts is to improve our understanding of the human-climate nexus. To achieve this, four objectives were identified, each with specific research aims:

Objective 1: Focusing on the transport sector, develop a Winter Severity Index (WSI) that reflects the sensitivity of road maintenance operations to winter weather. The objective is to develop a WSI that works well in predicting WRM activity (as measured by equipment hours) across space and time in the provincial jurisdiction of Ontario, Canada.

Aim 1: Describe an approach for developing a context-specific weather index for use in WRM decision-making using Road Weather Information System data.

Aim 2: Identify the climatic thresholds that are reflective of organizational climate sensitivity, and the relative importance of these thresholds for WRM in Ontario. This will be completed through an exploration of how an optimization algorithm can simultaneously calibrate weather-attribute thresholds and scores, reflecting the specific maintenance regimes in each jurisdiction.

Aim 3: Assess the utility of the resulting WSI for use across 20 climatically unique jurisdictions throughout the province of Ontario.

Objective 2: Present an empirical extension to Objective 1 through the development of a WSI based solely on publicly available and open access weather observation data to develop a WSI that can be applied to weather and climate products at multiple timescales highlighting the important role of co-production in the development of CS.

Aim 1: Redevelop the WSI from Objective 1 based solely on publicly available and open access weather observation data to create a WSI that can be applied to both historical weather observations and modelled climate data.

Aim 2: Apply the WSI to 30 years of observed weather data for the 20 maintenance jurisdictions in Ontario and to assess whether there are any detectable trends and their significance in the frequency of these climatic conditions.

Aim 3: Improve our understanding of the potential impacts of climate change on WRM, and how these projections differ spatially across the 20 maintenance jurisdictions in Ontario, and temporally over three future time periods into the end of the century.

Aim 4: Describe the role and nature of co-production of CS in the context of Ontario's WRM Planning.

Objective 3: Focusing on the tourism sector, explore the feasibility of developing a data-driven climate index for Ontario Provincial Parks that reflects the sensitivity of parks visitors to climatic stimuli. The objective is to develop a tool that can ultimately assist decision-makers in reducing climate risk by identifying climatic thresholds of importance for the management and operations of the parks.

Aim 1: Conduct an empirical validation and comparison of two existing climate indices for tourism, the Tourism Climate Index (TCI) and the Holiday Climate Index: Beach (HCI:Beach) as they apply to two provincial parks in Ontario, Canada.

Aim 2: Recalibrate an existing tourism index (HCI:Beach) using the methods developed in Objective 1 and refined in Objective 2 to identify the climatic thresholds, and the importance of these thresholds, for reflecting beach park visitor's sensitivity to weather in Ontario.

Aim 3: Examine whether two tourism segments (day visitors and overnight campers) are sensitive to climatic stimuli in the same ways and whether climatic sensitivity is similar between two geographic regions within the same provincial parks system.

Objective 4: Explore the transferability of developing a data-driven climate index for international tourism flows between two climatically diverse regions (Canada and the Caribbean). Undertake an empirical investigation of the historical relationship between intra- and extra-regional climate and Caribbean tourist arrivals using a data-driven climate index approach developed and refined in Objectives 1 to 3 for both climatic push factors and climatic pull factors.

Aim 1: Build on the work from Objective 3, which identified climatic pull-factors for shorter term tourism decision-making (day trips), and apply this method for longer term decision making (travelling to the Caribbean).

Aim 2: Conduct an empirical validation and comparison of three existing indices, the TCI, the Holiday Climate Index: Urban (HCI:Urban), and the HCI:Beach as they relate to arrivals at three Caribbean nations from Ontario, Canada.

Aim 3: Recalibrate an existing tourism index (HCI:Beach) using the methods developed in Objective 1 and refined in Objective 2 and Objective 3 in order to identify the climatic thresholds and the importance of these climatic thresholds for reflecting the climatic sensitivity of arrivals to Caribbean tourism destinations (climatic pull factors) from Ontario, Canada (climatic push factors). The result is two new indices, an optimized in-situ index that measures the pull factor of the destination and an optimized ex-situ index that measure the climatic push factor at the origin market of Ontario.

1.4 Outline of Dissertation

This doctoral dissertation is written in a manuscript structure and comprises four manuscripts (Chapters two to five) that have been submitted for publication; one in a peer-reviewed conference proceeding (Chapter two) and three in peer-reviewed journals (Chapters three to five). These four manuscripts are supported by this introduction (Chapter one) that outlines the problem context, methodological approach, and identifies the goals, objectives, and aims of this dissertation. Each of the four peer-reviewed manuscripts include specific literature reviews that are pertinent to each paper. Lastly a summary and conclusions section (Chapter six) summarizes the research findings, draws conclusions related to the thesis goal, and discusses the implications of this dissertation for weather, climate and society studies more broadly.

Chapter two is the first methodological contribution of this dissertation and has been published in the *Transportation Research Board's 2017 peer-reviewed Conference*

Compendium of Papers. The manuscript is entitled “Operational Winter Severity Indices in Canada – From Concept to Practice” (Matthews *et al.* 2017a). This manuscript uses expert knowledge in combination with mathematical optimization to address all three aims from Objective 1 to develop a WSI that works well in predicting WRM activity across 20 maintenance jurisdictions in Ontario. This index works by assigning daily weather scores for each day based on eight weather triggers and one warm-weather adjustment factor. These scores reflect the road authority’s sensitivity to different climatic conditions. These daily scores are aggregated to the 14-day period and are then correlated to maintenance activities. The WSI for Ontario provincial highways has a strong fit with maintenance activity that occurred, when measured as equipment-hours. Working at the provincial level, the R^2 values for equipment-hours vary from 0.959 to 0.989 over seven maintenance seasons. This study demonstrates the utility of a province-wide WSI and describes how a WSI can be developed for road authorities.

Chapter three is the second of two transportation-related papers and builds on this first paper through an empirical extension to broader timescales, including application to climate change projections, and provides a more nuanced discussion on the role of co-production in CS development while addressing Objective 2 of this dissertation. This manuscript is entitled “The development of climate services for winter transportation planning” and will be submitted to the *Journal of Climate Services*. This manuscript explores the frequency, and intensity of past and future winter weather as it relates to WRM of provincial highways in the various maintenance areas in the province of Ontario, Canada. This manuscript presents a refinement of the WSI developed in Chapter two to conduct an investigation of the changing nature of winter weathers in Ontario, Canada over the past 30 years and into the next century. An analysis of past trends is conducted using the nonparametric Mann-Kendall Test and Sen's Slope Estimator to reveal that winters are indeed changing in Ontario, but the significance and magnitude of these trends varies spatially throughout the province. The climate change analysis portion of the paper reveals that winter severity as it relates to WRM is projected to decrease through to the end of the century. This study provides a rich description of the changing and variable nature of winter weather in Ontario, as it relates to WRM operations and outlines how a climate index can be developed with the exclusive use of publicly available data and applied to climate products at different timescales.

Chapter four, published in the *International Journal of Biometeorology* is the first paper in this dissertation to explore the tourism-climate nexus. This manuscript entitled "Development of a data-driven weather index for beach parks tourism" (Matthews *et al.* 2019) addresses Objective 3 to explore the feasibility of developing a data-driven tourism climate index for Ontario Provincial Parks. Drawing on lessons learned from Objectives 1 and 2, this paper assesses the design of the TCI (Mieczkowski, 1985), the HCI:Beach (Scott *et al.* 2019), and a then proposes a newly developed and mathematically optimized index developed specifically for the unique contextual realities of beach parks tourism in Ontario, Canada. This method combines the use of expert knowledge, insights from stated-preference studies, and mathematical optimization to develop an index that assigns daily weather scores for each day based on four weather sub-indices. Using this approach, each weather variable sub-indices is ranged to identify thresholds of sensitivity, and these thresholds are then weighted and combined in an additive manner to quantify the integrated effects of weather. These daily scores are then averaged to the monthly level and correlated to visitation data at two provincial parks in Ontario. The optimized index demonstrates a strong fit (R^2=0.734, 0.657) with observed visitation at Pinery Provincial Park and Sandbanks Provincial Park, outperforming both the TCI (R^2= 0.474, 0.018) and the HCI:Beach (R^2=0.668, 0.427). This study advances our understanding of the magnitude and seasonality of weather's effect on tourist visitation and provides tourism planners, managers, and decision-makers with enhanced information to inform decision-making.

Chapter five is the final manuscript of this dissertation and has been accepted for publications in *Current Issues in Tourism*, and is entitled "Developing Climate Services for Caribbean Tourism: A Comparative Analysis of Climate Push and Pull Influences Using Climate Indices" (Matthews *et al.* Accepted). In this study, the intra-annual effect of weather on tourism demand is empirically tested based on monthly departures (2008-2017) to three Caribbean destinations (Barbados, Antigua and Barbuda, and Saint Lucia) from Ontario, Canada. This chapter addresses Objective 4 while building on the work in Chapter four. This paper undertakes an investigation of the historical relationship between intra- and extra-regional climate and Caribbean tourist arrivals. Specifically, the investigation explores the role of climatic push factors and an exploration of identifying sensitivity thresholds for undesirable winter weather that may drive tourists from Ontario to depart to the Caribbean. This study refines the HCI:Beach through optimization to develop two new indices: the optimized in-situ index, which estimates the climatic pull-factor of the destination, and the optimized ex-situ index, which estimates the climatic push-factor from the source market. Findings reveal that the optimized ex-situ climate index explains 83 per cent (R^2=0.830) of the variability in total monthly departures from Ontario and has greater predictive accuracy than the optimized in-situ indices for Barbados (R^2=0.480), Antigua and Barbuda

(R^2=0.629)., and Saint Lucia to (R^2=0.710). Using a flexible climate index approach, this study advances our understanding of the magnitude and seasonality of climactic push and pull factors on Caribbean visitation and describes the foundation of a CS tool for destination managers and tourism marketers.

Chapter 2:

Operational Winter Severity Indices in Canada – From Concept to Practice

Matthews, L., Minokhin, I., Andrey, J., Perchanok, M. (2017a). Operational Winter Severity Indices in Canada – From Concept to Practice, *Proceedings of the Transportation Research Board, Standing Committee on Winter Maintenance* (AHD65). Paper #17-03338.

This manuscript has been modified for use in this dissertation

2.1 Overview

Public agencies are under increasing scrutiny to use their resources effectively and to demonstrate their effectiveness through performance measures. A variety of measures have been developed for winter maintenance operations, but the measures only provide meaningful information when they are normalized to the weather conditions that vary significantly from year to year and place to place. One method of normalizing is to use a measure the severity of winter weather conditions as they relate to winter maintenance activities.   The challenge is to develop a WSI that explains temporal and spatial variations in WRM activities across varied geographic areas. In this paper, a methodology for developing a province-wide and simple-to-use WSI is described using a case study approach on the provincial highway system of Ontario, Canada. This methodology combines the use of expert knowledge and mathematical optimization to develop a WSI that assigns daily weather scores for each day based on weather triggers and an adjustment factor. These daily scores are aggregated to the 14-day period and are then correlated to maintenance activities. The WSI for Ontario provincial highways has a strong fit with maintenance measured as equipment-hours. Correlation of WSI values with equipment-hours at this temporal aggregation level vary from moderate to very high for each of the 20 maintenance areas across Ontario. When spatially aggregated to the provincial level fit improves further to between 0.959 and 0.989 over seven seasons. This study demonstrates the utility of a province-wide WSI and describes how a WSI can be developed for road authorities.

2.2 Introduction

Road authorities allocate a substantial portion of road budgets to snow and ice control. It is estimated that more than three billion dollars is spent annually on WRM activities on North American roads. However, WRM practices and expenditures vary both spatially and temporally for numerous reasons (Venäläinen & Kangas 2003). Temporal variations in expenditures are partially explained by the phasing in of new technologies such as innovations in plow design, fuel efficiency, Global Positioning System tools, anti-icing chemical compositions, and communication technologies. Spatial variations in WRM practices can be partially attributed to dissimilarities in road networks (*e.g.*, road classes, network length, population density). However, the most important consideration is variations in winter weather (Venäläinen & Kangas 2003).

Road authorities are seeking tools that facilitate the planning, management, and communication of maintenance operations in the context of variable and changing winter weather. One such tool is WSIs that are used to quantify the severity of winter weather conditions for a specific location at a particular time. An index is a measure that simplifies complex information (*e.g.,* a number of different weather variables) for a particular application, typically representing this information as a single numeric value. Research on transportation-related weather indices has been ongoing for more than three decades (Thornes 1993, Venäläinen & Kangas 2003, Suggett *et al.* 2006) and WSIs have gained increasing prominence over the past decade because they can explain how different weather conditions impact maintenance costs or materials use.

A variety of WSIs have been developed in North America and Europe with the goal of helping road authorities plan for and communicate WRM programs and expenditures. The most widely cited is the WSI designed by the US Strategic Highway Research Program (SHRP) (Thornes 1993); this WSI has been used to benchmark winter maintenance activities in some jurisdictions (McCullouch *et al.* 2004). The regression-type approach used in developing the SHRP model was also used in subsequent efforts by Venäläinen (2001), Venäläinen and Kangas (2003), and Strong and Shvetsov (2006). These WSIs are based on temporally aggregate data (*e.g*., monthly snowfall) and a small number of key weather variables as model inputs: temperature, snowfall and ground frost or freezing rain. A key disadvantage of this approach is that the weather severity scores cannot be directly linked to discrete storms or weather events. Furthermore, many of these WSIs can only be used for comparing WRM activities or expenditures between seasons in a single location. While these regression-type models may work well for the specific areas for which they were developed, sometimes reporting R^2 values above 0.9, they do not perform as well when applied to jurisdictions in Canada (Andrey *et al.* 2001).

There have since been efforts to create an operational WSI for Canadian jurisdictions (Suggett *et al.* 2006, AMEC 2009, Andrey & Matthews 2012). These more recent approaches have assigned a point value to each day, and the points were then aggregated at coarser temporal resolutions and correlated to materials use. An important advantage of working at the daily level and then aggregating the scores is that these indices are more easily interpretable as they are linked to distinct daily weather conditions/events. Another important innovation is the application of an optimization algorithm to define the key weather thresholds and weightings for daily scores which are then summed to the weekly, monthly, or seasonal levels and correlated to maintenance activities or expenditures. A similar approach has been used in the development of generic WSIs (Mayes Boustead *et al.* 2015) and has shown promise for use in a WRM context (Andrey & Matthews 2012, Matthews *et al.* 2015, Andrey *et al.* 2015).

By comparing the performance of three WSIs that were developed for snow and ice control activities, Gustavsson (1996) outlined four attributes of a functional WSI. A WSI must 1) show a relationship between weather attributes and the need for WRM; 2) provide numeric values that can be easily interpreted on physical grounds; 3) use data at a time resolution that reflects the need for maintenance activities; and 4) include weighting functions that are directly related to maintenance demand. The WSI developed in this study for the province of Ontario meets all four of these conditions. The WSI has the advantage of being transferable over space and time, having a strong relationship with WRM activity at the 14-day period, using variable weights that are directly related to WRM demand, and being easy to interpret.

2.3 Research Context

In this paper, an optimization approach is used to develop, test and implement a WSI with application to snow and ice control activities on provincial highways in Ontario, Canada. The Province of Ontario, located in central Canada, extends approximately from 42°N at the United States border to 57°N and from 75°W at the provincial border with Quebec to 95°W with the provincial border of Manitoba (16). Ontario is approximately one million square km in size and has a mostly humid continental climate with cool winters and warm summers (Baldwin *et al.* 2000). Ontario has a population of 13.8 million and a provincial highway network that is 45,169 single-lane kilometres long.

The highway network is grouped into 20 Area Maintenance Contracts (AMCs), and five winter maintenance road classes, mainly by traffic level and with adjustment for surrounding population. Class 5 highways have WADT<500 and Class 1 have WADT >10,000. Classes 3 through 5 are found mostly in the northern and rural areas of the province, whereas areas around the Greater Toronto Area are exclusively Class 1. Contract areas have centerline length of 600 to 1000 km, and each area has a different mix of highway classes. Direct annual costs of WRM on provincial highways amounts to approximately $140 million annually (Office of the Auditor General Ontario 2015). As of 2014, five contractors are responsible for WRM in the 20 AMCs

Developing a WSI that works equally well across the entire provincial network is a challenge given the variations in geography throughout the province. Ontario is a large province and is characterized by variations in topography, meteorology, road network attributes, population density, and traffic volume. Dissimilarities between north and south, and east and west of the province are notable and thus the purpose of this research is to develop a WSI that performs equally well across the province. For this study, the WSI is developed at the AMC (contract) level. This is an appropriate spatial unit of analysis because of the terms of maintenance contracts, purchases of equipment, implementation of practices, and monitoring of service performance are conducted at the AMC level.

2.4 Data and Methods

2.4.1 Information Needs

As its name implies, a WSI is based entirely on weather information. There are two data sources that are used in this research—weather station networks and Road Weather Information Systems (RWIS). Weather stations operated by ECCC have many positive attributes including high levels of quality control, extensive historical records, and stations with trained personnel (usually airports), that report a range of precipitation variables such as blowing snow, freezing rain, and fog. The records are publicly available and can be downloaded online for all stations and time periods of interest. However, the relatively sparse network of stations, especially in the north, is a limitation for their utility in developing WRM indices on a province-wide basis, and this data source does not include information on road surface conditions.

RWIS networks record data that is directly relevant to WRM operations and are collected specifically for use by road authorities including variables such as road surface conditions and pavement temperature. Despite the added benefit of the transport-specific variables, the RWIS data have a lower level of quality control than ECCC stations, and few RWIS stations have historically recorded rain and snowfall data – two variables that are crucial for WRM decisions. Both data sources were used in this project to provide the benefits of each. Overall, 103 RWIS sites and 64 ECCC climate stations were selected to cover all 20 AMCs. This resulted in two to four ECCC stations and three to nine RWIS stations in each AMC area (Figure 2-1).

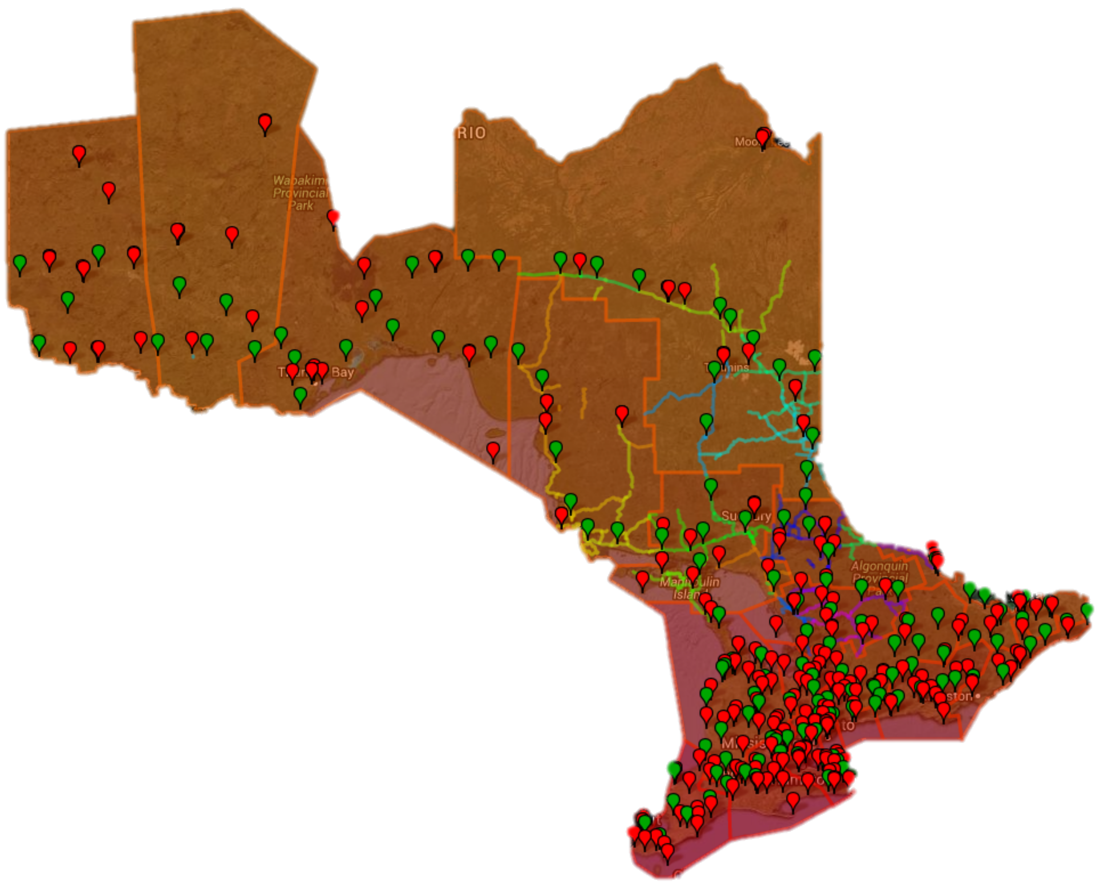


Figure 2-1. ECCC (red) weather stations and RWIS (green) station locations with AMC boundaries

While weather data are required for developing the WSI, there is also a need for maintenance data to be used as the response variable for model calibration. Winter maintenance data for provincial highways is collected through a Maintenance Management Information System (MMIS). Once the data are quality-controlled all of the MMIS data are then aggregated to the daily level for each AMC. While the intention was to include data for each season for all 20 AMCs in Ontario, only 132 AMC-seasons were included due to incomplete MMIS data. Equipment-hours of operation during the seven-year study period varied by AMC. The seasonal equipment-hours recorded range from 2,750 hours for one AMC in the 2011-2012 season to 48,801 hours in the 2013-2014 season. In the 2014-2015 season (the season that was selected as the testing set) 432,744 equipment-hours were recorded across the province, marginally higher than the average of 387,958 equipment-hours were recorded over the six seasons in the training set (2008-2009 to 2013-2014). Altogether, there were over 2.7 million hours of maintenance recorded in the MMIS system during the seven-year study period across all 20 AMCs.

2.4.2 Approach to Index Development and Testing

The WSI is designed so that each day during the study period is characterized as a single weather condition with an associated weather-severity score. The study period includes seven complete seasons of data. Six seasons were used to calibrate or train the model (2008-2009, 2009-2010, 2010-2011, 2011-2012, 2012-2013, and 2013-2014) and 2014-2015, was used to test the model. Daily weather severity scores range from zero (no weather that would reasonably trigger winter maintenance occurred) to a possible maximum of 1.5. The actual maximum value is determined though the optimization process. The daily scores are summed to provide a 14-day or seasonal score.

Six weather conditions were selected for inclusion in the WSI based on both previous work (Andrey & Matthews 2012, Andrey *et al.* 2015) and data availability:

1. Snowfall (snowfall data from ECCC)
2. RWIS pavement ice warnings (ice warnings based on RWIS data)
3. Rain with low temperatures (rainfall data from ECCC, temperature data from RWIS)
4. Blowing snow (wind speed data from RWIS, snowfall data from ECCC)
5. Series of cold days (temperature data from RWIS)
6. Warm-weather adjustment factor (temperature data from RWIS)

The first five weather conditions represent different weather triggers of maintenance activity. The sixth condition is a warm-weather adjustment factor that reduces daily weather severity scores during the times of the year when the average mean temperature remains above freezing for an extended period. The numerical order listed above reflects the hierarchy of weather triggers used in assigning daily scores. If two (or more) conditions were observed on the same day, the daily score was based on the condition that is higher on the hierarchy. For example, if measurable snowfall is observed on a given day, that day is assigned a 'snowfall' score, even if pavement ice warnings or blowing snow are also observed. Similarly, if measurable snowfall is not observed on a given day and there are no RWIS pavement ice warnings on that day, but rain with low temperatures are observed, that day would be assigned a 'rain with low temperatures' score, even if there is also blowing snow.

After the weather triggers are selected it is also necessary to decide the temporal unit of analysis for the calibration of the WSI itself. The first option is to work at a fine resolution. However, working at a fine resolution, such as the day, compromises model fit because of the maintenance lag that occurs after active winter weather, especially large snowfalls. A second possibility is to work at a coarse resolution, such as a season or month, but this approach violates Gustavsson's (1996) third criteria for a useful WSI, *i.e.* that the temporal resolution should connect with how maintenance decisions are made. The best alternative, therefore, is to work at an intermediate resolution. Thus, it was decided that 14-day reporting periods would be used. These reporting periods are predetermined by the provincial road authority and correspond directly to their reporting schedule. There are up to 18 reporting periods in a given winter season and the reporting periods are consistent across all AMCs.

Once the weather triggers are identified and the unit of analysis is determined then an optimization routine is executed in Microsoft *Excel* to simultaneously define weather trigger thresholds values as well as the daily scores. For example, for the snowfall trigger each day with measureable snowfall is identified (*i.e.*, ≥ 0.2 cm of snowfall or ≥ 0.2 mm liquid precipitation equivalent). The optimization routine allocates each day to one of the possible three categories: low accumulation, moderate accumulation, or high accumulation. In addition to determining the cutoff values, the optimization algorithm assigns a score of between 0.0 and 1.5 for each of the weather triggers. This is completed in a way that maximizes the average fit across the 20 AMCs over the six years in the training set. Days that do not meet the criteria for any of the weather triggers are assigned a daily score of zero. The benefit of using an optimization approach is that the method ensures that thresholds and weighting of the triggers are directly related to maintenance demand (Gustavsson 1996).

The daily upper limit determines that a value of 1.0 represents weather that typically triggers continual maintenance throughout the day of a weather event, and a score of 1.5 representative more severe weather that is associated with continual maintenance throughout the day with additional clean-up operations extending into the next day. The extra 0.5 points reflect the maintenance lag that can be observed on the day following a winter weather event. A score of zero indicates an absence of weather sufficient to trigger WRM.

2.4.3 Index Components and Optimization

The information produced by the WSI can be used to characterize the winter weather for any given place and time using a single number. More specifically, for each AMC in the province of Ontario, every day in the winter maintenance season is assigned a winter severity score. The optimized threshold values and WSI scores for days with weather falling within each threshold are shown in Table 2-1. This table is valid for all highways in the Province or for any Contract Area within it. The table is organized such that, for each of the six weather triggers of winter maintenance, information is provided on the how 'trigger days' are classified and also on the weather scores for each category. Further, the number of days (n) in the study period that were classified to that weather trigger are identified in the last column. For example, snowfall days are organized into three categories – low, moderate and high amounts of daily snowfall accumulation – with threshold cutoffs that are determined through optimization. The corresponding weather scores for these three types of days are 0.5, 1.0 and 1.3; again these were derived through optimization.

Table 2-1. Optimized weather thresholds and weather severity scores for winter weather factors in Ontario

Weather Component	Component Thresholds	Score	% of total WSI score*	n days
Snowfall component	Low amount of snow (0.2 to 1.9 cm)	0.5	84.9%	8,161
	Moderate amount of snow (1.91 to 4.9 cm)	1.0		
	High amount of snow (> 4.91 cm)	1.3		
Surface ice warning component	Low: < 0.2 cm daily snowfall, and between 25% and 70% of road surface ice warnings	0.3	7.5%	1,890
	High: < 0.2 cm daily snowfall, and more than 70% of road surface ice warnings	0.8		
Rainfall with low temperatures	Daily snowfall < 0.2 cm, Conditions for ice warnings not met, Daily rainfall ≥ 0.4 mm, Min temp < -0.2 °C	0.4	5.8%	1,148
Series of cold days	Daily precipitation < 0.2 mm, Conditions for ice warnings not met, Conditions for rainfall with low temperatures not met, Conditions for blowing snow not met, Max temp in previous three days < -12 °C	0.5	0.9%	137
Blowing snow	Daily precipitation < 0.2 mm, Conditions for ice warnings not met, Conditions for rainfall with low temperatures not met, Wind speeds ≥ 15 km/h, Snowfall accumulations of previous three days ≥ 5 cm	0.5	1.0%	150
Warm-weather adjustment factor	If ANY of the WSI weather triggers have been met AND The average mean temperature for the ***6-day*** period centered on the day for which the score is being assigned is >-1 °C	-45% removed from daily score	18.8%**	5,029

* Average % of total WSI score that is from that weather component before the warm-weather adjustment factor is applied.
**On average, the warm-weather adjustment factor reduces seasonal WSI scores by 18.8%.

The second last column of Table 2-1 indicates that snowfall is the most frequent weather condition that triggers winter maintenance activity on provincial highways in

Ontario. The second most frequent condition for which daily scores are assigned is ice warnings, based on recordings in the RWIS data. The ice warning variable for each AMC is calculated by recording the total number of valid surface readings per day for each of the 19 pavement surface conditions. Subsequently five ice readings (‘Black ice warning’, ‘Ice warning’, ‘Ice watch’, ‘Snow/ice warning’, and ‘Snow/ice watch’) are counted to obtain the daily total number of ice warning readings. The surface ice warning component is normalized to a percentage of all valid surface readings. In previous studies the use of surface ice warnings was defined as a binary variable where either a threshold had been triggered and that day was given a score — or there was no trigger and thus a score of zero was assigned. Given the significant influence of the surface ice warning trigger in Ontario, other options were explored. The decision was made to split this trigger into two categories, low and high.

Rainfall with low temperatures, series of cold days, and blowing snow are triggered less frequently. It should be noted that in the absence of RWIS data, these final three weather components would be triggered more frequently. A situation that can lead to potential icing occurs when rainfall is coincident with or followed by cold temperatures. Since this component of the index is about liquid precipitation, only those days when measurable rainfall of 0.2 mm is recorded, are considered. With a daily score of 0.4, the rainfall with cold temperatures component accounts for an average of 5.8 per cent of the weather severity scores in Ontario. Secondly, some have found a clear link between very cold temperatures and the need for WRM, which may relate to the polishing effect that tire friction can have on snow-covered roads in very cold temperatures. The criterion for this series of cold days component simply counts days when the maximum temperature does not exceed -12 °C at any point in the previous three days.

The final weather trigger in the index is blowing snow – an important driving hazard. Often blowing snow happens during precipitation events, and these occurrences are included in the snowfall component described earlier. Here the focus is on days where there is no measurable precipitation but where higher winds may be relocating snow from nearby fields and roadside deposits. While at times ECCC reports on hourly occurrences of blowing snow, these observations can be inconsistent. As such, we allowed for inclusion of a proxy variable for blowing snow based on two criteria: fresh snowfall accumulation above 5cm over the preceding three days, and average daily wind speed that exceeds 15 km/h. These last two weather triggers in the WSI both contribute a score of 0.5 points per day and each contribute approximately 1 per cent of the total WSI scores in Ontario.

One significant aspect of this WSI is the attention given to seasonality, based on residual analysis. In the initial iterations of the models through residual analysis, we appreciated the importance of seasonality. This analysis highlighted the extent to which warm weather mitigates the demand for WRM. Thus a warm-weather adjustment factor was included to reduce the WSI scores in periods that are relatively warm (>-1 °C over the course of six days). The warm-weather adjustment factor takes into account the fact that weather triggers that occurs in autumn or spring may not result in as much maintenance activity because of warmer temperatures. If this trigger occurs, then 45 per cent is removed from any day with a score exceeding zero. Overall, average annual WSI scores were reduced by 18.8 per cent because of the warm-weather adjustment factor.

The advantage of this approach is that while the focus is on the shoulder seasons, the warm-weather adjustment factor with reduce the scores at any time of year with warmer temperatures. For a province with substantial geographic variations in climate, the warm-weather adjustment factor is crucial for ensuring the WSI performs equally well across the whole province.

After the weather trigger thresholds and weights are identified, the WSI can then be calculated at different spatial scales (AMC, regions, or province-wide) and different levels of temporal aggregation (reporting-period level, monthly, seasonal). This enables maintenance personnel or managers to compare the severity of the winter across both space and time. For each AMC, daily scores are calculated for each day during the seven-year study period. The daily scores are then aggregated to the 14-day and seasonal level (simple addition), with seasonal values ranging from 13.4 for an AMC in the 2011-2012 season to 99 in another AMC for the 2013-2014 season (Table 2-2).

2.5 Results

Seasonal scores for all contract areas and the Province as a whole are shown in Table 2-2 and Figure 2-2 and the overall model fit is illustrated in Table 2-3. The scores and the model fit illustrate geographic and temporal trends in winter severity that can be used to understand and communicate variations in highway maintenance performance. Of the seven years for which seasonal weather severity scores could be calculated, the highest values occurred for the 2013-2014 season with an average provincial WSI score of 64.9. The least severe season was 2011-2012, with an average provincial WSI score of

33.6. Overall the scores displayed a near-normal distribution between a score of 10 and 100 at the AMC-season level (Figure 2-2).

Table 2-2. Seasonal winter severity scores 2008-2009 to 2014-2015

AMC	2008-09	2009-10	2010-11	2011-12	2012-13	2013-14	2014-15	Mean	Stdev
A	49.1	26.0	44.2	30.9	40.4	46.6	44.8	40.3	8.0
B	39.7	29.6	45.8	19.6	35.1	58.4	46.1	39.2	11.7
C	69.4	53.8	65.8	65.4	71.1	83.0	72.5	68.7	8.2
D	43.5	23.5	41.3	19.6	28.0	35.8	30.4	31.7	8.3
E	32.7	18.3	29.7	13.4	19.4	35.2	28.1	25.3	7.6
F	70.8	42.8	65.1	45.7	65.2	80.5	74.4	63.5	13.2
G	58.6	40.0	58.4	39.1	57.1	77.8	67.1	56.9	12.8
H	45.0	30.5	41.0	21.6	31.0	54.4	44.4	38.3	10.3
I	38.1	18.1	44.2	17.9	28.5	51.0	37.5	33.6	11.7
J	62.2	34.8	64.8	24.4	37.7	60.0	52.0	48.0	14.5
K	33.6	19.9	33.4	16.8	24.2	43.2	37.2	29.8	8.9
L	70.4	41.2	51.4	50.6	63.1	76.9	63.2	59.5	11.5
M	46.0	34.2	47.4	35.6	44.9	56.0	52.8	45.3	7.5
N	70.4	47.2	68.8	40.2	57.4	88.2	64.2	62.3	14.7
O	78.0	49.9	49.1	46.3	77.6	99.0	89.1	69.9	19.7
P	62.3	36.1	58.4	32.5	57.4	69.1	52.6	52.6	12.5
Q	69.0	41.1	55.0	43.4	61.3	81.1	60.9	58.8	13.0
R	59.7	40.7	56.6	49.5	64.6	81.8	71.4	60.6	12.7
S	61.2	39.5	57.3	45.3	53.2	79.8	67.5	57.7	12.6
T	40.1	21.4	35.6	14.3	24.9	39.6	31.0	29.6	9.0
Provincial	55.0	34.4	50.7	33.6	47.1	64.9	54.4	48.6	10.5

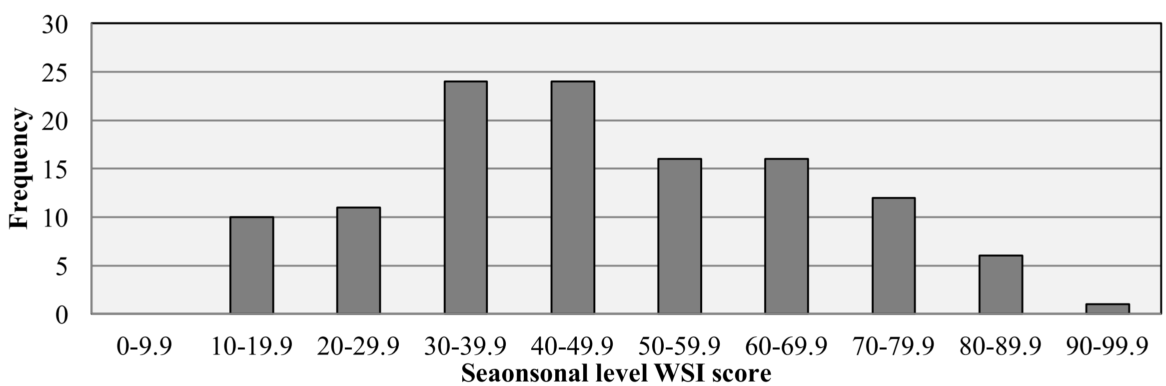


Figure 2-2. Frequency distribution of WSI scores at the seasonal level (n=140, 7 seasons x 20 AMCs)

Table 2-2 illustrates how the average annual WSI scores vary across province. Northern areas of the province have the harshest winters and the southern, especially south-eastern, areas of the province experience the least severe winters (Figure 2-3). Furthermore, there is value in recognizing that winter weather is more variable year-to-year in some AMCs than in others. On average, there is a 10.5-point standard deviation in seasonal weather severity scores. At the AMC level the standard deviations range from 7.5 to 19.7. The AMC with the highest variation in winter weather experienced their most mild winter in 2010-2011 with a score of 49.1, then in 2013-2014 this AMC experienced a very harsh winter with a score of 99.0. This 50-point spread in one AMC is particularly important to recognize when undertaking planning for equipment, materials, and labour requirements.

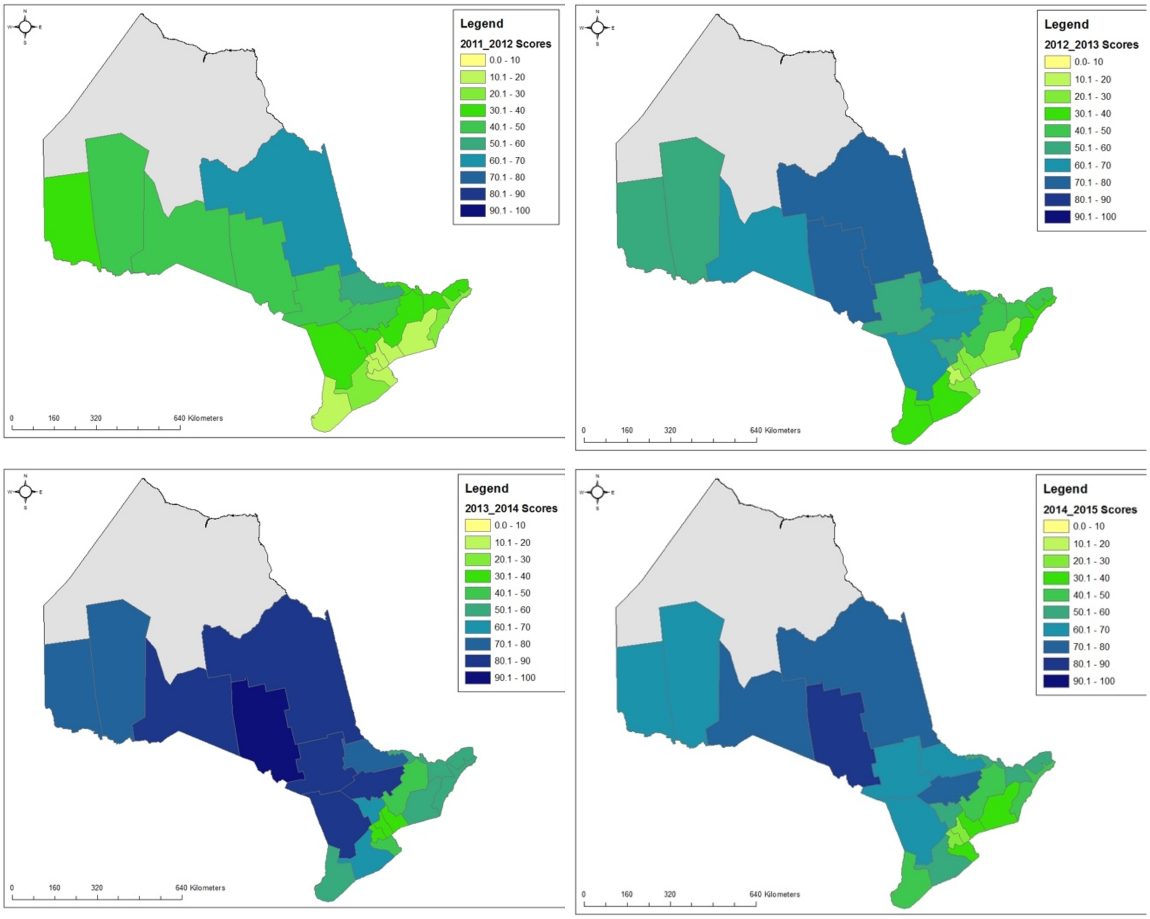


Figure 2-3. Maps of WSI scores for the 2011-2012 to 2014-2015 winter season for 20 Ontario AMCs

As an overall measure of fit, a correlation analysis is conducted between the 14-day level weather severity scores and the 14-day level maintenance activity. As indicated by the R^2 values, there is good fit across the AMCs. This indicates that the index explains the majority of the temporal variability in WRM equipment-hours. Overall, as the WSI increases, equipment-hours increases proportionately. Similarly, as the WSI decreases, equipment-hours also decrease. The coefficient of determination (R^2) between reporting-period WSI scores and reporting-period equipment-hours ranges from 0.588 to 0.985 (Table 2-3). Furthermore, confidence intervals are reasonably narrow for the majority of

AMCs. While the R^2 values at the AMC level vary, the majority of seasons have an R^2 above 0.800. On average, for any given season, 15 of the AMCs have a fit above 0.800 and five of the AMCs are below this level. Overall spatial aggregation increases fit. The R^2 for 14-day, provincial-level data (total provincial equipment-hours vs. average provincial WSI scores at the reporting-period level) is between 0.959 (2012-2013) and 0.989 (2009-2010) season. These values indicate that there is nearly perfect fit at the provincial level. Overall the R^2 values are very high thus indicating the WSI is an accurate tool for explaining variations in equipment-hours at both the AMC and provincial levels.

Table 2-3. Seasonal R^2 values between reporting-period level WSI scores and reporting-period level equipment-hours (2008-2009 to 2014-2015)

AMC	2008-09	2009-10	2010-11	2011-12	2012-13	2013-14	2014-15
A	0.933	0.932	0.888	0.886	-	0.904	0.932
B	0.959	0.864	0.931	0.774	0.943	0.946	0.942
C	0.888	0.949	0.705	0.885	0.874	0.887	0.911
D	0.849	0.766	0.886	0.588	0.818	0.695	0.928
E	0.927	0.639	0.912	0.753	0.745	0.932	0.843
F	0.966	0.985	0.835	0.983	0.873	0.909	0.975
G	0.856	0.747	0.922	0.930	0.721	0.904	0.909
H	0.950	0.934	0.948	0.808	0.962	-	0.968
I	0.960	0.917	0.938	0.880	0.689	0.941	0.936
J	0.926	0.636	0.860	0.784	0.931	0.932	0.931
K	0.940	0.965	0.907	0.893	0.676	-	0.776
L	0.960	0.925	0.845	0.952	0.938	0.896	0.891
M	0.910	0.958	0.972	0.911	-	-	-
N	0.892	0.917	0.942	0.905	-	-	0.964
O	0.941	0.939	0.712	0.788	0.831	0.934	0.937
P	0.838	0.928	0.944	0.831	0.798	0.968	0.964
Q	0.957	0.874	0.921	0.878	0.783	0.948	0.952
R	0.798	0.708	0.917	0.874	0.616	0.858	0.853
S	0.737	0.725	0.976	0.647	0.736	0.940	0.857
T	0.972	0.684	0.960	0.835	0.897	0.928	0.777
Provincial	**0.985**	**0.989**	**0.982**	**0.978**	**0.959**	**0.975**	**0.983**

- Data unavailable

Another way to ensure that the WSI is capturing winter maintenance activities is to compare the number of winter maintenance equipment-hours that were recorded during days with WSI scores compared to maintenance hours that occurred on days without a WSI score. Of the total winter maintenance equipment-hours that were recorded during the study period, 85.0 per cent (2.35 million equipment-hours) occurred on days that had a weather score triggered by one of the above conditions, and a further 8.5 per cent (234,642 equipment-hours) occurred on days that did not have a weather score but where the previous day did (*e.g.*, cleanup after snowfall). Most of the remaining hours of maintenance involved localized or short-duration winter maintenance.

It is evident that this WSI is an effective tool for explaining variations in equipment-hours due to weather and is therefore an effective communication tool. There are three indications that this WSI will be a useful tool for explaining WRM activities due to weather in future seasons. First, the WSI has a broad spatial transferability across a province that includes a variety of climates. As measured by fit (R^2), the fit is very similar in all areas of the province suggesting there is limited spatial bias. Secondly, the WSI works well in the boundary conditions of the harshest and mildest seasons. The largest residuals tend not to be found in these mild and harsh time periods. Lastly, the WSI was calibrated on the training set of data and the 2014-2015 season was reserved as the independent test period. An analysis of residuals was conducted to confirm that the WSI works equally well in the training and test periods. The Fligner-Killeen Test of Homogeneity of Variances is used to explore the assumption that the variances in the training and test set are equal. The results indicate that the variances of the residuals in the training and test sets are the same (Figure 2-4).

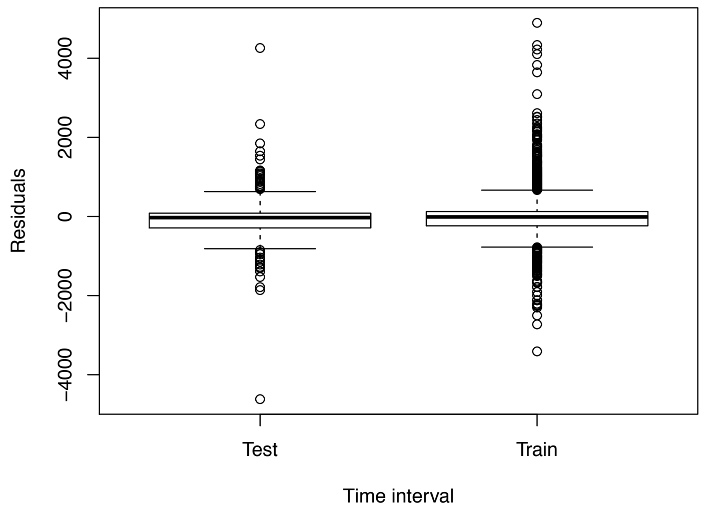


Figure 2-4. Boxplot of residuals for the training set (2008-2009 to 2013-2014 seasons) and test set (2014-2015 season)

It is important to note that, while the WSI is calculated in the same way for all parts of the province, the number of equipment-hours varies by AMC, primarily because of differences in the road network (length of network, mix of road classes). Jurisdictions with larger networks, typically in the north, as well as time periods where the weather is more severe, have a greater variability of equipment-hours. Differences between AMCs can be illustrated by considering the way in which maintenance activity (equipment-hours) increases when the two-week weather severity score increases from 2 (for example, during the shoulder season) to 8 (more typical of moderately severe winter). For example, in a southern AMC, this difference in weather would result in an increase in maintenance activity from less than 400 to just over 1500 equipment-hours. In a northern AMC, by comparison, one would see much larger increases in maintenance activity—from approximately 1100 hours to more than 4700.

To further understand whether these differences in network attributes could impact WSI performance, a multiple linear regression was conducted. The multiple linear regression was developed where the 14-day level residuals are the response variable and attributes that could possibly impact WSI performance are the explanatory variables (n= 2,418 reporting periods). The following variables were tested for their significance: road network length (km), per cent of the road network that is a 1st class highway (%), location (north or south), month of year, WSI score (no score, low, medium, high). The results of the multiple linear regression indicate that these explanatory variables are all insignificant at 5% significance level (p=0.079, F-statistic= 1.723, R^2= 0.007), suggesting that there is no spatial bias in the applicability of the WSI across Ontario.

2.6 Conclusions

The WSI that has been developed for Ontario highways meets a number of attributes that are necessary for an operational index. First, the WSI for Ontario highway maintenance is simple to calculate and understand since it is based on a small number of weather triggers, all of which are easily understood. Further, when the same index is used across the province, comparisons of winter weather severity can be made across regions and over time. Second, the WSI for Ontario highway maintenance draws on available data that can be updated regularly, as they originate with the ECCC observation network (especially important for acquiring daily snowfall and rain amounts) and Ontario's RWIS network (critically important for surface ice warnings). Third, the WSI for Ontario highway maintenance has strong fit with maintenance activity that occurred, when measured as equipment-hours. The majority of seasons have a fit above 0.800. At the provincial level, the WSI works well with an R^2=0.982 in the most recent 2014-2015 season. Lastly, the WSI for Ontario Winter Highway Maintenance performs well across different climatic regions and maintenance regimes.

The WSI that has been developed for Ontario Winter Highway Maintenance has the potential to be used in several different ways to support highway operations. A WSI can enable informed decision-making by clearly documenting the relationship between weather and WRM activities that can be applied in at least three ways to aid in agency accountability to the public. First, the WSI can be used as a tracking mechanism to monitor the severity of winter weather. As such, the WSI can be used to describe, quantify, review and compare winter weather severity from any time period to another and from one region to another. Second, it could be useful as a season-to-season risk management tool. Lastly, this WSI enables road authorities to clearly communicate winter weather severity to the public and other stakeholders in relation to observed levels of service.

Map acknowledgements:
Figure 2-1 was produced by Derrick Hambly
Figure 2-3 was produced my Amel Badri

Chapter 3:

The Development of Climate Services for Winter Transportation Planning

Matthews, L., Andrey, J., Fletcher, C., Oozeer, Y. (Submitted). The development of climate services for winter transportation planning. *Climate Services.* Manuscript ID: CLISER-D-20-00027.

This manuscript has been modified for use in this dissertation

3.1 Overview

Snow and ice control programs are critical for the efficiency and safety of transportation systems in all winter climates. However, climate variability and change present particular challenges for the tactical and strategic planning of snow and ice control. Accordingly, tools that help road authorities and snow and ice control practitioners plan for, assess, and communicate the relationship between climate and winter maintenance activities are increasingly requested. Furthermore, there is increasing evidence that the development of these CS tools is an iterative, evolving, and long-term process between the producers and users of this climate information. This co-production of climate information is shown to increase the usability and application of climate science in a variety of sectors including transportation. This paper presents a case study describing the co-production of a climate translation service for a Canadian road authority grappling with the impacts of climate variability and change on WRM operations. Climatic indices that can rate the severity of winter conditions in a given time period at a specific location, are one subset of CS translation tools. The purpose of this study is to: 1) refine an existing WSI to better understand how winter weather translates into inter-annual variations in WRM activities using publicly available data; 2) apply the index to historical weather observations to assess the magnitude and significance of historical winter weather trends, and 3) apply the index to modelled climate data to project the impacts of climate change for three future time periods on WRM operations in Ontario, Canada. Results indicate that the WSI for Ontario highways has strong fit with maintenance activity that occurred, when measured as equipment-hours. An analysis of trends reveals that winters are indeed changing in Ontario, but the magnitude and significance of these trends varies spatially throughout the province. Furthermore, the climate change analysis reveals that winters will continue to experience a reduction in overall weather severity.

3.2 Introduction

Global transportation systems are affected by weather in a variety of ways. It is because of the significant and varied impacts of weather and climate on transportation that this sector was the world's first user of weather information for decision-making (Koetse & Rietveld 2009, Markolf *et al.* 2019). The marine shipping sector is touted as the first user of wind records for optimizing sailing routes (Lewis, 1996, Anderson *et al.* 2015), and modern marine operations use weather/ information to inform evasive maneuvers such as avoiding sea ice and hurricanes (Mannarini *et al.* 2013, Pietrzykowski *et al.* 2017, Lee *et al.* 2018) as well as the siting and construction of port facilities (Hallegatte 2009). The rail system uses weather observations to manage vulnerability to extreme heat and extreme cold (Doll *et al.* 2014), flooding (Changnon 2013, Koetse &

Rietveld 2009), and extreme weather events such as hurricanes and storm surges (Markolf *et al.* 2019). Aviation is also sensitive to a suite of climatic conditions including fog, storms, extreme heat, extreme cold, and high-winds (Krozel *et al.* 2008), and it is estimated that more than 70% of air travel delays are due to weather (Kulesa 2003). Lastly, weather impacts road transportation in a multitude of ways (Markolf *et al.* 2019)—mobility patterns (Shah *et al.* 2003, Mahmassani *et al.* 2009, Maze *et al.* 2006, Strong *et al.* 2010), road safety (Andrey *et al.* 2003, Andrey 2010, Hambly *et al.* 2013, Dey *et al.* 2014), active transportation (Saneinejad *et al.* 2012, Flynn *et al.* 2012), transit ridership (Guo *et al.* 2007, Zhou *et al.* 2017), and mode choice (Böcker *et al.* 2013, Böcker *et al.* 2016).

In recent years, road transportation has been arguably the most extensive developer and user of weather information, especially in the transportation sector's development and use of Maintenance Decision Support Systems (MDSS). Short-term weather products from federal weather service providers issue warnings and alerts to inform the public and road authorities about impending snowfall or ice storms (Kilpeläinen & Summala 2007, Pilli-Sihvola *et al.* 2012). Sub-daily to daily forecasts inform tactical decisions such as when to implement pre-wetting or plowing activities (Strong & Shi 2008, Petty & Mahoney 2008, Ye *et al.* 2009) and one particularly widespread MDSS was developed by the United States Federal Highways Administration (USFHA). The USFHA Maintenance Decision Support System (USFHA-MDSS) for WRM is an online tool that predicts and visualizes forecasted road weather conditions and presents multiple potential maintenance treatment options on a location-specific level. The USFHA-MDSS, for example, further takes into account resource availability (*e.g.*, equipment, staffing, materials) in the suggested maintenance treatment options (Petty & Mahoney 2008, Ye *et al.* 2009). In the longer term, weekly to seasonal forecasts can inform road authorities of when there is a need to stockpile additional salt and aggregate, or the timing of paving operations (Strong & Shi 2008, Ye *et al.* 2009). At the decadal timescale, climate projections inform long-term decisions in regards to infrastructure investments such as the design of bridges, pavement engineering standards, and culvert capacity upgrades in response to projections of more frequent and intense rainfalls (Mills *et al.* 2007, Fletcher *et al.* 2016, Markolf 2019).

Shorter term decisions in the transportation sector have increasingly relied on RWIS (Usman *et al.* 2010, Ye *et al.* 2014) and other decision support tools such as the USFHA-MDSS (Petty & Mahoney 2008, Ye *et al.* 2009, Macharis & Bernardini 2015). However, the use of seasonal to inter-annual climate projections for informing strategic planning related to staffing, equipment needs, public engagement, or the establishment of decades-long road maintenance contracts is in its infancy. In recent years, an emerging body of literature has examined how climatic variability and change will alter transportation risks and opportunities (Chapman 2007, Koetse & Rietveld 2009, Andersson & Chapman 2011, Markolf 2019). Much of this work focuses on flooding, sea level rise, and permafrost depletion in northern regions. One area that has received relatively limited attention—both in the climate change and CS fields—is the impact of climate variability and change on WRM (Warren *et al.* 2004, Mills *et al.* 2007, Millerd 2011, Andersson & Chapman 2011). This is despite the serious impacts of winter weather on travel risks, mobility delays, and government budgets (Norrman *et al.* 2000, Knapp *et al.* 2000, Maze *et al.* 2006, Strong *et al.* 2010, Mills *et al.* 2019).

Road authorities are responsible for reducing winter weather-related driving risk through a variety of interventions such as the use of electronic signage to warn of hazardous weather conditions, closing roads that are too dangerous, and providing up real-time intelligence on road conditions (Andersson & Chapman 2011). The most prevalent response by road authorities to winter weather is WRM. WRM involves clearing the snow and ice from roads (*e.g.*, plowing) and using materials to improve pavement friction (*e.g.*, salt, de-icers, sand, aggregate). However, these WRM activities are costly for road authorities globally and, as such, developing CS tools that can better enable WRM planning, especially for strategic decisions, could result in significant fiscal savings.

Road authorities allocate substantial resources to snow and ice control; it is estimated that more than USD$3.3 billion is spent annually on WRM activities on North American roads (Venäläinen & Kangas 2003, SIMA 2016). More striking is the estimated USD$23 billion spent for snow and ice control in the private sector with retail and industrial markets spending approximately USD$11.8 billion while hospitals, airports, and educational institutions spend approximately USD$3.3 billion (SIMA 2016). However, snow and ice control activities vary considerably over space and time – making the budgeting, management, planning, and monitoring of WRM activities a complex and challenging endeavor (Venäläinen & Kangas, 2003). Temporal variations are partially explained by the phasing in of new technologies such as innovations in plow design, Global Positioning System tools, anti-icing chemical compositions, and communication technologies. Spatial variations can be partially attributed to dissimilarities in road networks (*e.g.,* road classes, network length, population density) and the proportion of surfaces that require maintenance. However, the most important considerations over time and space are variations in winter weather (Venäläinen & Kangas 2003, Kangas *et al.* 2015). It is precisely this uncontrollable variability in winter weather that creates strategic planning challenges for road authorities globally and predicates the need for further CS development in the transportation sector.

Strategic planning for WRM operations is challenging in part due to this temporal variability, but long-term changes in climate are adding further complexity and uncertainty to the planning process (Palin *et al.* 2016). While it has been established that there is a need to study the impacts of climate variability and change on transportation infrastructure and services, concrete adaptations in this sector are only beginning to gain traction (Koetse & Rietveld 2009, Picketts *et al.* 2015, Matthews 2017c, Markolf *et al.* 2019). The use of weather and climate information for tactical and strategic purposes, such as planning for the staffing, equipment needs, or public engagement initiatives remains challenging. Part of this challenge stems from the poor correlation between individual climatic stimuli (*e.g.,* temperature or snowfall amount) and behavioural responses (*e.g.*, hours worked, money spent, salt used, potholes fixed, collisions avoided). The larger issue, however, is that winter maintenance responses are intended to achieve specified standards, and these standards reflect conditions associated with multiple weather variables in particular ranges or beyond particular thresholds.

The challenge of identifying societal thresholds that reflect organizational sensitivity to climatic stimuli has been a longstanding issue. In the 1993 edition of *Environment as Hazard*, Burton *et al.* (1993) emphasize the impact of weather thresholds for understanding the non-linearity, and the context-dependency of society's sensitivity to snowfall. Burton *et al.* (1993) articulate that there are critical thresholds for snowfall accumulation after which damages or impacts increase more quickly. Further complicating the situation is that, in the context of WRM, the response to a specific condition varies geographically for social, cultural, economic, or political reasons; and there is sensitivity to a range of conditions. While attempts have been made to integrate the different climatic variables into models and indices (Rissel & Scott 1985, Boselly *et al*. 1993, Cornford & Thornes, 1996, Venäläinen 2001, Carmichael *et al.* 2004, Suggett *et al.* 2006), there is no universal physical unit of 'winter weather'.

Over the past four decades, road authorities and industry practitioners have been seeking tools that facilitate the planning, management, and communication of maintenance operations. One such set of tools is weather indices that are used to quantify the severity of conditions for a specific location at any particular time (Carmichael *et al.* 2004, Nixon & Qui 2005, Matthews *et al.* 2017a,b,c, Walker 2019). An index is a measure that simplifies complex information (*e.g*., a number of different weather variables) for a particular application; typically representing this information as a single numeric value. Overall, the purpose of an index is to provide decision-makers with easily usable, interpretable, and credible information in relation to a given objective (Malkina-Pykh 2000). Weather and climate indices have been proposed as tools for CS in other sectors such as tourism (Damm *et al.* 2019), but to date transportation-related climatic indices have not been integrated into the CS landscape despite their prevalence and value in practice by numerous road authorities internationally (*e.g.*, McCullouch *et al.* 2004, Carmichael *et al*. 2004, Strong & Shvetsov 2006, Matthews *et al.* 2017c).

Tools such as indices can enable road authorities and industry practitioners to plan, communicate, manage, and assess WRM operations and expenditures. WSIs can be used to explore how specific weather conditions translate into higher- or lower-than-average maintenance costs on a variety of temporal scales (Nixon & Qui 2005), and they can be used to anticipate the probable resource requirements based on forecast conditions or projected longer term changes (Strong & Shvetsov 2006). Strong and Shvetsov (2006) recommend that indices should be used as a public communication tool and disseminated through traditional media to warn drivers of the severity of the weather. Others such as Carmichael *et al.* (2004) promote the use of WSIs not only for public communication, but also for a variety of strategic decision-making contexts. Accordingly, integrating WSIs into the CS toolbox for the transportation sector is a promising endeavor to further expand their use for both weather risk management and climate change adaptation.

While more than 20 WRM WSIs have been developed since the 1980s, WSIs have not been widely published or cited in the CS literature to date despite their utility as a weather and climate translation tool. A fundamental role of climate translation services is to effectively contextualize weather and climate information (Cash *et al.* 2006). Translation service providers create tailor-made information to bridge the interface between the scientific community and the users. The challenge for these boundary organizations is to develop a system that enables the creation of salient weather and climate information that can be understood and used by decision makers (Kirchhoff *et al.* 2013). In the context of WRM, WSIs have been used as a translation weather service for over four decades, albeit in a limited extent in practice, and this is only the second study to extend beyond the historical assessment, and explore the impacts of the climate change through this WSI tool.

The most widely cited WSI is the SHRP (Strategic Highway Research Program) index (Boselly *et al*. 1993) which was proposed by the US Strategic Highway Research Program. The SHRP index was subsequently adapted in a number of other studies (see Andrey *et al.* 2001, Decker *et al.* 2001) and most include some combination of common winter weather variables (*e.g.,* temperatures, snowfalls, freeze-thaw cycles, and freezing rain). Despite the prevalence of WSI development and a fair degree of agreement on variable usage within the WSIs, a core challenge remains in developing an index where the variable thresholds and weighting functions are directly related to maintenance demand. While most extant indices use multiple linear regression to assign weights, McCullouch *et al.* (2004) conducted interviews and Nixon & Qui (2005) conducted surveys with maintenance crews and management to identify which weather events that had the largest impact on WMR activities. However, the determination of variable thresholds is not explicitly articulated in these studies. The categorization of variables based on thresholds (*e.g.,* temperature ranges, specific snowfall amounts) is often highly subjective (Ebert & Welsch, 2004), and none of the aforementioned studies, with the exception of Matthews *et al.* (2017b,c), have clearly articulated how the variable ranges are determined.

Understanding climatic thresholds is critically important for the development of CS and impact-based forecasting more broadly. The specific climatic thresholds that induce a transportation authorities' response to weather vary over space and time because of the importance of context. As such, the development of a method that can identify societal thresholds to climatic stimuli is an important scholarly and practical endeavor. One novel approach by Matthews *et al.* (2017b) uses an optimization algorithm to simultaneously determine both variable weights and the thresholds for these weather variables. However, a disadvantage of the approach used by Matthews *et al.* (2017b) is their reliance on RWIS station data that can be cost prohibitive. As outlined by Hewitt *et al.* (2012), CS development should rely on publicly and freely available data. Furthermore, the management and processing of the RWIS data is cumbersome, and smaller road authorities or private snow and ice control firms may not have either access to the installations, or the means to store, process, and analyze the RWIS data. More acutely, the lack of RWIS in historical meteorological observations prohibits the ability to explore long-term trends and the development of CS. These RWIS data are not available in the historical weather record, nor are these types of measurements incorporated into climate models. Relying on weather variables that are available in both historical records and in climate models is an important consideration for long term planning of CS development in the transportation sector.

In this research, a reassessment of the index by Matthews *et al.* (2017a) is conducted to explore whether similar levels of fit can be achieved with exclusive reliance on publicly available data. This paper then provides the first comprehensive analysis of past variability and trends of winter weather that affect snow and ice control, and the study further extends the analysis to future projections of climate change for Ontario, Canada. Previous explorations of winter weather in Ontario have focused on the severity of the weather, and to date, there has been little examination of the historical trends and future projections of WRM-related weather events.

3.3 Study Objectives

This article serves not only to outline the process of developing a WSI, but also to document the development of CS for WRM with both a historical and future climate perspective. The investigation began in 2016, when the research team received a request from the MTO to develop a WSI for Ontario Winter Highways Maintenance (see Matthews *et al.* 2017a). This initial WSI development for Ontario was favourably received and was integrated into the provincial RWIS system. At present, daily WSI scores are calculated and disseminated as part of the short-term RWIS forecasts for WRM managers, and these WSI scores are then recorded as part of the historical RWIS record, and also communicated on the provincial website for public announcement. Given the success of this initial project, the research was then extended to answer two more research questions. After discussions and feedback with road maintenance personnel on the findings from the 2016 project, the Ontario Ministry of Transportation (MTO) was interested in exploring whether a substitution in variables (*i.e.,* snowfall intensities [cm/hr] instead of daily snowfall accumulation [cm]) would improve the WSI. This variable substitution did not result in an improvement in model fit. However, a second extension of the project was then granted to explore the long-term trends and future projections of climate change – results of which are presented in this paper. This long-term relationship building with the climate information users underscores the importance of an iterative, evolving, and long-term process between researchers and users of climate information.

Overall, this paper aims to increase the capability of road authorities to perform climate risk management by estimating the extent to which winter maintenance needs have changed since the establishment of maintenance procedures and protocols and how they are projected to change into the future. This is achieved through three main objectives. The first objective is to recreate the WSI developed by Matthews *et al.* (2017a) using only publicly available weather observations in order to assess the robustness of the WSI should it be used in situations where proprietary data are not available. The second objective is to document trends in historical winter weather from the 1980-81 season to the 2014-15 season in order to understand the changing nature of winters in the study area. The third objective is to compute the WSI for the modelled climate data to assess the impact of climate change for each of the study area's 20 AMCs to inform long-term thinking of maintenance needs for three future time periods. Furthermore, this paper provides a transferable framework for the development of a context-specific WSI that can be applied to weather and climate products at multiple timescales and highlights the important role of co-production in the development of CS in the transportation sector.

3.4 Study Area

The Province of Ontario, located in central Canada and is approximately one million square kilometers in size. There are approximately 332,000 two-lane kilometers of roadways (Transport Canada, 2015) in Ontario and the MTO is responsible for maintaining 43,000 single-lane kilometers of highways. These highways under the jurisdiction of the provincial government are mainly high-speed highways (90 – 100 km/hr) and, as such, timely and effective maintenance is critical for maintaining good driving conditions, even during periods of snowfall and other winter weather.

The degree to which winter driving conditions in Ontario are changing is a matter of practical planning relevance. There is increasing concern that inter-seasonal variability and change will require re-thinking and adjustments in approaches to WRM, particularly as they relate to equipment complement requirements and the pricing of long-term maintenance contracts. In Ontario, there has been a trend of increasing winter precipitation since the 1960s (Vincent *et al.* 2015) and Regional Climate Models (RCMs) indicate that this trend will continue in the future (Wang *et al*. 2015). Similarly, winter temperatures in Ontario have been increasing and are projected to continue increasing in the future (Wang *et al*. 2015).

3.4.1 Information Needs

ECCC provides public access to historical weather records for numerous observation sites in Ontario. In the current study, suitable stations for each of the AMCs were selected. The AMC is the primary spatial unit of analysis as this is the spatial unit that is most relevant to WRM operations on Ontario provincial highways. For objectives 1 and 2, daily level rainfall, snowfall, precipitation, and maximum and minimum temperature data were obtained from the ECCC stations for the period between January 1, 1980 and December 31, 2016. The 1993 calendar year is not included due to data quality issues. As such, the 1992/1993 season and the 1993/1994 season are not included in this assessment.

While weather data are required for developing the WSI, there is also a need for maintenance data to be used as the response variable in refining a data-driven weather index that reflect the MTO's particular sensitivity to weather conditions. Winter maintenance data for provincial highways is collected through a MMIS system. The MMIS data were processed, quality controlled, and aggregated to the daily level for each AMC. Equipment-hours of operation were available for seven years from the 2008-09 season to the 2014-15 season. The seasonal equipment-hours recorded range from 2,750 hours for one AMC in the 2011-2012 season to 48,801 hours for another AMC in the 2013-2014 season. Altogether, there were over 2.7 million hours of maintenance recorded in the MMIS system during the seven-year model calibration period across all 20 AMCs.

For objective 3, the climate change data were obtained from the North American - Coordinated Regional Climate Downscaling Experiment (NA-CORDEX) data archive (Mearns *et al*. 2017). The NA-CORDEX project involves a series of RCMs run over a North American domain driven by historical and future boundary conditions. The NA-CORDEX simulations span the period 1950 – 2100, and simulations are available at finer (0.22°/25km) and coarser (0.44°/50km) spatial resolutions. The use of finer models is particularly important for the current study, as Ontario is a large and geographically diverse area. Two different types of simulation are available in the NA-CORDEX collection. The first involves multiple RCMs driven by boundary conditions from the ERA-Interim historical (observation-based) reanalysis system, which are primarily used to quantify biases in the RCMs. The second type of simulation, which are used for this project, involves multiple RCMs driven by historical (1950-2005) and future scenario (2006-2100) output from multiple Global Climate Models (GCMs) that participated in phase five of the Coupled Model Intercomparison Project. The four RCM-GCM combinations used in this project are shown in Table 3-1, and this selection reflects the set of models for which all required output variables were available at the finer spatial resolution (25 km). All four of these simulations use Representative Concentration Pathway (RCP) 8.5.

Table 3-1. Summary of RCM-GCM model combination selected from NA-CORDEX experiments

RCM	Driving GCM
Canadian RCM v4 (CanRCM4)	Canadian Earth System Model v2 (CanESM2)
Canadian RCM v5 (CRCM5-UQAM)	Canadian Earth System Model v2 (CanESM2)
Canadian RCM v5 (CRCM5-UQAM)	Max Planck Institute Earth System Model – Low Resolution (MPI-ESM-LR)
Canadian RCM v5 (CRCM5-UQAM)	Max Planck Institute Earth System Model – Medium-Resolution (MPI-ESM-MR)

For the historical analyses and assessment of trends, the Durham AMC uses the same data as the Toronto and Halton AMCs due to the lack of suitable ECCC data in these nearby AMCs. Similarly, the Sudbury and North Bay AMCs also share a weather dataset. However, because the climate change models are gridded products, a climate change assessment was conducted for each of the AMCs separately based on the AMC boundary GIS files provided by the MTO. As such, during the historical analyses section, the results for Toronto, Halton, and Durham are identical; similarly, the results for Sudbury and North Bay are also identical. However, in the climate change assessment the results for these AMCs diverge because of the fine spatial resolution provided by the NA-CORDEX climate products. For the climate change assessment, analysis was conducted in R (R Core Team 2019) with figures produced using the package ggplot2 (Wickham 2016).

3.5 Objective 1: WSI Development

The WSI presented in this paper uses mathematical optimization to determine variable thresholds and weights, based on the previous methods outlined by Matthews *et* *al.* (2017 a,b,c). The recent publication by Matthews *et al.* (2017a) in particular demonstrates the potential in using mathematical optimization to create context-specific and robust WSIs for WRM practitioners. Matthews *et al.* (2017a) developed a WSI to explain spatio-temporal variations in WRM activity (as measured by equipment hours) for 20 maintenance jurisdictions in Ontario over the course of seven years. The index was composed of eight weather triggers and one warm-weather adjustment factor (for a total of fifteen different 'weather days'). This index was calculated daily but reported in 14-day periods, to coincide with the reporting periods used by the MTO, and at the seasonal level. The resulting index values were shown to have a strong fit with maintenance activity, measured as equipment-hours. However, the limitation of this approach for exploring long-term trends and future projections in winter weather severity is its reliance on RWIS data, which are not available historically or in climate models. Furthermore, RWIS data are a paid product/service, and as underscored by the GFCS, CS should be based on freely accessible weather and climate data to facilitate CS use (Hewitt *et al.* 2012). Accordingly, in this current study, the index is recalibrated based exclusively on the publicly available ECCC data.

The removal of the RWIS data led to the exclusion of two weather triggers, the surface ice warning and blowing snow triggers. The selected WSI conditions are outlined in Table 3-2. The optimization algorithm was run for all seven seasons to optimize the fit (R^2) between the index and equipment hours. The thresholds and component scores did not change despite the removal of the two previous triggers and the two additional seasons of data relative to the work in Matthews *et al.* (2017a). The previous work in Ontario used training and testing datasets and two seasons of data were omitted from the model training datasets. Given that the purpose of this study is to explore the historical observation period as well as future projections into 2099, it is reasonable to train the index on the entirety of the available response/ impact dataset (equipment-hours). Daily weather severity scores range from zero (none of the weather triggers occurred) to a maximum of 1.3. The numbering system in Table 3-2 reflects the order of consideration in assigning the daily scores. This order also reflects the relative frequency with which these conditions occurred. If two (or more) conditions are observed on the same day, the daily score is based on the condition that is higher on the hierarchy.

Table 3-2. Summary of constants for the Ontario WSI for highway maintenance

Day type	Component thresholds	Score	WWAF adjusted Score
Snowfall days	High amount of snow (> 4.91 cm)	1.3	0.715
	Moderate amount of snow (1.91 to 4.9 cm)	1.0	0.55
	Low amount of snow (0.2 to 1.9 cm)	0.5	0.275
Series of cold days	Daily precipitation < 0.2 mm, Max temp in previous three days < -12 °C	0.5	NA
Rainfall with low temperatures days	Daily snowfall < 0.2 cm, Conditions for series of cold days no met, Daily rainfall ≥ 0.4 mm, Min temp < -0.2 °C	0.4	0.22
Warm-weather adjustment factor (WWAF)	If ANY of the WSI weather triggers have been met AND The maximum temperature for the *6-day* period centred on the day for which the score is being assigned is >-1 °C	-45% removed from daily score	

Once the WSI constants were defined, the WSI scores were calculated for each of the 248,200 AMC-days (20 AMCs x 34 years x 365 days) during the study period. Although the winter season is approximately seven months in duration, index score calculations were computed for all days in all years, as winter weather is known to occur outside of the institutionalized maintenance season. Across the 20 AMCs, on average, 77 days required winter maintenance each season. The average seasonal WSI score in Ontario is 46 and seasonal WSI score are approximately normally distributed. However, as is evident in Figure 3-1, there is considerable variation in the seasonal WSI scores across Ontario.

Figure 3-1 clearly shows that the Cochrane AMC consistently experiences the most severe winter weather and the AMCs of Toronto, Halton, Durham, and Chatham experience the least severe weather on average, and the most consistent weather as shown by the smallest spread in seasonal index values and the smallest standard deviations. Conversely, Sault Ste. Marie, Owen Sound, Thunder Bay West, and Bancroft have more variable seasonal WSI values all with standard deviations greater than 12 index points (Table 3-3). This inter-seasonal variability can be particularly challenging for road authorities as it suggests that the personnel, equipment and materials use in one year may be markedly different than those in previous or subsequent seasons. The highest WSI score was experienced in Cochrane during the 1995-96 winter season with a score of 92.0. The least severe winter season occurred in the Chatham AMC in the 1982-83 winter season with a score of 12.9. On average for Ontario the 2013-14 winter season had the most challenging winter conditions with a WSI score of 61.3. The second highest average seasonal WSI score was 57.7 in the 1995-96 winter season. The lowest average seasonal WSI score for the province occurred in the 2009-10 season (average 32.1) followed by the second least severe winter season in 2011-2012 (average 32.2).

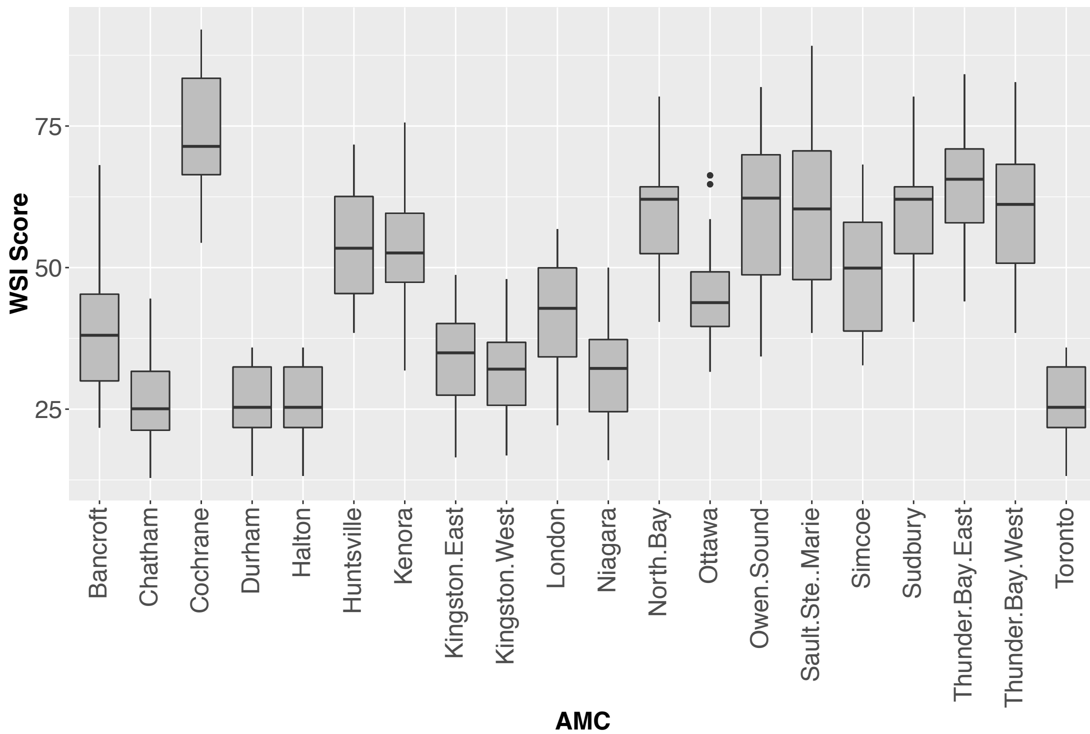


Figure 3-1. Boxplots showing the interquartile range (25% to 75%) for observed seasonal WSI scores in each AMC from 1980-81 to 2015-16.

In most cases, as the WSI increases, equipment-hours increase proportionately. Similarly, as the WSI decreases, equipment-hours decrease proportionately. With the exclusion of the RWIS data the fit is, on average 0.1% lower than in the WSI presented in Matthews *et al.* (2017a). The coefficient of determination (R^2) between reporting-period level WSI scores and reporting-period level equipment-hours range from 0.607 (2012-13) to 0.990 (2010-11), as summarized in Table 3-3. The average annual R^2 value (R^2 values for each AMC-season averaged) is 0.874, which indicates that on average 87.4% of the variability in 14-day reporting period equipment-hours in the 20 Ontario AMCs is explained by the WSI. Overall the R^2 values are high, thus indicating the WSI is reliable in explaining variations in equipment-hours.

Table 3-3. Seasonal R^2 values between observed reporting-period level WSI scores and reporting-period level equipment-hours

AMC	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015
A	0.934	0.908	0.896	0.815	NA*	0.881	0.866
B	0.953	0.931	0.875	0.748	0.861	0.886	0.955
C	0.869	0.95	0.665	0.881	0.869	0.863	0.875
D	0.969	0.779	0.945	0.846	0.863	0.775	0.842
E	0.913	0.652	0.975	0.758	0.716	0.926	0.837
F	0.962	0.946	0.815	0.948	0.888	0.924	0.961
G	0.907	0.655	0.935	0.93	0.717	0.939	0.905
H	0.937	0.934	0.92	0.741	0.909	NA*	0.96
I	0.936	0.962	0.976	0.891	0.661	0.922	0.926
J	0.920	0.768	0.801	0.809	0.93	0.934	0.916
K	0.944	0.981	0.92	0.901	0.799	NA*	0.763
L	0.950	0.902	0.788	0.937	0.934	0.928	0.91
M	0.936	0.965	0.963	0.901	NA*	NA*	NA*
N	0.951	0.959	0.89	0.853	NA*	NA*	0.947
O	0.950	0.945	0.632	0.768	0.655	0.89	0.902
P	0.790	0.928	0.958	0.824	0.865	0.97	0.956
Q	0.970	0.842	0.935	0.904	0.794	0.929	0.965
R	0.823	0.744	0.912	0.851	0.607	0.83	0.841
S	0.734	0.666	0.99	0.611	0.934	0.963	0.828
T	0.988	0.833	0.882	0.817	0.88	0.96	0.771

*AMC-season not included in the analysis due to incomplete data and AMC names omitted for contractor privacy

Table 3-3 Legend

Range	**Classification**	**Colour**
≥ 0.90	= Very strong	
0.80 to 0.89	= Strong	
0.70 to 0.79	= Moderately strong	
0.60 to 0.69	= Moderate	

3.6 Objective 2: Trends in Winter Severity

Given this validation of the WSI for estimating WRM demand based on publicly available data, it is possible to assess how winter severity has changed in the past and how winter weather severity is projected to change into the future. With the computed WSI scores, the Mann-Kendall Test is used to detect if the trends in winter severity (WSI scores) over the past 34 years are statistically significant at the 5% significance level (p<0.05). The Mann-Kendall Test used in this study is the rank-based nonparametric Mann-Kendall, a common test used to detect trends in climate and environmental data (Yue *et al.* 2002, Hamed 2008, Lacombe *et al.* 2012, Ahmad *et al.* 2015, Wani *et al.* 2017). In the Mann-Kendall Test, the null hypothesis is that there is no trend in WSI scores over the past 34 seasons. The alternate hypothesis is that there is a significant trend, either decreasing or increasing over the study period. This study uses the Trend: Non-Parametric Trend Tests and Change-Point Detection R package developed by Pohlert (2018). This package is also used to detect the magnitude of the slope (Sen's Slope Estimator Test). While the Mann-Kendall Test detects the statistical significance of the trends over time, it does not tell us the magnitude of the trend. As such, Sen's Slope Estimator Test is used to detect the magnitude of the trends, if present (Wani *et al.* 2017, Pohlert 2018). A summary of the historical trend analysis for the 20 AMCs is summarized in Table 3-4. The test results for historical WSI trends reveals that 13 AMCs experienced a negative trend in winter severity, five AMCs show a positive trend in WSI scores, and two AMCs showed no trend. However, the MK statistic reveals that only two of these locations show a statistically significant decreasing trend at the 5% significance level (Bancroft and Niagara, also shown in Figure 3-2).

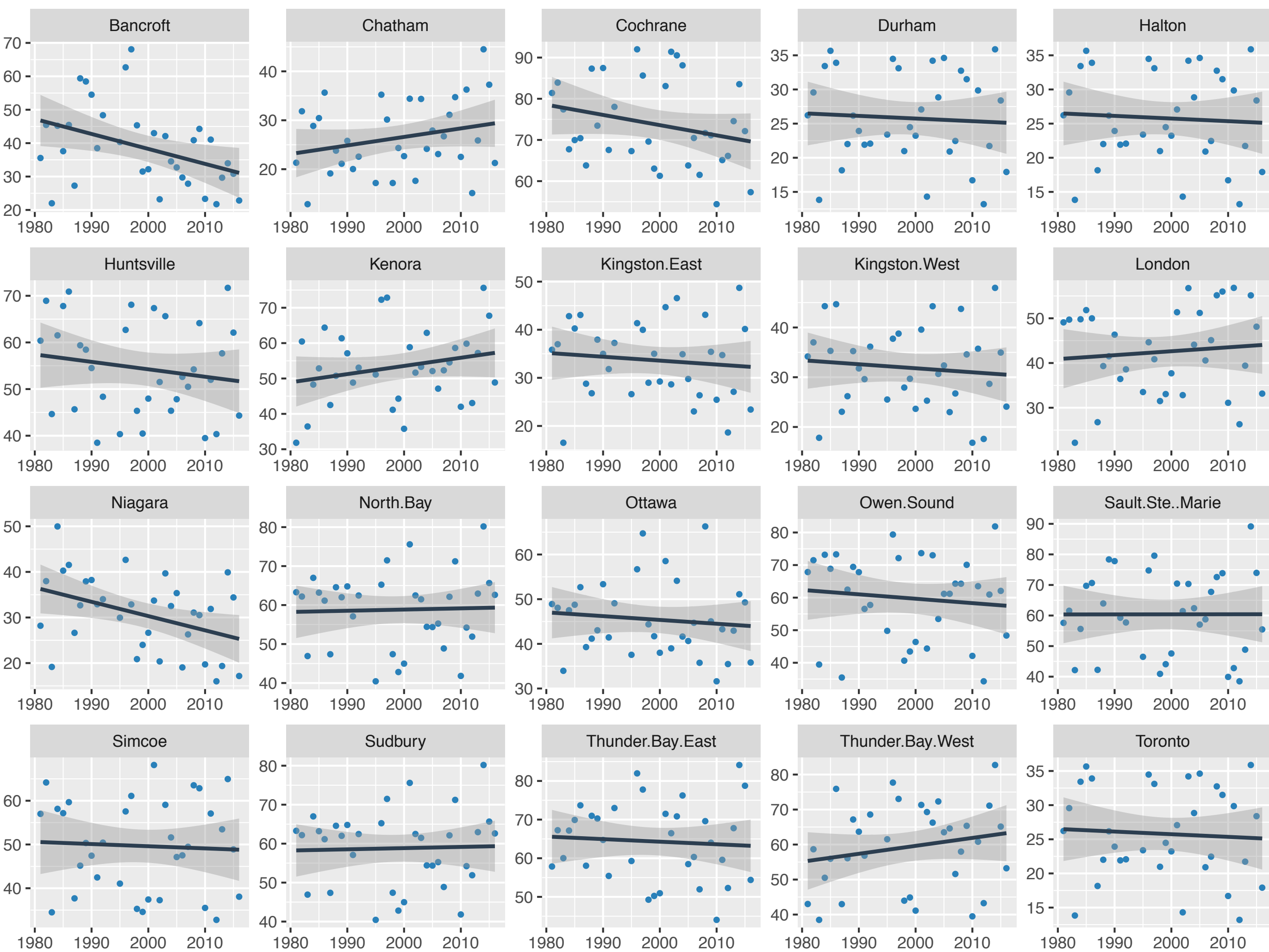


Figure 3-2. Linear trends in observed winter severity scores over time for 20 AMCs from 1980/81-2015/16 (shading represents the 95% confidence interval)

Table 3-4. Mann-Kendall and Sen's Slope Estimate test results for the observed seasonal time series 1980-2015

	WSI Scores			
	Mean	**StDev**	**M-K (Z)**	**Sen's Slope**
Bancroft	38.81	12.06	-2.55*	-0.54
Chatham	26.39	7.38	1.29	0.17
Cochrane	73.89	10.44	-1.27	-0.29
Durham	25.79	6.75	-0.44	-0.04
Halton	25.79	6.75	-0.44	-0.04
Huntsville	54.43	10.24	-0.83	-0.17
Kenora	53.27	10.54	1.33	0.25
Kingston East	33.67	8.02	-1.01	-0.15
Kingston West	31.90	8.18	-0.65	-0.08
London	42.52	9.60	0.42	0.10
Niagara	30.69	8.44	-2.28*	-0.38
North Bay	58.81	9.72	0.03	0.00
Ottawa	45.46	8.35	-0.65	-0.15
Owen Sound	59.83	13.11	-0.77	-0.22
Sault Ste Marie	60.39	13.59	0.03	0.02
Simcoe	49.66	10.57	-0.18	-0.04
Sudbury	58.81	9.72	0.03	0.00
Thunder Bay East	64.36	10.08	-0.24	-0.05
Thunder Bay West	59.36	12.10	1.04	0.23
Toronto	25.79	6.75	-0.44	-0.04
Ontario	45.98	7.94	-0.47	-0.10

*Statistically significant at the 5% significance level

3.7 Objective 3: Analysis of Future Change

Using the optimized index parameters, the daily WSI scores were then calculated for each of the four modelled datasets for the simulated historical (1980-2009) and future periods (2010-2099) for each of the 20 AMCs. While the NA-CORDEX data experiments are provided with a high degree of spatial and temporal precision, there are two notable limitations that were resolved as explained below. The first limitation is that these climate experiments have temperature and precipitation biases that need to be resolved. To overcome this, the commonly used assumption that the model biases are constant in time was adopted; *i.e.,* both the simulated historical (1980-2009) and future periods (2010-2099) have very similar biases relative to observations. As such, comparisons of the difference between the future and past temporal periods within the same climate experiment can be regarded as accurate, because the biases are subtracted when taking the difference. It is precisely for this reason that it would be erroneous to compare the observed weather data from ECCC stations with simulated future projections. Accordingly, climate change is assessed as the model-simulated difference (future minus past). Consideration is also given to the imperfect representation of climate in an individual model, by presenting the results as the multi-model average of four different simulations.

The second limitation of the modelled data is that climate models do not differentiate between snowfall (solid precipitation) and rainfall (liquid precipitation). Since the available output data from the NA-CORDEX models did not include separated liquid and solid precipitation, a temperature threshold is used to partition rain and snow from simulated total precipitation. While a 0°C average daily temperature threshold could be used to make this distinction, it may result in either an under or over estimation of snowfall and rainfall. To identify the optimal temperature threshold, all snowfall days, rainfall days, and days with mixed precipitation in the historical weather observations from ECCC were organized by both minimum daily temperatures and maximum daily temperature. It was found that for Tmin between 0°C and -0.5°C, the number of snowfall days becomes fewer, and the number of mixed precipitation days (those with both snow and rainfall) becomes larger. This same analysis was completed based on maximum daily temperature and it was found that a threshold of Tmax 3.5°C could also be used to differentiate between rain and snowfall. The decision was made to use the daily minimum temperature of less than -0.5°C to define snowfall and rainfall in the modelled climate data.

While the assessment of the historical observations reveals mixed results for Ontario, the climate change experiments unanimously project a net decrease in WSI scores for all AMCs and for all three future time periods. These projections are summarized in Table 3-5 and Figure 3-3 and the uncertainty in these historical and future simulations stems from bother inter-annual variability (30 years of WSI scores in each time period) and the variability between models (four different climate models). This results in a sample of 120 annual WSI scores for each AMC for each of the four time periods.

During the near-term (2010-2039), all AMCs are projected to have decreasing WSI scores relative to the baseline time period (1980-2009). In the near-term (2010-39) WSI scores are projected to decrease by a seasonal average of -12% (Table 3-5). As shown in Table 3-5, Niagara (-19.6%), Durham (-17.9%), and Toronto (-17.6%) are projected to experience the largest decreases in WSI scores during the near-term. However, much of this decrease would be within the range of normal interseasonal variability that is already observed in Ontario Exploring the impacts of climate change into the 2050s (2040-2069), an Ontario-wide average of 24.2% decrease in WSI scores seasonally is projected. Looking even further into the future indicates that by the end of the century (2070-2099), winters will be approximately half as severe as today with an average decrease of 43.7% in WSI scores.

Table 3-5. Future climate change simulations for seasonal mean WSI scores* relative to the 1980-2009 simulated historical time period

	1980-09 $\bar{x}$WSI	2010-39 $\bar{x}$WSI	Δ WSI vs. 1980-09	2040-69 $\bar{x}$WSI	Δ WSI vs. 1980-09	2070-99 $\bar{x}$ WSI	Δ WSI vs. 1980-09
Bancroft	52.9(±2.4)	46.8(±2.4)	-11.6%	41.0(±2.2)	-22.6%	29.8(±2.3)	-43.8%
Chatham	35.1(±2.2)	29.5(±2.1)	-15.8%	24.7(±2.0)	-29.5%	16.8(±1.7)	-52.0%
Cochrane	85.4(±2.7)	80.8(±2.8)	-5.4%	71.7(±2.7)	-16.1%	59.6(±3.1)	-30.3%
Durham	40.5(±2.1)	33.3(±2.2)	-17.9%	27.6(±2.0)	-31.9%	18.6(±1.8)	-54.2%
Huntsville	61.5(±2.5)	54.0(±2.8)	-12.1%	46.8(±2.5)	-23.9%	34.2(±2.6)	-44.3%
Kenora	64.1(±2.6)	58.8(±2.6)	-8.2%	54.2(±2.3)	-15.5%	45.0(±2.4)	-29.8%
Kingston East	41.1(±1.9)	34.8(±2.0)	-15.2%	28.7(±1.7)	-30.0%	19.1(±1.7)	-53.5%
Kingston West	40.5(±2.1)	33.7(±2.1)	-16.8%	27.9(±1.9)	-31.1%	18.9(±1.8)	-53.4%
London	41.7(±2.4)	34.8(±2.4)	-16.6%	29.4(±2.3)	-29.5%	20.1(±1.9)	-51.8%
Niagara	33.9(±2.2)	27.3(±2.3)	-19.6%	22.0(±2.1)	-34.9%	13.6(±1.7)	-60.0%
North Bay	60.5(±2.4)	55.0(±2.4)	-9.1%	48.1(±2.3)	-20.5%	35.9(±2.4)	-40.6%
Ottawa	48.7(±2.1)	42.4(±2.1)	-12.9%	36.2(±1.9)	-25.6%	25.3(±1.9)	-47.9%
Owen Sound	53.3(±2.8)	44.3(±3.0)	-16.8%	36.9(±2.8)	-30.7%	25.0(±2.5)	-53.1%
Peel Halton	38.3(±2.3)	32.1(±2.3)	-16.0%	26.5(±2.1)	-30.7%	18.3(±1.8)	-52.1%
Sault Ste Marie	76.0(±2.8)	70.6(±2.6)	-7.2%	61.4(±2.4)	-19.2%	49.4(±2.5)	-35.0%
Simcoe	52.2(±2.5)	45.0(±2.7)	-13.7%	37.8(±2.5)	-27.6%	26.3(±2.4)	-49.7%
Sudbury	58.9(±2.7)	52.3(±2.9)	-11.2%	43.9(±2.6)	-25.5%	32.6(±2.5)	-44.7%
Thunder Bay East	72.8(±3.0)	66.2(±3.3)	-9.1%	57.3(±3.0)	-21.2%	45.9(±3.0)	-36.9%
Thunder Bay West	76.2(±2.8)	71.1(±3.1)	-6.6%	65.8(±2.8)	-13.6%	54.8(±3.1)	-28.0%
Toronto	37.6(±2.2)	31.0(±2.3)	-17.6%	25.7(±2.1)	-31.6%	17.4(±1.8)	-53.6%
Ontario	52.8(±2.3)	46.4(±2.4)	-12.0%	40.0(±2.2)	-24.2%	29.7(±2.1)	-43.7%

*mean WSI scores presented with margin of error for the 95% confidence interval

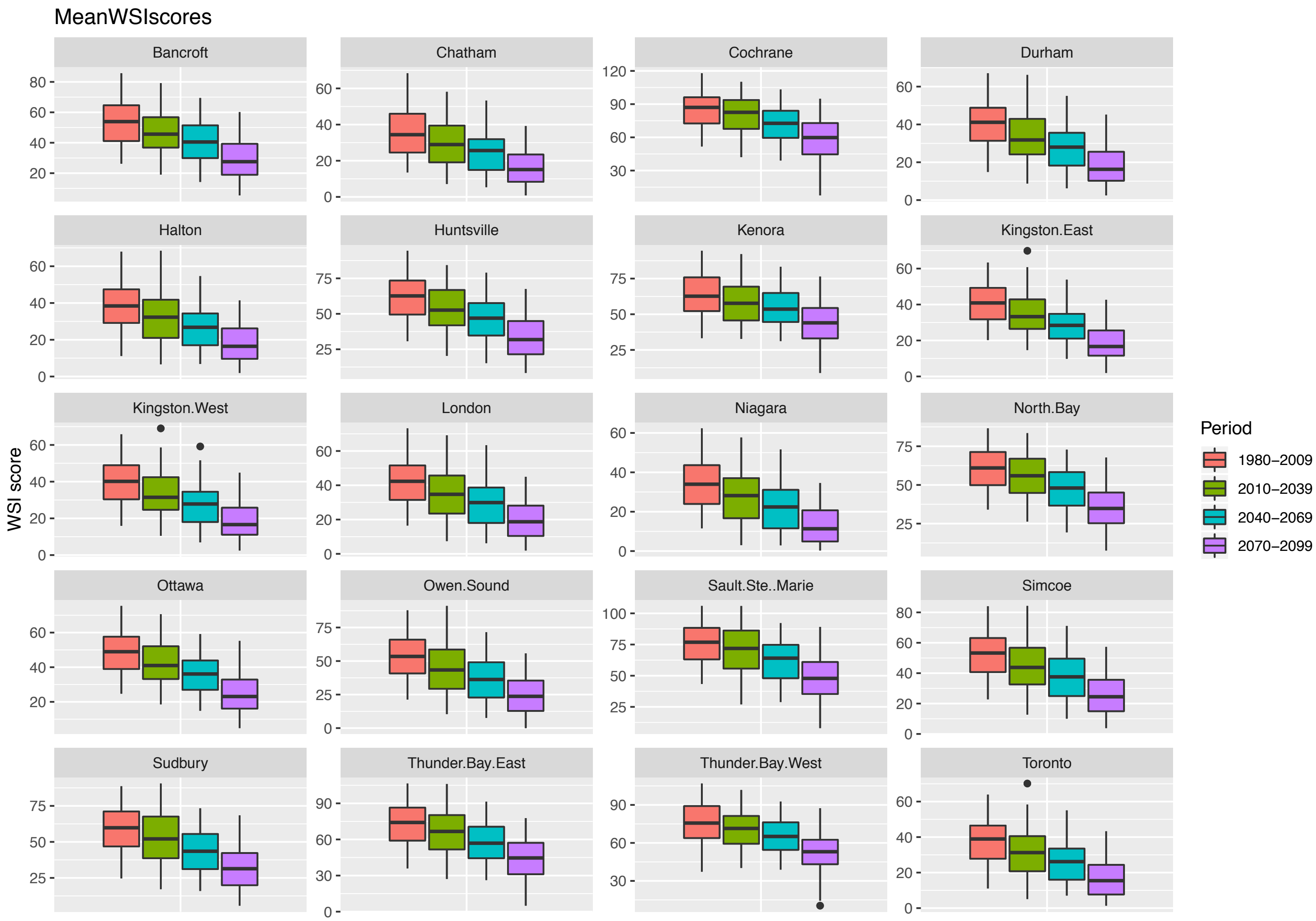


Figure 3-3. Boxplots of mean WSI scores computed from modelled climate data for four time periods

3.8 Discussion and Conclusions

Overall, the WSI developed here demonstrates the utility of a CS translation tool that has the potential to be used in several different ways to support highway operations. This CS tool informs decision-making by clearly documenting the relationship between weather and WRM activities that can be applied in at least three practical ways to support in institutional accountability to the public or shareholders. First, the WSI can be used as a tracking mechanism to monitor the severity of winter weather. As such, the WSI can be used to describe, quantify, review and compare winter weather severity from any time period to another and from one region to another. Secondly, this WSI enables road authorities and private snow and ice control professionals to clearly communicate winter weather severity to the public and other stakeholders in relation to observed levels of service. Third, this WSI can be applied to climate projections to estimate the future demands for WRM activities in different jurisdictions. This application of a WSI on climate projections fills an important gap in the current weather and climate information offerings for the provincial road authority. The use of seasonal to inter-annual climate predictions to inform strategic planning; such as planning for staffing, equipment needs, materials stock-piling, or the establishment of multi-year road maintenance contracts is an important area of CS development that is demonstrated in this study.

More importantly, the method proposed in this study can foster the development of CS more broadly, as there is a clear market for the development of tools and techniques that provide easy to understand metrics of weather sensitivity and risk that also have strong statistical fit with the transportation impacts or responses. This paper illustrates the value of using customized indices as a translation service to generate tailor-made information in the context of WRM to bridge the interface between the scientific community and the weather and climate information users. The creation of salient and robust weather and climate information that can be easily understood and used by decision makers and the public is an important trait of CS provision (Kirchhoff *et al.* 2013), especially a tool that can efficiently and effectively identify both the societal or institutional thresholds of weather variability but simultaneously determines their importance through weighting. A tool such as a data-driven index can then be utilized and applied to multiple weather and climate products such as observed weather data, short-term weather forecasts, medium-range forecasts as well as multi-decadal climate projections, all of which are part of the CS landscape (Vaughan *et al.* 2016). This information can then be used to then guide policy, inform strategic planning, and aid in decision-making more generally.

The development of CS is important for both weather risk management and climate change adaptation, especially in the transportation sector. During the development of this index the provincial road authority clearly expressed a need to first explore the current and past relationships between weather and WRM and the final phase in this multi-year process was to then apply the WSI to the climate change projections; a phase that was initiated only after fostering a rapport and trust with the road authority through sound science and evidence. This process underscores that the development of CS is long-term processes that requires input from both the user (road authority), researcher, and the eventual long-term producer of this information; the private weather service provider contracted by the provincial road authority. While developed in an academic setting, the index presented in in Matthews *et al.* (2017a) is now mandated in the weather service contract with the province's weather provider. Furthermore, the index values are disseminated on the provincial website to manage constituent expectations of WRM operations.

In summary, the results presented in this paper are the culmination of a multi-year effort to identify and measure the sensitivity of WRM operation to weather in an easy to understand but robust fashion. The co-production of this information involved multiple iterations between the researcher and the provincial road authority and an exploration of alternative models and variable inclusions. The final step in this process was then to assess the impacts of climate change. In summary, this research describes the development of a WSI that has strong fit with observed maintenance activity based entirely on publicly available data. On average, the R^2 value indicating the fit between WSI scores and equipment-hours is 0.874, which indicates that on average 87.4% of the variability in 14-day reporting period equipment-hours in the 20 Ontario AMCs is explained by the WSI. While the R^2 values at the AMC level vary, the vast majority of seasons have a fit above 0.800. The second part of this paper analyzed trends in winter severity across Ontario, Canada over a 34-year study period of 1980-81 to 2015-16. The results obtained with the Mann-Kendall Test and Sen's Slope Estimator Test reveal that the nature of winter weather in the province of Ontario is indeed changing but the nature of this change is complex; the WSI trends include a mix of positive and negative trends. The climate change experiments unanimously project a net decrease in WSI scores for all AMCs and for all three future time periods, suggesting that climate change may provide maintenance cost saving opportunities for road authorities.

Chapter 4:

Development of a Data-driven Weather Index for Beach Parks Tourism

Matthews, L., Scott, D., & Andrey, J. (2019). Development of a data-driven weather index for beach parks tourism. *International Journal of Biometeorology*, 1-14. doi:10.1007/s00484-019-01799-7

This manuscript has been modified for use in this dissertation

4.1 Overview

The complexity of the human-environment interface predicates the need for tools and techniques that can enable the effective translation of weather and climate products into decision-relevant information. Indices are a category of such tools that may be used to simplify multi-faceted climate information for economic and other decision-making. Climate indices for tourism have been popularized in the literature over the past three decades, but despite their prevalence, these indices have a number of limitations, including coarse temporal resolution, subjective rating and weighting schemes, and lack of empirical validation. This paper critically assesses the design of the TCI, the HCI:Beach, and a new, mathematically optimized index developed for the unique contextual realities of Great Lakes beach tourism. This new methodology combines the use of expert knowledge, stated visitor preferences, and mathematical optimization to develop an index that assigns daily weather scores based on four weather sub-indices (thermal comfort, wind speed, precipitation, and cloud cover). These daily scores are then averaged to the monthly level and correlated to visitation data at two beach parks in Ontario (Canada). This optimized index demonstrates a strong fit (R^2=0.734, 0.657) with observed visitation at Pinery Provincial Park and Sandbanks Provincial Park, outperforming both the TCI (R^2= 0.474, 0.018) and the HCI:Beach (R^2=0.668, 0.427). This study advances our understanding of the magnitude and seasonality of weather impact on beach tourist visitation and can inform decision-making of tourism marketers and destination managers.

4.2 Introduction

There is substantial evidence that weather and climate have significant influence on tourist motivation (Gössling *et al.* 2012, Cocolas *et al.* 2016, Jeruing *et al.* 2017), destination choice (Hamilton & Lau 2005, Scott *et al.* 2008, Steiger *et al.* 2016), destination attractiveness (Gössling *et al*. 2016), and destination spending (Wilkins *et al.* 2018). While the relationship between climate and tourism is well-documented, the climate-tourism nexus is particularly acute for beach tourism where climate has been repeatedly identified as a critical pull factor (Rutty & Scott 2013, Rosselló & Waqas 2016). Additionally, there is clear evidence that weather and climate has an influence on park visitation in many geographic contexts (Scott *et al.* 2007, Fisichelli *et al.* 2015) and more specifically relevant to this study, beach park visitation at Ontario Provincial Parks (Jones & Scott 2006, Hewer *et al.* 2015, 2016, 2018). It is well documented that this relationship between climate and tourism is highly important for beach tourists (Rutty & Scott 2010, 2013, 2015); however, the strength and attributes of this relationship vary geographically and temporally. Advancing our understanding of the magnitude and seasonality of weather's effect on tourist visitation would provide tourism planners, managers, and marketers with enhanced information for contemporary decision-making as well as better inform climate change impact studies that have featured prominently in academic literature, media, business, and government discourses.

An evaluation of climate information utilization in the tourism sector by Scott and Lemieux (2010) revealed that while weather/climate products and services are increasingly available, an understanding of how these weather/climate products are used to inform decision-making remains limited. Furthermore, despite numerous studies that show a strong relationship between tourism and weather (*e.g.*, de Freitas *et al.* 2008, Jones & Scott 2006, Rutty & Scott 2015, Hewer *et al.* 2016, 2018), the application of this research to inform decision-making is only beginning to be explored (Scott *et al.* 2011, Damm *et al.* 2019).

This challenge is not limited to the tourism sector. Despite the ever-increasing availability of weather/climate data, its use in informing decision-making for a range of climate sensitive sectors, such as energy use and production, retail, water management, finance, (re)insurance, transportation, agriculture, and forestry, remains limited due to the complexity of the human-environment nexus (Soares & Dessai 2015, Soares *et al.* 2018). The specific climatic thresholds that induce behavioural or societal responses vary over space and time because of complex interactions of social, technological, institutional, economic, political, and environmental relationships. It is precisely this complexity of the human-environment interface that predicates the need for tools and techniques that can efficiently and effectively translate weather/climate products into salient information for decision-making. Weather/climate indices are a category of such tools that can be used to simplify multi-faceted weather/climate information to enable an efficient societal response.

There has been discussion in the climate and tourism literature for over 30 years on using indices for decision-making such as destination marketing, operations, and planning (Mieczkowski 1985, Scott *et al.* 2016, Dubois *et al.* 2016). The tourism research community is advanced in the application of tourism indices to project potential impacts of climate change. A number of studies have been conducted that apply existing indices to estimate the potential impacts of changing climate resources for tourism at continental and global scales (Scott *et al.* 2004, Amelung *et al.* 2007). However, their use as weather risk management decision-support tools has yet to be explored. This is perhaps not surprising because the intent of tourism climate index development to date has not been focused on weather risk management at the business or destination level, but rather as a way to objectively evaluate climate resources for tourism and compare between destinations (Dubois *et al.* 2016, Scott *et al.* 2016).

Despite the prevalence of climate indices as a tool for evaluating climatic resources, there are a number of limitations to these indices, including coarse temporal resolution, subjective rating and weighting schemes, and lack of empirical validation (de Freitas *et al.* 2008, Scott *et al.* 2016, Dubois *et al.* 2016). In particular, the majority of these indices are too coarse in spatial and temporal resolution to provide decision-relevant information for decision-making by comparing entire nations or regions rather than destination-specific information (de Freitas *et al.* 2008, Scott *et al.* 2016, Dubois *et al.* 2016). Indices such as the TCI use monthly level data and are not contextual nor activity specific, neglecting the reality that different types of tourism such as ski tourism, urban tourism, or beach/coastal tourism have very different climatic needs and optimal conditions (de Freitas *et al.* 2008, Rutty & Scott 2010, Rutty & Scott 2014, Scott *et al.* 2016, Dubois *et al.* 2016). This literature has demonstrated that a 'one-size-fits-all' approach to tourism climate index development is neither conceptually sound (see de Freitas *et al.* 2008, Scott *et al.* 2016) nor valuable for tourism management decision-making. Barnett *et al.* (2008) were broadly critical of the propensity of environmental researchers to develop indices that are applied to large-scale systems (often without validation or sector expert input, let alone sector stakeholders and potential users), and encouraged researchers to focus on smaller scales of analysis because climate sensitivity and risk is so context-specific. In the context of climate and tourism research this idea is supported by de Freitas *et al.* (2008: 405) who stated that "one necessary requirement for a useful tourism climate index is that the index is specifically designed for and relevant to a type of tourism." de Freitas *et al.* (2008) went further and suggested that indices might need to be recalibrated to take into account cross-cultural differences in climate preferences, a sentiment supported by Damm *et al.* (2019).

However, there is potential to explore the value and operationalization of activity- or market-segment specific and location-specific indices for weather risk management. The business community has begun this endeavour of developing activity-specific indices, as exemplified by the suite of indices developed by the weather channel (Scott & Lemieux 2010). The Weather Channel developed the 'golf index', 'ski index', 'fishing index', and 'spectator index'. All of these indices are rated on a 0-10 scale; however, the exact calculation of these indices and the parameters used are not known and cannot be critiqued (Scott & Lemieux 2010). Furthermore, the 2019 version of the Weather Channel application for iPhone includes a 'sweat index', 'umbrella index', 'mosquito index', 'allergy index', as well as a personally customizable 'running index'. Despite the lack of transparency in the development of these recreation indices, these early developments and more recent workshops (Damm *et al.* 2018) demonstrate the demand for easily interpretable indicators.

Much of the development of tourism indices has adopted a stated-preference methodology (Scott *et al.* 2016, Dubois *et al.* 2016), despite calls by de Freitas (2003) and de Freitas *et al.* (2008) who argue for a broader adoption of revealed preference methodologies. Visitation data can be used as an indicator of demand and tourist perception of the suitability of weather conditions for beach tourism (de Freitas *et al.* 2008, Jones & Scott 2006, Hewer *et al.*

2016, Scott *et al.* 2016). When the observed or forecast weather conditions are not satisfactory for the tourism activity being considered, then individuals are less likely to visit that destination (Rutty & Andrey 2014). The challenge is in determining the weather thresholds and defining the climatic conditions that are deemed suitable or satisfactory by the potential visitors.

This study presents a new approach for developing a data-driven tourism climate index than can be used for predicting visitation in the Great Lakes region based on a methodology that uses visitation data to reveal the multiple thresholds for visitation at Ontario beach parks. This new index is then compared against two existing indices, the TCI (Mieczkowski, 1985) and the HCI:Beach specification. An optimization algorithm (as used in Matthews *et al.* 2017a,b,c) is applied to the HCI:Beach sub-indices, which are based on stated tourist climate preferences from Rutty and Scott (2014, 2015), to determine sub-index weights and weather variable rating thresholds that best correlate with park visitation.

4.3 Study Area

Two high-visitation provincial parks with major beach assets and complete visitation and meteorological data were selected for the study. Pinery Provincial Park was chosen due to its history as a study site in a number of weather/climate and park visitation studies (see: Jones & Scott 2006, Hewer *et al.* 2015, 2016, 2018). Pinery is located in southwestern Ontario on the shore of Lake Huron and boasts an impressive 10 km-long sand beach (Ontario Parks, 2018a). The Pinery beach is popular with day visitors from nearby urban centers, including Windsor, Detroit, Sarnia, London, and Kitchener-Waterloo. Average annual visitation at Pinery during the study period is 598,000 with 19% as day visitors and 81% as overnight visitors. Sandbanks Provincial Park was selected as an additional site with a different tourism market catchment.

Sandbanks is located in southeastern Ontario on the shore of Lake Ontario and is home to the world's largest baymouth barrier dune formation which draw visitors from across Ontario, Quebec and the Northeast USA (Ontario Parks, 2018b). Average annual visitation at Sandbanks during the study period is 520,000 with 57% as day visitors and 43% as overnight visitors.

4.4 Data and Methods

4.4.1 Park Visitation Data

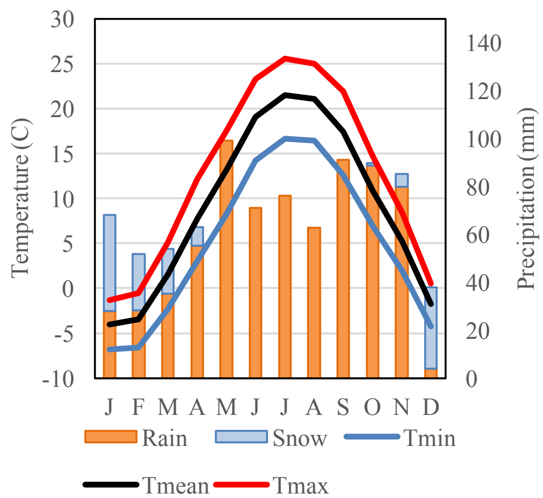
Visitation data used in this study were obtained from the Ontario Parks Service. Daily visitation data were obtained for Pinery and Sandbanks Parks from 2000 to 2010. This time period was selected to facilitate comparisons with previous related studies (*i.e.,* Jones & Scott 2006, Hewer *et al.* 2015, 2016). The visitation data reveal marked seasonality, with a strong summer peak in both beach parks. At the Pinery, the highest median monthly visitation is in July (192,298 visitors) and August (187,339 visitors) with the lowest median monthly visitation in December (1,646 visitors). Sandbanks sees similar visitation during the summer months with median visitation peaks in July (188,561) and August (178,134), with no visitation during the winter months because the park is closed.

4.4.2 Weather Data

All Meteorological Service of Canada climate stations in close proximity to Pinery and Sandbanks Parks were examined to determine the completeness of the nine variables required for calculation of the TCI and HCI:Beach indices (*i.e.,* daily temperature, precipitation, wind, relative humidity, sunshine hours and cloud cover). For Sandbanks, the Trenton A station

(Climate ID: 6158875) was used and is approximately 36 km away from the park. For Pinery, two stations located approximately 50 km from the park were used to obtain the required daily climate variables: Sarnia station (Climate ID: 6127514, timeframe: 2000.01.01-2007.09.30) and the Sarnia Airport station (Climate ID: 6127519, timeframe: 2007.10.01-2010.12.31). Unfortunately, despite the better proximity to the park and its coastal location, the Sarnia stations did not have complete cloud cover data; as a result, the London International station (Climate ID: 6144475, timeframe: 2000.01.01-2010.12.3) located approximately 60 km from the Pinery was used to obtain cloud cover and sunshine data. The climographs for the two parks are shown in Figure 4-1.

a)



b)

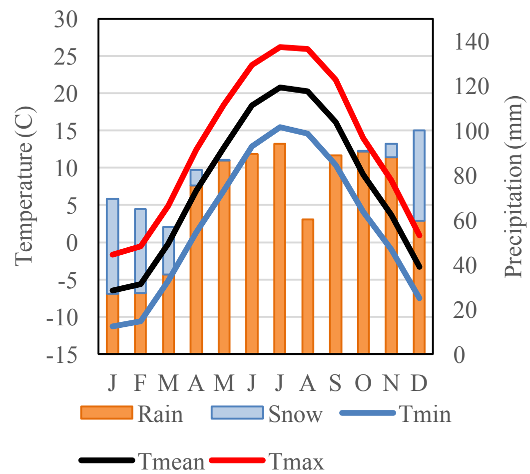


Figure 4-1. Study period climographs at a) Pinery Provincial Park and b) Sandbanks Provincial Park (January 2000 to July 2010).

4.4.3 Index Calculations

The first TCI was developed in the mid-1980s by Mieczkowski (1985), who created the TCI as a means of integrating climatic conditions at a destination into a single numeric value. In this instance, a total value of 100 is computed where the variable weights are interpreted as a percentage influence of the overall weather experience. The TCI was intended to provide a holistic interpretation of the climatic resources at each destination. Mieczkowski (1985) used mean monthly values to calculate the TCI, which ranges from scores of -30 to 100. The calculation for the TCI is provided as:

$TCI = 4CID + CIA + 2P + 2S + W$, where:

CID (daytime comfort index) is a combination of the maximum daily temperature and minimum daily relative humidity) accounts for 40% of the index;

CIA (daily comfort index - combination of mean daily temperature and mean daily relative humidity) is used for evening comfort and accounts for 10%;

P is precipitation (mm) and accounts for 20%;

S is sunshine (hours) and accounts for 20%;

W is wind (m/s), accounting for 10%.

The variable rating scales (outlined in Tables 4-1 to 4-4) and variable weighting (outlined in Table 4-5) of the TCI were based on expert opinion and an additive approach is used for aggregation. The TCI has been used for climate assessments and climate change impact studies in over 30 known studies between 1994 and 2018. Notwithstanding the extensive application of the TCI, it has been extensively criticized with the most common criticism being the subjective nature of the variable ranking schemes and the component weighting (Gomez-Martin 2005, de Freitas *et al.* 2008, Rutty & Scott 2010, Rutty & Scott 2014, Scott *et al.* 2016, Dubois *et al.* 2016). For the purposes of this research the TCI is calculated daily and averaged to the monthly level and, because beach tourism is a daytime activity, evening temperatures are not included as a separate component and the calculation will be *TCI = 5CID + 2P +2S +W.*

Similar to the TCI, the HCI:Beach is based on five weather variables that are used to calculate three sub-indices based on the work of de Freitas (2003): thermal comfort, aesthetic, and physical dimensions of climate relevant to tourism. The calculation for the HCI:Beach specification is derived from Scott *et al.* (2019) and is represented as:

HCI = 2 (TC) + 4(A) + (3(P) + W), where:

TC is the thermal comfort sub-index (combination of daily maximum temperature and mean relative humidity) and accounts for 20% of the index;

A represents the aesthetic sub-index and is based on the daily per cent of cloud cover and accounting for 40%;

the physical sub-index is a combination of P (precipitation) and W (wind speed), which represent 30% and 10%, respectively.

The HCI:Beach furthers the development of indices for the tourism sector by using daily level data and tailoring the index to a specific tourism segment based on the stated preferences of beach tourists (*i.e.,* the development of variable ratings and the variable weightings, including an over-riding effect of P and W) (Rutty & Scott 2010, 2014, 2015). Despite the advances made by the HCI:Beach, there remain areas for improvement in calibrating indices to the realities of placed-based and market segment specific tourism decision-making (as recommended by Dubois *et al.* 2016).

The initial list of weather variables and rating thresholds by Mieczkowski (1985) was developed through expert judgment, and the HCI:Beach furthered this research by incorporating stated preference evidence from tourist target markets to refine rating scales (Scott *et al.* 2019). The current study uses mathematical optimization to further improve the fit of the index so that the information becomes more 'useful, useable, and used' by tourists, tourism planners, and managers. Thus, based on the previous empirical work for the TCI and HCI:Beach, an optimization routine is employed on the HCI:Beach index to explore if improvements in model fit can be achieved, while maintaining the integrity of the index structure. Further, the subsequent index adheres to the six characteristics of a useful index set out by de Freitas *et al.* (2008): 1) theoretically sound, 2) integrates the effects of all relevant facets of climate, 3) simple to calculate, 4) easy to understand, 5) recognizes the overriding effect of certain weather conditions, and 6) empirically tested.

The approach taken adapts an optimization routine developed by Matthews *et al.* (2017a,b,c) for road transport WSIs, using observed weather conditions and reported visitation to define weights of the sub-indices, thresholds in the sub-indices, and index scores assigned on a daily basis. The optimization routine is set to maximize the fit (R^2) values between daytime visitors (excluding overnight campers) during the peak months of June to September. The optimization routine utilizes the Generalized Reduced Gradient (GRG2) algorithm that is standard in *Microsoft Excel* to simultaneously identify threshold values and sub-index scores. These daily index scores are then averaged to create weekly, monthly, or seasonal beach tourism index scores. The optimization routine is run for each of the sub-indices sequentially, as to maximize the fit between the sub-index scores and visitation, and then the weights of the sub-indices are optimized. The resulting constants (threshold values, sub-index scores, sub-index weights) for each of the sub-indices are outlined in the following section.

4.5 Results

4.5.1 Thermal Comfort Facet

The TCI and the HCI:Beach use two different rating schemes for the thermal comfort facet (Table 4-1). The thermal comfort rating scheme for the TCI assigns days to 23 different temperature ranges and assigns a score from minus six for ‘very undesirable’ temperatures to plus ten for ‘ideal’ temperatures. The HCI:Beach is similarly designed with 20 different temperature ranges and associated scores ranging from minus ten for ‘very undesirable’ temperatures to plus ten for ‘ideal’ temperatures. For this study, the optimization algorithm was set to maximize the R^2 values between the sub-index scores, and visitation at Pinery and Sandbanks (as measured by the average R^2 between the two parks). The algorithm was set to allow for any number of temperature ranges, but the sub-index scores were constrained to values between zero and ten. The justification for removing the penalty functions (scores of less than zero) was due to the impossibility of having negative (less than zero) visitors at a destination.

All three of the indices, the TCI, HCI:Beach, and optimized index use a combination of daily temperatures and relative humidity for the thermal comfort components. The challenge is that different studies, including Mieczkowski (1985) and Scott *et al.* (2016), use different heat index algorithms and these algorithms are not explicitly identified or defined in much of the literature (Anderson *et al.* 2013). Complicating the situation, there have been more than 100 bioclimatic indices have been developed over the past century (Blazejczyk *et al.* 2012); and in the past three decades, there has been an explosion in algorithms developed to calculate thermal perception indices (Anderson *et al.* 2013). The variety of calculations used makes inter-comparison studies challenging as the basic assumptions of the studies may be dissimilar (Anderson *et al.* 2013). It is especially problematic when the exact calculations for these thermal indices are not explicitly stated. Anderson *et al.* (2013) conducted an assessment of over 20 heat index algorithms to determine which ones most closely matched the original conceptual heat index developed by Steadman (1979), based off the seminal work of Missenard and Balthazard (1933). Anderson *et al.* (2013) found that the majority of algorithms matched quite closely to one another. Based on the findings from Anderson *et al.* (2013), and given that this is a Canadian study, the Humidex, a Canadian innovation, was used to calculate the thermal component of the indices. This is also consistent with the work of Scott *et al.* (2019) who used the Canadian Humidex in the development of the HCI:Beach index.

Table 4-1. Thermal comfort facet rating schemes

TCI		HCI:Beach		Optimization	
Rating	THumidex (°C)	THumidex (°C)	Rating	THumidex (°C)	Rating
0	≥36.0	≥39.0	0	≥41	0
		38.0 - 38.9	2		
1	35.0 - 35.9	37.0 - 37.9	4	39.0 - 40.9	7
2	34.0 - 34.9	36.0 - 36.9	5		
3	33.0 - 33.9	35.0 - 35.9	6	35.0 - 38.9	8
4	32.0 - 32.9	34.0 - 34.9	7		
5	31.0 - 31.9	33.0 - 33.9	8	30.0 - 34.9	9
6	30.0 - 30.9	31.0 - 32.9	9		
7	29.0 - 29.9	28.0 - 30.9	10	23.0 - 29.9	10
8	28.0 - 28.9	26.0 - 27.9	9		
9	27.0 - 27.9	23.0 - 25.9	7		
10	20.0 - 26.9	22.0 - 22.9	6		
9	19.0 - 19.9	21.0 - 21.9	5		
8	18.0 - 18.9	20.0 - 20.9	4	21.0 - 22.9	9
7	17.0 - 17.9	19.0 - 19.9	3	19.0 - 20.9	8
6	16.0 - 16.9				
5	10.0 - 15.9	18.0 - 18.9	2	14.0 - 18.9	6
4	5.0 - 9.9	17.0 - 17.9	1		
3	0.0 - 4.9	15.0- 16.9	0	11.0 - 13.9	5
2	−0.1 - −5.9	10.0 - 14.9	-5	7.0 – 10.9	2
0	−6.0 - −10.9			1.0 – 6.9	1
−1	−11.0 - −15.9	≤9.9	-10	≤0.9	0
−2	−16.0 - −20.9				
−6	≤−21.0				

As shown in Table 4-1, the optimization algorithm identified eleven different thermal comfort ranges and assigned sub-index scores between zero and ten. Interestingly, the range for 'ideal' THumidex (°C), or THumidex (°C) rated as a ten, is broader than what was considered in the HCI:Beach. Furthermore, the drop in sub-index scores as THumidex increased was less pronounced than in the previous indices. Findings reveal that tourist visitation numbers are highest when THumidex °C is between 23.0 - 29.9°C whereas the HCI:Beach index had ideal thermal comfort as between 28.0 - 30.9 °C indicating that tourists in this geographic context may be more accepting of cooler temperatures than in other markets, particularly those of Caribbean beach holiday destinations surveyed by Rutty and Scott (2014, 2015). While the TCI assigns a score of zero for THumidex ≥36°C, and the HCI:Beach assigns a zero for ≥39°C, the optimization algorithm assigns a score of zero for days with THumidex ≥41°C. However, the algorithm assigns a score of zero because there are too few days with such high temperatures and as such there are few visitors.

A regression analysis between THumidex (°C) and visitation reveals that thermal comfort is the dominant factor for the climatological preferences of visitors to the Pinery and Sandbanks (Table 4-6 and Table 4-7). In fact, the relationship is evident for both day use visitors (R^2= 0.709, 0.610), overnight campers (R^2= 0.721, 0.691), and total visitors (R^2= 0.734, 0.657), at the Pinery and Sandbanks, respectively. When assessing day visitors, findings reveal that at Pinery, there is an improvement in fit from an R^2 of 0.408 for the TCI thermal comfort sub-index and R^2= 0.678 for the HCI:Beach to R^2= 0.705 for the optimized thermal comfort sub-index when all months of the year are assessed. This relationship is strongest when all months in a year are analyzed and the relationship is least evident during July and August months alone. Findings reveal that at Sandbanks, the highest fit came from the optimized sub-index (R^2= 0.632) and the lowest was for the TCI thermal comfort sub-index (R^2= 0.114), revealing that day use visitor behaviours are similar between the two parks though the strength of the relationship is dissimilar.

4.5.2 Aesthetic Facet

The TCI and the HCI:Beach use two different rating schemes for the aesthetic facet (Table 4-2). The original TCI uses the number of sunshine hours in a day for the aesthetic factor. In contrast, the HCI:Beach index uses percentage of cloud cover for calculating the aesthetic facet. In their work on the HCI:Urban, Scott *et al.* (2016) selected cloud cover data due to the absence of sunshine data from some meteorological stations and this decision was extended to the development of the HCI:Beach (Scott *et al.* 2019). The rating scheme developed for the

HCI:Beach aesthetic facet assigns the highest score to days with 15% to 25% cloud cover instead of on days with completely clear skies (zero% cloud cover) as this was revealed to be the ideal preference for tourists from studies on stated and revealed climate preferences of tourists (*e.g.,* Rutty & Scott 2010, 2014, 2015).

Table 4-2. Aesthetic facet rating schemes

TCI		**HCI:Beach**		**Optimization**	
Rating	Sunshine hours	Cloud cover (%)	Rating	Cloud cover (%)	Rating
10	10	0-0.9%	8	0.0-2.9%	9
9	9	1.0-14.9%	9	3.0-14.9%	10
8	8	15.0-25.9%	10		
7	7	26.0-35.9%	9		
6	6	36.0-45.9%	8	15.0-36.9%	7
5	5	46.0-55.9%	7		
4	4	56.0-65.9%	6	36.0-44.9%	5
3	3	66.0-75.9%	5	45.0-65.9%	6
2	2	76.0-85.9%	4	66.0-76.9%	4
1	1	86.0-95.9%	3	77.0-97.9%	2
0	0	≥96.0%	2	≥98.0%	0

The optimization routine was utilized to calibrate the cloud cover sub-index where the percentage of cloud cover was used instead of sunshine hours to ensure consistency with the work from Scott *et al.* (2016, 2019). As outlined in Table 4-2, the optimization algorithm identified eight different cloud cover ranges and assigned sub-index scores between zero and ten. Findings are mostly consistent with those of the HCI:Beach index with two notable exceptions. First, the optimization approach assigns all cloud cover between 15% and 36.9% a score of seven whereas the HCI:Beach assigns three separated categories in this cloud cover range. This indicates that there is minimal, if any, difference in visitation based on moderate cloud cover. Similarly, between 77% and 97.9%, a single aesthetic range was identified rather than the three separate ranges in the HCI:Beach. This again underscores that visitors may not be as discerning to smaller differences in aesthetic conditions and that climatological thresholds may be more important than incremental changes.

A regression analysis between the aesthetic facet variables and visitation revealed that sunshine and cloud cover are not dominant factors for the climatological preferences of visitors to the Pinery and Sandbanks (Table 4-6 and Table 4-7). At the monthly level R^2 values between total visitors are lower at Sandbanks (R^2= 0.034, 0.039) for both per cent cloud cover and the number of sunshine hours than what is seen at the Pinery (R^2= 0.253, 0.337) for cloud cover and the number of sunshine hours, respectively. At Sandbanks, there is not strong evidence to suggest that per cent cloud cover or the number of sunshine hours has an influence on visitation to the park. This may be influenced by the distance of the park to main day trip markets, so that some cloud cover will not deter visitation, or perhaps that the world-class dune complex is an important enough attraction that the importance of typical beach activities is lower at Sandbanks.

4.5.3 Physical Facet: Precipitation

The TCI and the HCI:Beach use two different rating schemes for the precipitation component of the index (Table 4-3). The TCI has ten evenly sized ranges with one point being removed for each additional 0.50 mm of precipitation. Any day that receives more than 4.99 mm of precipitation is assigned a score of zero. The HCI:Beach has six categories, and only after 12 mm of precipitation is a zero assigned. An additional difference is the inclusion of a -1 penalty function in the HCI:Beach that is assigned on days with more than 25 mm of precipitation, an event that occurs 59 times at the Pinery and 75 times at Sandbanks over the 10-year study period. This penalty function is employed with the rationale that these high precipitation days will have an overriding effect on tourist activities (*i.e.,* even if temperature conditions are suitable, a large rain event will cause people to leave the beach or cancel their trip). In this current research, penalty functions are not permitted during the optimization routine for the same reason that a penalty function was eliminated in the temperature sub-index: the impossibility of negative (less than zero) tourists and as such, zero is the lowest score assigned to any given day.

Table 4-3. Physical facet: precipitation rating schemes

TCI		**HCI:Beach**		**Optimization**	
Rating	Precipitation (mm)	Precipitation (mm)	Rating	Precipitation (mm)	Rating
10	0.00-0.49	0	10	0	10
9	0.50-0.99				
8	1.00-1.49			0.01-1.99	5
7	1.50-1.99	0.01-2.99	9		
6	2.00-2.49				
5	2.50-2.99				
4	3.00-3.49				
3	3.50-3.99				
2	4.00-4.49	3.00-5.99	8	2.00-6.99	4
1	4.50-4.99				
		6.00-8.99	6		
0	≥5.00			7.00-8.99	3
		9.00-11.99	4		
		12.00-24.99	0	≥9.00	0
		≥25.00	-1		

As shown in Table 4-3, the optimization algorithm identified five different precipitation ranges and assigned sub-index scores between zero and ten. Findings are not consistent with those of the TCI or the HCI:Beach. While days with zero precipitation receive a score of ten, any precipitation at all is assigned a score of five or lower. This again underscores that visitors may not be as discerning to smaller difference in physical climate conditions and that precipitation thresholds may be more important than incremental changes. As shown in Table 4-6 and Table 4-7, for both daily visitors and overnight campers, the fit between all precipitation variables and visitation is less than $R^2 = 0.500$. When assessing the whole year, the spring months, and the summer months, the R^2 values are nearly all less than $R^2 = 0.100$. However, during the autumn months there is a notable improvement in fit to $R^2 = 0.212$ for the Pinery and $R^2 = 0.439$ for Sandbanks with the optimized precipitation sub-index component. This indicates that, in general, visitors during the summer months attend regardless of precipitation. However, in the autumn months as temperatures drop, there is stronger evidence that visitors may avoid visiting parks on cool and rainy days, a finding supported by Hewer *et al*. (2016). One area of future research is to explore the timing of precipitation events as evening and nighttime precipitation may not impact visitation as strongly as morning and daytime precipitation (Yu *et al.* 2009).

4.5.4 Physical Facet: Wind

The original TCI has four different rating schemes for wind (Table 4-4). Each of these four schemes, 'normal', 'trade wind', 'hot climate', and 'wind chill' has a unique rating system and the selection of which rating scheme to use is based on daily maximum temperatures. In Mieczkowski's (1985) TCI the wind chill rating system is only used when the wind speed is faster than 8 km/hr and the daily maximum temperature is below 15.0°C. Given that the purpose of this article is to assess beach tourism, the fourth wind speed rating system is excluded. The HCI:Urban advanced the development of the wind sub-index by acknowledging that temperature and aesthetics are already accounted for in other sub-indices and the inclusion of another temperature constraint in the wind index would lead to double counting of the temperature aspect of weather (Scott *et al.* 2016, 2019). As such, the HCI:Beach includes one rating scheme with eight wind speed categories and it is the sub-index from the HCI:Beach that is optimized in this study.

Table 4-4. Physical facet: wind rating schemes

TCI					HCI:Beach		Optimization	
Wind speed (km/hr)	Wind chill*	Normal (<-23.9 °C)	Trade wind (24-32.9 °C)	Hot climate (≥33 °C)	Wind speed (km/hr)	Rating	Wind speed (km/hr)	Rating
		Rating						
							= 0	8
					0-0.5	8		
≤2.88	10	10	4	4			0.1-9.4	10
2.89-5.75	9	9	5	3				
					0.6-9.9	10	9.5-18.9	5
5.76-9.03	8	8	6	2				
9.04-12.23	7	7	8	1				
					10.0-19.9	9		
12.24-19.79	6	6	10	0				
19.80-24.29	5	5	8	0			19.0-39.9	1
24.30-28.79	4	4	6	0	20.0-29.9	8		
28.80-38.51	3	3	4	0				
≥38.52	0	0	0	0	30.0-39.9	6		
					40.0-49.9	3		
							≥40.0	0
					50.0-69.9	0		
					≥70.0	-10		

* The wind chill category was not included due to the focus on beach tourism

As shown in Table 4-4, the optimization algorithm identified five different wind speed ranges and assigned sub-index scores between zero and ten. The highest rating (ten) is given to wind speeds of between 0.1 and 9.4 km/hr. The lowest ratings are for wind speeds above 40.0 km/hr whereas the HCI:Beach assigned a zero for wind speeds above 50.0 km/hr. Given the moderate R^2 values of the wind variables alone it is evident that wind is a factor for the climatological preferences of visitors to the Pinery and Sandbanks (Table 4-6 and Table 4-7). At Pinery there is an improvement in fit between the wind sub-indices and total visitation from an R^2 of 0.428 for the TCI temperature sub-index and 0.518 for the HCI:Beach, to R^2 of 0.596 for the optimized temperature sub-index. At Sandbanks, a strong relationship between wind and visitation was not found for all months of the year ($R^2 < 0.3$).

4.6 Overall Results and Discussion

Through the calibration of the sub-indices, this research makes a number of empirical advancements. First, the number of categories for the sub-indices is dramatically reduced in every instance, indicating that tourists are not as sensitive to incremental variations in weather as expert-based or stated-preference methods might suggest. This finding further underscores that tourists' sensitivity to weather is non-linear, and that a proportionately large change in visitation can result from a relatively small change in weather conditions when a key threshold is surpassed. Secondly all of the sub-indices perform better during the shoulder seasons and when all months in a year are taken into account, rather than when the summer months are explored in isolation, despite the calibration of the index on day visitors for the peak visitation period. This confirms that the July and August months are fundamentally different than the other months of the year (as argued by Jones & Scott 2006). This is true even though the weather is similar in June and September as it is in July and August, suggesting that the institutional seasonality may exert and overriding influence on visitation.

Overall, both the TCI and HCI:Beach utilize an additive approach whereby each of the sub-indices is weighted to represent the proportional impact of each climatic variable. While Mieczkowski (1985) used expert judgment and the HCI:Beach uses insights from tourists' stated preferences, the optimization algorithm using visitation data determined notably different weights for each of the sub-indices (Table 4-5). The optimization routine gave an overwhelming 75%of the index weight to the thermal comfort facet of the index, with 15% going towards the aesthetic facet and 5% to each precipitation and wind facets.

Table 4-5. Optimized beach weather components and calculation

Index component	Weather variable	TCI weight (%)	HCI:Beach weight (%)	Optimization weight (%)
Thermal comfort (TC)	Humidex Temperature (a combination of maximum daily air temperature °C and minimum daily relative humidity %)	50%	20%	75%
Aesthetic (A)	Cloud cover (%)	20%	40%	15%
Precipitation (P)	Total precipitation (mm)	20%	30%	5%
Wind (W)	Mean wind speeds (km/hr)	10%	10%	5%
Overall index score range		-30 to 100	-25 to 100	0 to 100
Index calculation for optimized index: *Index = 7.5 (TC) + 1.5(A) + 0.5(P) + 0.5(W)*				

The TCI, HCI:Beach, and optimized index scores were then calculated for each day in the 10-year study period for both Pinery and Sandbanks Parks to assess the empirical relationship between index scores and beach visitation. For each beach park, the monthly index value is the mean of daily scores. The results of the regressions are shown in Table 4-6 and Table 4-7 and illustrated in Figure 4-2 and Figure 4-3. As indicated by the R^2 values, there is good fit at the monthly levels indicating that most of the variability in beach parks visitation is explained by the index. This suggests that using an optimization routine, to determine threshold values and scores is a viable method for developing a beach parks tourism climate index.

At Pinery, the index derived through mathematical optimization has greater predictive accuracy at the monthly level than the TCI or HCI:Beach for both day use visitors and campers. The results outlined in Table 4-6 and Table 4-7 are separated by season and by visitor type. The highest fit (R^2 = 0.802) is found when the 19 autumn months are assessed for all visitors. The second highest fit (R^2 = 0.734) is found when all 126 months in the study period are assessed for all visitors. At Sandbanks, the highest fit (R^2 = 0.866) is found when the 21 spring months in the study period are used for total visitors. As shown in Figure 4-3, the optimized index is more refined at capturing the seasonality of visitation than the TCI or HCI:Beach at both Sandbanks and Pinery Parks. What is evident in Figure 4-3 is that there is enormous potential to increase visitation during

June and September where the climatic resources are only moderately less welcoming than in July and August. Potential policy implications are to encourage more visitation during these shoulder months through differential pricing and/or increasing marketing and educational group visitation to the parks during these shoulder season months.

This highlights a noteworthy finding that while all three indices perform well during the shoulder seasons and when all months in a year are taken into account, there is a consistent finding that these indices have a weak relationship with visitation during the months of July and August. This underscores the importance of other socio-cultural and institutional factors, *i.e.,* regardless of the weather during July and August, visitation is consistently high. The narrative of climatic influence is more compelling for the shoulder seasons in this study, further confirming the findings of Jones and Scott (2006) and Hewer *et al.* (2016) who found that for parks in the Great Lakes region the shoulder seasons are primarily influenced by climatic factors whereas the summer months are not. This highlights a limitation of a weather index approach that is based entirely on climate data. These indices do not account for social, cultural, economic and institutional factors that are of importance in explaining visitation patterns. Future studies may further explore these other factors in conjunction with a climate index approach through multiple linear regression or other econometric modelling techniques.

Table 4-6. Relationships between index scores and visitation at Pinery Provincial Park by visitor type and season (monthly from January 2000 to July 2010)

			Day users				Overnight campers				Total visitors			
			All year (N=126)	**Spring (n=21)**	**Summer (n=20)**	**Autumn (n=19)**	**All year (N=126)**	**Spring (n=21)**	**Summer (n=20)**	**Autumn (n=19)**	**All year (N=126)**	**Spring (n=21)**	**Summer (n=20)**	**Autumn (n=19)**
Pinery Provincial Park	**Thermal facet (T)**	Humidex °C	**0.654**	0.426	0.502	**0.731**	**0.640**	0.593	0.007	**0.686**	**0.656**	**0.626**	0.060	**0.729**
		TempTCI	0.408	0.029	0.466	**0.604**	0.441	0.067	0.006	**0.750**	0.445	0.038	0.052	**0.764**
		TempHCI:B	**0.678**	0.312	0.062	**0.767**	**0.697**	0.597	0.006	**0.805**	**0.709**	**0.603**	0.016	**0.841**
		TempOpt	**0.705**	0.310	0.260	**0.737**	**0.722**	0.590	0.021	**0.764**	**0.735**	0.596	0.062	**0.800**
	Aesthetic facet (A)	%cloud	0.365	0.205	0.088	**0.618**	0.230	0.028	0.043	0.335	0.253	0.052	0.013	0.394
		SunHrs	0.447	0.260	0.108	**0.654**	0.312	0.077	0.048	0.401	0.337	0.113	0.013	0.461
		AesTCI	0.455	0.260	0.121	**0.647**	0.317	0.078	0.048	0.401	0.342	0.114	0.012	0.460
		AesHCI:B	0.416	0.227	0.101	**0.626**	0.277	0.048	0.035	0.388	0.301	0.078	0.008	0.445
		AesOpt	0.423	0.308	0.077	**0.653**	0.291	0.052	0.050	0.417	0.315	0.090	0.018	0.475
	Physical facet: precip (P)	Prcp (mm)	0.004	0.219	0.046	0.012	0.013	0.035	0.137	0.005	0.012	0.062	0.144	0.006
		PrcpTCI	0.010	0.274	0.002	0.295	0.003	0.025	0.134	0.189	0.004	0.055	0.098	0.215
		PrcpHCI:B	0.000	0.225	0.022	0.094	0.001	0.050	0.119	0.067	0.001	0.079	0.116	0.075
		PrcpOpt	0.026	0.274	0.002	0.257	0.012	0.035	0.167	0.192	0.014	0.067	0.138	0.212
	Physical facet: wind (W)	Wind (km/hr)	0.473	0.498	0.002	0.440	0.575	0.577	0.106	0.572	0.571	**0.627**	0.078	0.579
		WindTCI	0.355	0.043	0.298	**0.742**	0.430	0.273	0.004	**0.624**	0.428	0.244	0.034	**0.676**
		WindHCI:B	0.424	0.488	0.000	0.453	0.523	0.560	0.133	0.551	0.518	**0.610**	0.105	0.563
		WindOpt	0.500	0.505	0.004	0.484	0.599	0.494	0.097	0.553	0.596	0.552	0.084	0.571
	Total Index Score	TCI	0.463	0.061	0.330	**0.777**	0.465	0.152	0.062	**0.759**	0.474	0.149	0.127	**0.802**
		HCI:Beach	**0.680**	0.472	0.030	**0.798**	**0.651**	0.482	0.065	**0.727**	**0.668**	0.535	0.034	**0.777**
		Optimized	**0.709**	0.394	0.177	**0.756**	**0.721**	**0.614**	0.002	**0.763**	**0.734**	**0.637**	0.019	**0.802**

Table 4-7. Relationships between index scores and visitation at Sandbanks Provincial Park by visitor type and season (monthly from January 2000 to July 2010)

			Day users				**Overnight campers**				**Total visitors**			
			All year (N=52)	**Spring (n=21)**	**Summer (n=20)**	**Autumn (n=9)**	**All year (N=52)**	**Spring (n=21)**	**Summer (n=20)**	**Autumn (n=9)**	**All year (N=52)**	**Spring (n=21)**	**Summer (n=20)**	**Autumn (n=9)**
Sandbanks Provincial Park	**Thermal facet (T)**	Humidex °C	**0.693**	**0.870**	0.320	0.145	**0.644**	**0.760**	0.000	0.005	**0.688**	**0.876**	0.234	0.067
		TempTCI	0.114	0.003	0.349	0.249	0.028	0.041	0.000	0.484	0.073	0.004	0.261	0.407
		TempHCI:B	0.518	**0.742**	0.079	0.275	**0.637**	**0.792**	0.130	0.116	0.578	**0.817**	0.016	0.228
		TempOpt	**0.632**	**0.802**	0.003	0.256	**0.719**	**0.837**	0.073	0.084	**0.682**	**0.874**	0.017	0.194
	Aesthetic facet (A)	%cloud	0.039	0.066	0.170	0.282	0.025	0.030	0.076	0.027	0.034	0.051	0.070	0.155
		SunHrs	0.045	0.090	0.135	0.251	0.029	0.034	0.108	0.015	0.039	0.066	0.044	0.126
		AesTCI	0.048	0.101	0.164	0.240	0.030	0.044	0.106	0.016	0.041	0.077	0.059	0.124
		AesHCI:B	0.079	0.080	0.151	0.217	0.063	0.044	0.080	0.020	0.074	0.066	0.058	0.119
		AesOpt	0.096	0.082	0.072	0.236	0.086	0.064	0.127	0.010	0.094	0.079	0.013	0.112
	Physical facet: precip (P)	Prcp (mm)	0.036	0.050	0.022	0.043	0.019	0.008	0.000	0.009	0.029	0.028	0.014	0.006
		PrcpTCI	0.037	0.031	0.006	0.477	0.027	0.000	0.146	0.104	0.034	0.010	0.036	0.320
		PrcpHCI:B	0.054	0.024	0.001	0.481	0.038	0.000	0.039	0.123	0.048	0.006	0.007	0.338
		PrcpOpt	0.029	0.054	0.001	**0.619**	0.012	0.000	0.253	0.163	0.022	0.018	0.019	0.439
	Physical facet: wind (W)	Wind (km/hr)	0.089	0.218	0.110	0.392	0.157	0.203	0.052	0.127	0.117	0.225	0.044	0.297
		WindTCI	0.191	0.417	0.010	0.002	0.250	0.592	0.020	0.000	0.219	0.526	0.017	0.001
		WindHCI:B	0.059	0.139	0.212	0.390	0.116	0.123	0.002	0.018	0.082	0.141	0.145	0.189
		WindOpt	0.051	0.188	0.172	0.489	0.109	0.173	0.013	0.078	0.074	0.193	0.102	0.303
	Total Index Score	TCI	0.038	0.021	0.357	0.554	0.002	0.101	0.028	0.362	0.018	0.053	0.317	0.541
		HCI:Beach	0.401	**0.623**	0.019	0.399	0.442	0.543	0.023	0.094	0.427	**0.626**	0.005	0.274
		Optimized	**0.610**	**0.805**	0.009	0.336	**0.691**	**0.819**	0.003	0.111	**0.657**	**0.866**	0.010	0.256

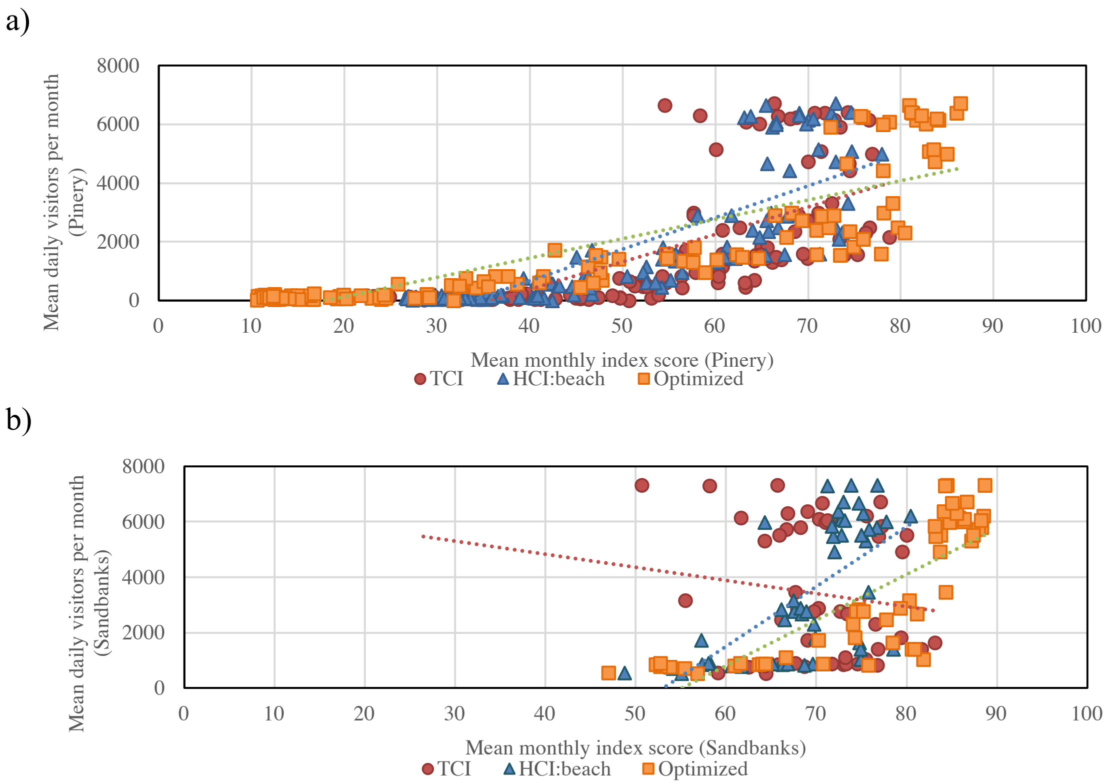


Figure 4-2. Regression plots showing the relationship between monthly level index scores and total park visitation at a) Pinery and b) Sandbanks (January 2000 to July 2010)

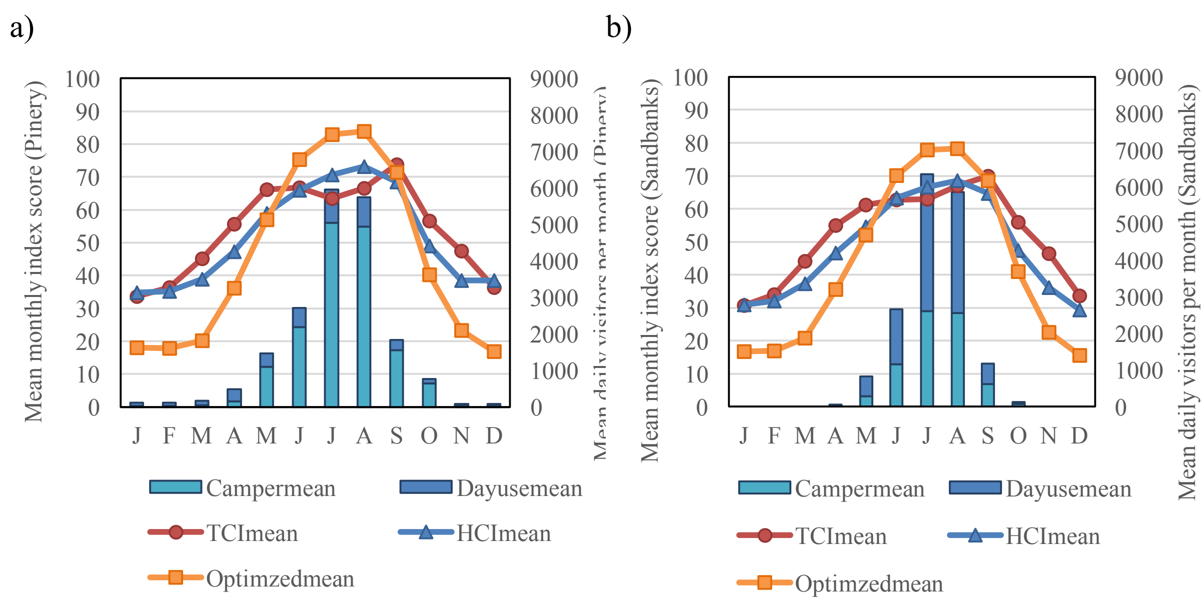


Figure 4-3. Mean daily visitation and mean monthly index scores at a) Pinery Park and b) Sandbanks Park (January 2000 to July 2010).

4.7 Conclusions

This research advances our understanding of the magnitude and seasonality of weather's effect on beach park tourism in Ontario. Here a weather translation service tool is outlined that can be utilized by tourism managers and visitors to improve weather risk management in the recreation sector. This climate-visitation index developed for Ontario beach parks makes extensive use of regularly updated weather observations from the Meteorological Service of Canada in order to create an index that can be used to describe, benchmark, and compare the appeal of weather for beach tourism in the Great Lakes region.

This research highlights that precipitation is critical in the shoulder seasons and future empirical investigations could explore seasonal refinements of the index for specific times of year and/or specific recreational activities. This research could be further improved through the use of hourly meteorological and visitation data; as the timing of climatological events and visitation is an intriguing area of future inquiry that could lend further insights into the relationship between weather and beach parks visitation. Related to this, an exploration of extreme events, such as the presence of extreme thunderstorms could be conducted. Lastly, this climate-visitation index could be an influential tool in the development of CS for the beach tourism sector in Ontario and this research enables a new approach for conducting climate change impact assessments with a focus on multiple thresholds rather than single specific temperature threshold that is commonplace in the literature. As such, the next steps are to conduct a climate change assessment to explore climate variability and change and the projected impacts on visitation at beach parks in Ontario to enable the provision of decision-relevant CS for beach parks management in Ontario.

In summary, this paper provides a methodological and empirical contribution to the tourism field by outlining a method for developing a decision relevant tourism-climate index, an index that show considerable potential to be integrated with weather and CS providers for the Ontario region. The index that has been developed for Ontario Parks meets the six criteria that were identified by de Freitas *et al.* (2008) as being necessary for an operational index. First, this study presents a theoretically sound index built on the theoretical foundations ubiquitous in the tourism research community for three decades. Secondly, the index integrates all relevant facets of climate, utilizing the same climatic variables from previous works. Third, this index is simple to calculate and understand since it is based on only four weather sub-indices, using the same premise of the extant tourism climate indices, but fine-tuned through mathematical optimization to the specific and unique context of Ontario beach parks. Fourth, this index is easy to understand as the scores are confined to a maximum score of 100, representing an ideal beach experience. Fifth, this index recognizes the overriding effect of certain weather conditions. And lastly, this index has been empirically tested and validated with actual observed visitation data; demonstrating its superior predictive abilities over existing tourism climate indices in the literature.

Chapter 5:

Developing Climate Services for Caribbean Tourism: A Comparative Analysis of Climate Push and Pull Influences Using Climate Indices

Matthews, L. Scott, D., Andrey, J., Mahon, R., Trotman, A., Burrowes, R., Charles, A. (Accepted). Developing Climate Services for Caribbean Tourism: A Comparative Analysis of Climate Push and Pull Influences Using Climate Indices, *Current Issues in Tourism.*

This manuscript has been modified for use in this dissertation

5.1 Overview

The complexity of the tourism-climate nexus and sensitivity to changing global climate conditions predicates the need to develop new CS for the tourism sector. Climate indices have a long history of use to combine multi-faceted climate information for tourism resource evaluation. Most available indices have been criticized for their subjective rating and weighting schemes and limited predictive capabilities. Traditionally, indices have been used to assess tourists' sensitivity to destination climatic pull factors, not tourists' sensitivity to source market climate as a push factor for seasonality-driven markets. Recent works have begun to explore the dual influence of push and pull climatic factors, but these studies have not been conducted in the realm of CS development to inform decision making. This study addresses this gap by using tourism climate indices to assess the influence of climatic push and pull factors for seasonal fluctuations in arrivals to Antigua and Barbuda, Barbados, and Saint Lucia, from the province of Ontario, Canada (from January 2008 to December 2017). Building on the conceptual foundation of the HCI:Beach, this study uses an optimization algorithm to develop two indices: (1) an optimized in-situ index that estimates the climatic pull-factor of the destination, and (2) an optimized ex-situ index that estimates the climatic push-factor from the source market. Findings reveal the optimized ex-situ (push) index explains 83% (R^2=0.830) of the variability in total monthly arrivals from Ontario and has greater predictive accuracy than the in-situ (pull) index. The research advances understanding of climatic influences on Caribbean tourism arrivals and provides the foundation for new seasonal forecast-based CS for destination managers and marketers. Additional analysis with other main source markets from the US, Europe, and Canada to other countries of the Caribbean is needed to advance this index and sectoral CS development in the future.

5.2 Introduction

Global tourism receipts are estimated at USD$1,260 billion (UNWTO, 2016), with USD$37 billion estimated to be spent in the Caribbean (CTO, 2018). In 2016, the World Travel and Tourism Council (WTTC) ranked the Caribbean region as the most tourism-dependent destination in the world with 14.8% of GDP in the region originating from the tourism sector (Mackay & Spencer 2017, WTTC 2016). Despite this high level of dependence on tourism, The United Nations World Tourism Organization (UNWTO) estimates slowing tourism growth for the Caribbean region through 2030 given the changing dynamics of global tourism flows and the emergence of alternative tourism markets and destinations (UNWTO 2016, Mackay & Spencer 2017). In addition to economic and political drivers, the potential impacts of global climate and environmental change are deeply concerning for the region (Laframboise *et al.* 2014, Mycoo 2018, Spencer 2019, Scott *et al.*

2019). Projected increases in sea level rise (Sweet *et al.* 2017, Nerem *et al*. 2018), ocean acidification (Albright & Langdon 2011, Weijerman *et al.* 2018), and increased intensity of hurricanes (Kossin *et al.* 2017) could all affect coastal tourism in the Caribbean region (Mackay & Spencer 2017). In fact, according to the 2019 Climate Change Vulnerability Index for Tourism (CVIT), the Caribbean region is projected to become one of the global tourism regions most highly vulnerable to climate change into the future (Scott 2019).

The influence of climate on the global and Caribbean travel and tourism systems is also well documented (Martin 2005, Scott & Lemieux 2010, Rosselló-Nadal 2014). There is significant evidence that climate stimuli have an important influence on tourist motivation (Ryan & Glendon 1998, Gössling *et al.* 2012), destination attractiveness (Steiger *et al.* 2016, Gössling *et al.* 2016), destination choice (Hamilton & Lau 2005, Scott *et al.* 2008), and seasonal tourism demand (Kulendran & Dwyer 2012, Goh 2012, Li *et al.* 2018). Studies consistently emphasize that, outside of pricing, the suitability or attractiveness of the destination is one of the most critical factors for tourist decision-making and climate is a central characteristic of attractiveness (Hamilton *et al.* 2005, Li *et al.* 2018). Much of this literature is conceptualized on the notion that climatic resources of destinations are a crucial pull factor (Goh 2012, Li *et al.* 2018). What has been less explored is the effect of origin or source market climate as a push factor for tourism patterns (Eugenio-Martin & Campos-Soria 2010, Scott & Lemieux 2010, Li *et al.* 2018). Even less explored is the dual or combined effect of destination and origin climate on tourism flows (Hamilton *et al.* 2005), an area of research that only recently is gaining attention (Chen *et al.* 2017, Li *et al.* 2018).

While it is clear that a tourists' decision-making process is influenced by climate resources at the destination, quantifying the salience and impact of this influence is less-well understood (Rutty & Scott 2016). Advancing our understanding of the seasonal and inter-annual climatic push factors and pull effects on tourist flows would enable the development of decision-relevant CS for tourism planners, managers, and marketers. In a multi-sectoral investigation of CS perspectives and priorities, Vaughan *et al.* (2016) found that a key barrier to the production of decision-relevant weather and climate information is a limited understanding of extent and ways in which weather/climate impacts specific individuals, businesses/organizations, and sectors; a finding supported by Weaver *et al.* (2013). This CS literature is an emerging area of scholarship that explores the extent to which weather and climate information is actionable for decision-makers across diverse economic sectors and professions (Kirchhoff *et al.* 2013).

In the tourism sector, there is clear evidence that climate and weather services are being used to some degree in the management of tourism operations and destinations (Scott & Lemieux 2010, Damm *et al.* 2019). Short-term weather products like warnings and alerts inform emergency management decisions, such as an impending thunderstorm or hurricane, where tourism business may opt to close facilities and implement evacuation protocols (Cahyanto *et al.* 2014). Daily to weekly forecasts can inform destination management decisions, such as when to commence snowmaking at the start of the season or a mid-season melt (Doyle 2014, Steiger *et al.* 2019). Daily to weekly forecasts also can influence tourists' decision-making (Scott & Lemieux 2010). A suite of tailored CS tools such as the Weather Channel's 'running index', 'ski index', 'golf index', and 'spectator index' can target tourism and recreation participants directly (Scott & Lemieux 2010). The long-term climate projections can inform decision-making with regards to infrastructure investments, such as whether to build a resort in a coastal area that may be at risk of changing storm surge and/or sea level rise (Bosello *et al.* 2007, Scott *et al.* 2012). However, evidence of the development and use of CS for strategic planning on seasonal or annual scales remains elusive in the tourism sector.

Notwithstanding the improved availability of weather and climate products, seasonality is consistently cited as one of the most challenging issues for tourism destinations (Scott & Lemieux 2010, Goh 2012, Li *et al.* 2018). Natural seasonality (the combined effect of temperature, precipitation, wind, sun and humidity) has long been considered one of the most significant elements that cause seasonal fluctuations in tourist flows (Butler 1998, Baum 1999, Ridderstaat *et al.* 2014, Li *et al.* 2018). Seasonality has an impact on resource and supply utilization, the marketing and pricing of tourism packages, and human resources and operational decisions at the destinations (Li *et al.* 2018). It is critical to develop methods of appropriately integrating these climatic elements into a measure that reflects the complete influence of climate on tourism demand (de Freitas *et al.* 2008, Scott *et al.* 2008, Li *et al.* 2018).

Climate indices for tourism, such as the seminal TCI or the more recent HCIs have been used as tools to evaluate the climate resources, or the climatic pull factor, of destinations (usually for the purpose of objectively comparing multiple destinations). Furthermore, these indices have been applied to numerous climate assessments and climate change impact studies by applying the index under climate projections in order to estimate future changes in climate resources for tourism (*e.g.*, Rotmans *et al.* 1994, Scott & McBoyle 2001, Scott *et al.* 2004, Amelung & Viner 2006, Amelung *et al.* 2007, Hein *et al.* 2009, Moore 2010, Amelung & Nicholls 2014, Grillakis *et al.* 2016, Jacob *et al.* 2018).

Notwithstanding the widespread application of the TCI (developed by Mieczkowski 1985), it has been criticized extensively. The most frequent criticisms being the subjective nature of the variable ranking schemes and the component weighting (Gomez-Martin 2005, de Freitas *et al.* 2008, Eugenio-Martin & Campos-Soria 2010, Scott *et al.* 2016, Dubois *et al.* 2016). Scott *et al.* (2016) further expressed concerns that there was an unjustified over-emphasis on thermal comfort. This criticism may be especially valid in Caribbean sun-sand-surf (3S) tourism, where spatial and annual variability of air temperature is much less pronounced than at higher latitudes. Furthermore, the results of the TCI are not contextual and are not tourism segment/activity specific (*i.e.*, tailored to the different climate requirements of say city, beach or mountain tourism). Mieczkowski (1985) did note that the TCI could be calibrated by modifying the rating and weighting schemes for different tourism activities, but there has been limited discussion of how this can be completed rigorously.

More recently, the HCI:Urban was introduced (Scott *et al.* 2016) to directly address several of the limitations of the TCI. The HCI:Urban overcame some limitations of the TCI by using daily level data instead of monthly level data and being tailored to a specific tourism segment (urban tourism whereby the destination is the cities and its attractions), and by establishing the rating schemes and sub-index weighting based on a comprehensive review of tourist preference and perceptions research. The specification for the HCI:Urban specification is outlined in Scott *et al.* (2016); the sub-index weighting schemes are included in Table 5-1 to Table 5-4; and the overall index calculation is outlined in Table 5-5.

This HCI:Urban index has been recently specified for beach tourism in the HCI:Beach by Scott *et al.* (2019) and Rutty *et al.* (2020) and recalibrated by Matthews *et al.* (2019) for the Canadian domestic beach parks market. The HCI:Beach uses a similar structure to the HCI:Urban but the HCI:Beach is tailored to a specific tourism segment based on the stated preferences of beach tourists (Rutty & Scott 2013, 2015). The calculation for the HCI:Beach specification is outlined in Rutty *et al.* (2020) and the sub-index weighting schemes are included in Table 5-1 to Table 5-4; and the overall index calculation is outlined in Table 5-5.

The use of these tourism climate indices has been lauded as an important piece of CS for tourism (Damm *et al.* 2019), in part due to the ability of indices to account for the integrated or combined effects of weather (de Freitas 2003). However, the limited CS for tourism literature has focused only on the use of indices as a tool to measure climatic pull of destinations. There is a need to assess the potential use of these indices to measure the climatic push factor from the source market, not solely as a unidirectional tool to assess the pull factor of a destination. Li *et al.* (2018) were the first to expand the application of these indices to assess the impact of climate as a push factor for seasonality-driven tourism markets. They found that the pull factor was stronger than the push factor for travel to different cities in China from Hong Kong. However, this analysis of climatic push factors is particularly important where the major regional tourism flows are thought to be cold climate driven (*e.g.,* North America to the Caribbean, Scandinavia and Northern continental Europe to the Mediterranean). As such, this paper will be the first study to use a data-driven tourism index approach to assess climatic push factors from a temperate region of North America to the Caribbean, with important implications for research into global tourism flows.

Furthermore, few of the indices developed to date have been empirically validated with observed tourist flows, particularly destination specific arrivals that would be of interest for CS development. Accordingly, this research will further progress the development of tourism climate indices in support of CS. If CS for tourism are to expand and improve their predictive capacity, there may be a need to re-conceptualize CS provision in the tourism sector to account for salient climate push factors, or to evaluate the use of tourism indices as a tool that can account for climatic pull factors as well as climatic push factors. This speaks to the broader necessity to develop CS for the tourism industry; where there is a need to reflect on the types and scales of weather and climate information that is important for travelers, tourism operators and marketers, and other decision makers (Scott *et al.* 2011). If climate elements, such as temperature and precipitation, are not well correlated with actual visitation, but the ex-situ climate in major source markets is strongly correlated with departures, then there is a need to foster partnerships between CS providers in different geographic locations to support international CS use. Given the highly climate-sensitive nature of Caribbean tourism, and 3S tourism globally, there is a practical need to better understand this climate-tourism nexus both in-situ and ex-situ.

There is an acute awareness of the region's vulnerability to climate variability and change. Regional tourism institutions, including the Caribbean Tourism Organization (CTO) and the Caribbean Hotel and Tourism Association, are exploring novel methodologies of integrating climate information into tourism decision-making processes to foster climate risk management. It is evident that the development, application, and integration of CS tools, particularly CS translation tools, that can be tailored to the unique contextual realities of Caribbean tourism are increasingly sought. Regional CS providers such as the Caribbean Institute for Meteorology and Hydrology (CIMH) are looking to provide this useable climate information to users. CIMH is operating as the World Meteorological Organization's-designated Regional Climate Center to promote the region-wide implementation of the Global Framework for Climate Services (CIMH 2018). Accordingly, the CTO, in partnership with the CIMH, organized this international CS research team to investigate the development of new data-driven CS tools to enable climate risk management for tourism in the Caribbean region.

The purpose of this research is to examine the capacity of climate indices for tourism (encompassing temperature, rainfall, snowfall, wind, and cloud coverage), representative of both climatic push and pull factors, to explain fluctuations in tourism demand from Ontario, Canada to three Caribbean countries (Antigua and Barbuda, Barbados, and Saint Lucia). It is hypothesized that for the mid-latitude Ontario source market, climatic push factors are more important in accounting for seasonal and inter-annual variability in arrivals than climatic pull factors at the destination. Furthermore, despite the enhancements made by the HCI:Beach, there remain areas for improvement in calibrating indices to the context-specific realities of tourism decision-making (Dubois *et al.* 2016). While Mieczkowski (1985) used expert judgment and the HCI:Urban (Scott *et al.* 2016) and HCI:Beach (Rutty *et al.* 2020) use insights from tourists' stated preferences, in this study an optimization algorithm, as applied by Matthews *et al.* (2019) to parks arrivals in Ontario, Canada, will be implemented using arrivals data to determined different weights for each of the sub-indices and for the overall index calculations.

This study has three objectives related to the tourism-climate nexus. This first is to use a mathematical optimization algorithm to refine the HCI:Beach to develop to new two indices: (1) an optimized in-situ index which estimates the climatic pull-factor of the destination, and (2) an optimized ex-situ index which estimates the climatic push-factor of the source markets. Both of these data-driven and empirically validated indices assign daily weather scores based on four weather sub-indices (thermal comfort, wind speed, precipitation, and cloud cover). These daily scores are then averaged to the monthly level and correlated to tourist flows to Antigua and Barbuda, Barbados, and Saint Lucia. This methodology identifies the climatic thresholds, and the importance of these climatic thresholds for arrivals to Caribbean tourism destinations (climatic pull factors), and departures from Ontario (climatic push factors). The second objective of this study is to compare and contrast the index structure and variable rating schemes of the newly optimized data-driven indices against three existing indices, the TCI, HCI:Urban, and HCI:Beach. The third objective is to calculate and assess the degree to which each of these indices can be used to explain variations in visitor flows from Ontario to the three Caribbean nations. This analysis of model fit using the ordinary least squares regression (R^2) provides insights into the relative importance of climatic push and pull factors as refined through a data-driven revealed preference methodology.

5.3 Data and Methods

5.3.1 Visitation Data

Monthly level visitation data for arrivals from January 2008 to December 2017 were obtained from the Caribbean Tourism Organization (CTO) for three countries in the Caribbean. These visitation data were processed from arrival declaration forms submitted by travelers upon entry to each country. Data provided by the CTO were disaggregated by country of residence and separated by residency status in the destination country. For the purposes of this research, expatriate visitors were not included in the analysis. There are some limitations to the use of these visitation data. First, these data do not capture the length of stay for each visitor or represent the nature of the visit, as they include business, family, and leisure travel, which are thought to have differential climate sensitivities. While the expatriate visitors were excluded from the analysis this does not account for second or third generation immigrants who may visit family in the Caribbean.

5.3.2 Climate Data

Weather observations for the three Caribbean study areas were obtained from the Caribbean Institute for Meteorology and Hydrology for the period of January 2008 to December 2017. Monthly climographs for the three Caribbean destinations and the Ontario source market are shown in Figure 5-1, showing strong consistency among the destinations and strong contrast to the Canadian source market. The destination observations provided at the daily level included temperature, rainfall, relative humidity, cloud cover and wind speed. Weather data for the Ontario source market region were obtained from ECCC. The Toronto

International Airport station was selected as this location is representative of the Greater Toronto Area, a metropolitan area in Ontario that is largest provincial source of outbound flights to the Caribbean region. Weather variables that are only available at the hourly resolution (wind speed, relative humidity, and cloud cover) were downloaded and computed to the daily average values. The temperature and precipitation (rainfall and snowfall) data were downloaded at the daily scale.

For an assessment of thermal comfort, the temperature and relative humidity data were combined to calculate Humidex values, a Canadian innovation used by public and private sector weather service and public heat-stress warnings (Anderson *et al.* 2013). The Canadian Humidex is used instead of other thermal indices such as Effective Temperature (ET) or Apparent Temperature (AT) because the humidex is more salient to the outbound travel market (Canada) in this study and the Humidex is thermal comfort unit provided in Canadian weather forecasts and has been used in numerous studies to assess heat exposure in Canada (Chebana 2013, Ho 2016). The Humidex is defined as:

$$\text{Humidex} = \text{Air temperature} + 0.5555 \times (6.11 \times e^{5417.7530 \times \left(\frac{1}{273.16} - \frac{1}{\text{dewpoint in kelvins}}\right)} - 10)$$

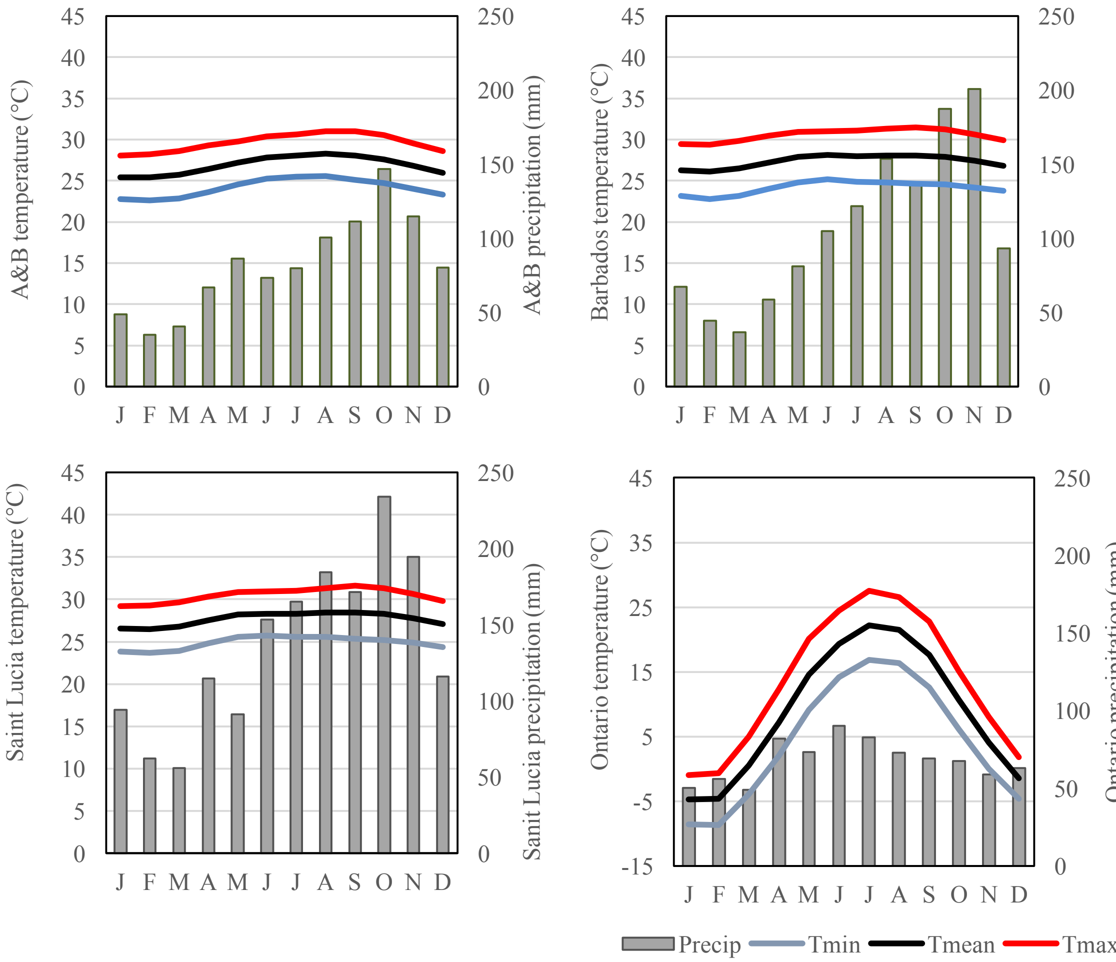


Figure 5-1. Climographs for Antigua and Barbuda, Barbados, Saint Lucia, and Ontario - Canada (January 2008 to December 2017)

5.3.3 Index Calculations

The method used in this research adapts an optimization routine developed by Matthews *et al.* (2017a,b,c) for road transport weather indices, and as applied in Matthews *et al.* (2019) for beach park visitation in Ontario, Canada. The optimization algorithm is set to maximize the fit (R^2) values between monthly tourist flows between Ontario and the three Caribbean destinations. The optimization routine utilizes the Generalized Reduced Gradient

(GRG2) algorithm that is standard in *Microsoft Excel* to simultaneously identify threshold values and sub-index scores. The algorithm was set to maximize the R^2 values between the sub-index scores, and tourism flows and is set up in such a way to allow for any number of weather variable ranges, but the sub-index scores were constrained to values between zero and ten. After each of the sub-indices are optimized, the algorithm is run again to determine the weights for each of the climatic facets. The optimization routine is run for each of the sub-indices sequentially (*i.e.*, thermal comfort, aesthetic, precipitation, and wind). These daily index scores are then averaged to create weekly, monthly, or seasonal beach tourism index scores. The resulting constants (threshold values, sub-index scores, sub-index weights) for each of the sub-indices are outlined in the following section.

For this study, the optimization is applied to develop two indices. The first in-situ index is optimized to quantify the relationship between arrivals and climate at the destination, which represents the climatic pull-factor. The method uses the average fit (R^2) between arrivals and index scores for the three Caribbean destinations individually. The second ex-situ index is optimized to quantify the relationship between the source . This ex-situ climate index is developed on the premise that there is an inverse relationship between climate rating and outbound departures – (*i.e.*, low index scores for a source market represents a higher climatic push and thus higher departures), whereas for the in-situ index there is a positive relationship between climate and arrivals (*i.e.,* low index scores represent lower pull and reflect low numbers of arrivals).

5.4 Results and Discussion

5.4.1 Optimized Index Design and Index Inter-comparison

For thermal comfort, an ordinary least squares regression analysis with monthly THumidex (°C) as the explanatory variable and monthly tourism flows as the dependent variable (January 2008 to December 2017) reveals that, for Ontario-to-Caribbean tourism, thermal comfort is a dominant pull-factor and push-factor (Table 5-6). The relationship is evident for both in-situ (pull) THumidex (°C) (R^2= 0.553, 0.462, 0.678), and ex-situ (push) THumidex (°C) (R^2= 0.639, 0.619, 0.675) for Antigua and Barbuda, Barbados, and Saint Lucia, respectively. Notably, the relationship between THumidex (°C) in Ontario and total departures to all three countries (R^2= 0.716) is stronger than the relationship between THumidex (°C) in Ontario and departures to the individual countries. As shown in Table 5-1, the optimization algorithm identified ten different thermal comfort rating categories for the in-situ index and seven different rating categories for the ex-situ index, both with sub-index scores between zero and ten. Interestingly, for the ex-situ index, the range for THumidex (°C) rated as a zero, is much broader than what was determined for any of the other indices in the literature. All temperatures below THumidex 7°C are rated as a zero, indicating that this is when most tourists depart from Ontario to these Caribbean destinations. Interestingly, temperatures above THumidex 36°C are also rated as a zero, indicating that during peak summer temperatures in Ontario, travelers continue to visit to the Caribbean. This can be explained by the confounding variable of institutional seasonality from school breaks which is not accounted for in the current analysis.

Table 5-1. Thermal comfort facet rating schemes

TCI		HCI:Beach		HCI:Urban		Pull-factor (in-situ index)		Push-factor (ex-situ index)	
Rating	THumidex (°C)	THumidex (°C)	Rating	THumidex (°C)	Rating	THumidex (°C)	Rating	THumidex (°C)	Rating
0	≥36.0	≥39.0	0	≥39.0	0	≥42.0	0		
		38.0 - 38.9	2	37.0 - 38.9	2	38.0-41.9	1	≥36.0	0
1	35.0 - 35.9	37.0 - 37.9	4						
2	34.0 - 34.9	36.0 - 36.9	5	35.0 - 36.9	4	34.0 – 37.9	2		
3	33.0 - 33.9	35.0 - 35.9	6					33.0 – 35.9	2
4	32.0 - 32.9	34.0 - 34.9	7	33.0 - 34.9	5			29.0 - 32.9	6
5	31.0 - 31.9	33.0 - 33.9	8	31.0 - 32.9	6				
6	30.0 - 30.9	31.0 - 32.9	9	29.0 - 30.9	7	26.0 - 33.9	3		
7	29.0 - 29.9	28.0 - 30.9	10	27.0 - 28.9	8			26.0 – 28.9	8
8	28.0 - 28.9	26.0 - 27.9	9	26.0 - 26.9	9				
9	27.0 - 27.9	23.0 - 25.9	7	23.0 - 25.9	10	23.0-25.9	10		
10	20.0 - 26.9	22.0 - 22.9	6	20.0 - 22.9	9	21.0-22.9	6		
9	19.0 - 19.9	21.0 - 21.9	5			20.0-20.9	5		
8	18.0 - 18.9	20.0 - 20.9	4	18.0 - 19.9	7	19.0-19.9	4	10.0 - 25.9	10
7	17.0 - 17.9	19.0 - 19.9	3	15.0 - 17.9	6	17.1 - 18.9	3		
6	16.0 - 16.9			11.0 - 14.9	5				
5	10.0 - 15.9	18.0 - 18.9	2	7.0 - 10.9	4				
4	5.0 - 9.9	17.0 - 17.9	1	0 - 6.9	3				
3	0.0 - 4.9	15.0 - 16.9	0					7.1 - 9.9	8
2	−0.1 - −5.9	10.0 - 14.9	-5	−0.1 - −5.9	2	≤17.0	0		
0	−6.0 - −10.9								
−1	−11.0 - −15.9	≤9.9	-10	≤−6.0	1				
−2	−16.0 - −20.9							≤7.0	0
−6	≤−21.0								

The aesthetic facet is the second strongest climactic factor for Caribbean-bound travelers. The ordinary least squares regression analysis with monthly cloud cover (%) as the explanatory variable and monthly tourism flows as the dependent variable (January 2008 to December 2017) reveals a relationship for both in-situ cloud cover (%) (R^2= 0.338, 0.252, 0.330), and ex-situ cloud cover (%) (R^2= 0.279, 0.226, 0.219) for Antigua and Barbuda, Barbados, and Saint Lucia, respectively. As outlined in Table 5-2, the optimization algorithm identified seven different cloud cover rating categories for the in-situ index and nine rating categories for the ex-situ index. Interestingly, the number of categories for the sub-indices is reduced suggesting that travelers may not be as sensitive to incremental fluctuations in cloud coverage as the expert-based or stated-preference based indices may suggest. Of note, Mieczkowski's TCI uses the number of sunshine hours in a day for the aesthetic factor, whereas the HCI:Beach, the HCI:Urban, and optimized indices use cloud cover (%) for calculating the aesthetic facet because of much wider international data availability.

Table 5-2. Aesthetic facet rating schemes

<table>
<tr><th colspan="3">TCI</th><th colspan="2">HCI:Beach</th><th colspan="2">HCI:Urban</th><th colspan="2">Pull-factor (in-situ index)</th><th colspan="2">Push-factor (ex-situ index)</th></tr>
<tr><th>Rating</th><th>S-hours</th><th>CC (%)*</th><th>CC (%)</th><th>Rating</th><th>CC (%)</th><th>Rating</th><th>CC (%)</th><th>Rating</th><th>CC (%)</th><th>Rating</th></tr>
<tr><td>10</td><td>10</td><td>0.0-16.6</td><td>0-0.9</td><td>8</td><td>0.0-0.9</td><td>8</td><td rowspan="2">0.0-1.9</td><td rowspan="2">9</td><td rowspan="2">0.0-1.9</td><td rowspan="2">0</td></tr>
<tr><td>9</td><td>9</td><td>16.7-24.9</td><td>1.0-14.9</td><td>9</td><td>1.0-9.9</td><td>9</td></tr>
<tr><td>8</td><td>8</td><td>25.0-33.2</td><td>15.0-25.9</td><td>10</td><td>11.0-20.9</td><td>10</td><td>2.0 -2.9</td><td>10</td><td>2.0 -2.9</td><td>5</td></tr>
<tr><td>7</td><td>7</td><td>33.3-41.6</td><td>26.0-35.9</td><td>9</td><td>21.0-30.9</td><td>9</td><td rowspan="3">3.0-56.9</td><td rowspan="3">7</td><td>3.0-14.9</td><td>4</td></tr>
<tr><td>6</td><td>6</td><td>41.7-49.9</td><td>36.0-45.9</td><td>8</td><td>31.0-40.9</td><td>8</td><td>15.0-25.9</td><td>10</td></tr>
<tr><td>5</td><td>5</td><td>50.0-58.2</td><td>46.0-55.9</td><td>7</td><td>41.0-50.9</td><td>7</td><td>26.0-36.9</td><td>7</td></tr>
<tr><td>4</td><td>4</td><td>58.3-66.6</td><td>56.0-65.9</td><td>6</td><td>51.0-60.9</td><td>6</td><td rowspan="2">57.0-77.9</td><td rowspan="2">6</td><td rowspan="2">37.0-64.9</td><td rowspan="2">3</td></tr>
<tr><td>3</td><td>3</td><td>66.7-74.9</td><td>66.0-75.9</td><td>5</td><td>61.0-70.9</td><td>5</td></tr>
<tr><td>2</td><td>2</td><td>75.0-83.2</td><td>76.0-85.9</td><td>4</td><td>71.0-80.9</td><td>4</td><td>78.0-83.9</td><td>4</td><td rowspan="2">65.0-84.9</td><td rowspan="2">2</td></tr>
<tr><td>1</td><td>1</td><td>83.3-91.6</td><td>86.0-95.9</td><td>3</td><td>81.0-90.9</td><td>3</td><td rowspan="2">84.0-97.9</td><td rowspan="2">3</td></tr>
<tr><td rowspan="2">0</td><td rowspan="2">0</td><td rowspan="2">≥91.7</td><td rowspan="2">≥96.0</td><td rowspan="2">2</td><td>91.0-99.9</td><td>2</td><td>85.0-97.9</td><td>1</td></tr>
<tr><td>100.0</td><td>1</td><td>≥98.0</td><td>0</td><td>≥98.0</td><td>0</td></tr>
</table>

*S-hours=sunshine hours; CC%= percentage of cloud cover. Sunshine hours were not available so the CC% were transformed to hours of sunshine

For the TCI, HCI:Beach, HCI:Urban and the in-situ index, total precipitation (mm) is used as the explanatory variable. However, for the ex-situ index, which represents the climate in the Ontario source market, total snowfall (cm) is used. This decision was made based on an exploratory analysis with monthly rainfall (mm) and snowfall (cm) used as explanatory variables in two ordinary least squares regression analyses, and total monthly departures from Ontario as the dependent variable for the study period (Table 5-6). These analyses found that snowfall was more strongly related with departures (R^2 = 0.434) than rainfall (R^2 = 0.275).

The relationship between arrivals in the Caribbean and precipitation at the destination is quite small with R^2 values of 0.173, 0.093, and 0.191 for Antigua and Barbuda, Barbados, and Saint Lucia, respectively. The relationship between departures and snowfall in Ontario is stronger with R^2 values of 0.396, 0.362, and 0.423 for the same three countries. Similar to the findings with temperatures, the relationship between weather and departures is strongest when calculating total departures from Ontario (R^2 =0.434). This suggests that it is perhaps less important to which Caribbean/warm weather destination one travels, and more important to escape the cold and snowy winter weather. As shown in Table 5-3, the optimization algorithm identified only four different precipitation rating categories for the in-situ index and seven rating categories for the ex-situ index. The findings for the in-situ index are quite consistent with those of the HCI:Beach and HCI:Urban, but the ex-situ index has remarkably different results, as one would expect. For the ex-situ index, days with no snow were assigned a score of zero, however the scores drop dramatically to six with even 0.1cm of snow. This indicates that even a small amount of frozen precipitation is correlated with higher departures from Ontario. In contract, the in-situ index assigned a score of ten for up to 1.9mm of precipitation, and even upwards of 9mm of precipitation was assigned a score of nine. This underscores that tourists may be more sensitive to frozen precipitation as a push-factor.

Table 5-3. Physical facet: precipitation rating schemes

TCI		**HCI:Beach**		**HCI:Urban**		**Pull-factor (in-situ index)**		**Push-factor (ex-situ index)**	
Rating	Precipitation (mm)		Rating	Precipitation (mm)	Rating	Precipitation (mm)	Rating	Snow (cm)	Rating
10	0.00-0.49	0	10	0	10	0-1.9	10	0	10
9	0.50-0.99							0.1-1.9	6
8	1.00-1.49								
7	1.50-1.99	0.01-2.99	9	0.01-2.99	9				
6	2.00-2.49								
5	2.50-2.99								
4	3.00-3.49					2.0-8.9	9	2.0-6.9	5
3	3.50-3.99								
2	4.00-4.49	3.00-5.99	8	3.00-5.99	8				
1	4.50-4.99								
								7.0-8.9	4
		6.00-8.99	6	6.00-8.99	5	9.0-12.4	6		
0	≥5.00							9.0-11.9	3
		9.00-11.99	4	9.00-11.99	2				
		12.00-24.99	0	12.00-24.99	0	≥12.5	0	12.0-24.9	5
		≥25.00	-1	≥25.00	-1			≥25.00	0

In terms of the physical wind facet, as shown in Table 5-4, the optimization algorithm identified five different wind speed rating categories for both the in-situ and ex-situ indices and assigned sub-index scores between zero and ten. The relationship between in-situ wind and arrivals to Antigua and Barbuda (R^2 =0.003), Barbados (R^2 =0.037), and Saint Lucia (R^2= 0.195) are all small. Similarly, the relationship between ex-situ wind and departures to Antigua and Barbuda (R^2 = 0.059), Barbados (R^2= 0.058), and Saint Lucia (R^2= 0.098) are all small. Given the small R^2 values of the wind variables as both a push-factor and a pull-factor it is evident that wind is not a factor for the climatological preferences of tourists to the three Caribbean nations (Table 5-6), nor is it a push factor for tourists departing Ontario. This stands in important contrast to the TCI and HCIs stated preference ratings where wind represents 10% of the index scores.

Table 5-4. Physical facet: wind rating schemes

TCI				HCI:Beach		HCI:Urban		Pull-factor (in-situ index)		Push-factor (ex-situ index)	
Wind (km/hr)	Normal (<-23.9 °C)	Trade wind (24-32.9 °C)	Hot climate (≥33 °C)	Wind (km/hr)	Rating	Wind (km/hr)	Rating	Wind (km/hr)	Rating	Wind (km/hr)	Rating
								= 0	10		
≤2.88	10	4	4	0-0.5	8	= 0	8	0.1 – 0.9	8	0-0.9	8
2.89-5.75	9	5	3								
				0.6-9.9	10	0.1 – 9.9	10	1.0-9.9	6	1-9.4	10
5.76-9.03	8	6	2								
9.04-12.23	7	8	1								
				10.0-19.9	9	10.0 – 19.9	9			9.5-18.9	5
12.24-19.79	6	10	0								
19.80-24.29	5	8	0								
24.30-28.79	4	6	0	20.0-29.9	8	20.0 - 29.9	8	10-39.9	1		
28.80-38.51	3	4	0							19.0-39.9	1
≥38.52	0	0	0	30.0-39.9	6	30.0 - 39.9	6				
				40.0-49.9	3	40.0-49.9	3				
				50.0-69.9	0	50.0-69.9	0	≥39	0	≥40.0	0
				≥70.0	-10	≥70.0	-10				

This research makes a number of empirical discoveries through the calibration of the sub-indices. First, all of the individual weather variables have a stronger relationship when exploring the relationship between weather in Ontario and departures, rather than the relationship between weather in the Caribbean and arrivals. Secondly, the relationship is strongest when assessing total departures from Ontario rather than departures to specific countries. This indicates that for seasonality-dependent source markets, it is perhaps less important where in the Caribbean one travels, it is more important for tourists to escape the harsh winter climate, regardless of specific destination.

After the calibration of the sub-indices it was then necessary to weight each of the sub-indices. While Mieczkowski (1985) used expert judgment and the HCI:Urban and HCI:Beach use insights from survey-derived tourist stated preferences, the optimization algorithm using travel data determined different weights for each of the sub-indices (Table 5-5). For the in-situ climate index, the optimization routine gave 40% of the index weight to the thermal comfort facet of the index, with 50% going towards the aesthetic facet, 10% to precipitation and no weight to the wind sub-index. This most closely matches the HCI:Beach index outlined in Rutty *et al.* (2020). For the ex-situ climate index, the optimization routine gave 55% of the index weight to the thermal comfort facet of the index, with 20% going towards the aesthetic facet, and 25% to precipitation (snow) and no weight to the wind sub-index. Interestingly, this most closely matches the Mieczkowski's (1985) TCI. Given the non-existent relationship between wind and tourism flows it is not included in the optimized index. Eugenio-Martin & Campos-Soria (2010) report similar findings in their work on traveler climate preferences for tourists in Europe and hypothesized that it may not be appropriate to include wind conditions in their model because of the large variations in wind speeds over relatively small spaces and timescales. While averaging temperatures or sunshine over larger areas was deemed more reasonable, the spatial heterogeneity of wind makes it unsuited for inclusion in such climate indices of tourism (Eugenio-Martin & Campos-Soria 2010).

Table 5-5. Comparison of beach climate index component weightings

Index component	**TCI weight (%)**	**HCI:Beach weight (%)**	**HCI:Urban weight (%)**	**Optimization weight (%) (in-situ weather)**	**Optimization weight (%) (ex-situ weather)**
Thermal comfort (TC)	50%	20%	40%	40%	55%
Aesthetic (A)	20%	40%	20%	50%	20%
Precipitation (P)	20%	30%	30%	10%	25%*
Wind (W)	10%	10%	10%	0%	0%
Overall index score range	-30 to 100	0 to 100	0 to 100	0 to 100	0 to 100
In-situ Caribbean pull-factor index = 4 (TC) + 5(A) + 1(P)					
Ex-situ Ontario push-factor index = 5.5 (TC) + 2(A) + 2.5(P)					

*for the optimized ex-situ index snowfall is used as the predictor variable instead of total precipitation.

5.4.2 Comparisons in Model Fit

The daily scores for the TCI, HCI:Urban, HCI:Beach, and optimized indices were calculated daily for the 10-year study period for the three Caribbean destinations and the Ontario source market region to explore the relationship between index scores and tourism flows (January 2008 to December 2017). For each country, the monthly index value is the mean of the daily scores and serves as the explanatory variable in the subsequent results. The results of the ordinary least squares regressions are shown in Table 5-6. As indicated by these R^2 values, there is moderate fit at the monthly level indicating that some of the variability in Caribbean visitation is explained by the climate indices, and that an improvement in fit can be achieved through the optimization approach. In the Caribbean, the in-situ index derived through optimization has greater predictive accuracy at the monthly level than the TCI, HCI:Urban, or HCI:Beach for Antigua and Barbuda (R^2= 0.629), Barbados (R^2=0.480), and Saint Lucia (R^2=0.710). The ex-situ index, representing the climatic push factor, also has greater predictive accuracy at the monthly level than the TCI, HCI:Urban, or HCI:Beach for Antigua and Barbuda (R^2= 0.703), Barbados (R^2=0.735), and Saint Lucia (R^2=0.783). When taken as a whole, the ex-situ climate index explains 83% (R^2=0.830) of the variability in total monthly departures from Ontario (*i.e.,* total departures from Ontario to the three Caribbean nations).

Table 5-6. Relationships between weather variables and visitation to three Caribbean nations from Ontario (January 2008 to December 2017)

	In-situ climate Pull-factor index			Ex-situ climate Push-factor index			
	Antigua & Barbuda	Barbados	Saint Lucia	Antigua & Barbuda	Barbados	Saint Lucia	Total departures
Thumidex-min (°C)	0.520	0.353	0.475	0.668	0.629	0.707	0.740
Thumidex-max (°C)	0.553	0.462	0.678	0.639	0.619	0.675	0.716
%cold days **	NA	NA	NA	0.511	0.433	0.579	0.553
Rain (mm)	0.173	0.093	0.191	0.290	0.209	0.275	0.275
% raindays	0.063	0.020	0.079	0.273	0.202	0.302	0.276
Snow (cm)	NA	NA	NA	0.396	0.362	0.423	0.434
% snowdays *	NA	NA	NA	0.562	0.520	0.567	0.607
% cloud	0.338	0.252	0.330	0.279	0.226	0.219	0.261
Wind	0.003	0.037	0.195	0.059	0.058	0.098	0.078
Relative Humidity (%)	0.263	0.153	0.439	0.033	0.043	0.022	0.037
TCI	0.584	0.317	0.620	0.637	0.657	0.717	0.751
HCI:Urban	0.583	0.372	0.572	0.508	0.530	0.533	0.587
HCI:Beach	0.595	0.449	0.673	0.573	0.609	0.606	0.670
Optimized	0.629	0.480	0.710	0.703	0.735	0.783	**0.830**

As shown in Figure 5-2, the optimized ex-situ index is more capable of capturing the seasonality of departures from Ontario than the TCI, HCI:Urban, or HCI:Beach at all three of the destinations. Furthermore, this inverse relationship between the source market weather and departures is stronger than the relationship between the destination weather and arrivals. This suggests two important findings. First, climate indices can be used not only to assess the climate resources at a destination, but in this seasonality-driven market they can be more effective in quantifying the climatic push-factor of the source market. The second key finding is that using an optimization routine to define threshold values and scores is a promising approach for developing a more robust market specific tourism climate index for both climatic pull-factors and climatic push-factors.

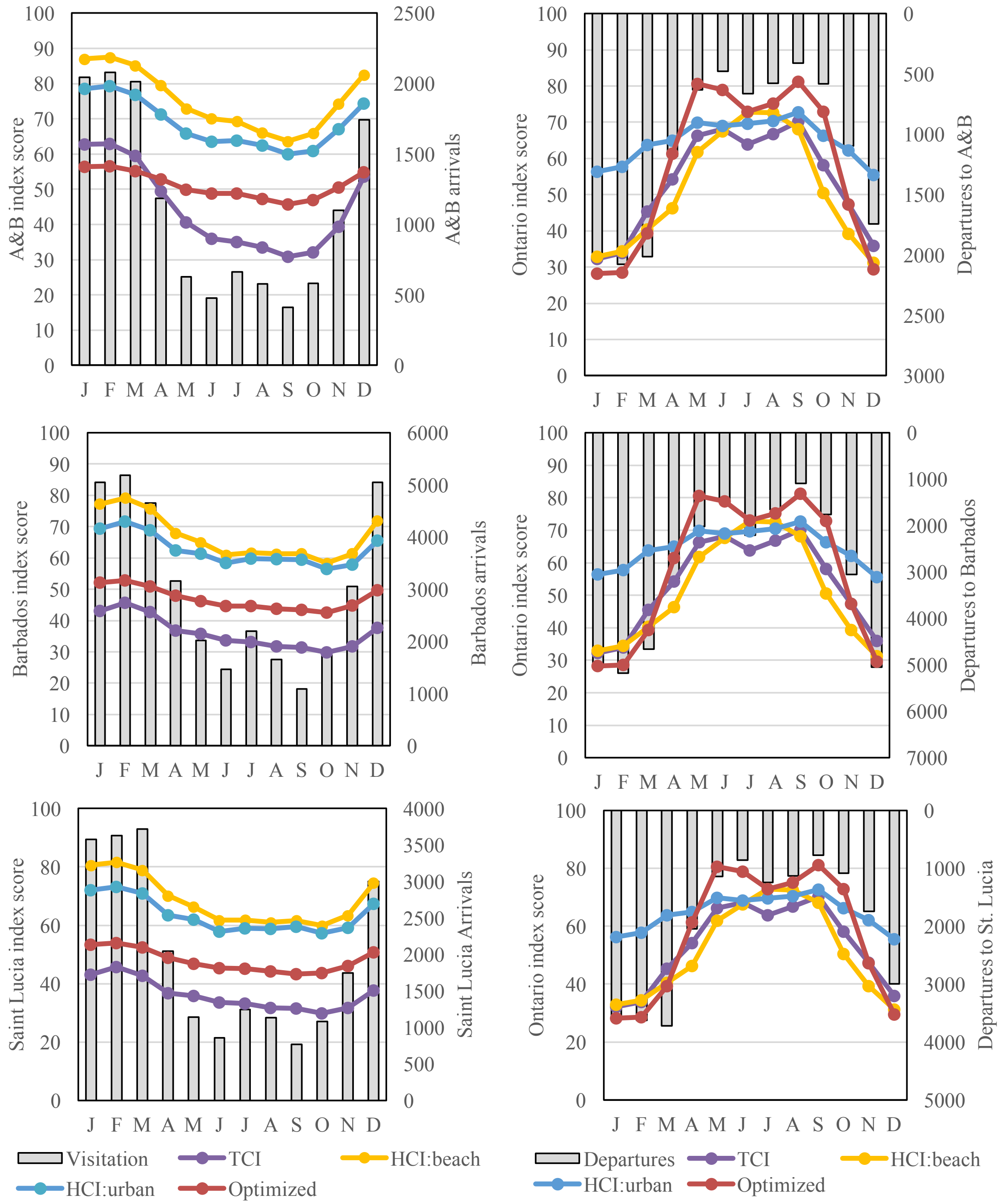


Figure 5-2. Mean monthly tourist flows and mean monthly index scores for Antigua and Barbuda, Barbados, and Saint Lucia (January 2008 to December 2017)

The relationship between individual weather variables and departures, as well as the relationship between the total index scores and departures, is strongest when exploring total departures from Ontario rather than destination-specific departures. While Figure 5-2 illustrates the dual-directional value of tourism indices for explaining the seasonality of tourism flows as a function of both the destination and source market climate, the relationship is actually strongest when total departures from Ontario are explored rather than that country-specific basis shown in Figure 5-2. Following this, Figure 5-3a demonstrates how the tourism indices can better capture the seasonality of total departures to the Caribbean from Ontario. Furthermore, Figure 5-3a illustrates how the optimized index has the closest relationship with departures – making progress towards the development of a usable CS tools for tourism decision-making. Similarly, Figure 5-3b displays the relationship between individual weather variables and departures from Ontario. Figure 5-3b evidently illustrates that while individual weather variables have a weak relationship with departures, the integrated effects of the variables have a considerably stronger relationship with 83% of the variability in departures explained by the optimized ex-situ index.

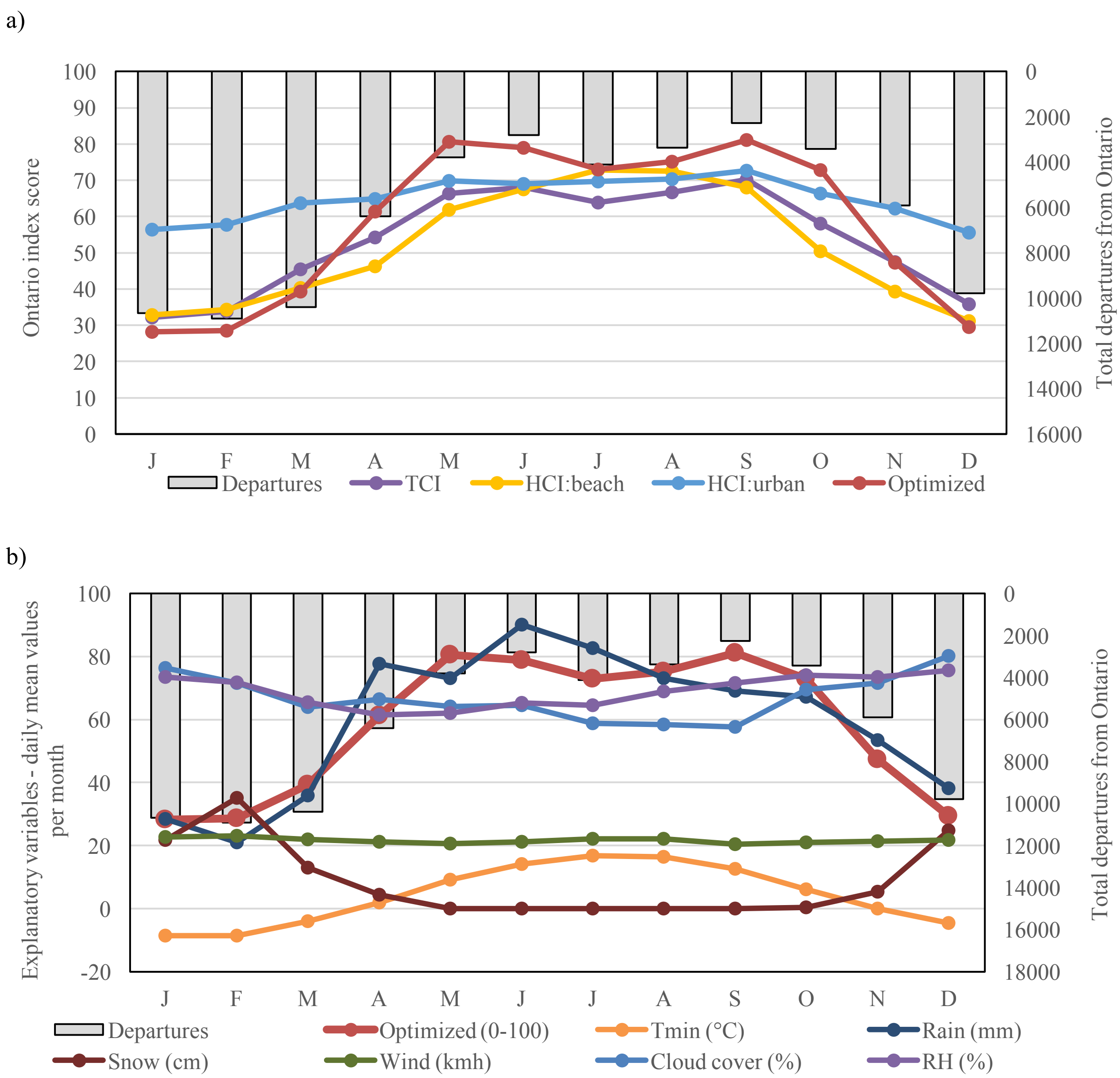


Figure 5-3. Depiction of a) mean monthly departures from Ontario and mean monthly index scores for the ex-situ TCI, HCI:Urban, HCI:Beach and optimized index; and b) the relationship between individual weather parameters and mean monthly departures from Ontario.

Despite this strong relationship between total departures and the optimized ex-situ index, there are large residuals that occur during the months of November and March. For November, the optimized ex-situ index predicts that departures should be greater than what has actually been observed. The opposite is found in March where the optimized ex-situ index predicts that departures should be less than what was observed. There are a number of possible explanations for this. First, there could be a time lag in decision-making or a degree of cumulative impact of winter weather that occurs before some Ontarians decide travel south. Second, for the March residuals this could be due to institutional factors such as the spring break holiday that occurs in March for Ontario schools. Third, for the November residuals, the lower than expected departures could also be a response to the higher possibility of extreme weather events at the destinations (*i.e.,* hurricane season). These higher residuals in the months of March and November do highlight a limitation of a weather index approach for tourism - the singular focus on daily weather data; there are a multitude climatic events that occur on different temporal scales that may exert an influence on tourists' travel behaviours. The singular focus on daily level data which is then aggregated to weekly, monthly, seasonal, or annual scales neglects to account for low frequency high-impact weather events.

5.5 Conclusion

Tourism climate indices are lauded for their application to observational, present, near future, and long-term weather and climate products (Rosselló-Nadal 2014). Importantly, Damm *et al.* (2019) promote the use of tailored climate information, including the TCI, as an important tool for CS provision in the tourism sector. However, the results from this research draw attention to two fundamental limitations with the conceptualization of the TCI and of other generic climate indices for tourism in the provision of CS. First, the

TCI, and most extant tourism climate indices, are conceptualized to assess the climatic pull factor, or the climate resources, of the destination. A novel innovation is to invert these tourism climate indices to measure the push factor from the source market. A second limitation of the extant indices is that they have not been empirically validated against visitation data (*i.e.*, revealed preference).

While indices such as the HCI:Urban and HCI:Beach make progress towards developing activity-specific climatic indices based on stated tourist climate preferences and thresholds, these are not mathematically defined or calibrated to either the activity or regional tourism arrivals data that would facilitate CS development. However, revealed preference methodologies are also imperfect for study of tourists' sensitivity to climate given the bias introduced from institutional seasonality, economic, and political factors that are imbedded in these data. In exploring these two limitations of the extant tourism indices, this study reveals three principal conclusions.

First, for the source market of Ontario, Canada there is a stronger relationship between the source market climate and departures than there is between the destination market climate and arrivals. If a similar relationship holds for other temperate climate source markets across Canada and the northern US and European latitudes, this research indicates that information about the source market climate may be more important for destination managers in the Caribbean for strategic planning than the in-situ climate. While nearly all tourism weather indices developed to date have used indices to assess climatic resources at the destination (Mieczkowski 1985, Rotmans *et al.* 1994, Scott & McBoyle 2001, Scott *et al.* 2004, Amelung & Viner 2006, Amelung *et al.* 2007, Hein *et al.* 2009, Amelung & Nicholls

2014, Scott *et al.* 2016), this research provides groundbreaking evidence that it is the impact of climatic push factors that are more important in predicting tourist flows in the Caribbean. Further, the use of tourism indices, especially when empirically calibrated, are an effective measure of climatic push factors. Therefore, the provision of CS for the tourism sector needs to be re-conceptualized to account for tourists' sensitivity to climatic push factors both on their own and in combination with destination characteristics. If long-term trends in climate for the Caribbean for in-situ variables such as temperature and precipitation are not correlated with actual visitation, but the ex-situ climate is more strongly correlated with departures, then there is a need to foster relationship building between CS providers in different geographic locations to support CS use.

Second, this research finds that the original TCI has the lowest predictive accuracy, as measured by R^2, relative to the HCI:Urban, HCI:Beach or the optimized indices for both in-situ and ex-situ analyses. This highlights a fundamental limitation with using the TCI as a fit-for-purpose CS tool – the information elucidated from the TCI is not tailored to the unique decision-making arrangements or impacts on the locations in question. This has important implications for climate change impact assessments in the tourism sector that have utilized the TCI and applied the TCI to climate change projections (Amelung & Viner 2006, Amelung & Nicholls 2014, Grillakis *et al.* 2016, Jacob *et al.* 2018). If the TCI is not reflective of actual tourism activities in a particular location, then its application to climate change projections perpetuates the uncertainty in future projections of impacts on the tourism sector. Accordingly, for destination or activity-specific decision-making there is a necessity to tailor the CS tools to the contextual realities of this unique climate-tourism nexus. Even if organizations continue to explore the development of in-situ climatic indices for tourism, then there is a need to calibrate the indices to the unique context of a given sector and region in order to develop tailored CS translation tools.

Third, a notable finding of this research reveals that the sub-index weights and rating schemes can be mathematically optimized to improve model fit with tourism flows, whether as push factors or pull factors. This research clearly shows that an improved understanding of tourists' sensitivity to climate, and improved CS for tourism more broadly, will depend less on the weight of the climatic elements, and more on the thresholds within the sub-index rating categories. To date, none of the tourism indices have been data driven in either their weighting of climate parameters, but especially in the establishment of thresholds within the sub-indices; a limitation of the existing approaches (Eugenio-Martin & Campos-Soria 2010).

A number of future research directions emanate from the findings. First, the influence of hurricane season avoidance is an intriguing area of future inquiry. Research has been conducted on tourist's responses to hurricane exposure (Villegas *et al.* 2013, Laframboise *et al.* 2014, Cahyanto *et al*. 2014, 2016), yet the influence of hurricane risk on decision-making weeks or months in advance has not been studied extensively. This is an important area of future research, especially in light of the continually evolving accuracy of seasonal hurricane forecasts that may have an increasing influence on traveler's decisions of when and whether to travel to the Caribbean during the hurricane season. Furthermore, the Caribbean is a region-wide tourism destination and it is unknown whether high-impact events on one island may impact visitation on adjacent islands that may have been included in the hurricane forecast zone. It is unknown whether these high-impact events in the Caribbean would result in a decrease in total departures from Ontario or perhaps a transfer from the affected destination to an alternative, unaffected destination in the Caribbean.

A second area of future research to further the development of CS for the tourism sector could explore other main Caribbean tourism source markets such as the United States, European nations, and other regions of Canada. This second area of research would allow for a deeper exploration of the optimization approach for different source markets visiting the same destinations. This could be further extended to explore of 3S destinations. While a crucial strength for market and activity-specific CS development, the generalizability of these data-driven indices could be limited. Future research, however, can explore whether similar rating schemes emerge for other destinations and source markets that might provide broader guidance on adjustments to the broader resource rating indices in the literature. Thirdly, the indices presented in this paper do not account for economic, social, cultural, promotional, and institutional influences that are of significance in explaining visitation patterns. An exploration of other source markets and destination should further explore these other factors, possibly in conjunction with a tourism climate index approach. Fourth, in the drive for decision-relevant and real-time decision support tools, particularly the use of artificial intelligence, which are promising given the ability of these algorithms to model travel flows in a way that allows for the differential timescales of the predictor weather variables and multiple temporal lags for decision-making (Wu *et al.* 2017).

Overall, this paper provides a contribution to the tourism and CS fields by describing a method and approach for developing a decision relevant climate-tourism index. This study utilized a mathematical optimization algorithm to refine the HCI:Beach to develop two new indices: the optimized in-situ index which estimates the climatic pull-factor of the destination, and the optimized ex-situ index which estimates the climatic push-factor of the source markets. The results indicate that the seasonal importance of climatic pull factors in the three Caribbean nations is not as strong as the influence of climatic push factors on the seasonal distributions of tourism demand from Ontario, Canada. In the Caribbean, the in-situ index derived through mathematical optimization has greater predictive accuracy at the monthly level than the TCI, HCI:Urban, or the HCI:Beach. Furthermore, the optimized ex-situ index, representing the climatic push factor, has greater predictive accuracy than any of the in-situ indices, including the optimized in-situ index. When taken as a whole, the optimized ex-situ climate index explains 83% (R^2=0.830) of the variability in total monthly departures from Ontario. This study improves our knowledge of the degree and seasonality of climactic pull and push factors on Caribbean visitation and outlines a CS tool that can be used to by tourism marketers and destination managers to inform strategic decision-making.

Chapter 6:

Dissertation Summary and Conclusions

This dissertation focuses on two climate-sensitive sectors with specific interest paid to the issues of planning for snow and ice control in the transport sector, and modelling tourist flows in the tourism sector. Collectively, the four manuscripts lend novel and important insights into the development of climate indices as a CS tool with detailed attention paid to the concepts of thresholds, timescales, transferability, usability and fit. This summary and conclusions chapter commences with a synopsis of important findings and is followed by a discussion of the scholarly and practical implications of these findings; future research directions; and concluding remarks. The scholarly benefit of this research is its contribution to an understanding of the climatic thresholds at which individuals and organizations respond to weather and climate stimuli. The practical benefit of this research is that it is intended to increase the level of climate risk management across sectors and outlines a framework for CS tool development that can inform decision making.

6.1 Study Synopsis

Geographers have long been interested in sensitivity, vulnerability, and risk to environmental change (Barnett *et al.* 2008), and the complexity of the human-environment system predicates the need for tools and methods that can consolidate information to support decision-making. Indices are a category of such tools that are used to simplify multifaceted information about the outcome of a process or the state of a phenomenon. They are particularly valuable because of the multiple ways in which they capture societal sensitivities to external climatic conditions. The purpose of an index is to provide decision-makers with easily usable, interpretable, and credible information in relation to a given objective (Malkina-Pykh 2000). While originally developed for the social sciences (e.g., GDP, World Corruption Index, Cost of Living Index, Government Stability Index), indices are used extensively in a variety of contexts (Jones & Andrey 2007). In the natural sciences, climatological indices such as the UV index, air quality index, humidex, and the drought index have all been developed and applied internationally (Vicente-Serrano & López-Moreno 2005, van den Elshout *et al.* 2014, Spinoni *et al*. 2015, Zhang *et al*. 2016). There has also been an array of thermal comfort and stress indices developed to explain the thermal relationship between weather and the human body (Fanger 1970, Steadman 1979, Kalkstein & Valimont 1986, Anderson *et al.* 2013). In the context of environmental studies, there has been an especially intense interest in the development of indices that explore the spatial patterns of vulnerability to natural hazards (Odeh 2002, Cutter *et al.* 2003, Chakraborty *et al.* 2005, Cutter & Finch 2008, Jones & Andrey 2007).

Climate indices are a specific subset of environmental indices with a unique set of characteristics that look to explore specific climate-society sensitivities. Further, there have been various efforts since the 1990s to develop indices that can be applied to climate change projections in order to obtain an estimate of projected impacts. However, the development and application of climate indices to inform decision-making as a CS tool is still in the early stages, with a number of limitations to be overcome.

With specific regard to climate indices, Eugenio-Martin & Campos-Soria (2010) identified the establishment of non-subjective thresholds as one of the greatest challenges in index development and in researching climate-society sensitivities more broadly. This perspective is shared by Kovats *et al.* (2005) and Lorenzoni *et al.* (2005) who contend that scientific explorations of climatic thresholds for societal and economic studies in climate adaptation planning are an impossible endeavor because of the complexity in human and social responses to climatic stimuli. The non-linearity and non-transferability of human and societal responses to weather/climatic stimuli have posed conceptual and methodological challenges in part due to the difficulty of establishing climatic thresholds for climate-society interactions (Kovats *et al.* 2005, Lorenzoni *et al.* 2005, Eugenio-Martin & Campos-Soria 2010, Fellman 2012). Furthermore, while the demand for climate indices is unequivocal in the transportation and tourism contexts, many of the weather and climate indices developed to date have only been empirically validated against actual societal responses in areas where societal response data have been available (*e.g.,* expenditures, hours, visitors) and, as such, have not been able to illuminate the ways in which thresholds are linked to societal impacts.

Following this, a unifying approach to index development that works across systems and sectors and works for both individual decisions and decisions in the context of institutional structures had yet emerge. Accordingly, this dissertation explores a framework for improved index construction that improves fit, improves usability, is understandable, and addresses some of the core challenges faced by weather, climate, and society scholars in these sectors. Specifically, this dissertation explores whether a framework for CS tool development could be used to first, identify multiple societal thresholds of sensitivity; and second be applied to data products at multiple timescales. Furthermore, this dissertation assessed whether the same framework for index development can work for different agencies, making diverse decisions, in two separate sectors.

6.1.1 Climate Indices for Transportation

Tools such as WSIs can enable road authorities and maintenance practitioners to plan, communicate, manage, and assess WRM practices and expenditures (Carmichael *et al.* 2004, McCullouch *et al.* 2004, Walker *et al.* 2019). A WSI can be used to explore how specific weather conditions translate into higher or lower than average maintenance costs on a variety of temporal scales (Nixon & Qui 2005), and WSIs can be used to anticipate the probable resource requirements based on forecasted weather conditions (Strong & Shvetsov 2006). Strong and Shvetsov (2006) recommend that WSIs can be used as a public communication tool and disseminated through traditional media to warn drivers of the severity of the weather. WSIs have only recently been used to explore the possible implications of climate change (Matthews *et al.* 2017c). Carmichael *et al.* 2004 outline the diverse ways in which WSI can be operationalized for road authorities:

> "*The winter weather index will be used by the IADOT to judge how well all maintenance personnel performed statewide during each winter season. The index will estimate what costs should have been incurred, along with the amount of hours that should have been spent treating roads. The index can be used on smaller scales to identify particular regions (or even garages) that were particularly efficient or perhaps could benefit from additional training. Those garages that performed well could be highlighted and their practices used as a guide for training procedures. Systematic deviations from the index values over periods of several years could indicate more efficient techniques being used statewide or identify policy changes that may have been more costly than expected*."

- Carmichael *et al.* (2004, p. 1790)

The development of WRM indices has been dominated by the geographers working closely with the engineering community and more than 20 WSIs have been developed and used throughout North America and Europe since the 1980s. The most widely cited WSI is the SHRP index (Boselly *et al*. 1993) which was proposed by the US Strategic Highway Research Program. Many of these early WSIs reported good model fit; however, many of these models did not perform well when transferred to other geographic areas, even after they had been locally calibrated (McCullouch *et al.* 2004). Accordingly, Objective 1 of this dissertation sought to develop a WSI that works well in predicting WRM activity (as measured by equipment hours) across space and time in the provincial jurisdiction of Ontario, Canada using daily level data that can be linked to discrete weather events. This research was furthered in Objective 2 through an empirical extension that applies a modified and daily level WSI to climate products at multiple timescales.

6.1.1.1 Objective 1 Synopsis

Road authorities are facing mounting pressure to use their resources efficiently and to demonstrate the value and efficacy of their WRM services through performance measures. Road authorities are seeking tools that can explain temporal and spatial variations in WRM activities due to weather. These tools are required to communicate within the road authority but also as a communication tool for public stakeholders. The WSI developed for Objective 1 addresses many of the characteristics that are required for a useful and usable WSI.

The first manuscript describes an approach for developing a context-specific WSI for use in WRM decision-making using RWIS data. The conceptualization of the WSI is simple:

each day (24-hour period) is allocated a score that denotes winter weather severity in a way that communicates WRM activities. These scores are then aggregated to the reporting-period (14 days), monthly, or seasonal level and are correlated against maintenance activity as measured by maintenance equipment hours.

This approach is similar to previous index studies (*e.g.,* Rissel & Scott 1985, Andrey *et al.* 2001, McCullouch *et al.* 2004); however, the assignment of scores was conducted in a novel way. An optimization algorithm was used to simultaneously calibrate weather-attribute thresholds and scores in such a way as to reveal the specific maintenance requirements in the province. This approach has the benefit of being locally calibrated to reflect the MTO's unique sensitivity to winter weather. The WSI was then used to quantify temporal and spatial variations in WRM behaviours across a sizable and diverse geographic region. Ontario is approximately one million square km in size (Baldwin *et al.* 2000) and is home to 20 unique AMCs, each with a different contractor. Despite this variability, the resulting WSI substantiates the feasibility of developing WSIs that has similarly high levels of fit (as measured by R^2) for diverse climatic regions and maintenance regimes, indicating limited spatial bias in the WSI. The vast majority of seasons in this study have a fit above 0.800. At the provincial level, the WSI works extremely well with an R^2 between 0.959 and 0.989 over seven seasons.

This broad spatial transferability across the province of Ontario indicates that the WSI is a useful tool for explaining WRM activities due to weather in future seasons. In fact, the MTO is currently calculating and disseminating daily, 14-day, monthly, and annual WSI scores through their online WRM portal. The WSI is communicated to WRM managers, recorded as part of the historical RWIS record, and communicated on the provincial website for public announcement.

The WSI developed for Objective 1 can be applied in numerous ways to support highway operations. This WSI can facilitate informed decision-making by clearly calculating the connection between winter conditions and WRM and can be useful in at least three practical ways. First, the WSI can be used as a tracking mechanism that quantifies and compares winter severity over space and time. Secondly, this WSI supports road authorities in clearly communicating winter weather severity to the public and other stakeholders in relation to observed levels of service. Further to this, significant deviations from historical WSI scores can detect unusually severe or unusually mild winter seasons which can inform the allocation of performance and/or salt expense bonuses. Lastly, the WSI also could be used to design maintenance contracts; maintenance contracts in the province of Ontario are often in excess of ten years long. Therefore, an understanding of historical climatic norms and projections of future winter weather severity can enable informed contract establishment.

6.1.1.2 Objective 2 Synopsis

The second manuscript of the dissertation addresses explores the feasibility of developing and applying a data-driven WSI for climate change impact assessment that relies on publicly available and open access weather observation data. Open access data is an important attribute of CS development (Hewitt *et al.* 2012) and ensures transparency and accessibility for stakeholders and other researchers and practitioners. The redevelopment of the WSI from Objective 1 was applied to 30 years of observed weather data for the 20 AMCs to assess whether there are any detectable trends and their significance in the severity of winter weather conditions as measured by the WSI.

Findings from the historical analysis reveal that winters have changed, but the magnitude and direction of these trends varies geographically. The results indicate that 13 AMCs experienced a negative trend in winter severity, five AMCs show a positive trend in winter severity, and two AMCs showed no trend. However, the MK statistic reveals that only two of these locations show a statistically significant decreasing trend at the 95% confidence interval. However, the results from the climate change assessment suggest that winters will become decreasingly severe into the future.

When the WSI was computed for the modelled climate data from the four climate experiments, the results indicate that there will be a net benefit for the province of Ontario. Despite projections of increasing total precipitation, the warmer temperatures are projected to result in much less precipitation falling as snowfall. Because a substantial portion of WRM expenditures and equipment hours are allocated to snow removal, it is anticipated that there will be a net benefit for WRM expenditures in Ontario. Based on the average of the four climate experiments, it is estimated that seasonal demand for WRM activities, as measured by the WSI scores, will decrease by -15.3% to -38.6% for the 2050s with a province-wide mean decrease of -25.1%. Overall, the empirical results from the second manuscript increases our scholarly understanding of climate change on WRM, and how these projections of climate change will have differential impacts both spatially across the 20 maintenance jurisdictions in Ontario, and temporally over three future time periods into the end of the century.

More broadly, this manuscript also describes the role and nature of co-production of CS in the context of Ontario's WRM planning. This work was conducted in an effort to support evidence-based decision-making for WRM planning. While this particular WSI was co-produced and user driven in its inception, the use of this data-driven WSI for WRM climate change adaptation has yet to be explored. However, the WSI meets a number of the criteria previously identified as valuable for the development of climate translation services. First, this climatic index is based on a limited number of variables which are easy to understand and the resulting index scores are salient for the CS users (Vaughan & Dessai 2014). Additionally, this second manuscript describes the development of a climate index that can be used and applied to both historical and future weather and climate products, an important attribute of useable CS (Vaughan *et al.* 2016, Damm *et al.* 2019).

A crucial role of climate translation services is to effectively contextualize weather and climate information in such a way as to correlate with the climatic risks and sensitivities (Cash *et al.* 2006, Damm *et al.* 2019). Accordingly, the high coefficients of determination (R^2) between reporting-period level WSI scores and reporting-period level equipment-hours are another indication that this approach to climate index development is a promising direction for climate translation services. The R^2 values range from 0.607 (2012-13) to 0.990 (2010-11) with average annual R^2 value (R^2 values for each AMC-season averaged) being 0.874, which indicates that on average 87.4% of the variability in 14-day reporting period equipment-hours in the 20 Ontario AMCs is explained by the WSI over the course of seven years. Lastly, the WSI is transferable over space, a fourth criteria for useful and usable CS.

There are consistently high levels of fit across the large and diverse geographic area that is the province of Ontario.

6.1.2 Climate Indices for Tourism

Climate indices for tourism have been used extensively to assess the climatic resources of a destination and to objectively compare the climatic resources between destinations. In the context of 3S tourism, it is the integrated or combined effects of weather that are essential to tourist preferences and satisfaction (de Freitas 2003). Consequently, an index approach that integrates the multi-faceted nature of climatic influence is appropriate. A generally applicable index can serve as an efficient means to assess climate change impacts across temporal and spatial scales (Scott *et al.* 2016). However, the tourism climate indices published to date have not been predictive of tourist flows and, as such, their utility as a tourism CS tool has been uncertain as the relationship between climatic influence and actual tourist activity is not clearly defined. While the extant indices have not been predictive in their conceptualization, these indices have been developed with the intention of informing decision-making processes to some degree. For example, de Freitas *et al.* (2008) state that an index could be used by tourism operators to plan when and where to hold activities and promotions, and could be used in the resort planning stages to estimate potential visitor numbers (de Freitas *et al.* 2008).

While there has been much debate in the tourism climatology literature on using indices for local decision making and informing destination marketing, operations, *etc.* (de

Freitas *et al.* 2008); as it stands, existing indices are sometimes too coarse in resolution and do not provide sufficient actionable information to trigger an actual response or adaptation.

Furthermore, nearly all of the tourism indices to date have focused on the tourism pull factors of a destination or the climatic assets at that destination, and little work has been done to develop a tourism push factor index for areas where tourists are leaving due to unfavourable winter weather as well as being drawn to certain climatic conditions. There is potential in the tourism industry to explore the value and use of context-specific indices for climate risk management. Specifically, there is value in empirically validating indices against visitation or expenditures in an effort to develop actionable CS for the tourism sector as they relate to the influence of climate as a push and pull factor for tourist decision-making.

6.1.2.1 Objective 3 Synopsis

The third manuscript of this dissertation explores the feasibility of developing a data-driven and empirically validated tourism climate index for Ontario Provincial Parks. Methodologically, the goal of this research was to explore whether the framework developed in Objective 1 and refined in Objective 2 was transferrable to the tourism sector in an effort to identify the climatic thresholds, and the importance of these thresholds, for beach parks visitation in Ontario.

The first aim of this paper was to conduct an empirical validation and critical assessment of two existing indices, the TCI and the HCI:Beach as they apply to two provincial parks in Ontario, Canada. In this analysis it was found that the HCI:Beach has stronger fit with visitation (R^2=0.668, 0.427) than the TCI (R^2= 0.474, 0.018) at both Pinery

Provincial Park and Sandbanks Provincial Park. This is unsurprising as the HCI:Beach was developed specifically for the beach tourism segment (Scott *et al.* 2019), whereas the TCI uses monthly level data and is not market segment or activity specific.

The second aim of this research was to recalibrate the HCI:Beach index using the methods developed in Objective 1 and refined in Objective 2. This was accomplished in an effort to identify the climatic thresholds, and the importance of these thresholds, for beach parks visitation in Ontario using revealed preference data (park visitation). Additionally, an empirical aim of this research was to examine the differential climate sensitivities between two tourism segments: day visitors and overnight campers at two unique geographic regions within a single provincial parks system in Canada.

The index optimized for beach parks visitation demonstrates the strongest fit with observed visitation (R^2=0.734, 0.657), outperforming both the TCI and HCI:Beach. This manuscript provides a methodological and empirical contribution to the study of tourism climatology by describing the design of a method for producing a decision relevant climate translation tool for beach parks tourism.

The data-driven index created in this research demonstrates substantial potential for being integrated with weather and CS providers for Ontario Parks. Most importantly, this research provides critical insights into climatic thresholds for beach parks users in Ontario and can be used to assist decision-makers in reducing climate risk by identifying climatic thresholds of importance for the management and operations of the parks. This study furthers our understanding of the influence and seasonality of weather on beach tourist visitation and can increase the capability of decision-makers to perform climate risk management.

6.1.2.2 Objective 4 Synopsis

The fourth manuscript of this dissertation explores the transferability of developing a data-driven tourism climate index for international tourism flows between two climatically diverse regions (Ontario, Canada and the Caribbean). The purpose of this final manuscript was to extend the application of climate indices to explore the historical relationship between intra- and extra- regional climate and Caribbean tourist arrivals using a data-driven climate index approach developed and refined in Objectives 1 to 3.

The first aim of this paper was to extend the work from Objective 3, which identified climatic pull-factors for shorter term tourism decision-making (day trips) and apply the methodology for longer-term decision making (travelling to the Caribbean). This manuscript recalibrated the HCI:Beach using the methods developed in Objective 1 and refined in Objective 2 and Objective 3 in order to identify the climatic thresholds, and the importance of these climatic thresholds for arrivals to Caribbean tourism destinations (climatic pull factors). Findings reveal that because the climate in the destination market is climatically steady throughout the year (very little seasonal fluctuations in climate elements), there was an insignificant relationship between the in-situ climate and tourist arrivals. However, the in-situ index derived through optimization did have greater predictive accuracy at the monthly level than the TCI, HCI:Urban, or HCI:Beach for Antigua and Barbuda (R^2= 0.629), Barbados (R^2=0.480), and Saint Lucia (R^2=0.710).

The second aim of this manuscript was to explore the role of source market (ex-situ) climate as a push factor for tourists from Ontario, Canada. Despite the extensive use of climate indices for tourism to assess the climatic resources of a destination, they have rarely utilized to assess the climate push factor for seasonality-driven markets (Li *et al.* 2018). This study addressed this gap by using an index-based approach to assess the influence of climatic push factors for seasonal fluctuations in arrivals to the Caribbean from Ontario, Canada. The optimized ex-situ index, representing the climatic push factor, is found to have greater predictive accuracy at the monthly level than the TCI, HCI:Urban, or HCI:Beach for Antigua and Barbuda (R^2= 0.703), Barbados (R^2=0.735), and Saint Lucia (R^2=0.783). When taken as a whole, the ex-situ climate index explains 83% (R^2=0.830) of the variability in total monthly departures from Ontario to the Caribbean.

The implications of this research are twofold. First, this research illustrates that for the tourists travelling from Ontario to the Caribbean there is a stronger relationship between the source market climate and departures than there is between the destination market climate and arrivals. As such, this research indicates that information about the source market climate may be more important for destination managers in the Caribbean for strategic planning than the in-situ climate. Secondly, this research again establishes that the use of context-specific and data-driven indices are an effective measure of climatic influence on tourists. This research advances the scientific understanding of climatic influences on Caribbean tourism and provides the foundation for new seasonal forecast based CS for destination managers and marketers.

6.2 Reflections and Opportunities for Future Research

Flexible climate indices provide a unique avenue to explore weather and climate sensitivity across sectors and scales. Furthermore, if integrated within the CS landscape, tools such as climate indices can enable the efficient translation of weather phenomena into societal responses. These have the potential to transform the knowledge landscape of the ways in which climatic stimuli impacts individuals, businesses, and government organizations more broadly. This dissertation addresses the complex interaction between climatic stimuli and societal responses to these stimuli by focusing on the development of context-specific and data-driven climate indices, which are still in their infancy. Although there is a plethora of studies that demonstrate the importance of the transportation- and tourism-climate nexus, few studies have focused on the development of a practical and applied CS tool for climate risk management. Accordingly, opportunities for future research are plentiful. There are a number of potential lines of inquiry that can contribute to an improved understanding of weather and CS and their role in climate risk management. With a vision of supporting evidence-based decision-making for climate risk management and the advancement of CS more broadly, numerous areas for future explorations are outlined below.

First, it is acknowledged that in order for scientific information to be used by decision makers the information needs to be understood and credible. Lemos and Morehouse (2005) contend that the usability of scientific information is affected by three related factors: *quality, fit, and interplay*. The quality of the information relates to the credibility and scientific rigor of the information. Fit relates to how well the information provided meets the needs of the individuals or institutions using the information. Lastly, interplay relates to how well the produced information can be integrated with the existing decision-making frameworks currently used by an organization. The four manuscripts presented in this dissertation make significant progress towards achieving these goals. All four manuscripts provide scientific rigour, and the resulting indices have high fit with the societal responses explored.

Future studies could foster further dialogue with CS users to assess the role of interplay through an assessment of CS user needs. There is a need to understand their needs with regard to usability and value of CS products and services. Although it is widely acknowledged that institutions use and need CS, there have not been many studies to date that explicitly investigate the means by which these products are obtained, how they are being used, and how valuable these products and services are for their organization. CS scholarship may benefit from a more comprehensive study to obtain a richer understanding of the uses and values of these CS. This could be done through surveys, workshops, and interviews with CS users. This will create the foundation for subsequent research into developing tools and techniques that can enable an efficient and salient translation of weather and climate products for the contextual realities of different decision-making environments.

6.2.1 Future Areas of Research for the Transportation Sector

Exploring flexible climate indices as a tool that can quickly and accurately create location-specific and activity-specific indicators of weather sensitivity is a promising academic and practical endeavor. Consistent with the findings from a climate change assessment of WRM in British Columbia, Canada (Matthews *et al.* 2017c), this dissertation also finds that climate change is projected to result in a net benefit for WRM Ontario. While this dissertation provides strong evidence that flexible climate indices are an important tool for climate risk management for WRM in the transportation sector, it remains to be seen whether this framework can be applied to other facets of the transportation system such as road safety, traffic demand management modelling, or pavement deterioration .

Transportation infrastructure, planning, and maintenance are all sensitive to climatic stimuli in a variety of complex ways (Koetse & Rietveld 2009, Markolf *et al.* 2019). This is particularly pertinent for transportation infrastructures that are constructed for multi-decadal lifespans that will be exposed to changing climatic conditions (Eisenack *et al.* 2012, Schweikert *et al.* 2014, Markolf *et al.* 2019). Accordingly, there are significant expenses that may be accumulated through inadequate design and management of these transportation features and as such there is a need to further integrate CS into the design and management of transportation services and infrastructure (Koetse & Rietveld, 2009, Mills *et al.* 2009, Hambly *et al.* 2013, Stamos *et al.* 2015, Jacobsen *et al.* 2016).

The findings from the second manuscript confirm that Ontario is projected to experience a warming trend into the future. This warming trend may be of specific concern for road authorities, construction companies, and maintenance organizations in all warming climates. One area of particular concern is related to pavement performance during high heat events. Future research could explore the projected impacts of high heat stress on asphalt performance under climate change (Mills *et al*. 2007, Fletcher *et al.* 2016). Identifying the specific thresholds of extreme heat that result in a disproportionate or rapid deterioration of the pavement could aid road authorities, construction companies, and maintenance organizations in planning for and implementing anticipatory adaptations (Chinowsky *et al.* 2013).

An additional facet of the transportation system that has been long researched in the transportation-climate nexus is the field of road safety. There is considerable evidence that rainfall and snowfall increase the frequency and seriousness of collisions (Andrey & Olley 1990, Andrey & Yagar 1993, Andrey 2010, Jaroszweski & McNamara 2014, Mills *et al.* 2019). Moreover, assessments of climate change and road safety from diverse jurisdictions (Andersson & Chapman 2011, Hambly 2011, Hambly *et al.* 2013, Amin *et al.* 2014), reveal that increasing trends in precipitation may result in increased collision rates. While it has been long established that rainfall and snowfall increase the risk of road collisions, the precise thresholds at which the relative risk of collisions increases is unknown. This is an area of potential research that may be of interest to road authorities and insurance companies (Husnjak *et al.* 2015, Fan & Wang 2017). Determining the specific thresholds of rain or snowfall that results in disproportionate increases in collisions could aid road authorities in implementing variable speed limits (Lee *et al.* 2006, Liu *et al.* 2015), in initiating road closures (Jacobsen *et al.* 2016, Frauenfelder *et al.* 2017), and inform the pricing of telematics insurance that is customized for each vehicle trip (Husnjak *et al.* 2015, Fan & Wang 2017).

6.2.2 Future Areas of Research for the Tourism Sector

This dissertation further demonstrates that predictive climate indices are attainable for both domestic and international tourism, however the transferability to other facets of the tourism sector such as winter tourism, urban tourism, mountain tourism, remains to be explored. Activity-specific indices such as those developed for skiing, golfing, or running are calculated and promoted by companies such as the Weather Channel, but these indices do not take into account geographic variations in participants' climatic perceptions, preferences, and thresholds to participating in these activities (Scott & Lemieux 2010). Furthermore, these rating systems remain a black box and their scientific basis and validation remain unknown (Scott & Lemieux 2010).

Accordingly, while manuscript four explores the relationship between source market climate and departures to three Caribbean nations, next steps could include an extension to other Canadian source markets. The development of CS in this context would allow for destination management to potentially alter future pricing based on the climatic push-pull factors for diverse geographic source markets. More importantly from a vulnerability perspective, the current approach does not include an analysis of hurricane impacts on Caribbean tourism. The WTTC (2016) has identified hurricane damages and lost revenues from these major tropical storms as a critical for Caribbean tourism. Future research could examine the impact of both direct landfalls and near landfalls for destinations that may have been in the hurricane warning zone. An important piece of this investigation could explore whether travelers cancel their trips in their entirety, or whether there is an amount of intra-regional substitution to other unaffected destinations in the Caribbean region. Lastly, with this improved information about thresholds, a reassessment of climate change impacts on the tourism sector in the Caribbean, and other winter getaway destinations, is required and there is a clear obligation to tailor this information to the contextual realities of each unique climate-tourism nexus.

More broadly, there is the potential to advance CS scholarship in the use of climate indices to other sectors such as energy use, water use, or public health impacts. Exploring the potential for flexible climate indices to serve as a weather and climate translation service in a variety of applications is an important avenue for further the development and application of CS. Moreover, there is a need to explore the ways in which flexible indices can be used in conjunction with data products at multiple timescale. While the second manuscript applied the WRM WSI to climate change projections, the application of data-driven indices for climate change assessments in the tourism sector has not been conducted to date. Future research could conduct an evaluation of how climate indices are used and valued in practice by organizations after they have been developed for specific applications. Understanding the roles and applications of these indices in both individual and institutional decision-making for a variety of timescales is an intriguing line of inquiry for the future.

6.3 Concluding Remarks

Collectively, the four manuscripts that comprise this dissertation provide compelling evidence that a data-driven and flexible framework approach to climate index development is an important tool in the climate risk management toolbox. A crucial role of CS providers is to operate as a translator to effectively contextualize weather and climate information in such a way as to correlate with the risks and opportunities for these sectors (Cash *et al.* 2006, Damm *et al.* 2019). Translation service providers develop tailor-made information to connect the scientific community and the climate information users. The challenge is for these CS organizations to develop a system that enables the creation of *salient* weather and climate information that can be understood and used by decision makers (Kirchhoff *et al.* 2013). In order to further the development of CS, investigations of climate and society interactions must embrace the variability, complexity, and uncertainty of these context-dependent relationships. Part of embracing this contextual variability and complexity can be accomplished through an exploration of the multiple climatic thresholds for a combination of atmospheric events at which there is an increasing or decreasing response in behaviours and actions.

CS are important for both weather risk management and climate change adaptation and the information provided by tailored CS products can be used to inform policy, planning, and decision-making (Goddard *et al.* 2010). However, societal responses to climatic stimuli vary geographically and temporally and, as such, there is a necessity to develop metrics that can be calibrated geographically, and updated periodically, to better reflect the particular society-environment interaction in question as these climate-society relationships evolve over time. The challenge for researchers and practitioners is to consider the decision-response timescales and ensure that the timescale of the explanatory variables in the index development aligns the timescale of decisions. Developing tools that are effective for multiple timescales of application and can be applied to products and services that are used at different temporal scales (*i.e.*, near-term forecasts, mid-range, seasonal, and multi-decadal projections) is an important continuing need in the CS field as decision makers continue to grapple with the multiple sources of uncertainty inherent in long-term decision making.

Related to the difficulty of developing a framework for CS tool development that works across temporal scales is the challenge of developing a framework that enables tool development that can lend insights into both individual decision-making as well as organizational and institutional decision-making. The processes that govern decision-making in these contexts are fundamentally different. In the context of tourism, individual travelers are actively seeking experiences, and can select to travel at any undefined time in the future. However, in the context of WRM, organizations are mandated to respond to climatic stimuli for risk reduction on an immediate timescale. Furthermore, within road maintenance organizations, individual drivers and maintenance managers have the agency to adjust how maintenance is performed. These are two fundamentally different contexts with different actors, operating on different timescales, and responding to climatic stimuli in variable and complex ways. This solicits a novel scholarly question of whether a framework for CS tool development can be created in such a way that works for both individual decisions and decisions in the context of organizational structures across two disparate sectors. The evidence presented in this dissertation suggests that a framework for CS development can achieve these goals.

Based on these considerations, the four manuscripts that comprise this dissertation were designed to demonstrate that these conceptual challenges can be addressed through the use of data-driven climatic indices. Further, in addition to the overarching conceptual and methodological contributions, this dissertation makes a number of empirical contributions that can be used to inform decision-making in a variety of contexts. The scholarly benefit of this research is its contribution to an understanding of the varying and multiple thresholds at which individuals and institutions respond to climatic stimuli and the degree to which this response can be captured through a data-driven index-based approach.

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Glossary

Climate: “climate in a narrow sense is usually defined as the average weather, or more rigorously, as the statistical description in terms of the mean and variability of relevant quantities over a period of time ranging from months to thousands or millions of years. The classical period for averaging these variables is 30 years, as defined by the World Meteorological Organization. The relevant quantities are most often surface variables such as temperature, precipitation and wind. Climate in a wider sense is the state, including a statistical description, of the climate system” (IPCC 2018, p. 544).

Climate Services (CS): “may be defined as providing scientifically based information and products that enhance users’ knowledge and understanding about the impacts of climate on their decisions and actions. These services are made most effective through collaboration between providers and users” (AMS 2015).

Climate Services (CS) – Basic Services: “those services delivered at public expense to discharge a government’s sovereign responsibility for protection of life and property, for the general safety and well-being of the national community and for provision for the essential information needs of future generations” (Anderson *et al.* 2015, p. 19).

Climate Services (CS) – Special Services (climate translation services): “those services beyond the basic services aimed at meeting the needs of specific users and user groups and that may include provision of specialized data and publications, their interpretation, distribution and dissemination. Many services, particularly special services, often go well beyond the simple dissemination of information to include consultative advice or scientific investigation into particular meteorological and hydrological phenomena and events or their impacts” (Anderson *et al.* 2015, p. 19).

Climate Service (CS) Users: “employ climate information and knowledge for decision making; they may or may not participate in developing the service itself. In some cases, climate information users may also pass information along to others, making them both users and providers” (Vaughan & Dessai 2014, p. 588).

Climate Service (CS) Providers: “supply climate information and knowledge. Climate service providers may operate on international, national, regional, or local levels and in a range of different sectors; they may be public or private, or some mixture of both” (Vaughan & Dessai 2014, p. 588).

Climatic Thresholds: deals with the establishment and measurement of climatic thresholds within a particular societal context, defining a threshold value for a climatic variable, or a combination of climatic variables (temperature, humidity, wind, etc.) that play a key role in modulating human action or behaviour (adapted from Meze-Hausken 2008, p. 300).

Exposure: “the presence of people, livelihoods, species or ecosystems, environmental functions, services, and resources, infrastructure, or economic, social, or cultural assets in places and settings that could be adversely affected” (IPCC 2018, p. 549).

Index: An index is intended to measure that which cannot be measured by common units of measurement (such as mm of precipitation). The purpose of an index is to provide decision-makers with easily usable, interpretable, and credible information that integrates multiple facets of climatic conditions in relation to a given objective.

Risk: “the potential for adverse consequences where something of value is at stake and where the occurrence and degree of an outcome is uncertain. In the context of the assessment of climate impacts, the term risk is often used to refer to the potential for adverse consequences of a climate-related hazard, or of adaptation or mitigation responses to such a hazard, on lives, livelihoods, health and well-being, ecosystems and species, economic, social and cultural assets, services (including ecosystem services), and infrastructure. Risk results from the interaction of vulnerability (of the affected system), its exposure over time (to the hazard), as well as the (climate-related) hazard and the likelihood of its occurrence" (IPCC 2018, p. 557).

Sensitivity: "the degree to which a system is affected, either adversely or beneficially, by climate-related stimuli" (IPCC, 2001).

Threshold: "a threshold is defined with respect to a causal stimulus and an exposure unit exhibiting a response to that stimulus. When the stimulus exceeds a certain point or value, the exposure unit reacts, and no longer functions in its usual way, either for a given time or with respect to certain elements" (Meze-Hausken 2008, p. 302).

Tourism: "Refers to the activity of visitors" (UNWTO 2008, p. 10).

Visitor: "A visitor is a traveller taking a trip to a main destination outside his/her usual environment, for less than a year, for any main purpose (business, leisure or other personal purpose) other than to be employed by a resident entity in the country or place visited" (UNWTO 2008, p. 10). "A visitor (domestic, inbound or outbound) is classified as a tourist (or overnight visitor), if his/her trip includes an overnight stay, or as a same-day visitor (or excursionist) otherwise" (UNWTO 2008, p. 10).

Vulnerability: "the propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt" (IPCC 2018, 560).

Winter Road Maintenance (WRM): WRM involves prevention and clearing of snow and ice from roads (*e.g.*, plowing) and using materials to improve pavement friction (*e.g.*, salt, de-icers, sand, aggregate).