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A Framework for Integrating Climate Change Information with Low Flow Estimation Methods for Ontario Streams

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Executive Summary

In many parts of the world, freshwater resources are coming under stress due to increasing population, economic development activities and construction of dams and reservoirs to meet various societal needs. Alteration of natural river flow regimes due to the influence of anthropogenic activities has serious implications for aquatic, riparian, and wetland ecosystems. These pressures and activities are increasing overtime and therefore it is important to ensure river sustainability, integrity of associated ecosystems, and the well-being of humans who depend on the river for their livelihoods. These targets can be achieved by maintaining sufficient flows in the river during low flow periods so that the river can continue to provide all of its services. Freshwater resources are not only under stress due to the above mentioned pressures, they have also become susceptible to climate change. This is an emerging threat, which has drawn considerable attention from around the world and is also the main topic of this report. Among several impacts of climate change on low and high flow characteristics and seasonal water availabilities, it may also impact stream water temperatures and chemistry, as well as oxygen and nutrient contents of streams during low flow periods. Thus, the physical habitat of streams is also at risk due to future climate change.

Climate change is expected to prolong and intensify droughts (i.e. extreme low flow periods) and exacerbate precipitation storms resulting in severe flooding. Droughts embed in slowly and steadily, destroy livelihoods due to severe impacts on agriculture, impact aquatic life due to reduced availability of water and higher temperatures, and harm regional economies due to cascading impacts from various sectors of society. Floods cause immediate turmoil, destroy infrastructure and remobilize debris, including chemical toxins. Thus, appropriate actionable science needs to be generated to support climate change adaptation measures and avoid substantial social and economic risks of inaction.

This report does not attempt to answer what the future will bring in Ontario streams, but tries to develop a framework based on guidance from the literature regarding how climate change can be integrated with low flow estimation methods. A clear guidance on the estimation of future low flows to support actionable adaptation strategies has been lacking. This report presents a systematic framework for integrating climate change information available from global and regional climate models with low flow estimation methods.

In Ontario, low flow analyses were conducted in 1990 using observational data, until the year 1986, from over 340 gauging locations and a software package developed by Inland Waters Directorate (currently Water Survey of Canada) of Environment and Climate Change Canada. As the software has become obsolete and there is roughly 35 years of additional data, the Ministry of Environment, Conservation and Parks (MECP) desired to have the software redeveloped using a present day programming language and a user-friendly interface, and all associated reports to be updated. The specific deliverables of the project were identified as: (1) an updated low flow frequency analysis (LFFA) software, (2) a report pertaining to LFFA of Ontario streams using

most recent data, (3) a documented review of regional LFFA techniques, and (4) development of a framework for integrating future climate change with low flow estimation procedures. The National Research Council Canada (NRC) led this effort through an inter-departmental agreement between the MECP and NRC. This report is the fourth deliverable in the above list and it specifically presents a framework for integrating climate change information with low flow estimation procedures for Ontario streams based on guidance from the literature.

This report is divided into four chapters and a section on references. Some general information and insights on the potential impacts of climate change on extreme weather events such as droughts and floods and how they impact riverine ecosystems is provided in Chapter 1, along with the basic information on frequency analysis procedures involved in the derivation of low flow indices, which are commonly used in Canadian jurisdictions. Objectives and limitations of the report are also discussed in this chapter. Since this report is related to the impacts of climate change on low flow indices, a basic introduction to the topic of climate change, emissions scenarios, global and regional climate models, post-processing techniques often used in climate change related studies, and modelling and projection related uncertainties are covered in Chapter 2. The information provided in this chapter is useful for the reader to understand the material covered in Chapter 3 on the development of a framework for integrating climate change information with low flow analyses. Two broad avenues have been identified for developing projected changes to low flow indices. One is based on regional statistical relationships that are often used in ungauged hydrology and the second stems from the use of process-based hydrological modelling, which is routinely practiced to simulate long sequences of streamflow for water resources management related projects. The developed framework can be used in future studies to estimate projected changes to low flow indices based on transient climate change simulations available from global and regional climate models. The final chapter, Chapter 4, explores avenues of future research, and discusses potential recommendations and steps to be followed for developing future low flow estimates for Ontario’s streams, rivers and creeks in the context of a changing climate. A list of references cited is available at the end of the report.

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List of Acronyms

Acronym	Description
AD	Anderson-Darling
AIC	Akaike Information Criterion
AMT	Annual Mean Temperature
AMP	Annual Mean Precipitation
AMS	Annual Mean Snowfall,
ANN	Artificial Neural Network
AR3	Third Assessment Report of IPCC
AR4	Fourth Assessment Report of IPCC
AR5	Fifth Assessment Report of IPCC
BCCA	Bias Correction Constructed Analogues
BCSD	Bias Corrected Spatial Disaggregation
BIC	Bayesian Information Criterion
CCA	Canonical Correlation Analysis
CCCS	Canadian Centre for Climate Services
CI	Climate Imprint delta method
CMIP5	Climate Model Inter-comparison Phase 5
CMIP6	Climate Model Inter-comparison Phase 6
CPMs	Convection Permitting Models
DA	Drainage Area
FDC	Flow Duration Curve
GCM	Global Climate Model
GHG	Greenhouse Gases
GLM	Generalized Linear Model
IAHS	International Association of Hydrological Sciences
IPCC	Intergovernmental Panel on Climate Change
KS	Kolmogorov-Smirnov
LARS-WG	Long Ashton Research Station Weather Generator
LFFA	Low Flow Frequency Analysis
MAF	Mean Annual Flood
MBS	Mean Basin Slope
MCL	Main Channel Length
MCS	Main Channel Slope
MECP	Ministry of Environment, Conservation and Parks
NRC	National Research Council Canada
OCRE	Ocean, Coastal and River Engineering
PCA	Principal Component Analysis
PF	Percent Area Covered by Forests
PWB	Percent Area Occupied by Waterbodies
RCM	Regional Climate Model
RCPs	Representative Concentration Pathways
ROI	Region of Influence
SD	Statistical Downscaling
SRES	Special Report on Emissions Scenarios

SSPs	Shared Socioeconomic Pathways
TLFN	Time-Lagged Feed-Forward Neural Network
VIC	Variable Infiltration Capacity model
VIF	Variance Inflation Factor
WG	Weather Generator
WMO	World Meteorological Organization

1 Introduction

1.1 Background

Ever increasing population, economic development targets and construction of dams and reservoirs put lot of pressure on freshwater resources of a region. Alteration of natural river flow regimes due to anthropogenic influences has serious implications for aquatic, riparian and wetland ecosystems. These pressures and freshwater demands are increasing overtime and therefore it is important to ensure river sustainability, integrity of associated ecosystems, and the well-being of humans who depend on the river for their livelihoods. These targets can be achieved by maintaining sufficient flows in the river during low flow periods. This has given rise to low flow hydrology, a specialized area of hydrologic science which is popular among engineers, ecologists, and environmentalists. Globally, the majority of rivers is ungauged, i.e. no quantitative information on flow magnitudes exist for these rivers. Therefore, to satisfy tenacious societal needs and to generate quantitative information on river flows at ungauged locations along a river, hydrologists have developed regional regression equations, either in a global manner or within the framework of hydrologic regionalization, by relating indicators of low flow conditions with watershed attributes. The low flow indicators are generally derived using statistical frequency analysis procedures or obtained from flow duration curves (FDCs). Watershed attributes could include some descriptors of physiography, climate, and geology of a given watershed. These tasks generally fall within the realm of ungauged hydrology, which is another important area of hydrologic science. Freshwater resources are not only under stress due to the aforementioned pressures, they have also become susceptible to climate change. This is an emerging threat, which has drawn considerable attention from around the world and is also the main topic of this report. Among other impacts, climate change may also impact stream water temperatures and chemistry and oxygen and/or nutrient contents. Thus, the physical habitat of streams is also at risk due to future climate change (IPCC, 2013).

Climate change is expected to prolong and intensify droughts (i.e. extreme low flow periods) and exacerbate precipitation storms resulting in severe flooding. Droughts embed in slowly and steadily, destroy livelihoods due to severe impacts on agriculture, impact aquatic life due to reduced availability of water and higher temperatures, and harm regional economies due to cascading impacts from various sectors. It is generally understood that after a prolonged drought disaster, severe lack of vegetation in the region leaves a heightened risk of rapid runoff and movement of contaminants for at least sometime until the vegetal cover re-establishes. Floods cause immediate turmoil, destroy infrastructure, and remobilize debris, including chemical toxins. Therefore, appropriate actionable science needs to be generated to support timely decision-making and to avoid the social and economic risks of inaction.

The present report does not attempt to answer what the future will bring in Ontario streams, but tries to develop a framework based on guidance from the literature regarding how climate change can be integrated with low flow estimation methods. Climate change is not uniform across space and time and therefore calls for an integrated interdisciplinary approach, collaborating with communities and sectors which will be disproportionately affected by climate change.

At present, a clear guidance on the estimation of future low flows for Ontario streams in a changing climate is lacking, limiting the development of actionable adaptation strategies. This report presents a systematic framework for integrating climate change information available from global and regional climate models (i.e. GCMs and RCMs) with low flow estimation methods. The report also highlights the need and scale of interdisciplinary collaborations that the watershed management authorities have to undertake to help foster a climate-resilient future for Ontario streams.

Low flow analysis procedures generally pertain to establishing a relationship between low flow magnitudes and their frequency of occurrences using a statistical approach and long-term observational records. This procedure is commonly known as low flow frequency analysis, which helps estimate streamflow quantities like 7Q20, 7Q10 or 7Q2, which are among the commonly used low flow indices in Canadian and US jurisdictions. The 7Q20 flow is the average 7-day low flow magnitude corresponding to 20-year return period and, in a similar manner, 7Q10 or 7Q2 can also be defined. The frequency analysis can be performed at a single site or at the level of a specific region of interest. The main purpose of the latter analysis is to improve the quality of selected low flow indices at gauged locations and to facilitate a framework for estimating the same indices at ungauged locations within the same region. In the literature on low flow hydrology, this approach is generally referred to as regional low flow frequency analysis. Some of the approaches for estimating low flow indices at individual sites within the regionalization framework at gauged and ungauged locations is covered in a companion report (Khaliq, 2021). In addition to the above indices, some studies use specific percentiles or exceedance points of FDCs to characterise low flow regimes of a stream. A FDC quantifies the percentage of time a particular value of flow in a river equalled or exceeded over a given period of time. An example of a low flow index often derived from a FDC is Q95, which is the flow that is exceeded 95% of the time over the period of record used in developing the FDC. This index is commonly used in European countries to characterize low flow conditions. Hereafter, all indicators of low flow conditions mentioned above are referred to as low flow indices, which is a generic term.

In Ontario, low flow analyses were conducted in 1990 using observational data, until the year 1986, from over 340 gauging locations and a software package developed by Inland Waters Directorate (currently Water Survey of Canada) of Environment and Climate Change Canada. As the software has become obsolete overtime and there is roughly 35 years of additional data, the MECP desired to have the software redeveloped using a present day programming language and a user-friendly interface, and all associated reports to be updated. The specific deliverables of the project were identified as: (1) an updated low flow frequency analysis (LFFA) software, (2) a report pertaining to LFFA of Ontario streams using most recent data, (3) a documented review of regional LFFA techniques, and (4) development of a framework for integrating future climate change with low flow estimation procedures. The National Research Council Canada (NRC) led this effort through an inter-departmental agreement between the MECP and the NRC. This report specifically presents a framework for integrating climate change information with low flow estimation procedures for Ontario streams based on guidance from the literature. In doing so, two broad avenues are identified for developing projected changes to low flow indices. One is based on regional statistical relationships that are often used in ungauged hydrology and the second stems from the use of process-based hydrological modelling, which is routinely employed to simulate long sequences of streamflow for water resources design and management related projects.

All low flow indices mentioned above are estimated using recorded streamflow data and assuming a stationary climate. Due to the impending climate change as projected by GCMs and documented in various reports of the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2007, 2013, 2018), the assumption of a stationary climate has become questionable and therefore the applicability of low flow indices, derived from recorded historical observations, and their transposition at ungauged locations under the assumption of stationarity, has also become questionable. Given the significance of climate change impacts on various sectors of the society and riverine ecosystems, it is important to understand how low flow indices will evolve in response to future climate change. Therefore, as pointed out earlier, the focus of this report is to develop a systematic framework that can be used in future studies to estimate projected changes to low flow indices based on transient climate change information available from global and regional climate models.

1.2 Objectives

The objectives of this report were to:

- Develop a systematic framework for integrating climate change information available from climate models with low flow estimation procedures in order to derive projected changes to low flow indices for Ontario streams;
- Document strengths and weaknesses of the approaches included in the framework, based on insights gained from the literature; and
- Layout future directions for the research required to be undertaken for estimating future low flows, thus enabling the MECP to deliver superior services to Ontarians.

1.3 Organization of the Report

This report is divided into four chapters, including this introduction chapter, and a section on references. Some general information on the potential impacts of climate change on extreme weather events such as droughts and floods and how they impact riverine ecosystems is provided in Chapter 1, along with the basic information on frequency analysis procedures involved in the derivation of low flow indices, which are commonly used in Canadian jurisdictions. Objectives and limitations of the report are also discussed in this chapter. Since this report is related to the impacts of climate change on low flow indices, some basic introduction to the topic of climate change, emissions scenarios, global and regional climate models, post-processing techniques often used in climate change related studies, and modelling and projection related uncertainties are covered in Chapter 2. This sets the stage for the reader to absorb the material covered in Chapter 3 on the development of a framework for integrating climate change information with low flow analysis procedures. The final chapter, Chapter 4, explores avenues of future research, and discusses potential recommendations and steps necessary to be followed for developing future low flows for Ontario's streams, rivers and creeks in the context of a changing climate. A list of references cited in the report is available at the end.

1.4 Convention on the Usage of Acronyms and Other Considerations

Several acronyms are used in this report, which are based on various acronyms used previously in the literature. Some of the acronyms are chapter-specific, while others are utilized throughout the report. Therefore, to facilitate easy comprehension and smooth readability, the acronyms are reintroduced in their expanded form in each chapter so that each chapter can be read independently.

In this report, the terms like river flow, streamflow, or simply flow, reflecting open channel flow conditions, are considered equal in terms of meanings. It is necessary to state it upfront since different terms are used in the literature on low flows. Selected percentiles of FDCs from the lower portion of the curve and low flow magnitudes or quantiles corresponding to selected return intervals or return periods are referred to as low flow indices in this report.

When developing the climate change integration framework for low flow analysis in Chapter 3, often the reference is made to physiographical, climatic, and geological characteristics of watersheds. There are several features that one can derive from the corresponding datasets for developing regression relationships between low flow indices and these features. In this report, the features that can be derived from these datasets are jointly referred to as watershed attributes for simplicity reasons.

The above mentioned strategies were also adopted in another report which was also developed as part of this project (i.e. Khaliq, 2021). This homogeneity in the presentation style helps keep the reader focused and avoids ambiguity and confusion.

1.5 Scope and Limitations

The information provided in this report is intended for individuals who have some basic understanding of runoff-generating mechanisms in riverine environments, statistical concepts involved in low flow frequency analysis, hydrological analyses specific to gauged and ungauged watersheds, in addition to know-how of climate change impact analysis, climate modelling and downscaling, and the value of climate change adaptation strategies across many sectors of the society. The documents and technical/scientific information sources considered for this report are mostly publicly available or available through dedicated publication portals.

The scope of this report is limited to the development of the framework for deriving projected changes to low flow indices for Ontario streams. The concepts and the approaches that underpin the framework are gathered from the literature, mainly from the fields of ungauged hydrology, deterministic and stochastic hydrology, and climate change science. The approaches included in the framework are not tested on historical and climate model data, however, some directions are provided for additional research and evaluation of the framework in future studies. For comprehensive knowledge on all technical and scientific aspects of the approaches covered in this report, the reader is referred to the cited publication sources.

2 A Basic Introduction to Climate Change, Climate Downscaling and Climate Projections

2.1 General

Most of the information provided in this chapter is based on the work of the Intergovernmental Panel on Climate Change (IPCC) and several other researchers who have significantly contributed to the area of climate modelling, and analysis of climate change impacts on various sectors of the society, including socioeconomic, environmental and built infrastructure systems. The intent of the chapter is to provide the reader with some basic knowledge of the area of climate modelling, climate downscaling and emissions scenarios in the context of climate change. Somewhat similar information as reported here is also available in another study (i.e. Khaliq, 2019), which was compiled in the context of climate change and floodplain mapping in Canada. In order to have more comprehensive information than the general information provided here on the topics discussed in this chapter, the reader is referred to IPPC reports and the references cited in here. The number of studies in the area of climate change and its implications is constantly increasing and hence it is impossible to cover all of those studies in this basic introductory chapter.

Climate change can be defined in numerous ways and definition choice can be sector dependent. According to the IPCC, climate change is defined as any change caused directly or indirectly by human activity that modifies the global climate and remains over a significant period of time (IPCC, 2013). Climate change can be caused by natural earth processes (e.g. volcanic eruptions, periodic changes in solar irradiance, etc.) or greenhouse gases (GHGs) (e.g. carbon dioxide, nitrous oxide, methane, etc.) emissions resulting from burning fossil fuels. The impacts of climate change are reflected in observations of many climate-related direct and indirect fields such as surface temperature, precipitation, wind speed, atmospheric moisture, snow-cover, sea-ice extent, sea level, and patterns of large scale oceanic and atmospheric circulations (IPCC, 2013), among others. According to the Fourth Assessment Report (AR4) of the IPCC, global surface temperature has increased by 0.74 ± 0.18 °C between 1906 and 2005 (IPCC, 2007). Compared to this, the annual average surface air temperature over Canada has increased by 1.5 ºC between 1950 and 2010 (Warren and Lemmen, 2014). All reports of the IPCC corroborate that the increase in global surface temperature has a direct correlation with increasing concentrations of GHGs in the atmosphere, resulting from human activities, such as burning of fossil fuels and deforestation. Increases in the earth’s surface temperature will cause intensification of the hydrologic cycle and drastic changes are expected in the amount, pattern and frequency of precipitation in different regions of the world. The Fifth Assessment Report (AR5) of the IPCC has projected that the global surface temperature will increase in the range of 0.3ºC (corresponding to low emissions scenario) to 4.8ºC (corresponding to high emissions scenario) by the end of the 21st century, compared to 1986–2005 levels (IPCC, 2013; see Figure

2.1). Climate change driven variations in precipitation are harder to predict compared to changes in atmospheric temperature because of the huge variability of precipitation in both space and time. Scientists often resort to observational records to ascertain changes in precipitation patterns. Figure 2.2 (IPCC, 2013) shows many areas with increases greater than 25 mm/year per decade while some other areas are associated with decreases in precipitation (10 to 25 mm/year per decade), particularly Africa and south-east Asia. With warmer temperatures, a greater proportion of precipitation is expected to fall as rain, rather than snow (IPCC, 2013).

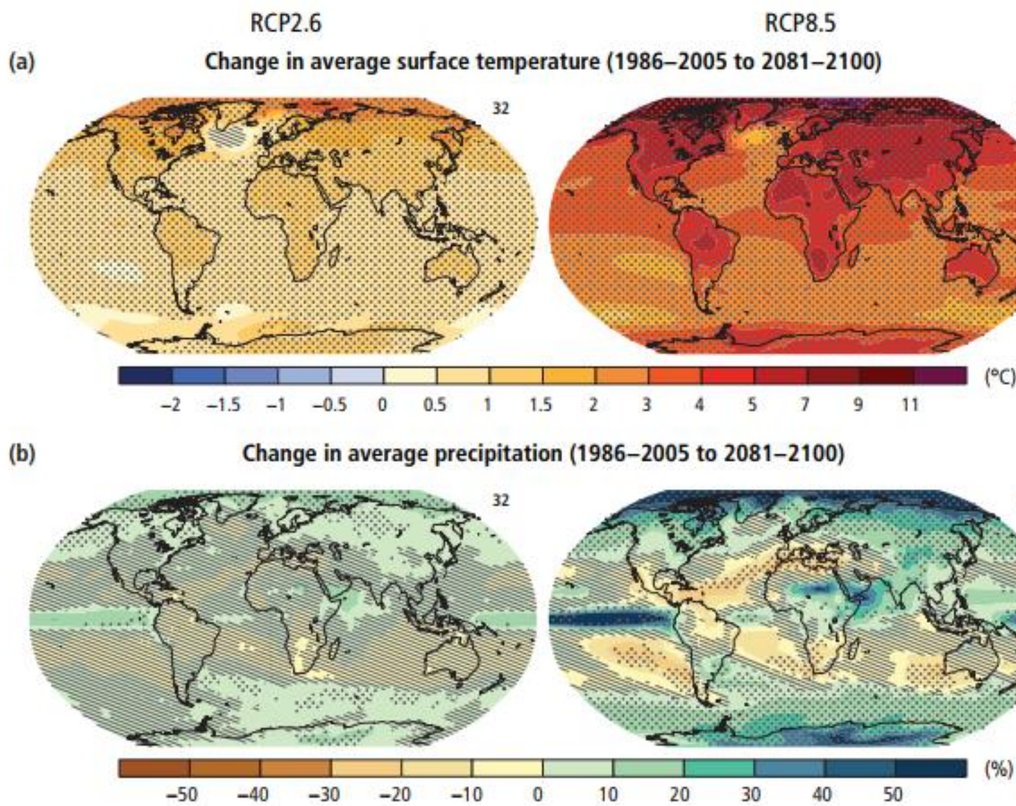

Figure 2.1: Projected changes in (a) average global surface temperature and (b) average precipitation, derived based on CMIP5 GCM simulations, for the 2081–2100 with respect to the 1986–2005 period for two Representative Concentration Pathway (RCP) scenarios. The number of models/simulations used to derive these results is shown at the top right side of each panel. Stipulated areas show regions where at least 90% of the models agree in the sign of change. Figure adapted from IPCC (2013).

Simulating future changes in precipitation is one of the difficult elements of climate modelling because precipitation generating mechanisms are driven by complex non-linear processes with several feedback mechanisms. Due to this complexity, climate models are generally not able to predict changes in the intensity and frequency of extreme precipitation events with a higher level of reliability, other than the likely sign of expected change. The IPCC has made the following important statements in the context of climate change: (1) changes in the global water cycle in response to the warming over the 21st century will not be uniform. The contrast in precipitation between wet and dry regions and between wet and dry seasons will increase, although there may be regional exceptions; and (2) extreme precipitation events over most of the mid-latitude land masses and over wet tropical regions will very likely become more intense and more frequent by the end of this century, as global mean surface temperature increases. According to the projected changes to global average precipitation shown in Figure 2.2, some regions will experience up to –50% decreases while some others will experience up to +50% increases by the end of the 21st century, compared to 1986–2005 levels (IPCC, 2013). Although some regions may experience positive effects of climate change (e.g. increased amounts of precipitation could relieve water stress but may also result in increased risk of flooding), other places may suffer from additional water stresses and prolonged droughts. The risks and expected losses associated with climate change are expected to far outweigh the benefits (IPCC, 2007, 2013, 2018; Warren and Lemmen, 2014).

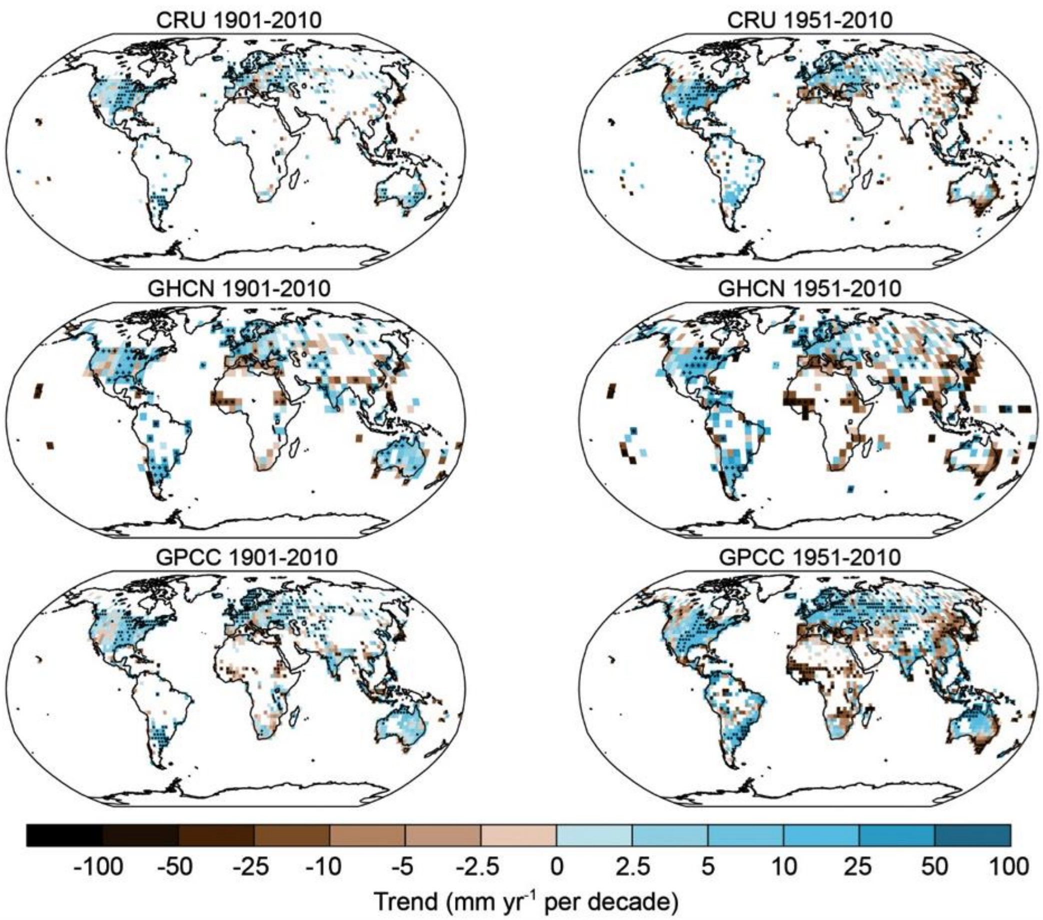

Figure 2.2: Maps of observed precipitation change over land from 1901 to 2010 (left-hand panels) and 1951 to 2010 (right-hand panels) from the Climatic Research Unit (CRU), Global Historical Climatology Network (GHCN) and Global Precipitation Climatology Centre (GPCC) datasets. Trends in annual accumulation have been calculated only for those grid boxes with greater than 70% complete records and more than 20% data availability in first and last decile of the period. White areas indicate incomplete or missing data. Black plus signs (+) indicate grid boxes where trends are significant (at the 90% confidence interval). Source: IPCC (2013) Supplementary Material.

According to IPCC's global analysis (IPCC, 2013), the annual runoff increases in higher latitude regions (Finland, China and coterminous US), with a decreasing pattern in lower latitude regions, such as parts of West Africa, southern Latin America and southern Europe (see Figure 2.3). Labat et al. (2004) observed a direct relationship between global annual temperature rise and global runoffs for the last century. It is estimated that global runoff increases by 4% per 1ºC increase in global temperature. Future projections of runoff and soil moisture at the global scale are shown in Figure 2.3. These projections are dependent on precipitation, which is itself subject to considerable uncertainties. However, it is important to understand what climate models are projecting for the future and its implications at local and regional scales. The left panel in Figure 2.3 predicts changes in surface runoff, with significant declining patterns in runoff throughout the southwestern US and southern Europe/northern Africa and parts of South America. This same trend is amplified in predictions of soil moisture, which is a primary control on plant growth, and can have severe implications for low flow regimes in riverine environments.

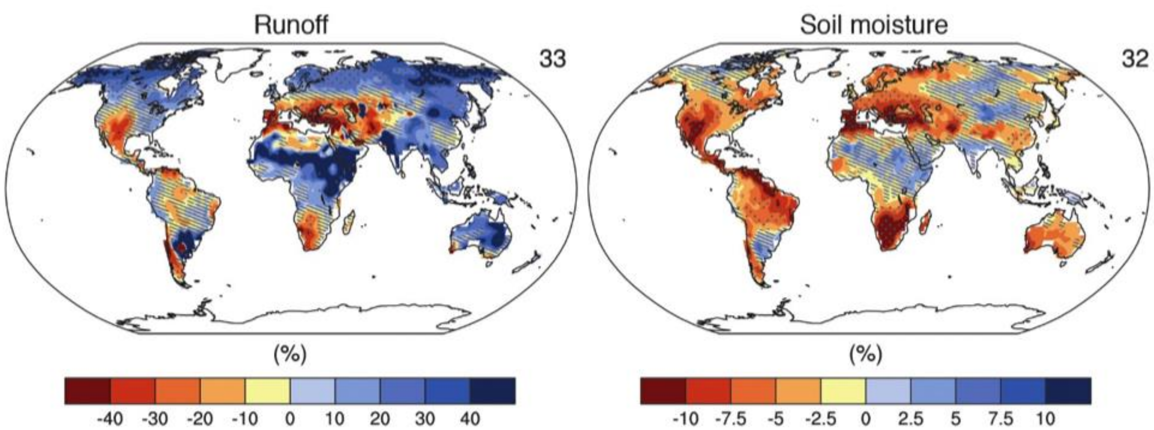

Figure 2.3: Annual mean changes in runoff and soil moisture for 2081–2100 relative to 1986–2005 under the RCP8.5. The number of Coupled Model Inter-comparison Project Phase 5 (CMIP5) models to calculate the multi-model mean is indicated in the upper right corner of each panel. Hatching indicates regions where the multi-model mean change is less than one standard deviation of internal variability. Stippling indicates regions where the multi-model mean change is greater than two standard deviations of internal variability and where 90% of models agree on the sign of change. Source: IPCC (2013).

Canada's climate has also changed significantly. The rate of warming in the Canadian Arctic has been almost double the rate of change for the rest of the world. Annual mean temperature for Canada has increased by 1.6°C for the 1948–2013 period, with increases of 1.3°C for southern Canada (i.e. south of the 60°N parallel) and 2.2°C for northern Canada (i.e. north of the 60°N parallel) (Bush et al., 2014; Environment and Climate Change Canada, 2016). Seasonally, winter and spring has seen the greatest warming. A warming climate will also lead to changes in precipitation characteristics, including the frequency and severity of precipitation extremes. In general, Canada has become wetter, as the total annual precipitation has increased by about 16% over the 1950 to 2010 period. However, there are regional and seasonal differences across the country. Many land regions, including Canada, have also observed increases in the number of heavy precipitation events (e.g. 95th percentile and larger values) (IPCC, 2013; Vincent et al., 2007; Bush et al., 2014). The increases in daily precipitation extremes have been found to be greater than the increase in mean precipitation (IPCC, 2013). The increases in precipitation have been consistent with observed increases in atmospheric water vapour content over Canada and other parts of the world.

Compared to the 1986–2005 period and depending on the emissions scenario, temperatures for Canada are anticipated to increase by 1.8˚C to 6.3˚C by the end of the century (Figure 2.4a). Seasonally, summer temperatures are projected to increase by 1.4˚C to 5.4˚C and winter temperatures to increase by 2.4˚C to 8.2˚C (Environment and Climate Change Canada, 2016). Projected changes in precipitation are expected to vary by region and season across Canada (Figure 2.4b; Environment and Climate Change Canada, 2016). Overall, winter precipitation is projected to increase by 9.1 to 37.8% by the end of the century compared to the 1986–2005 period, depending on the future emissions scenario (see Figure 2.4b). Greater increases are projected for northern Canada. Compared to the winter precipitation, summer precipitation is projected to increase by 5.2 to 10.6% (Environment and Climate Change Canada, 2016).

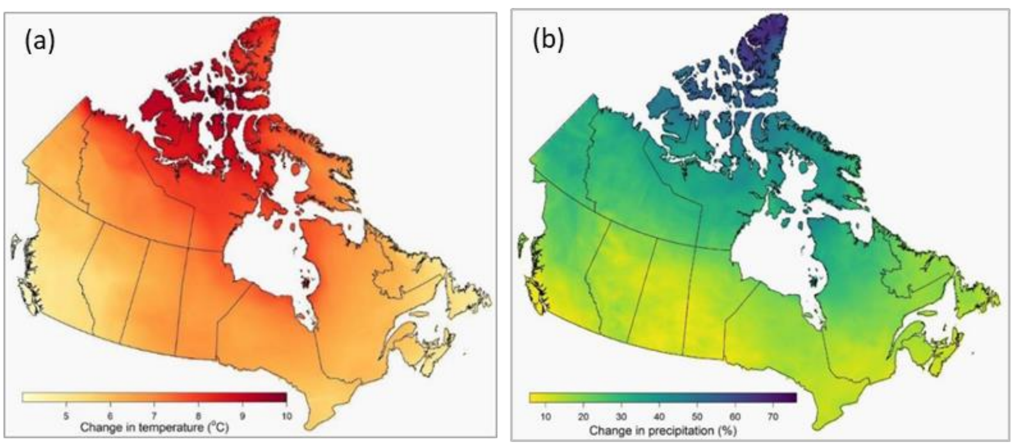

Figure 2.4: (a) Projected changes in the annual mean temperature by the end of the 21st century, with reference to the 1986–205 period, across Canada for the RCP8.5 scenario (Environment and Climate Change Canada, 2016). (b) Same as in (a), but for the annual mean precipitation.

For Ontario, McDermid et al. (2015) estimated an average increase of 4.0 ˚C and 4.9 ˚C, by mid-century, and 5.1 ˚C to 8.5 ˚C, by the end of the century, respectively for the RCP4.5 and RCP8.5 scenario (see Figure 2.5). RCP scenarios are discussed in Section 2.2 of this chapter. Total annual precipitation is projected to increase in most of the province. For the annual mean precipitation, McDermid et al. (2015) projected increases of 64–69 mm by the 2050s and 65–82 mm by the 2080s depending on the RCP scenario (see Figure 2.6). In all scenarios the projected increases in the mean annual precipitation are driven mainly by expected increases in the winter and spring precipitation.

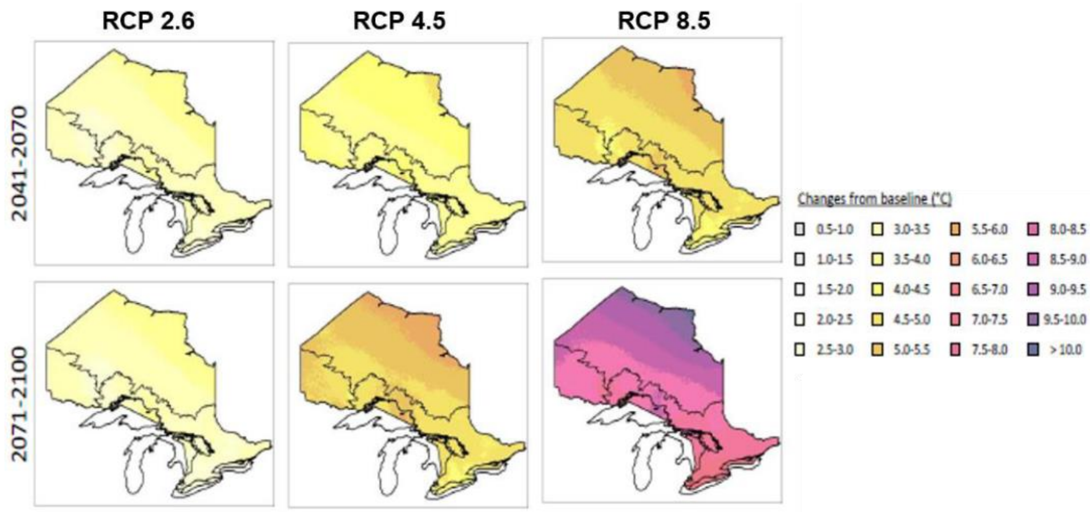

Figure 2.5: Projected changes in the mean annual temperature, with reference to the 1971-2000 period, for the RCP2.6, RCP4.5, and RCP8.5 scenarios for two future time periods (i.e. 2041-2070 and 2071-2100). Figure adapted from McDermid et al. (2015).

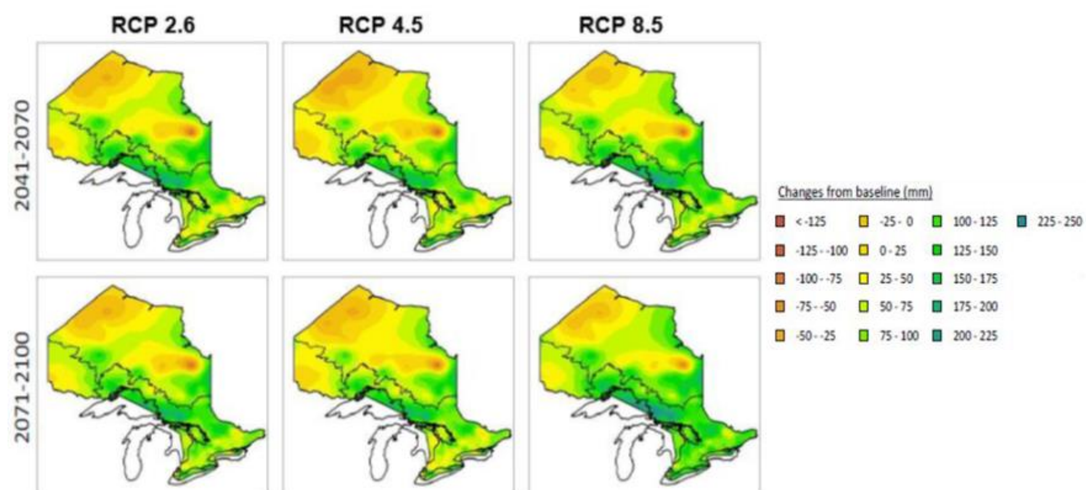

Figure 2.6: Projected changes in the mean annual precipitation, with reference to the 1971-2000 period, for the RCP2.6, RCP4.5, and RCP8.5 scenarios for two future time periods (i.e. 2041-2070 and 2071-2100). Figure adapted from McDermid et al. (2015).

The above discussed changes in historical climate and projections of future climate will have significant implications for river flows, urban runoffs, storminess in coastal regions, seasonal precipitation amounts, and timing and amount of snowmelt. These changes will have significant implications for low flow magnitudes that are often used for regulating riverine environments and high flows that are used to inform design of water storage and flood mitigation measures. Consequently, it is natural to expect that the future low and high flows will be quite different from those derived from historical observations in many regions of Canada. A brief but an educated description of climate models, emissions scenarios, climate downscaling, and future projections and associated uncertainties is provided below to equip the reader with sufficient background on the topic of climate change. In addition to the selection of a hydrological model, discussed in Chapters 3 and 4, selection of global models and their outputs, along with the selection of appropriate downscaling methods is an integral part of the entire process of generating future low flows in Ontario's rivers and streams via direct hydrological modelling or index-based statistical approaches.

2.2 Global Climate Models and Emissions Scenarios

Global Climate Models (GCMs) are the primary tools that the climate modelling community uses to study climate change. These models are integrated from the recent past to some time-point in the future with prescribed, time-evolving emissions scenarios for anthropogenic GHGs and aerosols (IPCC, 2007) to produce transient climate change simulations which are often used in climate change impact analysis studies. These models numerically represent the climate system by encapsulating the current understanding of this complex system, the complicated interactions between the atmosphere, ocean, land surface, snow and ice; the global ecosystem; and a variety of chemical and biological processes (IPCC, 2013).

GCMs produce global climate variables at grid cells that range from 100 to 300 km in horizontal resolution. Due to this coarse spatial resolution, GCMs are unable to capture local features (such as undulating topography, local waterbodies, sub-grid glaciers, etc.) and non-smooth climatic fields, such as precipitation originating from local convection activity. In spite of these limitations, GCMs have been found to embody considerable skill in capturing large scale climatic features (IPCC, 2007, 2013). To overcome limitations of GCMs for studying the impacts of climate change at local and regional scales, scientists have devised downscaling methods, which are often employed to derive local and regional scale information from coarse-scale climate information available from GCMs. These methods are also discussed here in the section to follow.

Climate modelling as described above requires estimates of future emissions and concentrations of GHGs in the atmosphere. The IPCC has developed many long-term emissions scenarios. In the Third and the Fourth Assessment Reports, the IPCC discussed six families of scenarios: A1F1, A1T, A1B, A2, B1 and B2. These are commonly known as Special Report on Emissions Scenarios (SRES). Detailed information on SRES scenarios is available in Nakicenovic et al. (2000). For its Fifth Assessment Report (AR5), the IPCC developed a new set of long-term scenarios for concentrations of GHG in the atmosphere, known as Representative Concentration Pathways (RCPs) (IPCC, 2013). RCPs were developed based on emissions of GHGs and they do not consider natural emissions such as volcanic eruptions. These scenarios describe how radiative forcing may influence future emissions scenarios and associated uncertainties. Based on total radiative forcing level in the year 2100, compared to a baseline year before industrialization (the 1750 is used by the IPCC), four RCPs have been described in the AR5 to characterize future climates, i.e. RCP2.6, RCP4.5, RCP6.0 and RCP8.5 (IPCC, 2013). These RCPs, respectively, correspond to 2.6 Wm^{-2}, 4.5 Wm^{-2}, 6.0 Wm^{-2} and 8.5 Wm^{-2} radiative forcings, which are reflected in the naming convention. The IPCC refers to RCP2.6 as the mitigation scenario and RCP4.5 and RCP6.0 as the stabilization scenarios. RCP8.5 scenario corresponds to the maximum and unabated GHGs emissions and therefore, represents a sort of upper bound scenario.

An international team of climate scientists, economists and energy systems modellers have built a range of new “pathways” that examine how global society, demographics and economics might change over the next century. They are collectively known as the Shared Socioeconomic Pathways (SSPs). The SSPs are now being used as important inputs for the latest climate models, feeding into the sixth assessment report of the IPCC. The RCPs and SSPs complement each other. The RCPs set pathways for greenhouse gas concentrations and, effectively, the amount of warming that could occur by the end of the century. Whereas the SSPs set the stage on which reductions in emissions will – or will not – be achieved. They include: a world of sustainability-focused growth and equality (SSP1); a “middle of the road” world where trends broadly follow their historical patterns (SSP2); a fragmented world of “resurgent nationalism” (SSP3); a world of ever-increasing inequality (SSP4); and a world of rapid and unconstrained growth in economic output and energy use (SSP5). The above description of SSPs is adopted from https://www.carbonbrief.org/explainer-how-shared-socioeconomic-pathways-explore-future-climate-change.

2.3 Climate Downscaling

Since the interest in climate change analyses is at the local and small regional scales and GCMs provide information only at the large scale, specialized approaches and tools are required for transferring that large scale information from GCM grids to local and regional scales in order to drive several impact analysis models. The output of these models is used to assess impact of climate change on targeted assets (e.g. built infrastructure systems – such as buildings, roads, bridges, communication networks, etc.), various sectors of society, various components of the hydrologic cycle, and several environmental and ecosystem components (e.g. low and high flow characteristics, seasonal water availability, sediment regimes, landslides, agricultural droughts, etc.). As mentioned above, to make best use of the large scale GCM climate change simulations for impact analysis at local and regional scales, scientists have devised downscaling approaches. These approaches can be classified into two main categories: (i) dynamical downscaling and (ii) statistical downscaling. These approaches, along with the selected techniques often used for generating local scale information are briefly described below. Additional detail can be found in the references cited.

2.3.1 Dynamical Downscaling

This approach of climate downscaling involves running Regional Climate Models (RCMs). Like coarse scale GCMs, RCMs also numerically describe various atmospheric processes, but at finer spatial resolutions. The typical resolution of an RCM used to be of the order of 50 km x 50 km (e.g. the RCMs used in the NARCCAP – North American Regional Climate Change Assessment Program; Mearns et al., 2009), but many climate modelling groups are now running RCMs at much finer scales, ranging from 5 to 10 km. Efforts are still on-going to further improve RCM resolutions, which will be useful to study city scale features and processes. The regional models are applied over limited-area domains, with boundary conditions taken from global models (Caya and Laprise, 1999; Pall et al., 2007; Scinocca et al., 2015; Diro and Sushama, 2019). Although physical representations of climate processes in RCMs are comparable to those in GCMs, typically RCMs are run without interactive ocean and sea-ice. Compared to GCMs, RCMs offer higher spatial resolution, allow for greater topographic complexity and finer-scale atmospheric dynamics to be simulated and hence provide more adequate tools for generating fine scale climate change information required for many impact and adaptation studies (e.g. Feser and Barcikowska, 2012; Curry et al., 2016). Due to these advantages of RCMs, numerous studies have used RCM simulations for assessing future changes to various characteristics of climate variables in different parts of the world, including Canada (e.g. Booij, 2002; Christensen and Christensen, 2003; Semmler and Jacob, 2004; Fowler et al., 2005; Ekström et al., 2005; Frei et al., 2006; Sushama et al., 2006a; Beniston et al., 2007; May, 2008; Nikulin et al., 2011; Poitras et al., 2011; Mladjic et al., 2011; Mailhot et al., 2012; Monette et al., 2012; Huziy et al., 2013; Jeong et al., 2014, 2015, 2016; and Jeong and Sushama, 2018, among many others).

RCMs are able to explicitly resolve regional waterbodies, land surface heterogeneities and even urban regions, thus allowing realistic feedback processes, which are important to reasonably simulate the climate system. Accounting for local land features is essential for regions like Great Lakes and surrounding urban communities, as their influence on regional climate can be considerable (Martynov et al., 2012; Huziy and Sushama, 2016a, 2016b). Huziy and Sushama (2016a, 2016b) demonstrated significant improvements to the timing and magnitude of winter low flows and spring peak flows when lake-river interactions were taken into account in the Canadian Regional Climate Model. Similarly, incorporating dynamic vegetation (Garnaud et al., 2012, 2014), interactive permafrost (Sushama et al., 2006b), and localized processes (such as lake-effect-snow; Huziy et al., 2017) help produce more realistic current and future climate simulations. Another emerging benefit of RCMs is that they are quite useful in performing anthropogenic attribution type studies for targeted catastrophic weather and climate events, e.g. 2013 Alberta flood and 2017 Montreal and Gatineau floods (Teufel et al., 2016, 2018). Similar investigations as conducted for these regional floods, other localized and regional weather and climate events of significant social and economic importance can be undertaken based on RCMs. For example, the climate causes and contribution of climate change to the occurrence of 2021 British Columbia floods and landslides (https://www.theguardian.com/world/2021/nov/16/canada-fatalities-storm-pacific-north-west-washington) can also be conducted. The major drawback that one can think of the dynamical downscaling approach is its high computational cost, dependence on boundary conditions from

GCMs and difficulty of direct transferability of a working RCM from one region to another region. The inheritance of weaknesses and limitations of the driving data to the RCM outputs are among the prominent criticisms of RCMs.

2.3.2 Statistical Downscaling

Broadly speaking, statistical downscaling (SD) methods use empirical relationships between large-scale GCM simulated climate variables as predictors and local scale climate variables as predictands. For example, GCM-derived values of specific humidity, sea level pressure, geopotential heights and areal precipitation and temperature as predictors versus observed precipitation or temperature as a predictand at a given point of interest. These approaches are used under the assumption that (1) predictor variables are realistically modelled by GCMs; (2) the empirical relationship between predictors and predictand is valid for current and future climate conditions; and (3) the predictors fully represent the climate change signal (Wilby and Wigley, 1997). However, under time evolving climatic conditions, it is difficult to satisfy all of these assumptions.

Although single site downscaling is quite common, techniques have also been developed to consider multiple climatic variables simultaneously at multiple sites in order to preserve some physical consistency across variables and across the region being studied (e.g. Zhang and Georgakakos, 2012; Jeong et al., 2012; Khalili et al., 2013; Asong et al., 2016; Alaya et al., 2016; Khalili and Nguyen, 2018). Sources of model errors and uncertainties in statistical downscaling depend on the choice of method, including the choice of predictors, estimation of empirical relationships between predictors and predictands from limited datasets, and also on the quality of data used to estimate predictors (e.g. Frost et al., 2011; Wilby and Dawson, 2002). The relationships inferred from historical data may not remain valid under a changing climate in the future. A good performance of a statistical downscaling method as assessed against observations does not guarantee credible future climate projections. These relationships may also break down if far out in the future climate change happens in a dramatic manner and new feedback emerges that climate science is not expecting and has never been experienced in the past since the instrumental records existed. The statistical downscaling approach is not based on physical laws, ignores climate feedbacks and often underestimates extreme values (such as precipitation extremes). Despite these drawbacks, statistical downscaling is more adaptable and flexible and is popular also because of low computational cost and ease of use. There are numerous statistical downscaling methods, and the findings are difficult to generalize (IPCC, 2013). However, SD methods can be classified broadly into three categories (Wilby and Wigley, 1997): (i) weather typing methods; (ii) regression or transfer function type methods, and (iii) stochastic weather generators (WGs). Another class of SD methods that downscale as well as bias-correct climate model outputs is described below in a separate section (Section 2.4). There are a number of studies wherein these methods have been used. Only selected studies are referred to. It is important to note that generally the SD approaches have been used for downscaling global model outputs, but they are equally suitable to further downscale outputs from RCMs (Teutschbein and Seibert, 2012).

Weather Typing: This method of downscaling approach is based on specific weather classification schemes and exploits relationships between local climate variables and synoptic-scale atmospheric circulation patterns. For developing such relationships, approaches like principal component analysis (PCA) (e.g. Wetterhall et al., 2005), fuzzy rules (Bardossy et al., 1995), canonical correlation analysis (CCA) (e.g. Gyalistras et al., 1994), and analogue procedures (Martin et al., 1997) have been used. Some investigators have also used pattern recognition approaches based on correlation analyses (e.g. Wilby and Wigley, 1997). Although this approach is appealing because it is founded on sensible physical linkages between climate on the large-scale and weather at the local-scale, it is known to have difficulty in simulating extreme events (Wilby, 1997). The major drawback of weather typing approaches is that they use the same stationary relationships, between local climate variables and synoptic-scale atmospheric circulation patterns, from historical to future climates. Furthermore, the additional effort of adopting a suitable weather classification scheme makes them further unattractive for downscaling GCM outputs. No additional advancements and large scale adoption of these approaches have been seen, apart from the published literature.

Regression or Transfer Function Type Methods: These methods assume that information about local-scale climate variables can be obtained from large scale GCM outputs using suitable linear and nonlinear functional relationships. Local variables are assumed as predictands and GCM outputs as predictors in developing multivariate linear or nonlinear regressions (e.g. Vrac et al., 2007; Chen et al., 2014), non-parametric regressions (e.g. Sharma and O'Neill, 2002; Kannan and Ghosh, 2013) and Machine Learning (ML) approaches (e.g. Tripathi et al., 2006; Ghosh, 2010). These approaches are more frequently used for statistical downscaling purposes. In developing these relationships, it is possible to use several large-scale predictors, but a smaller number of surface/pressure variables has often been used (e.g. specific humidity, sea level pressure, geopotential height, and U and V components of wind velocity) to avoid undue noise in the relationships. Some investigators have found that nonparametric statistical methods like the K-nearest neighbors (Brandsma and Buishand, 1998; Sharif and Burn, 2006; Eum and Simonovic, 2012; King et al., 2014) and Kernel density estimators (Kannan and Ghosh, 2013) can be considered as plausible alternative approaches for statistical downscaling. Although non-parametric methods can capture the spatial dependence of observed climatic variables, they were found to be unable to simulate extreme observations, specifically precipitation extremes. Coulibaly et al. (2005) used a time-lagged feed-forward neural network (TLFN) method for downscaling purposes. A major assumption of the method was that the local climate variables (e.g. precipitation and temperature) depend on both present and past large-scale states of the atmosphere. The performance of TLFN method was found better than many other methods available at the time (e.g. the downscaling method proposed by Wilby et al., 2002). Some deficiencies were also reported by the authors, e.g. overestimated values of wet-spell length. A number of ML methods that perform similarly or better than the TLFN method have emerged since then (e.g. Kundu et al., 2017; Pham et al., 2019).

Weather Generators: Weather generators (WGs) are a combination of many statistical approaches that stochastically simulate random sequences of climate variables. The name is somewhat misleading, but it has some historical significance since Richardson (1981) used this approach to simulate precipitation and temperature variables for hydrological modelling purposes and to overcome limitations imposed by short observational records. When fitted to observed sequences of climate variables, they tend to preserve their statistical properties (e.g. Wilks and Wilby, 1999; King et al., 2014). Using the K-nearest-neighbor non-parametric approach, Mehrotra and Sharma (2005) introduced the nonhomogeneous hidden Markov model for downscaling multisite rainfall sequences. Following insights from this study, King et al. (2014) developed another non-parametric multisite WG based on the K-nearest-neighbor approach. This WG was used for downscaling daily temperature and precipitation data in the Upper Thames River basin, Ontario. In addition to simulating historical climate, this WG was also able to simulate extreme values beyond the range of historical observations when applied in a downscaling setting (King et al., 2014). Srivastava and Simonovic (2014) developed a non-parametric multisite, multivariate maximum entropy based WG for simulating daily precipitation and minimum and maximum temperatures. This WG can capture temporal and spatial dependencies of historical temperature and precipitation variables along with other basic statistical properties (such as mean and standard deviation) in downscaled climatic variables. Parametric approaches developed based on the generalized linear model (GLM) structure benefit from the strengths of both regression- and WG-based techniques. Using GLMs, Chandler and Wheater (2002) found that such WGs give accurate simulations of mean rainfall at the seasonal scale. Inspired by the flexibility of the GLM framework, Chun et al. (2013) compared Long Ashton Research Station weather generator (LARS-WG) and GLM approach for single-site downscaling of daily precipitation at four selected locations in western Canada. The GLM based approach out-performed the LARS-WG in terms of simulating various characteristics of extreme events, as well as inter-annual variability. Albeit with some drawbacks, the GLM based approach seems to be quite suitable for SD of GCM outputs.

2.4 Downscaling and Bias Correction

Those techniques which downscale climate model outputs and simultaneously bias correct downscaled variables are discussed here. By construction, bias correction pertains to the process of adjusting climate model outputs in order to reduce their disparities from observations for a selected historical period, often termed as reference period climate. Sometimes the differences between the two climates could be due to systematic errors in climate models, originating from deficiencies in numerical parametrizations used in GCMs. Once identified based on a given reference historical climate period, the same bias correction method is assumed to be valid for future climate projections. Bias correction methods were originally designed to downscale GCM outputs and therefore they are also categorized as statistical downscaling methods. For example, the quantile mapping or the probability mapping procedure which directly maps quantiles of GCM outputs (e.g. temperature and precipitation) onto the quantiles of observations of corresponding variables at a given point in space, lying within the domain of the GCM grid cell, downscales as well as bias corrects GCM outputs. The mechanics of these approaches are generally not elaborated by many authors. Following Edwards and McKee (1997), the quantile mapping is an equiprobability transformation (Panofsky and Brier, 1958) which states that the essential features of transforming one variate from one distribution to another prescribed distribution such that the probability of being less than a given value of the variate shall be the same as the probability of being less than the corresponding value of the transformed variate.

Over the last several years, many bias correction methods have been developed to bias correct climate model outputs and their performance varies from one application to another and also from one climate variable to another (e.g. Johnson and Sharma, 2011). These methods can be classified in various ways. According to Teutschbein and Seibert (2012), bias correction of climate model outputs considerably improves hydrological simulations, but the major drawback is that nearly all methods assume stationary model structures (e.g. the algorithms and their parameters) and that may not be valid under changing climate conditions (Maraun, 2012). The majority of bias correction methods can also be used for bias correcting RCM outputs and to further downscale them. In Canada, Werner (2011) has used Bias Corrected Spatial Disaggregation (BCSD) algorithm, based on the work of Wood et al. (2004), Salathé (2005) and Slathé et al. (2007), to downscale and bias correct GCM outputs at the grid resolution of the VIC (Variable Infiltration Capacity) model (Liang et al., 1994) for hydrological modelling purposes in British Columbia. This method is further evaluated in Bürger et al. (2012). A few variants of the BCSD algorithm, along with bias correction constructed analogues (BCCA), double BCCA, BCCA with quantile mapping reordering, the climate imprint delta method (CI), and bias corrected CI methods have been reported and evaluated in Werner and Cannon (2016) to downscale precipitation and temperature outputs from CMIP5 (Climate Model Inter-comparison Project Phase 5) simulations to drive the VIC model over the Peace River basin in British Columbia. Despite many advantages of bias correction methods, climate modelling community has raised several concerns and it is important to list them here:

- A proper physical foundation for these methods does not exist (Teutschbein and Seibert, 2012). The physical causes of climate model biases are totally ignored when developing bias correction methods and bias corrected model outputs may become physically inconsistent;
- Conservation of mass and momentum principles and feedback mechanisms on which the climate models are based are not preserved in these methods (Ehret et al., 2012);

- The stationarity of the parameters and structure of the bias correction method from the reference historical period to the future time period is difficult to justify (as also mentioned in the above discussion);
- The likelihood of altering the true climate change signal cannot be ruled out (Dosio et al., 2012);
- As multiple methods exist, the choice of bias correction method introduces an additional source of uncertainty in the results of impact models (Teutschbein and Seibert, 2012); and
- Given other major sources of uncertainties, the added value of bias correction may become insignificant.

In spite of these limitations of bias correction methods and physically inconsistent resulting outputs, they are commonly used in climate change impact analysis studies, particularly for hydrological and environmental applications.

2.5 Climate Projections and Uncertainties

The downscaled climate information obtained following the above mentioned dynamical and statistical downscaling approaches is subject to considerable amount of uncertainty that originates from several sources, such as:

- Inter-GCM variability due to different structures of various modelling components,
- Quality of emissions scenarios and inter-scenario variability due to different types of emissions scenarios (different SRES families and the RCPs and SSPs),
- Intra-model variability due to different parametrization schemes, and
- The choice of a downscaling method, i.e. statistical and dynamical downscaling. Both statistical and dynamical downscaling methods introduce many other sources of uncertainties, apart from those related to GCMs and emissions scenarios.

The AR5 of the IPCC (IPCC, 2013) demonstrates that scenario related uncertainties dominate by the end of the 21st century, while some other investigators (e.g. Prudhomme and Davies, 2009a, 2009b) have found that GCM related uncertainties dominate all other uncertainties if a single downscaling method is used. For all practical applications, e.g. hydrological modelling purposes, it is important to quantify various sources of uncertainties in climate variables as these uncertainties propagate further in the outputs of impact models that are driven by these variables. For example, hydrological models which are forced with projected meteorological variables (e.g. precipitation, temperature, evapotranspiration, etc.) can be used to predict future low and high flows from a given watershed under climate change conditions. The projected flows from these models will carry uncertainties present in the downscaled outputs. Apart from this, for certain watersheds, some investigators even use multiple hydrological models, having different structures and different process representations, that could introduce many additional sources of uncertainties (e.g. Dibike and Coulibaly, 2005; Najafi et al., 2011; Schnorbus et al., 2011;

Surfleet and Tullos, 2013). Given these various sources of uncertainties, it is advisable to quantify uncertainties in a reasonable manner in order to provide enough buffer around the climate change signal. In this regard, many scientists tend to use multiple GCMs, multiple scenarios, multiple downscaling techniques, multiple bias-correction methods, and multiple impact models. This approach, being resource and effort demanding, may not be feasible for all projects focused at climate change impact assessment and adaptation planning.

2.6 Concluding Remarks

In the above five sections basic information on climate change science, climate modelling and downscaling and emissions scenarios is provided. This information is necessary as a baseline knowledge to understand the objectives and various components of the generalized framework, presented in Chapter 3 on the integration of climate change information with low flow estimation procedures. Climate change science is still evolving. Confidence in climate model predictions is also increasing overtime as climate scientists are continuously improving their models from the viewpoints of increasing realism with natural physical processes, improving parametrization schemes and more importantly improving spatial resolution of model outputs. In this regard, concerted efforts are being made to generate super-resolution regional climate simulations, of the order of a few hundred meters to a few kilometers, using convection permitting models (CPMs). Such fine resolution simulations are useful for studying climate change at local scales, such as the scale of a city/town or a whole region (e.g. Diro and Sushama, 2019; Kurkute et al., 2020). Scientists are also trying to employ rapidly expanding ML approaches to climate change (see, for example, Scher, 2018; Stengel et al., 2020; Wu et al., 2021). Specific national and international initiatives have also been started around the prospective use of ML approaches in climate sciences, e.g. the Climate Change AI (https://www.climatechange.ai/), which is supporting research at the intersection of climate change and ML, and AI for Good (https://aiforgood.itu.int/), which is an international effort on the use of AI for various sectors of the society, including climate change, in support of the United Nations' Sustainable Development Goals.

Some regional centres supporting climate change and adaptation related studies and climate data distribution portals have also emerged in some parts of Canada. For example, Ouranos Consortium (https://www.ouranos.ca/en/ouranos/) in Quebec, Pacific Climate Impacts Consortium (https://www.pacificclimate.org/) in British Columbia, Atlantic Climate Impacts Consortium (https://atlanticadaptation.ca/) for Atlantic provinces, Ontario Centre for Climate Impacts and Adaptation Resources (http://www.climateontario.ca/), Ontario Climate Consortium (https://climateconnections.ca/), and Canadian Institute for Climate Choices (https://climatechoices.ca/). Some of these centres and consortia have made available ready to use climate simulations from several climate models, as well as already downscaled climate change simulations using both dynamical and statistical downscaling approaches. In addition, federal government funded Canadian Centre for Climate Services (CCCS; https://www.canada.ca/en/environment-climate-change/services/climate-change/canadian-centre-climate-services.html) is also supporting many climate related products to support climate change and adaptation related studies across Canada. The CCCS has also setup regional hubs with the same objectives, e.g. CLIMAtlantic in New Brunswick and ClimateWest for Prairies. Due to the availability of ready to use climate model simulations, the interest in developing more advanced statistical downscaling approaches has now been shifted to adaptation related studies, thus leaving a higher degree of responsibility, regarding quality of climate model data, to distribution centres.

3 A Framework for Integrating Climate Change Information with Low Flow Estimation Procedures

3.1 General

In this chapter, many different approaches are presented that can be used to estimate projected changes to low flow sequences as well as to the derived low flow indices. Most of these approaches were originally developed to address the problem of prediction in ungauged watersheds. These approaches involve statistical as well as hydrologic modelling. For the application of these approaches under climate change conditions, one would also require information on future climate change projections from global and regional climate models (i.e. GCMs and RCMs, discussed in Chapter 2 of this report). In the presentation of these approaches, essential background information is also provided in order to contextualize their original development. Consequently, the reader may find some resemblance with the contents presented in a companion report (Khaliq, 2021), where the focus was on regional frequency analysis of low flows at ungauged locations in Ontario. Several approaches that were specifically developed for the estimation of low flows at ungauged locations can also be adapted for evaluating projected changes to low flows at both gauged and ungauged locations. Consequently, one can aim to fulfill multiple objectives with the same set of approaches. This chapter can be read independently of Khaliq (2021), as all of the necessary background information on the original development of the selected approaches and their objective applications are also provided below for the convenience of the reader.

For planning and designing of water resources management projects, estimates of continuous streamflow or information on selected indices of low and high flow regimes at various points within a watershed are generally needed. To achieve this objective, it is important to understand temporal and spatial dynamics of runoff generation within a watershed. Therefore, to develop an understanding of runoff generation mechanisms within a watershed, available meteorological and hydrological data are initially explored and then appropriate physical processes are identified for modelling purposes. In doing so, it is recognized that watersheds are complex and diverse hydrologic systems that manifest different hydrologic response signatures as a result of various runoff generation mechanisms (Blöschl et al., 2013). For continuous simulation of streamflow, recourse is often made to process-based hydrological models, i.e. lumped or detailed distributed hydrological models. Lumped models view the entire watershed as a single unit and thus various physical processes (e.g. infiltration, deep percolation, evaporation, etc.) are conceptualized and modelled at the watershed scale. Compared to this, distributed models divide the entire watershed into smaller blocks or grid cells and thus model all physical processes at that scale. Lumped models are simple to develop, setup and execute, while distributed models require considerable expertise and are also computationally expensive. The biggest advantage of the distributed models is that one can derive estimates of continuous streamflow or selected indices of low and high flows at any point of interest within a target watershed after having a working model. When these models are integrated with stochastic weather generators, one can generate an ensemble of several realizations of simulated streamflow for the watershed of interest to inform various management and design strategies. The ensemble of simulations can also be used to develop uncertainty bands.

As a majority of the world's watersheds is ungauged, the desire to have low and high flow information available at these locations for water resources development and management projects has given rise to a specialized field of hydrology, i.e. ungauged hydrology. The International Association of Hydrological Sciences (IAHS) Decade on Prediction in Ungauged Basins (PUB) was a major international collaborative research initiative to promote the development of scientific and applied engineering techniques for generating hydrological information at those locations where observational records are needed, but are non-existent. For ungauged watersheds, the hydrologist has to develop and use modelling techniques for generating hydrologic information from known meteorological measurements. These modelling techniques can easily be adapted to generate information on future low flow sequences and derived indices of low flows under projected climate change conditions. These techniques are described below under two headings, i.e. (1) index-based direct statistical approaches and (2) process-based hydrological modelling, in an effort to develop a framework for generating future low flows in Ontario streams. The underlying modelling assumptions as well as some additional assumptions that are required for the application of these approaches in a climate change setting are also discussed below. Some insights on the categorization of these approaches can also be seen in the work of Blöschl et al. (2013), Hrachowitz et al. (2013), Parajka et al. (2013), Salinas et al. (2013), among many other researchers.

As pointed out above, some of the techniques and hydrologic concepts presented here resemble with those already documented in the companion report, i.e. Khaliq (2021). In particular, the index-based approaches reported previously can easily be adapted for the estimation of low flows under future climate conditions, as described in the next section.

3.2 Index-Based Direct Statistical Modelling

From an applied and water resources management standpoint, the main driver behind the development of index-based statistical modelling of low flows is to pursue information on low and high flow indices or some other indices of interest at locations where observational records are not available, i.e. ungauged watersheds. Thus, several approaches that have been developed prior to and under the IAHS initiative on PUB are directly useful for generating information on potential future indices of low and high flows using future climate model projections. Additional detail on the background and development of these approaches and their suitability under future climatic conditions are described below.

In many environmental management projects and for supporting water extraction applications and deciding on waste load allocations, information on low flow regimes of a stream in the form of low flow magnitudes corresponding to certain return periods of interest are generally required. For example, 7Q20, 7Q10, 7Q2, and 30Q5 low flow magnitudes are commonly used in many Canadian jurisdictions. The 7Q20 is the 7-day averaged low flow magnitude that is expected on average to occur once every 20 years in a given river reach. The 7Q10/7Q2/30Q5 low flow magnitude can also be defined in an analogous manner. In addition to these frequency based indices, Q95 flow is also used to support many environmental management functions. Q95 is the flow that is equated or exceeded 95% of the time over the period of record of a given watershed. This index is derived by developing a flow duration curve (FDC) and is commonly used in several European countries in low flow related projects. The FDC represents how often a given flow magnitude was exceeded over the entire period of record or during a specific period of interest. Here, as mentioned in Chapter 1, the frequency based low flow indicators (e.g. 7Q10, 7Q2 or other similar characteristics of low flow conditions) and FDC-based percentiles (i.e., Q95, Q90, Q85, etc.) are jointly referred to as low flow indices for the presentation convenience. Some river management authorities also use “environmental flow” terminology to refer to these indices. Determination of these indices does not require field work and therefore they remain to be the most widely used low flow indices in the world.

It is straightforward to derive 7Q20, 7Q10, 7Q2 or 30Q5 flows for gauged watersheds using long-term streamflow observations and low flow frequency analysis techniques. These techniques are described in a greater detail in a companion report, i.e. Khaliq (2021). In general, frequency analysis techniques are routinely included in hydrology text books (e.g. Haan, 1977; Chow et al., 1988; Viessman et al., 2002). However, it is not possible to derive these estimates for locations and watersheds where observational records are either not available or persist just over a period of a few years. Therefore, alternate approaches based generally on hydrologic regionalization concepts have been developed to generate this information for ungauged watersheds. These techniques utilize statistical relationships between the target low flow indices and physiographic, climatic and geological characteristics of watersheds; hereafter, these characteristics are referred to as watershed attributes. The statistical relationships are first developed using data from gauged watersheds and then are transposed to ungauged watersheds to derive low flow indices on the provision of required watershed attributes. A generalized form of these relationships is provided in the following equation.

$$LF_{index} = f(W_1, W_2, \dots, W_m) = \alpha_0 W_1^{\alpha_1} W_2^{\alpha_2} \dots W_m^{\alpha_m} = \alpha_0 \prod_{i=1}^{m} W_i^{\alpha_i} \qquad (3.1)$$

where, LF_{index} is the target low flow index (i.e. 7Q20, 7Q10, 7Q2 or 30Q5); $W_1, W_1, \dots, W_m$ are the *m* watershed attributes; and $\alpha_0, \alpha_1, \alpha_1, \dots, \alpha_m$ are regression parameters/coefficients. The same relationship is also valid if the target low flow index is based on Q95. In the literature on ungauged hydrology, this approach is also known as regression-on-quantiles. The form of $LF_{index} = f(W_1, W_2, \dots, W_m)$ can take on any nonlinear form because such relationships had never been found linear in watershed hydrology. Consequently, power, exponential, logarithmic or other nonlinear forms can be possible choices.

For developing these relationships, first at-site low flow frequency analysis is required to be performed to estimate desired quantiles of interest. This may involve selection of a suitable distribution, an efficient parameter estimation method and adoption of some goodness-of-fit measures. The distributions that are commonly used for low flow frequency analysis include the Weibull, Gumbel, Lognormal, Gamma, Pearson Type III and Log-Pearson Type III distributions (Ouarda et al., 2008). The parameter estimation methods that are generally used are the method of maximum likelihood, method of product moments and method of L-moments. For goodness-of-fit analysis of a set of candidate distributions, Kolmogorov-Smirnov (KS) test (Haan, 1977), Anderson-Darling (AD) test (Stephens, 1974), Probability Plot Correlation Coefficient (Chowdhury et al., 1991), Akaike Information Criterion (AIC; Akaike, 1974), and Bayesian Information Criterion (BIC; Schwartz, 1978) have often been used. Some studies employ several watershed attributes while many others rely merely on drainage area. For example, Myronidis and Ivanova (2020) have used 27 different watershed attributes.

The list of physiographical and landscape features may include: watershed drainage area and perimeter; main channel slope and length; mean watershed slope and elevation; gaging station latitude, longitude and elevation; drainage density; maximum and minimum watershed elevations; watershed relief; elevation of watershed centroid; proportions of watershed covered by forests, waterbodies, barren land, impervious areas; among others. Climatic attributes may include: average annual precipitation; average annual snowfall; average annual rainfall; mean seasonal values of precipitation, snow and rain; mean annual daily minimum and maximum temperatures; evapotranspiration; and several measures of degree days. Geological attributes may include geological features like glaciers, mud, sand, peat, rock type, gravel, etc.

It is alluring to think that a large number of variables will help develop a stronger relationship, but that in fact is not the case. Many of these variables may be inter-correlated and that impacts the quality of the resulting model and makes it difficult to discern the variables which are genuinely important in explaining the majority of the variance of the dependent variable (e.g. 7Q20, 7Q10, 7Q2 or Q95). Therefore, firstly, when dealing with large number of variables, it is important to screen out those variables which are not correlated with the dependent variable. It is better to work with fewer variables which are correlated with the dependent variable. Secondly, it is also important to perform inter-variable correlation analyses in order to avoid issues of multicollinearity. A formal way to screen mutually correlated variables is to employ variance inflation factors (VIF) by adopting a reasonable screening threshold, following suggestions from the literature (e.g. Eng et al., 2005; Fox, 2008). Alternatively, variable importance analysis often used in machine learning approaches, e.g. Random Forests (Theobald, 2017), can also be exploited to support the choice of dominant variables or features. The software to support this analysis is readily available on many platforms, including the open source R and Python platforms.

In hydrology, the functional relationships are generally developed within a regionalization framework, i.e. the relationships are developed based on a homogeneous region. The homogeneity of a given region could be viewed in terms of hydrologic aspects or in terms of climatic aspects or based on some other relevant features of interest. Some studies employ geographic proximity as the basis for developing these relationships; this is generally the case when regions are delimited by political or jurisdictional boundaries. Irrespective of the criteria used for identifying homogeneous regions, the target region for which the functional relationships are to be developed needs to have sufficient number of gauged locations or watersheds. Once these relationships are developed, they are assumed to be applicable for the entire region. Where feasible, such relationships can also be developed in a global sense, i.e. the relationships that are applicable for an entire country without regional partitions.

The beauty of these regional relationships is that they can directly be employed in a climate change setting in order to generate information on future low flow indices. To ensure the usefulness of such approaches under future climatic conditions, it is important to include some important climatic characteristics, e.g. some measures of annual/seasonal precipitation, temperature, snowfall (solid precipitation) and rainfall (liquid precipitation), in the development of these relationships. The reason behind these choices is that the projections of climatic variables are readily available from both global and regional climate models. A process diagram showing how the climate change information can be integrated with low flow estimation procedures for developing future changes to low flow indices is given in Figure 3.1.

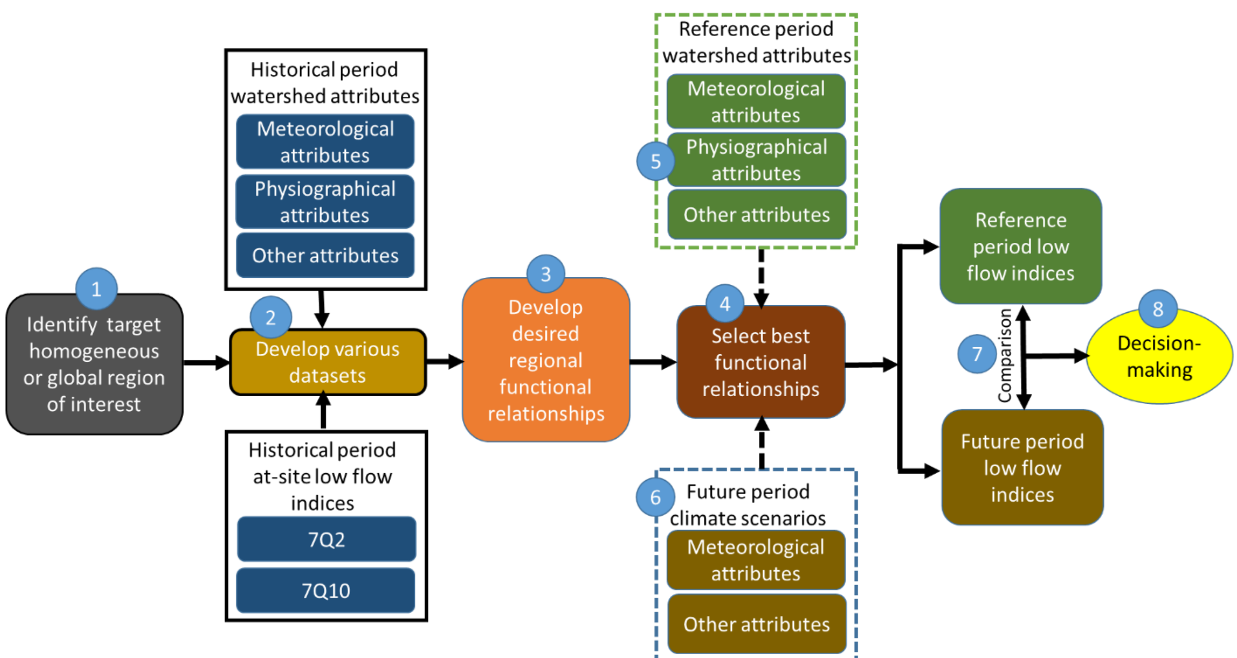

Figure 3.1: Process diagram showing the various steps (1-8) involved in modelling and predicting climate change informed low flow indices and associated changes for future time periods with respect to a reference historical period. Long-term datasets for the historical period serve to train an ensemble of candidate regional functional relationships.

This is a generalized framework that can be used to develop expected changes to low flow magnitudes in Ontario streams. This framework can be divided into two parts – one related to the development of relationships for historical conditions and the other related to the development of future projections of low flows. These parts are separately explained below:

Steps involved in the development of historical relationships:

1. Identify homogeneous target regions on the basis of hydrologic or climatic homogeneity concepts in a statistical or physical setting.
2. Develop at-site estimates of desired low flow indices, based on available systematic streamflow records, for the historical period.
3. Identify a set of watershed attributes related to physiographic, climatic and geological attributes, with the inclusion of as many climatic characteristics as reasonably possible due to our focus on climate change and climate change projections.
4. Identify a set of independent attributes through inter-variable correlation analyses and the VIF approach. Principal component analysis can also provide useful information in this regard.
5. Develop regional functional relationships of desired low flow indices and watershed attributes, identified in the previous step.
6. Evaluate the robustness of functional relationships based on leave-one-out cross-validation type assessment and/or statistical hypothesis testing.

Steps 4 and 5 require additional considerations. After identifying the set of independent variables, the development of functional relationships is generally attempted within a regression framework following step-wise regression procedures (e.g. Walpole et al., 2011; Selvanathan et al., 2016; Zhang et al., 2016). Both forward and backward elimination of variables can be experimented to optimize the relationship by eliminating redundant variables. These procedures are generally available on many commercial statistical computational platforms such as Matlab, Minitab, R, SPSS (Statistical Package for the Social Sciences) and SAS (Statistical Analysis Software). In addition, it is also important to perform regression diagnostics and understand behaviours of various variables involved. It must be noted that the readily available statistical toolbox of Microsoft Excel is not so useful in this regard, although some preliminary insights can be gained through this toolbox. Furthermore, once the independent variables are decided upon then the regression can be carried out within Excel even by a less experienced analyst. In general, some experience in the use of above mentioned software and strong understanding of fundamental principles of multiple regression are generally required. It is dangerous to be fully dependent on automated procedures without due statistical understanding of background principles. In certain situations, it may not be advisable to ignore certain variables, merely based on statistical reasoning because of their physical relevance in the problem being addressed.

Steps involved in integrating climate change information and estimating projected changes to low flow indices:

1 Identify a set of climate model simulations for the historical reference period (to be chosen by the analyst) and for the targeted future period corresponding to selected emissions scenarios.
2 Develop information on climatic attributes identified in the historical functional relationships for both the reference and future periods and apply bias correction where applicable.
3 Develop estimates of desired low flow indices both for the reference and future periods.
4 Determine percentage changes in low flow indices based on the values obtained in the previous step.
5 Employ outputs from multiple climate models and devise robust estimates of projected changes. This can also help develop uncertainty intervals if deemed necessary.

In developing projected changes to low flow indices, it is implicitly assumed that the parameters of the functional relationships are applicable for future periods and all watershed attributes, apart from climatic attributes, also remain valid for future periods. These assumptions are necessary since it is not possible to project how, for example, the geology or topographic features of watersheds will change in the future.

3.2.1 Other Relevant Considerations and Insights

The regional relationships discussed above can potentially be used to derive first-hand information on how future low flows will be impacted by projected climate change in gauged and ungauged watersheds throughout a region of interest. The insights gained using this approach should be complemented with similar results obtained from detailed process-based hydrological modelling (see Section 3.3). The index-based functional relationships are useful in the sense that, while being easily interpretable, they require less resources and analyses compared to the hydrological modelling option. It is important to note that the projected changes derived based on index-based approaches are applicable for pristine watersheds, i.e. those watersheds which are minimally impacted by anthropogenic interventions (e.g. damming, diversion and storage mechanisms). Therefore, the developed projected changes to low flow indices will not be so valuable for highly regulated watersheds.

For the development of these relationships, availability of historical observational records from several gauging stations is quite important. Therefore, every effort should be made to include historical records even from pre-dam periods. With respect to available length of observational records, stations with at least 10 or more years of data should be preferred. Shorter records are unable to capture cyclic variations associated with large scale atmospheric mechanisms, such as

Pacific Decadal Oscillation and El Niño–Southern Oscillation. The role of extremely small and very large watersheds should be carefully examined when developing these relationships due to scaling issues.

Since at-site frequency analysis is an important component of the entire framework for evaluating projected changes to low flow indices, additional discussion is warranted on this topic. Apart from distribution selection and consistency analysis discussed above, one could also use a previously identified statistical distribution for at-site frequency analysis than going through detailed distribution fitting and evaluation procedures for several candidate distributions. In general, a three parameter distribution is more flexible than a two parameter distribution in capturing the underlying parent distribution, which is generally unknown. However, the principle of parsimony can also play a deciding role when a final choice for a distribution is made. The main objective of having a fitted parametric distribution for low flow sequences is the ability to extrapolate beyond the length of recorded observations. This aspect is quite important for high flow analysis. In low flow analysis, the interest is generally in quantiles of low return periods and those corresponding to 50- or 100-year return periods are rarely used. Due to this reason, non-parametric frequency analysis procedures can also be considered as they can also provide reasonable estimates of low return period quantiles. For low flow analysis, zero values are likely to be encountered, particularly in dry regions and in regions where extreme frozen conditions prevail during winter. The zero values in low flow frequency analysis can be handled either by adopting conditional distribution fitting procedures (e.g. Stedinger et al., 1993) or by considering low flow sequences as censored samples (e.g. Durrans et al., 1999; Ouarda et al., 2008). Additionally, the suggestions of Condie and Cheng (1983) can also be followed, who suggest estimating probability of observing zero flows for samples containing zero values.

Based on the literature cited above, it is found that drainage area, gauging station elevation, and some descriptors of channel length (e.g. length of main channel) and topographic features (e.g. mean basin slope) are among the significant independent variables from the set of physiographical features considered. However, due to the stress on developing projections of future low flows, it is important to focus more on the identification of climatic attributes that can explain a majority of the variance in the target low flow indices. This may involve recalibration of functional relationships than merely using the ones already available for certain regions (e.g., see AECOM, 2013). Annual/seasonal mean precipitation and annual/seasonal mean temperature are the potential climatic attributes that can be considered.

Low flows in Ontario streams may occur in winter due to frozen conditions or in summer and early fall due to lack of rainfall and high evaporation demand. Therefore, it is necessary to consider summer and winter low flows separately as they are characterised by completely different generating mechanisms, and complex relationships between precipitation, soil moisture deficit and evaporation demand. In addition, it is also likely that they are represented by different statistical distributions and are being controlled by different sets of watershed attributes.

Seasonal considerations become even more important in climate change related studies since seasonal precipitation and temperature are not uniformly impacted by climate change related factors. This has been demonstrated in several studies cited in Chapter 2.

Inter-variable correlation analysis is very useful in applications involving regression analyses for identifying statistically defensible and physically meaningful variables. However, the results should not be confused with causality and then misinterpreted in establishing hypotheses. Having a pair of correlated variables simply means that the variables co-vary and there is an association between the two variables. Having non-correlated variables included in the watershed attributes have many benefits, such as higher interpretability and less bias.

The functional relationships can be developed based on homogeneous regions or merely based on a global concept. When these relationships are developed based on the former consideration, the resulting relationships generally perform better than the latter case. Regarding identification of homogeneous regions, it is possible to define these regions using many different methods. Most of these methods utilize multivariate statistical analyses, such as hierarchical cluster analysis (Hosking and Wallis, 1997) or principal component analysis (e.g. Ouarda et al., 2008). Geographically contiguous regions can be identified based on the geographic proximity concept. Geographically non-contiguous regions can be identified based on hydrological neighbourhoods using the region of influence (ROI; Burn, 1990) approach or canonical correlation analysis (CCA; Ouarda et al., 2001). For identifying regions based on the ROI and CCA methodologies, available watersheds are pooled together and a group of similar watersheds is identified within the attribute space. The advantage of these approaches is that one can easily overcome lack of data related issues.

As seen in Equation (3.1) and discussed above, the regional functional relationships are generally found to be nonlinear. Given this fact, it is readily possible to develop these relationships using Machine Learning approaches, which are rapidly expanding for solving applied problems in engineering and sciences. Along similar lines, Ouarda and Shu (2009) conducted a regional low flow frequency analysis using Artificial Neural Networks (ANN), considering low flow quantiles separately from summer and winter seasons for Quebec. Through cross-validation experiments, they found that ANN-based ensemble modelling approach outperformed other nonlinear approaches for estimating low flow quantiles at ungauged locations. Similar findings are also reported by Jung et al. (2019).

3.3 Processed-Based Hydrological Modelling

In this section, the use of process-based hydrological models is described as an alternative approach for developing projected changes to low flow indices. As for the case of index-based statistical approach described in the previous section, this approach also involves hydrologic regionalization in order to extend hydrologic modelling procedures to ungauged watersheds. In addition, statistical frequency analysis of low flows discussed in the above section also needs to be implemented. Therefore, there are some resemblances between this and the previous section, specifically with respect to regionalization and frequency analysis aspects. Having said that, most of this section can be read independently. However, links between both sections are identified where necessary. A considerable portion of this section is also devoted to ungauged hydrology. This was deemed necessary since information on future low flows is also required for ungauged watersheds.

For any water resources management related project where continuous streamflow simulations are required, a new hydrological model needs to be developed for the target watershed after identifying dominant features and processes and a methodological framework. However, there already exist several hydrological models that were developed over the last several decades for a variety of watersheds, located in different parts of the world. These models vary in complexity and data requirements. Some models are general purpose models while others were developed for certain geophysical conditions and topographical and land scape features. For example, the University of British Columbia (UBC) Watershed model (Micovic and Quick, 1999) is specifically more suitable for snow dominated mountainous catchments, while the Streamflow Synthesis and Reservoir Regulation (SSARR) model (USACE, 1991) and HEC-HMS (Feldman, 2000) are more suitable for rain dominated watersheds. Similarly, Soil and Water Assessment Tool (Arnold et al., 1998) is suitable for modelling nutrient regimes of a watershed in addition to rainfall-runoff processes. There are several other similar examples available in the literature. For the sake of this report, it is assumed that an analyst/engineer is free to adopt an existing model for a target watershed and therefore the focus here is more on the applied usage of the model, ranging from model calibration to validation, regionalization of model parameters and adaptation of the model to simulate hydrological regimes in the context of a changing climate, the major focus of this report.

Both lumped and distributed hydrological models are calibrated and validated using known meteorological and hydrological observations before using them for operational purposes to achieve intended management targets. These models could vary from simple event-based to continuous simulation models. These models can simulate streamflow at sub-daily, daily, or even longer time steps (e.g. Singh and Frevert, 2005; Singh, 2012) depending upon the target usage of the model. For ungauged watersheds in a larger region of interest, a few candidate models need to be identified, calibrated and validated for gauged watersheds and a best performing model can be selected. In situations where such detailed analyses are not feasible due to resource constraints, an expert judgement on the choice of a suitable model can be exercised. Afterwards, functional relationships of model parameters and watershed attributes (i.e. physiographic, climatic and geological characteristics) of gauged watersheds are developed. These relationships are transposed to target ungauged watersheds, where continuous streamflow simulations are required. Alternatively, the model parameters can be spatially interpolated using geostatistical techniques or one could also use averaged parameter values for simplicity reasons (e.g. Post and

Jakeman, 1999; Merz and Blöschl, 2004; Samuel et al., 2011). For generating sequences of streamflow at ungauged watersheds, the model with the estimated parameters, obtained by either of the above mentioned approaches, is run with the given meteorological inputs (Wagener et al., 2004; Zhang and Chiew, 2009; He et al., 2011; Wagener and Montanari, 2011; Razavi and Coulibaly, 2013; Viglione et al., 2013). Streamflow sequences obtained so can be used to inform water management related decisions at ungauged watershed.

The development of aforementioned functional relationships between model parameters and watershed attributes require delineation of homogeneous hydrologic regions based on regionalization techniques. This is an important research area in hydrology and some insights on regionalization have been discussed in the above section. A hydrological homogeneous region can be defined based on geographic proximity, similarity of streamflow characteristics alone or by combining them with other watershed attributes. When geographic proximity is used for classification purposes, assignment of a watershed to a region is straightforward. On the contrary, when the hydrological response of an ungauged watershed is similar to that of watersheds belonging to more than one region, expert judgement is generally exercised. This situation arises for boundary watersheds when region delineation is based on streamflow and watershed attributes. Furthermore, even if a homogenous region is correctly defined and an ungauged watershed is assigned to that region, there needs to be enough watersheds with sufficiently long meteorological and streamflow records in order to develop statistically significant functional relationships. Where such a requirement cannot be satisfied due to lack of gauged watersheds, spatial interpolation or the possibility of using averaged model parameters should be explored.

For developing future projections of streamflow for any watershed of interest, whether gauged or ungauged, it is assumed that a well calibrated and validated model is already available. This model is then run for a historical reference period (e.g. 1990-2020) and a targeted future period (e.g. 2071-2100) using selected reference period and future period climate model outputs (i.e. precipitation, temperature and other variables). Future climate model outputs generally correspond to a climate change scenario (e.g. RCP8.5 or RCP4.5). For low flow analyses, samples of low flows from both periods are extracted and subject to low flow frequency analysis and resulting quantiles are compared to ascertain how low flows will change due to future climate change influences. For longer time windows it is also possible to perform non-stationary low flow frequency analyses. For example, assuming that the parameters of the selected statistical distribution vary as a function of time or as a function of temperature magnitudes. This procedure can be extended for the entire study period than just focusing on specific smaller time windows, with the availability of longer simulations. It must be noted that it is implicitly assumed that the hydrological model parameters and model structure remain valid for the entire period of the study, including the reference and future periods. The entire framework for integrating climate change information with low flow estimation procedures in the form of a process diagram is shown in Figure 3.2. For performing low flow frequency analyses, the same formal procedures as normally used in frequency analyses need to be executed, i.e. distribution selection, parameter estimation and evaluation of the fitted distributions based on some goodness-of-fit measures, such as the KS test, AD test, AIC or BIC.

An alternate approach is to develop a stochastic weather generator for the historical period and then use that weather generator to generate an ensemble of meteorological data series for both reference and future periods. These series are then integrated with the selected hydrological model. This procedure helps to address some data related uncertainties, but has become less attractive as future temperature and precipitation data are becoming increasingly available from several climate models (e.g. CMIP5 and CMIP6 simulations). It is beneficial to use outputs from multiple climate models and, if feasible, integrate them with multiple hydrological models in order to address uncertainties associated with the choice of a single climate model as well as with the choice of a single hydrological model.

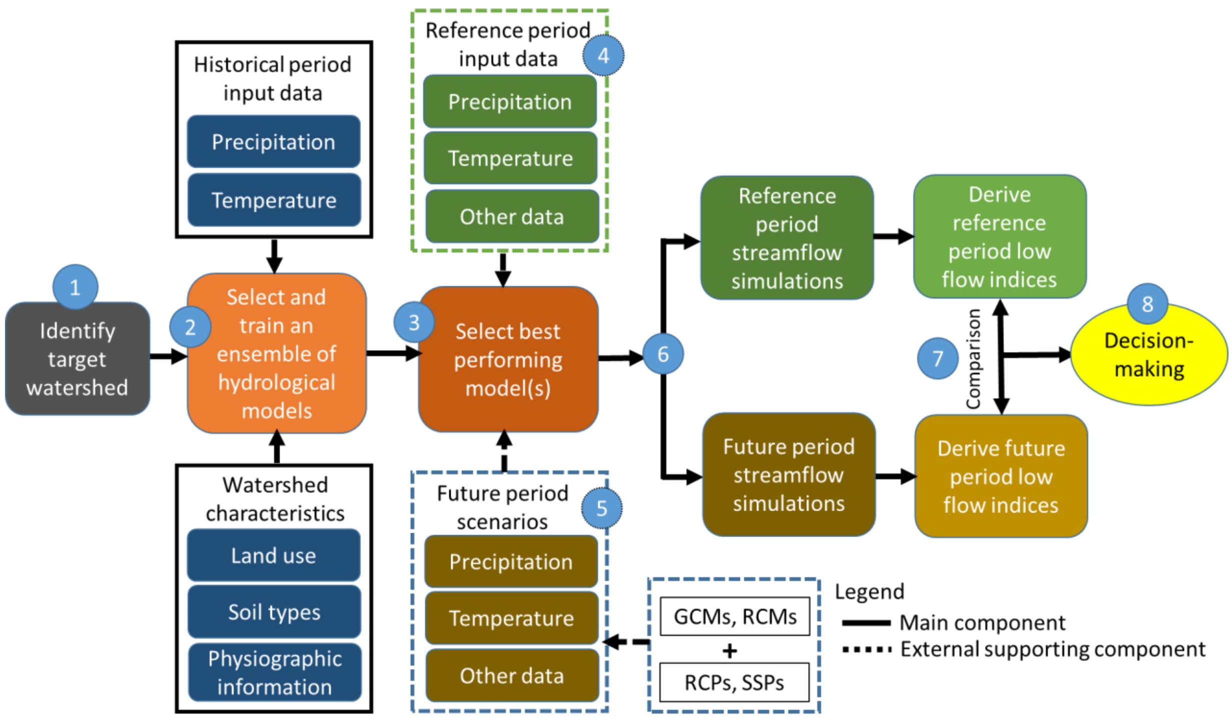

Figure 3.2: Process diagram showing the various steps (1-8) involved in modelling and predicting climate change informed low flow indices and associated changes for future time periods with respect to a reference historical period, based on process-based hydrological modelling approach. Depending upon the path followed for deriving projected changes, bias-correction can be applied at steps 4 and 5, if required.

3.3.1 Other Relevant Considerations and Insights

From a hydrological viewpoint, the quality of future projections of low flows very much depends on the quality and length of meteorological and hydrological data used for model calibration because the resulting model will be only as good or as bad as the data used for model calibration. Several studies from the hydrological field have suggested that for an acceptable hydrological model calibration sufficiently longer records including both wet and dry cycles are required for complex models (e.g. Sorooshian et al., 1983; Yapo et al., 1996; Duan et al., 2003; Singh, 2012; Lokas and Yasiliades, 2014). For the case of HBV model with 12 free parameters, Harlin (1991) suggested that two to six years of streamflow data are needed for an optimal calibration of the model. For data scarce regions, however, the same studies as quoted above also suggest at least one hydrological year as a minimum requirement. For example, Perrin et al. (2007) showed that for a simple rainfall-runoff model like GR4J with four parameters, 100-350 observations would be quite useful to have a working model. Although long-term observations are necessary for calibrating a reliable hydrological model, an indirect message is that even shorter observational records would be quite useful for constraining modelling uncertainties in data scarce situations. Compared to detailed distributed hydrological models, lumped conceptual models are simple and often have a small number of parameters and therefore can perform better when calibrated with even shorter records. On the other hand, not much guidance is available in the literature for distributed models with several free parameters, though some models (e.g. Watflood) utilize grouped response units concept to overcome model complexity without compromising quality of simulated flows (Kouwen et al., 1993, 2005). It would be useful to produce some general guidance on the minimum length of observational records required to have a reasonable performance of distributed models. On the model evaluation aspects, Moriasi (2007) and Ritter and Muñoz-Carpena (2013) have provided sufficiently detailed guidance. It is also important to be aware that models ought to be simple and should also avoid over-parametrization that requires excessive calibration (Ajmal et al., 2015; Skaugen et al., 2015). Among others, Kirchner (2006) and Archibald et al. (2014) caution that over-parameterization and/or over-calibration of hydrologic models may lead to misrepresentation of physical processes that contribute to runoff generation in a watershed. Therefore, in real world situations, expert judgement based on hands-on-experience with various models plays a significant role in having well calibrated models for research and operational purposes. After calibration, model validation on independent data of reasonable length is another important step that should not be neglected as this helps develop a certain degree of confidence in the model performance (Singh, 2012).

The regionalization approach discussed above emphasizes the role of comparative hydrology as an effective tool for learning about ungauged watersheds through analysis of hydrologic similarities. For example, exploring similarities between physical characteristics or runoff generation mechanisms. Some studies have shown that the results of regionalization are found acceptable, however, the performance varies across temporal and spatial scales and also depends on the location within the region of interest (e.g. Kult et al., 2014). Vandewiele and Elias (1995) used two different regionalization approaches using model parameter values from only a limited number of neighbouring watersheds to estimate monthly water balance in 75 watersheds in Belgium. Similarly, Oudin et al. (2008) compared regression, spatial proximity and physical similarity based regionalization approaches to estimate daily streamflow in 913 watersheds in France using two lumped rainfall-runoff models. Parajka et al. (2005) evaluated multiple regionalization techniques (i.e. by utilizing the concepts of local/global averaging, spatial proximity, regression and similarity measures) for 320 Austrian catchments and found that kriging based on spatial correlation performed better among the best identified methods. They also found that four to seven donor catchments were required to achieve optimal performance in regional calibration of the conceptual model they used. Although the regionalization approach forms a strong basis for extending hydrologic models from gauged to ungauged watersheds, practical applications of this approach are still limited and therefore efforts must continue to bring research innovations into practice in genuinely ungauged watersheds. Despite the promise of regionalization of model parameters, the density of available gauging stations in the region surrounding the ungauged watershed considerably influences the reliability of streamflow simulations (e.g. Oudin et al., 2008; Parajka et al., 2015; Lebecherel et al., 2016). Thus, the applicability of regionalization methods that require higher density of gauging stations may be limited in poorly gauged areas, where the density of gauging stations is below the recommendations of World Meteorological Organization (WMO, 2008). Although the focus of this report is on future low flows under changing climate conditions, the discussion on ungauged watersheds is provided so that one can also derive future low flows for ungauged watersheds.

3.4 Other Methods

In certain situations, environmental flows are also used to support similar functions and management practices as those served based on index-based low flow magnitudes (i.e. 7Q20, 7Q10, 7Q2 or Q95). Environmental flows are determined by applying the Tennent method (Tennent, 1976). According to Karakoyun et al. (2018), this probably is the best-known method for environmental flow assessments due to ease of use and straightforward computational procedure. As advocated by these authors, it determines the flow that is required for protecting aquatic life in both warm and cold water streams. The Tennant method defines stream ecological classes based on various percentages of the mean annul flow (MAF). A different percentage of the MAF is allocated for wetter and drier periods of the year. It is not the intention of this report to provide a detailed review of this method, therefore, further information on the ecological classes can be found in Tennent (1976), Liu et al. (2016) and Karakoyun et al. (2018). Here, the intention is to establish a link between this method and the methods presented above. As the Tennent method utilizes the MAF as the basis for defining different environmental flows, the index-based approaches discussed above can also be used to derive projected changes to MAF. In addition, using the approaches discussed above in the process-based hydrological modelling section, one can directly estimate projected changes to MAF based on the continuous streamflow simulations for the reference and future periods.

There are also a few coupled climate-hydrology modelling systems (e.g. WRF-Hydro; https://ral.ucar.edu/projects/wrf_hydro/overview) that can directly simulate streamflow for historical and future periods for climate change assessment and analysis purposes. This is an alternative way to evaluate projected changes to low flows. However, some of the approaches and insights discussed above would be applicable as well. For example, the application of low flow frequency analysis and related procedures and data requirements cannot be ignored.

4 Summary, Concluding Remarks and Recommendations for Future Work

4.1 An Overview

Various estimates of low flows are generally used for management of stream water quality, licencing water withdrawals, regulating waste load allocations, and preserving aquatic life and riverine habitat (e.g. Smakhtin, 2001; Wallingford HydroSolutions Ltd, 2006). Often these estimates are represented in terms of low flow statistics or in the form of low flow indices to characterize low flow conditions in rivers and streams. Globally, the 7Q10 index is commonly used. This is defined as the annual average 7-day minimum flow that can occur on average once in 10 years (Smakhtin, 2001; Tallaksen and van Lanen, 2004; EPA, 2018). These estimates are obtained by conducting low flow frequency analyses. A parallel low flow index is Q95, which is also commonly used in many parts of the world to support various environmental management decisions. It is defined as the flow that is exceeded 95% of the time over the history of observations. This index is estimated by developing flow duration curves. In Ontario, 7Q2, 7Q10 and 7Q20 indices are used in low flow management related projects (Pyrce, 2004; OFAT, 2020). A detailed account of low flow estimation methods, covering both at-site and regional approaches, and insights on distribution selection and fitting methods, development of regional regression equations between low flow indices and watershed attributes, the choice of duration and frequencies for low flow analyses and insights on emerging Machine Learning (ML) approaches are presented in a companion report, i.e. Khaliq (2021). This report was also completed within the framework of the same project.

Irrespective of the estimation method, low flow indices are generally obtained from historical observations, assuming a stationary climate. It is also assumed that the indices derived from historical observations will also be applicable for future periods. However, with the anticipated climate change as projected by Global Climate Models (GCMs) and documented in several reports of the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2007, 2013, 2018), the indices derived from historical observations will no longer be representative of future climatic conditions (e.g. Sushama et al., 2006b; Khaliq et al., 2006; Khan and Coulibaly 2010; Liu et al., 2011; Salas et al., 2018; Wu and Xue, 2018). Therefore, appropriate provisions for climate change need to be considered when developing low flow management plans and regulations to avoid unexpected future mishaps. Integration of climate change with low flow estimation procedures can be accomplished using several different approaches. The differences between these approaches are driven mainly by the way climate change projections are developed and integrated with low flow estimation procedures, often involving statistical, hydrologic and geospatial analyses. The variations between the underlying methodological aspects of low flow estimation procedures are additional sources that also drive the differences between these approaches.

Some insights on the potential approaches that can be used for integrating climate change information with low flow estimation procedures are presented in this report in an attempt to develop a generalized framework for estimating future low flows in Ontario streams. The approaches considered for this purpose were originally formulated to address low flow estimation problems in ungauged hydrology. These approaches are quite flexible and therefore can be adopted and further developed and modified for evaluating projected changes to low flow indices for Ontario streams. It is important to note that such approaches rely heavily on the quality of observational data and future climate projections available from GCMs. In fact, GCMs are the primary tools that climate scientists use to study climate change and the same GCMs were used to develop Climate Model Inter-comparison Project Phase 3, Phase 5 and Phase 6 simulations (i.e. CMIP3, CMIP5, and CMIP6) to support IPCC's reports. Tens of thousands of highly trained, independent scientists around the world collect and analyze climate data and develop models of global and regional climate change, which are typically tested using historical data and projected into the future, to support IPCC's work on climate change (IPCC, 2007, 2013), as well as several impact and adaptation related studies around the world.

As the focus of this report was set out on climate change aspects of low flow regimes in Ontario, it was quite relevant to provide a basic introduction to the topic of climate change for the reader from an applied perspective. For this reason, a general introduction to climate change and the tools and approaches that are required to study climate change, along with short descriptions of emissions scenarios and associated uncertainties are provided in Chapter 2. This information on climate change science and the various tools and approaches used in developing hydro-climatic projections was necessary to establish a minimal understanding of the terminology often used when integrating climate change information with low flow estimation methods. A framework for estimating projected changes to low flow indices and how one could estimate future low flows are presented in Chapter 3, based on the guidance and knowledge gained from the literature on low flow analysis, hydrological and meteorological aspects of low flow generating mechanisms and potential climate impacts on river flow regimes. The strengths and weaknesses of these approaches, from both applied and climate change perspectives, are also discussed in Chapter 3 to support future research and decision-making in the face of a changing climate.

In Section 4.2 of this chapter, a synthesis of the information on climate change science, the role of GCMs and greenhouse gas (GHG) emissions/concentration scenarios in climate change related studies, downscaling approaches, and various uncertainties associated with hydro-climatic projections are summarized. Concluding remarks on the proposed framework for the integration of climate change information with low flow estimation procedures is provided in Section 4.3, followed by a set of recommendations for additional studies to develop information on future low flows in Ontario streams in Section 4.4.

4.2 Climate Change, Climate Downscaling and Climate Projections

A general introduction to climate change and the tools and approaches required to study climate change across multiple spatial and temporal scales, along with short descriptions of GHG emissions/concentration scenarios and uncertainties associated with future projections is presented in Chapter 2, in an attempt to equip the reader with some basic knowledge of climate change science. In the literature on climate change, the term global warming is often used and refers to the observation that earth's average surface temperature is rising due to increased levels of GHGs in the atmosphere. The term "climate change" is much broader in scope as it encapsulates not only global warming, but also several other changes to earth's climate system that are caused by rising temperatures, including changes in precipitation, evaporation and air pollution; and movement of air currents (such as frontal systems or convective systems, hurricanes or a polar vortex), etc. Consistent to physical laws, a warmer air can hold more water, i.e. warmer air has a higher saturation vapor pressure, and therefore it is reasonable to expect higher amounts of water vapor in the air. These changes in the atmospheric water content can trigger numerous changes in the global and regional water cycles and can have severe implications for the management of regional water resources, and environmental and built infrastructure systems.

The review of selected literature on downscaling techniques provided in Chapter 2 highlights that considerable progress has been made in the development and application of downscaling methods for conducting climate change impact analyses at local and regional scales. All methods have certain limitations and there is no perfect way to downscale GCM outputs. The dynamical downscaling approach that involves Regional Climate Models (RCMs) has the great advantage of being physically based and, as such, it is the most useful approach for investigating the influence of various processes and atmospheric feedback mechanisms on climate change and its attribution. It is very likely that this approach will become very popular in the years to come as the spatial resolution of both GCMs and RCMs increases with time, and our understanding of various atmospheric processes and complex feedback mechanisms improves, along with increased computing resources and availability of efficient numerical algorithms. Surprisingly, some climate modelling groups have already started generating super-resolution climate simulations using RCMs and physics-informed ML approaches (e.g. Jia et al., 2019; Reichstein et al., 2019; Wu et al., 2021), which appears to be a remarkable advancement in super-resolution climate modelling.

Several statistical downscaling (SD) approaches are discussed in Chapter 2. From these approaches, transfer function and regression type approaches are quite popular. However, they can only explain a fraction of the observed variability in the dependent variable, which is being downscaled. ML approaches to SD also fall within this category. Although very powerful in capturing the complex inter-variable non-linear associations, ML-based approaches have also been criticised due to the difficulty in mapping their internal mechanics onto physical processes. The weather typing approach considers relationships between local climate variables and different types of atmospheric circulations. Availability of a limited range of circulation patterns is an obvious shortcoming of this approach. In the case of weather generators (WGs), one has to deal with a number of parameters. WGs are unable to accurately model observed temporal and spatial variability and inter-variable dependencies (e.g. Wilby et al., 2004). Often, in the application of WGs, it is also assumed that probability distribution types of various characteristics of observed and future climate variables will remain the same. This assumption seems to be unrealistic, but has been used frequently in several studies. Until recently, most statistical downscaling methods were unable to describe spatial dependencies. However, downscaling approaches that simultaneously model multiple variables at multiple sites have now been developed. These approaches are able to consider many organized spatial structures, often reflected in observational records of target variables.

In an inter-comparison study conducted by Goodess et al. (2005), it was found that no single near-perfect downscaling method can be identified among the several methods they considered. Additionally, downscaling skill depends on several factors. For example, temperature can be downscaled with more skill than precipitation; winter climate can be downscaled with more skill than summer due to stronger relationships with large-scale circulations; and wetter climates can be downscaled with more skill than drier climates (Fowler and Kilsby, 2007; Fowler et al., 2007). Direct comparison of the skill of different downscaling methods is also difficult due to: (i) the range of climate statistics assessed in the literature; (ii) the large range of predictors used; and (iii) the different ways of assessing model performance. Rather than devoting time to inter-comparison type of studies, it will be prudent to focus on the identification of an appropriate downscaling method for the specific applied problem. For example, one can consider generation of low flows, high flows or integrated flows for a given season of interest as separate problems, because it is not necessary that the set of predictors that perform exceptionally for low flows will also perform well for high flows. Therefore, identifying climatic variables that are necessary to accurately downscale global model outputs for specific applications should be encouraged in future studies. However, the interest in developing new downscaling approaches is on the decline due to the availability of ready to use downscaled products, available through several data distribution portals and national/regional climate services.

4.3 Climate Integration with Low Flow Estimation Procedures

The question addressed here is how best to estimate future low flow indices at sites where historical observations exist and at those sites where no records exist or where only a nominal number of measurements are available. Two different approaches are proposed for integrating climate change information with low flow estimation methods. The origins of these approaches lie in the field of ungauged hydrology, although the concepts have been borrowed from areas like statistical frequency analysis, hydrologic regionalization, deterministic modelling of rainfall-runoff processes, and climate change science. An overview of the historical background and how these approaches can be used for future low flow estimation are summarized below based on the scientific/technical material covered in Chapter 3 of this report. The reader is also reminded that low flow estimation science continues to improve and evolve with time and thus this report builds on the most relevant estimation methods currently available in the literature and practiced in low flow modelling and management related projects.

It is straightforward to estimate low flow indices at locations along a river where observational records are available, i.e. the locations where hydrometric gauges are located. A large majority of the world's rivers and watersheds is ungauged and the same is the case of Ontario. For low flow management oriented projects in ungauged watersheds, it is important to have some basic information on low flow regimes of such watersheds. To address these situations, hydrologists have devised indirect approaches for developing low flow estimates at ungauged locations, specifically in the form of low flow indices and occasionally for generating continuous streamflow sequences. Additional comprehensions on these aspects are provided below.

For the case of low flow indices, regression equations are generally used. These equations are developed based on known estimates of low flow indices and watershed attributes from gauged locations. Subsequently, these equations are transposed to ungauged locations for the estimation of desired indices, e.g. 7Q10 or Q95. In the case where interest lies in the estimation of continuous streamflow sequences, deterministic hydrologic modelling approaches are used. That is, a process-based hydrological model is selected, calibrated at gauged locations and then regression-based functional relationships between the dominant and/or influential model parameters and watershed attributes are developed for a selected region of interest. These relationships are assumed to be valid for all locations within the region and therefore, on the provision of meteorological data, long-term streamflow sequences can be generated at any point of interest along a river reach. These streamflow sequences are then used to derive 7Q10 and Q95 type low flow indices, following respectively statistical frequency analysis approaches and by developing flow duration curves.

World's climate is projected to change as documented in all reports of the Intergovernmental Panel on Climate Change (IPCC). Ontario's climate is also projected to change, which will have alarming impacts on low flow regimes of Ontario streams. As mentioned above, the question addressed in this report is how best one can estimate future low flows in Ontario streams, in order to plan for a better future that supports sustainability, ecosystem health and responsible stewardship of Ontario streams. To answer this question, two generalized approaches are proposed. These approaches are driven by an impressive amount of published work in the field of ungauged hydrology and the recent advancements that have been made on the estimation of low lows at ungauged locations. The first approach relies on the direct use of regression based functional relationships of low flow indices and watershed attributes and the second is based on the use of process-based hydrologic modelling. Both of these approaches are discussed above in the context of ungauged hydrology.

Regression based functional relationships are often sought between low flow indices and watershed attributes, reflecting physiographical, climatological and other relevant features. The features like drainage area (DA), mean basin slope (MBS), annual mean precipitation (AMP), annual mean snowfall (AMS), annual mean temperature (AMT), length of the main channel (MCL), slope of the main channel (MCS), percent area occupied by waterbodies (PWB), percent area covered by forests (PF), etc., are frequently used. For developing future projections of low flow indices, it is important to stress more on climatological features in developing these relationships. For example, one could also consider including some measures of seasonal quantities pertaining to precipitation, temperature, and evapotranspiration; cooling degree days; heating degree days; mean number of consecutive dry days longer than, e.g., 30 days; proportion of precipitation occurring below the long-term 25th percentile value; and several other measures that influence occurrence and persistence of low flow conditions in riverine environments. The main impetus in a climate change context is that many of the above mentioned features will act as static quantities (e.g. DA, MBS, MCL, MCS, and PWB) and therefore more stress should be put on climatological quantities (e.g. AMP, AMS, AMT, etc.) to make sense of these relationships. Following such a framework, climate change information available from global and regional climate models in the form of change patterns can be directly integrated with these relationships to derive future changes to low flow indices. The advantage of this approach is its simplicity and less analyses involved compared to the case of process-based hydrologic modelling, discussed below. For the applicability of these relationships for future conditions, it is generally assumed that the regression parameters estimated based on historical observations and underlying modelling assumptions will remain valid for future conditions as well. This could also be seen as a limitation of the regression based approaches.

The process-based hydrological modelling approach is a more comprehensive alternative to the index-based approach and therefore involves lot more work and modelling diagnostics. The success of this approach, however, is founded on the identification of a suitable hydrological model for the entire region of interest. It is desirable that the selected model should be able to describe the hydrology of the region, while explaining dominant runoff generation mechanisms. Careful calibration and validation of the selected model for a chosen historical period and identification of dominant model parameters that impact model’s performance are other important aspects to be considered. This approach also involves development of regression relationships between model parameters and watershed attributes for transferring them to ungauged locations. For this purpose, the same watershed attributes as conventionally used can be employed and it is not necessary to include more climatological features as in the case of index-based direct regression relationships. Probably, it will be better to have more physiographical features than climate features because the latter set of features is directly integrated with these models. After having a working regional hydrologic model, it can readily be used for generating streamflow sequences for any future time window assuming that the model structure and its parameters are valid for future conditions as well. Projected changes to low flow indices can be generated by performing low flow frequency analyses for the historical reference and future periods. Permitting time and resources, it will be useful to apply both approaches because both complement each other and the combined application will also furnish an opportunity to investigate the usefulness of detailed deterministic modelling over the simple index-based approach.

4.4 Recommendations for Future Work

The impact of climate change in Canada is now impossible to ignore, given the information available from the IPCC's reports and the Canada's Changing Climate Report (https://www.nrcan.gc.ca/climate-change/impacts-adaptations/canadas-changing-climate-report/21177). Unlike before, the science behind climate change was not questioned at the United Nations Climate Change Conference (COP26) in Glasgow in 2021. Glasgow Climate Pact not only covers emissions reductions targets, but also climate change adaptation and financial aspects. Intelligent risk management strategies are essential to effective governance, supporting ecosystem health and ensuring a safe future for rivers and streams upon which Ontarians can persevere and thrive, without surpassing environmental thresholds. In the face of an uncertain future due to looming climate crisis, the ability to respond to the challenge and adapt effectively will be crucial for various levels of the government. Although challenges are significant, if the riverine ecosystems are not made resilient to climate related stressors, the future changes may considerably damage our interconnected social, riverine, and environmental systems.

National and regional governments often face extreme weather and climate events that threaten their financial stability, create unemployment and increase the demand for social support services, in addition to the disastrous impacts on the environment, agriculture and ecosystem health. Based on the work of IPCC, there is a greater likelihood of such extreme events to occur more often in the future due to projected climate change, which has left the governments with a clear imperative, i.e. respond to the challenge, support research to generate new knowledge to bridge the knowledge-to-action gap and help planners to design and develop adaptation strategies before the disaster exposes our frayed social and economic systems. It is important that the changes should be made at the grassroots level and should be deep rooted to support a thriving ecosystem of healthy rivers and streams for the well-being and prosperity of all Ontarians. So now begins the hard work for the MECP for creating a meaningful, lasting change and develop a vision based on the United Nations' sustainability principles for managing low flow regimes in the near and far futures. In the beginning, there may be lack of clarity on the delivery mechanisms for adaptation solutions, government departments and private agencies have to take concrete actions, given the evidence that the general public want action is increasing overtime.

A systematic framework has been proposed in this report to develop projected changes to low flow indices for Ontario streams. As a first step, it is recommended to apply index-based approaches using future climate projections from both GCMs and RCMs for hydrologic homogeneous regions of Ontario. In the case of lack of gauged locations for a certain region to satisfy certain statistical assumptions, region of influence approach could be exploited by extending the definition of contiguous homogeneous regions to global regions, spanning multiple regions and watersheds. This will help develop robust regression relationships between low flow indices and watershed attributes and that in turn will help develop robust climate change signals. After having developed estimates of potential changes to low flow regimes, appropriate corrective and adaptation actions can be devised and executed.

As a second step and to complement the results of index-based approaches, it is desirable to follow the route of process-based hydrologic modelling. The framework for integrating climate change information with these models and then deriving projected climate change signals for low flow indices has been presented in Chapter 3 of this report. Although this approach is resource intensive, it may uncover some change patterns that may not be possible using simple index-based approaches. In the case of distributed hydrologic modelling, it is even possible to develop climate change signals at the grid-cell level of the selected models and that could be as small as a km in aerial extent. However, care must be exercised when implementing this approach regarding over-parametrization and over-calibration of the models involved. Several configurations of hydrologic and climate models are possible, for example (1) interfacing single output from a single climate model with a single hydrological model, (2) interfacing multiple outputs from a single climate model with a single hydrological model, (3) interfacing multiple outputs from multiple climate models with a single hydrological model, and (4) interfacing multiple outputs from multiple climate models with multiple hydrological models. The last of these configurations helps address both hydrologic and climate modelling related uncertainties, though resource constraints may preclude this option. Given the advances that have been made in producing CMIP6 simulations and regional climate modelling, option 3 seems to be an optimal choice because some information on projected changes can be generated from the application of index-based approaches.

Finally, stochastic and deterministic modelling of hydrology and water resource systems whether in a synchronous or in an asynchronous manner have played a significant role in understanding our highly interconnected and complex water-food-energy-social-ecological systems to support economic development activities for a long time. Perhaps it is likely that these conventional approaches now require innovative ideas to further improve our ability to manage these complex systems even more efficiently and objectively. Given this desire, researchers are becoming progressively more inclined towards experimenting with data-driven models and solutions. These models can learn from complex data patterns and exclusive experiences and therefore can be quite powerful in making accurate predictions. In the above suggested approaches for evaluating projected changes to low flow indices, ML-based approaches can also be used for developing regression-oriented nonlinear relationships and simulating complex precipitation-runoff processes in all watersheds of a region of interest.

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