Effects of Climate Variability and Change on Surface Water Storage
within the Hydroclimatic Regime of the Athabasca River, Alberta, Canada

by
Gillian Sarah Walker
B.Sc. McGill University, 2006

A Thesis Submitted in Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

in the Department of Geography

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University of Victoria

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ABSTRACT

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Warmer air temperatures projected for the mid-21st century under climate change are expected to translate to increased evaporation and a re-distribution of precipitation around the world, including in the mid-latitude, continental Athabasca River region in northern Alberta, Canada. This study examines how these projected changes will affect the water balance of various lake sizes. A thermodynamic lake model, MyLake, is used to determine evaporation over three theoretical lake basins – a shallow lake, representative of perched basins in the Peace-Athabasca Delta near Fort Chipewyan; an intermediate-depth lake representative of industrial water storage near Fort McMurray; and a deep lake representative of future off-stream storage of water by industry, also near Fort McMurray. Bias-corrected climate data from an ensemble of Regional Climate Models are incorporated in MyLake, and the water balance is completed by calculating the change in storage as the difference between precipitation and evaporation. Results indicate that evaporation and precipitation are projected to increase in the future by similar magnitudes, thus not significantly changing the long-term water balance of the lakes. However, intra-annual precipitation and evaporation patterns are projected to shift within the year, changing seasonal water level cycles, and the magnitudes and frequencies of extreme 1-, 3- and 5-day weather events are projected to increase. These results demonstrate that future climate change adaptation and mitigation strategies should take into account increases in intra-annual variability and extreme events on water levels of lakes in mid-latitude, interior hydroclimatic regimes.
# TABLE OF CONTENTS

Supervisory Committee ................................................................................................................................. ii

Abstract .................................................................................................................................................................. iii

Table of Contents ................................................................................................................................................... iv

List of Tables ....................................................................................................................................................... viii

List of Figures ..................................................................................................................................................... x

Acknowledgements ............................................................................................................................................... xiv

1. Chapter 1: Introduction ........................................................................................................................................ 1
   1.1 Background....................................................................................................................................................... 1
   1.2 Goal and Objectives ...................................................................................................................................... 3
   1.3 Thesis Structure .......................................................................................................................................... 4
   1.4 Presentations and Publications .................................................................................................................... 5
   1.5 References .................................................................................................................................................. 6

2. Chapter 2: Literature Review ............................................................................................................................ 8
   2.1 Introduction .................................................................................................................................................. 8
   2.2 Water Balance Modelling ............................................................................................................................ 8
       2.2.1 Initial Development ........................................................................................................................... 8
       2.2.2 Modern Water Balance Modelling ..................................................................................................... 10
       2.2.3 Water Balance Variable Selection ..................................................................................................... 12
       2.2.4 Estimating Water Balance Parameters ............................................................................................ 15
   2.3 Climate Variability and Change ................................................................................................................ 23
       2.3.1 Annual and Seasonal Climate Change ............................................................................................ 24
       2.3.2 Climate Modelling ............................................................................................................................ 26
       2.3.3 Climate Scenarios ............................................................................................................................. 26
       2.3.4 Heat Storage in Lakes ....................................................................................................................... 29
       2.3.5 Downscaling ...................................................................................................................................... 30
       2.3.6 Bias Correction .................................................................................................................................. 34
       2.3.7 NARCCAP Ensemble Modelling ....................................................................................................... 37
       2.3.8 Analysing Changes in Climate ........................................................................................................... 37
       2.3.9 Extreme Climate Events ................................................................................................................... 40
       2.3.10 Indices and Statistical Modelling .................................................................................................... 42
       2.3.11 Trend Testing for Climate Variables ............................................................................................... 46
   2.4 Study Area ................................................................................................................................................ 47
       2.4.1 The Athabasca River Region .............................................................................................................. 47
       2.4.2 Evaporation Studies at Fort McMurray ............................................................................................... 52
       2.4.3 Water Balance Studies in the Athabasca River Region ..................................................................... 54
       2.4.4 Water Storage .................................................................................................................................... 55
3. Chapter 3: Methodology and Data ................................................................. 77
   3.1 Lake Water Balance and Study Basins ..................................................... 77
   3.2 Data ........................................................................................................... 80
      3.2.1 Current and Future Periods ................................................................. 80
      3.2.2 NARCCAP and NARR Data ............................................................... 80
      3.2.3 Bias Corrected Datasets ................................................................ 84
      3.2.4 Extreme Datasets ............................................................................ 86
   3.3 MyLake Model ......................................................................................... 86
      3.3.1 Basin Morphometry ....................................................................... 88
      3.3.2 Water Temperature Profile ............................................................... 89
      3.3.3 Ice Cover Module ........................................................................... 95
      3.3.4 MyLake’s Estimation of Evaporation ............................................. 98
   3.4 Validation (Other Evaporation Estimates) ................................................ 102
   3.5 Evaluating Average and Cumulative Water Balance ............................. 107
   3.6 Evaluating Extreme Events ................................................................... 107
   3.7 Defining Extremes ................................................................................ 109
      3.7.1 Peaks-Over-Threshold (POT) Index ............................................... 109
      3.7.2 Extreme Value Distributions ............................................................. 110
   3.8 Conclusions ............................................................................................ 110
   3.9 References .............................................................................................. 112

4. Chapter 4: EFFECTS OF PROJECTED CHANGES IN REGIONAL PRECIPITATION AND EVAPORATION ON LAKE WATER BALANCES IN THE ATHABASCA REGION, ALBERTA, CANADA ................................................................. 117
   4.1 Background ............................................................................................ 117
   4.2 Study Site ............................................................................................... 122
      4.2.1 Study Basins .................................................................................. 123
   4.3 Data and Methods .................................................................................. 124
      4.3.1 Water Balance .............................................................................. 124
      4.3.2 Data ............................................................................................... 125
      4.3.3 Bias Correction ............................................................................. 127
      4.3.4 Validation of Bias Correction ......................................................... 129
      4.3.5 The MyLake Model ....................................................................... 130
      4.3.6 Other Common Evaporation Estimates ....................................... 134
      4.3.7 Water Balance Analysis ................................................................. 135
   4.4 Results .................................................................................................... 135
      4.4.1 Ice Cover Duration ....................................................................... 135
5. Chapter 5: PROJECTED CHANGES IN EXTREME LAKE WATER LEVELS IN THE ATHABASCA RIVER REGION, ALBERTA CANADA

5.1 Introduction ............................................................................................................. 182
5.2 Study Site .................................................................................................................. 185
5.3 Data ............................................................................................................................ 189
5.4 Methods: Analysis of Extreme Wetting and Drying Events ........................................... 192
  5.4.1 Calculating the Water Balance .............................................................................. 192
  5.4.2 Defining Extremes ............................................................................................... 193
  5.4.3 Peaks-Over-Threshold (POT) ............................................................................ 194
  5.4.4 Extreme Value Distributions ............................................................................. 194
  5.4.5 Annual Maxima (AM) and Annual Minima (AMin) .............................................. 195
5.5 Results ........................................................................................................................ 196
  5.5.1 Selection of Extreme Gridpoints ......................................................................... 196
  5.5.2 High Extremes – Values of the 90th Percentile ..................................................... 197
  5.5.3 Low Extremes – Values of the 10th Percentile ...................................................... 199
  5.5.4 1-Day Peaks Over Threshold (POT) ................................................................. 201
  5.5.5 3-day and 5-day Peaks Over Threshold (POT) ...................................................... 206
  5.5.6 Generalized Extreme Value (GEV) Distribution .................................................. 210
  5.5.7 Most Extreme Changes in Water Level ............................................................... 218
5.6 Discussion ................................................................................................................. 226
  5.6.1 Extreme Changes in Water Level ....................................................................... 226
  5.6.2 Climate Model Uncertainty ............................................................................... 229
  5.6.3 Extremes and Surface Water Design Specifications ............................................ 230
5.7 Conclusions ............................................................................................................... 232
LIST OF TABLES

Table 1: The ensemble of Regional Climate Models (RCMs) nested in Global Climate Models (GCMs), available through the North American Regional Climate Change Program (NARCCAP). Adapted from Mearns et al. (2012; p. 1340) .................................................. 38

Table 2: Sizes of proposed End Pit Lakes in the Athabasca River region ........................................... 59

Table 3: The theoretical study basin sizes, based on similar existing or proposed lakes in the Athabasca River region ........................................................................................................... 78

Chapter 4:

Table 4: Duplication of Table 3 ............................................................................................................. 124

Table 5: Average Total Annual Precipitation over 1971 – 2000 for the NARCCAP model data (ensemble mean) and EC Climate Normals, and over 1979-1999 for the NARR data ......... 129

Table 6: Average annual ice cover breakup and freeze-up dates for the current period (1971 – 2000) and the future period (2041 – 2070) at the two study sites ............................................. 136

Table 7: Ensemble mean average total annual evaporation modelled by MyLake using RCM_GCM input climate data for 1971 – 2000 ................................................................. 137

Table 8: Ensemble mean annual totals for the three water balance variables, for the current (1971 – 2000) and future (2041 – 2070) periods ................................................................. 141

Table 9: Difference between current and future annual totals for the water balance. ....................... 141

Table 10: Total monthly precipitation averaged over all years in the current period (1971 – 2000) from the NARCCAP ensemble mean at Fort McMurray and Fort Chipewyan .............. 151

Table 11: Total ensemble mean evaporation and precipitation in the ice cover season versus the open-water season for the current period (1971 – 2000) .................................................. 153

Table 12: Daily cumulative water balance (metres) at the end of the current and future 30-year periods. The difference is calculated as future minus current values ..................................... 162

Chapter 5:

Table 13: Duplication of Table 3 ......................................................................................................... 186

Table 14: Latitude, Longitudes, and identifiers of all gridcells used to create the “Max Precip” and “Max Temp” climate data for the Fort Chipewyan and Fort McMurray study sites ... 197

Table 15: Values of the 90th percentile of daily evaporation, precipitation, and change in water level in the current period (1971 - 2000) for the Max Precip and Max Temp gridcells ... 197

Table 16: Value of the 90th percentile for the distribution of 3-day moving sums ......................... 199

Table 17: Value of the 90th percentile for the distribution of 5-day moving sums ......................... 199

Table 18: The values of the 10th percentile of the change in water level variable for the study lakes at Fort McMurray and Fort Chipewyan in the current period (1971 – 2000) ............. 200

Table 19: Value of the 10th percentile for the distribution of 3-day moving sums ......................... 200

Table 20: Value of the 10th percentile for the distribution of 5-day moving sums ......................... 201

viii
Table 21: Future number of days per year (dy/yr) exceeding the 90\textsuperscript{th} percentile current period threshold (high POT) from the Max Precip and Max Temp gridpoints. .............................. 202

Table 22: Future minus Current change in the number of days per year (dy/yr) of daily high POT. ....................................................................................................................... 202

Table 23: Future number of days per year (dy/yr) below the 10\textsuperscript{th} percentile current period threshold (low POT) from the Max Precip and Max Temp gridpoints. ....................... 206

Table 24: Future POT for high extremes of the 3-day cumulative sums of evaporation, precipitation and change in water level ........................................................................................................ 207

Table 25: Future minus Current POT for high extremes of 3-day cumulative sums............... 207

Table 26: Future POT for high extremes of the 5-day cumulative sums of evaporation, precipitation and change in water level ................................................................. 208

Table 27: Future minus Current POT for high extremes of 5-day cumulative sums............. 208

Table 28: Low POT for change in water level 3-day cumulative sums below the 10\textsuperscript{th} percentile ..................................................................................................................... 209

Table 29: Low POT for change in water level 5-day cumulative sums below the 10\textsuperscript{th} percentile ..................................................................................................................... 209

Table 30: Maximum Annual Maximum (AM) 3-day cumulative changes in water level, and the difference between the current (1971 – 2000) and future (2041 – 2070) periods.......... 220

Table 31: Maximum Annual Maximum (AM) 5-day cumulative changes in water level, and the difference between the current (1971 – 2000) and future (2041 – 2070) periods........ 221

Table 32: 3-day sum minimum AMin for change in water level (mm/dy), and the difference between current and future periods. ....................................................................................... 223

Table 33: 5-day sum minimum AMin for change in water level (mm/dy), and the difference between current and future periods. ....................................................................................... 224

Table 34: Dates of maximum Annual Maxima (AM) and minimum Annual Minima (AMin) changes in water level in the current period (Year, Month, Day). ................................. 225
LIST OF FIGURES

Figure 1: Western Canada including the Athabasca River region (white box) in northern Alberta and the Fort McMurray and Fort Chipewyan study sites (Google Earth, 2013). ........................................... 49

Figure 2: The “Athabasca River region” including the Lower Athabasca River and surrounding area in northern Alberta, Canada (from WWF Canada: Lebel et al., 2011; page 5). ......................... 49

Figure 3: Typical mine site water balance showing new addition of off-stream water storage, from the Phase 2 Committee Framework Report for the Oil Sands Development Group (Ohlson et al., 2010: p.10). .......................................................... 61

Figure 4: Spatial resolution of NARCCAP RCM_GCMs used to calculate the water balance for the average regional and extreme local climates of both Fort McMurray and Fort Chipewyan. . 82

Figure 5: Overlay of the 50 km$^2$ resolution and 10 km$^2$ resolution NARCCAP model gridpoints, and the 32 km$^2$ resolution NARR model gridpoints around Fort Chipewyan............................... 84

Figure 6: Example of a lake modelled by MyLake (Adapted from Saloranta & Andersen, 2004: Figure 1, p.8). .................................................. 88

Figure 7: Lake Morphometry of the three hypothetical study basins, representative of existing and planned surface water storage in the Athabasca River region. ........................................ 89

Chapter 4:

Figure 8: A) Average monthly temperature (°C/dy) and B) total monthly precipitation (mm/month), from Environment Canada climate stations Fort McMurray A (Station #3062693) and Fort Chipewyan A (Station #3072658), averaged over the 1971 – 2000 climate normal period (Environment Canada, 2013). ........................................................................ 123

Figure 9: Basin morphometry for A) the shallow lake (1.5 m deep, 20 km$^2$), intermediate-depth lake (28.5 m deep, 1 km$^2$), and deep lake (76.5 m deep, 30 km$^2$); and B) Zoom on the morphometry of the shallow lake. ............................................................... 132

Figure 10: Mean, Maximum, and Minimum evaporation rates from the ensemble mean of the MyLake results using NARCCAP input data for 1971 – 2000. .................................................. 138

Figure 11: Ensemble mean monthly evaporation rates in the current period (1971 – 2000) at A) Fort McMurray and B) Fort Chipewyan. ........................................................................ 139

Figure 12: Difference between future and current average evaporation by month, calculated by subtracting the current period from the future monthly means of the ensemble mean MyLake results. ........................................................................ 142

Figure 13: Average Ensemble Water Balance for the current (1971 – 2000) and future (2041 – 2070) periods at Fort McMurray. ........................................................................ 143

Figure 14: Average ensemble mean water balance for the current (1971 – 2000) and future (2041 – 2070) periods at Fort Chipewyan. ........................................................................ 144

Figure 15: Average daily open-water evaporation rates using bias-corrected NARCCAP ensemble mean input data for Fort McMurray from 1971 – 1999, calculated using the MyLake, Penman, Priestley-Taylor, Hamon, and Bowen Ratio methods. ........................................................................ 146
Figure 16: Average monthly evaporation rates modelled by MyLake and by four other estimates: Penman, Priestley-Taylor, Hamon, and the Bowen Ratio. Input data for all methods is bias-corrected NARCCAP ensemble for 1971 – 1999.

Figure 17: NARCCAP and NARR precipitation and evaporation at Fort McMurray and Fort Chipewyan, 1979 – 1999.

Figure 18: Ensemble mean average daily precipitation by month in the current period (1971 – 2000) and the change to the future period (2041 – 2070).

Figure 19: Total annual ensemble mean water balance components in the current period (1971 – 2000) for A) Fort Chipewyan and B) Fort McMurray.

Figure 20: Total monthly change in water level (mm/month) in the current period (1971 – 2000) at A) Fort Chipewyan and B) Fort McMurray.

Figure 21: Ensemble mean average daily change in water level by month in the current period (1971 – 2000) and the difference to the future period (2041 – 2070), calculated by subtracting the current period monthly means from the future monthly means.

Figure 22: Future minus current ensemble mean water balance at Fort McMurray. Plots A, C and E show the difference in the 30-year average for each Julian day, and plots B, D and F show the difference in the mean value for the entire 30-year future and current periods.

Figure 23: Future minus current ensemble mean water balance at Fort Chipewyan.

Figure 24: Current (1971 – 2000) and future (2041 – 2070) cumulative water balance at Fort McMurray and Fort Chipewyan for shallow (1.5 m), intermediate (28.5 m), and deep (76.5 m) lakes.

Figure 25: Cumulative change in water level (metres) by study site, current (1971 – 2000) and future (2041 – 2070) from the NARCCAP ensemble mean.

Figure 26: Cumulative change in water level (metres) by depth, current (1971 – 2000) and future (2041 – 2070) from the NARCCAP ensemble mean.

Figure 27: Cumulative precipitation, evaporation and change in water level in the current period, from each of the three NARCCAP RCMs used in the ensemble.

Chapter 5:

Figure 28: Annual “high POT” for the Max Precip BCCI dataset in the Current (1971 – 2000) and Future (2041 – 2070) periods.

Figure 29: Annual “high POT” for the Max Temp BCCI dataset in the Current (1971 – 2000) and Future (2041 – 2070) periods.

Figure 30: Annual “high POT” for the Max Precip BCSD dataset in the Current (1971 – 2000) and Future (2041 – 2070) periods.

Figure 31: Annual “high POT” for the Max Temp BCSD dataset in the Current (1971 – 2000) and Future (2041 – 2070) periods.

Figure 32: Annual “low POT” for “change in water level”, for the current (1971 – 2000) and future (2041 – 2070) water balances.
Figure 33: Average increase in the number of days exceeding the high (90th percentile) and low (10th percentile) thresholds in the future for 1-, 3- and 5-day change in water level events. ..... 209

Figure 34: Cumulative distribution functions (cdf) of daily high extremes of “change in water level” at Fort McMurray from the BCCI dataset, in the current (1971 – 2000) and future (2041 – 2070) periods. ................................................................. 213

Figure 35: Cumulative distribution functions (cdf) of daily high extremes of “change in water level” at Fort McMurray from the BCSD dataset, in the current (1971 – 2000) and future (2041 – 2070) periods. ................................................................. 213

Figure 36: Cumulative distribution functions (cdf) of daily high extremes of “change in water level” at Fort Chipewyan from the BCCI dataset, in the current (1971 – 2000) and future (2041 – 2070) periods. ................................................................. 214

Figure 37: Cumulative distribution functions (cdf) of daily high extremes of “change in water level” at Fort Chipewyan from the BCSD dataset, in the current (1971 – 2000) and future (2041 – 2070) periods. ................................................................. 214

Figure 38: Location ($\mu$) and scale ($\sigma$) parameter estimates for the CDF distributions of high extremes of change in water level, averaged across all lake depths. ................................................................. 215

Figure 39: Cumulative distribution functions (CDF) of daily low extremes of “change in water level” at Fort McMurray from the BCCI dataset, in the current and future periods. ................................. 216

Figure 40: Cumulative distribution functions (CDF) of daily low extremes of “change in water level” at Fort Chipewyan from the BCCI dataset, in the current (1971 – 2000) and future (2041 – 2070) periods. ................................................................. 216

Figure 41: Cumulative distribution functions (CDF) of daily low extremes of “change in water level” at Fort McMurray from the BCSD dataset, in the current (1971 – 2000) and future (2041 – 2070) periods. Lines for the three models and three lake depths are plotted using the same colour. ................................................................. 217

Figure 42: Cumulative distribution functions (CDF) of daily low extremes of “change in water level” at Fort Chipewyan from the BCSD data, in the current (1971 – 2000) and future (2041 – 2070) periods. ................................................................. 217

Figure 43: Location ($\mu$) and scale ($\sigma$) parameter estimates for the CDF distributions of low extremes of change in water level, averaged across all lake depths. ................................................................. 218

Figure 44: Maximum Annual Maximum (AM) daily changes (increases) in water level in the current period at Fort McMurray and Fort Chipewyan, calculated from the water balance modelled using the Max Precip and Max Temp gridpoints. ................................................................. 219

Figure 45: Future minus current 1-day change in water level events. ................................................................. 219

Figure 46: Minimum Annual Minimum (AMin) daily changes (decreases) in water level (mm/dy) in the current period at Fort McMurray and Fort Chipewyan, from the water balance modelled using the Max Precip and Max Temp gridpoints. ................................................................. 222

Figure 47: Future minus current 1-day changes in water level (mm/dy). ................................................................. 222

Appendices:
Figure 48: Sensitivity of evaporation rates to lake depth. MyLake was run with 23 different lake depths ranging from 1.5 m to 76.5 m deep, using climate data from the CRCM CCSM model in the current period (1971 – 2000).

Figure 49: Effects of MyLake’s sediment heat flux switch on evaporation based on lake depth.
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1. CHAPTER 1: INTRODUCTION

1.1 Background

All phases of the hydrologic cycle are sensitive to climate variability and change. Surface water in particular is affected by the temperature, precipitation and aerodynamic regimes of the region in which it is located (Lins et al., 1990; Oke, 1987). Water-atmosphere exchanges, including evaporation, sublimation, condensation and precipitation, are driven by the energy balance at the Earth’s surface, mainly through latent and sensible heat fluxes (Rouse, 1990). In some places and at varying temporal scales, slight shifts in climate affecting these heat fluxes can result in significant alteration of the area’s hydrology (Dooge & Kuusisto, 1998).

To evaluate changes in the hydrologic cycle, the nature of the current, and the projected future, “water balance” in a catchment or region are compared (Kane & Yang, 2004; Wanchang et al., 2000). The water balance combines the hydrologic inputs and outputs of a catchment; any difference between the two represents a change in surface water storage (negative or positive) at a particular spatial and temporal scale (Oke, 1987). The storage component of the hydrologic cycle can take a variety of forms: snow, ice, glaciers, groundwater, soil moisture, and natural and anthropogenic surface water ranging from small ponds and shallow wetlands to the largest lakes in the world (Prowse, 1990). Changes to surface water storages are reflected by changes in water levels (Lenters et al., 2005). Water levels of lakes located in a mid-latitude, sub-humid, dry, interior continental hydroclimatic regime are of particular concern as high variability in both precipitation inputs and evaporation outputs create fluctuations in the amount of water stored (Devito et al., 2005). A prime example is found in Western Canada in the Athabasca River region of northern Alberta, which contains a wide range of types of surface water storage and is therefore an appropriate place to study the interactions between climate and surface water.
Water stored in lakes and ponds is important for both ecosystem services and anthropogenic uses. Stored water serves ecosystems by providing drinking water, supporting the growth of vegetation, and acting as habitat for animals of all kinds (Mitchell, 1991). Humans also use stored water for a variety of purposes, including municipal and industrial water supply (Ohlson et al., 2010), reservoirs for flood control (Jones, 2011) and hydropower (Gebre, 2014), landscape reclamation (Westcott, 2007), irrigation, and recreation (Schertzer & Taylor, 2009). Storage of water as freshwater ice is also important to humans and ecosystems as it affects lake biodiversity, contributes to ice jam-induced flooding in rivers, and has important socio-economic uses such as transportation and recreation (Prowse et al., 2009).

While natural climate variability causes fluctuations in the levels of surface water storage over time, climate change projected for the 21st century is expected to cause never before seen changes to the hydrologic cycle (IPCC, 2014). Specifically, it is recognized that climate warming causes an overall intensification of the hydrologic cycle (i.e. Huntington, 2006; Prowse, 2009). As global mean temperature increases, surface air can become saturated more quickly to produce precipitation, and evaporation is likewise sped up by the increased availability of surface energy (Milly et al., 2005). This intensification results not only in an increase in globally averaged precipitation, evaporation, and mean water vapour, but also in dramatic changes to the temporal and spatial distribution of the planet’s water, in the form of extreme climate events (Meehl et al., 2007). In the past, the assumption that climate was stationary meant that analysts could assume that the mean, variance, and extremes of climatic variables remained stable over time (Klein Tank & Zwiers, 2009). However, it is now accepted that climate change is causing a shift to a non-stationary climate where average and extreme conditions are changing over time (IPCC, 2007; IPCC, 2014).
In recent years the world has experienced an unprecedented number of extreme climate events (Coumou & Rahmstorf, 2012). The occurrence of these extremes forms the basis of society’s concept of climate change, and in many cases, of climate itself (Randall et al., 2007). This is because extreme events, especially of unexpected magnitudes and frequencies, can have dramatic consequences to society and the biosphere, such as human suffering, costly damage to housing and infrastructure, and positive or negative impacts on natural systems (Klein Tank & Zwiers, 2009; Rahmstorf & Coumou, 2011; Randall et al., 2007). It is more difficult for society to adapt to changes in patterns of extreme events than to gradual changes in mean climate (Wagner, 1996). Therefore, the evaluation of the changing frequency and magnitude of extreme events such as floods, droughts, heat waves, and tropical storms is important to develop adaptation and mitigation strategies for extreme events to reduce their impact on society and ecosystems (IPCC, 2012; Klein Tank & Zwiers, 2009).

1.2 Goal and Objectives

The goal of this project is to assess the effects of global climate variability and change on freshwater storage in 1st-order basins in a mid-latitude, sub-humid, interior continental hydroclimatic regime. This is accomplished through two primary objectives:

1. To assess changes between the current and future water balances of surface water storages of differing depths by evaluating changes in regional patterns of precipitation, evaporation, and changes in water level using the simplified water balance equation:

\[ P - E = \Delta WL, \]  \[1\]

where \( P \) = precipitation, \( E \) = evaporation, and the change in water level (\( \Delta WL \)) represents the change in water storage; and
(2) To analyze changes in the variability of the calculated water balances, with special attention to future changes in the magnitudes and frequencies of extreme events.

To address both objectives, climate data from an ensemble of Regional Climate Models (RCMs) nested within Global Climate Models (GCMs) are bias-corrected and used to calculate the water balance. Precipitation from the RCMs is used directly in the water balance, while a suite of variables from the same models is used to estimate evaporation via a comprehensive lake model, MyLake, which takes into account heat storage in water bodies.

1.3 Thesis Structure

Chapter 2 provides a literature review of the methods and study site chosen to address the main research goal. Water balance theory and past work on water balance components are reviewed, followed by a description of climate variability, climate modelling, and the hydroclimatic regime of interest. Chapter 3 describes the methodology and data used to produce the results presented in Chapters 4 and 5. A detailed description of the estimation of evaporation by the MyLake model is also provided. Chapters 4 and 5 are stand-alone scientific papers detailing the results of objective 1 and 2, respectively. As this thesis is presented in manuscript format, some material from Chapters 2 and 3 is repeated in Chapters 4 and 5, as necessary. Chapter 6 summarizes the conclusions of the study overall and makes suggestions for future work.
1.4 Presentations and Publications

The following is a comprehensive list of conference presentations and published proceedings that contain portions of the methodology and results in Chapters 4 and 5.


Walker, G.S., Prowse, T.D., Dibike, Y.B. and Bonsal, B.R. 2013. Projected Impacts of Climate Change on the Water Balance in the Athabasca River Region, Northern Alberta, Canada. Oral Presentation at the Department of Geography Graduate Symposium, December 5, 2013 at the University of Victoria, Victoria, BC.

1.5 References


2. CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Water balance studies have been undertaken in a multitude of watersheds of varying sizes around the world, using a wide range of parameters and types of data sources. In some cases measured and observed data are available to calculate the water balance of lakes (e.g., Blackie, 1993). However, the quantity and quality of available observed data often varies, making data availability a significant factor in the choice of methodology (Arnell, 2004). Solutions to data availability problems include altering the timescale or spatial scale of the study, modelling certain variables off-line, or using modelled or reanalysis climate data as inputs to the water balance (Mesinger et al., 2006).

This chapter reviews the development of water balance theory and relevant examples of water balance calculation in the literature. Factors relevant to the choice of water balance methodology for this study are summarized, including climate variability and the use of climate models, downscaling, and bias-correction techniques to prepare model results for use in water balance calculations. A literature review of the Athabasca River region study site is also presented, including a description of the variety of surface water storage it contains. Rather than being an exhaustive review, the methods and studies described here were selected to be relevant to the thesis goal and the hydrological regime of the Athabasca River region. Here the term “water balance” is used throughout as analogous to “water budget”; the two terms are used interchangeably in the literature.

2.2 Water Balance Modelling

2.2.1 Initial Development

In 1948, C. W. Thornthwaite published a paper entitled “An approach toward a rational classification of climate,” in which he pointed out that “the modern study of climate has been
dictated largely by the development of meteorological instruments…and the collection of weather data” (Thornthwaite, 1948: 55). He believed that the dependence on measured aspects of climate was leading researchers astray, and that “the sum of the climatic elements that have been under observation does not equal climate” (Thornthwaite, 1948:55). His paper names evaporation as the most significant overlooked climatic element. Thornthwaite (1948) went on to define and coin the terms “evapotranspiration” and “potential evapotranspiration.” He deduced that there is a difference between the amount of evaporation occurring in a watershed, and the amount that has the “potential” to occur if there was endless supply of available water. Using these concepts, Thornthwaite devised a climate classification system that provided a better scientific basis than the then-popular Köppen climate classification system (Keim, 2010). The system he developed delineates climate zones using evaporation in combination with latitude (to calculate energy based on day length). His system is different than the empirical Köppen system because it defines its classes using natural breaks in the evaporation and latitude values instead of simply using the recorded temperature and precipitation ranges associated with observed vegetative zones (Keim, 2010).

Although Thornthwaite’s (1948) classification system itself didn’t gain popularity, the underlying concepts devised were seminal to the way scientists study the hydrological cycle today (Black, 2007; Keim, 2010). With his colleague J. R. Mather, Thornthwaite expanded on his early evapotranspiration work and published a compilation on the subject, entitled “The Water Balance” (Thornthwaite & Mather, 1955). Together they went on to develop a series of two-parameter (soil moisture capacity and water storage fraction), monthly water balance models (Xiong & Guo, 1999). The theory behind these models is still used as the foundation for many
contemporary water balance models (e.g., Eder et al., 2005; Kerkides et al., 2000; Kling & Nachtnebel, 2009; Mouelhi et al., 2006; Pimenta, 2000; Xiong & Guo, 1999).

2.2.2 Modern Water Balance Modelling

Modern computer-based water balance models can be based on top-down or bottom-up theoretical development. A “bottom-up”, or physically-based, approach begins with an understanding of the individual physical processes occurring in the basin, and builds the water balance based on this \emph{a priori} information (Mouelhi et al., 2006; Portoghese et al., 2005). A “top-down”, or conceptual, approach, on the other hand, starts with how the basin operates, usually based on streamflow response at the outlet of the catchment, and builds downward to identify the processes causing these responses (Arnell, 1999; Sivapalan et al., 2003; Xu & Singh, 1998). Top-down models usually operate in a stepwise, hierarchical manner; at first a very simple version of the model with very few parameters is applied, and complexity is added one parameter at a time in an attempt to explain basin responses that are not yet being reproduced by the model outputs (Sivapalan et al., 2003). This means that only as much complexity as is required is added to the water balance equation to explain the basin’s hydrological processes, however the parameters have no physical meaning and cannot be measured in the catchment for validation purposes. Top-down conceptual models are often easier to calibrate to a catchment; however, bottom-up physically-based models may provide more realistic modelling of catchment processes allowing them to be applied to the basin under varied conditions (e.g., under climate change) or to other basins (Sivapalan et al., 2003).

Models also vary in the type of input data required. “Lumped” water balance models require data averaged over the chosen timescale and cell-size (either a grid cell or a catchment) (Arnell, 1999). This is useful since meteorological input data such as precipitation and
temperature are usually collected at this scale (see Environment Canada’s National Climate Archive: [http://climate.weather.gc.ca/](http://climate.weather.gc.ca/)). “Distributed” models require computationally-complex, spatially distributed input data, which usually comes in much larger datasets and with more demanding computational requirements (Sivapalan et al., 2003). Working with these large datasets can be worthwhile as physically-based, distributed models often out-perform their lumped, conceptual counterparts (Wanchang et al., 2000). The requirement for large, spatially-distributed datasets is where models benefit from the use of Geographical Information Science (GIS) to manipulate input data. The inherent spatial component of remotely sensed data eliminates the need for spatial averaging across the basin, allowing them to be used directly by distributed models as long as the appropriate spatial and temporal resolution is available (Kling & Nachtnebel, 2009; Portoghese et al., 2005).

The choice of model, on the spectrum from lumped, conceptual models to distributed, physically-based models, depends on the objectives of the study. When the objective is to analyze the effects of climate variability, as in this study, using a physically-based model is important to have a higher level of confidence in the applicability of the physical processes under a future climate. In cold regions, physical processes are more complex and require a physically-based model to account for snow and ice formation and melt. The scale of interest is also important for the choice of model; if a large set of data points is to be modelled at once, this requires the ability to run using distributed gridded data. In this study, the MyLake and water balance models used to estimate evaporation and calculate the water balance are physically-based models run with both lumped regional input data and localized point data.

As the effects of climate change have become increasingly clear and mitigation and adaptation efforts have moved into the public light (see IPCC, 2007; IPCC, 2014), more water
balance studies have been geared towards evaluating the water cycle to study global climatic changes. Gleick (1987) presented the first of many applications of water balance modelling to climate change science (Pacific Institute, 2011). In the 1990s, the first water balance models were adapted to examine aspects of climate change (Xiong & Guo, 1999; Xu & Singh, 1998), including studies of the changing seasonality of runoff (Panagoulia & Dimou, 1997), and incorporating climate change scenarios to examine climate controlling factors in the UK (Arnell, 1992). Arnell (1999) developed a macro-scale water balance model based on Moore’s (1985) Probability Distributed Model (PDM), with changes to allow it to project the effects of future climate change over large geographical areas, and Wanchang et al (2000) developed a model to study the effects of various climate change scenarios on hydrologic behaviour using inputs from climate models. Studies using water balance models to assess climate change related to water resources continue to be released (e.g., Gibson et al., 2006; Pomeroy et al., 2013; Wang et al., 2011).

2.2.3 Water Balance Variable Selection

The objective of a water balance is to quantify the water in all hydrologic phases within a defined catchment (Deitch et al., 2009). A water balance can be summarized by a simplified equation: “inputs minus outputs equals the change in storage” in a watershed (Kane & Yang, 2004: p.1). The main input to any water balance model is usually precipitation (rain and snow). Frequently used outputs include, but aren’t limited to, surface runoff, evaporation, and transpiration (Xu & Singh, 1998). Storage refers to the water held in the catchment for longer than the temporal scale of the model; if the inputs do not equal the outputs, there will be a change in the remainder storage term (Oke, 1987). Other hydro-climate variables are added to the water balance depending on the basin-specific processes and temporal and spatial scale of the study; or because added complexity (an increase in hierarchical controls) is deemed necessary to
accurately recreate the outputs (Sivapalan et al., 2003). However, most studies avoid adding extra variables; it has been shown that using fewer can actually produce a better replication of the catchment outflows (Deitch et al., 2009; Wang et al., 2011; Xu & Singh, 1998).

Stream inflow and outflow, and overland runoff from the surrounding watershed, are often included in the water balance, especially when the objective is to recreate runoff based on precipitation and climate (Xiong & Guo, 1999). However, these variables can be excluded from the water balance when the study basins are of 1st-order and therefore have only negligible inputs and outputs from the land and streams (e.g., perched wetland basins (Nielsen, 1972)). Anthropogenic basins such as reservoirs and contaminated storage ponds also often specifically exclude overland flow through the construction of freeboard siding. Leaving inflows and outflows out of the equation also serves to not conflate changes in water storage due to precipitation and evaporation outputs with changes due to changing streamflow regimes.

Some models also build an error term into the water balance equation, to quantify any uncertainty in the hydro-climate variables. However, an error term can only be used if all other variables in the water balance are represented (Kane & Yang, 2004). Other models consider the storage term itself to account for any residual in the water balance equation (Marsh, Onclin, & Russell, 2004). In many studies, error in the equation isn’t mentioned at all (Winter, 1981).

Mesoscale regional water balance modelling allows the exclusion of hydro-climate variables representing temporally or spatially small processes, such as groundwater fluxes (Menció, Folch, & Mas-Pla, 2010), soil moisture fluxes (Kane & Yang, 2004), and sublimation and condensation. The processes associated with these variables are often of a trivial magnitude or are generally averaged out over the proposed catchment sizes and timescales (seasonal or
annual), producing a zero net effect on the water balance for the timescale at hand (Arnell, 1999; Kling & Nachtnebel, 2009; Sivapalan et al., 2003; Zhang et al., 2008).

Groundwater flow is a variable that is often excluded from water balance calculations. In some cases, groundwater is not a factor as lakes are either isolated from groundwater flow due to underlying aquitards, or anthropogenically built to be isolated from groundwater flow, such as storage of contaminated water or reservoirs for human use. Some studies do attempt to quantify groundwater contributions, either by fully accounting for all the dynamics of subsurface flow (e.g., Portoghese et al., 2005), or by including terms such as the contribution to streamflow from groundwater or the short-term storage of water as groundwater, (e.g., Han et al., 2011; Wang et al., 2011). It is due to the complexity of the groundwater system, and its lack of synchronicity with the surface water system, that many other studies omit it from the water balance entirely (Menció et al., 2010). The exclusion of groundwater terms is justified when either inflow and outflow of groundwater in the catchment are of similar magnitudes and cancel each other out, or groundwater flow is unimportant to the aspect(s) of the basin’s water flux being studied, such as when studying water-atmosphere exchanges (Menció et al., 2010).

At small temporal and spatial scales, the processes associated with soil water percolation and soil water storage have increased control on the water balance (Kling & Nachtnebel, 2009). Over short timeframes the percolation of water into the soil is more likely to be considered a storage in the catchment as the water doesn’t return to the surface within the timeframe modelled. Over longer timescales, soil moisture can make its way back into the stream channel via base flow contributions or interflow, producing a zero net effect on the water balance (Kane & Yang, 2004). Over larger areas soil moisture content is also less likely to be considered a storage or outflow from the water balance the water lost to soil moisture is more likely to be
balanced by the re-introduction of surface water at other locations, resulting in insignificant net fluxes (Kane & Yang, 2004; Portoghese et al., 2005).

The modelling of a catchment that experiences uncommon hydrological processes can require additional hydro-climate variables. For example, some regions experience a large amount of blowing snow that transports solid-phase water into the catchment (see Marsh et al., 2004). Sublimation may also be significant to the water balance of a catchment; this transformation of solid-phase water to water vapour can account for a loss of 15-47% of winter precipitation, depending on the location and hydroclimatic regime (Jackson & Prowse, 2009).

Another often cited reason for the inclusion or exclusion of variables in a water balance is simply the availability of data. As each water balance is performed over a specific geographical area and time scale, access to data of appropriate quality and resolution will determine the equation used (Arnell, 1999; Wanchang et al., 2000; Xu & Singh, 1998). As manipulation or averaging of data can decrease the accuracy of the study (Sivapalan et al., 2003), methodologies that can be easily supplied with appropriate data should be chosen whenever possible.

2.2.4 Estimating Water Balance Parameters

The following sections review the data sources and estimation methods used in relevant water balance studies for three common hydro-climate variables – evaporation, precipitation, and change in storage.

2.2.4.1 Evaporation

Evaporation is the process of moving liquid water from the earth’s surface to the atmosphere in the form of vapour, as the water is cooled (Derecki, 1975; Shuttleworth, 1993). This flux is an important part of the water cycle because it impacts the energy balance at the
surface, driving hydrologic and biologic systems (Oke, 1987). The accurate measurement or estimation of evaporation is therefore vital to any water balance (Bothe & Abraham, 1990).

The rate of evaporation that occurs over an open-water surface depends on the local availability of water, the net energy available at the surface, and the diffusivity of the atmosphere to carry vapour away (Oke, 1987). The transformation of water from liquid to vapour occurs when there is a vapour pressure deficit; a gradient in the amount of liquid water at the surface to the amount of vapour in the air (the vapour density). This gradient causes water to move from the saturated surface to the drier air above, by absorbing radiative energy that loosens the bonds between the molecules causing a phase change (Oke, 1987; Shuttleworth, 1993). This loss of water to the air not only depletes the surface water storage but also the energy storage at the surface, thereby lowering the surface and air temperatures in the area. While land surfaces and vegetation often have limited water availability for evaporation and evapotranspiration, surface water such as lakes and reservoirs generally provide an unlimited supply of water. This leads to much higher evaporation rates over open water. In semi-arid areas, evaporative losses over surface water can have magnitudes several times greater than precipitation, indicating the importance of evaporation in the water balance (Feng et al., 1989).

The energy used in the evaporative phase transformation is called latent heat ($Q_l$). The amount of latent heat required to transform liquid to vapour is called the latent heat of vapourization ($\lambda$) and is equal to 2.501 MJ kg$^{-1}$ at 0°C, changing by 0.002361 for each degree Celsius of air temperature (Shuttleworth, 1993). This quantity links water and energy balances by the relationship

$$Q_l = \lambda \times E$$  \hspace{1cm} (Oke, 1987)  \hspace{1cm} [2]

where $Q_l$ is the latent heat at the surface (W m$^{-2}$), $\lambda$ is the latent heat of vapourization
(MJ kg\(^{-1}\)d\(^{-1}\)), and \(E\) is evaporation (mm d\(^{-1}\)). The wind speed, fetch and turbulence of the atmosphere also contribute to the vertical transport of heat and water vapour by reducing saturation and mixing in drier air, creating room for more surface water to evaporate (Eichinger et al., 1996; Oke, 1987). This processes continues until the air reaches saturation vapour pressure, which depends on temperature; warmer air holds more water vapour (Oke, 1987).

There are a multitude of methods to measure and estimate evaporation, including direct measurement, degree-day (index) models, water balance and budget equations, and mass transfer and aerodynamic models (Derecki, 1975; Schertzer & Taylor, 2009). Direct measurement methods include evaporation pans, which evaluate evaporation based on a difference in the water volume in the pan before and after the experiment (e.g., Canada-British Columbia Okanagan Basin Agreement, 1974), and the eddy correlation method for large deep lakes, which measures the vertical flux of water vapour based on variations in absolute humidity and wind speed at the water-air interface (Winter, 1981). However, these require expensive, time consuming field work (Valiantzas, 2006) and are still not always representative of true evaporation; neither method properly represents heat storage in the lake depth, and depending on the type of evaporation pan, wind regimes may affect the results (Berry & Stichling, 1954; Schertzer & Taylor, 2009; Winter, 1981). Instead, it is common to estimate evaporation rates using equations and inputs from standard meteorological observations from climate stations (Shuttleworth, 1993; Valiantzas, 2006). Five well known types of evaporation estimates are described below.

Degree-day (index) models such as the Hamon approach \((E_H)\) are the simplest method of estimating evaporation. These methods require only air temperature and day length input data, making them easy to use in situations of limited data availability (Feng et al., 1989). The physical basis for these models is that air temperature and day length are proxies for energy
inputs that drive evaporation (Schertzer & Taylor, 2009). However, these models are simplistic and should only be used when temperature is the only information available, and even then results should be averaged monthly (Shuttleworth, 1993).

The water balance method of estimating evaporation uses all the other variables in the local water budget to solve for the missing evaporation component (Derecki, 1975). This is a commonly used method (Winter, 1981) and is robust in that no empirical constants are required. However, this method often adds error from other terms in with the evaporation term, and long-term change in storage is difficult to estimate separately from these errors (Derecki, 1975). This method is more reasonable for large lakes over longer timescales as input and output errors are more likely to cancel over a month or a season (Schertzer & Taylor, 2009).

The energy budget method is similar to the water balance method in that it solves for one unknown term in the budget, but in this case it is the net radiative flux from the energy balance rather than the evaporation rate from the water balance that is unknown (Derecki, 1975; Schertzer & Taylor, 2009). The Bowen Ratio-Energy Budget method ($E_B$) is commonly used to estimate evaporation through the partitioning of turbulent heat flux components in the Bowen Ratio (Schertzer & Taylor, 2009). This method is based on the idea that the aerodynamic resistance that restricts the transport of water vapour from the surface to a specified height in the atmosphere is directly proportional to the resistance that restricts the diffusion of sensible heat to the same height in the atmosphere. This is analogous to saying pressure difference ($\Delta e$) between the surface and the atmosphere is directly proportional to the temperature difference ($\Delta T$) between these two heights (Shuttleworth, 1993). In other words, the Bowen Ratio ($\beta$) is the ratio of sensible heat to latent heat and can be calculated using a proportional ratio of change in
temperature to change in pressure, when both sensible and latent heat values are not available (Oke, 1987):

\[ \beta = \frac{\text{Sensible Heat} (Q_H)}{\text{Latent Heat} (\lambda E)} \propto \frac{\Delta T}{\Delta e} \quad \text{[unitless]} \quad [3] \]

The advantage of using the energy balance method is that it avoids dependence on large water budget factors and the empiricism of the mass transfer method (Derecki, 1975). The Bowen ratio-energy budget approach is considered more robust than aerodynamic methods of calculating evaporation because the profiles of both temperature and vapour pressure are included, so any error due to changes in surface roughness or topography cancel out as the two profiles are affected by these factors equally (Shuttleworth, 1993).

The mass transfer method is based on the removal of water from the surface by turbulent diffusion (Derecki, 1975). The difference in saturation vapour pressure between the water surface and the air above is used to estimate evaporation, like the first portion of the Bowen ratio as described above. A wind function is also included, and, unique to this method, a mass transfer coefficient (Derecki, 1975). The mass transfer method requires either on-site calibration or calculation using the water budget or energy budget to determine the mass transfer coefficient specific to the study lakes (Winter, 1981).

Combination estimates consider both the mass transfer concept and the energy balance (Schertzer & Taylor, 2009). The Penman equation \( (E_P) \) was the first combination evaporation estimate, combining an estimation the energy required for evaporation with an empirical evaluation of the diffusion of energy during evaporative phase changes (Shuttleworth, 1993). The inclusion of aerodynamic processes in the Penman method means that the vapour pressure deficit and a wind function is explicitly included (Schertzer & Taylor, 2009). These functions
help account for the effect of atmospheric buoyancy on the evaporation estimate (Shuttleworth, 1993). The Priestley-Taylor ($E_{PT}$) approach is also a combination method and uses a similar equation to Penman, however $E_{PT}$ does not include a wind function. It assumes that evaporation occurs without any limitation on water availability, as is the case over open water, and in conditions of minimal advection (Fernandes et al., 2007). In the $E_{PT}$ equation a dimensionless coefficient represents potential evaporation, and its value varies depending if the study location is arid or humid (Eichinger et al., 1996). The Priestley-Taylor approach has been proven to provide better results over boreal forest and permafrost ground cover, as it relies on net surface radiation rather than air temperature, which, although they are generally considered to vary together and both increase alongside increases in greenhouse gases, may not always follow the same trends (Fernandes et al., 2007).

When evaporation is calculated using these four methods, the major differences in the values are due to the inclusion or exclusion of an estimate of turbulent aerodynamics over the lake, and an estimate of heat storage at depth in the lake (advection). The modelling of turbulent aerodynamics is important because wind near the lake surface acts to remove saturated air, increasing the vapour pressure deficit between the lake and the air, and allowing more evaporation to occur (Oke, 1987). Methods such as the Priestley-Taylor and Hamon approaches are expected to estimate much lower evaporation rates than the other methods because a wind function is not included in the equation. The Penman and the Priestley-Taylor methods are otherwise very similar, but the aerodynamic Penman method includes the vapour pressure deficit and a wind function and therefore estimates much higher values of evaporation (Schertzer & Taylor, 2009). While the Bowen ratio-energy budget method doesn’t use a wind function, it is even more robust than the aerodynamic methods of calculating evaporation because the profiles
of both temperature and vapour pressure are included, so any error due to changes in surface roughness or topography cancel out as the two profiles are affected by these factors equally (Shuttleworth, 1993).

None of the evaporation estimation methods described above include heat storage at depth in the net energy available for evaporation. In the estimation of evaporation the “heat storage” term refers to the change in heat advected to the water body, often from energy in rain and streamflow, or from solar radiation penetrating to depth, and it’s transference to deeper water (and soil) through conduction and thermal convection (Shuttleworth, 1993). Heat storage is known to augment evaporation by increasing the air-water vapour pressure deficit (Gibson et al., 1996). Some of the evaporation estimates such as the Penman, Priestley-Taylor and Bowen Ratio approaches could include a pre-calculated heat storage term. However, the calculation of heat storage is complex and is best done by measurement in the water body itself, or by evaluating it at a variety of depth layers in a model of the lake (Gibson et al., 1996; Werner, 2007). Therefore, further comprehensive lake modelling is required to obtain values for heat advection for the accurate estimation of evaporation over deep water bodies.

A comparison of values calculated by a selection of these evaporation estimation methods is provided in this study; methods are described in detail in Section 3.4, and results are reported in Section 4.4.2.3.1.

2.2.4.2 Precipitation

There are several available datasets for precipitation in Canada that are appropriate for use in water balance modelling. Environment Canada (EC) collects observations of climate data at over 3000 climate stations across Canada (Environment Canada, 2012). The second generation “Adjusted Precipitation for Canada – Daily” (APC-2) is a database of precipitation from 464 EC
stations from 1900 – 2013 for the whole country, and from 1950 – 2013 for the northern regions (north of 60°N). The data have been adjusted for a series of systematic biases introduced by the collection methods, making it the most homogeneous dataset available (Hutchinson et al., 2009; Mekis & Hogg, 1999; Mekis & Vincent, 2011; Zhang et al., 2000). Based on EC station data, Hutchinson et al. (2009) developed a Canada-wide interpolated spatial model of daily temperature and precipitation from 1950 – 2010, referred to as the “Gridded Climate Dataset for Canada” (GCDC). The GCDC provides continuous daily data at a 10 km² resolution within 40° – 84°N, 50° – 153°W, which covers most of Canada (Hutchinson et al., 2009; McKenney et al., 2011).

When the desired observations of precipitation are not available, modelled data is another option. Weather forecast models provide nowcasted continuous precipitation data, for example the Canadian Precipitation Analysis (CaPA) dataset developed by EC to produce real-time gridded precipitation data through the combination and interpolation of surface, radar, satellite and atmospheric direct and indirect measurements (Friesen & Rasmussen, 2014). Reanalysis products contain spatially continuous data across a variety of climate variables, including precipitation. GCMs and RCMs can also provide climate data appropriate for water balance calculation. However, bias correction (see Section 2.3.6) is required for results taken directly from GCM and RCM projections, to ensure the accuracy of the results for hydrological applications (Teutschbein & Seibert, 2010). See more on climate modelling in Section 2.3.2, and more on available datasets in Sections 2.3.7 and 3.2.

2.2.4.3 Water Levels and Storage

While other parameters vary, changes in water storage in a basin are evaluated in almost every water balance study (Winter, 1981). A common method of quantifying changes in stored
water in a catchment over a defined timescale is by calculating the residual of the water balance (e.g., inputs minus outputs) when all other relevant factors are measured or modelled (Bengtsson, 2012; Deitch et al., 2009; Marsh et al., 2004). The accuracy of this method varies depending if there are any other missing water balance components, and if the error associated with the other variables in the water balance has been taken into account (Kane & Yang, 2004).

Changes in lake water levels are often used to represent changes in the volume of water stored in the basin (Gibson et al., 2006). Sometimes it is possible to measure water levels directly. Where water level gauges are available, records of water level height above sea level can be used either to quantify the storage change itself, or to calibrate and validate a water balance model to predict storage changes (Gibson et al., 2006). The inclusion of water level records helps constrain the error in the other water balance parameters, allowing more of the remaining error to be attributed to lack of groundwater information, uncertainty in discharge estimates, or other unmeasured inputs and outputs (Gibson et al., 2006).

2.3 Climate Variability and Change

Climate is one of the major controls on hydrological processes. Evaluating changes in the water balance of lakes requires an understanding of the study site’s unique past, present and future climate system and variability (Brown, 2010). The global climate system includes inherent natural variability at a variety of magnitudes and timescales. Throughout recorded history, cycles of atmospheric, glacial, and oceanic processes have fluctuated within broad envelopes ranging from instantaneous to annual for atmospheric processes, and from decadal to centurial and beyond for oceans and ice sheets (Hegerl et al., 2007). Climate stationarity is the concept that this range of variability within which natural systems operate is fixed (Milly et al., 2008). In the past, the assumption that climate was stationary meant that analysts could assume that the mean,
variance, and extremes of climatic variables remained stable over time (Klein Tank & Zwiers, 2009). However, it is now generally accepted that climate change has caused, or is causing, a shift to a non-stationary climate where average, seasonal and extreme conditions are changing (Collins et al., 2013). The non-stationarity of hydrological variables can be attributed to a climate change-driven intensification of the hydrologic cycle, which increases and redistributes precipitation and increases the energy available for evaporation, among other changes (Huntington, 2006). To assess climate change effects on watersheds, projected future magnitudes of climate variables under non-stationarity need to be modelled and understood.

2.3.1 Annual and Seasonal Climate Change

Annual sums and averages for many climate variables are expected to change in the future. Increasing global average air and ocean temperatures, rising global average sea level and widespread melting of snow, ice and glaciers have already been observed (IPCC, 2014). In Northern Alberta, the average annual increase in both precipitation and evaporation is projected to be around 0.1 – 0.2 mm/dy, as reported by the IPCC (2007) from an ensemble of GCMs run for 2080 – 2099 with the A1B scenario, compared to 1980 – 1999 (Meehl et al., 2007). How exactly these average annual changes balance for a particular local climate will dictate the needed human and ecosystem responses to climate change.

On a seasonal scale, the effects of climate change differ. Many hydrological and ecological systems will be more impacted by shifts in seasonal climatic cycles than by average annual changes. There is high confidence that future increases in air temperature will change the thermal structures of lakes and rivers (IPCC, 2007), resulting in shorter freezing seasons and shifted spring and fall shoulder seasons that are characterized by the arrival and retreat of 0°C air temperatures (Bonsal & Prowse, 2003). Systems will likely respond with a loss of storage
(Barnett et al., 2005): reduced winter snowpack, increased evaporation from a longer open-water season (Mitchell, 1991), and improved conditions for sublimation due to the earlier snowmelt season and less winter precipitation falling as snow (Jackson & Prowse, 2009). These increases in the outputs of the water balance of lakes will cause lower water levels at unexpected times of year. While annual precipitation is expected to increase and may balance the loss of storage annually, models do not predict a shift in precipitation and therefore changes in precipitation are not likely to offset the effects of climate warming during the dry shoulder seasons (Barnett et al., 2005).

Exacerbating matters is the warming of snowpacks and glaciers, meltwater from which is a dominant control on hydrologic systems in nival and glacial regimes (Jones, 2011). Warming of snowpacks and glaciers is expected to cause an alteration of streamflow and runoff regimes, including increased runoff and earlier spring peak discharge in many locations in the short term (Collins et al., 2013). However, in the Canadian Rocky Mountains glacial melt contributions to streamflow are already past the increased flow phase (Demuth & Pietroniro, 2003); in the future, declining glacial runoff will result in reduced summer flow in associated rivers, further reducing the reliability of river and lake water levels (Casassa et al., 2009). Significant biological processes occur in the spring and fall shoulder seasons (Bonsal & Prowse, 2003) and changes to the timing and intensity of seasonality will impact the livelihoods of those that depend on freshwater from lakes and rivers. Informed management of natural and reservoir-based water storage is required to manage seasonal shifts in temperature and precipitation without affecting humans and ecosystems (Barnett et al., 2005).
2.3.2 Climate Modelling

GCMs have been used for decades to simulate possible future climate conditions (Randall et al., 2007). These models are developed to represent the large-scale physical processes that govern the global climate; fundamental physical laws are approximated through mathematical discretization and used to reproduce observed climate features (Randall et al., 2007). The discretization of climate processes can only be done down to a certain resolution due to computational constraints, below which the model simulation uses parametrization to adequately resolve particular processes, such as cloud cover, radiative heat flux and boundary layer interactions (Christensen et al., 2007). There is considerable confidence in the scientific community that credible quantitative estimates of future climate have been projected by current climate models, especially for temperature projections (Randall et al., 2007), and the models continue to improve with subsequent iterations (IPCC, 2013). Climate models output projected future moisture and energy fluxes, which can be used to estimate future precipitation and evaporation rates, two of the major variables required to calculate a water balance (Abramowitz et al., 2008; Koster, 2004).

2.3.3 Climate Scenarios

Climate scenarios are stories about how the future might unfold on Earth. They attempt to describe future changes in the economy, demographics, societal constitution and technological advancements, to quantify how these driving forces might impact future greenhouse gas (GHG) emissions and therefore climate (Nakicenovic & Swart, 2000). Climate models use input data from climate scenarios to inform the model of variety of parameters and boundary conditions and therefore these scenarios define the particular future climate attempting to be modelled. In 1996 the Intergovernmental Panel on Climate Change (IPCC) developed a comprehensive set of climate scenarios for use in ongoing international climate modelling. These scenarios, named
“SRES” for the Special Report on Emissions Scenarios in which they were first published (Nakicenovic & Swart, 2000), are divided into four main narrative storylines, or scenario “families”: A1, A2, B1 and B2. Each family represents a different range of driving forces and emissions levels, but does not consider any changes in climate policies such as international agreements and accords. Within each family, a group of scenarios was developed based on different modelling approaches, all using the same assumptions for the driving forces. Each of the six SRES scenario groups (three under A1, and one each under A2, B1 and B2) contains an illustrative marker scenario. Each marker scenario is a harmonized scenario (HS), meaning it shares all assumptions on population, economy and future energy levels with the other scenarios in the group, unlike the unharmonized (OS) scenarios which explore uncertainty in the driving forces within the group (Nakicenovic & Swart, 2000).

The most optimistic narrative storylines in terms of GHG emission reductions are represented in the A1 and B1 scenarios. Both A1 and B1 tell of rapid economic growth and global population that peaks mid-century and declines afterwards. The A1 scenario uses a global world that has rapidly embraced efficient technology to deal with GHG emissions, be it fossil-fuel intensive, non-fossil, or a balance of both (A1F1, A1T, A1B, respectively), whereas in B1 the rapid changes are in the economic structures, moving away from material intensity and towards a service and information economy that uses clean and resource-efficient technology.

The A2 and B2 scenarios expect less reduction in GHG emissions with continuously increasing populations that remain heterogeneous; the preservation of local identities and a focus on regional and local environmental protection rather than the global convergence predicted by A1 and B1. The A2 scenario is most like the status-quo, with the highest population and slowest rates of per capita economic growth and technological change than the other narratives.
(Nakicenovic & Swart, 2000). The illustrative marker scenario from the A2 SRES narrative is the most pessimistic scenario with respect to GHG emissions and is often used for modelling as any mitigation and adaptation efforts derived from modelling using this scenario could easily be applied to “smaller” climate changes in the other scenario families.

The SRES scenarios were used for the climate change projections reported in the IPCC’s Third Assessment Report (TAR) and in many of the studies reported in the Fourth Assessment Report (AR4) (IPCC, 2007; Nakicenovic & Swart, 2000). However, since the SRES scenarios were developed in 2000, new data on emerging technologies and environmental responses have become available, and the desire to represent climate policies in climate scenarios, something missing from SRES, has increased (Moss et al., 2010). A set of new emissions scenarios have been developed to include the time-evolving paths to target climate scenarios, including estimates of concentrations of radiatively active constituents and land cover and land use changes. These Representative Concentration Pathways (RCPs) represent possible scenarios that would lead to specific emissions concentrations. Four RCPs have been developed: RCP2.6, RCP4.5, RCP6.0 and RCP8.5, with the numbers representing the radiative forcing in W m\(^{-2}\) expected by 2100 (Moss et al., 2010). The RCP scenarios are used for climate modelling reported in the IPCC’s Fifth Assessment Report (AR5) (IPCC, 2014), however, many studies still use the SRES scenarios and, in fact, post-SRES modelling results have been shown to produce very similar climate change results (IPCC, 2007). The climate projections in this study are based on the A2 SRES scenario, which is considered sufficiently up-to-date within the scope of this project.
2.3.4 Heat Storage in Lakes

Currently, most RCMs do not model land surfaces that include water bodies more than a few metres deep (Meehl et al., 2007). Global and regional models consider gridcells to represent either land or water surfaces, and most inland lakes are small enough that they fall within the gridcells of the models and remain unresolved (Alapaty et al., 2014). Lake surfaces interact differently with the atmosphere than do land surfaces (Henderson-Sellers, 2006; Swayne et al., 2005). Radiative and turbulent fluxes, which represent the link between the earth’s surface and the atmosphere, are impacted by the storage of heat within deep water. If these fluxes are not modelled correctly including over deeper lakes, resulting regional estimations of evaporation, wind forcing, and energy fluxes will be affected (Swayne et al., 2005). In recent years there have been attempts to include lakes in RCMs, such as improvements in the representation of lakes in the U.S. Weather Research and Forecast (WRF) model (Alapaty et al., 2014), and via coupling of RCMs to lake models such as the ‘FLake’ model, which contains a global dataset of lake coverage and depth (Rockel, 2015). However, outputs from RCMs at the time of this research are lacking in modelling of complex water-atmosphere exchanges over small water bodies, and improvements in lake modelling within RCMs was not noted as a major advance by the global modelling community between the IPCC’s AR4 (2007) and AR5 (2014) synthesis reports. Considering the millions of lakes across Canada, this is a critical issue for Canadian climate projections (Swayne et al., 2005).

To address the underrepresentation of lakes as heat-storing basins in climate model projections, climate variables that are affected by heat storage in water, namely heat fluxes at the water-atmosphere boundary and therefore evaporation and condensation, can be modelled offline using comprehensive lake temperature models. An example of such a model is MyLake, which can be run for small lakes of analyst-defined size and shape, using input climate data generated
by RCMs (Saloranta & Andersen, 2004). The use of the MyLake model in this research is addressed in Section 3.3.

2.3.5 **Downscaling**

While GCMs remain the most frequently used models for climate change projections, their relatively coarse grid cell resolution, usually around 200 km², is too coarse to resolve important local and regional hydro-climatological processes (Hay et al., 2000). Therefore, GCM projections require downscaling for the results to be relevant to local adaptation and impact studies (Mearns et al., 2009). The resolution of many precipitation events is a major reason that the GCM grid cell scale is inappropriate. High intensity, or extreme, precipitation events caused by small or mesoscale convective cells are usually shorter in duration than frontal precipitation (Oouchi et al., 2006). These cells can deliver large amounts of precipitation over small areas and therefore impact local water balances (Friesen & Rasmussen, 2014). The small size of convective cells makes them difficult to model because they land within the grid cells used by most GCMs (Mladjic et al., 2011; Randall et al., 2007), while their short duration makes them hard to model due to a lack of available meteorological input data at a small enough temporal scale, such as daily or hourly values (Mailhot et al., 2012).

Downscaling is a process that generates sub-grid scale data from the results of GCMs, to address the issue of local phenomena (Christensen et al., 2007). Downscaling methods include the “delta method”, parameterization, and statistical and dynamical downscaling (Hay et al., 2000; Randall et al., 2007). The most common method of resolving sub-grid hydroclimatic processes from GCMs is the “delta method” or the “delta change method” (Fowler et al., 2007; Hay et al., 2000). The delta method is based on the assumption that the relative change in climate (delta values) produced by models is more trustworthy than the absolute projections.
This is the case when the absolute projections include a constant bias over time (Fowler et al., 2007). In the delta method the difference between current and future coarse resolution GCM projections is applied to finer-scale observations or time series to create spatially or temporally adjusted future climate data (Wilby et al., 2004). The delta method is intended to improve the accuracy of model results at any scale and can be applied to downscale GCM and RCM outputs, or to create a future projection from observations (Lenderink et al., 2007). Hay et al. (2000) showed that while the delta change method is constrained by GCM accuracy, it produces better results than more complex statistical downscaling relationships, especially since empirical statistical relationships may not hold true under future non-stationary climates. However, the delta method can only be used when simple changes to the probability distribution of a climate variable are expected, meaning that the variance or the coefficient of variation of the variable remains unchanged, and any changes in correlation between various climate variables are not considered (Lenderink et al., 2007).

Parameterization can also be used to capture intra-cell variability of processes that cannot be resolved at the scale of the model (Dibike & Coulibaly, 2005). Assigning static sub-grid parameters within GCM modelling is useful to retain regional feedbacks built into the GCMs that aren’t accommodated by post-model downscaling methods (Christensen et al., 2007). However, static parameters do not allow for dynamic modelling of climate variables. Chosen parameter values are also often a major reason for differing results between model results, therefore the number of parameters should be minimized where possible, in many cases requiring further downscaling to complete the conversion of the data to a regional scale (Randall et al., 2007).

Statistical downscaling is the application of the relationship between observed global and regional climate to GCM outputs, interpolating them to finer-scale regional results (Fowler et al.,
Regression methods, stochastic weather generators, and weather typing schemes are some of the techniques used to determine the relationships between observed synoptic and local weather patterns (Dibike & Coulibaly, 2005; Hay et al., 2000). These processes rely on the assumption that local climates are driven by large-scale atmospheric processes represented in GCMs, and that a mathematical function can be developed to predict the local or regional climate variables (the predictands) from the global variables (predictors) (Fowler et al., 2007). The global predictor(s) used must therefore be variables that are physically meaningful, stationary, well-reproduced by the chosen GCM and actually include the processes responsible for climatic variability at the spatiotemporal scale(s) of interest (Fowler et al., 2007).

Two methods of statistical downscaling include Bias-Correction Spatial Disaggregation (BCSD) and Bias-Correction Climate Imprint (BCCI). In a study carried out by the Pacific Climate Impacts Consortium (PCIC) (Murdock et al., 2013), the BCCI and BCSD methods were both used to downscale 50 km$^2$ RCM temperature and precipitation data to a target resolution of 300 arc seconds, or approximately 10 km$^2$. Both the BCCI and BCSD methods include bias correction based on an ANUSPLIN historical dataset to produce spatially disaggregated data. In the BCSD method, bias correction is done using quantile mapping onto the raw, low resolution GCM data, and then the bias-corrected data are scaled to the 10 km$^2$ local grid using rescaled randomly sampled observations from the historical record. Murdock et al. (2013) did this using monthly data that was then downscaled temporally to a daily time step by applying daily variability from historical data using a stochastic technique (Werner, 2011). The BCCI method differs in that the bias-correction (also using quantile mapping) is done directly on daily data after it has been rescaled to the high resolution 10 km$^2$ grid via the climate imprint method (Murdock et al., 2013). The climate imprint method goes beyond basic interpolation, using long
term average maps of climate variables that have been interpolated based on terrain and other environmental factors to provide a “spatial imprint” of environmental gradients onto station data that have been interpolated using kriging (Hunter & Meentemeyer, 2005).

A performance evaluation of the BCCI and BCSD methods carried out by Murdock et al. (2013) ranked the two methods as equally successful, but with differing strengths and weaknesses. BCCI had the highest skill on sequencing of daily events because the daily record comes from the climate model directly, whereas daily variation is added stochastically as the last step in the BCSD method. However, the BCSD method produced better spatial distribution in the downscaled results when compared to station data as the spatial disaggregation is done using historical data instead of interpolation. Murdock et al. (2013) went on to recommend that both the BCCI and BCSD statistical downscaling methods be used in climate studies, to benefit from the strengths of each.

Dynamical downscaling embeds a secondary model, a high-resolution RCM, within a GCM to dynamically add regional detail to coarse climate data modelled by GCMs (Fowler et al., 2007; Giorgi, 1990; Graham et al., 2007; Mackay et al., 2008). By nesting RCMs within GCMs (RCM_GCMs) the modelling effort benefits from the strengths of both types of models – boundary conditions related to large-scale global circulation are provided by the GCMs, and the realistic simulation of regional forcings are modelled at the necessarily smaller RCM scale (Mearns et al., 2009; Mladjic et al., 2011; Randall et al., 2007). RCMs generally have a smaller grid cell size of 15 to 50 km², relative to their 100 to 200 km² resolution GCM counterparts (Christensen et al., 2007).

Nesting an RCM within a GCM to improve the spatial scale of the projections does come at the cost of a new level of uncertainty in the model results (Christensen et al., 2007). The
nesting process itself could introduce some uncertainty, as current models only include one-way nesting between the RCM and the GCM (Mearns et al., 2003). One-way nesting means that the circulations produced by the RCM, while forced by the overarching GCM, do not feed back into that GCM and therefore any affects that local climate may have on global circulation are not considered (Giorgi, 1990). This is relevant to areas with large amounts of surface water as sub-gridscale lakes can significantly alter regional climate through heat storage at depth, as described above. However, the largest portion of the uncertainty in an RCM output is generally derived from the often biased GCM inputs (Fowler et al., 2007; Mearns et al., 2003). Therefore, the most important factor is to have good large-scale driving climatology from the GCM and the RCM will be able to produce accurate regional climatologies (Giorgi, 1990).

The major advantage of nested modelling is that it addresses the issue of sub-grid scale intense precipitation events more accurately than parametrization or statistical methods of downscaling (Wi et al., 2012). The inclusion of physically-based orographic forcing of precipitation due to complex topographical terrain dramatically improves the simulation of convective cloud development, precipitation and snowpack (Mearns et al., 2003; Wi et al., 2012). Other regional climate effects are also simulated much better at the RCM scale, including extreme climate events and regional climate anomalies, or non-linear effects produced by global cycles like the El Nino Southern Oscillation (Fowler et al., 2007). Therefore, RCM_GCM climate data are suitable to study changes in the water balance when a focus on extreme climate events is desired.

2.3.6 Bias Correction

Climate model outputs are biased representations of climate. No model is a perfect representation of reality; even when outputs from nested RCM_GCMs are at the correct spatial
resolution for the study, imperfect model aspects such as parameterization, conceptualization of physical processes, and spatial averaging within gridcells can cause systematic errors that affect the results (Teutschbein & Seibert, 2010). Therefore, model outputs cannot be used directly to obtain realistic outputs from secondary models without some sort of prior bias correction (Piani et al., 2010). “Bias Correction” refers to the process of correcting for systematic model errors by scaling the output variables either by a constant factor or by using a more complex statistical transfer function (Teutschbein & Seibert, 2010). Teutschbein & Seibert (2010)’s review of regional climate models outlines a variety of bias correction functions to correct temperature and precipitation projections. The simplest bias correction method uses a scaling factor calculated by comparing a hindcast of the climate variable to observations for the same time period. The scaling factor, usually a ratio of monthly average data from the two datasets, is then applied to both the hindcast data and future projections from the model. This scaling will correct any model bias by adjusting the mean of the model dataset to match the real-world mean (Durman et al., 2001). The variance of the two datasets, however, will remain unique (Lenderink et al., 2007).

Beyond using a simple ratio, a linear or power transformation, or a distribution transfer function derived from the modelled and observed datasets can be used for bias correction. Distribution functions that have been used in past studies include the cumulative distribution function (CDF), gamma distribution, and beta or Gaussian empirical and theoretical distributions (see Ines & Hansen, 2006; Piani et al., 2010). Further to correcting the modelled data based on observations, for precipitation at least, advanced “weather generator” models can simulate variability within the modelled data (Booij, 2005). Finally, the most complex bias correction method uses empirical correlation to correct modelled data again based on the ratio of modelled
to observed data, but with adjustments based on the residuals, the standard deviation, and normalized variables (Teutschbein & Seibert, 2010).

Selection of a downscaling and bias correction method depends on the goal of the study. For example, a common problem is that precipitation modelled by GCMs generally contains too much light precipitation (<10 mm/dy) and not enough heavy precipitation (>10 mm/dy) as compared to 20th century observations (Randall et al., 2007). This under-estimate of the number of dry days is called the “drizzle effect” (Piani et al., 2010). On the other hand, observed data from Canadian precipitation gauges are affected by the opposite problem, where days with “trace precipitation” (less than 0.2 mm/dy) are under-estimated due to inability of the instruments to measure these small amounts (Mekis & Vincent, 2011; Mekis, 2005). Bias correction can be used to correct these uncertainties by adjusting model data to observed data, or vice versa. Unlike using the delta change downscaling method to create future projections, bias correction directly on current and future model results allows the precipitation projections to retain their unique variability. This means that the future projection can contain a different sequence of dry days (less than 1 mm/dy of precipitation; Klein Tank & Zwiers, 2009) than the current data, with only the magnitudes on wet days affected by the correction (Fowler et al., 2007). The distribution of dry days is important when referring to the ability of precipitation to alleviate drought conditions in the watershed (Fowler et al., 2007).

All bias correction methods depend on the availability of observed data for the same variable over a long enough period (20 – 30 years). In the absence of a full observational record, reanalysis such as the North American Regional Reanalysis (NARR) or the global 40-yr European Centre for Medium-Range Weather Forecasts Reanalysis (ERA-40) can be used to represent true climate in the bias correction (Mesinger et al., 2006; Teutschbein & Seibert, 2010).
While reanalysis datasets are considered representative of true climate in many cases, confidence in temperature results is much higher than for precipitation and other more complex climate variables (Randall et al., 2007). See more on reanalysis in Section 3.2.2.

Bias corrected data have been proven to produce better results from secondary models than un-corrected RCM data (Lenderink et al., 2007), while also preserving the climate change signal between current and future climates (Teutschbein & Seibert, 2010). Bias corrected hindcasts can be used as baseline input data instead of direct observations, and in fact is preferable as the period of record produced can be longer than the average 30-year observational record (Lenderink et al., 2007). Using bias corrected model results rather than a delta change applied to observations is also valuable when trying to include examples of rare (extreme) events not seen in the observed record, and to increase comparability of results between current (hindcast) and future periods (Lenderink et al., 2007).

2.3.7 NARCCAP Ensemble Modelling

Ensemble modelling is a standard method that uses results from a group of climate models to represent a range of responses to a climate scenario (Randall et al., 2007). Multi-model ensemble mean values are commonly used, as averaging reduces variability in the results caused by differing model skill, parametrization and calibration (Christensen et al., 2007). The range of results produced by a multi-model ensemble can also help evaluate the biases and uncertainties within each model.

The North American Regional Climate Change Assessment Program (NARCCAP) produced a set of regionally resolved climate change projections from RCM_GCMs specifically designed to be used together in an ensemble approach (Mearns et al., 2009; Meehl et al., 2007). The set of models in the program is chosen to represent the variety of model physics currently
available, and to include previously tested models. The models are all run using the same emissions scenario (A2; see Section 2.3.3), and boundary conditions for each RCM are provided by different GCMs to characterize the multiple uncertainties resulting from the model combinations (Mearns et al., 2012). The models have a 50 km$^2$ resolution with observations every three hours (UCAR, 2007). Limited funding precluded using the full matrix of four GCMs and six RCMs, so instead the matrix was statistically sampled (Table 1) to represent half of the model combinations and maximize the differences between combinations (Mearns et al., 2012).

<table>
<thead>
<tr>
<th>RCM</th>
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<th>GFDL</th>
<th>CGCM3</th>
<th>HadCM3</th>
<th>CCSM3</th>
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<tbody>
<tr>
<td>MM5</td>
<td>X</td>
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<td>MM5_CCSM3</td>
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<td>MM5I</td>
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<td>RCM3</td>
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<td>CRCM</td>
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<td>CRCM_CGCM3</td>
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<td>HadRM3</td>
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Table 1: The ensemble of Regional Climate Models (RCMs) nested in Global Climate Models (GCMs), available through the North American Regional Climate Change Program (NARCCAP). The acronyms indicate models used to calculate the results in Chapters 4 and 5, and the Xs indicate models available but not used in this research. More information available at http://www.narccap.ucar.edu/data/model-info.html. Adapted from Mearns et al. (2012; p. 1340).

Mearns et al. (2012) summarized the biases found in the six NARCCAP RCMs. The largest temperature bias was found in the HadRM3 model, results for which were significantly warmer than observations for all seasons, across most of North America. In the Athabasca River region in particular, the HadRM3 indicated air temperatures up to 12°C warmer than observed in the winter (DJF), and up to 8°C warmer in summer (JJA). In the winter four other RCMs had a warm bias in the Athabasca River region. The MM5I had a small warm bias around 2°C, while CRCM is the exception with a small cold bias around -2°C – winter temperature biases of similar magnitudes but opposite signs. Summer temperatures show smaller biases than winter temperatures. The HadRM3 and RSM models still had a small warm bias in the Athabasca River
region while the MM5I had about a -2°C bias, CRCM has a -4°C bias, and the other two RCMs had almost zero summer temperature bias in the region.

For precipitation, Mearns et al. (2012) found that most RCMs in the NARCCAP ensemble showed wet biases in the winter and dry biases in the summer. RSM had an extreme winter wet bias of over 80% more precipitation than observed over most of North America. The MM5I winter wet bias is slightly larger in the Athabasca River region than the CRCM winter wet bias, with values about 20% and 10% larger than observations, respectively. Only the WRF model had a dry bias in the Athabasca region in the winter. In the summer there were more models with dry biases, meaning they underestimate summer precipitation. This includes the MM5I model which projected about 10% less precipitation than observed. The CRCM model, however, is a little wetter than observations, with about 10% more precipitation than observed. The CRCM model had the lowest error (RMSE) of all models in the winter, spring and fall, but not in the summer. In general the precipitation errors amount to about 0.6 – 1.4 mm/dy different than observations in the continental US, which is similar to other regional precipitation bias studies.

In general all NARCCAP models simulated climate well (Mearns et al., 2012). Temperature was better reproduced than precipitation, and there was more difficulty in reproducing the variability in the variables than the means. Seasonal temperature biases were lowest for RSM and MM5 and highest for HadRM3. For seasonal precipitation it is less clear which models perform best, but CRCM had the lowest RMSE for all seasons combined and the quartile method showed MM5, CRCM and RSM as having the least bias. The ensemble mean performs well overall but is not always the best; CRCM out-performed the ensemble for precipitation based on RMSE, and the ensemble of “nudged” models out-performed the total ensemble, noting the importance of greater GCM constrain on nested RCM regional climate
modelling. Leung et al., 2003 note that in their study the RCMs were 20% to 75% too wet, but also that the same RCM (MM5), when run with different global reanalysis data, can produce different results due to difficulty constraining moisture fluxes over oceans (Mearns et al., 2012).

2.3.8 Analysing Changes in Climate

Changes in climate variables are often assessed by analyzing changes and trends in daily, monthly, seasonal or annual means. This can be done by simply comparing the values of the means over time and between study sites (Devito et al., 2005), or the medians and percentiles between datasets (Saloranta et al., 2009b), or using regression techniques (e.g., Zhang et al., 2000) or trend tests such as the Mann-Kendall (e.g., Dibike et al., 2011a; Gan, 1998; Whitfield, 2001). Variability around means within a distribution can be evaluated using the standard deviation and the coefficient of variation of the distribution of a climate variable (Raisanen, 2002). Furthermore, probability distributions can be fitted to climate variables and used to evaluate the expected occurrence of the whole range of possible values based on the sample of climate data available for a particular place and time (Wagner, 1996).

2.3.9 Extreme Climate Events

By definition, extreme climate events are those whose properties place them far into the tails of the reference distribution of a climate variable for a particular place and time (Klein Tank & Zwiers, 2009). Extreme, or rare, events are often characterized as those of sufficient magnitude (or lack of magnitude) to cross an analyst-defined threshold near the upper (or lower) ends of the observed range of values (IPCC, 2012). In the past few decades the world has been experiencing increasing numbers of climate extremes with significant effects on society, such as floods, droughts and heat waves (Coumou & Rahmstorf, 2012; Hegerl et al., 2011; Sillmann et al., 2013). Analysis of the changing frequency and magnitudes of extreme events is needed to develop climate change adaptation and mitigation strategies to reduce human suffering, costly
damage to housing and infrastructure, and negative impacts on natural systems (IPCC, 2014; Rahmstorf & Coumou, 2011; Randall et al., 2007).

Climate events are often only considered extreme by society if they result in environmental disasters that noticeably, and usually negatively, impact human lives and property (Huntington, 2006; Klein Tank & Zwiers, 2009). While statistical techniques detect extreme climate conditions that lead to “meteorologic” floods and droughts, based on their magnitude and intensity (Rogers & Armbruster, 1990), the societal impact of a climate event also depends on local antecedent conditions, physiological thresholds, preparedness, and the timing of the event in the seasonal cycle (Hegerl et al., 2011). On the other hand, climate events do not need to have immediate societal impacts or be counted as statistical extremes to have an impact on the environment and society in the long term (Zhang et al., 2000). Climate events of moderate magnitudes can still be stressful on ecosystems and people, and cumulative impacts over time could be important, especially if the frequency of occurrence were to increase (Klein Tank & Zwiers, 2009). Furthermore, future climate change could cause a step-change in mean climate, shifting the distribution of climate events and causing some events that do have negative impacts on society to cease to be rare occurrences and therefore no longer statistically considered extremes (Hegerl et al., 2011).

Meaningful analysis of changes in extremes is challenging in a number of ways, since records of events with high societal impacts are biased towards recent years, and comparison of impacts between events is difficult because the lived experience of people in the midst of disasters is subjective. The effects of extreme events reflect the vulnerability of the local ecosystem and hydrologic cycle as much as the magnitude of the event itself (Klein Tank & Zwiers, 2009). The projection of extremes for climate change mitigation and adaptation
strategies should take into account events that are both rare in context of historical data and extreme according to amplitude of effects on society or ecosystems (Hegerl et al., 2011).

2.3.10 Indices and Statistical Modelling

There are two main ways to assess the occurrence of extreme events: descriptive indices, and statistical models (Klein Tank & Zwiers, 2009). Both methods have been applied in the literature to analyze the occurrence and trends in past, present, and predicted future extreme climate events (e.g., Frich et al., 2002; Mladjic et al., 2011; Rahmstorf & Coumou, 2011; Wagner, 1996; Zhang et al., 2000). Descriptive indices can be used to monitor changes in extreme event occurrence and have a broad range of applications for climate model evaluation and assessment of future climate (Klein Tank & Zwiers, 2009). Targeted descriptive indices of extremes have been developed for individual regional studies, such as for the United States by Karl et al. (1996). Generalized versions have also been developed through international workshops for use at global scales (Frich et al., 2002). A commonly used suite of globally applicable descriptive indices was developed by the World Meteorological Organization (WMO)’s Expert Team on Climate Change Detection, Monitoring and Indices (ETCCDMI) to describe trends in precipitation and evaporation, especially of their extremes (Klein Tank & Zwiers, 2009; Zhang et al., 2011; and online at http://etccdi.pacificclimate.org/indices.shtml). These ETCCDMI indices have been used in a variety of studies, sometimes modified to suit particular research goals, results from which allow comparisons of extremes in climates around the world (e.g., Klein Tank et al., 2006; Sillmann et al., 2013; Vincent & Mekis, 2006).

Descriptive indices usually consist of a calculation of the number of days, or the evaluation of the magnitudes, of climate events that exceed a chosen threshold in a specified period (Alexander et al., 2006). The most common approaches to descriptive indices are the Block
Maxima method, often known as the Annual Maxima (AM), and the Peaks-Over-Threshold (POT) method of evaluating extreme events in a time series (Klein Tank & Zwiers, 2009). The AM method considers the magnitude of the maximum or minimum value in each year (or other time “block”, such as season) and is simpler as only one value per period is returned (Mladjic et al., 2011). However, in actual application, the analyst might be interested in evaluating all of the events that are considered extreme in each year, rather than simply the one largest. This is done using the POT method, which is calculated as the count of climate events whose magnitudes cross the chosen threshold in the relevant time period (Katz et al., 2002; Sushama et al., 2010). More on these methods is found in Section 3.6.

The threshold that defines an event as “extreme” for a descriptive index is usually either an absolute value, or a percentile in the distribution of the climate variable in question (Alexander et al., 2006). An absolute value can be used as the extreme threshold when research is being conducted for an individual study site within which climate doesn’t vary greatly, or when a real-world absolute value is relevant, for example for structural engineering purposes. Examples of absolute value thresholds include defining high precipitation extremes as more than 20 mm/dy of precipitation (Madsen et al., 2009), or defining “dry days” as less than 1 mm/dy of precipitation (Sun et al., 2006; Sushama et al., 2010). However, as climate varies with location, events that exceed an absolute value threshold may be considered extreme in one location, but be common for the same variable at a different location. If the analysis of extremes spans across study sites with varying climates, or results are intended to be comparable between studies, a percentile, or other statistical measure that varies with the distribution, should be used as the threshold that defines an extreme.
Using the value of a specified percentile from each variable’s distribution as the threshold allows the particular value to vary between study sites and datasets, and therefore changes in the occurrence of rare events as defined for each site can be counted and compared (Bonsal et al., 2001). In many studies the 90th percentile is used to represent the threshold beyond which events are considered “high extremes” and the 10th percentile is used to represent the threshold for “low extremes” (see Frich et al., 2002; Klein Tank & Zwiers, 2009; Rogers & Armbruster, 1990; Zhang et al., 2011, 2000). The ETCCDMI indices use both absolute values and percentiles as thresholds to assess the occurrence of extreme events (Alexander et al., 2006). Most extreme indices, including those in the ETCCDMI set, use thresholds calculated for a base period that are then also applied to future climate model projections (Klein Tank & Zwiers, 2009; Peterson et al., 2012). This allows the analysis of future changes in climate extremes, relative to past trends in the climate of the study region (Hegerl et al., 2011).

The occurrence of very rare events that lie far in the tails of the distribution may not be able to be evaluated using descriptive indices alone, especially if their magnitudes are not captured by the historical data series used to calculate the index. This is a problem when the research objective is to project changes in extreme climate in the future under a non-stationary climate (Klein Tank & Zwiers, 2009). Instead, statistical modelling of climate variables, based on knowledge of the regional climate system and on climate model results, can be used to project the occurrence of even never-before-seen magnitudes and frequencies of extreme events (Wagner, 1996).

Probability distributions demonstrate the full range of possible values based on assumptions about the variable’s source population, and assign a probability of a particular variable having a specific value or falling within a specific range of values. A common approach
involves fitting a statistical model to the extremes in a time series, and then estimating quantiles of interest from the extreme value distribution, such as the magnitudes and frequencies of the Peaks-Over-Threshold (POT) or the Annual Maxima or Minima (Klein Tank & Zwiers, 2009). A number of studies evaluating expected future frequencies and magnitudes extreme climate events use probability distributions fitted to the POT and AM of climate variables (e.g., Alexander et al., 2006; Kharin et al., 2013; Sushama et al., 2010; Wagner, 1996).

The underlying assumption required for estimating distributions is that the time series consists of normally distributed observations, and the probability of an individual event is independent of the underlying distribution (Rahmstorf & Coumou, 2011; Wagner, 1996). In hydrology the Maximum Likelihood method of evaluating the parameters of a distributions is commonly used, since time-dependent covariates can be easily incorporated if necessary (Katz et al., 2002). The L-Moments and the Ordinary Method of Moments can also be used to estimate the parameters of the distribution, however it is more difficult to incorporate the non-stationarity of climate (Klein Tank & Zwiers, 2009) such as trends and cycles in the climate data, or the influence of physical variables such as the El Nino Southern Oscillation (ENSO) (Katz et al., 2002). Non-stationarity of climate variables can be seen as either a shift in the mean or a change in the shape of the distribution. A shift in the mean indicates a step change in overall climate, while a modified distribution affects the tails and peak where extreme events lie (Rahmstorf & Coumou, 2011). Once properly fitted, distributions can be used to test if climate variables in different time periods, or based on different scenarios, are significantly different from each other (Alexander et al., 2006).
2.3.11 Trend Testing for Climate Variables

The IPCC defines a “trend” as the generally progressive change in a variable over longer timescales than the natural variability of the particular climate process being studied (Klein Tank & Zwiers, 2009). The slope of the linear trend in a dataset with a normal distribution can be modelled by regression to assess if there is a change over time in the variable (Klein Tank & Zwiers, 2009). However, climate data rarely conforms to normality without some statistical manipulation (Karl et al., 2008), therefore regression cannot be applied directly to the actual magnitudes of climate variables (Sen, 1968). Instead, in the presence of a non-normal distribution, non-parametric statistical techniques can be applied to evaluate the presence of a trend in a time series. The Mann-Kendall, Kruskal-Wallis, and Distribution Free CUSUM are examples of non-parametric trend tests (Grayson et al., 1996; Karl et al., 2008).

Valid trend testing also requires that the variables consist of independent and identically distributed observations (Katz et al., 2002). In a time series that is not independent or identically distributed, observations are linked to their past and future values – this is called autocorrelation, or serial correlation (Crawley, 2007). Autocorrelation is expected in climate variables and can interfere with statistical testing for trend over time (Alexander et al., 2006; Zhang et al., 2000). For example, the probability of precipitation occurring on any particular day is related to whether or not precipitation occurred on previous days (Kotz & Neumann, 1959). However, seasonal or annual averages of precipitation values are less likely to be autocorrelated than daily values (Kotz & Neumann, 1959). Other than the effects of large-scale atmospheric processes such as El Nino – Southern Oscillation (ENSO), precipitation magnitudes between years are not likely related because timescales precipitation formation are shorter than annual (Oouchi et al., 2006).
Two options to manipulate climate variables in preparation for trend testing are to roll the data up to seasonal, annual or other “block averages” rather than using daily values, or to evaluate POT counts, which will have normal distributions, rather than using magnitudes of the observations. However, when only the difference in climate between current and future periods is of interest, the magnitudes of daily events can be analyzed directly rather than manipulating the data to remove autocorrelation and test for trend within the periods. Trend detection within the two 30-year periods studied in this study is beyond the scope of this project.

2.4 Study Area

In regions where precipitation and evaporation are of similar magnitudes and are the dominant hydrologic fluxes of the water balance, micro variations in meteorology can cause climatic variability to which environmental systems are extremely susceptible (Brown, 2010). Surface water storage is particularly affected by climatic variability since hydrologic fluxes control lake water balances. Interior continental watersheds often have warm climates that provide energy for high evaporation, and have atmospheric thermodynamics conducive to the vertical lift required for convective precipitation (Raddatz & Hanesiak, 2008). The combination of high evaporation with intense intermittent precipitation from convective cells (Friesen & Rasmussen, 2014) results in high climatic variability affecting hydrologic inputs and outputs. Examples of regions in the mid-latitudes with interior continental hydroclimatic regimes with similar hydrologic fluxes include the Tien-Shan interior plains in Kazakhstan between the Caspian Sea and Lake Balkhash and north of the glaciated mountain range in Kyrgyzstan; the plains east of the Andes in South America (although lacking a steady period of air temperatures below freezing); and the boreal plains east of the Rocky Mountains in Western Canada (Kotlyakov, 1997). These watersheds all have similar characteristics – the altitudes of glaciers
and plains, rivers fed by glacial runoff, precipitation and evaporation rates, and, other than the Andes plains, seasonal air temperatures and freeze-up durations. The Western Canada region also includes significant and varied surface water storage. In particular, the Athabasca River region at the confluence of the Peace and Athabasca Rivers includes a wide range of surface water sizes and depths, from wetlands, to deep lakes, to anthropogenic reservoirs. Therefore, this region, due to its variety of surface water storage in a sensitive mid-latitude, sub-humid, dry, interior hydroclimatic regime, is used to study the interaction between climate and surface water. The following section is a literature review of the geology, ecosystems, climate, and surface water storage types of the region, including relevant studies of water balance parameters.

2.4.1 The Athabasca River Region

The Athabasca River watershed is located in the interior plains of northern Alberta, Canada, part of the Western Boreal Forest of North America (Brown, 2010). The watershed is east of the Rocky Mountains, south of the discontinuous permafrost zone of the Canadian subarctic (Peters et al., 2006a), and north of the driest part of the Canadian Prairies – the Palliser Triangle (Dale-Burnett, 2012) (Figure 1). The Athabasca River flows from its headwaters in the Columbia Icefields of the Rocky Mountains, northeast into the interior plains, past the town of Fort McMurray, AB (56.72°N, 111.37°W), and through the Peace-Athabasca Delta (PAD) before terminating in Lake Athabasca near the town of Fort Chipewyan, AB (58.77°N, 111.13°W). The river’s hydrologic regime is classified as proglacial due to its dependence on glacial melt (Church, 1974). Currently, the “glacier compensation effect” means that glacial meltwater augments the rest of the precipitation- and snowmelt-based streamflow, creating a relatively smooth annual hydrograph that peaks in late summer and does not have a distinct spring freshet (Moore & Demuth, 2001; Prowse & Ommanney, 1990). The study region (the “Athabasca River region”) is the downstream, northern portion of the watershed along the
Athabasca River between the cities of Fort McMurray and Fort Chipewyan, just south of the PAD (Figure 2).

Figure 1: Western Canada including the Athabasca River region (white box) in northern Alberta and the Fort McMurray and Fort Chipewyan study sites (Google Earth, 2013).

Figure 2: The “Athabasca River region” including the Lower Athabasca River and surrounding area in northern Alberta, Canada. The study watersheds are centered around the cities of Fort McMurray and Fort Chipewyan, shown here as red circles (from WWF Canada: Lebel et al., 2011; page 5).
Located in the Boreal Mixedwood Forest ecoregion within the Western Boreal Plain ecozone in the Western Boreal Forest, the Athabasca River region is important to the global freshwater cycle as a carbon sink and a waterfowl habitat (Brown, 2010; Mitchell, 1991). The landscape is composed of upland areas of deciduous forests consisting of trembling aspen, white spruce, balsam, and jack pine, as well as widespread lowland wetlands surrounded by black spruce, white birch, and tamarack muskeg (BGC Engineering Inc., 2010; Westcott & Watson, 2007).

The geology of the interior plains of North America is mostly previously-glaciated terrain that slopes gently eastward from the Rocky Mountain Cordillera and includes plains, rolling hills, stream valleys, lakes, ponds and bogs (Saxton & Shiau, 1990). The soils in the area consist of a deep layer of glacial till underlain by the limestone, shale and sandstone sedimentary bedrock that contains much of Alberta's petroleum, coal and oil sand resources (AB Environment, 2013; Schneider, 2002). Bitumen deposits are found in the sandy soil, industrial extraction of which gives the area the name of the “Athabasca Oil Sands” (Westcott, 2007). The large oil and gas exploration and extraction industry in the region continues to accelerate in scale and pace (Canadian Association of Petroleum Producers, 2013; Devito et al., 2005).

The climate of the area is characteristic of a dry, mid-latitude, continental climate in the major cold-region portion of North America (AB Environment, 2013; Dibike et al., 2011a). The region experiences high natural hydro-climatic variability, with long cold winters and short cool summers. The highly variable precipitation peaks in July (Environment Canada, 2013) and is largely delivered by high-intensity, short-duration convective storms (Devito & Fraser, 2004). A large portion of the annual precipitation falls as convective storms in the summer, as for most of the Canadian Prairie provinces (Raddatz & Hanesiak, 2008). The winter snowpack has fairly low
accumulation (<25% of annual precipitation) and high sublimation (Devito et al., 2005). In Canada snowpack losses due to sublimation can range from 15-47% of the snow water equivalent, depending on the local climate (Jackson & Prowse, 2009). The combination of low accumulation and high sublimation means that the volume of spring snowmelt is small in the Athabasca River basin.

Past work indicates that the Athabasca River region operates in a moisture deficit regime, where evaporation exceeds precipitation, meaning the annual P-E equation is negative (Brown, 2010; Devito et al., 2005; Mitchell, 1991b; Winter & Woo, 1990). There is also large variation in precipitation from year to year, and coupling of extreme evapotranspiration events with low precipitation years further exacerbates the moisture deficit and reduces streamflow in the area (Devito et al., 2005). The high hydro-climatic variability in this a sub-humid climate makes the system extremely susceptible to any changes in average or extreme precipitation and temperature regimes (Brown, 2010). The area experiences a cycle of infrequent wet years within periods of droughts, on a 10-20 year scale (Brown, 2010; Devito et al., 2005). Due to these frequent drought periods, wetland and ponds can become decoupled from upland areas, isolating them hydrologically until a flood year occurs and replenishes the water storage (Devito et al., 2005). Flood years are rare since extreme precipitation usually occurs in the summer months when evaporation is also high and soil moisture capacity is available to absorb incoming precipitation and abate flooding (Devito et al., 2005). External factors, such as ice-jamming in the rivers, are required in addition to extreme precipitation to create flows high enough to flood the landscape (Peters et al., 2006b).
2.4.2 Evaporation Studies at Fort McMurray

No estimates of future evaporation in the Athabasca River region in particular have been reported in the scientific literature. A handful of published studies have measured and modelled evaporation in the 20th century, or more commonly actual and potential evapotranspiration, but none have used projected future climate to estimate future evaporation over open water. Of the studies focusing on the current period, most are estimates of evapotranspiration over land surfaces such as forests and grasslands (Gan, 1998). The scientific literature reports some estimates of open-water evaporation for the Fort McMurray region in the current period, with average annual evaporation ranging from 450 mm/yr to 693 mm/yr, or an average of 574 mm/yr (Bennett et al., 2008; Berry & Stichling, 1954; Lins et al., 1990). There are also a number of consultant reports which estimate open-water evaporation for specific industrial sites in the Athabasca River region, although almost all of them use the same data source: values from the Environment Canada climate station Fort McMurray A (Station 3062693), the only full-year climate station in the region. These reports estimate annual average evaporation in the region as 500 mm/yr to 629 mm/yr, or an average of 569 mm/yr (Devon NEC Corporation, 2012; JDEL Associates Ltd., 2005; Southern Pacific Resource Corp., 2011). None of these reports address future climate scenarios to evaluate possible changes in future evaporation rates.

Environment Canada (EC) published a series of reports in the 1990s on evaporation and evapotranspiration. Many of the studies use the Complementary Relationship Lake Evaporation (CRLE) and Complementary Relationship Areal Evapotranspiration (CRAE) models developed by Morton (1983) to compute evaporation and evapotranspiration, respectively (Bothe & Abraham, 1990; Gan, 1998; WMA, 1999; Yue et al., 2003). The CRAE model uses input data on air temperature, relative humidity, and global incoming radiation to calculate evapotranspiration and evaporation (Yue et al., 2003). The National Hydrology Research Institute at EC computed
evaporation and evapotranspiration using the CRLE and CRAE models using input data from the Environment Canada climate stations at Fort McMurray and Cold Lake for 1912 – 1988 (Bothe & Abraham, 1990). Results indicate average annual potential evaporation at Fort McMurray of 575 mm/yr, averaged over the years 1968 – 1988 (Bothe & Abraham, 1990). The results of Alberta Environmental Protection Agency’s calculations of potential and areal evapotranspiration calculated with Morton’s (1983) CRAE model averaged 350 mm/yr for 13 stations in Alberta; specifics for each station are reported by Gan (1998). The Basin Storage and Analysis Program (BSTOR) also employed the CRAE model, using it to calculate model areal evapotranspiration, wet surface evaporation and lake evaporation at a variety of Ontario study sites (WMA, 1999; Yue et al., 2003). Other applications of the CRAE model were done in watersheds across North American and Europe (Yue et al., 2003).

Other EC studies calculate lake evaporation from Lake Okanagan (Schertzer et al., 1987) and from the Great Lakes (Schertzer & Taylor, 2009), and there are NOAA studies on evaporation from Lake Erie (Derecki, 1975, 1976). Fernandes et al. (2007) studied trends in actual evapotranspiration (AET) across Canada using a physically-based land surface model called the Ecological Assimilation of Land and Climate Observations (EALCO) model, driven by observed meteorological parameters. While Potential Evapotranspiration (PET) was included in some calculations due to the assumption of unlimited water supply in certain areas, the evaporation equations used (Thornthwaite and Preistly-Taylor) were calibrated over wet grass and over ground and canopy surfaces, not over open water, and final results were only reported for AET calculations.
2.4.3 Water Balance Studies in the Athabasca River Region

Few studies have been done on the water balance particular to Western Canada’s dry, mid-latitude, continental hydroclimatic regime. The only western Canadian studies found in the literature have study sites located entirely or primarily in the arctic (e.g., Gibson et al., 2006). Much work has been done on water balances, energy balances, and overall hydrology of the Mackenzie River basin, mainly by the Northern River Basins Study (NRBS) (Marsh et al., 2004; Prowse & Conly, 2002; Szeto et al., 2008). This basin, which spans Alberta, British Columbia, NWT, YK and some of Alaska, starts just north of the Athabasca River region and is mainly controlled by Arctic and Subarctic hydroclimatic regimes (Prowse & Ommanney, 1990).

Winter & Woo (1990) calculated isolines showing the balance between precipitation and lake evaporation across Canada based on 1989 USGS data, and both Fort McMurray and Fort Chipewyan lie between the -200 and -300 mm, indicating a moisture deficit (Fort Chipewyan is slightly wetter with a higher value closer to -200 mm annually). Results of the CRAE model (Morton, 1983) reported by Gan (1998) indicate that EC station precipitation exceeds evaporation by approximately 100 mm/yr in the province of Alberta as a whole, but this includes the whole range of precipitation and evaporation regimes from the arid South Saskatchewan River Basin containing the drought-prone Palliser Triangle (Dale-Burnett, 2012) to the wet northern Boreal forests. No other examples of the actual $P - E$ values used to indicate a moisture deficit or surplus climate were available in peer-reviewed articles for the Athabasca River region.

Several consultant reports report both average annual precipitation and estimated average annual open-water evaporation in the region, with precipitation taken from the EC Fort McMurray climate station ranging from 435 mm/yr to 475 mm/yr (varying due to the study periods), and evaporation estimated between 500 mm/yr and 629 mm/yr, for an average moisture
deficit of 110 mm/yr (Devon NEC Corporation, 2012; JDEL Associates Ltd., 2005; Southern Pacific Resource Corp., 2011). Many studies also indicate that evapotranspiration is greater than precipitation in the region, even though Actual Evapotranspiration is usually much less than open-water evaporation due to water availability limitations (Devito et al., 2005; Serreze et al., 2003).

Studies on the water balance and thermodynamic regimes of industrial water storage ponds in the Athabasca River region have been carried out to address specific needs and design requirements. However, among the many studies done by Golder Associates Ltd. (Golder 2004, 2006a, 2011) and for the Cumulative Environmental Management Association (CEMA, 2012; Westcott & Watson, 2007), very few consider the effects of climate change, except as recommendations for future work (Golder, 2006a; Westcott, 2007) or using approximate percentages as scenarios of future changes (Golder, 2006b). Comprehensive research on projected changes to the water balance of surface water in this region is required for safe development and disaster prevention and mitigation in the future.

2.4.4 Water Storage

In the Athabasca River region near the confluence of the Athabasca and Peace Rivers, water is abundant and glacial depressions have filled to create a vast array of geologically young (~12000 years old) natural lakes varying from wide, shallow lakes, to deep kettle lakes (Mitchell, 1991). The PAD, one of the largest inland freshwater deltas in the world, is also located at this confluence (Peters et al., 2006a). Human activity in the Athabasca River region has caused additional lakes to be proposed. These anthropogenic lakes will serve a variety of purposes, including clean water storage, hydropower reservoirs and landscape reclamation (Ohlson et al., 2010; Westcott, 2007). The following sections review three types of surface water storage in the
Athabasca Region, which are used to model the study basins for this research, described below (Section 3.3.1).

2.4.4.1 Shallow, Natural Surface Water Storage

The 6000 km² area of the PAD consists of three large hydrologically connected lakes as well as > 1000 perched (elevated) basins of low relief (less than 1.5 m deep), many of which are perched, or hydrologically isolated from the surrounding water flow (Peters et al., 2006a). There is no intermediate flow between these perched basins due to the low relief in the delta, and there is negligible groundwater flow between water bodies (Nielsen, 1972). The perched basins are only connected hydrologically and refreshed with water when the Peace River stage rises higher than that of the delta lakes and flow reverses into the delta. This occurs when extreme hydroclimatic events are combined with ice-jamming in the rivers to create extremely high flows (Peters et al., 2006b). In 1982 the delta was named a wetland of international importance by the RAMSAR convention (Peters et al., 2006a). Extensive work has been done on the hydrology and ecology of the PAD and the surrounding ecosystem (see Beltaos et al., 2006; Pietroniro et al., 2006; Prowse & Conly, 1998; Prowse & Beltaos, 2002; Prowse et al., 2006; Toth et al., 2006; Wolfe et al., 2005).

2.4.4.2 End Pit Lakes – Intermediate-depth Water Storage

Alberta Environment (AENV) and Alberta Sustainable Resource Development (ASRD) require oil sands operators to reclaim landscapes on which they have completed surface mining operations (BGC Engineering Inc., 2010). To be considered successfully reclaimed, the land must achieve “equivalent land capability” (Jones & Forrest, 2010), which means the area must support land uses that are equivalent, if not identical, to the uses that existed before the disturbance (Bacon, 2006). End land uses such as forestry, recreation, traditional use, and natural
wildlife habitat are considered to contribute to the goal of returning disturbed areas to self-sustaining boreal ecosystems (BGC Engineering Inc., 2010).

Two types of surface water storage appear as components in plans for Oil Sands landscape reclamation: End Pit Lakes (EPLs) and constructed wetlands (BGC Engineering Inc., 2010; Golder, 2006b). End Pit Lakes (EPLs) are artificial lakes designed to store and promote the degradation of toxic residual organic compounds found in tailings disposed of by the oil sands industry (Golder, 2011). They will be built not as temporary holding sites for contaminated materials during mining operations as are tailings ponds, but as permanent fixtures in the post-Oil Sands reclaimed landscape (Golder, 2006a; Westcott & Watson, 2007). Located in Oil Sands post-mining pits, the bottom substrate of EPLs will be covered by a layer of process-affected materials such as soft tailings, lean old sands and overburden, and the lake will then be capped by clean water sourced from precipitation, runoff, process-affected waters, or water diverted from local streams and rivers (Westcott & Watson, 2007). In at least the initial phases of EPL development, extreme climate events such as intense precipitation and drought are a threat to the EPLs, risking contamination of the surrounding environment through flooding or by drying out of the water cap which would expose the sequestered materials. In the far-future the lake is expected to achieve meromixis and to be safely hydrologically reconnected and support a natural biotic community in the freshwater cap (Westcott & Watson, 2007). Constructed wetlands will initially serve as treatment systems for water that passes through them, over time developing into self-sustaining systems resembling naturally occurring wetlands (Golder, 2006b). If the constructed wetlands are successful in functioning without management they will play a large part in achieving equivalent land capability (BGC Engineering Inc., 2010).
While no land reclamation has yet to be implemented beyond the test phase (Golder, 2006a, 2011; Westcott, 2007), much research has been undertaken, such as by the Reclamation Working Group (RWG) of the Cumulative Effects Management Association (CEMA) (Bacon, 2006; Golder, 2006a), to understand how EPLs and wetlands can be created to mitigate the effects of mining operations in the Athabasca River region. There is only one EPL currently in existence, Base Mine Lake, an atypical EPL built by Oil Sands extractor Syncrude out of an old tailings pond (Westcott, 2007). The construction of about 30 EPLs is proposed for the Athabasca Oil Sands region in coming decades (Golder, 2011).

Modelling efforts by Golder Associates Ltd. (2004a) have determined that the ideal EPL should be at least 20 m deep with a small surface area of 1 to 8 km² to remain stratified (in a state of meromixis), keeping the contaminated materials from mixing with the clean freshwater cap. Shallow lakes less than 5 m deep will always experience full turn-over annually and are therefore not appropriate as EPLs, while deeper lakes require much higher inflow rates and even as such may not be able to sustain meromixis. Data from Beaver Creek Reservoir and Base Mine Lake are used to approximate lake dimensions in the models, but no analogous lakes exist from which to calibrate the EPL models (Golder, 2006a). Other studies on EPLs show similar proposed depths (Devon NEC Corporation, 2012; Golder, 2004; Westcott, 2007; see Table 2).

<table>
<thead>
<tr>
<th>Report Source</th>
<th>Surface Area (km²)</th>
<th>Depth (m)</th>
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<td>Min</td>
<td>Max</td>
<td>Median</td>
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<tr>
<td>Westcott, F. (2007). Oil Sands End Pit Lakes: A Review to 2007. CEMA.</td>
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<td>Golder Associates Ltd. (2006). Predicted Water Quality of Oil</td>
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<td>1 (base case)</td>
</tr>
</tbody>
</table>
### Table 2: Sizes of proposed End Pit Lakes in the Athabasca River region. Most information taken from published modelling efforts undertaken by consultants for CEMA.

<table>
<thead>
<tr>
<th>Sands Reclamation Wetlands: Impact of Physical Design and Hydrology (CEMA) (p. 61).</th>
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<th>EPL similar to MacKay Lake</th>
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<tr>
<td></td>
<td>2.97</td>
<td>5</td>
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</table>

**2.4.4.3 Deep Industrial Water Storage**

Another type of surface water storage expected in the Athabasca River region is off-stream storage of freshwater. The Athabasca River is the main source of water for local mining operations, which use approximately two cubic metres of water per barrel of bitumen to extract and upgrade it to light crude oil (Bacon, 2006). Water requirements of the mines do not vary much over a year, whereas the river has a typical seasonal cycle of high flows in the summer months (May – September) and low flows in the winter months (October – April) (Westcott, 2007). The winter low-flow period is the most sensitive time of year for rivers. Many leading water management plans for other rivers in Canada and around the world include critical low-flow limits, known as Ecosystem Base Flow (EBF), at or below which withdrawals from the rivers cannot be made (Lebel et al., 2011). This protects the aquatic life of the rivers from threats due to detrimentally reduced habitat and oxygen levels (Pembina Institute, 2015). For the Athabasca River, low-flow periods will also be more likely in the future as the natural variability of flow is exacerbated by climate change driven reductions in glacier runoff that reduce summer flow (Casassa et al., 2009), and as the occurrence of extreme precipitation and evaporation events increases (Coumou & Rahmstorf, 2012; Peterson et al., 2012), both contributing to increased flashiness of the river discharge.
The Alberta Government released a series of “Management Frameworks” between 2007 and 2015 to address the withdrawals of river water for oil sands operators (see Government of Alberta, 2015). In 2007, Alberta Environment developed a Water Management Framework to regulate when, and how much, water can be extracted from the Athabasca River for cumulative oil sands uses. The interim Phase 2 Committee Framework Report for the Oil Sands Development Group (Ohlson et al., 2010) proposed to require recent water license holders to (and recommend that senior license holders) offset 50% of their withdrawals when the streamflow rate is below the EBF threshold by using stored water instead of river withdrawals (AB Environment & Fisheries and Oceans Canada, 2007). Further work in collaboration with the Phase 2 Framework Committee, CEMA and First Nations and Metis resulted in the 2015 Surface Water Quantity Management Framework for the Lower Athabasca River, which, while still requiring recent water license holders to offset their withdrawals with stored water in the low-flow period, gives precedence to water withdrawals for senior license holders, and allows a minimum withdrawal of 4.4 m$^3$ s$^{-1}$ regardless of the flow in the river (Government of Alberta, 2015). This has been criticized by environmental groups, such as the Pembina Institute, who stated that without the implementation of an EBF limit, below which no water withdrawals can be made, the Government of Alberta has failed to protect the lower Athabasca River in the most sensitive low-flow period (Pembina Institute, 2015). The Alberta Wilderness Association indicates that off-stream water storage to avoid river withdrawals during the low-flow period could be built by senior license holders Syncrude and Suncor “for about a one percent increase in per-barrel capital costs” (Pembina Institute, 2015).

The changing variability of streamflow and desire to protect the lower Athabasca River is creating the need for industry in the Athabasca River region to build off-stream surface water
storage (Figure 3) to buffer their water consumption when river water withdrawals are low or restricted (Ohlson et al., 2010). This stored clean water could also be released back into the river to supplement flows during low-flow periods if necessary (Westcott, 2007). No size specifications for such off-stream storages could be found in the literature, but it is assumed that a large amount of water would be needed to continue industrial operations in the case of river withdrawal restrictions, making these lakes deeper and larger than EPL design specifications.

Development of hydropower is also expected in northern Alberta in the future, especially as a tool to balance future intermittent power generation technologies such as wind and solar (Gebre, 2014). The development of hydropower in the region would mean construction of deep reservoirs behind dams (Kumar et al., 2011). This is type of anthropogenic deep surface water storage is also considered in modelling of future surface water storage in the Athabasca River region in this project.

Figure 3: Typical mine site water balance showing new addition of off-stream water storage, from the Phase 2 Committee Framework Report for the Oil Sands Development Group (Ohlson et al., 2010: p.10).
2.5 Conclusions

Water balance modelling is a useful tool to evaluate how climate change and variability is reflected in the storage capacity of lakes. For 1st-order basins, a simple precipitation minus evaporation (P-E) water balance is sufficient to determine changes in storage (reflected as changes in water level), especially when aquitards and freeboard sides exclude groundwater and overland flow. Climate model projections can be used as input data to the water balance equation in the current and future periods. However, current models do not properly account for heat storage at depth in a water body. Therefore, for land areas with widespread surface water storage, such as is found in the Athabasca River region of Western Canada, modelling of surface heat fluxes must be done outside of RCM_GCMs to properly estimate evaporation rates. In this research the MyLake model is used for offline modelling of evaporation, using climate model inputs. To examine changes in climate at local and regional scales, RCM_GCM results must be downscaled. In this work the preferred methods are to apply bias correction directly to dynamically downscaled 50 km$^2$ resolution RCM_GCM results (to represent average regional climate), and the same data further downscaled to a 10 km$^2$ resolution by the statistical BCCI and BCSD methods (to represent small-scale local climate). The following chapter on Methodology (Chapter 3) provides the details of how the RCM data are used to calculate the long-term cumulative, and short-term extreme, water balance of shallow, intermediate and deep theoretical basins in the Athabasca River region in the current and future periods. This is done to assess the effects of climate change on surface water storage in a mid-latitude, sub-humid, dry, interior hydroclimatic regime.
2.6 References


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3. CHAPTER 3: METHODOLOGY AND DATA

This chapter describes the methods and datasets used to address the two main objectives of this thesis: 1) to quantify the average water balance of lakes of varying depths using regional-scale climate data for the current and future periods at the Fort McMurray and Fort Chipewyan study sites (Chapter 4), and 2) to estimate projected changes in patterns of extreme climate events at the study sites and time periods, using high-resolution local climate data (Chapter 5).

3.1 Lake Water Balance and Study Basins

The water balance for the 1st-order study basins is calculated using the inputs minus outputs equation (Equation [1]). Lake evaporation (E) outputs are subtracted from precipitation (P) inputs on a daily basis for the entire year, with the remainder indicating the change in storage, represented by the change in water level (ΔWL). All variables are measured in units of millimeters per day (mm/dy). This water balance applies to the open-water lake only, not a wider watershed.

The water balance is calculated for three theoretical 1st-order study basins chosen to represent the three types of surface water storage in the region (as described in section 2.4.4): a “shallow”, an “intermediate-depth” and a “deep” basin. The water balances of all three basins are evaluated based on modelled current and future climate at both Fort McMurray, AB and Fort Chipewyan, AB, the latter located 220 km further north on the edge of the PAD. The smallest basin is 1.5 m deep, has a surface area of 20 km² and is representative of a shallow perched (elevated) lake in the PAD. The intermediate-depth basin is 28.5 m deep, has a small surface area of 1 km² and is representative of End Pit Lakes (EPLs). The deep basin is 76.5 m deep, has a large surface area of 30 km² and is representative of off-stream storage of freshwater by industry,
for hydropower and more (Table 3). These sizes are based on the depths and areas of existing and proposed lakes in the Athabasca River region (see Section 2.4.3).

<table>
<thead>
<tr>
<th>Study Basin</th>
<th>Depth</th>
<th>Surface Area</th>
<th>Represents</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shallow</td>
<td>1.5 m</td>
<td>20 km$^2$</td>
<td>PAD perched basins</td>
<td>Fort Chipewyan, AB</td>
</tr>
<tr>
<td>Intermediate</td>
<td>28.5 m</td>
<td>1 km$^2$</td>
<td>End Pit Lakes</td>
<td>Fort McMurray, AB</td>
</tr>
<tr>
<td>Deep</td>
<td>76.5 m</td>
<td>30 km$^2$</td>
<td>Off-stream industrial storage</td>
<td>Fort McMurray, AB</td>
</tr>
</tbody>
</table>

Table 3: The theoretical study basin sizes, based on similar existing or proposed lakes in the Athabasca River region.

The variables used in the water balance were chosen based on the hydrology and scale of the study basins, as well as the goal of the proposed study. Since the basins are of 1st-order and therefore have only negligible inputs and outputs from the land and streams, inflow and outflow are excluded from the equation. This is especially true within the PAD, where the low relief means negligible intermediate flows between basins (Nielsen, 1972). Landscape-based runoff processes are also not considered, because the objective of this study is to quantify climate change effects on open water and not over entire watersheds, and since the anthropogenic intermediate and deep basins would have freeboard siding to specifically exclude the stored water and overland water from interacting.

The scale of the proposed regional modelling allows the exclusion of more specific parameters representing temporally or spatially large-scale processes, such as groundwater fluxes (Menció et al., 2010), soil moisture fluxes (Kane & Yang, 2004), and sublimation and condensation. These parameters are not considered in the water balance because the associated processes are either of a relatively small magnitude or are averaged out over the proposed catchment sizes and timescales (seasonal or annual), producing a zero net effect on the water balance (Arnell, 1999; Kling & Nachtnebel, 2009; Sivapalan et al., 2003; Zhang et al., 2008).
Furthermore, the lakes represented by the study basins are all expected to have an aquitard separating the stored water from the groundwater system; either due to the geology of the area or to the nature of anthropogenically-built water storage that is again not intended to be hydrologically connected to the surrounding environment. For the shallow basin in the PAD, although perched lake basins have less interaction with groundwater than the surrounding wetlands, some flow between the lake and the groundwater is more likely. However, complex wetland groundwater modelling is beyond the scope of this study.

Precipitation depth (mm/dy) is added to the water balance at a daily scale, regardless if it falls onto the basin as rain or snow. In reality, when the air temperature is below zero incoming precipitation is stored in the snowpack and is not added to the lake as liquid water until snowmelt. However, instead of modelling snowmelt, daily precipitation rates are used to represent changes in snowpack affecting the water level of the study lakes even during the ice cover season. Over the winter the weight of a snowpack depresses the ice cover on a lake, changing the water level proportionally to the snow load to ice thickness ratio (Prowse et al., 2011). If free water pathways existed, this depression could force water out from under the ice, causing spikes in winter streamflow if the lake has outlets (Prowse et al., 2011). This is not considered to be the case here as the 1st-order study basins do not have outlets. Another impact of ice cover depression is snow-ice formation due to flooding of the snowpack (Saloranta, 2000). However, snow-ice formation, as with ice formation, does not change the water balance – water from the lake volume frozen into the ice cover is released back into the lake upon melt. In this study, any incoming precipitation is considered to stay within the 1st-order lake basin and therefore, the “change in water level” variable of the water balance is calculated all year by the
addition of precipitation in snow water equivalents, from which evaporation is subtracted during the open-water season.

3.2 Data

3.2.1 Current and Future Periods

This research compares the water balance of the study basins over a 30-year “current period” to the water balance over a 30-year “future period”. Thirty years is considered long enough to represent average climate, including complete cycles of variability, and is a temporal window used in numerous studies. The “current period” is chosen as the most recent 30-year climate normal period for which climate model data were available from the NARCCAP program (see Section 2.3.7) at the time of data acquisition: from 1971 to 2000. The near-future mid-21st century period from 2041 – 2070 was chosen as the “future period,” also based on availability of the NARCCAP model data. Bias correction (see below) is applied to the dynamically downscaled model results, preserving unique variability and extremes between the current and future projections (see Section 2.3.5).

3.2.2 NARCCAP and NARR Data

To calculate the water balance at the study sites, six climate variables are required. Precipitation is used directly in the water balance, but evaporation is modelled via the MyLake comprehensive lake temperature model (see Section 3.3) using cloud cover (fraction), relative humidity (%), surface pressure (hPa), wind speed (m s\(^{-1}\)), and surface air temperature (°C). MyLake models the lake temperature profile and the heat flux at the surface of the lake (Saloranta & Andersen, 2004), from which evaporation is estimated (see Section 3.3.4).

Data for all six climate variables are taken from a subset of the NARCCAP RCM_GCMs to create the model ensemble for this research: CRCM_CGCM3, CRCM_CCSM, and
MM5I_CCSM (see Table 1). The two GCMs that provide boundary conditions to the RCMs are the Canadian Centre for Climate Modelling and Analysis (CCCma)’s Canadian Global Climate Model version 3 at the T47 spatial resolution (CGCM3); and the National Centre for Atmospheric Research (NCAR)’s Community Climate Model version 3 (CCSM). The two RCMs that are nested within the global models are the OURANOS and Université du Québec à Montréal (UQAM)’s Canadian Regional Climate Model / le Modèle Régional Canadien du Climate (CRCM / MRCC); and Iowa State University’s run of the Pennsylvania State University / National Center for Atmospheric Research (PSU / NCAR) mesoscale model MM5I. More information can be found at http://www.narccap.ucar.edu/data/model-info.html.

The RCM_GCM data from NARCCAP include values every three hours (UCAR, 2007), which are averaged to daily values to calculate the daily water balance. Two of the variables required further transformation; wind speed is calculated as the hypotenuse of vertical and horizontal u and v wind variables, and relative humidity is determined from the available specific humidity output (using pressure, temperature and partial pressure of water vapour) (Nievinski, 2009). The data are available at two spatial resolutions: the 50 km$^2$ resolution gridcells of the dynamically downscaled RCM_GCM datasets available directly from NARCCAP; and a 10 km$^2$ resolution dataset produced by the Pacific Climate Impacts Consortium (PCIC) after further statistical downscaling using the BCCI and BCSD methods (Murdock et al., 2013; see Section 2.3.5). The 10 km$^2$ dataset includes only precipitation (mm/dy) and minimum and maximum daily temperature (°C); mean daily air temperature is calculated as the mean of the minimum and maximum temperature and the remaining variables are filled in from a 50 km$^2$ gridcell, as described below. As this study aims to address both regional and extreme climate change at the
study sites, a larger-scale spatially-averaged dataset is created from a set of nine 50 km\(^2\) gridcells, and datasets created from individual 10 km\(^2\) gridcells are also used (Figure 4).

Figure 4: Spatial resolution of NARCCAP RCM_GCMs used to calculate the water balance for the average regional and extreme local climates of both Fort McMurray and Fort Chipewyan. Original data sources are in the white boxes and the final datasets are in the blue boxes.

The RCM_GCMs were run using the illustrative marker scenario from the A2 SRES narrative (Mearns et al., 2012). The A2 scenario assumes continued greenhouse gas (GHG) emissions similar to the late 20\(^{th}\) century and sustained population growth. It projects a large change in climate was therefore chosen for this study as any mitigation and adaptation efforts derived from results using this scenario could easily be applied to “smaller” climate changes, and because the 1990 - 2007 trajectory of emissions matches the A2 scenario best (UCAR, 2007). By using this same scenario for all model runs, the NARCCAP model ensemble is likely to predict
larger climate change than if other scenarios were used, and differences in results will be due to
differences in model parametrizations rather than different emissions futures.

Other RCM_GCM pairs from the NARCCAP ensemble were not selected, as either some
or all of the required climate variables were not available at the time of data acquisition. Model
pairs that use the GFDL GCM were not selected since the RCM3_GFDL and RSM3_GFDL runs
had no cloud cover data, and the HadRM3_GFDL model was missing air temperature, humidity
and windspeed in the future period. The RCM3_CGCM3 was also missing cloud cover, and the
WRFP_CGCM3 was missing variables for the years 2065 – 2070. The HadCM3 GCM runs were
also not selected, as the MM5I and RSM runs had not been completed, and not all variables from
the HadRM3 run were ready for dissemination. Since two of the RCM_GCM pairs selected for
the study use the CCSM GCM, the third CCSM model pair, WRFP_CCSM, wasn’t included so
as not to bias the ensemble towards CCSM-forced model runs. Some observations were missing
from the datasets that are used, see Section 4.3.2 for details.

The NARR dataset is used as reference data for bias correction of all the NARCCAP
current and future RCM variables. Reanalysis datasets produce values, for extreme events in
particular, at scales similar to RCMs, and therefore can be used as a reference in the absence of
observations (Sillmann et al., 2013). The NARR model assimilates high quality observations into
the NCEP (National Centres for Environmental Prediction) Eta model, resulting in a long-term,
high resolution climatic dataset covering North America. The NARR data are available at a 3-
hourly time step spanning 1979 to near present at a spatial resolution of 32 km² (Mesinger et al.,
2006). The data are averaged to daily values for use in this study.
3.2.3 Bias Corrected Datasets

The spatially averaged, “Bias Corrected” datasets are created by averaging data from nine 50 km$^2$ gridcells into one time series for each RCM and study site. The selected gridcells for each site are the nine closest to the Fort McMurray and the Fort Chipewyan EC climate stations, representing a ~22,500 km study areas around each site (Figure 5). This study area size is chosen to represent the scale of synoptic climate events and to smooth out the influence of any extremely local climate events in the regional analysis.

Figure 5: Overlay of the 50 km$^2$ resolution and 10 km$^2$ resolution NARCCAP model gridpoints, and the 32 km$^2$ resolution NARR model gridpoints around Fort Chipewyan. The same spatial resolutions are used around Fort McMurray, located 200 km south along the Athabasca River.
Bias correction is applied to the spatially averaged datasets for each RCM_GCM to adjust the direct outputs of the NARCCAP models for systematic model biases (see Section 2.3.6). Here the bias is calculated by comparing the RCM_GCM results for 1979 – 1999 to the NARR results in the same period and over the same area. First, bias correction factors for all six climate variables from each of the three models are calculated by dividing the mean monthly values of the RCM_GCMs by the mean monthly values from NARR (or, for air temperature, subtracting the RCM_GCM mean from the NARR mean). For temperature only, interpolation is used to create a set of daily correction factors, instead of monthly factors, to avoid jumps in temperature values between the last day of the month and the first day of the next month.

Next, the bias correction factors (based on 1979 – 1999) are applied to the full daily spatially-averaged datasets of the climate variables from each NARCCAP model for both the current (1971 – 2000) and future (2041 – 2070) periods. A multiplicative function is used for all variables except temperature, for which an additive function is used to ensure that the daily minimum never exceeds the daily maximum (Ahmed, 2011; Lenderink et al., 2007; Teutschbein & Seibert, 2010). The equations used for bias correction are as follows, where NARR represents the reference period and NARCCAP the simulated climate:

For temperature (T), $T_{BiasCorrected} = T_{NARCCAP} + (T_{NARR} - T_{NARCCAP})$ \[\text{[4]}\]

For cloud cover, relative humidity, surface pressure, wind speed, and precipitation (Var), $Var_{BiasCorrected} = Var_{NARCCAP} \div \left(\frac{Var_{NARCCAP}}{Var_{NARR}}\right)$ \[\text{[5]}\]

The bias-corrected, spatially averaged datasets are used to run MyLake and calculate the water balance, and as a last step the three models in each ensemble are averaged to the multi-model mean to produce the final results reported in Chapter 4.
3.2.4 Extreme Datasets

The “Extreme” datasets, representing local extreme wet and dry conditions, are created by extracting data from individual 10 km$^2$ resolution gridcells from the BCCI and BCSD datasets. To represent extreme moisture surplus conditions, one gridcell, from any of the three models, with the highest average daily precipitation over 30 years in the current period is selected (Max Precip). To represent extreme moisture deficit conditions, one gridcell, from any of the three models, with the highest average daily temperature (a proxy for high evaporation) over 30 years in the current period is selected (Max Temp). This is repeated for both the Fort McMurray Fort Chipewyan study areas, and the same gridpoint is used for the future period. For Max Precip, temperature data from the same gridcell are used, and vice versa for Max Temp. The remaining climate variables (air pressure, wind, relative humidity and cloud cover) are filled in from the closest gridcell in the 50 km$^2$ bias-corrected dataset (prior to spatial averaging). The BCCI and BCSD datasets are used in Chapter 5 to analyze extreme single- and multi-day changes in the water balance. See section 3.6 for details on which individual gridcells were selected.

3.3 MyLake Model

MyLake (“Multi-year simulation model for Lake thermo- and phytoplankton dynamics”) is a one-dimensional, process-based, comprehensive lake model that simulates the vertical distribution of lake water temperature (Saloranta & Andersen, 2004). MyLake is designed to include only the most significant physical, chemical and biological lake processes: the vertical temperature distribution, density profiles of snow and ice cover, and basic water quality variables such as phosphorous-plankton dynamics (Saloranta & Andersen, 2004; Saloranta et al., 2009). The model outputs include time-series profiles of light attenuation, water temperature, turbulent heat fluxes, sediment-water heat fluxes, water quality parameters, and ice, snow-ice, and snow thicknesses (Saloranta & Andersen, 2007). The model simulations are run at a fixed daily (24
hour) time step, while the vertical resolution is set by a user-defined number of horizontally homogeneous layers (Saloranta et al., 2009). MyLake has been shown to produce accurate water temperature profiles for a variety of northern hemisphere lakes and is therefore deemed applicable to the study site of the Athabasca River region in northern Alberta (see Dibike et al., 2011a; 2011b; Gebre, 2014; Saloranta & Andersen, 2007; Saloranta et al., 2009).

Water temperature is not used directly in this work; however the calculation of the energy balance at the surface of lakes used by MyLake to create the water temperature profile is used to estimate evaporation over open water. MyLake calculates the surface energy balance using Matlab’s Air-Sea Toolbox (USGS, 2013). Evaporation is then estimated from the latent heat flux, extracted from the turbulent flux at the water surface. The energy balance is calculated taking into account various factors that affect evaporative rates, including heat storage at depth, the exchange of heat between water and the surrounding sediment, dynamically calculated albedo, surface aerodynamics and concurrently modelled ice-cover dynamics (Saloranta & Andersen, 2004). The inclusion of these factors means that the outputs of MyLake are appropriate for modelling evaporation over open-water surfaces. The MyLake sub-modules evaluating water quality and plankton dynamics are not needed for this research and were switched off during the model runs.

To run MyLake simulations, input parameters of lake morphometry, initial conditions, and daily meteorological data on air temperature, relative humidity, wind speed, surface air pressure, precipitation and cloud cover are required (Dibike et al., 2011a). The input parameters define the maximum depth and surface area of the study basin, and vertical layers of equal depth are modelled within the water column, with corresponding sediment layers in the soil surrounding the water body (Figure 6; Saloranta & Andersen, 2004). The water layer thickness (∆z) used is
0.5 m. The ∆z and other parameters are chosen based on the calibration of MyLake by Saloranta and Andersen (2007) and the application of MyLake to Baker Lake, Nunavut by Dibike et al. (2011a). Baker Lake is a similar lake to the study lakes as it has a maximum depth of 60 m and is also located in continental northern Canada, although further north at 64°N compared to the study sites at 56°N and 58°N. In the sensitivity analysis run by Saloranta & Andersen (2007), none of the water quality output variables tested (phosphorous, chlorophyll, suspended inorganic particulate matter) showed significant sensitivity to ∆z.

![Diagram](https://via.placeholder.com/150)

**Figure 6:** Example of a lake modelled by MyLake. The vertical dimension of the lake is partitioned into N horizontal slices, labeled 1 to i, the depth of layer i being \( z_i \leq z < z_{i+1} \).

(Adapted from Saloranta & Andersen, 2004: Figure 1, p.8)

### 3.3.1 Basin Morphometry

The input morphometry of the intermediate and deep lakes used to run MyLake is elliptical sinusoidal (Figure 7), a shape representative of average lakes in Canada (Neumann, 1959; Wetzel, 2001). The surface area of each layer was calculated using the hypsometric curve for the elliptical sinusoid. First the maximum depth \( (H_z) \) of the elliptical sinusoid is calculated based on the surface area at the top of the lake \( (A_0) \), by

\[
H_z = 0.52 \times \left( \sqrt{A_0} \right)^{0.58} \quad \text{(Gorham & Boyce, 1989).} \tag{6}
\]

The radius \( (r) \) of each subsequent 0.5 m-deep elliptical lake layer, based on the depth of the layer \( (z) \) within the elliptical sinusoid, is then calculated by
The morphometry of the shallow lake, on the other hand, was not modelled after an elliptical sinusoid as using this shape would mean that most of the lake would be shallower than the maximum 1.5 m depth, which is not realistic. Instead, the shallow lake morphometry is modelled using the “bucket” approach, with the top three layers decreasing in surface area from 20 km² to 5 km², ending with a flat lake bottom 2,523 m wide (equal to the surface radius) (Figure 7).

![Figure 7: Lake Morphometry of the three hypothetical study basins, representative of existing and planned surface water storage in the Athabasca River region.](image)

### 3.3.2 Water Temperature Profile

The vertical water temperature profile of the lake is calculated by MyLake by estimating the volume-averaged temperature for each lake layer at mid-depth. Starting with an initial
surface temperature set at 4°C, the time series of the temperature profile is created by calculating
the change in temperature of all lake layers \((i = 1 \ldots i)\) at each daily time step in the study
period. The change in temperature \(\frac{dT}{dt}\) between time steps is modelled based on the local
heating of each layer and the diffusion of heat from surrounding layers and from the water-
sediment interface (Saloranta & Andersen, 2004). The thermodynamics of vertical lake profiles
are solved by MyLake using the heat conservation equation:

\[
A \frac{dT}{dt} = \sum \frac{\delta z}{\delta z} \left[ KA \frac{dT}{dz} \right] + A \frac{Q^*}{\rho_w C_p} \tag{8}
\]

Here \(T\) is the layer water temperature (°C), \(\delta z\) is the layer depth (m), \(K\) is the vertical diffusion
coefficient (m² d⁻¹), \(A\) is the surface area of the layer (m²), which decreases for each layer until
reaching zero at the bottom, \(Q^*\) is the net radiative flux, \(\rho_w\) is the density of water \((\rho_w = 1 g mL^{-1})\) and \(C_p\) is the specific heat capacity of water \((C_p = 4186 J kg^{-1} °C^{-1})\). The first right-
hand term represents the diffusive mixing process that distributes heat between layers, and the
second term represents local heating in each layer due to incoming radiation and transfer of heat
from the surrounding sediment (Saloranta & Andersen, 2004).

3.3.2.1 Surface Heating

The temperature profile of lake water is strongly governed by local open-water heating at
the surface of the lake. In MyLake, the net heat flux in the surface water layer \((\bar{Q}_{i=1}^*)\),
consisting of shortwave, longwave, latent and sensible heat fluxes, is calculated based on the
input climate variables (cloud cover, air temperature, relative humidity, air pressure and wind
speed), the global insolation, the previous temperature profile of the lake, the latitude and
longitude of the lake, the existing snow water equivalent (WEQs) on the lake, if any, and the
albedo of the surface, be it water, ice or snow. The global insolation can be entered as input data, or, as in this case, calculated as a function of solar altitude and cloud cover (Gebre et al., 2013a).

The total temperature change between time steps in the surface water layer due to local heating is calculated by:

$$\Delta T_i = \left( Q_{ws,norm,i} + Q_{turb,1} + Q_{lw,1} + Q_{sw,abs,i} \right) * A_i \div (\rho_w * C_p * V_i)$$ \[9\]

where $Q_{ws,norm,i}$ is the heat flux at the water-sediment interface, $Q_{turb,1}$ is the turbulent heat flux at the surface, $Q_{lw,1}$ is the net longwave radiation at the surface, $Q_{sw,abs,1}$ is the incoming solar radiation absorbed by the first layer of the lake, and $V_i$ is the volume of the layer (Saloranta & Andersen, 2004). Any energy from melting any ice remaining from the previous time step is also added to the total temperature change in the MyLake code, when relevant.

During open-water periods there is a difference between daytime and nighttime heating. During the day, shortwave incoming solar radiation (insolation) dominates the local heating of the surface layer; energy from insolation that reaches a lake surface is reflected, absorbed and attenuated to various extents. The amount of insolation that is absorbed into the water and contributes to local heating of the water layers ($Q_{sw,abs,i}$) is calculated by MyLake based on the albedo of the lake and a light extinction coefficient for each layer, among other factors (Saloranta & Andersen, 2004). In the open-water season, the albedo for each day is calculated dynamically using the sun altitude at the latitude and longitude of the lake, and the atmospheric transmittance – the ratio of outside-atmosphere solar radiation and measured insolation based on the most recent sunspot period 1979 – 1995 (Payne, 1972). This time period aligns with the current period in this study (1971 – 2000).
At night, the energy balance of surface layer includes only longwave, sensible and latent heat; there is no shortwave solar radiation input. These fluxes are calculated based on the fraction of the day without solar inputs, which is determined by MyLake using the latitude and longitude of the study site for each day. The energy from these fluxes does not reach below the surface layer. The net longwave heat flux is defined as the net flux of greybody emissions from the water surface, clouds and atmospheric gases (Dickey et al., 1994). Longwave radiation is generally the third largest term in the full energy balance equation, sometimes overtaking latent heat depending on the season and the time of day (Dickey et al., 1994). Parameterization of the emissivity of the water surface is an important factor in calculating the amount of radiation emitted as longwave and is dependent on water temperature as well as the wavelength of the incoming light. Dickey et al. (1994) calculated the spectrally weighted emissivity of ‘pure’ (fresh) water at a surface temperature of 300 K to be 0.985 using indexed refraction data. MyLake uses this value in the calculation of the energy budget of the lake.

Wind has a strong influence on the thermal stratification of lakes. During open-water wind stress at the surface causes water motion which propagates into underlying layers up to a certain depth (Gebre et al., 2013). Higher windspeeds over the lake surface increase the input of energy into the lake, increasing the diffusion of thermal energy from the surface downwards (Forsius et al., 2010). In MyLake wind-induced mixing is accounted for by the turbulent kinetic energy (TKE) accumulated over the daily time step (Saloranta & Andersen, 2004).

During the ice-covered period only a fraction of shortwave radiation penetrates the ice and contributes to local surface heating (Saloranta & Andersen, 2004). As described below as part of the Ice Cover Module, MyLake calculates the amount of attenuated insolation reaching the water profile during ice cover based on coefficients that include the albedos and densities of ice and
snow. Convective mixing, also described below, is also modelled under-ice to establish a stable density profile. Unlike during open-water conditions, water under ice is not heated differently during daytime and nighttime, and wind effects are not relevant. Ice cover inhibits heat flux out of the lake; latent heat and therefore evaporation is mostly, if not entirely, inhibited while the lake is frozen (Derecki, 1975).

3.3.2.2 Sub-Surface Heating

Once the surface energy is calculated, the local heating of subsurface layers is modelled. The area and volume of subsequent subsurface water layers decreases towards the lake bottom. For each layer $\Delta T_i$ is calculated using equation [9] modified to exclude the influence of the turbulent and longwave heat fluxes, which do not affect the subsurface layers, similar to the surface heating at night. Based on the open-water energy profile, convective mixing between layers is modelled, mixing successive layers below the first stable layer until a stable density profile is established. This is done using the convection module of MyLake and includes water quality parameters, when relevant, as well as water density and temperature. An unstable density profile triggers the convective mixing module and it represents wind-induced mixing or spring/autumn turnover, depending on the situation.

3.3.2.3 Diffusive Mixing

Diffusive mixing between layers is estimated based on the surface area between layers and the volume-averaged temperature of the layers at mid-depth. To calculate the diffusive mixing, as represented by the first right-hand term in equation [8], first the layer temperature change between time steps is calculated, governed by the relationship between heat and temperature. Integrating over the time step and between the top and bottom of each layer gives the change in heat content in each constant-volume layer. There is zero diffusion at the air-water surface, but there is diffusion of heat at the interface between each subsequent layer. The diffusion is
estimated by the vertical diffusion coefficient (K) [m² d⁻¹], which is estimated using equation [10] based on the Brunt-Vaisala stability frequency (N²) (Hondzo & Stefan, 1993) and a parametrization of the surface area of the lake (ak) (Fang & Stefan, 1996).

\[ K = a_k \cdot (N^2)^{-0.43} \]  

The diffusion of heat at the water-sediment interface (Qws_norm_i) between the surrounding sediment and each lake layer is calculated based on layer geometry, the heat capacity of water and again includes the vertical heat diffusion coefficient (K) (equation [10]) (Saloranta & Andersen, 2004). Sediment heat flux is first modelled in a layer 10 m thick below the lake bottom, using layers of 0.2 m thickness from 0-2 m below the lake and layers of 0.5 m thickness from 2-10 m below the lake. After this depth into the sediment the temperature from geothermal heat becomes a constant and the heat flux simulation is no longer needed (Saloranta & Andersen, 2004). The temperature at the top of the 10 m sediment layer is set equal to the temperature of the bottom layer of water. Each water layer is in contact with the sediment along the side of the lake, so there are as many sediment layers as water layers (Figure 7). The area of the water-sediment interface is approximated by the difference in horizontal area between the depth of the layer and that above it. The temperature gradient between subsequent sediment layers is approximated using the difference in sediment heat flux between the top two layers only (Saloranta & Andersen, 2004).

Solar energy hitting the bottom of the lake directly from incoming radiation is not considered to heat up the lake bottom in the MyLake code. Instead, the extra energy is added to the water column based on the calculation of absorbed incoming solar radiation, using the ratio of the area of the penultimate layer to the bottom layer (Saloranta & Andersen, 2004). The diffusion rate between pore water and the water column, and the re-suspension rate of dry
particles, are used in the calculation of sediment-water interactions (Saloranta & Andersen, 2007). The heat transfer to and from sediment is more important for small lakes such as the study basins than for large lakes, as the ratio of lake bottom to water volume is more significant (Schertzer & Taylor, 2009).

### 3.3.3 Ice Cover Module

Snow depth accumulation and ice cover formation are calculated by the ice cover module of MyLake, with depths measured in metres of snow water equivalent (WEQs). Unlike the accumulation of snow depth from the input of new precipitation during the winter, ice formation and melt do not change the water balance over an annual time period. The ice cover is formed by phase-change storage of lake water (Beltaos & Prowse, 2009). When the ice cover melts the water is released back into the lake at breakup, resulting in zero net change to the lake volume over the water year.

The MyLake ice cover module is activated when the average daily air temperature above the lake falls below 0°C. During initial freezing, ice crystals form within the supercooled surface water and float to the surface to form a slushy layer. When this layer freezes upon contact with the air, frazil ice is formed (Gebre et al., 2013a). To model frazil ice thickness, MyLake converts the sensible heat deficit in the supercooled surface water into the latent heat of freezing and compares it to the energy available for freezing. MyLake turns frazil ice into solid ice if it crosses the threshold of 0.1 m thickness, after which regular ice formation is modelled (Anderson & Saloranta, 2005). The official freeze-up date is defined as the timing of the first formation of the solid ice cover, not of frazil ice formation (Gebre et al., 2013a).

After frazil ice thickens, solid ice cover grows whenever the temperature at the ice surface is below freezing. The ice layer thickness grows based on Stefan’s law, which states that ice
thickness is proportional to the squared difference of the freezing point of freshwater \((T_f = 0°C)\) and the air temperature above the ice \((T_{ice})\) (Leppärinta, 1983):

\[
H_{i,\text{new}} = \sqrt{(H_i + dH_{si})^2 + \left(\frac{2 \cdot K_{ice}}{\rho_{ice} L_{ice}}\right) \cdot (T_f - T_{ice})}
\]  

[11]

where the density of ice \((\rho_{ice})\) is 910 kg m\(^{-3}\), the thermal conductivity of ice \((K_{ice})\) is 2.1 W m\(^{-1}\) K\(^{-1}\), and the latent heat of freezing \((L_{ice})\) is 333 500 J kg\(^{-1}\). The previous time step’s ice thickness \((H_i)\) and the change in flooded snow frozen as “snow ice” \((dH_{si})\) are added to get the new ice thickness \((H_{i,\text{new}})\). If there is a snow layer, the density of snow causes an insulating effect that warms the ice surface and affects ice cover growth (Prowse et al., 2011). To account for this, MyLake calculates the ice conduction coefficient based on the density of snow (Yen, 1981) and uses this to update the ice surface temperature used in equation [11].

Snow ice thickness \((H_{si})\) can grow when there is existing snow on the ice cover. If the ice and snow layers outweigh the buoyancy of the ice cover, and there are always free water flow pathways through the ice, the lower layers of snow are flooded and snow-ice is created. The change in snow-ice thickness is modelled based on the thickness of existing ice, the ratio of ice to freshwater densities, and the snow water equivalent of the snow layer. MyLake assumes that the new snow-ice is compacted directly to the density of congelation ice and the snow-ice thickness is subtracted from the snow depth and added to the ice thickness (Dibike et al., 2011a). Note that snow ice thickness is not modelled based on incoming precipitation, but on existing snow cover from the previous time step.

Once an ice cover is established, new precipitation falling when the air temperature is below 0°C is modelled as snow instead of rain. The change in snow depth \((d\text{WEQs})\) is calculated by converting the input precipitation in millimeters to snow water equivalent in metres
(WEQs_new) and subtracting any new snow converted directly to ice (dH_{si}). The total accumulated snow depth (H_s) is then updated by adding the change in snow depth to the total snow thickness of the previous time step. In the code, freshwater density remains constant at 1000 kg m$^{-3}$, while snow density varies. MyLake sets the density of new snow at 350 kg m$^{-3}$, and this can increase due to compaction up to a maximum of 450 kg m$^{-3}$. However, in this study the snow compaction switch was turned off so snow density remains at 350 kg m$^{-3}$.

Snowmelt occurs when average daily air temperature rises above 0°C, whether it be during spring breakup after a season of snow and ice growth, or during a mid-winter melt event. When the air temperature rises above freezing, MyLake first models snow melt, followed by ice melt once all the snow is gone. Any energy remaining after all the ice is melted is applied to raise the temperature of the surface water. Snowmelt rates vary depending how much shortwave radiation penetrates into the snowpack. The amount of attenuation of insolation caused by the snow and ice is accounted for using a coefficient ($IceSnowAttCoeff$). In the open-water season $IceSnowAttCoeff = 1$, indicating no light attenuation due to ice and snow, but when there is ice cover $IceSnowAttCoeff$ is calculated based on the PAR light attenuation coefficients for ice ($\lambda_i$) and snow ($\lambda_s$), densities of ice and snow, and the thickness of the ice ($H_i$) and the snowpack in snow water equivalents (WEQs) (equation [12]). The $\lambda_i$ and $\lambda_s$ light attenuation coefficients are based on the albedos of ice and snow, however, instead of dynamically calculating albedo as during the open-water season, MyLake uses constant values of 0.3 for the albedo of ice, and 0.77 for the albedo of snow.

\[
IceSnowAttCoeff = \exp(-\lambda_i \cdot H_i) \cdot \exp(-\lambda_s \cdot \frac{\rho_{fw}}{\rho_{snow}} \cdot WEQs) \tag{12}
\]
Snowmelt, or a negative change in the snowpack (dWEQs), is calculated by multiplying the insolation by the IceSnowAttCoeff and adding longwave radiation, and sensible and latent heat, all divided by the density of water times the latent heat of freezing. There is no accommodation in the code for snowmelt due to added energy from rain-on-snow events, nor is there re-distribution of snow by wind transport within the year.

3.3.4 MyLake’s Estimation of Evaporation

Evaporation is calculated using a version of the energy balance method (Schertzer & Taylor, 2009) by dividing the available latent heat flux at the surface of the lake (after a correction; $H_{L,\text{webb,corrected}}$) by the heat of vaporization required to evaporate freshwater:

$$\text{Evaporation} = \frac{H_{L,\text{webb,corrected}}}{\lambda};$$

[13]

The latent heat flux was extracted from the lake energy balance calculated by MyLake based on local and diffusive heating into and throughout the water column. To calculate the sensible and latent heat fluxes from the meteorological input data (wind speed, air temperature, relative humidity and air pressure) and the depth of the lake, MyLake uses Matlab’s Air-Sea toolbox (USGS, 2013). First, the heat of vaporization ($\lambda$) over the lake is calculated using:

$$\lambda = (2.501 - 0.00237 \times T_s) \times 10^6; \ [\text{J kg}^{-1}]$$

[14]

where $T_s$ is the water surface temperature [°C] and 2.501 MJ kg$^{-1}$ is the energy needed to convert liquid water to vapour at 0°C, modified as the air temperature changes (Oke, 1987).

The latent heat flux ($H_l$) into the lake is then calculated based on the heat of vapourization ($\lambda$), modified by air density ($\rho_{air}$), the wind velocity friction scale ($U_{\text{star}}$), and the humidity scale ($Q_{\text{star}}$):

$$H_l = \rho_{\text{air}} \times \lambda \times U_{\text{star}} \times Q_{\text{star}} \ [\text{W m}^{-2}]$$

[15]

Air density ($\rho_{air}$) is calculated by
\[ \rho_{\text{air}} = \frac{P \times 100}{R \times T_v} \quad [\text{kg m}^{-3}] \]  

where \( P \) is air pressure [kPa], \( R = 287.1 \) [J kg\(^{-1}\) K\(^{-1}\)] is the gas constant for dry air, and \( T_v \) is the air virtual temperature [K], which is the temperature at which a dry parcel of air would have to be to have the same pressure and density as the moist air (Smith, 1988). Virtual temperature is calculated by 
\[ T_v = T \times (1 + o61 \times Q) \],
using air temperature \( T \), specific humidity of air \( Q \) and a moisture correction for temperature \( o61 \), calculated as 
\[ o61 = \text{eps}_\text{air}^{-1} - 1 \],
where \( \text{eps}_\text{air} = 0.62197 \) is the molecular weight ratio of water to air.

The rate of release of latent heat from the lake also depends on windspeed (velocity and gustiness) over the lake; surface winds increase the rate of release of heat from water to the atmosphere (Oke, 1987). \( U_{\text{star}} \) accounts for the effect of wind velocity and friction:
\[ U_{\text{star}} = cdnhf \times S \quad [\text{m/s}] \]  

where \( cdnhf \) and \( S \) are initial neutral scaling coefficients for wind drag on the water surface (Smith, 1988).

\[ S = \sqrt{u^2 + \text{min}_\text{gustiness}^2} \]  

where \( u \) is wind speed, and \( \text{min}_\text{gustiness} \) represents unresolved wind fluctuations and is set to 0.5 m s\(^{-1}\) (Fairall et al., 1996).

\[ cdnhf = \sqrt{cdntc(S, z, Ta)} \]  

using Smith (1988)'s neutral drag coefficient \( (cdntc) \) at reference height \( (z) \), which assumes that, in neutral air stratification, the aerodynamic roughness height of the water surface is proportional to the wind stress that generates short surface waves (Smith, 1988):
\[ cdntc = \left[ K/\ln \left( \frac{z}{z_0} \right) \right]^2 \]
The roughness length of the surface \((z_0)\) is calculated using the friction velocity \((u_*)\), which is wind stress \((\tau)\) divided by the density of the air \((\rho_{air})\), the viscosity of air \((v = 14 \times 10^{-6} \ m \ s^{-1})\), the Charnock coefficient \((\alpha = 0.011)\), and gravity \((g = 9.8 \ m \ s^{-2})\):

\[
z_0 = \alpha \frac{u_*^2}{g} + 0.11 \frac{v}{u_*} \tag{21}
\]

Next, the air-water specific humidity difference modified by wind drag \((Q_{star})\) is calculated using:

\[
Q_{star} = cqnhf \times Dq \tag{22}
\]

where \(cqnhf\) is Smith (1988)'s neutral drag coefficient, described above, and the air-water specific humidity difference \((Dq)\) is calculated by subtracting the saturation specific humidity \((Q_{sat})\) from the modelled specific humidity of the air over the water body \((Q)\), both in \([\text{kg kg}^{-1}]\):

\[
Dq = Q - Q_{sat} \tag{23}
\]

For air, specific humidity \((Q)\) is calculated by

\[
Q = (0.01 \times RH) \times qsat(T_a, P) \tag{24}
\]

where relative humidity \((RH)\) and air temperature \((T_a)\) are input time series data. The saturation specific humidity constant \((qsat)\) is calculated by:

\[
qsat = 0.62197 \left( \frac{e_w}{P-0.378*e_w} \right) \tag{25}
\]

Calculation of the vapour pressure of water \((e_w)\) is based on Buck (1981)'s formula and depends on temperature:

\[
e_w = 6.1121 \times (1.0007 + 3.46e^{-6} \times P) \times \exp \left( \frac{17.502+T_a}{240.97+T_a} \right) \tag{26}
\]

The dependence of the specific humidity of the air \((Q)\) on pressure \((P)\) is small (<0.5%) and therefore \(P\) can be set to a default value, in this case the average daily pressure from 1971 – 1999.
is used, from the Fort McMurray or the Fort Chipewyan RCM ensemble mean input data (956 mb or 988 mb, respectively).

For the saturated water surface, saturation specific humidity \((Q_{sat})\) is also calculated using the saturation specific humidity constant \((q_{sat})\), but using \(T_s\) instead of air temperature in the calculation of the vapour pressure.

\[
Q_{sat} = Q_{sat\_coeff} \times q_{sat}(T_s, P).
\]

where \(T_s\) is water surface temperature, \(P\) is the default mean surface pressure, and \(Q_{sat\_coeff}\) can be used to reduce the saturation specific humidity, since vapour pressure over saline water would be 2% less than over freshwater (USGS, 2013). In this study, only fresh surface water is considered, therefore \(Q_{sat\_coeff} = 1\).

Webb et al. (1980) proposed a correction to the calculation of latent heat flux to account for the slightly higher velocity of ascending versus descending parcels of air. This “Webb effect” is corrected by adding a small mean vertical velocity to the latent heat \((H_l)\) to keep the net dry mass flux equal to zero (Fairall et al., 1996). The Webb correction \((H_{l webb})\) is calculated by:

\[
H_{l webb} = \rho_{air} \times Le \times W \times Q; \quad \text{(Fairall et al., 1996: Eq'n 22, p. 3751)}
\]

where \(Q\) is the specific humidity of air [kg kg\(^{-1}\)] as described above, and

\[
W = 1.61 \times U_{star} \times Q_{star} + (1 + 1.61 \times Q) \times U_{star} \times T_{star}/T,
\]

using the velocity friction and humidity scales \(U_{star}\) and \(Q_{star}\) described above, as well as the temperature scale \(T_{star}\).

\[
T_{star} = ctnhf \times Dt
\]

where \(ctnhf\) is again Smith (1988)’s neutral drag coefficient, and \(Dt\) is the adiabatic temperature difference based on height change, \(Dt = (Ta + 0.0098 \times z_t) - T_s\) (Smith, 1988). The Webb
correction is added to the latent heat flux, resulting in a corrected latent heat flux for the lake (Fairall et al., 1996):

\[ H_{l,\text{webb, corrected}} = H_l + H_{l,\text{webb}} \quad [31] \]

Finally, evaporation is calculated by dividing the available heat flux in the lake by the heat of vaporization required to evaporate freshwater, as shown in equation [13]. The resulting units of kg s\(^{-1}\) m\(^{-2}\) can be converted to an evaporation rate in standard mm d\(^{-1}\) units using the density of water \((10^3 \text{ km m}^{-3})\) to replace 1 kg m\(^{-2}\) of water with a 1 mm-deep layer of water.

### 3.4 Validation (Other Evaporation Estimates)

Successful modelling has three main steps: creating the model based on data availability, estimating the model parameters, and validating model performance (Arnell, 2004). Precipitation from the RCM_GCM ensemble used in this study (after bias correction using NARR) has been previously validated by various modelling groups in the NARRCAP project. Evaporation to complete the water balance in this study, however, is modelled offline using the MyLake model, and requires validation.

The first two steps in the process of modelling evaporation using MyLake were accomplished in previous work; Saloranta & Andersen (2004) developed the MyLake model, and model parameters used here are based on work by Saloranta & Andersen (2004) and tailored to a northern Canadian lake, Baker Lake, by Dibike et al. (2011a). The third step is accomplished by validating the evaporation values modelled using MyLake for the specific study basins and sites in two ways: 1) by comparing the MyLake results using the NARCCAP input data, to MyLake results using the NARR reanalysis data, and 2) by comparing evaporation results from the MyLake model to those calculated by other common evaporation techniques using the same bias-corrected NARCCAP input data. To this end, MyLake is run using the same parameters and
climate variables but different input datasets and the results are compared on a monthly and annual basis.

The following section describes the methods used to calculate evaporation using four other commonly used methods for over-lake evaporation. The methods chosen represent three of the five different types of evaporation estimation (Section 2.2.4.1); the Bowen Ratio is an energy balance estimate, Penman and Priestley-Taylor are “combination” estimates, and Hamon is a degree-day estimate based on temperature and day-length (Schertzer & Taylor, 2009; Valiantzas, 2006; Werner, 2007). Actual results of a comparison between methods can be found in Section 4.4.2. The water budget method was not used since it requires all other components of the water balance to be known, to solve for evaporation, but in this study evaporation is calculated in advance to solve for the change in storage later. The mass transfer method also was not used, since either on-site calibration or calculation using the water budget or energy budget would be required to determine the mass transfer coefficient specific to the study lakes (Winter, 1981).

Bias corrected daily climate data from the NARCCAP RCMs for 1971 – 1999 are used as input data to calculate evaporation over open water at the Fort McMurray, AB study site. Along with air temperature, pressure, relative humidity and wind speed (also used in MyLake), net radiation from the RCMs and day length based on the latitude of Fort McMurray are required for evaporation calculation using the other three methods. For the Bowen ratio, surface water temperature is also required; since no other surface water data are available for the study sites, MyLake results from the intermediate-depth lake at Fort McMurray are used. The MyLake model includes the dynamic calculation of heat storage at depth, and while some of the other formulas include a term for heat storage, this was excluded due to a lack of available data.
The Hamon approach \((E_H)\) is the simplest method as it uses only air temperature and day length, making it easy to use in situations of limited data availability (Feng et al., 1989). \(E_H\) calculates evaporation by the formula:

\[
E_H = 2.98 \times L \times \frac{e_s(T)}{T+273.2} \quad \text{[mm d}^{-1}\text{]} \tag{32}
\]

where \(L\) is the day length (hours) and \(e_s(T)\) is the saturation vapour pressure (kPa) at air temperature \(T\) (°C). Day length is calculated based on the latitude of the Fort McMurray study site, for all days in the 1971 – 1999 data analysis period (NOAA, 2013). The saturation vapour pressure \((e_s)\) at mean daily temperature \((T\) in °C\) is calculated by:

\[
e_s(T) = 0.611 \times e^{\left(\frac{17.27 - T}{T+237.2}\right)} \quad \text{[kPa]} \tag{33}
\]

The Penman \((E_P)\) and Priestley-Taylor \((E_{PT})\) energy budget approaches are part of the “combination group.” They require more data, but can still be calculated from data available from standard meteorological stations (Werner, 2007). These two approaches, along with others in the combination group, require an estimate of net available energy as well as an estimate of the aerodynamics over the surface (Schertzer & Taylor, 2009). The Penman equation is:

\[
E_P = \frac{s}{s + \gamma} \frac{R_n}{\lambda} + \frac{\gamma}{s + \gamma} \frac{6.43 + f_u D}{\lambda} \quad \text{[mm d}^{-1}\text{]} \tag{34}
\]

where \(s\) is the slope of the saturation vapour pressure at temperature \(T\) (kPa °C\(^{-1}\)); \(\gamma\) is the psychrometric coefficient (kPa °C\(^{-1}\)); \(R_n\) is the net radiation at the earth’s surface (the difference between net shortwave and net longwave radiation in MJ m\(^{-2}\) d\(^{-1}\)); \(\lambda\) is the latent heat of vaporization (MJ kg\(^{-1}\)) that depends on \(T\) (°C); \(f_u\) is the wind function (m s\(^{-1}\)); and \(D\) is the vapour pressure deficit (kPa).

The Priestley-Taylor \((E_{PT})\) approach (equation [35]) uses a similar equation to Penman, but does not include the wind function (Fernandes et al., 2007):
\[ E_{PT} = \nu \left( \frac{s}{s + \gamma} \right) \cdot \frac{R_n}{\lambda} \text{ (mm d}^{-1}) \]  

[35]

The coefficient \( \nu = 1.74 \) (dimensionless), represents the potential evaporation for arid locations (Shuttleworth, 1993). Rather than using air temperature, the Priestley-Taylor approach includes an estimate of net surface radiation, which are generally considered to vary together but may not always match (Fernandes et al., 2007).

The following formulas suggested by Shuttleworth (1993) are used to calculate the Penman, Priestley-Taylor, and Bowen Ratio methods. The slope of the saturation vapour pressure \( (s) \) is calculated by:

\[ s = \frac{4098 \cdot e_s}{(T+237.3)^2} \text{ [kPa °C]}; \]  

[36]

using the saturation vapour pressure \( (e_s) \) described above; the vapour pressure deficit \( (D) \) is the difference between the actual vapour pressure \( (e_a) \) and the saturation vapour pressure \( (e_s) \) at air temperature \( (T) \), and can be estimated by:

\[ e_a = e_s(T_a) \cdot \frac{RH}{100} \text{ [kPa]} \]  

[37]

\[ D = e_s - e_a \text{ [kPa]} \]  

[38]

where RH is relative humidity (%) (Lenters et al., 2005); the latent heat of vapourization \( (\lambda) \) is calculated using equation [14], and the psychrometric coefficient \( (\gamma) \) is

\[ \gamma = 0.0016286 \cdot \frac{P}{\lambda} \text{ [kPa °C}^{-1}] \]  

[39]

where P is the atmospheric pressure (kPa) at the study site.

Unique to the Penman estimate is the inclusion of wind function \( (f_u) \),

\[ f_u = a + b \cdot u \text{ [m s}^{-1}] \]  

[40]

where \( u \) is windspeed (m/s) measured at 2 m above the surface and \( a=1 \) and \( b=0.536 \) are coefficients originally derived by Penman (1948). These coefficients were later refined by
Penman (1956) and others (see Valiantzas, 2006) to \( a=0.5 \) since evaporation was being over-estimated over large lakes where aerodynamic resistance is larger, reducing evaporation (Werner, 2007), but a study by Shuttleworth (1993) confirmed that for small, shallow lakes the original coefficients are the most accurate (Valiantzas, 2006).

The Bowen Ratio-energy balance method \( (E_B) \), is another commonly used method to estimate evaporation (Schertzer & Taylor, 2009). The Bowen Ratio \( (\beta) \) is the ratio of sensible heat to latent heat, which can be calculated using a proportional ratio of change in temperature to change in pressure (Oke, 1987) as shown in equation [3]. In this case, the Bowen Ratio is calculated using the equation recommended by Schertzer & Taylor (2009):

\[
\beta = c_B * P * \frac{(T_s-T_a)}{(e_s-e_a)} \text{ [unitless]} \tag{41}
\]

where \( c_B \) is an empirical constant equal to 0.61 °C\(^{-1}\) (Bowen, 1926; Schertzer & Taylor, 2009). Here pressure \( (P) \) is in kPa, but the saturation vapour pressure at the water surface temperature \( (e_s) \) and atmospheric vapour pressure \( (e_a) \) are in Pa (Schertzer & Taylor, 2009).

Evaporation using the Bowen Ratio-energy balance method is then calculated as:

\[
E_B = \frac{R_n}{\rho * (\lambda + (1+\beta)+c* T_s)} \text{ [m s\(^{-1}\)]} \tag{42}
\]

\( \rho \) is the density of water [kg m\(^{-3}\)], \( \lambda \) is the latent heat of vapourization [MJ kg\(^{-1}\)], \( \beta \) is the Bowen ratio, \( c=4186 \) [J kg\(^{-1}\) °C\(^{-1}\)] is the specific heat capacity of water, \( T_s \) is the surface water temperature [°C], and \( R_n \) is the net radiation [W/m\(^2\)] (Schertzer & Taylor, 2009). MyLake results from the intermediate-depth lake at Fort McMurray are used for \( T_s \). \( E_B \) should be multiplied by 8.64 x 10\(^7\) to convert evaporation into mm/dy. For results of the calculations using each method, see Section 4.4.2.3.1 in Chapter 4.
3.5 Evaluating Average and Cumulative Water Balance

To analyze changes in the future water balance, current patterns in both evaporation and precipitation variables are first assessed. Results of evaporation modelling are analyzed for intra-annual patterns and sensitivity to basin depth and climate inputs (Fort McMurray versus Fort Chipewyan). Once combined with precipitation to calculate the water balance, annual, seasonal and monthly patterns are evaluated and compared between study sites and datasets. Future water balance, calculated in the same way, is then compared to the current water balance, with differences in evaporation, precipitation, and change in water level explored through annual and monthly sums and averages. Lastly, the cumulative daily water balance is calculated over both periods, to assess differences in lake storage over 30 years under current climate compared to 30 years under projected future climate.

3.6 Evaluating Extreme Events

This research uses three methods to evaluate changes in extreme climate events impacting the water balance of the study basins: 1) the calculation of the Peaks-Over-Threshold (POT) index of extreme events; 2) estimation of the generalized extreme value (GEV) distributions of both high and low extremes; and 3) a comparison of the magnitudes of the Annual Maxima (AM) and Annual Minima (AMin) and overall Maximum and Minimum of extreme events, for each study site in the current and future periods. The magnitudes of the analyst-defined low and high thresholds, beyond which climate events are considered “extremes”, are also compared, to characterize differences between the water balances modelled using different datasets. For all three methods the focus is on the extremes of the “change in water level” variable, representing changes in the amount of water stored in the shallow, intermediate-depth and deep lakes at Fort McMurray and Fort Chipewyan in the current and future periods. Some of the methods are also
applied to the evaporation and precipitation variables of the water balance to explain the variations in the “changes in water level” variable.

Extreme events of large magnitudes are more frequently caused by small-scale local meteorological events rather than larger regional mesoscale events (Christensen et al., 2007; Oouchi et al., 2006). As described in section 3.2.4, to better capture local extremes the water balance is modelled using data extracted from individual gridpoints from the 10 km² resolution downscaled BCCI and BCSD datasets (Chapter 5), rather than using the spatially-averaged water balance (Chapter 4). An individual gridpoint is selected from the BCCI and BCSD results to represent the local area with the most extreme precipitation, based on the highest average daily (and total) precipitation over 30 years (Max Precip), and a second individual gridpoint is selected to represent the local area with the most extreme evaporation with the highest average daily (and total) temperature over 30 years (Max Temp). The selection is made using climate variables from the current period, and the same gridpoints are used for the future period.

The MyLake model is run for each of the selected 10 km² gridpoints using the 12 different scenario combinations – for the two study sites (Fort McMurray and Fort Chipewyan), the three lake depths (shallow, intermediate and deep), and the two time periods (current and future). The results are analyzed for each model separately, rather than using the ensemble mean used in Chapter 4, although averaging among the three models is done at the last step for simplicity in reporting. To compare local extremes to averaged regional scale results, the same methods are applied to the ensemble mean of the spatially averaged datasets (Bias Corrected, BCCI and BCSD). As all data are from the NARCCAP subset of RCM_GCM climate models, the values are comparable across downscaling types.
3.7 Defining Extremes

The values of the 90th and 10th percentiles of the full distributions of current 1-, 3- and 5-day climate events are used as the high and low thresholds beyond which events are considered “high extremes” or “low extremes”, respectively. The multi-day time series are calculated as the cumulative sum of the daily data within 3- and 5-day moving windows, resulting in 363 and 361 events per year, respectively. The percentiles are calculated from the current period data for each model and dataset separately and applied to the corresponding future datasets.

The 90th and 10th percentiles are chosen as they provide a robust way to capture all extremes of interest. Using smaller sections of the distribution (like the 95th or 99th percentile) leaves room for error in not capturing slightly less extreme events that still impact the ecosystems and human populations where they occur. The advantage of using percentiles rather than absolute value thresholds is that they can be tailored to each study site (Bonsal et al., 2001). This makes the set of climate events with magnitudes exceeding the thresholds representative of events considered extreme for that particular climate and allows for robust comparisons between datasets and study sites. These thresholds were also chosen because the 90th and 10th percentiles are used as the threshold in many studies of extremes, and comparability between studies is important (e.g., Frich et al., 2002; Klein Tank & Zwiers, 2009; Rogers & Armbruster, 1990; Zhang et al., 2011, 2000).

3.7.1 Peaks-Over-Threshold (POT) Index

The Peaks-Over-Threshold (POT) index is a count of climate events whose magnitudes cross an analyst-defined threshold in a relevant time period (Katz et al., 2002). Here the POT is calculated as the number of 1-, 3- and 5-day events per year with magnitudes that exceed the 90th percentile, or are below the 10th percentile for the corresponding distribution. The thresholds are calculated using all days in the 30-year current period and applied to each year in both the
current and future periods. For the current period, the number of 1-day exceedances of the 90th percentile threshold is by definition 1095 out of the 10950-day, 30-year record. The annual count varies year to year and can be plotted to examine changes in the occurrence of extremes over both the current and future periods. The POT count calculated for the future period will vary from the current counts, showing differences in the frequency of extreme events in the mid-21st century (2041 – 2070) compared to the late 20th century (1971 – 2000).

3.7.2 Extreme Value Distributions

To describe events of extreme magnitudes and frequencies that are not seen in the historical data series, the statistical probability distributions are modelled for each water balance scenario in the current and future period (Wagner, 1996). First, the values of the Peaks-Over-Threshold (POT), or the exceedances of the 90th and 10th percentiles, are extracted to create the “partial duration series”, of the distribution (Katz et al., 2002). Then the generalized extreme value (GEV) distribution is fitted, using goodness-of-fit criteria on the data to choose which of three distributions are appropriate in each case – Type I (Gumbel), Type II (Frechet) or Type III (Weibull) (Mathworks Inc., 2015). Next, the cumulative distribution function (CDF) is evaluated from the GEV distribution to model all possible values of the largest or smallest extreme values of the climate variable. The Maximum Likelihood (ML) method is used to estimate the values of the location ($\mu$), scale ($\sigma$) and shape ($k$) parameters for the distributions and the fit of the distribution evaluated (Katz et al., 2002). Once these distributions are created they can be used to compute summary statistics and to describe differences between the values in various datasets (Alexander et al., 2006).

3.8 Conclusions

Water balances for the shallow, intermediate, and deep study basins in the current and future periods can be calculated using two variables: precipitation from bias-corrected climate
data dynamically downscaled using RCMs from the NARCCAP ensemble, and evaporation modelled offline by the MyLake comprehensive lake model using input data from the same RCMs. MyLake allows estimation of evaporation through the calculation of latent heat at the surface of the water, depending on the water temperature profile, sediment-water diffusion, and ice cover dynamics. The use of this model ensures dynamic estimation of ice-on and ice-off dates, which translate to the boundaries of the evaporation season, and inclusion of heat storage at depth, two factors important to accurate water balance modelling. The water balances calculated for the average regional climate, and the extreme precipitation and extreme temperature local gridpoints, can be compared monthly, seasonally and annually to determine differences in the basins based on climate, lake depth, and future climate change and variability. Changes in extreme 1-, 3- and 5-day climate events for the same set of basins and scenarios can be evaluated using the Annual Maxima and Minima, the number of Peaks-Over-Threshold, and the probability distributions for the relevant variables. The following two chapters are stand-alone articles that present the results of the methods here-described and therefore some of the background information and methodology included in Chapters 2 and 3 is re-iterated. Chapter 4 presents the results of the current and future water balances on a regional scale, while Chapter 5 describes expected changes in extreme climate events at a smaller local resolution. Overall conclusions and a description of future work are provided in Chapter 6.
3.9 References


(AMAP).


CHAPTER 4: EFFECTS OF PROJECTED CHANGES IN REGIONAL PRECIPITATION AND EVAPORATION ON LAKE WATER BALANCES IN THE ATHABASCA REGION, ALBERTA, CANADA

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ABSTRACT

Climate change is causing an intensification of the hydrologic cycle. Warmer air temperatures projected for the mid-21st century are expected to translate to increased evaporation around the world, including in the mid-latitude, interior continental climate of the lower Athabasca River region in northern Alberta, Canada. Mean and extreme precipitation are also expected to increase in the future in this area. This study examines how these projected changes in evaporation and precipitation patterns will affect the annual and seasonal water balance of various lake sizes. A thermodynamic lake model, MyLake, is used to determine evaporation over three theoretical lake basins – a shallow lake at Fort Chipewyan, representative of perched basins in the Peace-Athabasca Delta; an intermediate-depth lake at Fort McMurray representative of industrial water storage; and a deep lake also at Fort McMurray, representative of future off-stream storage of water by industry. Bias-corrected climate data from an ensemble of Regional Climate Models are incorporated in MyLake, and the water balance is completed by calculating the change in storage as the difference between precipitation and evaporation. Results indicate that although evaporation is projected to increase in the future, precipitation is likely to increase by a similar magnitude, thus not significantly changing the long-term, annual and cumulative water balance of the lakes. However, inter-annual variability will continue and may increase, and seasonal cycles of water levels are expected to shift within the year. These results demonstrate that non-stationarity of climate requires future planning and climate change adaptation and mitigation measures to take into account higher intra-annual variability on water levels of lakes in mid-latitude, interior hydroclimatic regimes.

KEYWORDS
Water balance; Lakes; Athabasca River; Regional Climate Model; Climate Change; Precipitation; Evaporation

4.1 Background

Lakes are an integral part of the landscape in Northern Alberta, Canada. In the Athabasca River region near the confluence of the Athabasca and Peace Rivers, water is abundant and glacial depressions have filled to create a vast array of natural lakes (Mitchell, 1991). The Peace-
Athabasca Delta (PAD), one of the largest inland freshwater deltas in the world, is located at this confluence. The 6000 km$^2$ wetland area of the PAD includes three large, shallow lakes and thousands of small, shallow, perched basins less than 1.5 m deep that are hydrologically isolated from the surrounding water flow (Peters et al., 2006a). Lake Athabasca, located at the outlet of the PAD, is a very large lake that drains north along with the rest of the Mackenzie River watershed to the Arctic Ocean (Prowse et al., 2011).

Human activity in the Athabasca River region has also caused additional lakes to be planned and built. These proposed anthropogenic lakes will serve a variety of purposes, including industrial and municipal clean water storage, reservoirs for hydropower, and landscape reclamation. Water requirements for industry in the Athabasca River region do not vary much over a year, whereas the volume of river flow varies seasonally (Westcott, 2007). To protect the aquatic ecosystem of the river during low-flow periods, regulations have been developed that require certain water license holders to offset their withdrawals from the river with stored water at certain times of the year (Government of Alberta, 2015; Westcott, 2007). To buffer the existing and climate change-induced seasonality of flow in the Athabasca River (see Casassa et al., 2009; Stewart, 2009) while also allowing industries to operate all year without water shortages, new reservoirs will be built to store clean, freshwater offstream (Ohlson et al., 2010). Anthropogenic surface water storage is also likely to increase due to construction of deep reservoirs for hydropower. Development of hydropower is expected in northern Alberta in the future, especially as a tool to balance increased use of intermittent power generation technologies such as wind and solar (Gebre, 2014; Kumar et al., 2011).

New lakes are also proposed to be built in the region as an integral part of landscape management and reclamation strategies for industry (Golder, 2006b; Westcott, 2007). End Pit
Lakes (EPLs) are artificial lakes used to store and promote the degradation of toxic residual organic compounds (Golder, 2011). Located in Oil Sands post-mining pits, the bottom substrate of EPLs will be covered by a layer of process-affected materials, and the lake will then be capped by clean water. The lakes are designed to have no annual mixing cycle, therefore sequestering contaminated materials below the freshwater cap (Westcott & Watson, 2007). As of 2007, 27 new EPLs have been planned to be built in the Athabasca River region, including Base Mine Lake, the first large-scale EPL (Westcott & Watson, 2007). Constructed wetlands could also play a role in reclamation strategies to restore the landscape to an equivalent land capability as before industrial development (Bacon, 2006).

Climate has an impact on lakes through the temperature, precipitation and aerodynamic regimes of the regions in which they are located (Lins et al., 1990; Oke, 1987). In turn, lakes affect local and regional climates through the exchange of moisture and energy between their surface and the atmosphere (Swayne et al., 2005). Climate effects the thermal structure of lakes in particular, altering moisture and energy fluxes from lake surfaces (Dibike et al., 2011a). There is high confidence that future climate change is causing the warming of lakes and rivers (IPCC, 2007). Changes in water temperature patterns are likely to alter rates of open-water evaporation (Mitchell, 1991). The increase in average annual evaporation is projected to be around 0.1 – 0.2 mm/dy in Northern Alberta, as reported by the IPCC (2007) from an ensemble of Global Climate Models (GCMs) run for 2080 – 2099 with the A1B scenario, compared to 1980 – 1999 (Meehl et al., 2007). In conjunction with this increase in evaporation, climate change is also expected to cause an increase in average and extreme precipitation, especially in continental regions (Mailhot et al., 2012). The same ensemble of GCMs projects a precipitation increase of around 0.1 – 0.2 mm/dy in Northern Alberta, the same magnitude as for evaporation (Meehl et al., 2007).
Calculating the water balance is one way to quantify the water in all hydrologic phases within a defined catchment (Deitch et al., 2009). The difference between precipitation inputs and evaporation outputs from a lake forms the basic water balance, especially for lakes hydrologically isolated from inflow, outflow, and groundwater, as is the case with many perched lakes in the PAD (Mitchell, 1991b; Peters et al., 2006b) and the proposed anthropogenic lakes in the Athabasca River region. The water balance can be used to quantify changes in the water level and flooding and drying cycles of a lake. As development of anthropogenic surface water storage continues in the Athabasca River region, especially due to the expansion of industry (Canadian Association of Petroleum Producers, 2013), the effects of future changes in climate on lake water levels require consideration. Among the many lake modelling studies done in the region by Golder Associates Ltd. (2004, 2006a, 2011) and for the Cumulative Environmental Management Association (CEMA, 2012; Westcott & Watson, 2007), few include climate change effects except as recommendations for future work (Golder, 2006a; Westcott, 2007), or by using simple percentages to estimate future scenarios from current data (Golder, 2006b). Comprehensive water balance studies using climate change projections particular to this region are required for responsible development under future climate conditions.

Despite some recent efforts to couple lake models to Global and Regional Climate Models (GCMs and RCMs) (e.g., Alapaty et al., 2014; Rockel, 2015), most available climate model results are not applicable to local and regional surfaces with an array of surface water bodies more than a few metres deep (Meehl et al., 2007). This is important because, together with insolation, heat stored in a lake provides the latent heat energy required for open-water evaporation, and controls the seasonal cycles of evaporative losses (Lins et al., 1990). Evaporation from shallow lakes is governed by insolation entering the lake, whereas over deeper
lakes the dominant control on evaporation is the storage of heat within the water volume (Henderson-Sellers, 2006; Lins et al., 1990; Swayne et al., 2005). Larger volumes of water take more time to heat and cool, causing a lag in surface water temperature in comparison to seasonal patterns of insolation and air temperature. Since open-water evaporation is largely driven by the vapour pressure gradient between the lake surface and that of the air above (Oke, 1987), heat storage causes different patterns of evaporation over different depths of lakes at the same location. Due to the large amount of surface water in the Athabasca River region, climate change modelling without the inclusion of heat storage by water bodies will result in inaccurate estimations of evaporation, wind forcing, and energy fluxes (Swayne et al., 2005). This study addresses heat storage by modelling evaporation using an offline specialized lake model, MyLake. MyLake takes into account lake depth, volume, latitude, and climate to model the thermal structure of lakes (including heat storage), from which ice cover duration and open-water evaporation can be calculated (Saloranta & Andersen, 2004; see section 4.3.5).

The objective of this study is to determine how lake levels will be affected by projected changes in climate in the Athabasca River region of northern Alberta, Canada. This is done by comparing the competing roles of precipitation and evaporation in the water balances of three depths of hypothetical study lakes located both at Fort Chipewyan, AB and at Fort McMurray, AB, in the current (1971 – 2000) and future (2041 – 2070) periods. An ensemble of RCM_GCMs is used to project future precipitation and provide input data to model evaporation using MyLake. Understanding the changes in the water balance caused by climate change will inform future municipal, environmental, and industrial plans, allowing them to proceed based on expected future conditions surrounding the abundant surface water storage in the Athabasca River region of northern Alberta, Canada.
4.2 Study Site

The Athabasca River watershed is located in the interior plains of northern Alberta, Canada, a dry, mid-latitude sub-humid climate in the major cold-region portion of North America (AB Environment, 2013; Carey, 2009; Dibike et al., 2011a). The study region (the “Athabasca River region”) is in the downstream, northern portion of the watershed (see Figures 1 and 2 in Chapter 2). The area is located in the lee of the Canadian cordillera, south of the discontinuous permafrost zone of the Canadian subarctic (Peters et al., 2006a) and north of the Palliser Triangle, the driest part of the Canadian Prairies (Dale-Burnett, 2012). Within the region there are two major population centres: the city of Fort McMurray, AB (56.72°N, 111.37°W) and the town of Fort Chipewyan, AB (58.77°N, 111.13°W), the latter located 200 km north on the edge of the PAD.

The climate of the Athabasca River region includes high natural hydro-climatic variability, with long cold winters, short cool summers and highly variable precipitation that peaks in July (Environment Canada, 2013) and, like much of the Canadian Prairies, is largely delivered by high-intensity, short-duration convective storms (Raddatz & Hanesiak, 2008). This highly variable, drought-prone climate makes the region especially sensitive to any changes in precipitation and temperature regimes expected with climate change.

The study sites around Fort McMurray and Fort Chipewyan have similar yet distinct climatic regimes. Environment Canada’s climate normal for the 1971 – 2000 period recorded average annual air temperature of 0.7 °C at the Fort McMurray A climate station (ID #3062693), with the average at the Fort Chipewyan A station (ID #3072658) somewhat cooler at -1.9 °C (Environment Canada, 2013). In the winter months of October to April, Fort McMurray’s 6-month average daily air temperature was higher than Fort Chipewyan’s by up to 5 °C, while
summer air temperatures in May to September are within 1 degree at the two study sites (Figure 8). Annual precipitation in the same period was 391.7 mm/yr at Fort Chipewyan and 455.5 mm/yr at Fort McMurray. Precipitation at both sites is lower in the winter and higher in the summer months (Figure 8). This pattern of peak precipitation in the summer is expected in an interior plains mid-latitude climate. The dominance of summer rainfall is partially due to the stabilizing effect of cold air temperatures on air masses during the winter months, and the reduction in convective storms in the winter when the local moisture supplies are ice covered (Prowse, 1990). Note that the extreme maximum and minimum average daily precipitation rates are at Fort Chipewyan, and there is a greater standard deviation of daily temperature at Fort Chipewyan as well, indicating higher climatic variability at the more northern site (Environment Canada, 2013).

![Figure 8: A) Average monthly air temperature (°C/dy) and B) total monthly precipitation (mm/month), from Environment Canada climate stations Fort McMurray A (Station #3062693) and Fort Chipewyan A (Station #3072658), averaged over the 1971 – 2000 climate normal period (Environment Canada, 2013).](image)

4.2.1 Study Basins

The three study sites consist of theoretical 1st-order lake basins with dimensions based on average sizes of naturally occurring or anthropogenic (existing or proposed) lakes in the region.
The shallowest basin is representative of a 1.5 m deep perched basin in the PAD, near Fort Chipewyan. The intermediate-depth basin is representative of EPLs located near Fort McMurray, which are expected to become permanent fixtures in the post-industrial landscape (Golder, 2011; Westcott & Watson, 2007). Modelling studies by Golder Associates Ltd. (2006) have determined that the ideal EPL should be at least 50 m deep with a small surface area around 1 to 4 km\(^2\) to remain stratified, keeping contaminated materials from mixing with the clean freshwater cap. The deep basin is representative of off-stream storage of freshwater for use by industry or for hydropower. The deep basin depth and size is chosen to be similar to, but deeper than, the intermediate-depth EPLs near Fort McMurray, and similar to existing hydropower reservoirs around the world (e.g., Gebre et al., 2013). See section 4.3.5 for the geometry used for the model simulations.

<table>
<thead>
<tr>
<th>Study Basin</th>
<th>Depth</th>
<th>Surface Area</th>
<th>Represents</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shallow</td>
<td>1.5 m</td>
<td>20 km(^2)</td>
<td>PAD perched basins</td>
<td>Fort Chipewyan, AB</td>
</tr>
<tr>
<td>Intermediate</td>
<td>28.5 m</td>
<td>1 km(^2)</td>
<td>End Pit Lakes</td>
<td>Fort McMurray, AB</td>
</tr>
<tr>
<td>Deep</td>
<td>76.5 m</td>
<td>30 km(^2)</td>
<td>Off-stream industrial storage</td>
<td>Fort McMurray, AB</td>
</tr>
</tbody>
</table>

Table 4: The theoretical study basin sizes, based on similar existing or proposed lakes in the Athabasca River region.

4.3 Data and Methods

4.3.1 Water Balance

The water balance is calculated using the equation:

\[
P - E = \Delta WL, \tag{43}\]

where precipitation (P) minus evaporation (E) equals the change in water level (\(\Delta WL\)). The change in water level is a proxy for changes in water storage in the basin, or water held on the landscape for longer than the temporal scale of the model. This method takes into account precipitation added to the lake on a daily basis all year, rather than considering winter
precipitation stored in the snowpack to be added to the volume of lake storage only during
snowmelt. Over the winter the weight of the snowpack depresses the ice cover, changing the
water level of the lake proportionally to the snow load to ice thickness ratio (Prowse et al., 2011).

Stream inflow and outflow are excluded from the equation since the study basins are of 1st-
order and therefore have negligible inputs and outputs from overland runoff and streams
(Nielsen, 1972). Groundwater is also excluded; the basins are all isolated from subsurface flow,
either due to an aquitard in the geology or an anthropogenic aquitard designed to keep the lake
from interacting with the soil and groundwater. The mesoscale of the study also allows the
exclusion of temporally and spatially small processes such as soil moisture fluxes and
sublimation and condensation (Kane & Yang, 2004; Zhang et al., 2008).

4.3.2 Data

The climate variables required to model the water balance are cloud cover (fraction),
relative humidity (%), surface pressure (hPa), wind speed (m/s), surface air temperature (°C) and
precipitation (mm/dy). Precipitation is used directly in the water balance, while the other
variables are used by the MyLake model to calculate evaporation over open water (see section
4.3.5). Daily values for the “current period” from January 1, 1971 to December 31, 2000 and the
“future period” from January 1, 2041 to December 31, 2070, representing climate around the
Fort McMurray and Fort Chipewyan study sites, are used to run MyLake.

These variables are extracted from a subset of Regional Climate Models nested within
Global Climate Models (RCM_GCMs) provided by the North American Regional Climate
Change Assessment Program (NARCCAP) (see Section 2.3.7). The NARCCAP RCM_GCMs
have a 50 km² resolution with observations every three hours (UCAR, 2007); here the data are
averaged to daily values for use in MyLake. All NARCCAP RCM_GCMs use the A2 emissions
scenario, with boundary conditions for each RCM provided by a variety of GCMs to characterize the uncertainties resulting from the model combinations (Mearns et al., 2012). The A2 emissions scenario for the 21st century was one of the Intergovernmental Panel on Climate Change (IPCC)’s “marker” scenarios (Mearns et al., 2009; UCAR, 2007). The A2 scenario family is characterized by a high rate of human population growth, high greenhouse gas emissions, and slow adaptation to new technologies and mitigation strategies, relative to other SRES scenarios (Nakicenovic & Swart, 2000). The A2 scenario is one of the most pessimistic with regards to emissions, as it assumes little technological innovation or change in late-20th century high rates of GHG emissions. This scenario is used in a wide variety of studies, which also makes it appropriate for use in this study as comparability between scientific research is desired.

A subset of three NARCCAP RCM_GCMs is used to model the water balance: CRCM_CGCM3, CRCM_CCSM, and MM5I_CCSM (see Table 1). These three models were chosen based on data availability in the current and future time periods; at the time of data acquisition other models in the NARCCAP ensemble were missing key data (see Section 3.2.2). Data for the six climate variables were extracted from nine grid cells closest to the Fort Chipewyan and Fort McMurray EC climate stations and temporally and spatially averaged to produce one dataset at the daily scale covering a 22,500 km² area around each study site. This regional extent is chosen to represent the scale of synoptic climate and to smooth out the influence of any extremely local weather events.

Values are missing from the CRCM_CCSM model for November 30 to December 31, 1999, November 30 to December 31, 2069, and September 29, 2045 to December 31, 2046. For these days, all climate variables from a year prior (1998, 2068, and 2043-2044, respectively) are inserted to fill in the gaps. Two of the variables needed further transformation; wind speed is
calculated as the hypotenuse of vertical and horizontal u and v wind variables, and relative humidity is determined from the available specific humidity output (using pressure, air temperature and partial pressure of water vapour) (Nievinski, 2009). Shortwave and longwave radiation are extracted for the same gridpoints from the three RCM_GCMs and averaged in the same way, for validation of results by other common formulas (see Section 4.3.6).

To correct for bias in the RCM_GCM pairs, reanalysis data are used. The North American Regional Reanalysis (NARR) dataset is commonly used as a reference climate as it assimilates high quality observations into the NCEP (National Centres for Environmental Prediction) Eta model, resulting in a long-term, high resolution climatic dataset covering North America. The same six climate variables were extracted from the NARR dataset with 3-hourly time steps spanning 1979 – 2000 and a spatial resolution of 32 km$^2$ (Mesinger et al., 2006). As the NARR dataset has a slightly finer spatial resolution than the RCM_GCMs, the data are extracted from twelve NARR gridpoints closest to the Fort McMurray and Fort Chipewyan study sites. These NARR values were then averaged to create daily datasets covering 12,288 km$^2$ centered on the two study basin locations.

### 4.3.3 Bias Correction

Climate model outputs cannot be used directly to obtain realistic outputs from secondary models without some prior bias correction (Piani et al., 2010). Since changes in the variability of climate variables are being examined in this study, the often used “delta method” of bias correction, in which modelled changes between current and future climate are applied to the observed climate, is not appropriate as the distribution would remain the same with only the mean changing (Lenderink et al., 2007). Instead, absolute future climate simulations are used after an interpolated average monthly bias correction factor is applied. The bias correction factor
scales model outputs to correct for any systematic model errors while retaining the differences in the current and future distributions (Teutschbein & Seibert, 2010).

Bias correction factors for all six climate variables from the four RCMs are created by comparing data for the current period (1979 – 1999) from each RCM to that from the NARR dataset for the same period. NARR data are used for bias correction in place of station observations as it provides the same variables across the same spatial extent as the NARCCAP models. The bias correction factors are calculated by dividing the mean monthly values from NARCCAP by the mean monthly values from NARR (or subtracting the NARCCAP mean from the NARR mean, in the case of air temperature). Interpolation to create a set of unique daily correction factors is done for the air temperature variable only, to avoid jumps in values between the last day of the month and the first day of the next month. This results in a set of values that represents the difference between the reference climate and the values produced by the NARCCAP models. The bias correction factors are then applied to the full daily datasets of the climate variables from each NARCCAP model for both the current and future periods. A multiplicative function is used for all variables except air temperature, which used an additive function to ensure that the daily minimum never exceeds the daily maximum (Ahmed, 2011; Lenderink et al., 2007; Teutschbein & Seibert, 2010). The equations used for bias correction are as follows, where NARR represents the reference climate and NARCCAP the simulated climate:

For air temperature (T),

\[ T_{\text{BiasCorrected}} = T_{\text{NARCCAP}} + (T_{\text{NARR}} - T_{\text{NARCCAP}}) \]

and

\[ 44 \]

For cloud cover, relative humidity, surface pressure, wind speed, and precipitation (Var),

\[ Var_{\text{BiasCorrected}} = Var_{\text{NARCCAP}} \div \left( \frac{Var_{\text{NARCCAP}}}{Var_{\text{NARR}}} \right). \]

\[ 45 \]
4.3.4 Validation of Bias Correction

To validate the results of the NARCCAP model after bias correction, the total annual precipitation from the NARCCAP ensemble is compared to total annual precipitation from both the reference climate dataset, NARR, for 1979 – 1999, and from EC’s climate normals for 1971 – 2000 (Table 5). From 1979 to 1999 average annual precipitation from the NARR dataset is 389.3 mm/yr at Fort Chipewyan and 458.0 mm/yr at Fort McMurray. Bias correction on the NARCCAP model data is correct when the average annual precipitation from the ensemble of NARCCAP models for 1979 – 1999 matches that from NARR exactly, which is the case.

EC’s climate normals for 1971 – 2000 also showed a similar annual precipitation as the NARCCAP ensemble and the NARR hindcasts, with 391.7 mm/yr at the Fort Chipewyan A station and 455.5 mm/yr at the Fort McMurray A station (Environment Canada, 2013). These values are only 5.8 mm/yr and 4.6 mm/yr lower (1.5% and 1% lower) than the NARCCAP estimates for the same period. The similarity between the bias corrected NARCCAP data, the NARR reference dataset, and the recorded EC observed data validates that the precipitation data used for the current period are accurate, lending confidence that model bias has been removed correctly from the future NARCCAP projections as well. This same bias correction method is applied to the remaining NARCCAP RCM climate variables required to run MyLake.

<table>
<thead>
<tr>
<th>Average Annual Precipitation (mm/yr)</th>
<th>Time Period</th>
<th>Fort Chipewyan</th>
<th>Fort McMurray</th>
</tr>
</thead>
<tbody>
<tr>
<td>EC Climate Normals</td>
<td>1971 – 2000</td>
<td>391.7</td>
<td>455.5</td>
</tr>
<tr>
<td>NARR</td>
<td>1979 – 1999</td>
<td>389.3</td>
<td>458.0</td>
</tr>
<tr>
<td>NARCCAP</td>
<td>1979 – 1999</td>
<td>389.3</td>
<td>458.0</td>
</tr>
<tr>
<td>NARCCAP</td>
<td><strong>1971 – 2000</strong></td>
<td><strong>397.5</strong></td>
<td><strong>460.1</strong></td>
</tr>
</tbody>
</table>

Table 5: Average Total Annual Precipitation over 1971 – 2000 for the NARCCAP model data (ensemble mean) and EC Climate Normals, and over 1979-1999 for the NARR data.
4.3.5 The MyLake Model

MyLake ("Multi-year simulation model for Lake thermo- and phytoplankton dynamics") is a one-dimensional, process-based, comprehensive lake model that simulates the vertical distribution of lake water temperature at a fixed 24-hour time step (Saloranta & Andersen, 2004). The model calculates the energy balance at a lake surface using Matlab’s Air-Sea Toolbox (USGS, 2013), to determine the water temperature profile. The latent heat flux can be extracted from the turbulent flux component of the energy balance and used to estimate evaporation rates at the lake surface. MyLake is expected to estimate open-water evaporation better than traditional evaporation estimates since it includes simulation of heat storage and ice-cover dynamics and dynamically calculates albedo and surface aerodynamics.

MyLake has been shown to produce accurate water temperature profiles for Baker Lake, Nunavut and a variety of Northern Hemisphere lakes and is therefore deemed applicable to the study site of northern Alberta (see Dibike et al. 2011a; 2011b; Saloranta & Andersen, 2007; Saloranta et al., 2009). Inclusion of the snow and ice module is a major reason that MyLake is suitable for modelling lakes in cold climates (Saloranta & Andersen, 2007).

4.3.5.1 MyLake simulations

To run MyLake simulations, input parameters of lake morphometry, initial conditions, and daily meteorological data are required (Dibike et al., 2011a). The vertical resolution of the model is defined by setting the number of horizontally homogeneous lake layers to an equal depth thickness of $\Delta z = 0.5$ m (Saloranta et al., 2009). The basin morphometry is defined by input parameters that define maximum depth and the surface area of each horizontal lake layer. The vertical layers each correspond to sediment layers in the soil surrounding the water body. The $\Delta z$ and other parameters are chosen based on the calibration of MyLake by Saloranta and Andersen (2007) and the application of MyLake to Baker Lake, Nunavut by Dibike et al. (2011a). Baker
Lake is a similar lake to the study lakes as it has a maximum depth of 60 m and is also located in continental northern Canada, although further north at 64°N compared to the study sites at 56°N and 58°N. In the sensitivity analysis run by Saloranta & Andersen (2007), none of the variables tested showed significant sensitivity to $\Delta z$.

4.3.5.2 Basin Morphometry

For each study basin, a depth and a starting surface area was assigned (Table 4). A series of horizontally homogeneous vertical layers were then defined, each 0.5 m thick and decreasing in surface area towards the bottom of the lake. The morphometry, or area-depth relationship, of the intermediate and deep lakes is elliptical sinusoidal (Figure 9 A), a shape representative of average lakes in Canada (Neumann, 1959; Wetzel, 2001). The surface area of each layer was calculated using the hypsometric curve for the elliptical sinusoid. First the maximum depth ($H_z$) of the elliptical sinusoid is calculated based on the surface area at the top of the lake ($A_0$), by

$$H_z = 0.52 \times (\sqrt{A_0})^{0.58}$$  \hspace{1cm} \text{(Gorham & Boyce, 1989).} \hspace{1cm} [46]$$

The radius ($r$) of each subsequent 0.5 m-deep elliptical lake layer, based on the depth of the layer ($z$) within the elliptical sinusoid, is then calculated by

$$r = R_0 - \left[\frac{2}{\pi} \cdot \sin^{-1}\left(\frac{z}{H_z}\right)\right].$$  \hspace{1cm} \text{[47]}$$

The morphometry of the shallow lake, on the other hand, was not modelled after an elliptical sinusoid since the shallow 1.5 m depth would mean that most of the lake would be shallower than that, which is not realistic. Instead, the shallow lake morphometry is modelled using the “bucket” approach, with the top three layers decreasing in surface area from 20 km$^2$ to 5 km$^2$, ending with a flat lake bottom 2,523 m wide (the same as the surface radius) (Figure 9 B).
4.3.5.3 Modelling the Water Temperature Profile

The vertical temperature profile of the lake is calculated by MyLake by estimating the volume-averaged temperature for each lake layer at mid-depth. Starting with an initial surface temperature set at 4°C, the time series of the temperature profile is created by calculating the change in temperature of all lake layers \((i = 1 \ldots i)\) at each daily time step in the study period. The change in water temperature \(\frac{\delta T}{\delta t}\) between time steps is modelled based on the local heating of each layer and the diffusion of heat from surrounding layers and from the water-sediment interface (Saloranta & Andersen, 2004). The thermodynamics of vertical lake profiles are solved by MyLake using the heat conservation equation:
\[
\frac{A}{\delta t} \frac{\delta T}{\delta t} = \frac{\delta}{\delta z} \left[ K A \frac{\delta T}{\delta z} \right] + A \frac{Q^*}{\rho_w c_p}
\]  \[48\]

Here \( T \) is the layer water temperature (°C), \( z \) is the layer depth (m), \( K \) is the vertical diffusion coefficient (m\(^2\) d\(^{-1}\)), \( A \) is the surface area of the layer (m\(^2\)), which decreases for each layer until reaching zero at the bottom, \( Q^* \) is the net radiative flux, \( \rho_w \) is the density of water (\( \rho_w = 1 \text{ g mL}^{-1} \)) and \( C_p \) is the specific heat capacity of water (\( C_p = 4186 \text{ J kg}^{-1} \text{ °C}^{-1} \)). The first right-hand term represents the diffusive mixing process that distributes heat between layers, and the second term represents local heating in each layer due to incoming radiation and transfer of heat from the surrounding sediment (Saloranta & Andersen, 2004; see Section 3.3).

**4.3.5.4 Evaporation Method**

Evaporation is estimated using the latent heat flux calculated by MyLake as part of the lake energy balance (Saloranta & Andersen, 2004). The shortwave sensible and latent heat fluxes are calculated by MyLake from meteorological input data (wind speed, air temperature, relative humidity and air pressure) and the depth of the lake, using the Matlab Air-Sea toolbox (USGS, 2013). Evaporation is then calculated using a version of the energy balance method (Schertzer & Taylor, 2009), where the available latent heat flux (\( H_l \)) at the surface of the lake is divided by the heat of vaporization (\( \lambda \)) required for freshwater, also calculated by MyLake:

\[
\text{Evaporation} = \frac{H_l}{\lambda};
\]

Finally, the evaporation in units of kg s\(^{-1}\) m\(^{-2}\) is converted to standard mm d\(^{-1}\) units using the density of water (\( 10^3 \text{ km}^{-1} \text{ m}^{-3} \)) to replace 1 km m\(^{-2}\) of water with a 1 mm-deep layer of water, which means multiplying by 86400. More details on the estimation of evaporation using MyLake can be found in Section 3.3.
4.3.6 Other Common Evaporation Estimates

To validate the evaporation calculated by MyLake, comparisons with four other commonly used open-water evaporation methods were carried out. These methods included: the Bowen Ratio (Schertzer & Taylor, 2009); an energy balance estimate, the Penman and Priestly-Taylor methods (Shuttleworth, 1993; Valiantzas, 2006); both “combination” estimates, and the Hamon method; a degree-day estimate based on air temperature and day-length (Werner, 2007). See Chapter 3 for more details on these methods. The water budget method was not used since it solves for evaporation using all the other components of the water balance (Derecki, 1975), and in this project all components of the water balance are not known independently. The mass transfer method was also not used since either on-site calibration or calculation using the water budget or energy budget would be required to determine the mass transfer coefficient specific to the study lakes (Winter, 1981).

The four evaporation formulas are calculated using daily bias corrected RCM data at the Fort McMurray study site for 1971 – 1999 (2000 was excluded for this validation exercise only, due to data gaps). Along with the air temperature, pressure, relative humidity and wind speed variables that are also used as inputs to the MyLake model, net radiation from the RCMs and day length based on the latitude of Fort McMurray were used. In the case of the Bowen ratio approach, surface water temperature was also required. Since no observed surface water data is available for the study sites, surface water temperature modelled by MyLake was used. Further detail on evaporation estimates is found in Section 2.2.4.1, the methodology and equations used for this study are found in Section 3.4, and results of the comparison of evaporation estimates are reported in Section 4.4.2.3.1, below. Appendix A and B include further investigations into the sensitivity of MyLake to depth and sediment heat flux.
4.3.7 Water Balance Analysis

MyLake is run for the three basin depths, using bias corrected input data from the three NARCCAP RCM_GCMs for both Fort Chipewyan and Fort McMurray. These 18 scenarios are run for both the current (1971 – 2000) and future (2041 – 2070) periods, resulting in 36 separate MyLake runs. Results are averaged daily across the three RCM_GCMs to create the daily ensemble mean for each relevant variable. Results of evaporation modelling are analyzed for seasonal patterns and sensitivity to basin depth (shallow, intermediate, and deep basins) and climate inputs (Fort McMurray and Fort Chipewyan study sites). Once combined with precipitation rates to calculate the water balance, annual, seasonal and monthly patterns are analyzed. Future water balance, calculated in the same way, is then compared to the current water balance, with differences in evaporation, precipitation, and change in water level explored through annual and monthly sums and averages. Lastly, the cumulative daily water balance is calculated over both periods. The daily values of the ensemble mean for each variable are added consecutively over the 30 year periods. The cumulative water balance serves to assess differences in lake storage over 30 years under current climate compared to 30 years under projected future climate.

4.4 Results

4.4.1 Ice Cover Duration

The ensemble mean results from MyLake show that spring ice breakup dates in the current period vary based on lake location, occurring on average on June 1 – 2 at Fort Chipewyan, and slightly earlier on May 24 – 25 at Fort McMurray, 200 km to the south (Table 6). The breakup dates at each site are similar regardless of lake depth, with the shallow lake breaking up 1 day earlier than the deeper lakes in both cases.
Fall freeze-up dates vary more with lake depth than do spring breakup dates (Table 6). The modelled freeze-up dates range from early- to mid-November for both sites in the current period, but there are large 5- to 10-day differences based on depth. At both sites the freeze-up date is earliest for the shallow lake (November 3 and 4) and is delayed proportionately to lake depth. The intermediate-depth lake is expected to freeze on November 11 or 12, and the deep lake is expected to freeze on November 15-17.

Based on future projections, modelled freeze-up dates are expected to shift by 5 – 8 days later in the year on average (Table 6). This is likely driven by warmer air temperatures in the future climate scenarios. The shift is 5 days for the shallow lake at both study sites, and is one to two days larger at Fort McMurray than at Fort Chipewyan, for the intermediate and deep lakes, respectively. Future changes to breakup dates are larger than the changes to freeze-up dates, with the loss of ice occurring 10-11 days earlier at Fort Chipewyan and 20-21 days earlier at Fort McMurray, on average. Again the shift is one-day larger for the deeper lakes compared to the shallow lake, at both study sites.

<table>
<thead>
<tr>
<th></th>
<th>Breakup</th>
<th>Freeze-up</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Current</td>
<td>Future</td>
</tr>
<tr>
<td>Fort Chipewyan</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>June 1</td>
<td>May 21</td>
</tr>
<tr>
<td>Intermediate</td>
<td>June 2</td>
<td>May 23</td>
</tr>
<tr>
<td>Deep</td>
<td>June 2</td>
<td>May 23</td>
</tr>
<tr>
<td>Fort McMurray</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>May 24</td>
<td>May 13</td>
</tr>
<tr>
<td>Intermediate</td>
<td>May 25</td>
<td>May 15</td>
</tr>
<tr>
<td>Deep</td>
<td>May 25</td>
<td>May 15</td>
</tr>
</tbody>
</table>

Table 6: Average annual ice cover breakup and freeze-up dates for the current period (1971 – 2000) and the future period (2041 – 2070) at the two study sites. Dates are calculated as the ensemble mean date of the MyLake model runs using three NARCCAP models.
4.4.2 Evaporation

4.4.2.1 Current Evaporation Patterns

Modelled evaporation varies based on both the climate of the study site, and the morphometry of the study lakes (Table 7). Average annual evaporation in the current period is highest over the intermediate-depth lake at both sites, with a total of 408 mm/yr at Fort McMurray and 362 mm/yr at Fort Chipewyan. The deep and shallow lakes at both sites have similar, but slightly lower, annual evaporation than the intermediate-depth lakes. Lakes at Fort McMurray have on average 43 mm more evaporation annually than lakes at Fort Chipewyan.

<table>
<thead>
<tr>
<th>Average Annual Evaporation (mm/yr)</th>
<th>Fort Chipewyan</th>
<th>Fort McMurray</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shallow</td>
<td>360</td>
<td>399</td>
</tr>
<tr>
<td>Intermediate</td>
<td>362</td>
<td>408</td>
</tr>
<tr>
<td>Deep</td>
<td>354</td>
<td>400</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>359</strong></td>
<td><strong>402</strong></td>
</tr>
</tbody>
</table>

Table 7: Ensemble mean average total annual evaporation modelled by MyLake using RCM_GCM input climate data for 1971 – 2000.

Intra-annual evaporation patterns differ depending on lake depth; modelled evaporation is greater over the shallow lakes earlier in the open-water season, and greater over the deep lakes at the end of the open-water season. Ensemble mean estimates of current daily (Figure 10) and monthly (Figure 11) evaporation show rates for the shallow lake rising quickly from zero just after breakup and reaching much higher rates by June (2.9 and 3.5 mm/dy for Fort Chipewyan and Fort McMurray, respectively) than the deeper lakes (1.1 and 1.7 mm/dy over the intermediate lake; 1.0 and 1.5 mm/dy over the deep lake). Peak evaporation is seen in July for all three lakes. The highest peak is over the shallow lake with 3.9 mm/dy for both Fort McMurray and Fort Chipewyan, compared to 3.0 mm/dy over the intermediate lake at both sites, and 3.1 and 3.2 mm/dy over the deep lake for Fort Chipewyan and Fort McMurray, respectively.
After the July peak, daily evaporation rates begin to drop off quickly for the shallow lake, while rates stabilize over the deeper volumes for the open-water season, staying above 2.0 mm/dy until November over the intermediate-depth lake, and until October over the deep lake, with slight variation between the two study sites. By November the shallow lake evaporation falls to zero, when freeze-up occurs earlier than the deeper two lakes. Modelled evaporation in November continues over the intermediate-depth and deep lakes, with low rates of 0.5 mm/dy in November over the intermediate-depth lake and 1.0 mm/dy in November over the deep lake.

Figure 10: Mean, Maximum, and Minimum evaporation rates from the ensemble mean of the MyLake results using NARCCAP input data for 1971 – 2000. The mean is the average of each day from the ensemble mean over 30 years while the maximum (minimum) values are the ensemble mean value for each day in the year it is the highest (lowest) out of the 30-year period.
A sensitivity analysis was carried out to ensure the variation in evaporation by lake depth isn’t simply due to the difference between the “bucket” shape morphometry of the shallow lake and the elliptical sinusoid morphometry of the intermediate-depth and deep lakes. Results show that the average annual evaporation patterns change gradually as the depth changes, with a crossover between highest evaporation from the shallow versus the deep lake in August and September, validating the effect of lake depth, and not simply morphometry, on evaporation. See Appendix A for details.

The effect of sediment heat flux on the evaporation from the study lakes was found to be negligible. When calculating evaporation, MyLake can take into account the heat exchanged...
between the water and the surrounding lake bed sediment, and heat diffused between pore water and the water column. A separate MyLake run was undertaken to determine the difference in evaporation if this sediment heat flux portion of the model is turned “off”. The results indicate that lake bed sediment has a small moderating effect on lake water temperature, but the percent difference in evaporation is less than 1% in all cases. See Appendix B for details.

4.4.2.2 Future Evaporation Patterns

Overall, average annual evaporation for the future period (2041 – 2070; Table 8) is projected to increase at both the Fort Chipewyan and Fort McMurray study sites, and intra-annual patterns are projected to shift within the year. Calculated annually, results show that future evaporation will increase the most over the shallow and intermediate lakes, with 53 mm/yr more evaporation at both Fort Chipewyan and Fort McMurray, compared to 51 mm/yr over the deep lakes in the future (Table 9). The increases in evaporation can be attributed to higher lake temperatures corresponding to overall higher air temperatures in the A2 climate scenario, as well as increased spring (May and June) and fall (October and November) evaporation due to a longer open-water evaporation season, allowing evaporation to occur in months in which it was previously trapped under ice.

Modelled ensemble mean average monthly evaporation in the future compared to the current period shows increases in every open-water month except October at both Fort McMurray and Fort Chipewyan, with the largest percent changes occurring in May, November and December, the shoulder months around the open-water season (Figure 12). This shift in evaporation in the shoulder seasons can also be seen in the difference between the current and future daily evaporation rates in Figures 13 and 14.
<table>
<thead>
<tr>
<th></th>
<th>Annual Precipitation (mm)</th>
<th>Annual Evaporation (mm)</th>
<th>Annual Change in Water Level (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Current</td>
<td>Future</td>
<td>Current</td>
</tr>
<tr>
<td><strong>Fort Chipewyan</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>--</td>
<td>--</td>
<td>360</td>
</tr>
<tr>
<td>Intermediate</td>
<td>--</td>
<td>--</td>
<td>362</td>
</tr>
<tr>
<td>Deep</td>
<td>--</td>
<td>--</td>
<td>354</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>398</td>
<td>454</td>
<td>359</td>
</tr>
<tr>
<td><strong>Fort McMurray</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>--</td>
<td>--</td>
<td>399</td>
</tr>
<tr>
<td>Intermediate</td>
<td>--</td>
<td>--</td>
<td>408</td>
</tr>
<tr>
<td>Deep</td>
<td>--</td>
<td>--</td>
<td>400</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>460</td>
<td>516</td>
<td>402</td>
</tr>
</tbody>
</table>

Table 8: Ensemble mean annual totals for the three water balance variables, for the current (1971 – 2000) and future (2041 – 2070) periods. Precipitation is the same for the three lake depths at each site.

<table>
<thead>
<tr>
<th></th>
<th>Future minus Current</th>
<th>Change in Precipitation (mm)</th>
<th>Change in Evaporation (mm)</th>
<th>Change in Annual Water Level Rise/Fall (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fort Chipewyan</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>--</td>
<td>53</td>
<td></td>
<td>4</td>
</tr>
<tr>
<td>Intermediate</td>
<td>--</td>
<td>53</td>
<td></td>
<td>4</td>
</tr>
<tr>
<td>Deep</td>
<td>--</td>
<td>51</td>
<td></td>
<td>5</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>57</td>
<td>52</td>
<td></td>
<td>4</td>
</tr>
<tr>
<td><strong>Fort McMurray</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>--</td>
<td>53</td>
<td></td>
<td>3</td>
</tr>
<tr>
<td>Intermediate</td>
<td>--</td>
<td>52</td>
<td></td>
<td>4</td>
</tr>
<tr>
<td>Deep</td>
<td>--</td>
<td>51</td>
<td></td>
<td>5</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>56</td>
<td>52</td>
<td></td>
<td>4</td>
</tr>
</tbody>
</table>

Table 9: Difference between current and future annual totals for the water balance (future minus current). Precipitation is the same for the three lake depths at each site.

May evaporation over the shallow lake increases by 15 mm at Fort Chipewyan and by 28 mm at Fort McMurray, a lot more than over the intermediate and deep lakes, for which evaporation increases by only 1 mm at Fort Chipewyan, and by 5 and 6 mm, respectively, at Fort McMurray. For all lake depths and study sites, the percent change in evaporation in May constitutes the largest difference between the current and future periods in any month.
Evaporation increases more in June than over the summer months of July, August and September for all three lake depths. June evaporation increases by 23 mm at Fort Chipewyan and 10 mm at Fort McMurray over the shallow lake, by 21 mm at Fort Chipewyan and 16 mm at Fort McMurray over the intermediate-depth lake, and by 19 mm at Fort Chipewyan and 16 mm at Fort McMurray over the deep lake. These are all larger that the changes to May evaporation except for the shallow lake at Fort McMurray. However, the percent increases in June aren’t as high as in May, since evaporation was already occurring in June in the current period, unlike in May. In July, August and September evaporation increases by 4 – 13%. The magnitude of the future increase is larger in July (9 mm) than in August (6 mm) and September (3 mm) for the two deeper lakes. For the shallow lake the magnitude of the increase is steady at 5 mm in July and August, and evaporation only increases by 3 mm in September in the future period.
Figure 13: Average Ensemble Water Balance for the current (1971 – 2000) and future (2041 – 2070) periods at Fort McMurray.

In October the evaporation actually decreases between the current and future period over all lakes except the intermediate-depth lake at Fort McMurray. The decrease is very close to zero, and represents a -3% and -4% decrease for the shallow lake at Fort Chipewyan and Fort McMurray, respectively, an increase of 0% and 1% at the two study sites respectively for the intermediate lake, and a decrease of -6% and -4% at the two study sites respectively for the deep lake. The decrease in evaporation in October between current and future periods indicates the end of the seasonal shift in evaporation to earlier in the year in the future period.
November evaporation has the next highest percent increase to the large May changes. This increase can be partially attributed to the modelled shift to later freeze-up dates (by 5 – 8 days) in the future, allowing significantly more evaporation in November. The effect is more pronounced over the intermediate and deep lakes, for which evaporation increases by 12 to 15 mm depending on the site, while evaporation over the shallow lake in November is only projected to increase by 2 mm.

Figure 14: Average ensemble mean water balance for the current (1971 – 2000) and future (2041 – 2070) periods at Fort Chipewyan.
4.4.2.3 MyLake Model Validation

4.4.2.3.1 Evaporation Methods

MyLake evaporation is compared to four other commonly used methods of open-water evaporation estimation (see Sections 2.2.4.1 and 3.4). Results show that three of the five evaporation estimates for the open-water period are at the same scale (Figures 15 and 16) – the MyLake, Penman, and Bowen Ratio methods estimate average open-water evaporation of 2.4 mm/dy, 2.6 mm/dy and 2.8 mm/dy, respectively – whereas the Priestley-Taylor and Hamon methods estimate a much smaller scale of evaporation, with average open-water evaporation of 0.3 mm/dy and 0.2 mm/dy, respectively (Figure 15). This difference can be explained by the incorporation of wind speed and vapour pressure deficit in the formula. The Priestley-Taylor and Hamon approaches estimate lower evaporation rates because they do not take into account wind speed over the lake nor do they directly include the vapour pressure deficit (VPD). The Penman and the Priestley-Taylor method are otherwise very similar, but the aerodynamic Penman method includes the VPD and a wind function (Schertzer & Taylor, 2009) and therefore estimates much higher values of evaporation. While the Bowen ratio-energy budget method doesn’t use a wind function, it is even more robust than the aerodynamic methods because the profiles of both temperature and vapour pressure are included, so any error due to changes in surface roughness or topography cancel out as the two profiles are affected by these factors equally (Shuttleworth, 1993). Another reason the MyLake and Bowen ratio methods have similar results here is that MyLake outputs were used for the surface water temperature data, as this was not available for Fort McMurray from any other source.

Note the unusual results for the Bowen method in Figure 16; in April and May condensation is predicted instead of evaporation (negative average daily evaporation), and extremely large values of evaporation are estimated during break-up in June. These values could
not be properly corrected or explained during analysis of the data, however these evaporation estimates are used only for comparison with the MyLake results and the Bowen values are not used in subsequent analyses in this study.

Figure 15: Average daily open-water evaporation rates using bias-corrected NARCCAP ensemble mean input data for Fort McMurray from 1971 – 1999 (2000 excluded for this exercise, due to data gaps), calculated using the MyLake, Penman, Priestley-Taylor, Hamon, and Bowen Ratio methods.
Figure 16: Average monthly evaporation rates modelled by MyLake and by four other estimates: Penman, Priestley-Taylor, Hamon, and the Bowen Ratio. Input data for all methods is bias-corrected NARCCAP ensemble for 1971 – 1999.

4.4.2.3.2 NARR versus NARCCAP Evaporation

To validate the MyLake evaporation results, evaporation modelled for the current period using the NARCCAP climate input data is compared to evaporation modelled using the NARR reference as input data. Studies evaluating the performance of historical back-casting of climate models, precipitation and air temperature are generally considered to be more easily adjusted to match historical records, while other climate variables demonstrate how well the model represents climate as a whole (Werner, 2011). Therefore, as the calculation of evaporation encompasses a variety of climate variables including air temperature, comparing the evaporation modelled by MyLake using the NARR and NARCCAP datasets should be sufficient to validate the input climate data. Correct hindcasting of current climate data by a model validates its
accuracy in the study region in particular, although it doesn’t always reflect how the model will respond to future climate forcing (Werner, 2011).

When the MyLake model is run using NARR at the two study sites, very similar evaporation rates are calculated over the three lake depths as when it is run with the three NARCCAP ensemble models for the same period (1979 – 1999) (Figure 17). This is to be expected as the NARCCAP models were bias corrected using monthly correction factors from the NARR dataset. However, there are some small differences in the ensemble mean evaporation rates between the NARR and NARCCAP model runs. At Fort Chipewyan the annual ensemble-mean evaporation modelled using NARCCAP is 0.7% higher (2.4 mm/yr) over the shallow lake than when modelled with NARR, whereas for the intermediate-depth and deep lakes the NARCCAP evaporation is 6.3% and 8% lower (23.1 mm/yr and 28.7 mm/yr). At Fort McMurray the NARCCAP ensemble mean annual evaporation is 0.6% higher (2.3 mm/yr) for the shallow and intermediate-depth lakes, and 0.3% lower (1.2 mm/yr) for the deep lake. The pattern of the highest evaporation occurring over the intermediate depth lake is retained at both study sites in both NARR and NARCCAP results. Furthermore, Figure 17 demonstrates that seasonal patterns in daily evaporation are very similar between the NARCCAP and NARR runs in an average year. The only noticeable difference is over the deep lake, where evaporation modelled using NARCCAP data shows a larger heat storage effect in the fall than with NARR data (Figure 17 E and F). However since the annual totals are so similar, especially at Fort McMurray, this is accounted for by a seasonal shift in NARR versus NARCCAP, and not an overall difference. The similarity in the values of evaporation modelled by MyLake using input climate data from NARR and the NARCCAP ensemble indicate that the bias corrected NARCCAP data properly represents current climate.
4.4.3 Current and Future Precipitation

Total annual precipitation from the bias-corrected NARCCAP ensemble for the current period is slightly higher at Fort McMurray than at Fort Chipewyan, with a total of 460 mm falling on average at the former, compared to 398 mm at the latter (Table 8). The modelled data shows the expected pattern of low precipitation in the winter and high precipitation in the summer (Figure 18 and Table 10), as seen in the EC observations (see Section 4.2). Precipitation peaks in June, July and August for both study sites, with an average monthly total of 57 mm at Fort Chipewyan and 71 mm at Fort McMurray over those three months. This compares to the low average monthly totals of 21 mm at Fort Chipewyan for November to April, and of 21 mm at Fort McMurray for November to March.

Future precipitation modelled by the NARCCAP ensemble is higher on average compared to the current period (Table 8 and Figure 18). The total annual increase in precipitation is 57
mm/yr at Fort Chipewyan and 56 mm/yr at Fort McMurray (Table 9). The seasonal patterns of precipitation are retained in the future; unlike evaporation, no seasonal shift is present in the future precipitation results (see Figures 13 and 14). On a monthly scale, precipitation is similar in the current and future periods from January to April at both study sites, increasing by less than 3 mm per month on average (Figure 18). April precipitation is projected to decrease at Fort McMurray, but by a negligible amount. The precipitation increase is greatest in June for both study sites, increasing by 12 mm. The next highest increases are projected for September, for which the rise is 9 mm at Fort Chipewyan and 6 mm at Fort McMurray. October and November precipitation increases by 6 mm at Fort Chipewyan and by 3 mm/dy at Fort McMurray. Estimated future precipitation represents a 5% to 25% increase over current monthly precipitation totals, with higher percent increases in the spring months at Fort McMurray and in the fall at Fort Chipewyan.
Figure 18: Ensemble mean average daily precipitation by month in the current period (1971 – 2000) and the change to the future period (2041 – 2070). Error bars show maximum and minimum values within the 3-model ensemble.

<table>
<thead>
<tr>
<th>Precipitation (mm/month)</th>
<th>Fort Chipewyan</th>
<th>Fort McMurray</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>20</td>
<td>21</td>
</tr>
<tr>
<td>February</td>
<td>19</td>
<td>18</td>
</tr>
<tr>
<td>March</td>
<td>19</td>
<td>19</td>
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<tr>
<td>April</td>
<td>19</td>
<td>27</td>
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<tr>
<td>May</td>
<td>32</td>
<td>41</td>
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<tr>
<td>June</td>
<td>54</td>
<td>72</td>
</tr>
<tr>
<td>July</td>
<td>58</td>
<td>73</td>
</tr>
<tr>
<td>August</td>
<td>59</td>
<td>68</td>
</tr>
<tr>
<td>September</td>
<td>40</td>
<td>43</td>
</tr>
<tr>
<td>October</td>
<td>30</td>
<td>32</td>
</tr>
<tr>
<td>November</td>
<td>26</td>
<td>24</td>
</tr>
<tr>
<td>December</td>
<td>22</td>
<td>24</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>398</strong></td>
<td><strong>460</strong></td>
</tr>
</tbody>
</table>

Table 10: Total monthly precipitation averaged over all years in the current period (1971 – 2000) from the NARCCAP ensemble mean at Fort McMurray and Fort Chipewyan.
4.4.4 Current Water Balance

4.4.4.1 Annual Changes in Water Level

When modelled evaporation and precipitation for the current period are combined to calculate the water balance for the study lakes, precipitation exceeds evaporation on average annually at both study sites and over all three lake depths (Figure 19 and Table 11). The surplus of precipitation is represented by the positive value of the average annual “change in water level” for each lake, ranging from 35 to 61 mm/yr, depending on lake depth and geographic location (climate). The increase in water level is slightly larger at Fort McMurray, where the intermediate lake level is projected to rise by 52 mm/yr, the shallow and deep lakes both by 61 mm/yr. At Fort Chipewyan the water level of the intermediate lake is expected to increase by 35 mm/yr, the shallow lake by 38 mm/yr, and the deep lake by 43 mm/yr (Table 11).

Since precipitation only varies by site and not by lake depth, the differences in the change in water level values for different lakes at the same site are driven by differing evaporation rates. The intermediate-depth lake has the highest evaporation, and therefore balances the incoming precipitation to a greater extent, meaning the change in water level is smallest for these lakes. The larger change in water levels at Fort McMurray is due to a bigger difference between evaporation and precipitation annually, however both evaporation and precipitation totals are higher at that site than at the further north Fort Chipewyan.
<table>
<thead>
<tr>
<th>Lake Depth</th>
<th>Current Water Balance</th>
<th>Total Precipitation (mm)</th>
<th>Total Evaporation (mm)</th>
<th>Change in Water Level (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fort Chipewyan</td>
<td>Fort McMurray</td>
<td>Fort Chipewyan</td>
<td>Fort McMurray</td>
</tr>
<tr>
<td>Shallow</td>
<td>Ice Cover</td>
<td>167</td>
<td>168</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>Open Water</td>
<td>231</td>
<td>292</td>
<td>350</td>
</tr>
<tr>
<td></td>
<td>Annual</td>
<td>398</td>
<td>460</td>
<td>360</td>
</tr>
<tr>
<td>Intermediate</td>
<td>Ice Cover</td>
<td>160</td>
<td>162</td>
<td>8</td>
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<tr>
<td></td>
<td>Open Water</td>
<td>237</td>
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<tr>
<td></td>
<td>Annual</td>
<td>398</td>
<td>460</td>
<td>362</td>
</tr>
<tr>
<td>Deep</td>
<td>Ice Cover</td>
<td>156</td>
<td>158</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>Open Water</td>
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<td></td>
<td>Annual</td>
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<td>460</td>
<td>354</td>
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<tr>
<td>Average (all depths)</td>
<td></td>
<td>398</td>
<td>460</td>
<td>359</td>
</tr>
</tbody>
</table>

Table 11: Total ensemble mean evaporation and precipitation in the ice cover season versus the open-water season for the current period (1971 – 2000). The open-water season is defined by the ensemble mean of the ice on/off dates modelled by MyLake for each NARCCAP RCM_GCMs; evaporation occurring in the ice cover period is only due to averaging in the ensemble.

Figure 19: Total annual ensemble mean water balance components in the current period (1971 – 2000) for A) Fort Chipewyan and B) Fort McMurray.
4.4.4.2 Intra-Annual Changes in Water Level

Seasonally, the model results show that current total evaporation outweighs precipitation in the open-water season, resulting in negative changes in lake levels (Table 11). The open-water season is from approximately May to November, defined for each study lake by the ensemble mean ice on/off dates modelled by MyLake depending on climate and lake depth. At Fort McMurray over the shallow lake, for example, total evaporation is 389 mm in the open-water season, and precipitation is almost 100 mm less than that (292 mm) in the same seven months, resulting in a lowering of lake levels by the same amount. However, winter precipitation makes up more than the difference annually, with 168 mm of rain or snow falling in the remaining months while the lake is frozen and evaporation is zero. This results in an annual precipitation surplus of 61 mm/yr on average annually for the shallow basin. For all three lake depths at both study sites the change in water level as modelled by MyLake is positive in the ice-cover season and then moves to a negative value in the open-water season.

Lake depth has an impact on water levels due to its control on evaporation, as described above. In the winter months from January to May the change in water level is positive for all lakes (approximately 20 mm per month), since only precipitation is contributing to the storage in the lake (Figure 20). In mid-May breakup begins to occur, on average on May 22 and May 13 at Fort Chipewyan and Fort McMurray, respectively, but monthly precipitation still exceeds evaporation resulting in 27 mm (shallow lake) and 33 mm (intermediate and deep lakes) increase in lake levels per month, averaged between the study sites. After breakup, the increases in water level are greatly reduced as evaporation begins in the now-open-water lakes. Decreases in water level occur earlier over the shallow lake compared to the two deeper lakes. Two factors contribute to this difference; breakup occurs later in the deeper lakes, stalling the addition of evaporation to the water balance equation, and evaporation does not rise as sharply in the spring.
over deeper lakes due to the time it takes for larger water bodies to heat up. The water level of the shallow lake begins to drop in June, with a monthly total change of -32 mm and -34 mm at Fort Chipewyan and Fort McMurray, respectively. For the deeper lakes, the change in water level is still positive in June, albeit smaller than in May, with 23 mm and 22 mm of water being added to the intermediate lake, and 26 mm and 38 mm being added to the deep lake, at Fort Chipewyan and Fort McMurray, respectively.

Figure 20: Total monthly change in water level (mm/month) in the current period (1971 – 2000) at A) Fort Chipewyan and B) Fort McMurray.

Summer water level change is negative for from June to October over the shallow lake, from July to October over the intermediate-depth lake, and from July to November over the deep lake. The largest monthly water level change in either direction is over the shallow lake at Fort Chipewyan in July, making it the most at risk of drying out. Mid-summer extreme precipitation
events are noticeable even in the average annual water balance (Figures 13 and 14). Days with very high precipitation, which are more common in the summer when convective storms are more likely, affect lakes by creating sharp daily increases in water level. An analysis of the effects of extreme events on the water balance is presented in Chapter 5.

In the fall, freeze-up dictates the return of increases in lake water levels. Once evaporation ends, which is sooner for the shallow lake and later and more abrupt for the two deeper lakes, precipitation once again dominates the water balance, adding storage to the lakes. Figures 13 and 14 show that evaporation from the shallow lake tapers off more slowly; the change in water level becomes positive in October. The intermediate-depth lake still has negative storage in October and moves to an increase in water level in November; it takes until December for the deep lake to move back to a positive change in storage.

4.4.5 Future Water Balance

4.4.5.1 Future Annual Changes in Water Level

Ensemble mean model results indicate that the water balance components will all increase in magnitude on average annually in the future at both study sites, with precipitation increasing slightly more than evaporation (Tables 8 and 9). On average over the 30-year future period at Fort Chipewyan, the modelled change in water level is 42 mm/yr over the shallow lake, an average annual increase of 4 mm/yr from the current period (Table 9). The average annual change in water level also increases by 4 mm/yr and 5 mm/yr in the future for the intermediate and deep lakes. This is also true for the lakes at Fort McMurray; the increases in lake level are expected to be 5 mm/yr, 4 mm/yr and 3 mm/yr larger in the future for the deep, intermediate-depth, and shallow lakes, respectively. The future water balance at both sites shows that the intermediate-depth lake has a smaller change in water level than the shallow and deep lakes, as
in the current period, since the intermediate depth has more evaporation to balance precipitation and moderate lake levels.

### 4.4.5.2 Future Intra-Annual Changes in Water Level

Differences in the monthly change in water level between current and future periods reflect differences in evaporation and precipitation patterns over the study lakes. Figure 21 shows that the difference between the current and the future average monthly water level changes (future minus current) is positive in the fall, winter and spring, and negative in the summer. This means that the already positive changes in storage in the months from December to May become more positive in the future, resulting in water levels increasing more in the winters in the future compared to the current period. The reverse is also true; the negative changes in storage in the summer months from June to November are expected to become more negative in most months in the future period, drawing down the water level in the lakes in the summer by more than in the current period.

Seasonally the daily rate of change in water level shifts the most for the shallow lake as increased early season evaporation in the future period means much larger average daily increases in water level in May and June than during the rest of the open-water season (Figures 22 and 23). For the deep lake the opposite is true; increased late-season evaporation means larger increases in water level in November and December.
Figure 21: Ensemble mean average daily change in water level by month in the current period (1971 – 2000) and the difference to the future period (2041 – 2070), calculated by subtracting the current period monthly means from the future monthly means. Subplots A, C and E are for Fort Chipewyan, and B, D, and F for Fort McMurray.
Figure 22: Future minus current ensemble mean water balance at Fort McMurray. Plots A, C and E show the difference in the 30-year average for each Julian day, and plots B, D and F show the difference in the mean value for the entire 30-year future and current periods.
Figure 23: Future minus current ensemble mean water balance at Fort Chipewyan. Plots A, C and E show the difference in the 30-year average for each Julian day, and plots B, D and F show the difference in the mean value for the entire 30-year future and current periods.

4.4.6 Cumulative Water Balance

The cumulative daily water balance is used to show how climate affects these lakes over the long term. Subtracting evaporation from precipitation on a daily basis over 30 years yields the cumulative change in water level at each study lake. Figure 24 show the cumulative changes in precipitation, evaporation and change in water level over 30 years in the current and future periods, while Table 12 shows the cumulative change from the start to the end of each period. In all cases the water level increased over the 30-year periods, indicating higher annual precipitation rates than evaporation rates. Details of the variations in cumulative change in water
level in the current period due to study site, lake depth, choice of climate model ensemble, and climate change are described in the following sections are displayed in Figure 25 to 27.

Figure 24: Current (1971 – 2000) and future (2041 – 2070) cumulative water balance at Fort McMurray and Fort Chipewyan for shallow (1.5 m), intermediate (28.5 m), and deep (76.5 m) lakes. The change in water level is calculated by subtracting evaporation from precipitation.
Fort Chipewyan

<table>
<thead>
<tr>
<th></th>
<th>Evap</th>
<th>Precip</th>
<th>ΔWL</th>
<th>Evap</th>
<th>Precip</th>
<th>ΔWL</th>
<th>Evap</th>
<th>Precip</th>
<th>ΔWL</th>
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<tbody>
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<td>1.3</td>
<td>12.4</td>
<td>1.3</td>
<td>1.6</td>
<td>0.2</td>
<td></td>
<td></td>
</tr>
<tr>
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<td>1.2</td>
<td>12.4</td>
<td>1.2</td>
<td>1.6</td>
<td>0.1</td>
<td></td>
<td></td>
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<tr>
<td>Deep</td>
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<td>1.5</td>
<td>12.2</td>
<td>1.5</td>
<td>1.7</td>
<td>0.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
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<td>1.3</td>
<td>12.3</td>
<td>1.3</td>
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<td>0.1</td>
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Fort McMurray

<table>
<thead>
<tr>
<th></th>
<th>Evap</th>
<th>Precip</th>
<th>ΔWL</th>
<th>Evap</th>
<th>Precip</th>
<th>ΔWL</th>
<th>Evap</th>
<th>Precip</th>
<th>ΔWL</th>
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</thead>
<tbody>
<tr>
<td>Shallow</td>
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<td>1.8</td>
<td>1.9</td>
<td>13.5</td>
<td>1.9</td>
<td>1.6</td>
<td>0.1</td>
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<tr>
<td>Intermediate</td>
<td>12.2</td>
<td>1.6</td>
<td>1.7</td>
<td>13.8</td>
<td>1.7</td>
<td>1.6</td>
<td>0.1</td>
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<tr>
<td>Deep</td>
<td>12.0</td>
<td>1.8</td>
<td>2.0</td>
<td>13.5</td>
<td>2.0</td>
<td>1.7</td>
<td>0.2</td>
<td></td>
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</tr>
<tr>
<td>Average</td>
<td>12.1</td>
<td>1.7</td>
<td>1.9</td>
<td>13.6</td>
<td>1.9</td>
<td>1.6</td>
<td>0.2</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 12: Daily cumulative water balance (metres) at the end of the current and future 30-year periods. The difference is calculated as future minus current values.

4.4.6.1 Current Cumulative Water Balance

4.4.6.1.1 Variations by Study Site and Lake Depth

In the current period at Fort McMurray and Fort Chipewyan, all three lake depths have a value for cumulative change in water level of between 1.1 and 1.8 metres after 30 years (Table 12). The positive gains are because cumulative precipitation exceeds evaporation in the long term at both sites. Over 30 years the water level at Fort McMurray increased by 1.7 m on average across the three lake depths, while it increased by a smaller 1.2 m on average across the lake depths at Fort Chipewyan (Figure 25). Modelled cumulative precipitation is 13.8 m over 30 years at Fort McMurray compared to cumulative evaporation of 12.1 m, and cumulative precipitation at Fort Chipewyan is 11.9 m over 30 years compared to cumulative evaporation of 10.8 m, averaged over the three lake depths. The difference in cumulative precipitation (1.9 m) between the two study sites is more than the difference in cumulative evaporation (1.3 m).
Figure 25: Cumulative change in water level (metres) by study site, current (1971 – 2000) and future (2041 – 2070) from the NARCCAP ensemble mean.

At Fort McMurray the change in water level is greatest for the shallow lake and the deep lake, both lakes showing a rise in water level of 1.8 m, while the water level of the intermediate-depth lake increases by 1.6 m over 30 years (Table 12). At Fort Chipewyan the increase in water level is greatest over the deep lake with 1.3 m over 30 years, followed by an increase of 1.1 m over both the shallow and intermediate lakes, the smallest increase of all the lakes (Figure 26).

The intermediate-depth lake has the smallest change in storage at both study sites because evaporation is highest over this lake, which serves to balance more of the incoming precipitation. At Fort McMurray current cumulative evaporation over 30 years adds up to 12.0 m over the shallow and the deep lakes, while the intermediate depth lake has a slightly larger evaporation
total of 12.2 m over the 30 years. At Fort Chipewyan, total cumulative evaporation over the shallow and deep lakes adds up to 10.8 m and 10.6 m, respectively, compared to 10.9 over the Fort Chipewyan intermediate-depth lake.

Figure 26: Cumulative change in water level (metres) by depth, current (1971 – 2000) and future (2041 – 2070) from the NARCCAP ensemble mean.

4.4.6.1.2 Variations by Climate Model

The choice of GCM_RCM pairings also influences the results. Figure 27 shows the water balance calculated from the three climate models separately: CRCM_CCSM, CRCM_CGCM3 and MM5I_CCSM. MyLake run with input data from the MM5I_CCSM model estimated slightly lower evaporation than the other two RCMs, for both Fort Chipewyan and Fort McMurray (Figure 27 A and B). However, MM5I_CCSM projects precipitation as higher than
the other two models, with a step jump in 1976 at Fort Chipewyan and Fort McMurray, and another step jump around 1980 at Fort McMurray (Figure 27 C and D). Because these are cumulative values, step jumps cause all the following values to be significantly higher. Unusually high precipitation or evaporation in a particularly wet or warm season causes the cumulative total to rise by more than in the average year, increasing the cumulative values of the variables for all subsequent years. This is seen for the MM5I_CCSM model at both study sites (Figure 27 E and F), where lower cumulative evaporation and higher cumulative precipitation causes the water level change to be much higher than for the other two models in the long run. This in turn increases the overall ensemble mean change in water level.

As described in Section 3.2.3., the results from each model in the study ensemble have been corrected for bias based on reanalysis data for the same area and time period. Prior to bias correction, however, each model had particular air temperature and precipitation biases. Mearns et al. (2012) show that the MM5I GCM has a summer cold bias around -2°C and the CRCM GCM a summer cold bias around -4°C in the Athabasca River region. For precipitation, most RCMs in the NARCCAP ensemble show wet biases in winter and dry biases in summer. In the Athabasca River region, the winter wet bias is larger in the MM5I model than the CRCM, with values about 20% and 10% larger than the observations, respectively. In the summer there are more models with dry biases, meaning they underestimate summer precipitation. This includes the MM5I model which projects about 10% less precipitation than observed. The CRCM model, however, is a little wetter than observations, with about 10% more precipitation than observed.

Another factor that sets apart the CRCM-driven RCMs from the MM5I-driven RCM is spectral nudging. Spectral nudging provides information from the driving GCM throughout the domain and vertical levels rather than for only the boundary and initial conditions as is the case
with non-nudged models (Mearns et al., 2012). This means the RCM results are more directly constrained by the nesting GCM. The nudged RCMs (CRCM and RSM) are proving to outperform the non-nudged NARCCAP ensemble models (Mearns et al., 2012). This indicates that the CRCM results are likely more reliable than the MM5I results in the project ensemble, prior to bias correction.

**Figure 27**: Cumulative precipitation, evaporation and change in water level in the current period, from each of the three NARCCAP RCMs used in the ensemble.

### 4.4.6.2 Future Cumulative Water Balance

The 30-year future cumulative water balances for the three lake depths at both study sites are similar to the current period. While cumulative precipitation and evaporation are both larger in the future at all of the study basins (blue and green lines in Figure 24), their increases are
proportional, resulting in precipitation exceeding evaporation again in the future period by a similar magnitude as in the current period (Figure 25). Therefore, a similar, but slightly larger, rise in water level is projected over 30 years in the future period as in the current period, for all study lakes. Patterns in cumulative change in storage due to lake depth are preserved in the future (Figure 26).

Compared to a water level rise of 1.1 m over 30 years in the current period, the water level of the shallow lake at Fort Chipewyan is projected to rise by 1.3 m over 30 years in the future period, an increase of 0.2 m, or 6.7 mm/yr (Table 12). The water level of the intermediate-depth lake at Fort Chipewyan increases from a gain of 1.1 m in the current period to a gain of 1.2 m in the future period, a change of 0.1 m over 30 years or 3.3 mm/yr. Climate change affects the deep lake the most, with an increase from a water level gain of 1.3 m in the current period at Fort Chipewyan to a 1.5 m gain in the future period, a change of 0.2 m or 6.7 mm/yr. The same pattern is seen at Fort McMurray – the increase in cumulative water level over 30 years is largest over the deep lake than over the shallower lakes – however the cumulative change in water level is larger at this southern study site. At Fort McMurray the change in shallow lake water level increases from a gain of 1.8 m over 30 years in the current period to a gain of 1.9 m in the future period. The water level of the intermediate-depth lake at Fort McMurray increases from a gain of 1.6 m in the current period to a gain of 1.7 m in the future period. The deep lake water level rise increases from a gain of 1.8 m in the current period to a gain of 2.0 m in the future, or an increase of 0.1 m over 30 years. Overall, the increases in water level expected cumulatively over 30 years range from 1.1 to 1.8 m in the current period, and 1.2 m to 2.0 m in the future period, for an increase attributable to climate change of 0.1 m to 0.2 m higher water levels in the future. This means that water levels in lakes and reservoirs in the Athabasca River region are expected
to be 9 to 16 cm higher after 30 years of accumulation in the future period compared to the current period.

4.5 Discussion

4.5.1 Climate Change Signal

Climate change in northern Alberta, Canada between the late-20th century (1971 – 2000) and the mid-21st century (2041 – 2070) is expected to have only a minor effect on the average water balance of lakes in the Athabasca River region. Based on current and future water balances modelled using an ensemble of RCM_GCMs run using the IPCC’s A2 emissions scenario (Nakicenovic & Swart, 2000), and the MyLake comprehensive lake model (Saloranta & Andersen, 2004), projected increases in ensemble mean average and cumulative precipitation are expected to match or slightly exceed projected increases in evaporation. The similarity of the increases in the competing precipitation and evaporation water balance variables means that 30-year cumulative changes in water levels of varying depths of natural and anthropogenic water storage are expected to remain relatively stable in the future.

Shifts in intra-annual seasonal water level patterns under future climate are larger in the modelled water balance results than changes to average annual and cumulative variables. These seasonal shifts vary in magnitude depending on location and lake depth. Future warmer air temperatures mean earlier breakup and later freeze-up of the ice cover for all lake depths, extending the open-water season and therefore increasing annual evaporation rates and lowering water levels. Fall evaporation in particular is shown to increase the most, especially for the deep lake. This increase in fall evaporation in a warmer climate is caused not only by the longer open-water season, but by cool fall air masses coinciding with deep water bodies that remain unfrozen later in the year due to heat stored at depth. The cool air over the warm water creates a higher vapour pressure difference than seen in the current period and drives high late season
evaporation (Prowse et al., 2012). This has an impact on water levels, drawing November levels of the deep lake down more than 200% in the future compared to current November water-level decreases. This decrease in water levels just before freeze-up could have effects on the aquatic habitat over the winter, and on the structure and strength of the ice cover itself, which is important for lakes and reservoirs used for recreation and hydropower (Gebre et al., 2013).

Despite a future increase in fall evaporation, the results show that the current pattern of water level recharge in the winter months (December to May), and water level drop in the warm summer months (June to November), will be exacerbated in the future. This means larger decreases in summer water storage in the basin, which coincides with climate change-driven reductions in streamflow in the basin due to reduction of the glacier compensation effect (Casassa et al., 2009; Demuth & Pietroniro, 2003). Although the perched basins modelled in this study are not affected by streamflow, a possible future transition of the low-flow season for the Athabasca River from winter to summer may cause water managers to build more offstream reservoir storage, further increasing the total amount of surface water storage in the region. Understanding the water balance of these new water storages is important to mitigate flooding and drying cycles and associated impacts on the surrounding landscape.

While in the future, fall water levels are expected to be impacted by increased evaporation, during the spring season the ensemble mean results show an increase in water added to lakes. Higher precipitation in the spring prior to breakup, when evaporation is zero, results in an increase in water levels and an increased risk of overtopping from snowmelt and rain-on-snow events (Rains, 2011). Differences in evaporation due to lake depth mean there is variation in the water balances seasonally. Right after breakup, evaporation output from the shallow lake rises quickly from zero compared to the other lake depths, balancing precipitation inputs earlier in the
year. This is because the shallow depth allows the lake temperature profile to heat up quickly, increasing energy available for evaporation. The shallow depth may also allow direct heating of the lake bottom, again increasing the energy available for evaporation. While MyLake does not model direct heating of the lake bottom in the sediment heat flux module, it adds any extra solar energy reaching the lake bottom to the temperature of the bottom layer of water, increasing evaporation estimates. Sediment heat flux itself was shown to have a negligible impact on the Mylake model results (see Appendix B). Spring flooding may therefore be more of a risk over deeper lakes where evaporation takes longer to balance precipitation in the spring.

4.5.2 Heat Storage at Depth

One reason that offline lake modelling is currently a necessary addition to regional climate model results is that the energy balance at the surface of a lake is controlled in part by the volume of water in a lake. If this energy balance is not modelled taking into account heat storage in the water volume, the resulting annual and intra-annual evaporation and ice cover patterns will be affected. The dates of ice cover freeze-up and breakup are important to the water balance of the lake because ice cover inhibits the release of latent heat, and therefore evaporation, from the lake (Duguay et al., 2003; Winter & Woo, 1990). Results show that fall freeze-up dates vary more with lake depth than spring breakup dates, but that breakup occurs earlier in the year at the warmer Fort McMurray study site. This demonstrates that breakup is controlled more strongly by radiative warming, which varies by latitude, than by differences in lake depth and morphometry. This finding is corroborated by testing in MyLake that found when the model was run using RCM_GCM climate data for Fort McMurray, but the latitude for Fort Chipewyan was set in the parameters of the model, evaporation from the shallower lakes took longer to rise above the rates of the intermediate to deep lakes, compared to the expected pattern. However, later in the year, the pattern of evaporation was unaffected. The fact that latitude affected the spring but not the
fall evaporation supports the concept that the spring surface energy balance of a lake is driven mainly by incoming solar radiation (insolation) whereas the fall energy balance is more strongly controlled by heat storage in the volume, for which deeper lakes have a greater capacity.

The reason that evaporation modelled by MyLake was highest overall for the intermediate-depth lakes is due to a balance between both heat storage at depth and high early season evaporation. Testing of various lake depths in MyLake showed peak evaporation for mid-depth lakes as they have enough volume to store energy during the warm summer season to be released as late-season evaporation, but not so much volume that they take too long to heat up and produce evaporation at the start of the open-water season. In many cases in the results, the shallow and deep lakes actually had more similar evaporation than the intermediate lakes, as they benefit more exclusively from one or the other of these phenomena, not both.

**4.5.3 Flooding and Drying**

Flooding can be both beneficial and detrimental to surface water storage in the Athabasca River region. While floods are often associated with damage to infrastructure and housing (Rahmstorf & Coumou, 2011), for the shallow perched basins in the PAD, flood cycles are necessary to sustain the ecosystem. Many ponds, wetlands, and channels in the delta are not hydrologically connected in an average year and require high precipitation and river ice jams to cause floods that recharge the landscape on a regular cycle (Peters et al., 2006b). Future increases in precipitation modelled in this study indicate that the flood cycles may be sustainable under future climate. However, warmer air temperatures and heat advected from increased rain-on-snow events are also likely to increase the incidence of thermal, as opposed to dynamic, breakup of the region’s rivers, which is less likely to cause the ice jam-induced flooding needed to recharge the perched basins in the PAD (Beltaos & Prowse, 2001).
Both flooding and drying could have severe consequences for the intermediate-depth lakes in this study representing EPLs that are planned to be used by the Oil Sands industry (Golder, 2011). In the short term EPLs will contain contaminated water, which will later be sequestered under a freshwater cap, depending on the ability of the lake to sustain meromixis (Golder, 2004a). Therefore, overflow from these lakes in the near- and mid-term would mean contamination of the surrounding environment. Drying out of the lake also poses an environmental risk, as exposure of the sequestered mature fine tailings to the air and the ecosystem could have a toxic effect. Changes in precipitation and evaporation patterns, even without a significant loss of water, could in themselves alter the temperature and salinity profile of the lake, causing turnover and removing confidence that the surface of an EPL is safe.

For deep reservoirs, not only can flooding pose a risk to local communities and infrastructure, but drying out would also pose a risk to industry and would defeat the purpose of their construction. The results of this study indicate that in the future, increased fall evaporation from longer open-water seasons will exacerbate low winter water levels, calling for implementation of industrial water withdrawal restrictions. The coincidence of future lower water levels in surface water storages and low-flow seasons and years for the Athabasca River means that careful management of these deep offstream reservoirs is important to sustain the water requirements of industry.

4.5.4 Moisture Surplus or Moisture Deficit?

Cumulative changes in water level of the study lakes remained positive after 30 years in both the current and future periods, indicating that lakes in the Athabasca River region are dominated by a moisture surplus regime. This means the difference between precipitation and evaporation, often used to characterize climate, is positive: $P - E > 0$. However, in the
literature, the Athabasca River region of northern Alberta is considered to have a moisture deficit, or $P - E < 0$ (Brown, 2010; Devito et al., 2012; Mitchell, 1991; Peters et al., 2006b; Winter & Woo, 1990). This suggests that the area is mildly arid and that water bodies without inflow from surface water or groundwater sources could not be sustained over the long term. Perched and anthropogenically isolated water bodies would therefore dry up if not maintained by wet years, extreme precipitation events, or controlled inflows (JDEL Associates Ltd., 2005; Mitchell, 1991). However, open-water evaporation modelled in this study specifically for surface water storages indicates a surplus of precipitation at both the Fort McMurray and Fort Chipewyan study sites in both the current and the future periods, with $P - E = 58 \text{ mm/yr}$ at Fort McMurray and $P - E = 39 \text{ mm/yr}$ at Fort Chipewyan in the current period. Since average annual precipitation from the NARCCAP ensemble is similar to the EC climate normal value (see Section 4.3.4) and similar to the precipitation values used in the literature, it is the difference in evaporation estimates that results in a negative, rather than positive, $P - E$ ratio.

Compared to average annual evaporation for Fort McMurray of 450 to 690 mm/yr from observations and models reported in the literature (see Section 2.4.2), the MyLake estimate of average annual evaporation at Fort McMurray is 402 mm/yr, and 359 mm/yr at Fort Chipewyan, on average across the three study lake depths. This means that the average annual evaporation modelled by MyLake is 1.4 times lower than the average reported in the literature. These lower MyLake values for evaporation are due to the method of calculation used in this study. The advantages of using MyLake rather than other standard methods such as Priestly-Taylor or Penman, are that the model takes into account heat storage at depth, aerodynamic processes at the lake surface, and the timing of ice cover formation. Increased heat storage in deeper lakes, and the inclusion of aerodynamic processes, causes higher evaporation estimates, but the
calculation of evaporation based on accurate ice cover on/off dates can greatly reduce annual evaporation estimates in a cold region climate such as the Athabasca River region.

4.5.5 Variability of Climate Models

All climate model ensembles includes a variety of biases and uncertainty (Christensen et al., 2007). Results presented here represent water balance estimates for the three-model ensemble mean of the CRCM_CGCM3, CRCM_CCSM, and MM5I_CCSM models run using the A2 SRES climate change scenario. Bias-correction was used to adjust each model for inherent differences between the direct model results and reanalysis data for the region. However, there is still a level of uncertainty associated with any model, which increases when an RCM is embedded in a GCM to dynamically downscale the results (Randall et al., 2007). The results would vary if a different, ideally larger, ensemble of models had been used for the input data to the water balances, or if a different downscaling method was used. Using RCM results from a different climate change scenario, such as another SRES scenario or a newer RCP scenario (Moss et al., 2010), would also yield variations on the results. The A2 scenario is one of the most pessimistic SRES scenarios with respect to GHG emissions (Nakicenovic & Swart, 2000) and was therefore chosen to estimate larger changes to variability in the water balance; if larger changes are anticipated and planned for, society can more easily adapt to smaller changes.

4.6 Conclusions

Climate models can be used to project future changes in climate, but without the integration of comprehensive lake modelling into RCMs and GCMs, differences in the latent heat component of the energy balance at the surface of small lakes, compared to land surfaces, is not properly accounted. The differences in latent heat, and therefore evaporation, affect water levels and can cause feedback back into the surrounding regional climate. Currently, coupled
RCM_GCMs incorporate one-way feedback from the global to the regional climate system, but the effect of small-scale variations in land surface types is not yet factored into model projections. The results of this study show that using the comprehensive lake model MyLake to model evaporation offline, in combination with RCM precipitation, is a good option to properly estimate the future water balances of surface water storage more than a few metres deep.

The accuracy of water balance calculations for small lakes is important in a climate such as the dry, interior, continental regime of the Athabasca River region, especially considering the intent of industry to build additional EPLs and reservoirs on the landscape (Ohlson et al., 2010; Westcott, 2007). In this climate, evaporation and precipitation are of similar magnitudes, and therefore even small changes in air temperature and precipitation patterns could shift water balances in the area from moisture deficit to moisture surplus regimes. The future changes to the water balance reported in this study are estimates of the average effect of climate change on water levels of lakes in the region. The effects of extreme 1-, 3- and 5-day climate events on the water balance are explored in Chapter 5. The height of freeboard sides required to isolate EPLs and reservoirs from the environment could be calculated from a large model ensemble, using a variety of emissions scenarios, to determine the largest envelope of water levels at the study sites in the future. Proper design of surface water storages using model ensembles will help ensure protection of infrastructure and the ecosystem from moisture surplus and deficit conditions.
4.7 References


CHAPTER 5: PROJECTED CHANGES IN EXTREME LAKE WATER LEVELS IN THE ATHABASCA RIVER REGION, ALBERTA CANADA

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ABSTRACT

In recent years the world has experienced an unprecedented number of extreme climate events. Water levels of surface water storages are affected by extreme evaporation and precipitation; overtopping or drying out of such lakes can pose risks to people, infrastructure and ecosystems. This research evaluates the frequency and magnitude of extreme changes in water level of lakes of varying depths located at Fort McMurray, AB and Fort Chipewyan, AB in the Athabasca River region of northern Alberta, Canada. The lake water balance is modelled with the MyLake comprehensive lake model, using input data from an ensemble of NARCCAP Regional Climate Models (RCMs), in the late-20\textsuperscript{th} century (1971 – 2000) and the mid-21\textsuperscript{st} century (2041 – 2070). Extremes are defined as 1-, 3- and 5-day precipitation, evaporation and “change in water level” events with sufficient magnitude (or lack of magnitude) to cross thresholds defined as the 90\textsuperscript{th} and 10\textsuperscript{th} percentiles of the corresponding distribution. Results show that the extremes extracted from the Generalized Extreme Value (GEV) distributions for each scenario are increasing in frequency (Peaks-Over-Threshold) and magnitude (Annual Maxima and Minima) in the future. This indicates increased variability of water levels for lakes in the Athabasca River region under a future warmer climate, as described by the IPCC’s A2 climate scenario.

KEYWORDS
Extremes; water balance; lakes; water level; climate change, Athabasca River

5.1 Introduction

In recent years, the world has experienced an unprecedented number of extreme climate events, leading to impacts such as floods, droughts and heat waves (Coumou \& Rahmstorf, 2012). The increase in extreme events has been attributed to an intensification of the hydrologic cycle caused by changes in global climate (Huntington, 2006). Increases in mean global air temperature cause spatial and temporal re-distribution of precipitation, increases in intense precipitation events, and increases in surface energy for evaporation, all of which contribute to
more frequent extreme wet and dry conditions around the world (Meehl et al., 2007). Extreme events, especially of unexpected magnitudes and frequencies, can have dramatic consequences on society and the biosphere, such as human suffering, costly damage to housing and infrastructure, and positive or negative ecological changes in natural systems (Klein Tank & Zwiers, 2009; Rahmstorf & Coumou, 2011; Randall et al., 2007).

At local and regional scales, climate events of extremely large magnitudes or durations can alter the volume of water stored on the surface of the earth at any given time, as noted by Gibson et al. (2006) for large lakes in this region. Water in lakes and ponds is important for both ecosystem services and anthropogenic uses. Stored water serves ecosystems by providing drinking water, supporting the growth of vegetation, and providing habitat for a variety of animals and their predators (Mitchell, 1991). Humans also use stored water for a variety of purposes, including municipal and industrial water supply (Ohlson et al., 2010), reservoirs for flood control (Jones, 2011), hydropower (Gebre, 2014), landscape reclamation (Westcott, 2007), irrigation, and recreation (Schertzer & Taylor, 2009). Reliable estimates of expected fluctuations in water levels is necessary to avoid impacts from overtopping or drying out of surface water storages, and for the development of climate change adaptation and mitigation strategies (IPCC, 2014; Klein Tank & Zwiers, 2009; Rahmstorf & Coumou, 2011).

By definition, extreme – or rare – climate events are those whose properties place them far into the tails of the normal reference distribution of the variable for a particular place and time period (Klein Tank & Zwiers, 2009). Extreme events are usually characterized as those of sufficient magnitude (lack of magnitude) to cross an analyst-defined threshold near the upper (lower) ends of the range of expected values for the variable (IPCC, 2012; Wagner, 1996). In the past, the assumption that climate is stationary meant that analysts could consider the mean,
variance and extremes of climatic variables stable over time (Klein Tank & Zwiers, 2009). This allowed for the estimation of expected magnitudes and frequencies of climate extremes from the historical record (Hegerl et al., 2011; Klein Tank & Zwiers, 2009). Products developed from the historical climate record have been used for a variety of public health and safety purposes over the years, such as using intensity-duration-frequency (IDF) curves to predict rainfall inputs for urban drainage system design (Madsen et al., 2009), or to determine filling times for End Pit Lakes based on streamflow and precipitation rates (Westcott, 2007). It is now generally accepted that climate change has caused, or is causing, a shift to a non-stationary climate where average and extreme conditions are changing over time (IPCC, 2014). To responsibly plan for the construction and maintenance of infrastructure and water supplies in the face of a more variable climate, future frequencies and magnitudes of extreme climate events must be estimated. Projections of future climate using global and regional climate models and statistical modelling can be used to estimate never-before-seen magnitudes and frequencies of extreme climate (Wagner, 1996).

The effects of extreme climate events on water levels are particularly dramatic in regions with climates that are already sensitive to weather extremes, and that contain a large amount of surface water storage. Climate extremes have larger effects on interior continental regions in the mid-latitudes since inland areas are dominated by small- and meso-scale convective cells that produce intense, short-duration precipitation events (Raddatz & Hanesiak, 2008; Shook & Pomeroy, 2012). In the continental Athabasca River region of the lee of the Rocky Mountain Cordillera, Alberta, Canada, this sensitivity is exacerbated by the already variable and drought-prone climate. At the same time, the amount of water held on the surface will continue to increase due to both industrial demands for clean water (Ohlson et al., 2010) and requirements.
for storage of process-affected water (BGC Engineering Inc., 2010). Construction of anthropogenic surface water storage will complement the already abundant surface water of the Boreal forest landscape.

Water levels of a 1st-order lake basin can be estimated using a simplified water balance calculation, since the water balance of such basins is predominantly controlled by precipitation inputs and evaporation outputs alone (Brown, 2010). There are several types of 1st-order surface water storage basins in the Athabasca River region, including perched lakes in the Peace-Athabasca Delta (PAD) and the reservoirs expected to be built to contain pre- and post-process water for industry. Without the stabilizing effect of streamflow, runoff or groundwater flows in and out of the lakes, extreme changes in precipitation and evaporation have a dominant control on the lake water levels. Large inputs or outputs over one, or several, days can cause step jumps in the storage volume of the lakes. This research aims to evaluate the effects of projected future changes in the distributions of precipitation and evaporation events on the water levels of surface water storages located in a climate sensitive to climate extremes. To this end, extreme changes to the water balance of theoretical basins representing shallow, intermediate-depth and deep lakes in the mid-latitude, interior continental hydroclimatic regime of the Athabasca River region are analyzed for the current (1971 – 2000) and future (2041 – 2070) periods.

5.2 Study Site

The Athabasca River watershed is located in the interior plains of northern Alberta, Canada, east of the Rocky Mountains, part of the Western Boreal Forest of North America (Brown, 2010). The region is also just north of the driest part of the Canadian Prairies, the Palliser Triangle (Dale-Burnett, 2012). The Athabasca River flows from its headwaters in the Columbia Icefields of the Rocky Mountains, northeast into the interior plains, past the town of
Fort McMurray, AB, and through the Peace-Athabasca Delta (PAD) before terminating in Lake Athabasca near the town of Fort Chipewyan, AB. The study region (the “Athabasca River region”) is the downstream, northern portion of the watershed along the Lower Athabasca River between Fort McMurray and Fort Chipewyan (see Figures 1 and 2 in Chapter 2).

The Athabasca River region has a highly variable climate, with common occurrences of both intense precipitation and drought conditions. A large portion of the annual precipitation falls in the summer, with peak precipitation rates in July (Environment Canada, 2013). Rain in the inland, continental region is largely delivered by small scale convective cells as opposed to regional scale frontal systems that dominate on the coastal side of the Rocky Mountains (Raddatz & Hanesiak, 2008). It is a sub-humid climate where average evaporation generally exceeds average precipitation (Brown, 2010; Devito et al., 2005; Mitchell, 1991b; Winter & Woo, 1990). The climate near Fort McMurray (56.72°N, 111.37°W) is marginally warmer and wetter than that of the 200 km further north Fort Chipewyan, AB (58.77°N, 111.13°W) (see Section 4.2). The region experiences large variation in precipitation year to year, and the coupling of extreme evapotranspiration with low precipitation can further exacerbate the moisture deficit in the area (Devito et al., 2005). This high hydro-climatic variability makes the system extremely susceptible to changes in precipitation and air temperature regimes (Brown, 2010).

<table>
<thead>
<tr>
<th>Study Basin</th>
<th>Depth</th>
<th>Surface Area</th>
<th>Represents</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shallow</td>
<td>1.5 m</td>
<td>20 km²</td>
<td>PAD perched basins</td>
<td>Fort Chipewyan, AB</td>
</tr>
<tr>
<td>Intermediate</td>
<td>28.5 m</td>
<td>1 km²</td>
<td>End Pit Lakes</td>
<td>Fort McMurray, AB</td>
</tr>
<tr>
<td>Deep</td>
<td>76.5 m</td>
<td>30 km²</td>
<td>Off-stream industrial storage</td>
<td>Fort McMurray, AB</td>
</tr>
</tbody>
</table>

Table 13: The theoretical study basin sizes, based on similar existing or proposed lakes in the Athabasca River region.
Widespread surface water storage in the Athabasca region comes in a broad variety of depths and sizes of natural and anthropogenically built lakes and wetlands. The following three hypothetical study basins (see Table 13) represent real and proposed lakes in the Athabasca River region near the towns of Fort McMurray, AB (56.72°N, 111.37°W) and Fort Chipewyan, AB (58.77°N, 111.13°W). The three basins of different depths and morphologies are used to investigate the range of possible effects of extreme precipitation and evaporation on natural and anthropogenic surface water storage.

The first study basin (“Shallow”) represents natural surface water storage found in the Peace-Athabasca Delta (PAD) near the community of Fort Chipewyan, AB in the northern part of the Athabasca River region. Along with the three large lakes, the 6000 km² area of the PAD includes > 1000 perched (elevated) basins of low relief, most of which are less than 1.5 m deep (Peters et al., 2006a). These perched basins are not hydrologically connected in an average year, and rely on floods caused by high precipitation events in combination with river ice jams to replenish their wetlands (Prowse & Conly, 1998). Particular snow and ice pack conditions and breakup and runoff types are also required for the flood conditions to be met. If climate change causes a reduction of winter precipitation, or causes high temperatures that prevent the formation of river ice or inhibit dynamic breakup, the return interval of these ice-jam induced floods may be reduced, with negative impacts to the entire delta ecosystem (Prowse & Conly, 1998). Changes to the magnitude and frequency of extreme events can also impact the ecology of the vulnerable delta ecosystem (Cox & Campbell, 1997). In 1982, the PAD was recognized as a wetland of international importance by the RAMSAR convention (Peters et al., 2006a), to help protect the wetland ecosystem and the large variety of species that depend on it. Many studies have been undertaken to understand the sensitive ecology and hydrology of the region in
connection with the delta’s flood cycles (see Beltaos et al., 2006; Pietroniro et al., 2006; Prowse & Conly, 1998; Prowse & Beltaos, 2002; Prowse et al., 2006; Toth et al., 2006; Wolfe et al., 2005). This research is continued here with a focus on the effects of extreme climate events on water levels of perched basins in the PAD.

For the “Intermediate-depth” study basin, both extreme wetting and extreme drying can have potentially disastrous consequences. Here the intermediate-depth basin (28.5 m deep) represents End Pit Lakes (EPLs) proposed to be built in the oil sands region of the Athabasca River catchment (Golder, 2006a; Westcott, 2007). EPLs will be built by depositing Mature Fine Tailings (MFTs) as a bottom layer, followed by filling the rest of the pit with clean freshwater to create a lake (Golder, 2011). At least initially, efforts need to be made to keep the lake from mixing and from connecting hydrologically to the surrounding water, to avoid contamination of the surrounding environment with the MFTs. The hydroclines and residence time of the water column are intended to then allow the consolidation, assimilation and degradation of the residual compounds enough that over time the lake can be reconnected to the surrounding environment (Golder, 2011). As such, EPLs will be used as part of the closure and reclamation strategy of the oil mining operations (Westcott & Watson, 2007). The reduction of water levels can also be harmful for EPLs. Since the water in these holding ponds is designed to seal off the MFTs from the ecosystem (Golder, 2011), if the water cap were to dry out the result would be the exposure of the tailings to the surrounding air and land surface, with contamination or chemical reactions as a consequence. Extreme evaporation events, caused in part by high temperatures, could be one of the causes of such a drying event.

Deep water storage represented by the third (“Deep”) study basin (76.5 m deep) could also be negatively impacted by both extreme precipitation and extreme evaporation. The purpose of
proposed new deep off-stream storage is to buffer for seasonal changes in streamflow in the Athabasca River. Although flows are high, variability is also high, and future conditions where stabilizing inputs from glacier runoff are gone or at least significantly past their historical peak (Demuth & Pietroniro, 2003), and where industrial demands for large withdrawals are high (Ohlson et al., 2010), will mean significant stress on the resources of the river. If extreme evaporation were to deplete the water levels of off-stream storage built specifically to mitigate the stress of withdrawals from the river, it would defeat the purpose of these proposed artificial lakes. Rising water levels would also pose a threat; these new bodies of water should be managed to balance the need for space for precipitation extremes and flood waters, and the desire to hold the maximum volume of water (van den Honert & McAneney, 2011). To avoid damage to co-located industrial infrastructure and housing developments, design requirements should take into account current and future expected frequencies and magnitudes of extreme events (Klein Tank & Zwiers, 2009).

5.3 Data

Climate model data are used to calculate the water balance. Six climate variables are required, five of which are used to model evaporation (mm/dy) using the MyLake model: air temperature (maximum and minimum daily temperature averaged to mean daily; °C/dy), air pressure (hPa), specific humidity (converted to relative humidity using pressure, air temperature and partial pressure of water vapour (Nievinski, 2009); %), cloud cover (fraction), and wind speed (calculated as the hypotenuse of the vertical and horizontal u and v wind variables; m/s). Precipitation (mm/dy) is used directly in the water balance. Time series for the six variables are extracted from the results of an ensemble of three Regional Climate Models forced by Global Climate Models (RCM_GCMs), available through the North American Regional Climate
Change Assessment Program (NARCCAP): CRCM_CCSM, CRCM_CGCM3 and MM5I_CCSM (see Mearns et al., 2012 and Section 2.3.7). The data are available over the time periods 1971 – 2000 (“Current”) and 2041 – 2070 (“Future”) at a 3-hourly time step. Most results are calculated for each climate model separately, and rolled up to the ensemble mean only for reporting and plotting in the Tables and Figures in Section 5.5.

The Intergovernmental Panel on Climate Change (IPCC)’s “A2” future climate scenario was used to run the RCM_GCMs (Mearns et al., 2012; Nakicenovic & Swart, 2000). The A2 scenario is a narrative storyline describing future life on earth that includes less of a reduction in GHG emissions compared to the A1 and B1 scenarios, a continuously increasing population that remains heterogeneous, and a focus on regional and local environmental protection rather than global convergence. The A2 scenario is most like the status-quo, and the most pessimistic with regards to GHG levels, with the highest population and with per capita economic growth and technological change changing slower than in the other scenarios (Nakicenovic & Swart, 2000). See Chapter 2 and 3 for more detail on the NARCCAP model ensemble and the time periods chosen for this research.

Air temperature and precipitation from the NARCCAP models are available at a 10 km\(^2\) resolution from the Pacific Climate Impacts Consortium (PCIC). PCIC produced the 10 km\(^2\) datasets by statistically downscaling the 50 km\(^2\) RCM_GCM NARCCAP data using two techniques: Bias Correction Spatial Disaggregation (BCSD) (Werner, 2011) and Bias Correction Climate Imprint (BCCI) (Hunter & Meentemeyer, 2005; see details in Section 2.3.5). The 10 km\(^2\) scale of the BCCI and BCSD datasets is more appropriate for capturing extreme climate events whose small size may mean that they fall within the gridcells of larger resolution models (Mladjic et al., 2011; Randall et al., 2007). Air temperature and precipitation are extracted from
individual 10 km$^2$ gridcells of the BCCI and BCSD datasets for each of the three models. To represent extreme moisture surplus conditions, the gridcell from each model (not from the ensemble mean) with the highest average daily precipitation over 30 years in the current period is selected (Max Precip), and to represent extreme moisture deficit conditions, the gridcell with the highest average daily air temperature (a proxy for high evaporation) over the 30 years is selected (Max Temp). This is repeated for both the Fort McMurray and Fort Chipewyan study areas, and the same gridpoints are used for the future period (see Table 14 for the list of gridcells chosen for each model). The remaining climate variables (air pressure, wind, relative humidity and cloud cover) are taken from the closest 50 km$^2$ gridcell for each model from the Bias-Corrected RCM_GCM dataset used in Chapter 4.

Values are missing from the CRCM_CCSM model for November 30 to December 31, 1999, November 30 to December 31, 2069, and for September 29, 2045 to December 31, 2046. For these days all climate variables were copied from a year prior (1998, 2068, and 2043-2044, respectively) to fill in the gaps. Furthermore, precipitation and air temperature data from the BCCI and BCSD datasets is not available for the year 2000 or 2070 for all models, and December 1999 was missing from the MM5I_CCSM and CRCM_CCSM models. Therefore, the final year of data (2070) is replaced for all variables in the BCCI and BCSD downscaled datasets by re-using data for December 1, 1998 (2068) – November 30, 1999 (2069).

Unfortunately, data corruption issues with the final datasets precluded further analysis of the data after the final results presented here were generated. The data have been fully explored to the degree initially planned, but additional information to explain some results in section 5.5.7 was not possible. The areas where further analysis would be helpful are noted in the results.
5.4 Methods: Analysis of Extreme Wetting and Drying Events

5.4.1 Calculating the Water Balance

This study uses a variety of methods to assess the frequencies and magnitudes of extreme climate events impacting lake water balances in the Athabasca River region. First, the current and future water balance at the regional and local scales is calculated for the 1st-order study basins (see Chapter 4). Changes over time to the volume of water stored in the lakes is represented by the “change in the water level” variable (ΔWL), calculated by subtracting evaporation (E) outputs from precipitation (P) inputs on a daily basis, for each of the three study basin depths:

\[ P - E = \Delta WL \]  

[50]

Evaporation is estimated using the latent heat leaving the surface of the study lakes, and is dependent on climate and lake depth. The latent heat is modelled for the study lakes using the MyLake comprehensive lake temperature model (see Chapter 4; Saloranta & Andersen, 2004), driven by input climate data from the 10 km² Max Precip and Max Temp extreme gridpoints from the BCCI and BCSD datasets. Precipitation is extracted from the same BCCI and BCSD gridcells for use in the water balance calculation. Other inputs and outputs of the study basins are not considered in the water balance due to the temporal and spatial mesoscale of the analysis, and since the lakes are considered to be 1st-order basins not connected to streamflow. All variables are measured in units of millimeters per day (mm/dy).

Three methods are used to evaluate extreme events affecting the water balance of the study lakes 1) calculation of the Peaks-Over-Threshold (POT) index of extreme events; 2) estimation of the generalized extreme value (GEV) distributions of both high and low extremes; and 3) a comparison of the magnitudes of the Annual Maxima (AM) and Annual Minima (AMin) and overall Maximum and Minimum of extreme events, for each study site in the current and future
periods. These methods are applied to the daily values of the evaporation, precipitation and “change in water level” variables, as well as to multi-day cumulative sums calculated within 3- and 5-day moving windows within each year. This results in 363 three-day sums and 361 five-day sums per year.

5.4.2 Defining Extremes

The 90th and 10th percentiles of the respective distributions of climate variables in the current period (1971 – 2000) are used as the high and low thresholds to define 1-, 3- and 5-day extreme climate events (e.g., Klein Tank & Zwiers, 2009; Rogers & Armbruster, 1990; and see Section 3.6 on the use of thresholds). “High extreme” events are as those of sufficient magnitude to exceed the 90th percentile of the distribution for the variable at each study basin. “Low extreme” events are defined as those whose magnitude is below the 10th percentile value for each distribution. The percentiles and resulting extreme datasets are calculated for each set of model input data separately, not using the ensemble mean. The percentiles are calculated using all days in the 30-year current period, including days when the value of the variable is zero, and the current period value applied to the future period as well. Extremes 3- and 5-day events are defined using the 90th and 10th percentiles of the multi-day distributions themselves.

While the high extremes are calculated for all three variables, the low extremes for precipitation and evaporation have zero or near-zero magnitudes and therefore are not generally of interest. Low extremes of precipitation and evaporation are only meaningful if they contribute to an extreme of the “change in water level” variable on a particular day; for example, extremely low precipitation is of interest on a high evaporation day, as average or high precipitation on the same day would moderate the change in water level. Therefore, the low extremes of evaporation and precipitation are not calculated on their own, but instead are accounted for in the extreme
values of the “change in water level” variable. In this way, the focus of the analysis is on the distribution of extreme changes in water level, which represents changes in the volume of water stored in the basin (Gibson et al., 2006). High extremes of change in water level address the risk of lakes overtopping, while the low extremes are important to understand the risk of lakes losing water or drying out.

5.4.3 Peaks-Over-Threshold (POT)

The Peaks-Over-Threshold (POT) method is a descriptive index used to evaluate the number of times in a specified period that an event exceeds the analyst-defined threshold (Katz et al., 2002). Here the POT index is calculated annually by counting the 1-, 3- and 5-day cumulative events exceeding (below) the 90th (10th) percentile threshold values of the respective distributions. All calculations are conducted using the daily data and percentile threshold for each climate model in the ensemble separately, and results are later averaged to the ensemble mean. The current period threshold value is then used to calculate the POT from the future period distribution, to evaluate projected changes extreme events in the 21st century compared to in the 20th century (Hegerl et al., 2011). The high POT counts are calculated for all three variables (evaporation, precipitation, and “change in water level”), and the low POT counts are calculated only for the “change in water level” variable.

5.4.4 Extreme Value Distributions

While descriptive indices are a robust, standard way to evaluate climate extremes, the occurrence of very rare events that lie far in the tails of the distribution may not be able to be evaluated using indices alone. This is particularly true for magnitudes and frequencies not previously seen in the historical record. Statistical modelling is required when the objective is to predict never-before-seen extreme magnitudes that may occur in a future non-stationary climate (Klein Tank & Zwiers, 2009). To estimate the full range of possible magnitudes and frequencies
of a climate variable, the statistical probability distribution is estimated based on assumptions about the source population of the variable. The probability distribution estimates the likelihood of a particular occurrence having a specific value or falling within a specific range of values (Wagner, 1996).

Here the probability distribution for the “change in water level” variable is evaluated for both the BCCI and BCSD Max Precip and Max Temp gridpoints in the current and future periods. First, the values of the Peaks-Over-Threshold (POT), or the exceedances of the 90th and 10th percentiles, are extracted to create the “partial duration series” of the distribution (Katz et al., 2002). Then the generalized extreme value (GEV) distribution is fitted, using goodness-of-fit criteria on the data to choose which of three distributions are appropriate in each case – Type I (Gumbel), Type II (Frechet) or Type III (Weibull) (Mathworks Inc., 2015). Next, the cumulative distribution function (CDF) is evaluated from the GEV distribution to model all possible values of the largest or smallest extreme values of the climate variable. The Maximum Likelihood (ML) estimates of the location (μ), scale (σ) and shape (k) parameters are calculated for the distributions and used to plot the CDF for each dataset (Katz et al., 2002). The CDF distributions are used to compute summary statistics and the parameters are used to describe differences between the distributions; the μ shifts the distribution along the real line, while σ expands or contracts the distribution (Mathworks Inc., 2015).

5.4.5 **Annual Maxima (AM) and Annual Minima (AMin)**

The Annual Maxima (AM), or Block Maxima, method is a descriptive index used to describe extreme events in a time series (Klein Tank & Zwiers, 2009). The maximum values within each defined period of time, or “block” (often a year or season), are extracted and used to evaluate the most extreme magnitudes within and between the periods. It is a simpler way to
compare extremes year to year or between datasets than using distributions, as only one value per period is returned (Mladjic et al., 2011). The AM method used here considers the magnitude of the annual maximum (AM) and annual minimum value (AMin) in each year. The values of the largest AM and the smallest AMin of the “change in water level” variable are then reported for each dataset, to compare extremes of the water balance between the Max Precip and Max Temp gridpoints from the BCCI and BCSD datasets, in the current and future periods, for the shallow, intermediate, and deep lakes at both Fort Chipewyan and Fort McMurray. The magnitudes are selected from individual models in the ensemble, rather than using the ensemble mean value, to locate the highest possible modelled values, rather than a tempered mean value.

5.5 Results
5.5.1 Selection of Extreme Gridpoints
The gridpoints with maximum precipitation (Max Precip) and maximum air temperature (Max Temp), selected from each model to represent the highest precipitation and highest evaporation cases, are the same for all three models (CRCM_CCSM, CRCM_CGCM3 and MM5I_CCSM) and both downscaling techniques (BCCI and BCSD) – they vary only by study site (see Table 14). The 50 km² RCM_GCM gridcells used for the remaining climate variables, and the NARR gridcells used to bias-correct them, do vary based on the model, due to different projections used by the different NARCCAP models. All results reported below are averaged to the three-model ensemble mean after calculations of occurrences and magnitudes of extremes are extracted from each model dataset, separately. Overall average daily values for the current and future periods are an average of all days in the 30-year periods.
5.5.2 High Extremes – Values of the 90th Percentiles

In the current period, the 90th percentile of daily evaporation averaged for the ensemble mean over the 30-year period is approximately 2 mm/dy for both the Max Precip and Max Temp extreme gridcells (Table 15). This value is consistent for all three lake depths at both Fort McMurray and Fort Chipewyan. For precipitation, the value of the average ensemble mean 90th percentile varies more between study basins than for evaporation, ranging from a maximum of 3.9 mm/dy at the Fort McMurray Max Precip gridcell to a minimum of 3.0 mm/dy at the Fort Chipewyan Max Temp gridcell. As the “change in water level” variable is calculated from precipitation and evaporation, the value of its 90th percentile follows the same pattern as the more variable precipitation component, with a maximum 90th percentile of 3.4 mm/dy change in water level at the Fort McMurray Max Precip gridcell, and a minimum of 2.3 mm/dy change in water level at the Fort Chipewyan Max Temp gridcell. The values of the 90th percentiles in the current period are used as the “high extreme” thresholds to calculate the POT for each study basin, reported in the next section.
<table>
<thead>
<tr>
<th></th>
<th>Evaporation</th>
<th>Precipitation</th>
<th>Change in Water Level</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Shallow</td>
<td>Intermediate</td>
<td>Deep</td>
</tr>
<tr>
<td>Max Precip</td>
<td>2.1</td>
<td>2.1</td>
<td>2.1</td>
</tr>
<tr>
<td>Max Temp</td>
<td>2.2</td>
<td>2.1</td>
<td>2.1</td>
</tr>
<tr>
<td>Max Precip</td>
<td>2.1</td>
<td>2.0</td>
<td>2.0</td>
</tr>
<tr>
<td>Max Temp</td>
<td>2.2</td>
<td>2.1</td>
<td>2.0</td>
</tr>
<tr>
<td>Max Precip</td>
<td>2.0</td>
<td>2.0</td>
<td>2.0</td>
</tr>
<tr>
<td>Max Temp</td>
<td>2.2</td>
<td>2.2</td>
<td>2.0</td>
</tr>
<tr>
<td>Max Precip</td>
<td>2.1</td>
<td>2.1</td>
<td>2.1</td>
</tr>
<tr>
<td>Max Temp</td>
<td>2.2</td>
<td>2.2</td>
<td>2.0</td>
</tr>
<tr>
<td>Max Precip</td>
<td>2.0</td>
<td>2.0</td>
<td>2.0</td>
</tr>
<tr>
<td>Max Temp</td>
<td>2.2</td>
<td>2.2</td>
<td>2.0</td>
</tr>
</tbody>
</table>

Table 15: Values of the 90\textsuperscript{th} percentile of daily evaporation, precipitation, and change in water level in the current period (1971 - 2000) for the Max Precip and Max Temp gridcells.

The magnitudes of high extreme 3-day (Table 16) and 5-day (Table 17) precipitation and evaporation events are proportionately higher than the 1-day extremes. For evaporation, the overall average ensemble-mean value of the 90\textsuperscript{th} percentile ranges from 5.7 mm to 6.4 mm over 3 days, and from 9.4 mm to 10.7 mm over 5 days, compared to 2.0 mm for daily evaporation as described above. For precipitation, the average 90\textsuperscript{th} percentile for 3-day events ranges from 7.7 mm to 12.0 mm, and for 5-day events it ranges from 12.1 mm to 19.0 mm. Finally, for the change in water level, the overall average 3-day 90\textsuperscript{th} percentile values range from 6.0 mm to 9.4 mm, and the 5-day values range from 8.6 mm to 14.5 mm. For all three variables, when the value of the 90\textsuperscript{th} percentile for the 3- and 5-day distributions are divided by the number of days included in each sum, the results are of a similar magnitude to the 1-day values.
### Table 16: Value of the 90th percentile for the distribution of 3-day moving sums (millimetres over 3 days).

<table>
<thead>
<tr>
<th>90th Percentile, 3-Day Sum (mm)</th>
<th>Fort McMurray</th>
<th>Fort Chipewyan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BCCI</td>
<td>BCSD</td>
</tr>
<tr>
<td></td>
<td>MaxPr MaxT</td>
<td>MaxPr MaxT</td>
</tr>
<tr>
<td>Evaporation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>6.2 6.4</td>
<td>6.2 6.4</td>
</tr>
<tr>
<td>Intermediate</td>
<td>6.0 6.2</td>
<td>6.1 5.9</td>
</tr>
<tr>
<td>Deep</td>
<td>5.7 6.1</td>
<td>6.0 5.8</td>
</tr>
<tr>
<td>Precipitation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>All Depths</td>
<td>11.1 9.4</td>
<td>8.2 7.7</td>
</tr>
<tr>
<td>Change in Water Level</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>8.5 6.9</td>
<td>6.2 5.8</td>
</tr>
<tr>
<td>Intermediate</td>
<td>8.6 7.0</td>
<td>6.3 5.8</td>
</tr>
<tr>
<td>Deep</td>
<td>8.9 7.0</td>
<td>6.3 5.8</td>
</tr>
</tbody>
</table>

### Table 17: Value of the 90th percentile for the distribution of 5-day moving sums (millimetres over 5 days).

<table>
<thead>
<tr>
<th>90th Percentile, 5-Day Sum (mm)</th>
<th>Fort McMurray</th>
<th>Fort Chipewyan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BCCI</td>
<td>BCSD</td>
</tr>
<tr>
<td></td>
<td>MaxPr MaxT</td>
<td>MaxPr MaxT</td>
</tr>
<tr>
<td>Evaporation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>10.3 10.5</td>
<td>10.7 10.3</td>
</tr>
<tr>
<td>Intermediate</td>
<td>9.9 10.1</td>
<td>10.1 9.8</td>
</tr>
<tr>
<td>Deep</td>
<td>9.4 10.1</td>
<td>9.9 9.7</td>
</tr>
<tr>
<td>Precipitation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>All Depths</td>
<td>17.6 14.8</td>
<td>12.9 12.1</td>
</tr>
<tr>
<td>Change in Water Level</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>12.9 10.3</td>
<td>9.3 8.6</td>
</tr>
<tr>
<td>Intermediate</td>
<td>13.2 10.3</td>
<td>9.4 8.7</td>
</tr>
<tr>
<td>Deep</td>
<td>13.4 10.4</td>
<td>9.4 8.7</td>
</tr>
</tbody>
</table>

#### 5.5.3 Low Extremes – Values of the 10th Percentile

The 10th percentile threshold for the change in water level variable is negative in all cases, indicating a decrease in water level in all cases of “low extremes” (Table 18). In the current period, the value of the 10th percentile ranges from -1.3 mm/dy to -1.6 mm/dy for all study basins, with the Max Temp gridcell at Fort McMurray displaying the largest drawdown value. Both the largest and smallest values of the 10th percentile of decrease in water level are for the Fort McMurray study site, indicating a larger range in local climate at this more southern region than further north at Fort Chipewyan. This larger variation is also true for the high extremes in
water level, described above. As the low extremes of the precipitation and evaporation variables have magnitudes of zero or near-zero, they are not evaluated separately. Extremes created by high evaporation and low precipitation days, or vice versa, are instead represented by the high and low change in water level extremes.

<table>
<thead>
<tr>
<th>Current Period 10th percentile (mm/dy)</th>
<th>Fort McMurray</th>
<th>Fort Chipewyan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Max Precip</td>
<td>Max Temp</td>
</tr>
<tr>
<td></td>
<td>BCCI BCSD</td>
<td>BCCI BCSD</td>
</tr>
<tr>
<td>Change in Water Level</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>-1.5 -1.4</td>
<td>-1.6 -1.6</td>
</tr>
<tr>
<td>Intermediate</td>
<td>-1.4 -1.4</td>
<td>-1.6 -1.6</td>
</tr>
<tr>
<td>Deep</td>
<td>-1.3 -1.3</td>
<td>-1.6 -1.6</td>
</tr>
</tbody>
</table>

Table 18: The values of the 10th percentile of the change in water level variable for the study lakes at Fort McMurray and Fort Chipewyan in the current period (1971 – 2000).

The average 10th percentile values of 3- and 5-day weather events are again proportionally larger in magnitude than for the 1-day events, and all consist of negative changes in water level, or draw-downs of the lake levels. The 10th percentile of 3-day change in water level events ranges from -2.8 mm to -3.8 mm over three days (Table 19), and the 10th percentile of 5-day change in water level events ranges from -3.6 mm to -5.0 mm over 5 days (Table 20). Variation is small between datasets, with slightly larger magnitudes of change in water level 3- and 5-day events over the shallow basins and at the Fort Chipewyan site.

<table>
<thead>
<tr>
<th>10th Percentile, 3-Day Sum</th>
<th>Fort McMurray</th>
<th>Fort Chipewyan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BCCI BCSD</td>
<td>BCCI BCSD</td>
</tr>
<tr>
<td></td>
<td>MaxPr MaxT</td>
<td>MaxPr MaxT</td>
</tr>
<tr>
<td>Change in Water Level</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>-3.2 -3.8</td>
<td>-3.1 -3.6</td>
</tr>
<tr>
<td>Intermediate</td>
<td>-3.0 -3.6</td>
<td>-3.0 -3.6</td>
</tr>
<tr>
<td>Deep</td>
<td>-2.8 -3.6</td>
<td>-2.8 -3.6</td>
</tr>
</tbody>
</table>

Table 19: Value of the 10th percentile for the distribution of 3-day moving sums (millimetres over 3 days).
### 10th Percentile, 5-Day Sum

<table>
<thead>
<tr>
<th></th>
<th>Fort McMurray</th>
<th></th>
<th>Fort Chipewyan</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BCCI</td>
<td>BCSD</td>
<td>BCCI</td>
<td>BCSD</td>
</tr>
<tr>
<td>MaxPr</td>
<td>MaxT</td>
<td>MaxPr</td>
<td>MaxT</td>
<td>MaxPr</td>
</tr>
<tr>
<td>Change in Water Level</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>-4.1</td>
<td>-5.2</td>
<td>-4.0</td>
<td>-5.0</td>
</tr>
<tr>
<td>Intermediate</td>
<td>-3.9</td>
<td>-5.0</td>
<td>-3.8</td>
<td>-5.0</td>
</tr>
<tr>
<td>Deep</td>
<td>-3.6</td>
<td>-5.0</td>
<td>-3.4</td>
<td>-4.9</td>
</tr>
</tbody>
</table>

Table 20: Value of the 10th percentile for the distribution of 5-day moving sums (millimetres over 5 days).

#### 5.5.4 1-Day Peaks Over Threshold (POT)

By definition, in the 30-year, 10950-day current period (1971 – 2000) there are 1095 days where the magnitude of precipitation, evaporation or change in water level variables exceed the 90th percentile threshold of their respective datasets. Averaged over 30 years, there are 36.5 extreme events per year for each of the water balance variables in the current period. However, within the 30-year current and future periods there is high variability in the POT count inter-annually (Figures 28 to 31). The variability is seen to increase between the current and future periods, with an increasing number of POT notably in the later part of the future 30-year period. When the distributions of the variables projected for the future are compared to the current period high threshold, the average annual high POT over 30 years increases in all cases (Table 21; Table 22).

For evaporation, future POT of ensemble mean projections of daily magnitudes is on average 42.7 – 45.4 days per year at Fort McMurray, and 43.4 – 44.9 days per year at Fort Chipewyan (Table 21). For precipitation in the future period, the average annual POT is 36.7 – 38.3 days per year at Fort McMurray, and 39.3 – 40.0 days per year at Fort Chipewyan, depending on the dataset. For change in water level, future POT is projected to be 37.6 – 42.7 days per year at Fort McMurray, and 41.4 – 45.0 days per year at Fort Chipewyan.
Overall, these increases translate to 1 to 6 more days per year with extreme lake water-level increases of at least ~2.5 mm/dy in the future for all basins at Fort McMurray, and 5.0 to 8.5 more days at Fort Chipewyan. There are larger increases in the number of extreme change in water level days for the shallow lakes compared to other depths, and at the further north Fort Chipewyan site (Table 22). The differences between the POT projected for the future by the Max Precip and Max Temp gridpoints, and the BCCI and BCSD downscaling methods, is minor.

<table>
<thead>
<tr>
<th>Future High POT (dy/yr)</th>
<th>Fort McMurray</th>
<th>Fort Chipewyan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BCCI</td>
<td>BCSD</td>
</tr>
<tr>
<td>Evaporation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>44.5</td>
<td>44.8</td>
</tr>
<tr>
<td>Intermediate</td>
<td>43.1</td>
<td>44.5</td>
</tr>
<tr>
<td>Deep</td>
<td>42.9</td>
<td>43.4</td>
</tr>
<tr>
<td>Precipitation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>All Depths</td>
<td>36.7</td>
<td>37.7</td>
</tr>
<tr>
<td>Change in Water Level</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>41.5</td>
<td>42.5</td>
</tr>
<tr>
<td>Intermediate</td>
<td>41.1</td>
<td>42.3</td>
</tr>
<tr>
<td>Deep</td>
<td>38.4</td>
<td>42.0</td>
</tr>
</tbody>
</table>

Table 21: Future number of days per year (dy/yr) exceeding the 90th percentile current period threshold (high POT) from the Max Precip and Max Temp gridpoints.

<table>
<thead>
<tr>
<th>Difference in High POT (dy/yr)</th>
<th>Fort McMurray</th>
<th>Fort Chipewyan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BCCI</td>
<td>BCSD</td>
</tr>
<tr>
<td>Evaporation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>8</td>
<td>8.3</td>
</tr>
<tr>
<td>Intermediate</td>
<td>6.6</td>
<td>8</td>
</tr>
<tr>
<td>Deep</td>
<td>6.4</td>
<td>6.9</td>
</tr>
<tr>
<td>Precipitation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>All Depths</td>
<td>0.2</td>
<td>1.2</td>
</tr>
<tr>
<td>Change in Water Level</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>5.0</td>
<td>6.0</td>
</tr>
<tr>
<td>Intermediate</td>
<td>4.6</td>
<td>5.8</td>
</tr>
<tr>
<td>Deep</td>
<td>1.9</td>
<td>5.5</td>
</tr>
</tbody>
</table>

Table 22: Future minus Current change in the number of days per year (dy/yr) of daily high POT.
Figure 28: Annual “high POT” for the Max Precip BCCI dataset in the Current (1971 – 2000) and Future (2041 – 2070) periods. The straight line is the 30-year average for the shallow lake.

Figure 29: Annual “high POT” for the Max Temp BCCI dataset in the Current (1971 – 2000) and Future (2041 – 2070) periods. The straight line is the 30-year average for the shallow lake.
Figure 30: Annual “high POT” for the Max Precip BCSD dataset in the Current (1971 – 2000) and Future (2041 – 2070) periods. The straight line is the 30-year average for the shallow lake.

Figure 31: Annual “high POT” for the Max Temp BCSD dataset in the Current (1971 – 2000) and Future (2041 – 2070) periods. The straight line is the 30-year average for the shallow lake.
For low POT counts (Figure 32 and Table 23), a similar pattern is seen in the future as for the high POT counts. Again the low extremes of “change in water level” exceed the 10th percentile threshold by definition 36.5 times per year in the current period, while in the future period the number of low extremes increases to 40.6 – 43.4 days per year at Fort McMurray, and 39.7 – 43.2 days per year at Fort Chipewyan, on average over the 30 years, depending on the dataset (Table 23). The POT varies inter-annually, as shown in Figure 32. This is a slightly smaller increase in the POT count than for the high POT counts, which is also seen in the value of the 10th percentile, which decreases less in the future period compared to the increase of the 90th percentile in the future. The variation in POT between datasets is smaller for the low extremes compared to the high extremes.

Figure 32: Annual “low POT” for “change in water level”, for the current (1971 – 2000) and future (2041 – 2070) water balances. The straight line is the 30-year average for the shallow lake.
Table 23: Future number of days per year (dy/yr) below the 10th percentile current period threshold (low POT) from the Max Precip and Max Temp gridpoints.

5.5.5 3-day and 5-day Peaks Over Threshold (POT)

For the 3- and 5-day cumulative sum distributions, there are by definition 36.3 and 36.1 exceedances, respectively, of both the 90th or 10th percentiles in the current period. The POT counts for the modelled distributions of the future multi-day events exceed the current period POT in all cases. The estimates of 3-day evaporation POT range from 44.0 – 46.6 days per year on average at both Fort McMurray and Fort Chipewyan in the future (Table 24). This means that approximately 8 to 10 more 3-day extreme evaporation events are expected under a future warmer climate. For precipitation, the POT of 3-day events increases from the current period average of 36.3 days per year, to 41.6 – 48.7 days per year in the future, or 5 to 12 more days of extreme precipitation than in the current period. For the change in water level variable, projections estimate 37.0 – 50.5 days per year of high exceedances in the future. This translates to up to 8 more extreme 3-day “change in water level” events at Fort McMurray, and up to 14 more 3-day extreme increases in water level at Fort Chipewyan (Table 25).
Future High POT, 3-Day Sum

<table>
<thead>
<tr>
<th></th>
<th>Fort McMurray</th>
<th>Fort Chipewyan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BCCI</td>
<td>BCSD</td>
</tr>
<tr>
<td>Evaporation</td>
<td>MaxPr</td>
<td>MaxT</td>
</tr>
<tr>
<td>Shallow</td>
<td>47.0</td>
<td>46.6</td>
</tr>
<tr>
<td>Intermediate</td>
<td>45.3</td>
<td>46.4</td>
</tr>
<tr>
<td>Deep</td>
<td>44.7</td>
<td>45.1</td>
</tr>
<tr>
<td>Precipitation</td>
<td>MaxPr</td>
<td>MaxT</td>
</tr>
<tr>
<td>All Depths</td>
<td>43.7</td>
<td>44.7</td>
</tr>
<tr>
<td>Change in Water Level</td>
<td>MaxPr</td>
<td>MaxT</td>
</tr>
<tr>
<td>Shallow</td>
<td>43.2</td>
<td>44.2</td>
</tr>
<tr>
<td>Intermediate</td>
<td>43.5</td>
<td>43.6</td>
</tr>
<tr>
<td>Deep</td>
<td>39.9</td>
<td>43.3</td>
</tr>
</tbody>
</table>

Table 24: Future POT for high extremes of the 3-day cumulative sums of evaporation, precipitation and change in water level.

<table>
<thead>
<tr>
<th>Difference in High POT, 3-Day Sum</th>
<th>Fort McMurray</th>
<th>Fort Chipewyan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BCCI</td>
<td>BCSD</td>
</tr>
<tr>
<td>Evaporation</td>
<td>MaxPr</td>
<td>MaxT</td>
</tr>
<tr>
<td>Shallow</td>
<td>10.7</td>
<td>10.3</td>
</tr>
<tr>
<td>Intermediate</td>
<td>9.0</td>
<td>10.1</td>
</tr>
<tr>
<td>Deep</td>
<td>8.4</td>
<td>8.8</td>
</tr>
<tr>
<td>Precipitation</td>
<td>MaxPr</td>
<td>MaxT</td>
</tr>
<tr>
<td>All Depths</td>
<td>7.5</td>
<td>8.4</td>
</tr>
<tr>
<td>Change in Water Level</td>
<td>MaxPr</td>
<td>MaxT</td>
</tr>
<tr>
<td>Shallow</td>
<td>6.9</td>
<td>7.9</td>
</tr>
<tr>
<td>Intermediate</td>
<td>7.2</td>
<td>7.3</td>
</tr>
<tr>
<td>Deep</td>
<td>3.7</td>
<td>7.1</td>
</tr>
</tbody>
</table>

Table 25: Future minus Current POT for high extremes of 3-day cumulative sums.

For cumulative 5-day events, evaporation POT projected for the future ranges from 43.6 – 50.9 days per year on average, precipitation POT ranges from 43.2 – 50.2 days per year, and change in water level POT ranges from 41.6 – 52.0 days per year in the future period (Table 26). This translates to up to 10 more 5-day exceedances of the change in water level variable in the future than the current period at Fort McMurray, and up to 16 more exceedances at Fort Chipewyan (Table 27). The modelled five-day exceedances of the high threshold occur more frequently in the future period than the 1- and 3-day exceedances, with up to 50-52 days per year.
projected to exceed the 90th percentile for all three water balance variables, compared to 46-50 days of POT for 3-day events, and 38-45 days for 1-day events, per year in the future period.

<table>
<thead>
<tr>
<th>Future High POT, 5-Day Sum</th>
<th>Fort McMurray</th>
<th>Fort Chipewyan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BCCI</td>
<td>BCSD</td>
</tr>
<tr>
<td></td>
<td>MaxPr</td>
<td>MaxT</td>
</tr>
<tr>
<td>Evaporation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>47.8</td>
<td>47.6</td>
</tr>
<tr>
<td>Intermediate</td>
<td>45.9</td>
<td>47.0</td>
</tr>
<tr>
<td>Deep</td>
<td>50.9</td>
<td>45.6</td>
</tr>
<tr>
<td>Precipitation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>All Depths</td>
<td>45.2</td>
<td>46.4</td>
</tr>
<tr>
<td>Change in Water Level</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>44.8</td>
<td>45.5</td>
</tr>
<tr>
<td>Intermediate</td>
<td>44.5</td>
<td>45.9</td>
</tr>
<tr>
<td>Deep</td>
<td>41.2</td>
<td>45.2</td>
</tr>
</tbody>
</table>

Table 26: Future POT for high extremes of the 5-day cumulative sums of evaporation, precipitation and change in water level.

<table>
<thead>
<tr>
<th>Difference in High POT, 5-Day Sum</th>
<th>Fort McMurray</th>
<th>Fort Chipewyan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BCCI</td>
<td>BCSD</td>
</tr>
<tr>
<td></td>
<td>MaxPr</td>
<td>MaxT</td>
</tr>
<tr>
<td>Evaporation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>11.7</td>
<td>11.5</td>
</tr>
<tr>
<td>Intermediate</td>
<td>9.8</td>
<td>10.9</td>
</tr>
<tr>
<td>Deep</td>
<td>14.8</td>
<td>9.5</td>
</tr>
<tr>
<td>Precipitation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>All Depths</td>
<td>9.1</td>
<td>10.4</td>
</tr>
<tr>
<td>Change in Water Level</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shallow</td>
<td>8.7</td>
<td>9.4</td>
</tr>
<tr>
<td>Intermediate</td>
<td>8.4</td>
<td>9.8</td>
</tr>
<tr>
<td>Deep</td>
<td>5.1</td>
<td>9.1</td>
</tr>
</tbody>
</table>

Table 27: Future minus Current POT for high extremes of 5-day cumulative sums.

The 3- and 5-day low exceedances show similar patterns as the high exceedances (Table 28; Table 29). All low exceedances in the future occur more often than in the current period, although not by as much as the high exceedances (Figure 33). Three- and five-day sums with magnitudes below the threshold occur 4 to 8 more times in 30 years at both Fort McMurray and Fort Chipewyan, with the lowest change in the future seen in the BCCI data at Fort Chipewyan.
Future Low POT, 3-Day Sum

<table>
<thead>
<tr>
<th>Future POT</th>
<th>Fort McMurray</th>
<th>Fort Chipewyan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BCCI</td>
<td>BCSD</td>
</tr>
<tr>
<td>MaxPr</td>
<td>MaxT</td>
<td>MaxPr</td>
</tr>
<tr>
<td>Shallow</td>
<td>42.2</td>
<td>42.5</td>
</tr>
<tr>
<td>Intermediate</td>
<td>41.1</td>
<td>41.9</td>
</tr>
<tr>
<td>Deep</td>
<td>41.1</td>
<td>41.0</td>
</tr>
</tbody>
</table>

Difference Future minus Current

| Shallow | 5.9 | 6.2 | 7.6 | 8.0 | 4.3 | 4.3 | 7.7 | 5.2 |
| Intermediate | 4.8 | 5.6 | 6.5 | 7.7 | 4.0 | 4.7 | 7.1 | 5.7 |
| Deep | 4.8 | 4.7 | 5.0 | 6.9 | 3.8 | 3.8 | 7.7 | 6.1 |

Table 28: Low POT for change in water level 3-day cumulative sums below the 10\textsuperscript{th} percentile

Table 29: Low POT for change in water level 5-day cumulative sums below the 10\textsuperscript{th} percentile

Figure 33: Average increase in the number of days exceeding the high (90\textsuperscript{th} percentile) and low (10\textsuperscript{th} percentile) thresholds in the future period for 1-, 3- and 5-day change in water level events.
5.5.6 Generalized Extreme Value (GEV) Distribution

The frequency and magnitude of modelled extreme 1-day “change in water level” events are plotted to evaluate the range of magnitudes expected in the current and future periods (high extremes Figures 34 to 37; low extremes Figures 39 to 42). The cumulative distribution function (CDF), calculated from the Generalized Extreme Value (GEV) distribution, demonstrates the magnitudes of the extremes in ascending order. The location ($\mu$), scale ($\sigma$) and shape ($k$) parameters, estimated from the GEV and used to plot the CDF, quantify differences in the CDFs. For the shape parameter, all the “change in water level” distributions have a value of $k<0$, indicating the Weibull distribution is the best fit, and the tails are finite. The Weibull distribution does not allow for negative values, therefore the CDFs of low extremes were plotted as absolute values, and the negative signs added to the Figure axes afterwards. The other two parameters are used to compare the distributions between scenarios (Figures 38 and 43): the location parameter ($\mu$) shifts the distribution along the real line, changing the range of magnitudes in the distribution, while the scale parameter ($\sigma$) expands or contracts the distribution, changing the frequencies of the daily events (Mathworks Inc., 2015).

In each CDF, the x-axis indicates the magnitude of the change in water level, controlled by the $\mu$ parameter. The corresponding value on the y-axis indicates the cumulative number of days on which an event of that magnitude or smaller is predicted to occur, and is controlled by the $\sigma$ parameter. By definition, the maximum cumulative frequency of the change in water level CDFs in the current period is 1095 days exceeding the high threshold (y-axis), while in the future period the number of days exceeding the threshold varies by dataset. The three models and three lake depths are plotted in each Figure using the same colour, for simplicity.
The high extreme 1-day event magnitudes range from approximately 3 mm/dy (the 90th percentile) to 50 mm/dy and above, for all datasets in both the current and future periods (Figures 34 to 37). The majority of the extreme changes in water level (800 to 900 days out of 1095) have magnitudes between 3 and 10 mm/dy. After the 10 mm/dy mark the cumulative distribution curve flattens out, indicating fewer additional days with changes in water level of 10 mm/dy and higher. Using the plotted CDF curves and the location (μ) and scale (σ) parameters to understand the differences between the CDFs reveals two main patterns between datasets: 1) the Max Precip gridpoint has more large extreme 1-day changes in water level than the Max Temp gridpoint, and 2) in the future, the total number of 1-day extremes in 30 years exceeds the current period count in all but one case, a pattern previously noted in the count of POTs, above. For the high extremes, μ is higher in the future for all scenarios except the Max Precip gridpoint at Fort McMurray from the BCSD dataset (Figure 38), indicating a shift towards higher magnitude increases in water level in the future in most cases. The σ parameter is also higher in the future for all the same high extreme scenarios, indicating expanded future distributions that include more higher magnitude events. These differences agree with the hypothesis that climate change will cause more frequent, larger precipitation events, causing more large increases in water level in the future.

Both patterns are strongest for the BCCI gridpoints at Fort McMurray (Figure 34), where the Future Max Precip curve bends first, indicating a larger μ value, and therefore larger magnitude Max Precip exceedances in the future, compared to the other curves at the same frequency. For example, at a cumulative frequency of 600 days per 30-year period, the Current Max Temp gridpoint has the lowest magnitude exceedances (approximately 5 mm/dy), the Future Max Temp distribution and Current Max Precip distributions follow, respectively, and the
highest magnitude exceedances are expected at the Future Max Precip gridpoint (approximately 7 mm/dy). This is also seen in the value of the location parameter in Figure 38, where μ is lowest for Current Max Temp and highest for Future Max Precip.

These patterns are also seen to various extents in the other three high exceedance datasets (Figures 35, 36, 37), although the distributions, in these cases, are more similar and therefore the lines have greater overlap. For the BCSD model data at Fort McMurray (Figure 35), the Max Precip curves clearly show larger magnitudes compared to the Max Temp curves, for both the current and future periods. This is also shown by the values of the μ parameter, which are larger at the Max Precip gridpoint than the Max Temp gridpoint in both time periods. However, for this dataset there is not a large difference in the current and future distributions as the future curves mostly overlap the current ones. In fact, the BCSD Fort McMurray MaxPrecip distribution is the only case in the high exceedances where μ is higher for the current rather than the future period.

At Fort Chipewyan (Figures 36 and 37) there is less distinction between the Max Precip and Max Temp gridpoints, or the current and future periods, indicated by the overlap of most of the distribution lines, and by the similarity of μ for the Fort Chipewyan datasets (see Figure 38).
Figure 34: Cumulative distribution functions (cdf) of daily high extremes of “change in water level” at Fort McMurray from the BCCI dataset, in the current (1971 – 2000) and future (2041 – 2070) periods. The three models and three lake depths are plotted using the same colour.

Figure 35: Cumulative distribution functions (cdf) of daily high extremes of “change in water level” at Fort McMurray from the BCSD dataset, in the current (1971 – 2000) and future (2041 – 2070) periods. The three models and three lake depths are plotted using the same colour.
Figure 36: Cumulative distribution functions (cdf) of daily high extremes of “change in water level” at Fort Chipewyan from the BCCI dataset, in the current (1971 – 2000) and future (2041 – 2070) periods. The three models and three lake depths are plotted using the same colour.

Figure 37: Cumulative distribution functions (cdf) of daily high extremes of “change in water level” at Fort Chipewyan from the BCSD dataset, in the current (1971 – 2000) and future (2041 – 2070) periods. The three models and three lake depths are plotted using the same colour.
Figure 38: Location (μ) and scale (σ) parameter estimates for the CDF distributions of high extremes of change in water level, averaged across all lake depths.

For the low extremes of change in water level, the CDF curves are more segmented than for the high extremes, indicating clearer step changes in the cumulative number of days with change in water level magnitudes below the 10th percentile (Figure 39 to 42). The values begin at the value of the 10th percentile threshold, around -1.5 mm/dy on average, and rise very steeply to the 800 – 900 day mark. This means a large number of days with drawdowns between approximately 1.5 mm and 3 mm per day. The curves reach their tails shortly after, with very few days with water-level decreases between 5 mm and 20 mm/dy. The low extreme magnitudes show a weak pattern of the smallest daily drawdowns at the Current Max Precip gridpoint, and the largest daily drawdowns at the Future Max Temp gridpoint. This is the reverse of the high extremes, as the low extreme CDFs are driven by high extreme evaporation events linked to high air temperatures, as opposed to high extreme precipitation events.

The location parameter (μ) for the low extremes is also higher in the future period for most scenarios. However, for low extremes μ is much lower and more consistent between datasets than for the high extremes, indicating a smaller shift towards larger magnitude changes in water level (draw-downs) in the future, and less variation based on study site and downscaling method.
(Figure 43). The scale parameter (σ) values are also much lower for the low extremes than for the high ones, indicating a smaller spread in magnitudes of the extremes. However, σ is still larger in the future period, indicating an expansion of the distribution tail and a shift to larger low extreme events in the future.

Figure 39: Cumulative distribution functions (CDF) of daily low extremes of “change in water level” at Fort McMurray from the BCCI dataset, in the current and future periods. The three models and three lake depths are plotted using the same colour.

Figure 40: Cumulative distribution functions (CDF) of daily low extremes of “change in water level” at Fort Chipewyan from the BCCI dataset, in the current (1971 – 2000) and future (2041 – 2070) periods. Lines for the three models and three lake depths are plotted using the same colour.
Figure 41: Cumulative distribution functions (CDF) of daily low extremes of “change in water level” at Fort McMurray from the BCSD dataset, in the current (1971 – 2000) and future (2041 – 2070) periods. Lines for the three models and three lake depths are plotted using the same colour.

Figure 42: Cumulative distribution functions (CDF) of daily low extremes of “change in water level” at Fort Chipewyan from the BCSD data, in the current (1971 – 2000) and future (2041 – 2070) periods. Lines for the three models and three lake depths are plotted using the same colour.
5.5.7 Most Extreme Changes in Water Level

The maximum Annual Maximum (AM) and the minimum Annual Minimum (AMin) change in water level, for any year and any model in each of the current and future periods, were extracted from the distributions for each scenario to examine the range of climate extremes expected within the climate of the Athabasca Region in the future under climate change. These are not ensemble mean values, but the highest and lowest values overall from individual models.

5.5.7.1 Maximum 1-Day Increases in Water Level (AM)

Maximum 1-day AM increases in water level range from 39 mm/dy to 90 mm/dy in the current period, depending on study site, lake depth, and gridpoint (Figure 44). The magnitudes are larger at Fort McMurray in general, and the highest values are estimated by the BCCI dataset, with values 20 mm/dy higher than the other scenarios. In the future these maximum AMs are expected to increase by 10 to 50 mm/dy on average (Figure 45), with values ranging from 49 mm/dy to 125 mm/dy. Not only are the future values higher than in the current period, the highest values in the current period are expected to increase the most, with larger increases at Fort McMurray over Fort Chipewyan in most cases.
Maximum 3-day and 5-day Increases in Water Level

The 3- and 5-day maximum AM increases in water level from any year and any model are larger in magnitude than the 1-day increases. Three-day sums range from 65 mm to 200 mm AM change in water level in the current period (Table 30) and the 5-day sums range from 76 mm to 215 mm increases in water level (Table 31). Proportionately per day, these water level increases are smaller than the 1-day events; when divided by 3 and 5 days, respectively, the current period
daily amounts range from 22 to 68 mm/dy and 13 to 43 mm/dy, compared to the 1-day maximums of 39 to 90 mm/dy. The 3- and 5-day events are likely representative of frontal systems that produce steadier, multi-day precipitation, compared to the intense, short-duration precipitation of convective cells (Raddatz & Hanesiak, 2008). See more in discussion section.

In the future, the 3- and 5-day increases in water level for most cases at Fort Chipewyan rise by 15 to 36 mm over current period magnitudes. At Fort McMurray, the BDSC data shows increases in change in water level on a similar scale – 18 to 34 mm more precipitation in the future – however, the Fort McMurray BCCI extremely high maximums seen in the current period actually decrease in the future period by 35 to 47 mm for the Max Temp gridpoint and 70 to 80 mm for the Max Precip gridpoint. Further analysis to determine why magnitudes decreased, compared to the expected increase under a warmer climate, was not possible due to data corruption issues. Further work beyond the scope of this thesis could be done to determine why modelled 3- and 5-day magnitudes might decrease in the future at Fort McMurray.

<table>
<thead>
<tr>
<th>Maximum AM 3-Day Water level Change (mm/dy)</th>
<th>Current</th>
<th>Future</th>
<th>Difference (Future minus Current)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BCCI</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MaxPr Shallow</td>
<td>204</td>
<td>74</td>
<td>134</td>
</tr>
<tr>
<td>MaxPr Int</td>
<td>201</td>
<td>74</td>
<td>133</td>
</tr>
<tr>
<td>MaxPr Deep</td>
<td>201</td>
<td>74</td>
<td>133</td>
</tr>
<tr>
<td>MaxT Shallow</td>
<td>139</td>
<td>83</td>
<td>110</td>
</tr>
<tr>
<td>MaxT Int</td>
<td>136</td>
<td>81</td>
<td>110</td>
</tr>
<tr>
<td>MaxT Deep</td>
<td>136</td>
<td>81</td>
<td>110</td>
</tr>
</tbody>
</table>

| BCSD                                       |          |        |                                  |
| MaxPr Shallow                              | 101      | 77     | 127                              |
| MaxPr Int                                 | 102      | 76     | 127                              |
| MaxPr Deep                                | 105      | 76     | 127                              |
| MaxT Shallow                              | 86       | 65     | 105                              |
| MaxT Int                                  | 87       | 66     | 104                              |
| MaxT Deep                                 | 87       | 66     | 104                              |

Table 30: Maximum Annual Maximum (AM) 3-day cumulative changes in water level, and the difference between the current (1971 – 2000) and future (2041 – 2070) periods.
<table>
<thead>
<tr>
<th>Maximum AM 5-Day Water level Change (mm/dy)</th>
<th>Current</th>
<th>Future</th>
<th>Difference (Future minus Current)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fort McMurray</td>
<td>Fort Chipewyan</td>
<td>Fort McMurray</td>
</tr>
<tr>
<td>BCCI</td>
<td>Shallow MaxPr Int</td>
<td>216.4</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>Deep Shallow</td>
<td>213.3</td>
<td>100.4</td>
</tr>
<tr>
<td></td>
<td>Int MaxT Shallow</td>
<td>154.0</td>
<td>133.5</td>
</tr>
<tr>
<td></td>
<td>Deep Int</td>
<td>151.4</td>
<td>131.3</td>
</tr>
<tr>
<td></td>
<td>Deep Deep</td>
<td>151.6</td>
<td>131.6</td>
</tr>
<tr>
<td>BCSD</td>
<td>Shallow MaxPr Int</td>
<td>105.3</td>
<td>78.0</td>
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<td></td>
<td>Deep MaxPr Shallow</td>
<td>105.0</td>
<td>74.3</td>
</tr>
<tr>
<td></td>
<td>Shallow MaxT Int</td>
<td>110.6</td>
<td>74.7</td>
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<td></td>
<td>Shallow Deep</td>
<td>85.8</td>
<td>66.7</td>
</tr>
<tr>
<td></td>
<td>Deep MaxT Shallow</td>
<td>87.3</td>
<td>67.5</td>
</tr>
<tr>
<td></td>
<td>Deep Deep</td>
<td>87.3</td>
<td>67.5</td>
</tr>
</tbody>
</table>

Table 31: Maximum Annual Maximum (AM) 5-day cumulative changes in water level, and the difference between the current (1971 – 2000) and future (2041 – 2070) periods.

5.5.7.3 Maximum 1-Day Decreases in Water Level (AMin)

The largest decreases in water level are represented by the overall minimum Annual Minimums (AMin) from the modelled 1-, 3- and 5- day cumulative sums of the change in water level variable. In the current period, the maximum 1-day decreases in water level range from 10 mm/dy to 18 mm/dy, on average (Figure 46). The values of the minimums are similar across the datasets, with slightly larger magnitude draw-downs at Fort Chipewyan in most cases. Only the BCSD Max Precip gridcell has larger water-level decreases at Fort McMurray, which are also the largest magnitude decreases overall, reaching almost -18 mm/dy. The Max Temp gridcell would be expected to experience larger draw-downs of water level due to higher evaporation rates than at the Max Precip gridcell, however as these are the largest extremes of any model in the ensemble, low precipitation and high evaporation days are possible at any gridcell.

In the future, the magnitudes of low extreme changes in water level are projected to increase in all scenarios at Fort McMurray (Figure 47). However, at Fort Chipewyan, there are several instances of decrease in magnitude of the extreme draw-downs in the future. As
decreases in water level in the simple water balance are driven by evaporation, this indicates that maximum extreme daily evaporation rates are not expected to increase as much in the future as extreme daily precipitation rates. This dampening of the climate change signal applies more to the further north Fort Chipewyan study site than the Fort McMurray study site.

Figure 46: Minimum Annual Minimum (AMin) daily changes (decreases) in water level (mm/dy) in the current period at Fort McMurray and Fort Chipewyan, from the water balance modelled using the Max Precip and Max Temp gridpoints.

Figure 47: Future minus current 1-day changes in water level (mm/dy).
5.5.7.4 Maximum 3-Day and 5-Day Cumulative Decreases in Water Level

The largest 3- and 5-day decreases in water level (minimum AMin) are not much larger than the 1-day decreases. The 3-day cumulative sums range from 17 mm to 28 mm decreases, and the 5-day cumulative sums range from 22 mm to 33 mm decreases in water level, depending on the dataset (Table 32 and 33). When these sums are divided by the number of days they account for, they represent less than the 1-day draw-down rates (5.5 to 9 mm for the 3-day sums divided by 3 days, and 7.5 to 11 mm for the 5-day sums divided by 5 days, compared to the 10 to 18 mm 1-day decreases). However, any additional precipitation following larger 1-day events can still be important and cause significant impacts on the surrounding environment.

In the future, the 3- and 5- day decreases in water level are not expected to intensify in all cases (Tables 32 and 33). Both sites are expected to see both increases and decreases in extreme water-level decreases in the future. The magnitudes of the differences between current and future are very small, ranging from + 7 mm/dy to -9 mm/dy, resulting in a maximum modelled extreme draw-down of 29 mm/dy in the future for any of the lakes in the Athabasca River region.

<table>
<thead>
<tr>
<th>Minimum AMin 3-Day Water level Change (mm/dy)</th>
<th>Current</th>
<th>Future</th>
<th>Difference (Future minus Current)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fort McMurray</td>
<td>Fort Chipewyan</td>
<td>Fort McMurray</td>
<td>Fort Chipewyan</td>
</tr>
<tr>
<td>MaxPr Shallow</td>
<td>-19</td>
<td>-18</td>
<td>-22</td>
</tr>
<tr>
<td>MaxPr Int</td>
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</tr>
<tr>
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</tr>
<tr>
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<td>-19</td>
<td>-20</td>
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<tr>
<td>MaxT Int</td>
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<td>-21</td>
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<tr>
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<tr>
<td>MaxT Deep</td>
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<td>-28</td>
<td>-22</td>
</tr>
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</table>

Table 32: 3-day sum minimum AMin for change in water level (mm/dy), and the difference between current and future periods.
Table 33: 5-day sum minimum AMin for change in water level (mm/dy), and the difference between current and future periods.

### 5.5.7.5 Seasonality of Extremes

There is a seasonality to the maximum increases in water level. In both the current and future periods, the maximum AM increases in water level occur in June, July, August and September (Table 34). The occurrence of the low extreme (AMin) decreases in water level are more scattered throughout the year. There are several instances of the maximum draw-down occurring in the fall as late as October 16, and in the spring as early as May 30. Based on projections of longer open water seasons and higher evaporation in the future period described earlier in this paper, this pattern is projected to hold true in the future, with the dates of maximum evaporation extremes occurring over a wider range of time, and precipitation extremes remaining in the summer but increasing in magnitude. Unfortunately due to data corruption issues, the dates of future maximum AM and minimum AMin extreme events are not able to be reported here.
<table>
<thead>
<tr>
<th>Current Period Dates of Extreme Changes in Water Level</th>
<th>Fort McMurray</th>
<th>Fort Chipewyan</th>
</tr>
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<tr>
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<td>Year</td>
<td>Mon.</td>
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<tr>
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<td>BCCI</td>
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<td>1976</td>
<td>8</td>
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<tr>
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<td>8</td>
</tr>
<tr>
<td>Deep</td>
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<tr>
<td>BCSD</td>
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<td></td>
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<tr>
<td>Shallow MaxPr</td>
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<td>6</td>
</tr>
<tr>
<td>Int</td>
<td>1991</td>
<td>6</td>
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<tr>
<td>Deep</td>
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</tr>
<tr>
<td>Shallow MaxT</td>
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<td>6</td>
</tr>
<tr>
<td>Int</td>
<td>1994</td>
<td>6</td>
</tr>
<tr>
<td>Deep</td>
<td>1994</td>
<td>6</td>
</tr>
<tr>
<td><strong>Minimum AMin Water Level Change</strong></td>
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<td></td>
</tr>
<tr>
<td>BCCI</td>
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<tr>
<td>Int</td>
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<td>10</td>
</tr>
<tr>
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<td>1980</td>
<td>10</td>
</tr>
</tbody>
</table>

Table 34: Dates of maximum Annual Maxima (AM) and minimum Annual Minima (AMin) changes in water level in the current period (Year, Month, Day).
5.6 Discussion

5.6.1 Extreme Changes in Water Level

The water balance modelled using MyLake and an ensemble of RCMs indicates that the magnitudes and frequencies of extreme precipitation and evaporation are expected to increase in a future warmer climate described by the IPCC A2 climate scenario. Based on the model ensemble used here, more frequent intense climate events will cause larger variations in the water levels of lakes of all depths located in the Athabasca River region of northern Alberta, Canada. Hindcasts of the 1971 – 2000 current period indicate that maximum 1-day increases in water level range from 39 mm/dy to 90 mm/dy, and maximum 1-day decreases in water level range from -10 mm/dy to -18 mm/dy, on average. In the future period the magnitudes of extreme 1-day increases in water level are projected to increase to 49 mm/dy to 125 mm/dy, over 10 mm higher than in the current period, and future magnitudes of extreme 1-day decreases in water level are projected to increase to -11 mm/dy to -24 mm/dy, a smaller average increase than for the high extremes. The number of days per year that these extreme water level changes are expected is also projected to increase in the future by 1 to 6 more days per year at Fort McMurray, and 5 to 8.5 more days per year at Fort Chipewyan. Since the magnitudes and frequencies of both extreme draw-downs and extreme increases in water level are expected at both study sites in the future, results indicate larger variability in water storage due to climate change in the Athabasca River region.

The extreme changes in water level modelled in this study vary depending on physical aspects of the lakes such as depth, local climate and seasonal cycles, as well as being particular to the ensemble of climate models and future climate scenario used to calculate the water balance. Lake depth is a factor in controlling evaporation extremes. The evaporation extremes projected by the model ensemble are larger on average over the intermediate-depth lakes,
compared to both the deeper and shallower lakes, since they benefit from both early season radiation-driven evaporation and late season heat storage-driven evaporation. Evaporation extremes can cause large decreases in lake level on their own, or can balance extreme precipitation and dampen extreme increases in lake level.

Local climate is also important in controlling lake levels (Lenters et al., 2005). Warmer air temperatures at the south end of the study region are likely causing the higher evaporation extremes estimated by the model, and therefore larger draw-downs of lake levels are expected for lakes at Fort McMurray compared to lakes at Fort Chipewyan. The modelled results also indicate a larger number of extreme precipitation events at Fort McMurray than at Fort Chipewyan, in both the current and future periods. The dominant source of precipitation in the region is convective cells, which often produce more intense precipitation than frontal systems (Raddatz & Hanesiak, 2008). As convection requires heat to develop, it is logical that more of these cells are expected at Fort McMurray, causing a higher incidence of intense precipitation there over short time periods. There are only small variations in the results between the BCCI and BCSD datasets and between the Max Precip and Max Temp gridcells. The similarity of precipitation percentile values, POT counts, and 1-, 3- and 5-day magnitudes between the Max Precip and Max Temp gridpoints indicates that places in the study region with higher long-term average daily precipitation (by which the Max Precip and Max Temp gridcells were chosen) are not necessarily prone to larger increases in extreme precipitation than areas with lower long-term average daily precipitation.

The seasonality of evaporation and precipitation extremes affects the intra-annual cycle of maximum changes in water level. Maximum increases in water level are driven by precipitation extremes, which are most common mid-summer (June to September), when average precipitation
in the Athabasca River region is also highest. Extreme decreases in water level are driven by high evaporation, and model results indicate that the maximum decreases are distributed throughout the open-water season (approximately May to November). The early spring and late fall shoulder seasons are when the right conditions exist at the lake surface, such as strong winds and large temperature differences between the lake water and the cooler air above, to create extremely high evaporation events (Oke, 1987). The model results show that shoulder season extreme evaporation, and mid-summer precipitation, are expected to be magnified under a future warmer climate.

Estimated 3- and 5-day increases in water level are intended to identify larger-scale storm front weather events that produce steadier, lower intensity precipitation, compared to short-duration convective cells (Mailhot et al., 2012; Raddatz & Hanesiak, 2008). Results show that the frequency of 5-day “change in water level” events is expected to increase the most in the future, and the frequency of 1-day events the least. The modelled magnitudes of 3- and 5-day events indicate that less precipitation is received after the 1st day of an extreme weather event. Even with smaller magnitudes on successive days, the additional water added or removed from lakes during multi-day events can have important effects on surrounding infrastructure and ecosystems. Increased frequency and magnitudes of sustained multi-day changes in water level mean higher risk of overtopping, or drying out, of isolated or perched basins in the Athabasca River region in the future under the A2 climate change scenario. Longer-term extremes, such as droughts and excessive moisture conditions, can be caused by persistent extremes (Randall et al., 2007). The study of trends over longer periods is beyond the scope of this study, but future work on the sequence or persistence of extremes over longer periods is recommended to understand
the cumulative effect of changes in the magnitudes and frequencies of extremes over seasons, years or longer.

5.6.2 Climate Model Uncertainty

Results of climate modelling depend on the particular model ensemble, model parametrization, input data, bias correction and downscaling methods used. All climate models contain a level of uncertainty and bias at all stages of modelling, from the specification of emissions scenario to how the climate system will respond to emissions-based forcing (Meehl et al., 2007). The A2 SRES emission scenario used in this work is just one possibly version of the future climate system, and results presented here should be considered with that scenario’s assumptions in mind (see section 2.3.3). Modelling using a variety of emissions scenarios, instead of a single scenario, would help isolate uncertainty introduced by the climate projection itself. This could be done as future work using the updated “Representative Concentration Pathways” (RCP) set of scenarios (IPCC, 2013).

Errors in model results due to the quantification of the climate system itself can be associated with internal climate variability as well as with the representation of complex physical processes within the model code (Randall et al., 2007). Nesting an RCM within the global conditions of a GCM, while important to downscale the GCM outputs, adds an extra level of uncertainty to model results. Systematic model biases, often caused by imperfect parametrization of unresolved processes and spatial averaging within cells, can be mitigated using a variety of bias correction techniques and ensemble modelling (Teutschbein & Seibert, 2010). In this work, bias correction was previously applied to the RCM_GCM ensemble using the BCCI and BCSD downscaling methods (see Murdock et al., 2013), which removed any uncertainty caused by systematic model biases.
Another way to reduce uncertainty is to increase the size of the multi-model ensemble. The three models used in this study were chosen based on data availability for the six variables required to run MyLake. A larger ensemble would help refine the envelope of possible future climate and isolate differences in remaining uncertainty between models (Mearns et al., 2009; Palmer & Räisänen, 2002). Should a full dataset become available for other NARCCAP models, their addition to the ensemble would strengthen confidence in the modelled water balance.

The reported maximum changes in water level are estimated for the same gridpoint in both the current and future periods. The gridpoints chosen are those with the highest average daily air temperature and precipitation in the current period. This methodology was chosen to isolate changes in the water balance due to climate change, as opposed to differences due to the topography, land surface and latitude at a point location in the watershed, all of which affect the modelling of climate variables by RCMs (Wilby et al., 2004). Therefore, using the same gridpoint for both water balances ensures model results are consistent and comparable.

5.6.3 Extremes and Surface Water Design Specifications

The addition of even 0.2 m of water to a lake, the largest estimate of 5-day increases in water level, may not seem like a significant threat. This may be true for reservoirs with built-in freeboard sides that can protect against overtopping if properly designed. Some industrial areas around the world include catch basins or diversion ditches to route extreme precipitation or reservoir overflows away from contaminated surface water storage such as tailings ponds and End Pit Lakes (EPLs). Re-routing precipitation and overland flow helps to avoid connecting sequestered waters to the clean freshwater in the area (U.S. EPA, 1994). In Canada, the design of mining and tailings dams is done using operational considerations and Probable Maximum Flood (PMF) (Priscu et al., 2009). These calculations are usually done using a historical record of
climate and floods, and based on an expected lifespan of standard conventional water retention structures, for example 20 years (U.S. Environmental Protection Agency, 1994). However, surface water storages used for tailings at mine sites often have longer in-service life spans than that, and also remain in operation after decommissioning of the mine (Priscu et al., 2009). The unsuitability of conventional mine regulations for intermediate-depth EPLs, compounded with the prospect that climate change is causing a dramatic change to future extreme climate, means that design specifications for process-affected and contaminated surface water storage in Canada need to be updated to consider impacts under unforeseen magnitudes and frequencies of climate events now and into the future.

Reservoirs often serve two contradictory purposes: leaving room to store floodwaters entering the reservoir from overland flow or precipitation, and maximizing water storage for hydropower production or for use during drought periods (van den Honert & McAneney, 2011). For example, lessons learned from a 2013 flood event in Brisbane, Australia highlight the need for more accurate prediction of precipitation and evaporation extremes that affect water levels in surface water storages. On January 13, 2011 the area around Brisbane was flooded, resulting in disastrous damage to homes, agricultural lands, and loss of life (van den Honert & McAneney, 2011). While intense precipitation had been occurring in the region over the previous days, and in fact, months, the cause of the flood was determined not to be meteorologic, but due instead to management of Brisbane’s Wivenhoe Dam and reservoir. The management scenarios for the dam depended on precipitation forecasts to inform the operators how much water to hold or release, to balance the needs of power production and flood management (van den Honert & McAneney, 2011). However, the senior engineer reported that during the flood event the dam was operated under a “no further rainfall” scenario, and therefore emergency water releases from
the reservoir (to make space for flood waters) were not enacted (Dunlevy, 2011). When more precipitation did fall, antecedant conditions meant that the soil was saturated, decreasing infiltration and forcing the water to flow into the reservoir. The overtopping of the reservoir caused the event to be deemed a “dam release flood” instead of a meteorologic one (van den Honert & McAneney, 2011). Reservoir managers around the world now use this as an example of how weather extremes affect reservoir management, and to highlight the need for subjective management and intervention to determine when a statistical flood may become a disaster.

5.7 Conclusions
Surface water storage in the Athabasca River region will encounter altered climate inputs and outputs in the 21st century compared to the 20th century. Climate events that are currently considered “rare,” and associated with natural disasters, will become more frequent. Due to the large area of natural surface water storage in the region, and expanding anthropogenic water storage in the future, changing patterns of extreme events pose a threat to the surrounding ecosystem, infrastructure and communities. For the many perched basins and isolated reservoirs, a simple water balance that calculates the change in water level by subtracting evaporation from precipitation is appropriate to determine changes in water storage. However, for land surfaces with a large area of small lakes, climate model projections should be augmented with offline models or improved resolution of land surface schemes, as most current RCM do not properly account for heat storage at depth. This study uses MyLake to estimate evaporation while accounting for heat storage, to improve water balance calculation at small spatial and temporal scales relevant to weather extremes. Ensemble results of extreme changes in water levels under a future warmer climate can be used to inform industrial design, and climate change mitigation and adaptation strategies, in mid-latitude, sub-humid, interior continental hydroclimatic regimes.
5.8 References


Schertzer, W. M., & Taylor, B. (2009). *Assessment of the Capability to Compute Evaporation from Okanagan Lake, Other Mainstem Lakes and Basin Lakes and Reservoirs using the*
Existing Database. Final Report to the Okanagan Water Supply and Demand Study on Lake Evaporation. Environment Canada, Water Science and Technology Directorate. (105 pp.)


6. **CHAPTER 6: CONCLUSIONS**

Changes in climate between the late-20th century and the mid-21st century are projected to alter the distribution of precipitation and evaporation patterns, both on average and in the form of extreme events (Meehl et al., 2007). This thesis demonstrates how climatic changes between the current (1970 – 2000) and future (2041 – 2070) periods will impact the water balance of surface water storage in a mid-latitude, sub-humid, interior continental hydroclimatic regime. This goal is achieved by meeting two main objectives: analysis of the cumulative 30-year water balance of three lake depths each located at Fort McMurray and Fort Chipewyan, Alberta (Chapter 4); and analysis of the effects of extreme 1-, 3- and 5-day climate events on the water levels of each lake (Chapter 5). To support these analyses, Chapter 2 provides a literature review on climate change, climate modelling and bias-correction techniques, water balance modelling, and statistical analysis of extreme events. Chapter 3 describes the MyLake Model and the particular methodology used to produce the results in chapters 4 and 5. This study is the first to evaluate effects of climate change specifically on the water balance of surface water storage in the Athabasca River region of northern Alberta, Canada.

In Chapter 4 the first objective was met by calculating the long-term cumulative water balance of the shallow (1.5 m), intermediate-depth (28.5 m) and deep (76.5 m) theoretical first-order basins, using bias-corrected climate variables from an ensemble of three NARCCAP Regional Climate Models (RCMs) spatially averaged for the Fort McMurray and Fort Chipewyan study sites in the current and future periods. Evaporation was modelled offline using the MyLake comprehensive lake temperature model driven by the same bias-corrected variables. Results of this analysis show that both precipitation and evaporation rates are expected to increase in the future, however the magnitude of the increases are similar and therefore the long
term effects of climate change on the cumulative change in water level are minimal. The water level of the study lakes is expected to increase by 1.1 m to 1.8 m cumulatively over 30 years in the current period, depending on lake depth and location, while in the future period the cumulative increase over 30 years will rise to 1.2 m to 2.0 m. This means that water levels in lakes and reservoirs in the Athabasca River region are expected to be 9 to 16 cm higher after 30 years of accumulation in the future period compared to the current period. The range of water-level increases represents the varied response of the different study basin depths and different climate at the two study sites; intermediate-depth lakes demonstrate the highest annual evaporation rates due to higher late-season evaporation than shallow lakes (more heat storage at depth) and higher early season evaporation than deep lakes (deep lakes take longer to heat up via insolation); and lakes at Fort McMurray are expected to gain more water storage than those at Fort Chipewyan in both the current and future periods, since precipitation rates exceed evaporation by a wider margin at the further south location.

The most significant differences in the annual average water balances between the current and future periods are due to a projected seasonal shift of the open-water season. With climate change causing lake ice to breakup earlier in the spring and freeze-up later in the fall, the extended the open-water season allows for increased evaporation annually, and a seasonal shift of the bulk of the evaporation to later in the year. This phenomenon is especially important in the fall season for deep lakes, when air temperatures are cool and heat storage keeps the water temperature higher later in the year, increasing the vapour pressure difference and driving evaporation. The water levels of intermediate-depth lakes increase less than the shallow and deep lakes as the higher evaporation rate more closely balances the precipitation rate annually and over 30 years.
In Chapter 5, extremes are defined as 1-, 3- and 5-day events with sufficient magnitude (or lack of magnitude) to cross the thresholds defined as the 90\textsuperscript{th} and 10\textsuperscript{th} percentiles of the distribution. The frequencies (Peaks-Over-Threshold) and magnitudes (Annual Maxima and Minima) of the extremes extracted from the Generalized Extreme Value (GEV) distributions for each scenario demonstrate that both the magnitudes (AM and AMin) and frequencies (POT) of extreme precipitation and evaporation events, and therefore extreme changes in water level, are expected to increase for lakes in the Athabasca River region under a future warmer climate. To capture the most extreme climate conditions in the study areas, the water balance for the three lake depths at Fort Chipewyan and Fort McMurray was calculated using the NARCCAP RCM ensemble, as in Chapter 3, but here individual gridpoints downscaled to 10 km\textsuperscript{2} using two different methods were used (BCCI and BCSD). The two chosen gridpoints were those with the highest average precipitation, and highest average air temperature (as a proxy for evaporation) for each RCM. At these gridpoints the 90\textsuperscript{th} percentile of 1-day evaporation events is shown to increase from approximately 2.0 mm/\text{dy} to 2.3 mm/\text{dy}, on average for all study lakes and datasets. The number of days (POT) with evaporation events exceeding the 2.0 mm/\text{dy} threshold is expected to increase from 36.5 days/yr in the current period, to 43 – 45 days in the future period, depending on lake depth and downscaling method. The frequencies and magnitudes of precipitation events are also expected to increase in the future. The 90\textsuperscript{th} percentile of 1-day precipitation rates is expected to rise from 3.8 mm/\text{dy} to 4.4 mm/\text{dy} at Fort McMurray, and from 3.0 mm/\text{dy} to 3.6 mm/\text{dy} at Fort Chipewyan, and the count of days (POT) that exceed the 90\textsuperscript{th} percentile threshold will rise from 36.5 days/yr to 37 - 40 days/yr on average for both study sites, depending on lake depth and downscaling method.
Increases in extreme precipitation and evaporation events cause the frequency and magnitude of extreme “change in water level” events (precipitation minus evaporation) to also increase at both the high extreme (increase in water level) and low extreme (decrease in water level) ends of the water balance. High extreme changes in water level are driven by high extreme precipitation, whereas low extreme changes in water level are driven by high extreme evaporation. The average 90th percentile of the magnitude of change in water level events is expected to increase from 2.9 mm/dy to 3.4 mm/dy in the future period, and the average POT count of days with magnitudes exceeding the current period 90th percentile threshold increase from 36.5 days/yr to 38 to 45 days/yr, depending on lake depth and downscaling method. This translates to maximum one-day Annual Maxima increases in water level of 49 to 125 mm/dy in the future period compared to 39 to 90 mm/dy in the current period, an increase of over 10 mm per day. The maximum one-day Annual Minima decreases in water level will change from draw-downs of 10 to 18 mm/dy, to draw-downs of 11 to 24 mm/dy, on average, a smaller yet still noticeable difference from the current period. The large magnitude of both increases and decreases in water level are also seen in the 3- and 5-day extremes of change in water level, indicating larger variations in water level in the future period for all lakes in the region.

Both average and extreme climate conditions contribute to keeping the water levels of surface water storages within expected ranges. With small average increases in water stored in lakes in the Athabasca River region expected in the 21st century, and additionally larger increases in the frequencies and magnitudes of extreme weather events, variability in water levels of surface water storages in the region is expected to increase, making them more at risk of overtopping or drying under a future warmer climate. Many consultant and engineering studies undertaken for construction of new surface water storages in the region in recent years do not
even refer to the possibility of a changing climate, and rely only on historical climate records (e.g., Devon NEC Corporation, 2012; JDEL Associates Ltd., 2005; Southern Pacific Resource Corp., 2011). Changing patterns of extreme climate events pose a threat to the area surrounding these new lakes, especially since the amount of surface water in the Athabasca River region is increasing as new storages are being built for use by industry, and for power and water supply for expanding populations (Kumar et al., 2011; Ohlson et al., 2010; Westcott, 2007). Calculations of future water balance using climate models and a simple water balance can, and should, be used to inform industrial design of any proposed new surface water bodies in the future.

Future work on this topic could also include expanding the number of climate models in the ensemble, using more than one future climate scenario, analyzing trends in the sequence or persistence of extremes over longer periods, and expanding the calculation of the water balance to include site-specific characteristics. Site-specific factors that may affect the water balance, but were excluded in this work due to the spatial and temporal scale of the study, include the redistribution of snow by wind transport, high sublimation rates, overland runoff, and inflows and outflows. Future changes in the water balance may also affect lake shore erosion caused by floating ice and snow packs. Since ice closer to the shore melts first, ice covers on lakes are left to be blown by the wind (Gerard, 1990). The magnitude of shore erosion caused by this floating ice may change in the future due to projected overall reductions in ice cover of northern lakes (National Assessment Synthesis Team, 2001). All site-specific factors, along with data on historical as well as projected future climate, should be used to evaluate the effects of new and existing surface water storages on the landscape, and to develop appropriate climate change
mitigation and adaptation strategies specific to the mid-latitude, sub-humid, interior continental hydroclimatic regime.
6.1 References


7. APPENDIX A: EVAPORATION SENSITIVITY TO LAKE DEPTH

To ensure the variation in evaporation isn’t simply due to the difference between the “bucket” shape morphometry of the shallow lake and the elliptical sinusoid morphometry of the intermediate-depth and deep lakes, an analysis of the sensitivity of evaporation rates to a wider variety of lake depths is undertaken. MyLake is run using climate data at Fort McMurray from the CRCM_CCSM RCM for 10 lake depths between the shallow (1.5 m) and intermediate (28.5 m) study lake depths, and 10 lake depths between the intermediate and deep (76.5 m) study lake depths, for a total of 23 runs. Lake depth increases by 2.5 m per run between the shallow and intermediate-depth lakes, with the distance of flat lake bed decreasing from 2523 m to zero. Lake depth increases by 3 to 6 m for each lake between the intermediate-depth and deep lakes, all of which used the elliptical sinusoid lake morphometry (no flat lake bed). Lake surface area also changes as depth changes, to represent a smooth transition from the large surface area delta lake (shallow lake) to the small surface area End Pit Lake (intermediate depth lake) and back to the large surface area reservoir (deep lake).

Results show average intra-annual evaporation patterns that change gradually as the depth changes, with the shallower lakes having higher evaporation earlier in the year and deeper lakes having higher evaporation in the fall (Figure 48 A). During August and September there is a crossover where shallow lake evaporation drops and deep lake evaporation remains relatively stable, leaving the intermediate–depth lakes with the highest evaporation rates. When average total annual evaporation is examined (Figure 48 B), the same evaporation-depth relationship is seen. Maximum annual evaporation was found over the 9 m lake depth with 422 mm/yr, closely followed by the 11.5 m lake depth with 421 mm/yr. This depth is somewhat shallower than the 28.5 m intermediate-depth study basin, but both fall in the intermediate depth range that maintains higher annual evaporation than the shallow and deep lake extremes. Annual
evaporation per lake declines more abruptly from the 9 m depth lake to the shallowest lake than it does the other direction from the 9 m depth lake to the deepest lake. The difference in evaporation divided by the change in lake depth shows that in the shallower lakes, evaporation decreases at a rate of 2.5 mm per metre of depth (from the maximum 422 mm/yr at the 9 m depth to 403 mm/yr at the 1.5 m shallow lake), and in the deeper lakes evaporation decreases more slowly at a rate of 0.3 mm per metre of lake depth (from the maximum to 400 mm/yr over the 76.5 m deep lake). This confirms that even with varying morphologies between the shallow and deeper lakes used in MyLake for this study, evaporation from shallow lakes is strongly governed by air temperature, while deeper lakes experience heat storage that provides energy for late-season evaporation.

Figure 48: Sensitivity of evaporation rates to lake depth. MyLake was run with 23 different lake depths ranging from 1.5 m to 76.5 m deep, using climate data from the CRCM CCSM model in the current period (1971 – 2000).
8. APPENDIX B: EFFECTS OF SEDIMENT HEAT FLUX ON EVAPORATION

The sediment heat flux module of MyLake calculates the water temperature profile taking into account heat exchanged via conduction between the water and the surrounding lake bed sediment, and heat transferred through water diffusion between pore water and the water column. Results of two MyLake runs, one with the sediment heat flux switch turned “on”, and one with it turned “off”, indicate that lake bed sediment has a moderating effect on lake water temperature and therefore latent heat for evaporation (Figure 49).

Average total annual evaporation is lower when the MyLake sediment heat flux module is used, for all study lakes. For the shallow lake, evaporation is reduced by 1% when the sediment heat flux switch is on, at both Fort Chipewyan and Fort McMurray. For the intermediate depth and deep lakes, evaporation is reduced by 0.2% at both sites. These differences are attributed to differences in lake morphometry more than depth – heat transfer to and from the lake sediment is more important for small lakes where the ratio of lake bottom to water volume is more significant than for deeper lakes (Schertzer & Taylor, 2009). The morphometry of the shallow lake used in MyLake for this study is a “bucket” shape, while the two deeper lakes are ellipsoids without flat bottoms. The increased area of the sediment-water interface due to the flat lake bottom increases the amount of heat absorbed from the water column into the bed.

The seasonal effect of sediment heat flux generally reduces spring evaporation and increases fall evaporation over open water. Lake bed sediment absorbs heat from the water in the spring when incoming radiation is strong, especially for shallow lakes where insolation can reach the lake bed directly. This absorption of heat into the sediment reduces the amount of energy that remains in the water column to drive early-season evaporation. Later in the year, this heat stored
in the sediment is released into the water column as the water cools, extending the evaporation season and delaying ice freezeup (Figure 49).

MyLake does not model heat absorbed into the lake bed by direct incoming solar radiation. Instead, if radiation reaches the bottom the extra energy is added to the water column based on the calculation of absorbed incoming solar radiation, using the ratio of the area of the second last layer divided by the bottom layer \((A_{i+1}/A_i)\) (Saloranta & Andersen, 2004). Therefore, the model results will have less sediment heat storage and therefore higher evaporation rates than in reality, especially for the shallow flat-bottom lake.

The sediment heat flux also affects the length of the ice cover season modelled by MyLake. When the sediment heat flux module is switched on, the average breakup date for the shallow lake shifts two days earlier and the average freezeup date shifts three days later, therefore extending the open-water evaporation season by 5 days, at both Fort Chipewyan and Fort McMurray (see Table 6). The average breakup and freezeup dates over the intermediate lake only shifts by one day to widen the open-water evaporation season by two days, and the dates over the deep lake are unaffected at both study sites by sediment heat flux. Therefore, sediment heat may be contributing heat to initiate breakup in the spring, and to delay freezeup in the fall. These effects are more pronounced in the shallow lake which has both a larger water to lake bed ratio, and less ability to store heat in the water volume itself. It is worth noting that the lengthened open-water season resulting from the inclusion of sediment heat modelling increases the total number of days in the year when open-water evaporation is possible, and yet the total annual evaporation is still lower than without sediment heat flux modelling.
Figure 49: Effects of MyLake’s sediment heat flux switch on evaporation based on lake depth.