Climate Change Impacts Review and Method Development

NWMO-TR-2019-05 March 2019

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Wood

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ABSTRACT

Title: **Climate Change Impacts Review and Method Development**
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Abstract
The objective of this study is to review anticipated climate change impacts and develop a methodology to incorporate these changes into probable maximum precipitation (PMP) estimation appropriate for the five Adaptive Phased Management (APM) Deep Geological Repository (DGR) study sites (Ignace, Hornepayne, Manitouwadge, South Bruce, and Huron-Kinloss) in Ontario.

Recent climate projections indicate that all five study sites will likely experience average temperature changes on the order of 3-4°C by the 2050s and ~6°C by 2080s. Precipitation changes are highly variable and dependent on localized dynamics; however, it is likely that South Bruce and Huron-Kinloss will experience average precipitation increases in the 75-100 mm/year range by the 2050s and 125-150 mm/year by the 2080s. Hornepayne, Manitouwadge and Ignace are projected to experience increases in precipitation closer to 50-75 mm/year by the 2050s and 100-125 mm/year by the 2080s.

PMP studies attempt to estimate the upper bounds of what would result from plausible, previously unexperienced, ‘worst case’ precipitation events. A study often begins with a documentation of the largest recorded precipitation events for the location of interest and surrounding region (Local Method) and first order statistical extrapolations applied to available records (Statistical Method). From there some form of deterministic modeling is typically applied to create extreme versions of historical precipitation events. This can take the form of applying recorded extreme atmospheric profiles to a simulated storm event centered on the site of interest (Maximization and Transposition). Other approaches include complex dynamical models that maximize the precipitating from historical events (Numerical Modeling).

The review of available methodologies suggested that each application of the derivation of PMP using climate change projections presented methodological differences. These studies were organized into three broad categories (numerical modeling, deterministic, and hybrid). The impact of methodological differences within and across these categories, and ultimately on PMP estimates, remains a research area in-development. Numerical modeling uses high resolution numerical weather prediction models to re-create and amplify historical storms. The deterministic method focuses on projected impacts on the meteorological parameters (e.g., atmospheric moisture) typically used in conjunction with storm maximization and transposition. Hybrid approaches combine aspects of the deterministic and numerical modelling approaches.

To meet the objectives outlined above, a deterministic approach is recommended to incorporate climate change into PMP estimation. The recommended approach aims to leverage lessons learned from the literature reviewed, current engineering methodologies, and existing climate modeling efforts while incorporating extensive sensitivity analysis throughout to address uncertainty. The approach is based on storm maximization, transposition and envelopment while also incorporating results from existing literature and additional climate change analysis.

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LIST OF ABBREVIATIONS

Term	Definition
1D	One dimensional
2D	Two dimensional
3D	Three dimensional
AOGCM	Atmosphere-ocean General Circulation Models
APM	Adaptive Phased Management
AR5	Fifth Assessment Report of the IPCC
BCCA	Bias Corrected Constructed Analogue
BCSD	Bias Corrected Spatial Downscaling
CAPE	Convective Available Potential Energy
CanESM2	Canadian Centre for Climate Modelling and Analysis Second Generation Earth System Model
CanRCM4	Canadian Centre for Climate Modelling and Analysis Canadian Regional Climate Model 4
CCCS	Canadian Centre for Climate Services
CCDS	Canadian Climate Data and Scenarios
CCSM4	Community Climate System Model Version 4
CDA	Canadian Dam Association
CDF	Cumulative Distribution Function
CFSR	Climate Forecast System Reanalysis
CMIP5	Coupled Model Inter-comparison Project Phase 5
CMIP6	Coupled Model Inter-comparison Project Phase 6
CO_2	Carbon Dioxide
CORDEX	Coordinated Regional Climate Downscaling Experiment
CRCM4	See CanRCM4
CRU	Climatic Research Unit Timeseries
DAD	Depth-area-duration
DGR	Deep Geological Repository
ECCC	Environment and Climate Change Canada
ECMWF	European Centre for Medium-Range Weather Forecasts
ECS	Equilibrium Climate Sensitivity
ERA	ECMWF reanalysis product
EVD	Extreme Value Distribution

GCM	Global Climate Model or General Circulation Model
GEV	Generalized Extreme Value Distribution
GHG	Greenhouse gas
GIS	Geographic Information System
GMFD	Global Meteorological Forcing Dataset
GPCC	Global Precipitation Climatology Centre
GUM	Gumbel Distribution
HMR	Hydrometeorological Report
HYSPLIT	Hybrid Single Particle Lagrangian Integrated Trajectory Model
IAM	Integrated Assessment Model
IDF	Intensity Duration Frequency
IDFCC	Computerized Tool for the Development of Intensity-Duration-Frequency Curves under a Changing Climate
IEESC	Institute for Energy, Environment and Sustainable Communities
IPCC	The Intergovernmental Panel on Climate Change
LAMPS	Laboratory of Mathematical Parallel Systems
LOCA	Localized Constructed Analogs
LULC	Land Use and Land Cover Changes
MTO	Ministry of Transportation Ontario
NA-CORDEX	The North American Coordinated Regional Climate Downscaling Experiment
NARCCAP	North American Regional Climate Change Assessment
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environmental Prediction
NEX-GDDP	NASA Earth Exchange Global Daily Downscaled Projections
NWMO	Nuclear Waste Management Organization
OCCDP	Ontario Climate Change Data Portal
OFAT	Ontario Flow Assessment Tool
OMNR	Ontario Ministry of Natural Resources
PCIC	Pacific Climate Impacts Consortium
PMF	Probable Maximum Flood
PMP	Probable Maximum Precipitation
PMSA	Probable Maximum Snowpack Accumulation
PW	Precipitable Water Content
RAMS	Regional Atmospheric Modeling System

RCM	Regional Climate Model
RCP	Representative Concentration Pathways
RegCM	NCAR Regional Model Version 4
RH	Relative Humidity
SRES	Special Report on Emissions Scenarios
SST	Sea Surface Temperature
SWE	Snow Water Equivalent
Td	Near-surface Dewpoint Temperature
WMO	World Meteorological Organization
WRF	Weather Research and Forecasting Model

1. INTRODUCTION

The objective of this study is to review anticipated climate change impacts and develop a methodology to incorporate these changes into probable maximum precipitation (PMP) estimation appropriate for the five Adaptive Phased Management (APM) Deep Geological Repository (DGR) study sites (Ignace, Hornepayne, Manitouwadge, South Bruce, and Huron-Kinloss) as shown in Figure 1-1.

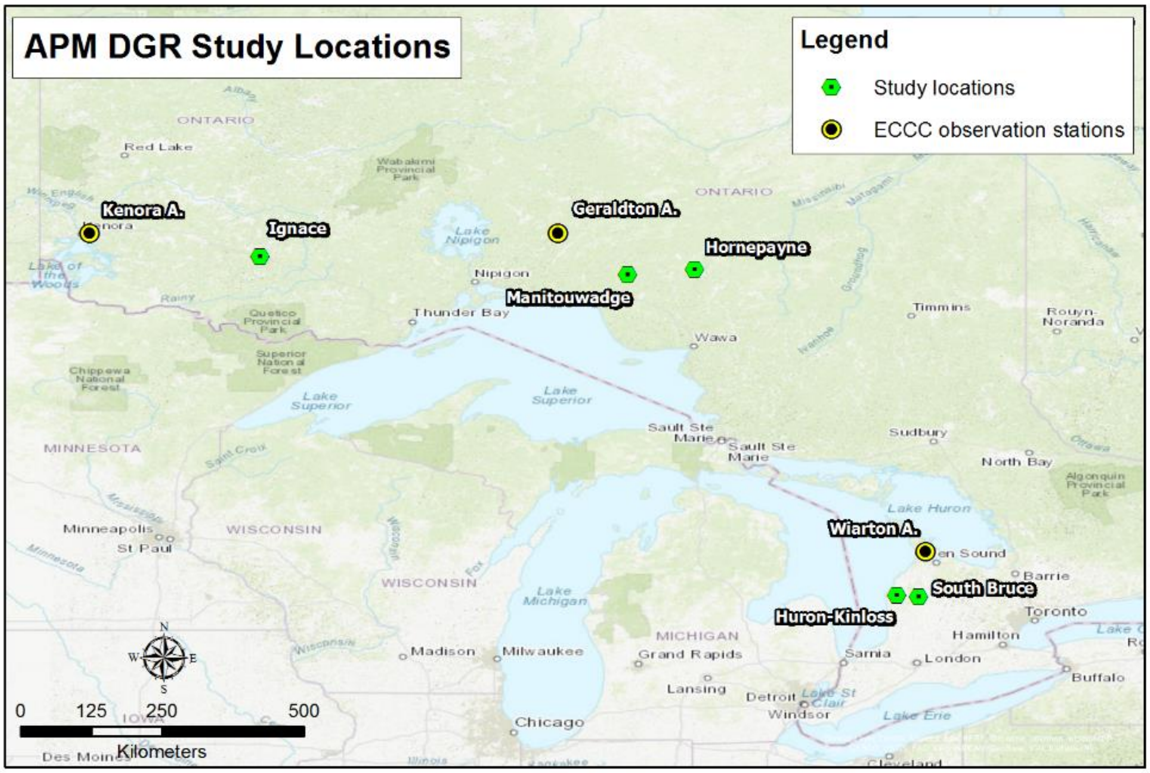


Figure 1-1: Approximate Locations of the Five APM DGR Study Sites

An illustration of the APM DGR concept is shown in Figure 1-2, while the implementation schedule for the DGR is illustrated in Figure 1-3 for planning purposes:

- 2023: Preferred site selection,
- 2023-2033: Site characterization and licensing,
- 2033-2043: Site preparation and construction,
- 2043: Start of operation,
- 2043-2083: Continued operation and panel development,
- 2083-2153: Extended monitoring period and finalized shaft sealing design,
- 2153: Start of decommissioning, removal of surface facilities, and sealing of access tunnels and shafts, and
- 2180: Completion of decommissioning.

The literature review and method development for this study followed the quality assurance processes and procedures laid out in Wood (2018a).

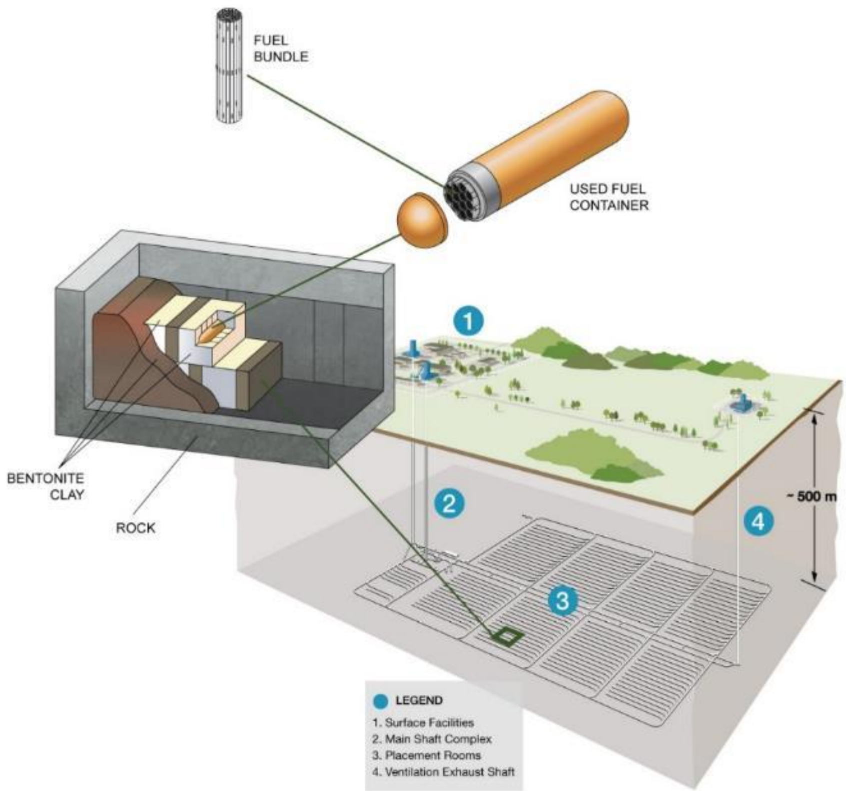


Figure 1-2: An Illustration of the Deep Geological Repository Concept

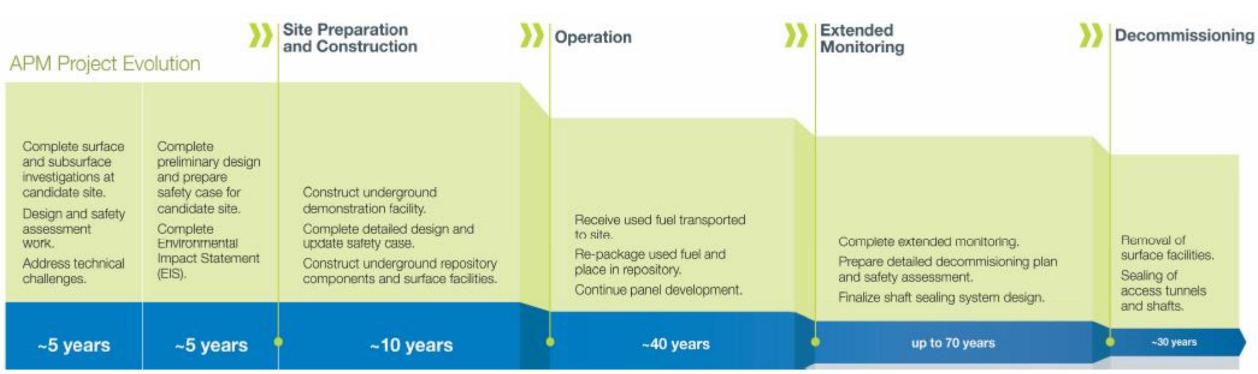


Figure 1-3: Illustrative APM Implementation Schedule for Planning Purposes

2. REVIEW OF HISTORICAL DATA

This section provides an overview of available historical meteorological data for the study sites, as well as a description of climate normals and recent significant storms. The historical observations data from Environment and Climate Change Canada's (ECCC) meteorological station network was queried to obtain estimates for the five study locations. Similarly, the National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis data was used to provide regional estimates. The NCEP/NCAR dataset employs a state-of-the-art analysis/forecast system to perform data assimilation using past meteorological data (1948-present)

The observations presented in this report were found to be largely consistent with the Phase 1 environment reports for the township of Manitouwadge, township of Hornepayne, communities of Huron-Kinloss, Brockton and South Bruce, as well as the township of Ignace (NWMO, 2013a; NWMO, 2013b; NWMO, 2014a; NWMO, 2014b). Some differences in the observations presented are due to station selection, time periods included in the estimates, and the way the data was compiled and presented.

2.1 HISTORICAL DATA SETS

Climate normals describe and summarize average climate conditions for a particular location, typically over a 30-year period. Climate normals data is presently available from ECCC for the periods 1961-1990, 1971-2000 and 1981-2010 for various stations across the country. Three stations (Kenora Airport, Geraldton Airport, and Wiarton Airport as shown in Figure 1-1) were selected because of their quality control measures, length of record, and their proximity to the regions of interest to illustrate daily temperature climate statistics by month, as well as to provide an example of the regional variability across Ontario.

Selection of historical datasets for analysis purposes depends largely on the variables and timeframes of interest, as well as methodology for the analysis. In areas where the station network is sparse, gridded observation data sets may be used. Gridded data products are either made using interpolation methods (e.g,. Climatic Research Unit Timeseries (CRU) and Global Precipitation Climatology Centre (GPCC)) or reanalysis (e.g., ECMWF reanalysis product (ERA)-5, and NCEP/NCAR). Because gridded datasets spatially average variables, there is in general an inverse relationship between the grid cell area and the magnitude of extreme values (Chen and Knutson, 2008). Most of the commonly used datasets are based on peer-reviewed methodologies, which improve confidence in the estimates used. There are various datasets that integrate the latest knowledge of climate science (e.g., CRU, GPCC, ERA-Interim, ERA-5). One of the latest supported global datasets is ERA-5 dataset (https://climate.copernicus.eu/climate-reanalysis) from the European Centre for Medium-Range Weather Forecasts (ECMWF). The ERA-5 dataset provides hourly estimates from 1950-present for 240 variables at a resolution of 0.25˚x0.25˚ degrees (~35 km x 35 km). Similarly, ERA5-land is currently in development and it will provide similar data at ~9 km x 9 km spatial resolution over land (1950-present).

2.1.1 Temperature

Ontario's annual near-surface temperatures range significantly across the province, as illustrated by Figure 2-1 (ESRL, 2018). Generally, the north-west is cooler than the south-west portion of the province.

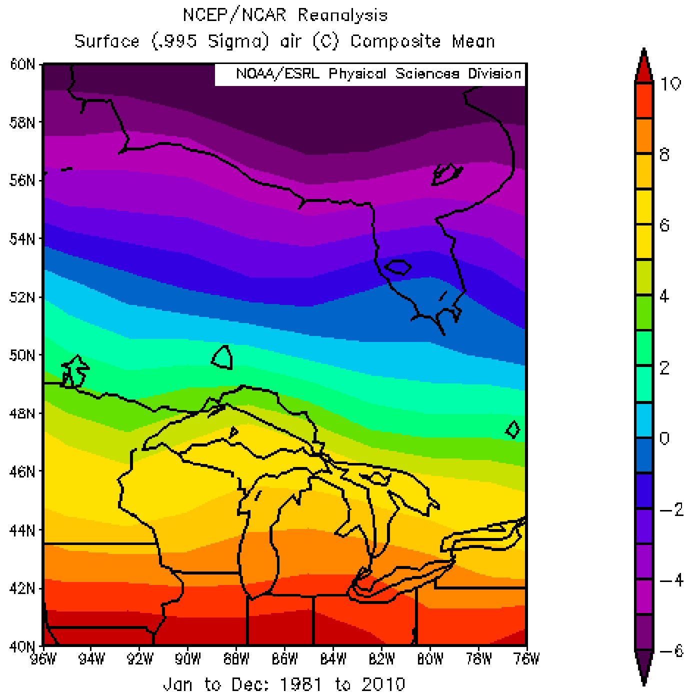


Figure 2-1: Annual Mean of Near Surface Temperature (˚C) for Ontario (1981-2010) (NCEP/NCAR Re-analysis)

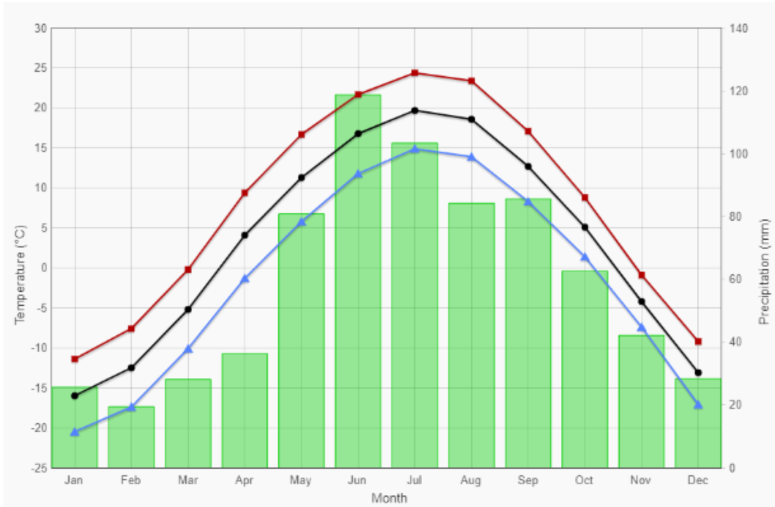
At Kenora Airport station (1981-2010), monthly average temperatures range from 19.7˚C (July) to -16.0˚C (January). Daily maximum and minimum temperatures can be as high as 24.4˚C (July) and -20.5˚C (January) respectively. At the Geraldton Airport Station (1981-2010), monthly average temperatures range from 17.2˚C (July) to -18.6˚C (January). Daily maximum and minimum temperatures can be as high as 23.5˚C (July) and -25.1˚C (January) respectively. At the southern and eastern most station Wiarton Airport Station (1981-2010), monthly average temperatures range from 18.9˚C (July) to -6.3˚C (January). Daily maximum and minimum temperatures can be as high as 35.6˚C (July) and -36.4˚C (January) respectively. Figure 2-2 shows the monthly mean, minimum and maximum temperatures for the aforementioned stations (as well as average monthly precipitation, discussed in Section 2.1.2) (ECCC, 2018a). Similarly, Table 2-1 summarizes the highest temperatures recorded (extreme maximum) and lowest temperatures recorded (extreme minimum) per month for the entire historical dataset at each of the stations (ECCC, 2018a).

Table 2-1: Summary of Extreme Daily Maximum and Minimum Events at Kenora Airport, Geraldton Airport and Wiarton Airport Stations

		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Kenora Airport	Extreme Maximum (°C)	9.1	8.8	23.3	30.6	35.4	35.6	**35.8**	35.0	34.6	26.7	19.4	9.4
	Date (yyyy/dd)	2003/07	2000/23	1946/27	1952/30	1986/29	1995/17	**1983/14**	1955/18	1983/02	1943/08	1975/05	1941/03
	Extreme Minimum (°C)	**-43.9**	-41.4	-36.1	-27.2	-12.2	-0.6	3.9	1.1	-6.7	-13.9	-31.3	-38.3
	Date (yyyy/dd)	**1943/20**	1996/02	1962/01	1954/02	1958/01	1969/13	1972/02	1938/28	1965/25	1951/31	1985/28	1967/31
Geraldton Airport	Extreme Maximum (°C)	5.9	9.5	17.4	25.8	32.8	**37.0**	35.0	33.7	32.7	24.8	17.7	10.8
	Date (yyyy/dd)	1999/31	1991/03	2010/31	1999/30	2010/25	**1995/18**	2006/13	2005/02	2002/08	2000/01	2008/04	1982/03
	Extreme Minimum (°C)	**-50.2**	-49.3	-40.4	-33.0	-11.3	-4.6	1.3	0.0	-7.8	-14.8	-36.4	-43.1
	Date (yyyy/dd)	**1996/31**	1996/01	1989/03	1982/05	1996/04	1983/08	1992/01	1989/24	1991/29	1997/27	1985/28	2004/25
Wiarton Airport	Extreme Maximum (°C)	17.8	16.9	23.1	30.0	32.1	33.3	33.4	35.0	**35.6**	28.3	23.3	18.1
	Date (yyyy/dd)	1950/25	2000/26	1990/14	1990/28	2006/30	1966/26	1993/05	1947/06	**1953/03**	1947/16	1950/01	2001/05
	Extreme Minimum (°C)	**-36.4**	-34.8	-30.7	-17.8	-5.0	-1.6	3.3	1.7	-3.4	-7.2	-18.0	-26.6
	Date (yyyy/dd)	**1977/18**	1979/18	1980/02	2003/06	1966/07	1977/08	1972/05	1965/30	1989/27	1965/28	1995/29	1980/17

Note: Bold values highlight the highest extreme maximum and minimum values for each station.

1)



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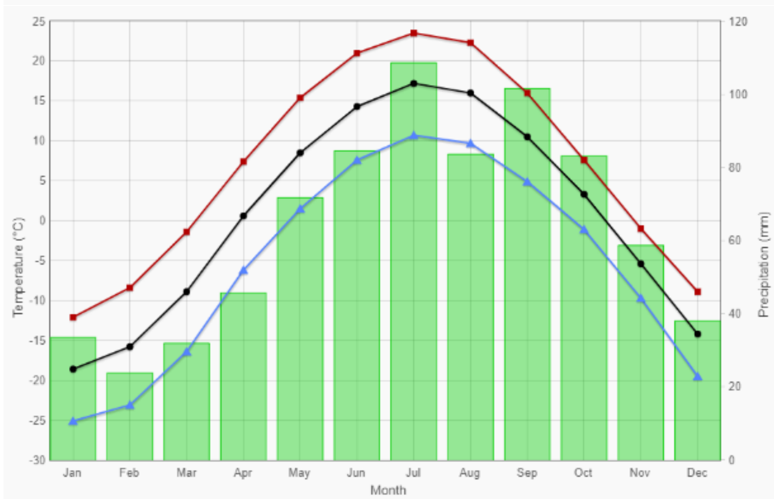

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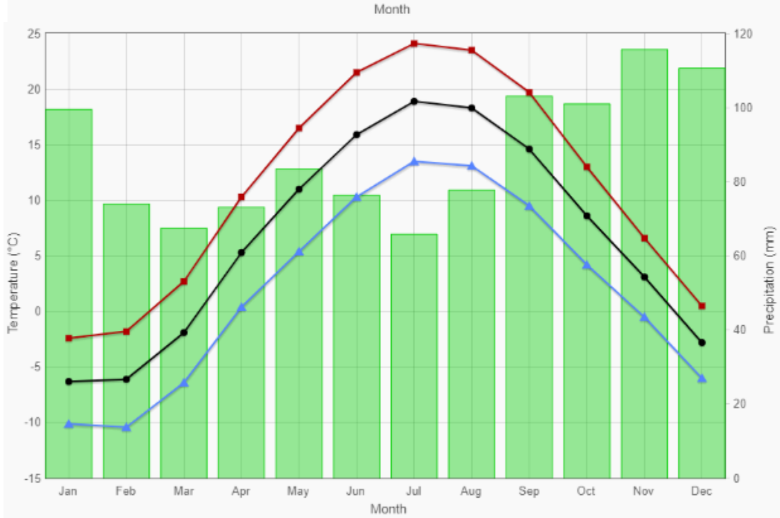


Note: Monthly mean of daily temperature estimates (˚C) are shown as a line graph, showing the average (black), minimum (blue), maximum (red). The bar graph (green bars) shows average monthly precipitation (rainfall + snowfall) totals (mm).

Figure 2-2: Summary Graph of Temperature and Precipitation for the 1981-2010 Climate Normal- 1) Kenora Airport 2) Geraldton Airport 3) Wiarton Airport

2.1.2 Precipitation

Figure 2-3 (from ESRL, 2018) demonstrates the regional variability of average annual precipitation across Ontario, with precipitation accumulation decreasing from southeast to northwest.

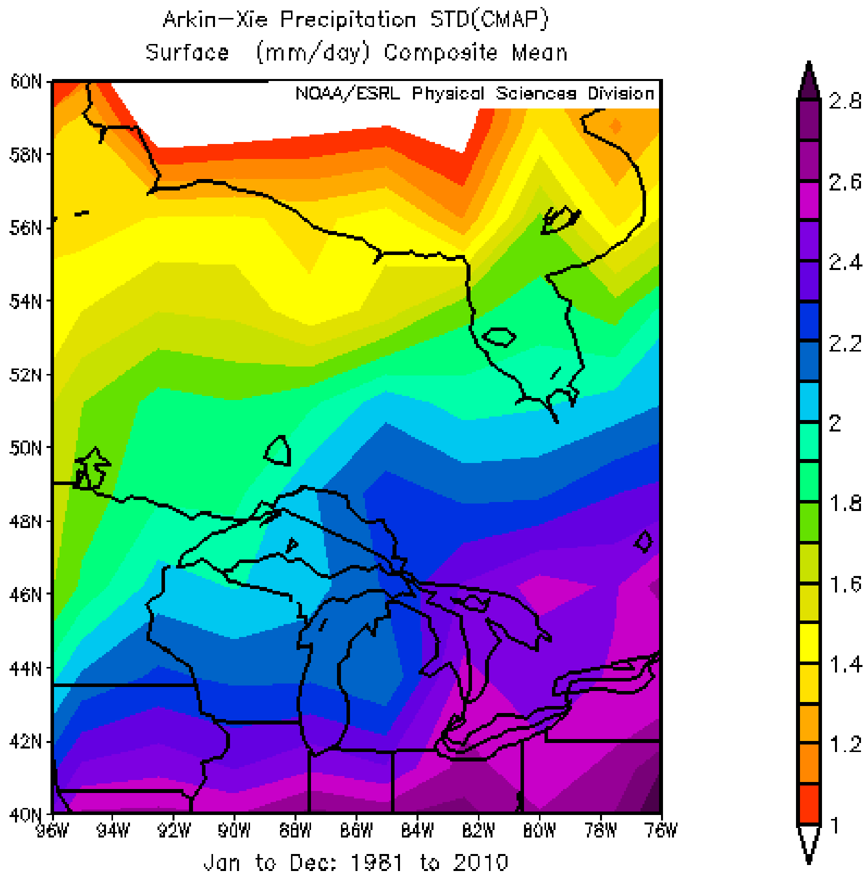


Figure 2-3: Average Annual Precipitation Estimates (mm/day) for Ontario (1981-2010) Using Arkin-Xie Precipitation STD (CMAP) Re-analysis Estimates

At Kenora Airport station (1981-2010), monthly average rainfall ranges from 118.6 mm (June) to 0.7 mm (January). Overall precipitation ranges from 118.7 mm in June to 19.4 mm in February. At Geraldton Airport station (1981-2010), monthly average rainfall ranges from 108.6 mm (July) to 0.4-0.6 mm (January-February). Overall precipitation ranges from 108.6 mm in July to 23.8 mm in February. At Wiarton Airport station (1981-2010), monthly average rainfall ranges from 103.1 mm (September) to 21.3 mm (February). Overall precipitation ranges from 115.7 mm in November to 65.8 mm in July. Figure 2-2 shows the monthly mean, minimum and maximum monthly rainfall estimates for all three stations. Similarly, Table 2-2 summarizes daily extreme rainfall and daily precipitation (rainfall + snowfall) recorded per month for the entire historical dataset at each of the stations (ECCC, 2018a).

Table 2-2: Summary of Extreme Maximum and Minimum Events at Each Station

		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Kenora Airport	**Extreme Daily Rainfall (mm)**	9.4	16.2	19.8	33.3	106.4	121.4	**153.5**	92.5	108	46.5	23	29.7
	Date (yyyy/dd)	2010/ 23	2000/ 26	1960/ 28	1974/ 21	2007/ 29	1999/ 25	**1993/ 27**	1972/ 20	1981/ 06	1940/ 04	2008/ 06	1951/ 03
	Extreme Daily Precipitation (mm)	24.6	26.9	26.9	36.3	106.4	121.4	**153.5**	92.5	108	46.5	32.8	37.1
	Date (yyyy/dd)	1975/ 11	1955/ 20	1966/ 04	1957/ 10	2007/ 29	1999/ 25	**1993/ 27**	1972/ 20	1981/ 06	1940/ 04	1977/ 09	1951/ 03
Geraldton Airport	**Extreme Daily Rainfall (mm)**	3.8	4.2	23.9	37.8	43	57.4	78.8	68.8	**124.6**	48	30.2	44.6
	Date (yyyy/dd)	2002/ 09	2000/ 26	2006/ 31	1991/ 28	2007/ 29	1990/ 17	1999/ 14	1988/ 14	**1985/ 19**	1995/ 01	2001/ 24	1984/ 16
	Extreme Daily Precipitation (mm)	56.2	18.8	29.4	37.8	43	57.4	78.8	68.8	**124.6**	49.4	34.2	57.2
	Date (yyyy/dd)	1996/ 18	2001/ 25	2006/ 31	1991/ 28	2007/ 29	1990/ 17	1999/ 14	1988/ 14	**1985/ 19**	2005/ 05	1985/ 02	1984/ 16
Wiarton Airport	**Extreme Daily Rainfall (mm)**	32	48	36.1	45.3	61.6	67.8	**104.6**	73.4	88.6	69.3	46	45.5
	Date (yyyy/dd)	1998/ 05	1997/ 21	1948/ 15	1988/ 03	2004/ 23	1950/ 23	**1969/ 28**	1968/ 20	1963/ 12	1954/ 15	1988/ 10	1962/ 06
	Extreme Daily Precipitation (mm)	47.6	48.6	47.2	45.3	61.6	67.8	**104.6**	73.4	88.6	69.3	46	45.5
	Date (yyyy/dd)	1982/ 31	1997/ 21	1973/ 17	1988/ 03	2004/ 23	1950/ 23	**1969/ 28**	1968/ 20	1963/ 12	1954/ 15	1988/ 10	1962/ 06

Note: Bold values highlight the highest extreme rainfall and extreme precipitation values for each station.

Historical precipitation intensity duration frequency (IDF) estimates for each station are presented in Table 2-3 (from IDFCC, 2018), which shows that intensities are generally stronger at the Kenora Airport station, while Wiarton and Geraldton Airport stations are similarly more moderate (also evidenced in Table 2-3).

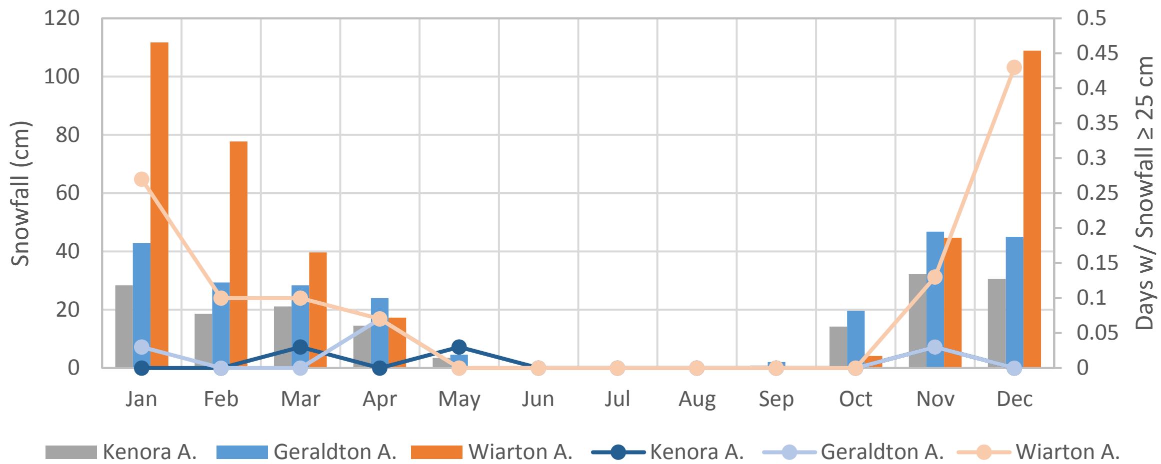
Table 2-3: Intensity Duration Frequency Estimates Using Gumbel Distribution for Each Station (mm/hr)

Station	Duration	T (years)					
		2	5	10	25	50	100
Kenora	5 min	117.04	155.26	180.56	212.53	236.25	259.8
Geraldton	5 min	77.19	103.36	120.69	142.58	158.82	174.94
Wiarton	5 min	85.16	110.41	127.13	148.25	163.92	179.47
Kenora	10 min	80.52	107.41	125.21	147.71	164.4	180.96
Geraldton	10 min	58.13	78.73	92.37	109.61	122.4	135.1
Wiarton	10 min	62.14	78.89	89.98	103.99	114.38	124.69
Kenora	15 min	65.38	89.39	105.28	125.36	140.26	155.05
Geraldton	15 min	47.43	64.88	76.44	91.04	101.88	112.63
Wiarton	15 min	51.43	66.19	75.95	88.29	97.45	106.53
Kenora	30 min	42.64	59.73	71.05	85.34	95.95	106.48
Geraldton	30 min	31.09	40.22	46.27	53.92	59.59	65.22
Wiarton	30 min	33.55	43.85	50.67	59.29	65.68	72.03
Kenora	1 h	26.48	37.84	45.37	54.87	61.93	68.93
Geraldton	1 h	19.01	25.19	29.28	34.44	38.27	42.08
Wiarton	1 h	21.26	30.08	35.91	43.28	48.75	54.18
Kenora	2 h	16.42	25.58	31.64	39.3	44.99	50.63
Geraldton	2 h	11.52	15.3	17.81	20.97	23.32	25.66
Wiarton	2 h	13.47	19.62	23.69	28.84	32.66	36.45
Kenora	6 h	7.67	11.37	13.82	16.91	19.21	21.48
Geraldton	6 h	5.31	6.98	8.08	9.47	10.5	11.53
Wiarton	6 h	6.04	8.25	9.72	11.58	12.95	14.32
Kenora	12 h	4.55	6.72	8.16	9.97	11.32	12.65
Geraldton	12 h	3.19	4.15	4.78	5.59	6.18	6.78
Wiarton	12 h	3.41	4.6	5.38	6.38	7.12	7.85
Kenora	24 h	2.51	3.64	4.39	5.33	6.04	6.73
Geraldton	24 h	1.91	2.58	3.02	3.58	4	4.41
Wiarton	24 h	2.01	2.54	2.89	3.34	3.67	4

Note: Colour coding is added to facilitate quick visual comparison of the three stations for each duration. The relative accumulations (from the maximum accumulation for each duration) are proportional to the amount of colour in each cell space. ”T (years)” is the return period.

2.1.3 Snowfall

At Kenora Airport station (1981-2010), the greatest amount of snowfall in a given month typically occurs in November (32.2 cm), and snowfall is often recorded as late as June (0.1 cm) and as early as September (0.8 cm). At Geraldton Airport station (1981-2010), the greatest amount of snowfall in a given month also tends to occur in November (46.8 cm), and snowfall is often recorded as late as May (4.6 cm), and as early as September (2.0 cm). At Wiarton Airport station (1981-2010), the greatest amount of snowfall in a given month typically occurs in January (111.7 cm), and snowfall is often recorded as late as May (0.5 cm) and as early as October (4.1 cm). Figure 2-4 (from ECCC, 2018a) shows the average monthly snowfall accumulation for the three stations, as well as the number of very heavy snowfall days (≥ 25cm) for each station. Table 2-4 (from ECCC, 2018a) summarizes daily extreme snowfall events for each station and provides the total precipitation for those events where the daily extreme snowfall was also recorded as the daily extreme precipitation.



Note: Bars show snowfall, while line graphs show days with snowfall estimates.

Figure 2-4: Summary of Average Monthly Total Snowfall for Each Station (1981-2010)

Table 2-4: Summary of Extreme Maximum Snowfall Events at Each Station

		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Kenora Airport	**Extreme Daily Snowfall (cm)**	24.6	26.9	33.8	**36.3**	35.6	1.4	0	0	30	26.2	32.8	22.8
	Date (yyyy/dd)	1975/ 11	1955/ 20	1966/ 04	**1957/ 10**	2004/ 11	1998/ 01	1939/ 01	1938/ 26	1964/ 26	1970/ 09	1977/ 09	1984/ 16
	Extreme Daily Precipitation (mm)	24.6	26.9	26.9	36.3	-	-	**-**	-	-	-	32.8	-
	Date (yyyy/dd)	1975/ 11	1955/ 20	1966/ 04	1957/ 10	-	-	**-**	-	-	-	1977/ 09	-
Geraldton Airport	**Extreme Daily Snowfall (cm)**	**56.6**	24.8	18	33	8.6	1	0	0	17.4	21.3	28	22
	Date (yyyy/dd)	**1996/ 18**	2001/ 25	1988/ 08	1996/ 30	2010/ 05	1982/ 01	1982/ 01	1981/ 01	1984/ 25	1983/ 14	1990/ 28	2007/ 23
	Extreme Daily Precipitation (mm)	56.2	18.8	-	-	-	-	-	-	**-**	-	-	-
	Date (yyyy/dd)	1996/ 18	2001/ 25	-	-	-	-	-	-	**-**	-	-	-
Wiarton Airport	**Extreme Daily Snowfall (cm)**	**51.4**	30.7	45.5	26.8	14.5	0	0	0	0.2	23.6	32.5	38.4
	Date (yyyy/dd)	**1982/ 31**	1965/ 25	1983/ 21	1992/ 10	1976/ 03	1948/ 01	1947/ 01	1947/ 01	1985/ 12	1997/ 26	1999/ 03	1989/ 20
	Extreme Daily Precipitation (mm)	47.6	**-**	**-**	**-**	**-**	**-**	**-**	**-**	-	-	-	**-**
	Date (yyyy/dd)	1982/ 31	**-**	**-**	**-**	**-**	**-**	**-**	**-**	-	-	-	**-**

Note: " - " indicates that the extreme daily snowfall value recorded did not match the event recorded as the extreme daily precipitation event. Bold values highlight the highest extreme snowfall and extreme precipitation values for each station.

2.1.4 Wind

Ontario's average wind speed varies across the province. Figure 2-5 (from ESRL, 2018) illustrates the annual average wind speed (m/s) variability across Ontario (approximately from 4 to 8 m/s) for the time period 1981-2010 from NCEP/NCAR reanalysis. Relatively low wind speeds are most common across the central portion of the northern regions of Ontario. Wind speeds range between 5 m/s to 5.5 m/s near Southern Ontario, and up to 6.5 m/s near the coast of the Hudson Bay.

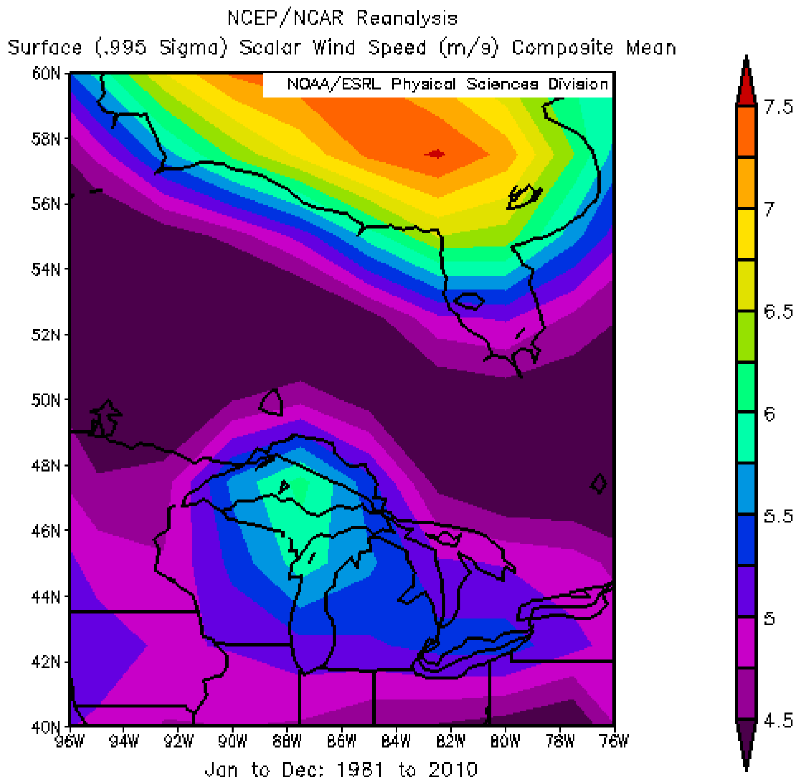


Figure 2-5: Mean Scalar Wind Speeds (1981-2010) for Ontario (NCEP/NCAR Reanalysis)

Table 2-5 summarises the average wind speeds, most frequent directions and maximum gust speeds for each of the three stations (ECCC, 2018a).

Table 2-5: Summary of Wind Speed, Most Frequent Direction and Gust Speeds at Each Station

		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Kenora Airport	**Speed (km/h)**	13.4	13.4	14.1	**14.5**	14.3	13.4	12.6	12.9	13.8	14.5	14.3	13.5
	Most Frequent Direction	S	S	S	S	S	S	S	S	S	S	S	S
	Maximum Hourly Speed (km/h)	58	51	56	53	56	**68**	64	64	57	64	58	59
	Maximum Gust Speed (km/h)	85	76	78	79	104	115	108	**129**	89	90	83	120
Geraldton Airport	**Speed (km/h)**	10.4	10.5	11.6	11.8	12.2	11.7	10.7	10.3	11.6	12.1	11.5	10.3
	Most Frequent Direction	W	W	W	N	S	S	W	W	S	S	NW	W
	Maximum Hourly Speed (km/h)	54	44	48	52	52	56	50	52	56	**59**	48	50
	Maximum Gust Speed (km/h)	72	70	82	82	82	85	98	**107**	78	87	82	78
Wiarton Airport	**Speed (km/h)**	16	14.4	13.7	14.1	11.6	9.8	9.8	10	11.6	14	15.4	15.8
	Most Frequent Direction	S	S	W	W	W	W	W	W	S	S	S	S
	Maximum Hourly Speed (km/h)	76	68	**84**	68	64	61	56	80	64	74	80	76
	Maximum Gust Speed (km/h)	108	96	108	**126**	104	93	105	119	113	102	111	111

Note: Bold values highlight the highest values for variable at each station. Wind Speeds and Most Frequent Direction are estimated based on the observations from 1981-2010. Maximum Frequency Direction, Maximum Hourly Speed and Maximum Gust Speeds are based on the entire period of record at each station.

2.1.5 Tornadoes

In the 1980-2009 climate normal, Canada experienced on average 61.3 (F0-F5) tornadoes per year. In Canada about 43 tornadoes occur across the Prairies, and about 17 occur across Ontario and Quebec. The peak season is June through August. The 1946 Windsor F4 event was the deadliest tornado in Ontario. The largest tornado outbreak in the province occurred on August 20, 2009 (19 tornadoes developed over southern Ontario) (ECCC, 2018b).

Figure 2-6 show the locations of all confirmed and probable tornadoes across Canada from 1980 to 2009 (ECCC, 2018b), while Figure 2-7 shows the locations of all confirmed tornadoes in Ontario over the same time frame (ECCC, 2018c).

It should be noted that it is likely that more tornadoes than the ones mapped in Figure 2-7 occurred in the 1980-2009 time period. Discrepancies between probable tornadoes (available evidence points to the likelihood of a tornado, but no direct evidence) and verified tornado counts (direct evidence e.g., visual evidence) are prone to population bias, as well as other meteorological and non-meteorological biases (e.g., radar locations, landscape, monitoring network, etc.) (Cheng et al., 2013). In Figure 2-8, predicted tornado occurrence in area and time (Tlatent, 10,000 $km^{-2}yr^{-1}$) are presented along with corresponding tornado probability (P_D*, yr^{-1}) and return period (years) (Cheng et al., 2013).

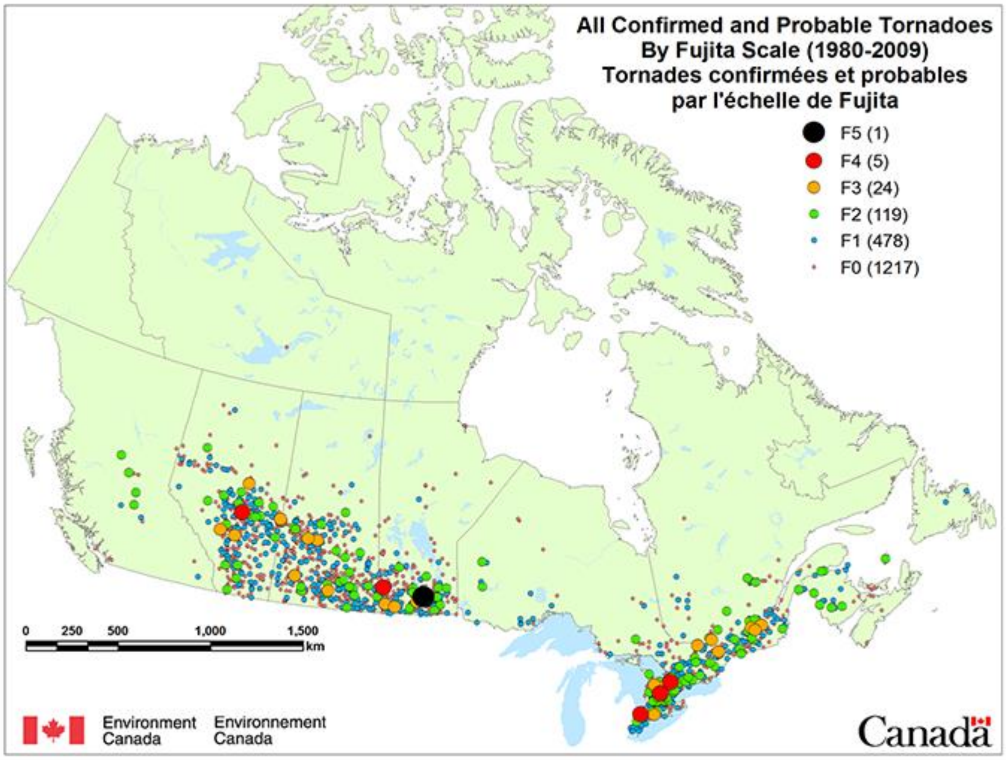


Figure 2-6: Confirmed and Probable Tornadoes Across Canada (1980-2009)

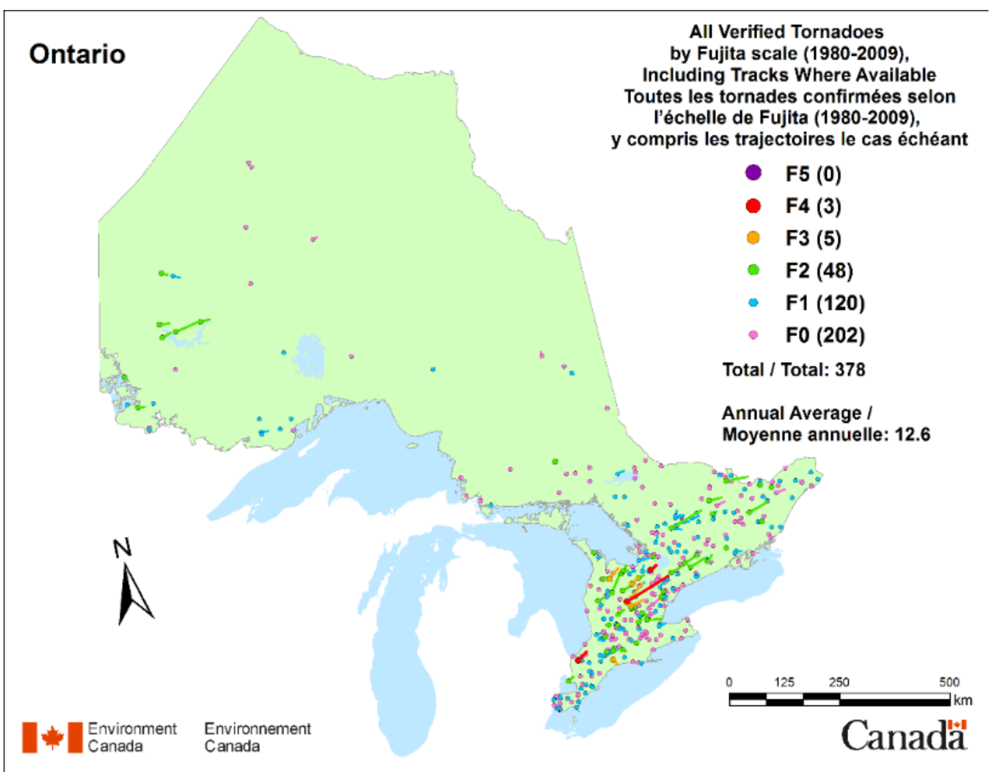


Figure 2-7: Verified Tornadoes in Ontario (1980-2009)

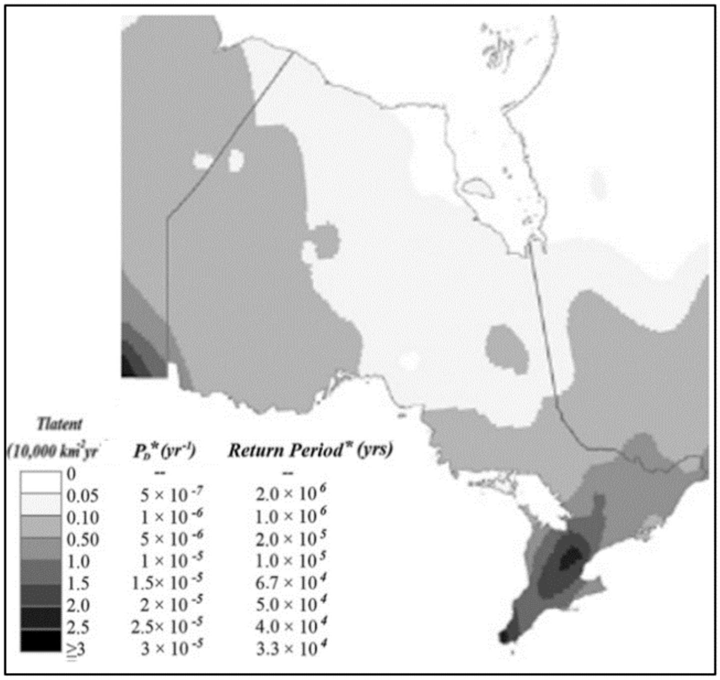


Figure 2-8: Estimated Predicted Occurrence and Return Period of Tornadoes Based on Mean Values

2.2 RECENT SIGNIFICANT STORMS

Table 2-6 provides a high-level summary of extreme storms which have occurred in the region since OMNR (2006) was published. A high-level comparison of these recent storms with those listed in OMNR (2006) shows that those in Table 2-6 fall within the distribution of the historical storms, as listed in OMNR (2006). However, a detailed analysis of storm events incorporating their duration and area would be needed to comprehensively compare the intensity and frequency of these storm events and the past storm events in the OMNR (2006) study.

The results of OMNR's (2006) PMP for Ontario estimates are presented in the form of a mapped regional estimate of PMP values across Ontario (one map for each duration and area). Figure 2-9 is an example of one of the maps mentioned above (OMNR, 2006). The contours of the 24-hour, 25 km^2 PMP were used to visually estimate PMP values for each of the five study locations: Ignace (510 mm), Manitouwadge (490 mm), Hornepayne (475 mm), Huron-Kinloss (600 mm), South Bruce (600 mm).

Table 2-6: Recent Extreme Storms in Studied Region

Location	Date	Total Rainfall Amount (mm)	Duration (hours)	1-hour Max Intensity (mm/hr)
Peterborough (Trent U)	July 14-15, 2004	250	16.5	87.2
Toronto (Finch Ave)	August 19, 2005	153.4	12.5	116.6
Hamilton (Stoney Creek)	July 25-26, 2009	135.5	35	60.8
Mississauga (Cooksville)	August 4, 2009	68	1	68
West-central GTA (Pearson)	July 8, 2013	125.6	3	96
Burlington	August, 2014	170	7	56

Note: Data abstracted from “Hydrology & Hydraulics, Adapting to New Weather Realities” Presentation to Technical Committee of Lake Ontario Integrated Sub watershed Study, March 24, 2014 by Neelam Gupta, Manager, Hydrology & Hydraulics, Credit Valley Conservation Authority. Available at http://www.creditvalleyca.ca/wp-content/uploads/2014/05/LOISS-Hydrology-Hydraulics.pdf as well as "Climate Change and Flood Resilience Practices" at the Water Environment Association of Ontario (WEAO) (Available at https://d3n8a8pro7vhmx.cloudfront.net/weao/pages/1523/attachments/original/1509715862/Stormwater_EdmundoFausto.pdf?1509715862).

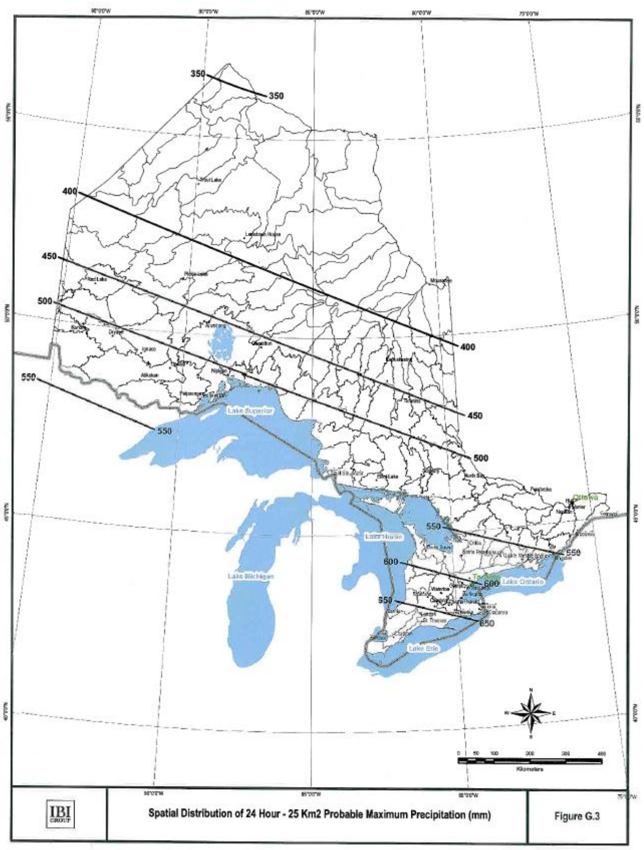


Figure 2-9: Regional Values of 24 Hour - 25 Km^2 PMP

3. LITERATURE REVIEW

The literature review presented here includes probable maximum precipitation (PMP) estimation methods, a discussion of climate change impacts in Canada and Ontario (including a focus on temperature, rainfall, snowfall, wind and tornadoes), an overview of the most pertinent climate model ensembles, and methods for incorporating climate change impacts into PMP estimation.

3.1 PROBABLE MAXIMUM PRECIPITATION ESTIMATION METHODS

As defined by the World Meteorological Organization (WMO), the "probable maximum precipitation" (PMP) is the theoretical maximum precipitation for a given duration under modern meteorological conditions" (WMO, 2009). PMPs are used as inputs to determine the probable maximum flood (PMF) for a given watershed at a certain time of year. There are many methods for PMP estimation, which are typically presented as equivalent despite being very different approaches. There are no quantitative methods to assess the accuracy of PMP values. Hence the importance of computing multiple values and/or using multiple approaches to understand the impact of decisions made within the analysis process.

A review of various established PMP estimation methods is provided here. Included are the six methods of PMP estimation discussed in WMO (2009), and other methods identified during the literature review process, as outlined below. Seasonal variations, recommendations given by the Canadian Dam Association and uncertainty associated with PMP development are also discussed in this section.

From WMO (2009), the PMP estimation methods are:

1) *The Statistical Method;*
2) *The Local Method;*
3) *The Inferential Method;*
4) *The Transposition Method;*
5) *The Combination Method; and*
6) *The Generalized Method.*

There are two methods from other sources:

1) *Numerical Modeling Method; and*
2) *Hybrid Method.*

Lastly, an overview is provided of the uncertainty quantification approach described by Micovic et al. (2015), which suggests a framework for expressing the implications of uncertainties within the analysis process.

It should be noted that not all situations allow for the explicit and exact adherence to the step-by-step methodology outlined below and professional judgement is often required. For instance, relatively short or sparse observation records may not allow for the incorporation of a 50-year dewpoint temperature record (as stated in the *Transposition Method* below) for each storm analyzed. However, such limitations need to be explicitly considered when evaluating the reliability of the resulting estimates.

3.1.1 WMO Analysis Methods

3.1.1.1 Statistical Method

The statistical approaches shown here are generally considered less reliable than those based on meteorological analysis, and so are typically used more in preliminary studies and/or as a "sanity check" to compare magnitudes against values produced by other methods.

For this approach, maximal rainfall, for a given site and duration, is described as:

$$\mathrm{PMP} = \overline{\mathrm{X}}_{\mathrm{n}} + K_m \sigma_n \qquad [1]$$

Where $\bar{X}_n$ and σ_n are the mean and standard deviation of a series of n annual rainfall maxima, and so K_m is then the number of standard deviations that need to be added to the mean to obtain the PMP value.

To generate a single point estimate from a data set, one would first define:

$$K_m = \frac{X_m - \overline{X_{n-1}}}{\sigma_{n-1}} \qquad [2]$$

Where $\overline{X_{n-1}}$ and σ_{n-1} are the mean and standard deviation of the annual maxima series with the maximal value, X_m, removed. This value of K_m is then used in the PMP equation. The WMO documentation suggests the following possible adjustments:

- Use the full data record when computing K_m; but to adjust $\bar{X}_n$ and σ_n for potential outliers, use curves defined by Hershfield (1961b). These approximations attempt to account for the fact that a limited (<30 years) observation period may contain rare extremes or represent an anomalously 'quiet' period for the site/region. If the mean and standard deviations calculated excluding the observed maxima are notably smaller than values derived from the full period, then the former situation is assumed to have occurred, and the parameters are reduced by a prescribed percentage. If the values derived from the subset and full data sets are similar, then the latter is assumed to have occurred, and the parameters are inflated by a prescribed percentage. Here "notably smaller" and "similar" are defined through simulations performed by Hershfield (1961b) and vary according to series length.
- Inflate, the $\bar{X}_n$ and $\sigma_n$value, to account for short station records, since short records increase odds that higher magnitude events are not included in the records. This is again possible using curves defined by Hershfield (1961b) which assign inflation percentages as a function of record length.
- Inflate estimates to address the concern that using values from fixed observation times underestimates the full maxima rainfall amount for a given duration (e.g., an annual maximum 1-day rainfall amount taken from daily measurements will often be significantly less than the maximal amount that would be observed that year over a 24-hour consecutive period with an arbitrary start time). The standard correction factor is 1.13 Hershfield (1961a), but the appropriate value can be as high as 2.0 (Micovic et al., 2015). When the measurement intervals are smaller than the analysed duration (e.g., 24-hour cumulative rainfall is derived from a time series of measurements taken on 6-hour intervals), different, smaller, correction factors are suggested by Weiss (1964) and Miller (1964).

If it is desired to generalize these estimates over a region, using isolines of station rainfall values, it is suggested to consider the coefficient of variation, $\mathrm{C_v} = \sigma_n/\overline{\mathrm{X_n}}$, as these values are believed to be more stable to interpolation than the standard deviation. Thus, one can estimate the PMP values as:

$$\mathrm{PMP} = \overline{\mathrm{X}}_\mathrm{n}(1 + \mathrm{K_m C_v}). \qquad [3]$$

It is important to note that the statistical PMP method is meant to describe a point (gauge station) precipitation depth, where a point is an area less than 25 km^2. If the analysis requires estimates of regional rainfall, then these values must be extrapolated with depth-area-duration curves. This is not recommended for regions over 1,000 km^2.

3.1.1.2 Local Method

This is the most straight forward approach, wherein values are taken from the worst/biggest storm in recorded history. One needs to be incredibly confident that that storm represents the worst possible scenario. As such, this method would only be appropriate for regions with records that extend longer than the desired return period, which, in itself, is a controversial definition of PMP. This approach does not appear advisable, and so is not discussed here in detail. However, knowledge of these values is important for setting hard minimums on acceptable outputs from other analyses. If anything, an estimate of maximal possible precipitation should be notably higher than any observed value (Micovic et al., 2015).

3.1.1.3 Inferential Method

In this estimate a simplified 3D model from a major event is created, built around the assumption that wind and moisture center on the site location, either assuming convergence from all sides or movement along a laminar surface. This approach is usually used only for orographic regions where mountain ridges create high and continuous barriers. As such, we provide a limited overview here as the approach does not appear applicable to the region of interest. Other important factors to consider when determining the applicability of this method are:

- This approach requires a dense sampling of high-quality observations of upper atmosphere behavior for the area.
- The convergence model is typically not feasible as there is no set empirical or theoretical procedure for assigning values to convergence or vertical motion. These values are required, along with estimates of maximum water vapor content. Such variables are difficult to observe, and often, unavailable, or estimated from unreliable proxies.
- The laminar flow model assumes that the rainfall driver is orographic, with moisture being pushed over a “relatively unbroken mountain ridge”. Transport is assumed to take the form of 2D laminar flow, meaning that the model is unable to address convective effects.
- In general, the assumption that levels of convergence and orographic forcing can be explicitly estimated is sometimes considered suspect (Micovic et al., 2015).

3.1.1.4 Transposition Method

This is the most commonly applied approach to PMP estimation. As well, most of the methods discussed in the following sections (except for *Numerical Simulations*) assume some form of the *Transposition Method* as the baseline approach that they expand upon. Storm transposition allows to increase the sample of historical extreme storms over a site/basin of interest (target location).

The first step is to select a storm from the historical record to base estimates on. It must be determined that said storm is the most extreme example for the watershed, as defined by climatic and topographical similarity. As well, one must be able to identify the meteorological causes (synoptic drivers) of said storm. It is important to note that storm records from different periods will have been recorded using different instruments and approaches, and comparing storms, even within the same historical record, is non-trivial (Micovic et al., 2015). Also, the further in the past that the storm was recorded, the more uncertain the associated values should be assumed to be (Micovic et al., 2015). It is considered expected practice to transpose several of the most extreme storms on record to produce a collection of values. This is discussed further in Section 3.1.1.8.

The next step is to determine the region for which the meteorological characteristics of the selected storm represent typical sources of heavy precipitation. From this an estimate is made of the geographic limits to storm transferability. This serves to check whether it is appropriate to transfer the selected storm from its original location to the site/basin of interest, usually with relatively minor modifications of the observed storm amounts.

Once a historical storm has been identified as appropriate for transposition and maximization, adjustments are applied to its precipitation characteristics. The essential formulation to obtain the resulting rainfall adjusted for transposition to the site/basin of interest is:

$$\mathrm{R}_m = \mathrm{R}_s\left(\frac{\mathrm{W_m}}{\mathrm{W}_s}\right) \qquad [4]$$

where $\mathrm{W_s}$ is precipitable water for the representative storm dewpoint, $\mathrm{W_m}$ is the precipitable water for the maximum dewpoint for the target location, $\mathrm{R_s}$ is the observed rainfall for the event, over a given duration and area. $\frac{\mathrm{W_m}}{\mathrm{W}_s}$ is the transposition factor. $\mathrm{W_s}$ is typically assigned by standard look-up-tables based on the dewpoint temperature, or sea surface temperature, and associated with the representative storm and the elevation of the reference site. $\mathrm{W_m}$ is also typically taken from these look-up-tables using the maximal observed dewpoint temperature, or sea surface temperature, that is considered appropriate for the season and location. In some circumstances these values can be taken from observation in the form of atmospheric soundings.

If maximizing a storm ‘in place’, without transposition, the dewpoints, both reference and maximal, can simply be taken from the site of the reference storm, and the ratio becomes the “maximization ratio”. If we are, however, transposing the reference storm to a new location, then the maximal dewpoint can be selected to be the maximum value found between the analysis site and a major moisture source that is within the same distance radius as the reference storm and the analysis site. Whether elevation adjustments should be made when transposing storms is subject of debate and situation dependent. The given rule of thumb is that no transposition is required between sites with less than a 700 m elevation difference. Thunderstorms are, as well, not adjusted for elevation in non-orographic regions (with elevation differences of less than around 1500 m). It is also possible to add additional adjustment for wind maximization, but this often has negligible impact in non-orographic zones, as the highest wind events do not typically coincide with the highest precipitation events.

A demonstration of how maximization and transposition factors can be applied to a storm depth-area-duration (DAD) table is presented in Figure 3-1.

Original Storm DAD Table

Area (mi^2)	Duration (Hours) 6	12	18	24
10	7.6	9.9	12.2	12.6
100	6.7	9.8	11.9	12.4
200	6.4	9.7	11.7	12.2
500	5.9	9.5	11.3	11.8
1000	5.5	9.1	10.8	11.3

Adjustment Factors

In-Place Maximization	Horizontal Transposition
x 1.50	x 0.93 =

Adjusted DAD Table

Area (mi^2)	Duration (Hours) 6	12	18	24
10	10.6	13.8	17.0	17.6
100	9.3	13.7	16.6	17.3
200	8.9	13.5	16.3	17.0
500	8.2	13.3	15.8	16.5
1000	7.7	12.7	15.1	15.8

Figure 3-1: Example Application of Storm Maximization and Transposition

Dewpoint values used in the above calculations are commonly selected from the “N-hour persisting dewpoint”, which is considered the lowest dewpoint temperature over a period of N-hours (typically 6, 12 or 24-hours, depending on the storm). These values (or comparable singular upper-air soundings) are only limited proxies for timing and location within the vertical profile of moisture flux chronology throughout the storm event. However, there is to date no practical way to determine these values directly (Micovic et al., 2015). Some important considerations when assigning dewpoint values are:

- Dewpoints should be from a period of at least 50 years or a suitable return period value from extreme value estimate.
- Dew points sampled from times/locations with large periods of direct sunlight, low air circulation and lakes, swamps, or rivers should not be considered.
- Artificial constraints on dewpoint values (such as “2σ above the mean“ rules) can dangerously undermine the benefits of longer historical records, as maximal values tend to increase the longer the observational records (Micovic et al., 2015).
- Where there is a topographic barrier between moisture source and the event, one can also estimate precipitable water assuming that the column begins at the peak of the ridge, although it is uncertain if ridges significantly reduce atmospheric moisture. Alternately, one can use official guidance dictating the ratio between specific humidity at the original and the topographically lifted layers to assign a reduction to the precipitable water. However, when possible it is better to simply use dew point values from the lee side of the obstructing topographic feature, especially for barriers more than 800 m above the reference site. As a special case, thunderstorms are not adjusted for barriers, to account for the possibility that they have transported their associated moisture over the barrier before the beginning of the precipitation event.

It is important to note that the maximization ratio formula presumes a linear relationship between precipitable water and precipitation, which may only hold empirically for certain spatial scales (Micovic et al., 2015). Precipitation increase depends on the ratio of wind convergence as well as precipitable water between the original and maximized storm. Wind convergence may in many situations increase with precipitable water, implying a steeper slope than that given by the above equation (Micovic et al., 2015). Also, at small spatial scales the precipitable water to precipitation ratio depends non-linearly on many local factors (Micovic et al., 2015).

This process is typically seen as ‘conceptually satisfying’, since it performs a physically tractable transformation of an observed event into an arguably “worst case scenario” version of said event. However, the process involves many subjective decisions and assumptions, including:

- Which location within the watershed of interest results in the largest possible PMP, or PMF, when a storm is transposed there, can be an open question within the analysis (Micovic et al., 2015).
- Ambiguity in determining how to best describe/identify the “center” of the historical storm, especially for events with long durations or that occur in complicated topography (Micovic et al., 2015).
- The *Transposition* formulation implicitly includes the simplifying assumption that the example storm functioned at “maximum efficiency”; i.e., performed the maximal possible conversion of precipitable water into accumulated precipitation (Micovic et al., 2015).

3.1.1.5 Combination Method

This approach is often used for large watersheds and considers multiple storms from the greater region, linked together to create a single long or spatially extended storm sequence.

The first component is Sequential Maximization. Here, multiple storm records are collected and rearranged such that the total precipitation falls within a shorter, singular, period. It is necessary to consider a “minimum time interval” between events, which is often dictated by moisture supply. That is, one must ask whether the atmosphere has the means to ‘recharge’ after the initial severe event. Also, does the nature of the first event affect atmospheric conditions in a way that would prevent the second? For this reason, maximized storms are not used in these sequences, with the occasional exception of the last storm in the sequence being a maximized estimate. The assumption behind this is that these are already low probability events and that a maximal precipitation event would typically use the entirety of regional moisture supply.

When multiple storms have occurred in the region within close time intervals of each other, Spatial Maximization may be applied. Here, the storm records of these neighboring storms are combined, presupposing the possibility that the location of interest could have been the center of all the regional activity. It is common practice to rotate storms, so that they more completely cover the basin containing the site of interest.

Typically, both Sequential and Spatial Maximization are used to create a final PMP estimate.

3.1.1.6 Generalized Method

In this approach the PMP estimates and/or resulting depth-area-duration (DAD) curves are “generalized”; i.e., smoothed and interpolated, over many watersheds. The end goal is to create spatial mapping(s) of PMP derived values over a large geographic region. An example result of this process (from USACE, 1978) is shown in Figure 3-2. This process is very labor intensive and has strict input requirements:

- The region must be “large” and “meteorologically homogeneous” and have good temporal and spatial observational coverage.
- It is discouraged to use this approach for durations greater than 72-hours, as the method assumes that the storms have a single center and peak, which is rare for prolonged rainfall events.
- Generally, given topographic variation, the *Generalized Method* is effective for regions of size at most 13,000 km^2 in orographic zones and at most 52,000 km^2 in non-orographic zones.

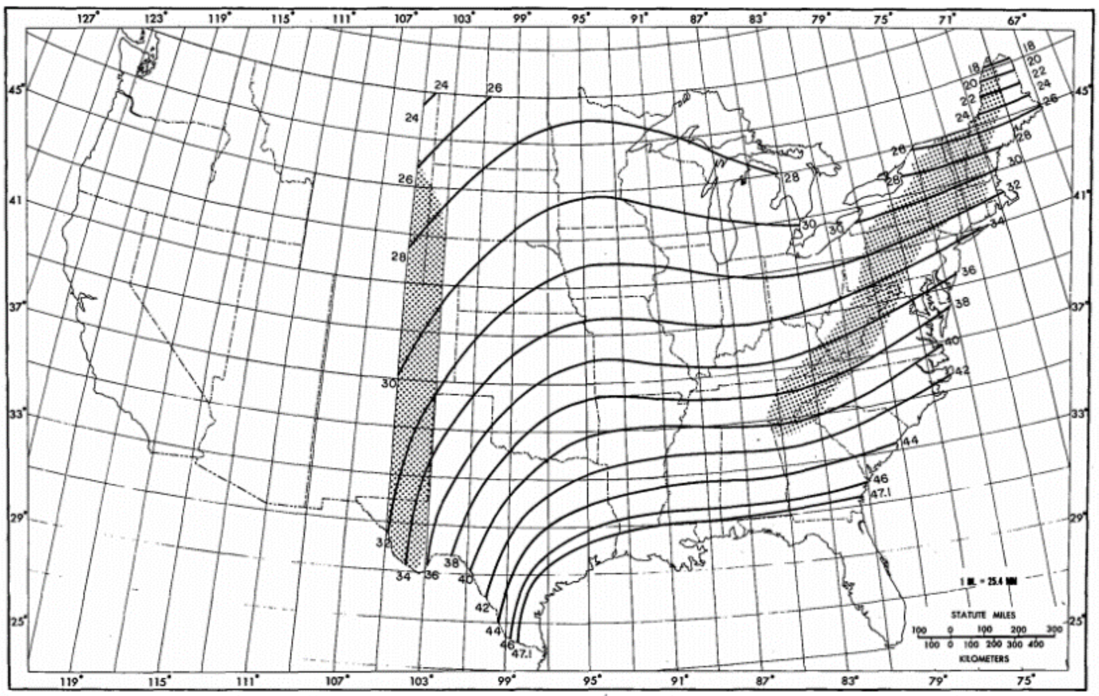


Figure 20.--All-season PMP (in.) for 24 hr 10 mi^2 (26 km^2).

Figure 3-2: Example Result from the Generalized Method

The advantage of this approach is that it incorporates larger amounts of data than site specific analyses and ensures consistency between basins in similar meteorological regions. In fact, generalized estimates are reported to give consistently higher values, as a result of having a wider variety of storms to pull from, than “site specific” analyses, which may have artificially narrow definitions of applicable storms (Micovic et al., 2015).

The mapping is done to a collection of assigned spatial grid points, with the procedure involving multiple implementations of using the *Transposition Method,* to transpose historical storms to multiple locations within the geographic range where they are considered representative. These grid points are defined along a grid, or along continuous lines defining the appropriate limits of transposition for the individual storms. The resolution/spacing of the grid points defining the final maps should be based on the variability of the topography and do not need to be uniform if certain sub-regions require more detail than others.

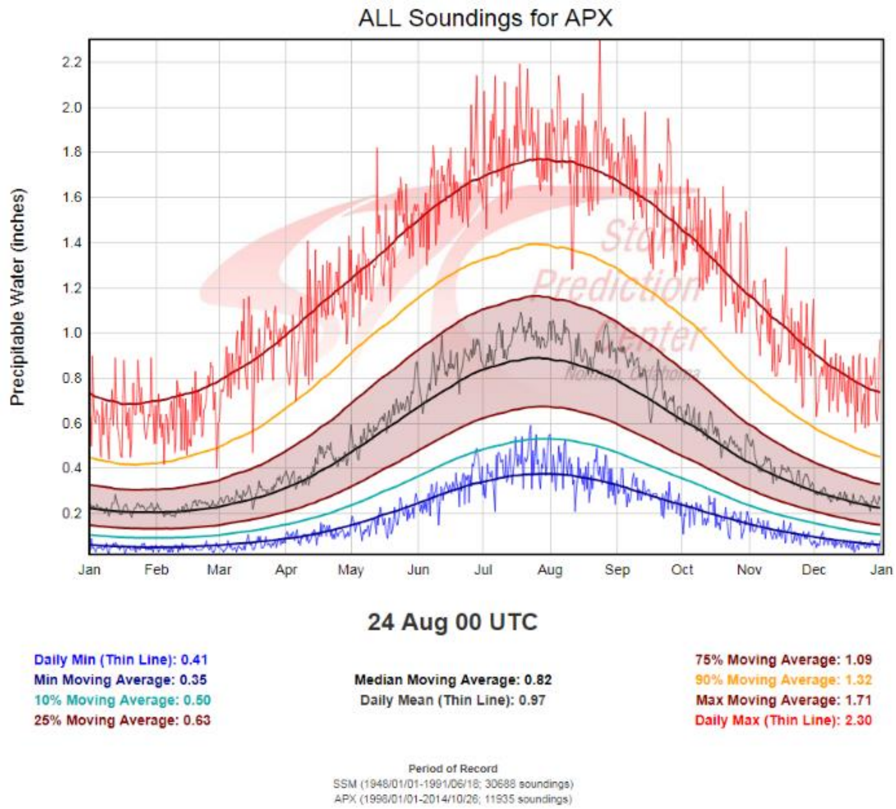
This mapping process is repeated many times, creating many maps for different durations and areas (e.g., 6-hour PMP for 100 km^2 areas, 24-hour PMP for 1,000 km^2 areas, and so on as needed). Values are smoothed, or “implicitly transposed”, across the full area. This provides the level of consistency of heavy rainfall risk that would be expected over a homogeneous region, as opposed to individual site estimates, where uneven data variability might make the distribution of PMP values appear more erratic. The first step in the smoothing procedure is to take the multiple maximal depth-duration and depth-area curves that have been produced using various storms for a given location and create a smooth curve which defines the upper limits of these values (known as envelopment). Next these values are mapped over the region, and these maps are then smoothed spatially. Typically, this is done as an iterative process which takes topographical and meteorological information into account when preparing the final gradient estimates. This iterative process also includes repeated checking for consistency along cross-sections and between different maps (e.g., maps of different durations). However, discontinuities that result from rainfall being produced by different storm types may be appropriate if these divisions are created by topographic and synoptic features. As well, for more complex regions a baseline map can be prepared, which is then modified by adjustment factors based on location, terrain type, and orography.

3.1.1.7 Seasonal Variation

PMP values likely vary seasonally and so it is often important to take the within-year timing of events into account, and to have an estimate of the seasonally varying risk. For example, peak flood risk in Canada may not occur at the peak PMP season, but rather when snowmelt potential and PMP overlap to create a higher value than can be produced by either factor alone.

There may not be enough recorded storm examples to determine the PMP seasonality maximum, in which case, persisting 12-hour dewpoint of the moisture inflow can be used as proxies. However, maximum dewpoints almost always occur in the summer (as illustrated by Figure 3-3), which means they are not sufficient for regions with the potential for major winter storms, or where the PMP of interest is the spring PMP. For such regions, it is important to also incorporate seasonality in the potential for wind driven moisture inflow. Seasonality might alternately be estimated from station precipitation records. If this approach is taken, it is recommended the seasonal cycle be described as percentages of peak values. Typically, weekly totals or monthly daily maximum values are used to filter the data in such a way as to highlight the seasonal cycle. It is also important to apply a variety of seasonal variation analyses and check for consistency, as any single estimation method or variable can potentially lead to a misleading characterization.

Snowmelt and temperature sequences are discussed in Section 3.1.5. Climate change considerations for these variables can be investigated by applying the general climate change impacts analysis methodology discussed in Section 3.2.1.



Source: https://www.spc.noaa.gov/exper/soundingclimo/

Figure 3-3: Illustration of Annual Cycle and Variability of Precipitable Water Content for a Location in Northern Michigan

3.1.1.8 Envelopment

PMP estimates typically produce multiple precipitation values for a given rainfall duration or area. In the Transposition Method this comes from transposing and maximizing a selection of historical storms to the target site. In the Combination Method the created chronologies may be shuffled to create different rainfall sequences. As discussed above, the Statistical Method can be performed with a variety of adjustments to input parameters. Also, the formulation of this approach allows for a variety of permutations to be tested, such as bootstrapping or Bayesian formulations. In the Generalized Method a given map location may be contained within the 'transposition range' of many historical storms. Since there is not a clear relationship between the results of any given storm maximization and the "true" PMP values, the final step of most of the above described analysis procedures is that their estimates must be "enveloped". That is, the largest possible values generated for any given rainfall duration or area serves define the PMP estimate. This means that different points on the final depth-area-duration curves likely come from different storms. Typically, these "worst case of the worst cases" are used to define smooth curves defining the 'envelope' of potential rainfall magnitudes. An example of envelopment is shown in Figure 3-4.

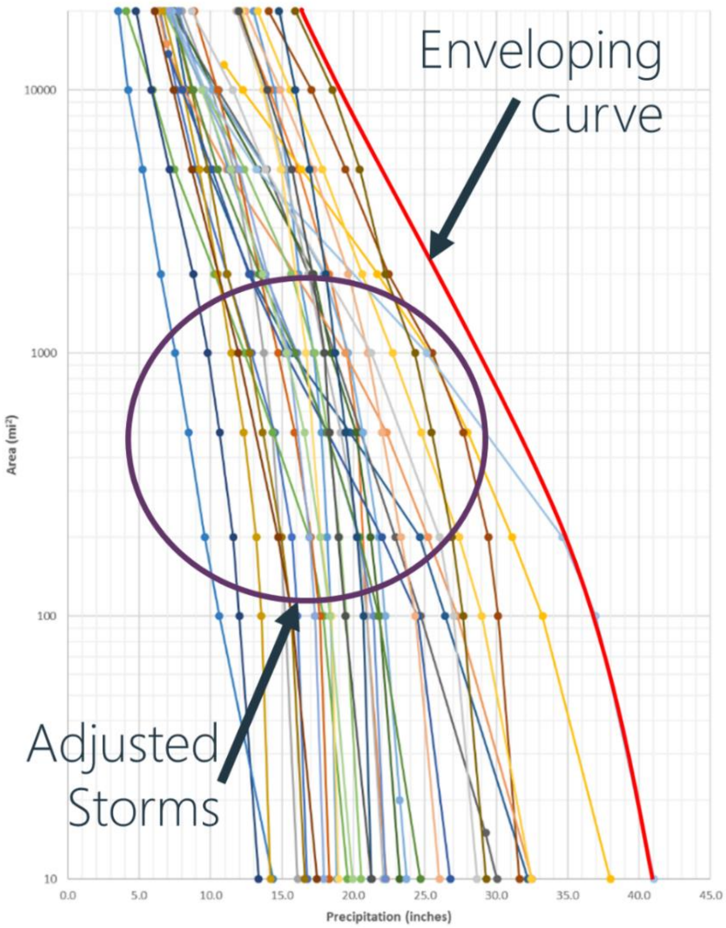


Figure 3-4: Example of an Enveloping Curve of 48-hour Duration Depth-Area Curves

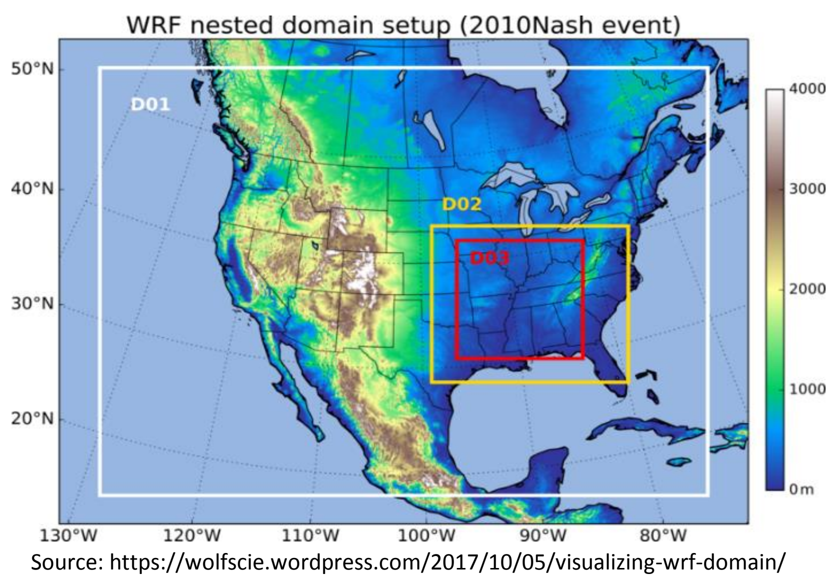
One consequence of this practice is that the PMP depth-area-duration curves do not often represent a realistic chronology of rainfall, and so do not produce the magnitude of runoff values that would result from the same magnitude of water dispensed over a different chronology. In using these values to estimate a PMF, a sequence of accumulations derived from a PMP depth-area-duration sequence can be rearranged chronologically to fit the pattern seen in rain events that created high historical runoff values (e.g., it can create an event that first saturates the soil with light rain prior to the maximal precipitation event). It can be important to experiment with different sequences to see which produces maximal runoff values. It is also important to understand the structure that is at risk (i.e., whether it is more affected by total volume or peak flow (Micovic et al., 2015). One approach to creating a sample storm with a realistic chronology, is to take an observed storm and “slide” its depth-area-duration curves to the point where they first intersect the PMP depth-area-duration curves and then use these inflated values for a sample rain event. Alternately, one can use the enveloped PMP values, accepting that this introduces an additional maximization, since these values may be drawn from several storms.

Sometimes enveloping creates estimates so conservative, it is believed not to be representative of the type of event which would occur over a given duration or area. For example, rainfall amounts associated with a local convective storm event that has been assigned over a large geographic area. In these cases, some “undercutting” (i.e., using less than maximal values for certain points on the curve) can be justified. It is important to remember that since PMP events are “maximal”, they should notably exceed observed records. However, these values ought to be plausible in the context of known global extremes. As well, it is important to note that using a limited number of storms strongly reduces the reliability of the analysis. Especially if the storm magnitudes for the region are quantifiably lower than those observed in a more extensive area or in regions with similar precipitation drivers, especially when these drivers are synoptic conditions. The standard guideline is that any differences between final estimates and observations or previous estimates for similar regions needs to be explainable in terms of climate or geographical factors.

3.1.2 Additional Analysis Methods

3.1.2.1 Numerical Simulation

Numerical simulation approach can be seen as a more sophisticated, more widely applicable and more computationally demanding, as an extension to the Inferential Method. Here a numerical weather model is used to create simulations of extreme storm events, using the same approach as taken for operational forecasts. An example domain used for modeling an extreme storm event is shown in Figure 3-5. These simulations are then “maximized” by changing boundary conditions and other atmospheric properties. Examples of such adjustments are, in the case of Ohara et al. (2011), maximizing atmospheric moisture, fixing boundary conditions at peak inflow, and/or centering moisture fluxes over the watershed. Ishida et al. (2015b) demonstrated adjusting moisture providing synoptic features, in their case associated to atmospheric rivers. Ishida et al. (2016) additionally showed the effects of increasing air temperature (moisture holding capacity), as a test of possible climate change effects on PMP values. In all cases these studies found that their PMP results were higher than those that would have been obtained by more conventional analysis. The advantage of such studies is that they directly simulate physical dynamics, rather than approximating their effects, and so offer a degree of realism and tractability. The downsides are that such experiments are very computationally and technically demanding, and their reliability is linked to the ability of the simulation approximations (gridded topography, parameterization schemes, etc.) to capture relevant processes.



Source: https://wolfscie.wordpress.com/2017/10/05/visualizing-wrf-domain/

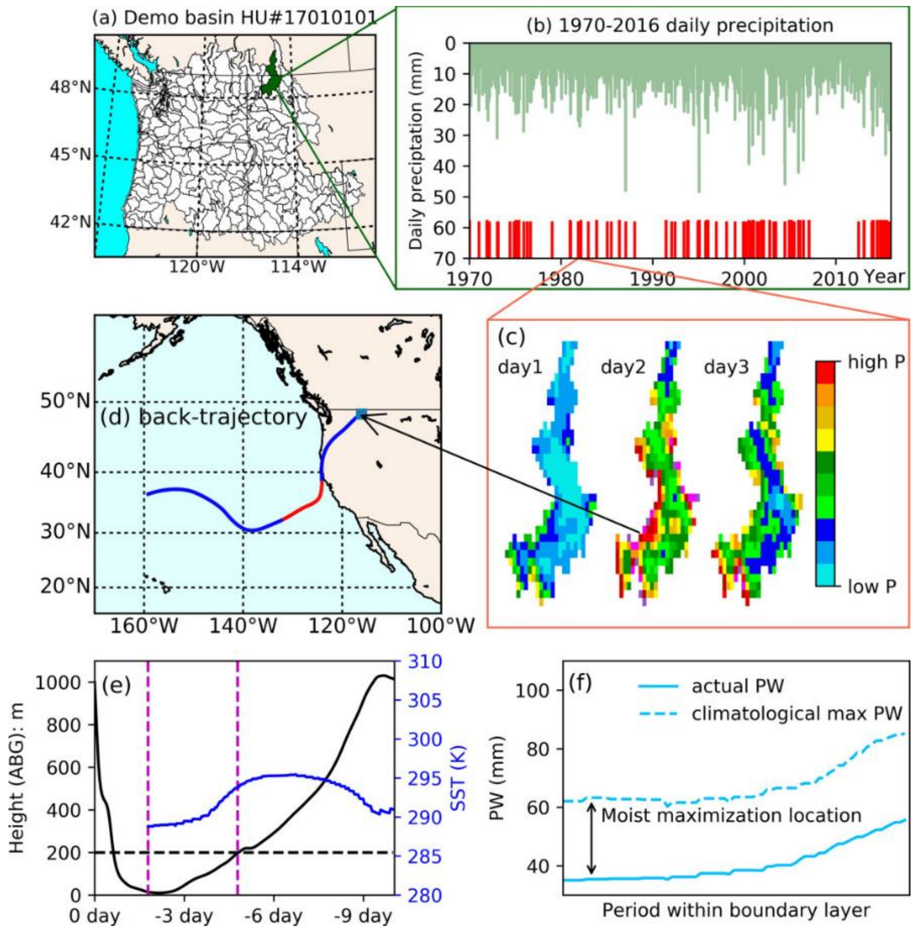
Figure 3-5: Example Nested Domains for High-Resolution Numerical Simulation of a Storm

3.1.2.2 Hybrid Method

The *Hybrid Method* of Chen et al. (2017) looks to apply the Transposition Method type techniques to synthetically generated data. The suggested procedure is summarized in Figure 3-6 (Figure 2 from Chen et al., 2017) and outlined as follows.

- Downscale long-range (multi-decade) contemporary climate simulations to needed resolution for the project area – authors suggest the Localized Constructed Analogues (LOCA) method of Pierce et al. (2014). As with other analogue approaches, this method fills in local values by searching the historical archive for values recorded under the same synoptic conditions as those being described by the simulation. The Pierce et al. (2014) method employs two extensions. Firstly, the domain over which synoptic conditions are matched is defined by correlations to the target location, rather than a potentially arbitrary 'bounding box'. Secondly, the region immediately surrounding the target location is checked to see if it is matched to the same historical event as the target location. If not, then a weighted average of all local area matches is used as the assigned value.
- Identify extreme events within the watershed - authors suggest 98th percentile 3-day rainfall events, so obtaining about 100 events per 50 years.
- Define the "storm centers" as the location of maximum precipitation for each event.
- Use the HYSPLIT Back Trajectory Model to back track the motion of an air parcel which would have been at 1,000 m above the assigned storm center to its location 3 days prior.
    - The Hybrid Single Particle Lagrangian Integrated Trajectory Model (HYSPLIT) is an online model, hosted by NOAA's Air Resources Laboratory, which is able to compute air parcel trajectories. One of the most common applications of HYSPLIT is backward trajectory analysis to determine the origin of air masses and to map inflow trajectories into a storm center (Stein et al., 2015).
- Identify the local dewpoint or sea surface temperature at the 3-day prior location and use this value and the WMO tables to determine a value for the W_s term in the maximization ratio equation given in the Transposition Method section above.
- Use the climatological maximum dewpoint or sea surface temperature value at this 'source location' (Chen et al., 2017 focuses on sea surface temperature, but if the study were conducted over a different region, comparable dewpoint temperatures could be found using the method described in Section 3.1.1.4) to obtain a value of the maximization ratio $W_m$term from WMO tables, and use the resulting $\frac{W_m}{W_s}$ ratio to maximize the storm.

The proposed advantages of this method are that the use of existing simulations reduces the computational expense, and that basing the analysis on simulation outputs, rather than direct observations means that the approach can be applied directly to climate change projections, and can potentially be used to extend observational records. Collections of such simulations, such as the Coupled Model Inter-comparison Project (CMIP, described further in Section 3.2.1), makes ensemble analysis possible, which allows for partial uncertainty estimates. However, the need to validate the downscaling approaches means that observational records are still necessary, and this step, as well as the original use of synthetic data, compounds uncertainties and reduces tractability. The approach also depends strongly on (elsewhere criticized) assumptions in the determination of the final adjustment term. Chen et al. (2017) report obtaining similar values to those obtained in older transposition studies. However, results from Numerical Simulation, Generalized Methods, and in-depth uncertainty analyses (Micovic et al., 2015) have called these older transposition studies into question as potentially being low biased.



Note (modified from Chen et al., 2017): (a) The location of the demo watershed, (b) the historical daily precipitation from LOCA-downscaled data and the top 100 3-day precipitation events for PMP estimation. For each event, (c) the grid/day with the most daily precipitation as the storm center is selected, and (d) an air parcel at 1,000 m height from this location/date in HYSPLIT is identified. (e) The air parcel is tracked for 10 days, and the height/SST along the track is recorded. When the air parcel is within 200 m height boundary layer above the ocean (the purple dashed line window), moisture maximization is applied, and (f) the maximum maximization ratio is used to maximize this storm to one maximized precipitation estimation. PMP is then estimated as the greatest maximized precipitation based on these 100 events.

Figure 3-6: Schematic of the Hybrid PMP Estimation Approach

3.1.3 Uncertainty Quantification

Micovic et al. (2015) point out that the prior described estimation methods are all deterministic approaches, and so even when a collection of estimates is considered, these create a pass/fail type criterion rather than being directly applicable to risk analysis. As well, there is ultimately no way to prove or refute the assumption that there is a physical upper bound to a precipitation event, and more importantly, that a given PMP estimate captures these values. As such, Micovic et al. (2015) propose creating ranges of PMP values rather than single best estimates or estimates which is assumed to be the central tendency of a Gaussian distribution of possibilities. They suggest defining

$$\mathrm{PMP} = \mathrm{PMP}_{\mathrm{base}} \times X_1 \times X_2 \times \ldots \times X_n \qquad [5]$$

where $\mathrm{PMP}_{\mathrm{base}}$ is the deterministic PMP estimate, and X_{i} terms are percentage adjustment factors relating to different uncertainty sources in the estimate (i.e., parameter values which must be selected as inputs to the PMP calculations). They suggest considering adjustments based on the following:

- In-place moisture maximization;
- Surface dewpoint;
- Storm horizontal transposition;
- Location of storm center; and
- Storm efficiency.

Each of these factors is assigned a likelihood function, based on meteorological analysis and simulation/experimentation, which defines the range of effect each factor may have on the analysis, and the probability that such a correction to the base estimate is appropriate. The X_{i} values are then sampled at random from these likelihood functions to provide a distribution of PMP values that account for possible over and under estimations within the analysis process. This creates a transparent and tractable way of communicating the effects of subjective decision making within the analysis process. However, it is worth noting that the authors do not discuss a means to estimate correlation between these factors, which would imply a more constrained probability space that is denser at one or the other range of possible values than what is reported under the current method.

Ben Alaya et al. (2018) discuss a technique for investigating the correlation between storm efficiency and precipitable water. As their experiment uses output from a regional climate model (RCM) simulation (CanRCM4, with boundary forcing provided by CanESM2), precipitable water can be assumed to be known, rather than inferred from dewpoint or other sources, and transposition can be accomplished by considering seasonal maxima located within a predefined window around a given grid cell. The relationship between storm efficiency and precipitable water is described through a bivariate extreme value distribution. A copula function models the relationship between the two variables and is fit, with the assumption of stationarity, with 6-hourly estimates from a 50-year period (1951-2000) drawn from the RCM. The assumption of a storm event being capable of converting 100% of available moisture to precipitation has long been understood as implausibly conservative, and even if such events are possible, it is highly improbable that they coincide with peaks in moisture availability. However, as there exists no physically inferable generally applicable alternative value, the conservative assumption must be applied as the ‘safe choice'. Ben Alaya et al. (2018) demonstrate that this ‘safe choice’ does result in an overestimation of the frequency of extreme events, relative to the range of simulated precipitation within the analysed RCM. Selecting efficiency and moisture values based on their ranking within the Cumulative Distribution Function (CDF) of the selected bivariate distribution, however, provides a means of quantifying the ‘extremity’ of the resulting PMP estimate. As well, multiple value pairs can be drawn from the bivariate distribution and used to create an ensemble of PMP estimates that represent the believed range and plausibility of events. Ben Alaya et al. (2018) find that this produces a distribution of estimated values that is well matched to the range of simulated precipitation events which occur within the analysed RCM. However, if this method is intended to be used for practical estimates, a careful evaluation of RCM biases must first be conducted.

3.1.4 Canadian PMP Studies

In this section an overview of Canadian Dam Association (CDA) Guidelines and Canadian PMP studies is provided.

3.1.4.1 Canadian Dam Association Guidelines

For reference, the CDA requirements for PMP/PMF estimates for installations that pose “extreme danger” to the public (CDA, 2007) are outlined here. Such an installation is one whose potential for failure permanently endangers at least 100 people and/or would result in major and irreparable habitat loss and/or damage to critical infrastructure services (hospital, industry, storage facility for dangerous substances). The CDA defines PMP in terms of the “transposition method” and PMFs are estimated using the PMP and initial conditions based on historical rainfall and snow accumulation values that maximize soil moisture.

Both a summer/fall PMF using PMP values obtained from summer/fall storms and a spring PMF are required. For the spring values, a PMF is computed with PMP based on spring storms and snow accumulation assumed to be at 100-year levels, and an additional PMF is computed Probable Maximum Snow Accumulation (PMSA, discussed on Section 3.1.5) and 100-year rainfall. The maximum of the two spring PMFs is retained.

3.1.4.2 Ouranos 2015

Clavet-Gaumont et al. (2017) is the peer-reviewed companion paper of Ouranos’s 2015 “Probable Maximum Floods and Dam Safety in the 21st Century Climate” (Ouranos, 2015). Pertinent information in the latter government report is contained within the former peer-reviewed report. The PMP methodology of Clavet-Gaumont et al. (2017) is inline with the Transposition Method and Envelopment (Sections 3.1.1.4 and 3.1.1.8, respectively). Additional discussion and an overview of the results are provided below. Climate change considerations relevant to the five study locations are further discussed in Section 3.3.3.1.

Clavet-Gaumont et al. (2017) applied an approach based on methodology developed by Rousseau et al. (2014), which incorporates “traditional” PMP estimation methods (i.e., Transposition and Envelopment), to take in account the non-stationarity of the climate by using 14 RCM simulations. The approach estimated values for the 100-year snowpack, as well as changes to Spring PMP and the Spring PMF for 1971-2000 and 2041-2070. One difference with the traditional method is the replacement of an arbitrary upper limit on the maximization ratio (Equation 4 in Section 3.1.1.4) by an upper limit on the monthly 100-year return value of precipitable water (w_{100}). A reasonable physical limit for w_{100} would be the precipitable water in a fully saturated atmosphere, but this value cannot be retrieved from existing simulation archives for every model. Based on simulations with one regional model having this capability, an upper limit for w_{100} was set to 120% of the maximum precipitable value in the 30-year record.

The study and discussion below focus on Spring PMP estimates for the basins nearest to the five study locations, as the spring PMF was determined to be the most significant for the basins investigated. It included five basins, which were selected due to their varied physiographic characteristics and geography: the Lower Nelson basin in Manitoba, Mattagami basin in Ontario, Kenogami in Quebec-Ontario, as well as the Saguenay-Lac-St-Jean and Manic-5 in Quebec. The Lower Nelson and Mattagami basins are the nearest to NWMO's five study locations.

The spread of uncertainty for the Spring PMP estimates was large, as expected, since PMP is based on extreme meteorological events among extreme estimates. This spread occurred for simulations from the same Regional Climate Model (RCM) driven by different members of the same Global Climate Model (GCM), therefore indicating that this uncertainty is related to natural climate variability.

For the two basins near this report's study locations, the estimates from the 14 RCM ensemble found the projected change to be "about as likely as not" (when between 33% and 66% of the models give the same sign) (see Table 3-1 and Table 3-7). This points to the need to use large ensembles to conduct this type of analysis.

Storm size (represented in the models by grid cells) was found to have a limited impact on the relative projected change of the PMP for all storm durations across all five basins. It should be noted that a detailed assessment using a similar or larger ensemble of climate models would be needed to provide Spring PMP estimates for the five study locations of interest in this report.

Table 3-1: Median Projected Changes of the Spring PMP

Projected changes in Spring PMP from 1971-2000 to 2041-2070					
Basins	**Confidence level on sign of change**	**24-h**	**48-h**	**72-h**	**120-h**
Lower Nelson, Manitoba	No consensus	-2%	-9%	-11%	-6%
Mattagami, Ontario	No consensus	8%	4%	5%	3%

3.1.4.3 OMNR 2006 and Other Canadian Studies

OMNR (2006) applied the Transposition Method and Envelopment (Sections 3.1.1.4 and 3.1.1.8, respectively), while they also applied the Statistical Method (Section 3.1.1.1) for comparison purposes and the Generalized Method (Section 3.1.1.6) to regionalize the PMP maps. While OMNR (2006) did not deal with climate change via climate model projections, they investigated potential trends in PMP input factors (e.g., dewpoint temperature) and found nothing significant. However, the report recommends revisiting PMP estimates every 10-15 years to re-evaluate climate change impacts. A discussion of some relevant results from OMNR (2006) can be found in Section 2.2, while the report should be consulted directly for full details.

The Canadian Electrical Association commissioned the "Probable Maximum Floods in Boreal Regions" by Atria Engineering Hydraulics (1994), covering a large portion of non-arctic Canada. This study used the Transposition Method, though their focus was primarily winter precipitation (discussed further in Section 3.1.5).

Newfoundland Hydro commissioned the “Churchill River Complex PMF Review and Development Study” based in Labrador using the Transposition Method and Envelopment (Acres International, 1999). The report also cites several previous studies of the same region (also by Acres International or its predecessors), all of which used similar methods. Hatch (2007) performed a follow up study for the Lower Churchill Project using the same methods as Acres International (1999) but with an expanded dataset.

Alberta Transportation (2004) issued “Guidelines on Extreme Flood Analysis” which covers a broad range of situations including PMP estimates for small basins (< 1000 km^2) and large basins (>5000 km^2), orographic regions as well as seasonal variation and snowmelt (discussed further in Section 3.1.5). For PMP estimates they recommend using the Transposition Method and Envelopment.

Kappel et al. (2016) authored “Updating PMP for the Elbow River: complex terrain, unique solutions” using the Traditional Method, with additional adjustments for topography (as a large portion of the watershed was mountainous). The geographic focus was just west of Calgary, Alberta. An earlier study in the Greater Calgary area, Guthrie (2001) applied the Traditional Method, Envelopment and the Statistical Method.

Amec NSS (2011) applied the Statistical methods for Ontario Power Generation’s Bruce Nuclear Site. Several other recent studies authored by Wood (formerly Amec Foster Wheeler, formerly AMEC) also used the Transposition Method and Envelopment, with the Statistical Method used for comparison purposes (listed below), as did nearly all of the studies referenced in the respective reports.

- AMEC (2014) for Newfoundland Power, focusing on Newfoundland’s Avalon Peninsula.
- Amec Foster Wheeler (2016) for the United States Army Corps of Engineers, Vicksburg District, focusing on Blakely Mountain Dam in Arkansas.
- Wood (2018b) for Agriculture & Agri Food Canada, focusing on the Gouverneur Dam in southern Saskatchewan. This was a follow up of Pentland and Abrahamson (2009), which assembled regional PMF results from a variety of studies and recommended a set of empirical equations for estimating PMF.
- Wood (2018c) for Minas Energy, focusing on two watersheds in central Nova Scotia.

Three American studies with relevance to the five study locations also used the Transposition Method and Envelopment. These included statewide regional PMP estimates for Wyoming (Kappel et al., 2014), Nebraska (Tomlinson et al., 2008), and Ohio (Tomlinson et al., 2013). Given the regional nature of these studies, the Generalized Method was also employed.

3.1.5 Snowpack and Snowmelt

The influence of snowmelt on flooding in high latitude regions is often emphasized (USACE, 1994), and it has been stated that a PMP study that does not address snow melt factors should be considered valid only for the summer months (Hopkinson, 1999). This is because boreal watersheds can experience heavier flooding due to spring melt than from extreme summer storms (Chow and Jones, 1994). This can result from a combination of the “priming” of soil moisture, rain on snow events and snowmelt run off (Alberta Transportation, 2004). Even for studies where procedures are generally standardized, there can be considerable variability in PMP/PMF estimates based on subjective decisions on how to account for antecedent conditions, including snowmelt (Pentland and Abrahamson, 2009).

This poses a challenge on several levels, the first being that snowpack can be a difficult feature to observe. Precipitation accumulation records have higher uncertainties when reporting amounts in frozen or mixed rather than pure liquid form (USACE, 1998). As well, snowpack is very rarely the same as accumulated snowfall, due to redistribution, melting, and evaporation (Alberta Transportation, 2004). Compounding this concern is that Snow Water Equivalent (SWE) (i.e., how much liquid water is present in a given volume of snow) is highly variable, especially as related to snowpack depth (Goodison et al., 1998). SWE to snow depth ratios vary even over short distances, due to differences in snow age, and other chronological factors (USACE, 1998). As well, snow density during snowmelt season is often much higher than during other times of the year (Gray and Prowse, 1993). It has been stated that without exact measurements or continuous simulation over the basin to determine SWE, a conservative 20% ratio of snow depth to SWE should be applied (USACE, 1998), although the commonly applied baseline is 10% (Amec, 2014).

3.1.5.1 Partial Season Method

The oldest and simplest approach to estimating Probable Maximum Snowpack Accumulation (PMSA) is the Partial Season Method (Alberta Transportation, 2004, and Sagen, 2017). The procedure is as follows:

- Acquire multiyear snow accumulation data set for location,
- Divide the winter season into pre-set windows (typically individual months),
- Find the maximum snow accumulation within each window over all the years on record, and
- Sum these maximums to give PMSA.

The approach has been seen to be very dependent on length of observation record (Chow and Jones, 1994). As well, it has been critiqued as being too conservative, as it does not account for melt or redistribution, and for being highly sensitive to the choice of window size (Chow and Jones, 1994). However, it is still commonly applied (USACE, 1998), as an alternative to simply considering observed values from high snow pack years. SNC-Shawinigan (1992) suggest the primary advantage of this method is its ease of computation; however, it was viewed to not be meteorologically rigorous and longer observation records would only cause SWE values to increase. The authors recommend against using this method due to this strong dependence on observation record length.

3.1.5.2 Statistical Approaches

It has been recommended to estimate both a PMSA and a 100-year snowpack event (AIL, 1999). The latter is done by fitting an extreme value distribution to observational records to define the 100-year event. The former has been done statistically, either by extrapolating from the 100-year event to a 10,000-year event (AIL, 1999), or by using variations of the PMP Statistical Method (WMO, 2009) for the PMSA values. This is done with prescribed extrapolation constants, as shown in Amec (2014). It has been observed that there is no particular extreme value distribution which appears to consistently depict snowpack statistics (Chow and Jones, 1994). A variety of distributions have been applied, including a Generalized Extreme Value Distribution (GEV) by Amec (2014), Chow and Jones (1994), and Hatch (2007), and a Gumbel Distribution fit to an amalgamation of three local observed annual max snowpack records by KGS Group (2017).

Because statistical estimates are based on observed snow depth values, they are credited with accounting for information regarding sublimation, thaws and snow redistribution (Chow and Jones, 1994). However, they have been criticized for being very sensitive to the choice of distribution and choice of representative return period (Chow and Jones, 1994). As well, snow depth and SWE measurements are understood to have high uncertainties relative to the sensitivity of the extreme value distributions (Sagen, 2017). These records are also typically of limited length relative to the extreme return periods to which they are extrapolated (Sagen, 2017). SNC-Shawinigan (1992) suggest that this is the easiest method to apply and only depends on observation stations having a reasonable record length (e.g., 20 years), while the primary disadvantage is the uncertainty resulting from trying to extrapolate to probabilities similar to a PMP type event (e.g. ≥10,000-year return period). SNC-Shawinigan (1992) stated that this was a common approach in Ontario and British Columbia at the time.

3.1.5.3 Snow Maximization

Another common approach, similar to the common PMP Transposition/Maximization Method, is Snow Maximization (Bruce, 1962 and CEHQ and SNC-Lavalin, 2004). In its most fundamental form, the procedure is to:

- Identify year(s) with particularly high spring snowpack. Then maximize the major snowstorms with that year using standard PMP Transposition Methods, and
- Sum up maximized and non-maximized storms to get the maximal version of the extreme snow pack year.

Several authors have raised concern over the use of surface dewpoint as a proxy for atmospheric column moisture when such maximization methods are applied over snow cover (AIL, 1999, Chow and Jones, 1994, and Hopkinson, 1999). Typically, during snow storms the bottom layer of the atmosphere is cold and dry, and the moist (precipitating) air is aloft. As well, moisture sources for winter storms are typically 100s of kilometers to the south and do not transport efficiently (Chow and Jones, 1994). It has even been suggested that all northern latitude PMP studies must consider upper air data, or else be explicitly labeled Summer PMPs (Hopkinson, 1999).

While the Snow Maximization Method follows similar meteorological principles as PMP storm maximization, it has been critiqued by SNC-Shawinigan (1992) and Chow and Jones (1994) for being “unduly conservative”, as for each additional storm in the winter sequence that is maximized, the more unlikely the occurrence of such a sequence becomes. Chow and Jones (1994) suggest that the unmodified method is appropriate only for regions that experience a limited number of late season snowstorms. As well, the Snow Maximization approach does not inherently account for snow melt, and so has been recommended only for regions where there is the possibility of winters without significant snow loss (Alberta Transportation, 2004).

SNC-Shawinigan (1992) recommends against applying this method (and the PMSA approach more broadly) for watersheds where the peak flow in the PMF is more of a concern than the total volume of water, which is the case for the five study locations. In these cases, they recommend combining the spring PMP with the 100-year snowpack SWE (outlined in Section 3.1.4.1).

3.1.5.4 Method Extensions

Chow and Jones (1994) propose some guidelines which they believe could increase the realism of Snow Maximization events. They suggest ideally capping the amount of moisture available for any given maximization and/or the number of events allowed to be maximized per season. They argue that large moisture contents would likely happen only at temperatures warm enough to result in mixed precipitation. However, it is acknowledged that determining guidelines for either limitation would require substantial additional research.

Alternately, they describe the idea of “Maximizable Snow Storms.” This takes under consideration the common PMP concept that only a limited number of storms from a long record will have occurred under “efficient” scenarios. In other words, the convergence factors are adequate for the storm to ‘make use of’ any additional moisture (what is added in the maximization). Chow and Jones (1994) defines several specific meteorological conditions related to the ability to transport warm moist air into the region and then advect it vertically. They state that only snowfalls occurring under these conditions should be maximized. Additionally, they suggest limiting selection of events to include snow-only periods or to establish a precipitable water limit of 25 mm. As well, they propose limitations on the period of the storm which should be maximized, considering that as the storm stalls in place or moves away, it will use up or transport away any additional moisture. They also suggest that events should not be considered at all, if their daily snowfall accumulation does not meet a minimum threshold. This idea provides a ‘safety net’ as it is suggested that if this minimum is exceeded, then an event should be considered regardless of meteorological potential. Suggest minimum values range from 4 cm/day to 8 cm/day. Finally, Chow and Jones (1994) suggests considering at a minimum the top three snowfall accumulation winters for the analysis.

Klein et al. (2016) describe a standardized implementation of the Chow and Jones (1994) approach, which can be applied to gridded RCM simulation output. Their motivation is to allow for an analysis that can account for non-stationarity (i.e., climate change). As well, the use of simulated values addresses the concern that upper atmospheric moisture estimates are needed for winter PMP estimations. The approach comes with the caveats that results from studies using simulated data are often highly dependent on the data set (Papalexiou and Koutsoyiannis, 2006), and the general issue of the “drizzle effect” (that RCMs tend to produce too much persistent light rain (Kendon et al., 2012)). Their general proposed procedure (performed on each grid cell within the study domain) is as follows:

- Calculate instantaneous precipitable water in air column for each simulation time step for “winter months” (October – May), for 1961 – 2100,
- Consider only values from time steps that experienced >= 0.25 mm/6-hr SWE of solid precipitation and < 0.1 mm/6-hr of liquid precipitation (values relate to what are typically considered the smallest possible measurable amounts in observed data sets),
- Find the annual maximum precipitable water level for each winter month,
- Fit extreme value distribution to these statistics, using a wide variety of distributions and trend models, and then ranking fits using Schwarz/Bayesian Information Criteria to identify preferred descriptor,
- Identify snowfall events and consider the maximum event precipitable water $\mathrm{w}_{\mathrm{event}}$ to be the max precipitable water value found either during the event or three timesteps prior (18-hr = 3*6-hr),
- Use the above extreme value distribution to determine the 100-year precipitable water level, w_{100}, to calculate the maximization ratio for that event: $\frac{\mathrm{w}_{100}}{\mathrm{w}_{\mathrm{event}}}$, and

- Annual PMSA is the sum of all maximized and non-maximized snowfall for a given year, and climatic PMSA is the highest of these values over a 40-year period.

A threshold is set for the maximization ratio limiting these values to a range of 1 to 2.5 (CEHQ and SNC-Lavalin, 2004). As well, an event must have a minimum daily accumulated snowfall of 5 cm, as a compromise value from the range of Chow and Jones (1994). In this study, “events” are of fixed 12-hr length, to ease automation. The authors suggest in future that it would be better to have an algorithm which determines the actual start/stop time of individual events. The study reports that not including partial rain events removes about 10% of total snowfall events, and so recommend including events that meet the minimum accumulation even if they include liquid precipitation. These events are, however, reduced by the ratio of solid to total precipitation.

3.1.5.5 Snowmelt and Temperature Sequences

USACE (1998) provides detailed technical guidance on estimating snowmelt via an energy balance approach as well as via temperature indexing. The energy balance approach includes relationships between a range of considerations including shortwave and longwave radiation, convective condensation melt, forest cover, rain melt, ground melt, and meteorological conditions using a variety of empirical equations. Temperature indexing is a more practical approach which does not require the availability of as many of the energy budget variables, alluded to above. It consists of applying a melt-rate coefficient and statistical relationship between a derived temperature sequence and the amount of melt.

To develop a critical temperature sequence, Chow and Jones (1994) used station data to derive cumulative temperatures of 1, 2, 3, 4, 5, 10, and 15 days with additional consideration for the cooling effects of snow cover. Similarly, Wood (2018c) estimated 1- through 15- day maximum and average air temperatures from January 1st to the last day with snow on the ground for each year at each relevant climate station. These values were used to fit extreme value distributions to determine the 100-year return period values, which were in turn used to create critical temperature sequences. A diurnal cycle was estimated (in 6-hour increments) by assigning the mean temperature (T_{mean}) to hours 0600 and 1800, the maximum temperature (T_{max}) to 1200 hours, and the minimum temperature ($2*T_{mean}-T_{max}$) to 0000 hours.

3.2 CLIMATE CHANGE PROJECTIONS

This section introduces climate change impact analysis, an overview of climate change projections for Canada and Ontario, and outlines available climate model ensembles. Discussion includes a review of projected changes in rainfall, snowfall, temperature, wind and tornadoes.

3.2.1 Climate Change Impact Analysis

Most studies that incorporate climate change rely on model-generated projections, regardless of which climate variables are of primary interest. These projections are created by global climate models (GCMs) driven by greenhouse gas (GHG) emission or concentration scenarios. GCMs are physically-based dynamical models that represent complex interactions between processes in the atmosphere, ocean, cryosphere and land surface, including vegetation (biosphere) and inland waters. These are currently the most advanced tools to estimate how the climate system may respond to natural and human driven stresses (e.g., increases in GHG emissions). These simulations serve as an alternative approach to extrapolating trends from historical data (e.g., Stratz and Hossain, 2014).

There are various research groups that conduct climate change modelling research and share their projections to the Coupled Model Inter-comparison Project (CMIP) Phase 5 (CMIP5). CMIP is a coordinated experiment, where every participating group adheres to a set of requirements making the simulations from each model comparable. The Intergovernmental Panel on Climate Change (IPCC) draws, among other sources, from published papers analyzing the outputs of these coordinated experiments. The IPCC is the secretariat coordinating the redaction and review of essentially a large-scale literature review done by the actual researchers. There were twenty (20) different climate modelling groups that lead the evolution of climate models used in CMIP5, resulting in a large repository of models available for various applications (Taylor et al. 2012).

It is unknown what GHG emissions will be in the future. To account for multiple possible future emissions scenarios, the IPCC supported the development four Representative Concentration Pathways (RCP) as part of a new initiative for the Fifth Assessment Reports (Taylor et al., 2012). RCP 2.6, 4.5, 6.0 and 8.5 reflect various levels of climate change mitigation efforts, with the numbers corresponding to potential radiative forcing levels reached by 2100. For example, RCP 2.6 results in an increase in radiative forcing to the global climate system reaching only 2.6 W/m^2 in 2100, while the business-as-usual GHG emissions RCP 8.5 would be expected to lead to an increase reaching 8.5 W/m^2 in 2100.

The RCP scenarios are used as boundary conditions for the CMIP5 GCMs. A given GCM that is driven by a higher GHG concentration scenario (e.g., RCP 8.5) will likely project more significant climate changes than one driven with a lower concentration scenario (e.g., RCP 4.5), as illustrated by projected mean global temperatures in Figure 3-7 (from Burkett et al., 2014). Much of the climate model output that originated from the CMIP5 ensemble have been produced using one of the RCP scenarios. Previous generations of GCMs (e.g., CMIP3) have used the Special Report on Emissions Scenarios (SRES) GHG scenarios, among others.

Peters et al. (2013) and Smith and Myers (2018) found that RCP 8.5 most closely resembles emissions from recent years. As such, some studies only focus on RCP 8.5 (e.g., Chen et al., 2017, Rastogi et al., 2017). That said, Raferty et al. (2017) provide some indication that RCP 8.5 may be on the outside of the range of plausible emissions scenarios.

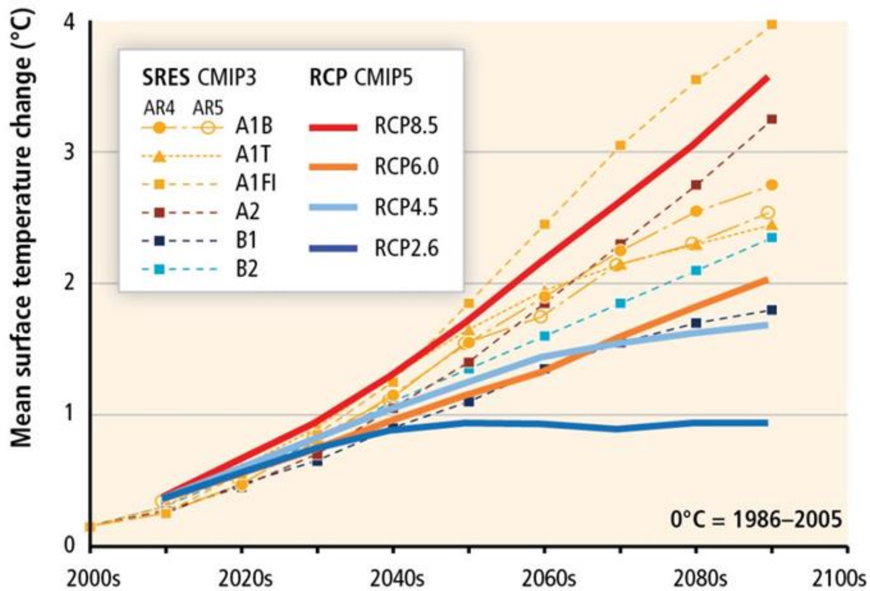


Figure 3-7: Global Mean Surface Temperature Change (°C) over the 21st Century Using the Special Report on Emissions Scenarios (SRES) and Representative Concentration Pathway (RCP) Scenarios

3.2.1.1 Uncertainty in Climate Change Impact Projections

Sources of uncertainty in climate change studies (Hawkins and Sutton, 2009, 2011) include:

1) Future GHG concentrations;
2) Physical and numerical formulation in GCMs or RCMs, including parameterizations and feedback mechanisms, that may lead to different responses to changes in radiative forcing (e.g., GHG emissions);
3) Downscaling technique (to adjust to impact scale and correct model bias) and impact model (e.g., hydrology model); and
4) Random internal variability of the climate system, linked to natural fluctuations (e.g., El Nino-Southern Oscillation, North Atlantic Oscillation) that arise in the absence of any changes to radiative forcing, and result from the chaotic non-linear nature of the climate system.

The relative degree to which these factors influence uncertainty in impact projections vary in time, in space (depending on location and on the dimension of the area studied) and depending on the variable of interest (usually more uncertainty for precipitation than for temperature; more uncertain for extremes than for mean values). For example, “Appreciation of [natural] fluctuations is an important matter for decision makers because they have the potential to reverse—for a decade or so—the longer-term trends that are associated with anthropogenic climate change” (Hawkins and Sutton, 2009). Wilby and Harris (2006) have examined these sources of uncertainty individually and described the “uncertainty cascade” which combines and propagates the above-mentioned sources of uncertainty.

Effectively representing the uncertainties involved in climate change impact projection is essential for helping decision makers create and adopt coherent and informed strategies (Maurer, 2007). Sparling et al. (2017) suggest that Environment Assessments should “describe the uncertainties and degree of confidence and belief in the estimate based on the uncertainties and degrees of confidence in the models, methods, data and key assumptions that were used, and how these uncertainties and degrees of confidence were determined.” This statement is broadly applicable to climate change studies in general; however, the key challenge is to quantify these uncertainties, as the spread in model results is merely an indicator of the underlying uncertainty, not the actual uncertainty.

It is well known that no single climate model produces an ideal simulation of all climate variables and their various statistics. A single projection represents only one of many possible realizations of the future climate and is not robust (Christensen and Christensen, 2007 and Maraun et al., 2010), as it does not capture the primary sources of uncertainty (i.e., bullet 1) and 2) from above). As each GCM provides a slightly different conceptualization of the earth-atmosphere system, the IPCC and others (e.g., Clavet-Gaumont et al., 2017) recommend using an ensemble approach. An ensemble is often a collection of various climate projections, though there are different kinds of ensembles. One can build an ensemble with one model but multiple initial conditions, or an ensemble with one GHG scenario and multiple models. The properties of the ensemble determine how well it represents different sources of uncertainty. Together, the models in an ensemble provide a better characterization of the future and its uncertainty than a single model used in isolation. Mote et al. (2011) found that an ensemble of at least 8-10 models is required to make a robust estimate of a projected future climate variable, as that number of GCMs was found to adequately represent ensemble spread. Lee and Kim (2018) found the ensemble spread (i.e., uncertainty) of PMP projections increases with time (especially after 2070) due to the divergence of GHG concentration pathways as well as model differences exacerbated by higher GHG concentrations.

Interpreting ensemble output is most straightforward if all the ensemble members agree on the direction of projected change and have relatively tightly grouped projections in terms of magnitude. In such cases, the ensemble mean may be an adequate metric on which to base decisions. That said, the range and distribution of the ensemble projections are indicative of some of the uncertainty introduced by various models and emissions scenarios. Simply employing the ensemble mean values ignores the range of possible outcomes, which can be important when aiming to cover the various ranges of uncertainties (future emissions, climate modelling, natural variability). Depending on the focus of the impact study and the cost-benefit of adapting to different levels of climate change, it may be more appropriate to focus on, for example, the 25th or 75th percentile of the ensemble, as opposed to the ensemble mean or median. For extreme event analysis such as PMPs, it is unlikely to find tightly grouped projections, so the analysis should account for the full distribution of results.

3.2.2 Overview of Climate Change in Canada and Ontario

3.2.2.1 Temperature

Increases in temperature across the country are not anticipated to be uniform. Generally, the north is projected to warm at a greater rate, particularly in winter. Compared to the recent past (1986 to 2005), and depending on the future emission scenario (RCP 2.6 to RCP 8.5, discussed in Section 3.2.1), temperatures for Canada are anticipated to increase by 1.8˚C to 6.3˚C by the end of the century (summer temperatures increasing by 1.4˚C to 5.4˚C and winter temperatures increasing by 2.4˚C to 8.2˚C) (ECCC, 2017). See Figure 3-8 (ECCC, 2017).

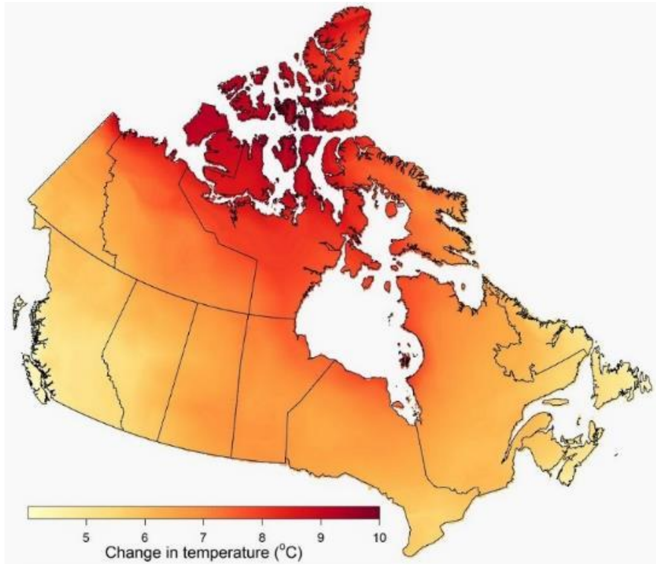


Figure 3-8: Projected Changes in Annual Mean Temperature by the End of the 21st Century across the Canadian Landmass under RCP8.5 (Reference Period: 1986-2005)

The Province of Ontario has experienced significant temperature changes (from 1950-2010). Vincent et al. (2015) indicated that mean annual daily temperatures in Ontario have increased by 0.5 ˚C to 1.5 ˚C (1950-2010). Southern Ontario experienced increasing mean annual temperatures, while changes in the north have been variable (McDermid et al., 2015b). Although Ontario is not anticipated to experience changes as significant as those in Arctic regions, McDermid et al. (2015b) estimates an average increase of 4.0 [3.1-4.8] ˚C (RCP 4.5) and 4.9 [4-5.9] ˚C (RCP 8.5) by mid-century, and 5.1 [3.9-6.2] ˚C (RCP 4.5) to 8.5 [6.7-10.3] ˚C (RCP 8.5) by the end of the century. Other downscaled analyses corroborate these projections and estimate Ontario will experience a significant increase in temperature by mid and end of century (4.0-4.5 ˚C by 2050s and 5.9-7.4 °C by 2080s from a 1961-1990 baseline, depending on the emissions scenario) (Wang et al., 2015 and CCCS, 2018). These results are summarized in Figure 3-9 (from McDermid et al., 2015b) and Table 3-2.

No significant changes in the current spatial pattern of daily average temperature are identified in the projections for the 2050s and 2080s (Wang et al., 2015). The projected temperatures often include a similar magnitude of change across cities in Ontario. For example, the City of Toronto is projected to increase by +2.9 ˚C (2050s) and +5.1 ˚C (2080s) from a 1986-2005 baseline (under RCP 8.5), while Big Trout Lake, in Northwestern Ontario, may see increases of +2.9 ˚C and +5.9 ˚C respectively (Wang and Gordon, 2015). This increase in average temperatures will be more substantial during winter months compared to summer months. More specifically, approximately 1.8 ˚C greater change in winter than in summer 2050s and approximately 2 ˚C in the 2080s (McDermid et al., 2015b). Similarly, Northern Ontario is expected to experience a relatively larger increase in temperature (McDermid et al., 2015a).

McDermid et al. (2015b) concluded that projected increases in mean annual air temperature across Ontario are highest by the 2080s for the Lake Superior sub-basin (3.2 to 8.3 °C above 1971–2000 baselines), followed by the Lake Huron sub-basin (3.1 to 7.9 °C), the Ottawa River sub-basin (3.1 to 7.9 °C), the Lake Ontario sub-basin (3 to 7.6 °C) and the Lake Erie sub-basin (2.8 to 7.2 °C).

Annual mean of daily maximum temperature is projected to increase along with daily average temperature. For example, the City of Toronto is projected to increase by 2.9°C (2040-2069 [2050s]) and a 5.1°C change (2070-2099 [2080s]) for RCP 8.5 scenario (Wang and Gordon, 2015). Big Trout Lake is projected to increase by 2.9°C (2040-2069 [2050s]) and a 5.9°C change (2070-2099 [2080s]) for RCP 8.5 scenario (Wang and Gordon, 2015).

Based on the available information, it is likely that all of the five study locations will experience average temperature changes similar to those experienced by most of Southern Ontario (~3-4°C by the 2050s and ~6°C by 2080s).

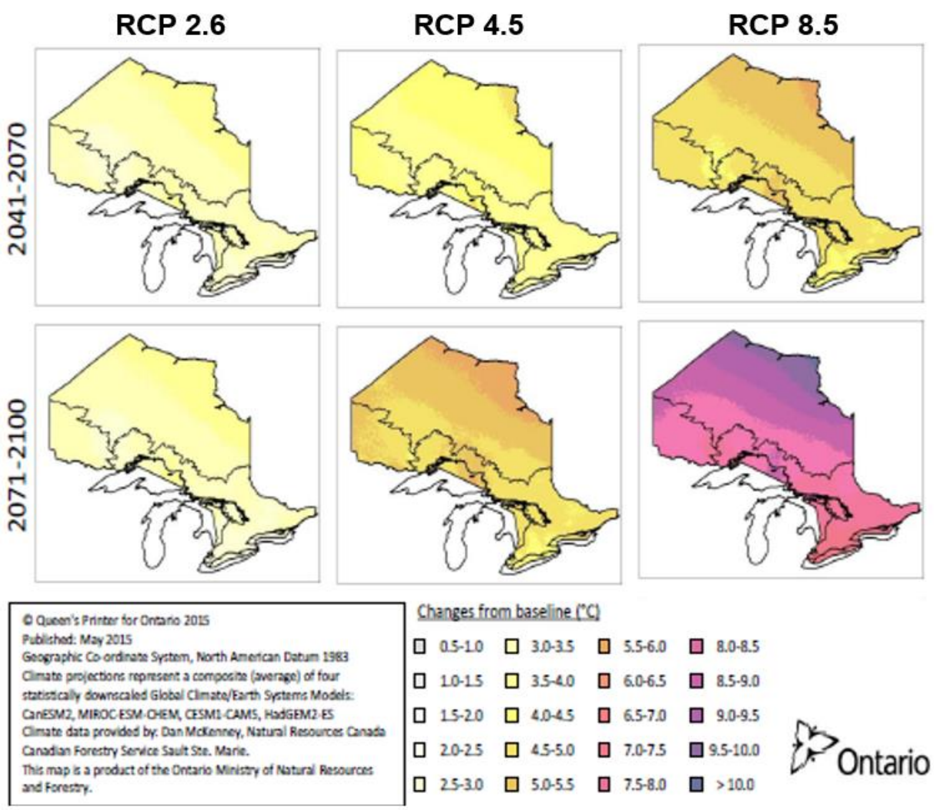


Figure 3-9: Projected Change in Mean Annual Temperature from 1971-2000 Baseline

Table 3-2: Summary of Projected Mean Annual Temperature for Canada, Ontario, and Example Areas in Ontario

	2050s	**2080s**
Canada (ECCC, 2017)		
RCP 4.5	+3.2 ˚C	+4.2 ˚C
RCP 8.5	+4.4 ˚C	+8.2 ˚C
Ontario (McDermid et al., 2015b)		
RCP 4.5	+4 [3.1-4.8] ˚C	+5.1 [3.9-6.2] ˚C
RCP 8.5	+4.9 [4-5.9] ˚C	+8.5 [6.7-10.3] ˚C
Toronto (Wang and Gordon, 2015)		
RCP 8.5	+2.9 [2-3.9] ˚C	+5.1 [3.3-6.5] ˚C
Big Trout Lake (Wang and Gordon, 2015)		
RCP8.5	+2.9 [1.7-4.2] ˚C	+5.9 [4-7.8] ˚C

3.2.2.2 Precipitation

Generally, Canada has seen an annual precipitation increase from 1948 to 2012 with the greatest changes taking place over Northern Canada, and little change over northeastern Ontario (ECCC, 2017). Drier summers have been felt in some regions while other parts of the province have become slightly wetter and more winter precipitation is falling as rain.

Climate change driven precipitation changes are expected to vary significantly by region and season across Canada (Figure 3-10 from ECCC, 2017). For example, winter precipitation overall is projected to increase by 9.1% to 37.8% by the end of the century compared to the recent past (1986-2005) and depending on the future emission scenario (RCP 2.6 to RCP 8.5), while summer precipitation is projected to increase by 5.2% to 10.6% (ECCC, 2017). Greater increases are projected for northern Canada.

In Ontario, total annual precipitation is projected to increase in most of the province. Wang et al. (2015) estimated overall values of 4.6-10.2% in the 2050s, and 3.2-17.5 % in the 2080s from a 1961-1990 baseline for SRES scenario A1B. McDermid et al. (2015b) reports projected annual mean precipitation increases of 63.9-69.2 mm by the 2050s, and 64.8-82.1 mm by the 2080s depending on the RCP scenario (RCP 2.6 to RCP 8.5) as seen in Figure 3-11 (from McDermid et al., 2015b). In all estimates the projected increase in annual precipitation is mainly driven by an expected increase in winter and spring precipitation, with no obvious temporal trends in summer and autumn precipitation.

For example, recent estimates using the RCP 8.5 scenario for annual precipitation may increase for the city of Toronto by 2.1% (2050s) and 11.0% (2080s), while Big Trout Lake may see increases of 11% (2050s) and 14.9% (2080s) from a 1986-2005 baseline (Wang and Gordon, 2015). See Table 3-3. Similar to temperature estimates, no significant changes in the spatial pattern were identified for annual total precipitation (current pattern: dry in the north and wet in the south, as shown in Figure 2-3) in the 2050s and 2080s (Wang et al., 2015).

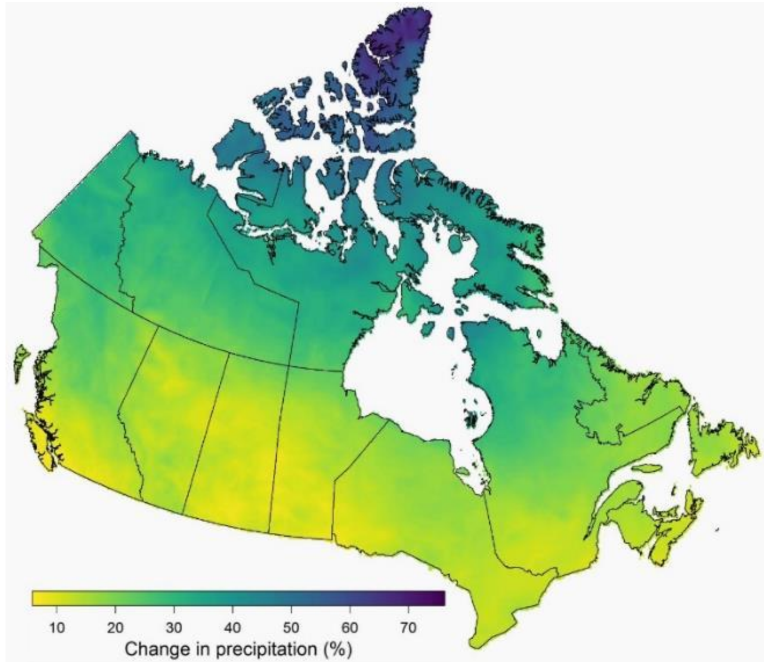


Figure 3-10: Spatial Distribution of Projected Changes in Annual Mean Precipitation by the End of the 21st Century under RCP8.5 (Reference Period: 1986-2005)

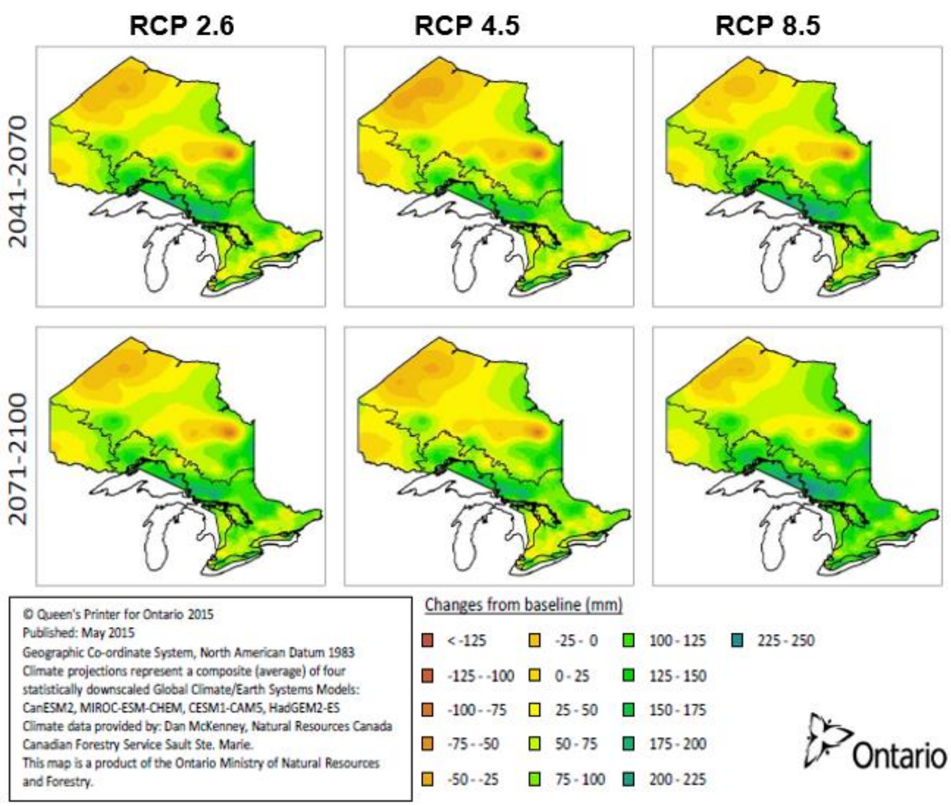


Figure 3-11: Projected Changes in Total Annual Precipitation from 1971-2000 for Ontario

The distribution of projected increases in intensity and volume of rainfall varies regionally (Wang et al., 2015 and Wang and Gordon, 2015). Results based on updates to Intensity Duration Frequency (IDF) curves across Canada using CMIP5 models indicate a reduction in extreme precipitation in central regions of Canada under specific analyses and increases in other regions (Simonovic et al., 2017). Similarly, updates to IDF curves suggest that there is likely to be an overall increase in the intensity of rainfall storms at most cities in Ontario (Wang et al., 2015). Spatial variability is high in these estimates. Tools outlined in Section 3.2.4 can be used to obtain IDF statistics to better understand localized impacts on precipitation.

Table 3-3: Summary of Total Annual Precipitation for Canada, Ontario, and Example Areas in Ontario

	2050s	**2080s**
Canada (ECCC, 2017)		
RCP 4.5	+ 12.9 %	+17.6 %
RCP 8.5	+ 18.1%	+37.8 %
Ontario (McDermid et al., 2015b)		
RCP 4.5	+53 [-100 to +206] mm	+57.2 [-94 to +205] mm
RCP 8.5	+69.2 [-95 to +225] mm	+82.1 [-81 to +240] mm
Toronto (Wang and Gordon, 2015)		
RCP 8.5	+2.1%	+11.0%
Big Trout Lake (Wang and Gordon, 2015)		
RCP8.5	+11.0%	+14.9%

There is significant uncertainty associated with the estimation of rainfall events' intensity and duration when incorporating climate change (presented in the form of IDF statistics and curves). Often results can show an increase and a decrease in rainfall intensity values. For instance, due to differences in climate model output, the projected relative change in intensity for the 30-minute 100-year return period event for the 2080s at Pearson Airport station can range from +127% to -25% compared to the current IDF statistics. Meanwhile, at the Windsor stations, there is a statistically significant trend of increasing storm intensity projected for the future, with variability in the magnitude of change within the ensemble (Figure 3-12 from Coulibaly et al., 2016). Generally, variability is greater for Southern Ontario for higher intensity storms (Switzman et al., 2017).

Other localized climatic factors are projected to see changes as well. For instance, lake-effect precipitation is anticipated to increase, and other extreme weather events (e.g., extreme rainfall, wind, ice storms) are expected to increase in frequency for some regions of Ontario (McDermid et al., 2015a and McDermid et al., 2015b). However, the specific rate of change is associated with greater uncertainties than the annual or seasonal precipitation estimates presented above.

Finally, a study of rainfall as ice (ice potential) in the Region of Peel (Southern Ontario) found that the conditions for this event did not change significantly from the baseline (2.4 days) to the time period of the 2050s (1.9 days) and 2080s (2.0 days). However, days below freezing showed a significant decrease. Changes to days below 0°C ranged between -26% (2050s) to -31% (2080s) for RCP 4.5, and -35% (2050s) to -52% (2080s) for RCP 8.5 (from a baseline of 1981-2010) (Auld et al., 2016).

Precipitation changes are highly variable and dependent on localized dynamics. Based on the information available, it is likely that the site locations of South Bruce and Huron-Kinloss may experience precipitation changes greater than those experienced by most of Southern Ontario (likely in the 75-100 mm/year range by the 2050s, and 125-150 mm/year by the 2080s). Meanwhile, the locations of Hornepayne, Manitouwadge and Ignace may experience changes in precipitation closer to the projected provincial annual average (50-75 mm by the 2050s and 100-125 mm by the 2080s).

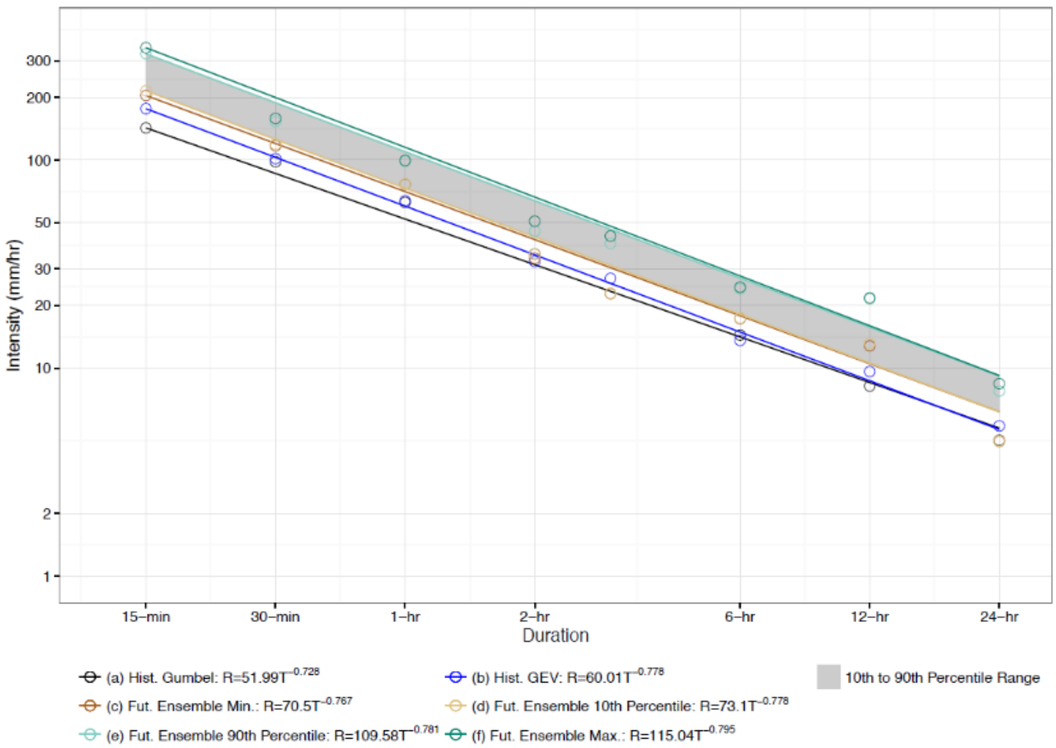
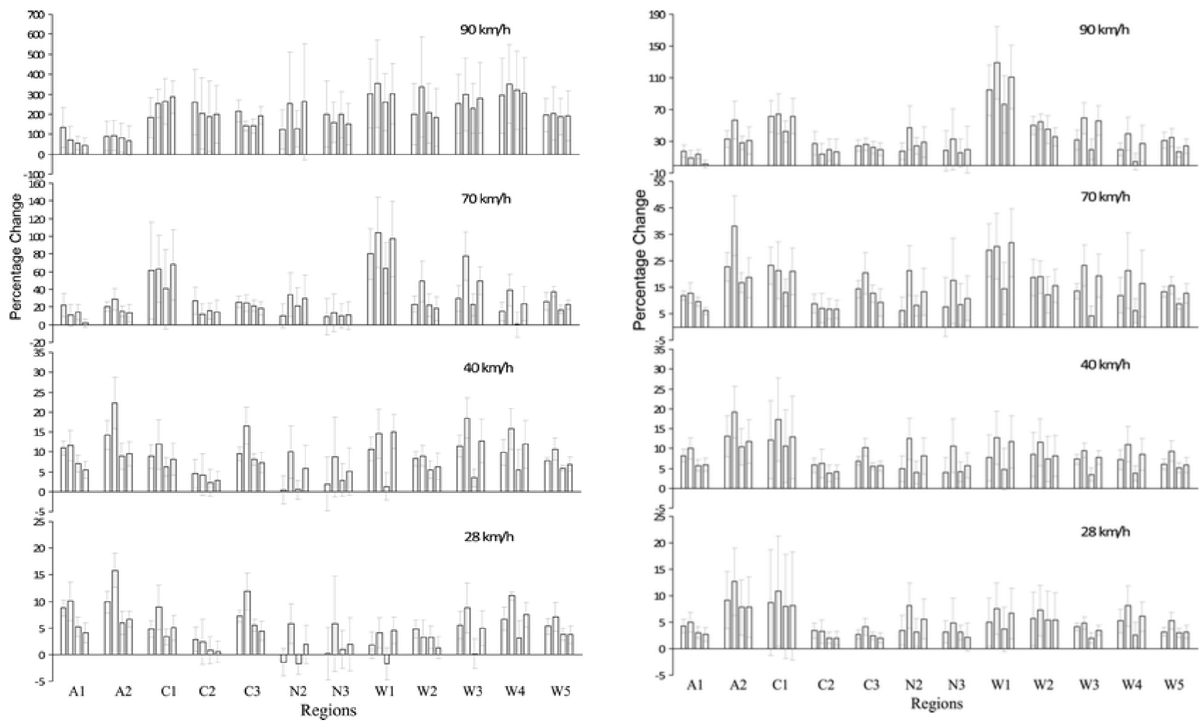


Figure 3-12: IDF Curve Comparison for Windsor Airport (2050), 100-year Return Period

3.2.2.3 Wind

There is significantly less confidence on the future trend of wind speed and direction changes than there is with temperature and precipitation trends. Canada is projected to experience higher hourly and daily wind gust events later this century, with the most severe winds seeing the most increase in frequency. The magnitude of the projected changes varies regionally (Cheng et al., 2014). However, uncertainties associated with these and other similar future wind estimates can be of the same magnitude as the estimated percent change. This applies particularly when assessing greater speed wind gusts events (e.g., ≥70 km h^{-1} and ≥90 km h^{-1}). Figure 3-13 presents Cheng et al. (2014) results for different regions across the country, with C1, C2 and C3 corresponding to northern, central-eastern and southeastern Ontario respectively (see Cheng et al., 2014 for detailed breakdown of regional boundaries).

Cheng et al. (2012) studied hourly and daily wind gusts in Ontario. The model results indicated the frequencies of future hourly and daily wind gust events are projected to increase towards the end of the century. For example, across the study area, the annual mean frequency of future hourly wind gust events >28, >40, and >70 km/h for the period 2080s (2081–2100) derived from the ensemble of downscaled models using the SRES A2 simulations is projected to be about 10–15%, 10–20%, and 20–40% greater than the observed average during the baseline period (1994–2007) respectively. The corresponding percentage increase for future daily wind gust events is projected to be 10%, 10%, and 15–25%, respectively. However, uncertainty (stemming from different GHG scenarios and GCMs, as discussed in Section 3.2.1.1) for each of these ranges include 90-100% (>28 km/hr), 60%-80% (>40 km/hr), 25-35% (>75 km/hr). An overview of projected changes is presented in Table 3-4 (from Cheng et al., 2012). Greater increases in some of these wind metrics were projected for Huron-Kinloss and South Bruce than for Ignace, Manitouwadge and Hornepayne, though without site-specific analyses, it is assumed the above projection ranges can be representative of all five study locations.



Note: Four bars in each of the panels: the first two for scenario A2 over the periods 2046–65 and 2081–2100; the last two for scenario B1 over the periods 2046–65 and 2081–2100.

Figure 3-13: Projected Percentage Change in Annual-Mean Frequency of Future Hourly (Left) and Daily (Right) Wind Gusts for Canada

Table 3-4: Mean Percentage Change and Spatial Variations in Wind Gusts for Ontario

Wind Gust Events (km/hr)	Mean Percentage Changes (Spatial Variations in Parentheses)	
	Downscaled Eight-GCM A2 Ensemble (2046-65)	Raw Five-RCM A2 Ensemble (2038-70)
≥40	7 (5 to 10)	-2 (-5 to +1)
≥60	10 (5 to 20)	-4 (-20 to +5)
≥70	15 (10 to 25)	-4 (-20 to +5)
≥80	20 (10 to 40)	-5 (-35 to +15)
≥90	20 (10 to 40)	-2 (-40 to +45)

Similarly, Kurlkarni and Huang (2014) used five CMIP5 GCMs to generate wind gust change estimates for the 2080s (2079-2099), compared to a 1979-1999 baseline. In summer, a general decrease is projected over Ontario. In winter, two models project increases, two models project decreases, and one model varies regionally depending on location. Auld et al. (2016) provides estimates for wind velocities for Region of Peel in Table 3-5. These estimates show little to no change with large ranges of uncertainty.

Table 3-5: Wind Velocity (m/s) Projection Estimates for Region of Peel

Emission Scenario	Baseline (1981-2010)	2050s	2080s
RCP 4.5	4.5	4.4	4.3
RCP 8.5	4.5	4.4	4.3

3.2.2.4 Tornadoes

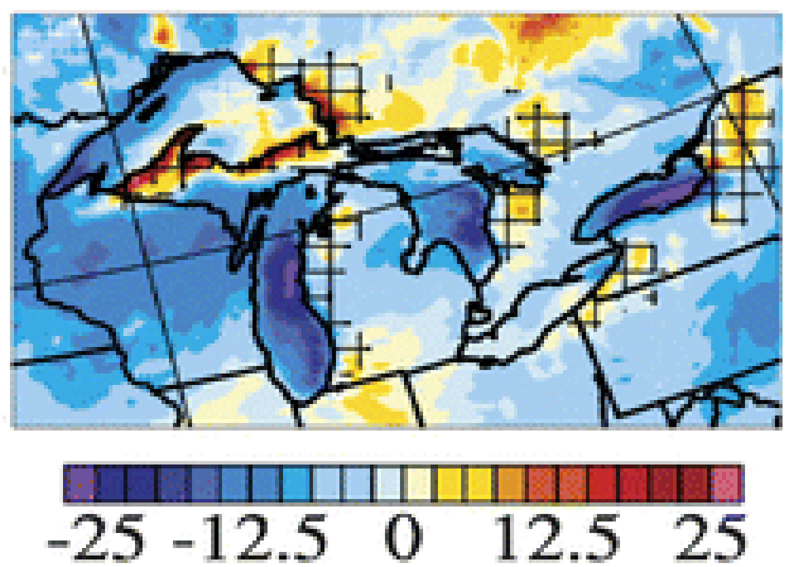
Analysis of historical data of tornados from Brooks (2013) states that tornadoes form mainly in thunderstorms with strong vertical shear of horizontal winds and high convective available potential energy (CAPE). The number of tornados varies strongly from one year to the next, making it difficult to find a significant trend.

King et al. (2003) linked lake breezes in Southern Ontario and their inland boundaries with the development of tornadoes. However, the link between tornadoes and climate change is an area in development. To date, literature shows few impact studies on climate change’s influence on tornado occurrence in Ontario. Generally, the components that are necessary for a tornado to form include energy (warm unstable air with moisture) and wind shear (changes in wind speeds and direction between the ground and high levels of the atmosphere) (Auld et al., 2016, The Royal Society, 2014). It is generally understood that conditions for thunderstorms that have spawned tornadoes are expected to increase in some regions with warming (convective storms; Paquin et al., 2014). More specifically, Paquin et al. (2014) found that CAPE is projected to increase, whereas vertical shear and horizontal winds are expected to decrease slightly in Ontario. It should be noted that these results could imply that a projected increase of thunderstorms (severe storms) may not produce an increase in tornados. Additional research, mainly with high-resolution climate models, is needed to have a better portrait of future evolution of tornados at each of the locations. This is evident because as noted above, analysis of the Regional Climate Models (RCMs) and the Canadian RCM’s convective precipitation outputs show that severe convective liquid precipitation events may become both more frequent and slightly more intense.

3.2.2.5 Snowfall

Overall, snow depth has decreased in Canada over recent decades in spring (ECCC, 2017). Natural Resources Canada reports that there has been a 10% decrease in extent of snow cover in the Northern Hemisphere (1972 – 2003), and a decrease of 20 days in duration of snow cover in the Arctic since 1950 (NRCAN, 2008). This trend is anticipated to continue for most regions in Canada except for the North, where snow cover extent is anticipated to increase due to local increases in snowfall as explained below. However, literature on specific Ontario estimates is scarce (ECCC, 2017). More specifically, winter precipitation overall is projected to increase by 9.1% to 37.8% by the end of the century compared to the recent past (1986-2005) and depending on the future emission scenario (RCP 2.6 to RCP 8.5).

Auld et al. (2016) found that by the 2080s, the Region of Peel temperature is still projected to be below freezing at the surface in winter, meaning that snow can still be expected, but the area affected will likely be reduced. Coupled with the possibility of ice-free conditions over Lake Huron and Georgian Bay to the northwest (the predominant wind direction in winter), this would also mean that lake-effect snowfall will remain likely. In most portions of Ontario, projected warmer temperatures imply that a higher percentage of winter precipitation would fall as rain instead of snow. These results are consistent with other studies that have previously examined future snowfall. For example, Peltier and Gula (2012) found that future changes in lake surface temperature and ice cover under warm conditions may locally increase snowfall as a result of increased evaporation and the enhanced lake effect. A summary of their results is shown in Figure 3-14 (from Peltier and Gula, 2012). Lake effect snow is discussed in Section 3.2.2.6.



Note: The gridded areas correspond to the snowbelt location computed from historical snowfall.

Figure 3-14: Mean Changes in Snowfall (mm Snow-Water-Equivalent) for January and February for the 2050-2060 Period Compared to 1979-2001 Baseline for Great Lakes

More research is needed to provide highly localized snowfall estimates. However, based on the available snowfall and temperature estimates, it is likely that all locations will experience a decrease in snowfall, with an increase in the proportion of winter precipitation falling as rain instead of snow.

3.2.2.6 Lake-Effect Snow

Lake-effect snow takes place as cold artic air travels across the warmer ice-free Great Lakes (e.g., every fall). The observation record shows a distinct positive trend in lake-effect snowfall, possibly due to a decline in lake ice cover, which enhances evaporation (Burnett et al., 2003). Notaro et al. (2015) uses a dynamically downscaled regional climate model simulation coupled with a 1D lake model to generate 25-km future temperature and precipitation estimates for mid and late twenty-first century. The results show atmospheric warming and increases in cold-season precipitation, consistent with estimates presented above.

The Great Lakes ice cover is projected to dramatically decline by both mid and end of the twenty-first century. The projected decrease in ice cover, as well as greater dynamically induced wind fetch enhances the model’s lake evaporation, and the total lake-effect precipitation. The results of these studies agree with other estimates shown in Section 3.2.2.2, which project an increase in winter precipitation falling as rain. It should be noted that all reviewed studies identified a lake-ice bias due to the lack of lake circulation in the models (Notaro et al., 2015, Gula and Peltier, 2012, Kunkel et al., 2002), which results in excessive ice cover and the lake stratifying too early (particularly the deep lakes) in the warmer seasons. This cold and/or wet bias results in an over-estimate of lake-effect snowfall.

Significant lake-effect snow events are projected to decrease across most of the Great Lakes basin in the mid and late century estimates (Figure 3-15 from Notaro et al., 2015). However, identifying with precision when this will take place near mid-century is difficult due to uncertainty factors such as the lake-ice bias. An exception to the decreasing trend is the region downwind from Lake Superior (Figure 3-16), which is in the coldest region, and is projected to see increases in snowfall (events >1 mm/day confined to January-March) up to mid-century, since air temperature remains low enough to allow for wintertime precipitation to be mostly snow. The trend is projected to decrease after mid-century for this region as well. The projections presented above are consistent with other studies (Gula and Peltier, 2012, Kunkel et al., 2002). Further research is needed on lake-effect snow projections, which should include the expansion of the ensemble presented by these studies by continuing to evaluate various GCMs, RCMs, and the use of other lake models and 3D lake models.

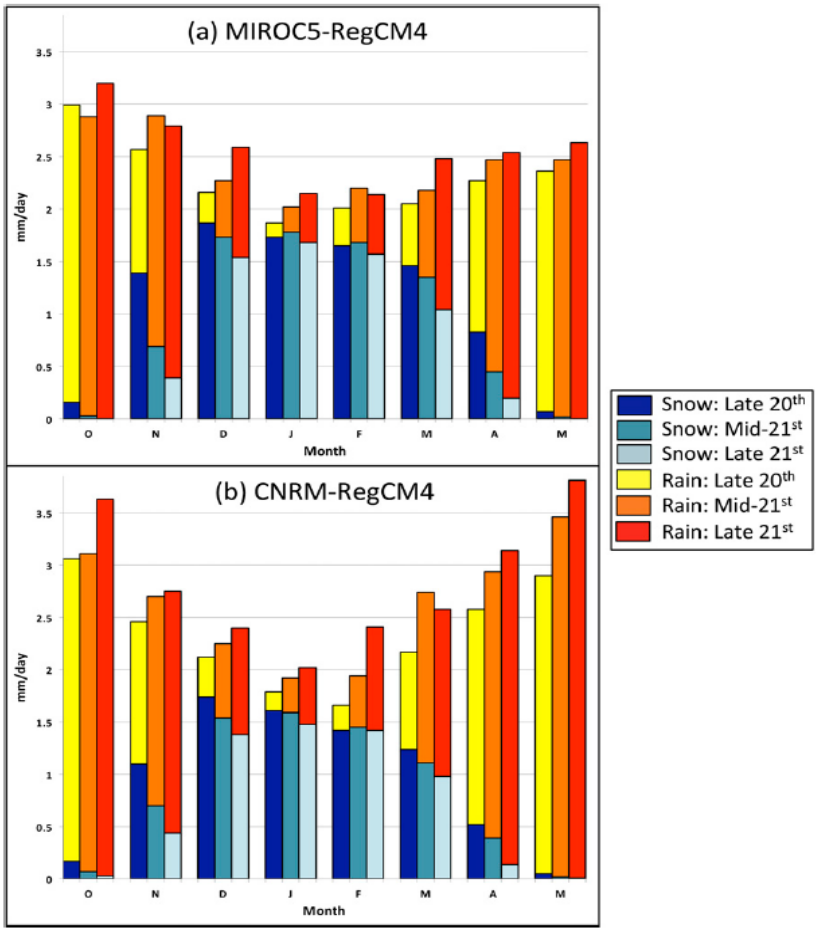
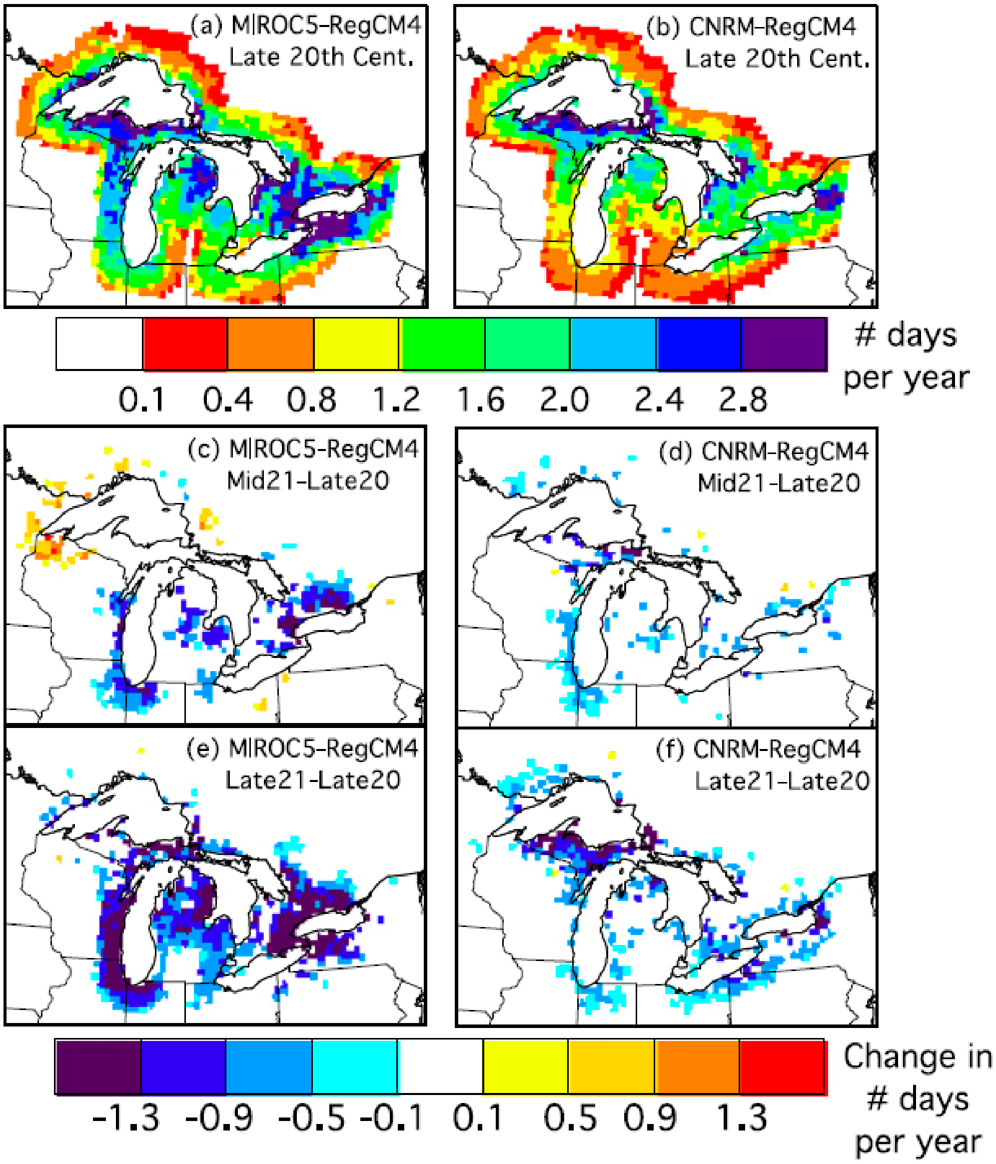


Figure 3-15: Seasonal Cycle (October–May) of the Distribution of Simulated Mean Total Precipitation (mm/day) as Rain or Snow in the Great Lakes Basin (Land only) for the Late Twentieth (1980–99), Mid Twenty-first (2040–59), and Late Twenty-first (2080–99) Centuries, according to (a) MIROC5-RegCM4 and (b) CNRM-RegCM4



Note: Projected changes are computed as the difference between either 2040–59 in (c) and (d) or 2080–99 in (e) and (f) and 1980–99. Only significant differences (p, 0.1) in (c) to (f) are displayed.

Figure 3-16: Mean Number of Simulated Heavy Lake-effect Snowfall Days per Year from (a) MIROC5-RegCM4 and (b) CNRM-RegCM4, for the Late Twentieth Century (1980–99), and Projected Changes are Shown for (c), (e) for MIROC5-RegCM4 and (d), (f) for CNRM-RegCM4

3.2.3 Overview of Climate Model Ensembles

This section provides an overview of widely used climate model ensembles, categorized according to global modeling experiments, regional modeling experiments, and statistically downscaled products. Each of the ensembles discussed in Section 3.2.3.4 are applicable to the five study locations, as they each include potentially relevant climate variables and their respective geographic coverages include the five study locations.

3.2.3.1 Global Modeling Experiments

3.2.3.1.1 Coupled Model Inter-comparison Project Phase 5 (CMIP5)

CMIP5 (https://cmip.llnl.gov/cmip5/) is the official body of science used by the Intergovernmental Panel on Climate Change (IPCC), which is a United Nations body founded with the purpose of evaluating climate change science. There are currently twenty (20) different climate modelling groups that participate in CMIP5 coordinated experiments, resulting in a large repository of models available for various applications. There is a wide range of available variables from CMIP5 experiments, and their resolution usually ranges between 80 km to 400 km grids. This dataset has been made available to users in various formats by Environment and Climate Change Canada (ECCC) through the Canadian Climate Data and Scenarios (CCDS http://climate-scenarios.canada.ca). The primary limitation of CMIP5 is the coarse resolution of the models, which may result in poor representation of extreme events in a site-specific context.

Model output from CMIP6, the sixth phase of the CMIP program, is expected to gradually become available beginning in 2019.

3.2.3.2 Regional Modeling Experiments

3.2.3.2.1 The North American Coordinated Regional Climate Downscaling Experiment Program (NA-CORDEX)

The North American CORDEX Program (NA-CORDEX) (https://na-cordex.org/) contains outputs from regional climate models (RCMs), which cover most of North America. The GCMs from CMIP5 are used as boundary conditions for the RCMs. The CORDEX simulations cover the time period 1950-2100 and provide data with a resolution of approximately 25 km or 50 km. Datasets are available at sub-daily (for some models and variables), daily and monthly frequencies. Limitations of NA-CORDEX include the limited number of variables available.

3.2.3.2.2 North American Regional Climate Change Assessment Program (NARCCAP)

The North American Regional Climate Change Assessment Program (NARCCAP) (http://www.narccap.ucar.edu/) is an international program that produces high resolution climate data for North America. The data includes coupled GCM-RCM pairs, and time-slice experiments. The modellers are running a set of RCMs driven by a set of atmosphere-ocean general circulation models (AOGCMs) over North America. The work has been focused on the SRES A2 scenarios and does not include the more recent RCP scenarios. Data is provided for time periods 1971-2000 and for 2041-2070. The resolution of the data is available at a resolution of 50 km grids and are recorded at 3-hourly intervals. Limitations of NARCCAP include the use of a single GHG emissions scenario (SRES A2) resulting in the inability to incorporate uncertainty across different future scenarios and the limited future timeframes (2041-2070) for which projections are available.

3.2.3.3 Statistically Downscaled Products

The statistically-downscaled datasets are based on a gridded reference dataset to bring the climate model to finer scale, and to adjust it (bias correct) towards the observational values. Such products do not add information beyond what is contained in the original climate model projection (e.g., CMIP5), and assumes that the relative spatial patterns in temperature and precipitation observed will remain constant under future climate change.

3.2.3.3.1 Pacific Climate Impacts Consortium (PCIC)

The University of Victoria's Pacific Climate Impacts Consortium (PCIC) (http://tools.pacificclimate.org/dataportal/downscaled_gcms/map/) provides daily Canada-wide statistically downscaled climate model outputs. This dataset is provided at a resolution of approximately 10 km grids, for 1950-2100 and all RCP scenarios. The data are downscaled projections (with the BCCAQ method: Bias-correction Constructed Analogues with Quantile mapping reordering) based on GCM projections from the CMIP5 and a historical gridded product for climate data in Canada (McKenney et al., 2011). PCIC provides ensembles of 12 climate models for different regions of Canada. The chosen models aim to provide the widest spread in projected future climate change with a smaller CMIP5 subset for various regions. The variables available include minimum temperature, maximum temperature, and precipitation. A primary limitation of the PCIC dataset is the small number of variables available at a daily time step. This gridded product is dependent both on the quality of the 10-km historical gridded product and on the downscaling method used, and the analogue part of the downscaling method seems linked to artifacts found in the geographical pattern of certain variables (namely precipitation) in some regions, for certain days.

3.2.3.3.2 NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP)

The NEX-GDDP dataset (https://cds.nccs.nasa.gov/nex-gddp/) is comprised of global downscaled climate scenarios that are derived from CMIP5 GCMs and across two of the four RCP scenarios (RCP 4.5 and RCP 8.5). The CMIP5 GCM runs were developed in support of the Fifth Assessment Report of the IPCC (IPCC AR5). The NEX-GDDP dataset includes downscaled projections with the Bias Corrected Spatial Downscaling (BCSD) method from the 20+ models and scenarios for which daily scenarios were produced and distributed under CMIP5. Each of the climate projections includes daily maximum temperature, minimum temperature, and precipitation for the periods from 1950 through 2100. The spatial resolution of the dataset is 0.25 degrees (~25 km), based on the GMFD (Global Meteorological Forcing Dataset; Sheffield et al., 2006) reference data used, which consists in a blend of reanalysis data with surface observations. The NEX-GDDP dataset is provided to assist the science community in conducting studies of climate change impacts at local to regional scales, and to enhance public understanding of possible future global climate patterns at the spatial scale of individual towns, cities, and watersheds. A limitation of NEX-GDDP is the small number of variables available at a daily time step.

3.2.3.3.3 Downscaled CMIP3 and CMIP5 Climate Hydrology Projections (GDO-DCP) - LOCA

This archive (https://gdo-dcp.ucllnl.org/downscaled_cmip_projections/) contains fine spatial resolution translations of climate projections over the contiguous United States (U.S.) and a large portion of southern Ontario. The estimates in the archive were developed using three downscaling techniques (monthly BCSD, daily BCCA, and daily LOCA). The results of the LOCA downscaling process include 1/16 degree projections, as well as 1 degree projections. The LOCA projection dataset uses the CMIP5 projections over the contiguous U.S. and portions of Canada.

The LOCA data includes daily estimates for the following variables: precipitation rate (mm/day), as well as minimum and maximum surface air temperature (˚C). The archive is meant to provide access to climate and hydrologic projections at spatial and temporal scales relevant to some of the watershed and basin-scale decisions facing water and natural resource managers and planners dealing with climate change. A limitation of this dataset is the limited number of variables available at a daily time step.

3.2.3.4 Summary of Climate Ensembles

A summary of climate ensembles is given in Table 3-6.

3.2.4 Tools Available for Ontario

3.2.4.1 Canadian Climate Data and Scenarios (CCDS) and Canadian Centre for Climate Services (CCCS)

Environment and Climate Change Canada (ECCC) and the University of Regina developed and launched the CCDS website (http://climate-scenarios.canada.ca) in February 2005. Since 2012, the CCDS has been solely supported by ECCC. The tool's goals are to support climate change and adaptation research in Canada through the provision of climate model and observational data, to support stakeholders requiring scenario information for decision making and policy development, and to provide access to research. More recently, the CCDS was formed as a dedicated multi-disciplinary team to work with stakeholders to support the Pan-Canadian Framework on Clean Growth and Climate Change. The website provides:

- Links to the historical climate observations archive from ECCC,
- Links to seasonal forecasts for the following year,
- CMIP5 climate model data,
- Climate change products using the CMIP3 and CMIP5 datasets (e.g., extreme indices, global ocean wave heights), and
- Training and a support desk.

Table 3-6: Summary of Global, Regional, Statistically Downscaled Climate Model Ensembles

Dataset	Coverage Area	Ensemble	Resolution	Period	Administrator	Output Climate Variables	Limitations
CMIP5	Global	CMIP5	80 km to 400 km	1850-2100	Lawrence Livermore National Laboratory	All	Not all variables available beyond 2100 or at daily and sub-daily timesteps, low resolution
NA-CORDEX	Regional	RCMs w/ CMIP5 as boundary	25 km or 50 km	1950-2100	National Center for Atmospheric Research	Precipitation and temperature*	Limited variables available
NARCCAP	Regional	RCMs w/ CMIP3 as boundary	50 km	1971-2000, 2041-2070	National Center for Atmospheric Research	Many**	One GHG scenario, limited future time frames
PCIC	Regional	Statistically Downscaled CMIP5	10 km	1950-2100	Pacific Climate Impacts Consortium (PCIC)	Precipitation and temperature	Daily data for only precipitation and temperature
NEX-GDDP	Regional	Statistically Downscaled CMIP5	25 km	1950-2100	National Aeronautics and Space Administration (NASA)	Precipitation and temperature	Daily data for only precipitation and temperature
GDO-DCP-LOCA	Regional	Statistically Downscaled CMIP5	~6 km	1950-2100	Cooperative Institute for Research in Environmental Sciences	Precipitation and temperature	Daily data for only precipitation and temperature

*Other variables are expected to be published in the future. See https://na-cordex.org/variable-list for detailed list.
** See http://www.narccap.ucar.edu/data/data-tables.html for detailed list.

3.2.4.2 University of Western Ontario IDF CC Tool (IDFCC)

The University of Western Ontario's Institute for Catastrophic Loss Reduction developed a "*Computerized Tool for the Development of Intensity-Duration-Frequency Curves under a Changing Climate*" (http://www.idf-cc-uwo.ca/). This computerized web-based IDF tool integrates a user interface with a Geographic Information System (GIS). By creating or selecting a station the user is able to carry out statistical analysis on historical data, as well as generate and obtain possible future change based on a methodology using a combination of global climate model outputs and locally observed weather data.

3.2.4.3 Ontario Climate Change Projections (York University)

The Ministry of the Environment and Climate Change funded the Laboratory of Mathematical Parallel Systems (LAMPS) Laboratory at York University to develop the Ontario Climate Change Projections portal (http://lamps.math.yorku.ca/WorldClimate/). This portal provides high resolution (10 km) daily temperature and precipitation projections. The data in the portal is named the "super ensemble", which is composed of 209 members from both GCMs and RCMs, including 47 members generated by NA-CORDEX, University of Toronto and University of Regina, and 162 members generated by statistical downscaling from LAMPS and Pacific Climate Impacts Consortium (PCIC). The outputs include probabilistic projections including the timeframes:1990s (1986-2005), 2050s (2040-2069), 2080s (2070-2099). The data can be viewed in maps, timeseries, or factsheets for Ontario, regions in Ontario, or by municipality. The variables include:

- Basic temperature and precipitation indices,
- Extreme temperature and precipitation indices, and
- Agroclimatic temperature-based indices.

3.2.4.4 Ontario Climate Change Data Portal (OCCDP)

The Ontario Climate Change Data Portal (http://www.ontarioccdp.ca) has incorporated high-resolution (25 km) climate projections developed by the Institute for Energy, Environment and Sustainable Communities (IEESC) at the University of Regina using the PRECIS model (under A1B emissions scenario) and the RegCM model (under RCP 8.5 emissions scenario). Presently, projected IDF data is only available based on climate projections under the A1B emissions scenario.

Using this tool, IDF relationships have been estimated for 1990, 2030, 2050 and 2080 as represented by the tri-decade periods 1960 to 1990, 2015 to 2045, 2035 to 2065, and 2065 to 2095, respectively.

The tool also allows you to download (temperature, rain, solar radiation, wind, and relative humidity) data in the form of:

- Climate model temporal averages
- Climate model time series
- Monthly averages
- Seasonal Averages.

3.2.4.5 Ministry of Transportation Ontario (MTO) Trending Tool

IDF Curve Lookup Tool (http://www.eng.uwaterloo.ca/~dprincz/mto_site/terms.shtml) is a web-based application provided by the Ontario Ministry of Transportation (MTO) and University of Waterloo for the purpose of retrieving IDF curves.

The Ontario Ministry of Transportation (MTO) has implemented a number of recent updates to its IDF curves to ensure they are as current as possible and regularly incorporate additional and recent rainfall data. MTO has also developed an IDF modelling tool (http://www.mto.gov.on.ca/IDF_Curves/) that allows generation of a unique rainfall intensity curve for any point or area in the province. The most recent update to this tool also includes a predictive modelling component to enable generation of a future IDF curve accounting for the predicted impacts of climate change. It is important to note that this tool does not incorporate the outputs of any climate models. Instead, it provides an extrapolation using a novel linear regression method using 2010 as the base year. The method is outlined here: http://www.eng.uwaterloo.ca/~dprincz/mto_site/database_status.shtml.

Using this tool, IDF relationships (Intensity or Depth) can be estimated for future years by selecting any future year of choice. The tool then estimates what the IDF relationship would look like using all past data. Upper and lower bounds to these estimates are also provided (in 95% confidence).

3.3 INCORPORATING CLIMATE CHANGE CONSIDERATIONS INTO PROBABLE MAXIMUM PRECIPITATION ESTIMATION

Topics addressed in this section include recent extreme storms (Section 3.3.1) and a discussion of how the scientific literature has considered climate change modeling results in PMP estimation (Section 3.3.3), including which climate variables impact PMP estimation (e.g., atmospheric moisture content) in Section 3.3.2. A summary table and diagram of methods to evaluate climate change impacts on PMPs are provided in Section 3.3.4.

An overview of climate change impacts analysis and projections of several variables can be found in Section 3.2.

3.3.1 Recent Extreme Storms

Extreme storms that have occurred in the region since the publication of OMNR (2006) are presented in Section 2.2. Without a detailed analysis it is uncertain if and how any recent extreme precipitation events would affect OMNR (2006) results; however, as the storms listed in Table 2-6 appear to fall within the distribution of storm characteristics included in the 2006 study, it is unlikely that they would have a major impact on the PMP estimates of the five study locations. These storms would need to be incorporated into an updated analysis in order to determine any specific impacts. It should be noted that by including recent extreme storms to update a PMP estimate does not imply that future climate change is inherently taken into consideration.

3.3.2 Relevant Climate Variables for PMP Estimation

The bulk of literature focusing on incorporating climate change impacts into PMP estimation emphases on projected changes of atmospheric moisture content, as indicated by the atmospheric column's precipitable water content (e.g., Clavet-Gaumont et al., 2017), near-surface dewpoint temperature (e.g., Lee and Kim, 2018) or sea surface temperature (e.g., Chen et al., 2017), and relative humidity (e.g., Rastogi et al., 2017). Other variables investigated include winds and storm efficiency (e.g., Kunkel et al., 2013), atmospheric dynamics (i.e., storm and moisture tracks) (e.g. Chen et al., 2017), precipitation, air temperature (e.g., Ishida et al., 2016), convective available potential energy (CAPE, a measure of atmospheric instability) (e.g., Rouhani and Leconte, 2016), and soil moisture (e.g. Gangrade et al., 2018).

While some of the studies in Sections 3.3.2 and 3.3.3 were developed using climate model ensembles reviewed in Section 3.2.3, the choice of ensemble (or specific climate model, in some cases) in the respective studies was dependent on several factors, including the date on which the analysis was conducted, the methodology applied as well as the variables and regions of focus. In this section, which variables are used in the respective studies are introduced. Further discussion on the methodology can be found in Section 3.3.3.

3.3.2.1 Atmospheric Moisture

Rousseau et al. (2014) suggest that a number of different methods can be used to consider the impacts of climate change on PMP; however, the analysis must include at a minimum some form of atmospheric moisture maximization. Their reasoning lies in the physical mechanism described by the Clausius-Clapeyron equation, which shows that warmer air can hold more moisture (on the order of an additional 6-7% moisture for every 1°C temperature increase). Westra et al. (2014) provides a useful discussion of the Clausius-Clapeyron equation and its applicability to extreme precipitation under climate change.

Kunkel et al. (2013) investigated the multi-model (seven GCMs) mean projected changes of the 12-hour persisting precipitable water across the globe. Rousseau et al. (2014) used output from CRCM projections to compare baseline and future 100-year precipitable water values. Similarly, Rouhani and Leconte (2016) used CRCM output to investigate projected changes in precipitable water.

Clavet-Gaumont et al. (2017) looked directly at the impacts of climate change on precipitable water content projected by NARCCAP (and supplemented by additional CRCM runs). As precipitable water was not a direct output for several of the NARCCAP RCMs, the total amount of moisture had to be calculated by vertically integrating the specific humidity at each pressure level. The ratio of future to baseline precipitable water was used to develop a climate change adjustment factor.

Lee et al. (2016a and 2016b) used a quantile mapping approach to bias-correct surface dewpoint temperature (calculated from daily average air temperature and relative humidity) projections from the Korea Meteorological Administration RCM ensemble. Lee and Kim (2018) used a similar approach with a small CORDEX RCM ensemble. Stratz and Hossain (2014) also focused on dewpoint temperature; however, they applied a historical trend extrapolation into the future as opposed to using climate model projections.

Chen et al. (2017) used sea surface temperatures in lieu of dewpoint temperatures as their study was focused on the Pacific Northwest where the storm moisture sources are ocean based.

It should be noted that Chen and Bradley (2006) found that using dewpoint temperature as a proxy for precipitable water can result in overestimation.

Those studies employing numerical weather models typically modify the domain boundary conditions (e.g., relative humidity) to maximize the precipitation of a given storm (e.g., Gangrade et al., 2018; Ishida et al., 2016; and Rastogi et al., 2017). These modified boundary conditions are developed by incorporating climate change projections in order to investigate how future maximized atmospheric conditions differ from historical maximized conditions. The resulting differences in modeled precipitation output represent the projected impacts of climate change.

3.3.2.2 Precipitation

Chen et al. (2017) state that PMP projections present larger uncertainty than extreme precipitation. Afrooz et al. (2015) and Jothityangkoon et al. (2013) use a statistical approach adapting Hershfield's method with climate model precipitation output, though Lee et al. (2016b) suggest that future PMP projections should be based on changes in atmospheric moisture as opposed to direct precipitation projections due to the relatively lower uncertainty of future temperature projections. Lee et al. (2016a) found future PMPs were unrealistically large when using precipitation output directly from RCM projections.

A detailed investigation into the impacts of climate change on sub-daily precipitation intensity is provided by Westra et al. (2014). Some of the authors' key findings based on observations include:

- Sub-daily extreme rainfall is intensifying more rapidly than daily timescales or longer (e.g., Lenderink and van Meijgaard, 2008; Haerter and Berg, 2009; Lenderink and van Meijgaard, 2009; Haerter et al., 2010; Berg et al., 2013; Westra et al., 2013).
- Short duration and small spatial scale extreme precipitation has been found to increase at double the Clausius-Clapeyron rate in certain parts of the world, scaling at 7% per °C up to 12°C and double this rate up to 22°C, with negative scaling after 22-24°C (e.g., Mishra et al., 2012; Utsumi et al., 2011).
- The super-Clausius-Clapeyron rate may be due to changes in dominant rainfall generating mechanisms with temperature (i.e., from stratiform to convective), but also occurs for convective rainfall alone (Haerter and Berg, 2009; Berg et al., 2013).
- Increasing precipitation intensity depends on dewpoint temperature up to 22°C, after which no dependency was found (Lenderink et al., 2011).
- Moisture availability (i.e., relative humidity) may decline as temperatures increase above ~24°C (Hardwick-Jones et al., 2010).
- Relative humidity is a limiting factor for the highest temperature ranges for inland regions of Canada (Panthou et al., 2014).

A summary of the authors' findings concerning the use of climate models to project extreme precipitation include:

- Very high uncertainty with convective parameterization schemes in GCMs,
- RCMs still have high uncertainty, although their higher resolution allows for improved local representation of precipitation events,
- Climate models need resolutions on the order of 1 km to resolve convection, and
- Projected precipitation increases have been found to roughly agree with the Clausius-Clapeyron relationship (~7%/°C), with a noted regional dependence (e.g., while the relationship is apparent in the tropics, further investigation is required to better identify regions that are projected to experience super-Clausius-Clapeyron changes).

Zang et al. (2017) provides additional insight into the challenges of projecting the impact of climate change on extreme precipitation with a relatively recent review and discussion paper. They found that very high-resolution models that can resolve convective processes are better able to simulate extreme rainfall than more widely available RCMs and GCMS; however, large uncertainty in their projections remain and their availability is quite limited. They also found that precipitation differences from projected circulation changes (i.e., shifting storm tracks) may differ in character (i.e., whether the precipitation is convective or stratiform in nature) from those rooted in thermodynamics (i.e., increasing temperatures). See Sections 3.3.2.1 and 3.3.2.3 for related discussion. Zang et al. (2017) conclude that based on available methods, the relationship between air temperature and the atmosphere's water holding capacity provides better guidance than alternatives such as direct climate model projections of extreme short-duration rainfall for the mid-latitudes. However, they also note that whichever methods are applied, large uncertainty remains.

3.3.2.2.1 Sub-Daily Precipitation

While most ensembles based on statistical downscaling (described in Section 3.2.3.3) provide precipitation projections at a daily timescale, sub-daily precipitation projections are often available through regional climate model ensembles, including NARCCAP and NA-CORDEX (both described in Section 3.2.3.2), and also for some models in the CMIP5 ensemble (Section 3.2.3.1.1).

It was found that studies which have a direct focus on sub-daily extreme precipitation projections (e.g., Zang et al., 2017, Westra et al., 2014) tend only to mention PMP as a related issue and do not address how to incorporate sub-daily precipitation projections in future PMP estimates.

Studies that focus on climate change impacts on PMP using a deterministic approach (as described in Section 3.3.3.1) rarely use precipitation projections directly, at any time scale (and often advise against doing so). Instead, they focus on how projected changes in atmospheric moisture and dynamics (Sections 3.3.2.1 and 3.3.2.3, respectively), for example, will influence future PMP estimates. This approach is more common than numerical modeling due to significantly lower computation requirements and direct applicability to the widely used Transposition (or Traditional) PMP estimation method (Section 3.1.1.4).

Studies applying a numerical modeling approach (as per Sections 3.3.3.2) to investigate climate change impacts on PMP often incorporate precipitation output directly, as it is typically the intended product of the numerical models being used. These high-resolution numerical models simulate changes in sub-daily precipitation as part of their atmospheric dynamics algorithms and physical parametrization schemes.

3.3.2.3 Winds and Atmospheric Dynamics

A simplified view in climate change precipitation studies is that projected future extreme precipitation events occur under similar atmospheric flow regimes and vertical stability as historical events, but with increased temperature and atmospheric moisture. Westra et al. (2014) provides some evidence to support this.

Kunkel et al. (2013) investigated vertical winds (uplift) from an ensemble of GCMs and found that on average projected changes in uplift were minimal compared to those of atmospheric moisture (i.e., precipitable water).

Chen et al. (2017) found that storm efficiency only had minor contributions to projected changes in PMP values in the Pacific Northwest United States, while projected changes to future moisture tracks tended to reduce future PMPs. In other words, projections indicated that atmospheric moisture originating over the Pacific Ocean was not transported, via winds, to the location of interest with the same degree of intensity. This finding also implies that projected moisture track changes could potentially contribute to higher future PMPs in other locations. In general, the authors found projected warming (thermodynamic effects) and moisture track changes (dynamical effect) were competing factors influencing future PMP changes in the Pacific Northwest.

Rouhani and Leconte (2016) used convective available potential energy (CAPE, a measure of atmospheric stability) to categorize the precipitation events into similar atmospheric conditions but did not investigate directly the projected impact of climate change on CAPE.

3.3.2.4 Soil Moisture and Land Use

Soil moisture and land use are typically only investigated in studies applying a numerical modelling approach, discussed in Section 3.3.3.2 (e.g., Gangrade et al., 2018).

3.3.2.5 Snowpack Variables for Probable Maximum Flood

The focus of this review is primarily PMP; however, PMPs are most often used to determine the probable maximum flood (PMF). To do so, ancillary variables are required as inputs in the hydrological models in addition to the (spring and summer/fall) PMP. These variables, including probable maximum snow accumulation (PMSA) and the 100-year snowpack are mentioned briefly here. Snowpack and snowmelt are discussed in Section 3.1.5.

Climate indices are commonly used to establish whether a simulated precipitation event should be included as a winter storm (i.e., snow), spring rainfall or summer/fall rainfall. For example, Rousseau et al. (2014) used a snow-water-equivalent threshold of 10 mm to differentiate between their focus on spring events (snow water equivalent > 10 mm) and summer/fall events (snow water equivalent < 10 mm). Similarly, Clavet-Gaumont et al. (2017) used surface temperature to differentiate whether precipitation was rain or snow. Identified snow events could then be incorporated into the snowpack analysis.

To simulate the impacts of climate change on the respective snowpacks, Klein et al. (2016) used RCM output to investigate projected changes in PMSA, with a focus on moisture maximization of winter storms (via precipitable water calculated by the vertical integration of specific humidity by pressure level). Clavet-Gaumont et al. (2017) examined the snow-water-equivalent output from the models to explore the impact of climate change on the 100-year snowpack (fitting an annual maxima series to the GEV distribution). Similarly, Rouhani (2016) extracted annual maxima snow water equivalent values from CRCM output, from which the 100-year snowpack was estimated.

With regards to the projected timing of the spring PMF, Clavet-Gaumont et al. (2017) found that the freshet (i.e., the spring melt) for five Canadian basins (Manic-5, Saguenay, and Kénogami in Quebec, Mattagami in Ontario and Nelson in Manitoba) is projected to occur approximately one week earlier on average by the middle of the century. The three northernmost of the five study locations can likely expect to see similar projected climate change impacts on their respective freshet timing. Roberts et al. (2012), which focused on a single watershed in Labrador, found that the freshet was projected to occur approximately two weeks earlier by the middle of the century.

3.3.3 Analysis Methodologies for Climate Change Impacts on PMP

In general, two categories of approaches have been found in the literature to estimate climate change impacts on PMP. The first, "deterministic" approach focuses on projected impacts on the meteorological parameters, such as atmospheric moisture, typically used in the common storm maximization and transposition approach (e.g., Clavet-Gaumont et al., 2017; Rousseau et al., 2014; Kunkel et al., 2013), as described in Section 3.1.1.4. The second, "numerical modeling" approach (similar to the approach described in Section 3.1.2.1) uses high-resolution numerical weather prediction models to re-create and amplify historical storms (e.g., Ishida et al., 2018; Ohara et al., 2011). A hybrid approach (as per Section 3.1.2.2) is also sometimes employed (e.g., Chen et al., 2017). This section highlights the specific methodologies applied within the respective categories. The representation of uncertainty due to climate change as discussed in Section 3.2.1.1 can be applied directly to the three approaches described below.

3.3.3.1 Deterministic Approach

Kunkel et al. (2013) investigated the influence of climate change on projected future maximum precipitable water content and vertical winds (i.e., uplift) globally by using an ensemble of seven CMIP5 GCMs, driven by RCP 4.5 and RCP 8.5. The study showed that projected changes in uplift are negligible compared to those of maximum precipitable water content. They found that ensemble average projected maximum precipitable water changes for Ontario were on the order of 25-35%, while changes in uplift were close to 0%. Kunkel et al. (2013) found that conceptual consideration and modeling results "suggest there are no compelling arguments for either increases or decreases of comparable magnitude in other factors used as inputs to PMP" (i.e., precipitable water changes dominate projected climate change impacts on PMP).

Clavet-Gaumont et al. (2017) used RCMs (NARCCAP and additional CRCM4 runs) to maximize precipitable water content in their study of climate change impacts on the 24-, 48- 72- and 120-hour PMP for five Canadian watersheds (as per Section 3.3.2.5). The study applied a buffer region (i.e., additional RCM grids) around each basin to help capture spatial variability and reduce sampling error. They also included an investigation into the 100-year snowpack snow water equivalent, for which they found a large spread in median projections across the various geographies (typically an increase in snow water equivalent in northern basins and a decrease in more southern basins). Clavet-Gaumont et al. (2017) adapted the IPCC confidence level descriptions to indicate the level of agreement amongst ensemble members as per Table 3-7.

Table 3-7: Confidence Verbal and Probability Descriptions

Verbal Expression	Probability (IPCC AR5 Mastrandrea et al., 2010)	Probability (Clavet-Gaumont et al. , 2017)
Virtually certain	99% - 100%	Not Used
Very Likely	90% - 99%	>90%
Likely	66% - 90%	66% - 90%
About as likely as not	33% - 66%	33% - 66%
Unlikely	10% – 33%	Not Used
Very unlikely	1-10%	Not Used
Exceptionally unlikely	1%	Not Used

Rousseau et al. (2014) used the CRCM4 (45 km grid spacing, 6-hour time steps) driven by a range of reanalysis data sets and GCMs to apply a non-stationarity frequency analysis framework to maximize precipitable water content. The study applied several extreme value distributions (EVDs), while allowing for non-stationarity, to account for statistical uncertainty, and used the best fitting EVD for each month and watershed. They also investigated changes in snow water equivalent. The authors consider the direct use of GCM data as inappropriate for PMP calculation due to coarse spatial resolution and suggest that statistical downscaling does not provide the required atmospheric humidity data. As such, they recommend RCMs to be the preferred source for PMP inputs, even though they are often limited in availability.

Rouhani and Leconte (2016) proposed a method to estimate storm maximization ratios which does not impose an upper limit. The approach is based on using the CRCM driven by various GCMs and re-analyses to construct an annual maxima precipitable water time series with precipitable water values for atmospheric situations (e.g., surface air temperature, CAPE) similar to the event to be maximized.

In a study focused on South Korea, Lee et al. (2016a and 2016b) used high-resolution RCMs (12.5 km) from the Korea Meteorological Administration to investigate climate change impacts on PMP out to the end of the century. The study applied a bias correction technique (known as quantile mapping) on dewpoint temperature (calculated from daily average air temperature and relative humidity) as well as a scale-invariance technique to scale the daily climate model output to sub-daily values. They found that all four RCP scenarios projected increases in PMP values with some spatial variability (due in part to complex topography) and the most extreme changes being projected by RCP 8.5, especially in longer duration and larger areas. In a complementary study, Lee et al. (2016a) found that future PMPs were unrealistically large when using precipitation output directly from RCM projections.

Lee and Kim (2018) used similar analysis techniques to Lee et al. (2016a and 2016b), but they used three 50 km resolution RCMs from CORDEX. They found that the future PMP spatial distribution is projected to be similar to that of present day and that further out in time, the longer the duration, and the larger the area, the more impact climate change has on PMP values. The authors noted that the WMO (2009) mid-latitude, non-orographic approach is standard in South Korea and that wind maximization is not typically used in non-orographic regions. This is similar to the approach used in several U.S. Hydro-meteorological Reports including HMR 51 and 52 (USACE, 1978 and 1982), which cover the eastern United States and the approach would be appropriate for the five study locations.

3.3.3.2 Numerical Modeling

Rastogi et al. (2017) used the Weather Research and Forecasting Model (WRF) to maximize available moisture via relative humidity in 120 storms across six experimental setups (i.e., using different driving data such as Climate Forecast System Reanalysis (CFSR) and the Community Climate System Model Version 4 (CCSM4) GCM) focused on the southeastern United States. They indicated that future studies should use a similar approach to investigate the influence of controlling factors in addition to atmospheric moisture, such as circulation patterns.

In a follow up study, Gangrade et al. (2018) also used WRF to examine the impact of Land Use and Land Cover changes (LULC) on PMF. They used a similar approach as Rastogi et al. (2017) to maximize storm humidity and found that PMF estimates were more sensitive to sources of meteorological forcing data sets and climate change than antecedent soil moisture and LULC.

Ishida et al. (2018) is the latest in a series of studies that also includes Ohara et al. (2011) and Ishida et al. (2015a and 2015b). The authors investigate what they call “Maximum Precipitation” derived by maximizing the precipitation of historical storms with respect to their physical mechanisms by enhancing the atmospheric boundary conditions (including relative humidity) of regional atmospheric models. These studies have focused on historical values (using reanalysis data to drive the regional models) and while the authors suggest that the approach could be adapted to investigate climate change impacts, but they do not provide clear direction on how to do so.

3.3.3.3 Hybrid Approach

Stratz and Hossain (2014) used a deterministic approach to investigate the impacts of climate change on three regions of the United States, while employing the Regional Atmospheric Modeling System (RAMS, Pielke et al. 1992) to investigate the impact of LULC. Their PMP analysis method followed guidance provided in HMR documents, while their dewpoint temperature projections were extrapolations of historical trends (i.e., 1°C per 100 years as found by Robinson et al. 2000). The authors recommended to use climate model projections to determine future dewpoint temperature values, but also to consider LULC changes.

Chen et al. (2017) propose a hybrid approach to combine traditional engineering practice and modern climate science, which they claim is easy to use by those familiar with traditional engineering approach and not as computationally intensive as some of the above numerical modeling studies. The approach consists of a four-step process to determine present day PMP, followed by similar steps incorporating climate models to consider the impacts of climate change:

1) Determine extreme storm event in watershed using CMIP5 GCMs statistically downscaled via Localized Constructed Analogs (LOCA from Section 3.2.3.3.3, Pierce et al., 2014 and 2015) – 98^{th} percentile 3-day precipitation events (~100 events / 50 years). No storm transposition was undertaken, as the authors suggest that their approach compensates for this.
2) Determine storm centers from location of maximum accumulation.
3) Track air mass backward (using HYSPLIT Back Trajectory Model) from storms center to beginning of 3-day period. Identify local dewpoint temperatures (sea surface temperature in this case), based on air 1000 m above ground at storm center.

4) Determine climatological max sea surface temperature and use it to maximize moisture availability of the storm.

The impact of climate change was then determined by estimating a historical PMP using the methods described above and in Section 3.1.2.2 and comparing it to an estimated future PMP. The future PMP was estimated based on projected changes in the future maximum sea surface temperature (SST) at the end-point of the HYSPLIT back-trajectory model (i.e., the moisture source for projected future extreme precipitation events identified with LOCA). This was undertaken using five statistically downscaled CMIP5 GCMs forced by RCP 8.5. Chen et al. (2017) estimated uncertainty in their climate projections by incorporating additional five GCMs. Several climate variables were used in this study (the majority of which were required for the back-trajectory modeling), including three-dimensional data of horizontal and vertical wind, temperature, geopotential height, relative humidity, and two-dimensional data of 10 m wind, 2 m temperature, and sea surface temperature. Historical daily precipitation data were also used to identify extreme precipitation events. The study found that under RCP8.5, 3-day PMP in the U.S. Pacific Northwest is expected to increase 50% +/- 30% by end of century.

Chen et al. (2017) state that "Extreme precipitation is projected to change in a changing climate, but whether future storms will exceed the design standards of existing infrastructures remains a question. This is a safety issue beyond analysis of PMP changes: if the current PMP is going to be surpassed by future storms, a safety reevaluation is more urgent than that prompted by the finding that PMP will increase."

3.3.4 Summary

The discussion of Section 3.3 is summarized below. General methodology in estimating climate change impact on PMP is summarized in Table 3-8 and an example methodology flow diagram is provided in Figure 3-17.

- While most of the studies reviewed were unique in many of the specifics of their respective analyses (a feature inherent in the peer-review process), the majority of studies applied a deterministic approach including maximization based on atmospheric moisture content.
- Atmospheric moisture has been found by multiple authors to be the dominant factor requiring investigation concerning the impacts of climate change on PMPs.
- Atmospheric dynamics (i.e., storm tracks) were projected to have some influence on future PMPs in certain situations, while projected changes in uplift and storm efficiency were relatively minimal. Several authors investigated this.
- Nearly all the reviewed literature investigated climate change up to 2100, but not beyond.
- The relatively few studies that incorporated the ancillary variables required to model PMF in Canadian snow-driven watersheds, found earlier spring melts, increased atmospheric moisture in winter, and (regionally dependent) changes in snowpack.
- Several of the studies included investigations into the influence of complex topography; however, due to the relatively uniform topographic (non-mountainous) nature of the five study locations, this information has not been included herein.
- None of the PMP studies reviewed explicitly considered the influence of lake effect under climate change.

- With respect to literature that focused on regions overlapping or proximity to the five study locations, it was found that PMP is generally projected to increase under climate change, driven by higher atmospheric moisture content.

Table 3-8: Summary Table on Methodology to Estimate Climate Change Impacts on PMP

General Approach	Methodology	Variables*	Climate Projections
Deterministic	Projected changes in atmospheric moisture	PW, Td, RH	CMIP5, NARCCAP, CORDEX, Select RCMs and GCMs
	Projected moisture advection changes	Moisture sources, uplift, CAPE	CMIP5, Select RCMs and GCMs
	Projected changes of ancillary variables	Snow water equivalent, seasonal PW	NARCCAP, Select RCMs
Numerical Modeling	Maximize storm boundary conditions	LULC, RH, soil moisture	Select GCMs and Numerical Models
Hybrid	Projected changes in moisture sources	Sea surface temperature, precipitation	LOCA, CMIP5

*PW is precipitable water content, Td is near-surface dewpoint temperature, RH is relative humidity, CAPE is convective available potential energy, and LULC is land use and land cover.

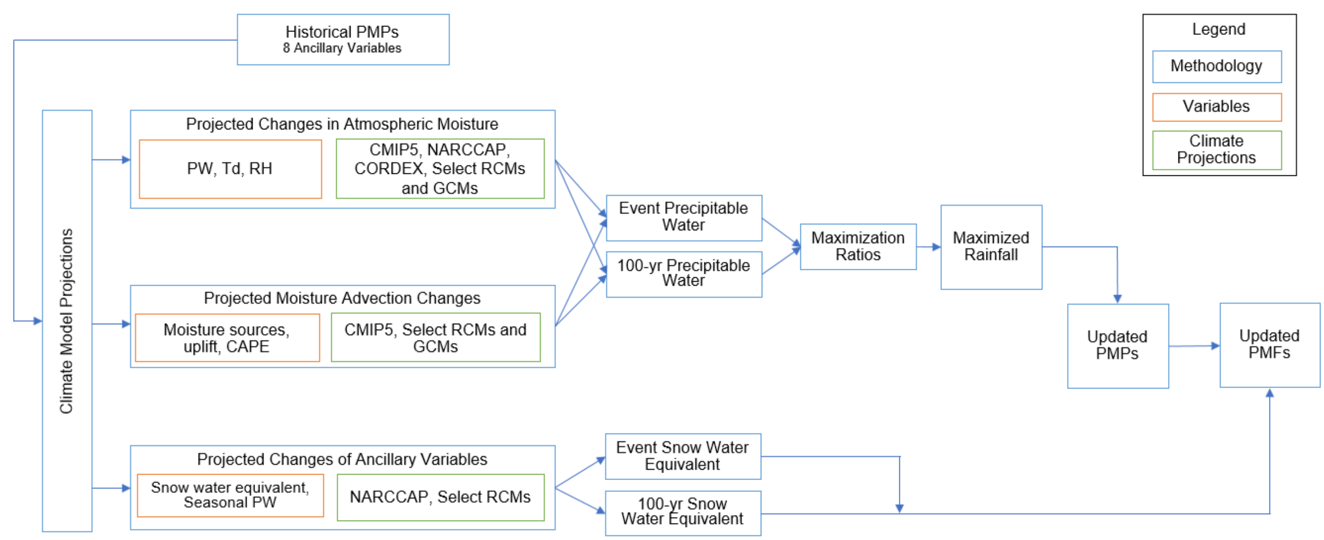


Figure 3-17: Overview of Methodology to Investigate Climate Change Impacts on PMP Estimates

4. RECOMMENDED METHODS FOR INCORPORATING CLIMATE CHANGE CONSIDERATIONS INTO PROBABLE MAXIMUM PRECIPITATION ESTIMATION

This chapter begins with a summary of PMP methods (Section 4.1.1) and climate change impacts for the five study sites (Section 4.1.2). Insights from the literature review on different PMP estimation method (Section 3.1), climate change impacts (Section 3.2.2), and the study of the climate datasets available (Sections 3.2.3 and 3.2.4) were used in conjunction with the findings of Section 3.3 to evaluate options for the development of a method to include climate change impacts in PMP estimates. The recommended approach uses a combination of climate projections directly from the literature review (Section 4.2.1), and traditional or “deterministic” PMP estimation methods (Section 4.2.2), and a thorough sensitivity analysis to account for high-levels of uncertainty (Section 4.3.2). Recommended methodology is outlined in Section 4.3 with justification in Section 4.3.1, uncertainty treatment in Section 4.3.2, methods, processes and relevant criteria in Section 4.3.3, and general limitations discussed in Section 4.3.4.

4.1 SUMMARY OF PMP METHODS AND CLIMATE CHANGE IMPACTS

4.1.1 PMP Methods

PMP studies attempt to estimate the “the greatest depth of precipitation … meteorologically possible for a … watershed or a given storm area at a particular location at a particular time of year” (WMO, 1986), that is, the upper bounds of what would result from plausible, previously unexperienced, ‘worst case’ precipitation events. As such, there are no quantitative measures for the accuracy of these assessments. As well, the impact of a precipitation event is often strongly influenced by antecedent conditions, such as snow cover and soil saturation. Various approaches to estimate PMP exist in the literature. Since these methods consider different aspects of the available records and influencing dynamics, in practice a PMP study often consists of several analyses which are jointly considered to provide a basis for reasoning and to envelope the upper bound of possible scenarios.

A study often begins with a documentation of the largest recorded precipitation events for the location of interest and surrounding region (Local Method), which can then be used as a hard minimum by which to gauge the output of other estimates. Similarly, first order statistical extrapolations can be applied to available records (Statistical Method), to provide additional checks. From there some form of deterministic modeling is typically applied to create extreme versions of documented conditions. This can take the form of applying recorded extreme atmospheric profiles to a simulated storm event centered on the site of interest. These simulations can be produced through descriptions of the major local drivers of precipitation events (Inferential Method) or applied as boundary conditions for complex dynamical models (Numerical Simulation). More commonly, recorded (Transposition Method) or simulated (Hybrid Method) storms which could potentially have occurred over the site of interest are identified. Estimates are then made on the degree that their output would change if they were centered on the site of interest under maximally productive conditions with respect to available moisture, antecedent conditions, and storm efficiency. In general, Canadian PMP studies use or are in line with the Transposition Method and Envelopment.

These estimates all have considerable associated uncertainties. The presumption of the co-occurrence of maximizing factors, such as precipitation efficiency (Ben Alaya et al., 2018) and antecedent snow pack conditions (Chow and Jones, 1994), can potentially produce estimates beyond the range of plausibility. On the other hand, as these individual factors must be estimated from limited historical records, it is very likely that their true upper bounds are unknown, and so there is a high risk of underestimation (WMO, 1986). Theoretically these concerns could be mitigated through high resolution *Numerical Simulations* of the local dynamical system. However, the design of such experiments presumes detailed knowledge of regional meteorological subtleties, and rigorous implementation of the required ensembles demands considerable computational expense and technical knowhow. Recently there has been an intensified push to create probabilistic representations of PMP values, to better capture sensitivity, analysis decisions and input uncertainties (Micovic et al., 2015). This appears appropriate, as contemporary understanding of extreme precipitation dynamics strictly limits the ability to deterministically prescribe physical upper bounds to relevant drivers and mechanisms (Ben Alaya et al., 2018).

4.1.2 Climate Change Impacts

Based on the available information, it is likely that all five study locations will experience average temperature changes comparable to those experienced by most of Southern Ontario (~3-4°C by the 2050s and ~6°C by 2080s, depending on the emission scenario). Precipitation changes are highly variable and dependent on localized dynamics, so a site-specific analysis is necessary. It is likely that the site locations of South Bruce and Huron-Kinloss will experience precipitation increases greater than those experienced by most of Southern Ontario (likely in the 75-100 mm/year range by the 2050s, and 125-150 mm/year by the 2080s) (McDermid et al., 2015b). The locations of Hornepayne, Manitouwadge and Ignace may experience increases in precipitation closer to the projected provincial annual average (50-75 mm by the 2050s and 100-125 mm by the 2080s) (McDermid et al., 2015b).

There is significantly less confidence on future projections for wind, tornadoes, and lake-effect precipitation. The available snowfall and temperature estimates appear to signal that it is likely that all locations will experience a decrease in snowfall, with an increase in the proportion of winter precipitation falling as rain instead of snow. Affected by this, lake-effect snow is anticipated to decrease by mid-century, with the exception of regions around Lake Superior. However, Lake Superior will also see a decreasing trend by the second half of the century (Notaro et al., 2015). Cheng et al. (2012) projected larger increases in some hourly and daily wind metrics for Huron-Kinloss and South Bruce than for Ignace, Manitouwadge and Hornepayne. Without site-specific analyses, it is assumed that the annual mean frequency of future hourly wind gust events (>28, >40, and >70 km/h) for the period 2080s (2081–2100, SRES A2) is projected to be about 10–15%, 10–20%, and 20–40% greater than the observed average during the baseline period (1994–2007) respectively. Furthermore, it is understood that the conditions that spawn tornadoes are expected to increase in some regions with warming. However, climate change impacts on future probabilities and intensity of tornado occurrence remains an area that needs more research.

4.2 ASSESSED OPTIONS

The review of available methodologies suggested that each application of the derivation of PMP using climate change projections presented methodological differences. This is in part due to the fact that most of the applications have been performed by academic researchers. These studies were organized into three categories (Numerical Modeling, Deterministic, and Hybrid Approach). The impact of methodological differences within and across these categories, and ultimately on PMP estimates, remains a research area in-development. Similarly, the impact of climate change on the various factors that affect PMP (e.g., lake effect precipitation, upward motion, precipitable water content) and how they will manifest in specific areas of Ontario (e.g., lake-effect precipitation across the Great Lakes Basin, convective storms in southern Ontario, and snow squalls in the Bruce Peninsula) is an area of active research (e.g., Notaro et al., 2015, Ouranos, 2015; Ganguli and Coulibaly, 2017; Switzman et al., 2017).

Therefore, this section does not present a consensus-based conclusion on the approaches reviewed, because no such consensus exists at the moment. Instead it presents a set of recommendations and considerations based on the viewpoints expressed in the reviewed literature and the experience of the authors and reviewers. These recommendations strive to strike a balance between scientific rigor and the practical constraints of engineering projects. These recommendations should be updated as advances in the field clarify what are robust options to integrate climate change projections in the estimation of PMP. Updates should also coincide with the availability of output from subsequent generations of global and regional climate model ensembles. These are often captured in IPCC Assessment Reports or IPCC special report on extremes (roughly once every 7-8 years).

4.2.1 Derivation Based on Literature Review Findings

The most straightforward option to include climate change information into PMP estimation would be to retrieve PMP change factors from the published literature and apply those changes to existing PMP estimates based on an up-to-date historical record. However, no single study (or grouping of studies) presents a full methodology with the specific geographic focus required to develop a straight-forward adjustment factor for existing PMP estimates in the region. Also, most of the literature focuses exclusively on rainfall, whereas both rain and snow are required for PMF analysis in Canada.

Although there is no published result that can be directly applied, the recommended approach presented in Section 4.3 incorporates piecemeal information from various scientific publications relevant to the area and variables of interest. The recommended approach is based on established PMP estimation methodologies (such as those discussed in Section 3.1 and summarized in Section 4.1.1) that also incorporate climate modeling (as introduced in Section 3.2.1) and sensitivity analysis to account for uncertainty. This is discussed further in the following sections.

4.2.2 Derivation Based on Site-Specific Climate Modeling Analysis

Most climate change projections come from long-term simulations produced by dynamical models (i.e., GCMs and RCMs). As such, the common feature of the reviewed PMP estimation approaches which extend to climate change is an initial attempt to perform a convincing PMP study using historical climate simulations. This allows direct comparison with PMP estimates derived from applying these same methods to simulations of future climate states.

Once an historical PMP has been estimated, climate change would then be accounted for via additional analysis. Table 4-1 provides a summary of the perceived benefits and challenges corresponding to the three categories of methodologies used for estimation of PMP incorporating climate change projections (discussed in Section 3.3.3). The deterministic approach (Section 3.3.3.1) focuses on projected impacts on the meteorological parameters (e.g., atmospheric moisture) typically used in conjunction with storm maximization and transposition. The numerical modeling approach (Section 3.3.3.2) uses high-resolution numerical weather prediction models to re-create and amplify historical storms. The hybrid approach (Section 3.3.3.3) combines aspects of the deterministic and numerical modeling approaches.

Table 4-1: Summary of Benefits and Challenges for Methodologies Used to Estimate Change Impacts on PMP

	Numerical Modeling	Deterministic Method	Hybrid Approach
Overview	Use high resolution numerical weather prediction models to re-create and amplify historical storms. Could be interpreted as an extension to the Inferential Method (Section 3.1.1.3).	Focus on projected impacts on the meteorological parameters (e.g., atmospheric moisture) typically used in conjunction with storm maximization and transposition.	Combine aspects of the deterministic and numerical modelling approaches.
Benefits	- Sophisticated with broad geographical applicability (e.g., meteorological models, re-analysis data and climate models). - Directly simulates physical dynamics of maximized extreme storms. - Offers an enhanced degree of realism and tractability - Can include soil moisture and land use considerations (another layer of assumptions and uncertainty).	- Directly compatible with most Canadian traditional PMP estimate methods (Sections 3.1.1.4 and 3.1.1.8). - Lower sophistication and lower demand computationally and technically than Numerical Modelling approaches. - Uses estimated factors of change, based on existing climate change projections. - Incorporates factors of change with traditional methods. - Lower effort (than Numerical Modeling) to integrate a greater spatial region in analysis. - Large number of iterations (uncertainty range) could be performed with relative ease.	- Could be interpreted as a balance of traditional engineering practice and modern climate modeling. - Medium level of computational and technical demand.
Challenges	- Computationally and technically demanding. - Reliability is highly linked to the simulation’s ability to capture relevant processes. - There is currently no agreement on how scale affects PMP estimates and therefore it may be difficult to define boundaries. - To date, used almost exclusively in academic environments. - Large number of iterations (uncertainty range) would be computationally demanding.	- Change factors evaluated could include the following variables, which may not be available or feasible, depending on the available climate model ensemble: • Precipitable water, • Moisture advection, • Uplift, • Extreme precipitation, and • Snow water equivalent.	- Significantly different from current practice. - Fewer case studies available. - Snow estimates could present issues in the region of interest. - Evaluation of climate models used should be carefully conducted. - Large number of iterations (uncertainty range) would be computationally demanding.

While the statements presented in Table 4-1 (and throughout the report in general) are based on the literature reviewed, it is possible that other applications of PMP estimates incorporating climate change exist but are not in the public domain.

Considering the respective benefits and challenges, the deterministic approach is recommended as the most suitable for incorporating the impacts of climate change into PMP estimates of the five study locations. Details with justification are discussed in Section 4.3.

4.2.3 Other Approaches

All identified methods that incorporate climate change into PMP estimation can be characterised using the categories discussed in Section 4.2.2. However, the objectives of these studies are to measure the potential impacts of climate change on PMP values, not to inform a decision-making process. The requirements for the later type of analysis are usually different from impact studies. The following sections discuss how the published literature can be folded into a methodology better designed to support decision-making in a context where uncertainties are large and can derail the decision-making process. This is discussed in detail in Sections 4.3.2 and 4.3.3.

4.3 RECOMMENDED APPROACH

The recommended approach for incorporating climate change impacts into PMP estimates is a deterministic method. Section 4.3.3 outlines the details of the proposed deterministic method.

While high resolution local numerical weather modeling (Ohara et al., 2011; Ishida et al., 2015a and b; Ishida et al., 2018) is a direct and flexible approach, it is computationally and technically demanding and often only conducted by academic research groups. Hybrid approaches attempt to make use of existing simulations by applying their methodologies directly to climate model outputs when constructing PMP estimates (Chen et al., 2017). This means that the results must be understood in the context of the limitations of the direct climate model output (e.g., without accounting for any potential biases), which may be difficult to quantify explicitly. These methods are also not common practice in Canadian industry.

While numerical modeling and hybrid methods appear to provide a more tractable, physical approach, one must distinguish between “theoretical PMP” and “operational PMP” (Ben Alaya et al., 2018,; WMO, 2009). Numerical modeling and hybrid methods may lead to a more theoretical PMP estimate, while deterministic methods are often applied to estimate an operational PMP that is more directly comparable to the majority of PMP studies conducted in Canada. It is common practice for engineers to use a rational (i.e., deterministic) method with careful judgement to develop an operational PMP when current scientific knowledge does not provide a more definitive answer (Ben Alaya et al., 2018). Due to the level of uncertainty associated with currently available climate change estimates, a deterministic approach with a strong focus on characterization of historical and future uncertainty is recommended to incorporate climate change in PMP estimations.

The recommended approach is consistent with existing guidance from CDA (2007), Ouranos (2015), Ouranos (2016), and Sparling et al. (2017).

4.3.1 Justification

The literature review presented in Section 3.2.2 (and summarized in Section 4.1.2) indicates with confidence that Ontario will experience significant changes in climate in the next 100 years. This may manifest differently at a local level, with some locations in Ontario experiencing varying degrees of precipitation increases, potential for precipitable water content increases, and changes in snow. It can be noted that precipitation is generally anticipated to remain within the historical climate variability for a few decades. However, temperatures are anticipated to exceed historical climate variability much faster than precipitation. Therefore, the impact that climate change may have on PMP should be incorporated in current analysis.

The justification for the selection of a methodology (detailed in Section 4.3.3) to derive climate modeling based PMP estimates is often influenced by several factors including, but not limited to those discussed in Table 4-2.

Table 4-2: Recommended Method Considerations and Justification for the Recommended Approach

Consideration	Justification for Recommended Approach
Precedence and available guidance	- Majority of historical PMP estimates developed using deterministic method (examples discussed in Section 3.1.4). - Majority of literature on climate change impacts on PMP recommended including atmospheric moisture (Section 3.3.2.1).
Tools and information available and associated confidence	- Kunkel et al. (2013) provides important climate variable results based on climate model output that are not publicly available, but they may be available upon request. - University of Western Ontario’s IDFCC Tool provides well documented IDF projections (Section 3.2.4.2). - CMIP5 (as below).
Anticipated life of the infrastructure	- Long APM DGR implementation schedule, but the operation period (roughly from 2043 to 2083) is more important for climate change impacts (Section 1). - A small subset of CMIP5 is the only ensemble with projections to 2180. - High-resolution ensembles (e.g., NA-CORDEX) only go to 2100.
Technical resources available	- Only a small number of research groups investigate with numerical modeling (highly technical and computationally expensive).

4.3.2 Incorporating Uncertainty

For this analysis, addressing uncertainty must be incorporated throughout the entire process and not simply added on to the end result. The following discussion provides recommendations on how this can be achieved.

Uncertainty analysis for PMP estimates is complicated by several inherent factors. A PMP typically represents an event which has been previously unobserved. That means that common validation approaches based on comparative statistics between predictions and observations cannot be applied. As well, the use, and thereby definition, of PMP estimates can vary between implementations. Analyses have been used to create test scenarios, estimate long return period events, or to serve as an assumed maximal upper threshold. The application and definition of a

PMP estimate has a large impact in the degree of confidence that can be held in the resulting values, as well as the severity of the consequences of underestimation or ambiguity. Furthermore, while PMP values are often applied to long time frame applications, few PMP estimation approaches are able to address non-stationarity (i.e., changes in climate). What shape such non-stationarity could take is also often an open question, where assigning likelihoods to potential regime shifts is ambiguous at best. Typically, this means that uncertainty estimates and descriptions for such analysis take the form of qualitative statements and caveats. A hypothetical example of this is "this analysis reports a 100-year return period event for the year 2025, under the assumption of a highly conservative snow pack potential - and is not valid under the circumstances that hurricane track potential extends beyond its current range". Such statements are essential and informative, but can be difficult to translate into defensible decision making.

Theoretically a rigorous statistical analysis of input variables, such as that proposed in Ben Alaya et al. (2018), can mitigate some of these concerns. Using a tractable, predefined, quantification scheme for the relative probability of events can showcase the range of possible outcomes for a PMP analysis. As well, such an approach removes much of the ambiguity about the relative degree of risk to the populace that different estimation assumptions allow. To date, however, such methods have only been explored within simulation experiments, where data availability and observational uncertainty do not have to be contented with. As well, since standard meteorological validation approaches are not applicable to PMP analysis, assignment of probabilities and risk levels can only be understood in relative terms. It is also important to remember that PMP estimates are influenced not only by meteorological inputs, as addressed by Ben Alaya et al. (2018), but also by subjective decisions regarding analysis design (Micovic et al., 2015). The sensitivity of results to such decisions must also be considered. This can require considerable effort, as such sensitivities typically need to be tested and documented within the course of an experiment, rather than appended to central estimates after the fact.

More classically, the WMO (1994) considers "envelopment" to be a crucial step within all the analysis methods they survey. In this practise collections of constructed scenarios are combined to define an outer envelope of "the worst case of the worst cases." This can potentially result in physically inconsistent, highly conservative scenarios. Of greater concern is when there is limited articulation of the distribution of contributing scenarios (e.g., from a limited observation base), it cannot even be safely assumed that the resulting estimate is in fact a cautious one. However, this analysis does provide a standardized baseline for situations where there is no mechanism to evaluate the relative likelihood of the input scenarios.

Given that it is currently not possible to define the physical limits for precipitation amounts (Ben Alaya et al., 2018) and that communicating the ranges and origins of analysis uncertainty is crucial for informed decision. PMP estimates should always be presented as a range of values to characterize the impacts of the significant uncertainties that are involved in the calculations (Micovic et al., 2015).

At minimum, any PMP analysis procedure must allow for a measure of the sensitivity to variation in inputs and procedures, as outlined by Micovic et al. (2015). This requires that the contributions of individual elements of the study to output variability are testable, and that gaps left by limited data can be articulated to some degree. This collection of marginal distributions can be used to tractably envelope the potential ranges suggested by available data and experiments to allow for informed decision making. Ideally, enough data can be produced to extend the approach to include correlation models to better constrain the viability of the produced estimates, but this is not always possible.

4.3.2.1 Accounting for Deep Uncertainty

The analysis of extreme events and climate change impacts both take place under conditions of 'deep uncertainty'. That is, the underlying assumptions which must be applied to produce quantitative estimates have inherent ambiguities. In the case of climate change, future greenhouse gas concentrations, as well as the climate system's sensitivity and response to the specific pathway which does emerge, cannot be explicitly prescribed (Mauer et al., 2007), as discussed further in Section 4.3.4. For extreme rainfall, there are numerous methods for estimating a PMP value, all of which rely on various approximations. This is in part due to it being unclear how, or if it is in fact possible, to define a hard, physical limit to local precipitation potential (Ben Alaya et al., 2018). Such circumstances mean that standard analysis approaches (i.e., agree on the correct values for underlying assumptions, perform calculations, then act according to the output) have a high risk of resulting in "brittle decisions" (Kalra et al., 2014). That is, those which are "optimal for a particular set of assumptions, but which perform poorly or even disastrously under other assumptions" (Kalra et al., 2014). Standard sensitivity testing is inadequate under conditions of deep uncertainty (Bonzanigo and Kalra, 2014). While such assessments might identify the most critical assumptions, they do not offer guidance on what might need to be considered if alternative circumstances come to pass. These alternative scenarios might be orders of magnitude worse than the assumed values, and/or they may be dominated by much more advantageous conditions (Kalra et al., 2014). The false confidence that can be assigned to such estimates and the degree to which this "removes responsibility for making important decisions as to degree of risk or protection" has long been cited as a serious ethical concern (Benson, 1973).

Robust analysis and decision making under these conditions is possible through a thorough evaluation of the possible interpretations of available information, rather than producing a limited collection of 'high likelihood' samples. Such an approach does not typically require new metrics or methods and, in fact, for the sake of communication and transparency, benefits from being undertaken within the perspective of common practices (Kalra et al., 2014). Values are estimated under the full range of justifiable assumptions and scenarios, and only then is the range of outcomes evaluated and constrained under considerations of relative probability and risk tolerance. This is in many ways analogous to the common practice of "envelopment" (WMO, 1986). However, rather than a focus on creating a threshold of adequate conservatism, the aim is to communicate the degree of accepted risk (Koutsoyiannis, 1999). As well, as wide a range of inputs and assumptions as possible are initially tested, rather than first assuming constraints on these choices.

In a PMP context such a study would look very much like the common practice of maximization, transposition and envelopment outlined in Section 4.1.1, with a strong emphasis on the sensitivity testing approach of Micovic et al. (2015) and also including additional value ranges for projected climate change inputs. Various uncertainties can be quantified by including the range of inputs for a given parameter and mapping how that impacts the output. The resulting range of output can be considered a measure of the uncertainty from that parameter. Unfortunately, it is untenable to structure such a study, such that the range of results represents a probability distribution of outcomes. Rather, this input-to-result mapping is used as a starting point for applying constraining relative probabilities based on conceptual and observational derived insights (e.g., the relationship between moisture availability and storm efficiency) (Ben Alaya et al., 2018).

Indigenous Knowledge can also be incorporated into the uncertainty analysis to support the evaluation of inputs and outcomes. The exact nature of the Indigenous Knowledge would inform how it is incorporated. For example, if an indication of flood levels with respect to existing markers is given, a comparison of output from hydrologic and hydraulic modeling would allow one to infer what discharge raised levels to that point. Then, if possible, validation could be accomplished using geomorphological traces of the event. In this case, it would require considerable effort for consultation, field campaigns, and modeling, and may best be undertaken as part of the final evaluation of PMF results, once all case studies have been completed. However, insight into previous extreme precipitation events or snow packs could be more readily integrated into the PMP estimation process.

4.3.3 Methods, Processes and Relevant Criteria

The approach recommended for incorporating climate change into PMP estimation, while addressing the criteria set out by this project (i.e., study objectives presented in Section 1) for the five study areas, aims to leverage lessons learned from the literature reviewed, current engineering methodologies, and existing climate modeling efforts while incorporating the sensitivity analysis (Section 4.3.2) throughout to address uncertainty. Also, as indicated in Section 4.3.2.1, Indigenous Knowledge from the five study areas can be integrated into the method outlined below, particularly with respect to observed historical data and establishment of baseline parameters. An overview of the recommended approach is as follows and summarized in Figure 4-1.

Establishing Baseline PMP Parameters

1) Explore available contemporary historical precipitation records (including previous studies in the region) to identify historical extreme storms that may be transpositional to the respective study areas. As part of this, one should identify the meteorological (synoptic) drivers of each storm.
2) Determine the region for which the meteorological characteristics of the selected storms represent typical sources of heavy precipitation. Determine if the storms are transpositionable to any or all the five study locations. If it is unclear whether a storm is transpositionable to a given location, it can be included and excluded from the analysis to investigate any impact on results.
3) Find or develop depth area duration (DAD) tables (based on historical data) for each storm, which are used in the maximization and transposition processes as introduced in Section 3.1.1.4.
4) Develop range of adjustment (in-place maximization and transposition) factors for the respective storms, based on historical data (Section 3.1.1.4). The 100-year and observed climatological maximum dewpoint temperatures can be used to partially define the range of adjustment factors.
5) Establish range of estimates for ancillary variables (defined by CDA, 2007).
    a) 100-year spring and summer/fall precipitation - based on fitting an extreme value distribution (EVD) with the annual maxima values (categorized by season) of observed precipitation. Choice of EVD should be made based on goodness of fit criteria (e.g., Kuipper and Hoijtink, 2011, Symonds and Moussalli, 2010, Anctil et al., 2005, Meylan et al., 2011, Opere et al. 2006, etc.). A range of values can be derived from different EVD choices.
    b) 100-year snowpack – using a comparable EVD approach to 100-year precipitation, but with snow accumulation observations.

c) Probable Maximum Snowpack Accumulation (PMSA) – following the recommendation outlined in Section 3.1.5.3, the Spring PMF analysis should focus on the 100-year snowpack combined with the Spring PMP.
d) Snowmelt temperature sequence - per the critical temperature sequence approach outlined in Section 3.1.5.5.

Incorporating Climate Change impacts

6) If available data permits, use the APM Planning Schedule (Section 1) as a rough guide for grouping relevant time periods (i.e., up to 2043, 2043-2083, 2083-2153, 2153-2180).
    a) Time periods should include at least 20 to 30 years to ensure climate variability is captured.
    b) As indicated by NWMO, the “operations” component (from 2043-2083, as indicated in Section 1) is the priority period on which to focus.
    c) Time periods beyond 2100 will have a reduced number of climate projections available as well as greater uncertainty.
7) Based on existing literature and tools, establish an initial, inclusive range of possible PMP-relevant variable values with respect to future climates, partially defined by, but not limited to, the following sources. (It is recommended to use ranges of values going beyond what is found below in an attempt to cover every possible combination, even if unlikely.)
    a) Maximum precipitable water – Maps from Kunkel et al. (2013) including supplementary materials, which account for RCP 4.5 and RCP 8.5 for the time periods 2041-2070 and 2071-2100.
    b) Maximum uplift – Maps from Kunkel et al. (2013).
    c) 100-year rainfall – University of Western Ontario IDFCC Tool (Section 3.2.4.2) which incorporates PCIC’s statistically downscaled GCMs (Section 3.2.3.3.1) and provides an uncertainty range out to 2100 for RCP 4.5 and RCP 8.5.
    d) Snowpack SWE – use historical values as conservative assumption for future values.
8) Use climate model ensembles to better define what future values may be.
    a) Precipitable water – Only monthly projections are publicly available (aside from NARCCAP, Section 3.2.3.2.2, which is relatively limited in time periods and GHG scenarios). The relationships between 12-hour maximum persisting precipitable water (as included in Kunkel et al., 2013) and monthly mean precipitable water (as available through CMIP5) is unknown and additional research would be required to be able to use existing projections to infer a direct relationship. CMIP6 projections will start being available this year. If daily (or ideally sub-daily) precipitable water is a published variable, then it should be incorporated into the analysis.
    b) Uplift – CMIP5 daily uplift projections (the corresponding CMIP5 variable name is “omega”) consist of four RCP 8.5 and eight RCP 4.5 ensemble members available out to 2180, which should be used to quantify the range of projected changes for each month.
    c) 100-year precipitation – NA-CORDEX precipitation projections, with a focus on high-resolution and sub-daily ensemble members, should be used to investigate projected changes in extreme precipitation. Estimates should be developed using traditional extreme value analysis methods including the selection of a best-fit extreme value distribution. While CMIP5 has daily precipitation projection available out to 2180, the literature typically advises against using coarse resolution GCMs for extreme precipitation projections.

d) Temperature – CMIP5 projections (with the same ensemble members used for uplift, above) of daily maximum, average and minimum temperatures can be used to quantify a range of potential future melt sequences out to 2180.

9) Determine climate change factors based on above ranges to the adjusted historical DAD tables (an example of how DAD tables are adjusted is provided in Figure 3-1).
10) Conduct envelopment of all storms (Section 3.1.1.8) adjusted for maximization, transposition and climate change to estimate multiple future PMPs based on various combinations of the variable ranges, determined above. This will provide a mapping of various inputs to future PMP estimates. Some of the resulting PMP estimates can be classified as unlikely, depending on the combined values of the input parameters, which would narrow the range of feasible PMP estimates.
11) Compare the ranges of projected PMP estimates for the five study locations (rather, the three groupings of locations, discussed in Section 4.3.5). Here one can establish whether or not some sites have larger ranges of PMPs for the same input value ranges, or how changes in PMP are affected by site relative to precipitable water or uplift.

Independent quality control checks should include at least the following:

1) Review near-by PMP estimates to ensure recent records do not significantly contradict estimated PMP values (OMNR, 2006 recommends updates of PMP every 10-years to 15-years).
2) First order statistical extrapolations can be applied to available records (Statistical Method, Section 3.1.1.1).
3) Review of highest magnitude recorded events near the study locations and the surrounding region (Local Method, Section 3.1.1.2), used as a hard minimum by which to gauge the output of other estimates.

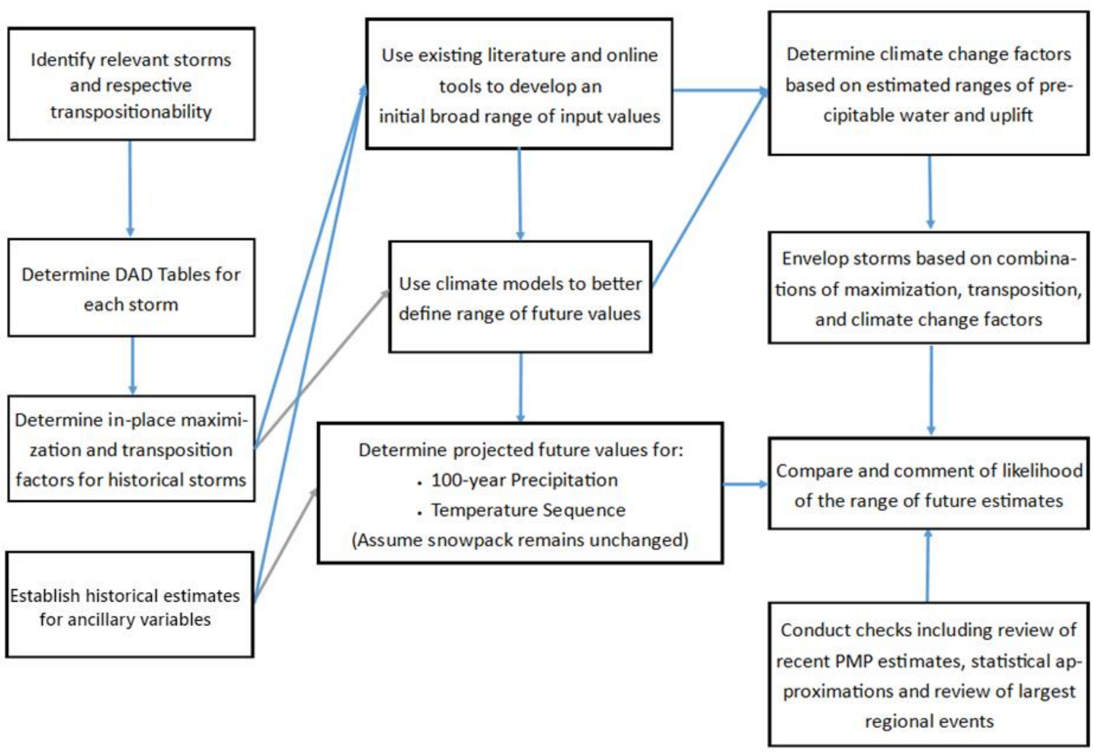


Figure 4-1: High-Level Overview of Recommended Approach

4.3.4 Limitations

4.3.4.1 Climate Projections Are Conditional on GHG Emissions

Climate model projections are conditional on GHG emission pathways. The current archive of model simulations includes experiments with a number of these pathways: 1% increase in CO_2 per year, abrupt quadrupling of CO_2 concentrations, RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5. There is as of now no consensus on the relative likelihood of these emission pathways. This implies that for projections beyond 2040 (when the various pathways could meaningfully diverge as seen in Figure 3-7), climate simulations should not be interpreted as forecasts, but rather as data points in a sensitivity analysis. This leaves the decision-maker with the burden of selecting the emission pathway that will inform the design.

To support decision-makers, researchers are developing Integrated Assessment Models (IAMs) that combine demography, policy, technology, economics and biophysics to explore the consequences of various socio-economic scenarios on emissions. Weyant (2017) provides a review of recent IAM work. Some IAMs are used to generate probabilistic simulations of future emissions (Raftery et al., 2017), providing likelihoods of exceeding certain emission threshold. This type of analysis could potentially be used to inform decisions on the emission pathways to use for risk analysis.

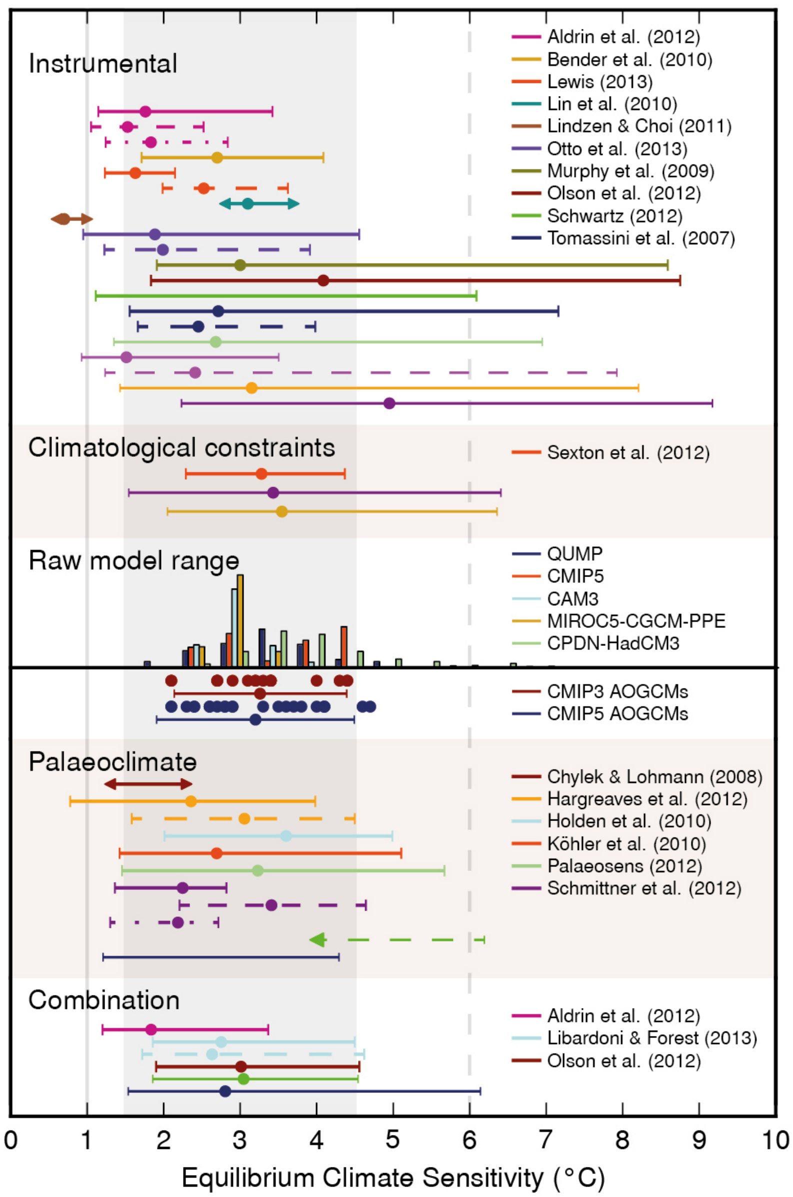
4.3.4.2 Climate Models May Be Conservative

The response of the climate system to changes in GHG concentrations is highly complex, but there are a few metrics designed to capture an aggregate effect. One of these metrics is the equilibrium climate sensitivity, which measures the global temperature change after a doubling of CO_2 concentrations. This climate sensitivity can be estimated for climate models, but it can also be estimated from contemporary observations and paleo-climate records.

Figure 4-2 (from IPCC, 2013 - AR5 Working Group 1, Chapter 12, box 12.2, Figure 1) shows that model estimates are centered in the middle of the distribution estimated from paleoclimate and instrumental sources.

To characterize climate sensitive, metrics such as the equilibrium climate sensitivity (ECS), which represents the global climate system's temperature response to an externally imposed radiative forcing, can be used. ECS is defined as the equilibrium change in annual mean global surface temperature following a doubling of the atmosphere's CO_2 (by a linear increase over 70 years). ECS determines the eventual warming in response to stabilization of atmospheric composition on multi-century time scales. Figure 4-2 presents a summary of experiments, which summarize the estimated ECS globally using various datasets and models. The experiments include the evaluation of ECS from studies driven by instrumental observations (e.g., meteorological station data), climatological constraints (where metrics known to be sensitive to change are synthetically perturbed to estimate the variability of the climatic system), raw GCM model outputs (i.e., un-bias-corrected output from a climate model ensemble), paleoclimate information (using proxy indicators of past climatic conditions such as ice cores to characterize the climate during the geological past), and combination studies which incorporate the previously mentioned methods.

One interpretation of this figure is that climate models are conservative, in the sense that they do not capture the tail ends of the climate sensitivity distribution. This suggests that even the climate models that are most sensitive to GHG concentrations might still underestimate the actual impacts of climate change. Inversely, even the models that are the least sensitive to GHG could overestimate the impacts of climate change.



Note: The grey shaded range marks the likely 1.5°C to 4.5°C range, with the grey solid line the extremely unlikely less than 1°C, and the grey dashed line the very unlikely greater than 6°C.

Figure 4-2: Probability Density Functions, Distributions and Ranges for Equilibrium Climate Sensitivity and Results from CMIP5

4.3.4.3 Accuracy of Projections

Climate models are approximations of the Earth system. Physical processes occurring at the molecular scale, like nucleation for rainfall, need to be simplified and discretized at scales of tens to hundreds of kilometers to be included in a climate model. Different modeling groups use different approaches to simplify a given process, even in cases where there is a shared common understanding of the physics of the process.

In a climate projection ensemble, the spread of climate projections from different models driven by the same emission scenarios is a partial indication of this model uncertainty. (An example of this spread can be seen in the 10^{th} to 90^{th} percentile range of Figure 3-12, while an example difference between two RCMs is shown in Figure 3-16.) Another source of uncertainty contributing to the spread is natural variability. Indeed, the same model driven with the same emission scenario, but launched with slightly different initial conditions will yield an independent simulation after a few months of simulation due to the chaotic nature of the climate system. The relative contribution of emission scenario, model uncertainty and natural variability to the overall uncertainty depends on the variable considered, the spatial extent of the analysis and the time horizon. For example, emission uncertainty plays a relatively minor role up until 2040, when for variables such as precipitation, natural variability is often the dominant uncertainty. Conversely, by the end of the century, the dominant uncertainty for global scale temperature is the emission scenario (Hawkins and Sutton, 2009; Northrop and Chandler, 2014).

In a study combining different variables, it is therefore difficult to assess *a priori* the relative importance of these uncertainties and sensitivity analyses can help determine which factors have the greatest influence on the final results.

4.3.4.4 Single Future PMP Estimates Are Not Possible

Given the deep uncertainty discussed in Section 4.3.2 necessitating the recommended sensitivity analysis-based approach, it is not possible to provide a single high-confidence estimate for future PMP values for any given location. However, some comment of the range of estimates resulting from the recommended approach is possible by inferring the likelihood of values from the various input variables.

4.3.5 Case Study Candidates

Given the nature of climate change impact analysis, where large datasets need to be acquired and processed for analysis, there are considerable efficiencies to be gained by conducting analyses on all study locations concurrently. If a single case study is selected, the climate model data can be acquired and stored for the remaining study locations. Much of the observation data (including extreme storms) will also be applicable across several locations. Also, given the inability of coarse resolution GCMs to effectively discern between locations which are relatively close geographically, and also the similar climatic characteristics of several of the study locations (see overview in Sections 2.1 and 3.2.2), it is proposed to group them for climate change analyses as below:

- Ignace
- Manitouwadge and Hornepayne
- Huron-Kinloss and South Bruce

There is no clear location, or pair of locations, identified as an ideal case study candidate.

REFERENCES

Acres International Limited (AIL). 1999. Churchill River Complex: PMF Review and Development Study. Prepared for Newfoundland and Labrador Hydro. St. John's, Newfoundland (Available at: http://www.pub.nf.ca/applications/MuskratFalls2011/files/exhibits/Exhibit51.pdf and http://www.pub.nf.ca/applications/MuskratFalls2011/files/exhibits/Exhibit50.pdf)

Afrooz, A., A. Hassan, A. Poortoyserkani, and G. Rakhshandehroo. 2015. Climate Change Impact on Probable Maximum Precipitation in Chenar-Rahdar River Basin, Southern Iran. 10.1061/9780784479322.004. (Available at: https://ascelibrary.org/doi/abs/10.1061/9780784479322.004)

Alberta Transportation. 2004. Guidelines on Extreme Flood Analysis. Transportation & Civil Engineering Division, Civil Projects Branch. (Available at http://www.transportation.alberta.ca/Content/doctype125/Production/gdlnextrmfld.pdf)

Amec. 2014. Probable Maximum Precipitation Study for Avalon Peninsula, Newfoundland. Newfoundland Power.

Amec Foster Wheeler. 2016. Blakely Mountain Basin Site-Specific PMP Report. US Army Corps of Engineers, Vicksburg District.

Alberta Transportation. 2004. Guidelines on Extreme Flood Analysis. Transportation and Civil Engineering Division, Civil Projects Branch. (Available at: http://www.transportation.alberta.ca/Content/doctype125/Production/gdlnextrmfld.pdf)

Amec NSS. 2011. OPG's Deep Geologic Repository for Low & Intermediate Level Waste - Maximum Flood Hazard Assessment. NWMO Report DGR-TR-2011-35. Toronto, Ontario. (Available at: https://www.opg.com/generating-power/nuclear/nuclear-waste-management/Deep-Geologic-Repository/Documents/Submission/26.Maximum-Flood-Hazard-Assessment.pdf)

Anctil F., J. Rousselle, and N. Lauzon. 2005. Hydrologie: Cheminements de l’eau. Editions Presse Internationale Polytechnique, 317 p.

Atria Engineering Hydraulics Inc. 1994. Probable Maximum Floods in Boreal Regions. Canadian Electrical Association. CEA No 911 G 839. Mississauga, Ontario.

Auld, H., H. Switzman, N. Comer, S. Eng, S. Hazen, and G. Milner. 2016. Climate Trends and Future Projections in the Region of Peel. Ontario Climate Consortium. Toronto, ON, 103 pp. (Available at: https://climateconnections.ca/app/uploads/2017/07/Climate-Trends-and-Future-Projections-in-the-Region-of-Peel.pdf)

Berg, P., C. Moseley, and J.O. Haerter. 2013. Strong Increase in Convective Precipitation in Response to Higher Temperatures. Nature Geoscience, 6, 181–185. (Available at: https://www.nature.com/articles/ngeo1731)

Ben Alaya, M. A., F. Zwiers, and X. Zhang. 2018. Probable Maximum Precipitation: Its Estimation and Uncertainty Quantification Using Bivariate Extreme Value Analysis. J. Hydrol., 19, 679-694. (Available at: https://Doi.Org/10.1175/Jhm-D-17-0110.1)

Benson, M. A. 1973. Thoughts on the Design of Design Floods. Floods and Droughts. Proceedings of the 2nd International Symposium in Hydrology, 27-33, Water Resources. Publication. Fort Collins, Colorado.

Bonzanigo, L., and N. Kalra. 2014. Making Informed Investment Decisions in an Uncertain World: A Short Demonstration. Policy Research Working Paper 6765. World Bank. (Available at: http://documents.worldbank.org/curated/en/465701468330278549/pdf/WPS6765.pdf)

Brooks, H.E. 2013. Severe Thunderstorms and Climate Change. Atmospheric Research, 123, 129–138. (Available at: https://doi.org/10.1016/j.atmosres.2012.04.002)

Bruce, J.P. 1962. Snowmelt Contributions to Maximum Floods. Proc. Eastern Snow Conference, pp. 85-103.

Burkett, V.R., A.G. Suarez, M. Bindi, C. Conde, R. Mukerji, M.J. Prather, A.L. St. Clair, and G.W. Yohe. 2014. Point of departure. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK and New York, NY, USA, 169-194. 2014.

Burnett, A. W., M. E. Kirby, H. T. Mullins, and W. P. Patterson. 2003. Increasing Great Lake–Effect Snowfall during the Twentieth Century: A Regional Response to Global Warming? J. Climate, 16, 3535–3542, (Available at https://journals.ametsoc.org/doi/10.1175/1520-0442%282003%29016%3C3535%3AIGLSDT%3E2.0.CO%3B2)

Canadian Centre for Climate Services (CCCS). 2018. Climate Data Viewer. Retrieved from: https://www.canada.ca/en/environment-climate-change/services/climate-change/canadian-centre-climate-services.html

Canadian Dam Association (CDA). 2007. Dam Safety Guidelines (Rev. 2013). (Available at https://cda.ca/EN/Publications/Dam_Safety/EN/Publications_Pages/Dam_Safety_Publications.aspx?hkey=7726b6d1-7ca6-4c8b-a096-c5f93d0ebc40)

Centre d’Expertise Hydrique du Québec (CEHQ) and SNC-LAVALIN. 2004. Estimation des Conditions Hydrométéorologiques Conduisant aux Crues Maximales Probables (CMP) au Québec. Rapport Final. CEHQ et SNC-LAVALIN, Division Énergie, Rapport 014713–3000-40RT-001-00. (Available at: https://www.oieau.org/eaudoc/system/files/documents/41/208296/208296_doc.pdf)

Chen, C., and T. Knutson. 2008. On the Verification and Comparison of Extreme Rainfall Indices from Climate Models. Journal of Climate, 21, 1605-1621. (Available at: https://doi.org/10.1175/2007JCLI1494.1)

Chen, L., and A. A. Bradley. 2006. Adequacy of Using Surface Humidity to Estimate Atmospheric Moisture Availability for Probable Maximum Precipitation. Water Resources Research, 42, 1–17. (Available at: https://doi.org/10.1029/2005WR004469)

Chen, X., F. Hossain, and L.R. Leung. 2017. Probable Maximum Precipitation in the U.S. Pacific Northwest in a Changing Climate. Water Resources Research. (Available at: https://doi.org/10.1002/2017WR021094)

Cheng, C. S., E. Lopes, C. Fu, and Z. Huang. 2014. Possible Impacts of Climate Change on Wind Gusts Under Downscaled Future Climate Conditions: Updated for Canada. Journal of Climate, 27, 1255–1270. (Available at: https://doi.org/10.1175/JCLI-D-13-00020.1)

Cheng, C.S., G. Li, Q. Li, H. Auld, and C. Fu. 2012. Possible Impacts of Climate Change on Wind Gusts under Downscaled Future Climate Conditions over Ontario, Canada. Journal of Climate, 25, 3390–3408. (Available at: https://doi.org/10.1175/JCLI-D-11-00198.1)

Cheng, V., G. Arhonditsis, D. Sills, H. Auld, M. Shephard, W. Gough, and J. Klaassen. 2013. Probability of Tornado Occurrence across Canada. Journal of Climate, 26, 9415-9428. (Available at: https://doi.org/10.1175/JCLI-D-13-00093.1)

Chow, K.C.A. and S.B. Jones. 1994. Probable Maximum Floods in Boreal Regions. Atria Engineering Hydraulics Inc. for Canadian Electrical Association. No. 9111 G 839. (Available at: http://www.worldcat.org/title/probable-maximum-floods-in-boreal-regions/oclc/35540890)

Christensen, J.H. and O.B. Christensen. 2007. A Summary of the PRUDENCE Model Projections of Changes in European Climate by the End of This Century. Climatic Change, 81(1), 7-30. (Available at: https://doi.org/10.1007/s10584-006-9210-7)

Clavet-Gaumont, J., D. Huard, A. Frigon, K. Koenig, P. Slota, A Rousseau, I. Klein, N. Thiemonge, F. Houdre, J. Perdikaris, R. Turcotte, J. Lafleur, and B. Larouche. 2017. Probable Maximum Flood in a Changing Climate: An Overview for Canadian Basins. Journal of Hydrology: Regional Studies, 13(April), 11-25. (Available at: https://doi.org/10.1016/j.ejrh.2017.07.003)

Coulibaly, P., D. H. Burn, H. Switzman, J. Henderson, and E. Fausto. 2016. A Comparison of Future IDF Curves for Southern Ontario. Toronto and Region Conservation Authority and Essex Region Conservation Authority. Ontario Climate Consortium. (Available at: https://climateconnections.ca/app/uploads/2014/01/IDF-Comparison-Report-and-Addendum.pdf)

Earth System Research Laboratory (ESRL). 2018. Monthly/Seasonal Climate Composites. (Retrieved from: https://www.esrl.noaa.gov/psd/cgi-bin/data/composites/printpage.pl?var=COADS%20Wind%20Speed%20enhanced;level=Surface%20%28.995%20Sigma%29;mon1=0;mon2=11;iy=;iy=;iy=;iy=;iy=;iy=;iy=;iy=;iy=;iy=;iy=;iy=;iy=;iy=;iy=;iy=;iy=;iy=;iy=;iy=;ipos%5B1%5D=1981;ipos%5B2%5D=2010;ineg%5B1%5D=;ineg%5B2%5D=;timefile0=;tstype=0;timefile1=;value=;typeval=1;compval=1;lag=0;labelc=Color;labels=Shaded;type=1;scale=100;labelcon=1;switch=0;cint=;lowr=;highr=;proj=Custom;xlat1=40;xlat2=60;xlon1=-96;xlon2=-76;custproj=Cylindrical%20Equidistant;level1=1000mb;level2=10mb;Submit=Create%20Plot)

ECCC (Environment and Climate Change Canada). 2017. Climate Data and Scenarios: Synthesis of Recent Observation and Modelling Results. Government of Canada. (Retrieved from: https://www.canada.ca/en/environment-climate-change/services/climate-change/publications/data-scenarios-synthesis-recent-observation.html)

ECCC. 2018a. Canadian Climate Normals. (Retrieved from: http://climate.weather.gc.ca/climate_normals/index_e.html)

ECCC. 2018b. Canadian Tornado Fact Sheet. (Retrieved from: http://donnees.ec.gc.ca/data/weather/products/canadian-national-tornado-database-verified-events-1980-2009-public/CanadianTornadoFactSheet.pdf)

ECCC. 2018c. ON_VerifiedTornadoes-TornadesVrifis_1980-2009. (Retrieved from: http://donnees.ec.gc.ca/data/weather/products/canadian-national-tornado-database-verified-events-1980-2009-public/ON_VerifiedTornadoes-TornadesVrifis_1980-2009.png)

Gangrade, S., S.C. Kao, B.S. Naz, D. Rastogi, M. Ashfaq, N. Singh, and B.L. Preston. 2018. Sensitivity of Probable Maximum Flood in a Changing Environment. Water Resources Research. (Available at: https://doi.org/10.1029/2017WR021987)

Ganguli, P. and P. Coulibaly. 2017. Assessment of Future Changes in Intensity-Duration-Frequency Curves for Southern Ontario Using North American (NA)-CORDEX Models with Nonstationary Methods. Journal of Hydrology: Regional Studies, 22 (2019), 100587. (Available at: https://www.sciencedirect.com/science/article/pii/S2214581818302064)

Goodison, B.E., P.Y.T. Louie, and D. Yang. 1998. WMO Solid Precipitation Measurement Intercomparison, Final Report. World Meteorological Organization (WMO) WMO/TD-No. 872. Geneva. (Available at: http://www.wmo.int/pages/prog/www/reports/WMOtd872.pdf)

Gray, D.M., and T.D. Prowse. 1993. Handbook of Hydrology, Maidment D.R. (ed.): Snow and Floating Ice. McGraw-Hill: New York; 7.1–7.58. ISBN-13: 978-0070397323

Gula, J., and W. R. Peltier. 2012. Dynamical Downscaling over the Great Lakes Basin of North America Using the WRF Regional Climate Model: The Impact of the Great Lakes System on Regional Greenhouse Warming. J. Climate, 25, 7723–7742. (Available at: https://journals.ametsoc.org/doi/full/10.1175/JCLI-D-11-00388.1)

Guthrie H.J. 2001. Extreme Rainfall in the Greater Calgary Area. University of Calgary, Department of Geography. Calgary, Alberta. (Available at: https://dspace.ucalgary.ca/bitstream/1880/40796/1/64957Guthrie.pdf)

Haerter, J.O., and P. Berg. 2009. Unexpected Rise in Extreme Precipitation Caused by a Shift in Rain Type? Nature Geoscience 2, 372–373. (Available at: https://www.nature.com/articles/ngeo523)

Haerter, J.O., P. Berg, and S. Hagemann. 2010. Heavy Rain Intensity Distributions on Varying Time Scales and at Different Temperatures. Journal of Geophysical Research, 115(D17). (Available at: https://doi.org/10.1029/2009JD013384)

Hardwick-Jones, R., S. Westra, and A. Sharma. 2010. Observed Relationships Between Extreme Sub-daily Precipitation, Surface Temperature and Relative Humidity. Geophysical Research Letters, 37(22), L22805. (Available at: https://doi.org/10.1029/2010GL045081)

Hatch. 2007. The Lower Churchill Project: GI1140 - PMF and Construction Design Flood Study. Prepared for Newfoundland and Labrador Hydro. (Available at: http://www.pub.nf.ca/applications/MuskratFalls2011/files/exhibits/abridged/CE-13-Public.pdf)

Hawkins, E. and R. Sutton. 2009. The Potential to Narrow Uncertainty in Regional Climate Predictions. Bulletin of the American Meteorological Society, 90, 1095–1107. (Available at: https://doi.org/10.1175/2009BAMS2607.1)

Hawkins, E. and R. Sutton. 2011. The Potential to Narrow Uncertainty in Projections of Regional Precipitation Change. Climate Dynamics, 37, 407–418. (Available at: https://doi.org/10.1007/s00382-010-0810-6)

Hershfield, D.M. 1961a. Rainfall Frequency Atlas of the United States. Technical Paper No. 40, Weather Bureau, United States Department of Commerce, Washington, D.C. (Available at: https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=2&cad=rja&uact=8&ved=2ahUKEwjs4YPVuJ3hAhVI3IMKHcnYA8UQFjABegQIAxAC&url=http%3A%2F%2Fwww.nws.noaa.gov%2Foh%2Fhdsc%2FPF_documents%2FAtlas14_Vol1_Ver5_Addendum.pdf&usg=AOvVaw3rfMaZfJnqdHGJTmp70K-7)

Hershfield, D.M. 1961b. Estimating the Probable Maximum Precipitation. Journal of Hydraulics Division: Proceedings of the American Society of Civil Engineers, 87, 99-106. (Available at: https://cedb.asce.org/CEDBsearch/record.jsp?dockey=0012307)

Hopkinson, R.F. 1999. Point Probable Maximum Precipitation for the Prairie Provinces. Environment Canada, Prairie Section, Atmospheric and Hydraulic Sciences Division, Atmospheric Environment Branch, Report No. AHSD-R99-01. Regina, Saskatchewan.

IDFCC. 2018. Computerized Tool for the Development of Intensity-Duration-Frequency Curves under Climate Change – Version 3.0. (Retrieved from: https://www.idf-cc-uwo.ca)

IPCC. 2013. Climate Change 2013. The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 1535 pp. (Available at: https://www.ipcc.ch/report/ar5/wg1/)

Ishida, K., M.L. Kavvas, S. Jang, Z.Q. Chen, N. Ohara, and M.L. Anderson. 2015a. Physically Based Estimation of Maximum Precipitation over Three Watersheds in Northern California: Atmospheric Boundary Condition Shifting. Journal of Hydraulic Engineering 20(4), 04014052. (Available at: http://dx.doi.org/10.1061/(ASCE)HE.1943-5584.0001026)

Ishida, K., M. L. Kavvas, S. Jang, Z. Q. Chen, N. Ohara, and M.L. Anderson. 2015b. Physically Based Estimation of Maximum Precipitation over Three Watersheds in Northern California: Relative Humidity Maximization Method. Journal of Hydraulic Engineering, 20(10). (Available at: https://ascelibrary.org/doi/10.1061/%28ASCE%29HE.1943-5584.0001175)

Ishida, K., N. Ohara, M.L. Kavvas, Z.Q. Chen, and M.L. Anderson. 2018. Impact of Air Temperature on Physically-based Maximum Precipitation Estimation through Change in Moisture Holding Capacity of Air. Journal of Hydrology, 556, 1050-1063. (Available at: https://doi.org/10.1016/j.jhydrol.2016.10.008)

Jothityangkoon, C., C. Hirunteeyakul, K. Boonrawd, and M. Sivapalan. 2013. Assessing the Impact of Climate and Land Use Changes on Extreme Flooding in a Large Tropical Catchment. J. Hydrol. 490, 88-105. (Available at: https://www.sciencedirect.com/science/article/pii/S002216941300245X)

Kalra, N., S. Hallegatte, R. Lempert, C. Brown, A. Fozzard, S. Gill, and A. Shah. 2014. Agreeing on Robust Decisions: New Processes for Decision Making under Deep Uncertainty. Policy Research Working Paper; No. 6906. World Bank, Washington, DC. World Bank. License: CC BY 3.0 IGO. (Available at: https://openknowledge.worldbank.org/handle/10986/18772)

Kappel, B., G. Muhlestein, D. Hultstrand, D. McGlone, K. Steinhilber, B. Lawrence, J. Rodel, T. Parzybok, and E. Tomlinson. 2014. Probable Maximum Precipitation Study for Wyoming. Applied Weather Association. (Available at: http://wwdc.state.wy.us/PMP/final-report.pdf)

Kappel, B., S. Abbas, S. Figliuzzi, S. Guangul, J. Menninger, and G. Sabol. 2016. Updating PMP for the Elbow River: Complex Terrain, Unique Solutions. Canadian Dam Association 2016 Annual Conference. (Available at: http://www.appliedweatherassociates.com/uploads/1/3/8/1/13810758/kappel_bill_2016-3a__01.pdf)

Kendon, E.J., N.M. Roberts, C.A. Senior, and M.J. Roberts. 2012. Realism of Rainfall in a Very High-resolution Regional Climate Model. J. Clim. 25, 5791–5806. (Available at: https://journals.ametsoc.org/doi/pdf/10.1175/JCLI-D-11-00562.1)

Koutsoyiannis, D., 1999. A Probabilistic View of Hershfield's Method for Estimating Probable Maximum Precipitation. Water Resources Research, 35(4), 1313-1322, American Geophysical Union. (Available at https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/1999WR900002)

KGS Group. 2017. Probable Maximum Flood Study at Lafleche Dam Probable Maximum Precipitation & Probable Maximum Flood Report. Agriculture & Agri Food Canada, Saskatchewan.

King, P.W.S., M.J. Leduc, D.M.L. Sills, N.R. Donaldson, D.R. Hudak, P. Joe, and B.P. Murphy. 2003. Lake Breezes in Southern Ontario and Their Relation to Tornado Climatology. Weather and Forecasting, 18, 795-802. (Available at: https://doi.org/10.1175/1520-0434(2003)018<0795:LBISOA>2.0.CO;2)

Klein, I. M., A.N. Rousseau, A. Frigon, D. Freudiger, and P. Gagnon. 2016. Evaluation of Probable Maximum Snow Accumulation: Development of a Methodology for Climate Change Studies: Journal of Hydrology, 537, 74–85. (Available at: https://doi.org/10.1016/j.jhydrol.2016.03.031)

Kuipper R. M., H. Hoijtink, and M.J. Silvapulle. 2011. An Akaike-type Information Criterion for Model Selection under Inequality Constraints. Biometrika, 98 (2): 495-501. (Available at: https://www.jstor.org/stable/23076167?seq=1#page_scan_tab_contents)

Kulkarni S. and H. P. Huang. 2014. Changes in Surface Wind Speed over North America from CMIP5 Model Projections and Implications for Wind Energy. Advances in Meteorology, vol. 2014, Article ID 292768, 10 pages. (Available at https://doi.org/10.1155/2014/292768).

Kunkel, K. E., N. E. Westcott, and D. A. R. Kristovich. 2002. Assessment of Potential Effects of Climate Change on Heavy Lake-effect Snowstorms near Lake Erie. J. Great Lakes Res., 28, 521–536. (Available at: https://www.sciencedirect.com/science/article/pii/S0380133002706035)

Kunkel, K.E., T.R. Karl, D.R. Easterling, K. Redmond, J. Young, X. Yin, and P. Hennon. 2013. Probable Maximum Precipitation and Climate Change. Geophysical Research Letters, 40(7), 1402–1408. (Available at: https://doi.org/10.1002/grl.50334)

Lee, O. and S. Kim. 2018. Estimation of Future Probable Precipitation in Korea Using Multiple Regional Maximum Climate Models. Water, 10. (Available at: https://doi.org/10.3390/w10050637)

Lee, O., Y. Park, E.S. Kim, and S. Kim. 2016a. Projection of Korean Probable Maximum Precipitation under Future Climate Change Scenarios. Advances in Meteorology, 2016(2). (Available at: https://doi.org/10.1155/2016/3818236)

Lee, O., M.W. Park, J.H. Lee, and S. Kim. 2016b. Future PMPs Projection According to Precipitation Variation under RCP 8.5 Climate Change Scenario. Journal of Korea Water Resources Association, 49(2), 107–119. (Available at: https://www.researchgate.net/publication/304336383_Future_PMPs_projection_according_to_precipitation_variation_under_RCP_85_climate_change_scenario)

Lenderink, G. and E. van Meijgaard. 2008. Increase in Hourly Precipitation Extremes Beyond Expectations from Temperature Changes. Nature Geoscience, 1, 511–514. (Available at https://www.nature.com/articles/ngeo262)

Lenderink, G. and E. van Meijgaard. 2009. Unexpected Rise in Extreme Precipitation Caused by a Shift in Rain Type? Reply to comment by Haerter et al. Nature Geoscience, 2, 373. (Available at: https://www.nature.com/articles/ngeo524)

Lenderink, G., H.Y. Mok, T.C. Lee, and G.J. Van Oldenborgh. 2011. Scaling and Trends of Hourly Precipitation Extremes in Two Different Climate Zones—Hong Kong and the Netherlands. Hydrology and Earth System Sciences, 8, 4701–4719. (Available at: https://doi.org/10.5194/hess-15-3033-2011)

Maraun D., F. Wetterhall, A. M. Ireson, R. E. Chandler, E. J. Kendon, M. Widmann, S. Brienen, H. W. Rust, T. Sauter, M. Themeßl, V. K. C. Venema, K. P. Chun, C. M. Goodess, R. G. Jones, C. Onof, M. Vrac, and I. Thiele-Eich. 2010. Precipitation Downscaling under Climate Change: Recent Developments to Bridge the Gap Between Dynamical Models and the End User. Rev. Geophys., 48, RG3003 (Available at: https://doi.org/10.1029/2009RG000314)

Mastrandrea, M. D., C.B. Field., T. F. Stocker, O. Edenhofel, K. L. Ebi, D. J. Frame, H. Held, E. Kriegler, K. J. Mach, P.R. Matschoss, G. Plattner, G. W. Yohe, and F. W. Zwiers. 2010. Guidance Notes for Lead Authors of the IPCC Fifth Assessment Report on Consistent Treatment of Uncertainties. (Available at: http://ipcc-wg2.awi.de/guidancepaper/ar5_uncertainty-guidance-note.pdf)

Maurer, E.P. 2007. Uncertainty in Hydrologic Impacts of Climate Change in the Sierra Nevada, California, Under Two Emissions Scenarios. Climatic Change, 82(3-4), 309-325. (Available at: https://doi.org/10.1007/s10584-006-9180-9)

Maurer, E.P., L.D. Brekke and T. Pruitt. 2010. Contrasting Lumped and Distributed Hydrology Models for Estimating Climate Change Impacts on California Watersheds. Journal of the American Water Resources Association, 46(5), 1024-1035. (Available at: https://doi.org/10.1111/j.1752-1688.2010.00473.x)

McDermid, J.L., S.K. Dickin, C.L. Winsborough, H. Switzman, S. Barr, J.A. Gleeson, G. Krantzberg, and P.A. Gray. 2015a. State of Climate Change Science in the Great Lakes Basin: A Focus on Climatological, Hydrological and Ecological Effects. Prepared jointly by the Ontario Climate Consortium and Ontario Ministry of Natural Resources and Forestry to advise Annex 9 – Climate Change Impacts under the Great Lakes Water Quality Agreement, October 2015. (Available at: https://climateconnections.ca/app/uploads/2014/07/OCC_GreatLakes_Report_Full_Final.pdf)

McDermid, J., S. Fera, and A. Hogg. 2015b. Climate Change Projections for Ontario: An Updated Synthesis for Policymakers and Planners. Ontario Ministry of Natural Resources and Forestry, Science and Research Branch, Peterborough, Ontario. Climate Change Research Report CCRR-44. (Available at: www.climateontario.ca/MNR_Publications/CCRR-44.pdf)

McKenney, D. W., M.F. Hutchinson, P. Papadopol, K. Lawrence, J. Pedlar, K. Campbell, E. Milewska, R. Hopkinson, D. Price, and T. Owen. 2011. Customized Spatial Climate Models for North America. Bulletin of American Meteorological Society-BAMS December: 1612-1622. (Available at: https://journals.ametsoc.org/doi/pdf/10.1175/2011BAMS3132.1)

Meylan P., A. Favre and A. Musy. 2011. Predictive Hydrology: A Frequency Analysis Approach. Published by Science Publishers, CRC Press Taylor & Francis Group. ISBN: 13: 1978-1-4398-8341-9, 219.

Micovic, Z., M.G. Schaefer, and G.H. Taylor. 2015. Uncertainty Analysis for Probable Maximum Precipitation Estimates. Journal of Hydrology, 521, 360-373. (Available at: https://www.researchgate.net/publication/270053146_Uncertainty_analysis_for_Probable_Maximum_Precipitation_estimates)

Miller, J.F. 1964. Two-to-Ten-Day Precipitation for Return Periods of 2 to 100 Years in the Contiguous United States. Technical Paper No. 49, Weather Bureau, United States Department of Commerce, Washington D.C. (Available at: https://www.nws.noaa.gov/oh/hdsc/PF_documents/TechnicalPaper_No52.pdf)

Mishra, V., J.M. Wallace, and D.P. Lettenmaier. 2012. Relationship between Hourly Extreme Precipitation and Local Air Temperature in the United States. Geophysical Research Letters 39(16). (Available at: https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2012GL052790)

Mote, P., L. Brekke, P.B. Duffy, and E. Maurer. 2011. Guidelines for Constructing Climate Scenarios. Eos, Transactions American Geophysical Union, 92(31), 257–264. (Available at: https://doi.org/10.1029/2011EO310001)

Natural Resources Canada (NRCAN). 2008. From Impacts to Adaptation: Canada in a Changing Climate. Ch. 2. Government of Canada, Ottawa, ON. (Available at: https://www.nrcan.gc.ca/sites/www.nrcan.gc.ca/files/earthsciences/pdf/assess/2007/pdf/full-complet_e.pdf)

Nuclear Waste Management Organization (NWMO). 2013a. Phase 1 Desktop Assessment, Environment Report: Township of Hornepayne, Ontario. November 2013. Golder Associates. NWMO Report APM-REP-06144-0002. Toronto, Ontario. (Available at: https://www.nwmo.ca/~/media/Site/Reports/2015/11/20/08/33/2190_apmrep061440002_1211520026_4005_hornepayne_en.ashx?la=en)

Nuclear Waste Management Organization (NWMO). 2013b. Phase 1 Desktop Assessment, Environment Report: Township of Ignace, Ontario. November 2013. Golder Associates. NWMO Report APM-REP-06144-0010. Toronto, Ontario. (Available at: https://www.nwmo.ca/~/media/Site/Reports/2015/11/20/08/34/2191_apmrep061440010_1211520026_4001_ignace_enviro.ashx?la=en)

Nuclear Waste Management Organization (NWMO). 2014a. Phase 1 Desktop Assessment, Environment Report: Township of Manitouwadge, Ontario. October 2014. Golder Associates. NWMO Report APM-REP-06144-0074. Toronto, Ontario. (Available at: https://www.nwmo.ca/~/media/Site/Reports/2015/11/20/11/57/2482_apmrep061440074_1211520026__4105__rpt_nwmo_ma.ashx?la=en)

Nuclear Waste Management Organization (NWMO). 2014b. Phase 1 Desktop Assessment, Environment Report: Communities of Huron-Kinloss, Brockton and South Bruce, Ontario. October 2014. Golder Associates. NWMO Report APM-REP-06144-0107. Toronto, Ontario. (Available at: https://www.nwmo.ca/~/media/Site/Reports/2015/11/20/09/17/2450_apmrep061440107__environment_report__bruce_co.ashx?la=en)

Northrop, P.J. and R.E. Chandler. 2014. Quantifying Sources of Uncertainty in Projections of Future Climate. Journal of Climate, 27, 8793-8808. (Available at: https://doi.org/10.1175/JCLI-D-14-00265.1)

Notaro, M., V. Bennington, and S. Vavrus. 2015. Dynamically Downscaled Projections of Lake-Effect Snow in the Great Lakes Basin. J. Climate, 28, 1661–1684, (Available at: https://doi.org/10.1175/JCLI-D-14-00467.1)

Ohara, N., M.L. Kavvas, S. Kure, Z.Q. Chen, S. Jang, and E. Tan. 2011. Physically Based Estimation of Maximum Precipitation over American River Watershed, California. J. Hydrol. Eng. 16, 351–361. (Available at: http://dx.doi.org/10.1061/(ASCE)HE.1943-5584.0000324)

Ontario Ministry of Natural Resources (OMNR). 2006. PMP for Ontario. Draft completed by the IBI Group for the Ministry of Natural Resources.

Ontario Climate Change Data Portal (OCCDP). 2018. (Retrieved from: http://www.ontarioccdp.ca)

Ouranos. 2015. Probable Maximum Floods and Dam Safety in the 21th Century Climate. Report submitted to Climate Change Impacts and Adaptation Division, Natural Resources Canada, 39 p. (Available at: http://docplayer.net/34754486-Probable-maximum-floods-and-dam-safety-in-the-21stcentury-climate.html)

Ouranos. 2016. A Guidebook on Climate Scenarios: Using Climate Information to Guide Adaptation Research and Decisions, 2016 Edition. Ouranos, 94p. (Available at: https://www.ouranos.ca/publication-scientifique/Guidebook-2016.pdf)

Opere A. O., S. Mkhandi, and P. Willems. 2006. At Site Flood Frequency Analysis for the Nile Equatorial Basins. Physics and Chemistry of the Earth 31 (2006) 919–927. (Available at: https://doi.org/10.1016/j.pce.2006.08.018).

Panthou, G., A. Mailhot, E. Laurence, and G. Talbot. 2014. Relationship between Surface Temperature and Extreme Rainfalls: A Multi-Timescale and Event-Based Analysis. Journal of Hydrometeorology, October 2014. (Available at: https://doi.org/10.1175/JHM-D-14-0020.1)

Papalexiou, S.M., D. Koutsoyiannis. 2006. A Probabilistic Approach to the Concept of Probable Maximum Precipitation. Adv. Geosci. 7, 51–54. (Available at: http://dx.doi.org/ 10.5194/adgeo-7-51-2006)

Paquin, D., R. de Elia, and A. Frigon. 2014. Change in North American Atmospheric Conditions Associated with Deep Convection and Severe Weather using CRCM4 Climate Projections. Atmosphere-Ocean, 52(3), 175–190. (Available at: https://doi.org/10.1080/07055900.2013.877868)

Peltier, R.W. and J. Gula. 2012. Dynamical Downscaling over the Great Lakes Basin of North America Using the WRF Regional Climate Model: The Impact of the Great Lakes System on Regional Greenhouse Warming. Journal of Climate, 25, 7723–7742. (Available at: http://dx.doi.org/10.1175/JCLI-D-11-00388.1)

Pentland, R.S. and B.T. Abrahamson. 2009. Probable Maximum Flood Estimator for the Canadian Prairies. Agriculture and Agri-Food Canada, Prairie Farm Rehabilitation Administration and Environment Branch. (Available at: http://www.pfra.ca/doc/Hydrology/PMF_Estimator-Final%20Report_March%202009.pdf)

Peters, G.P., R.M. Andrew, T. Boden, J.G. Canadell, P. Ciais, C. Le Quéré, G. Marland, M.R. Raupach, and C. Wilson. 2013. The Challenge to Keep Global Warming Below 2°C, Nature Climate Change, 3(1), 4–6. (Available at: https://doi.org/10.1038/nclimate1783)

Pielke, R.A., W.R. Cotton, R.L. Walko, C.J. Tremback, W.A. Lyons, L.D. Grasso, and J.H. Copeland. 1992. A Comprehensive Meteorological Modeling System—RAMS. Meteorology and Atmospheric Physics, 49(1–4), 69–91. (Available at: https://doi.org/10.1007/BF01025401)

Pierce, D. W., D. R. Cayan, and B. L. Thrasher. 2014. Statistical Downscaling Using Localized Constructed Analogs (LOCA), Journal of Hydrometeorology, 15(6), 2558-2585. (Available at: https://journals.ametsoc.org/doi/abs/10.1175/JHM-D-14-0082.1)

Pierce, D. W., D. R. Cayan, E. P. Maurer, J. T. Abatzoglou, and K. C. Hegewisch. 2015. Improved Bias Correction Techniques for Hydrological Simulations of Climate Change. J. Hydrometeorology, 6, 2421-2442. (Available at: http://dx.doi.org/10.1175/JHM-D-14-0236.1)

Raftery, E.A., A. Zimmer, D.M.W. Frierson, R. Startz, and P. Liu. 2017. Less than 2 °C Warming by 2100 Unlikely. Nature Climate Change 7, 637–641. (Available at: https://doi.org/10.1038/nclimate3352)

Rastogi, D., S.C. Kao, M. Ashfaq, R. Mei, E.D. Kabela, S. Gangrade, B.S. Naz, B.L. Preston, N. Singh, and V.G. Anantharaj. 2017. Effects of Climate Change on Probable Maximum Precipitation: A Sensitivity Study over the Alabama-Coosa-Tallapoosa River Basin. Journal of Geophysical Research, 122(9), 4808-4828. (Available at: https://doi.org/10.1002/2016JD026001)

Roberts, J., A. Pryse-Phillips, and K. Snelgrove. 2012. Modeling the Potential Impacts of Climate Change on a Small Watershed in Labrador, Canada. Canadian Water Resources Journal, 37(3), 231-251. (Available at: https://doi.org/10.4296/cwrj2011-923)

Robinson, P.J. 2000. Temporal Trends in United States Dew Point Temperatures. International Journal of Climatology, 20(9), 985–1002. (Available at: https://rmets.onlinelibrary.wiley.com/doi/pdf/10.1002/1097-0088%28200007%2920%3A9%3C985%3A%3AAID-JOC513%3E3.0.CO%3B2-W)

Rouhani, H. 2016. Climate Change Impact on Probable Maximum Precipitation and Probable Maximum Flood in Québec. Thèse de Doctorat, Universite de Sherbrooke, Sherbrooke, Canada. (Available at https://savoirs.usherbrooke.ca/bitstream/handle/11143/8824/Rouhani_Hassan_PhD_2016.pdf;sequence=5)

Rouhani, H. and R. Leconte. 2016. A Novel Method to Estimate the Maximization Ratio of the Probable Maximum Precipitation (PMP) Using Regional Climate Model Output. Water Resources Research. (Available at: https://doi.org/10.1002/2016WR018603)

Rousseau, A.N., I.M. Klein, D. Freudiger, P. Gagnon, A. Frigon, and C. Ratté-Fortin. 2014. Development of a Methodology to Evaluate Probable Maximum Precipitation (PMP) under Changing Climate Conditions: Application to Southern Quebec, Canada. Journal of Hydrology, 519, 3094–3109. (Available at: https://doi.org/10.1016/j.jhydrol.2014.10.053)

Royal Society, The. 2014. Climate Change Evidence and Causes: An Overview from the Royal Society and the US National Academy of Science. (Available at: https://royalsociety.org/~/media/Royal_Society_Content/policy/projects/climate-evidence-causes/climate-change-evidence-causes.pdf)

Sagen, K.A.B. 2017. Sensitivity of Probable Maximum Flood Estimates in the Lower Nelson River Basin. M. Science thesis submitted to the University of Manitoba. (Available at: https://mspace.lib.umanitoba.ca/bitstream/handle/1993/32778/sagan_kevin.pdf?sequence=1)

Sheffield, J., G. Goteti, and E. F. Wood. 2006. Development of a 50-yr High-Resolution Global Dataset of Meteorological Forcings for Land Surface Modeling. J. Climate, 19(13), 3088-3111. (Available at: https://journals.ametsoc.org/doi/10.1175/JCLI3790.1)

Simonovic, S. P., A. Schardong, and D. Sandink. 2017. Mapping Extreme Rainfall Statistics for Canada under Climate Change Using Updated Intensity-Duration-Frequency Curves. J. Water Resources Planning Management, 143(3). (Available at: https://ascelibrary.org/doi/abs/10.1061/%28ASCE%29WR.1943-5452.0000725)

Smith M.R. and S.S. Myers. 2018. Impact of Anthropogenic CO_2 Emissions on Global Human Nutrition. Nature Climate Change, 834(8), 834-839. (Available at: https://doi.org/10.1038/s41558-018-0253-3)

SNC-Shawinigan. 1992. Recommendations of the Expert Committee on the Determination of a Realistic Scenario for Probable Maximum Flood on the St. Maurice Basin. Hydro-Quebec Direction Amenagements de Centrales.

Sparling, E., P. Byer, P. Cobb, and H. Auld. 2017. Best Practices for Consideration of the Effects of Climate Change in Project-Level Environmental Assessments. Ontario Centre for Climate Impacts and Adaptation Resources (OCCIAR) and Risk Sciences International (RSI). (Available at http://www.climateontario.ca/doc/reports/BestPracticesForConsiderationOfEffectsOfClimateChangeInProjectEAs2017.pdf)

Stein, A.F., R.R. Draxler, G.D. Rolph, B.J.B. Stunder, and M.D. Cohen. 2015. NOAA's HYSPLIT Atmospheric Transport and Dispersion Modeling System. Bulletin of the American Meteorological Society, 96(12), 2059-2078. (Available at: https://doi.org/10.1175/BAMS-D-14-00110.1)

Stratz, S.A. and F. Hossain. 2014. Probable Maximum Precipitation in a Changing Climate: Implications for Dam Design. Journal of Hydrologic Engineering, 19(12), 06014006. (Available at: https://doi.org/10.1061/(ASCE)HE.1943-5584.0001021)

Switzman, H., T. Razavi, S. Traore, P. Coulibaly, D. Burn, J. Henderson, E. Fausto, and R. Ness. 2017. Variability of Future Extreme Rainfall Statistics: Comparison of Multiple IDF Projections. Journal of Hydrologic Engineering, 22(10). (Available at: https://doi.org/10.1061/(ASCE)HE.1943-5584.0001561)

Symonds, M.R.E. and A. Moussalli. 2010. A Brief Guide to Model Selection, Multimodel Inference and Model Averaging in Behavioural Ecology Using Akaike's Information Criterion. Behav. Ecol. Sociobiol., 65: 13-21. (Available at: https://link.springer.com/article/10.1007/s00265-010-1037-6)

Taylor, K.E., R.J. Stouffer, and G.A. Meehl. 2012. An Overview of CMIP5 and the Experiment Design. Bulletin of the American Meteorological Society, 93, 485-498. (Available at: http://dx.doi.org/10.1175/BAMS-D-11-00094.1)

Tomlinson E., W. Kappel, T. Parzybok, D. Hultstrand, and G. Muhlestein. 2008. Site-Specific Probable Maximum Precipitation (PMP) Study for Nebraska. Applied Weather Association. (Available at: https://dnr.nebraska.gov/sites/dnr.nebraska.gov/files/doc/dam-safety/resources/Nebraska-PMP-Study.pdf)

Tomlinson E., W. Kappel, D. Hultstrand, G. Muhlestein, and S. Lovisone. 2013. Probable Maximum Precipitation Study for the State of Ohio. Applied Weather Association. (Available at: https://water.ohiodnr.gov/portals/soilwater/pdf/dam/1.0_Ohio-Statewide-PMP-Final-Report.pdf)

U.S. Army Corps of Engineers (USACE). 1978. Hydrometeorological Report No. 51 – Probable Maximum Precipitation Estimates, United States, East of the 105th Meridian. U.S. Department of Commerce, National Oceanic and Atmospheric Administration. (Available at: http://www.nws.noaa.gov/oh/hdsc/PMP_documents/HMR51.pdf)

U.S. Army Corps of Engineers (USACE). 1982. Hydrometeorological Report No. 52 – Application of Probable Maximum Precipitation Estimates - United States East of the 105th Meridian. U.S. Department of Commerce, National Oceanic and Atmospheric Administration. (Available at http://www.nws.noaa.gov/oh/hdsc/PMP_documents/HMR52.pdf)

U.S. Army Corps of Engineers (USACE). 1994. Hyrdometeorological Report No. 57 Probable Maximum Precipitation – Pacific Northwest States, National Weather Service, Silver Spring, MD, US. (Available at: http://www.nws.noaa.gov/oh/hdsc/PMP_documents/HMR57.pdf)

U.S. Army Corps of Engineers (USACE). 1998. Runoff from Snowmelt. Publication EM 1110-2-1406, U.S. Army Corps of Engineers, Washington D.C. (Available at: https://www.publications.usace.army.mil/LinkClick.aspx?fileticket=BUgc6czM8As%3d&tabid=16439&portalid=76&mid=43544)

Utsumi, N., S. Seto, S. Kanae, E.E. Maeda, and T. Oki. 2011. Does Higher Surface Temperature Intensify Extreme Precipitation? Geophysical Research Letters, 38(16). (Available at: https://doi.org/10.1029/2011GL048426)

Vincent, L.A., X. Zhang, R.D. Brown, Y. Feng, E. Mekis, E.J. Milewska, H. Wan, and X.L. Wang. 2015. Observed Trends in Canada's Climate and Influence of Low-Frequency Variability Modes. J. Climate, 28, 4545–4560. (Available at: https://doi.org/10.1175/JCLI-D-14-00697.1)

Wang, X. and H. Gordon. 2015. Technical Report: Development of High-Resolution Climate Change Projections under RCP 8.5 Emissions Scenario for the Province of Ontario. IEESC, University of Region, Canada. (Available at http://ontarioccdp.ca/Technical_Report_RCP85.pdf)

Wang, X., G. Huang, J. Liu, L. Zhong, and Z. Shan. 2015. Ensemble Projections of Regional Climatic Changes over Ontario, Canada. Journal of Climate, AMS 18(28), 7327-7346. (Available at: https://doi.org/10.1175/JCLI-D-15-0185.1)

Weiss, L.L. 1964. Ratio of True to Fixed-Interval Maximum Rainfall. Journal of Hydraulics division, 90, 77-82. (Available at: https://cedb.asce.org/CEDBsearch/record.jsp?dockey=0013210)

Westra, S., H.J. Fowler, J.P. Evans, L.V. Alexander, P. Berg, F. Johnson, E.J. Kendon, G. Lenderink, and N.M. Roberts. 2014. Future Changes to the Intensity and Frequency of Short Duration Extreme Rainfall. Rev. Geophys., 52, 522–555. (Available at: https://doi.org/10.1002/2014RG000464)

Westra, S., J.P. Evans, R. Mehrotra, and A. Sharma. 2013. A Conditional Disaggregation Algorithm for Generating Fine Time-Scale Rainfall Data in a Warmer Climate. J. Hydrol., 479, 86–99. (Available at: https://www.sciencedirect.com/science/article/pii/S0022169412010128)

Weyant, J. 2017. Some Contributions of Integrated Assessment Models of Global Climate Change. Review of Environmental Economics and Policy, 11(1). (Available at: https://doi.org/10.1093/reep/rew018)

Wilby, R.L. and I. Harris. 2006. A Framework for Assessing Uncertainties in Climate Change Impacts: Low-Flow Scenarios for the River Thames, UK. Water Resources Research, 42(2). (Available at: https://doi.org/10.1029/2005WR004065)

World Meteorological Organization (WMO). 2009. Manual on Estimation of Probable Maximum Precipitation (PMP). (Available at http://www.wmo.int/pages/prog/hwrp/publications/PMP/WMO%201045%20en.pdf)

World Meteorological Organization (WMO). 1994. Guide to Hydrological Practices (fifth edition) (WMO-No. 168), Geneva.

World Meteorological Organization (WMO). 1986. Manual for Estimation of Probable Maximum Precipitation. 2nd Ed. Operational Hydrology Rep. 1, Wmo-332, 269 Pp. (Available at: https://library.wmo.int/pmb_ged/wmo_332.pdf)

Wood. 2018a. Climate Change Impacts Review and Method Development. Project Quality Plan. Wood Document TA1883301–PLN-01. Revision 1. Burlington, Canada.

Wood. 2018b. Gouverneur Dam – Probable Maximum Flood Study. Agriculture & Agri Food Canada, Saskatchewan.

Wood. 2018c. Probable Maximum Precipitation Study St. Croix and Halfway River Systems. Minas Energy, Nova Scotia.

Zhang, X., F.W. Zwiers, G. Li, H. Wan, and A.J. Cannon. 2017. Complexity in Estimating Past and Future Extreme Short-Duration Rainfall. Nature Geoscience, 10, 255-259. (Available at: https://www.nature.com/articles/ngeo2911)