British Journal of Environment & Climate Change
2(4): 318-338, 2012

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Assessment of Uncertainty in Flood Flows under Climate Change Impacts in the Upper Thames River Basin, Canada

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Authors' contributions

This work was carried out in collaboration between both authors. Author SD designed the study, performed the statistical analysis, wrote the protocol, and wrote the first draft of the manuscript. Author SPS assisted the study design, supervised the analyses, reviewed the first draft of the manuscript and helped with the revisions. Both authors read and approved the final manuscript.

Research Article

Received 18th December 2012
Accepted 7th January 2013
Published 19th January 2013

ABSTRACT

The assessment of climate change impacts on frequency of floods is important for management of flood disasters. It is recognized that methods for the assessment are subject to various sources of uncertainty (choice of climate model and emission scenario, course spatial and temporal scales, etc.). This study investigates the climate change related uncertainty in the frequency of flood flows for the Upper Thames River basin (Ontario, Canada) using a wide range of climate models. Climate model outputs are downscaled using the change factor approach for 30-year time slices centered on years 2020, 2050 and 2080. To estimate natural variability, a stochastic weather generator is used to produce synthetic time series for each horizon and for each climate scenario. A number of realizations out of historical range are also produced for the 1979-2005 baselines using the weather generator. A continuous daily hydrologic model was then used to generate daily flow series for the baseline and for the future time horizons. A

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peak-over-threshold (POT) with Generalized Pareto Distribution is used to produce flood frequency curves for the four time horizons. The uncertainty involved with the POT modelling is also considered. The results indicate that use of unbounded GPD model should be employed for flood frequency analysis. A large uncertainty exists in all the projected future design floods. Probabilistic assessment of the uncertainty is carried out and it provides the estimation of flood magnitude-return period relationship with high level of confidence.

Keywords: Flood frequency; climate change; uncertainty; peak-over-threshold; hydrology; river flow.

1. INTRODUCTION

It is widely recognized that hydrologic cycle will be intensified by increasing global temperatures, resulting from increased anthropogenic emissions of greenhouse gases 1. This will produce an effect on climate variables and will result in changes in climate. One of the expected consequences of climate change is the increase in terms of magnitude and frequency of extreme hydrologic events 2. A number of studies in the Canadian context conform to the findings of IPCC 2. Particularly, a study that was carried out by the Environment Canada 4 on four selected river basins in Ontario using a modeling approach, suggests that the impacts of future climate change on the frequency and magnitude of river flow, precipitation, and associated flooding risks will increase in that part of Canada. It is also noted that the monthly total number of rainfall related water damage insurance claims and incurred loss could increase by about 20% to 30% in the 2nd half of the 21st century. Also, a study that was carried out by the Public Infrastructure Engineering Vulnerability Committee of Engineers Canada 5, concludes that the failures of water resource’s infrastructure due to climate change will become increasingly common across Canada. It is thus suggested 6 that water resource’s infrastructure design criteria should be revised to adapt to the expected changes in magnitude and frequency of extreme flood events 6.

The traditional approach to quantifying the expected changes in frequency of extreme flood events under climate change is to develop climatic variables time series from GCMs and link the scenarios to a hydrological model from which peak flows are analysed through a flood frequency approach 78. It is recognized that the above approach is subject to various sources of uncertainty. Climate data (GCM structure, future emission scenarios, climate variability, course spatial and temporal scales) and simulated hydrologic regimes (future land use scenarios, hydrological model structure, model parameters) are the main sources of uncertainty 910,11. Considering most of the uncertainty sources in the study by Jung et al. 11 it is found that changes in flood frequency are more sensitive to climate change and the uncertainty caused by climate models is higher than due to other sources. The similar findings were also obtained in 12.
.
Quantifying uncertainty linked with climate data has been a research topic over the last decade and has been assessed generally by generating a large ensemble of climate scenarios using Monte Carlo simulation 9 or using climate projections obtained from the combinations of several GCMs and emission scenarios 13,14,12. It is understood from the above studies that to better encompass the uncertainty linked with climate data, the incorporation of many GCMs and carefully chosen emission scenarios is necessary. Also, there has been less attention focused on the flood frequency approach in terms of modeling in changing climate conditions. However it can be noted that the spread of a multiple model

ensemble is rarely a direct measure of uncertainty, particularly given that models are unlikely to be independent, but the spread can help to characterize uncertainty 15.

The main objective of this study is to investigate the climate change related uncertainty in the estimation of extreme flood flows for the Upper Thames River basin (Ontario, Canada) using climate models and emission scenarios. A previous climate change study performed in the Upper Thames Basin 16 indicates that the basin will experience more frequent and severe flooding. Another recent study Das et al. 17 indicates a similar hydrological behavior in terms of extreme rainfall intensity when they select a distribution for future datasets obtained from a wide range of climate scenarios derived from Atmosphere-Ocean Global Climate Models (AOGCM). In this study peak over threshold (POT) approach of flood frequency is used to estimate flood magnitude - return period (Q-T) relationship. The suitability of the distributions associated with the POT model, and the uncertainty involved with the POT modeling under climate change is also considered. This paper can contribute to a better understanding of climate change impacts on flood frequency, and is expected to help water practitioners to assess flood risk in a changing climate. The outline of the paper is organized as follows. Section 2 describes the methodology applied in this study for assessing climate change impacts on flood frequency. Section 3 describes the study area of the Upper Thames River Basin (UTRB), along with the production of peak over threshold (POT) series for the Byron gauging station located in the UTRB. Section 4 presents and discusses the results. Finally the paper is concluded in Section 5.

2. METHODOLOGY

The methodologies applied in this study for the assessment of climate change impacts on flood frequency differ from other similar studies 9,13,1412 in one or many of the following key points.

1. Climate data was obtained from fifteen different climate projections from a combination of six Atmosphere-Ocean Global Climate Models (AOGCMs) and three emission scenarios “A1B”, “B1” and “A2” out of the family of emission scenarios.
2. A KNN-based stochastic weather generator was used to downscale climate data from AOGCMs.
3. The hydrological simulations were performed in a continuous mode using the HEC-HMS model and
4. The peak flows extracted from the simulated flow series were assessed through the peak over threshold (POT) flood frequency approach.

2.1 Climate Models

Coupled Atmosphere-Ocean Global Climate Models (AOGCMs) are current state of the art in climate impact research. AOGCMs are the most viable tools for simulating physical processes in the atmosphere, ocean, cryosphere and land surface that determine global climate 2. They are based on various assumptions about the effects of the concentration of greenhouse gases in the atmosphere coupled with projections of CO_2 emission rates 18. AOGCMs are associated with model structure developed by various countries, and the emission scenarios. Three emission scenarios “A1B”, “B1” and “A2” out of the family of emission scenarios 19 are most commonly used in climate impact studies. These represent respectively medium, low and high emission scenarios for the 21st century 20. In this study, a total of 15 climate projections from 6 AOGCMs, each with two to three emission scenarios are selected for investigation. A list of these models including their origin and associated scenarios is provided in Table 1.

Table 1. List of AOGCM models and emission scenarios used

GCM models	Sponsors, Country	Emission Scenarios	Atmospheric Resolution	
			Lat	Long
CGCM3T47, 2005	Canadian Centre for Climate Modelling and Analysis, Canada	A1B, B1, A2	3.75º	3.75º
CGCM3T63, 2005		A1B, B1, A2	2.81º	2.81º
CSIROMK3.5, 2001	CISRO, Australia	B1, A2	1.875º	1.875º
GISSAOM, 2004	NASA/ GISS, USA	A1B, B1	3º	4º
MIROC3.2HIRES, 2004	JAMSTEC, Japan	A1B, B1	1.125º	1.125°
MIROC3.2MEDRES, 2004		A1B, B1, A2	2.8º	2.8º

2.2 Downscaling Technique: Weather Generator

Downscaling is employed to address the deficiencies (i.e. coarse spatial and temporal resolution) of global climate models for use at local scales. Downscaling based on weather generator is widely used in climate impact studies 21,22,1623. Weather generator stochastically simulates climate information for an area by combining both, local and global weather data. The KnnCAD weather generator, developed at the University of Western Ontario was used in this study to produce synthetic data sets 24. The model is based on K-Nearest Neighbour (K-NN) algorithm of 25, modified in 26 and completed in 24. The K-NN algorithm of 25 is an improvement of the model introduced in 22. The K-NN algorithm of 22 is not able to generate values outside the observed data. An improved K-NN technique is presented in Sharif and Burn 25 by introducing a perturbation process to generate new data outside of the observed data range. Modifications Eum and Simonovic 2726 have been made to a K-NN algorithm by incorporating the principal component analysis to reduce high computational requirements. The first principal component is used in 26 to modify the K-NN algorithm of 25. The model operates by generating weather for a new day for a station of interest. This has been done by extracting all days with similar characteristics, known as nearest neighbours, from the historic record from which a single value is selected according to a defined set of rules. The detailed presentation of the KnnCAD weather generator is described in 24. The addition of principal component analysis provides reduction in computational requirements and allows more variables to be included for an improved selection of nearest neighbours. The inclusion of a perturbation mechanism allows newly generated values to be outside of the observed range. The data sets produced in this way are believed to allow researcher to take into account natural variability when predicting the future effects of climate change 24.

2.3 Hydrological Model

This study uses HEC-HMS model developed by the US Army Corps of Engineers (USACE) to carry out hydrological simulations in a continuous mode. The model has been widely applied in many geographical locations for solving a variety of hydrological problems 28293031 and used by the local water authority (the Upper Thames River Conservation Authority-UTRCA), in everyday practice. Precipitation, air temperature, and estimated potential evapotranspiration are used as input data for HEC-HMS model. Additionally, soil information and land use data are required for estimating initial parameter sets for the model.

The overall structure of the continuous simulation version of the HEC-HMS model used in this study is presented in Fig. 1. The model includes four components. Each component represents a module that mathematically represents a physical processes functioning in the river basin. Snow module takes precipitation and air temperature (maximum and minimum) data obtained from the weather generator as inputs to separate solid and liquid form of precipitation. The algorithm of the snow module is based on a degree-day method30. The output of the snow module is adjusted precipitation, used for computation of losses.

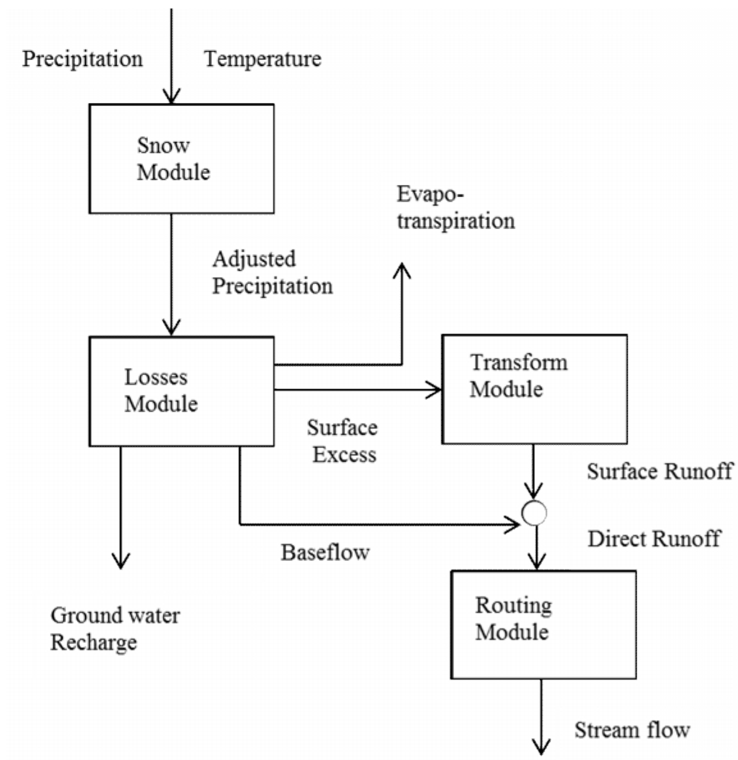

Fig. 1. Continuous HEC-HMS hydrologic model structure

The losses module integrated with HMS is soil-moisture accounting (SMA). The module is used to estimate and subtract the losses (interception, infiltration and evapotranspiration) from adjusted precipitation. The 5-layer SMA module is based on Precipitation-Runoff modeling System, PRMS 32 designed to compute runoff discharge on a continuous time basis. The SMA uses four types of conceptual storage: canopy- interception, surface - interception, soil profile, and a number of ground water storage. The inflow and outflow rates (i.e. evapotranspiration, infiltration, percolation, surface runoff and ground water flow) between the reservoirs regulate the amount of water stored in each conceptual reservoir. Surface excess, groundwater flow and ground water recharge are outputs from the losses module. The Clark unit hydrograph 33 is used to convert surface excess to direct runoff. The groundwater flow is transformed into baseflow by a series of linear reservoir model. Both direct runoff and baseflow enter the river. The translation and attenuation of flow in river reach is simulated by the modified puls method 33. The ground water recharge enters deep aquifers and does not return to the stream.

2.4 Flood Frequency Approach: POT Model

In this study the peaks-over-threshold (POT) approach is chosen for flood frequency analysis. POT model has been widely used in climate change impact studies 891312,34. In a POT model, a series of well-defined flood peaks above a specified threshold (q_0) is fitted with a continuous probability distribution. The flood events are modelled by a discrete probability distribution, such as Poisson distribution, and the model is of the form:

$$1 - F(Q / Q > q_0) = \frac{1}{\lambda T} \tag{1}$$

where $F(\ )$ is the cumulative frequency distribution of flood magnitude, $Q > q_0$. λ is the number of peaks per year included in the POT series. According to Cunnane 35, the POT model is statistically more efficient than the Annual Maximum (AM) model when λ > 1.65.

The generalized pareto distribution (GPD), of which the exponential distribution 3637 is a special case, with Poisson arrival rate has been the most popular model for POT series analysis 3839. This follows from the result shown in 40 that the GPD arises as a limiting form for the distribution of independent exceedances over a high threshold. The cumulative distribution function of GPD is given by

$$F(Q / Q > q_0) = 1 - \left[1 - \frac{k}{\beta}(Q - q_0)\right]^{\frac{1}{k}} \tag{2}$$

where q_0 is the threshold β is a scale parameter and k is a shape parameter.

When k =0, this is reduced to exponential distribution of the form

$$F(q) = 1 - \exp\left[-\frac{1}{\beta}(q - q_0)\right] \tag{3}$$

The inverse form of the GPD is

$$q(F) = q_0 + \frac{\beta}{k}\left[1 - (1 - F)^k\right] \quad ,k \neq 0 \tag{4}$$

$$q(F) = q_0 - \beta \ln[1 - F] \quad ,k = 0 \tag{5}$$

In this study the GPD with Poisson arrival rate is used to model POT series. Flood peaks were extracted at an average rate of three per year (i.e. threshold is implicit) by applying the independence criteria outlined in 4142 using the WETSPRO software developed by the Hydraulics Laboratory of K.U. Leuven in Belgium 4142. The fitting of a GPD to a POT series is carried out using the method of L-moments 4344.

2.5 POT Modelling under Climate Change: Test of GPD and Poisson Process

The suitability of Generalized Pareto Distribution (GPD) can be assessed with the help of L-moment ratio diagrams. The L-moment ratio diagrams are considered as a reliable diagnostic tool for identifying a probability distribution 43. The L-moment ratio diagram is a plot between L-kurtosis and L-skewness. A two-parameter distribution with a location and a scale parameter plots as a single point while a three parameter distribution with location, scale and shape plots as a line or curve on the diagram. Generally the distribution selection process involves plotting the sample L-moment ratios as a scatter plot and comparing them with theoretical L-moment ratio points or curves of candidate distributions 43. The GPD is plotted as a line that corresponds to the varying shape parameters. The Exponential distribution (a 2-parameter distribution) which is a special case of the GPD plots as a single point. The L-moment ratio diagram has been successfully used in regional/pooling flood frequency analysis45 to select a distribution for a region46. In this context, a good number of POT series obtained from different AOGCMs allow the L-moment ratio diagram to be used.

A test of the Poisson process can be conducted on a flow series of peaks exceeding q_0. The simplest Poisson model states that such a series conforms to a Poisson process, the number occurring in any year being a Poisson variate with parameter λ, $p(m\ \ peaks > q_0\ \ in\ \ a\ \ year) = P_m = e^{-\lambda}\lambda^m / m!$ and that the flood peaks are identically, independently distributed (i.i.d) with distribution function $F(Q / Q > q_0)$ 37. The Poisson dispersion test 37 provides a powerful method for testing the adequacy of the fitted Poisson distribution. The test is based on the fact that the Poisson distribution, the mean and variance are equal.

The test statistic (D) is as follows:

$$D = \frac{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2}{\bar{x}} \tag{6}$$

However it is shown in 37 in the context of POT analysis that while the Poisson assumption is a sufficient condition for flood magnitude-return period relationship, it is not a necessary one.

3. CASE STUDY

The methodology described in the previous section is applied to the Upper Thames River Basin (UTRB) in Canada.

3.1 Description of the Watershed

The Upper Thames River basin has an area of 3,842 km^2 located between Lake Huron and Lake Erie in Southwestern Ontario, Canada. Majority of the river basin is covered with agricultural land (80%), with forest cover and urban uses taking about 10% each. London is the major urban centre with a population of around 366,200 inhabitants, many of whom experience the effects of flooding as the Thames River runs directly through the City. The length of the Thames River is 273 km with an average annual discharge of 35.9 m^3/s. The UTRB receives approximately 1,000 mm of annual precipitation; however 60% of this is lost due to evapotranspiration 47. Fig. 2 shows a schematic map of the Upper Thames River basin. Flooding represents one of the major hydrologic hazards in the Upper Thames River basin. Flooding most frequently occurs after snowmelt, typically in early March; it also occurs as a result of summer storms usually taking place in July and August. In 1937, the City of London experienced a massive flooding event which eventually sparked the creation of the Upper Thames River Conservation Authority. Since then, three major water management reservoirs were created, namely Pittock, Wildwood, and Fanshawe 48. Most recently the Thames River has experienced several extreme flood events such as in July 2000, April 2008 and December 2008. Several weather stations are located throughout the basin to provide point measurements of climatic variables. Stations chosen for this study are indicated in Fig. 2.

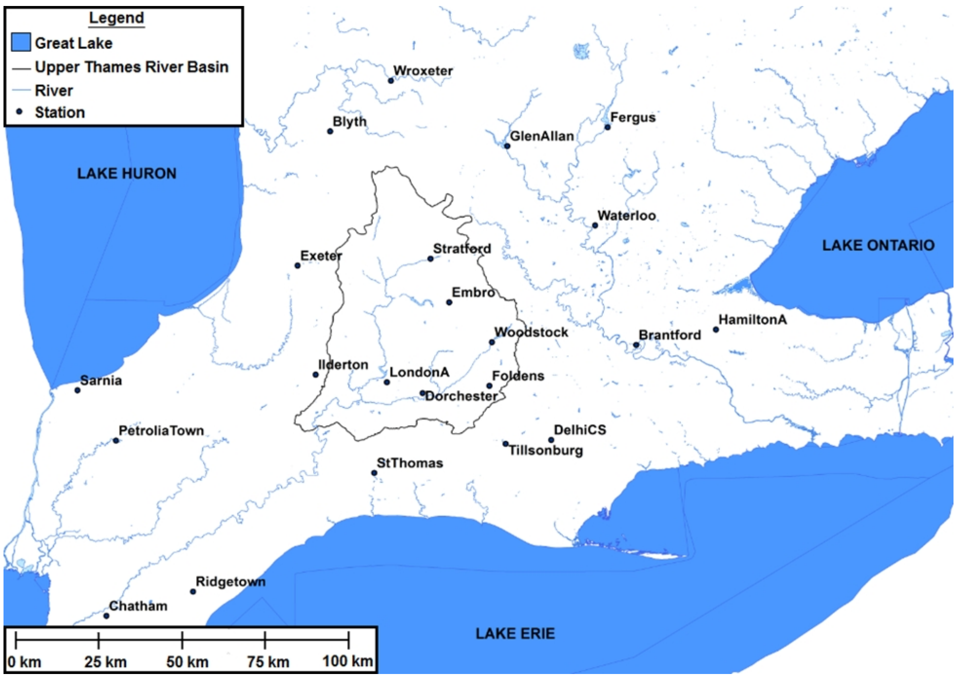

Fig. 2. Map of the upper Thames river basin after census of Canada 49

3.2 Hydrological Model Setup, Calibration and Validation

The hydrologic model used in this study was originally developed and applied to the Upper Thames River in the work by Cunderlik and Simonovic 30,16. The model consists of thirty three sub-basins, twenty one river reaches, and three reservoirs namely Wildwood, Fanshawe and Pittock 47. Each sub-basin is provided with interpolated precipitation and maximum and minimum temperature data. The outputs of each sub basin are flow hydrographs joined by junctions where the flows are added together. River reaches represent the major rivers in the basin connected between two junctions. The routing module (i.e. modified puls) is applied to each river reach, and thus acts as a passage of a flood wave as it moves through the river system. The same routing rules are also applied to the reservoirs. The model was calibrated and verified with extensive sensitivity analyses in the work by Cunderlik and Simonovic 30,16. The model is seasonal in nature with different parameters referring to the summer and winter seasons. The parameter sets for the summer and winter seasons are presented in 30 and 48. In this paper no attempt has been made to recalibrate the model.

3.3 Data Source and Production of POT Series

The following steps are implemented to produce POT series for a stream gauge under climate change. The Byron stream gauge, located in South-East of the Upper Thames River basin, is selected for this study.

1. Daily weather data (precipitation, maximum temperature and minimum temperature) for the period of 1979-2005 was obtained from Environment Canada (http://www.climate.weatheroffice.gc.ca/climateData/canada_e.html) for each of the stations used in this study. Stations were chosen based on the completeness and length of the observed data. The historic daily flow data for the Byron gauging station was obtained from Environment Canada (http://www.wateroffice.ec.gc.ca).
2. Climate data for each of the fifteen AOGCM's scenarios have been collected from the nearest grid points surrounding the Upper Thames River Basin. The Canadian Climate Change Scenarios Network (CCCSN) provides access to those AOGCM models and emissions scenarios. Data have been obtained for four time slices: 1961-1990, 2011-2040, 2041-2050 and 2071-2100. Seven variables were chosen: minimum temperature, maximum temperature, precipitation, specific humidity, northward wind component, southward wind component and mean sea level pressure.
3. Climate variables from the nearest grid points have been interpolated to provide a data set for each of the stations of interest. For the purpose of interpolation the inverse distance weighting method 50 is used.
4. Calculation of change factors for future climate is performed. Using the AOGCM datasets for each station, monthly averages are computed for each variable for both the baseline (1960-1990) and the future time slices (2011-2040, 2041-2070 or 2071-2100). For maximum temperature, minimum temperature, northward wind speed, eastward wind speed and mean sea level pressure, the monthly change factors are computed as the difference between the baseline and the future averages. For precipitation and humidity, the change factors are taken as the percent change between the baseline and the future averages. The change factors have then been used to modify the historic datasets for each station. The historical daily data for humidity and precipitation are multiplied by the monthly change factors. For the rest of the variables, the change factors are added to modify the historical data. This has been done because daily modeled climate data was not available. It is understood that the way historic data was modified, it does not allow for more complex changes in daily extreme climate data.
5. Modified historic data sets, are used as input into the weather generator model (knnCADV3) to produce synthetic data series of precipitation, maximum and minimum temperature for future climate. This study uses data from 22 stations for the period of 1979-2005 (N=27) to simulate data series. Another scenario "baseline" is developed by perturbing historical data. Each case is simulated 25 times to account for inter climate variability.
6. The locations of 22 stations for climate data do not correspond to the locations of the sub-basins. The synthetic data series derived from the weather generator is therefore spatially interpolated in order to be used by the HEC-HMS hydrologic model. The inverse distance weighting method 50 is used for interpolation. The interpolated synthetic data series of precipitation, maximum and minimum air temperature are fed into the calibrated hydrological model to get the simulated flow series.

7. Peaks are extracted from the flow series for the Byron station at an average rate of three per year (i.e. the peak threshold is implicit), using the set of rules outlined in 42. Thus 81 most extreme floods are selected for each of the flow series.

4. RESULTS AND DISCUSSION

This section presents the results of the statistical procedures applied to the POT data series produced for the Byron stream gauging station located in the Upper Thames River basin under changing climate conditions.

4.1 Peak Flows

POT series are obtained for each future time horizon (2020, 2050 and 2080) and for the baseline (1979-2005). A total of 375 POT series (15 AOGCMs x 25 model runs each) are derived for each future climate projection (i.e. 2020, 2050 and 2080). For baseline, 25 POT series are obtained by perturbing historical data 25 times using the weather generator. Fig. 3 shows the Box-plots of peak discharges for each AOGCM for all the time horizons. Baseline is included in each future time horizon for the comparison.

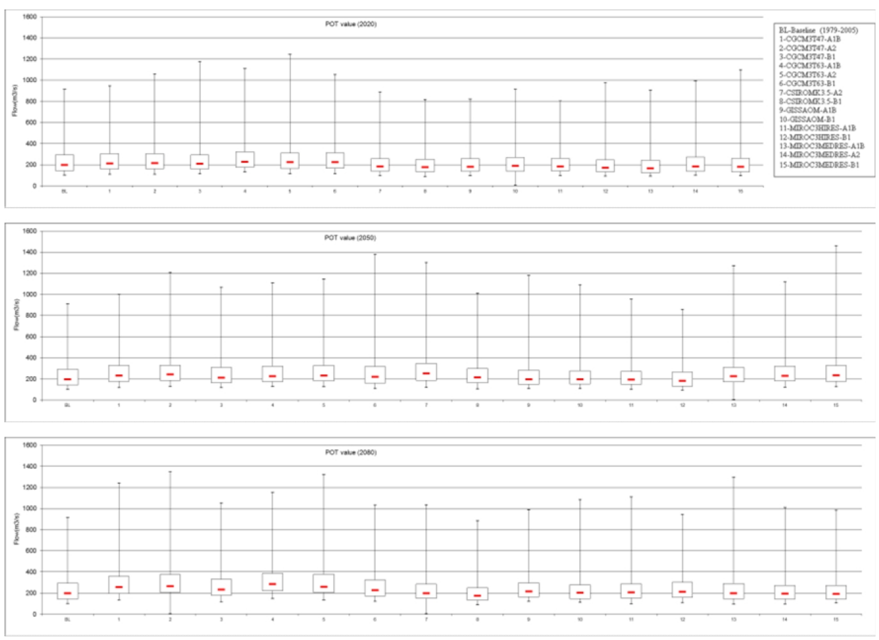

Fig. 3. Box-plots of peak discharges for all AOGCMs considered in this study. Results are for the Byron gauging station in the Upper Thames River basin at the 2020, 2050 and 2080 time horizons. The baseline period (BL) is also included with each future time horizon

By 2020, Canadian climate models (CGCM3T47 and 63) under scenarios A1B, A2, B1, suggest a 7-16% (median) increase in peak discharge, whereas rest of the models propose a 4-16% (median) decrease compared to the baseline period. By 2050, climate models MICROC3HIRES and GISSAOM under scenarios A1B and B1, suggest a 1-8% (median) decrease in peak discharge, whereas rest of the AOGCMs propose an 8-28% (median) increase in peak discharge compared to the baseline period. The largest increase is projected by CSIROMK3.5-A2. By 2080, climate models, MICROC3HIRES under scenarios A1B and B1 and CSIROMK3.5 under scenario B1 propose a 2-11% median decrease, whereas rest of the AOGCMs suggest a 2-44% (median) increase in peak discharge compared to the baseline period. The largest increase at 44% is projected by CGCM3T63-A1B. The maximum discharge is projected by CGCM3T63-A2, MICROC3MEDRES-B1 and CGCM3T47-A2, respectively for the 2020, 2050 and 2080 time horizon. This shows the variability of peaks projected by different climate models under different emission scenarios at different time horizons.

4.2 Evaluation of POT Modelling

The L-moment ratio diagrams (LMR) were constructed for all four time horizons and they are displayed in Fig. 4. The LMR for baseline is constructed with 25 data points, one for each model run. The LMRs for future time horizons are constructed with 375 data points (15 AOGCMs x 25 model runs each). The average of the data points is shown as square. The GPD is shown as a curve whereas the Exponential distribution which is a special case of GPD is shown as a single point (circle). Fig. 4 shows, except for baseline, the peaks follow the GPD distribution very well. The average data point is also very close in those cases to the population L-moments of an exponential distribution. This indicates that the two parameter GPD distribution is also capable of describing the data very well. Therefore either GPD or its special case Exponential distribution can be used to describe peak flow data under climate change.

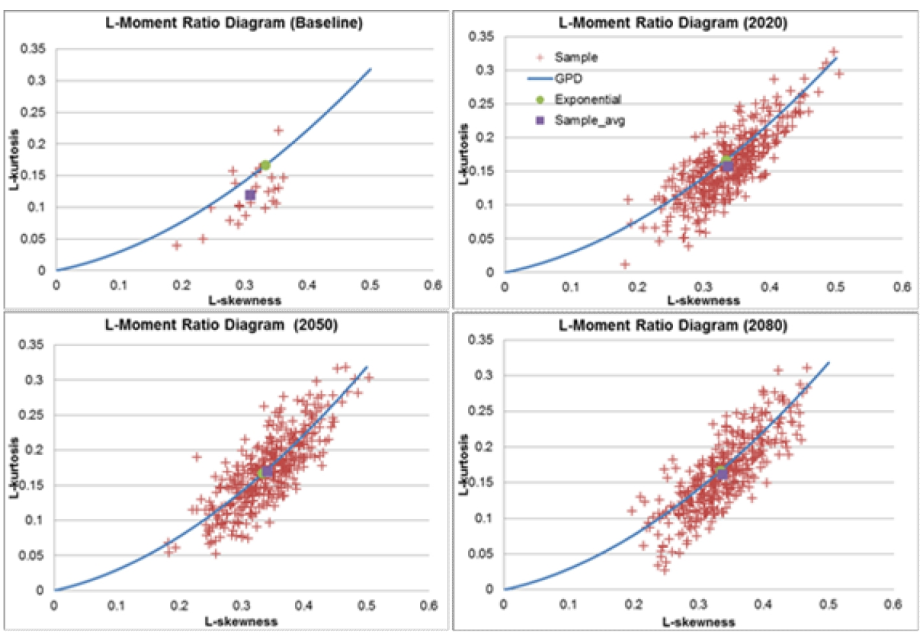

Fig. 4. L-moment ratio diagrams for POT series obtained for all future climate projections, and for the baseline period (BL)

The value of the shape parameter and its precision is important in POT modelling using the GPD. Estimated shape parameter from a data series has a significant amount of uncertainty.

Therefore an evaluation of the parameter for all data sets is needed, and is performed in this section. Fig. 5 displays the boxplots for the shape parameter for all time horizons. This shows how the parameter values vary for each of the data sets in each time horizons. It is suggested that the upper and lower values indicated by the box i.e. containing the middle 50% of values, ought to give a good indication of the range of true values. For baseline period (BL), the range is between -0.09 and 0.1 (median value .05), which indicates most of the cases the distribution is upper-bounded. For the future time horizons (no particular trend was observed among the three horizons) the ranges are between -0.1 and 0.1 with median value zero indicates a decreasing trend compared to BL. Thus overall results show that the future data should be modelled with a non-upper bounded GPD with shape parameter, k = 0.

Dispersion test described in Section 2.5 is used to test the Poisson process. The dispersion index, D, is calculated for POT series obtained for all the future time horizons. The test is evaluated at the 0.05 significance level, which means that it is expected that if the Poisson model is reasonable for the data, it is rejected in about 5% of cases. Table 2 summarizes the % of times out of x datasets (for BL, x = 25; for future climate, x = 375) that Poisson is rejected by the test. The D rejected Poisson about 50% of all cases suggesting that peaks derived in this study follow Poisson distribution in about 50% cases. It can be mentioned here that for obtaining a flood magnitude-return period relationship using a POT series, the Poisson assumption is not a necessary one 37.

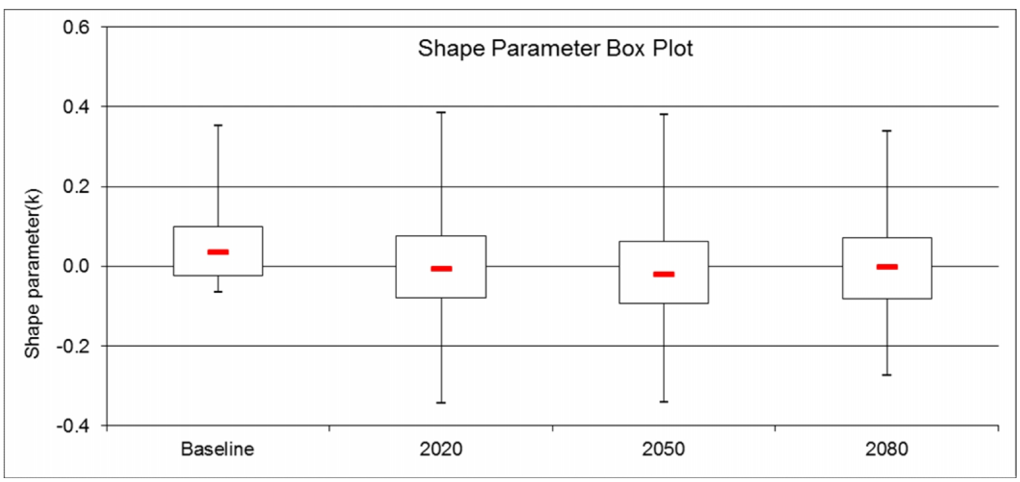

Fig. 5. Box plots of shape parameter of GPD distribution at the four time horizons

Table 2. Percentage of rejections at the 5% significance level for the dispersion test

	Baseline	**2020**	**2050**	**2080**
Poisson	52%	42%	55%	47%

4.3 Flood Magnitude - Return Period Relationship and Uncertainties

POT series derived from different AOGCMs are used to estimate flood magnitude - return period relationships (Q-T curves) for all time horizons. It is hoped that employing a good number of different AOGCM models and scenarios the many variations of climate change encompassing all uncertainties were taken into account, which give a wide variety of results to analyze. The flood frequency curves for all climate model scenarios are produced using the GPD (Generalized Pareto Distribution) model.

Fig. 6 displays the flood frequency results (Q-T curve) for all the time horizons. The flood frequency curve derived from historic data is also shown for information only. The AOGCMs for the highest and the lowest frequency curves at T= 250 are highlighted in the figure. For example, the highest and lowest frequency curves (i.e. upper and lower boundary) for 2020 are obtained from a model run derived from CGCM3T63-A2 and MICRO3MEDRES-A1B, respectively. It is found that the corresponding magnitudes for 100 (250)-year floods are respectively 1175(1626) and 391(478) m^3/s. It is to be mentioned that the corresponding 100 and 250-year floods based on historic data are 955 and 1107 m^3/s, respectively. These indicate how the return values vary with the application of different AOGCMs, due to the assumptions made in each model. It is to be noted that the upper and lower boundary for the future time horizons are provided by different climate models. In terms of emission scenarios, A2 accommodates the upper boundary most often, which is expected. A1B provides the lower boundary in 2 out of 3 cases, while B1 provides the remaining one. That suggests uncertainty linked with climate data should be better-quantified by incorporating climate projections from available GCMs and carefully chosen emission scenarios.

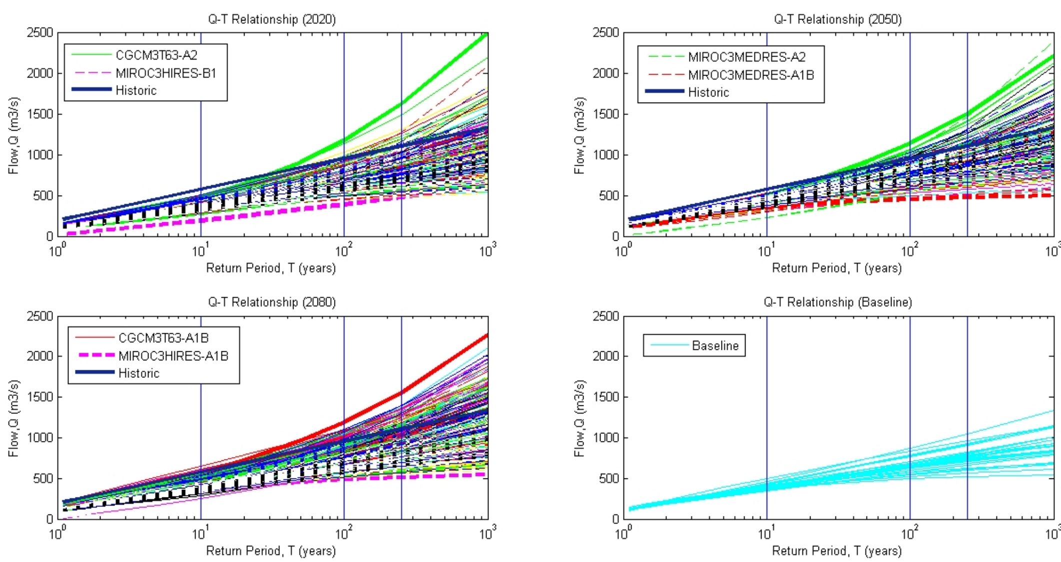

Fig. 6 Simulated flood frequency results for climate data. Each plot relates to different time horizons. Data from 375 scenarios (15 climate model scenarios x 25 model runs each) are used for future climate. Each line with a specific color represents a different AOGCM. The upper and lower bound frequency curves are indicated in the plots. The flood frequency curve derived from historic data is also shown for information only. Data from 25 runs are used to produce a range of results for baseline

The frequency curves for Canadian models (CGCM3T47 and 63) under emission scenarios A1B, A2 and B1 are grouped together to show how Canadian models performed in terms of Q-T relationship. They are displayed in Fig. 7 for the different time horizons. These climate models are of particular interest because the study region is located in Canada. The upper and lower bound frequency curves for the future time horizons are provided by different combinations of Canadian climate models and emission scenarios, suggesting that both these models associated with the above scenarios should be used to better quantify an uncertainty envelope.

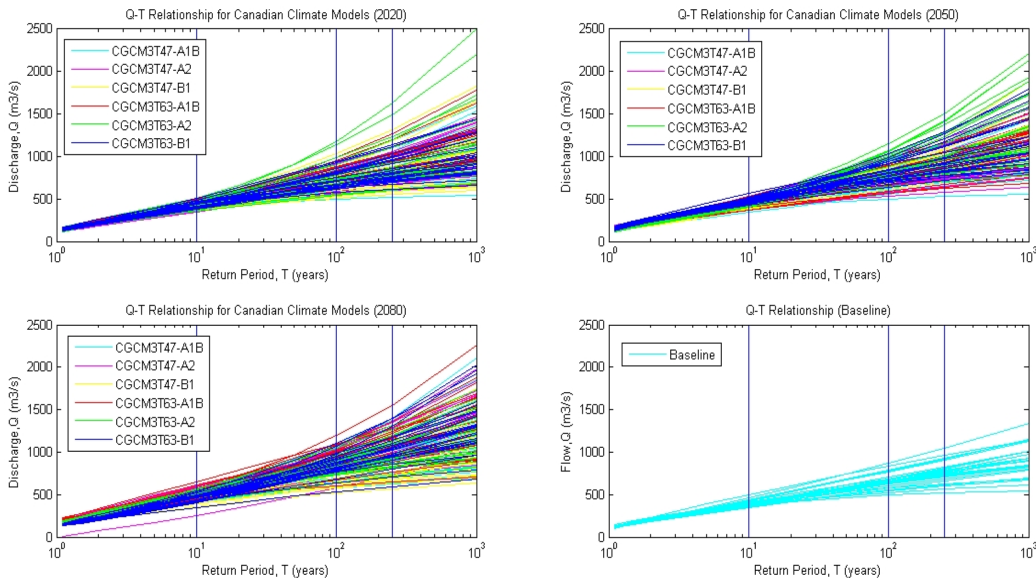

Fig. 7. Simulated flood frequency results for climate data obtained from Canadian climate models. Each plot relates to different time horizons. Data from 150 scenarios (6 Canadian climate model scenarios x 25 model run each) are used for each plot for the future climate. Simulated flood frequency results for climate data at baseline are also shown

A large number of design flow values (15 AOGCMs X 25 model runs each = 375 data series) obtained for different model scenarios for a particular return period can be assumed to be a good representation of flow variability under climate change and these can be used to derive an uncertainty measure. Other than simple normal assumption, non-parametric assumption 51,23 or Bayesian approach 52 can be employed to estimate an uncertainty bound. Non parametric based approach, normal kernel function 53, is used in this study to construct probability density functions (PDF). Fig. 8 shows, for example, the PDFs of 100-year return period flood for each AOGCM at time horizon 2050. The PDFs are constructed for each AOGCM using 25 model runs. The PDFs are different for different AOGCMs. A greater variance is observed for the climate models, CGCM3T63-A2 and MICROC3MEDRES-B1. Probability density plots are also constructed by incorporating data from all the 15 climate projections. They are displayed in Fig. 9 for floods at return periods, T = 10, 100 and 250 at the four time horizons for comparison. The plots show that variability increases with time, as PDFs become wider. With wider PDFs, a greater variance of design floods is noticed. It is found that the average percentage changes of the 100-year flood magnitude between the future climate (2020, 2050 and 2080) and the baseline (1979-2005) are respectively 8, 12 and 12.3%. The corresponding percentage changes for the 250-year flood are respectively 19, 32 and 32.5%. In case of 10-year flood, very little changes have been observed between future and baseline climate projections. The information from Fig. 9, are converted to cumulative distribution functions (CDFs). They are displayed in Fig. 10. The CDFs allow the uncertainty of design flood to be quantified with high level of confidence.

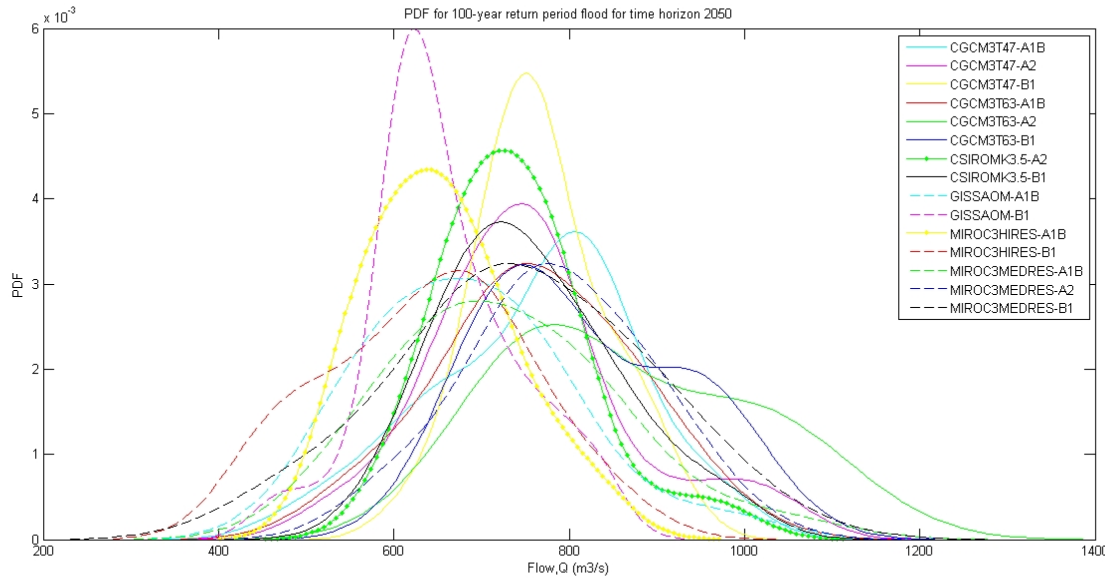

Fig. 8 Probability density functions (PDFs) of 100-year return period flood for all AOGCMs at the time horizon 2050. Each PDF is constructed using 25 model runs.

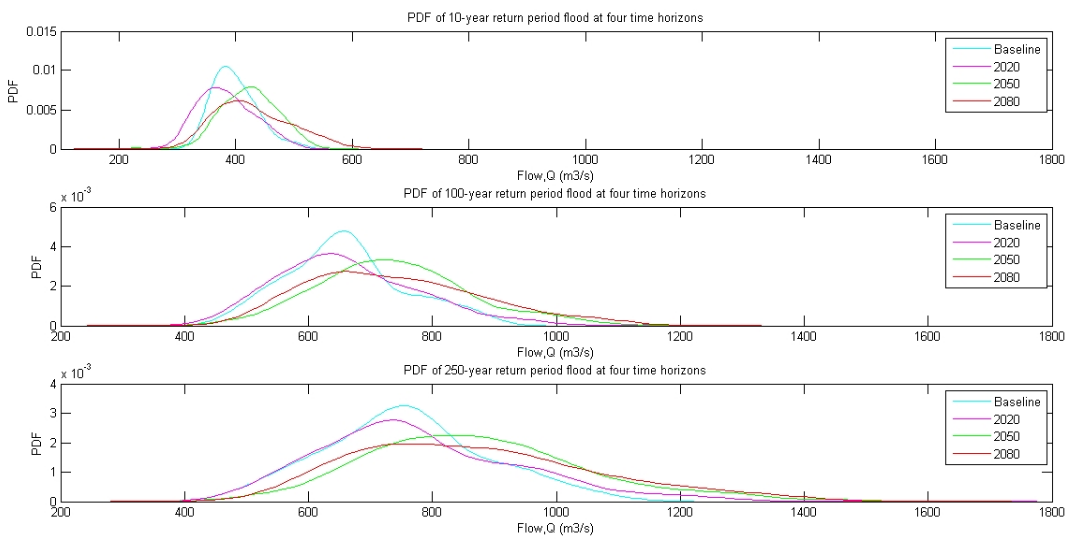

Fig. 9 Probability density plots for flood magnitudes at return period, T = 10, 100 and 250 at the four time horizons

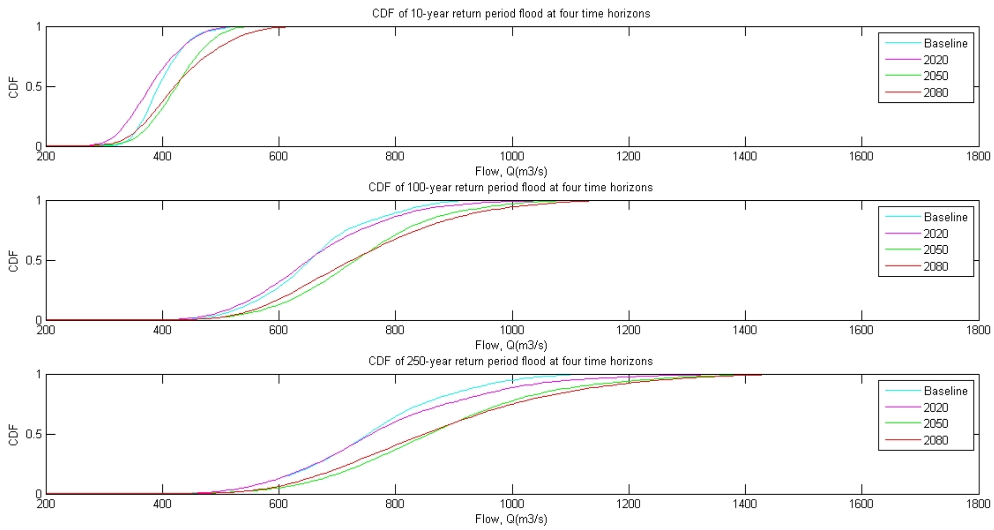

Fig. 10. Cumulative distribution functions for flood magnitudes at return period, T = 10, 100 at the four time horizons

From the results of flood magnitude – return period relationship (Q-T) it can be said that there is significant variation between climate model scenarios and this variation contributes more when an effort is carried out to predict floods for a far distant future. Hence, climate change impact studies based on only one AOGCM and/or emission scenario should be considered with a great care. The use of two carefully chosen climate projections (dry and wet projections, for example) may be more appropriate than using single model and this has been done in several recent climate change impact studies 47.

4.4 Limitations of the Assessment Procedure

One of the limitations to the approach presented in this paper is linked to hydrologic model calibration. In this research no attempt has been made to recalibrate the model. The approach implicitly assumes that the calibration is equally acceptable for the baseline and the future conditions. Therefore the average % changes of return flood values between future climate and baseline period indicated above should be used as a guideline for engineering practice.

Another limitation is in the way weather generator generates the data series. The input AOGCM data for the weather generator only varies from the historical dataset in terms of the mean, maximum and minimum values; the variance remains the same. That does not allow for more complex changes in daily extreme climate data for the future. The technique of perturbation has been applied to overcome the limitations i.e. to enhance generation of extreme precipitation values to some extent. However a methodology is needed for creating AOGCM modified input datasets for KnnCAD weather generator from the daily AOGCM outputs that takes into account changes in both, the mean and variance in the precipitation. The Interpolation procedure (IDW, in this study) is also one more source of uncertainty. These could affect the results and might lead to an underestimation of changes in future flood frequency. For incorporating inter climate variability of a climate model, 25 model runs are performed in this study. A greater number of model runs should provide a better variability incorporated by a climate model.

5. CONCLUSIONS

This study employs a multi-model, multi-scenario approach to produce flood magnitude - return period relationships of future extreme flood flows. A use of wide range of climate model scenarios allows investigating the climate change related uncertainty in the design flood flows for the Upper Thames River basin (Ontario, Canada). Fifteen different climate model scenarios from a combination of six Atmosphere-Ocean Global Climate Models (AOGCMs) and three emission scenarios “A1B”, “B1” and “A2” are used to determine an uncertainty envelope. To account for the natural variability of the hydro-climatic system, a KNN based weather generator was employed to generate sequences of precipitation and air temperatures (minimum and maximum) in daily basis. A total of 375 (15 AOGCMs X 25 model runs) climate scenarios were produced for the future time horizons centred on 2020, 2050 and 2080, and 25 for baseline period (1979-2005). A continuous daily hydrologic model, calibrated for the basin, was then used to generate daily flow series for the baseline period and for the future time horizons. A peak-over-threshold (POT) modeling approach with Generalized Pareto Distribution is used to produce flood frequency curves for the four time horizons. The uncertainty involved with the POT modelling was also considered in this study. Major findings of the study are summarized below:

1. Analyses of the GPD shape parameter for different datasets confirm that the POT modelling with GPD using $k = 0$ (i.e. Exponential distribution) should be used for flood frequency analysis at the Byron gauging station in the Upper Thames River basin.
2. A large uncertainty exists in all the projected future design floods. The application of a wide range of climate models and scenarios allows performing probabilistic approach to better outline the uncertainty linked with climate data. The probabilistic approach also provides estimate of flood frequency curve with high level of confidence.
3. Based on the study results, it is rational to believe that the hydrologic behaviour of the Upper Thames River basin would be changed over the next century. While it is impossible to predict the future floods accurately, the recommendation of this study is to include the uncertainty associated with future design floods into engineering and management practices. Based on the comparison made with the baseline period it is recommended, for engineering practice that design extreme floods established from observed data should be increased for at least 30% to account for climate change.

ACKNOWLEDGEMENTS

The authors would like to acknowledge the financial support made available by the Canadian Foundation for Climate and Atmospheric Sciences. Comments and suggestions from two reviewers, Dingbao Wang and one anonymous reviewer are gratefully acknowledged.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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