Statistical rainfall downscaling of a CMIP5 ensemble in urban catchments: An Auckland area case study

Akhter Muhammad Saleem[1], Shamseldin Asaad Yahia[1] and Melville Bruce William[1]

[1] Department of Civil and Environmental Engineering, University of Auckland, New Zealand.
Corresponding author's E-mail: amuh139@aucklanduni.ac.nz

Abstract

As a result of rapid urbanization, installation of complex infrastructure and variations in rainfall, anthropogenic climate change is making cities increasingly vulnerable to flooding. Downscaling of climate change results from Global Circulation Models (GCM) to urban catchment scales are needed because these models are not able to describe accurately the rainfall process at the required high temporal and spatial resolution for urban drainage studies. In the present study, the applicability of a statistical downscaling model (SDSM) is evaluated in downscaling the rainfall. The Coupled Model Intercomparison Project phase 5 (CMIP5) ensemble forced by three Representative Concentration Pathways (RCPs) (i.e. RCP 2.6, RCP 4.5 and RCP 8.5) scenarios is adapted. The daily rainfall data of a small urban catchment Lucas Creek located in Auckland, New Zealand, covering the period 1985 to 2015 is used as baseline data for calibration and validation of SDSM. While future downscaled rainfall data is analysed in three time slices 2030s (2011-2040), 2060s (2041-2070) and 2090s (2071-2100). SDSM performed well during calibration and validation. The mean daily rainfall showed a trend of insignificant changes in 2030s; excess rainfall in the 2060s; and a deficit of rainfall in the 2090s under all the three scenarios. The mean monthly, seasonal and annual daily rainfall increased in the catchment under all the scenarios. Rainfall frequency analysis was performed by fitting the Gumbel distribution to the observed and SDSM downscaled rainfall time series. The frequency analysis was performed for 2, 3, 4, 5, 10, 15, 20, 30, 50 and 100 year return periods which indicated increasing rainfall trends in the future generated time slices. The current results illustrate that SDSM have good ability to simulate the rainfall events at the urban catchment scale and, therefore, can be adopted with confidence for climate change impact studies of similar nature.

***Keywords*: Climate change, Global Climate Models (GCM), Statistical downscaling, Statistical Downscaling Model (SDSM), urban catchments, rainfall.**

1. INTRODUCTION

A rise in the Earth's temperature and variations in the associated weather conditions across the globe are termed as climate change. Climate change is likely to affect major sectors of the world and increase disaster risks. Disaster risks are increased in two ways. Firstly, the frequency and/or severity of weather and climate hazards will likely be increased (IPCC 2007). Secondly, communities' vulnerability to natural hazards will simultaneously be increased as a result of the ecosystem degradation, reduced availability of resources, and changes in peoples' livelihoods (Molavi, Muttil et al. 2011). In urban catchments, anthropogenic effects, like transforming the natural drainage to fast collecting facilities, have increased the risk of flash flooding. The duration and volume of runoff are changed by the pattern of drainage systems, permeability and the capacity of recharging (Karamouz, Hosseinpour et al. 2010, Willems, Arnbjerg-Nielsen et al. 2012). Urbanization leads to more impervious areas, and therefore, decreasing time of runoff concentration and increasing the maximum flood discharge. The change in rainfall behaviour and intensity because of climate change will exaggerate the flooding risks in urban catchments (Willems et al. 2012). Therefore, it is necessary to investigate the impacts of climate change on the rainfall patterns in urban areas so that proper planning and management can be done in advance for minimizing the flood risks.

At present, Global Climate Models (GCMs) are considered to be the most reliable tool to provide climate change information (IPCC 2007). However, GCMs have spatial resolutions too coarse for hydrologic impact models and downscaling is usually employed to obtain the desired information in terms of hydrometeorology variables (temperature, rainfall etc.) at a very fine spatial resolution or station scale (IPCC 2013, Xu 1999a). Statistical and dynamical downscaling are the two major existing techniques for downscaling. The former, used by hydrologists to obtain station scale climatic information, employs multiple regression models and stochastic weather generators. It is computationally less demanding, simple to apply, and efficient (Dibike and Coulibaly 2005, Hashmi et al. 2009, Wilby and Dawson 2007, Willems et al. 2012). While the later, involves Regional Climate Models (RCMs) which can use initial and boundary conditions from the output of GCMs for selected time periods of the global simulation. An extensive detail about these techniques as well as their benefits and shortcomings can be found in Xu (1999b) Wilby et al. (2004), Fowler et al. (2007) and Rummukainen (2010).

In the Fifth Assessment Report (AR 5) of the Intergovernmental Panel on Climate Change (IPCC), new climate change scenarios called RCPs were established based on the CMIP5 (IPCC 2013). These RCPs are termed as RCP 2.6, RCP 4.5, RCP 6 and RCP 8.5. RCP 2.6 is the lowest of the four, peaks at 3.0 W/m^2 (~490 ppm CO_2 eq.) before 2100 and then declines to 2.6 W/m^2 by 2100 (Van Vuuren et al. 2011). RCP 4.5 gains stabilization without overshoot pathway to 4.2 W/m^2 (~650 ppm CO_2 eq.) at stabilization after 2100 (Thomson et al. 2011). Similarly, RCP 6 gets stabilization without overshoot pathway to 6 W/m^2 (~850 ppm CO_2 eq.) at stabilization after 2100 (Masui et al. 2011). The rising radiative forcing pathway in RCP 8.5 leads to 8.5 W/m^2 (~1370 ppm CO_2 eq.) by 2100 (Riahi et al. 2011). Extensive details about RCP 2.6, RCP 4.5, RCP 6 and RCP 8.5 can be find in Van Vuuren et al. (2011), Thomson et al. (2011), Masui et al. (2011) and Riahi et al. (2011), respectively. The CanESM2 (Second Generation Canadian Earth System Model) simulates the climate data under CMIP 5 for RCP 2.6, RCP 4.5 and RCP 8.5. However, the spatial resolution of CanESM2 is too coarse to be compatible with hydrological models, the downscaling method can be utilized to bridge these two different scales (Chylek et al. 2011, Zhang et al. 2016).

Among the statistical downscaling techniques, SDSM is commonly used (Wilby and Dawson 2007, Wilby et al. 2002). SDSM is a hybrid of a stochastic weather generator and regression based downscaling methods. It is the first tool of its nature available to the wider climate change impacts community (Wilby et al. 2002), and had been coded into software that is freely accessible. The large scale circulation patterns and atmospheric moisture variables are used to linearly condition local scale weather generator parameters (e.g. rainfall occurrence and intensity) (Wilby et al. 1998). Several studies have documented the use of SDSM and have revealed that this model is simple to handle and operate (Borges et al. 2017, Hassan et al. 2014, Khan et al. 2006, Wilby et al. 2002, Wilby et al. 1998). However, little is known about the applicability of SDSM in urban catchments.

The primary objectives of this study are: (1) to investigate the adaptability of SDSM for downscaling rainfall in a small urban catchment, such as the Lucas Creek catchment in the Auckland area; (2) to generate local rainfall scenarios in the Lucas Creek catchment under future emission scenarios and project a comprehensive temporal characteristic of rainfall; (3) to perform frequency analysis to the extreme events. After the screening of appropriate predictors from CanESM2 GCM under RCP scenarios, calibration and validation of the SDSM is performed. The characteristics of rainfall as projected for future scenarios are discussed at daily, monthly, seasonal and annual temporal scales using different indices. This is followed by frequency analysis to investigate the behaviour of extreme rainfall events. The findings presented here may provide a scientific reference for decision making regarding small urban catchment scale flood control and water resources management in the Lucas Creek or any other region that share similar climatic characteristics.

2. STUDY AREA AND DATA

The Lucas Creek catchment located on the northern fringe of Auckland was selected as the case. The catchment map is shown in Figure 1. The catchment covers an area of 626.35 ha. Since 1980's, the catchment has undergone significant urban development and more than 75% of the catchment area is urbanized. The existence of Water Sensitive Design (WSD) infrastructure favoured the choice of this catchment as the location for the study which will be further investigated for climate change impacts on WSD infrastructure. Auckland Council (AC) has installed a number of meteorological station in the surroundings to measure rainfall and storm water quantity and quality. Daily rainfall data of last 30 years (1985-2015) were obtained from AC at the nearest rainfall station. The weather station under concern, called Oteha at Rosedale Pond, is located at latitude -36.74759, longitude 174.71563. The mean annual rainfall in the catchment is between 1104 mm to 1155 mm. The re-analysis data of the National Centre of Environmental Prediction (NCEP) large scale predictors ranging from 1948-2015 were obtained from SDSM website maintained by Wilby (2015) for the Auckland region. Similarly large scale predictors of CanESM2 for the AR5 were downloaded from the website of Government of Canada (Canada 2017) at daily time step. Three CanESM2 outputs of CMIP5 under RCP 2.6 (low forcing scenario), RCP 4.5 (medium stabilization scenario, and RCP 8.5 (high emission scenario) were utilized to project future climate scenarios. The large scale predictor's data of CanESM2 range from 1961-2005 for current climate and from 2006-2100 for future climate. The period 1985-2005 was used to represent the current period and called "baseline" for the future scenarios (Wilby and Dawson 2015). The future time series were divided into three slices 2030s (2011-2040), 2060s (2041-2070) and 2090s (2071-2100). The selection of the future time slices allows assessment of the climate change impact on rainfall in a distant future within the catchment.

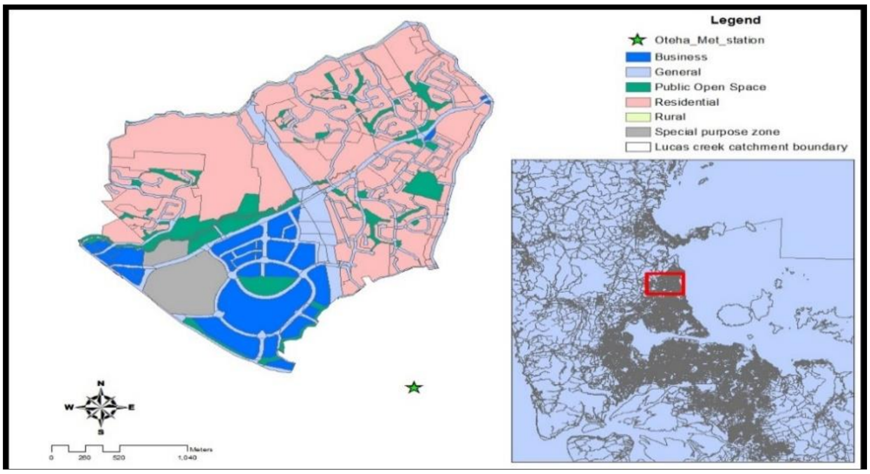

Figure 1. Location of study area (Lucas Creek) catchment and major land use descriptions

3. METHODOLOGY

SDSM was developed by Wilby et al. (2002) in United Kingdom. It is categorized as a hybrid model, utilizing a linear regression method and a stochastic weather generator. The GCM's outputs are used to a linearly conditional or non-conditional process of the local scale weather generator parameters at single stations. Rainfall is a conditional process, and it is modelled using a stochastic weather generator conditioned on the predictor variables. Five discrete processes performed in the software are: (1) screening of predictors; (2) model calibration; (3) synthesis of observed data; (4) generation of climate change scenarios; (5) diagnostic testing and statistical analysis (Wilby et al. 2002). In the present study, version 4.2 of SDSM was used and a schematic diagram of statistical downscaling was established to investigate climate change influence on the rainfall patterns (Figure 2).

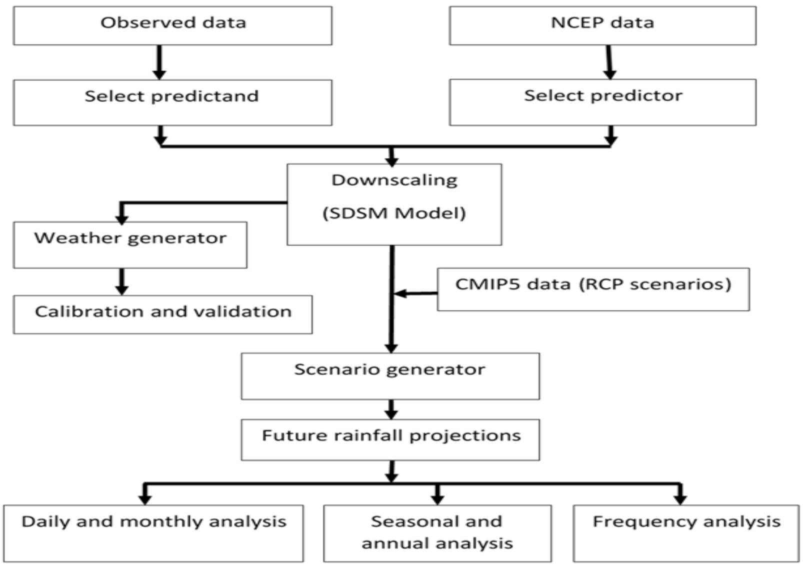

Figure 2. Schematic illustration of the present study

A transformation of the fourth root was applied, to take account for the skewed nature of the rainfall distribution. During the calibration of SDSM, some parameters such as event threshold and bias correction were adjusted in order to obtain the best statistical agreement between observed and simulated climate variables (Chen et al. 2012, Wilby and Dawson 2007).

3.1 Predictor selection

Twenty six different atmospheric variables were used, and these were derived from the daily re-analysis dataset of the NCEP for 1948–2015, as well as outputs of RCP 2.6, RCP 4.5 and RCP 8.5 scenarios of CanESM2 from 2006 to 2100. All the atmospheric data was normalised (Hassan et al. 2014) as given by equation 1;

$$\hat{u}_t = \frac{u_t - \bar{u}}{\sigma_u} \tag{1}$$

In which $\hat{u}_t$ is the normalized atmospheric variable at time t, u_t is the original data at time t, $\bar{u}$ is the multiyear average during the period, and σ_u is the standard deviation.
Predictor selection was based on physically and conceptually reasonable linkages between large scale forcing and local climate response. Explained variance and correlation coefficients statistically support the selection of predictors (Huang et al. 2011, Wilby et al. 2002). To obtain the highest coefficient of determination and the lowest standard error, the best set of predictors was defined according to the partial correlation at a confidence level of 95% with the predictand ($p<0.05$) (Wilby et al. 2002).

3.2 Calibration and validation of SDSM

The rainfall data of the Lucas Creek and the NCEP predictors for the period 1985-2015 were split into two slices: 1985-2005 and 2006-2015. The first slice (1985-2005) was set for model calibration, while the second slice (2006-2015) was used for model validation (as an independent set of data). SDSM was calibrated for each month of the year using the same set of seven selected NCEP predictors for the calibration period. This model calibration strategy is in line with the one explained in Dibike and Coulibaly (2005) and Hashmi et al. (2009). Model validation is performed by testing it on the validation (i.e. independent) data set (2006-2015).
The model calibration and validation was evaluated in terms of coefficient of determination (R^2), root mean square error (RMSE) and percentage bias (PBIAS) as in equations 2, 3 and 4:

$$R^2 = \frac{\sum_{i=1}^{n}(X_{obs,i}-\bar{X}_{obs})(X_{sim,i}-\bar{X}_{sim})}{\sqrt{\sum_{i=1}^{n}(X_{obs,i}-\bar{X}_{obs})^2 \sum_{i=1}^{n}(X_{sim,i}-\bar{X}_{sim})^2}} \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i}-X_{sim,i})^2}{n}} \quad (3)$$

$$PBIAS = \frac{\sum_{i=1}^{n}(X_{obs,i}-X_{sim,i})}{\sum_{i=1}^{n}(X_{obs,i})} X100 \quad (4)$$

where n is the number of time steps; $X_{obs,i}$ and $X_{sim,i}$ are the obse

rved and simulated values at time step i respectively.
In addition to the above three indices, the downscaled rainfall series was analysed in terms of mean monthly daily rainfall and standard deviation in the comparison of observed and simulated data.

3.3 Downscaling future rainfall

In this study, the period of 1985-2005 was taken as baseline, and the future period was divided into 2030s (2011–2040), 2060s (2041–2070) and 2090s (2071–2100). The patterns of change about future rainfall scenarios compared to baseline were then analysed, using RCP 2.6, RCP 4.5 and RCP 8.5 data. Taking the simulation results of SDSM in the modelling rainfall into account, the change of daily, monthly, seasonal and annual mean rainfall of Lucas Creek would be analysed.
Additionally, frequency analysis was performed to investigate the variation in extreme rainfall behaviour using annual maximum (AM) data. Frequency analysis helps us to obtain return period of the events. Different generated scenarios using predictors from NCEP and CanESM2 had been used for this purpose. Frequency analysis can show the effects of future greenhouse gases development on the variability of the events quantity. In this research, Extreme Value type I, the Gumbel distribution was fitted to AM data. According to Wilby and Dawson (2007), the Gumbel distribution to the data using the AM series in SDSM is given as below after the method of Shaw (1994) given in equation 5:

$$F(x) = 1 - e^{-e^{-(x-\mu)/\sigma}} \quad (5)$$

Where μ is mean and σ is standard deviation. Thus, the annual maximum for a return period of T-years can be calculated from equation 6 and 7:

$$Q_T = \bar{Q} + K(T)S_Q \quad (6)$$

$$K(T) = -\frac{\sqrt{6}}{\pi}\left(\gamma + \ln\ln\left[\frac{T(X)}{T(X)-1}\right]\right) \quad (7)$$

In which $\bar{Q}$ is the mean of the annual maximums, S_Q is the standard deviation of these maximums, $K(T)$ is a frequency factor, $T(X)$ is the return period in years, and γ is the Euler constant (0.577215655).

4. RESULTS AND DISCUSSIONS

4.1 Predictor selection

Initially, the correlation analysis performed within SDSM between the rainfall of the Lucas Creek and the NCEP re-analysis predictors revealed very poor results. Consequently, offline statistical analysis was undertaken to improve the results to an acceptable limit. In this regard, a cross-correlation analysis between the daily rainfall of the Lucas Creek and the NCEP predictors was performed. An optimal lag or time shift, required to improve the correlation between each predictor–predictand pair, was identified. All the predictors were lagged one day (lag -1). The absolute correlation coefficient values of results after this analysis are shown in Figure 3. Examination of the Figure shows that the correlation coefficient values obtained are well within the acceptable limit as indicated in previous studies (Borges et al. 2017, Hashmi et al. 2011a, Hassan et al. 2014). In general, the correlation between the predictor variables and each predictand is not high in the case of daily rainfall (Wilby and Dawson 2007, Wilby et al. 2002). Screening of the most relevant predictors' set was performed in SDSM on the basis of correlation, explained variance and p-value among the predictand and the individual predictors, and a set of seven predictors was chosen. This is shown in bold text in Table 1. The seven chosen predictors were used for calibration of the downscaling model. This predictor selection process is consistent with that adopted in similar studies (Dibike and Coulibaly 2005, Hashmi et al. 2011a, Huang et al. 2011).

Table 1. Name and description of all NCEP predictors on CanESM2 grid (the one in bold text is selected in model calibration)

Pr#	Variable	Description	Pr#	Variable	Description
1	**ncepmsl**	**Mean sea level pressure**	14	ncepp8-f	Geostrophic airflow velocity at 850 hPa
2	ncepp1-f	Geostrophic airflow velocity near the surface	15	ncepp8-u	Zonal velocity component at 850 hPa
3	ncepp1-u	Zonal velocity component near the surface	16	ncepp8-v	Meridional velocity component at 850 hPa
4	ncepp1-v	Meridional velocity component near the surface	17	**ncepp8-z**	**Vorticity at 850 hPa**
5	**ncepp1-z**	**Vorticity near the surface**	18	ncepp8th	Wind direction at 850 hPa
6	ncepp1th	Wind direction near the surface	19	ncepp8zh	Divergence at 850 hPa
7	ncepp1zh	Divergence near the surface	20	ncepp500	500 hPa geopotential height
8	ncepp5-f	Geostrophic airflow velocity at 500 hPa	21	**ncepp850**	**850 hPa geopotential height**
9	ncepp5-u	Zonal velocity component at 500 hPa	22	**nceprcp**	**Precipitation total**
10	ncepp5-v	Meridional velocity component at 500 hPa	23	nceps500	Specific humidity at 500 hPa height
11	ncepp5-z	Vorticity at 500 hPa	24	**nceps850**	**Specific humidity at 850 hPa height**
12	ncepp5th	Wind direction at 500 hPa	25	ncepshum	Near surface specific humidity
13	**ncepp5zh**	**Divergence at 500 hPa**	26	nceptem	Mean temperature at 2m

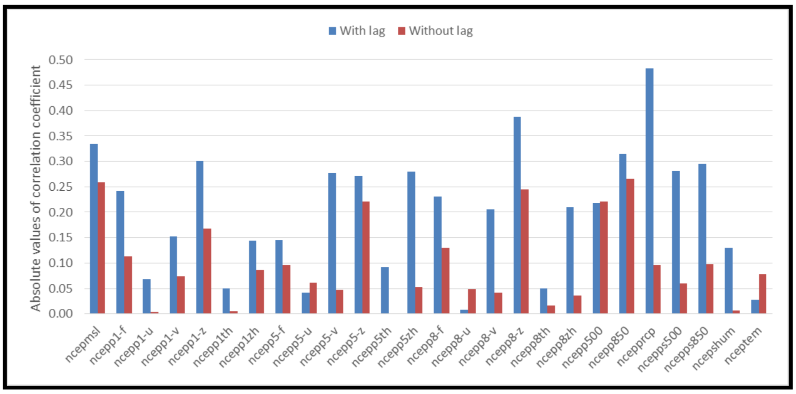

Figure 3. Absolute values of correlation coefficient between the Lucas Creek rainfall and NCEP predictors with and without lag

4.2 SDSM performance during calibration and validation

A comparison of the observed and the simulated daily rainfall values during calibration are shown in Figure 4. The results for the calibration period showed that there is a difference in the observed and simulated daily rainfall (Figure 4 (a)). SDSM simulated the daily rainfall series from NCEP with the R^2, RMSE and PBIAS values being 0.2863, 6.85 mm/day and -1.20 respectively. This lower R^2 value indicated that, SDSM underperformed by missing some of the daily extreme rainfall events which is comparable with literature which observed even lower values of R^2 (Fealy and Sweeney 2007, Khan et al. 2006, Pervez and Henebry 2014). Additionally, Figure 4(b) shows comparisons of the observed and the simulated monthly mean daily rainfall and its standard deviation. Examination of Figure 4(b) shows that the calibrated model reproduced the monthly mean daily rainfall values quite well. It slightly underestimated the mean daily rainfall for the months of January and December and almost equally overestimated it in the months of June, August, September, October and November. Wilby et al. (2004) noted that the ability of downscaling models is often regarded as low to simulate the standard deviation (or variance) of the observed rainfall with great accuracy. Nevertheless, as it can be seen in Figure 4(b), SDSM model reproduced the observed standard deviation reasonably well for the Lucas Creek catchment. Standard deviation of only four months of the year (January, February, April and May), simulated by SDSM was below that of the observed data. For the remaining eight months, the simulated and the observed standard deviations are in good agreement with each other.

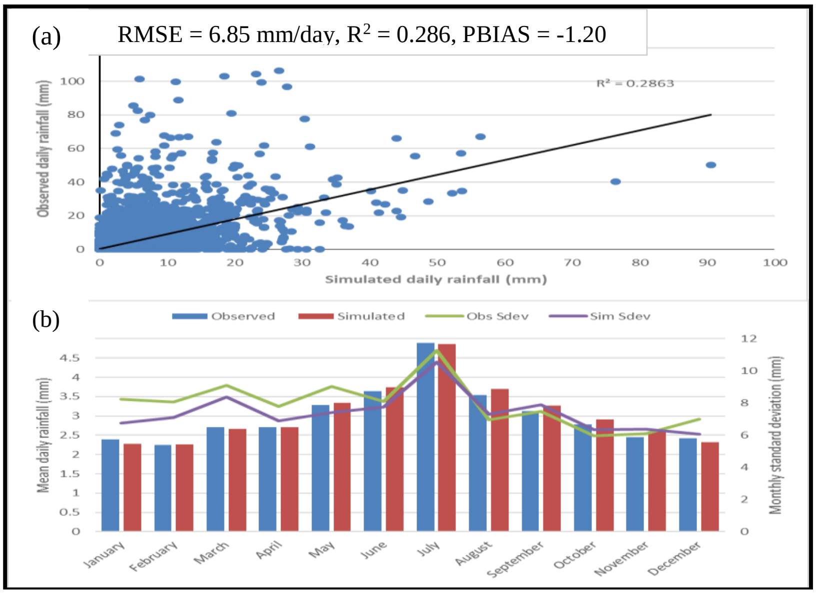

Figure 4. SDSM performance during calibration period (1985-2005): (a); evaluation on daily basis (b); evaluation on monthly basis

Similarly, a comparison of the observed and the simulated daily rainfall during validation are shown in Figure 5. SDSM simulated the daily rainfall series with R^2, RMSE and PBIAS values being 0.319, 6.36 mm/day and 3.86, respectively (Figure 5 (a)). Monthly mean daily rainfall and its standard deviation are shown in Figure 5 (b). The mean daily rainfall was slightly underestimated for the months of May, June and December and almost equally overestimated it in the months of January, April and July. Nevertheless, the standard deviation of four months of the year (January, February, April and May), simulated by SDSM was higher that of the observed data. SDSM is a regression-based model, and a regression-based method can often explain only a fraction of the observed variability in the provided calibration dataset (Nasseri et al. 2013). Therefore, simulating extreme rainfall events using regression methods is challenging because extreme events tend to lie at the margins or beyond the range of the variability captured by the regression models (Wilby et al. 2002).

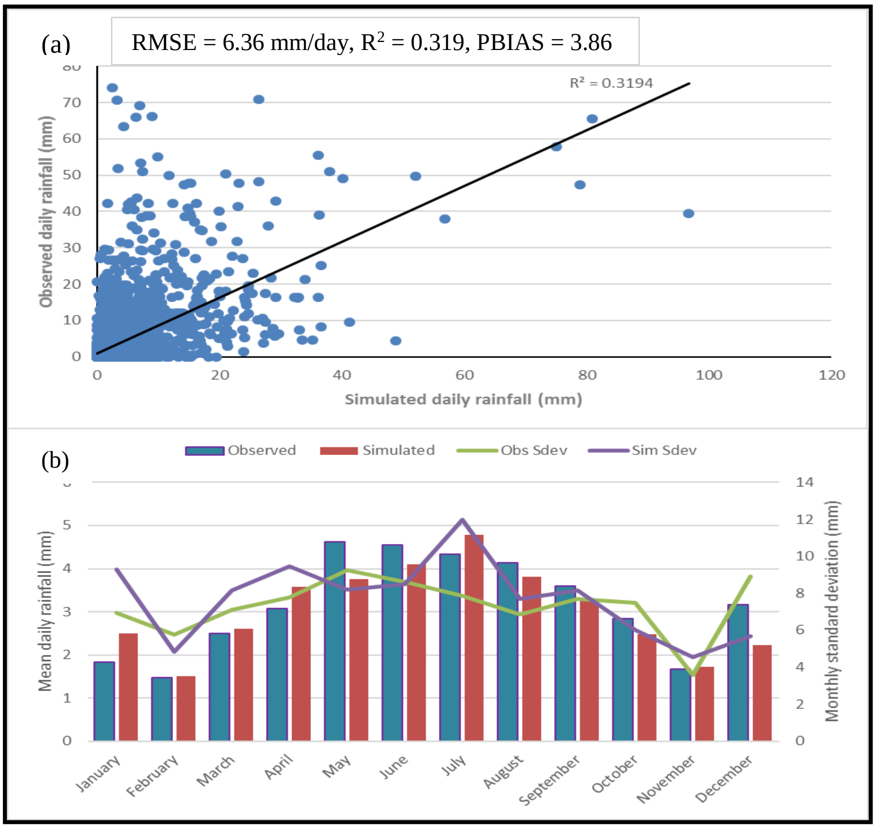

Figure 5. SDSM performance during validation period (2006-2015): (a); evaluation on daily basis (b); evaluation on monthly basis

4.3 Downscaling rainfall under future emission scenarios

The calibrated SDSM model was used for future scenario generation. The future scenario generation used predictors from CanESM2 for RCP 2.6, RCP 4.5 and RCP 8.5 emission scenarios for the period of 2006-2100. The average of twenty ensembles of generated scenarios was compared with the baseline. The anomaly was obtained from the absolute difference between the average future periods from the baseline monthly average. The positive or negative anomaly indicated that there will be increase or decrease of the variable in future time periods, respectively.

4.4 Statistics of future monthly mean daily rainfall

The projected change of daily rainfall pattern for the Lucas Creek for all the three RCP scenarios under 2030s, 2060s and 2090s are shown in Figure 6. The model projected an increase in mean daily rainfall in the 2030s, 2060s and 2090s under all the three RCP scenarios. As for RCP 2.6 scenario, the change in mean daily rainfall in all the three time slices would not be significant. While under RCP 4.5 and RCP 8.5 an increasing trend would be noticed in 2060s and 2090s, respectively. Although the 2060s experienced the highest increase under RCP 2.6 while 2090s under RCP 4.5 and RCP 8.5. The increments are ranging from 0.18 to 3.30 mm/day during 2060s under RCP 2.6 and 0.07 to 3.34 mm/day and 0.38 to 4.04 mm/day during 2090s under RCP 4.5 and RCP 8.5, respectively. The difference between 1st and 3rd quartiles, and median would be decreasing with the shift from RCP 2.6 to RCP 4.5 and finally to RCP 8.5 indicating obvious variations in the daily rainfall.
The best way of evaluating the characteristics of change in rainfall pattern is the monthly statistics. Although the mean daily rainfall for these three time slices will increase compared to the baseline period, this increment would be different in different months. While some months would have increased rainfall and others would experience decline in rainfall (Figure 7 and 8). An increasing

pattern is observed from January to May. The maximum positive monthly anomalies are in March, April and May in 2060s, March, April and May in 2090s and January and March in 2090s under RCP 2.6, RCP 4.5 and RCP 8.5 respectively. In contrast, there will be a steady decline in rainfall during all the three time slices under all the three RCP scenarios from July to October. The maximum negative anomaly in rainfall is 1.068 mm/day in 2030s under RCP 2.6, 1.18 mm/day in 2030s under RCP 4.5 and 1.28 mm/day in 2060s under RCP 8.5. Furthermore, it is important to note that June and August would not observe any significant change in rainfall under RCP 2.6 and RCP 4.5 for all the three time slices.

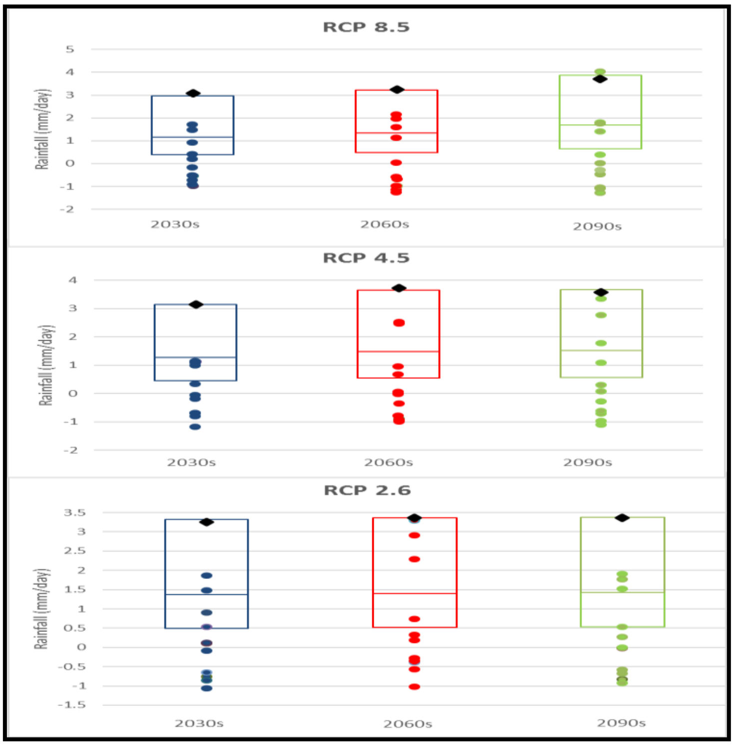

Figure 6. Boxplot showing summarized representation of change in rainfall (compared to base period) in 2030s, 2060s, and 2090s under scenarios RCP 2.6, RCP 4.5 and RCP 8.5. The lower and the upper boundary of the box indicate 1st and 3rd quartile and middle line represents median. The diamonds and dots denote the daily averages and the variation in monthly anomalies, respectively.

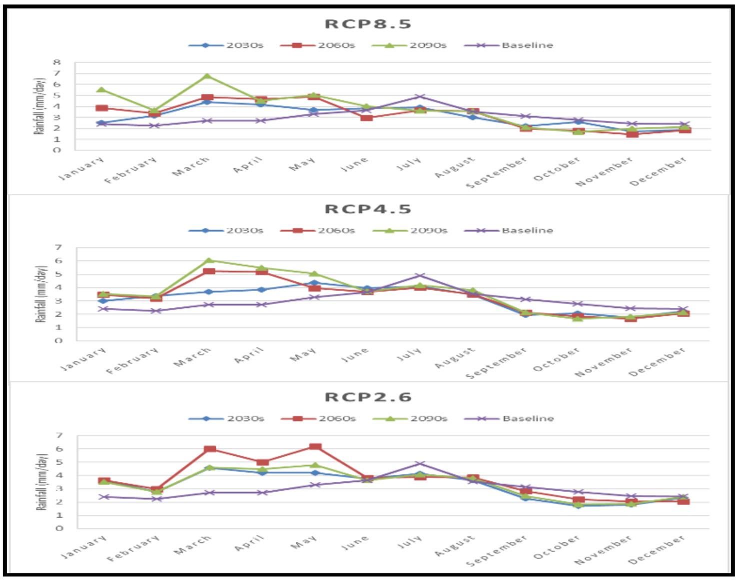

Figure 7. Comparison of the projected rainfall in 2030s, 2060s, and 2090s under scenarios RCP 2.6, RCP 4.5 and RCP 8.5 to the base period

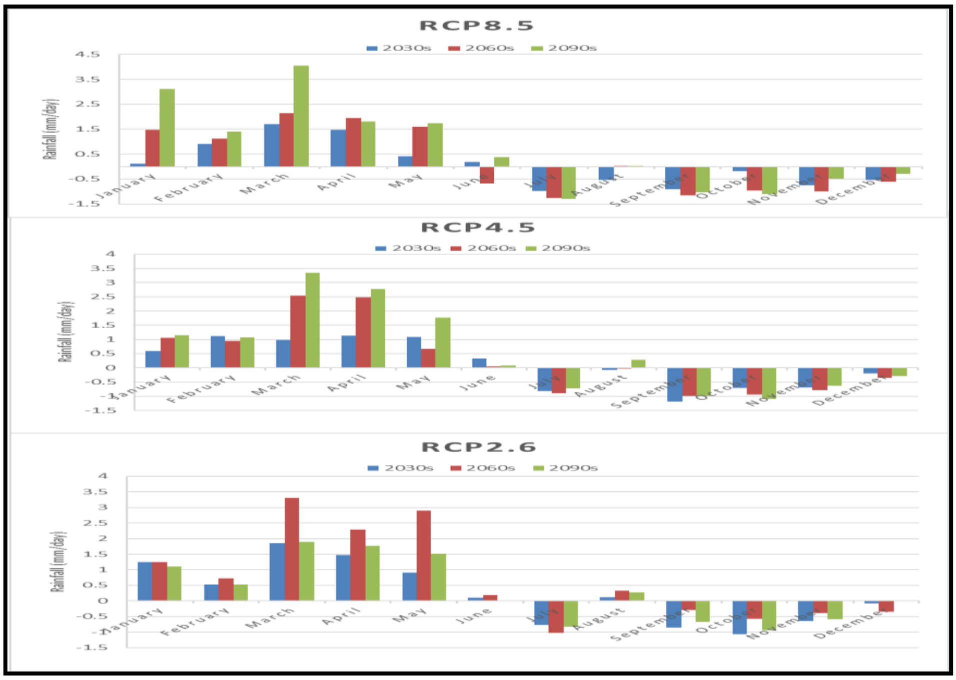

Figure 8. Anomalies in rainfall (compared to base period) in 2030s, 2060s, and 2090s under scenarios RCP 2.6, RCP 4.5 and RCP 8.5

4.5 Future changes of seasonal and annual rainfall

The changes of seasonal and annual daily mean rainfall (compared to baseline) in the Lucas Creek catchment under scenarios RCP 2.6, RCP 4.5 and RCP 8.5 are shown in Figure 9. It can be seen from Figure 9 that under scenario RCP 2.6, the annual mean daily rainfall of future periods (2030s, 2060s and 2090s) is 3.52 mm/day, 3.72 mm/day and 3.25 mm/day respectively as compared to baseline value of 3.02 mm/day. Similarly, under RCP 4.5, the annual mean daily rainfall of future periods (2030s, 2060s and 2090s) in the Lucas Creek catchment are 3.14 mm/day, 3.33 mm/day and 3.58 mm/day, respectively. While the annual mean daily rainfall amount of 3.09 mm/day, 3.24 mm/day and 3.72 mm/day is observed in 2030s, 2060s and 2090s, respectively under RCP 8.5. The change of the annual mean daily rainfall presents the overall situation of increase under all the three scenarios, and the change under scenarios RCP 4.5 and 8.5 are more distinct in 2090s compared to that of other time slices and scenario.

The changes of seasonal mean daily rainfall in the Lucas Creek catchment under scenarios RCP 2.6, RCP 4.5 and 8.5 show noticeable differences in different seasons. Under all the three scenarios, the seasons in which changes of seasonal mean daily rainfall are most remarkable in the future periods (2030s, 2060s and 2090s) are spring and autumn, respectively. The rainfall would be increased by almost two fold in the spring in 2060s and 2090s under RCP 2.6, RCP 4.5 and RCP 8.5. While the autumn would undergo almost one fold decline in the rainfall. Similar change trends are found for the results of winter and summer however with a nominal changing magnitude only. The sharp increment in the spring rainfall contradicts the Ministry for the Environment's assessment that suggests that spring rainfall is expected to decrease in the Auckland region (ME 2016). The weakness of SDSM simulating low extreme rainfall (not zero) may have contributed to these relatively higher spring rainfall estimates while downscaling (Pervez and Henebry 2014). Additionally, the source of predictor variables might influence the results as well, like CanESM2 is used in the present study which was not the part of GCMs used in the preparation of the Ministry for the Environment's assessment report.

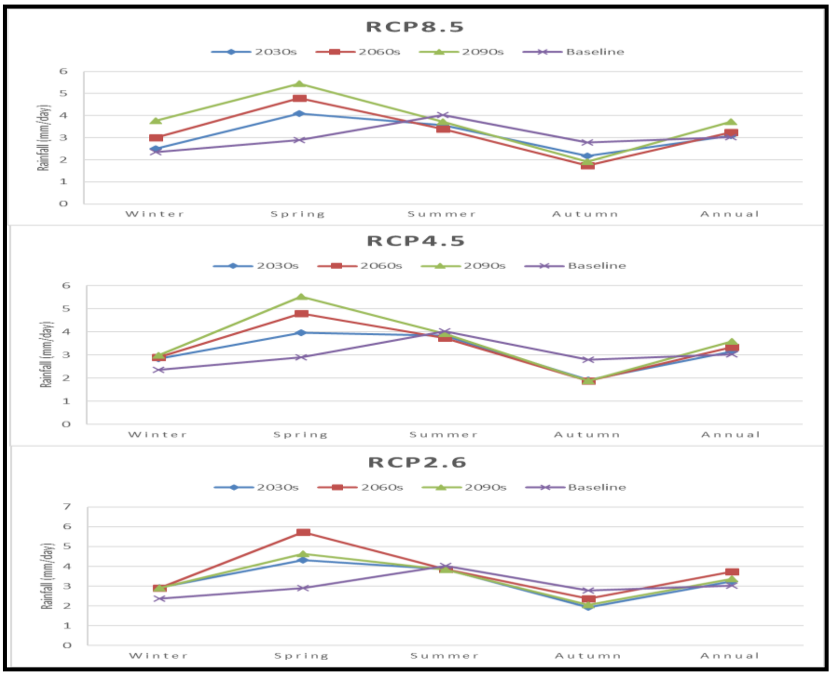

Figure 9. The changes of seasonal and annual mean rainfall (compared to baseline) in 2030s, 2060s, and 2090s under scenarios RCP 2.6, RCP 4.5 and RCP 8.5

The projection showed an increasing trend in the rainfall under RCP 4.5 and RCP 8.5 scenarios. Additionally, there will also be increasing trend under RCP 2.6, the rate of increase will be lower in compared to rest of the scenarios. This can be revealed based on the five years moving average, trend line and R^2 given in Figure 10. This suggests that the annual trend of projected rainfall has huge fluctuations over time. A steady increasing trend is observed by the end of 2040 under all the three RCP scenarios while massive fluctuation is clear during the period 2040-2070. Similarly, a significant increasing trend is observed under RCP 8.5 while consistent decreasing trend is shown under RCP 2.6 and RCP 4.5 towards the end of the century.

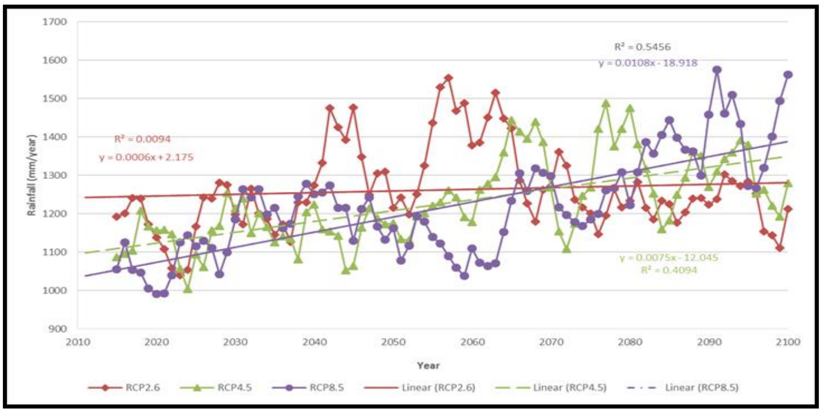

Figure 10. Five years moving average of projected annual mean rainfall from 2011 to 2100

4.6 Frequency analysis

Figure 11 shows the AM rainfall frequency analysis results in terms of the Gumbel distribution estimated magnitude of the ten chosen return periods (2, 3, 4, 5, 10, 15, 20, 30, 50 and 100 year). It can be seen from the Figure that SDSM successfully simulate the magnitudes of rainfall for the ten return periods. The Gumbel distribution estimates for simulated values are well within the 2.5% percentile and 97.5 percentile obtained using the observed series. However, it appears to simulate the low return period (N=1-10 year) rainfall better than high return period (N=30-100 year) rainfall, as the departure of simulated values from the corresponding observed values increases with increasing return period. On the basis of the results presented, it can be seen that SDSM is good at simulating AM rainfall as compared to the observed AM values and can be used for future frequency analysis.

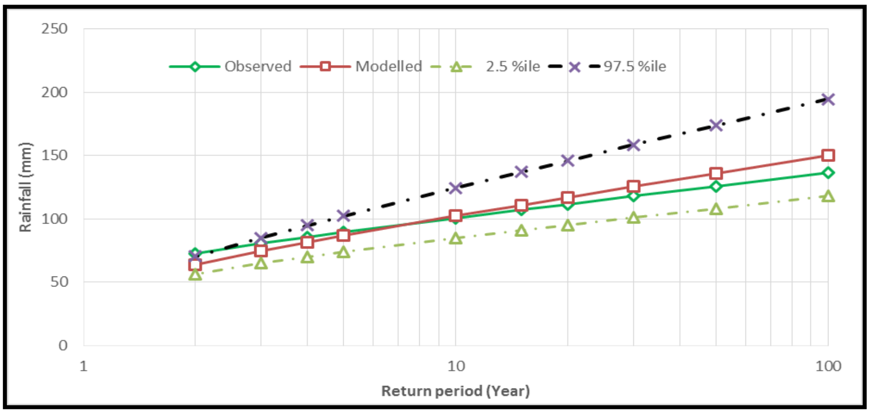

Figure 11. Comparison of Gumbel estimated magnitudes of rainfall for studied return periods using observed and simulated AM series

Rainfall frequency analysis based on the downscaled data by SDSM for the Lucas Creek catchment is shown in Figure 12. The Gumbel distribution estimated rainfall amounts for the ten chosen return periods obtained using the baseline, RCP 2.6, RCP 4.5 and RCP 8.5 in 2030s, 2060s and 2090s are plotted. The Gumbel distribution estimated values show a significant increase in both the frequency and the intensity of future extreme events of rainfall. The analysis suggests that a 100 year event at the current baseline would become a 3 year event in 2030s under RCP 2.6 and RCP 8.5. While a future 100 year event would be around 2.5 times that of the 100 year event now under RCP 4.5 in 2030s. On the other hand, the behaviour of future events in 2060s and 2090s under all the three scenarios would be the same. A future 10 year storm will have 139.4 mm/day, 149.1 mm/day and 167.5 mm/day under RCP 2.6, RCP 4.5 and RCP 8.5 respectively in both 2060s and 2090s. An increase in magnitude of low return period rainfall events would also be observed in all the time slices under all the three emission scenarios. Overall, the highest increment would be observed in 100 year storm in 2030s under RCP 4.5 while a decrease is projected under RCP 8.5. However, a 100 year storm in 2060s and 2090s will have the same and the highest values under RCP 8.5.

The response of GCMs is important in the estimation of future variations in rainfall due to increase in GHG concentrations. The changes in atmospheric circulation patterns in terms of the large scale predictors, as suggested by a GCM which can be considered more reliable, are used in SDSM (Hashmi et al. 2011b). As the spatial resolution of the current GCMs is still very coarse, their direct rainfall output is unreliable. As a result of these inherent uncertainties, the developed frequency analysis from CanESM2 might be unable to provide an accurate estimate of future extreme rainfall. However, it realizes the fact that the future climate will not be similar to the historical climate (Kabiri et al. 2012). Single site rainfall downscaling, in the presence of uncertainties, may suffer from under or overestimation of the risks (Harpham and Wilby 2005). In future, climate change will likely consequence an increase in the intensity and frequency of extreme rainfall events in the most regions of New Zealand (ME 2016). Therefore, frequency calculations might eventually be prepared under the climate change (Kabiri et al. 2012).

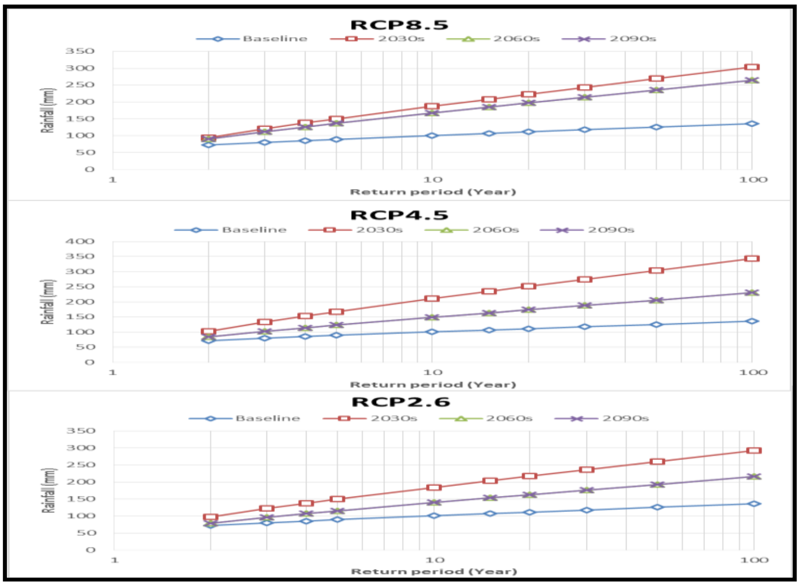

Figure 12. Comparison of Gumbel estimated magnitudes of rainfall for studied return periods using AM series for baseline, 2030s, 2060s and 2090s under RCP 2.6, RCP 4.5 and RCP 8.5

5. CONCLUSIONS AND RECOMMENDATIONS

Statistical downscaling methods are effective measures to construct the bridge between large scale climate change and local scale hydrological response. In this study, SDSM was applied to simulate and project the rainfall from a CMIP5 GCM ensemble (CanESM2) in the Lucas Creek catchment of the Auckland area. Some important conclusions could be obtained as follows:

- During calibration and validation, SDSM performed well in the simulation of the rainfall series. The rainfall downscaled by NCEP data had good linear relationship with the observed ones especially in modelling the monthly, seasonal and annual rainfall.
- The simulation results of future daily and monthly rainfall showed a variations in projected rainfall. The change patterns in the three time slices (2030s, 2060s and 2090s) would be observed differently under scenarios RCP 2.6, RCP 4.5 and RCP 8.5. As for RCP 2.6 scenario, no significant change will be in mean daily rainfall in all the three time slices. While under RCP 4.5 and RCP 8.5 an increasing trend will be noticed in 2060s and 2090s respectively. However, when it comes to monthly variations, some months would have increased rainfall and others would experience decline in rainfall. An increasing pattern would be observed from January to May. In contrast, there is a steady decline in rainfall during all the three time slices under all the three RCP scenarios from July to October.
- When compared to the baseline, there will be noticeable seasonal variations in the rainfall. The rainfall of the Lucas Creek catchment will increase more significantly in the spring, and decrease considerably in the autumn under all the three emission scenarios. Similarly, the change of annual mean rainfall presents the overall situation of increase under all the three scenarios. The change under scenarios RCP 4.5 and RCP 8.5 would be more distinct in 2090s compared to that of other time slices. Five year moving average showed that there would be nominal increase under RCP 2.6 while significant increase would be observed under RCP 4.5 and RCP 8.5.
- Frequency analysis of annual daily maximum of the downscaled rainfall in 2030s, 2060s and 2090s under three future scenarios was carried out to investigate the impact of climate change on the occurrence of storm depths. The investigation revealed that extreme rainfall values for future projection periods will be increased. A future 100 year event would be around 2.5 times that of the 100 year event now under RCP 4.5 in 2030s. While the behaviour of future events in 2060s and 2090s under all the three scenarios will be the same.

This study provided findings that clearly demonstrate the ability of SDSM to downscale the rainfall from a CMIP 5 model (CanESM2), as well as endorsing climate change impacts on rainfall in the urbanized Lucas Creek catchment. Further work should be done to convert the rainfall into runoff to investigate the impacts of variations in rainfall on flash floods. Additionally, any results coming from GCMs are subject to uncertainty and this fact should be taken into account in any assessment using GCMs. However, such studies allow urban catchment planners/managers to evaluate the flooding risks in urbanized catchments.

6. ACKNOWLEDGMENTS

We are thankful to the Auckland Council (AC) for providing observed rainfall data and geographical maps of the Lucas Creek catchment.

REFERENCES

Borges, P.D.A., Barfus, K., Weiss, H. and Bernhofer, C. (2017) Extended predictor screening, application and added value of statistical downscaling of a CMIP5 ensemble for single-site projections in Distrito Federal, Brazil. International Journal of Climatology 37(1), 46-65.

Canada, G.o. (2017) CanESM2 predictors: CMIP5 experiments. Retrived from http://www.cccsn.ec.gc.ca/?page=pred-canesm2

Chen, H., Xu, C.-Y. and Guo, S. (2012) Comparison and evaluation of multiple GCMs, statistical downscaling and hydrological models in the study of climate change impacts on runoff. Journal of Hydrology 434, 36-45.

Chylek, P., Li, J., Dubey, M., Wang, M. and Lesins, G. (2011) Observed and model simulated 20th century Arctic temperature variability: Canadian earth system model CanESM2. Atmospheric Chemistry and Physics Discussions 11(8), 22893-22907.

Dibike, Y.B. and Coulibaly, P. (2005) Hydrologic impact of climate change in the Saguenay watershed: comparison of downscaling methods and hydrologic models. Journal of Hydrology 307(1), 145-163.

Fealy, R. and Sweeney, J. (2007) Statistical downscaling of precipitation for a selection of sites in Ireland employing a generalised linear modelling approach. International Journal of Climatology 27(15), 2083-2094.

Fowler, H.J., Blenkinsop, S. and Tebaldi, C. (2007) Linking climate change modelling to impacts studies: Recent advances in downscaling techniques for hydrological modelling. International Journal of Climatology 27(12), 1547-1578.

Harpham, C. and Wilby, R.L. (2005) Multi-site downscaling of heavy daily precipitation occurrence and amounts. Journal of Hydrology 312(1), 235-255.

Hashmi, M., Shamseldin, A. and Melville, B. (2009) Statistical downscaling of precipitation: state-of-the-art and application of bayesian multi-model approach for uncertainty assessment. Hydrology and Earth System Sciences Discussions 6(5), 6535-6579.

Hashmi, M., Shamseldin, A.Y. and Melville, B.W. (2011a) Comparison of SDSM and LARS-WG for simulation and downscaling of extreme precipitation events in a watershed. Stochastic Environmental Research & Risk Assessment 25(4), 475-484.

Hashmi, M.Z., Shamseldin, A.Y. and Melville, B.W. (2011b) Statistical downscaling of watershed precipitation using Gene Expression Programming (GEP). Environmental Modelling & Software 26(12), 1639-1646.
Hassan, Z., Shamsudin, S. and Harun, S. (2014) Application of SDSM and LARS-WG for simulating and downscaling of rainfall and temperature. Theoretical and applied climatology 116(1-2), 243-257.

Huang, J., Zhang, J., Zhang, Z., Xu, C., Wang, B. and Yao, J. (2011) Estimation of future precipitation change in the Yangtze River basin by using statistical downscaling method. Stochastic Environmental Research and Risk Assessment 25(6), 781-792.

IPCC (2007) Climate change 2007: Synthesis Repor. Contribution of Working Groups I, II and III to the Fourth Assess-ment Report of the Intergovernmental Panel on Climate Change, Intergovernmental Panel on Climate Change, Geneva, switzerland.

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, Intergovernmental Panel on Climate Change, Cambridge, United Kingdom and New York, NY, USA.

Kabiri, R., Bai, R. and Chan, A. (2012) Estimation of Climate Change Impacts on Frequency of Precipitation Extremes Case study: Klang Watershed, Malaysia.

Khan, M.S., Coulibaly, P. and Dibike, Y. (2006) Uncertainty analysis of statistical downscaling methods. Journal of Hydrology 319(1), 357-382.

Masui, T., Matsumoto, K., Hijioka, Y., Kinoshita, T., Nozawa, T., Ishiwatari, S., Kato, E., Shukla, P.R., Yamagata, Y. and Kainuma, M. (2011) An emission pathway for stabilization at 6 Wm−2 radiative forcing. Climatic Change 109(1), 59.

ME (2016) Climate Change Projections for New Zealand: Atmosphere Projections Based on Simulations from the IPCC Fifth Assessment, Ministry for the Environment, Wellington, New Zealand.

Nasseri, M., Tavakol-Davani, H. and Zahraie, B. (2013) Performance assessment of different data mining methods in statistical downscaling of daily precipitation. Journal of Hydrology 492, 1-14.

Pervez, M.S. and Henebry, G.M. (2014) Projections of the Ganges–Brahmaputra precipitation—Downscaled from GCM predictors. Journal of Hydrology 517, 120-134.

Riahi, K., Rao, S., Krey, V., Cho, C., Chirkov, V., Fischer, G., Kindermann, G., Nakicenovic, N. and Rafaj, P. (2011) RCP 8.5—A scenario of comparatively high greenhouse gas emissions. Climatic Change 109(1), 33.

Rummukainen, M. (2010) State-of-the-art with Regional Climate Models. Wiley Interdisciplinary Reviews: Climate Change 1(1), 82-96.

Shaw, E.M. (1994) Hydrology in Practice (3rd Edition), Chapman & Hall, London.

Thomson, A.M., Calvin, K.V., Smith, S.J., Kyle, G.P., Volke, A., Patel, P., Delgado-Arias, S., Bond-Lamberty, B., Wise, M.A., Clarke, L.E. and Edmonds, J.A. (2011) RCP4.5: a pathway for stabilization of radiative forcing by 2100. Climatic Change 109(1), 77.

Van Vuuren, D.P., Stehfest, E., den Elzen, M.G.J., Kram, T., van Vliet, J., Deetman, S., Isaac, M., Klein Goldewijk, K., Hof, A., Mendoza Beltran, A., Oostenrijk, R. and van Ruijven, B. (2011)

RCP2.6: exploring the possibility to keep global mean temperature increase below 2°C. Climatic Change 109(1), 95.

Wilby, R., Charles, S., Zorita, E., Timbal, B., Whetton, P. and Mearns, L. (2004) Guidelines for use of climate scenarios developed from statistical downscaling methods. Supporting material of the Intergovernmental Panel on Climate Change, available from the DDC of IPCC TGCIA 27.
Wilby, R. and Dawson, C. (2007) SDSM 4.2–A decision support tool for the assessment of regional climate change impacts, User Manual. Department of Geography, Lancaster University, UK, ed.

Wilby, R. and Dawson, C. (2015) Statistical DownScaling Model – Decision Centric (SDSM-DC) Version 5.2 Supplementary Note. Department of Geography, Lancaster University, UK.

Wilby, R., Dawson, C. and Barrow, E. (2002) SDSM—a decision support tool for the assessment of regional climate change impacts. Environmental Modelling & Software 17(2), 145-157.

Wilby, R.L. (2015) SDSM: Data. Retrieved from http://co-public.lboro.ac.uk/cocwd/SDSM/data.html.

Wilby, R.L., Wigley, T., Conway, D., Jones, P., Hewitson, B., Main, J. and Wilks, D. (1998) Statistical downscaling of general circulation model output: a comparison of methods. Water Resources Research 34(11), 2995-3008.

Willems, P., Arnbjerg-Nielsen, K., Olsson, J. and Nguyen, V.T.V. (2012) Climate change impact assessment on urban rainfall extremes and urban drainage: Methods and shortcomings. Atmospheric Research 103, 106-118.

Xu, C.-y. (1999a) Climate change and hydrologic models: A review of existing gaps and recent research developments. Water Resources Management 13(5), 369-382.

Xu, C.-y. (1999b) From GCMs to river flow: a review of downscaling methods and hydrologic modelling approaches. Progress in physical Geography 23(2), 229-249.

Zhang, Y., You, Q., Chen, C. and Ge, J. (2016) Impacts of climate change on streamflows under RCP scenarios: A case study in Xin River Basin, China. Atmospheric Research 178, 521-534.