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ORIGINAL PAPER

Comparison of SDSM and LARS-WG for simulation and downscaling of extreme precipitation events in a watershed

Muhammad Zia Hashmi · Asaad Y. Shamseldin · Bruce W. Melville

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Abstract Future climate projections of Global Climate Models (GCMs) under different emission scenarios are usually used for developing climate change mitigation and adaptation strategies. However, the existing GCMs have only limited ability to simulate the complex and local climate features, such as precipitation. Furthermore, the outputs provided by GCMs are too coarse to be useful in hydrologic impact assessment models, as these models require information at much finer scales. Therefore, downscaling of GCM outputs is usually employed to provide fine-resolution information required for impact models. Among the downscaling techniques based on statistical principles, multiple regression and weather generator are considered to be more popular, as they are computationally less demanding than the other downscaling techniques. In the present study, the performances of a multiple regression model (called SDSM) and a weather generator (called LARS-WG) are evaluated in terms of their ability to simulate the frequency of extreme precipitation events of current climate and downscaling of future extreme events. Areal average daily precipitation data of the Clutha watershed located in South Island, New Zealand, are used as baseline data in the analysis. Precipitation frequency analysis is performed by fitting the Generalized Extreme Value (GEV) distribution to the observed, the SDSM simulated/downscaled, and the LARS-WG simulated/downscaled annual maximum (AM) series. The computations are performed for five return periods: 10-, 20-, 40-, 50- and 100-year. The present results illustrate that both models have similar and good ability to simulate the extreme precipitation events and, thus, can be adopted with confidence for climate change impact studies of this nature.

Keywords Global Climate Models · Statistical downscaling · Weather generator · Generalized Extreme Value distribution

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1 Introduction

A rising trend of the Earth's temperature and changes in the associated weather conditions across the globe are referred to as climate change. In the absence of suitable mitigation and adaptation measures, climate change is likely to affect major sectors of the world, such as agriculture, water resources, and tourism. Global Climate Models (GCMs), which are presently considered to be the most reliable source providing the climate change information, have spatial resolutions too coarse for hydrologic impact models. To provide hydrologists with the desired information in terms of hydrometeorologic variables at a very fine spatial resolution (in the order of a few kilometers) or station-scale, downscaling is usually employed. The existing downscaling techniques have two broad classes: statistical and dynamical. Extensive details about the theories behind these classes as well as their advantages and disadvantages can be found in Hewitson and Crane (1996), Xu (1999), Wilby et al. (2004), and Fowler et al. (2007), among others. Among the statistical downscaling techniques used by hydrologists to obtain station-scale climatic information, multiple regression models and stochastic weather generators have far more applications than the others (e.g. Wilks 1992, 1999), as they are computationally less demanding, simple to apply, and efficient (Semenov et al. 1998; Dibike and Coulibaly 2005; Kilsby et al. 2007; Kim et al. 2007).

Regression-based downscaling methods involve developing empirical relationships between large-scale GCM data or observed data as "predictor" variables and local- or small-scale climate variables as "predictand" variables (e.g. temperature, precipitation) using traditional linear and nonlinear regression methods (e.g. Heyen et al. 1996; Wilby et al. 2002). Examples of traditional regression-based downscaling methods include linear regression, canonical correlation analysis (CCA), and principal component analysis (PCA) (Dibike and Coulibaly 2005).

Weather generators are traditionally used to stochastically generate long synthetic series of data, fill in missing data, and produce different realizations of the same data (Wilby 1999). They employ random numbers and take the observed time series of a station/site as input. Stochastic weather simulation is not new, and has a long history starting from the 1950s, as reported by Racsko et al. (1991). Among the researchers who contributed to its evolution are Bruhn (1980), Bruhn et al. (1980), Nicks and Harp (1980), Richardson (1981), Richardson and Wright (1984), and Schoof et al. (2005). Wilby (1999) presented a comprehensive review of its theory and evolution over time. Weather generators have also been employed to simulate long time series of hydrometeorologic variables that can be used by crop growth models for forecasting agricultural production (e.g. Riha et al. 1996; Hartkamp et al. 2003), multi-site data generation (Khalili et al. 2009), and assessment of risk associated with climate variability (Bannayan and Hoogenboom 2008). Further details on the use of weather generators in crop production studies can be found in Semenov (2006).

Statistical downscaling methods are usually considered to be not very effective for simulation of extreme events of precipitation (Wilby et al. 2004). On the other hand, the frequency and intensity of extreme precipitation events are very likely to come under impact of envisaged climate change in most parts of the world (IPCC 2007), thus posing the risk of increased floods and droughts. In this situation, hydrologists should only rely on those statistical downscaling tools that are equally efficient for simulating means as well as extreme precipitation events. Thus, there is indeed a need for testing the available statistical downscaling tools for their ability to simulate extreme climatic events, especially precipitation (which is highly complex in nature and difficult to model) at the watershed scale. There have been some studies on this topic, but they have mainly used nonparametric methods based on extreme climatic indices (e.g. Tolika et al. 2008). Fowler et al. (2007) have commended the study by Goodess et al. (2007) as *the most comprehensive study* comparing skills of many different downscaling methods for simulating climatic extremes in terms of 10 extreme indices. They have also argued over the applicability of such indices-based studies for hydrologic impact assessment, as these studies deal only with *moderate extremes* while frequency of *rare events* is more desirable to hydrologists. Semenov (2008) has pioneered the evaluation of a weather generator in terms of simulating rare precipitation events through the use of parametric distributions.

The present study focuses on the evaluation and comparison of two very popular statistical downscaling models in terms of their ability to simulate extreme precipitation frequency using a parametric distribution at a watershed scale. The first model is the SDSM, which is a multiple-regression model (Wilby et al. 2002), and the second model is the Long Ashton Research Station Weather Generator (LARS-WG), which was specially designed for climate change studies (Semenov and Barrow 1997).

The rest of the paper is organized as follows. First, a brief description of the study watershed and data sources is given. Next, details of methods and analysis are provided, which include application of the two downscaling models and precipitation frequency analysis. This is followed by

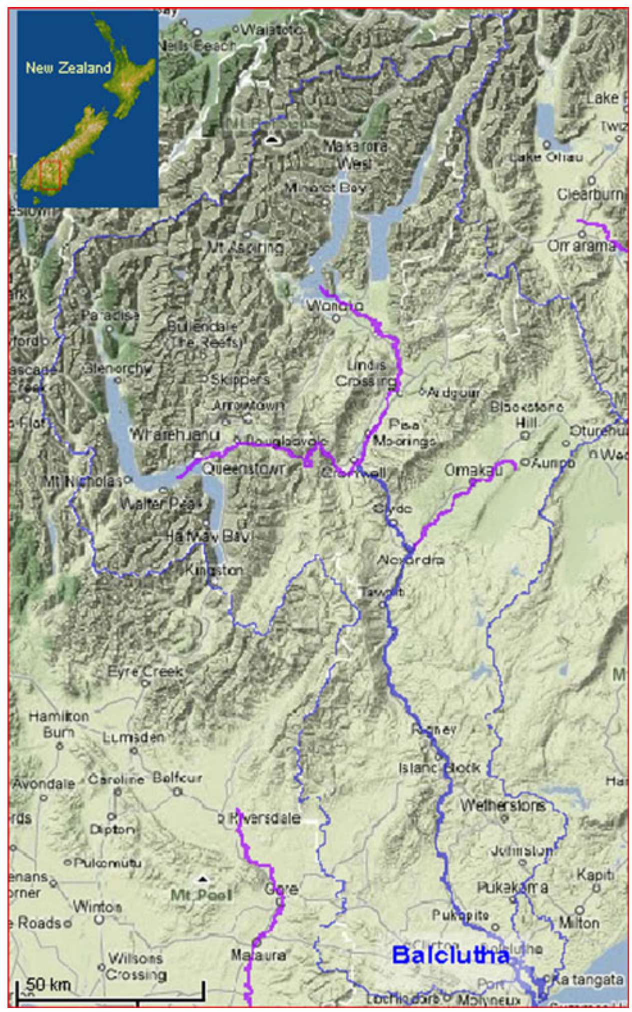

Fig. 1 Watershed boundary of Clutha river at Balclutha on terrain map of South Island, NZ (*Source* NIWA web model: http://wrenz.niwa.co.nz/webmodel)

presentation of results and their discussion. Finally, conclusions of the study are given.

2 Study watershed and data sources

The Clutha River is the biggest river in the South Island of New Zealand. Its catchment up to Balclutha (Fig. 1) is selected as a case study. The river is also the second longest in length (340 km) in New Zealand, and has been reported as the largest river in terms of volume and catchment area (McKerchar and Henderson 2003). Its long-term annual mean flow is approximately 614 m^3/s. The catchment area is about 20,515 km^2 up to Balclutha, and the mean annual precipitation is about 1,448 mm (derived using web model of the National Institute of Water and Atmosphere (NIWA), New Zealand; http://wrenz.niwa.co.nz/webmodel). The river starts from the high Southern Alps glaciers and is very hazardous due to its flooding potential. The climatic data used in this study are obtained from NIWA. Daily average precipitation data of 23 stations within the Clutha watershed, having record lengths of at least 40 years, are acquired for the period 1961–2000. The large-scale predictors of Hadley Center's GCM (HadCM3) for 1961–2099 (based on twentieth century run as well as SRES (Special Report on Emission Scenarios) A2 future scenario run) and re-analysis data predictors of the National Center of Environmental Prediction (NCEP) on HadCM3 computational grid for 1961–2000 are obtained from the Canadian Climate Impacts Scenarios (CCIS) website (http://www.cics.uvic.ca/scenarios/index.cgi) at daily time step. Among the SRES scenarios, A2 is considered among the worst case scenarios, projecting high emissions for the future (SRES 2000). In climate change studies, the period 1961–2000 is normally used to represent the current climate and is called the 'baseline period' (Wilby et al. 2002). The selection of the future time slice of 2080s allows assessment of the climate change impact on precipitation extremes in a distant future. In order to get a downscaled time series using a weather generator, the mean daily precipitation output of HadCM3 GCM, covering the whole globe, is obtained for the twentieth century run (1960–1989) as well as for the SRES A2 scenario run for 2080s (2070–2099) from Program for Climate Model Diagnosis and Intercomparison (PCMDI) data portal (https://esg.llnl.gov:8443/).

3 Methodology

3.1 Application of statistical downscaling model

The SDSM is a multiple regression-based tool for generating future scenarios to assess the impact of climate change. It has the ability to capture the inter-annual variability better than other statistical downscaling approaches, e.g. weather generators, weather typing (Wilby et al. 2002). The model is a combination of a stochastic weather generator approach and a transfer function model (Wilby et al. 2002) needing two types of daily data. The first type corresponds to local predictands of interest (e.g. temperature, precipitation) and the second type corresponds to the data of large-scale predictors (NCEP and GCM) of a grid box closest to the study area. Correlation and partial correlation analysis are performed in SDSM between the predictand of interest and predictors to select a set of predictors most relevant for the site in question (Wilby et al. 2002).

Initially, the precipitation data of a selected station from the study watershed (Ophir2) are used in SDSM. The correlation analysis performed within SDSM between the precipitation of this site and the NCEP re-analysis predictors (Table 1) reveals very poor results. Consequently, offline statistical analysis is undertaken to improve the results to an acceptable limit. A cross-correlation analysis between the daily precipitation of Ophir2 and the NCEP predictors is an attempt in this regard. An optimal lag or time shift, required to improve the correlation between each predictor–predictand pair, is identified. The correlation results after this analysis are shown in Fig. 2. Examination of the figure shows that the correlation coefficient values obtained are well below the acceptable limit as indicated in previous studies (e.g. Hessami et al. 2008). Further cross-correlation analysis using the data of other stations leads to conclusions similar to those obtained using the Ophir2 station. Accordingly, these predictors cannot be used directly for reliable downscaling at the station-scale.

As the outcome of the station-scale analysis is not favorable, an areal approach is adopted. The arithmetic average of the daily data from 23 stations within the Clutha watershed, with a record length of at least 30 years, is taken. This areal average precipitation time series is referred to herein as *Clutha precipitation*. Cross-correlation analysis is again performed between the *Clutha precipitation* and the NCEP predictors. Table 2 shows the results of this cross-correlation analysis in terms of predictand–predictor lag (in days) required to get the maximum correlation between them. After arranging each NCEP predictor against *Clutha precipitation* on the basis of Table 2, the predictor–predictand correlation is found to improve significantly. This is highlighted in Fig. 3. Examination of Fig. 3 shows that there are a number of the NCEP predictors that have correlation coefficient values in the range 13–25% for the *Clutha precipitation*. This range is considered to be acceptable when dealing with precipitation downscaling (cf. Wilby et al. 2002).

The lagged NCEP predictors and the *Clutha precipitation* obtained in the previous step are then used in SDSM

Table 1 Name and description of all NCEP predictors on HadCM3 grid (the one in bold text is selected in model calibration)

1	**ncepmslpaz**	**Mean sea level pressure**	14	ncepp500az	500 hPa geopotential height
2	ncepp5_faz	500 hPa airflow strength	15	**ncepp850az**	**850 hPa geopotential height**
3	**ncepp5_uaz**	**500 hPa zonal velocity**	16	ncepp__faz	Surface airflow strength
4	ncepp5_vaz	500 hPa meridional velocity	17	ncepp__uaz	Surface zonal velocity
5	**ncepp5_zaz**	**500 hPa vorticity**	18	ncepp__vaz	Surface meridional velocity
6	ncepp5thaz	500 hPa wind direction	19	**ncepp__zaz**	**Surface vorticity**
7	**ncepp5zhaz**	**500 hPa divergence**	20	ncepp_thaz	Surface wind direction
8	ncepp8_faz	850 hPa airflow strength	21	ncepp_zhaz	Surface divergence
9	**ncepp8_uaz**	**850 hPa zonal velocity**	22	**ncepr500az**	**Relative humidity at 500 hPa**
10	**ncepp8_vaz**	**850 hPa meridional velocity**	23	ncepr850az	Relative humidity at 850 hPa
11	**ncepp8_zaz**	**850 hPa vorticity**	24	nceprhumaz	Near surface relative humidity
12	ncepp8thaz	850 hPa wind direction	25	ncepshumaz	Surface specific humidity
13	ncepp8zhaz	850 hPa divergence	26	nceptempaz	Mean temperature at 2 m

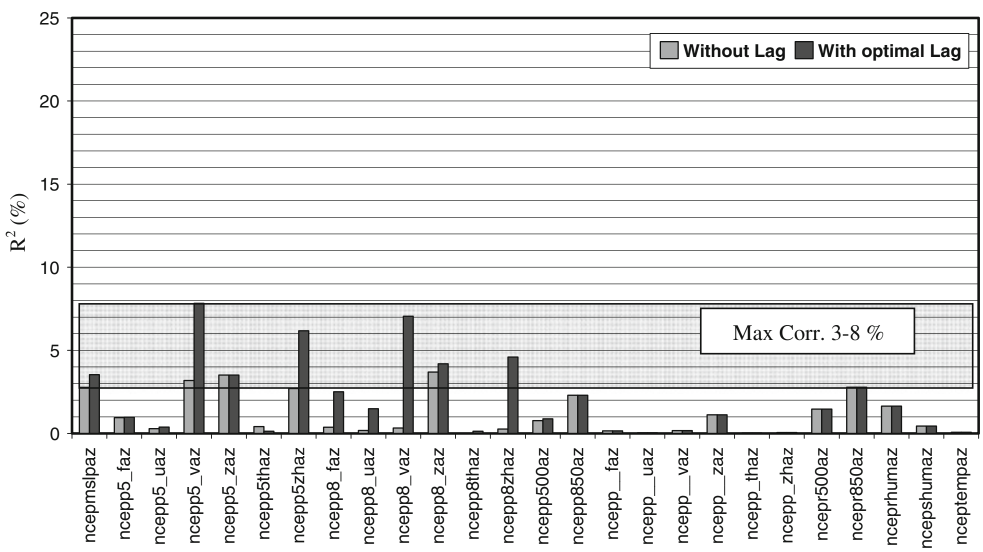

Fig. 2 Correlation between Ophir2 rainfall and NCEP predictors with *shaded area* showing maximum range of correlation

for the final analysis. Screening of the most relevant predictors' set is performed in SDSM on the basis of correlation and partial correlation analysis among the predictand and the individual predictors, and a set of 10 predictors is chosen. This is shown in bold text in Table 1. The predictor selection process is consistent with that adopted in similar studies (Dibike and Coulibaly 2005). The 10 chosen predictors are used for calibration of the downscaling model.

The data of *Clutha precipitation* and the NCEP predictors for the period 1961–2000 are split into two parts: 1961–1990 and 1991–2000. The first part (1961–1990) is set for model calibration, while the remaining data (1991–2000) are used for model validation (as an independent set of data). The SDSM is calibrated for each month of the year using the same set of 10 selected NCEP predictors for the calibration period. Different values of the SDSM set-up parameters, such as 'Variance Inflation' and 'Bias Correction,' are tried. The best combination of these parameters is obtained giving a calibrated model with maximum coefficient of determination (R^2) and identical standard deviation in the comparison of observed and simulated data. This model tuning/calibration strategy is in line with the one explained in Dibike and Coulibaly (2005). Model validation is performed by testing it on the validation (i.e. independent) data set (1991–2000), which also reveals satisfactory results (see Sect. 4 for further details). The model calibrated in SDSM is then used to get a synthetic precipitation time series of 40-year length using large-scale NCEP predictor set for 1961–2000. This time series is subsequently used in the annual maximum (AM) precipitation frequency analysis.

In order to get the downscaled time series of *Clutha precipitation*, the HadCM3 large-scale predictors are used. In the calibrated SDSM model, the NCEP predictors are

Table 2 Results of the cross-correlation analysis

Predictor name	Predictor description	Optimal lag with *Clutha precipitation*
ncepmslpaz	Mean sea level pressure	+1
ncepp5_faz	500 hPa airflow strength	+1
ncepp5_uaz	500 hPa zonal velocity	+1
ncepp5_vaz	500 hPa meridional velocity	+1
ncepp5thaz	500 hPa wind direction	−1
ncepp5zhaz	500 hPa divergence	+1
ncepp8_faz	850 hPa airflow strength	+1
ncepp8_uaz	850 hPa zonal velocity	+1
ncepp8_vaz	850 hPa meridional velocity	+1
ncepp8_zaz	850 hPa vorticity	+1
ncepp8thaz	850 hPa wind direction	+1
ncepp8zhaz	850 hPa divergence	+1
ncepp500az	500 hPa geopotential height	+3

All other predictors were having an optimal lag of ‘0’

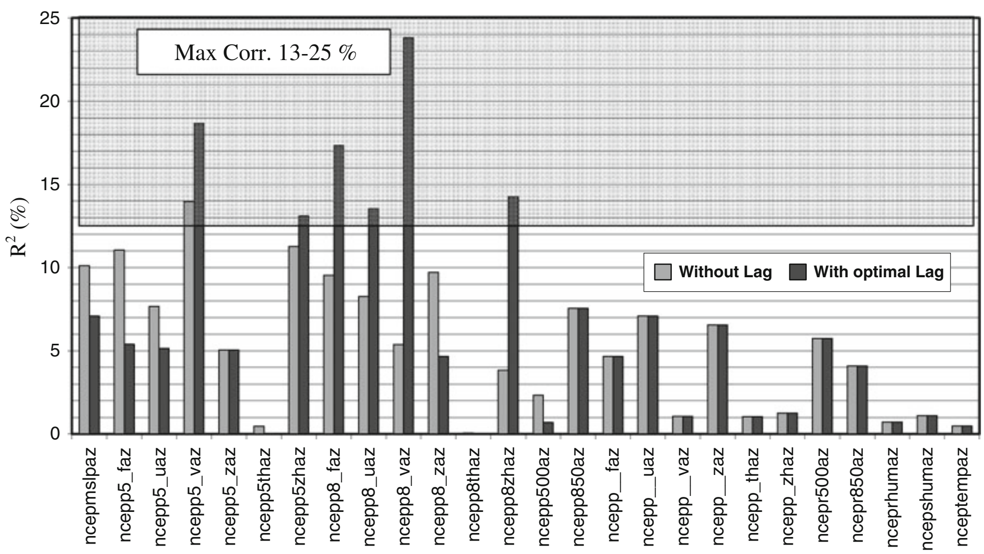

Fig. 3 Correlation between *Clutha precipitation* and NCEP predictors with *shaded area* showing maximum range of correlation

replaced by the corresponding HadCM3 predictors, and a synthetic time series is generated for 1961–2099.

3.2 Application of Long Ashton Research Station Weather Generator (LARS-WG)

The LARS-WG can be used to synthesize daily data and fill in missing values of a recorded climatic time series. It can also generate data of an ungaged site for the daily climatic parameters, such as precipitation, temperature, and solar radiation (using observed data properties of a neighboring gaged site). It takes as input the long-term daily information of the climatic parameter of interest for a site. It can also generate the scenarios of changed climate for a site by perturbing the parameters derived from the observed data to generate synthetic data, representing future climate change.

Before using the LARS-WG for downscaling, its performance on the *Clutha precipitation* time series for the period 1961–2000 is analyzed. This precipitation time series is used as an input to LARS-WG to generate synthetic daily precipitation time series with a record length of 500 years. The statistical properties of the synthetic time series are compared to those of the observed data using *t*-test, *F*-test, and Chi-square (χ^2) test in order to gage the ability of LARS-WG in reproducing the observed precipitation statistics (cf. Khan et al. 2006). The statistical properties include monthly mean and standard deviation of precipitation which are very similar to those used in previous studies (e.g. Dibike and Coulibaly 2005). The results

Table 3 Relative change in monthly statistics between baseline climate and future (2080s) climate as derived from HadCM3 daily output (present and A2 future scenario)

Month	Mean daily	Wet spell length	Dry spell length
January	1.01	0.90	1.13
February	1.13	0.99	1.21
March	1.01	0.82	1.05
April	0.98	0.99	1.14
May	1.30	1.17	1.09
June	1.16	1.10	1.13
July	1.20	1.47	1.11
August	1.10	1.03	1.08
September	1.10	1.15	1.28
October	1.14	1.38	1.06
November	1.07	0.92	1.07
December	0.96	0.98	1.06

obtained in these comparisons are quite satisfactory (see Sect. 4 for details), giving reasonable confidence about any output obtained from LARS-WG. Using the statistical properties of the observed data obtained in the previous step, the weather generator is used to generate a 40-year long daily precipitation time series. From this generated data, 40 values of AM precipitation are obtained and used in the subsequent frequency analysis.

Precipitation downscaling in LARS-WG is performed using the relative change factors (RCFs). These RCFs are derived using the two time series of HadCM3 precipitation output for the twentieth century run (1961–1989) and future run based on SRES A2 scenario (2070–2099). The RCFs are given in Table 3, and are provided to LARS-WG to generate a 30-year time series representing the future time slice of 2070–2099 (2080s).

3.3 Precipitation frequency analysis

Frequency analysis of precipitation is used in this study mainly to evaluate SDSM and LARS-WG in terms of simulating extreme precipitation events of present climate and downscaling future extreme events. This analysis is based on the AM data obtained from three time series: observed, SDSM, and LARS-WG.

In SDSM, the AM series is obtained from the 40-year long daily precipitation time series generated using the calibrated and validated model (discussed in Sect. 3.1) and the NCEP predictors' set for the period of 1961–2000. From the GCM-based generated data of 1961–2099, AM values are obtained only for the time slice selected as representative of the future climate, i.e. 2080s.

The LARS-WG is used after calibration to produce a 40-year daily precipitation time series without any perturbations to the precipitation properties and, based on derived RCFs, a 30-year precipitation time series representing a future time slice of 2080s. From these two sets of synthetic time series, the AM values are obtained for further analysis.

Precipitation frequency analysis is performed by fitting the Generalized Extreme Value (GEV) distribution to the three sets of AM. The GEV is a family of probability distributions, which actually combines the Type I (Gumbel), Type II (Fréchet), and Type III (Weibull) distributional families of Three Types Theorem (Coles 2001). It has three parameters, namely, a location parameter 'μ,' a scale parameter 'σ,' and a shape parameter 'ξ.' The cumulative distribution function (CDF), $F(x)$, of GEV distribution for an extreme-value data set x_i ($i = 1,\ldots,n$) is given by the following equations (Huang et al. 2008).

$$F(x) = e^{-(1+(\xi(x_i-\mu)/\sigma))^{-1/\xi}} \quad \text{for } -\infty < x_i \le \mu - \frac{\sigma}{\xi} \text{ with } \xi < 0 \tag{1}$$

$$F(x) = e^{-e^{-(x_i-\mu)/\sigma}} \quad \text{for } -\infty \le x_i < \infty \text{ with } \xi = 0 \tag{2}$$

In this study, the GEV parameters are estimated by the Maximum Likelihood Estimation (MLE) method, as recommended by Huang et al. (2008) and guidelines of Federal Emergency Management Agency (FEMA 2004). The MLE method gives the standard error in the estimation of these parameters and, hence, the 95% confidence interval (CI) for the estimated value of AM of a given return period.

Precipitation frequency analysis is performed using the GenStat 10 software package (Payne et al. 2007) by fitting the GEV distribution to observed, SDSM simulated/downscaled, and LARS-WG simulated/downscaled AM series. The computations are performed for five return periods: 10-, 20-, 40-, 50- and 100-year.

Semenov (2008) noted that, if an N-year return period precipitation amount derived from synthetic data falls within the 95% CI of the observed, the simulation can be considered to be successful. For mathematical details of the GEV distribution, readers are referred to Semenov (2008).

4 Results and discussion

Figure 4 shows comparisons of the observed and the SDSM-estimated month-wise mean daily precipitation and its standard deviation. Examination of Fig. 4 shows that the calibrated model reproduces the monthly mean daily precipitation values quite well. It slightly underestimates the mean daily precipitation for the months of Apr, Jun, Jul, and Sep (<1 mm) and almost equally overestimates it in the months of Jan, Feb, Mar, May, Aug, Oct, Nov, and Dec. As Wilby et al. (2004) point out, downscaling models are

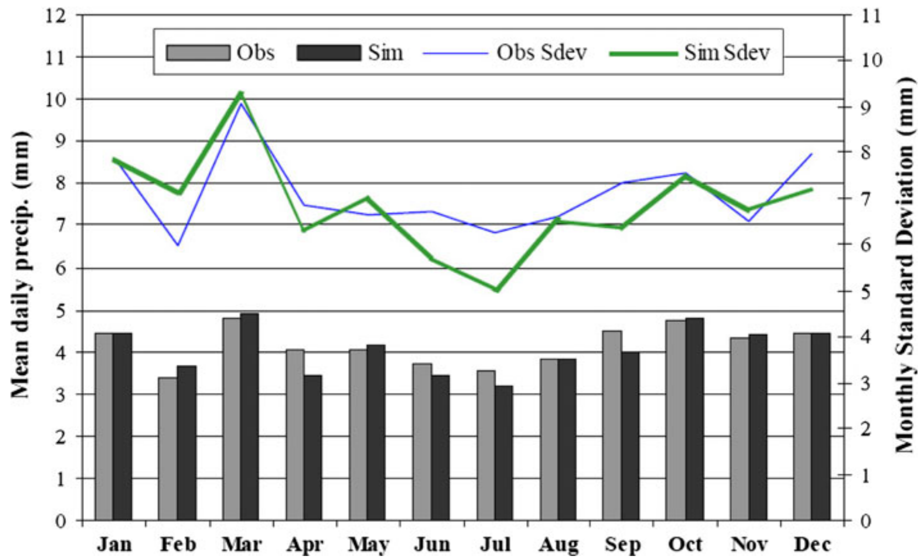

Fig. 4 SDSM model calibration for the *Clutha precipitation* of 1961–1990

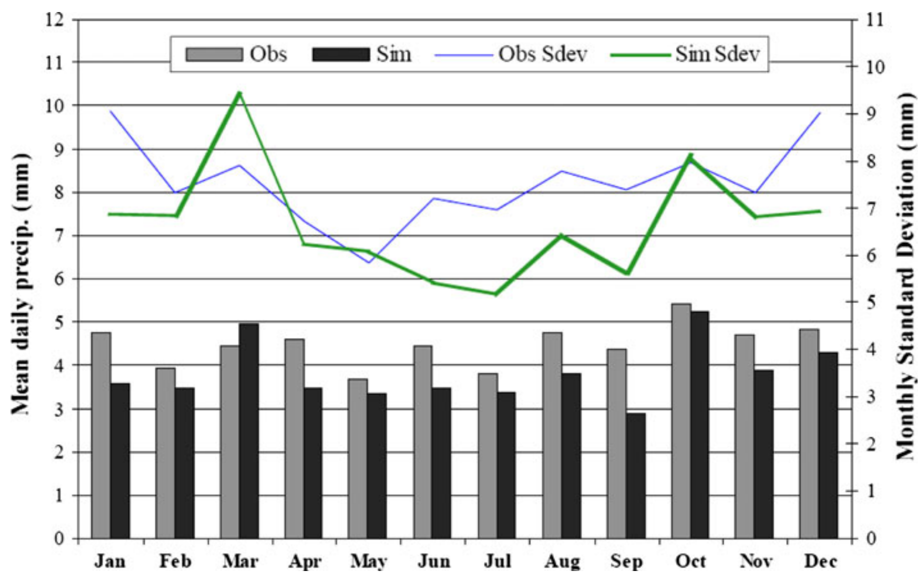

Fig. 5 SDSM model validation for the *Clutha precipitation* of 1991–2000

often regarded as less able to model the standard deviation (or variance) of the observed precipitation with great accuracy. However, as it can be seen in Fig. 4, the SDSM model reproduces the observed standard deviation reasonably well for the Clutha watershed. Only for 4 months of the year (Jun, Jul, Sep, and Dec), the SDSM-simulated standard deviation is below that of the observed data. For the remaining 8 months, the simulated and observed standard deviations are in good agreement with each other.

After accomplishing a satisfactory calibration, the multiple regression model is validated using the data of 1991–2000 (as an independent set of data outside the period for which the model is calibrated), and the results obtained are shown in Fig. 5. Examination of the figure reveals that the model is successfully validated.

Figure 6 shows the results obtained using LARS-WG. As can be seen, the means of daily precipitation for each month are very well modeled by LARS-WG, except for the summer months where it overestimates the mean precipitation. In terms of standard deviation, the LARS-WG shows an average performance, as it mostly underestimates the observed standard deviation, but overall gives much better results for the months of Feb–May and Jul than for the rest of the year (Fig. 6).

Before using GEV for fitting the generated as well as downscaled data, its suitability for the present study is analyzed using visual plotting of cumulative distribution functions, shown in Fig. 7. Examination of this figure shows that GEV distribution fits very well to the observed AM series, which affirms that the application of GEV

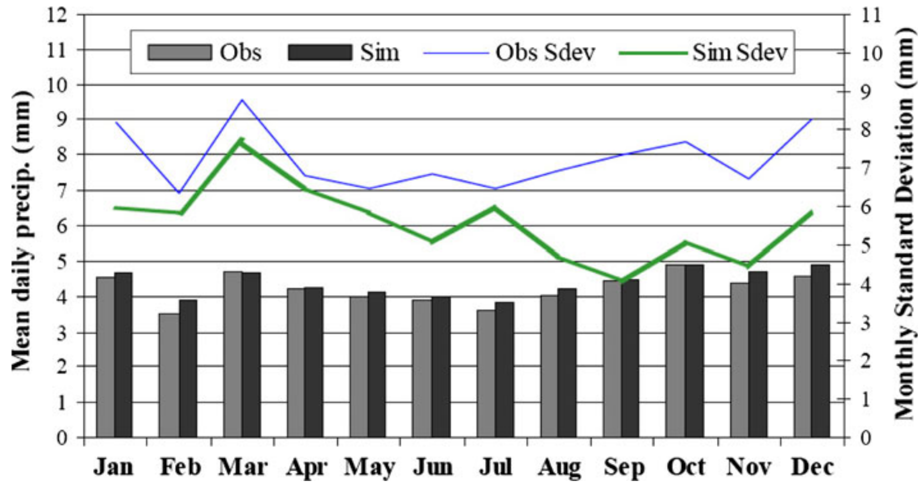

Fig. 6 Comparison of the *Clutha precipitation* and LARS-WG-simulated data for the period 1961–2000

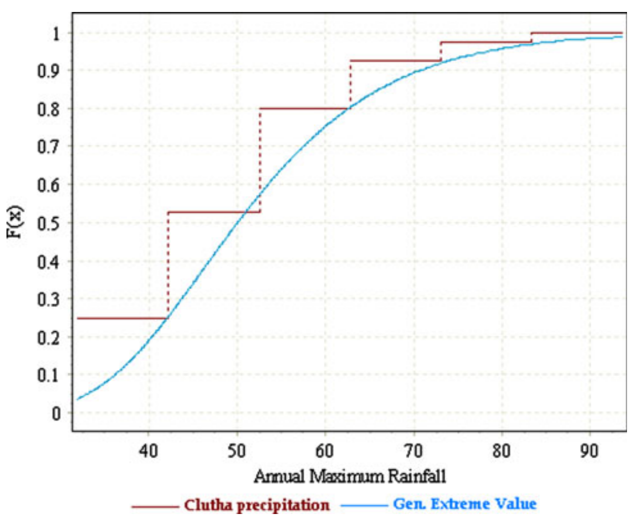

Fig. 7 Cumulative distribution plot of GEV distribution for observed AM data

distribution for precipitation frequency analysis of the study watershed is a reasonably good choice.

After confirming the suitability of GEV distribution for precipitation data of the study watershed, it is fitted to the three sets of AM series (observed, SDSM-simulated, and LARS-WG-simulated), and precipitation magnitudes corresponding to the five return periods are obtained. The values of three parameters of GEV distribution (μ, σ, and ξ) are obtained through the MLE method (discussed in Sect. 3.3). Table 4 shows the values of the three GEV parameters along with standard error in their estimation for all three sets of AM series. Examination of Table 4 indicates that the values of two of the GEV parameters (μ and σ) derived for observed and SDSM AM data are quite similar to each other. However, for the third GEV parameter (ξ), values derived for the two downscaling models are identical but they are significantly different to the one derived from observed AM precipitations. In terms of values of GEV parameters derived for the three sets of AM values, it seems very difficult to affirm one model as better of the two downscaling models used in this study.

Figure 8 shows the AM precipitation frequency analysis results in terms of the GEV-estimated magnitude of the *N*-year return period precipitation for three AM series. The diamond symbols represent the GEV-estimated AM precipitation magnitudes of 10-, 20-, 40-, 50-, and 100-year return period using the observed AM series. The bars extending vertically from the prism symbols are the corresponding 95% CI. The triangles and round dots joined by lines represent the GEV estimates using the simulated AM

Table 4 Estimated values of GEV parameters using MLE for three data sets used in the analysis (standard error in the estimation of a parameter is given in parenthesis as bold value)

Data type	μ	σ	ξ
Observed	45.97 (**2.797**)	10.89 (**2.063**)	−0.01 (**0.189**)
Simulated (LARS-WG)	48.29 (**2.153**)	8.62 (**1.516**)	−0.15 (**0.154**)
Simulated (SDSM)	45.69 (**2.666**)	10.20 (**1.968**)	−0.15 (**0.216**)

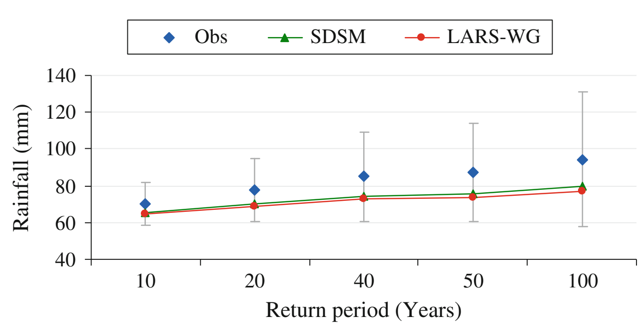

Fig. 8 Comparison of GEV-estimated magnitudes of rainfall for studied return periods using three AM series (observed, SDSM, LARS-WG, the *grey vertical bars* extending from *diamonds* represent the 95% CI of the GEV estimate)

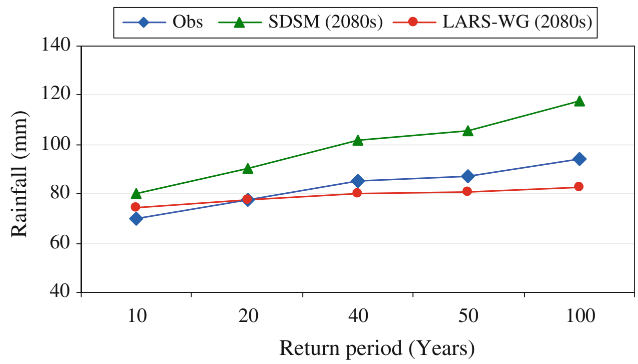

Fig. 9 Comparison of GEV-estimated magnitudes of rainfall for studied return periods using three AM series (observed, SDSM for 2080s, and LARS-WG for 2080s)

series of SDSM and LARS-WG, respectively. It can be seen from the figure that both the models (SDSM and LARS-WG) successfully simulate the magnitudes of precipitation for the five return periods, as GEV estimates for simulated values of both the models are well within the 95% CI obtained using the observed AM series (cf. Semenov 2008). Furthermore, both the models consistently underestimate the GEV AM values obtained using the observed data. However, they appear to simulate the low return period precipitation better than high return period precipitation, as the departure of simulated values from the corresponding observed values increases with increasing return period. On the basis of the results presented above, it can be seen that both models are acceptably good at simulating AM precipitation as compared to the observed AM values. Furthermore, they have similar capability, as there is no significant difference in their results.

Precipitation frequency analysis based on the downscaled data for the Clutha watershed is shown in Fig. 9. In the figure, the GEV-estimated precipitation amounts for the five studied return periods obtained using the observed data (1961–2000), the SDSM-downscaled data for 2080s, and the LARS-WG-downscaled data for 2080s are plotted. Figure 9 represents the ability of the two downscaling models for assessing the changes in the frequency of future extreme events and also presents two different pictures of the future. The GEV-estimated values obtained for the SDSM-downscaled data clearly show a significant increase in both the frequency and the intensity of future extreme events of precipitation. The SDSM-downscaled data suggest that a 100-year event will become a 20-year event and a future 100-year event will be around 1.5 times that of the 100-year event now. On the other hand, the GEV estimate based on the LARS-WG-downscaled data suggests an increase in magnitude of low-return period precipitation events, while a decrease is projected for the high return period events. These two contrasting pictures of the future are a result of the difference in the basic concept behind the two downscaling models. The SDSM makes use of the changes in atmospheric circulation patterns in terms of the large-scale predictors, as suggested by a GCM which can be considered more reliable. On the other hand, LARS-WG uses the RCFs derived from the direct precipitation output of a GCM. As the current GCMs are still very coarse in spatial resolution, their direct precipitation output is unreliable.

5 Conclusions

The performances of a multiple regression model, called SDSM, and a weather generator, called LARS-WG, were evaluated in terms of their ability to simulate present and downscale future frequency of extreme precipitation. Daily areal average precipitation data from the Clutha watershed in South Island, New Zealand, were used for the analysis. The GEV distribution was fitted to the AM series. Five sets of AM series were obtained: observed (1961–2000), the SDSM-simulated (1961–2000), the SDSM-downscaled (2080s), the LARS-WG-simulated (1961–2000), and the LARS-WG-downscaled (2080s). The GEV estimates of AM precipitation amounts for five return periods (10-, 20-, 40-, 50-, and 100-year) as well as their corresponding 95% CI were obtained. In simulating the five return periods, both model estimates are within 95% CI estimated by GEV for observed AM series, affirming reasonable confidence in the ability of both the models. Comparing the two models in terms of three GEV parameter values and the GEV-estimated precipitation magnitudes for all five return periods reveals that it is difficult to conclude in favor of either of them. On the whole, both the models (i.e. SDSM and LARS-WG) show similar results for simulating present-day extreme events of precipitation. Future precipitation frequency analysis, based on the downscaled data of both the models, presents two different pictures. The contrasting implication of the two models about the future is a result of the difference in their downscaling strategy and their basic concepts. These results further reinforce multi-model strategies for conducting climate change studies. On the basis of the results obtained in this study, both SDSM and LARS-WG models can be adopted with reasonable confidence as downscaling tools to undertake climate change impact assessment studies for the future.

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References

Bannayan M, Hoogenboom G (2008) Weather analogue: a tool for real-time prediction of daily weather data realizations based on a modified k-nearest neighbor approach. Environ Model Softw 23(6):703–713

Bruhn JA (1980) A stochastic model for the simulation of daily weather. Prot Ecol 2(3):199–208

Bruhn JA, Fry WE, Fick GW (1980) Simulation of daily weather data using theoretical probability distributions. J Appl Meteorol 19:1029–1036

Coles S (2001) An introduction to statistical modeling of extreme values. Springer, Berlin, ISBN 1-85233-459-2

Dibike YB, Coulibaly P (2005) Hydrologic impact of climate change in the Saguenay watershed: comparison of downscaling methods and hydrologic models. J Hydrol 307:145–163

FEMA (Federal Emergency Management Agency of the United States) (2004) Final draft guidelines for coastal flood hazard analysis and mapping for the Pacific Coast of the United States. http://www.fema.gov/library/viewRecord.do?id=2188

Fowler HJ, Blenkinsop S, Tebaldi C (2007) Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. Int J Climatol 27:1547–1578

Goodess CM, Anagnostopoulou C, Bardossy A, Frei C, Harpham C, Haylock MR, Hundecha Y, Maheras P, Ribalaygua J, Schmidli J, Schmith T, Tolika K, Tomozeiu R, Wilby RL (2007) An intercomparison of statistical downscaling methods for Europe and European regions—assessing their performance with respect to extreme temperature and precipitation events. Clim Change (accepted)

Hartkamp AD, White JW, Hoogenboom G (2003) Comparison of three weather generators for crop modeling: a case study for subtropical environments. Agric Syst 76:539–560

Hessami M, Gachon P, Ouarda TBMJ, St-Hilaire A (2008) Automated regression-based statistical downscaling tool. Environ Model Softw 23:813–834

Hewitson BC, Crane RG (1996) Climate downscaling: techniques and application. Clim Res 7:85–95

Heyen H, Zorita E, Von Storch H (1996) Statistical downscaling of monthly mean North Atlantic air-pressure to sea level anomalies in the Baltic Sea. Tellus Ser A 48:312–323

Huang W, Xu S, Nnaji S (2008) Evaluation of GEV model for frequency analysis of annual maximum water levels in the coast of United States. Ocean Eng 35:1132–1147

IPCC (2007) Climate Change 2007, the Fourth Assessment Report (AR4) of the United Nations Intergovernmental Panel on Climate Change (IPCC), Working Group I, The Physical Science Basis of Climate Change

Khalili M, Brissette F, Leconte R (2009) Stochastic multi-site generation of daily weather data. Stoch Environ Res Risk Assess 23:837–849

Khan MS, Coulibaly P, Dibike Y (2006) Uncertainty analysis of statistical downscaling methods. J Hydrol 319:357–382

Kilsby CG, Jones PD, Burton A, Ford AC, Fowler HJ, Harpham C, James P, Smith A, Wilby RL (2007) A daily weather generator for use in climate change studies. Environ Model Softw 22:1705–1719

Kim BS, Kim HS, Seoh BH, Kim NW (2007) Impact of climate change on water resources in Yongdam Dam Basin, Korea. Stoch Environ Res Risk Assess 21:355–373

McKerchar AI, Henderson RD (2003) Shifts in flood and low-flow regimes in New Zealand due to interdecadal climate variations. Hydrol Sci J 48:637–654

Nicks AD, Harp JF (1980) Stochastic generation of temperature and solar radiation data. J Hydrol 48:1–7

Payne RW, Harding, SA, Murray DA, Soutar DM, Baird DB, Welham SJ, Kane AF, Gilmour AR, Thompson R, Webster R, Tunnicliffe Wilson G (2007) The guide to GenStat release 10, Part 2: Statistics. VSN International, Hemel Hempstead

Racsko P, Szeidl L, Semenov M (1991) A serial approach to local stochastic weather models. Ecol Model 57:27–41

Richardson CW (1981) Stochastic simulation of daily precipitation, temperature, and solar radiation. Water Resour Res 17(1):182–190

Richardson CW, Wright DA (1984) WGEN: a model for generating daily weather variables. US Department of Agriculture, Agricultural Research Service, ARS-8, 83 pp

Riha SJ, Wilks DS, Simoens P (1996) Impact of temperature and precipitation variability on crop model predictions. Clim Change 32:293–311

Schoof JT, Arguez A, Brolley J, O'Brien JJ (2005) A new weather generator based on spectral properties of surface air temperatures. Agric For Meteorol 135:241–251

Semenov MA (2006) Using weather generators in crop modelling. Acta Hortic 707:93–100

Semenov MA (2008) Simulation of extreme weather events by a stochastic weather generator. Clim Res 35(3):203–212

Semenov MA, Barrow EM (1997) Use of a stochastic weather generator in the development of climate change scenarios. Clim Change 35(4):397–414

Semenov MA, Brooks RJ, Barrow EM, Richardson CW (1998) Comparison of the WGEN and LARS-WG stochastic weather generators for diverse climates. Clim Res 10:95–107

SRES (Special Report on Emission Scenarios) (2000) Intergovernmental Panel on Climate Change (IPCC). http://www.grida.no/climate/ipcc/emission/index.htm

Tolika K, Anagnostopoulou C, Maheras P, Vafiadis M (2008) Simulation of future changes in extreme rainfall and temperature conditions over the Greek area: A comparison of two statistical downscaling approaches. Glob Planet Change 63:132–151

Wilby RL (1999) The weather generation game: a review of stochastic weather models. Prog Phys Geogr 23(3):329–357

Wilby RL, Dawson CW, Barrow EM (2002) SDSM—a decision support tool for the assessment of regional climate change impacts. Environ Model Softw 17:145–157

Wilby RL, Charles SP, Zorita E, Timbal B, Whetton P, Mearns LO (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

Wilks DS (1992) Adapting stochastic weather generation algorithms for climate change studies. Clim Change 22(1):67–84

Wilks DS (1999) Multisite downscaling of daily precipitation with a stochastic weather generator. Clim Res 11(2):125–136

Xu CY (1999) From GCMs to river flow: a review of downscaling methods and hydrologic modelling approaches. Prog Phys Geogr 23:229–249