Performance evaluation of regional climate models (RCMs) in determining precipitation characteristics for Gothenburg, Sweden

Arun Rana, Shilpy Madan and Lars Bengtsson

ABSTRACT

Regional climate models (RCMs) are used for forecasting future climate including precipitation characteristics. Performances of five different RCMs for predicting the precipitation characteristics for Gothenburg, Sweden were evaluated against the daily observed precipitation over the period 1961 to 2009. Statistical analysis was done on annual, monthly, multi-daily, and daily data. The statistical techniques used include principal component analysis (PCA), comparison of annual maximum, frequency of exceedances determined from Poisson distribution, comparison of frequency distributions, and Mann–Kendall technique for investigating trend over time. Inter-annual variability and autocorrelation between years were also investigated. The results obtained point towards the usefulness of these high-resolution RCMs. It was observed that all the models give the annual maximum precipitation within 3 mm of the observed data. As for the observed series, no trends were found for monthly or seasonal data. The number of exceedances above threshold accepted Poisson distribution hypothesis with the mean exceedances from RCM-PROMES being very close to the mean exceedances from the observed data. PCA also indicated that PROMES came closest to explaining the observed data. The presented statistical methods can be used for bias correction of raw RCM data in future studies.

Key words | climate change, daily precipitation, extreme precipitation, Gothenburg, regional climate models (RCMs), statistical techniques

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INTRODUCTION

Climate change is expected to lead to changed precipitation patterns in many regions. Dore (2005) highlighted broad implications for future global precipitation suggesting that several regional precipitation trends can already be detected and are likely to increase in the future. In western Europe, mainly the daily winter precipitation has changed leading to increased annual precipitation shown for Sweden by Busuioc *et al.* (2011). For Britain, with a similar climate to western Sweden, Maraun *et al.* (2008) showed that the winter rains have become more intense but that the daily summer storms rather have decreased in intensity or show inter-decadal variability. Using 600 gauges within the Rhine basin, Hundecha & Bárdossy (2005) concluded that the large daily precipitation showed an increasing trend over 50 years in all seasons except summer, where it showed the opposite trend.

For predicting future climate trends, high resolution climate models must be used. Some of the earliest studies of the potential impacts of global warming in Europe were based on idealized global climate model (GCM) simulations. Some studies used results from only one model to illustrate potential impacts (e.g., Emanuel *et al.* 1985) and some used a range of models for impact studies to ensure consistency (e.g., Parry 1989). Later studies recognized inter-model uncertainties and adopted outputs from several GCMs (e.g., Rotmans *et al.* 1994). The precipitation characteristics

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vary so much from region to region and locally within regions so the precipitation pattern can only be caught when the scale in the climate models is reduced. Jones *et al*. (1997), among others, have pointed out the advantages of using regional climate model (RCM) data over GCM data for small-scale spatial studies. RCMs represent an advantage over GCM data for representing small-scale processes as pointed out by Durman *et al*. (2001). RCM simulations are more realistic, when scaled, in comparison to GCM simulation data. Gao *et al*. (2008) have also reached the same conclusion that RCM outperforms the driving GCMs in predicting future climate scenarios in terms of both spatial pattern and amount of precipitation.

Jones & Reid (2001) studied the plausible increase in heaviest precipitation over Britain using RCM integrations. Although any significant increase of extreme daily storms have not yet been observed in western Europe, these model simulations indicated that daily storms are expected to increase significantly in the future, as was also found for northwestern Europe by Raisanen & Joelsson (2001). Climate projections for Sweden indicate higher temperatures, especially during winter. The Commission on Climate and Vulnerability was appointed by the Swedish Government in June 2005 to assess regional and local impacts of global climate change on Swedish society. In the study it was concluded that 'Sweden will become warmer and wetter'. Precipitation is likely to increase in most parts of the country during the autumn, winter, and spring time. In summer-time, the climate will be warmer and drier, particularly in southern Sweden. Large storms are said to be expected to increase in future.

A comparison is sought, to see the extent of the local climatic/precipitation pattern that can be forecasted by RCMs as the model output ought to be compared with historic data. Jacob *et al*. (2007) did an inter-comparison of regional climate models' performance comparing with the present day climate. Jeong *et al*. (2011) studied the diurnal cycle of precipitation in Sweden and compared model output with observations. The intention with the present study is to do a similar test on how well different RCMs perform in determining precipitation characteristics on a local scale. The objectives of the study include: (1) analysis of raw RCMs output to represent local-scale precipitation processes; (2) comparative analysis using statistical methods of raw RCM output data with that of observations recorded; and, finally, (3) analysis of bias correction that can be implemented in RCM output for better representation of local phenomena in the future. Since the objective of the paper included study of RCM predictions in predicting climate/precipitation over a small spatial scale, comparison was made in terms of observed historic data and RCM output itself without bias correction. With that intention, performance of raw RCMs outputs and usefulness of different statistical methods for bias correction, only five RCMs were chosen for the present study. The five different RCMs were used for forecasting daily precipitation in Gothenburg, on Sweden's west coast. Their performance was analyzed for data period 1961–2009 by comparing with observed data for the same period. Annual, monthly, daily, and multi-daily precipitation events were considered for the statistical analysis. Statistical significance of various tests are checked to conclude if any model exists whose simulations can be relied upon for predicting future rain characteristics without bias correction. If not the case, the presented statistical methods can be further used for bias correction method for future impact studies. Similar studies for southern Sweden have been carried out by Achberger *et al*. (2003) where the authors have compared observations with output from RCMs.

DATA BASE

Observed precipitation

Gothenburg (Swedish: Göteborg) is the second largest city in Sweden. It is inhabited by approximately 500,000 people. It is situated on the west coast of Sweden at the mouth of the river Göta Älv, as shown in Figure 1; Gothenburg lies at 57°42′N, 11°55′E on the longitude–latitude grid. The annual mean precipitation is about 800 mm, 37% of days are wet days. The mean annual daily precipitation is 35 mm. The observed data are from the Säve gauge station which is about 15 km east of the central part of Gothenburg. The precipitation is rather uniformly distributed over the year with 200 mm in June–August and also 200 mm for the winter months of December–February. It is 250 mm in September–November and 150 mm in March–May. Most of the large daily rainfalls are a consequence of cyclonic

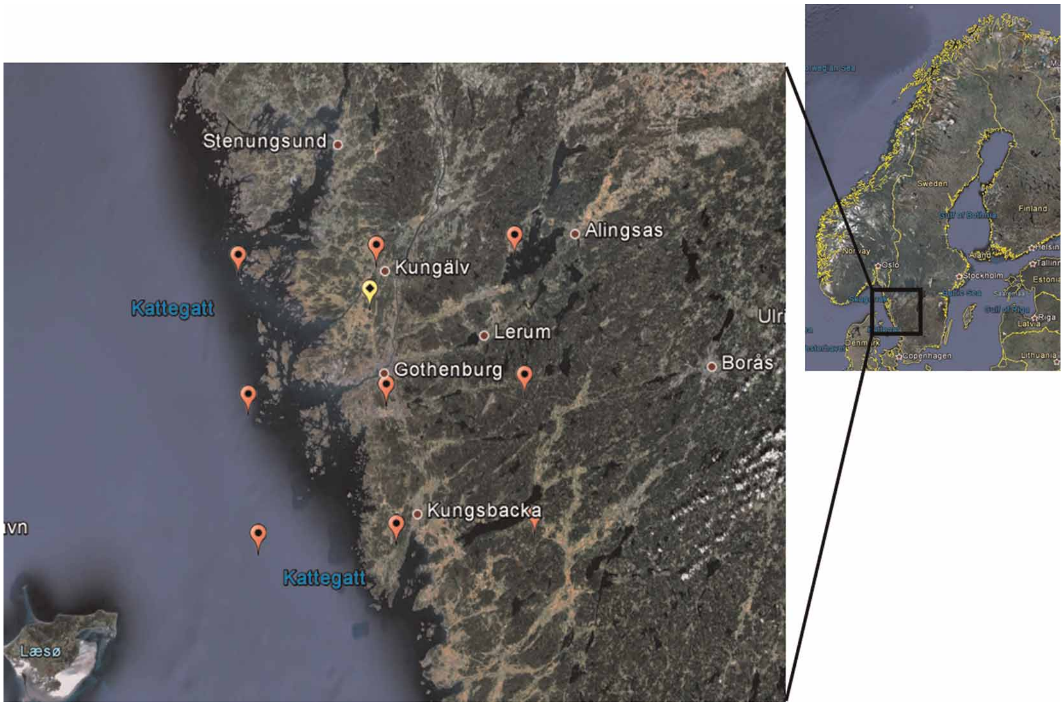

Figure 1 | Study area, Gothenburg, depicting the observation station and the grid points used in the study.

weather conditions (Hellstrom 2005). Large daily events are most common in July and August, but the largest daily rain was observed in December 1976. There are missing data in the stipulated period of year 2004–2005.

RCM data

The RCM data are a grid of 25 × 25 km resolution, shown in Figure 1. The grid size and dimensions was the same for all five RCMs. The five RCMs were derived from the two GCMs, HadCM3Q0 and ECHAM5-r3. An ensemble of 19 regional climate integrations with a resolution of 25 km has become available through the ENSEMBLES project coordinated by the Met Office Hadley Centre. These integrations are based on the A1B emission scenario and run up to year 2100, with the area of focus being Europe. The simulated data were obtained from the data archive of the Danish Metrological Institute (DMI) and can be accessed via http://ensemblesrt3.dmi.dk/. The statistical analysis was then performed on these daily data, either as daily values or derived monthly or annual values.

The models used in this study are given in Table 1. The RCMs chosen for the study are based on the criteria that they have same grid size of 25 km resolution and also the same grid coordinates around Gothenburg, as depicted in Figure 1. RCM CLM, the climate version of the Lokal

Table 1 | The members of the multi-model ensemble used in the study with grid resolution of 25 km

Model	Scenario	Global model	Regional model	Institute	Period
M1	A1	HadCM3Q0	CLM	ETHZ, Switzerland	150
M2	A1	HadCM3Q0	PROMES	UCLM, Spain	100
M3	A1	HadCM3Q0	HadRM3Q0	HC, United Kingdom	150
M4	A1	ECHAM5-r3	RACMO2	KNMI, The Netherlands	150
M5	A1	ECHAM5-r3	REMO	MPI, Germany	150

Model (LM), is a non-hydrostatic regional climate model. It was developed by the Swiss Institute of Technology. RCM REMO is based on the Europa model from the German Weather Service and is used by the Max Planck Institute for Meteorology. It uses a slightly modified physical parameterization scheme and has been tested in different climates (Frei *et al*. 2003). RCM PROMES is used by Universidad de Castilla La Mancha, Spain. It is a state of the art primitive equation model, hydrostatic and fully compressible. RCM RACMO2 is used by the Royal Netherlands Meteorological Institute, The Netherlands. It combines the land surface characteristics and the dynamical core of HIRLAM numerical weather prediction system with the physical parameterization scheme of the European Centre for Medium Range Weather Forecasting (ECMWF). RCM HadRM3Q0 is used by the Hadley Centre. The physical parameters incorporated in the model include calculation of large-scale cloud and also include assumptions about the radiative effects from convective clouds.

For comparison with observed precipitation in Gothenburg, three sets of data are used. The first set incorporates the daily precipitation data from 1 January 1961 to 31 December 2009. The second set is derived from daily observations and incorporates the monthly mean precipitation. Lastly, the third set accounts for annual mean precipitation values for the data period, i.e., 1961 to 2009.

STATISTICAL METHODOLOGY

The RCMs simulate precipitation with daily steps. In the statistical analysis as for the observed daily rain series precipitation less than 1 mm is considered to be a 'no event'. Comparison between simulations and observations is done on mean statistics, not between individual days or years. Statistical techniques are used to analyze how well RCMs track the observed precipitation and can be relied upon for future predictions of precipitation and bias correction.

Descriptive statistics and rainfall distribution (CDF)

The daily rainfall frequency distributions of the observed data and the model simulations are determined and compared with focus on rare events, but also the number of wet days was considered. Descriptive statistics were calculated for observations and predicted data sets including mean, median, and standard deviation. This was then followed by calculation of coefficient of variation (CV) in monthly precipitation over a year and averaging over all years and seasonal events (winter and summer) to analyze variability in the annual and seasonal patterns. The fit to different theoretical distributions was investigated. Cumulative distribution $F(x)$ can be defined as the proportion of observations lying below a certain value x. The cumulative distribution for all models simulation runs is compared with observed data.

Extreme event analysis

Extremes events of precipitation were studied by determining annual daily maximum, 2-day, 3-day, and 7-day annual maximum. Annual maxima are considered for fitting generalized extreme value (GEV) distribution and determining return periods. The type of extreme events considered here are the maximum of a sequence type, i.e., use annual maxima of daily precipitation amounts. The choice of block size is critical as too small a block size can lead to bias and blocks that are too large generate inadequate block maxima while performing the fit. This may lead to large estimation variance. The block maxima approach is closely associated with the use of the GEV family. All parameters are estimated by the method of maximum likelihood estimation. The GEV distribution functions have the form:

$$G(y) = \exp\left(-\left(1 + \gamma\frac{y-\mu}{\sigma}\right)_+^{-\frac{1}{\gamma}}\right)$$

where σ, μ, and γ are the scale, location, and shape parameters, respectively.

Poisson distribution is used to model the number of occurrences of extreme events (here daily precipitation exceeding a threshold value) within a given year. It can be used for data that involve random sums of rare events. We consider the extreme event exceedance of a threshold value. The cumulative function is:

$$F(k) = \frac{\tau(k+1,\ \lambda)}{k!}$$

where k is number of exceedances in a year, λ is the poisson parameter, and τ is the incomplete gamma function. An event was considered extreme if the daily precipitation exceeded 20 mm. An extreme event was defined as the event exceeding 99th percentile of the data. Number of rainy days (frequency) during summer and winter season was also calculated to analyze rain frequency during different seasons.

Inter-annual variability and autocorrelation

From investigations of 20th century precipitation in Germany, Trömel & Schönwiese (2007) found that the variation of annual precipitation between years has increased. Therefore, the variation between years was also investigated in the present study for annual, summer, and winter months. The inter-annual variability was determined by computing the relative change percentage (RC) of the sampled data. The inter-annual RC for the model outputs are compared with that of the observed annual precipitation. Large changes indicate that there is no correlation of precipitation between different years. The correlation between years can be checked, although not in a very straightforward manner, by computing the mean CV to determine a CV index. These two techniques have been used previously in studying climate change scenarios, for example by Giorgi et al. (2004) and Attema & Lenderink (2011). The annual relative change for observed and simulation is calculated as:

$$\text{RC} = \frac{\text{value in suceeding year} - \text{value in current year}}{\text{value in current year}}$$

The main advantage of using this method is that it removes the dependency of standard deviation on mean precipitation. The trend, if any, must be filtered out. A more straightforward way of investigating the dependence of the precipitation of a certain year to the precipitation of the previous year, is to compute the autocorrelation. This was also done and the autocorrelation for the model simulations was compared with the computed observed correlation value. A −0.2 to 0.2 band was taken as the confidence band for insignificant autocorrelation measure when using a 10-year lag period.

Mann–Kendall test

Any presence of trend over the 50 years was analyzed using the Mann–Kendall trend procedure for monthly rainfall over the years considering winter and summer conditions separately. The Mann–Kendall test is a popular statistical method used by contemporary climatologists, Wibig & Glowicki (2002), Lu et al. (2004), and Gadgil & Dhorde (2005) among others, as a significant test for checking the overall trend. Using the Mann–Kendall no assumptions about distribution are necessary. Also, it is not much affected by outliers because its statistic is based on the sign of differences and not directly on the values of the random variable. The significance level that there is no trend was set to 5%. Since the RCMs predict changes of precipitation in the future, tests showing that trends or no trends are the same for the model outputs as for observations are important for the confidence of the models.

Principal component analysis (PCA)

PCA is a multivariate statistical analysis, which attempts to simplify a complex set of interrelationships by creating one or few variables, with respect to those that allow a more convenient examination of the overall spatial relationship. The overall variance in a data set is explained by isolating a number of components with respect to newly defined axes, each of which corresponds to a variable (e.g., Richman 1986). It helps to identify patterns in the data and express the data such that these similarities and differences are highlighted. PCA can be understood as a variable reduction procedure. PCA is used on monthly precipitation.

RESULTS

Descriptive statistics and rainfall distribution

The cumulative distribution of monthly rainfall was computed for observed as well as for simulated precipitation and plotted in Figure 2. It is seen that all models generally fit a similar distribution as the observed one. PROMES captures the end tail of the observed distribution well, but the cumulative curve lies below the observed one. PROMES

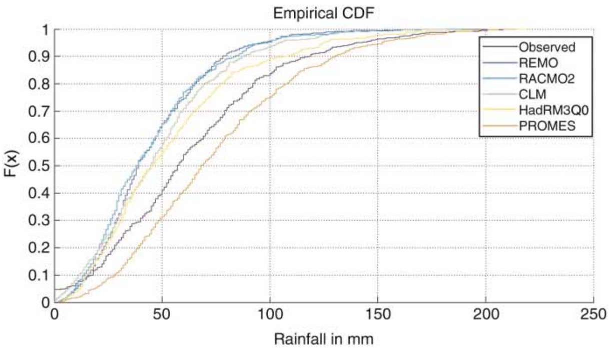

Figure 2 | The cumulative distribution function of monthly rainfall amounts from observations and various model simulations.

gives a wetter climate than the actual observed, while the other models give a rather much drier climate. Historic data are missing for year 2004–2005 which explains that $F(0) \approx 0.05$ for the observed CDF in the graph (Figure 2). The distribution parameters are shown and compared in Table 2. Similar observations can be made from the table that PROMES is predicting a wetter climate as compared to other models in the stipulated time period in terms of mean, median, and standard deviation. The first and second order moments of PROMES simulated data come closest to the moments of the observed set of data. The variability in recorded data is well captured by this model simulation while there exists a minor positive bias in mean value of the distribution. Other models' simulations give a negative bias in estimating the mean value of rainfall distribution and the spread of data is also not appropriately defined. The coefficients of variation for observed and simulated data are presented in Table 3 for annual, winter, and summer months. CV is less than 1 for all data sets, implying that there is no significant inter-annual variation in precipitation in Gothenburg. REMO (0.57) and PROMES (0.53) gave slightly smaller index values of CV in comparison to the observed (0.63). It has been found in other studies that wet RCMs usually underestimate the CV (Giorgi *et al.* 2004).

Extreme event analysis

Daily storms were analyzed for extreme events. It was found that all data sets fitted well to the GEV family. Apart from RACMO2, all data sets accepted the Gumbel distribution. The parameter estimates and plots are shown in Table 4 and Figure 3. It can be seen that CLM and PROMES data gave similar parameter estimates as the observed series. The return level plot of CLM and PROMES came closest to the ones generated by the observed data set. The annual daily maximum precipitation is shown against the return period. The 10-year daily storm is about 40 mm, which also was predicted from the PROMES and CLM simulations. It was observed that all the models give annual maximum precipitation within 3 mm of the observed values.

Poisson distribution was used to determine the frequency of extreme events occurring several times in a year. Daily rains exceeding 20 mm were analyzed. The fit of the different model simulations to the Poisson distribution

Table 2 | Distribution parameter estimates for monthly precipitation

	Observed	REMO	RACMO2	CLM	HadRM3Q0	PROMES
Mean	63.33	45.12	44.32	47.98	53.76	74.60
Median	57	39	38.50	45	45	68
Standard deviation	40.51	27.23	28.30	30.61	36.46	40.38

Table 3 | CV of variation of annual, summer, and winter precipitation for each model

CV	Observed	REMO	RACMO2	CLM	HadRM3Q0	PROMES
Annual	0.63	0.57	0.61	0.62	0.66	0.53
Summer	0.47	0.47	0.59	0.78	0.71	0.48
Winter	0.52	0.48	0.54	0.39	0.43	0.45

Table 4 | Maximum likelihood estimates of GEV parameters

	Observed	REMO	RACMO2	CLM	HadRM3Q0	PROMES
Mu (μ)	27.98	25.55	28.50	29.14	30.42	28.60
Sigma (σ)	12.19	8.79	6.46	8.82	8.21	6.09
Gamma (γ)	−0.07	0.29	0.09	−0.01	−0.16	−0.19
Gumbel hypothesis	Accept	Accept	Reject	Accept	Accept	Accept

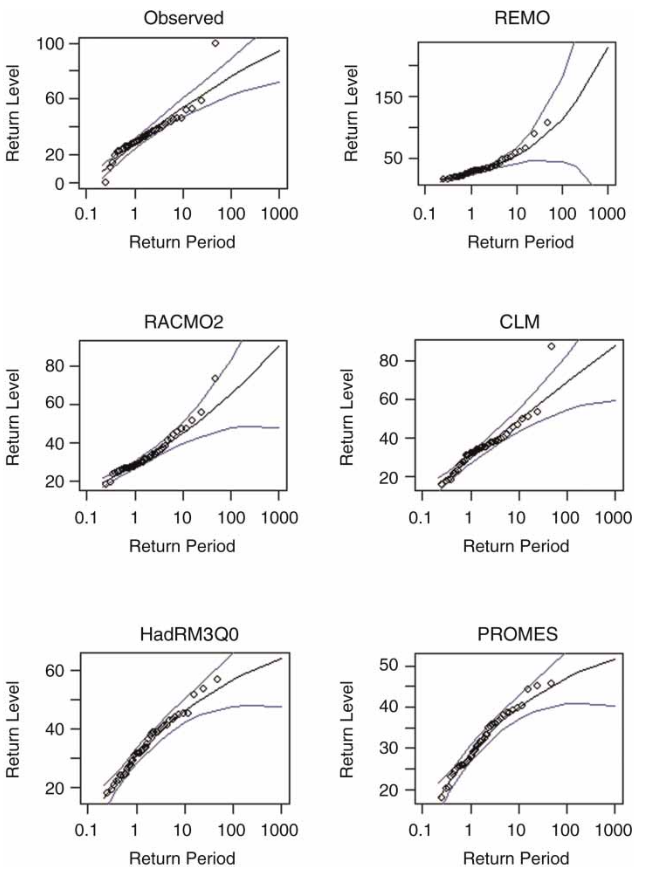

Figure 3 | GEV for fitted observed and climate model data with return level (intensity of precipitation in mm) and return period (years).

Table 5 | Poisson distribution fit to data set

	Lambda	*P* value	Poisson hypothesis
Observed	4.65	0.09	Accept
REMO	2.18	0.06	Accept
RACMO2	2.79	0.53	Accept
CLM	3.02	0.52	Accept
HadRM3Q0	3.79	0.02	Reject
PROMES	4.24	0.65	Accept

is reported in Table 5. All models accept the Poisson distribution hypothesis for the frequency of exceedances except HadRM3Q0. The parameter value for the Poisson distribution determined using PROMES data is almost the same as for the observed data indicating four to five occurrences of extreme rainfall in a year. The other models underestimate the frequency of such occurrences and predict two to three events in a year. Monthly average precipitation over years indicated that all models gave fairly close values of these averages as were seen in the recorded data. The output generated from model simulations are given in Table 6.

The mean values of the annual maxima of 1 day, 2 day, 3 day, and 7 day were computed. All models showed values close to the observed values for 1–3 day annual maximum precipitation, while for HadRM3QO and PROMES the 7-day annual maximum precipitation was computed too low (Table 6). The number of rainfall events in summer and winter months is presented in Table 7. It can be observed from the table that REMO and PROMES overestimate the number of rainy days for the summer season as compared to observed data whereas all others underestimate the same. In the winter season, all the models overestimate the number of rainy days in the area.

Inter-annual variability and autocorrelation

The annual precipitation at a location may be quite stable from year to year, vary rather a lot or be correlated to the precipitation in the previous year. The annual relative change is a measure of the inter-annual variability. It was determined for the simulated data from each model and for historic annual data series. Figure 4 shows the computed relative change for all the series. Figure 4(a) shows the variability during summer season, Figure 4(b) depicts variability during winter and Figure 4(c) depicts the same in annual

Table 6 | Annual mean maximum for daily and multi-daily precipitation

(Average)	Observed	REMO	RACMO2	CLM	HadRM3Q0	PROMES
Day max.	33.73	34.00	32.90	34.00	34.02	31.15
2-day max.	42.60	43.23	43.48	44.11	47.60	42.42
3-day max.	50.22	48.85	50.04	49.79	55.07	51.22
7-day max.	74.17	62.00	64.95	65.92	76.56	78.05

Table 7 | Number of rainy days in summer and winter months as predicted by the RCM data and observed data for the entire period

Season	Observed	REMO	RACMO2	CLM	HadRM3Q0	PROMES
Summer						
Rainy	1,813	2,172	1,703	1,236	2,178	2,691
Non-rainy	2,695	2,336	2,805	3,174	2,231	1,719
Total days	4,508	4,508	4,508	4,410	4,409	4,410
Winter						
Rainy	2,168	2,852	2,667	2,764	2,291	2,957
Non-rainy	2,254	1,570	1,755	1,646	2,119	1,453
Total days	4,422	4,422	4,422	4,410	4,410	4,410

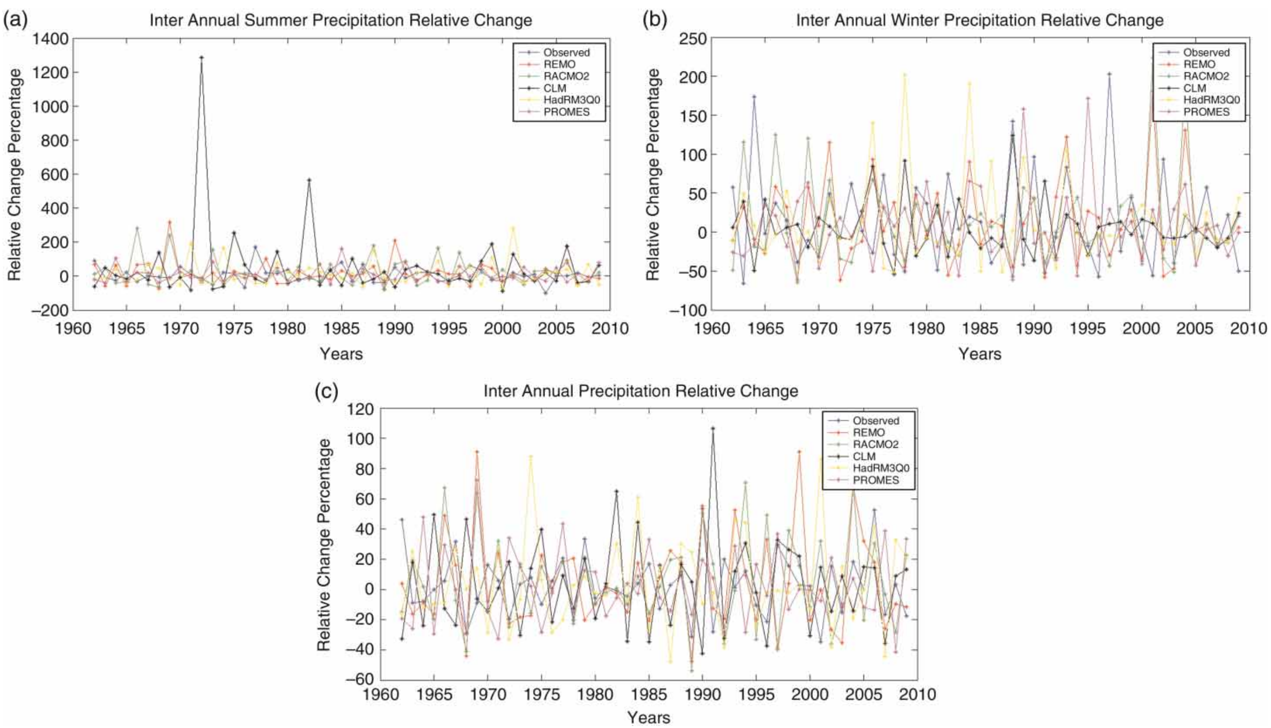

Figure 4 | Inter-annual relative change of precipitation as percentage during summer, winter, and annual time periods, respectively.

time series. A visual interpretation suggests that the observed pattern of change in annual precipitation is captured well by PROMES, while much less so by the other models. The average relative change in precipitation in Gothenburg from 1961 to 2009 has been 2.8%. PROMES gives an average relative change over these years of 2.3% followed by CLM with 3.6%. The variability can be associated with large-scale forcing which derives the local climatic conditions. Various studies have previously been performed to look at the effect of atmospheric circulations on precipitation in Sweden; notable among them is the study by Busuioc *et al.* (2011).

Autocorrelation was also performed on the observed and model data and the results are presented in Figure 5. It shows the autocorrelation for observed and model generated data for different lag periods in years. ACF between −0.2 and 0.2 was regarded as insignificant autocorrelation. It can be inferred that for a lag of 1 year, there is significant autocorrelation in annual precipitation in the observed data, which is duly captured by REMO, but not by the other models. However, except for PROMES, all the models showed significant autocorrelation. For a larger time lag, 10 years, there was insignificant autocorrelation in annual precipitation in the observed data set after a lag of 1 year.

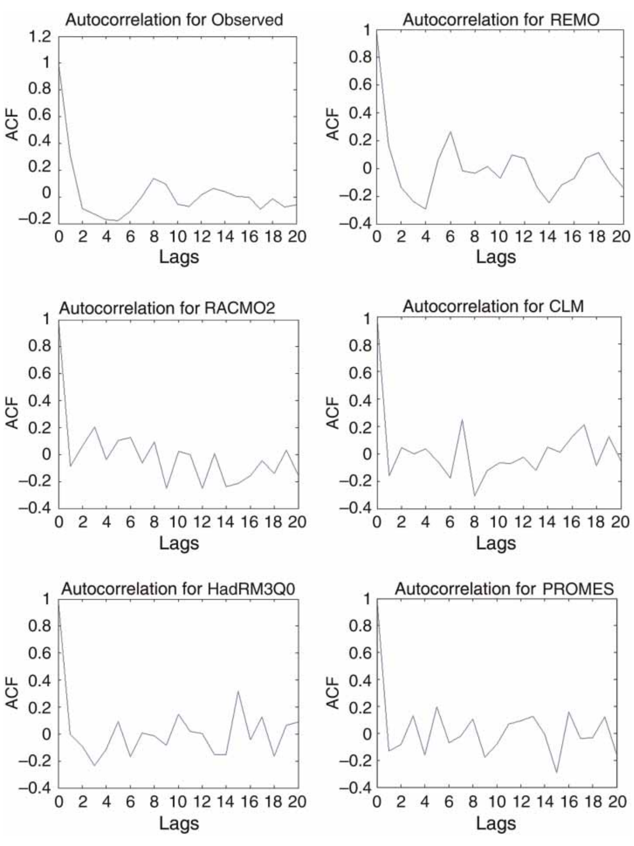

Figure 5 | Autocorrelation for observed and climate model data with time lag in years.

Mann–Kendall test

Results of transient regional climate model integrations are compared with the monthly precipitation observational data sets from January 1961 to December 2009. They are tabulated in Table 8. There is no significant trend in the recorded data. The null hypothesis is accepted at 5% level of significance. In accordance with the observed data set, none of the model simulations show the presence of any significant trend, nor for the winter precipitation do the models show any trend except PROMES. The *p* value, *Z* value and *S* counts of RCM-PROMES come closest to those of the

Table 8 | Mann–Kendall trend analysis of monthly precipitation for annual, summer, and winter seasons

Data	Trend	*P* value	*Z* value	*S* value
Monthly				
Observed	Absent	0.3178	0.999	4,755
REMO	Absent	0.9481	0.0651	311
RACMO2	Absent	0.418	0.8099	3,855
HadRM3Q0	Absent	0.6869	0.403	1,919
CLM	Absent	0.7445	0.3259	1,552
PROMES	Absent	0.4122	0.82	3,903
Summer				
Observed	Absent	0.8454	−0.195	−251
REMO	Absent	0.9645	−0.0445	−58
RACMO2	Absent	0.591	0.5374	690
HadRM3Q0	Absent	0.696	−0.3907	−502
CLM	Absent	0.416	−0.8135	−1,044
PROMES	Absent	0.4994	0.6754	867
Winter				
Observed	Absent	0.1193	1.5575	1,998
REMO	Absent	0.6691	0.4274	549
RACMO2	Absent	0.4447	0.7643	981
HadRM3Q0	Absent	0.2522	1.1449	1,469
CLM	Absent	0.3461	0.9422	1,209
PROMES	Present	0.0372	2.0832	2,672

Table 9 | Coefficients of principal components as explained by PCA from observed and simulated RCMs

Component/model	Observed	REMO	RACMO2	CLM	HadRM3Q0	PROMES
Component 1	−0.18	0.36	0.38	0.45	0.54	−0.44
Component 2	−0.05	0.61	0.57	−0.41	−0.31	0.20
Component 3	0.82	0.10	0.14	0.33	0.16	0.40
Component 4	−0.53	−0.03	0.04	0.33	0.16	0.76
Component 5	0.04	0.43	−0.51	−0.45	0.57	0.14
Component 6	0.04	−0.55	0.50	−0.46	0.48	0.08

observed. The observations show a positive trend during winter season if tested at 10% significance level. Other model simulations, however, exhibited an absence of any such trend. None of the model simulations depict the presence of any significant trend in summer precipitation, which is in line with the absence of a significant trend even in historic data sets.

Principal component analysis

Monthly observed and simulated precipitation is used for PCA analysis. In general, the number of components extracted is equal to the number of variables under consideration. Of these components, it must be decided which of them are worthy of being retained for further interpretation. Only the first few components will account for explaining meaningful variance. In our analysis, the first four components explained more than 80% of the variance. The first two components explained 28% and 23% of the variance, respectively. All eigenvalues were positive. The coefficients of principal components were plotted and are tabulated in Table 9. When the two components are plotted for the observed data, both the components lie close to the origin meaning that their impact is minor. It is important that the chosen principal components impact the observed data series. The first three principal components together explain approximately 70% variability in the data. Figure 6 depicts the plots for components, where Figure 6(a) represents the plot of component 1 with component 2 and Figure 6(b) represents component 1 with component 3. This plot of PCA suggests that observations are mostly influenced by component 3. The PROMES result lies in the same grid as the observed result while the output from the other models lies

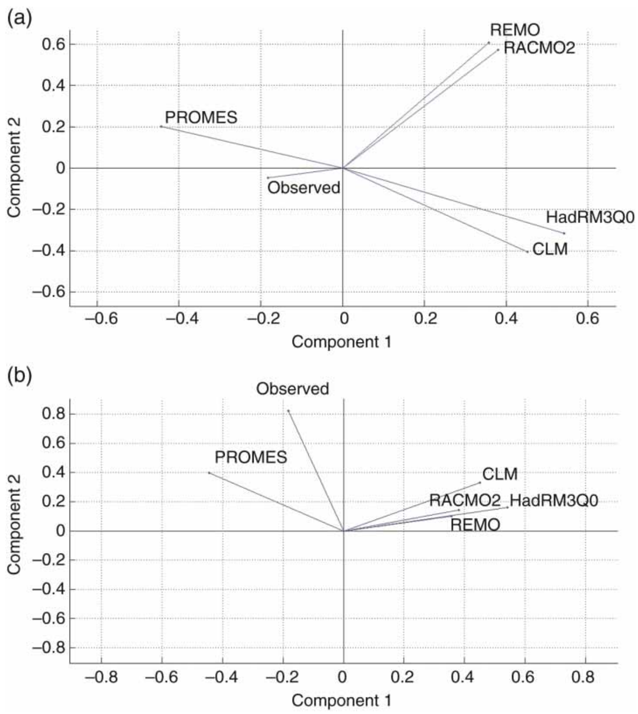

Figure 6 | PCA using component 1, component 2, and component 3: (a) represents plots of component 1 with that of component 2 and (b) represents component 1 with component 3.

in different grids. It is seen that PROMES and 'observed' lie in the same quadrant. This suggests that PROMES came closest to explaining the variability of the observations. Simulations generated by RCM-PROMES are of a similar nature as observed monthly precipitation.

DISCUSSION AND CONCLUSION

Given the potential implications of regional climate changes towards documenting national policies and building infrastructure that meets climate-related extreme events such as droughts, floods, and hurricanes, one needs to study how reliable are projections given by RCMs of future change. A way of testing models is to compute their performance over time and, as was done in this study, along with feasibility of the statistical methods to be used for bias correction. PCA analysis on monthly precipitation data sets revealed that RCM-PROMES simulations lie in the same phase as the observed series, whereas all other model simulations were found to lie in different phases. It was observed from CDF curves that the tail end of the observed distribution of monthly precipitation was captured by PROMES. The Mann–Kendall test showed no significant trend in monthly precipitation over the years either in historic data or in model simulations. All models except RACMO2 accepted the Gumbel distribution hypothesis. The observed data, RCM-PROMES, and CLM give similar parameter estimates of location, scale, and shape parameters of the GEV distribution and all estimated a return level of 40 mm in every 10 years. Also, the frequency of moderately large events as determined from the models accepted the Poisson distribution hypothesis except for RCM-HadRM3Q0. PROMES, in accordance with the historic data, predicts four to five events exceeding 20 mm in a year. The annual variability is well described particularly by PROMES. Model simulations followed in accordance with the autocorrelation as observed in annual precipitation of historic data. REMO best depicted the historic data autocorrelation measure, followed by PROMES.

One can conclude that regional climate models are able to capture the characteristics of daily precipitation on a rather local scale, but there is a need to realize the bias correction methods used for impact studies. Presented statistical methods can be used for correcting raw RCM data in accordance with observed values and can then be thoroughly used for impact studies. Among the five regional climate models considered RCM-PROMES simulation statistics are able to best define the patterns and occurrence of events as seen in the recorded historic data. Results also indicate that there are conceptual problems and practical limitations in using these high-resolution climate model outputs for predicting ecosystem responses. However, the mean statistics are well described in them which should be sufficient for most ecosystem problems.

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