Received: 12 October 2022 | Revised: 18 July 2023 | Accepted: 8 September 2023

DOI: 10.1002/met.2151

Meteorological Applications
Science and Technology for Weather and Climate
Open Access
RMetS

RESEARCH ARTICLE

Comparison between statistical and dynamical downscaling of rainfall over the Gwadar-Ormara basin, Pakistan

Raazia Attique[1] | **Tom Rientjes**[1] | **Martijn Booij**[2]

[1]Department of Water Resources, Faculty of Geo-Information Science and Earth Observation (ITC), University of Twente, Enschede, The Netherlands

[2]Department of Water Engineering and Management, Faculty of Engineering Technology, University of Twente, Enschede, The Netherlands

Correspondence
Raazia Attique, 115 Platform Street, Lidcombe, 2141 NSW, Australia.
Email: raazia.attique@gmail.com

Abstract

This paper evaluated and compared the performance of a statistical downscaling method and a dynamical downscaling method to simulate the spatial–temporal rainfall distribution. Outputs from RegCM4 Regional Climate Model (RCM) and the CanESM2 Atmosphere–Ocean General Circulation Model (AOGCM) were selected for the data scarce Gwadar-Ormara basin, Pakistan. The evaluation was based on the climatological average and standard deviation for historic (1971–2000) and future (2041–2070) time periods under Representative Concentration Pathways (RCP) 4.5 and 8.5 scenarios. The performance evaluation showed that statistical downscaling is preferred to simulate and project rainfall patterns in the study area. Additionally, the Statistical DownScaling Model (SDSM) showed low R^2 values in calibration and validation of the simulations with respect to observed data for the historic period. Overall, SDSM generated satisfactory results in simulating the monthly rainfall cycle of the entire basin. In this study, RegCM4 showed large rainfall errors and missed one rainfall season in the historic period. This study also explored whether the grid-based rainfall time series of the Asian Precipitation—Highly Resolved Observational Daily Integration Towards Evaluation (APHRODITE) dataset could be used to enlarge and complement the sample of in situ observed rainfall time series. A spatial correlogram was used for observed and APHRODITE rainfall data to assess the consistency between the two data sources, which resulted in rejecting APHRODITE data. For the future time period (2041–2070) under RCPs 4.5 and 8.5 scenarios, rainfall projections did not show significant difference for both downscaling approaches. This may relate to the driving model (CanESM2 AOGCM) and not necessarily suggests poor performance of downscaling; either statistical or dynamical. Hence, the study recommends evaluating a multi-model ensemble including other GCMs and RCMs for the same area of study.

KEYWORDS

climate change, dynamical downscaling, Gwadar-Ormara basin, Pakistan, rainfall, statistical downscaling

1 | INTRODUCTION

Climate change impact assessment studies help to understand the effects of changes in climatic variables on the hydrological cycle and water availability for any region. Impact studies also assess changes in extreme events like water scarcity, flooding and droughts. General Circulation Models (GCMs) serve to simulate the average, synoptic-scale, general-circulation patterns of the atmosphere for present climate, and to predict the future climate (Kour et al., 2016). GCMs provide climate projections for large spatial resolutions, ranging from 150 km × 150 km to 300 km × 300 km. At these resolutions, projections are not necessarily reliable for impact studies at the regional scale (<2500 km^2) or local scale (<500 km^2), and imply that spatial downscaling is necessary to provide meaningful information on impacts at regional scales (Fowler et al., 2007).

Downscaling can be through dynamical downscaling or statistical downscaling. Dynamical downscaling implies the application of a Regional Climate Model (RCM) for a region of interest and nested within a GCM. RCMs are aligned to GCMs as RCMs read the input of time-varying atmospheric forcing conditions generated by a GCM. Sunyer et al. (2012) describe that conditions are obtained for a finite domain of the GCM (one-way nesting) and applied to atmospherically force the RCM. Statistical downscaling, also known as empirical downscaling, relies on a statistical relationship between grid-based variables ('predictor'—either from GCM or RCM) and observed meteorological variables ('predictand'), as obtained by rainfall observations (i.e., gauges and/or sensors). Statistical downscaling techniques differ in complexity from linear regression to statistical neural networks and weather generators (Kour et al., 2016). Statistical downscaling is considered more direct in use as scaling relies on established relationships for individual ground meteorological stations.

RCMs simulate meteorological variables at spatial grid elements of typically 25 km × 25 km with improved spatial representation of meteorological variables as compared with GCMs. However, RCMs simulated climatic variables such as rainfall depth do not precisely match with observed ground-based counterparts. RCMs inherit errors from their driving GCM, but errors also result from RCMs by imperfect model conceptualization, parameterization physics, defined initial conditions, established boundary conditions and effects of spatial averaging over grid elements. Climatic models (GCMs and RCMs) differ in their approaches, leading to dissimilar results between historic simulation and future projections. As a result, outcomes from climate models must be associated with uncertainty. Uncertainty in climate model simulations for future periods also relates to the emission pathways. Further, the unique characteristics of respective dynamical and statistical downscaling method lead to differences in climate projections that add uncertainty to climate projections. Therefore, before using the climate model outputs for climate impact studies, the performance of downscaling approaches should be analysed with focus on error assessments and quantification of uncertainties associated with projections.

Studies by Mearns et al. (1999), Haylock et al. (2006), Gutmann et al. (2012), Flaounas et al. (2013), Tang et al. (2016) and Grigory et al. (2018) compared the performance of statistical and dynamical downscaling methods for different regions worldwide. The results of these studies showed that the changes in projected precipitation differed between the two downscaling methods and advocated further evaluation of global models, emission scenarios and downscaling methods. Schmidli et al. (2007) applied statistical and dynamical methods to downscale daily precipitation over the Alpine Region in Europe and stated that the performance of the methods varied significantly from region to region and from season to season. Overall, the study suggested that both downscaling methods contribute to uncertainty in future scenarios. Ayar et al. (2015) compared statistical and dynamical downscaling methods under the European and Mediterranean branch of the CORDEX initiative hindcast framework. Their results showed that the occurrence and intensity of rain were better simulated by statistical downscaling methods, whereas spatial variability and temporal variability of rain were better simulated by RCMs. Su et al. (2017) compared monthly rainfall generated from statistical and dynamical methods over the Heihe River basin in China and reported that the two downscaling methods reasonably reproduced the spatial pattern and monthly rainfall in the rainy season.

Although many climate change studies in Pakistan have been performed using either dynamical or statistical downscaling methods, none of them evaluated and intercompared results of the two downscaling techniques for a specific area of interest. In the Global Change Impact Studies Centre (GCISC) of Pakistan, most of the studies were conducted on climate change projections over entire Pakistan using PRECIS and RegCM3 RCMs (focusing on dynamical downscaling only) under the Special Report on Emission Scenarios (SRES)—A2 scenario. Such studies include Akhtar et al. (2008), Islam et al. (2009), Mehmood et al. (2009) and Saeed et al. (2009). Other studies like Khattak et al. (2011), Ghumman et al. (2013) and Khan et al. (2017) only made use of statistical downscaling methods for climate change assessment over entire or part of Pakistan.

Before the use of dynamical and statistical downscaling methods for Representative Concentration Pathway

(RCP) scenarios, the downscaling methods were used with Fourth Assessment Report (AR4) SRES emission scenarios (A1, A2, B1, B2) in the climate research community. Some recent studies have used statistical downscaling approaches with RCP scenarios for climate change projections over Pakistan. For example, Su et al. (2016) analysed the impacts of climate change on temperature and precipitation by evaluating GCM model ensembles using statistical downscaling within the Coupled Model Intercomparison Project Phase 5 (CMIP5) over the Indus River basin using different RCP scenarios (2.6, 4.5 and 8.5). Amin et al. (2017) performed statistical analysis of precipitation on monthly, seasonal and annual scales for Pakistan for 1996–2015 and 2041–2060. They used the SimCLIM model for future precipitation projections under RCP 6.0. Other studies like Ding and Ke (2013) used statistical downscaling approaches to assess predictions of seasonal (i.e., monsoon) precipitation for Pakistan.

A major research gap exists in comparing dynamical and statistical downscaling for precipitation in the southern part of Pakistan. The southern part is more arid and downscaling rainfall is more challenging compared with wet regions due to erratic and infrequent rainfall. The complexity is further enhanced due to scarcity of data and rapidly changing climatic settings from the Arabian Sea towards the Upper Indus area. Balochistan being geographically Pakistan's largest province, having an area of 347,190 km^2, has a climate lying in hyper-arid, arid and semi-arid domains. The Gwadar-Ormara basin, which is the study area in this research, is located on the south-western fringe of Balochistan. From literature review, it appears that the study by Ahmed et al. (2015) is the only study that has been conducted on the southern part (Balochistan) of Pakistan, using statistical techniques only to downscale rainfall. Further, this study took the province in its entirety and has not focused specifically on the Gwadar-Ormara basin. This study area is chosen because none of the climate change impact assessment studies has focused particularly on the Gwadar-Ormara catchment in Balochistan, Pakistan. Also, the area is geo-strategically important to Pakistan because of the ongoing China-Pakistan Economic Corridor (CPEC) project, which is worth 46 billion US dollars. The climate of Gwadar-Ormara basin is arid with warm summers, mild winters and erratic rainfall patterns. The mean annual rainfall varies from 75 to 100 mm. Most of the rain falls between December and February, with a monthly average rainfall of 20 mm. Analysis by the United Nations Development Programme (UNDP Report, 2016) showed that trends over the last 30–50 years suggested that rainfall has decreased in the south-western Balochistan and coastal areas. Therefore, accurate simulations and predictions of changes in rainfall are highly important for future planning and management of water resources (Boosik & Jorge, 2007).

The aim of this study is to compare a dynamical and statistical downscaling approach to determine which technique is better suited to simulate the spatial–temporal rainfall distribution over the Gwadar-Ormara basin for historic and future climatic windows using different RCPs. In order to analyse both approaches, model outcomes of one GCM, the CanESM2 Atmosphere–Ocean General Circulation Model (AOGCM), were downscaled to make the evaluation and comparison more objective. The comparison was developed for the baseline period (1971–2000) and for a future climatic window (2041–2070) using medium concentration pathway RCP 4.5 and high concentration pathway RCP 8.5. The evaluation and comparison of the downscaling methods were based on statistics of the mean and standard deviation of rainfall, for which daily observed data were used from gauging stations. The climatological averages on a monthly time scale served to understand the limitations and strengths of the two downscaling approaches driven by the same global climate model.

The novelty of this study is the comparison between the two downscaling methods under RCP scenarios for a data scarce study area of Gwadar-Ormara basin, Pakistan. Moreover, the comparison of observed in situ rainfall data and the APHRODITE gridded rainfall product focusing the study area, makes this study relevant for comparison and evaluation of climate models, as well as gridded rainfall products.

2 | DATA USED

2.1 | In situ data

For this study, daily rainfall time series data for eight stations were collected from the archive of the National Engineering Services Pakistan (NESPAK). Given the size of the study area, the number of stations was low and they were not uniformly distributed. A screening of the time series data showed that a number of stations had substantial data gaps over the time period of 1971–2000. To overcome the gaps in in situ data, missing daily rainfall data were imputed using two packages in R software, namely Multivariate Imputation via Chained Equations (MICE) and missForest. The results of both methods were compared with available observed rainfall data and the method giving a closer match to the available observed rainfall data was selected for every station.

2.2 | APHRODITE gridded data

In order to avoid the uncertainties that may arise from the imputation of the observed rainfall data, an independent alternative rainfall data source was considered for filling of relatively large data gaps in in-situ time series. For this purpose, the gridded dataset of the Asian Precipitation—Highly Resolved Observational Daily Integration Towards Evaluation of Water Resources (APHRODITE) project (version V1101) for monsoonal Asia (60°–150° E, 15°–55° N) with 0.25° resolution for daily rainfall was selected and evaluated with the available observed daily rainfall data using spatial correlograms. The APHRODITE gridded dataset is based on data collected from 5000 to 12,000 stations, with significant improvement in description of the areal distribution and variability of rainfall around the Himalaya, compared with other available products (Yatagai et al., 2012).

2.3 | NCEP reanalysis data

Daily reanalysis data from NCEP/NCAR (National Center for Atmospheric Research) for the period 1961–2005 was used for establishing statistical relationships with observed in situ data. The NCEP data are a set of observed large-scale atmospheric variables with a resolution of 2.5° × 2.5° (∼280 km × 280 km). NCEP reanalysis data are an important component for the set-up of the Statistical DownScaling Model (SDSM) used, as it supplies the predictor values for calibration and validation of the model. Throughout the SDSM literature, the NCEP/NCAR reanalysis has been the only dataset used to represent the past global-scale atmospheric state (Diaz-Nieto & Wilby, 2005; Dibike & Coulibaly, 2005; Gagnon et al., 2005; Khan et al., 2006; Mahmood & Babel, 2013, 2014; Wilby et al., 2002).

2.4 | Climate models data

The CanESM2 AOGCM was used in this research, as the model is one of the 10 CMIP5 AOGCMs driving 13 Coordinated Regional Climate Downscaling Experiment (CORDEX)—South Asia downscaled RCM simulations. The main reason of selecting CanESM2 as a driving model and NCEP reanalysis data was the ready-to-use atmospheric variables available in coherence with atmospheric variables of NCEP reanalysis data to be used directly in SDSM (Wilby et al., 2002). Section 2.5 further explains why the CanESM2 AOGCM was selected in the study. CanESM2 is a fourth-generation coupled global climate model developed by the Canadian Centre for Climate Modelling and Analysis (CCCma). Data are provided at a spatial resolution of 2.8125° × 2.8125° (∼315 km × 315 km). For this study, the CanESM2 daily atmospheric predictors for baseline (1971–2000) and future (2041–2070) periods and for the two pathways RCP 4.5 and RCP 8.5 were used. To evaluate dynamical downscaling, the IITM–RegCM4 RCM with a spatial resolution of 0.44° × 0.44° (∼50 km × 50 km) was selected, as this was the only RCM available that had CanESM2 as driving AOGCM in the CORDEX-SA experiment. The IITM-RegCM4 RCM precipitation dataset for historic (1971–2000) and future (2041–2070) climate windows under RCP 4.5 and RCP 8.5 was used.

2.5 | Selection of datasets

Both CanESM2 output and NCEP/NCAR reanalysis data use the same set of 26 predictor variables to keep consistency. It must be noted that the number and attributes of NCEP atmospheric predictors and any GCM daily atmospheric variables should be the same to perform statistical downscaling, as it is a requirement of SDSM. The GCM predictor variables must be normalized with respect to a reference period and available for all variables used in the model calibration (Dawson & Wilby, 2007). Keeping this in mind, only the CanESM2 AOGCM under CMIP5 had the data available to be normalized with NCEP predictors. To be able to compare the different data sources, a historic period from CMIP5 instead of CMIP6 has been chosen, as such was warranted given the scope of the study.

3 | METHODOLOGY

3.1 | Quality assessment of observed in situ and APHRODITE rainfall data

A comparison of the observed in situ and APHRODITE gridded rainfall product was carried out to identify inconsistencies in the observed rainfall data (1971–2000). The spatial correlation structure of the two datasets, that is, in situ and APHRODITE, was compared to assess the reliability of APHRODITE data to be used instead of in situ data in cases when data were missing or incomplete. The spatial correlograms were more useful than other statistics because they provided information about the correlation of each pair of spatial observations when the distance between pairs was varied. Hence, in the spatial correlograms, the correlation coefficient was plotted as a function of the distance to inspect which dataset shows high correlations for closely located points and smaller values for points at larger distances, which follows the Tobler's first law of geography (Tobler, 1970).

To construct spatial correlograms, daily observed in situ rainfall values were spatially interpolated using the

Inverse Distance Weighting (IDW) method for six stations (Pasni, Shadikaur, Tank, Hore, Chibkalamati and Basolmasjid). IDW was selected because it is simple and efficient compared with other interpolation techniques (Wu & Hung, 2016). Out of the period 1971–2000 for which data have been collected, a four-year period (1988–1991) was chosen because only for this period daily time series were available without missing values for a maximum number of six gauging stations. After interpolation, gridded maps of mean monthly rainfall depth were prepared from interpolated daily rainfall. The gridded maps were resampled at a grid scale equal to APHRODITE (25 km × 25 km) for comparison purposes. This resulted in 27 grid elements that covered the study area. To calculate cross-correlation coefficients between all combinations of grid elements, centre pixel values (locations shown in Figure 1) were extracted from each grid. Subsequently, cross-correlation coefficients were plotted against the corresponding distance for all combinations of elements. The same procedure was repeated for the APHRODITE dataset for which interpolation was not needed.

3.2 | Statistical downscaling of CanESM2 AOGCM data

The SDSM developed by Wilby et al. (2002) was used in this study. SDSM is a tool that establishes statistical relationships between large-scale variables (predictors) and local-scale variables (predictands) through the use of a combination of a Stochastic Weather Generator (SWG) and Multiple Linear Regression (MLR) empirical approaches. The development and application of SDSM involved five main steps: (1) predictand and predictor selection, (2) model calibration, (3) weather generator, (4) model validation, and (5) future climate scenario generator.

Calibration of the SDSM approach for respective gauge sites resulted in optimal coefficients of the regression relations, which facilitated the development of multiple scenarios of daily surface weather variables. Assuming that these statistical relationships remain valid for future periods, downscaled daily weather information was obtained for a future time period, considering the relationships with GCM-derived predictors (Dawson & Wilby, 2007).

Daily rainfall time series obtained for each of the 27 grid elements that cover the study area were used as predictand in SDSM. Predictand rainfall data (in mm/day) was retrieved by IDW interpolating data of eight rainfall stations (1971–2000) that was resampled to 25 km × 25 km grid cell size. For calibration of the SDSM, the period 1971–1990 was selected, whereas for validation, the period 1991–2000 was selected, for both NCEP reanalysis data and observed data. The data of the CanESM2 AOGCM have been processed by the Canadian Climate Scenario Center and could be applied as input to the SDSM model. For periodic rainfall analysis, the *seasonal* (June, July,

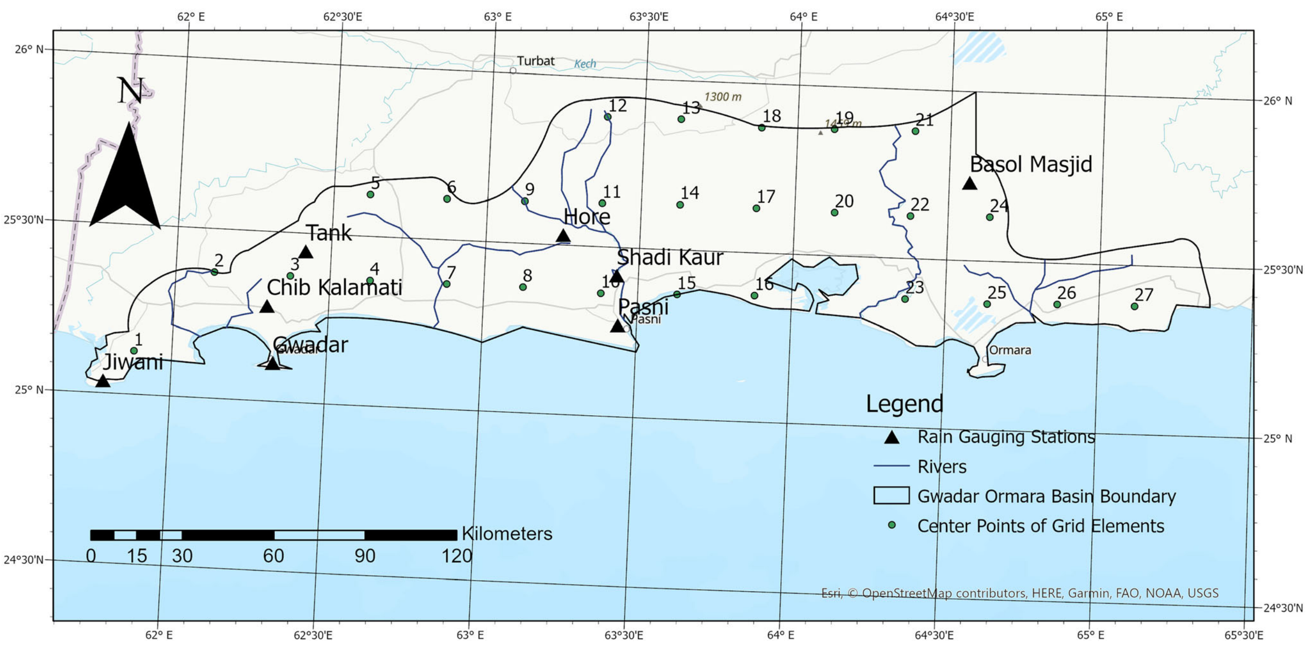

FIGURE 1 Location of (numbered) centre points of 27 grid elements (size of 25 km × 25 km) covering the study area along with the position of gauge stations (represented by triangles).

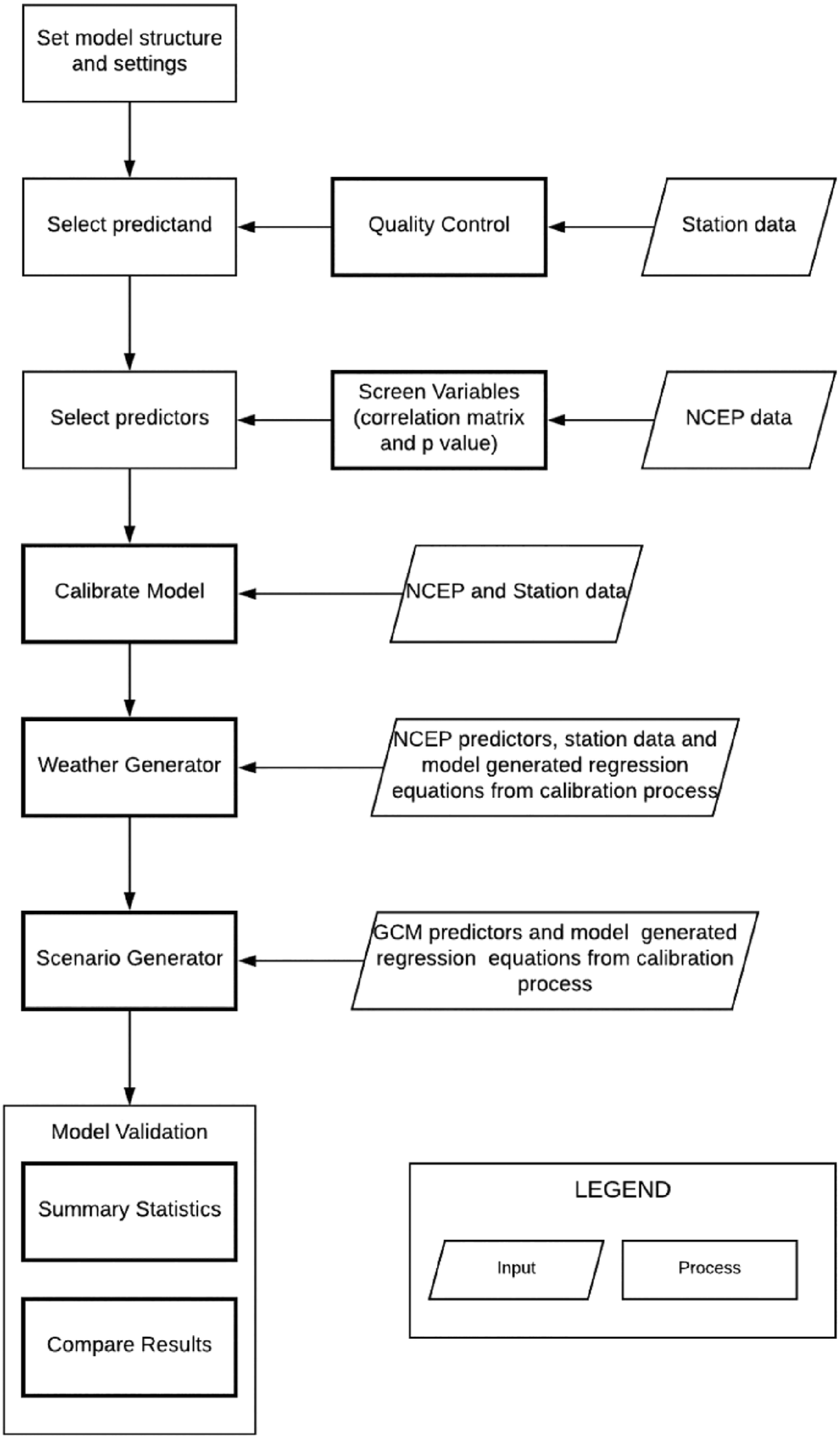

FIGURE 2 Statistical DownScaling Model workflow methodology used in this study.

August) option was selected. The June, July, August season was selected to analyse the model performance for wet monsoon months. The methodology described by Mahmood and Babel (2013) to statistically downscale CanESM2 AOGCM data using SDSM has been followed in this study and is shown in Figure 2.

3.3 | Dynamical downscaling using IITM-RegCM4 RCM

Raw RCM data are available in the CORDEX-SA dataset (downloaded from: https://climate4impact.eu/impactportal/data/esgfsearch.jsp). For this study, data for the RegCM4

RCM (see Section 2.4) were selected. Data are available in rotated-polar grids. For this study the data were re-gridded to a regular geographic grid with equally sized grid cells of 50 km × 50 km to facilitate spatial analysis over the study area. The RegCM4 RCM is a numerical climate prediction model influenced by specified lateral and ocean conditions from the CanESM2 AOGCM. It offers ready-to-use dynamically downscaled simulations of rainfall for 1951–2100, which was divided into two periods for this study: historical (1971–2000) and future (2041–2070) periods. After re-gridding RCM data, rainfall values in mm/day were extracted for each grid cell covering the study area. The extracted values were then utilized directly, without performing any bias correction, to calculate the monthly climatological average and monthly climatological standard deviation. These results were compared with the simulation results from the statistically downscaled CanESM2 AOGCM data and observed data. The comparison between dynamically downscaled RegCM4 RCM data and statistically downscaled CanESM2 AOGCM data was established at the basin scale, so that the comparison result was not affected by dissimilar grid cell sizes for the statistically downscaled AOGCM (25 km × 25 km) and RCM (50 km × 50 km).

4 | RESULTS

4.1 | Quality assessment of observed and APHRODITE data

Spatial correlograms for observed and APHRODITE data were used to assess the quality of each dataset. Results of respective correlograms indicated that the observed data (see Figure 3) followed Tobler's law better than the APHRODITE data (see Figure 4). Figure 3 shows a distinct pattern where the correlation coefficient decreases with the increase in distance for all combinations of the 27 central points of the grid elements that cover the study area. Despite Figure 3 shows substantial variation (indicated by the black dots), the correlation between grid element values at increasing distances showed the same and overall decreasing trend. To suppress variation in the spatial correlogram, average values of correlation coefficients at each distance step of 10 km were calculated and plotted with red dots in Figure 3. This shows a more lucid shape of the correlogram. Distance intervals of 10 km were selected, assuming that spatial rainfall occurrence over this distance does not change considerably. The APHRODITE data show a correlation of 0.8 at a distance of 200 km that must be considered unrealistic. The correlogram in Figure 4 suggests that pronounced correlation even extends up to a distance of 350 km, which is unrealistic as well. The correlogram in Figure 4 suggests a very slow decorrelation, indicating that the APHRODITE data set can be considered unreliable. Therefore, the APHRODITE data were rejected for further use. The likely reason that APHRODITE data are not fit for use in this study can be attributed to the low number of gauging stations in the study area (see Climate Data Guide, 2020). This guide describes that in regions where climate stations are scarce, APHRODITE may provide unrealistic spatial patterns of precipitation.

4.2 | Statistical downscaling of CanESM2 AOGCM data

4.2.1 | Calibration and validation of SDSM

Model calibration and validation are essential steps to analyse how well a model can simulate counterparts of observed, target data. Out of 27 grid elements, calibration and validation graphs of monthly rainfall data for five grid elements are shown in Figures 5 and 6, respectively.

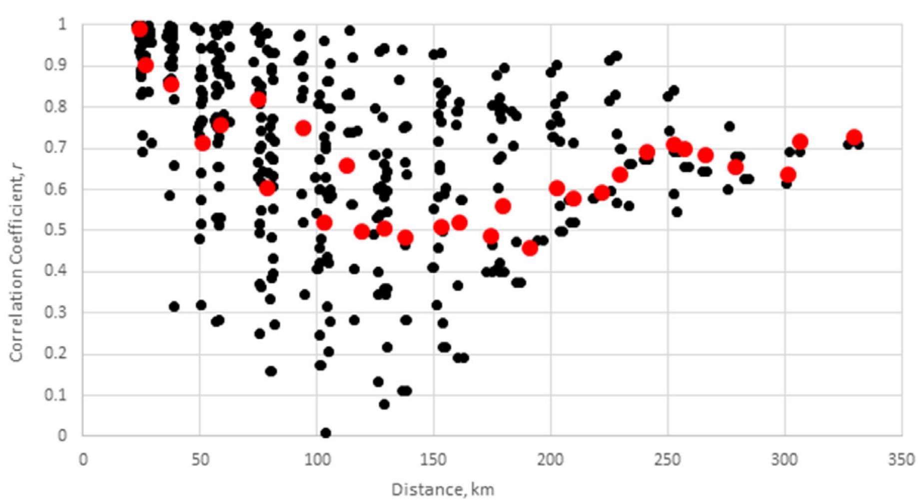

FIGURE 3 Spatial correlogram of in situ data (black points) and 10-km averaged correlogram (red points) for all combinations of pixels covering the study area.

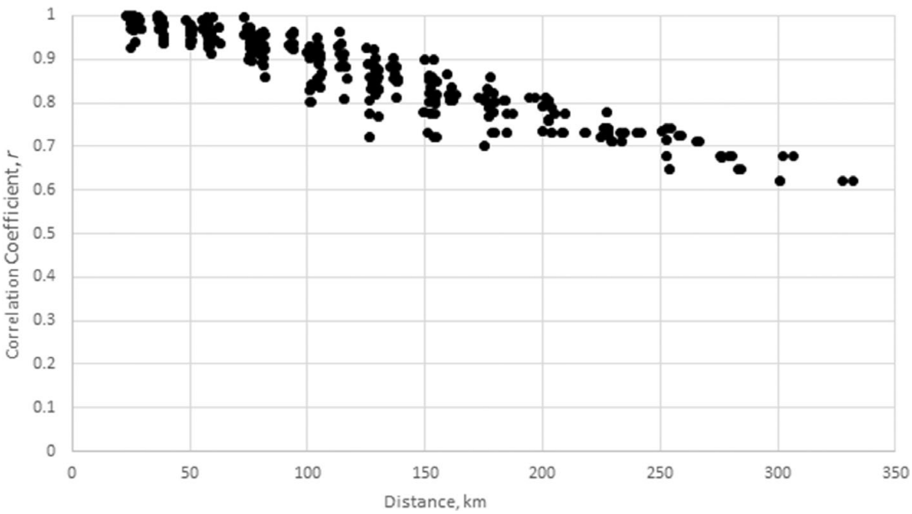

FIGURE 4 Spatial correlogram of APHRODITE data for all combinations of pixels covering the study area.

Grid elements 1, 3, 10, 11 and 24 were selected because these elements overlay locations of gauging stations. For all 27 grid elements, the coefficient of determination (R^2) was calculated after calibration, resulting in values between 0.2 and 0.08. The R^2 values are low as caused by erratic rainfall values in the observed dataset that was used as predictand. Also, the poor data quality affected the performance of the established transfer function by SDSM. Moreover, the unique topography and climatic conditions of the coastal basin could be another reason that statistically downscaled CanESM2 GCM and NCEP reanalysis data do not match with the observed data.

Figure 5 shows that December, January, February and June, July, August are the wettest months as indicated by observed, NCEP and CanESM2 data sources. Whereas March, April, May and September, October, November are the driest months, as shown by smaller rainfall values of observed, NCEP and CanESM2. For the validation period, no distinct rainfall pattern with drier and wetter seasons could be identified (Figure 6). The comparison between observed and simulated counterparts on a daily time step is not meaningful, as most of the days have no rainfall. Therefore, this study considered the evaluation of accumulated rainfall depths on a monthly time scale. Calibration and validation graphs show that observed and simulated counterparts do not match well and show large deviations. Due to the uncertainty in observed and statistically downscaled GCM outputs, a bias correction procedure was not carried out. Bias correction of the downscaled climate model data (see e.g., Khadka & Pathak, 2016; Mahmood & Babel, 2013, 2014) is meaningful when there is enough confidence in the observed dataset. However, this is not the case for the observed data in this study.

4.2.2 | Performance evaluation of statistical downscaling of rainfall

The results of statistical downscaling are further evaluated by means of climatological averages and standard deviations of rainfall that were compared with observed counterparts for 27 grid elements covering the study area for the historic period (1971–2000). Results of the evaluation are presented in Figures 7 and 8. Figure 7 shows the monthly average for observed and simulated rainfall, and Figure 8 shows the monthly average standard deviation for observed and simulated rainfall.

Further, a climate change impact assessment was done by comparing the observed historic data and statistically downscaled historic simulations with future projections of CanESM2 under RCP 4.5 and 8.5. Results of the monthly average and monthly standard deviation are shown in Figures 9 and 10, respectively.

Figure 7 shows that the downscaled CanESM2 rainfall for the historic period (1971–2000) has relatively low maximum and high minimum monthly rainfall values compared with observed counterparts. Simulated results satisfactorily represent the overall monthly rainfall cycle over the study area, that is, the wet and dry seasonal trend shown by the simulation is in coherence with the observed rainfall data. This shows that the calibration of SDSM is reasonable. Furthermore, the observed average rainfall in July is close to the downscaled counterparts for 1971–2000. Also, for November and December, the simulated data fit reasonably to the observed data. The performance evaluation of the statistical downscaling method based on the standard deviation showed poor results for NCEP and CanESM2 simulations compared with observed data for the historic time period (see Figure 8). The observed data show very high standard

Meteorological Applications Open Access Science and Technology for Weather and Climate RMetS

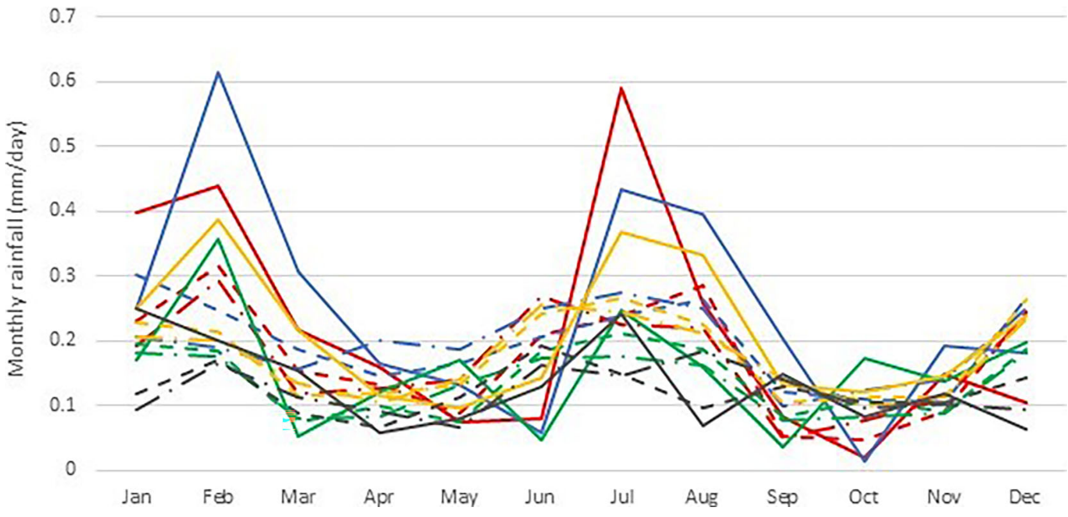

FIGURE 5 Observed versus simulated rainfall in the calibration for the period 1971–1990. Observed data are shown with straight lines, NCEP with dashed lines and CanESM2 with dotted lines for all five grid elements (GE 1: Red, GE3: Blue, GE10: Green, GE11: Yellow, GE24: Black).

deviation values and a large monthly variation due to the uncertainty in the rainfall data. This behaviour was not replicated well by the SDSM model, with lower standard deviation values for NCEP and CanESM2.

In the climate change impact assessment, the SDSM results (Figures 9 and 10) obtained for future projections (2041–2070) show almost no difference between CanESM2 simulations under emission scenarios RCPs 4.5 and RCPs 8.5 in terms of the monthly average rainfall and the monthly average standard deviation. Figures 9 and 10 also show that the statistically downscaled future projections of CanESM2 are close to the historic downscaled simulations. This is highly unlikely, as the increase in greenhouse gas concentrations in the atmosphere is expected to affect rainfall amounts. In this regard, it can be concluded that the selected NCEP predictors within SDSM are insensitive to different radiative forcing terms that results in an unreliable performance of SDSM in predicting future rainfall.

The pronounced difference between observed and simulated downscaled GCM rainfall for calibration and validation periods of SDSM was significantly less when monthly average rainfall for 27 grid elements was calculated. The climatological averaging of rainfall over 30 years for historic and future periods suppressed the erratic precipitation pattern and showed a temporal rainfall pattern that weakly matches the downscaled CanESM2 simulations.

4.3 | Dynamical downscaling using IITM-RegCM4 RCM

The performance of the dynamical downscaling approach (RegCM4 RCM) was evaluated by comparing simulated monthly average rainfall (Figure 11) and monthly average standard deviation (Figure 12) with observed data for the historic time period. Figure 11 shows that the RegCM4 historic simulation largely overestimates the monthly average rainfall in particular for the wet period (June, July, August), so that the climatological rainfall pattern of the observed data is no longer visible under the simulated patterns of the RegCM4 RCM. The RegCM4 RCM simulated average standard deviation values of monthly rainfall at the basin scale, which are unrealistically high compared with the observed counterparts for the baseline period (Figure 12). Overall, based on the results from dynamical downscaling, it can be concluded that the RCM results deviate largely from the observed counterparts and thus RCM results cannot be directly used in hydrological impact studies. Figures 11 and 12 confirm that the CanESM2 AOGCM provides a closer match to the observed rainfall than the RegCM4 RCM. Therefore, the error in the RCM data is much likely due to the characteristics of the RCM itself and not due to the driving AOGCM.

The climate change impact assessment from dynamically downscaled future climatic projections (2041–2070) under RCP 4.5 and RCP 8.5 showed higher monthly average rainfall and standard deviation values compared with the historic simulation. In comparison with historic RCM data, the RCM future climatic projections under RCPs showed no change in terms of monthly average rainfall for the months January to March and August to December (see Figure 13). The future projections from the RCM under the RCP scenarios showed an increase in rainfall variability compared with the historic simulated rainfall variability, except for September and October where the RCP scenarios showed a decreasing trend compared with

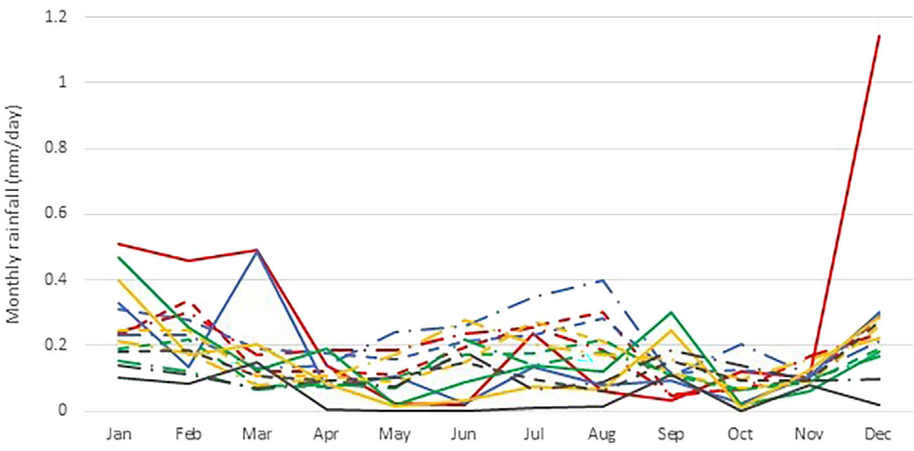

FIGURE 6 Observed versus simulated rainfall in the validation for the period 1991–2000. Observed data are shown with straight lines, NCEP with dashed lines and CanESM2 with dotted lines for all five grid elements (GE 1: Red, GE3: Blue, GE10: Green, GE11: Yellow, GE24: Black).

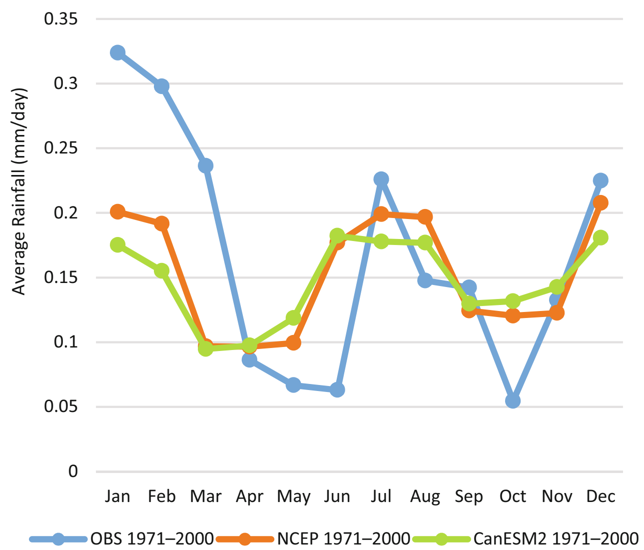

FIGURE 7 Observed and Statistical DownScaling Model simulated monthly average rainfall for historic period (1971–2000) for the entire basin.

historic RCM data (see Figure 14). Further, Figures 13 and 14 show that the difference between simulations of RegCM4 RCM for the two RCP scenarios is not significant. The projections under RCP 4.5 are identical to the projections under RCP 8.5 except for June, July and September.

Furthermore, the RCM also fails to simulate the seasonal pattern of rainfall over the study area. The dynamical downscaling method fails to simulate the precipitation season of December, January, February for historic and future climate periods (Figures 11 and 13).

The RCM data were also analysed for its spatial distribution of daily mean rainfall over the study area. The results of this analysis are shown in Figure 15. It shows the difference between the observed rainfall and RCM-simulated counterparts for the wet month of July (1971–2000). The figure shows that the RCM (50 km × 50 km grid cell size) has a similar spatial rainfall distribution as the observed counterpart that was based on gauged station data interpolated at a 25 km × 25 km grid cell size, despite that the RCM monthly average values are highly unrealistic. The rainfall from the coastline to the upland area decreases from high mean monthly to low mean monthly values, as shown in both maps. The observed rainfall pattern shows more variation from the west of the basin to the east, which is not satisfactorily represented by the RCM. For instance, in the central part of the basin, where three stations (Hore, Shadikaur and Pasni) are located, observed data showed a maximum mean rainfall of about 0.6 mm/day in July over the 30-year period. The RCM shows a mean rainfall of 25.7 mm/day in the same area. The maximum mean rainfall of 36.6 mm/day in the RCM data shown in the right corner of the basin does not correspond with the rainfall value of the observed dataset. This further indicates that the RCM outputs cannot be used directly for quantifying the

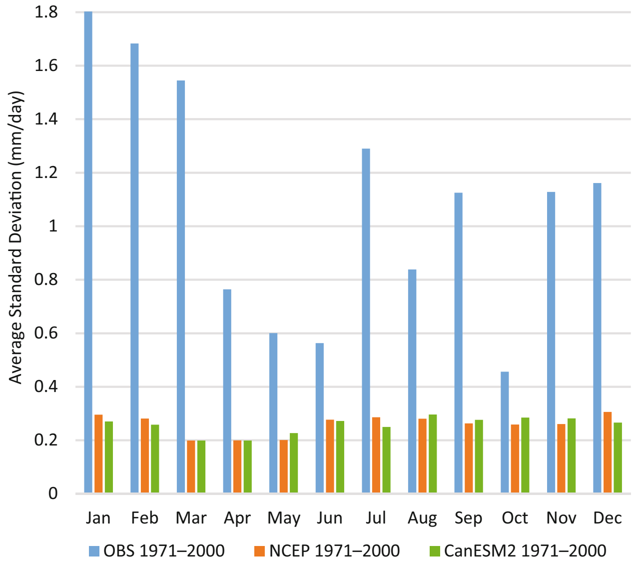

FIGURE 8 Observed and Statistical DownScaling Model simulated monthly average standard deviation of rainfall for historic period (1971–2000) for the entire basin.

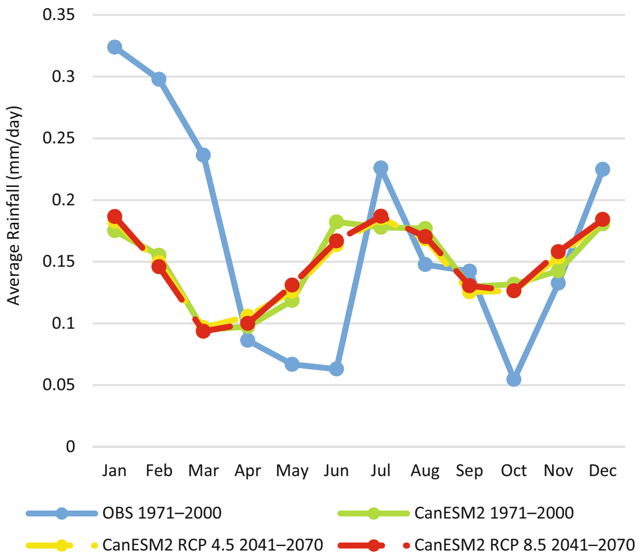

FIGURE 9 Observed and Statistical DownScaling Model simulated monthly average rainfall for historic period (1971–2000) and future period (2041–2070) for the entire basin.

hydrological impacts of climate change. Moreover, it should be noted that different classification scales in Figure 15 are applied to make the visual analysis and interpretation of both maps meaningful.

4.4 | Comparison of statistical versus dynamical downscaling

Findings in this study indicate that statistical downscaling performed better than dynamical downscaling. Despite the very coarse resolution of the AOGCM, the statistical downscaling method developed multiple regression equations between large-scale atmospheric variables and local climate surface variables, due to which the statistical downscaling method simulated the rainfall close to that of the observed one, and better than the dynamical downscaling method, for the baseline period (1971–2000). The monthly rainfall and seasonal trend over the Gwadar-Ormara basin is well represented by statistical downscaling for the historic period. The observed annual cycle of rainfall is noticeable and comparable to statistically downscaled CanESM2 AOGCM simulations, while this is not the case with dynamically downscaled simulations.

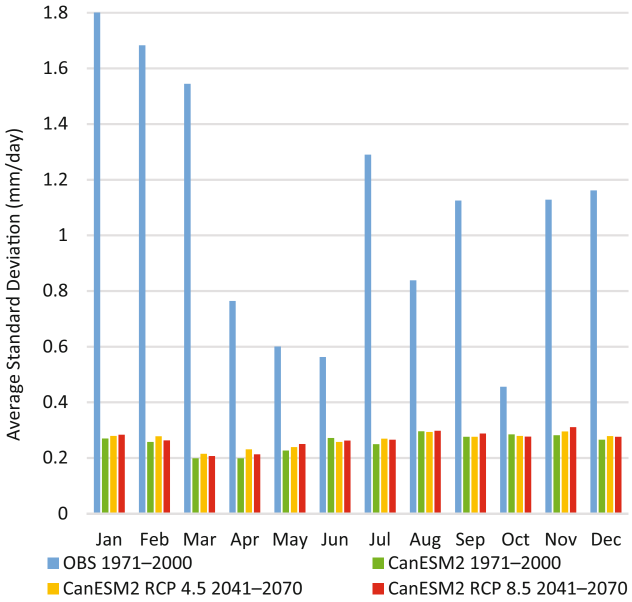

FIGURE 10 Observed and Statistical DownScaling Model simulated monthly average standard deviation of rainfall for historic period (1971–2000) and future period (2041–2070) for the entire basin.

The statistical downscaling method showed relatively low R^2 values for the SDSM calibration and validation periods, indicating a poor match between observed, NCEP and CanESM2 data. The SDSM method showed insensitivity of selected large-scale atmospheric predictors to different concentration pathways due to which the reliability of statistical downscaling is not satisfactory in projecting future rainfall (for the window 2041–2070). Average monthly rainfall values under RCP 4.5 and RCP 8.5 generated by SDSM are identical to each other, as shown in Figure 9. Also, these projections are similar to average monthly rainfall values simulated in the historic period (1971–2000).

The performance of the dynamical downscaling method is not satisfactory compared with statistical downscaling, as the RegCM4 RCM missed the December, January, February wet seasons over the Gwadar-Ormara basin in both historic and future periods. Further, RCM outputs show very high rainfall values in the wet season of June, July, August, which according to Almazroui (2016) might be due to the choice of the parameterization of cumulus convection schemes, mathematical algorithms, land–sea contrast and surface characteristics settings. The RCM showed poorer results in downscaling rainfall than SDSM. Figure 12 shows that the results obtained from the dynamically downscaled RegCM4 RCM lead to the conclusion that rainfall estimates by SDSM are significantly better than the estimates by the RCM. The uncertainty in RCM data for the historic period is higher than in the observed and statistically downscaled CanESM2 AOGCM data, as can be noticed from Figures 11 and 12.

While there are limitations with dynamical downscaling, there are few strengths associated with this approach including no additional use of a model to downscale rainfall unlike in statistical downscaling. Hence, model calibration and validation steps are not required. In case of dynamical downscaling, the rainfall values under greenhouse gas concentration scenarios are higher compared with the historic simulations, which is not observed in the case of statistical downscaling. Additionally, dynamical downscaling works better than statistical downscaling in terms of portraying spatial rainfall variation, due to the higher resolution of the RCM (refer Figure 15), when compared with the observed data. The statistical downscaling method underestimates the spatial variation of rainfall patterns because of statistical relationships between local and large-scale climate variables, which are assumed to remain constant and valid in the future.

For further comparison, basin-wide annual climatic mean values of observed and simulated rainfall (from both SDSM and RCM) for the historic (1971–2000) and future period (2041–2070) are provided in Table 1. Values show how each method performed in downscaling rainfall compared with the observed dataset. The comparison between statistical and dynamical downscaled future projections in the period 2041–2070 under the two RCPs shows that climatic mean values hardly differ. It is unclear what the cause of these small differences is. Apparently, the driving model used (CanESM2

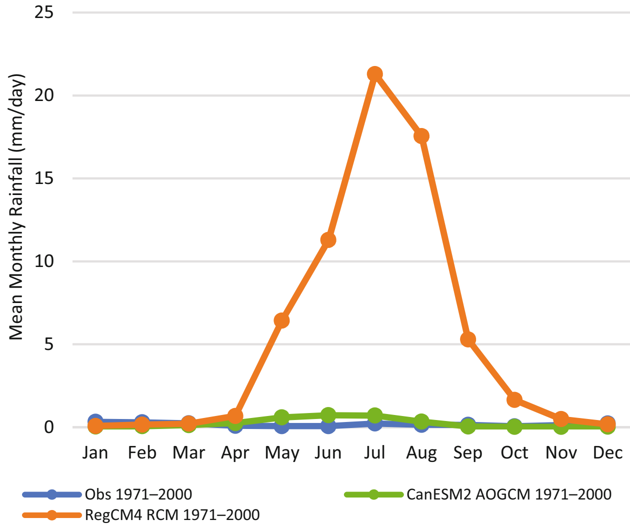

FIGURE 11 Observed and regional climate model simulated monthly average rainfall for historic period (1971–2000) for the entire basin.

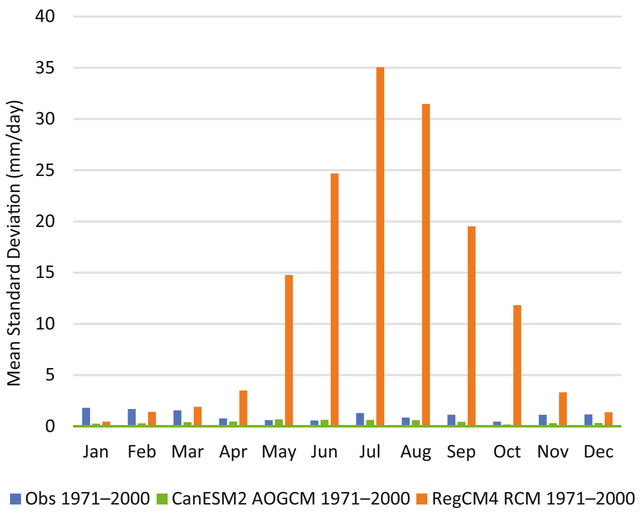

FIGURE 12 Observed and regional climate model simulated monthly average standard deviation of rainfall for historic period (1971–2000) for the entire basin.

AOGCM) shows a very low sensitivity to the two selected RCP scenarios (intermediate and intensive concentration scenarios).

5 | DISCUSSION

Sanjay et al. (2013) evaluated the performances of RCMs as part of the CORDEX-SA evaluation initiative. They evaluated RCMs in comparison with those of the AOGCMs being part of CMIP5 to inter-compare multiple models over South Asia. Among the selected 10 AOGCMs and five RCMs for a 15-year evaluation period (1990–2004), they found that the CanESM2 AOGCM showed a dry (negative) bias in simulating annual mean precipitation (mm/day) over central India and southern parts of Pakistan compared with the monthly mean rain gauge-based global land precipitation dataset from the Climate Research Unit (CRU) of the University of East Anglia. They also found that individual RCMs (driven by CMIP5 AOGCMs) resulted in biases varying from dry to wet over central India and southern parts of Pakistan in the historical simulations. Another main conclusion of the study was that the RCMs (including RegCM4) overestimate the spatial variability compared with observed CRU annual precipitation climatology over South Asia. A study conducted by Choudhary and Dimri (2017) came to similar results that RCMs under CORDEX-SA exhibit a large wet

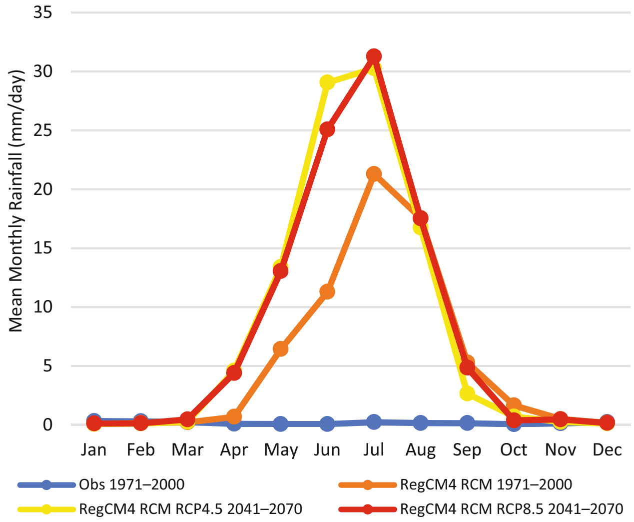

FIGURE 13 Observed and regional climate model simulated monthly average rainfall for historic period (1971–2000) and future period (2041–2070) for the entire basin.

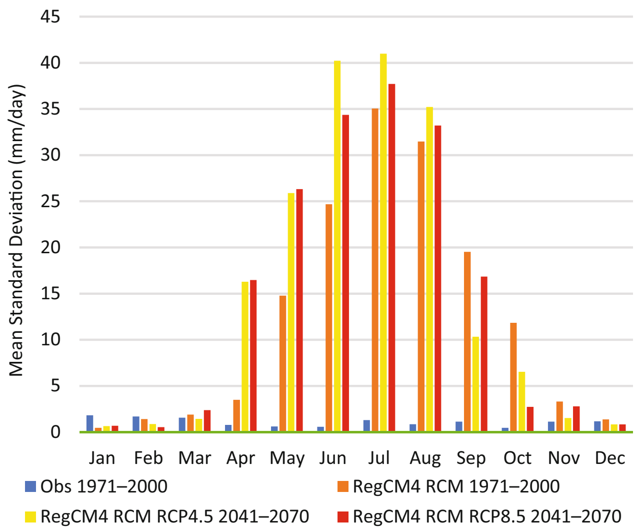

FIGURE 14 Observed and regional climate model simulated monthly average standard deviation of rainfall for historic period (1971–2000) and future period (2041–2070) for the entire basin.

bias over the region, which means overestimation of precipitation in historic as well as in future projections. The results of these past studies concur to results of this study undertaken over Gwadar-Ormara basin in Pakistan and show that results from climate models for historic periods may not always be reliable, and thus data must be analysed for reliability before data can be used for impact assessment studies.

To reduce uncertainties (or errors) from climate models, a bias correction step is generally applied. Studies by Teutschbein and Seibert (2012), Berg et al. (2012) and Chen et al. (2017) have recommended this step before further use of outcomes of the RCM simulations. In this study, overestimation of the seasonal (June, July, August) rainfall by RegCM4 over the entire basin should be corrected and then the performance of the RCM should be evaluated and compared with the statistical downscaled model results. However, due to poor quality of the observed data, bias correction has not been undertaken. Nevertheless, it is questionable whether in this case a bias correction procedure would be effective given the very large mismatch between simulated rainfall and observed counterparts. Considering observed in situ data, a correction factor as large as 180 for June in the historic period is needed to remove the bias from the RCM simulations. That is why the RegCM4 RCM is considered to be unreliable to represent spatial–temporal rainfall variability. Poor results have been reported for the same

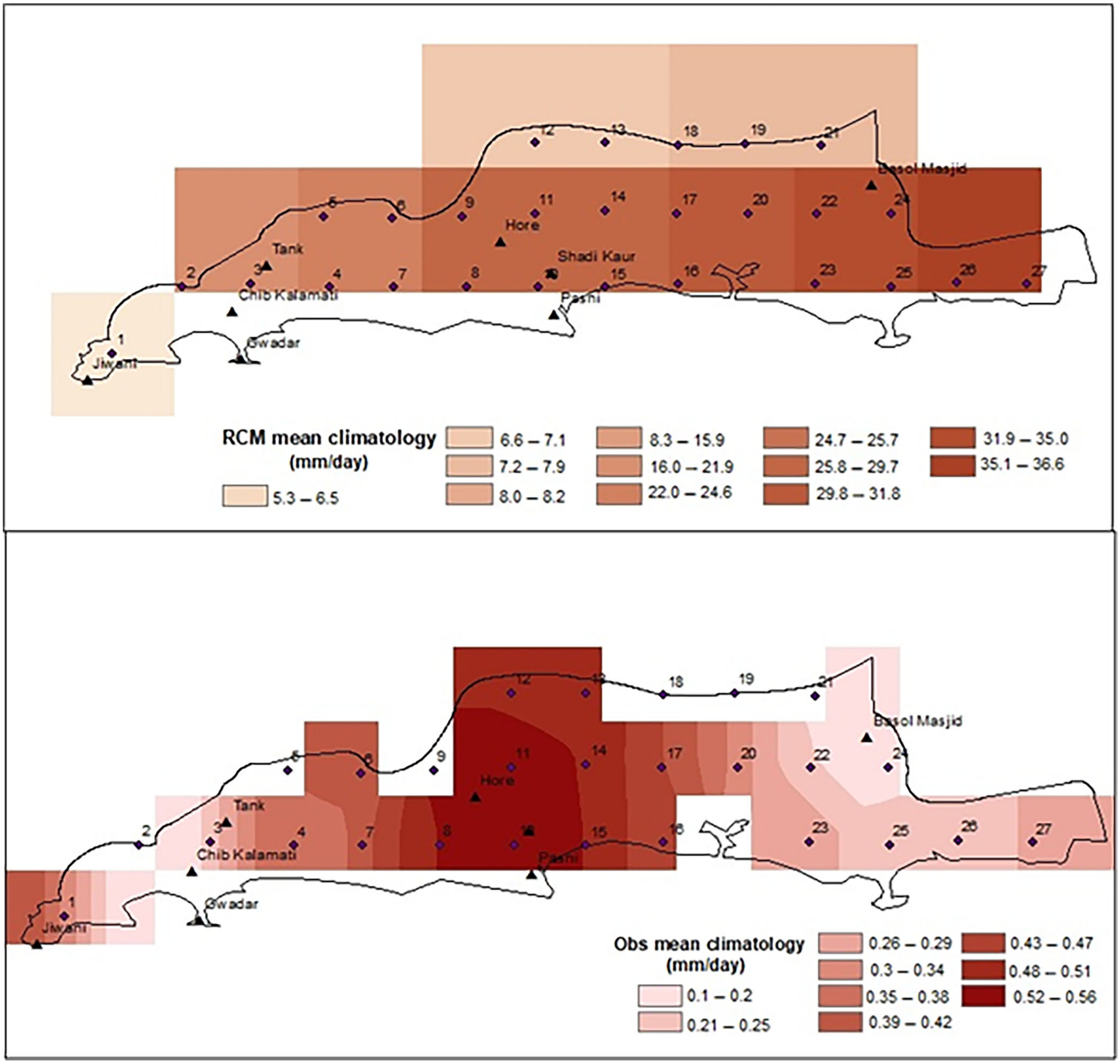

FIGURE 15 Spatial variation of regional climate model (above) and observed (below) daily mean rainfall values (1971–2000) for the wet month of July.

TABLE 1 Observed versus simulated annual climatological means.

Time period	Annual climatic mean (mm/day)
Observed historic (1971–2000)	0.2
RegCM4 historic (1971–2000)	5.4
RegCM4 RCP 4.5 (2041–2070)	8.2
RegCM4 RCP 8.5 (2041–2070)	8.1
CanESM2 AOGCM historic (1971–2000)	0.2
CanESM2 AOGCM RCP 4.5 (2041–2070)	0.1
CanESM2 AOGCM RCP 8.5 (2041–2070)	0.1

Abbreviations: AOGCM, Atmosphere–Ocean General Circulation Model; RCP, representative concentration pathways.

climate model in studies by Haile and Rientjes (2015) and Almazroui (2016). Furthermore, the RCM may require improvements in the physical parameterization, convection parameterization and land surface scheme settings (Sanjay et al., 2013).

The challenge in the study was to analyse the performance of the two downscaling approaches in simulating and predicting the spatial–temporal rainfall distribution over the Gwadar-Ormara basin, where the available observed data are not only scarce but also uncertain and erroneous. In such cases, precipitation products based on satellite measurements or gauge-based gridded observations are used due to their high spatial–temporal resolution and global coverage. Nonetheless, these products can be subject to substantial biases as well due to uncertainties in spatial sampling (e.g., spatial interpolation errors) and retrieval algorithms, sampling frequency and non-uniform field-of-view of sensors (Huffman et al., 2007; Joyce et al., 2004). Hence, it is essential to validate these precipitation products, using in situ observations, before further use in hydrological models.

Several studies (Anjum et al., 2018; Iqbal & Athar, 2018; Khan et al., 2014; Khandu & Forootan, 2016; Tan et al., 2020) have evaluated multi-gridded and multi-satellite based precipitation products at daily, monthly and annual scales over the Tibetan Plateau, Bhutan and Pakistan. Only a few have focused on APHRODITE validation over Pakistan. Faiz et al. (2020) performed a statistical evaluation of PERSIANN-CDR, CPC-Global, TRMM-3B42, CHIRPS and APHRODITE against precipitation gauge observations from six stations in Gilgit and Hunza catchments, for the period 2000–2004. Their analysis revealed that all datasets overestimate daily rainfall; however, after applying a bias correction technique (quantile mapping), the performance of precipitation datasets significantly improved. Overall, CHIRPS and APHRODITE showed the best performance among the five datasets after bias correction.

Ali et al. (2012) analysed APHRODITE on a decadal basis using data from 12 different gauge stations in the humid and sub-humid regions of Pakistan for the period of 1971–2007. They concluded that the APHRODITE data showed non-consistent correlation coefficient values with observed precipitation data from very poor (0.001–0.15) to very good (0.79–0.99) for different stations in several decades. The study did not include gauge station data from Balochistan province in Pakistan in the analysis. However, a study by Ahmed et al. (2019) assessed gridded precipitation datasets over the region of Balochistan specifically. They evaluated the performance of Global Precipitation Climatology Centre (GPCC), CRU, APHRODITE and Centre for Climatic Research—University of Delaware (UDel) rainfall data. The results revealed a clear superiority of GPCC over other products, whereas APHRODITE underestimated the precipitation, especially in the months of the monsoon. From the results of these studies and the current study, it is confirmed that APHRODITE is not suitable to be used as an alternative dataset to the observed rainfall data in the arid or semi-arid regions (in the south) of Pakistan. The very low number of rain gauges in the study area may attribute to the poor quality of APHRODITE data. The product may show satisfactory results in the northern part by the larger number of gauge stations.

Based on the results from the studies discussed in this section, supporting the results of the current study, it is evident that the study undertaken has provided reliable yet unconventional results for the performance evaluation of the two downscaling approaches. Despite limitations regarding the poor quality of observed rainfall data used, there is a high potential in this study offering other researchers to assess the weaknesses and strengths of the RegCM4 RCM driven by the CanESM2 AOGCM over arid systems. The unconventional results can be regarded as an invitation to further evaluate multi-model ensembles including other GCMs and RCMs for the same data scarce area of Gwadar-Ormara basin in Pakistan. Furthermore, there is a potential of obtaining more plausible results, if a different gridded precipitation dataset such as the GPCC dataset, as recommended by Ahmed et al. (2019), can be used as an alternative to in situ data.

6 | CONCLUSION

In this study, a data reliability analysis was first performed for observed rainfall and APHRODITE gridded rainfall data using spatial correlograms to address the problem of missing and possibly erroneous daily rainfall values in the available observed dataset. The spatial correlograms resulted in rejecting the use of APHRODITE for the Gwadar-Ormara study area, as for unknown reasons, APHRODITE data produced an unrealistic spatial variation pattern of rainfall. The very low number of rain gauges in the study area may attribute to the poor quality of APHRODITE data, such as shown in other studies and suggested in the literature.

To meet the research objectives, statistically downscaled CanESM2 AOGCM results were compared with observed data. Similarly, dynamically downscaled results of the RegCM4 RCM driven by the same AOGCM were compared with observed data and statistically downscaled results. The calibration and validation plots of the SDSM showed unrealistic monthly average rainfall values compared with observed counterparts that SDSM could not replicate well. However, overall statistical downscaling performed better in simulating the monthly rainfall cycle compared with dynamical downscaling for the historic period (1971–2000), without application of bias correction to the outputs of both downscaling methods. As the regression equations were established between local-scale predictands (observed) and large-scale atmospheric predictors (NCEP/NCAR and AOGCM) in the statistical downscaling method, rainfall was simulated relatively close to observed rainfall. Hence, the SDSM results are considered more trustworthy than the RCM results. In the period 2041–2070 under RCPs 4.5 and 8.5, rainfall projections did not show any significant difference in both downscaling approaches. This might highlight a limitation of the driving model (CanESM2 AOGCM) and does not necessarily suggest poor performance of any downscaling approach; either statistical or dynamical.

The dynamical downscaling method (using RegCM4 RCM) overestimated the monthly average rainfall over the study area in both historic and future time periods. The RCM showed a large difference between rainfall simulations for the historic period and future projections. The errors in RCM results can be attributed to uncertain initial conditions, the physical parameterization scheme and/or lateral atmospheric boundaries, which made the outputs from the RCM inconsistent with those from the CanESM2 AOGCM and observed data. Bias correction of the downscaled results (from both SDSM and the RCM) using a high-quality observational dataset should be carried out before using the outputs in hydrological (impact) studies. Dynamical downscaling, due to the higher resolution of RCMs, showed spatial rainfall variation, that well compared with observed data and was able to represent the large variation in rainfall over the study area similarly to that of observed rainfall.

AUTHOR CONTRIBUTIONS

Raazia Attique: Data curation (lead); methodology (lead); resources (lead); software (lead); visualization (lead); writing – original draft (lead). **Tom Rientjes:** Formal analysis (lead); supervision (lead); validation (lead); writing – review and editing (lead). **Martijn Booij:** Formal analysis (lead); supervision (lead); validation (lead); writing – review and editing (lead).

ORCID

Raazia Attique https://orcid.org/0000-0003-2220-3338
Tom Rientjes https://orcid.org/0000-0002-5185-8969
Martijn Booij https://orcid.org/0000-0001-6208-9045

REFERENCES

Ahmed, K., Shahid, S., Haroon, S.B. & Wang, X.-J. (2015) Multilayer perceptron neural network for downscaling rainfall in arid region: a case study of Baluchistan, Pakistan. *Journal of Earth System Science*, 124(6), 1325–1341.

Ahmed, K., Shahid, S., Wang, X., Nawaz, N. & Khan, N. (2019) Evaluation of gridded precipitation datasets over arid regions of Pakistan. *Water*, 11, 210. Available from: https://doi.org/10.3390/w11020210

Akhtar, M., Ahmad, N. & Booij, M.J. (2008) The impact of climate change on the water resources of Hindukush-Karakorum-Himalaya region under different glacier coverage scenarios. *Journal of Hydrology*, 355, 148–163.

Ali, G., Rasul, G., Mahmood, T., Zaman, Q. & Cheema, S.B. (2012) Validation of APHRODITE precipitation data for humid and sub humid regions of Pakistan. *Pakistan Journal of Meteorology*, 9(17), 57–69.

Almazroui, M. (2016) RegCM4 in climate simulation over CORDEX-MENA/Arab domain: selection of suitable domain, convection and land-surface schemes. *International Journal of Climatology*, 36, 236–251. Available from: https://doi.org/10.1002/joc.4340

Amin, A., Nasim, W., Mubeen, M., Kazmi, D.H., Lin, Z., Wahid, A. et al. (2017) Comparison of future and base precipitation anomalies by SimCLIM statistical projection through ensemble approach in Pakistan. *Atmospheric Research*, 194(January), 214–225. Available from: https://doi.org/10.1016/j.atmosres.2017.05.002

Anjum, M.N., Ding, Y., Shangguan, D., Ahmad, I., Ijaz, M.W., Farid, H.U. et al. (2018) Performance evaluation of latest integrated multi-satellite retrievals for global precipitation measurement (IMERG) over the northern highlands of Pakistan. *Atmospheric Research*, 205, 134–146. Available from: https://doi.org/10.1016/j.atmosres.2018.02.010

Ayar, P.V., Vrac, M., Bastin, S., Carreau, J., Déqué, M. & Gallardo, C. (2015) Intercomparison of statistical and dynamical downscaling models under the EURO-and MED-CORDEX initiative framework: present climate evaluations. *Climate Dynamics*, 46, 1301–1329.

Berg, P., Feldmann, H. & Panitz, H.-J. (2012) Bias correction of high resolution regional climate model data. *Journal of Hydrology*, 448-449, 80–92. Available from: https://doi.org/10.1016/j.jhydrol.2012.04.026

Boosik, K. & Jorge, A.R. (2007) Response of stream flow to weather variability under climate change in the Colorado rockies. *Journal of Hydrologic Engineering*, 12, 63–72. Available from: https://doi.org/10.1061/(ASCE)1084-0699(2007)12:1(63)

Chen, J., Brissette, F.P., Liu, P. & Xia, J. (2017) Using raw regional climate model outputs for quantifying climate change impacts on hydrology. *Hydrological Processes*, 31, 4398–4413.

Choudhary, A. & Dimri, A.P. (2017) Assessment of CORDEX-South Asia experiments for monsoonal precipitation over Himalayan region for future climate. *Climate Dynamics*, 50, 3009–3030. Available from: https://doi.org/10.1007/s00382-017-3789-4

Climate Data Guide. (2020) *APHRODITE: Asian precipitation—highly-resolved observational data integration towards evaluation of water resources*. Available from: https://climatedataguide.ucar.edu/climate-data/aphrodite-asian-precipitation-highly-resolved-observational-data-integration-towards

Dawson, C.W. & Wilby, R.L. (2007) *Statistical downscaling model SDSM, version 4.2*. Lancaster: Department of Geography, Lancaster University.

Diaz-Nieto, J. & Wilby, R.L. (2005) A comparison of statistical downscaling and climate change factor methods: impacts on low flows in the river Thames, United Kingdom. *Climatic Change*, 69(2), 245–268. Available from: https://doi.org/10.1007/s10584-005-1157-6

Dibike, Y.B. & Coulibaly, P. (2005) Hydrologic impact of climate change in the Saguenay watershed: comparison of downscaling methods and hydrologic models. *Journal of Hydrology*, 307(1–4), 145–163. Available from: https://doi.org/10.1016/j.hydrol.2004.10.012

Ding, T. & Ke, Z. (2013) A comparison of statistical approaches for seasonal precipitation prediction in Pakistan. *Weather and Forecasting*, 28(5), 1116–1132. Available from: https://doi.org/10.1175/WAF-D-12-00112.1

Faiz, M.A., Liu, D., Tahir, A.A., Li, H., Fu, Q., Adnan, M. et al. (2020) Comprehensive evaluation of 0.25° precipitation datasets combined with MOD10A2 snow cover data in the ice-dominated river basins of Pakistan. *Atmospheric Research*, 231 (2020), 104653. Available from: https://doi.org/10.1016/j.atmosres.2019.104653

Flaounas, E., Drobinski, P., Vrac, M., Bastin, S., Lebeaupin-Brossier, C., Stéfanon, M. et al. (2013) Precipitation and temperature space-time variability and extremes in the Mediterranean region: evaluation of dynamical and statistical downscaling methods. *Climate Dynamics*, 40(11–12), 2687–2705. Available from: https://doi.org/10.1007/s00382-012-1558-y

Fowler, H.J., Blenkinsop, S. & Tebaldi, C. (2007) Review linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. *International Journal of Climatology*, 27, 1547–1578.

Gagnon, S., Singh, B., Rousselle, J. & Roy, L. (2005) An application of the statistical downscaling model (SDSM) to simulate climatic data for streamflow modelling in Québec. *Canadian Water Resources Journal*, 30(4), 297–314. Available from: https://doi.org/10.4296/cwrj3004297

Ghumman, A.R., Hassan, I., Khan, Q.U.Z. & Kamal, M.A. (2013) Investigation of impact of environmental changes on precipitation pattern of Pakistan. *Environmental Monitoring and Assessment*, 185(6), 4897–4905. Available from: https://doi.org/10.1007/s10661-012-2911-7

Grigory, N., Shakeel, A., María, M., Sandro, C., Rita, C., Bhend, J. et al. (2018) Dynamical and statistical downscaling of a global seasonal hindcast in eastern Africa. *Climate Services*, 9, 72–85.

Gutmann, E.D., Rasmussen, R.M., Liu, C., Ikeda, K., Gochis, D.J., Clark, M.P. et al. (2012) A comparison of statistical and dynamical downscaling of winter precipitation over complex terrain. *Journal of Climate*, 25(1), 262–281. Available from: https://doi.org/10.1175/2011jcli4109.1

Haile, A.T. & Rientjes, T. (2015) Evaluation of regional climate model simulations of rainfall over the Upper Blue Nile basin. *Atmospheric Research*, 161-162, 57–64.

Haylock, M.R., Cawley, G.C., Harpham, C., Wilby, R.L. & Goodess, C.M. (2006) Downscaling heavy precipitation over the United Kingdom: a comparison of dynamical and statistical methods and their future scenarios. *International Journal of Climatology*, 26(10), 1397–1415. Available from: https://doi.org/10.1002/joc.1318

Huffman, G.J., Bolvin, D.T., Nelkin, E.J., Wolff, D.B., Adler, R.F., Gu, G. et al. (2007) The TRMM multi-satellite precipitation analysis (TMPA): quasi-global, multiyear, combined-sensor precipitation estimates at fine scales. *Journal of Hydrometeorology*, 8(1), 38–55. Available from: https://doi.org/10.1175/JHM560.1

Iqbal, M.F. & Athar, H. (2018) Validation of satellite based precipitation over diverse topography of Pakistan. *Atmospheric Research*, 201, 247–260. Available from: https://doi.org/10.1016/j.atmosres.2017.10.026

Islam, S., Rehman, N., Sheikh, M. & Khan, A.M. (2009) *High resolution climate change scenarios over South Asia region downscaled by regional climate model PRECIS for IPCC SRES A2 Scenario (GCISC-RR-06)*. Islamabad: Change Impact Studies Centre (GCISC).

Joyce, R.J., Janowiak, J.E., Arkin, P.A. & Xie, P. (2004) CMORPH: a method that produces global precipitation estimates from passive microwave and infrared data at high spatial and temporal resolution. *Journal of Hydrometeorology*, 5, 487–503.

Khadka, D. & Pathak, D. (2016) Climate change projection for the Marsyangdi river basin, Nepal using statistical downscaling of GCM and its implications in geodisasters. *Geoenvironmental Disasters*, 3(5), 15. Available from: https://doi.org/10.1186/s40677-016-0050-0

Khan, F., Pilz, J. & Ali, S. (2017) Improved hydrological projections and reservoir management in the upper Indus Basin under the changing climate. *Water and Environment Journal*, 31(2), 235–244. Available from: https://doi.org/10.1111/wej.12237

Khan, M.S., Coulibaly, P. & Dibike, Y. (2006) Uncertainty analysis of statistical downscaling methods. *Journal of Hydrology*, 319 (1–4), 357–382. Available from: https://doi.org/10.1016/j.jhydrol.2005.06.035

Khan, S.I., Hong, Y., Gourley, J.J., Khattak, M.U.K., Yong, B. & Vergara, H.J. (2014) Evaluation of three high-resolution satellite precipitation estimates: potential for monsoon monitoring over Pakistan. *Advances in Space Research*, 54(4), 670–684. Available from: https://doi.org/10.1016/j.asr.2014.04.017

Khandu, J.L.A. & Forootan, E. (2016) An evaluation of high-resolution gridded precipitation products over Bhutan (1998–2012). *International Journal of Climatology*, 36, 1067–1087. Available from: https://doi.org/10.1002/joc.4402

Khattak, M.S., Babel, M.S. & Sharif, M. (2011) Hydro-meteorological trends in the upper Indus River basin in Pakistan. *Climate Research*, 46(2), 103–119. Available from: https://doi.org/10.3354/cr00957

Kour, R., Patel, N. & Krishna, A.P. (2016) Climate and hydrological models to assess the impact of climate change on hydrological regime: a review. *Arabian Journal of Geosciences*, 9(9), 544. Available from: https://doi.org/10.1007/s12517-016-2561-0

Mahmood, R. & Babel, M.S. (2013) Evaluation of SDSM developed by annual and monthly sub-models for downscaling temperature and precipitation in the Jhelum basin, Pakistan and India. *Theoretical and Applied Climatology*, 113(1–2), 27–44.

Mahmood, R. & Babel, M.S. (2014) Future changes in extreme temperature events using the statistical downscaling model (SDSM) in the trans-boundary region of the Jhelum river basin. *Weather and Climate Extremes*, 5(1), 56–66. Available from: https://doi.org/10.1016/j.wace.2014.09.001

Mearns, L.O., Bogardi, I., Giorgi, F., Matyasovszky, I. & Palecki, M. (1999) Comparison of climate change scenarios generated from regional climate model experiments and statistical downscaling. *Journal of Geophysical Research*, 104(D6), 6603–6621. Available from: https://doi.org/10.1029/1998JD200042

Mehmood, S., Abid, M.A., Syed, F.S., Ahmad, M.M., Sheikh, M.M. & Khan, A.M. (2009) *Climate change projections over South Asia under SRES A2 scenario using regional climate model RegCM3 (GCISC-RR-08)*. Islamabad: Global Change Impact Studies Centre (GCISC).

Saeed, S., Sheikh, M.M. & Khan, A.M. (2009) *Validation of regional climate model PRECIS over South Asia (GCISC-RR-04)*. Islamabad: Global Change Impact Studies Centre (GCISC).

Sanjay, J., Ramarao, M.V.S., Kim, J., Sabin, T.P., Nikulin, G., Asharaf, S. et al. (2013) CORDEX regional climate models performance in present-day climate for South Asia. In: *Poster Presentation, International Conference on Regional Climate—CORDEX, Brussels, Belgium*.

Schmidli, J., Goodess, C.M., Frei, C., Haylock, M.R., Hundecha, Y., Ribalaygua, J. et al. (2007) Statistical and dynamical downscaling of precipitation: an evaluation and comparison of scenarios for the European Alps. *Journal of Geophysics*, 112, D04105. Available from: https://doi.org/10.1029/2005JD007026

Su, B., Huang, J., Gemmer, M., Jian, D., Tao, H., Jiang, T. et al. (2016) Statistical downscaling of CMIP5 multi-model ensemble for projected changes of climate in the Indus River Basin. *Atmospheric Research*, 178–179, 138–149. Available from: https://doi.org/10.1016/j.atmosres.2016.03.023

Su, H., Xiong, Z., Yan, X., Dai, X. & Wei, W. (2017) Comparison of monthly rainfall generated from dynamical and statistical downscaling methods: a case study of the Heihe River Basin in China. *Theoretical and Applied Climatology*, 129, 437–444.

Sunyer, M.A., Madsen, H. & Ang, P.H. (2012) A comparison of different regional climate models and statistical downscaling methods for extreme rainfall estimation under climate change. *Atmospheric Research*, 103, 119–128. Available from: https://doi.org/10.1016/j.atmosres.2011.06.011

Tan, X., Ma, Z., He, K., Han, X., Ji, Q. & He, Y. (2020) Evaluations on gridded precipitation products spanning more than half a century over the Tibetan Plateau and its surroundings. *Journal of Hydrology*, 582, 124455. Available from: https://doi.org/10.1016/j.jhydrol.2019.124455

Tang, J., Niu, X., Wang, S., Gao, H., Wang, X. & Wu, J. (2016) Statistical downscaling and dynamical downscaling of regional climate in China: present climate evaluations and future climate projections. *Journal of Geophysical Research: Atmospheres*, 121, 2110–2129. Available from: https://doi.org/10.1002/2015JD023977

Teutschbein, C. & Seibert, J. (2012) Bias correction of regional climate model simulations for hydrological climate-change impact studies: review and evaluation of different methods. *Journal of Hydrology*, 456-457, 12–29.

Tobler, W. (1970) A computer movie simulating urban growth in the Detroit region. *Economic Geography*, 46(Supplement), 234–240.

United Nations Development Program (UNDP) Report. (2016) *The vulnerability of Pakistan's water sector to the impacts of climate change: Identification of gaps and recommendations for action*.

Wilby, R.L., Dawson, C.W. & Barrow, E.M. (2002) SDSM—a decision support tool for the assessment of regional climate change impacts. *Environmental Modelling & Software*, 17(2), 145–157. Available from: https://doi.org/10.1016/s1364-8152(01)00060-3

Wu, Y.-H. & Hung, M.-C. (2016) Comparison of spatial interpolation techniques using visualization and quantitative assessment. *Applications of Spatial Statistics*, 17–34. Available from: https://doi.org/10.5772/65996

Yatagai, A., Kamiguchi, K., Arakawa, O., Hamada, A., Yasutomi, N. & Kitoh, A. (2012) Aphrodite constructing a long-term daily gridded precipitation dataset for Asia based on a dense network of rain gauges. *Bulletin of the American Meteorological Society*, 93(9), 1401–1415. Available from: https://doi.org/10.1175/BAMS-D-11-00122.1

How to cite this article: Attique, R., Rientjes, T., & Booij, M. (2023). Comparison between statistical and dynamical downscaling of rainfall over the Gwadar-Ormara basin, Pakistan. *Meteorological Applications*, *30*(5), e2151. https://doi.org/10.1002/met.2151