Sensitivity study of RegCM4.7 model to land surface schemes (BATS and CLM4.5) forced by MPI-ESM1.2-HR in simulating temperature and precipitation over Iran

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Abstract

In order to evaluate the performance of the Regional Climate Model version 4.7 (RegCM4.7) and understand the impact of land surface schemes in simulating precipitation and temperature over Iran, two thirty-year simulations were conducted using the Biosphere-Atmosphere Transfer Scheme (BATS) and the Community Land Model version 4.5 (CLM4.5). The boundary and initial conditions data of the MPI-ESM1.2-HR Earth system model were downscaled from an initial resolution of 100×100 km to 30×30 km. Both schemes were assessed against ECMWF Reanalysis v5 (ERA5) data, with temperature prediction using the BATS scheme generally reducing bias, except in spring. The CLM4.5 model exhibited a high correlation with ERA5 data, particularly in winter. Evaluation using Root Mean Square Error (RMSE), Nash-Sutcliffe Efficiency, and Kling-Gupta efficiency indices favored the CLM4.5 model in spring and winter. However, the annual temperature correlation coefficient between the two schemes showed minimal difference. In order to enhance precipitation simulation, the common linear scaling bias correction method was modified. Precipitation simulation demonstrated improved accuracy with Modified Linear Scaling (MLS) bias correction method, with the BATS scheme showing reduced bias and lower error rates. While the Kling-Gupta and Nash-Sutcliffe indices slightly favored the BATS scheme, the difference was marginal. Conversely, the Normalized RMSE (NRMSE) index favored RegCM-CLM4.5 in spring and winter. The values of the correlation coefficient and the relative standard deviation resulting from the two land surface schemes (models) had negligible differences with each other. Overall, Taylor diagram analysis suggested similar performance of both schemes at these scales.

1 Introduction

The application of climate models, aimed at understanding past climate conditions and making reliable future climate change projections, is of paramount importance. Analyzing the outputs of these models over a historical period is necessary for assessing accuracy and identifying models with the best performance. General Circulation Models (GCMs), or global climate models, are three-dimensional mathematical models that represent the physical processes of the climate system on a global scale. These models simulate climate variables on a three-dimensional grid with horizontal resolutions typically ranging from 100 to 500 km and 10 to 20 vertical layers (Iles et al. 2020). However, the coarse spatial resolution of GCMs may not adequately capture regional climate characteristics. Therefore, the direct application of these models in regional studies require high spatial resolution data (Prathom and Champrasert 2023). The fact that the average horizontal grid spacing of GCMs in the Coupled Model Intercomparison Project Phase 6 (CMIP6), still exceeds one degree underscores the importance of employing downscaling techniques (Rastogi et al. 2022). Downscaling techniques are widely used to bridge the gap between global climate predictions and the local climate information required (Giorgi et al. 2001; Adachi and Tomita 2020; Lukzade et al. 2016). Dynamical downscaling utilizes

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large-scale atmospheric conditions obtained from GCMs as boundary conditions (Dickinson et al. 1989; Adachi and Tomita 2020; Giorgi 2015). Among the most important applications of regional climate models are their roles in long-term climate estimation, analyzing climate variability, studying hydrological cycles, and generating inputs necessary for assessing climate change impacts (Tapiador et al. 2020).

The performance of regional climate models (RCMs) varies due to factors such as the surface conditions of the study area, the time period under investigation, climatic conditions, and spatial resolution (Li et al. 2023). Additionally, the global circulation models (GCMs) employed in RCMs introduce biases in simulations for various reasons such as simplifying assumptions, boundary conditions, physical or structural model processes, and input variables (Yazdandoost et al. 2021). Numerous studies have shown that, in many cases, data obtained from RCMs are not directly applicable in climatological research or hydrological models due to existing biases. Systematic biases in RCM outputs are attributed to deficiencies in model physics parameterizations, insufficient spatial resolution, and natural climate variability. Therefore, finding suitable parameterization schemes for physical processes and improving model configurations to achieve optimal performance are of paramount importance. On the other hand, preprocessing and bias correction of RCM output play an effective role in improving the results of these models for better climate interpretation (Mbienda et al. 2023). Mbienda et al. (2023) utilized two methods, Linear Scaling (LS) correction and variance correction, to improve precipitation simulation skill of RegCM4.7. The results of this study demonstrated that employing both methods enhanced the large biases present in the output of the climate model. Rashid Mahmood et al. (2018) developed a daily correction factor and applied linear scaling to correct biases in precipitation data from five different GCMs for the Jhelum River basin in Pakistan and India. The results showed that the application of this method improved the results obtained from the regional climate model. Teutschbein and Seibert (2012) investigated the correction of biases in precipitation data from 11 different RCM simulations using various bias correction methods, including linear scaling. According to the results of this study, applying bias correction methods improved the RCM output by correcting statistical indices such as mean and standard deviation. Additionally, the use of corrected RCM data in hydrological simulations showed better alignment with observed streamflow data compared to uncorrected RCM data.

The regional climate model RegCM, developed by the Abdus Salam International Centre for Theoretical Physics (ICTP) Earth System Physics group, is widely used in seasonal and decadal simulations. Various research studies have been conducted to investigate the performance of this model in simulating meteorological variables such as precipitation and temperature in different regions (Boulahfa et al. 2023; Bhatla et al. 2020; Alizadeh-Choobari 2019; Taghiloo et al. 2019). Due to the crucial role of interactions between the atmosphere and the Earth's surface in controlling energy balance, water transport, heat, and carbon cycles in the atmospheric boundary layer, examining these processes in dry and semi-arid regions is of greater importance. Climate variability, influencing factors such as albedo, thermal conductivity, soil temperature and moisture, thermodynamic and aerodynamic roughness, significantly affect surface characteristics. On the other hand, changes in surface parameters also create feedback on atmospheric properties such as energy fluxes, water, carbon, and momentum, the effects of which are more pronounced in dry and semi-arid climates (Dickinson 1989; Lu et al. 2022).

Due to the importance of surface conditions in regional climate modeling, different versions of land surface models have been evaluated by researchers. Mishra et al. (2023) reported acceptable performance of the CLM4.5 model in simulating extreme precipitation in South Asia within RegCM4.7, while the application of the BATS scheme in this study resulted in overestimation. Li et al. (2023) demonstrated in their sensitivity analysis of the RegCM4 model to different land surface schemes that temperature simulation in the Yangtze River Basin using the BATS scheme was more accurate. The results of this study also indicated that simulated precipitation and temperature values by the CLM model were respectively lower and higher compared to those with the BATS scheme. In a study conducted by Kouassi et al. (2022), the performance of land surface models CLM4.5 and BATS in simulating precipitation and temperature in West Africa using the RegCM4 model was investigated. The results of this study showed that the CLM4.5 land surface scheme, despite its more detailed formulation, performed similarly to the BATS scheme. Gu et al. (2020) aimed to evaluate the simulation of the RegCM4.6.1 model on the Tibetan Plateau using various parameterization features and reported that the use of the CLM3 land model improved the output accuracy. Nayak et al. (2017) evaluated the performance of the RegCM4 model in simulating precipitation and temperature using two different land surface models in the Indian region and reported the suitability of the BATS land surface scheme compared to CLM3.5. Tiwari et al. (2015), in examining the role of land surface schemes in the RegCM4 model for simulating winter precipitation and temperature in the western Himalayas, used BATS and CLM3.5 land surface schemes. The results of this study showed that coupling the CLM3.5 model with the RegCM model improved the accuracy of the regional climate model. Furthermore,

in another study, Wang et al. (2015) demonstrated that the application of the CLM3.5 land surface model in simulating Tibetan Plateau precipitation improved the performance of the RegCM4 model compared to the BATS land surface scheme. In Iran, the performance of the regional climate model RegCM has also been evaluated. Zargari et al. (2024) examined the spatiotemporal distribution of dust storms in the southern and southeastern regions of the country using the RegCM4 model. Mobarak Hassan et al. (2024) modeled summer dust storms in Khorasan using RegCM4.6. Babaeian et al. (2021) used the RegCM model with the BATS land surface scheme to predict precipitation patterns for March and April 2019 and evaluated model configurations focusing on various schemes for modeling convective precipitation (Tiedtke, Emanuel, Grell, Kain, Ku, and MM5) and two different boundary layer schemes (Holtslag and Washington University). When assessing the performance of each configuration using Taylor diagrams and the Kling-Gupta efficiency index, the results showed that the best configuration of the RegCM4.7 model for predicting the overall pattern of weekly cumulative precipitation was respectively related to the application of the Tiedtke-Holtslag, Tiedtke-UW, and Grell-UW schemes. Modirian et al. (2019) evaluated the performance of the RegCM4 climate model using temperature and precipitation data for the RCP4.5 scenario. The study area in this research was Khorasan Razavi province. The BATS scheme for modeling surface processes and the two Tiedtke and Emanuel schemes were employed, respectively, for modeling convective cloud formation over land and water surfaces. Lukzadeh et al. (2016) studied the performance of the regional climate model RegCM4 in simulating precipitation in northwestern Iran on a monthly, seasonal, and annual scale. In the study by Taghiloo et al. (2019), the performance of the RegCM4.3 model with the BATS land surface scheme was evaluated in simulating precipitation and temperature at eight selected stations. The results obtained from reviewing the sources confirm the sensitivity of the RegCM4 model in simulating surface precipitation and temperature to land surface schemes. To assess the accuracy of simulations using regional climate models, researchers necessitate a reference dataset. Jafarpour et al. (2022) compared five precipitation datasets—ERA5, PERSIAN-CDR, APHRODITE, NCEP CFSR, and CRU—against synoptic station data in Khuzestan province. ERA5 demonstrated the best performance based on the probability of detection index. Taghizadeh et al. (2021) confirmed ERA5's suitability for reanalyzing precipitation data in northern and northwestern Iran, and Mohammadi and Sharafi (2023) found that ERA5 performed well in estimating monthly mean temperature and precipitation datasets. Despite the widespread use of the RegCM4 model in various studies in Iran, only a limited number of studies have focused on the sensitivity of the RegCM4 model to land surface schemes. Therefore, in this study, the sensitivity of the MPI-ESM1.2-HR-RegCM4.7 model to land surface schemes in simulating precipitation and temperature in Iran was evaluated through two simulations on seasonal and annual time scales during the period from 1985 to 2014.

2 Methodology

2.1 Regional climate model

In this research, the Regional Climate Model (RCM) RegCM4.7 was employed to simulate temperature and precipitation in the study area. The dynamical component of RegCM4 is similar to the hydrostatic version of the MM5 model and is therefore considered a limited-area model with hydrostatic balance and sigma-pressure vertical coordinates, implemented on an Arakawa-Lamb horizontal grid (Elguindi et al. 2014). To account for the effects of ozone, water vapor, carbon dioxide, and oxygen, the RegCM4 model uses the National Center for Atmospheric Research (NCAR) CCM3 radiation scheme. In RegCM, two boundary layer schemes, Holtslag (Holtslag et al. 1990) and the Washington University model (Grenier and Bretherton 2001; Bretherton et al. 2004), are available for simulating gradient resulting from large-scale turbulent flows in an unstable atmosphere. The explicit moisture scheme (SUBEX) is employed in RegCM for solving equations related to precipitation from non-convective clouds (Sundqvist et al. 1989). To model convective precipitation in RegCM4, three modified Kuo schemes (Anthes 1977), Emanuel (1991; Emanuel and Zivkovic-Rothman 1999), and Grell schemes assuming Arakawa-Schubert and also assuming Fritsch and Chappell (Grell et al. 1994; Fritsch and Chappell 1980) are defined. The new cloud microphysics scheme developed by the ECMWF Integrated Forecast System is included in RegCM4.7 (Tiedtke 1993; Tompkins et al. 2007).

In RegCM4.7, the land surface scheme (LSM) is used to model the effect of vegetation cover and soil moisture in energy, momentum, and water vapor exchange between the land surface and the atmosphere. The BATS land surface package is designed to describe the role of vegetation cover and soil moisture in momentum, energy, and water vapor exchanges between the surface and atmosphere, consisting of a vegetation layer, a snow layer, a surface soil layer with a thickness of 10 cm, a root development region with a thickness of one to two meters, and a deep soil layer with a thickness of 3 m. Soil hydrology calculations include solving equations predicting soil moisture content. The BATS scheme encompasses 20 different types of vegetation cover. Different colors and textures of soil are considered for

albedo calculations. Modifications in the latest version of this land surface scheme are made to account for changes in topography and land cover under the sub-grid using a mosaic approach. As the first modification, in the fourth version of the RegCM, two land use types including urban and suburban environments have been added to BATS. The development of urban areas, in addition to altering surface albedo and surface energy balance, will have a considerable impact on runoff and evapotranspiration by creating impermeable surfaces. These effects in the BATS package are implemented through changes in surface characteristics such as maximum vegetation coverage, roughness length, albedo, and soil properties (Dickinson et al. 1993).

To consider more details of surface characteristics, the Community Land Model (CLM) is coupled with the RegCM4 model. In the CLM developed by NCAR, land surface heterogeneity in the climate model is interpreted using a hierarchy of sub-grid meshes. According to this approach, each grid cell consists of several land units, soil or snow columns, and a number of plant functional types (PFTs). Biogeophysical and biogeochemical processes for each sub-grid land unit, each column, and each PFT are simulated separately. Additionally, uniform atmospheric forcings are applied to all sub-grid units within a cell. Surface variables and required atmospheric fluxes are calculated by weighting the sub-grid values (Oleson et al. 2013).

2.2 Data

In the present study, the GMTED2010 (Global Multi-resolution Terrain Elevation Data 2011) elevation model was used as the topographic data required for the RegCM4.7 model. These data, produced by the United States Geological Survey and the National Geospatial-Intelligence Agency (NGA), consist of digital terrain elevation data (Danielson and Gesch 2011). Additionally, in this study, the Global Land Cover Characterization (GLCC) dataset with a spatial resolution of 10 degrees was employed as the land cover data for the regional climate model. Six-hourly data from the MPI-ESM1.2-HR model were used for initializing the

simulations. The MPI-ESM1.2-HR model is the latest version of Earth system models developed by the Max Planck Institute for Meteorology, serving as the basis for the sixth phase of the Coupled Model Intercomparison Project (CMIP6) and seasonal or decadal climate predictions. In this model, the atmospheric component ECHAM6.3 with a horizontal resolution of 100 km (T127~100 km) is coupled with the oceanic component MPIOM1.6.2 with a horizontal resolution of 0.4 degrees (Müller et al. 2018). For validating the model simulation results, ERA5 reanalysis data from the European Centre for Medium-Range Weather Forecasts (ECMWF) were utilized. ERA5 data are generated based on the Integrated Forecast System Cy41r2 and are available with a spatial resolution of 31 km at hourly intervals for the period from 1950 to the present (Hersbach et al. 2020).

2.3 Simulation

As mentioned earlier, in this study, the RegCM4.7 model was used to simulate temperature and precipitation variables in Iran through conducting a sensitivity analysis study. Table 1 outlines the overall simulation design to investigate the regional climate model's sensitivity to land surface schemes. The simulation domain in this study covers the latitude range of 18 to 42 degrees north and the longitude range of 25 to 78 degrees east. Figure 1 illustrates the model domain and its topography. For model execution, a horizontal resolution of 30×30 km was adopted, consisting of 90 grid points in the longitudinal direction, 150 grid points in the latitudinal direction, and 23 vertical levels covering from near the ground surface to the model top (10 hPa). The extent of the model domain was determined to encompass the study area while preserving the general topographic characteristics of the region and considering water bodies, circulation patterns, and atmospheric processes affecting climate variables, aiming to minimize disparities between boundary conditions and the model. Based on this, two simulations were designed, in which all aspects and schemes of the regional climate model were constant, differing only in the land surface scheme. In the first experiment, the BATS scheme was used, while in the second experiment, the CLM4.5 land surface model was employed.

In order to achieve balance in the earth's surface conditions, particularly with regards to evapotranspiration and soil moisture variables, it is important to allow for a sufficient period of time for the model to stabilize (Kumar and Dimiri 2020). Therefore, in this study, a two-year period from 1983 to 1984 was chosen for model stabilization. Subsequently, seasonal and annual temperature and precipitation variables from the years 1985 to 2014 were simulated using the regional climate model. To compare these

Table 1 The outline of RegCM4.7 model simulation in study area

Parameter	Description
Vertical Layers	23
Horizontal grid	30×30 km
Large Scale precipitation parameterization	SUBEX
Convective parameterization	Tiedtke/MIT-Emanuel
Land surface scheme (model)	• BATS • CLM4.5
Long/short wave radiation parameterization	NCAR CCM3
PBL parameterization	Holtslag
Ocean fluxes	Zeng (Zeng et al. 1998)
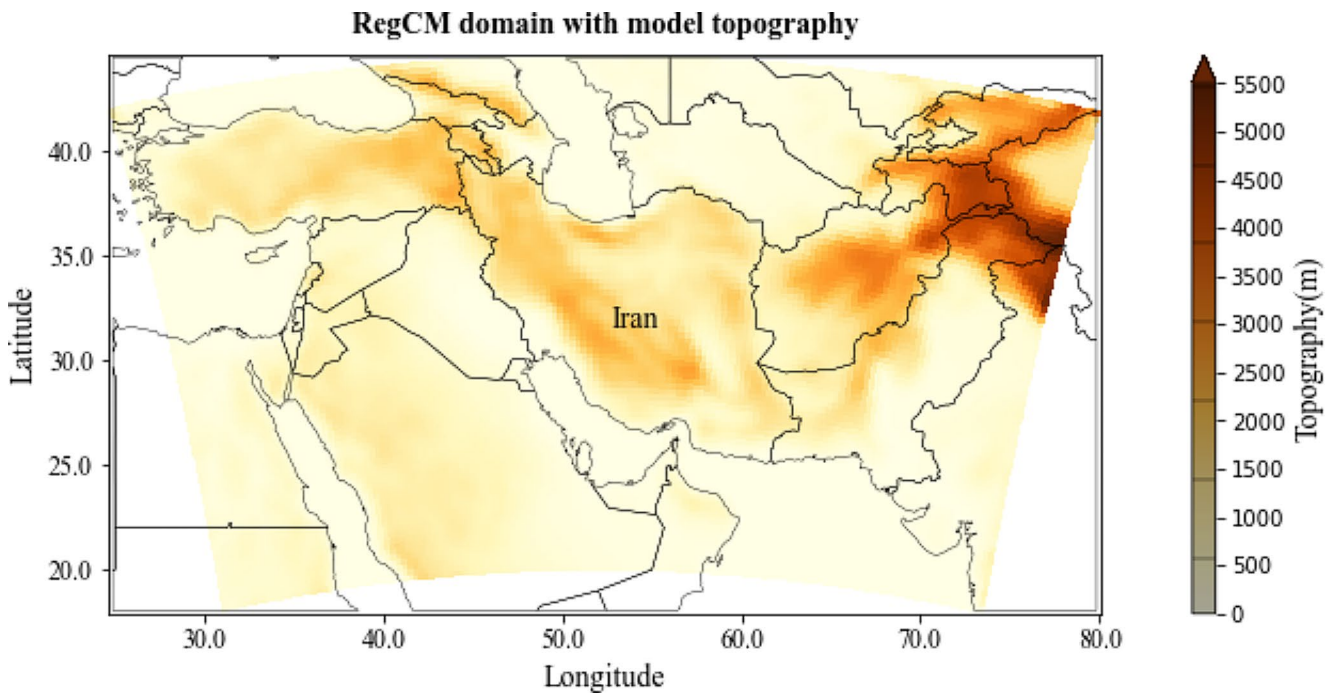
Fig. 1 Model domain and topography of the study area

simulated values with reanalysis data, the ERA5 dataset was interpolated onto the regional climate model grids.

2.4 Bias correction

The bias correction method involves adjusting the output of a climate model through rescaling, aiming to mitigate the impact of systematic errors inherent in the model (Derdour et al. 2022). In this study, after running the RegCM4.7 model using two configurations, precipitation biases were corrected using a Modified Linear Scaling (MLS) approach. Linear scaling approach entails calculating correction coefficients obtained by dividing the long-term monthly mean reanalysis/observational precipitation values by the simulated data at a similar time scale during the control period, and then applying this coefficient to the entire study period in each grid cell (Lenderink et al. 2007).

$$P_{cor}(t) = P_{uncor}(t) \times \left(\frac{\bar{P}_{obs}}{\bar{P}_{cont}} \right) \qquad (1)$$

In the above equation, P_{cor} represents the monthly corrected precipitation in month t, P_{uncor} denotes the uncorrected precipitation output of the regional climate model in the same month, $\bar{P}_{obs}$ indicates the average monthly precipitation of observational data in a control period, and $\bar{P}_{cont}$ represents the average monthly precipitation from modeling in the control period. Within this context, for each grid cell in the

study area, daily precipitation during the verification period (2005–2014) was scaled using the ratio of monthly mean observed precipitation to the monthly mean precipitation derived from the output of the RegCM4.7 model over the twenty-year control period (1985–2004). After comparing the raw precipitation results from the regional climate model during the verification period with the adjusted precipitation using statistical indices and ensuring the satisfactory performance of the modified linear scaling method, precipitation was adjusted for the entire period from 1985 to 2014. In this section, two key assumptions were made when applying the modified linear scaling method. First, if a grid's elevation exceeded 3200 m, the correction coefficient from the nearest grid with an elevation lower than or equal to 3200 m was used. Second, if the modeled precipitation for a grid was less than one millimeter, any correction coefficient was not applied. We considered these two assumptions because the model exhibited unrealistic precipitation values in the altitudes above 3200 m, which extremely exceeded the observed/reanalysis values. Additionally, the linear scaling factor values became unrealistically high when the model precipitation was either zero or nearly zero, suggesting an unrealistic scaling factor.

2.5 Statistical analyses

In the sensitivity assessment and validation of the model results, a wide range of statistical indicators is employed. Some of the most important statistical indicators in this study

include seasonal mean Bias (B), Root Mean Square Error (RMSE), Normalized Root Mean Square Error (NRMSE), Standard deviation (std), Pearson correlation coefficient ($_r$), Kling-Gupta Efficiency (KGE) index, Nash-Sutcliffe efficiency (NS) index, calculated over a domain covering Iran between latitudes 24°N to 42°N and longitudes 42°E to 66°E. Additionally, the results obtained from simulation outputs and observational data are compared using Taylor diagrams. The equations used in the calculation of statistical indicators are provided below.

$$B = \frac{\sum_{i=1}^{N}(P_i - O_i)}{N} \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(P_i - O_i)^2}{N}} \tag{3}$$

$$NRMSE = \frac{RMSE}{O_{max} - O_{min}} \tag{4}$$

$$std = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \mu)^2}{N}} \tag{5}$$

$$r = \frac{\sum_{i=1}^{n}(P_i - P_m)(O_i - O_m)}{\sqrt{\sum_{i=z}^{n}(P_i - P_m)^2}\sqrt{\sum_{i=z}^{n}(O_i - O_m)^2}} \tag{6}$$

$$KGE = 1 - \sqrt{(r-1)^2 + (c-1)^2 + (\alpha-1)^2} \tag{7}$$

$$NSE = 1 - \frac{\sum_{i=1}^{N}(O_i - P_i)^2}{\sum_{i=1}^{N}\left(O_i - \bar{O}\right)^2} \tag{8}$$

In the above equations, P_i represents the value of the simulated variable, O_i denotes the value of the variable obtained from reference ERA5 reanalysis data. The subscripts max, min, and m for each variable respectively denote the maximum, minimum, and average value of that variable. Additionally, $_r$ corresponds to the Pearson correlation coefficient, $_c$ represents the ratio of the standard deviation of simulated values to the corresponding values from reference data, and $_\alpha$ symbolizes the ratio of the mean of simulated values to the corresponding values of the variable from reference data. Moreover, to facilitate the comparison of the deviation magnitude in the model results, the relative standard deviation index (std_rel) replaces the standard deviation index. The magnitude of the relative standard deviation index is calculated by dividing the model's standard deviation by the standard deviation of reference data at a similar time scale. Below are presented the results obtained from the analysis

of two simulations of precipitation and temperature during the investigated period.

3 Results

In this section, the simulated temperature and precipitation variables using the Regional Climate Model (RegCM4.7) with the BATS land surface scheme and the CLM4.5 land surface model are compared.

3.1 Temperature

The spatial pattern of seasonal average simulated temperatures with the RegCM4.7 model using both the BATS and CLM4.5 land surface schemes, along with the seasonal average temperatures obtained from ERA5 reanalysis data for the study area during the period 1985–2014, is presented in Fig. 2. Analysis of this figure reveals the sensitivity of the Regional Climate Model RegCM4.7 to the land surface scheme. However, both simulations adequately capture the spatial pattern of seasonal temperatures similar to ERA5. In all seasons, the results from both simulations depict the minimum temperature along the rugged terrains of the Alborz and Zagros mountains.

Figure 3 illustrates the spatial pattern of the simulated annual average temperature derived from ERA5 reanalysis data, RegCM4.7-BATS and RegCM4.7-CLM4.5 during the period 1985–2014. The spatial distribution of annual average temperature in both configurations reasonably follows the ERA5 pattern. However, the results indicate that the RegCM4 model in both configurations shows cold bias in the central and southeastern parts of the country compared to ERA5 data. Moreover, the spatial distribution of simulated temperature with the CLM4.5 appears to be closer to ERA5 data.

To investigate systematic errors in the simulation, we calculated the mean temperature bias compared to ERA5 reanalysis data. Figures 4 and 5 illustrate the spatial distribution pattern of temperature bias on both seasonal and annual time scales with two different land surface schemes (models). In the spring season, central areas showed cold bias of up to 6 degrees Celsius with the BATS scheme, while the CLM4.5 model exhibited underestimation by about 4 °C. Conversely, both schemes demonstrated warm bias up to 4°C over the Caspian Sea and its coastal strip. During the summer season, the BATS scheme displayed a higher level of underestimation across the entire study area compared to the CLM4.5 model. Temperature bias in the BATS scheme ranged from −6 to 4 degrees Celsius, while in the CLM4.5 model, it ranged from −2 to 8 degrees Celsius. The pattern suggests that simulated temperatures using both schemes
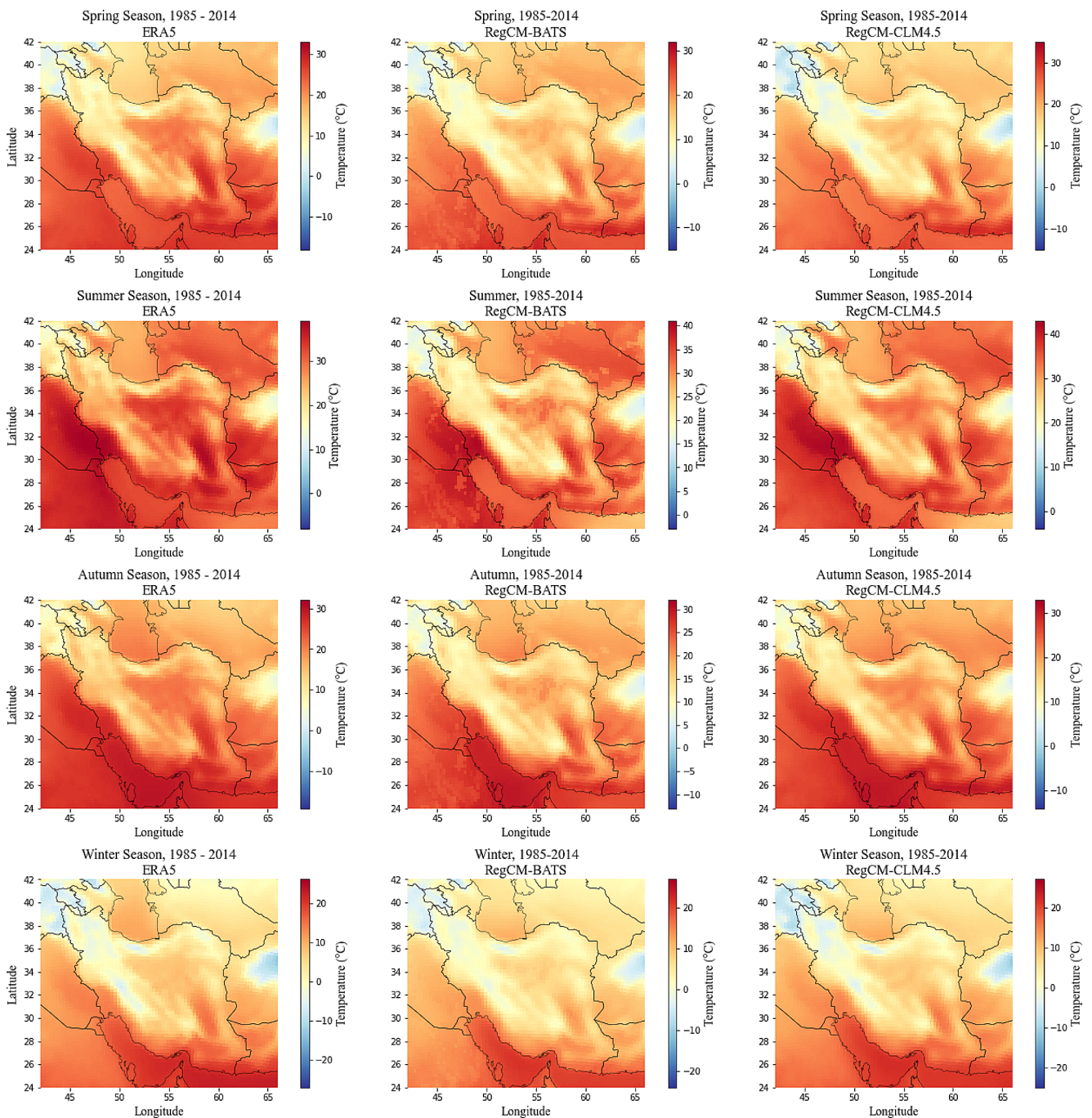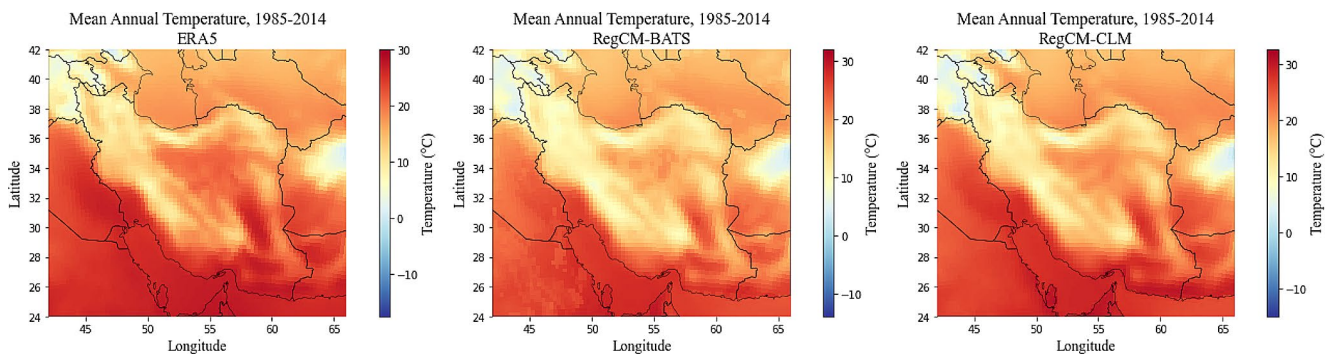
Fig. 2 Spatial pattern of seasonal average temperature derived from ERA5 reanalysis data, seasonal average temperature obtained from the RegCM4.7-BATS, and RegCM4.7-CLM4.5 during the period 1985–2014

are cooler in the warm half of the year in the inland plain of Iran, while warmer biases are observed over the Caspian Sea. Particularly in the high-altitude regions in the autumn season, the spatial pattern of bias is similar in both schemes/models; however, the minimum bias values in the BATS scheme were lower compared to the CLM4.5 scheme. Winter temperatures using the BATS scheme in the central and southeastern parts of the study area exhibit greater cold

biases, while on the northwest, Alborz and Zagross mountains, warmer biases are simulated. The pattern of bias in the colder half of the year indicates the presence of cold biases in major parts of the study area and over the Caspian Sea.

The analysis of annual temperature bias in the study area reveals a similar spatial pattern of bias for both schemes (Fig. 5). The CLM4.5 land surface model displays a cold bias in central Iran and the northwestern part of the study

Fig. 3 Spatial pattern of the annual average temperature derived from ERA5 reanalysis data, annual average temperature obtained from the RegCM4.7-BATS and RegCM4.7-CLM4.5 during the period 1985–2014
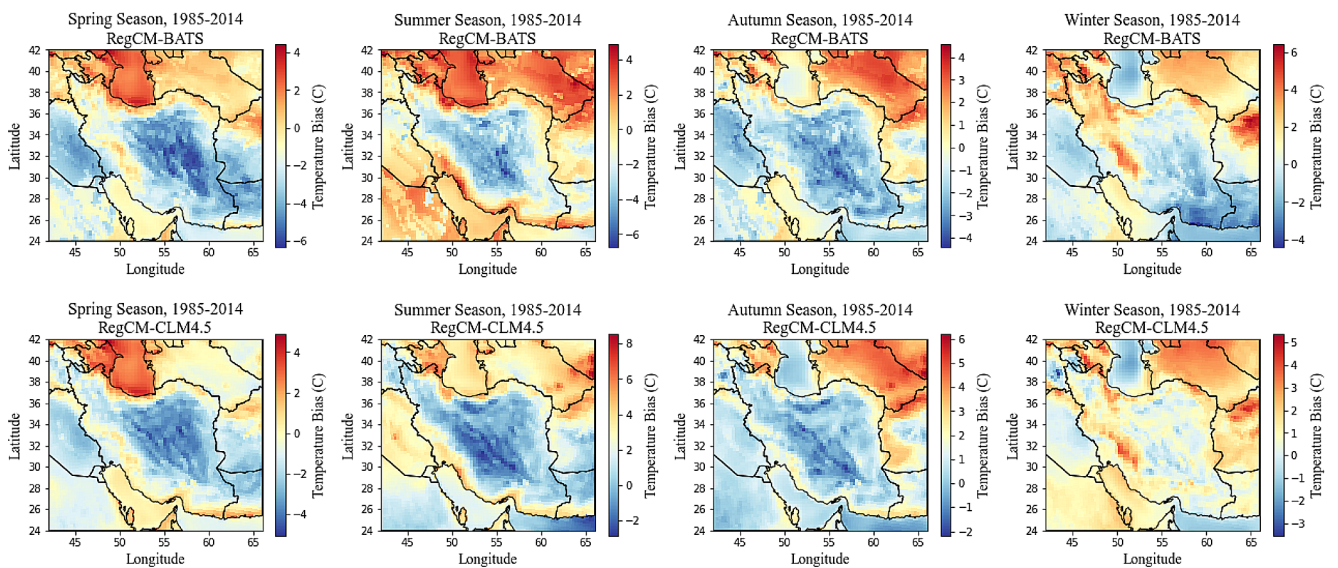
Fig. 4 Spatial pattern of seasonal temperature bias derived from the RegCM4.7-BATS and RegCM4.7-CLM4.5 models compared to the mean temperature derived from ERA5 data during 1985–2014
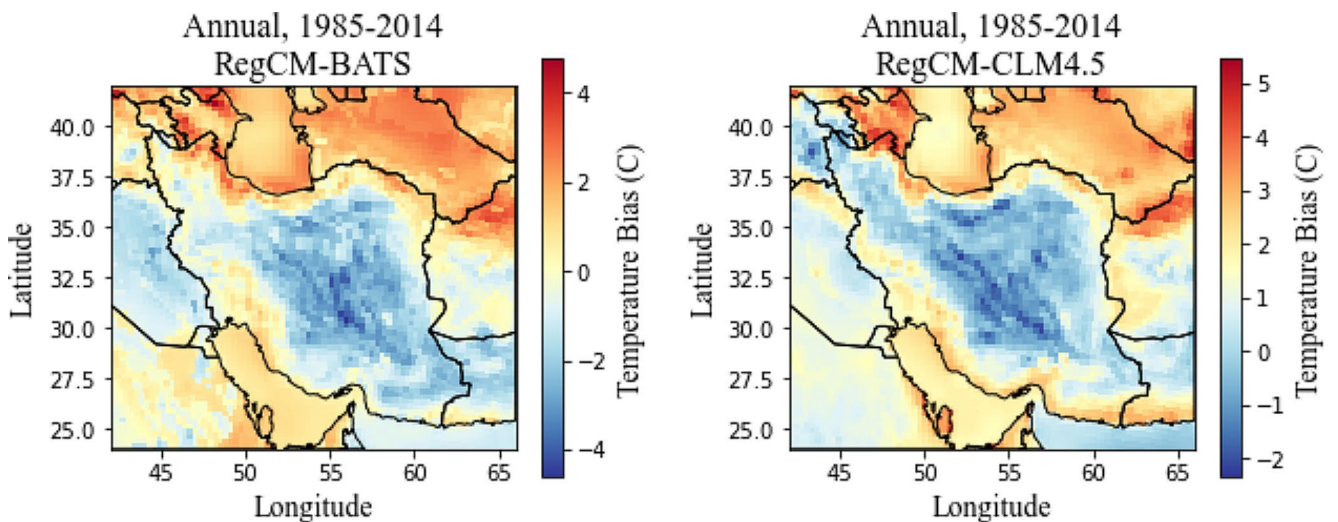
Fig. 5 Spatial pattern of annual temperature bias obtained from the RegCM4.7-BATS and RegCM4.7-CLM4.5 models compared to the annual temperature average derived from ERA5 data during the time period 1985–2014

area, with bias values generally ranging from − 2 to approximately 5 degrees Celsius. Bias values in the BATS scheme range from − 4 to 4 degrees Celsius. It appears that the CLM4.5 land surface model, exhibits a warmer bias compared to the BATS scheme, especially in the northern parts of the study area and the Caspian Sea.

Statistical indices for analyzing the temperature simulation results are provided in Table 2. The bias index (Bias) suggests that, except for the winter season, the BATS scheme generally exhibits cold biases in other seasons. Similarly, except for the spring, the CLM4.5 land surface model also shows warm biases in seasonal temperature prediction. In both schemes, the annual temperature values are reported higher compared to ERA5 data. According to the bias mean index, temperature simulation with the RegCM4 model and the BATS land surface scheme is associated with lower biases. Only in the spring season does the CLM4.5 land surface scheme lead to reduced biases. Examination of the RMSE and NRMSE indices indicates that temperature prediction using the CLM4.5 land surface model yields better results in the spring and winter seasons. However, in the summer and autumn seasons, as well as in the annual scale, the BATS scheme shows lower RMSE and NRMSE values. Evaluation of the relative standard deviation (Std-rel) index also indicates better performance in predicting seasonal and annual temperatures using the BATS scheme. Pearson correlation coefficient values for both seasonal and annual scales between the two land surface schemes (models) show very little difference; however, results obtained from the CLM4.5 scheme show slightly higher correlation. Based on the NS index, the performance of the CLM4.5 land surface model in simulating temperature in the spring and winter seasons is superior, while the performance of the BATS scheme is better in the summer and autumn seasons, as well as in the annual scale. According to the KGE index, the CLM4.5 land surface model performs better in simulating

temperature in the spring and winter seasons. The value of this index is the same for both schemes in the summer season. In other words, according to the KGE index, both land surface schemes exhibit the same performance in simulating temperature in this season. However, in the autumn season and in the annual scale, the application of the BATS scheme can be considered slightly better, with a very marginal difference.

To summarize the above evaluations and examine the differences between the results obtained from employing two land surface schemes (models) in the regional climate model RegCM4.7, Taylor diagrams for seasonal and annual temperatures are presented in Figs. 6 and 7. Despite the smaller standard deviation of temperatures obtained from the BATS scheme in the spring season, the performance of the CLM4.5 model is more favorable. As shown in the diagrams, the performance of the RegCM4 model with both land surface schemes (models) in the summer and autumn seasons shows very little difference; however, the use of the CLM4.5 land surface model can be considered more appropriate in both seasons. Similarly, in the winter season, like spring, despite the lower standard deviation in the BATS scheme, the performance of the CLM4.5 model was closer to the reference data.

The Taylor diagram analysis of annual temperature simulation using RegCM4.7 with both land surface schemes indicates that the performance of the coupled model with CLM4.5, characterized by lower RMSE and higher correlation coefficient, is closer to the reference dataset. Therefore, its application can be considered more favorable.

3.2 Precipitation

As previously mentioned, following the calculation of correction coefficients during the control period of 1985–2004, the daily precipitation values during the verification period

Table 2 Statistical indices of simulated temperature values using RegCM_BATS and RegCM_CLM4.5 on a seasonal and annual scale compared to ERA5 reference data

Statistical index	Scheme/model	Spring	Summer	Autumn	Winter	Annual
Bias	BATS	-1.44	-0.03	− 0.35	0.53	0.01
	CLM4.5	-0.60	2.04	1.42	1.05	1.34
RMSE	BATS	2.58	2.13	1.69	1.77	1.56
	CLM4.5	1.80	2.69	1.98	1.52	1.79
NRMSE	BATS	8.95%	8.00%	6.34%	5.13%	5.88%
	CLM4.5	6.26%	10.10%	7.44%	4.39%	6.77%
Std-rel	BATS	0.87	1.05	0.93	0.84	0.95
	CLM4.5	0.96	1.04	0.95	0.95	1.01
r	BATS	0.95	0.92	0.96	0.98	0.97
	CLM4.5	0.97	0.94	0.97	0.99	0.98
NS	BATS	0.84	0.83	0.92	0.94	0.93
	CLM4.5	0.92	0.74	0.89	0.96	0.91
KGE	BATS	0.84	0.90	0.92	0.83	0.94
	CLM4.5	0.94	0.90	0.91	0.86	0.93

Fig. 6 Taylor diagram for seasonal temperatures obtained from the RegCM4.7-BATS and RegCM4.7-CLM4.5 compared to the annual mean temperature from ERA5 data during the period 1985–2014
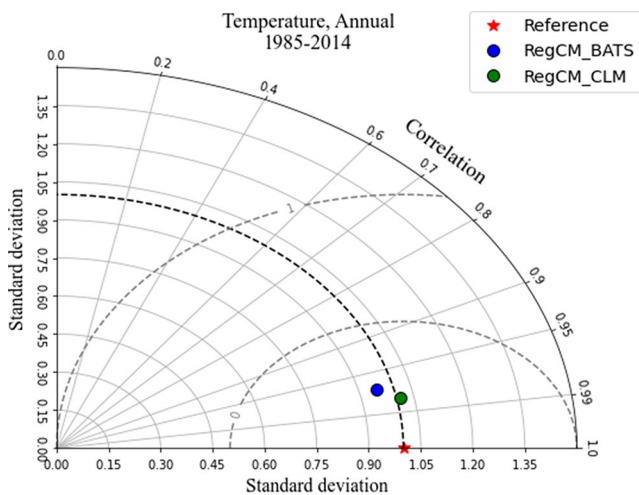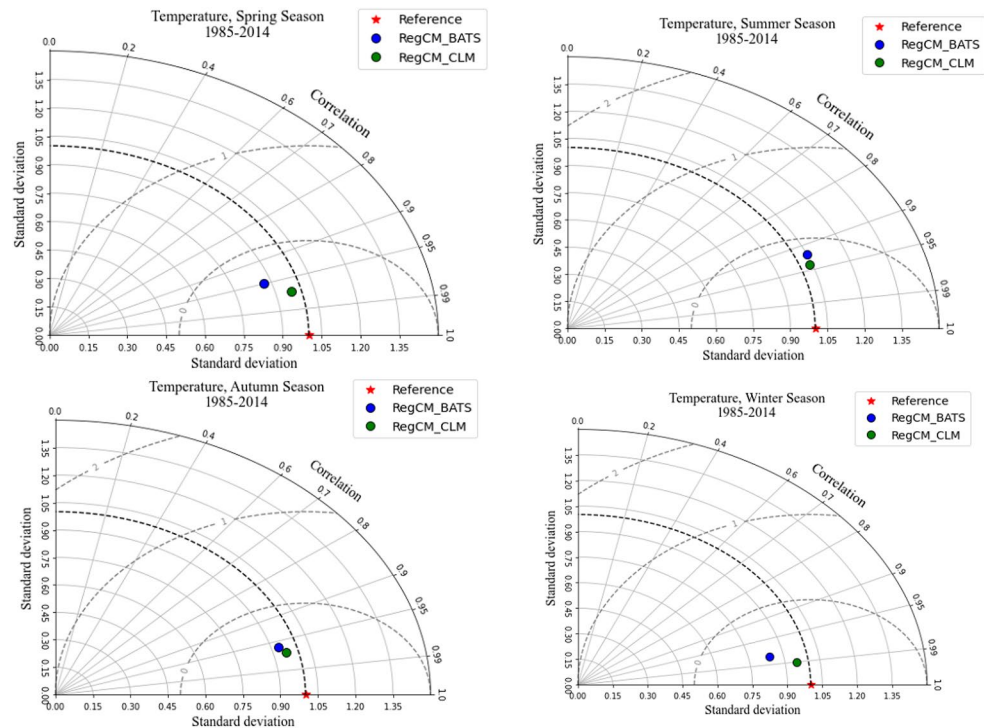
Fig. 7 Taylor diagram for annual temperature from RegCM4.7-BATS and RegCM4.7-CLM4.5 compared to the annual mean temperature from ERA5 dataset during the period 1985–2014

from 2005 to 2014 were adjusted. Tables 3 and 4 respectively present the statistical index values obtained from comparing the raw and corrected outputs of the RegCM4.7 model with observed data during the verification period. The statistical indices, including mean bias and RMSE, presented in Table 3 indicate a significant bias and error in the results of the RegCM4.7 model across both configurations, highlighting the imperative need for bias correction. Furthermore, the NS and KGE indices underscore the model's poor performance in both configurations. Comparing Tables 3 and 4 highlights a significant improvement in reducing average

bias and error in the model results for both surface configurations with the utilization of the Modified Linear Scaling (MLS) method. Additionally, the bias correction of the model has led to enhancements in the values of standard deviation and NRMSE. Furthermore, analysis of the correlation, Nash-Sutcliffe, and Kling-Gupta indices indicates a notable improvement in the model's performance following the application of Modified Linear Scaling.

In the next step, the linear scaling monthly indices was applied to the modeled precipitation values using both the RegCM_BATS and RegCM_CLM4.5 configurations throughout the entire study period. Figure 8 illustrates the spatial pattern of corrected seasonal precipitation using two land surface schemes, BATS and CLM4.5, alongside the seasonal mean precipitation derived from ERA5 reanalysis data for the study area during the period 1985–2014. Both land surface schemes adequately capture the spatial distribution pattern of precipitation. Furthermore, precipitation simulations by both schemes in all seasons, particularly in autumn and winter, exhibit higher precipitation values along the Caspian Sea and the Zagros mountain range.

Moreover, the spatial pattern of corrected annual precipitation indicates satisfactory performance of both surface schemes in simulating the spatial distribution of precipitation in the study area. As depicted in the Fig. 9, the RegCM4.7, in combination with both land surface schemes, simulates higher precipitation amounts along the Alborz and Zagros mountain ranges. Generally, similar to the seasonal scale, the simulation of precipitation values at the annual scale

Table 3 Statistical indices of raw simulated precipitation values using RegCM_BATS and RegCM_CLM4.5 on seasonal and annual scales, compared to ERA5 reference data in the verification period (2005–2014)

Statistical index	Scheme/model	Spring	Summer	Autumn	Winter	Annual
Bias	BATS	242.64	57.59	153.33	71.19	529.88
	CLM4.5	215.07	19.85	136.18	65.94	442.20
RMSE	BATS	311.33	157.58	215.75	113.75	731.59
	CLM4.5	284.12	76.51	190.54	109.16	608.15
NRMSE	BATS	3.83	6.07	3.71	1.21	2.88
	CLM4.5	3.50	2.95	3.28	1.16	2.39
Std-rel	BATS	1.26	0.78	0.76	0.62	0.88
	CLM	1.22	0.45	0.67	0.60	0.76
r	BATS	0.78	0.67	0.56	0.83	0.75
	CLM4.5	0.79	0.72	0.55	0.81	0.75
NS	BATS	-11.49	-4.46	-5.02	-1.03	-6.11
	CLM4.5	-9.40	-0.29	-3.70	-8.87	-3.92
KGE	BATS	-2.55	-1.82	-1.88	0.11	-1.56
	CLM4.5	-2.21	0.007	-1.53	-0.035	-1.08

Table 4 Statistical indices of corrected simulated precipitation values using RegCM_BATS and RegCM_CLM4.5 on seasonal and annual scales, compared to ERA5 reference data in the verification period (2005–2014)

Statistical index	Scheme/model	Spring	Summer	Autumn	Winter	Annual
Bias	BATS	17.11	-3.30	0.49	14.17	33.61
	CLM4.5	18.41	-4.59	9.07	17.71	45.73
RMSE	BATS	26.78	16.46	29.43	24.77	60.46
	CLM4.5	28.31	20.74	38.07	28.56	77.62
NRMSE	BATS	0.33	0.63	0.51	0.26	0.24
	CLM4.5	0.39	0.80	0.65	0.30	0.30
Std-rel	BATS	0.48	0.25	0.35	0.38	0.36
	CLM	0.49	0.24	0.40	0.40	0.37
r	BATS	0.98	0.97	0.94	0.97	0.98
	CLM4.5	0.98	0.96	0.92	0.97	0.97
NS	BATS	0.91	0.94	0.89	0.90	0.95
	CLM4.5	0.89	0.90	0.81	0.87	0.92
KGE	BATS	0.76	0.83	0.92	0.81	0.86
	CLM4.5	0.74	0.77	0.81	0.76	0.81

with both land surface schemes (models) closely resembles ERA5 precipitation values. Additionally, consistent with the ERA5 reference data, the maximum predicted precipitation is observed on the margins of the Caspian Sea with both land surface schemes (models).

The amount of corrected simulated precipitation compared to precipitation obtained from the ERA5 dataset in the study area is depicted in Fig. 10. Examination of the figure for the spring season indicates that precipitation simulation using the BATS scheme and CLM4.5 model is characterized by wet bias in most inland areas of the country and over the Caspian Sea. In the southeastern part of the study area, the predicted precipitation has been accompanied by a dry bias. Furthermore, analysis of bias in the summer season indicates that both schemes have a wet bias in the central part of the country, and in other parts of the country, the precipitation predicted by the model has been lower than the reference data. In the autumn season, precipitation predictions using both schemes (models) also exhibited a dry

bias in inland regions of the country. In the northern belt of the country as well as in most parts of the southern regions, predicted precipitation amounts with both schemes (models) were higher than the reference data. However, the wet bias in autumn precipitation from RegCM-CLM4.5 encompassed a wider range of inland areas, and its magnitude was greater compared to RegCM-BATS. It is noteworthy that the highest wet bias in this scheme was observed in the Caspian Sea coastal areas with both schemes (models). In the winter season, modeled precipitation by the BATS and CLM4.5 schemes in most parts of the study area in both configurations exhibited a wet bias. Overall, analysis of bias dispersion indicates that although precipitation modeling using RegCM-BATS and RegCM-CLM4.5 showed different bias values on a seasonal scale, the precipitation bias patterns of the two configurations were similar in each season.

The analysis of annual precipitation bias indicates that precipitation modeling with both land surface schemes has mostly exhibited a wet bias (Fig. 11). However, in the
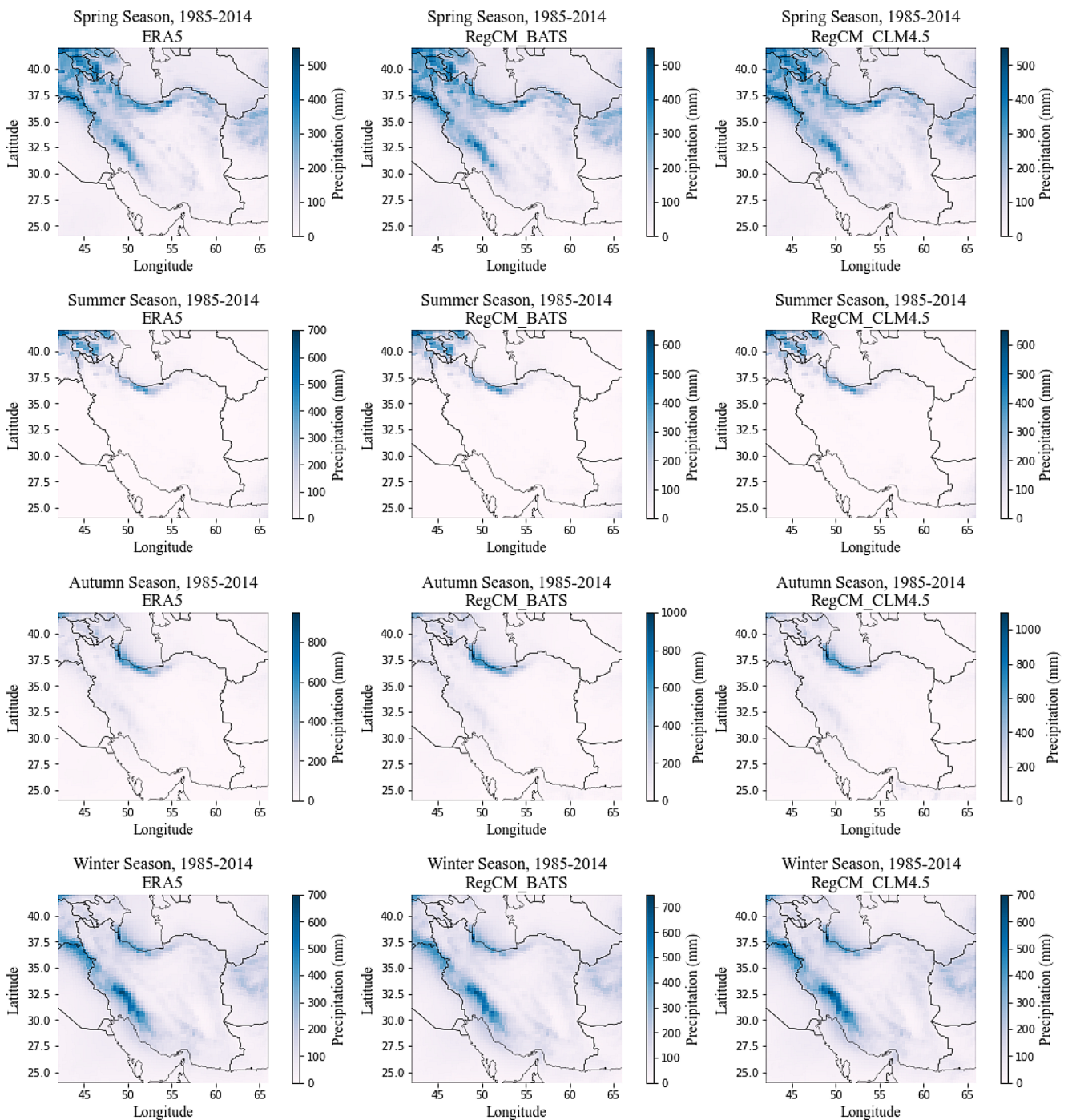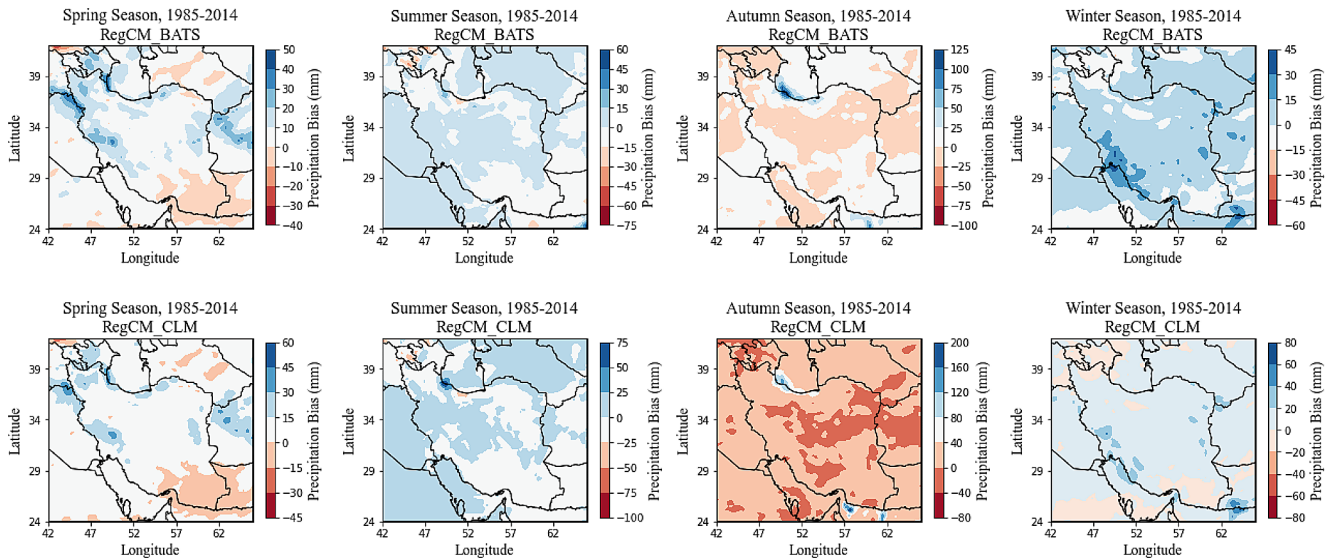
Fig. 8 Spatial pattern of seasonal mean precipitation derived from ERA5 reanalysis data, corrected average precipitation obtained from the RegCM4.7-BATS and RegCM4.7-CLM4.5 models during the period 1985–2014

southeastern part of the country and along the coast of the Sea of Oman, modeling with both schemes has shown a dry bias. The highest amount of wet bias is also observed in both configurations along the coast of the Caspian Sea, with the bias magnitude being higher in the RegCM-CLM4.5 compared to RegCM-BATS.

In order to evaluate the performance of the RegCM4.7 model with two different land surface schemes in simulating seasonal and annual precipitation compared to ERA5 reference data, several statistical indices were calculated. The examination of the seasonal bias in the Table 5 shows that the results obtained from the BATS scheme are generally associated with lower bias. Precipitation modeling
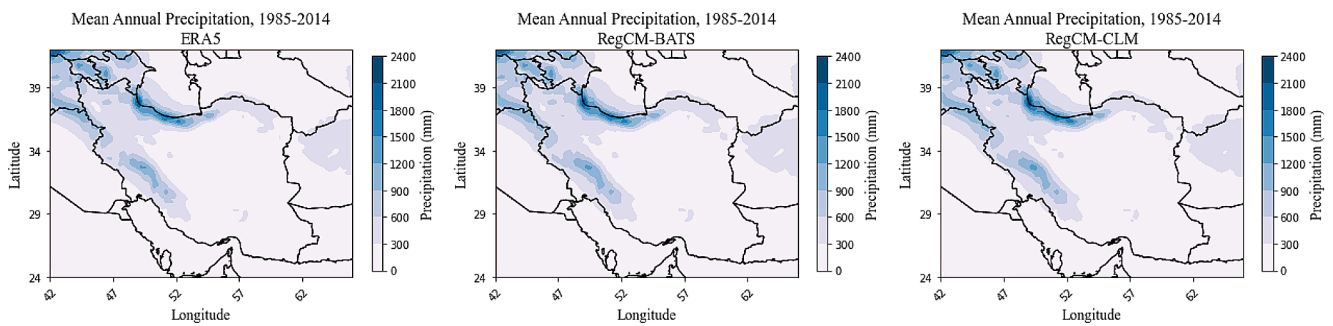
Fig. 9 Spatial pattern of annual average precipitation derived from ERA5 reanalysis data and corrected annual average precipitation obtained from the RegCM4.7-BATS and RegCM4.7-CLM4.5 models during the period 1985–2014

Fig. 10 Spatial pattern of seasonal precipitation bias obtained from the RegCM4.7-BATS and RegCM4.7-CLM4.5 models compared to the average precipitation from ERA5 data during the time period 1985–2014
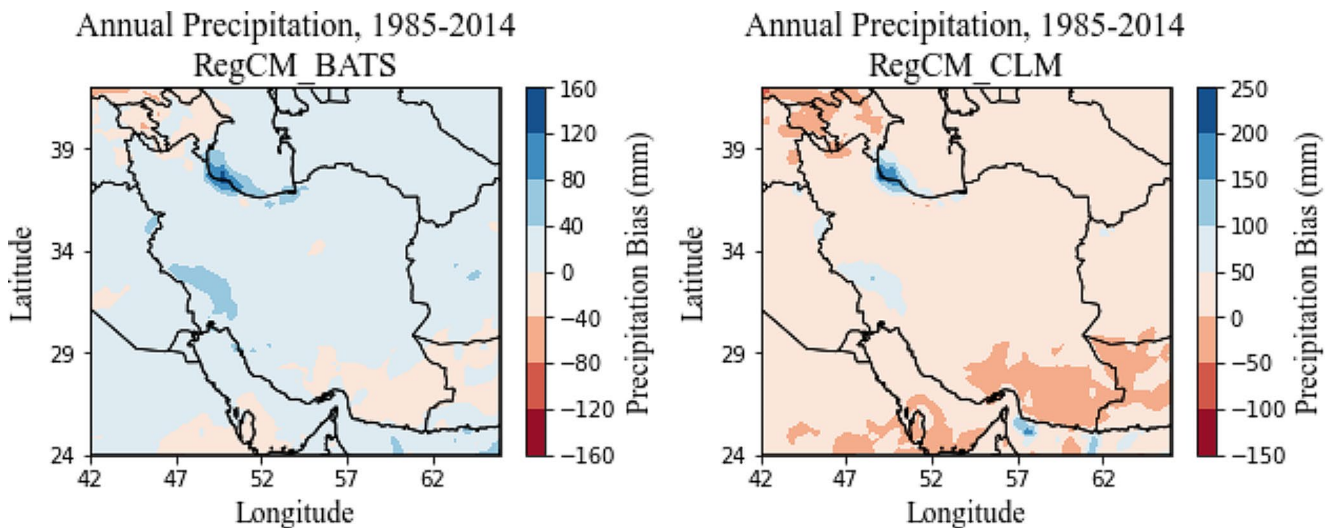
Fig. 11 Spatial pattern of annual precipitation bias obtained from the RegCM4.7-BATS and RegCM4.7-CLM4.5 models compared to the average precipitation from ERA5 data during the time period 1985–2014

using both schemes has exhibited a dry bias during the summer season. The annual average bias index shows that both schemes have overestimation, with the BATS scheme showing better performance. Examination of RMSE and NRMSE also shows that in the values of these indices are lower in the BATS scheme than CLM4.5 Except for the spring season, where the NRMSE index was the same in both schemes. The values of the relative standard deviation also show that the value of this index for both schemes is almost equal on a seasonal and annual scale. Additionally, examination of the r values indicates that precipitation modeling using both schemes has shown consistent and high correlation with ERA5 data. Examination of the Nash-Sutcliffe index indicates that the model performance on an annual scale and also in the spring season using both land surface schemes is similar. In other seasons as well, the performance of the BATS scheme has been reported to be slightly better. According to the values of the Kling-Gupta efficiency index, the ability of the RegCM-BATS model in seasonal and annual precipitation modeling has been higher.

To facilitate the comparison of the performance of the RegCM4 model with two different land surface schemes, Taylor diagrams were used. Examination of the Taylor diagrams for the all seasons indicates that the performance of both schemes is the same across different seasons (Fig. 12).

A Taylor diagram was also plotted to assess the model performance at the annual scale in Fig. 13. Examination of this diagram indicates that similar to the seasonal scale, the performance of the RegCM4.7 model using the BATS scheme and the CLM4.5 model in annual precipitation modeling is the same.

4 Discussion

The findings of this research suggest that the RegCM4.7 model, utilizing both configurations, effectively predicts the spatial distribution pattern of temperature on both seasonal and annual scales, similar to the ERA5 dataset. This aligns with previous studies such as Fuentes-Franco et al. (2014), Almazroui (2019), Babaeian et al. (2021), Ghosh et al. (2023) and Mbienda et al. (2023) which also demonstrated the model's capability in reproducing temperature distribution patterns. Specifically, the model captures lower temperatures in high-altitude regions, consistent with Kumar and Dimiri (2020), who attributed this to higher soil moisture fluxes at higher altitudes reducing sensible heat near the surface. However, discrepancies exist between the two configurations regarding temperature bias, with CLM4.5 generally simulating a warmer climate. This finding is supported by Nayak et al. (2017), who highlighted the higher sensible heat fluxes and Bowen ratio in the CLM model compared to BATS, leading to increased surface temperatures and decreased surface moisture. Statistical analyses further corroborate these findings, indicating that while CLM4.5 performs better in spring and winter seasons, BATS demonstrate superior performance in summer, autumn, and annual scales. Similar observations were made by Nayak et al. (2017) and Tiwari et al. (2015), who emphasized the respective strengths of each scheme in different seasons. Notably, the Taylor diagram analysis underscores the better performance of the CLM4.5 model in simulating seasonal temperatures. Regarding precipitation simulation, both configurations of the RegCM4.7 model effectively reproduce the spatial distribution pattern, particularly along the Alborz and Zagros Mountain ranges. However, the BATS scheme generally exhibits lower bias and better performance in simulating precipitation compared to CLM4.5. These findings align with previous research by Giorgi et al. (2012),

Table 5 Statistical indices for corrected simulated precipitation values using RegCM_BATS and RegCM_CLM4.5 at seasonal and annual scales compared to ERA5 reference data during the time period 1985–2014

Statistical index	Scheme/model	Spring	Summer	Autumn	Winter	Annual
Bias	BATS	5.70	-1.04	1.89	3.58	10.13
	CLM4.5	6.12	-1.52	4.71	4.89	14.22
RMSE	BATS	8.98	5.52	9.63	7.56	19.20
	CLM4.5	9.49	6.93	13.49	8.88	24.80
NRMSE	BATS	0.10	0.21	0.19	0.07	0.07
	CLM4.5	0.10	0.26	0.27	0.08	0.09
Std-rel	BATS	0.46	0.28	0.38	0.39	0.37
	CLM4.5	0.47	0.28	0.39	0.40	0.37
r	BATS	0.99	0.99	0.99	0.99	0.99
	CLM4.5	0.99	0.99	0.98	0.99	0.99
NS	BATS	0.98	0.99	0.98	0.99	0.99
	CLM4.5	0.98	0.98	0.97	0.98	0.99
KGE	BATS	0.92	0.94	0.95	0.96	0.96
	CLM4.5	0.91	0.92	0.89	0.94	0.94
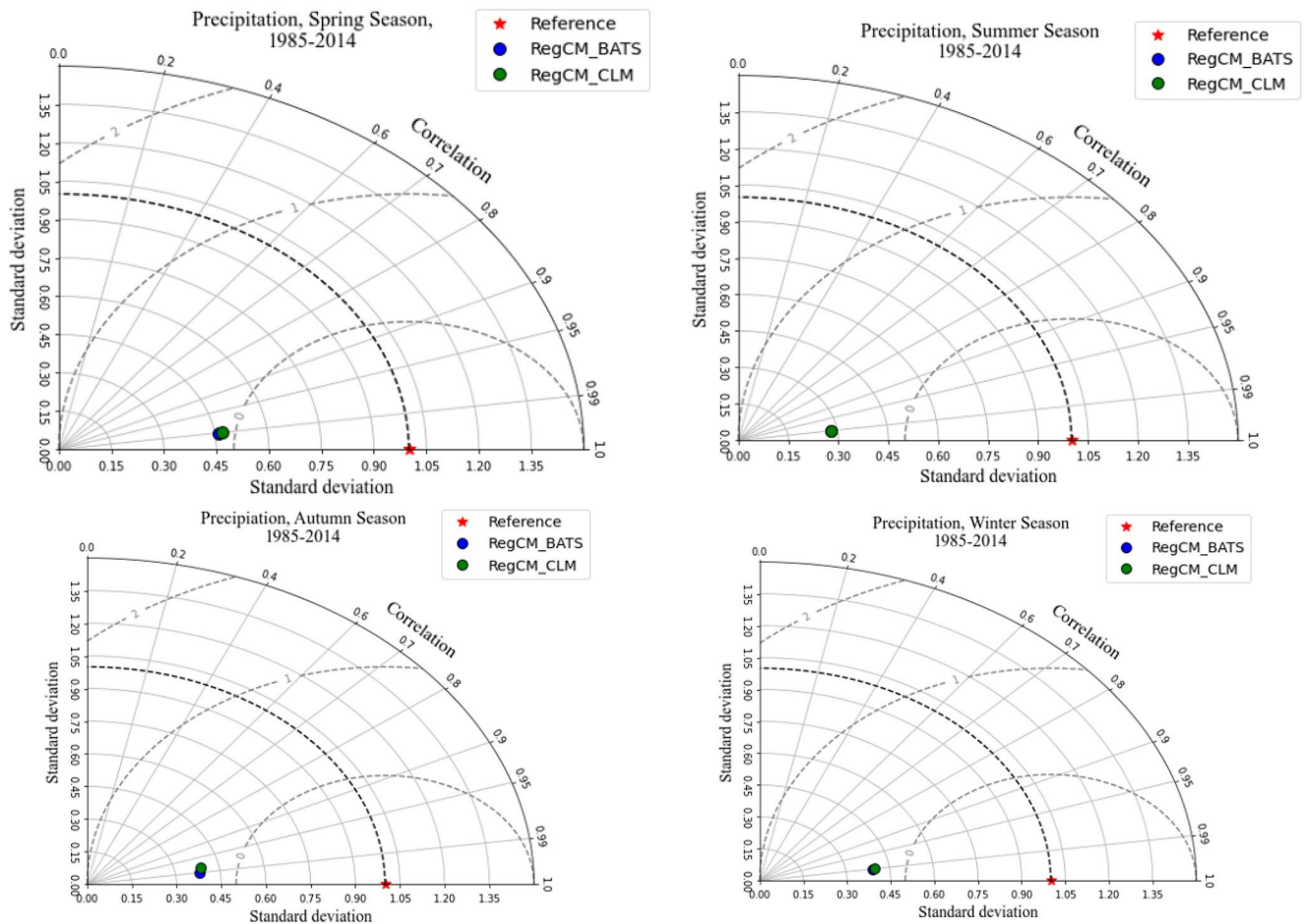
Fig. 12 Taylor diagram for corrected seasonal precipitation obtained from the RegCM4.7-BATS and RegCM4.7-CLM4.5 models compared to the annual average precipitation from ERA5 data during the time period 1985–2014
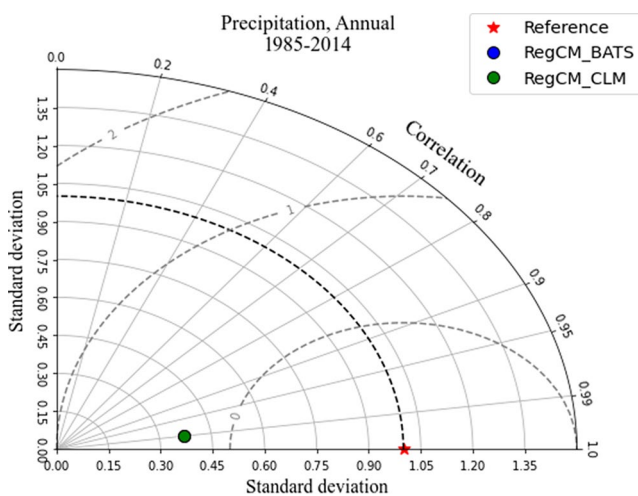
Fig. 13 Taylor diagram for corrected annual precipitation obtained from the RegCM4.7-BATS and RegCM4.7-CLM4.5 models compared to the annual precipitation from ERA5 data during the time period 1985–2014

Kouassi et al. (2022) and Li et al. (2023), confirming the model's capability in reproducing precipitation patterns. Despite these successes, except in summer, both schemes tend to overestimate precipitation, with CLM4.5 showing higher biases. While the model RegCM_BATS has shown better performance in terms of the RMSE, NRMSE, and KGE indices, the capability of both configurations in simulating precipitation is very close and desirable according to the NS index. The Taylor diagram analysis of precipitation modeling at seasonal and annual scales indicates a similar performance of both configurations in precipitation modeling. The study by Steiner et al. (2009) and Gu et al. (2020) also confirmed that the CLM model outperformed the BATS model in simulating precipitation. Saha et al. (2014), Wang et al. (2015) and Kouassi et al. (2022), highlighting the advantages of the BATS scheme in precipitation simulation.

5 Conclusion

In this study, we investigated the sensitivity of the RegCM4.7 regional climate model to different land surface schemes for simulating precipitation and temperature in Iran. Utilizing two identical configurations of the model, one with the BATS scheme and the other with the CLM4.5 land surface model, we conducted simulations over a thirty-year period at a spatial resolution of 30 km. Due to notable biases in precipitation obtained from the RegCM4.7 model, we applied a Modified Linear Scaling method to correct this variable in both configurations. Subsequently, we compared the results separately with ERA5 temperature and precipitation data on seasonal and annual scales. Our statistical analyses revealed that both configurations of the RegCM4.7 model adequately captured the seasonal and annual cycles of temperature and precipitation, as well as their spatial distribution patterns. CLM4.5 model showed a higher correlation with ERA5 data for temperature simulations. Additionally, the examination of the three indices of relative standard deviation, RMSE, and correlation coefficient using the Taylor diagram showed that overall, the results obtained from the application of the RegCM4.7-CLM4.5 model in simulating seasonal and annual temperatures were closer to ERA5 reference data. The execution of the RegCM4.7 model with the CLM4.5 land surface model and the BATS scheme predicted the spatial pattern of precipitation in Iran similar to the pattern obtained from ERA5 reference data. In the evaluation of precipitation modeling with two land surface models, it was found that both configurations yielded closely matched results based on statistical indices. While the RegCM_BATS model exhibited superior performance according to the mean bias index, the relative standard deviation and correlation coefficient values were comparable for both configurations. The Taylor diagram analysis indicated that the performance of the two land surface schemes in simulating seasonal and annual precipitation closely aligned with ERA5. In conclusion, our findings highlight the importance of considering the specific climatic variable and its characteristics when selecting the appropriate land surface scheme in regional climate modeling. We recommend further evaluation of various bias correction methods tailored to Iran's characteristics. Also, future studies could explore the use of other land surface schemes, such as Noah-MP or other advanced schemes, to further assess their suitability for precipitation and temperature modeling over Iran. Additionally, researchers could investigate the sensitivity of the model's precipitation and temperature performance to different spatial resolutions, including higher-resolution simulations, to better capture the spatial variability of precipitation. Furthermore, extending the comparative analysis beyond the BATS and CLM4.5 schemes to other regions, particularly

those with different climatic characteristics, to assess the generalizability of the findings. Finally, incorporating multiple observational datasets, including ground-based measurements, to better account for observational uncertainty and its impact on the model evaluation. This study primarily focused on the performance of the land surface schemes in temperature and precipitation simulation. Future research could explore the coupled land-atmosphere interactions and their influence on the model's ability to capture precipitation and temperature patterns and processes. These findings provide valuable insights for improving regional climate modeling and understanding climate dynamics in the study area.

Declarations

Competing interests The authors declare no competing interests.

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Statements & Declarations

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