Harmonized Land Dynamics in Regional Climate Simulations and Projection: A LUH2-Based RegCM-CLM Study over Iran

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Harmonized Land Dynamics in Regional Climate Simulations and Projection: A LUH2-Based RegCM-CLM Study over Iran

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Abstract

Land use and land cover change can significantly affect regional climate variables through land-atmosphere interactions. When these changes are not represented dynamically, models may underestimate key feedbacks, especially in regions undergoing rapid transformation. Despite the importance of land surface dynamics, most regional climate studies continue to use static land datasets and ignore evolving processes. To address this limitation, we employed the RegCM4.7 regional climate model coupled with the CLM4.5 land surface model over Iran. The model was run using both the default static land data configuration and the annually updated Land Use Harmonization version 2 (LUH2) datasets in place of the default configuration. Temperature and precipitation outputs were assessed for a historical period and two future intervals, using two shared socioeconomic pathway scenarios. Findings reveal that the application of Land Use Harmonization datasets leads to more accurate temperature outputs, particularly for daily minimum values. The dynamic configuration shows stronger warming trends and better agreement with ERA5 data. Based on the comparison with static land representation, temperature projections using dynamic LUH2 data are warmer by approximately 0.13°C to 1.2°C under SSP2-4.5 and 0.02°C to 0.26°C under SSP5-8.5 on a seasonal scale. These results suggest that the Sixth Assessment Report temperature projections may be optimistic, as incorporating dynamic land-change data leads to higher warming estimates. Although the static configuration performs better in simulating precipitation, the dynamic model provides a more detailed framework for long-term projections. Due to the dominant influence of large-scale atmospheric systems, land dynamics did not significantly improve precipitation outcomes. However, the adaptability of dynamic LULC data offers greater potential for capturing future variability and extremes under changing climate conditions. Overall, the findings underscore the importance of including land surface forcing in regional climate modeling, particularly for temperature and precipitation.

Keywords: Regional Climate Model, Dynamic Land Surface Data, Land Use Harmonization, Climate Change

1. Introduction

Changes in Land Use Land Cover (LULC) affect climate through changing emissions of greenhouse gases, surface albedo, evapotranspiration, and surface roughness, thereby influencing local to global climate systems (IPCC AR6 WGI, Chapter 2). Therefore, the use of reliable LULC data plays a crucial role in the accuracy of numerical simulations conducted with regional climate models (Chen et al., 2017). Application of different LULC datasets in regional climate models and the role of these changes on results of models has been addressed in some studies. For example, Li et al (2023) assessed the role of annually dynamic LULC dataset in simulation of temperature of China during 1984-2013 by using RegCM model. Finding of this research showed the changing in mean and extreme of seasonal temperature in different part of China that described by replacement of transient LULC with constant dataset. Nayak et al. (2021) examined how land use and land cover changes affected India's climate over 30 years using the RegCM4 model. They compared two simulations with static and dynamic LULC datasets. The differences revealed that LULC changes led to reduced annual precipitation and evapotranspiration, along with an increase in annual temperature between 1981 and 2010. Alexandru (2017) investigated the impact of land use land cover change (LULCC) on climate projections by using the CanESM2[1] as the driving GCM for the CRCM5 model. In this study, two simulation was performed with annual land data from GCAM[2] in North America. In the first simulation the model was ran during 1950-2100 with fixed land characteristics at 1990 as a present day LULC. In the next simulation the model was ran during 2006-2100 with LULC data changed seven times to identify land use land cover change in the future period. Findings of this study showed that season, location, extent and type of LULCC affect climate variables and extremes in different way and these changes also has biophysical effect on climate. LULCC plays a critical role in shaping environmental and socio-economic conditions in developing countries, where rapid population growth, agricultural expansion, and poverty place immense pressure on land resources. In Iran, recent studies have highlighted how land transformations mirror many of the pressures seen in developing countries, particularly in relation to agricultural expansion, declining forest cover, and the complex interplay between natural and human-driven change (Jalayer et al., 2022; Khoshnood Motlagh et al., 2021). For example, Zarandian et al. (2023), in their study of land use and land cover changes in Karaj from 2006 to 2017, found that the area of human-made landscapes increased, while the coverage of grasslands, agricultural lands, and gardens also expanded. The study further emphasized that these trends are expected to continue through 2028.

Given Iran's climatic diversity and the continuous trend of land use land cover change, it is necessary to study LULC dynamics within the framework of regional climate modeling. These changes not only have direct environmental impacts, but also play a crucial role in shaping the boundary conditions of regional climate models such as RegCM, thereby influencing the accuracy and relevance of climate projections. The Regional Climate Model (RegCM), developed by the International Centre for Theoretical Physics (ICTP), is one of the earliest limited-area models designed for long-term regional climate simulations (Elguindi et al., 2014). Over the years, it has contributed extensively to numerous regional climate modeling intercomparison projects, demonstrating its adaptability across diverse climatic zones (Kalmár et al., 2024; Ren et al., 2024). In the context of Iran, RegCM has been widely applied to investigate various climate variables, including temperature, precipitation, and extreme events. Several studies have evaluated its configurations and parameterizations, consistently reporting robust performance and reliable outputs for the region's complex topography and climatic conditions (Babaeian et al., 2024; Sabziparvar et al., 2024). Although the application of RegCM in Iran has demonstrated acceptable performance in regional climate

[1] Second generation of the Canadian Earth System Model
[2] Global Change Assessment Model

modeling, biases have been reported in most simulations (Yazdandoost et al., 2021). These biases can arise from various sources, including low accuracy in estimating vertical atmospheric mixing, errors in calculating components of the surface energy balance and inaccuracies related to lateral and boundary conditions. Additionally, the quality of land use and land cover datasets plays a critical role in shaping surface variables and is considered a major contributor to model bias (Mbienda et al., 2023). A more precise representation of surface characteristics and improved land–atmosphere feedbacks can enhance the accuracy of climate variable estimations and improve overall model performance (Nayak et al., 2018).

Building on our previous work, which demonstrated the superior performance of the CLM land surface scheme compared to BATS in simulating climate over Iran (Kosari Moghadam et al., 2024), this study extends that research by incorporating time-varying land data from the LUHv.2 dataset into the RegCM4.7-CLM4.5 coupled model. Unlike the default model configuration that uses land data from a fixed historical period treated as static throughout the simulation, we incorporated dynamic datasets to reflect evolving land conditions across both the historical period and the future under two Shared Socioeconomic Pathway scenarios (SSP2-4.5 and SSP5-8.5). This approach enables a more realistic representation of land–atmosphere interactions and allows us to evaluate the model's ability to capture climate responses to land transitions under changing environmental conditions in Iran.

2. Materials and Methods

2.1. Study Area and Model Domain

This study focuses on Iran, a region with complex topographical and climatic characteristics. The country features the Alborz Mountain range in the north and the Zagros range in the west, along with two major water bodies – the Capsian Sea to the north and the Persian Gulf in the south- both of which contribute to its distinct climate dynamics. To capture these features and relevant atmospheric processes, the simulation domain was defined using the RegCM4.7 regional climate model, spanning latitudes from 18°N to 42°N and longitudes from 25°E to 78°E. This domain, consistent with our previous work (Kosari Moghadam et al., 2024), ensures the inclusion of Iran's terrain, water bodies, and cyclone pathways. While the broader domain supports accurate modeling, the analysis presented in this paper is limited to the Iranian territory.

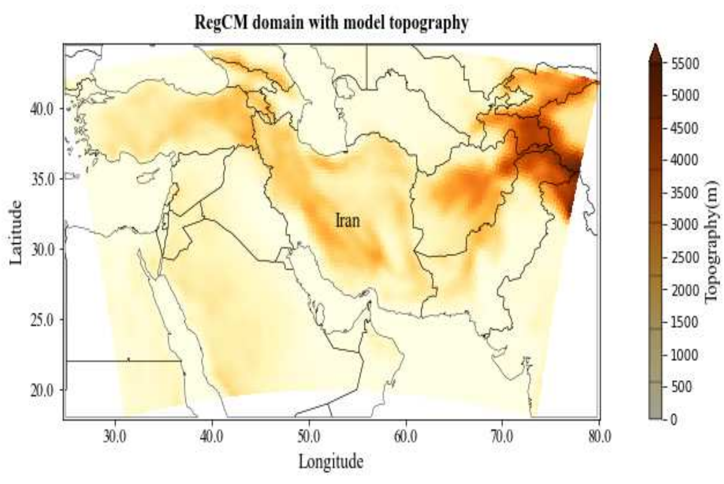


Fig. 1. Model domain and topography used in the RegCM4.7 simulations

2.2. Model Description

In this study, the RegCM version 4.7 regional climate model was used to simulate temperature and precipitation across Iran. RegCM system include terrain, lateral and boundary conditions, modeling and postprocessor. Terrestrial variables (including topography, land characteristic and sea surface temperature) as well as three-dimensional meteorological datasets were interpolated onto a user-defined projected coordinate system (Elguindi et al., 2017). In this study the Lambert Conformal was applied to maintain spatial consistency across simulations. A global elevation dataset known as GMTED2010 was used to represent Earth's land surface. This dataset was derived from digitized radar measurements and satellite imagery. For lateral and boundary conditions, the High Resolution Max Planck Institute Earth System Model version 1.2 (MPI-ESM1.2-HR) was selected. To simulate large-scale and convective precipitation, the SUBEX and Tiedtke/MIT-Emanuel schemes were employed. Longwave and shortwave radiation processes were parameterized using the NCAR CCM3 scheme (Kiehl et al., 1996), while planetary boundary layer dynamics and ocean fluxes were represented using the Holtslag (Holtslag et al., 1990) and Zeng (Zeng et al., 1998) schemes, respectively. The model was run at a horizontal resolution of 30 × 30 kilometers with 23 vertical levels. To capture the physical, chemical, and biological interactions between the terrestrial ecosystem and climate conditions, the Common Land Model version 4.5 (CLM4.5) was coupled with RegCM4.7 (hereafter referred to as RegCM-CLM).

2.3. Simulation Setup

Simulations were conducted for both historical (1983–2014) and future (2018–2040 and 2078–2100) periods, each preceded by a two-year spin-up to allow the model to reach stabilization. Future runs followed two CMIP6 Shared Socioeconomic Pathways, SSP2-4.5 and SSP5-8.5.

To evaluate the impact of land use and land cover (LULC) datasets on model performance, we first performed two historical simulations with the RegCM–CLM4.5 coupled system. In the first experiment, the model used the default CLM4.5 land dataset, which primarily derives its land cover and land use information from satellite-based products (most notably MODIS (2010–2015) and AVHRR (1992–1993)) and held these fields constant throughout the simulation. In the second experiment, temporally evolving LULC fields from the Land Use Harmonization version 2 (LUH2) project were incorporated to capture realistic changes in land cover and land use over time. Because most RegCM projections rely on static default LULC, both configurations were then applied to future simulations under SSP2-4.5 and SSP5-8.5. Hereafter, the static default LULC experiment will be referred to as RegCM–CLM–STAT, and the dynamic LUH2-based experiment as RegCM–CLM–DYN. This design allowed us to isolate and quantify the influence of land cover dynamics on projected climate variables. Based on comparative performance metrics, both LULC configurations were used in future simulations to enable a thorough evaluation of their respective impacts.

2.4. Dynamic Land Surface Integration

The static nature of default land datasets has been identified as a source of bias in regional climate modeling. To address this, we incorporated the LUH2 dataset in RegCM-CLM model. In CLM, land surface heterogeneity is represented by dividing each grid cell into multiple land units, with vegetated areas further resolved into a mosaic of up to 15 Plant Functional Types (PFTs). The CLM model primarily derives its land cover and land use information from satellite-based datasets, notably MODIS (2010–2015) and AVHRR (1992–1993), along with other sources (Olson et al., 2013). As part of CMIP6, the LUH2 dataset was developed to support new Earth System Models by providing consistent land-use scenarios that connect historical patterns with future projections (2015–2100). Based on History Database of the Global Environment (HYDE) data, LUH2 offers annual global land states estimates from 850 to 2100 at 0.25° resolution. It categorizes land into 12 types, including forested and non-forested areas, managed and natural pastures, urban zones, and various crop types such as C3/C4 annuals, perennials, and nitrogen-fixing plants (Hurtt et al, 2020).

Replacing static datasets with LUH2 in RegCM-CLM is expected to better reflect the evolving characteristics of earth's surface and their influence on climate. LUH2 provides detailed yearly transitions in land states, but its integration into CLM4.5 is limited by structural mismatches particularly in the representation of Plant Functional Types (PFTs). To enable dynamic land surface integration, the RegCM4.7-CLM4.5 preprocessing workflow was modified. To resolve this, the mksurfdata.F90 source code was revised and simulation-specific namelist configurations were adjusted to ensure compatibility with dynamic surface data. These enhancements enable the model to represent evolving land surface conditions over time, thereby improving the realism of regional climate simulations. The modifications were implemented in collaboration with the RegCM development team in ICTP and designed to preserve the integrity of the model's core architecture.

2.5. Statistical Evaluation

To evaluate the performance of the RegCM-CLM model using two different static and dynamic LULC datasets in simulating temperature and precipitation, the values of each variable were calculated at seasonal and annual scales over the study period. To evaluate the results of this study, we used the ERA5 reanalysis dataset as a reference over the same time period. The results indicated that precipitation required bias correction. Therefore, this variable was adjusted using the Modified Linear Scaling (MLS) method (Kosari Moghadam et al., 2024). Following the correction, both temperature and precipitation were statistically evaluated using several metrics, including Bias (B), Root Mean Square Error (RMSE), Normalized RMSE (NRMSE), Standard Deviation (STD), Correlation Coefficient (r), Kling-Gupta Efficiency (KGE), and Nash–Sutcliffe Efficiency (NSE). It is important to note that, for easier comparison between model results, relative standard deviation was used instead of absolute standard deviation. This index is obtained by dividing the model's standard deviation by the reference standard deviation.

$$Bias = \frac{\sum_{i=1}^{N}(P_i - O_i)}{N} \quad (1)$$

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

$$std = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \mu)^2}{N}} \quad (3)$$

$$r = \frac{\sum_{i=1}^{n}(P_i - P_m)(O_i - O_m)}{\sqrt{\sum_{i=z}^{n}(P_i - P_m)^2}\ \sqrt{\sum_{i=z}^{n}(O_i - O_m)^2}} \quad (4)$$

$$KGE = 1 - \sqrt{(r-1)^2 + (c-1)^2 + (\alpha - 1)^2} \quad (5)$$

$$NSE = 1 - \frac{\sum_{i=1}^{N}(O_i - P_i)^2}{\sum_{i=1}^{N}(O_i - \bar{O})^2} \quad (6)$$

Where P_i , O_i , c and α represent projected (simulated) variable, the observed (reanalysis_) data, the variability ratio and bias ratio, respectively.

3. Results and Discussion

In this section, the simulated temperature and bias-corrected precipitation results are analyzed for both the historical period (1985–2014) and future projections (2020–2040 and 2080–2100), under two LULC dataset and SSP2-4.5 and SSP5-8.5 scenarios.

3.1. Temperature

- **Historical simulation**

Figures 2 and 3 illustrate the spatial distribution of seasonal and annual mean temperatures during the historical period, simulated using RegCM-CLM with the default static dataset (RegCM-CLM-STS) and the LUH2 dynamic dataset (RegCM-CLM-DYN), in comparison with ERA5 reanalysis data. Despite the differences in configuration, both simulations successfully reproduce the spatial pattern of seasonal temperature as in the ERA5 reanalysis. Across seasonal and annual scales, the lowest temperatures consistently occur over the elevated regions of the Alborz and Zagros Mountains, while higher temperatures dominate in the central and eastern parts of the domain. Although the simulated minimum and maximum temperature values differ slightly from ERA5, the overall spatial patterns remain well captured. In both temporal scales, the RegCM-CLM-DYN configuration simulates slightly cooler mean temperatures compared to the static setup. These values are more consistent with the ERA5 reference data highlighting the influence of land cover dynamics on temperature outcomes.

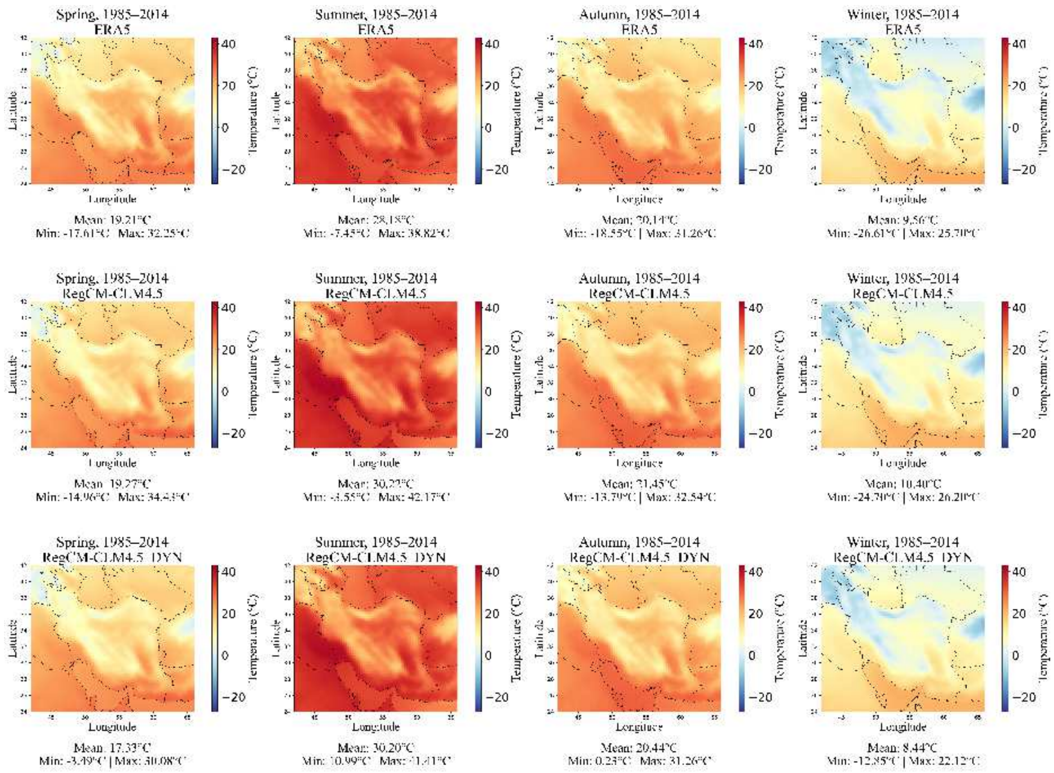


Fig. 2. Seasonal mean temperature spatial pattern from ERA5 reanalysis, RegCM-CLM-STAT, and RegCM-CLM-DYN over the period 1985–2014

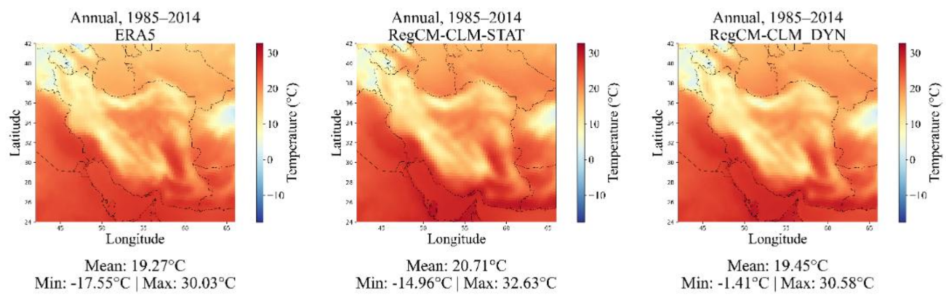


Fig. 3. Annual mean temperature spatial patterns from ERA5 reanalysis, RegCM-CLM-STAT, and RegCM-CLM-DYN over the period 1985–2014

To assess the systematic bias in the simulations, the mean seasonal and annual temperature biases were derived by comparisons the RegCM-CLM-STAT and RegCM-CLM-DYN configuration against ERA5. These biases are presented in Figures 4 and 5. Analysis of the mean bias in Figure 4 reveals that the colder half of the year exhibits improved bias in seasonal temperature simulations. When comparing the two configuration on both annual and seasonal scales, the incorporation of LUH2 in RegCM-CLM leads to improved accuracy in seasonal temperature predictions, except during spring. Furthermore, Figures 4 and 5, indicate that the northern and southern belts of the country generally exhibit a warmer temperature bias compared to Iran's interior regions.

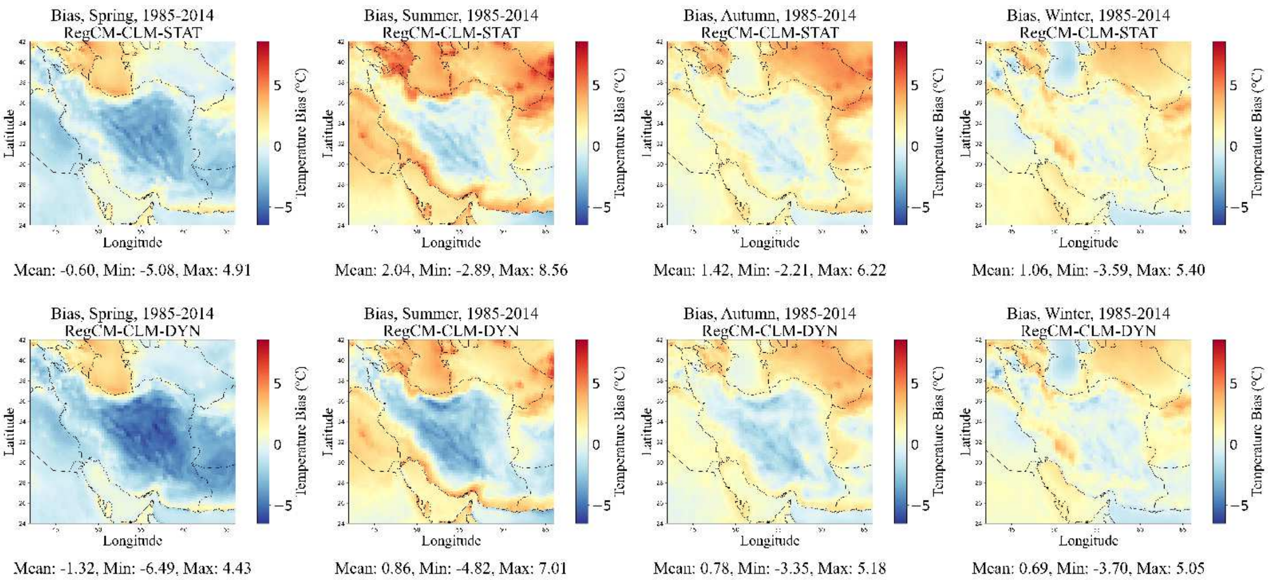


Fig. 4. Spatial distribution of seasonal mean temperature bias derived from ERA5 reanalysis, RegCM-CLM-STAT, and RegCM-CLM-DYN simulations over the period 1985–2014

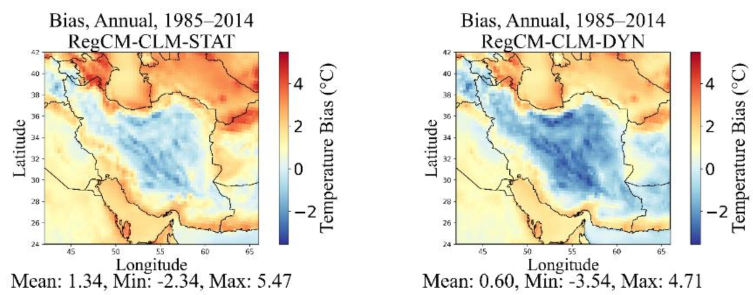


Fig. 5. Spatial distribution of annual mean temperature bias derived from ERA5 reanalysis, RegCM-CLM-STAT, and RegCM-CLM-DYN simulations over the period 1985–2014.

Statistical analysis of seasonal and annual temperature simulations, compared to the ERA5 reanalysis dataset, is presented in Table 1. The bias index in this table indicates that, except for spring, the magnitude of bias was reduced in other seasons and on the annual scale when the dynamic land cover dataset was incorporated into RegCM-CLM. A cold bias was observed in spring, while warm biases were present in the other seasons and on the annual scale. Assessment of the RMSE index shows that temperature simulations using RegCM-CLM-DYN produced lower errors in most seasons and on the annual scale. According to the Kling-Gupta Efficiency (KGE) index, RegCM-CLM-DYN also demonstrated better performance during the cold half of the year and on the annual scale. Additionally, the Nash–Sutcliffe Efficiency (NSE) index indicate that RegCM-CLM-DYN outperformed the static configuration in all seasons and on the annual scale, except in spring.

Table 1. Statistical metrics of simulated temperature values generated by the RegCM-CLM-STAT and RegCM-CLM-DYN models across seasonal and annual timescales, compared with ERA5 reference data

Statistical metric	Model Setup	Spring	Summer	Autumn	Winter	Annual
Mean Bias	RegCM-CLM-STAT	**-0.60**	2.04	1.42	1.05	1.34
	RegCM-CLM-DYN	-1.32	**0.86**	**0.78**	**0.69**	**0.60**
RMSE	RegCM-CLM-STAT	**1.80**	2.69	1.98	1.52	1.79
	RegCM-CLM-DYN	2.44	**2.19**	**1.61**	**1.29**	**1.52**
Std-rel	RegCM-CLM-STAT	0.96	1.04	0.95	0.94	1.01
	RegCM-CLM-DYN	**0.99**	**1.11**	**0.99**	**0.95**	**1.04**

r	RegCM-CLM-STAT	**0.97**	**0.94**	**0.97**	**0.98**	**0.98**
	RegCM-CLM-DYN	0.95	0.93	**0.97**	**0.99**	0.97
KGE	RegCM-CLM-STAT	**0.94**	**0.90**	0.91	0.86	0.93
	RegCM-CLM-DYN	0.91	0.87	**0.95**	**0.91**	**0.94**
NSE	RegCM-CLM-STAT	**0.92**	0.74	0.89	0.96	0.91
	RegCM-CLM-DYN	0.86	**0.82**	**0.93**	**0.97**	**0.94**

In next section, the results of future temperature simulations are presented, based on the RegCM-CLM model with two land data configurations. Figures 6 to 9 show the spatial patterns of mean temperature for the period 2021–2040 and 2081-2100 under the SSP2-4.5 and SSP5-8.5 scenarios, at both seasonal and annual scales.

- **Temperature Projection, during 2021–2040**

The comparison of spring temperatures for 2021-2040 reveals that RegCM-CLM-STAT under SSP2-4.5 simulates a slight decrease relative to the historical ERA5 mean, while RegCM-CLM-DYN shows a moderate increase. Under SSP5-8.5, both configurations simulate spring temperatures slightly above the ERA5 reference. In summer, both SSP2-4.5 and SSP5-8.5 scenarios project higher temperatures than the historical ERA5 mean. During autumn, temperatures increase under both scenarios relative to the historical mean. While warming is consistent across both model configurations, indicating a persistent trend. In contrast, winter projections show a slight decrease in temperature compared to ERA5. At the annual scale, RegCM-CLM-STAT under SSP2-4.5 is slightly cooler than ERA5, while slightly warmer under SSP5-8.5. RegCM-CLM-DYN shows higher annual mean temperatures under both SSP2-4.5 and SSP5-8.5 than historical ERA5 mean. This suggests that dynamic Land characteristics feedbacks contribute to enhance warming in future projections.

Comparing Figures 6 and 7 shows that RegCM-CLM-DYN generally produces higher average seasonal temperatures than RegCM-CLM-STAT, although, the magnitude of these differences varies by season and scenario. In spring, RegCM-CLM-DYN is slightly warmer than RegCM-CLM-STAT under SSP2-4.5 and SSP5-8.5. In summer and autumn, RegCM-CLM-DYN is warmer under SSP2-4.5 but shows little change or even a small cooling under SSP5-8.5. In winter, RegCM-CLM-DYN is consistently warmer than RegCM-CLM-STAT in both scenarios. Minimum temperatures in RegCM-CLM-DYN are higher across all seasons under SSP2-4.5, indicating reduction in cold extremes. Maximum temperatures in RegCM-CLM-DYN rise slightly in spring and winter, but remain close to or below the STAT values in summer and autumn under SSP5-8.5. An assessment of temperature projections under SSP2-4.5 shows that incorporating LUH2 data increases seasonal temperatures compared to the static dataset by 0.67 °C in spring, 1.17 °C in summer, 0.63 °C in autumn, and 0.34 °C in winter. Under SSP5-8.5 during the 2021–2040 period, using LUH2 data leads to seasonal temperature increases of 0.14 °C in spring, 0.12 °C in summer, 0.15 °C in autumn, and 0.26 °C in winter.

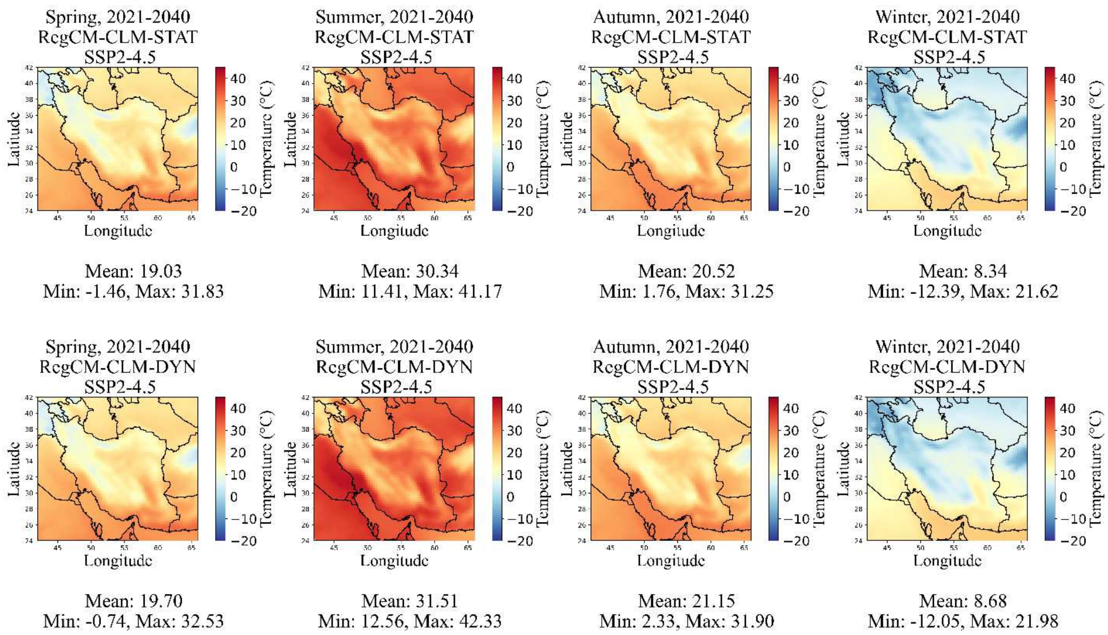


Fig. 6. Spatial pattern of simulated seasonal temperature under SSP2-4.5 for the period 2021–2040

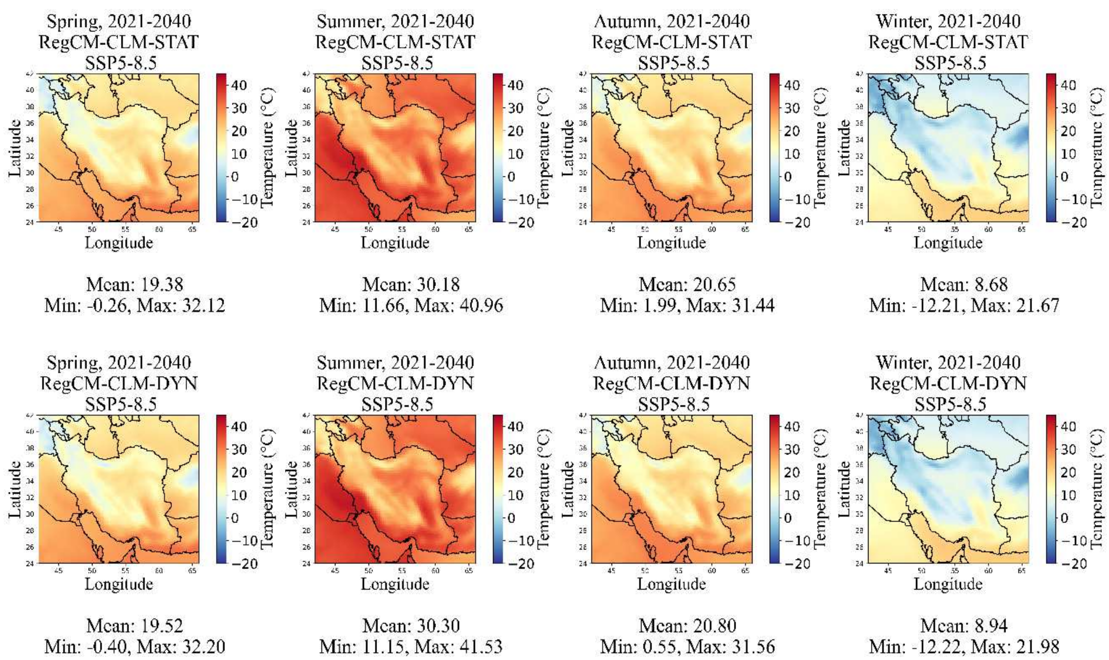


Fig. 7. Spatial pattern of simulated seasonal temperature under SSP5-8.5 for the period 2021–2040

Annual temperature projections presented in Figures 8 and 9, show that incorporating the LUH2 dataset into RegCM-CLM leads to slightly warmer mean and maximum temperatures compared to RegCM-CLM-STAT. In other words, at annual time scale, the RegCM4.7 model is sensitive to land-cover representation. Minimum temperatures are also higher in RegCM-CLM-DYN across both scenarios, further indicating a reduction in cold extremes.

In the RegCM-CLM-STAT configuration, SSP5-8.5 shows warming in spring, autumn, and winter, while in summer, it is slightly cooler than SSP2-4.5 (Fig. 6 and 7). In this configuration, the annual mean temperature is higher under SSP5-8.5, consistent with the stronger radiative forcing expected in this scenario (fig. 8 and 9). In contrast, the RegCM-CLM-DYN configuration shows different results. In spring, SSP5-8.5 is cooler than SSP2-4.5. The same pattern appears in summer and autumn. Only in winter does SSP5-8.5 show a slight warming. Overall, the annual mean temperature is lower under SSP5-8.5 than SSP2-4.5 in RegCM-CLM-DYN, which may reflect internal climate variability or dynamic LULC feedbacks that dampen warming under higher forcing (Fig.8 and 9).

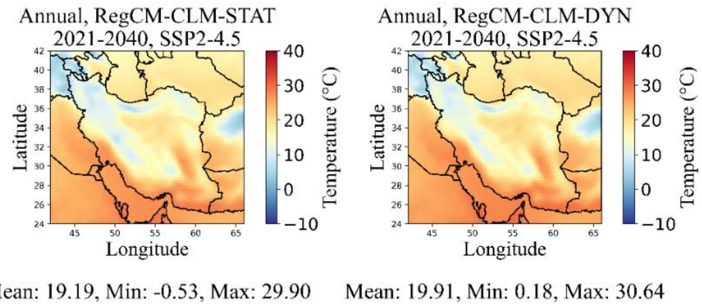


Fig. 8. Spatial pattern of simulated annual temperature under SSP2-4.5 for the period 2021–2040

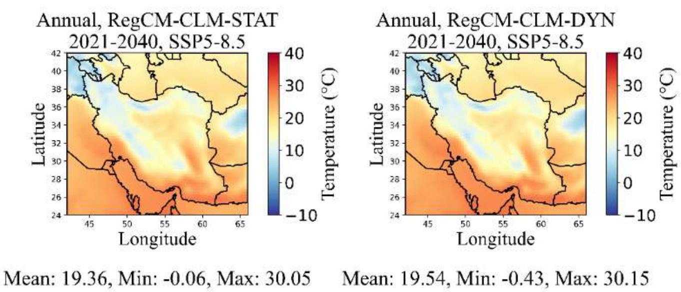


Fig. 9. Spatial pattern of simulated annual temperature under SSP5-8.5 for the period 2021–2040

- **Temperature Projection during 2081-2100**

Based figure 10 and 11, all seasons show warming in future projections compared to historical ERA5 data. Summer experiences the most dramatic increase, with temperature rising up to +6.4°C under SSP5-8.5. Winter warming is more modest but still significant, especially under SSP5-8.5. The warming trend is consistent across both models, with slight variations. Under SSP2-4.5, mean temperatures increase by ~1.3–1.5°C relative to ERA5. Under SSP5-8.5, the increase is more pronounced (~3.7–3.8°C). Cold extremes (minimum temperatures) become significantly warmer in future projections, especially in the RegCM-CLM-DYN configuration.

In future projections, the RegCM-CLM-DYN model shows slightly higher warming, particularly in winter. This enhancement warming may be attributed to dynamic LULC feedback in RegCM-CLM-DYN influencing land–atmosphere interactions. Assessment of the figures indicate that incorporating LUH2 data into RegCM-CLM under SSP2-4.5 increases mean seasonal temperatures by 0.17°C, 0.13°C, 0.19°C, and 0.24°C in spring, summer, autumn, and winter, respectively, compared to using the default static land dataset. Similarly, in SSP5-8.5 (Figure 11), RegCM-CLM-DYN projects temperatures increases of 0.03°C, 0.02°C, 0.05°C, and 0.25°C relative to RegCM-CLM-STAT for the same seasons.

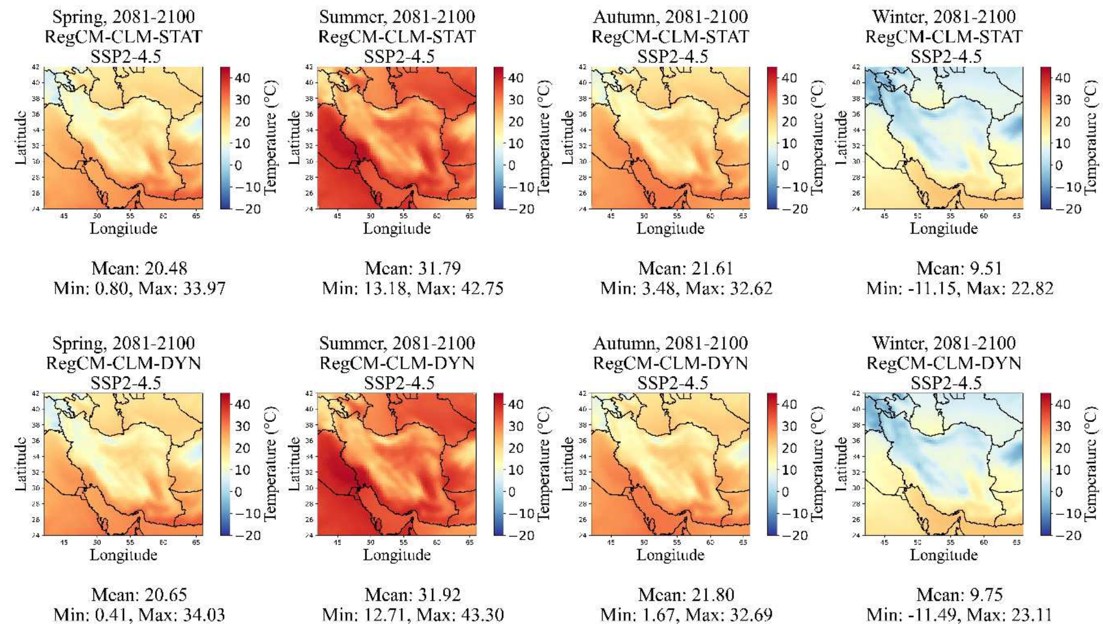


Fig. 10. Spatial pattern of simulated seasonal temperature under SSP2-4.5 for the period 2081–2100

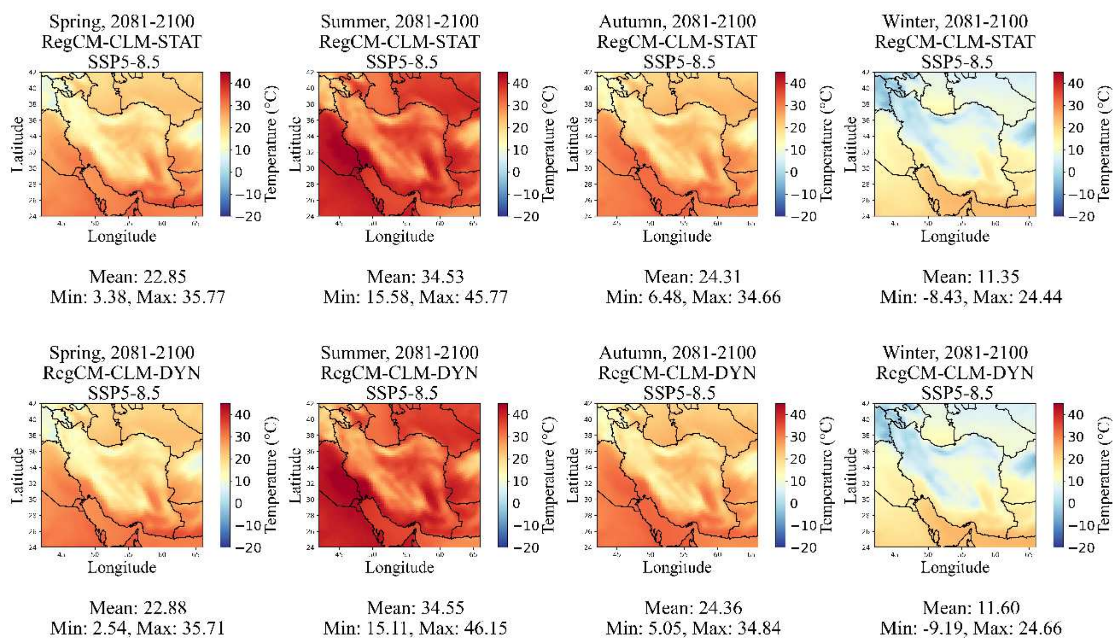
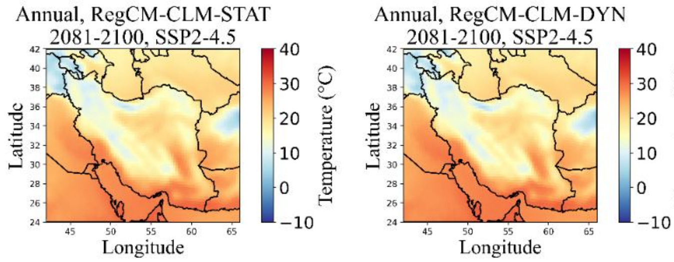


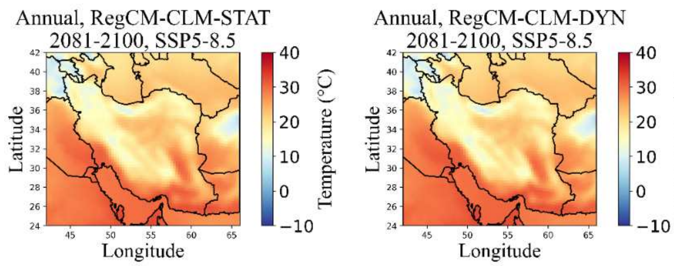
Fig. 11. Spatial pattern of simulated seasonal temperature under SSP5-8.5 for the period 2081–2100

Figures 12 and 13 also show that, in annual temperature simulations under both scenarios, the RegCM-CLM-DYN configuration produces slightly warmer annual mean temperatures than RegCM-CLM-STAT. While the differences are modest, they are consistent, suggesting that dynamic land cover contributes to enhance warming through land–atmosphere feedbacks.



Mean: 20.53, Min: 1.27, Max: 31.32 Mean: 20.73, Min: 0.66, Max: 31.46

Fig. 12. Spatial pattern of simulated annual temperature under SSP2-4.5 for the period 2081–2100



Mean: 22.95, Min: 3.97, Max: 33.44 Mean: 23.05, Min: 3.21, Max: 33.67

Fig. 13. Spatial pattern of simulated annual temperature under SSP5-8.5 for the period 2081–2100

Based Figures 10 to 13, SSP5-8.5 leads to significantly higher warming across all seasons and annually compared to SSP2-4.5. The difference between scenarios highlights the critical impact of emissions pathways on regional climate projection.

- Precipitation
- **Historical simulation**

As noted in the statistical evaluation section, the outputs of the RegCM-CLM model in both setups were corrected using the MLS method. The rationale for this correction and details of the methodology are described in Kosari Moghadam et al. (2024). The spatial distribution of corrected precipitation at seasonal and annual scale during the historical period is presented in Figures 14 and 15. Based on these figures, both RegCM-CLM-DYN and RegCM-CLM- STAT configurations demonstrate good performance in simulating the spatial pattern of precipitation compared to the ERA5 dataset. The maximum simulated precipitation, particularly during the cold half of the year, is concentrated over the Alborz and Zagros Mountain ranges. However, the mean precipitation simulated by RegCM-CLM-DYN using dynamic LULC data shows significant differences from ERA5 in spring, summer, autumn, and at the annual scale.

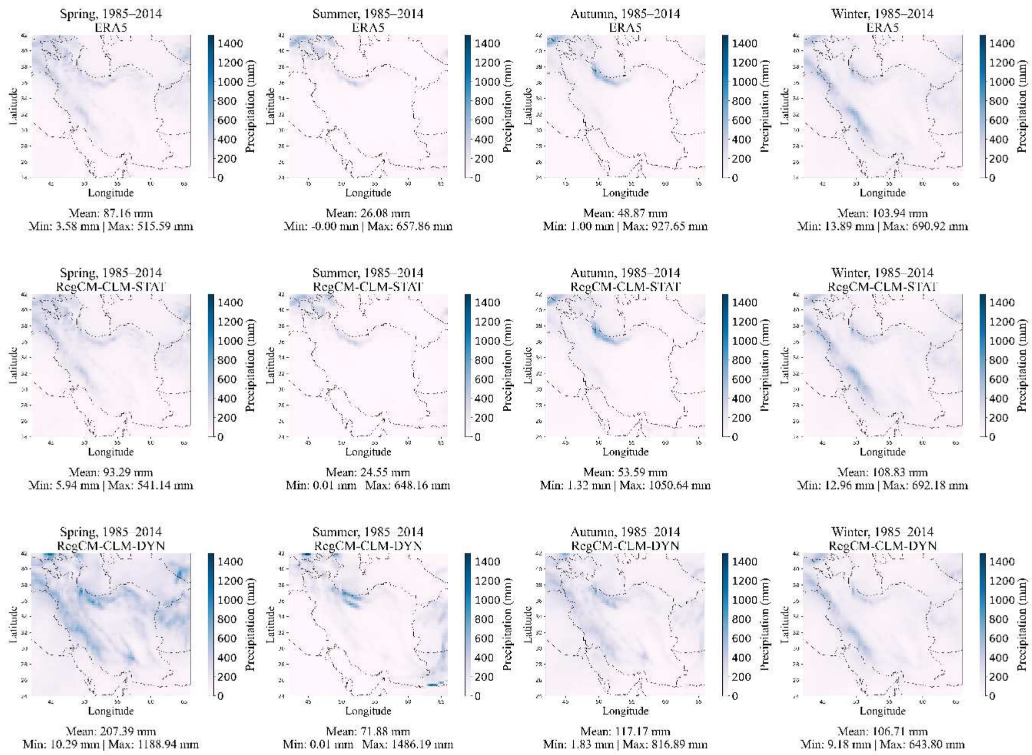


Fig. 14. Corrected seasonal mean precipitation spatial patterns from ERA5 reanalysis, RegCM-CLM-STAT, and RegCM-CLM-DYN for the period 1985–2014

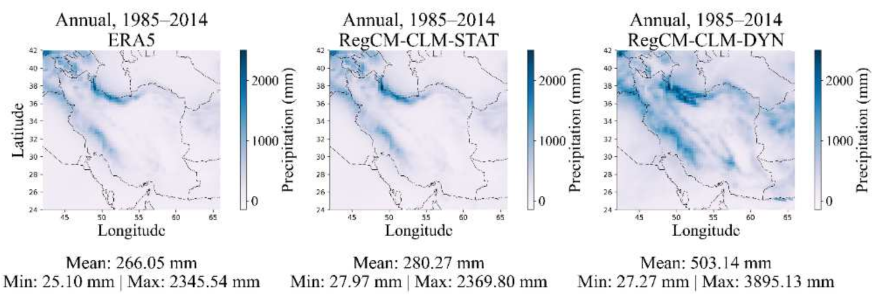


Fig. 15. Corrected annual mean precipitation spatial patterns from ERA5 reanalysis, RegCM-CLM-STAT, and RegCM-CLM-DYN over the period 1985–2014

The mean bias patterns in RegCM-CLM-STAT and RegCM-CLM-DYN are presented in Figures 16 and 17 at both seasonal and annual scales. These figures indicate that, across most seasons and at the annual scale, the RegCM-CLM models exhibit a wet bias or tend to overestimate precipitation. Notably, when using the dynamic LULC dataset, the strongest wet bias appears over the Alborz and Zagros mountain ranges and along the Caspian Sea coast, particularly in spring, summer, and annually. In contrast, during autumn and winter, the dynamic LULC experiment leads to an underestimation of precipitation along the Caspian coast. Additionally, RegCM-CLM-STAT shows a dry bias at both seasonal and annual scales over the southeastern part of the country.

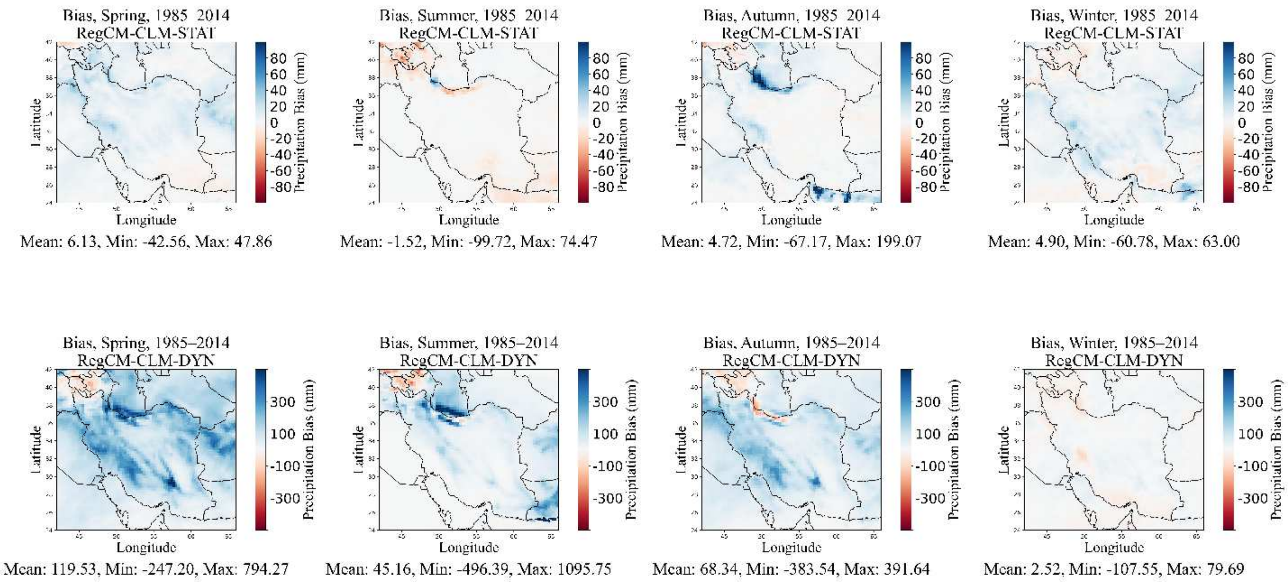


Fig. 16. Spatial distribution of corrected seasonal mean precipitation bias derived from ERA5 reanalysis, RegCM-CLM-STAT, and RegCM-CLM-DYN simulations over the period 1985–2014

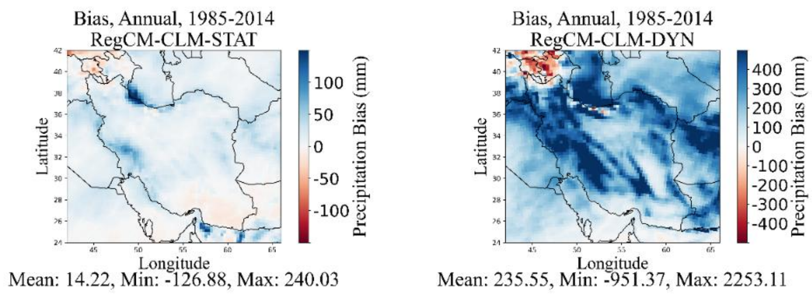


Fig. 17. Spatial distribution of corrected annual mean precipitation bias derived from ERA5 reanalysis, RegCM-CLM-STAT, and RegCM-CLM-DYN simulations over the period 1985–2014.

To assess the performance of the RegCM model in simulating precipitation, the results of the comparison between corrected precipitation values during 1985–2014 are presented in Table 2. The mean bias index shows that RegCM-CLM-STAT has moderate bias across seasons, with a slight underestimation in summer (−1.52 mm). In contrast, RegCM-CLM-DYN exhibits very high bias, especially in spring (119.53 mm) and annually (235.55 mm), indicating substantial overestimation. Based on the RMSE index, the STAT setup maintains relatively low RMSE across all seasons (range: 6.93–24.80 mm), while RegCM-CLM-DYN shows extremely high RMSE, particularly in spring (151.26 mm) and annually (315.61 mm), reflecting poor accuracy. The relative standard deviation (Std-rel) values indicate that the RegCM-CLM-DYN model demonstrates superior performance in reproducing the observed variability. Compared to the RegCM-CLM-STAT configuration, the RegCM-CLM-DYN yields Std-rel values closer to those of reference dataset, suggesting a more accurate representation of precipitation fluctuations. Based on the correlation coefficient (r), RegCM-CLM-STAT maintains strong correlation (≈0.99) across all seasons, while RegCM-CLM-DYN shows weaker correlation, especially in summer (0.52) and autumn (0.70). According to the Kling-Gupta Efficiency (KGE), RegCM-CLM-STAT performs well (0.89–0.94), indicating reliable simulation. RegCM-CLM-DYN, however, has negative KGE values in autumn, summer, and spring, suggesting poor agreement with ERA5. Similarly, based on the Nash–Sutcliffe Efficiency (NSE), RegCM-

CLM-STAT again shows strong performance (0.97–0.99), while RegCM-CLM-DYN has negative NSE values in autumn, summer, and spring, confirming poor predictive skill.

Table 2. Statistical metrics of corrected simulated precipitation values generated by the RegCM-CLM-STAT and RegCM-CLM-DYN models across seasonal and annual timescales, compared with ERA5 reference data

Statistical metric	Model Setup	Spring	Summer	Autumn	Winter	Annual
Mean Bias	RegCM-CLM-STAT	**6.12**	**-1.52**	**4.71**	4.89	**14.22**
	RegCM-CLM-DYN	119.53	45.15	68.33	**2.52**	235.55
RMSE	RegCM-CLM-STAT	**9.49**	**6.93**	**13.49**	**8.88**	**24.80**
	RegCM-CLM-DYN	151.26	103.114	95.64	16.44	315.61
Std-rel	RegCM-CLM-STAT	0.47	0.28	0.39	**0.40**	0.37
	RegCM-CLM-DYN	**0.75**	**0.47**	**0.45**	0.38	**0.5**
r	RegCM-CLM-STAT	**0.99**	**0.99**	**0.98**	**0.99**	**0.99**
	RegCM-CLM-DYN	0.79	0.52	0.70	0.98	0.83
KGE	RegCM-CLM-STAT	**0.92**	**0.92**	**0.89**	0.94	**0.94**
	RegCM-CLM-DYN	-0.51	-0.85	-0.44	**0.96**	0.04
NSE	RegCM-CLM-STAT	**0.98**	**0.98**	**0.97**	**0.98**	**0.99**
	RegCM-CLM-DYN	-1.83	-1.29	-0.51	0.96	-0.28

- **Precipitation projection during 2021-2040**

Precipitation projection for the 2021–2040 and 2080–2100 periods were conducted using both static and dynamic configuration under two SSP scenarios. In the baseline period, we found that the dynamic configuration (RegCM-CLM-DYN) tended to exaggerate precipitation values. Although less suitable in simulating rainfall amounts, it captured spatial and seasonal variability more effectively. Additionally, RegCM-CLM-DYN demonstrated strong performance in temperature simulations. This motivated us to continue using both configuration in future projections. It is important to note that future precipitation values were corrected using a correction factor derived from the baseline period based on the MLS method. Figures 18 and 19 show that both configurations simulate precipitation projection with similar spatial patterns for 2021-2040.

A comparative analysis of Figures 18 and 19 against ERA5 precipitation data for the historical period indicates a decreasing precipitation trend under the SSP2-4.5 scenario across both configuration across most seasons. In this scenario, the annual simulated precipitation shows minimal difference from the ERA5 dataset. Conversely, under SSP5-8.5, an increasing trend is observed in both LULC configuration at annual and seasonal scales.

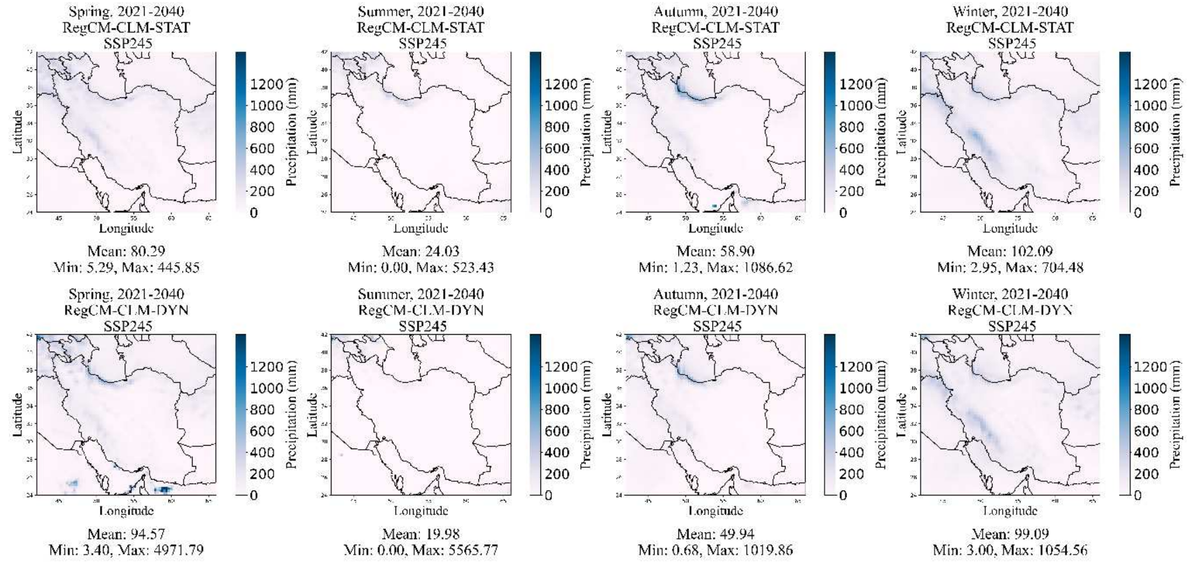


Fig. 18. Spatial pattern of simulated seasonal corrected precipitaion under SSP2-4.5 for the period 2021–2040

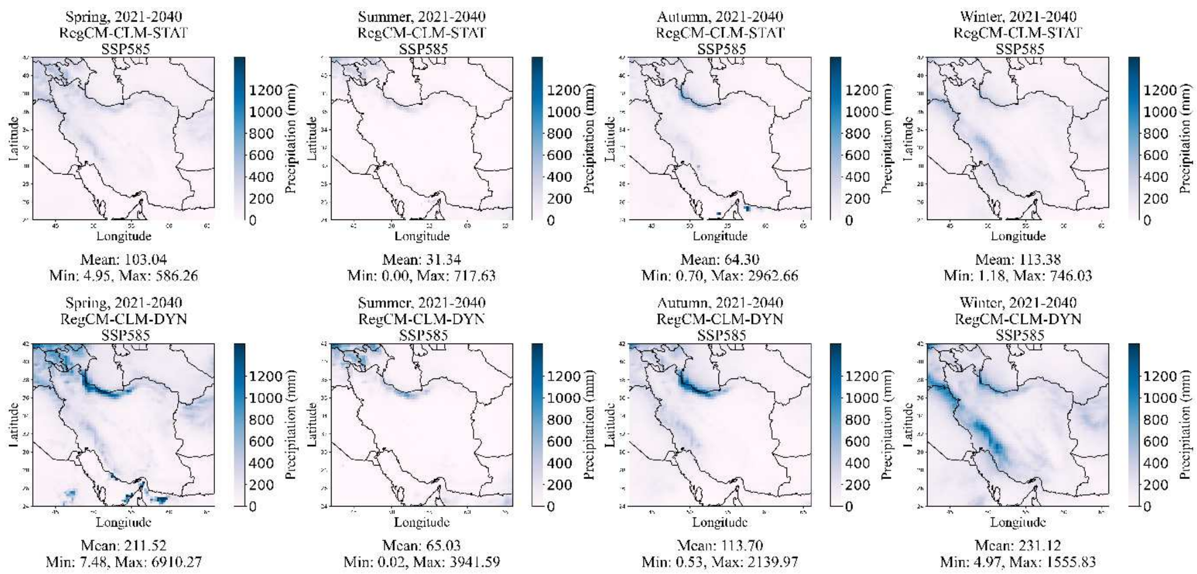


Fig. 19. Spatial pattern of simulated seasonal corrected precipitaion under SSP5-8.5 for the period 2021–2040

Although under the SSP2-4.5 scenario both configuration produce similar mean values, RegCM-CLM-STAT generally simulates higher precipitation than RegCM-CLM-DYN in all seasons except spring. However, in this scenario, the maximum precipitation value simulated by RegCM-CLM-DYN is significantly higher than that of RegCM-CLM-STAT. Under the SSP5-8.5 scenario, RegCM-CLM-DYN shows a marked intensification of precipitation extremes, particularly in spring and winter. For example, spring maximum values increase dramatically from historical levels. In summer, although the mean value slightly decreases, indicating high sensitivity of spring and summer precipitation to land cover dynamics. Autumn and winter also exhibit elevated mean values and extreme maxima, highlighting the role of dynamic vegetation in amplifying future variability. These results confirm that RegCM-CLM-DYN remains valuable for exploring the range and distribution of future changes, even if RegCM-CLM-STAT offers more stable estimates of total precipitation. Comparison among scenarios showed that, across both configuration and at annual and seasonal scales, the higher emissions scenario (SSP5-8.5) simulates greater precipitation than SSP2-4.5, while SSP2-4.5 indicates a more stable hydrological future (Figs. 18–21).

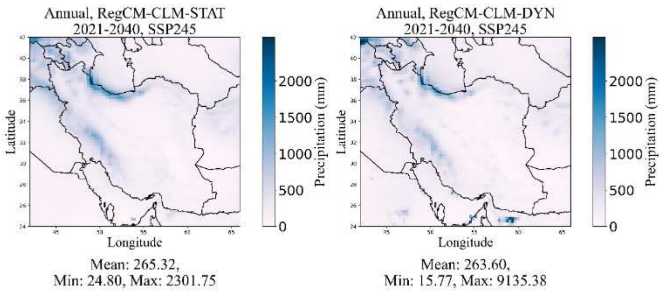


Fig. 20. Spatial pattern of simulated annual corrected precipitation under SSP2-4.5 for the period 2021–2040

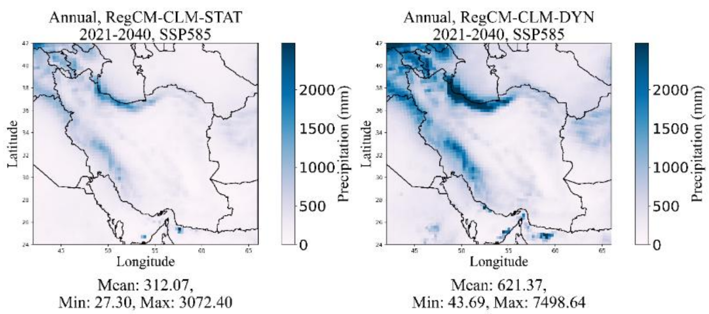


Fig. 21. Spatial pattern of simulated annual corrected precipitaion under SSP5-8.5 for the period 2021–2040

- **Precipitation projection during 2081-2100**

Based on Figures 22 to 25, the comparison between simulated precipitation and ERA5 data for the historical period shows a clear increasing trend under both SSP2-4.5 and SSP5-8.5 scenarios across both RegCM-CLM setups (static and dynamic). This increasing trend is notably stronger in the RegCM-CLM-DYN configuration, which incorporates dynamic land-use and land-cover changes, enhancing land–atmosphere feedbacks and amplifying precipitation responses compared to the static setup. For the period 2081–2100, RegCM-CLM-DYN simulates higher precipitation totals than RegCM-CLM-STAT. This difference is largely due to the dynamic model's ability to capture evolving vegetation and land surface processes, which increase variability and extreme precipitation under future climate forcings. These results emphasize the importance of including dynamic land surface processes in regional climate models to better represent potential future changes in precipitation patterns and extremes.

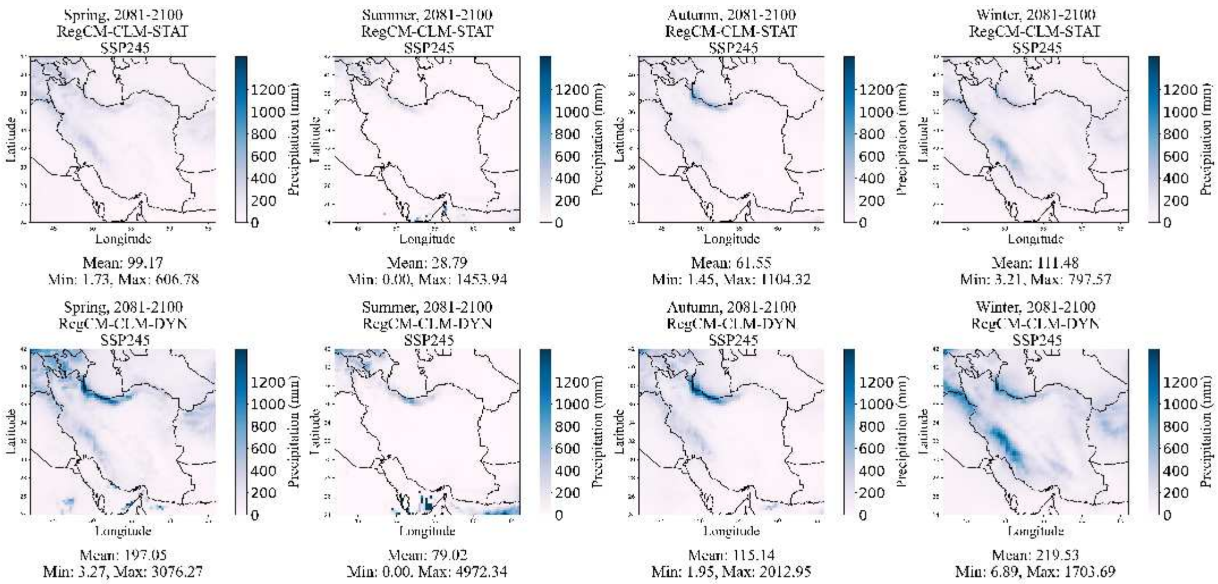


Fig. 22. Spatial pattern of simulated seasonal corrected precipitaion under SSP2-4.5 for the period 2081–2100

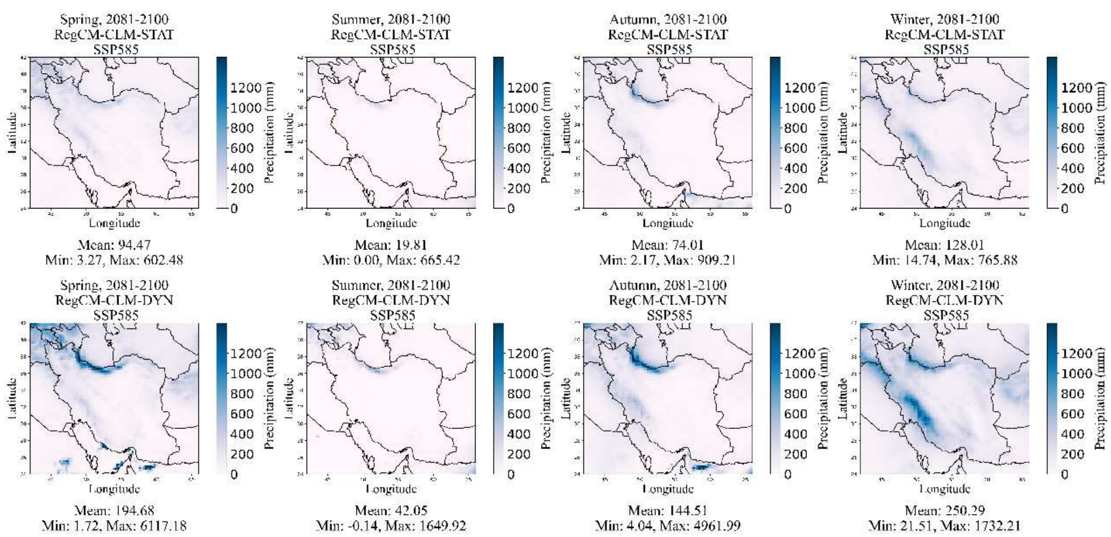


Fig. 23. Spatial pattern of simulated seasonal corrected precipitaion under SSP5-8.5 for the period 2081–2100

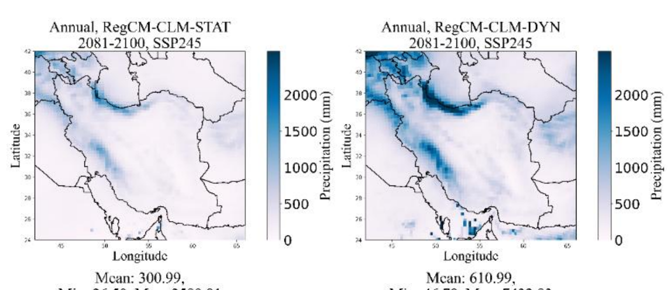


Fig. 24. Spatial pattern of simulated annual corrected precipitaion under SSP2-4.5 for the period 2081–2100

The assessment of precipitation simulations showed that under the high-emission SSP5-8.5 scenario, total precipitation is lower than under the moderate SSP2-4.5 scenario during the spring and summer seasons. Such seasonal drying could lead to increased drought risk and affect water resources and agriculture during these critical growing periods. In contrast, during the autumn and winter seasons, as well as on the annual timescale, the SSP5-8.5 scenario produces higher precipitation values compared to SSP2-4.5. These contrasting seasonal patterns highlight the complex and regionally variable nature of climate change.

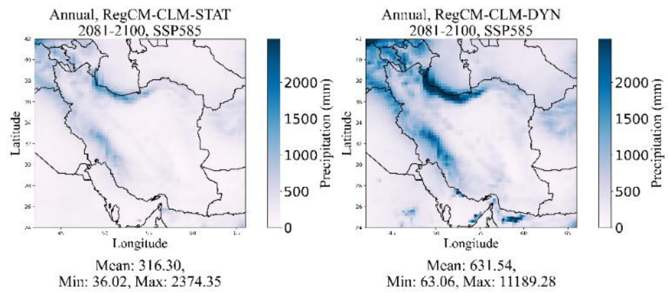


Fig. 25. Spatial pattern of simulated annual corrected precipitation under SSP5-8.5 for the period 2081–2100

4. Conclusion

The importance of climate change as a global issue on one hand, and the necessity of understanding how land characteristics influence climate conditions on the other, make it essential to study land–climate interactions. The use of regional climate models, which are among the most effective tools for studying climate systems, plays a key role in this effort. Identifying sources of bias in the outputs of these models is a crucial step toward improving their performance and reliability. In this regard, the present study was conducted to assess the effect of land surface characteristics on climate variables using the Regional Climate Model version 4.7 (RegCM4.7) coupled with the Community Land Model (CLM). The MPI-ESM1.2-HR model was employed to provide initial and boundary conditions. Additionally, this study utilized the Land Use Harmonization dataset version 2 (LUH2) from CMIP6 within the RegCM-CLM framework to evaluate the impact of incorporating annually dynamic land use datasets, as opposed to the default static dataset tied to a specific time period.

Analysis of historical temperature simulation showed that the spatial distribution closely matched the ERA5 reference dataset. Although both static and dynamic configurations of the RegCM-CLM model performed well historically, the incorporation of LUH2 datasets improved model performance based on statistical metrics. The RegCM-CLM-DYN configuration captured more realistic temperature distributions likely due to its dynamic land cover representation. Future temperature projections reveal clear warming trends across both time periods. Notably, the RegCM-CLM-DYN configuration projects a more pronounced warming trend, especially under high-emission scenarios. The SSP5-8.5 scenario intensifies warming across all metrics, underscoring the urgency of mitigation efforts. Moreover, the RegCM-CLM-DYN configuration shows slightly warmer future projections and better historical alignment with ERA5 data. Therefore, incorporating dynamic land use and land cover (LULC) datasets into the RegCM-CLM model yields warmer seasonal temperature projections compared to static land-use representation—ranging from approximately 0.13°C to 1.2°C under SSP2-4.5 and 0.02°C to 0.26°C under SSP5-8.5. These results suggest that the temperature projections presented in the Sixth Assessment Report (AR6) may reflect an optimistic outlook, as the inclusion of dynamic land-change data leads to higher warming estimates. Furthermore, temporal comparisons indicate a consistent rise in average temperature, with the most pronounced increase projected for the 2081–2100 period under SSP5-8.5. These insights are critical for informing climate adaptation strategies, particularly in agriculture, water resource management, and urban heat mitigation.

Analyzing the spatial patterns of seasonal and annual precipitation shows that RegCM-CLM, using both static and dynamic LULC datasets, simulates precipitation reasonably well compared to ERA5 reanalysis. When comparing the impact of LULC datasets, RegCM-CLM-STAT consistently performs better than RegCM-CLM-DYN across all statistical measures. Although RegCM-CLM-DYN does not outperform the static configuration in most metrics, it provides a more detailed physical framework by allowing land-surface properties to change over time. The dynamic LULC dataset responds to climate drivers like temperature, soil moisture, and radiation, making it more flexible. Under future climate conditions, static land assumptions become less reliable, while dynamic LULC can adjust to environmental changes and making it more suitable for long-term projections. Overall, large-scale processes—such as precipitation schemes, boundary layer dynamics, and convective mechanisms have a stronger effect on precipitation simulation than land-surface components. Therefore, improving model performance depends on better integration of these large-scale processes along with land-surface schemes. These results suggest that dynamic LULC still needs further tuning to improve its accuracy. With refined parameterizations, RegCM-CLM-DYN could potentially match or even surpass RegCM-CLM-STAT in both dynamical behavior and statistical performance.

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Statements & Declarations

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Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contribution

Conceptualization: Nozar Ghahreman, Parviz Irannejad, Iman Babaeian, Methodology: Nozar Ghahreman, Iman Babaeian ,Parviz Irannejad, and Lobat KosariMoghaddam; Formal analysis and investigation: Lobat Kosari Moghaddam, Iman Babaeian ; Writing - original draft preparation: Lobat Kosari Moghaddam; Writing - review and editing: Lobat Kosari Moghaddam, Iman Babaeian, Nozar Ghahreman, Funding acquisition: Nozar Ghahreman

Data Availability

Data sharing is not applicable to this article due to nature of research and national policies.