TYPE Original Research
PUBLISHED 16 April 2025
DOI 10.3389/feart.2025.1542536

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RECEIVED 10 December 2024
ACCEPTED 04 April 2025
PUBLISHED 16 April 2025

CITATION
Sharif RB, Maggioni V and Dollan IJ (2025) Changes in historical and future precipitation patterns across the contiguous United States. *Front. Earth Sci.* 13:1542536.
doi: 10.3389/feart.2025.1542536

Changes in historical and future precipitation patterns across the contiguous United States

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As anthropogenic climate signals have intensified, precipitation patterns have changed over the contiguous United States (CONUS) and may continue to change in the future. Comparing historical climate model simulations to ground-based observations can help us quantify uncertainties in climate models when simulating precipitation and its changes. This work evaluates precipitation simulated by the Community Earth System Model Version 2 large ensemble (CESM2-LE) against observations from the National Oceanic and Atmospheric Administration Climate Prediction Center Unified CONUS (CPC) during 1948–2022. Next, past precipitation patterns from CPC are compared to future projections (2023–2100) of CESM2-LE for a medium-to-high emission scenario (Shared Socioeconomic Pathways, SSP3-7.0) from a 70-member ensemble. A pixel-by-pixel bias correction is then conducted to remove systemic errors between the model and observations. Results indicate that precipitation variability is drastically reduced in the ensemble mean and suggest caution when using it to draw conclusions regarding precipitation changes. CESM2-LE is shown to underestimate (overestimate) ground observations over CONUS in summer (winter) during 1948–2022. Climate model simulations struggle particularly to capture high-magnitude precipitation (i.e., annual averages larger than 10 mm/day), especially in the Northwestern US. Historical precipitation data show slightly upward patterns in annual, spring, fall, and winter averages, patterns that are projected to continue in the future. Future annual precipitation will increase with respect to historical observations by as much as 11% and 15% in the Northeast and Southeast US (which are already wet regions), respectively, whereas the arid Northern Great Plains region will experience a 15% decrease. Overall results indicate drier summers and wetter winters in the future with respect to the past. Furthermore, the 75th and 95th percentiles of seasonal precipitation will become more extreme during winter by as much as 100% but will decrease during summer by as much as 80%. This study places a strong emphasis on understanding reliable future climate projections, which can be useful when designing community-driven adaptation and mitigation plans for climate change.

KEYWORDS

precipitation patterns, trends, climate model projections, CESM2, CPC observations

1 Introduction

Precipitation is the major driving force of the hydrologic cycle (Kidd and Huffman, 2011; Gajbhiye et al., 2015; Praveen et al., 2020) and changes in its patterns can impact the hydrological, meteorological, agricultural, environmental, and water resource management sectors (Ebert et al., 2007; Kanniah et al., 2011; Duan et al., 2016; Mallakpour et al., 2020; Sharif et al., 2020). Therefore, a better understanding of the variations in precipitation patterns is critical (Duan and Bastiaanssen, 2013; Chatterjee et al., 2016; He et al., 2022; Dollan I. J. et al., 2022). Global rising temperatures have the potential to increase climate variability (Held and Soden, 2006; Trenberth, 2011; Wasko et al., 2015; Rodgers et al., 2021). Such changes alter the hydrologic cycle and impacts precipitation variability (Trenberth et al., 2003; Meehl et al., 2009; Chen et al., 2013; Zhang et al., 2019; Sharif et al., 2022; Rahat et al., 2022; Saki et al., 2023), which can result in an intensification of extreme precipitation events (Easterling et al., 2000; Zhai et al., 2005; Hallegatte et al., 2013; Nguyen et al., 2018; Willner et al., 2018; Yang et al., 2020; Mathbout et al., 2021; Slater et al., 2021). Carbon emissions from agriculture, industry, transportation, and households drive climate change and trigger extreme weather events (Abbas et al., 2022a; Abbas et al., 2022b; Huang et al., 2024; Fan et al., 2024). According to the Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report (AR6), climate extremes like heavy precipitation, flooding, cyclones, sea level rise, droughts, and heat waves have already intensified (IPCC 2022). This is evident over mid-latitudinal regions, including the Contiguous United States, CONUS (Tebaldi et al., 2006; Kharin et al., 2013; Fischer and Knutti, 2016; Prein et al., 2017). Moreover, studies such as Kunkel et al. (2013), Easterling et al. (2017), and Prein and Holland (2018) indicate that extreme precipitation events are becoming more frequent and intense, particularly in the Northeast and Midwest contiguous US. However, the extent to which these trends are captured by climate models remains uncertain.

Past studies suggested that temperatures across CONUS might increase (Karmalkar and Bradley, 2017), which could intensify precipitation events (Kunkel, 2003; Monier and Gao, 2015; Neri et al., 2019) and worsen drought conditions (Strzepek et al., 2010). Mallakpour et al. (2022) showed statistically significant changes in annual precipitation maxima based on six daily gridded precipitation data over CONUS from 1983 to 2017. Furthermore, CONUS is characterized by different regional climates with high annual and seasonal variation, resulting in complex climate change patterns (Martin-vide 2004; Roy´e and Martin-Vide, 2017). For example, since the 1950s, eastern CONUS has experienced higher precipitation increase than the western side (Huang et al., 2021; Li et al., 2022). Gensini and Harold (2018) further observed that convective precipitation has been increasing, particularly in the Central U.S., with great implications for flooding and severe weather. Other studies have linked CONUS precipitation variability to large-scale atmospheric patterns, showing interannual variations that affect drought and flood risks (Seager et al., 2015; Swain et al., 2018). Nevertheless, a comprehensive analysis of the spatial and temporal variability of long-term precipitation changes across different CONUS regions is still lacking. This study aims to investigate historical and future precipitation patterns over CONUS using both observed data and climate projections.

An efficient strategy for developing effective climate change adaptation and mitigation strategies is to predict future climates using high-resolution climate models (Forestieri et al., 2018; Hosseinzadehtalaei et al., 2020; Ukkola et al., 2020; Alaminie et al., 2021). Global Climate Models (GCMs) are the primary source of information for assessing future climate changes (Navarro-Racines et al., 2015; Randall et al., 2019; Agel and Barlow, 2020; Akinsanola et al., 2020; Oruc, 2022). However, GCM simulations are affected by large uncertainties due to future emission scenarios, model resolution, internal climate variability, mathematical formulation, initial assumptions, and calibration processes (Gutowski et al., 2003; Latif, 2010; Ramirez-villegas et al., 2013; Su et al., 2013; Navarro-Racines et al., 2015; Xu et al., 2021). It is generally assumed that newer models with higher resolution and complexity outperform previous-generation models and provide more reliable projections (O' Neill et al., 2016). The CMIP6 ensemble now includes the latest state-of-the-art climate model experiments. In 1995, the World Climate Research Program's (WCRP) Working Group on Coupled Modelling (WGCM) launched the Coupled Model Intercomparison Project (CMIP), which used coupled simulations of the atmosphere, ocean, land surface, and sea ice (Meehl et al., 1997; Edwards, 2011). It has since evolved over five phases with scientific development and the progressively improved comprehension of the mechanisms underlying climate change (Meehl et al., 2000; 2007; Taylor et al., 2012), contributing to cutting-edge research activity based on an ensemble of models (Lalande et al., 2021) as well as to various IPCC assessment reports (IPCC, 2007; IPCC 2013). CMIP6 differs from its predecessors in links of forcing scenarios, carbon emissions, high spatial resolutions, different start year of the future scenarios and newly proposed SSPs, which describe different socioeconomic reference assumptions (Moss et al., 2010; Vuuren et al., 2014; Gidden et al., 2019; Almazroui et al., 2020). CMIP6 also has updated development of the intercomparison model, focusing on biases, enhanced parameters of the cloud microphysical process, and climate model feedback (Kawai et al., 2019).

Large ensemble (LE) simulations conducted with the Community Atmosphere Model version 6 (CAM6), namely, CESM2-LE, offer a novel tool for studying potential changes in climate and ecosystem statistics caused by human activities over various time periods. The simulations consist of a 100-member LE suite for the 1850–2100 period with SSP3-7.0 forcings. SSP3-7.0 is a medium-to-high reference scenario resulting from no additional climate policy under the SSP3 socioeconomic development narrative; it is characterized by high non-CO_2 emissions, including high aerosols emissions. The large ensemble size aids in overcoming difficulties in the estimation of higher order statistical moments (Milinski et al., 2020). The size of the ensemble combined with a 1° spatial resolution is unprecedented, as it enables robust forced changes in internal variability (Simpson et al., 2020; Fasullo, 2020). Earlier versions of LE GCMs also exist (Zelle et al., 2005; Drijfhout et al., 2008; Branstator and Selten, 2009) and were used to investigate the influence of global warming on precipitation variability (Raisanen, 2002; Wetherald, 2009; Pendergrass et al., 2017). Dollan IshratJahan et al. (2022) studied seasonal totals and long-term trends from 2015–2100 for SSP3-7.0 across CONUS. However, a comprehensive comparison between historical precipitation patterns and future projections in a medium-to-high emission scenario with a large ensemble remains a gap in the literature. This study aims to address such gap.

Evaluating the performance of climate model simulations is important to assess uncertainties in climate models and better understand long-term trends, climatology, and possible climate change impacts on hydrological variables (Rupp et al., 2015; Ahmadalipour et al., 2017; Raghavan et al., 2018). Moreover, evaluating individual climate models aids in gaining confidence in future model projections (Flato et al., 2013; Moise et al., 2015). The performance of climate models can only be evaluated over historical time series and is commonly assessed against observational data (Jiang et al., 2015). Jiang et al. (2012) reported that while models could replicate the spatial distribution of ground-based precipitation and trends of extreme distributions, differences between the two estimates still existed. While previous studies such as Fu et al. (2020), Gusain et al. (2020), and Zamani et al. (2020) have assessed CMIP6 historical simulations against ground observations and compared them with CMIP5, these analyses do not extensively examine the variability in seasonal distribution and regional precipitation patterns using large ensemble simulations, which are crucial for understanding long-term climate impacts. The multi-model ensemble method, which involves averaging simulations from multiple models, has been employed in previous studies to assess the model performance (Thackeray et al., 2018; Akinsanola et al., 2021). Following an evaluation of historical data, Chen et al. (2020) examined future precipitation projections and observed how climate indicators have changed in recent decades in comparison to historical records. However, these studies have not focused on CONUS specifically.

While previous studies have examined historical precipitation changes and future climate projections using different climate models, a comprehensive comparison of observed precipitation data with CMIP6-based large ensemble simulations in a medium-to-high emission scenario across CONUS remains limited. This work evaluates historical precipitation data (1948–2022) from the 70 ensemble members of CESM2-LE simulated precipitation against ground-based observations from the National Oceanic and Atmospheric Administration's (NOAA) Climate Prediction Center Unified CONUS (CPC) dataset. This is performed for three randomly selected ensemble members and for the average of all members (i.e., ensemble mean). As a second objective, this work compares past precipitation patterns (1948–2022) from observations to future projections (2023–2100) of CESM2-LE for a medium-to-high emission scenario (SSP3-7.0). This work aims to answer the following research questions: i) how does a LE climate model compares to ground observations when detecting changes in past precipitation? ii) how have precipitation patterns changed in the past century across CONUS? and iii) how will they change in the later decades of 21st century? By addressing these questions, this study provides insights into the reliability of large ensemble simulations for projecting future precipitation patterns and contributes to the growing knowledge of climate-induced precipitation variability over CONUS.

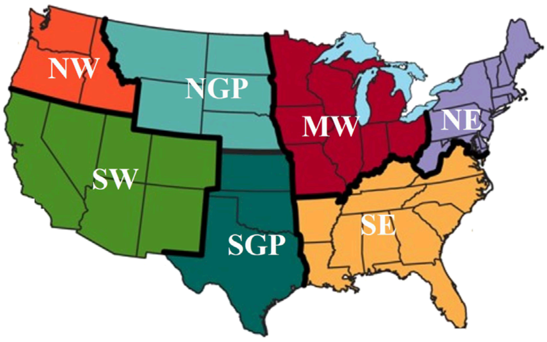

FIGURE 1
National Climate Assessment regions of CONUS (Source: https://www.c2es.org/content/national-climate-assessment/).

2 Methodology

2.1 Study area

The study investigates precipitation patterns across CONUS, which is divided into 7 NCA regions to ease the discussion (Figure 1). The NCA reports assess climate change impact, risk, and responses over CONUS (Melillo et al., 2014; Reidmiller et al., 2018).

NE is characterized by a humid continental climate with warm-summers (Beck et al., 2023). The average annual precipitation variation in the region is approximately 500 mm and is often hit by extreme hydroclimatic events such as floods, droughts, hurricanes, heat waves, and coastal floods caused by rising sea levels and storm surges (Horton et al., 2012; Horton et al., 2014; Dupigny-Giroux et al., 2018). Climate in SE is generally humid and sub-tropical, influenced by seasons, latitude, topography, and the proximity to the Atlantic Ocean and the Gulf of Mexico. There are large areas of low-lying inland terrain and coastal plains in the region that are highly vulnerable to sea level rise, extreme heat events, decreased water availability, heavy precipitation, and hurricanes (Carter et al., 2014; Carter et al., 2018). The MW region experiences humid continental climate with warm summers and its diverse landscape is dominated by agricultural land use. The region has a moderate amount of precipitation throughout the year, but winter and spring precipitation are important to flood risk (Angel et al., 2018). Temperature, heavy precipitation events, droughts, and floods are increasing in MW (Pryor et al., 2014). The predominantly arid NGP region features a highly variable climate with a strong east-to-west gradient of decreasing precipitation. Most of the precipitation in the area falls during the spring. The region is highly susceptible to a range of climate change effects, particularly those arising from hydrological changes, including seasonality and timing of precipitation events, and extreme flooding and droughts (Conant et al., 2018). SGP exhibits a range of climates, spanning from arid, high-elevation borders adjacent to the mountains in the western region to humid areas in the eastern region. The average annual precipitation varies between 255 mm and 1500 mm, from the western to the southeastern corner (Kloesel et al., 2018). Both Great Plains regions are characterized by frequent floods, droughts, severe storms, tornadoes, hurricanes, and winter storms. High regional diversity in the NGP and SGP climate is a result of changes in elevation (Shafer et al., 2014). The NW region exhibits an intricate and diverse topography and several climate zones ranging from dry-summer-sub-Arctic to dry-summer-Mediterranean with varying patterns of precipitation (Mote et al., 2014). Extreme weather occurrences like heat waves, droughts, and flooding, with associated landslide risk, together with climate change, have had a detrimental impact on the NW's regional ecosystem (May et al., 2018). SW, characterized by arid landscapes and desert-like conditions, is considered the driest region in CONUS, with hot summers and mild winters. The region is confronted with climate change challenges such as severe droughts, intermittent large-scale flooding, and high-water demand (Garfin et al., 2014; Gonzalez et al., 2018).

2.2 Datasets

The National Center for Atmospheric Research (NCAR) developed CESM2-LE, the most recent version of a coupled climate/Earth system model with 100-km grid spacing and a 100-member ensemble, in accordance with the CMIP6 protocols (Danabasoglu et al., 2020). CMIP6 is based on GCMs, which include high resolution ocean, atmosphere, land, sea-ice, land-ice, river, and wave models, as well as SSP scenarios (Babaousmail et al., 2021). SSPs integrate five distinct socioeconomic developments: sustainable development (SSP1), middle-of-the-road development (SSP2), regional rivalry (SSP3), inequality (SSP4), and fossil fuel-driven development (SSP5) ranging from aggressive climate action (SSP1-2.6) to the absence of climate change policy (SSP5-8.5) along with radiative forcing levels (Riahi et al., 2017; Alaminie et al., 2021; Supharatid et al., 2022). SSP3-7.0 with radiative forcing 7.0 W/m^2 falls between the moderate SSP4-6.0 and worst-case SSP5-8.5 scenarios. The CMIP6 projects have a simulation span from 1850 to 2100, comprising historical experiments (1850–2014) and future projections (2015–2100), with input from natural forcing and anthropogenic influence as well as scenarios for future climate change (Eyring et al., 2016). In this study, the simulated precipitation dataset from 70 ensemble members of the CESM2-LE of the CMIP6 for a medium-to-high emission scenario (SSP3-7.0) at 100-km resolution is used from 1948 to 2100. The reduced number of ensemble members (70 instead of 100) is based on data availability at the time of the study. However, the authors believe their results would not be largely impacted by the addition of 30 ensemble members.

The CPC dataset is available on a 0.25° regular grid (corresponding to approximately 28 km) over CONUS and is based on station measurements from the U.S. unified rain gauge data (Higgins et al., 2000). Station records are extensively quality controlled through comparison with available sources such as historical records, nearby independent *in situ* measurements, satellite estimates, and numerical model forecasts (Hou et al., 2014). The optimal interpolation algorithm is used to interpolate quality-controlled station data from NOAA/National Climatic Data Center (NCDC) River Forecast Centers (RFCs) to create CPC daily precipitation analyzed fields that account for orographic effects (Xie et al., 2007; Cui et al., 2017). According to past studies, the bias in the CPC dataset is less than 0.5% compared to the average amount of precipitation observed by gauges over CONUS (Chen et al., 2008).

This study evaluates historical climate model simulations against ground-based CPC daily observations across CONUS from 1948 to 2022. CPC has been chosen for this study because of its long record and its consistent, high-quality gridded precipitation product. In the second part of this study, the historical dataset CPC is used for comparison with future projections simulated by CESM2-LE.

2.3 Methodological approach

This study presents an assessment of CESM2-LE Climate Model precipitation simulations against CPC gauge data during 1948–2022 across CONUS. Specifically, the average of the 70 CESM2-LE ensemble members and three randomly selected members are compared to CPC ground-based observations. A seasonal analysis is performed, and seasons are defined as follows: spring includes March, April, May; summer includes June, July, August; fall includes September, October, November; and winter includes the months of December, January, and February. CPC observations at their native spatial resolution of 28 km are aggregated to a regular 100-km grid to match the spatial resolution of CESM2-LE using the nearest neighbor interpolation method. As models and ground observations are inherently biased (as proven in Section 3.1), a pixel-by-pixel bias correction is performed on future projections for the results presented in Section 3.2. The bias correction method used in this study follows a multiplicative bias ratio approach, which has been widely applied in climate model bias correction (e.g., Teutschbein and January 2012; Hempel et al., 2013). The bias ratio is computed as the ratio of the mean CESM2-LE model simulations to the mean CPC observations over the historical period (1948–2022). The CESM2-LE model projections are then bias-corrected by dividing the model data by this ratio. This approach ensures that the long-term mean climatology of the model aligns with observations while preserving interannual variability, making it suitable for hydrological applications. Historical annual and seasonal mean of CPC observations from 1948 to 2022 are also compared to future precipitation projections of CESM2-LE from 2023 to 2100. The selection of the historical period (1948–2022) and future projections (2023–2100) is based on data availability of both observations and future climate projections at the time of the study. The length discrepancy between the historical and future timeframes is not expected to impact our analysis of long-term climate trends. The two datasets are also compared based on the 75th and 95th probability distribution percentiles.

3 Results and discussions

3.1 Evaluation of historical climate model simulations

Monthly mean precipitation from three randomly selected CESM2-LE ensemble members and from the 70-member ensemble mean is compared to CPC precipitation. The box plots in Figure 2 present monthly precipitation averaged across CONUS during 1948–2022. As expected, larger magnitudes of precipitation are observed in winters compared to the summer months (especially July and August). Precipitation variability (i.e., the interquartile

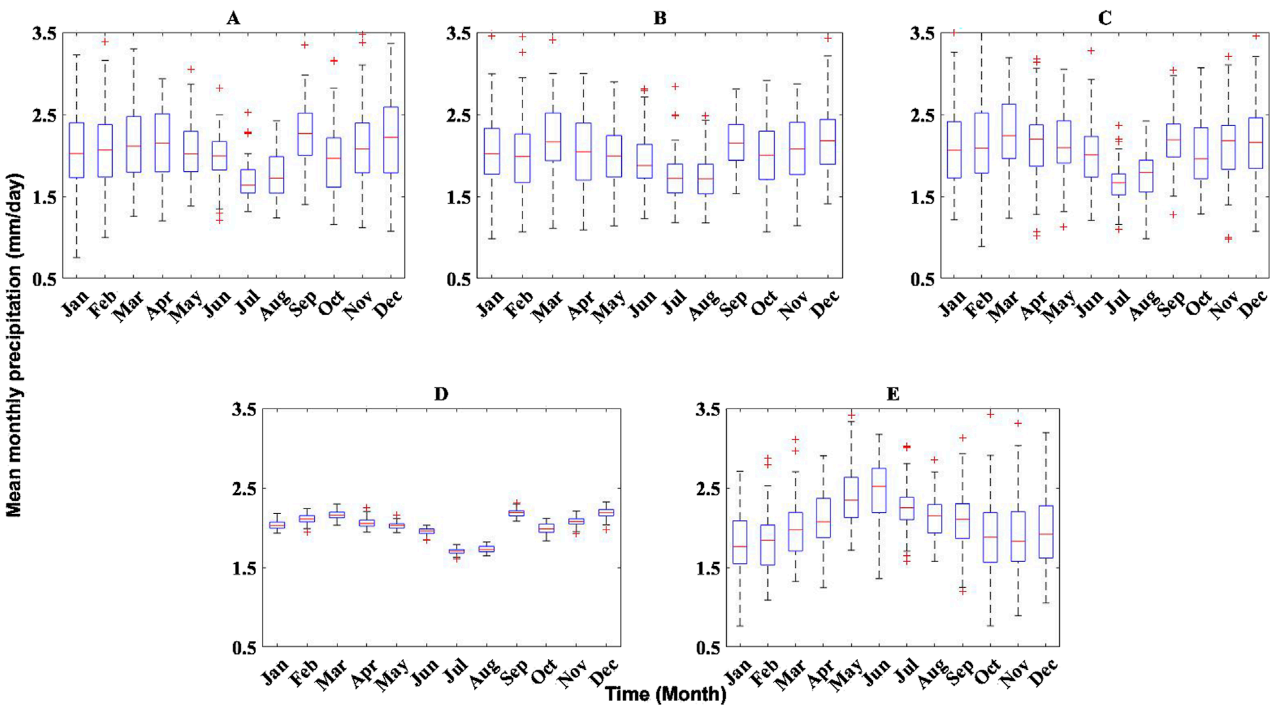

FIGURE 2
Box plots of monthly mean precipitation during 1948–2022 averaged over CONUS for **(A–C)** three randomly selected CESM2-LE ensemble members; **(D)** the mean of 70 ensemble members; and **(E)** CPC gauge observations. The central red mark indicates the median, and the bottom/top edges indicate the $25^{th}/75^{th}$ percentiles, the whiskers show the most extreme points not considered outliers, whereas the red crosses represent outliers.

range) during the summer months is narrower compared to other seasons. Although the three single ensemble members struggle to capture high precipitation magnitudes in June, precipitation variability as observed by CPC is well captured by the ensemble members. However, the ensemble mean shows a largely reduced variability in precipitation across all months due to the averaging of all 70 ensemble members. The ensemble mean exhibits reduced precipitation variability compared to individual ensemble members, as averaging inherently smooths internal climate fluctuations. While single ensemble members capture short-term variability more effectively, the ensemble mean provides a more stable representation of long-term climate signals, which is crucial for identifying trends in future precipitation patterns (Frankcombe et al., 2018).

Time series of seasonal and annual precipitation averages in Figure 3 corroborate what has been observed in the box plots, i.e., the ensemble mean does not fully capture precipitation variability as detected by the ground data and the single ensemble members. During the summer season, the ensemble mean remains consistently below 2 mm/day over the study period. The CESM2-LE single ensemble members show good agreement with CPC in spring and fall, but they present a strong negative bias in the summer (i.e., the model consistently underestimate the ground observations) and a strong positive bias in the winter (i.e., the model consistently overestimate the reference). Despite progressive improvements in the recent past, CMIP climate models are still affected by uncertainties due to errors in boundary conditions, inaccurate model parameterization as well as systematic summer warm biases in air temperature especially in the U.S. Central Great Plains (CGP) regions (Knutti and January 2012; Mueller and Seneviratne, 2014; Wang et al., 2014; Merrifield and Xie, 2016). As air temperature plays a central role in the interconnected feedback loops between various components of the climate system, warm biases can influence CMIP model simulations of different climate variables (Cheruy et al., 2014). When analyzing annual precipitation estimated by CESM2-LE, the three model ensemble members present a better agreement with CPC than the ensemble mean (Panel E in Figure 3). This is particularly evident when assessing precipitation variability throughout the study period, which is clearly dampened by the ensemble mean. This dampening effect occurs because averaging multiple ensemble members smooths out internal variability, reducing the influence of short-term fluctuations and stochastic climate processes (Deser et al., 2012; Kay et al., 2015).

In terms of spatial analysis, both CESM2-LE single ensemble members and the ensemble mean display similar patterns (Figure 4). However, CESM2-LE struggles to capture the high intensity daily precipitation in the NW (as high as 10 mm/day) measured by CPC. Furthermore, large annual precipitation is concentrated in the SE region (as high as 5 mm/day) in CPC, whereas CESM2-LE model shows high amount of daily precipitation (as high as 4 mm/day) in the NE and certain areas of MW. CESM2-LE tends to overestimate precipitation in NE (by as much as ~47%) as shown in relative difference maps in Figure 4. CESM2-LE exhibits a dry bias in the western US, particularly in the NW (as high as ~89%), southern SGP, and SE (up to ~63%). On the other hand, the model presents a wet bias in certain NGP, SW (as high as ~100%), and MW regions (with values up to ~62%).

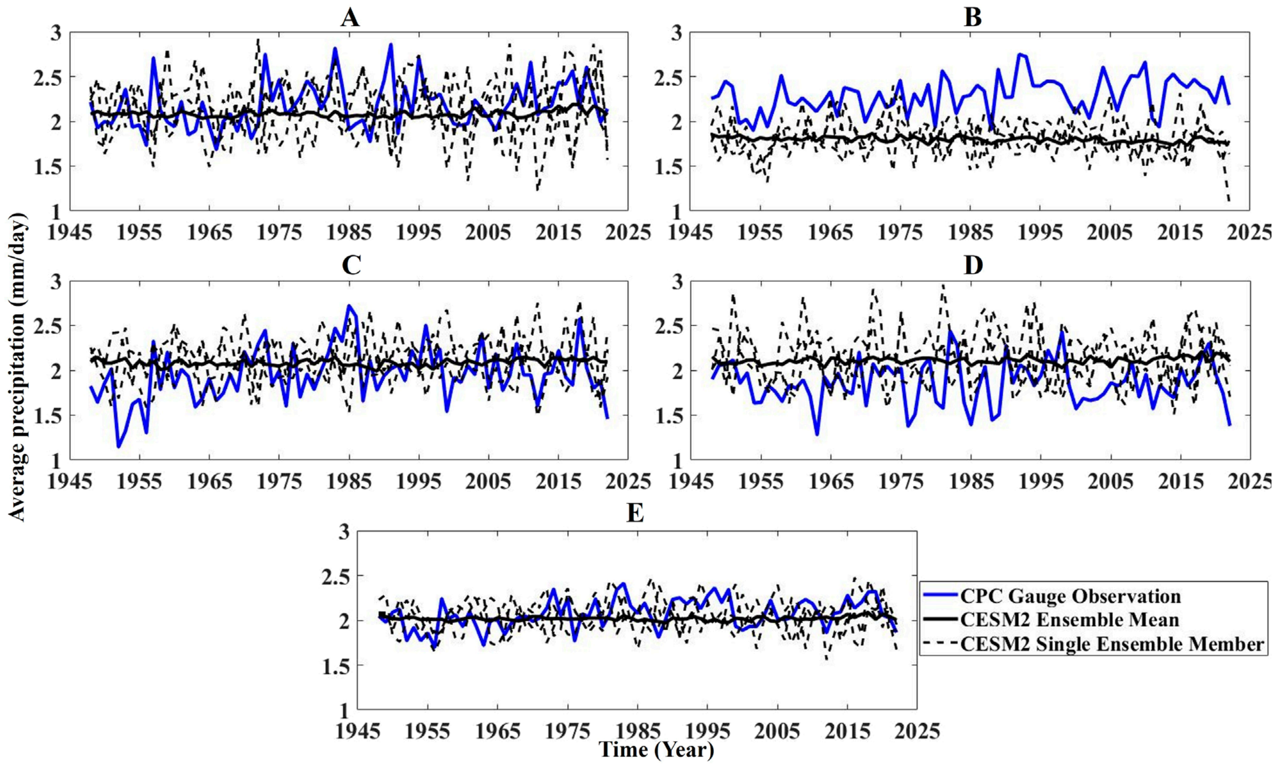

FIGURE 3
Time series of **(A)** spring; **(B)** summer; **(C)** fall; **(D)** winter; and **(E)** annual precipitation averages over CONUS in mm/day from 1948 to 2022 for CPC gauge observation (blue solid line), CESM2-LE mean of 70 ensemble members (black solid line), and three CESM2-LE ensemble members (black dashed line).

The missed precipitation patterns might be attributed to inaccurate simulations of mesoscale convective systems due to problematic convective parameterizations in models (Dai et al., 1999; Liang et al., 2007; Lin et al., 2017; Al-Yaari et al., 2019; Srivastava et al., 2020). Climate model simulations may not be able to account for small-scale convective processes to initiate short duration precipitation events (Maraun et al., 2010; Jones and Randall, 2011; Kendon et al., 2017; Barbero et al., 2019; Moustakis et al., 2021; Coelho et al., 2022; Emmanouil et al., 2022). Though improvements might be made by using convection permitting models, it can be computationally expensive and only available for limited regions and short time periods (Cannon and Innocenti, 2019; Ban et al., 2020).

3.2 Historical versus future precipitation patterns

As the three randomly selected ensemble members show very similar spatial patterns in our previous results, a single member will be used in this section. Furthermore, CPC observations are chosen here to study historical patterns and compare them to future projections. Given the biases observed in the model in the previous section, a pixel-by-pixel bias correction is performed on the model future projections prior to the analyses presented in this section. The annual cycles (1948–2022) of percentiles of CPC average precipitation are compared to the corresponding percentiles obtained from a CESM2-LE randomly selected ensemble member and the mean of the 70 ensemble members during 2023–2100 (Figure 5). The variability around the mean is higher in the future model projections than the historical CPC data when one single ensemble member is chosen, showing a very similar range of precipitation values. However, such variability is drastically reduced when considering the ensemble mean, with values very close to 2 mm/day across the year. Although historical data show a peak between June and July, future projections indicate a decay in summer precipitation with values lower than spring and fall precipitation. This will be critical for water resources management, e.g., irrigation of crops during the summer.

Historical and future time series of seasonal and annual precipitation averages are presented in Figure 6. For historical precipitation, CPC and bias-corrected model simulations are compared to future model projections. Future summer precipitation presents a slightly decreasing pattern with respect to historical CESM2, whereas it shows a large decrease (~50%) compared to the past observation of CPC, which can be attributed to the bias between the two datasets during this season that the overall bias correction was not able to fix. Nevertheless, this (even if slight) decreasing pattern is concerning and can have serious consequences especially for crops that require water in the root zone during the summer. On the other hand, an upward pattern is observed in winter future projections when compared to historical data. It would be interesting

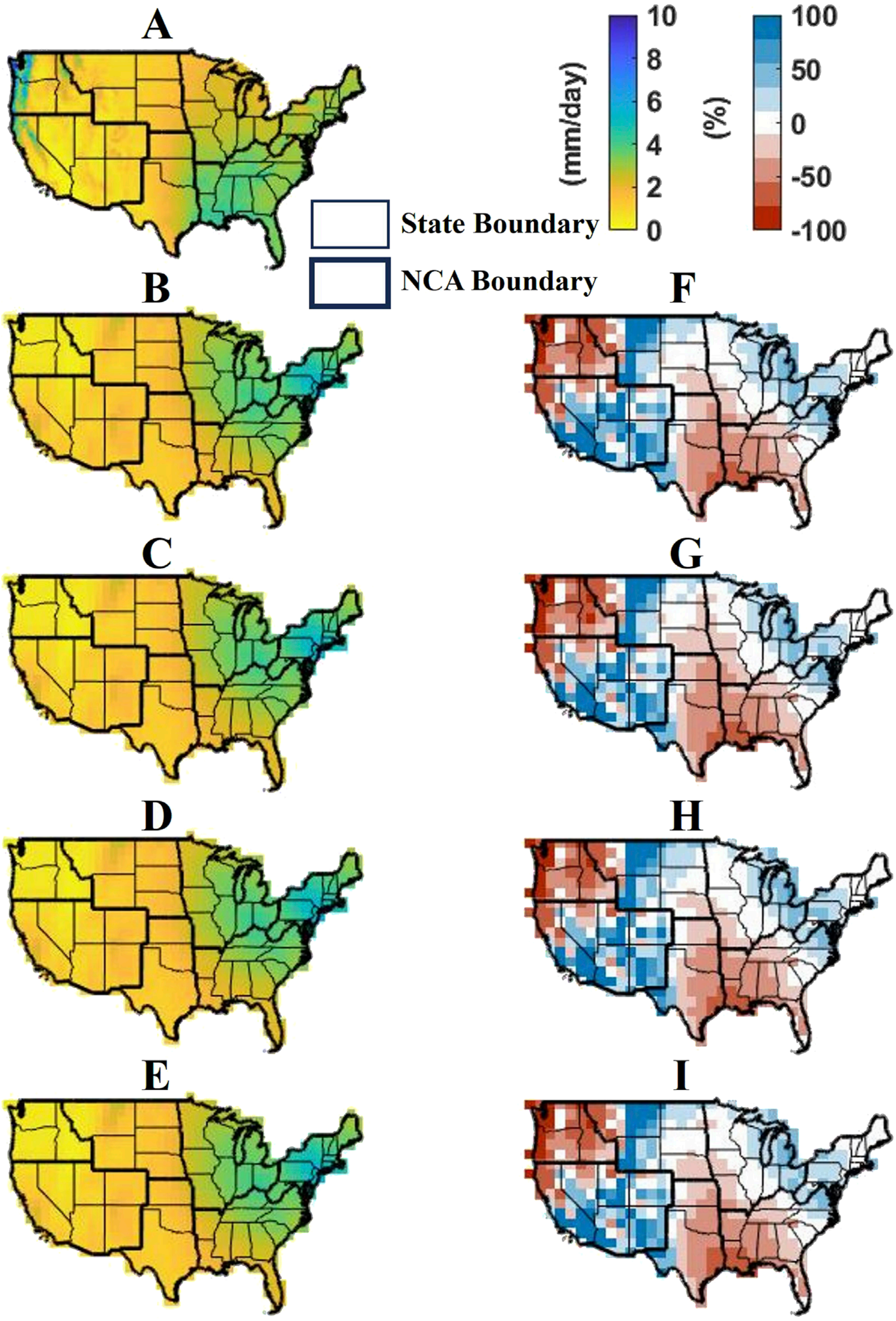

FIGURE 4
Mean annual precipitation during 1948–2022 for **(A)** CPC; **(B–D)** three CESM2-LE ensemble members; **(E)** CESM2-LE ensemble mean; The relative difference (%) between CPC and **(F–H)** each ensemble member and **(I)** the ensemble mean is presented in the second column panels. Red (blue) color refers to an underestimation (overestimation) of the model with respect to the reference.

to investigate whether this trend is mainly due to an increase of rainfall or snowfall, which can have very different effects on the local and regional hydrology. Spring, fall, and annual precipitation present a slight increase in the future compared to the historical records as well. The variability is reduced in the ensemble mean with respect to single ensemble member in the future, which aligns with our findings in the previous chapter. The intrinsic stochastic nature of individual ensemble members is clearly overlooked when averaging all the ensemble members, resulting in such reduced variability.

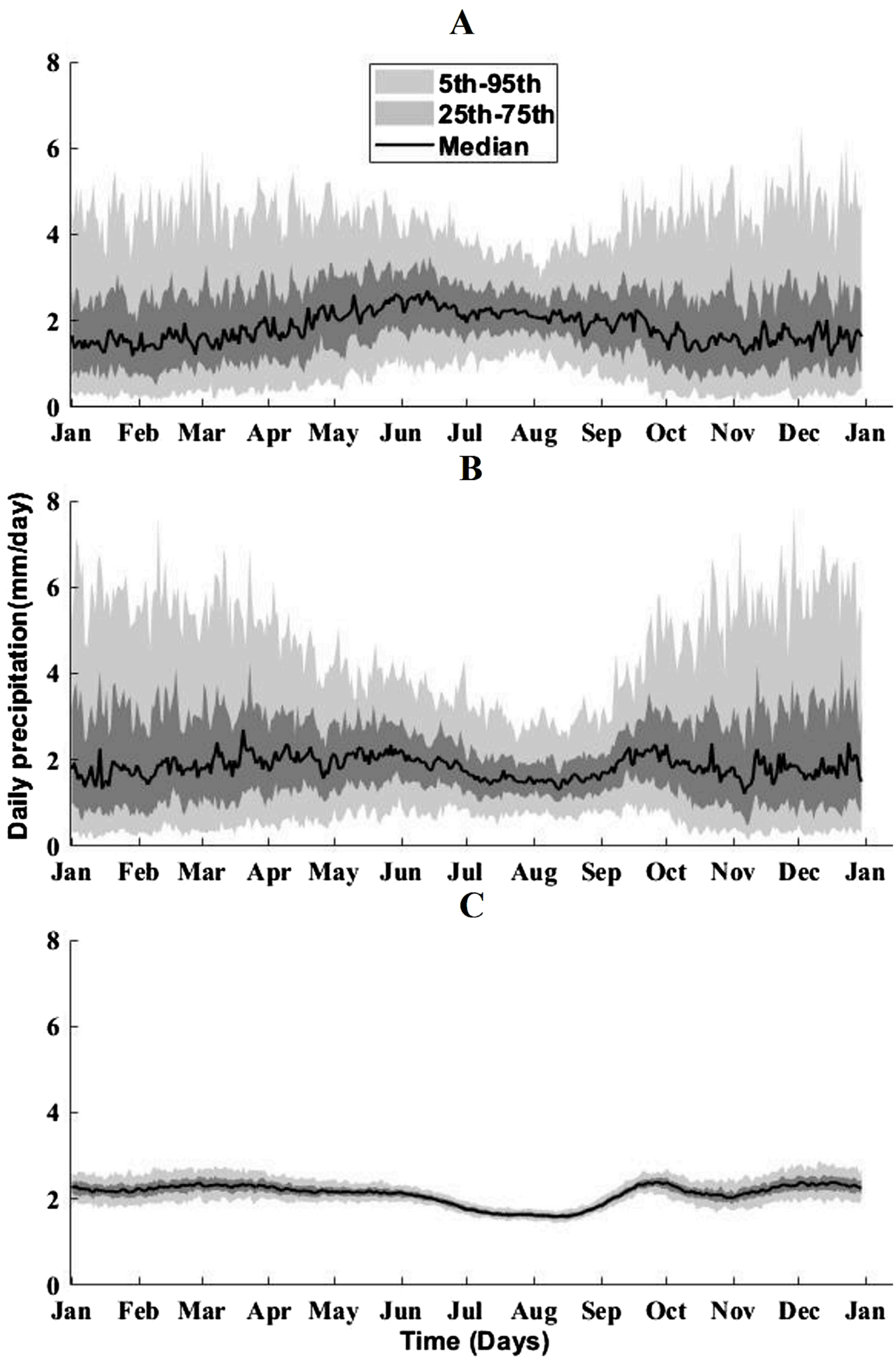

FIGURE 5
Time series of daily precipitation averaged across CONUS for **(A)** CPC observations (1948–2022); **(B)** a bias-corrected CESM2-LE single ensemble member (2023–2100); and **(C)** the bias-corrected ensemble mean (2023–2100). The 5th, 25th, 50th (median), 75th, and 95th percentiles of the precipitation distribution are shown.

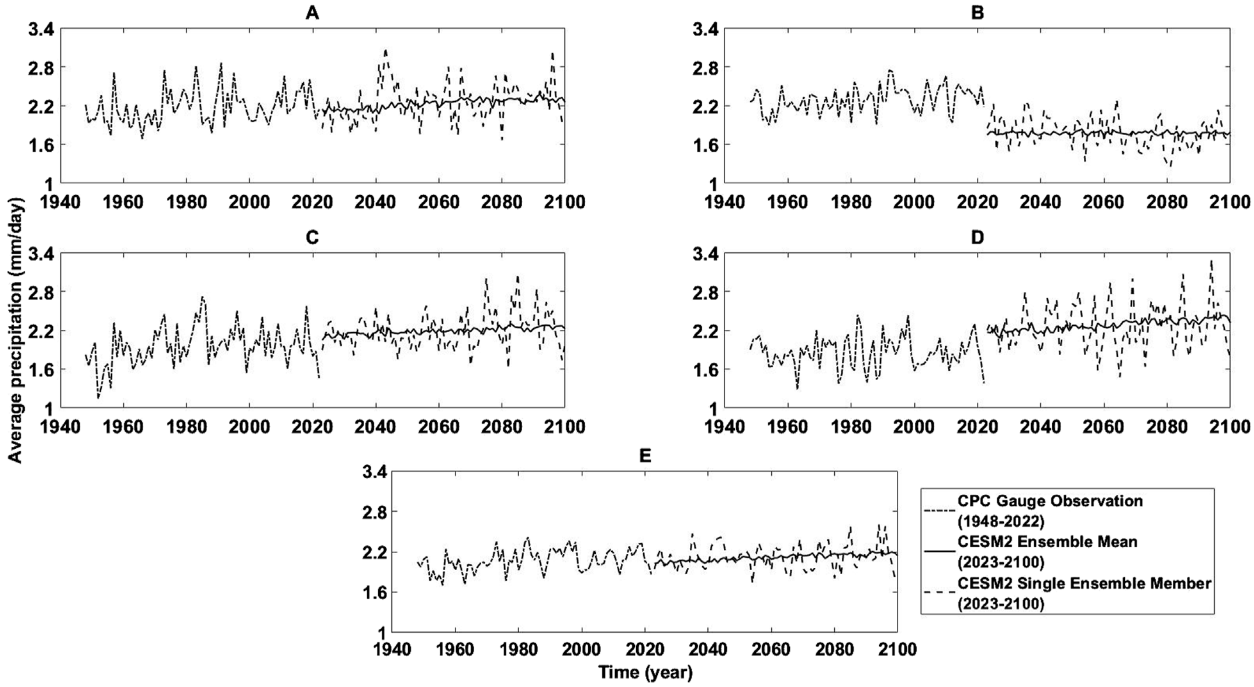

FIGURE 6
Time series of **(A)** spring; **(B)** summer; **(C)** fall; **(D)** winter; and **(E)** annual precipitation averages across CONUS from 1948 to 2100.

TABLE 1 Results of a M-K statistical significance test of time-series showed in Figure 6. For statistically significant trends, the relative confidence level (in %) is shown in parenthesis.

Time	Is the trend statistically significant?		
	Historical CPC	Future mean-ensemble	Future single ensemble
Spring	No	Yes (93%)	No
Summer	No	No	No
Fall	No	Yes (94%)	No
Winter	No	Yes (96%)	No
Annual	No	Yes (96%)	No

The Mann-Kendall (Mann, 1945; Kendall, 1948) test was applied to the time series in Figure 6 to assess the statistical significance of projected precipitation changes. M-K statistically assesses if there is a monotonic (upward or downward) trend in a time series, but the trend may or may not be linear. The M-K test is commonly employed to measure the significance of trends in hydrometeorological time series (Silva et al., 2015; Cooley and Chang, 2021). While historical trends were not found significant, the ensemble mean of future projections showed statistically significant increasing trends at a ~90–95% confidence level for spring, fall, winter, and annual precipitation (Table 1). Future trends from a single ensemble member were found not significant. This highlights the ensemble mean's effectiveness in capturing long-term precipitation patterns that individual ensemble members would not be able to.

Maps of average past and future precipitation are displayed in Figure 7. Past precipitation shows large magnitudes in NW (higher than ~2,500 mm) and northern SW (as much as ~2,400 mm). The SE region also receives large amount of precipitation (up to ~2,000 mm) along with NE (by as much as ~1,600 mm) and MW (up to ~1,300 mm). On one hand, SE, a historically wet region, shows an increase in the future with annual averages ~150 mm higher than in the past along with NE (also a historically wet region), which is projected to increase, with annual averages ~90 mm higher than in the past in some areas. On the other hand, the NGP, already an arid region, will get even drier in the future. The relative difference maps suggest that future precipitation could increase by as much as ~11% in the MW and NE, which are already susceptible to intense precipitation events, and up to ~15% in the already wet SE region.

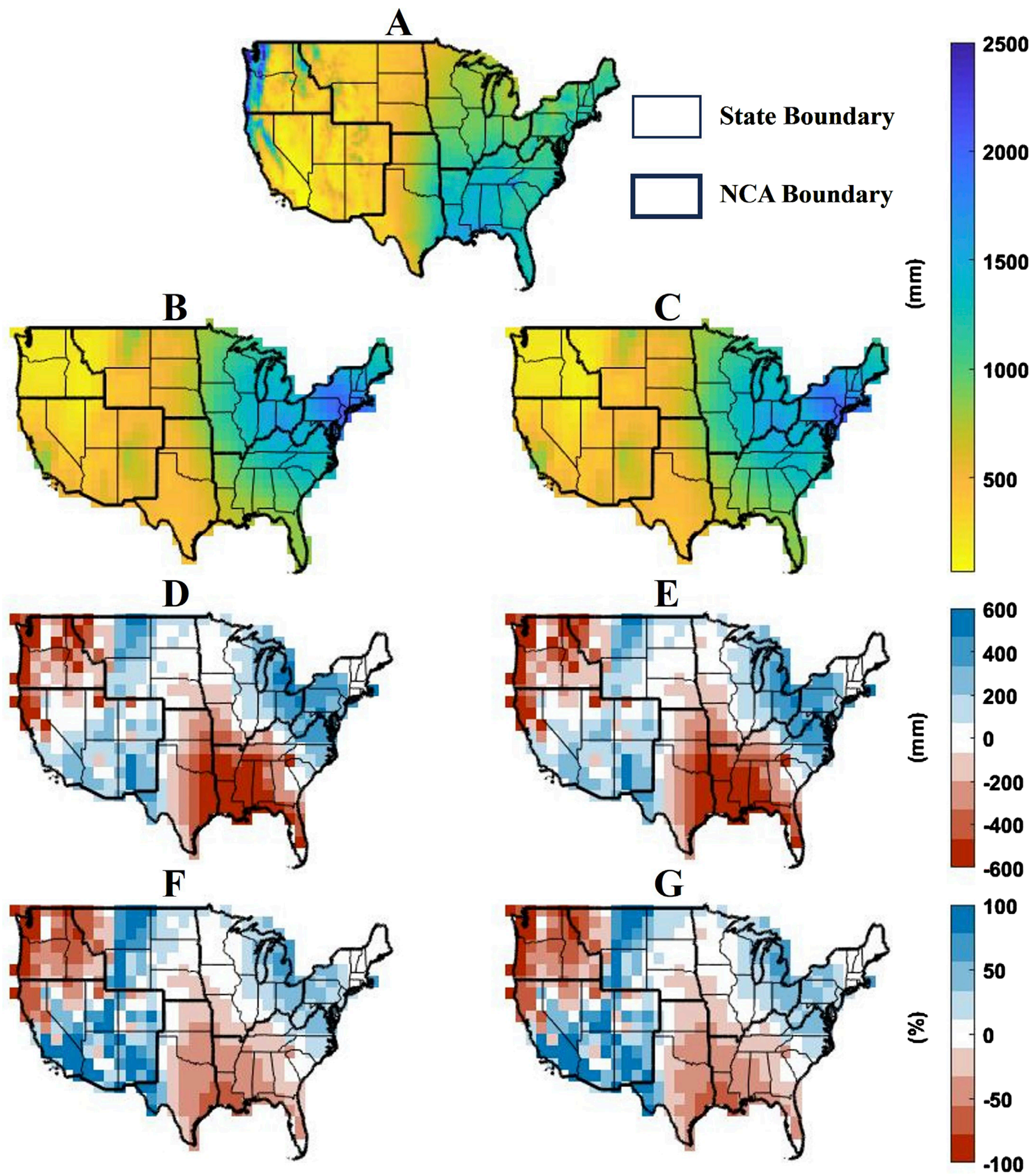

FIGURE 7
Annual average precipitation (mm) for **(A)** CPC historical observations; **(B)** future simulations from a single CESM2-LE ensemble member; **(C)** the ensemble mean of future CESM2-LE simulations. Panels in the third row show the difference in mm between **(D)** future projection from the single ensemble member; **(E)** future projection from the ensemble mean and historic CPC. The corresponding relative differences (%) are shown in panels **(F)** and **(G)**.

Certain areas in the eastern NGP show up to ~15% increase in future precipitation, which could favor the arid landscapes of these regions, but it may also worsen the already existing large-scale floods. Western NGP precipitation will decrease up to ~15%, which might exacerbate its arid conditions. Increased precipitation in already-wet regions and decreased precipitation in already-dry regions are observed globally and appear to persist into the future (Oki and Kanae, 2006; Feng and Zhang, 2015; Wu, 2015; Li et al., 2019). The

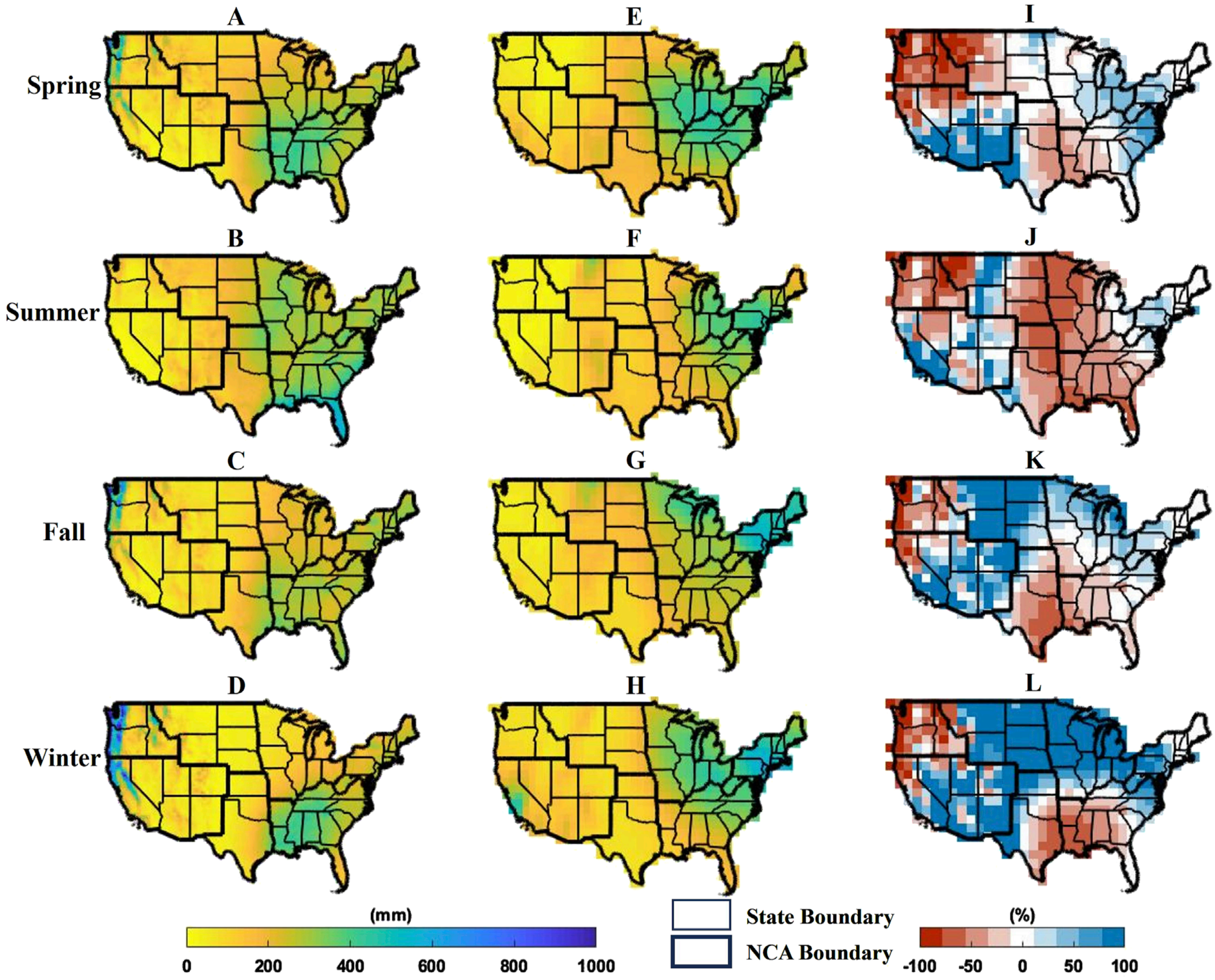

FIGURE 8
Total precipitation averages (mm) across different seasons (rows) for **(A–D)** historical CPC observations (1948–2022) and **(E–H)** future projections (2023–2100) from one CESM2-LE randomly selected ensemble member. Relative difference (%) between future projections and historic CPC are presented in **(I–L)**.

SW region precipitation will increase by up to ~10% in the future, which might be beneficial for the region's arid conditions. Certain regions of NW show some precipitation decrease up to ~11% in the future. Maps of future precipitation estimated by the single member and by the ensemble mean show similar patterns. However, the difference maps in Figure 7 highlight stronger decreases in precipitation in a few pixels in NW and SW, when one single member is used in place of the ensemble mean. Similarly, increases of future precipitation (compared to past precipitation) in the SE region are more evident in the single member analysis.

Figure 8 presents past (CPC) and future (CESM2) total seasonal precipitation. Historically, the western region of NW and northern SW received the largest amount of precipitation (>~1,000 mm) during the winter months, with relatively high magnitudes in spring and fall (up to ~800 mm and ~1,000 mm respectively), and low magnitudes (below ~260 mm) in the summer. In the eastern CONUS, SE receives precipitation during all seasons (as much as ~500 mm), with southern SE presenting higher magnitudes (as high as ~700 mm) during the summer. MW, NE, and eastern SGP show precipitation as high as ~400 mm during spring and summer. NGP records the lowest precipitation amounts among all regions, especially during fall (by as much as ~300 mm).

Precipitation patterns in the western NW and SW areas will not change much in the future, except for summer and spring increases (up to ~100%) in some sub-regions (e.g., southern SW). The precipitation amount in the southern SE will decrease during summer (~50%) and increase in other seasons (~100%). MW, NGP, and northern SGP precipitation will increase during winter (by as much as ~100%) and decrease during summer (by as much as ~75%, ~80%, and 60% respectively). NGP precipitation will also increase in fall (~100%) and decrease in spring (~80%), which might negatively affect the predominantly arid NGP region, where the majority of precipitation occur during the spring season. Winter precipitation in the already wet NE region will increase (~80%). Overall results indicate drier summers and wetter winters in the future with respect to the past. Only future projections from a single ensemble member of CESM2-LE model are shown here, as seasonal spatial patterns of the ensemble mean and the single member are quite similar.

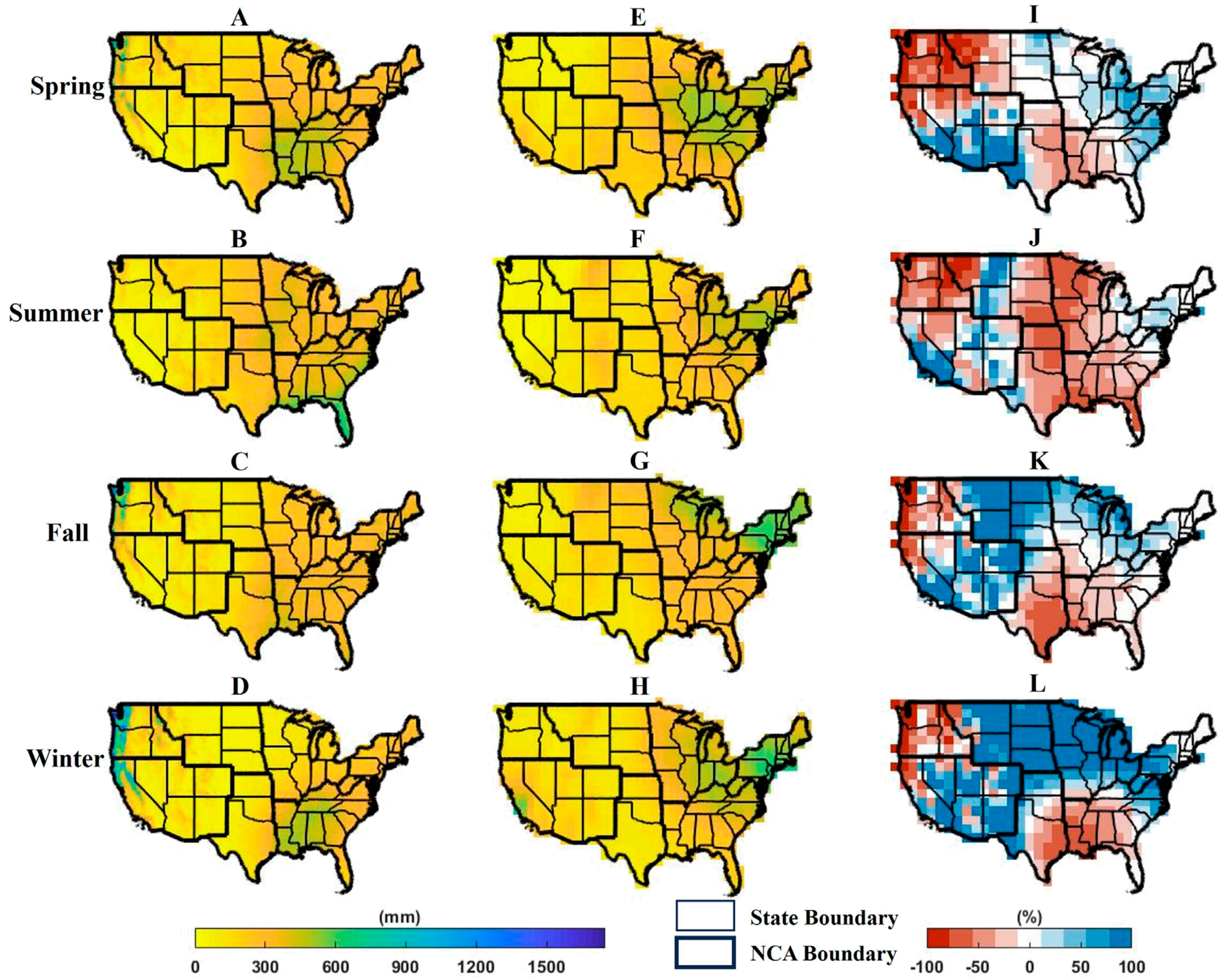

FIGURE 9
75th percentile of total seasonal precipitation averaged over the years (mm) across different seasons (rows) for **(A–D)** historical CPC observations (1948–2022) and **(E–H)** future projections (2023–2100) from one CESM2-LE randomly selected ensemble member. Relative difference (%) between future projections and historic CPC are presented in **(I–L)**.

The 75th percentiles of total seasonal precipitation are displayed in Figure 9. In the CPC observations, NW exhibits the largest values, especially in winter (>~1,800 mm). Other regions generally show less than ~600 mm for the 75th percentile in all four seasons, except for a few pixels in Florida during summer (as high as ~800 mm) and northern SW (up to ~1,500 mm) during winter, fall, and spring. Future precipitation projections present the largest magnitudes in NW and northern SW (as high as ~700 mm) during winter, while southern SW shows the lowest magnitudes (~10 mm) during summer. Relative difference maps between future and historical summer precipitation indicate a decrease in the 75th percentile in MW (up to ~70%), NGP (~80%), and eastern SW (~75%). However, western SW shows an increase in 75th percentiles (~95%) during summer and southern SW shows increased percentiles (~75%) during spring. In future winters, 75th percentiles are projected to increase (up to ~100%) in MW, northern SGP, and NGP. NGP also shows an increase (~100%) in fall and a decrease (~80%) in spring. Certain areas in NGP and SW show lower values in spring (as low as ~80%), whereas SW and SGP show decreases in fall (up to ~55%). Summer 75% percentiles are not projected to change much in SE. NE region shows an increase (~70%) in the 75th percentile during winter. Overall, 75th percentiles of precipitation show increases during winter and decreases during summer in most of the NCA regions.

The high end of the precipitation probability distributions is analyzed by looking at maps of the 95th percentiles for each season (Figure 10). NW shows the largest amount of historical extreme precipitation among all NCA regions during winter with magnitudes greater than ~2,000 mm, with future projections showing even higher percentiles (up to ~100% higher). Several other regions will also experience similar increases in extreme winter precipitation, i.e., NE, NGP, MW, and northern SGP. Summers will generally experience lower 95th percentiles with respect to the past in many areas across CONUS including SW, NGP, MW, and northern SGP.

Although SE presents high 95th percentiles in the historical time series, especially during summer (up to ~1,000 mm), changes are minimal in the future. The SW extreme precipitation will decrease in

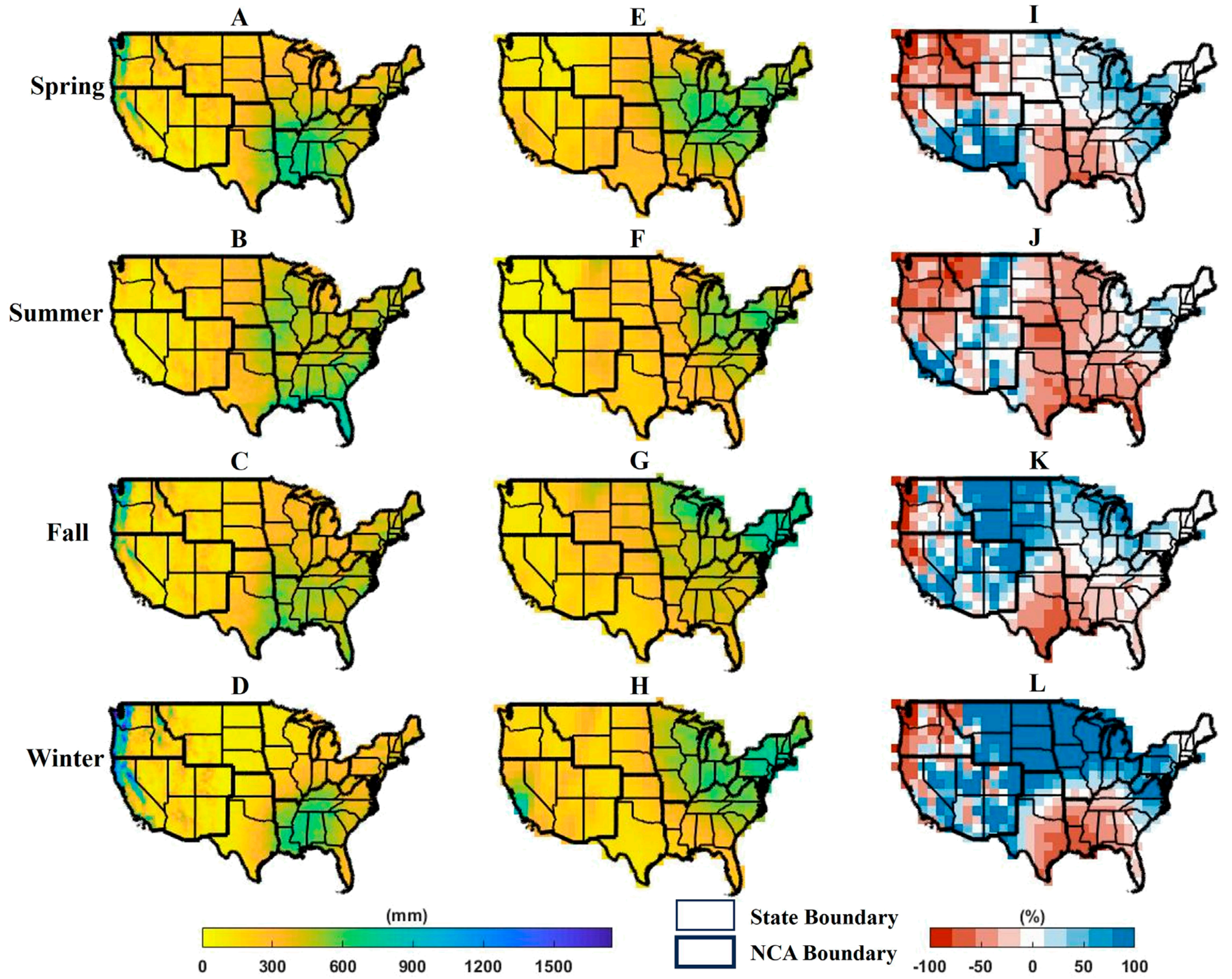

FIGURE 10
95th percentile of total seasonal precipitation averaged over the years (mm) across different seasons (rows) for **(A–D)** historical CPC observations (1948–2022) and **(E–H)** future projections (2023–2100) from one CESM2-LE randomly selected ensemble member. Relative difference (%) between future projections and historic CPC are presented in **(I–L)**.

all seasons, especially during the summer (up to ~75%). NGP shows the lowest extreme precipitation across CONUS, especially during fall (~70–500 mm), but future projections indicate an increase by ~100–1,100 mm. Spatial patterns of the 75th and 95th percentiles are similar for all NCA regions, except for NW which shows increases up to ~100% in 95th percentile precipitation (but lower in the 75th percentile) and some cases in which the 75th percentile shows larger future changes. For instance, spring precipitation in SGP presents changes by up to ~100% in the 75th percentile, but ~60% in the 95th.

Overall findings indicate that, in comparison to the past, extreme precipitation magnitudes will decrease in the summer and increase in the winter in most of the NCA regions across CONUS. If extremes become more extreme in the future, it will worsen existing climatic conditions for some NCA regions. Besides the NE, SE, and NGP regions, MW and SW also face critical climate challenges. Specifically, MW is already facing flood risk due to heavy precipitation during spring and winter–results from this study indicate that extreme precipitation will not change much in the spring but will get more extreme in winter threatening the existing conditions. Similarly, SW, characterized by arid conditions, may see further reductions in summer precipitation, intensifying drought risks and water scarcity concerns. These findings highlight the complex regional disparities in future precipitation trends. The projected increase in winter precipitation, particularly in flood-prone regions like MW and NE, may exacerbate flooding risks, threatening infrastructure, agriculture, and water resource management. Conversely, declining summer precipitation in regions like NGP and MW could intensify drought conditions, affecting crop yields and increasing water scarcity. These findings underscore the need for adaptive strategies in flood mitigation and water resource management to address changing hydroclimatic risks and minimize socio-economic impacts.

Although this study highlights broad seasonal trends, the complexity of inter-seasonal variability should not be overlooked. Transitional seasons (spring-to-summer and fall-to-winter) remain an important factor influencing agriculture, water availability, and ecosystem resilience. Fluctuations within seasons—such as shifts in the timing of precipitation onset, intensity variations, and extreme precipitation events—can significantly impact growing seasons, reservoir management, and biodiversity. Recent studies on South Asian precipitation extremes and variability suggest that large-scale climate drivers greatly influence these transitional periods, contributing to hydroclimatic uncertainties (Abbas et al., 2022b; Abbas et al., 2023; Wijeratne et al., 2023). Recognizing these variations is essential for developing more adaptive strategies in climate impact assessments.

4 Conclusion

This study assessed the performance of the CESM2-LE large ensemble climate model against ground observations and examined past and future precipitation patterns. Results indicate that precipitation variability is reduced when the ensemble mean is adopted in place of individual ensemble members. Nevertheless, the spatial patterns of precipitation for a single random ensemble member and for the average of the 70 ensemble members are very similar.

Considering CPC as reference, CESM2-LE was shown to underestimate summer precipitation and overestimate winter precipitation across CONUS. CESM2-LE struggles to capture the high daily precipitation in the NW (as high as 10 mm/day) measured by CPC. The missed precipitation patterns might be attributed to the problematic convective parameterizations in models. Bias correction was performed in the comparison of historical and future precipitation for model projections to remove any systematic error between model simulations and ground observations.

Historical precipitation observations show slightly increasing patterns in annual, spring, fall, and winter averages, which are projected to continue in the future. Wet regions like NE and SE will become wetter, on average, in the future by ~11% and ~15%, respectively, whereas already dry regions (like some NGP areas) will get drier by as much as ~15%. Seasonal spatial patterns show drier summers and wetter winters in the future with respect to the past. A ~100% increase is observed in most NCA regions (e.g., MW, NGP, and northern SGP) during winter, but precipitation will decrease during summer by as much as ~80%. Extreme (75^{th} and 95^{th} percentiles) precipitation will become more extreme during winter by as much as ~100% and less extreme during summer in the future by as much as ~80%. Spring and fall extreme precipitation will also increase in the future in most of the NCA regions, except for certain areas in NGP, SW, and SGP.

The findings place strong emphasis on reliable climate model projections to better understand long term-precipitation patterns, climatology, and possible climate change impacts. A fundamental step to develop climate change adaptation and mitigation strategies is to project future climates using high-resolution models and compare future precipitation patterns to past observations. Findings from this work point to future wetter winters and dryer summers, which may raise concerns in agriculture and water resources management. Investigating projected changes also offers information on regional vulnerability and encourages the development of region-specific policy implementation across CONUS. Actionable strategies, such as climate-resilient agriculture, sustainable infrastructure development, urban planning measures including improved stormwater management, and drought mitigation activities, can support community-driven adaptation plans. This study focuses on leveraging the large ensemble size of CESM2-LE to ensure consistent model physics and resolution, avoiding inter-model discrepancies. However, a single-model approach limits intercomparison, and results may not capture the full range of uncertainty that arises from structural differences in other models. While CESM2-LE offers valuable insights, its limitations in capturing high-magnitude precipitation highlight the need for inter-model comparisons. In addition, a single emission scenario is employed in this study and, although SSP3-7.0 aids in detecting strong climate signals for worst-case risk assessments, relying on a single emission scenario approach might limit policy-relevant insights across different future pathways. Future studies are encouraged to expand our analysis to multiple future scenarios. Further work should explore multi-model ensemble approaches and multiple emission scenarios, which may better characterize the uncertainty of future projections and provide more robust signals of changing climatology. Other regions in the world should also be investigated, given the global nature of climate models.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://www2.cesm.ucar.edu/CESM2-LENS2/.

Author contributions

RS: Formal Analysis, Investigation, Methodology, Validation, Writing – original draft, Writing – review and editing. VM: Conceptualization, Project administration, Resources, Supervision, Visualization, Writing – review and editing. ID: Conceptualization, Writing – review and editing.

Funding

The author(s) declare that no financial support was received for the research and/or publication of this article.

Acknowledgments

The authors acknowledge the CESM2 Large Ensemble Community Project for providing data. The authors also would like to thank Gustavo de A. Coelho, Assistant Professor of Water Resources at Furman University who originally downloaded and cropped the climate model data used in the analysis, while doing his PhD in George Mason university.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The author(s) declared that they were an editorial board member of Frontiers, at the time of submission. This had no impact on the peer review process and the final decision.

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Publisher's note

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