Assessment of Shared Socioeconomic Pathway (SSP) climate scenarios and its impacts on the Greater Accra region

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ABSTRACT

The effects of climate change (CC) have intensified in Ghana, especially in the Greater Accra region over the last two decades. CC assessment under the new IPCC scenarios and consistent local station data is limited. Consequently, CC assessment is becoming difficult in data-scarce regions in Ghana. This study utilizes six different Regional Climate Models under the 6th IPCC Report’s Shared Socioeconomic Pathway scenarios (SSPs) of the CMIP6, which were bias-corrected with CMhydro over Greater Accra using ground station and PUGMF reanalysis data. The study reveals a reduction and potential shift in the intensity of precipitation in the region under the SSPs. Maximum temperature is expected to increase by 0.81–1.45 $^\circ$C, 0.84–1.54 $^\circ$C, 0.96–1.70 $^\circ$C and 0.98–1.73 $^\circ$C, while minimum temperature would likely increase by 1.33–2.02 $^\circ$C, 1.49–2.22 $^\circ$C, 1.71–4.75 $^\circ$C and 1.75–4.83 $^\circ$C under SSP1–2.6, SSP2–4.5, SSP3–7.0, and SSP5–8.5 scenarios, respectively. Thus, temperature will likely increase, especially at night in the near future. Rising temperatures and changes in precipitation have impacts on all strata of society, from agricultural production to power generation and beyond. These findings can help

Abbreviations: CMIP6, Coupled Model Intercomparison Project; GCM, Global Climate Model; NDC, Nationally Determined Contributions; RCM, Regional Climate Model; RCP, Representative Concentration Pathway; SSP, Shared Socioeconomic Pathway; Tmax, Maximum temperature; Tmin, Minimum temperature; IPCC, Intergovernmental Panel on Climate Change; SDGs, Sustainable Development Goals; NADMO, National Disaster Management Organization; PUGMF, Princeton University Global Meteorological Forcing; NCEP, National Center for Environmental Prediction; NCAR, National Center for Atmospheric Research.

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1. Introduction

Pieces of evidence confirm that the mean temperature of the global land area is increasingly surging especially in recent years (Cheng et al., 2019). Beyond that, precipitation has varied significantly in intensity over time. Temperature and precipitation changes are expected to trigger a series of climate extremes (Duan et al., 2021; Kodinariya and Makwana, 2013). Heatwaves and droughts have increased, and floods have become more persistent, especially in urban areas (Guptha et al., 2021, 2022; Nandi and Swain, 2022; Patel et al., 2022; Sahoo et al., 2022; Swain et al., 2022a, 2022b, 2022c, 2022d). For example, the UK in 2021, Pakistan in 2022, and India in 2022 have experienced the most extreme heatwaves compared to records for the past 122 years (Newburger, 2022). In the UK, 2,500 excess deaths were recorded during the heatwave periods in the summer of 2020, in addition to the COVID-19 deaths (Lo, 2021). Also, the heat in India and Pakistan rose to 51 and 49.2 °C in May 2022, respectively (Dinne, 2022). It is therefore an undeniable fact that the intensification of climate change (CC) has globally impacted the development and survival of humanity (Feng and Hu, 2014).

Different sectors of the economy, such as fisheries, industry, animal husbandry, agriculture, and health, among others, have been affected by changes in temperature and precipitation. Therefore, the evaluation of future precipitation and temperature will assist to enhance the capacity to plan for climate-related impacts (Wang et al., 2018). Average global warming is targeted to be limited to below 2.0 °C according to the Paris Agreement until 2050 (UNFCCC, 2015). The Nationally Determined Contributions (NDC) of countries across the globe have been submitted to achieve the agreed goal (Nashwan and Shahid, 2022).

Precipitation and temperature in West Africa have observed tangible changes in recent decades (Sylla et al., 2016). For instance, 0.5 °C warming has been observed per decade in recent years (Sylla et al., 2016). Global warming leading to increased climate disasters will be a more prominent issue in West Africa. This will result in recurring climate disasters, such as extreme/low precipitation, high temperatures, intensified droughts, heatwaves, and related deaths as well as disruptions to agriculture/food production amounting to wide-scale disaster losses across the region. However, there is little or no study available on the climate change assessment in Ghana especially Greater Accra using the Coupled Model Intercomparison Project Phase 6 (CMIP6) data which encompasses new climate scenarios such as SSP1, SSP2, SSP3, and SSP5.

In this paper, we investigate the capability of CMIP6 models in simulating future temperature and precipitation over the Greater Accra region. We also model the future changes in seasonal and annual temperature and precipitation under four (4) climate scenarios (SSP1–2.6, SSP2–4.5, SSP3–7.0, and SSP5–8.5) until the 2050s, to provide support for understanding the implications of CC over megacities such as Accra. Understanding the changes in these climate variables is also critical for assessing the effects of climate change on the energy, socioeconomic and ecological systems in Greater Accra. Research on climate change in Greater Accra is inevitable since it helps to transfer scientific knowledge to decision-making processes. Therefore, the findings of the study are expected to inform policies in Ghana’s and Accra’s climate action plan for sustainable cities and communities, which satisfy goals 11 and 13 of the Sustainable Development Goals (SDGs). The findings of the study also support decision-making processes towards the implementation of national disaster reduction strategies in consonance with the Sendai Framework for Disaster Risk Reduction 2015–2030 (Kabo-bah et al., 2019), the integration of CC mitigation into local and national policies, and support the development of knowledge and capacity to meet CC challenges. The findings of the study are also expected to inform policies on the role of cities, regions, and local authorities in meeting NDCs and mitigating the threat of CC (The World Bank Group, 2021).

1.1. Background

1.1.1. Historical climate change trends in Ghana

Ghana is among the vulnerable countries in Africa to the adverse effects of CC due to the dependence of much of its population on rain-fed agriculture and hydropower (Arndt et al., 2015). Moreover, climate variability threatens other natural resources, such as forests, water, and marine life (Ahenkan et al., 2021). Ghana has already experienced coastal flooding and erosion (Boateng, 2012). According to Environmental Protection in Ghana (2005) as cited in (Boateng, 2012), coastal erosion has resulted in about 70% of building and road loss along the coast of Keta. Moreover, about 368 people were rendered homeless at Nkontombo, a suburb of Sekondi-Takoradi at the western end of the central coast (Boateng, 2012). Coastal areas in most cases have been affected by the rise in sea level of up to 1 m in the 21st century in many countries (Felsenstein and Lichter, 2014; Hadipour et al., 2020). For instance, Accra’s annual sea level rise has occurred at the rate of +/-2.1 mm per year (Accra Metropolitan Assembly and C40 Cities, 2019) since the 1960s.

Historical rainfall data in Ghana has shown an increase in rainfall during the 1960s (Stanturf et al., 2011). However, this has since declined to lower levels in the latter part of the 1970s and early 1980s. The study of Codjoe and Owusu (2011) quantified some of the variations observed in climate variables in Ghana and their respective periods. For instance, Ghana recorded very hot weather conditions from January to July 1976. This was followed by a drought from 1983 to 1984 which was accompanied by a yearlong wildfire (Codjoe and Owusu, 2011). Again, very hot weather conditions were recorded between October to December 1989. This was followed by massive rainfall throughout the year (Codjoe and Owusu, 2011). In 1995, the country recorded approximately 40 days of rainfall. Very cold winds were experienced in 2004 from March to April and November to December. This continued through to 2005, resulting in the death of animals. For instance, Ghana lost about 780 million dollars from 1900 to 2014 as a result of flooding (Sarkodie et al., 2016). A week of intense rains occurred in 2006, as well as a lot of Precipitation in August and September in 2007.
The historical temperatures of Ghana have shown an upward trend. Using 20-year data, the study of Ghana Statistical Service (2014) revealed that temperatures in Ghana are generally rising. For instance, the trend of temperature from 2010 to 2050 shows warming in all parts of Ghana with the smallest and largest temperature changes occurring in the Bono and Northern regions, respectively (World Bank, 2010). Therefore, based on multiple scenarios, the study of the World Bank (2010) revealed the temperature in the northern regions (Northern, Savannah, North East Upper West, and East regions) is expected to rise by 2.1–2.4 °C by 2050. On the contrary, the projected increase in the Central, Western, Ashanti, Volta, and Eastern regions is expected to be 1.7–2.0 °C, and that of the Brong Ahafo region is expected to be 1.3–1.6 °C. Moreover, the study of Siabi et al. (2021) revealed that the minimum temperature (Tmin) is expected to increase by 0.05–0.21 °C, 0.05–0.19 °C, 0.01–0.06 °C, 0.06–0.19 °C, 0.06–0.32 °C under A2, B2, RCP2.6, RCP4.5, and RCP8.5 scenarios respectively, by 2100 (IPCC, 2014). Maximum temperature (Tmax) was revealed to increase by 0.17–1.14 °C, 0.18–1.01 °C, 0.09–0.17 °C, 0.02–0.45 °C and 0.03–0.61 °C for A2, B2, RCP2.6, RCP4.5, and RCP8.5 scenarios, respectively, by 2100. However, precipitation was projected to vary based on the scenarios and months (Siabi et al., 2021). Similar results were revealed by Yeboah et al. (2022) in the Volta basin.

Regarding the long-term trends of climate change events and natural disasters under different scenarios, Ghana has already experienced an increase in the average temperature of >1 °C since 1960, and estimated heat-related mortality is expected to increase by a factor of five by 2080 (Asante and Amuakwa-Mensah, 2014). Its estimated precipitation has reduced by 2.4% per decade since the 1960s (Asante and Amuakwa-Mensah, 2014). The current average precipitation in Accra, for instance, is approximately 120 cm per year with 4 days of heavy rain (>2 cm) (Accra Metropolitan Assembly and C40 Cities, 2019).

Recent studies on the assessment of the performance of GCMs regionally and globally have reported an improvement in the performance of CMIP6 compared to the previous GCMs. For instance, the study of Kim et al. (2020) revealed the improved performance of the CMIP6 GCMs in simulating global extreme temperature and precipitation indices. Again, the findings of Ayugi et al. (2021) after assessing the performance of the CMIP5 and CMIP6 in simulating average extreme precipitation over East Africa revealed an improvement in the multi-model ensemble mean of the CMIP6 compared to the CMIP5. The study of Akinsanola et al. (2021) assessed the performance of sixteen CMIP6 models in simulating extreme precipitation in the rainy season over East Africa. The results revealed the robust performance of the multi-model ensemble mean in simulating extreme events. Similarly, the study of Agyekum et al. (2022) evaluated the performance of forty-one (41) models in simulating extreme precipitation events over the Volta basin of West Africa. The results revealed the improved performance of the multi-model ensemble mean in simulating extreme precipitation events.

However, the study of Annor et al. (2022) reveals otherwise. The study employed Global Coupled configuration 2 (GC2) of the Unified Model (UM) together with four CMIP6 models to simulate temperature and precipitation climatology over West Africa. The results found the UM outperformed the four CMIP6 models in simulating temperature and precipitation. Furthermore, Nashwan and Shahid (2022) assessed future precipitation changes in Egypt using CMIP6 multi-model ensemble. The results showed the capacity of the multi-model ensemble in simulating spatial patterns of annual summer and winter precipitation from 1971 to 2014. Other relevant studies also employed RCMs in the simulation of temperature and precipitation climatology (Ashaley et al., 2020; Okafor et al., 2019; Yeboah et al., 2022).

1.1.2. Climate change trends and research gaps in Greater Accra

Ghana’s capital city is Accra where CC events, such as sea level rise, coastal inundation, coastal erosion, heatwaves, floods, etc. are felt most in Ghana due to its large population. For instance, Stanturf et al. (2011) found that rainfall ranged from 52% decreases to 44% increases in the wet season by 2080 in Accra. An expected change in temperature of about 1.68 ± 0.38 °C and 2.54 ± 0.75 °C is also expected by 2050 and 2080 in the wet season, respectively. In the dry season, these figures are about 1.74 ± 0.60 °C and 2.71 ± 0.91 °C. Previous studies have assessed the climate changes in Accra and their future projections (Accra Metropolitan Assembly and C40 Cities, 2019; Stanturf et al., 2011). However, these studies failed to assess the climate changes under the new IPCC scenarios. For instance, the Climate Action Plan for Accra focused on the magnitude of changes in climate under RCP2.6 and RCP8.5 until 2050 (Accra Metropolitan Assembly and C40 Cities, 2019). The study employed national-level data largely due to the absence of downscaled climate projections specific to Accra. The study reveals higher temperatures of over 40 °C for an additional 21 days per year by 2050 relative to 1960. The waterfront of Accra is expected to lose an additional 150 m of coastline as a result of the rise in the level of the sea by 20 cm by 2050 relative to 1960. This, therefore, calls for emergency preparedness towards climate extreme conditions such as sea level rise, coastal inundation, costal erosion, heat waves, floods, etc. (Accra Metropolitan Assembly and C40 Cities, 2019). However, other scenarios, such as RCP4.5, and the latest SSP scenarios have not been assessed.

Moreover, the study of Stanturf et al. (2011) assessed climate projections over Ghana to the end of the 21st century. The study focused on seven representative meteorological stations and generalized climate conditions in Ghana. The study revealed that mean temperatures for the dry season are projected to increase by 1.5–2.0 °C to approximately 3.0 by 2080 in Ghana (Stanturf et al., 2011). The findings for rainfall by the climate models were uncertain and mixed due to the complexity of the atmospheric circulation patterns over West Africa. For this reason, the study revealed uncertainty in the projected rainfall. Thus, the findings of the study were mixed and inconclusive, lacking consistency, and predicting both increases and decreases in precipitation across stations.

Moreover, the Climate Change knowledge portal (World Bank Group, 2022) has current data on CRU (Observed), ERA5 (Reanalysis), CMIP5 (projections), and CMIP6 (projections) for essential climate variables such as precipitation, temperature, as well as additional variables such as growing season length and relative humidity. However, this portal fails to capture data for several ground stations per region. For instance, the whole of the Greater Accra region was represented by a single station.

Therefore, this current study tries to fill the identified research gap by exploring the new IPCC scenarios (i.e. SSP scenarios) utilizing the CMIP6 data which offers higher resolution and accuracy in terms of forecasting future projections and takes into consideration socioeconomic variables that affect climate change as well as new gap scenarios which were not covered previously in CMIP3 and 5.
Also, the study employs a more accurate reanalysis dataset from Princeton University Global Meteorological Forcing (PUGMF) as well as ground station data to explore the future projections of climate change across Greater Accra (i.e., location-specific station data) compared to previous studies which represented Accra with a single station (Stanturf et al., 2011) or focused only on Accra (Accra Metropolitan Assembly and C40 Cities, 2019; Wemegah et al., 2020).

In summary, the study makes the following main contributions to existing knowledge on climate change in Greater Accra:

1) considering the latest state-of-the-art SSP scenarios available;
2) employing more accurate historical data over the Greater Accra region for future forecasting compared to previous studies; and
3) focusing on different stations across the whole of Greater Accra compared to existing studies which focused only on parts of Greater Accra.

1.2. The coupled model intercomparison project phase 6 (CMIP 6)

The analysis and projection of future CC under the new SSP scenarios have relevant socio-economic significance (Ghosh and Mujumdar, 2007; Zhai et al., 2020) since it takes into consideration some socioeconomic variables such as population in its predictions. However, this is still lacking in Ghana, especially Greater Accra. Existing literature has assessed future CC in terms of temperature and precipitation in West Africa using multiple climate models such as regional and global climate models (Awotwi et al., 2021; Okafor et al., 2019, 2021; Siabi et al., 2021; Yeboah et al., 2022). The new generation of global climate models (GCMs) developed for the CMIP6 are released by the IPCC (AR6) and are now available (Wang et al., 2018). These experiments are based on state-of-the-art GCMs, which are more accurate in defining the sophisticated physical processes within the climate system compared to the previous CMIP5 GCMs (Newburger, 2022). Previous studies have examined plausible climate changes by employing idealized emission pathways to pursue 1.5 °C and 2.0 °C warming targets (Donnelly et al., 2017; Karmalkar and Bradley, 2017; Shi et al., 2018). In other studies, the representative concentration pathways (RCPs) and NDC scenarios were utilized to assess average temperature responses on the global scale and likewise, the expected changes in regional precipitation and related extremes (Siabi et al., 2021; UNEP, 2020; Yeboah et al., 2022; Zhang et al., 2018).

The scenario model intercomparison project embedded in the CMIP6 offers multi-model climate predictions based on several scenarios, showing a true picture of the socio-economic issues associated with climate change adaptation, mitigation, or implications (O’Neill et al., 2016). The newly-developed climate predictions are driven by a bundle of land-use scenarios and emissions built on the Shared Socioeconomic Pathways (SSPs) scenarios, new future social development pathways, and the updated versions of the RCPs introduced by the sixth assessment report most recently published by the IPCC (IPCC, 2021). In general, the new SSPs are scenarios that consider future socio-economic changes and contributions to mitigate climate change, in addition to the previous concepts of RCP. However, CMIP6 climate projections vary from those in the past phase (CMIP5), not only because of their newer forms of climate models coupled with SSP scenarios, but also because they reveal new gap scenarios which were not covered previously (Rogelj et al., 2016). The sixth assessment report (IPCC, 2021) outlined five (5) scenarios (SSP1-3.5, SSP1–2.6, SSP2–4.5, SSP3–7.0, and SSP5–8.5) that announced an increase in temperature by 1.5 °C in the near future (2021–2040), and 3.3–5.7 °C in the far future (2081–2100) if the situation proceeds according to the highest emission scenario.

1.2.1. SSP 1–2.6

The Paris Agreement, which focuses on limiting global warming to 2.0 °C by 2100 (Meinshausen et al., 2011), is related to the SSP1–2.6 scenario, which is one of the upgraded RCPs version (2.6 W/m²). The SSP1–2.6 scenario assumes a relatively optimistic evolution of future society towards sustainability with significant economic expansion, investment in health and education, and robust governance (O’Neill et al., 2016). This is the pathway that envisions that the world will cooperate to fight climate change (Riahi et al., 2017). The result is a world that will warm up between 1.3 °C and 2.4 °C relative to 1950, with a 7 billion global population (Hausfather, 2018; Irfan, 2021). This scenario follows the Paris Agreement goals of limiting warming to below 2.0 °C, as it assumes a 1.8 °C global average temperature rise by 2100 (Meinshausen et al., 2011; Rogelj et al., 2016).

1.2.2. SSP2–4.5

The SSP2–4.5 scenario, a “middle of the road” scenario, is consistent with the climate actions of various countries to fulfill their existing obligations to reduce emissions (Riahi et al., 2017). The result is a world that is expected to warm up between the range of 2.1 °C and 3.5 °C relative to 1950, with 9.6 billion people (Hausfather, 2018; Irfan, 2021). In SSP2–4.5, total radiative forcing is expected to rise to about 4.5 Wm² until 2070 and then drop. This is expected to lead to a decline in food production across the world due to more heat extreme and catastrophic flooding from precipitation extremes (Riahi et al., 2017). Here, inequality is expected to continue however, the focus is on achieving environmental goals through international cooperation.

1.2.3. SSP3–7.0

In the SSP3–7.0 scenario, countries tend to retreat from international cooperation and focus on their own economic goals. Here, nationalism is resurgent (Riahi et al., 2017). Zeke Hausfather (Hausfather, 2018) noted that “it’s a reasonable storyline for what a worst-case world could look like.” This would lead countries to support the exploitation of their fossil fuels further (Riahi et al., 2017). As a result, heat-trapping gases other than carbon dioxide, as well as methane and aerosols, are expected to increase to high levels. The global population is expected to increase to about 12.6 billion people by 2100 (Hausfather, 2018). However, investment in technological development and education would decline. The result is a world that will warm up between the range of 2.8 °C and 4.6 °C
relative to 1950 (Hausfather, 2018; Irfan, 2021). This is where radiative forcing levels are expected to rise to about 7.0 Wm$^{-2}$ (Meinshausen et al., 2020). Sea levels are also expected to catastrophically rise between 46 and 74 cm.

1.2.4. SSP5–8.5

Under the SSP5–8.5 scenario, humanity tends not to do anything about climate change but persistently makes it worse (Irfan, 2021; Riahi et al., 2017). This scenario envisages global economic growth fueled by natural gas, oil, and burning coal. The global population is expected to peak at 8.5 billion in the 2050s and drop to the current level of about 7 billion by 2100 (Hausfather, 2018). Here, resources are committed to adapting to climate change with little support to mitigate emissions (Riahi et al., 2017). The result is a world that will warm up between the range of 3.3 °C and 5.7 °C relative to 1950 by the end of the 21st century (Irfan, 2021; Riahi et al., 2017). This is where radiative forcing levels are expected to rise to about 8.5 Wm$^{-2}$ (Meinshausen et al., 2020). In this scenario, large-scale coastal inundation and extremely destructive weather are expected. This will render parts of the world unlivable, especially during the hottest events of the year.

1.3. Drivers of the SSP scenarios

Four major socio-economic drivers influence the SSPs (Kc and Lutz, 2017). These include urbanization, education, population, and economic development. Here, a multi-dimensional demographic model is used to project the population under the SSP scenarios. The design of the projections is such that it is consistent with the five SSP storylines. A cross-classification of gender, age, and educational level is done with assumptions of fertility affected by female education leading to population growth (Riahi et al., 2016).

The alternative assumptions of migration, fertility, and mortality are generated partially from the narratives depicting different structures of education of the populace (Riahi et al., 2016).

The results regarding the overall population sizes of the world under the SSP scenarios encompass a broad range. Conforming to the storylines, the population is minimal, reaching approximately 7 billion by 2100 under SSP1 and SSP5. However, the global population is expected to be high reaching about 12.6 billion under SSP3. Compared to the previous scenarios, the SSP scenarios cover a minor range (Nakićenović et al., 2000).

This may be attributed to the drop in the rate of fertility over the last two decades in developing economies and the current education expansion in the least developed countries, especially among young women (Riahi et al., 2016). The results regarding the composition of education which influences the growth of economies and susceptibility to the implications of climate change vary broadly in the SSP scenarios (Riahi et al., 2016). For instance, educational composition improves substantially under the SSP1 and SSP. Again, the worldwide mean level of education in 2050 similar to the recent levels in Europe. Moreover, a dramatic improvement in the composition of education will be seen under the SSP2 whereas a marginal increase will be seen in SSP3 and SSP4 with the global average in educational level declining somewhat late in the century (Riahi et al., 2016).

In the same way, quantifying trends of urbanization follows the narrative (Riahi et al., 2016). The forecasts reveal continuous urbanization globally under all the SSP scenarios. However, the rates of urbanization differ broadly across scenarios (Riahi et al., 2016). For instance, urbanization is expected to reach 60% and 80% for SSP3 and SSP2 respectively by 2100. However, urbanization is expected to reach 92% under SSP1, SSP4, and SSP5 respectively by 2100. This is a considerably wider range relative to previous projections (Grübler et al., 2007). The projections for the SSP2 align with the projection of the UN median (Riahi et al., 2016). There is an expected decline in urbanization under the SSP3 due to slow economic growth. This results in mobility issues in different regions and poor planning of urbanized areas renders them unappealing destinations.

Conversely, urbanization is expected to be rapid under the SSP1 and SSP5 with its related high-income growth (Riahi et al., 2016). However, urbanization under the SSP1 is preferable due to the high efficiency that compacts urban zones whereas cities are more appealing places as a result of other factors including fast technologies that support engineering projects that are large-scale for the construction of required buildings (Riahi et al., 2016). Under each SSP scenario, there are three sets of economic (GDP) projections (Cuaresma, 2017; Dellink et al., 2017; Leimbach et al., 2017). They were generated together with the demographic projections to maintain consistent assumptions with age and education. However, there are differences in the three economic projections regarding their target on different economic development drivers such as efficient energy use, human capital accumulation, technological progress, etc. (Riahi et al., 2016).

For energy systems under the SSP baseline scenarios, there is a description of different developments that are path-dependent of the energy system in consonant with the SSP storylines and the related limitations to adaptation and mitigation (Riahi et al., 2016). Generally, the SSP scenarios show broadly diverse futures of energy, encompassing a broad array of expected energy demand and supply (Riahi et al., 2016). These diversities emanate as a result of mixed assumptions concerning the major energy system drivers such as the growth of the economy, innovative energy services emergence, services for energy intensity, technological changes, and assumptions concerning costs and accessibility to future fossil fuels as well as their substitutes (Bauer et al., 2017). The structure and scale of the expected systems for energy supply under the SSP scenarios are relevant determinants of the limitations for mitigation and adaptation. For instance, the SSP3 and 5 are two scenarios under the SSPs that heavily rely on fossil fuels with a surging contribution of coal to the energy mix. Under these scenarios, the limitations for mitigation are high (Riahi et al., 2016). However, the SSP1 and 4 show economies having low constraints to mitigation and subsequently increasing renewable energy shares as well as other energy carriers with low-carbon. The “middle of the road” storyline of the SSP2 balances the energy system relative to the rest of the SSP scenarios, including a continuance of the recent energy mix that is dominated by fossil fuel with transitional constraints for adaptation and mitigation (Riahi et al., 2016).

For land-use change under the SSP scenarios, changes in land-use are a result of industrial and agricultural demands for example
Fig. 1. Map of the study area.
timber, bioenergy as well as food. The direction and nature of these changes are diverse for the SSPs (Riahi et al., 2016). They depict land use narratives that have been created based on the storylines of the SSPs (Popp et al., 2016) and that have directed assumptions on productivity, demand, environmental effects, regulation, as well as globalization level of the expected forestry and agricultural markets. Under the baseline scenarios for the SSP, there is a diverse array of future land-use change components (Riahi et al., 2016). For instance, the scenarios show a future where the overall agricultural land can increase or decline by millions of hectares by the end of the 21st century. High expansion in population with comparatively low agriculture production with less importance on the protection of the environmental makes the SSP3 a scenario that relatively places huge pressure on the global land use system (Riahi et al., 2016). The result is a land-use pattern with significant forest losses and other natural lands due to expansion in crop production and pasture lands (Riahi et al., 2016). Comparatively, the SSP1 encompasses a land transformation that is sustainable and results in relatively less pressure on land resources owing to low population growth, high agricultural production, and healthy diets with limited food waste. In agreement with its storylines, the SSP1 shows reversed historical trends, which include a steady, worldwide, and prevalent increase in forests and other natural lands. The rest of the scenarios feature marginal changes in land use with some expansion of overall cultivated lands (Riahi et al., 2016).

Concerning the emissions for the baseline and climate change, the land-use and energy systems pathways under the SSPs transcend into a broad array of Green House Gases and emission of pollutants (Riahi et al., 2016). For instance, the emission of CO2 agrees with the future mitigation constraints. The development of fossil fuels under the SSP3 and SSP5 results in higher CO2 emissions and more mitigation issues (Riahi et al., 2016). However, low-carbon dominated fossil fuel and augmented deployment of energy sources that are non-fossil under the SSP1 and SSP4 leads to fewer carbon emissions and fewer mitigation issues (Riahi et al., 2016). Compared to other baselines with high CO2 emissions, the intermediate emissions pathway is depicted by the SSP2 (Riahi et al., 2016).

Global warming is largely influenced by CO2 and CH4. Generally, emissions are largely influenced by non-energy sources such as manure emanating from livestock, cultivation of rice, and fermentation of enteric. However, emissions from the transport and production of oil, natural gas, and coal contribute to a smaller extent (Riahi et al., 2016).

Population growth which leads to higher food demands may be a tangible driver of expected CH4 emissions for the SSP scenarios. Thus, emissions of CH4 are lowest in the SSP1 compared to the SSP3 baseline (Riahi et al., 2016). The totality of diverse non-energy and energy drivers results under all other SSP to mid-range levels of CH4 emissions in the future.

However, the rapid rise in CH4 emission under the baseline scenario of the SSP5 in the near future is a result of the high usage of fossil fuel infrastructure, especially for the extraction and distribution of natural gas. The study of Riahi et al. (2016) revealed that the overall CO2 and CO2-eq greenhouse gas emissions as well as the corresponding radiative forcing associate well with the limitations to mitigation for the SSP scenarios. Comparatively, the SSP scenarios cover a broad range of air pollutant emissions than the RCP scenarios (Rao et al., 2016). This is due to the assumption of the stringency of respective standards would rise with raising affluence under the RCPs (Riahi et al., 2016). Conversely, the SSP scenarios are based on diverse air pollution narratives in consonance with the general SSP storylines. Especially, the upper bound projection of the SSP3 reveals a world with a slow introduction of air pollution policies and implementation of failures resulting in much higher levels of air pollution than in any of the RCP scenarios. For more details on the air pollution dimension of the SSP scenarios see (Rao et al., 2017) in this special issue.

2. Materials and methods

2.1. Study area description

Greater Accra has a total land area of about 786.59 km² with about 5,455,692 people (Ghana Statistical Service, 2021). The study area lies between Latitude 5°.30 and 5°.53 North and Longitude 0°.03 and 0°.25 West, and it is characterized by occasional hills and lowlands with a mean height of about 20 m above sea level. Moreover, Greater Accra generally has gentle slopes of about 11%, except in some places such as areas around Abokobi, Kwabenya, and McCarthy hills where most slopes are over 22%. The water table lies between 4.80 and 70 m below the surface (Nyarko, 2002). Greater Accra falls within the anomalous dry equatorial climatic region with double maxima Precipitation and a prolonged dry season (with occasional dry Harmattan conditions). February and March are noted to be the hottest months in the study area with a mean monthly temperature of about 27 °C (Ghana Statistical Service, 2014). However, the coldest months are June to August with a mean monthly temperature of about 21 °C (Ghana Statistical Service, 2014). Precipitation is characterized by two peaks, from March to July (major season) and September to November (minor season), with about 780 mm to 1200 mm of annual precipitation (Nyarko, 2014). However, the mean precipitation is about 812 mm as reported by the Ghana Meteorological Agency (Nyarko, 2014). The study area has two major vegetation types: the coastal scrub and grasslands, and the mangrove forest. The coastal scrub and grasslands are noted in some parts of Greater Accra with occasional tree patches, including Baobab and Nim trees. The mangrove forests are found in the coastal lagoon areas where the soil is known to be salty and waterlogged. A map of the studied area is shown in Fig. 1. Due to the lack of ground station data in some parts of the Greater Accra region, virtual (Virt) stations were used to represent these areas. In total, six virtual stations were added to the three ground stations.

2.2. Observed hydroclimatic data

The study employed data from the Princeton University Global Meteorological Forcing (PUGMF) (Sheffield et al., 2006), as well as station data (GMet, 2022) from three available weather stations in the Greater Accra region. This PUGMF forcing dataset is based on the National Center for Environmental Prediction (NCEP) and National Center for Atmospheric Research (NCAR) reanalysis, which
The Climate Model data for Hydrologic Modeling (CMhyd) tool was used for statistical bias correction. This tool is developed to bias-correct climate data attained from RCMs and GCMs (Rathjens et al., 2016). Bias correction is required due to the coarse nature of GCM and RCMs data. The procedure for bias correction uses a transformation algorithm to simulate the output of the model. The process assumes that the algorithm for bias correction and its parameterization for the present climate conditions are to be valid for future conditions as well. The CMhyd has been generally employed for different applications (Andrade et al., 2021; de Carvalho et al., 2021; Tian et al., 2020). The study used the CMhyd due to its CMIP6 data compatibilities in simulating historical and future climates. The study by Zhang et al. (2018) recommended compared to employing a single model (Xu and Xu, 2012). Therefore, projected Precipitation, Tmax, and Tmin in Greater Accra are derived from a multi-model ensemble of the six RCMs.

2.4. Statistical bias-correction

The CMhyd tool offers eight different bias-correction algorithms. These include distribution mapping, linear scaling (additive and multiplicative), precipitation local intensity scaling, delta change correction (additive and multiplicative), power transformation of correction methods could be applied easily. The PUGMF reanalysis dataset is a combination of a suite of global, observation-based precipitation datasets, temperature, and radiation. These contributing datasets include NCEP–NCAR reanalysis, Climatic Research Unit Timeseries (CRU TS) 2.0, The Global Precipitation Climatology Project (GPCP), Tropical Rainfall Measuring Mission (TRMM), and NASA Langley Surface Radiation Budget (SRB) datasets.

The quality control of the three ground station datasets is shown in Table 1. The percentage of missing data for precipitation, Tmin, and Tmax varied between 0.14 and 1.98%, 2.74–28.74%, and 2.83–12.36%, respectively. The PUGMF dataset was compared to the ground station at Accra to validate its accuracy (see Fig. 2). Fig. 2 shows the mean monthly and annual correlations for precipitation, Tmin, and Tmax at Accra. The strong correlation indicates that the PUGMF dataset can be applied in the study area.

Table 1

<table>
<thead>
<tr>
<th>Longitude</th>
<th>Latitude</th>
<th>Elevation (m)</th>
<th>Name of station</th>
<th>% of Missing Data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Precipitation (Precp)</td>
<td>Minimum Temperature (Tmin)</td>
</tr>
<tr>
<td>0.166</td>
<td>5.60</td>
<td>67.7</td>
<td>Accra</td>
<td>0.14</td>
</tr>
<tr>
<td>0.15</td>
<td>5.67</td>
<td>14</td>
<td>Tema</td>
<td>0.19</td>
</tr>
<tr>
<td>0.28</td>
<td>5.68</td>
<td>50.3</td>
<td>Pokuase</td>
<td>1.98</td>
</tr>
</tbody>
</table>

Where:

\[
f_g(x|\alpha, \beta) = \frac{x^{\alpha-1}}{\beta^\alpha \Gamma(\alpha)} e^{-\frac{x}{\beta}}; x \geq 0; \alpha, \beta > 0
\]

\[(1)\]
Fig. 2. Validation of PUGMF dataset.
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x = random variable.
\( f_x \) = Gamma cumulative distribution function (CDF).
\( \Gamma \) = Gamma function;
\( \alpha \) and \( \beta \) = form and scale parameters, respectively.

However, for temperature events, a Gaussian distribution with parameter “\( \mu \)” and scale parameter “\( \sigma \)” has been confirmed as the most suitable for bias-correction of precipitation and temperature, as confirmed from the previous studies (Schoenau and Kehrig, 1990; Teutschbein and Seibert, 2012).

### 2.5. Future change analysis

The outputs of the model for Tmax, Tmin, and precipitation until 2059 were compared to the reference period (1970–2014 and 1979–2010 for the observed and virtual stations, respectively). Eqs. (2) and (3) were used to estimate the underlying anomalies in absolute and percentage differences for temperature and precipitation, respectively.

\[
\Delta_{\text{future}} = (Q_{\text{future}} - Q_{\text{base}}) \\
\Delta_{\text{future}} = \left(\frac{Q_{\text{future}} - Q_{\text{base}}}{Q_{\text{base}}}\right) \times 100
\]

Where,
\( \Delta \) = absolute and relative changes,
\( Q_{\text{base}} \) = Tmax, Tmin, or Precipitation, for the baseline period.
\( Q_{\text{future}} \) = Tmax, Tmin, or Precipitation, for the future period.
The rise and fall of the variables for the future period are signified by positive and negative signals.

### 2.6. Model performance evaluation

The study employed various evaluation metrics to investigate the performance of the bias-corrected model. The Root Mean Square Error (RMSE) (Eq. (4)), coefficient of determination (R\(^2\)) (Eq. (5)), percent bias (Pbias) (Eq. (6)), and Nash-Sutcliffe coefficient (NSE) (Eq. (7)) were used to evaluate the bias-corrected model accuracy. RMSE was employed as a goodness-of-fit showing the standard deviation of the modeled and observed data. As such, model performance is enhanced when RMSE is smaller. Also, the R\(^2\) was used to assess the goodness-of-fit of the modeled and the observed data. The model performance is enhanced when R\(^2\) approaches one. The NSE ranges from negative infinity to one. However, where NSE is equal to or >0.5, the model is seen as satisfactory. For values >0.7, the model is seen as a very good fit (Nash and Sutcliffe, 1970). To assess whether the model is under or overestimating the observed

![Bias-correction framework in CMhyd modified from [55].](image-url)
Fig. 4. Comparison of ensemble bias-corrected and raw precipitation relative to the baseline periods. Obs = Observed, mod = modeled.
Fig. 5. Comparison of ensemble bias-corrected and raw Tmax relative to the baseline periods. Obs = Observed, mod = modeled.
data, Pbias was used. The accuracy of the model increases when Pbias approaches zero.

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n} (Q_{obs} - Q_{sim})^2}{n}}
\]

\[
R^2 = \frac{\left[\sum_{i=1}^{n} \left( \frac{(Q_{obs} - \bar{Q}_{obs})}{\sum_{i=1}^{n} (Q_{obs} - \bar{Q}_{obs})} \times (Q_{sim} - \bar{Q}_{sim}) \right) \right]^2}{\sum_{i=1}^{n} (Q_{obs} - \bar{Q}_{obs})^2}
\]

\[
PBIAS = \frac{\sum_{i=1}^{n} (Q_{obs} - Q_{sim})}{\sum_{i=1}^{n} (Q_{obs})} \times 100
\]

\[
NSE = 1 - \frac{\sum_{i=1}^{n} (Q_{obs} - Q_{sim})^2}{\sum_{i=1}^{n} (Q_{obs} - \bar{Q}_{obs})^2}
\]

Where \( Q_{obs} \) = observed data, \( Q_{sim} \) = predicted data, \( \bar{Q}_{obs} \) = mean observed data, \( \bar{Q}_{sim} \) = mean predicted data and \( n \) = number of observations.

### 3. Results

#### 3.1. Performance evaluation of the bias-correction

The graphical comparisons of the ensemble bias-corrected and raw precipitation, Tmax, and Tmin are shown in Figs. 4 to 6. These

![Graphs of graphical comparisons of the ensemble bias-corrected and raw precipitation, Tmax, and Tmin](image_url)

**Fig. 6.** Comparison of ensemble bias-corrected and raw Tmin relative to the baseline periods. Obs = Observed, mod = modeled.
Fig. 7. Temporal variations in annual mean precipitation from 1970 to 2059 for SSP1–2.6, SSP2–4.5, SSP3–7.0 and SSP5–8.5.
Fig. 8. Temporal variations in annual mean $T_{\text{max}}$ from 1970 to 2059 for SSP1–2.6, SSP2–4.5, SSP3–7.0 and SSP5–8.5.
Fig. 9. Temporal variations in annual mean Tmin from 1970 to 2059 for SSP1–2.6, SSP2–4.5, SSP3–7.0 and SSP5–8.5.
reveal a good agreement between the observed and modeled precipitation, Tmax and Tmin. However, the statistics for the performance of the models are presented in Appendix A. In terms of $R^2$, the bias-corrected precipitation was able to capture the month-on-month precipitation distribution compared to the raw precipitation across all the models (Appendix A). As such, $R^2$ for the bias-corrected precipitation generally ranged from 0.93 to 0.99 compared to 0.01–0.80. Similarly, the performance of the bias-corrected Tmax and Tmin ranged from 0.78 to 99 compared to the raw Tmax and Tmin (0.01–94).

For the Pbias, performance ranged from about −7.1 to 5.7 for the bias-corrected precipitation compared to about −66 to 77 for the raw precipitation (Appendix A). In terms of bias-corrected Tmax and Tmin however, performance ranged from 0.01 to 0.23 compared to −103 to 9.2 (Appendix A). The performance of the model in terms of NSE ranged from 0.92 to 0.99, 0.77–0.99, and 0.94–0.99 for the bias-corrected precipitation, Tmin, and Tmax, respectively (Appendix A). However, for the raw precipitation, NSE ranged from −0.89–0.57, −390–0.35, and −5.9–0.83 respectively (Appendix A). Concerning RMSE, the general performance of precipitation, Tmax, and Tmin ranged from 57.87 to 531.94 mm, 0.01–0.34 mm, and 0.02–0.36 mm compared to 1657.81–7396.94 mm, 0.81–25 mm and 0.9–11 mm respectively (Appendix A).

The results, therefore, reveal an overestimation of the raw simulations. The statistics for the bias-corrected precipitation in terms of $R^2$, RMSE, Pbias, and NSE show good results (see Appendix A). This is evident in the graphical comparison of the ensemble mean of the models shown in Fig. 4-6. Moreover, Tmin recorded the lowest performance. This may be due to the quality of the Tmin data used. Tmin had a percentage of missing data between 2.74 and 28.74% which could affect the performance of the models, especially at Pokuase.

3.2. Projected mean precipitation under multiple scenarios until 2059

The projected mean precipitation for Greater Accra under SSP1–2.6, SSP2–4.5, SSP3–7.0, and SSP5–8.5 is presented in Fig. 7. The results reveal a general drop in precipitation in the future until 2059 under all the scenarios compared to the baseline period. For instance, average annual precipitation is expected to drop between 600 and 800 mm/year in the virtual stations under all the scenarios relative to the baseline of between 1000 and 1200 mm/year (see Fig. 7). However, average annual precipitation is expected to further decline to about 400 mm in the virtual stations, particularly in the 2020s, 2040s and 2050s under the worst-case scenario (SSP5–8.5). The case of synoptic stations, such as Accra, is expected to be more severe. Average annual precipitation is about 500 mm/year under all the scenarios compared to about 900 mm/year in the baseline period at Accra, Tema, and Pokuase. This indicates an average annual drop of about 400 mm. However, the drop becomes even more severe in the worst-case scenario in Accra, with approximately 200 mm/year compared to the baseline period. Despite this, there are two major spikes between 2030 and 2040 under the SSP3–7.0 and SSP5–8.5 in Accra (see Fig. 7). Under the worst-case scenario (SSP5–8.5), annual mean precipitation is expected to rise above 1200 mm/year in Accra in 2036 (Fig. 7), compared to the general trend of the future annual mean precipitation (i.e., 900 mm/year). This is projected to be more intense in Tema and Pokuase where annual mean precipitation is expected to rise above 1600 mm/year under SSP2–4.5 in 2050 compared to the overall future annual mean precipitation between 600 and 800 mm/year. This shows more intense future flood cases in Accra, Tema, and Pokuase.

3.3. Projected mean Tmax under multiple scenarios until 2059

Fig. 8 presents the projected mean maximum temperature for Greater Accra under SSP1–2.6, SSP2–4.5, SSP3–7.0, and SSP5–8.5. Future Tmax is projected to increase until 2059 under all the scenarios compared to the baseline period (Fig. 8). For instance, future annual mean Tmax is expected to increase up to 33–34 °C/year in the virtual stations under all the scenarios until 2059 (see Fig. 8) compared to the baseline period (30–32 °C/year). However, this is expected to further increase to about 36 °C in the virtual station 6, particularly in the 2050s in the worst-case scenario (SSP5–8.5), compared to 31 °C/year in the baseline period. Tmax at the synoptic stations, such as Accra, is expected to rise to about 33.5 °C/year under all the scenarios compared to the average annual Tmax of about 32 °C/year in the baseline period. However, Tmax is expected to be severe in the worst-case scenario (SSP5–8.5), with approximately 34 °C/year compared to the baseline period at Accra (see Fig. 8). Thus, daytime temperatures are expected to surge in the near- to mid-term, especially in the 2050s. This signals severe daytime temperatures, especially at Accra station. However, the lowest annual mean Tmax is expected under the SSP1–2.6 scenario across all the selected stations (see Fig. 8).

3.4. Projected mean Tmin under multiple scenarios until 2059

The projected mean Tmin for Greater Accra under SSP1–2.6, SSP2–4.5, SSP3–7.0, and SSP5–8.5 is presented in Fig. 9. The results show a general rise in the future annual mean Tmin until 2059 under all the scenarios compared to the baseline period (see Fig. 9). For instance, the future average annual Tmin is expected to rise to between 25.5 and 26.5 °C/year in the virtual stations under SSP1–2.6 and SSP2–4.5 until 2059 (see Fig. 9). However, the highest future annual average Tmin of about 28 °C/year is expected at Accra and Tema in the worst-case scenario (SSP5–8.5) compared to the annual mean Tmin of about 23 °C/year in the baseline period. Therefore, the increase in Tmin denotes an intensification in night temperatures, especially at Accra, Virtual station 6, and Tema. Thus, night temperatures in Accra are expected to be warmer in the medium term. This has an increasing relationship with other socio-economic
Fig. 10. Mean monthly precipitation changes (%) in periods of 2021–2059 (relative to 1970–2010 for the virtual stations and 1970–2014 for the ground stations) under SSP1–2.6, SSP2–4.5, SSP3–7.0 and SSP5–8.5.
3.5. Projected future net precipitation, Tmax and Tmin changes under multiple scenarios

The mean monthly change in precipitation shows a general drop in almost all the months under all the scenarios across all the stations (Fig. 10). For instance, the mean monthly precipitation at Accra and the virtual stations shows a drop in all months except July and August under SSP1–2.6, SSP2–4.5, and SSP3–7.0. The highest mean monthly increase in precipitation of about 31% relative to the baseline period is expected to occur in August under the SSP2–4.5 scenario at Accra. However, under SSP5–8.5, the mean monthly change in precipitation shows a drastic drop in expected precipitation in all months at Accra station (see Fig. 10). Greater Accra is expected to observe a severe drop in precipitation up to about 50% especially under the worst-case scenario (see Fig. 13). This shows a change in the rainfall pattern from bimodal to unimodal until 2050. For stations such as Tema, the mean monthly change in precipitation reveals spikes in most of the months under different scenarios except for January and February (Fig. 10). The magnitude of precipitation deficits is expected to worsen in the worst-case scenario (see Fig. 10). Precipitation is expected to drop by 13.61–38.22%, 7.61–39.9%, 1.8–37.25%, and 16.73–42.99% under SSP1–2.6, SSP2–4.5, SSP3–7.0, and SSP5–8.5, respectively, in Greater Accra (see Table 2).

The mean monthly changes in Tmax under the different scenarios are presented in Fig. 11. Tmax is expected to increase in all months across the selected stations. Mean monthly change in Tmax ranges from (0.81–1.73 °C), with the highest increase (of about 1.73 °C) observed in the worst-case scenario (SSP5–8.5) across all months (see Fig. 11). Tmax is expected to increase from December to January and from April to July under all the scenarios in the future (see Fig. 11). Generally, Accra is expected to be the hottest station under all scenarios (Fig. 14) in terms of Tmax. Tmax is expected to increase by 0.81–1.45 °C, 0.84–1.54 °C, 0.96–1.70 °C and 0.98–1.73 °C until 2059 under SSP1–2.6, SSP2–4.5, SSP3–7.0 and SSP5–8.5, respectively, in Greater Accra (Table 2).

Similarly, Tmin is expected to increase in all months across all future scenarios (see Fig. 12). Again, the mean monthly Tmin increased as the radiating forcing of the scenarios increased. Generally, the results reveal a bimodal temperature pattern over Greater Accra under all the scenarios. Similarly, Tmin is expected to increase from December to January and from April to July. However, Accra is expected to experience the highest change in mean monthly Tmin of about 6.9 °C in January under all the scenarios. However, Pokuase is expected to record an increase in the mean monthly Tmin of 4 °C until 2059 under SSP5–8.5 (Fig. 12). Pokuase and parts of Accra are expected to be the hottest in terms of Tmin under SSP3–7.0 and SSP5–8.5 (see Fig. 15). Therefore, Tmin is generally expected to increase by 1.33–2.02 °C, 1.49–2.22 °C, 1.71–4.75 °C, and 1.75–4.83 °C under SSP1–2.6, SSP2–4.5, SSP3–7.0, and SSP5–8.5, respectively, in Greater Accra (see Table 2).

These changes signify that Greater Accra is expected to be warmer up to 1.73 °C and 4.83 °C during the day and night, respectively until 2059.

4. Discussion

4.1. Model performance evaluation

Generally, the model performed well compared to previous studies. For instance, the performance of the ensemble bias-corrected precipitation, Tmax, and Tmin in terms of R², NSE, Pbias, and RMSE outperformed that of the ensemble raw data (Yeboah et al., 2022). However, Tmin recorded the lowest performance. This may be attributed to the conditional quality of the input data which makes it difficult for GCMs to simulate the observed data (Siabi et al., 2021), thus affecting the performance of the model. Observed data quality is an important part of climate modeling due to its effect on the output of the model. For instance, the gap seen in the historical and projected data at Pokuase in Figs. 11 and 12 may be attributed to missing data within the observed dataset used. However, the gap between the historical and projected data for the virtual stations seen in Figs. 10 to 12 is as a result of the end year (2010) of the PUGMF data and the start year (2015) of the projected data.

The raw GCMs were found to generally overestimate Tmax and Tmin, although the monthly discrepancies in the observed data are

<table>
<thead>
<tr>
<th>Station</th>
<th>Precipitation (mm)</th>
<th>Tmax (°C)</th>
<th>Tmin (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SSP1</td>
<td>SSP2</td>
<td>SSP3</td>
</tr>
<tr>
<td>Virt1</td>
<td>–19.11</td>
<td>–22.99</td>
<td>–15.17</td>
</tr>
<tr>
<td>Virt2</td>
<td>–34.18</td>
<td>–37.50</td>
<td>–32.13</td>
</tr>
<tr>
<td>Virt3</td>
<td>–29.69</td>
<td>–33.47</td>
<td>–27.64</td>
</tr>
<tr>
<td>Virt4</td>
<td>–24.21</td>
<td>–30.66</td>
<td>–24.53</td>
</tr>
<tr>
<td>Virt5</td>
<td>–24.34</td>
<td>–28.16</td>
<td>–21.72</td>
</tr>
<tr>
<td>Virt6</td>
<td>–38.22</td>
<td>–39.90</td>
<td>–37.25</td>
</tr>
<tr>
<td>Accra</td>
<td>–33.88</td>
<td>–31.20</td>
<td>–30.24</td>
</tr>
<tr>
<td>Tema</td>
<td>–13.61</td>
<td>–7.61</td>
<td>–1.80</td>
</tr>
<tr>
<td>Pokuase</td>
<td>–28.50</td>
<td>–13.16</td>
<td>–10.94</td>
</tr>
</tbody>
</table>
Fig. 11. Mean monthly Tmax changes (°C) in periods of 2021–2059 (relative to 1970–2010 for the virtual stations and 1970–2014 for the ground stations) under SSP1–2.6, SSP2–4.5, SSP3–7.0 and SSP5–8.5.
Fig. 12. Mean monthly Tmin changes (°C) in periods of 2021–2059 (relative to 1970–2010 for the virtual stations and 1970–2014 for the ground stations) under SSP1–2.6, SSP2–4.5, SSP3–7.0 and SSP5–8.5.
Fig. 13. Changes in annual mean precipitation in percentage change for the climate scenarios SSP1, SSP2, SSP3 and SSP5, with respect the baseline periods 1970–2010 for the virtual stations and 1970–2014 for the ground stations.
Fig. 14. Changes in annual mean Tmax in °C for the climate scenarios SSP1, SSP2, SSP3 and SSP5, with respect the baseline periods 1970–2010 for the virtual stations and 1970–2014 for the ground stations.

Fig. 15. Changes in annual mean Tmin in °C for the climate scenarios SSP1, SSP2, SSP3 and SSP5, with respect the baseline periods 1970–2010 for the virtual stations and 1970–2014 for the ground stations.
slightly captured. This means that the raw data generally failed to simulate the observed Tmax and Tmin. However, on monthly basis, the models were able to slightly simulate the observed data. However, the simulated raw GCM data overestimated the relatively low precipitation while underestimating the peaks. This is in line with the findings of Yeboah et al. (2022). The application of distribution mapping bias correction, therefore, revealed an efficient reduction in the discrepancies in the raw GCM. Therefore, there was an improvement in the bias-corrected data despite some marginal existing discrepancies. Moreover, the RMSE and the Pbias indicate some level of uncertainty across the stations. Other studies have reported the association of such uncertainties after applying the distribution mapping and linear scaling bias-correction methods (Zhang et al., 2018). The power transformation enhances statistical variability but fails to capture the distribution of the probability (Zhang et al., 2018). Linear scaling, on the other hand, was able to efficiently reduce the bias in the average precipitation (Zhang et al., 2018). In the study of Zhang et al. (2018), all other bias-correction methods revealed advantages and disadvantages. Therefore, for raw GCMs or RCMs to be used for any impact assessment, bias correction must be employed.

Generally, the performance of the CMIP6 data shows better performance in terms of simulating the observed data, especially for precipitation, compared to the previous CMIP5 models presented in (Ajayi and Ilori, 2020; Nourani et al., 2022; Okafor et al., 2019). This signifies the enhancement in modeling precipitation in CMIP6. However, the available ground station data were found to have data gaps. This was known to affect model performance (Gebrechorkos et al., 2019; Gulacha and Mulungu, 2017; Siabi et al., 2021; Yeboah et al., 2022). Therefore, it is recommended that further studies combine ground station, reanalysis, and satellite products to get better model performance. It is also relevant, that policymakers in Ghana invested in the establishment of more ground stations across each region in the country. This will reduce uncertainties and prediction errors inherent in future climate projections which leads to realistic future projections for precise and better planning. Future studies can also consider employing the statistical downscaling approach. Despite the relatively higher resolution of dynamic downscaling offered by RCMs compared to GCMs, its applicability in impact assessment research at a local scale is constrained due to model complexity, requirements of resources such as computational capacities, uncertainties, and biases as well as model sensitivity to the boundary conditions of GCMs (Hamlet et al., 2010; International Research Institute for Climate and Society, 2012; Wilby et al., 2002). The utilization of statistical models conversely requires fewer requirements for processing and computational capacities rendering it more simple, faster, and more effective than dynamic downscaling (Gebrechorkos et al., 2019). Siabi et al. (2021) noted that statistical downscaling is noted for its accuracy in missing data infilling in data-scarce countries such as Africa and Middle-east.

Moreover, a recent study by Amnor et al. (2022), which compared the four CMIP6 models with a Global Coupled Configuration 2 (GC2) of the Unified Model (UM) revealed that the UM model’s performance in simulating precipitation and temperature was higher than the four CMIP6 data.

4.2. Projected climate change

Precipitation is projected to decline until the 2050s with a marginal increase in July and August across most of the stations under all the future scenarios. The southern part of Ghana is characterized by two rainy seasons. For instance, Accra is expected to record precipitation events from May to August and from September to November. However, the heaviest precipitation events are expected to occur in July and August. These findings do not only reveal a potential shift in the rainy seasons but a potential shift in the amount and intensity of precipitation to occur, especially in the two major rainy seasons in southern Ghana. Alizadeh-Chooobari and Najafi (2018) found that a rise in temperature drives the water vapor inland before precipitating in coastal regions. This may be a cause for the reduced amount and intensity of the projected precipitation. This finding is also in-line with the findings of Yeboah et al. (2022), which found that the pattern of precipitation is expected to shift towards the Volta Basin by 2100. However, the magnitude of change across the SSP scenarios does not reveal a consistent pattern across the stations. This reveals the erratic nature of precipitation variability and the uncertainties associated with its predictions under all the scenarios. For instance, the highest change in precipitation in Accra under SSP1–2.6 is about 1.4% in August until 2059. This is below the 4.8% area-mean change in Africa under the SSP1–2.6 revealed by Almazroui et al. (2020). For Tema and Pokuase, the highest change in precipitation is about 14.1% and 10% in June and March, respectively., precipitation is expected to drop by between 13.6% and 38.2% relative to the baseline period across Greater Accra in terms of the overall change from 2021 to 2050. This shows that Greater Accra will be below the area-mean change leading to severe drought in parts of Greater Accra in the forthcoming years. However, the highest mean annual precipitation of over 1200 mm shown in Fig. 7 is expected to occur under the SSP5 scenario in Accra in the 2030s. This indicates that unexpectedly heavy precipitation events are to occur, making precipitation-driven floods more frequent, especially in Accra. These uncertainties call for emergency preparedness towards extreme precipitation events that are likely to occur in the future (Accra Metropolitan Assembly and C40 Cities, 2019; Stanturf et al., 2011). This finding is in line with the findings of Kwaku and Duke (2007) on the intensity of precipitation in Accra, which predicted that every 2 years (since 1975–2004), a maximum of about 84.05 mm, 91.06 mm, 100.40 mm, 105.67 mm, and 109.47 mm in 1, 2, 3, 4 and 5-day frequency respectively, are expected to occur at Accra.

The projected Tmax and Tmin are expected to gradually increase in the low-level radiative forcing scenario and become severe in the high-level radiative forcing scenario until 2050 as revealed in previous studies (Sylla et al., 2016). Daytime and nighttime temperatures are expected to become high in the near future and intensify until 2050 across all seasons. This aligns with existing studies over West Africa which reveal that seasonal temperature-related indices indicate great patterns of warming in all seasons (Barry et al., 2018).

The change in mean monthly Tmin is expected to be higher than the expected mean monthly change in Tmax. The study by Barry et al. (2018) indicated that the annual average daily Tmin has risen more than the annual average daily Tmax, resulting in a decrease in the diurnal temperature range, whereby warm days and nights have become more frequent, and cold days and nights have been less
frequent. This is expected to intensify as revealed by the study, especially under the worst-case SSP scenarios (SSP3–7.0 and SSP5–8.5). This has rather, severe potential implications on water, food, and energy resources among others (IPCC, 2007; James et al., 2013; Mustafa et al., 2016). For instance, high temperatures would result in hydrological effects, thus, improving transpiration via higher leaf-to-air vapor pressure deficits. This could further exacerbate dry season water stress (James et al., 2013).

Generally, precipitation is expected to be erratic under SSP1–2.6 and become severe under SSP5–8.5 due to a rise in temperature (higher ET will lead to higher precipitation). However, the lowest and highest change in mean monthly Tmax and Tmin is expected to occur under the SSP1–2.6 and SSP5–8.5 scenarios in all the selected stations. Therefore, if Greater Accra achieved the 1.5 °C and 2.0 °C global warming goals under the Paris Agreement under the SSP1–2.6, the drop in precipitation is expected to be marginal (−13.61–38.22%) by 2059. Again, Tmax and Tmin will increase in the range of 0.81–2.16 °C and 1.33–2.02 °C respectively, as revealed by the results of this study. This falls within the projected warming levels between 1.3 °C and 2.4 °C under the SSP1–2.6 (Riahi et al., 2017) though the periods for the current study and that of Riahi et al. (2017) vary (i.e 2059 and 2100 respectively). For the SSP2–4.5, although, precipitation is expected to marginally drop with some peaks in some months, Tmax and Tmin are expected to increase by 0.84–2.35 °C and 1.49–2.22 °C, respectively, if policies worldwide focused on environmental goals through international cooperation.

Under SSP3–7.0, if Greater Accra and the world retreat from international cooperation and focus on its economic goals only, precipitation will severely drop with some peaks, whereas Tmax and Tmin increase by 0.96–1.70 °C and 1.71–4.75 °C respectively by 2059. Under SSP5–8.5, if Greater Accra and the world continue to increase emissions and nothing is done fight climate change, precipitation is expected to severely drop, whereas Tmax and Tmin are expected to increase by 0.98–1.73 °C and 1.75–4.83 °C, respectively by 2059.

One key finding of this study is that night temperatures are expected to increase more than daytime temperatures in Greater Accra until 2050. Thus, night warming will be faster and more common than day warming across Greater Accra in the forthcoming years. This finding agrees with that of Wemegah et al. (2020) that night temperatures warmed faster than daytime temperatures in Greater Accra resulting in a tangible reduction in the diurnal temperature range. The accumulation of CO₂ in the atmosphere as a result of anthropogenic emissions decreases the radiation amount released into the atmosphere (Davy et al., 2017). This surge both daytime and nighttime temperatures. However, due to the much smaller volume of air that gets warmed at night, the excess energy coupled to the climate system from CO₂ leads to a higher degree of warming at night than during the day (Davy et al., 2017). Other regionalized feedback effects such as precipitation, soil moisture, and cloud cover changes may also contribute (Davy et al., 2017).

Generally, Accra and its environs are expected to observe severe changes in climate in the near- to mid-term. This also has impacts on other factors such as population growth, rural-urban migration, and urban sprawl, which may worsen, especially under worst-case scenario conditions.

5. Implications of the study

According to Pachauri et al., (2015), the global temperature is expected to rise between 0.3 and 4.8 °C by the end of the 21st century relative to 1986–2005 under the RCP scenarios. However, McSweeney et al. (2010) found that the average annual temperatures of Ghana will rise by 1.0–3.0 °C in the 2060s and 1.5–5.2 °C by the 2090s relative to 1960–2006 under the A2, A1B, and B1 scenarios. These findings are in line with that of this study. However, annual minimum temperatures are expected to increase above the 3.0 °C shown by McSweeney et al. (2010) to about 4.8 °C relative to 1970–2014 under the SSP scenarios by 2059 in Greater Accra. There are potential related implications of the findings of this study on the natural environment, which will also impact other facets, such as socio-economic, agriculture, health, and energy sectors. For instance, water quantity and quality are expected to be affected as a result of changes in the climate in Africa (IPCC, 2007; Okafor et al., 2019), which impacts aquifers, lakes, reservoirs, and storage in rivers (Obahoundje et al., 2017; Siabi et al., 2021). Moreover, climate-sensitive energy sectors, such as hydro power, will also be impacted as a result of climate variability and changes in water resources (Akpoti et al., 2016; Kabo-Bah et al., 2016; Obahoundje et al., 2017), leading to challenges in sustainable energy management. The highest precipitation per year revealed in this study serves as a warning regarding the likelihood of extreme precipitation events in Accra. Results can guide stormwater and land-use infrastructure planning. Therefore, natural water and soil conservation strategies, such as the development of storm and dam water management drains must be taken into consideration in future policies in Accra and Ghana. One major implication of present and future extreme precipitation events is the change in the urban hydrology of Accra resulting in perennial flood events (Odag, 2009; Simister, 2010). However, changes in urban land use and land cover, as well as rapid urbanization may exacerbate the situation. Therefore, extreme precipitation events are noted to be the fundamental cause of flooding if associated stormwater and run-offs are not properly managed in flood-prone areas. Other factors, such as low-lying topography, encroachments by slums, and the presence of water bodies render significant areas vulnerable to flood events in Accra. In June 2015, a flood that occurred in a day resulted in approximately $120 million in damages in Accra (Accra Metropolitan Assembly and C40 Cities, 2019).

An increase in daytime temperatures can also positively or negatively affect the installation of solar photovoltaics (PVs) at stations such as Accra, Tema, and Pokuase. Solar PVs have specific optimal temperatures to increase performance. Temperatures above this optimal range may retard performance. Several studies have shown the effects of temperature on the power output of solar PVs, where
high temperatures cause a reduction in PV cell voltage and consequently the power output of the solar PV system (Adeeb et al., 2019; Al-Badi et al., 2012; Dubey et al., 2013). A 1 °C increase in the temperature of a PV cell can reduce the power output of the PV system by 0.5–0.6% (Al-Badi et al., 2012; Hajiah et al., 2012; Kazem and Khatib, 2013). For instance, the study of Fadlallah and Benhadji Serradj (2020) revealed that the operating temperature for the Studer VarioTrack VT-65 with Generic PV was 45 °C. However, temperatures between 20 and 30 °C were found to be optimal and increased performance.

Generally, another important aspect of the economy that will be affected in the future is the hydropower sector in Ghana. The generation of hydropower is highly dependent on the available water resources. The effect of temperature and precipitation variability has a direct impact on the generation of electricity. Thus, an increase in temperature will increase the rate of evapotranspiration which may result in severe drought and water stress. This is projected to affect water accessibility and availability, as well as further, affect the performance of hydropower as typified at Bui, Akosombo, and Kpong in Ghana. An in-depth analysis of the Akosombo dam by Kabo-Bah et al. (2016) revealed that the level of water frequently drops reaching its minimal range in May/June each year which has detrimental effects on hydropower generation at the Akosombo dam. This will affect Greater Accra the most since it is the highest consumer of electricity in Ghana (Energy Commission, 2021).

The results of the study also reveal that Greater Accra will be vulnerable to drought under all the scenarios. This may lead to devastating effects on water resources, agriculture, and related socio-economic activities and, as a result, further, lead to severe consequences on food security and water resource management (Addi et al., 2021). The study of Addi et al. (2021) revealed that stations such as Accra and Tema observed very short drought periods and less extreme drought conditions beyond 2005–2013. This indicates that these stations have had wetter conditions in recent years. However, the future projections under the SSP scenarios contradict these findings. Extreme events are expected to regionally escalate one another (Seneviratne et al., 2021). For instance, droughts and heatwaves together with high temperatures and intense radiative forcing may cause drying tendencies on land due to surged evapotranspiration and drier soils leading to reduced evapotranspiration and higher sensible hot temperatures and heat flux (Seneviratne et al., 2021).

Moreover, cooling demands for thermal power plants are also expected to increase; higher temperatures may lead to heat waves in the region, especially at night. Therefore, the amount of energy consumption during the night is going to increase due to the demand for cooling systems to maintain room temperatures.

Higher ambient temperatures will also subject animal and plant species to heat stress. Thus, there is a risk to agricultural production in the Greater Accra region due to temperature increases as well (van Oort and Zwart, 2018).

### 6. Practical policy recommendations based on the prediction results

The results of the study call for a rapid climate adaptation strategy since many of the vulnerabilities and impacts are interrelated. Therefore, policy recommendations to tackle these issues may encompass different stakeholders to help prioritize actions.

In the face of increasing precipitation which is known as a threat to the region, the study recommends municipalities in Greater Accra enact policies that reduce the use of hardscapes in flood-prone areas. This has the potential to abate surface runoff which leads to localized flooding or flash floods. However, one of the major challenges in the Greater Accra region is poor solid waste management and the lack of a proper drainage system. Therefore, the study recommends that the municipalities in Greater Accra incentivize residents to dump their waste at the communal collection points instead of dumping waste into drains, on beaches, and roads. Moreover, the municipalities such as Accra Metropolitan Assembly (AMA) should increase collection points to encourage proper disposal of waste. Also, adequate protection must be given to storage infrastructure from surface flow to prevent contamination and infrastructural damage in the case of local water and sanitation providers. The study again, recommends the rehabilitation of existing drains and the building of new ones across the region. For instance, Clemenz et al. (2020) noted that new drainage is required in Shiabu and Chorkor to excess water from the “beach road” into the sea. There is an urgent need for a drainage system directing the water into the lagoon to prevent flooding. Furthermore, the municipality must dredge and stabilize the existing waterways which serve as natural drains, and protect them from rubbish to reclaim the land. This is an urgent action to fight climate change and its adverse effects and make Greater Accra safer, more inclusive, sustainable, and more resilient which addresses SDGs 11 and 13.

For a decrease in precipitation, the study makes the following recommendations, residents are encouraged to expand their household water storage capacity and harvest rainfall as a preparation for future water shortages. Also, urban water service providers are to expand their safe water storage capacity and treat stored water. The Ghana Water Company Limited should consider climate adaptation strategies in their planning to develop adequate treatment and distribution infrastructure for future precipitation decline. For instance, the findings of Clemenz et al. (2020) revealed that the Ghana Water Company Limited should alleviate the non-revenue water which is about 50% to store water and increase revenue which could be used to subsidize a pro-poor tariff and hence increase household connections. Again, public toilet owners who dwell on boreholes for their operations must invest in getting a generator to mitigate the adverse impact of power outages which is likely to rise in frequency if precipitation decline.

For sea-level rise which is expected to increase coastal erosion, fringe communities must stop development along the beach as well as sand winning. Also, National Disaster Management Organization (NADMO) must sensitize fringe communities about sand winning and place a ban on this operation. Municipalities must consider relocating communities along the coast in the long run as well as constructing a sea defense system.
7. Conclusion

Developing tools to address future climate changes is critical to the success of climate policy in the sustainable development context. Currently, there is little or no known study on climate change assessment using the CMIP6 data under the Shared Socio-economic Pathways climate scenarios in Greater Accra. This study used data from seven regional climate models to statistically bias-correct ground station data and reanalysis data over Accra until 2059. The results showed the bias-corrected precipitation, Tmax, and Tmin had better performance compared to the raw data in simulating the observed data.

Moreover, the results revealed a decline in projected precipitation up to about 50% relative to the baseline period by 2059. This reveals a potential drop in rainfall intensity and a shift in the rainfall pattern of Accra from bimodal to unimodal by 2059. This is expected to cause severe droughts in parts of Greater Accra. However, the study revealed an extreme event in the 2030s where precipitation is expected to rise as high as 1200 mm (about a 31% increase compared to the baseline period) in the worst-case scenario. This could trigger unexpected natural disasters, such as flash floods, in parts of the Greater Accra region. However, the overall trend of precipitation reveals a significant decline until 2059. This is expected to trigger severe droughts in parts of Greater Accra. The maximum temperature is expected to increase by 0.98–1.73 °C in the worst-case scenario. The highest maximum temperature is expected to occur from 2030 to 2050, especially in the worst-case scenario (SSP5–8.5). Similarly, the minimum temperature is expected to increase by 1.75–4.83 °C under SSP5–8.5. Therefore, day- and nighttime temperatures are expected to increase, especially under the worst-case scenario (SSP5–8.5) in the Greater Accra region until 2050. An increase in daytime temperatures can affect solar PVs in the region. However, cooling demands for thermal power plants are expected to increase. Nighttime energy consumption will also increase due to cooling demands to maintain room temperatures as a result of potential heat waves. Generally, the increasing and declining trend in temperature and precipitation respectively are projected to harm the performance of hydropower dams in Ghana. This may further affect energy consumption in Greater Accra. Therefore, sustainable management challenges are expected to occur. This calls for urgent policies to support climate action to combat climate-related hazards in the region. Therefore, efforts to mitigate and adapt to climate changes must be increased leading to the rising complexity of interactions including connections among water, human health, energy, biodiversity, and land use. Mitigation approaches can take the form of achieving societal goals such as those connected to food security, human health, energy access, livelihood, environmental quality, and sustainable development.

The study reveals that Greater Accra is projected to be vulnerable to climate change in the future. This is expected to affect various parts of the economy (e.g. hydropower). This implies that Ghana will need to diversify its energy sources to build a resilient power sector as an approach to supplement its energy demand during drastic water level drops and levels of variability in hydropower generation. This will require the government of Ghana and energy providers to invest and capitalize on renewable energy sources such as solar energy and thermal power plants to augment electricity generation. Therefore, future investments in the energy sector must carefully consider the impacts of temperature and precipitation on the potential for energy generation. Beyond this, the “Go Green” agenda must be carefully looked at by the government, non-governmental organizations, and individuals which supports the decentralization of the broader goal of climate resilience to the grassroots level. Such climate actions appreciate the interdependency between humanity and its natural system. For instance, converting hardscapes at vantage parts in Greater Accra into Green zones and afforestation. This will reduce extreme temperature effects and floods as well as their related cost. The study serves as a guideline for evidence-based decision-making by stakeholders to directly relate actions to immediate needs based on scenario modeling. As such, actions towards energy, transportation, building and construction, land use and spatial planning, solid waste, and wastewater, as well as several measures targeting mainstreaming the climate change threat into development processes in the future.

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Declaration of Competing Interest

The authors declare no competing interests.

Data availability

Data will be made available on request.

Acknowledgment

This study was supported by the Swiss National Science Foundation (SNF) (grant number IZSTZ0_193649). The authors are grateful for the support.

Appendix A. Appendix
Fig. 1. Model performance evaluation in terms of $R^2$ across models.
### Fig. 2. Pbias of the models.

<table>
<thead>
<tr>
<th>Model</th>
<th>BCC-CSM2.1-G</th>
<th>CANESM5</th>
<th>ESM2M</th>
<th>IPSL-CM5A-LR</th>
<th>MPI-ESM1-2-HR</th>
<th>MPI-ESM2-0</th>
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<td>Bias</td>
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<td></td>
<td></td>
<td></td>
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<td>0.07</td>
<td>0.05</td>
<td>0.02</td>
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<td>0.1</td>
<td>0.06</td>
<td>0.02</td>
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</tbody>
</table>

| Tmax | Bias           |                 |                 |                 |                 |               |
| 0.03 | -1.5           | 3.7             | 4.7             | -1.3            | 5.6            |
| 2.1  | -16            | 1.3             | -35             | -34             | -38            |
| 5.4  | -4.7           | 4.8             | -6.2            | -4.6            | -10           |
| 0.8  | -0.9           | 0.8             | -6.6            | -6.2            | -4.9          |
| -0.6 | -0.4           | 8.1             | -0.6            | -0.6            | -6.2          |
| -2.1 | 2              | 1.6             | 6.5             | -3.4            | -7.5          |
| -0.9 | 0.7            | 0.6             | 7.8             | -2.2            | -0.8          |
| 7.7  | -4.4           | 5.7             | 9.2             | 5.2             | 6.5          |

### Fig. 2. Raw of the models.

<table>
<thead>
<tr>
<th>Model</th>
<th>BCC-CSM2.1-G</th>
<th>CANESM5</th>
<th>ESM2M</th>
<th>IPSL-CM5A-LR</th>
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</table>

| Tmax | Raw           |                 |                 |                 |                 |               |
| -48  | 62            | -44             | -42             | -30             | -37            | 77            |
| -19  | -53           | -30             | -53             | 2.4             | -22            | 7.1           |
| -42  | -66           | -50             | -66             | -26             | -44            | 23            |
| -12  | -48           | -25             | -51             | 12              | -14            | 18            |
| -17  | -51           | -29             | -54             | 12              | -14            | 11            |
| -13  | -48           | -25             | -51             | 12              | -14            | 17            |
| -16  | -50           | -26             | -53             | 6.7             | -17            | 12            |
| -14  | -49           | -26             | -52             | 9.9             | -15            | 16            |
| -29  | -40           | -20             | 32              | -5.7            | -55            | 1.4e+02      |
Fig. 3. Model performance evaluation in terms of NSE.
Fig. 4. Model performance evaluation in terms of RMSE.
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