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Assessment of Future Climate under CMIP6-Based Shared Socioeconomic Pathways (SSP) Scenarios in the Nouhao Sub-Basin, East-Central Burkina Faso

Abdérahim Toguyeni[1], Ali Doumounia[1,2*], Wendkuni Ghislain Noba[1], Lucien Damiba[3], François Zougmore[1]

[1]Laboratory of Materials and Environment, Joseph Ki-Zerbo University, Ouagadougou, Burkina Faso
[2]Institute of Science and Technology, Ecole Normale Supérieure, Ouagadougou, Burkina Faso
[3]WaterAid, International Program Department, Research and Knowledge Management in West Africa, Ouagadougou, Burkina Faso
Email: *doumounia80@gmail.com

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Abstract

This study assesses future climate projections for the Nouhao sub-basin at three key temporal horizons (2050, 2070, and 2100) under different SSP scenarios. Using recent precipitation and temperature data from 17 global CMIP6 models downscaled at a 0.25˚ resolution, the multi-model approach was applied to capture the range of future climate changes. The CMIP6 models were validated against CHIRP and ERA5 reference datasets, demonstrating strong performance for precipitation (r = 0.76, RMSE = 29.14 mm, MAE = 24.72 mm) and moderate accuracy for temperature (r = 0.27, RMSE = 0.30˚C, MAE = 0.26˚C), with all metrics calculated at the annual timescale. Results indicate a projected 35% increase in precipitation across the basin by 2100, alongside a gradual temperature rise of 1˚C to 4˚C. However, the analysis reveals significant uncertainties, particularly for temperature and precipitation projections, with some individual models suggesting a slight decline in precipitation and even cooling trends over the basin. These discrepancies underscore the challenges in modelling regional climate impacts and the need for more robust projections. These findings highlight the urgency of developing basin-specific adaptation strategies, focusing on agriculture, water management, and climate resilience. Policymakers are thus provided with critical insights to guide proactive decision-making, ensuring that the basin is better prepared for future climate challenges.

Keywords

Climate Change, CMIP6, Multi-Model, Nouhao Sub-Basin, SSP

1. Introduction

Climate change is intensifying extreme weather events (such as droughts, floods, and heatwaves) across most regions of the planet, increasing both their frequency and severity [1]. This is why, today, there is strong demand for reliable and accurate hydro-climatic forecasts in order to cope with these climatic hazards [2]. Burkina Faso, a Sahelian country, is highly vulnerable to this climatic variability due to its geographical position and underdevelopment [3]. This situation affects, for example, the availability of water resources for various uses. The Nouhao sub-basin, located in the center-east of the country, is not immune to these challenges, given its socio-economic structure, which is largely based on agriculture. In this context, it is crucial to provide decision-makers with up-to-date information on expected future climate trends for this strategic sub-basin. This will enable them to better anticipate the risks of flooding disasters and, more importantly, droughts, which often exacerbate conflicts between water users.

Several studies have been proposed in the literature to address the impacts of climate change in Burkina Faso. For example, [4] projected temperatures and precipitation in Burkina Faso using NEX-GDDP-CMIP6 data from 35 models following SSP scenarios. Using the ensemble mean of these models, they obtained results suggesting a sustained temperature increase of around 4.3˚C under SSP5-8.5 and a precipitation increase of around 30% by the end of the century. [5] analyzed temperature and rainfall projections to 2090 under Representative Concentration Pathways (RCP) scenarios in Burkina Faso. They also adopted the multi-model approach and concluded that the country's current warming trend will continue at a steady pace until mid-century, whatever the scenario. For precipitation, an increase of 5% to 20% by the end of the century is predicted for the high-emission scenario (RCP8.5). Burkina Faso's Climate Change Adaptation Program commissioned an update of this study in 2021 [6]. This study, which uses recent data with projections according to SSP scenarios, suggests that air temperature will increase according to SSP scenarios until the end of the century. As for rainfall, it will increase until the end of the century, according to 80% of the models and whatever the scenarios. At the scale of the Nouhao sub-basin, several studies have been carried out in an attempt to understand climate change. [7] has investigated the future climate in the sub-basin using low-resolution projection data (50 km × 50 km), unsuitable for the small size of the basin, and also using RCP scenarios, now obsolete, instead of the SSP (Shared Socio-economic Pathways) promoted by the 6th IPCC report [8]. [9] investigated climate variability in the Nouhao sub-basin, based on the period 1982-2014. They highlighted an overall increase in rainfall patterns over the period, with a more marked increase of 4.5%

over the period 1995-2014. They also noticed an increase in temperatures over the period. [10] performed forecasts of hydro-climatic parameters in the Nouhao sub-basin. This study was based on rainfall and piezometric data collection campaigns over a relatively short period, 2012-2018. They came up with a statistical forecast model that exhibited good scores. For example, from 2016 to 2018, the gap between forecasts and historical data varied from 5% to 24%. However, a longer data period is needed to strengthen the model. In light of its results, there is a need to update the future climate projections in the Nouhao sub-basin using recent data (with better resolution) to better understand the various hazards that are expected in 2050, 2070, and 2100 based on SSP scenarios. In this view, the NEX-GDDP-CMIP6 dataset, with a spatial resolution of 0.25˚ (approximately 25 km × 25 km, or 625 km^2 per grid cell), is well-suited for representing the relatively small Nouhao sub-basin, which spans an area of 4261 km^2. At this resolution, the sub-basin is covered by approximately seven (7) grid cells. In comparison, a coarser resolution, such as 0.5˚ (50 km × 50 km, or 2500 km^2 per grid cell), would yield fewer than two (2) grid cells for the same area, making it less appropriate for detailed spatial analysis within the basin.

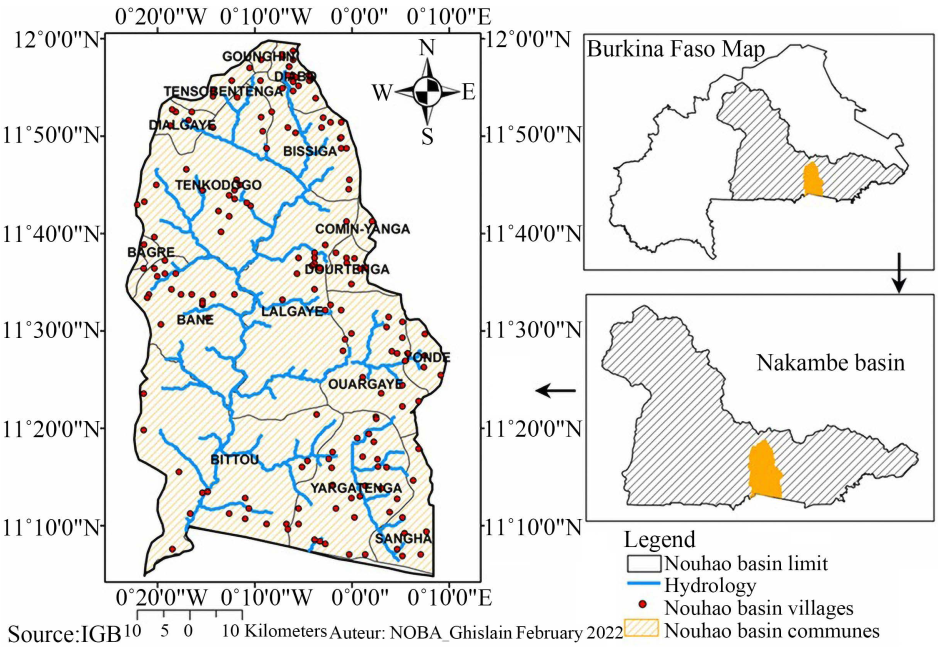
The main objective of this study is to analyze the future climate characteristics of the Nouhao sub-basin in East-Central Burkina Faso. Specifically, it aims to assess the spatio-temporal distribution of projected precipitation and temperature, and to evaluate future climate change patterns under various Shared Socioeconomic Pathway (SSP) scenarios. Prior to this analysis, a comparison among the CMIP6 historical dataset, CHIRPS, and ERA5 reference datasets is conducted to evaluate the performance of the climate models.

This document is organized as follows: Section 2 provides an overview of the study area, details on the historical data used for model ensemble-mean validation, the NEX-GDDP-CMIP6 data, and the methodology. Section 3 presents the results and discussion on the model evaluation and projected climate changes. Finally, Section 4 offers the conclusion.

2. Materials and Methods

2.1. Study Area

This study focuses on the Nouhao sub-basin, located in the national Nakambé river basin (**Figure 1**). Its administrative boundaries lie mainly in the Centre-Est region of Burkina Faso. It covers sixteen (16) municipalities and nearly 180 villages, with an estimated population of 340,000 and surface area of 4261 km^2 [11]. The West African monsoon is the main driver of rainfall in this basin, which can be divided into two climatic zones [12]. In the extreme south, the Sudanian zone receives between 900 and 1200 mm of annual rainfall with a rainy season lasting around 5 to 6 months. Elsewhere, a Sudano-Sahelian zone has annual rainfall of 600 to 900 mm and an average rainy season of 4 to 5 months. Runoff comes from the main river, the Nouhao, and its tributaries, the most important of which is the Sablogo [9]. These are non-perennial rivers, with floods coinciding with the peak of the August-September rainy season [13].



Source: NOBA Ghislain.

Figure 1. Study area.

2.2. Data

In this study, we utilized two types of data in NetCDF format: historical data and projection data. Historical daily precipitation data were obtained from the CHIRP dataset, with a spatial resolution of 0.25˚, covering a 30-year period from 1981 to 2010. CHIRP data are acknowledged to be adequate for model evaluation with regard to the precipitation parameter [14] [15]. Historical daily temperature data are derived from ERA5 reanalyses, also with a resolution of 0.25˚ and covering a 30-year period (1981-2010). ERA5 reanalysis data are produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5 data perform very well in the evaluation of temperature model outputs [16].

The projection data used are from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) as part of the Climate Model Intercomparison Project (CMIP6). These are the most recent data from the NEX-GDDP program, statistically downscaled to 0.25˚ [17]. These include daily precipitation, minimum, and maximum temperature data from seventeen (17) models (**Table 1**).

Table 1. Models used.

N˚	Models	Institutions	Country/Area
1	ACCESS-CM2	ACCESS	Australia
2	ACCESS-ESM1-5	ACCESS	Australia
3	BCC-CSM2-MR	BCC-CSM	China
4	CanESM5	CanESM	Canada

Continued

5	CMCC-CM2-SR5	CMCC	Italy
6	CMCC-ESM2	CMCC	Italy
7	GISS-E2-1-G	GISS	USA
8	HadGEM3-GC31-LL	Hadley Centre	UK
9	MIROC-ES2L	MIROC	Japan
10	MIROC6	MIROC	Japan
11	MPI-ESM1-2-HR	MPI	Germany
12	MPI-ESM1-2-LR	MPI	Germany
13	MRI-ESM2-0	MRI	Japan
14	NESM3	NESM	China
15	NorESM2-LM	NorESM	Norway
16	NorESM2-MM	NorESM	Norway

These data cover the period 2020-2100 according to the three scenarios selected (SSP1-2.6, SSP2-4.5, and SSP5-8.5). The choice of these scenarios from the five (SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) developed in the 6th report of the Intergovernmental Panel on Climate Change (IPCC) is justified by their scientific relevance for sectoral impact studies [12]. Moreover, these three scenarios provide a link with previous RCPs [18].

As a reminder, the SSPs assess the climate response to five socio-economic scenarios that encompass all possible future developments in anthropogenic factors (Population, Education, Urbanization, and GDP). The five scenarios selected by the IPCC are as follows [8]:

- 2 scenarios with high and very high greenhouse gas (GHG) emissions **SSP3-7.0** and **SSP5-8.5**.
- A scenario with intermediate GHG emissions: **SSP2-4.5**.
- 2 scenarios with very low and low GHG emissions: **SSP1-1.9** and **SSP1-2.6**.

2.3. Processing Tools

Data processing and analysis were conducted using a combination of tools tailored to climate data workflows. The Climate Data Operator (CDO), developed by Uwe Schulzweida at the Max Planck Institute for Meteorology (MPI-M), was employed for manipulating and analyzing climate model outputs. Tasks performed with CDO included file concatenation, format conversion, and the calculation of ensemble means [19]. For visualizing the spatio-temporal distribution of climate variables within the Nouhao sub-basin, the Ferret software, developed by the National Oceanic and Atmospheric Administration (NOAA), was used. Ferret applies bilinear interpolation by default and uses nearest-neighbor interpolation for regridding operations, making it suitable for handling large, gridded datasets common in climate analysis [20]. In addition, Python programming was used to assess the inter-annual variation of climatic parameters. The analysis was conducted within a Jupyter Notebook environment on Ubuntu 24.04, utilizing key libraries such as xarray for multidimensional data handling, numpy for numerical operations, and matplotlib for visualization. Together, these tools provided an efficient and robust framework for data processing, visualization, and statistical analysis.

2.4. Method

This study employs the NEX-GDDP-CMIP6 multi-model ensemble mean approach to project expected changes in precipitation and temperature through the end of the century. This method is particularly valuable for reducing the uncertainties associated with individual climate models and offers decision-makers a clearer understanding of potential climate change impacts [21] [22]. However, before using this multi-model approach for projections, it must first be validated to ensure its reliability and relevance [4].

2.4.1. Multi-Model Validation

This study begins by evaluating the multi-model's ability to replicate historical data. To do so, we compared the spatial distribution of the two variables (temperature and precipitation) for both the historical data and the ensemble mean of the control data from 17 models. Additionally, we plotted the biases, highlighting the discrepancies between the historical data and the ensemble mean.

Due to the unavailability of data, the 1981-2010 period will be used to calculate the climatology of these two parameters across the entire sub-basin. The climatological mean precipitation $\left(\bar{R}\right)$ will be calculated at each grid point using the following formula (Equation (1)):

$$\bar{R} = \frac{1}{30} \sum_{i=1}^{30\times365} R_i , \tag{1}$$

The climatological mean temperature $\left(\overline{\mathrm{T}}\right)$ will be calculated at each grid point using the following formula (Equation (2)):

$$\bar{T} = \frac{1}{30\times365} \sum_{i=1}^{30\times365} T_i , \tag{2}$$

The precipitation bias (BiasR) will be calculated as a percentage (%) using the following Equation (3):

$$\mathrm{BiasR}\left(\%\right) = 100 \times \frac{R_{\mathrm{ensembleMean}} - R_{\mathrm{observations}}}{R_{\mathrm{observations}}} , \tag{3}$$

The mean temperature bias (BiasT) will be calculated in ˚C using the following Equation (4):

$$\mathrm{BiasT}\left(^{\circ}\mathrm{C}\right) = T_{\mathrm{ensembleMean}} - T_{\mathrm{observations}} , \tag{4}$$

2.4.2. Analysis of Future Climate

The analysis of climate projections focuses on the spatio-temporal evaluation of future climate at key horizons: 2050 (H50: 2021-2054), 2070 (H70: 2041-2070), and 2100 (H100: 2071-2100). This will be based on the SSP scenarios: SSP1-2.6, SSP2-4.5, and SSP5-8.5. The results of this analysis will provide future data for impact studies in vulnerable sectors, particularly agriculture, forestry, and water resources [12]. It should be noted that no bias correction was applied to the NEX-GDDP-CMIP6 data following the validation step. Therefore, the original NEX-GDDP-CMIP6 dataset at 0.25˚ spatial resolution was used directly for the projection analyses.

The 1981-2010 period will serve as the reference for analyzing changes in rainfall and temperature (mean, minimum, and maximum) across the 2050, 2070, and 2100 horizons. The data for the 1981-2010 period from each model are stabilization data, referred to as "model control runs" [12].

For each of the three SSP scenarios and each horizon, a relative difference will be calculated to detect changes in projected precipitation (Equation (5)). For projected mean temperature, an absolute difference will be applied (Equation (6)). This calculation will be performed for each of the seventeen models, followed by an analysis of the ensemble mean and the magnitude of uncertainties across the models.

$$\Delta R(\%) = 100 \times \frac{R_{\text{Scenario,Horizon}} - R_{\text{mean}(1981\text{-}2010)}}{R_{\text{mean}(1981\text{-}2010)}}, \quad (5)$$

$$\Delta T\left({}^{\circ}\mathrm{C}\right) = T_{\text{Scenario,Horizon}} - T_{\text{mean}(1981\text{-}2010)}, \quad (6)$$

3. Results and Discussion

3.1. Multi-Model Validation

For each parameter (annual precipitation and mean temperature), **Figure 2** presents the mean of the CHIRP and ERA5 data, the ensemble mean (Ensmean), and the biases for the Nouhao sub-basin. For precipitation, the "eyeball" analysis shows that the models are able to reproduce precipitation, even though the gradient at the observation level (CHIRP and ERA5 data) is North-West/South-East, whereas it is North/South at the Ensmean level. The latter is confirmed by the bias, which is less than 5% in absolute terms for the entire basin. In terms of mean temperatures, the eyeball shows that Ensmean reproduces ERA5 temperatures well, and even captures the low values located in the south-east of the basin (around 28˚C). This is confirmed by the absolute bias of around 0.5˚C. To further assess the performance of the multi-model, several standard statistical metrics were computed (**Table 2**): Pearson correlation coefficient (r), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). With the exception of the temperature correlation coefficient (r = 0.27), the multi-model shows generally good performance for both parameters.

Despite being minimal, biases are present between the NEX-GDDP-CMIP6 data and the historical datasets (CHIRP, ERA5). These biases may stem from inherent inaccuracies in the CHIRP and ERA5 data or from the downscaling method applied to obtain the NEX-GDDP-CMIP6 data. Nevertheless, larger biases have been considered acceptable in other studies, particularly in the validation of CMIP5 data [23]-[25]. This justifies our confidence in using the NEX-GDDP-CMIP6 data for the remainder of the study, even though applying a bias correction would have been appropriate to enhance the accuracy of the dataset. The absence of bias correction thus represents a limitation of this study.

Table 2. Multi-model performances.

Parameter	r	RMSE	MAE
Precipitation	0.76	29.14	24.72
Temperature	0.27	0.30	0.26

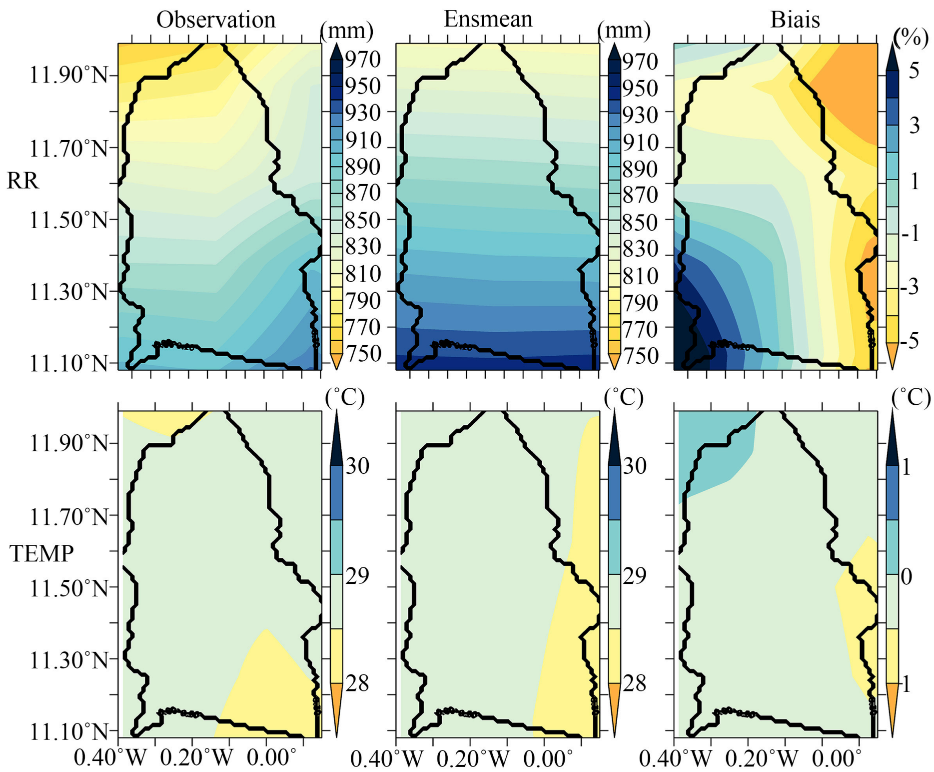


Figure 2. Annual mean precipitation (RR) and air temperature (TEMP) for historical data (CHIRPS and ERA5) and ensemble mean NEX-GDDP-CMIP6 (Ensmean), along with their biases.

3.2. Expected Changes by SSP Scenario

3.2.1. Expected Changes in Precipitation

The analysis of projected changes in precipitation at the spatial level focuses on the SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios, associated with the three time horizons: 2050, 2070, and 2100. Figure 3 displays the ensemble mean of the models for the aforementioned scenarios and horizons. A closer examination of this figure reveals the following for each scenario:

- **SSP1-2.6:** overall, it is expected that rainfall in the Nouhao sub-basin will be stationary or increase by 5% to 30% compared to the reference period (1981-2010) for all horizons;

- **SSP2-4.5:** an increase in rainfall of 5% to 30% compared with the reference period is expected for all three horizons;
- **SSP5-8.5**: a net increase in rainfall of 5% to 35% is expected for the three (3) horizons.

We notice that in the near future (2050), all the scenarios agree on a net increase in precipitation (20%) in the northern half of the basin. This aligns with the results of [26] that also predict an increase in precipitation in Burkina Faso by 2050.

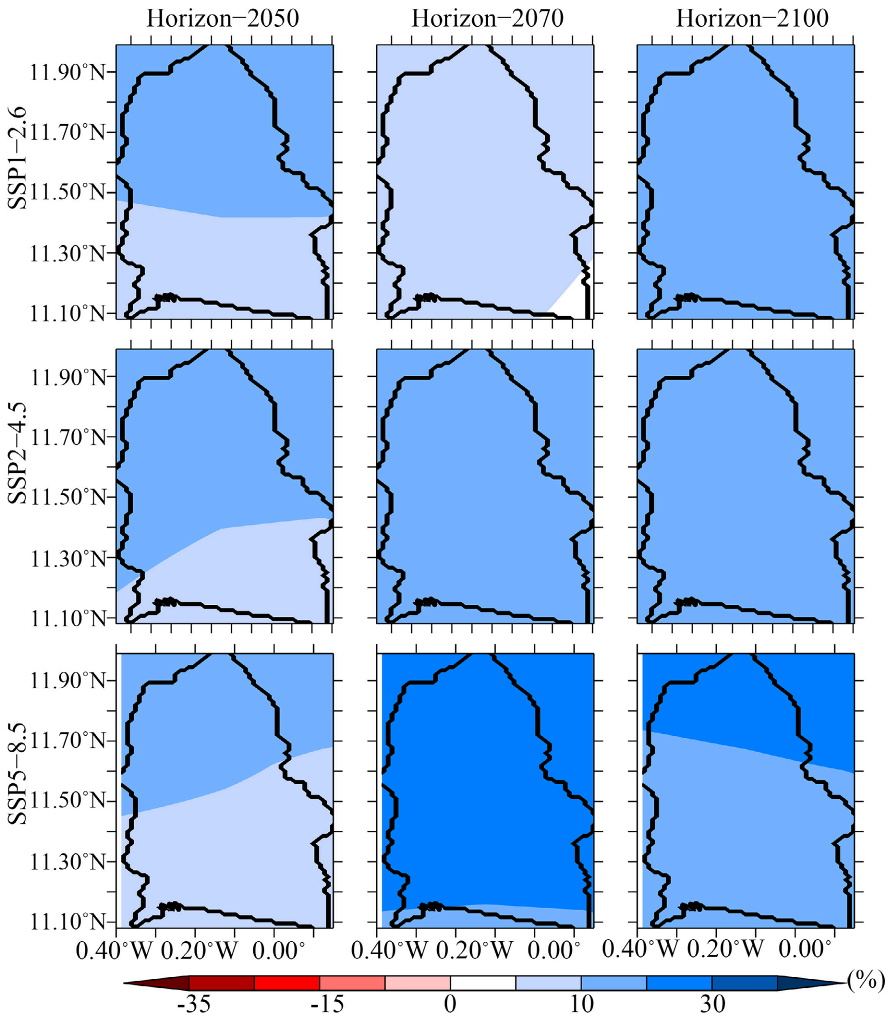


Figure 3. Average changes in cumulative annual rainfall for the three scenarios (SSP1-2.6, SSP2-4.5, SSP5-8.5) at time horizons H50, H70, and H100.

It should be noted that the direction (increase or decrease) of changes in precipitation varies considerably across climate models, underscoring the uncertainties surrounding future rainfall variability (Croix-Rouge Burkina, 2024). **Figures 4(a)-(c)**, which show the spatial distribution of the minimum and maximum values of future rainfall changes as simulated by the models, illustrate this high variability for the horizons H50 (2050), H70 (2070), and H100 (2100).

For the SSP1-2.6 scenario (**Figure 4(a)**), some models predict a maximum increase in rainfall of nearly 60%, while others forecast an increase of less than 20%. The same variability is noticed for the minimum rainfall change: some models show a decrease of over 25%, while others predict reductions of less than 10%.

In the case of the SSP2-4.5 scenario (**Figure 4(b)**), some models project a maximum increase in rainfall of over 60%, while others forecast a minimum decrease of more than 35%.

Finally, for the SSP5-8.5 scenario (**Figure 4(c)**), while the models generally agree on maximum increases (ranging between 40% and 60%), significant variability is noticed for minimum changes, with some models predicting decreases exceeding 30%. These discrepancies highlight the uncertainties inherent in individual models, as pointed out by authors such as [27].

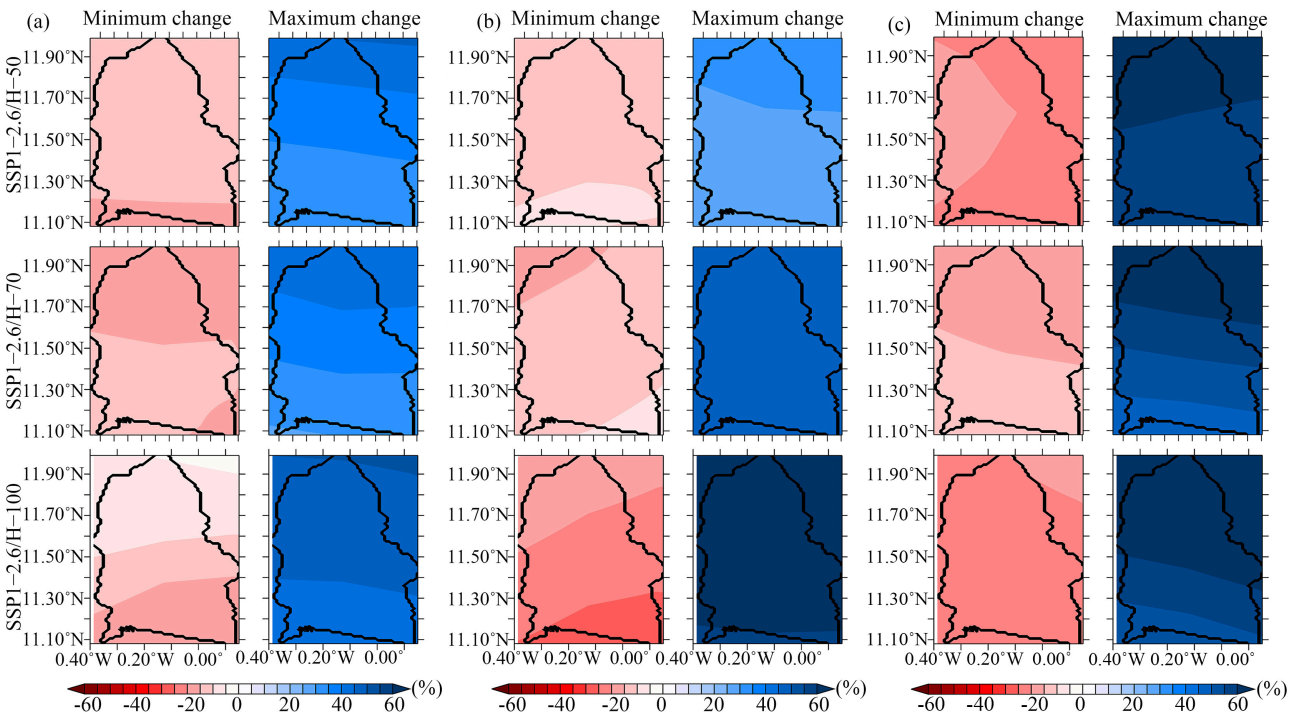


Figure 4. Minimum and maximum changes in cumulative annual rainfall for the 3 scenarios: SSP1-2.6 (a), SSP2-4.5 (b), and SSP5-8.5 (c) at time horizons H50, H70, and H100.

The analysis of inter-annual variation in precipitation projections over the period from 2021 to 2100 (**Figure 5**) reveals that the expected average changes in cumulative rainfall range from 2% to 22% across the three scenarios (SSP1-2.6, SSP2-4.5, and SSP5-8.5). This fluctuating pattern makes it difficult to identify any clear trend in precipitation [28]. Additionally, it is important to note that the three scenarios diverge as we progress through the three time horizons.

Considering the uncertainties between climate models, we notice that the range of variability in precipitation changes across models spans from 1% to 25% over the entire basin.

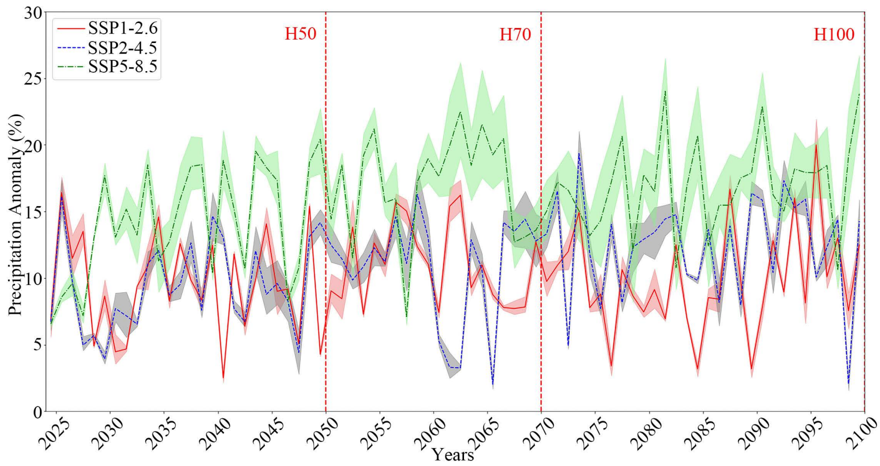


Figure 5. Inter-annual variation in projected cumulative annual rainfall for the three scenarios.

3.2.2. Expected Changes in Mean Temperature

It is clear that average temperatures are projected to rise across all three time horizons (H50, H70, and H100). Analysis of **Figure 6** indicates that, under

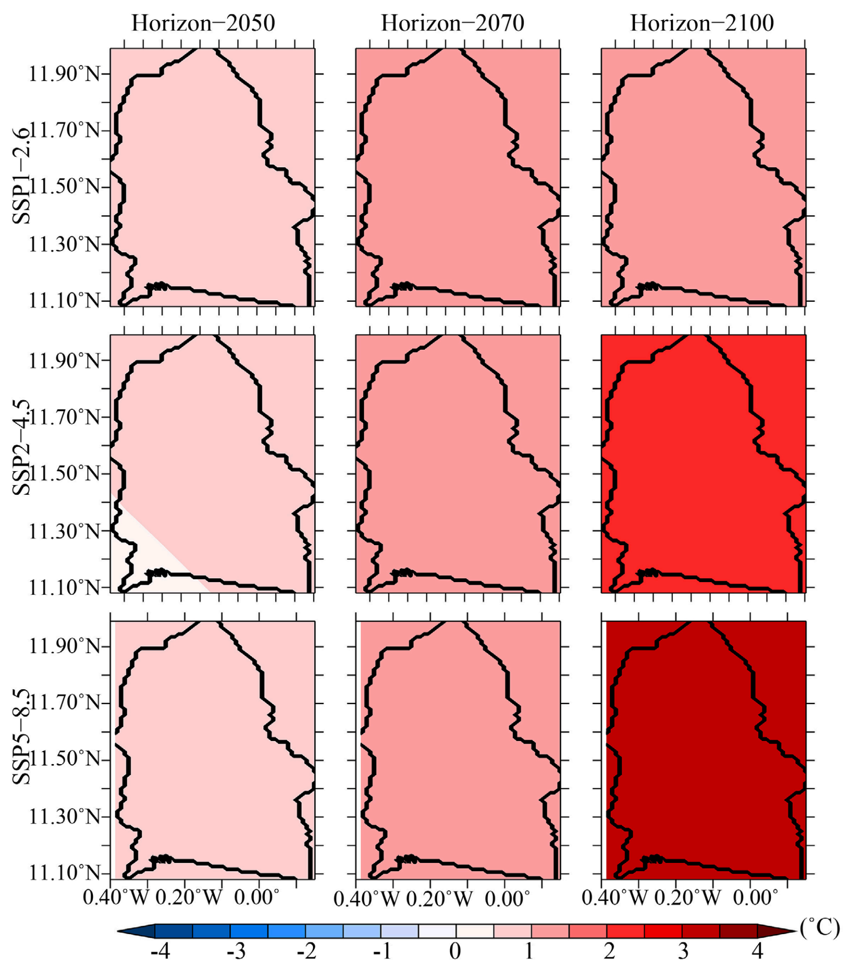


Figure 6. Average changes in mean temperature for the three scenarios at the time horizons 2050, 2070, and 2100.

the SSP1-2.6 scenario, temperatures are expected to increase by 0.5˚C to 2˚C over the basin. The increase is more pronounced for the SSP2-4.5 and SSP5-8.5 scenarios, with a rise of approximately 5˚C across the basin from the H70 horizon onward. From a spatial perspective, temperature changes are uniformly distributed, with temperature increases being nearly identical throughout the basin. This uniformity can be attributed to the relatively small size of the basin, as temperature is a climatic parameter that typically has a low horizontal gradient [29].

An analysis of **Figures 7(a)-(c)**, which illustrate extreme changes (minimum and maximum) in mean temperature, reveals that the models are generally in agreement. For the first scenario, SSP1-2.6 (**Figure 7(a)**), all models project a maximum rise of approximately 3˚C across all horizons (H50, H70, and H100). For the minimum variation, however, there is a notable outlier, with one model predicting a cooling of nearly 1˚C. In the case of SSP2-4.5 (**Figure 7(b)**), the models converge on a warming range of 2˚C to 5˚C across the entire basin. It is also worth noting that some models predict a cooling of around 1˚C in the short term (2050). Finally, similar patterns are noticed for the last scenario, SSP5-8.5 (**Figure 7(c)**), with the added feature that some models show cooling until the medium term (2070).

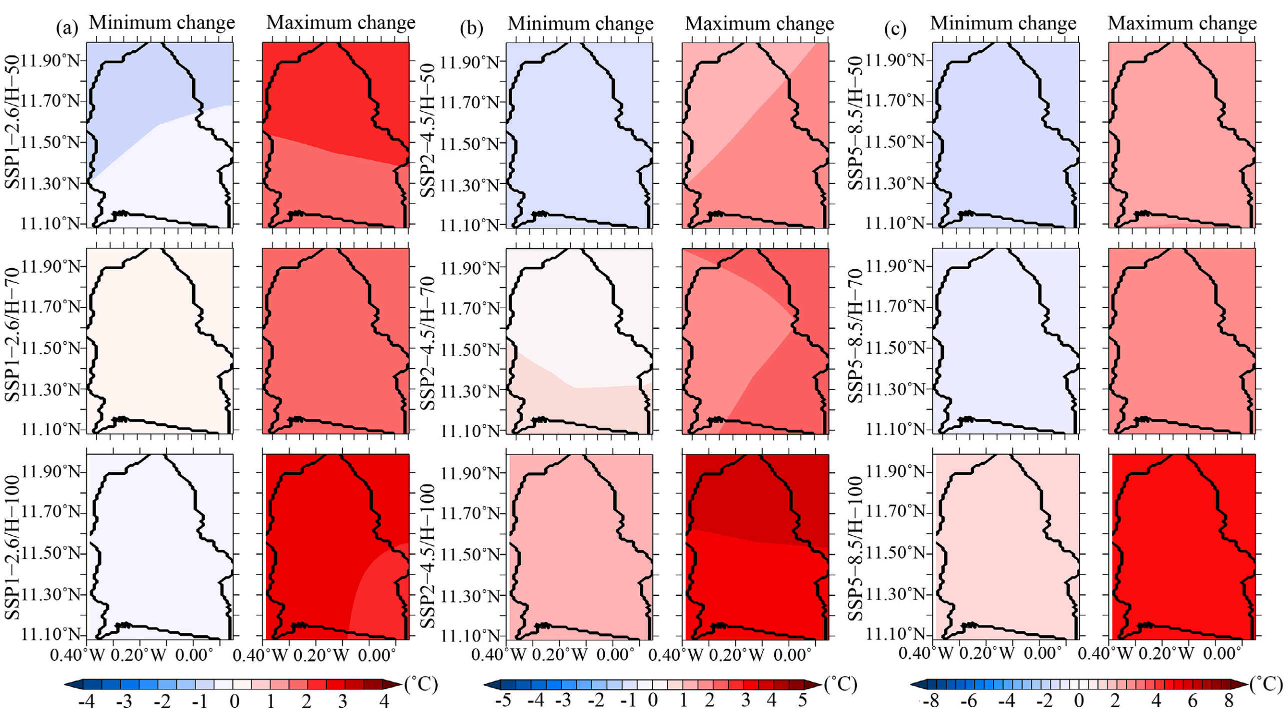


Figure 7. Minimum and maximum changes in mean temperature for the 3 scenarios: SSP1-2.6 (a), SSP2-4.5 (b), and SSP58 (c) at time horizons H50, H70, and H100.

An analysis of the inter-annual variation in mean temperature projections from 2021 to 2100 (**Figure 8**) reveals a clear upward trend in temperatures. Specifically, the expected average changes in mean temperature range from 0.2˚C to 5˚C across all scenarios (SSP1-2.6, SSP2-4.5, and SSP5-8.5). By the H50 horizon, the scenarios show some convergence, with temperature changes ranging from 0.5˚C to 1.5˚C. However, as we move to the H70 and H100 horizons, the differences between the three scenarios become more pronounced. This pattern aligns with several studies on temperature projections for Burkina Faso. For example, the results of [4] show that, after 2040, the models start to deviate from each other in terms of temperature. An analysis of the uncertainties associated with the climate models reveals that the range of variability in mean temperature change between the models is virtually negligible. In fact, the uncertainty range per scenario, varying between 0˚C and 0.1˚C across the entire basin, is barely noticeable on the figure. This indicates the strong performance of all models, which predict nearly identical warming trends.

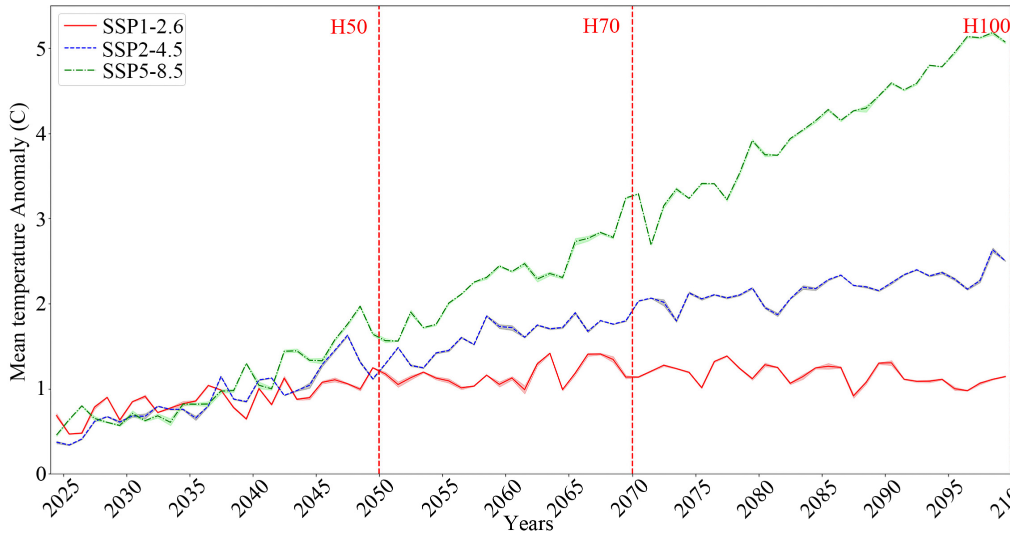


Figure 8. Inter-annual variation in projected mean annual temperature for the three scenarios.

3.2.3. Expected Changes in Minimum Temperature

A comparison of projected minimum temperatures with the reference period (1981-2010) reveals an increase of 0.5˚C to 3˚C across the basin for all scenarios and horizons (**Figure 9**). Specifically, the first scenario, SSP1-2.6, shows a clear rise of 1˚C to 2˚C across all three horizons. The SSP2-4.5 and SSP5-8.5 scenarios, on the other hand, project increases ranging from 0˚C to over 3˚C as the horizons progress.

Analysis of **Figures 10(a)-(c)** reveals the variability among the different models used to project minimum temperatures. As with mean and maximum temperatures, the models generally converge for the SSP1-2.6 scenario, forecasting an average rise of 2˚C to 4˚C. However, some models predict a cooling of the basin, with temperatures dropping as low as −5˚C. Similar patterns are noticed for the other two scenarios, although the amplitude of the temperature changes varies, with some models projecting increases over 8˚C and decreases of a similar magnitude.

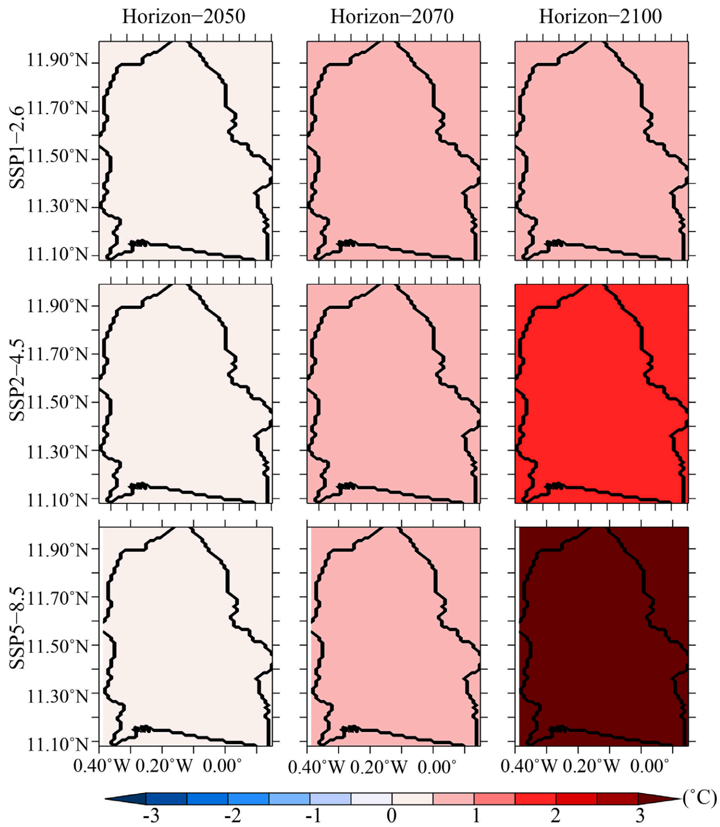


Figure 9. Average changes in minimum temperature by scenario for the time horizons 2050, 2070, and 2100.

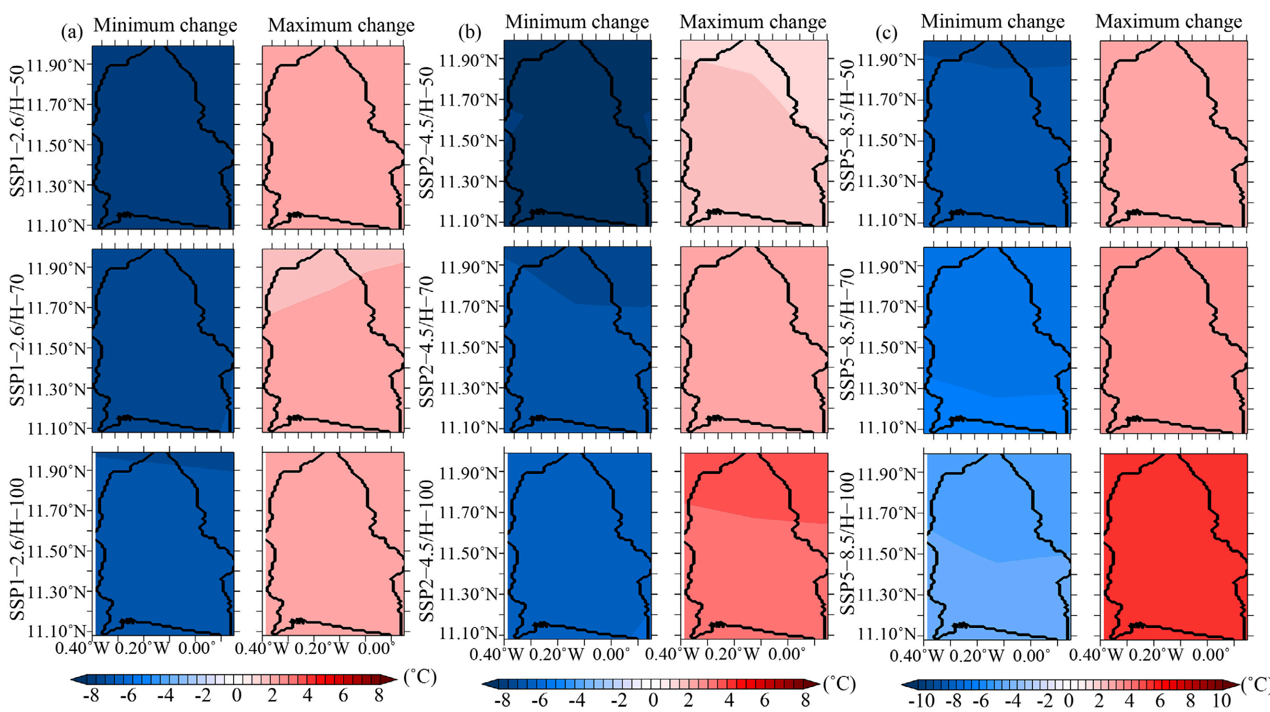


Figure 10. Minimum and maximum changes in minimum temperature for the 3 scenarios: SSP1-2.6 (a), SSP2-4.5 (b), and SSP5-8.5 (c) at time horizons H50, H70, and H100.

In terms of inter-annual variation in minimum temperature projections, the same trends noticed for mean temperatures apply (**Figure 11**). The primary difference lies in the amplitude, with variations ranging from 0˚C to 5˚C. While model uncertainties remain minimal, they are more noticeable here compared to the mean temperature projections.

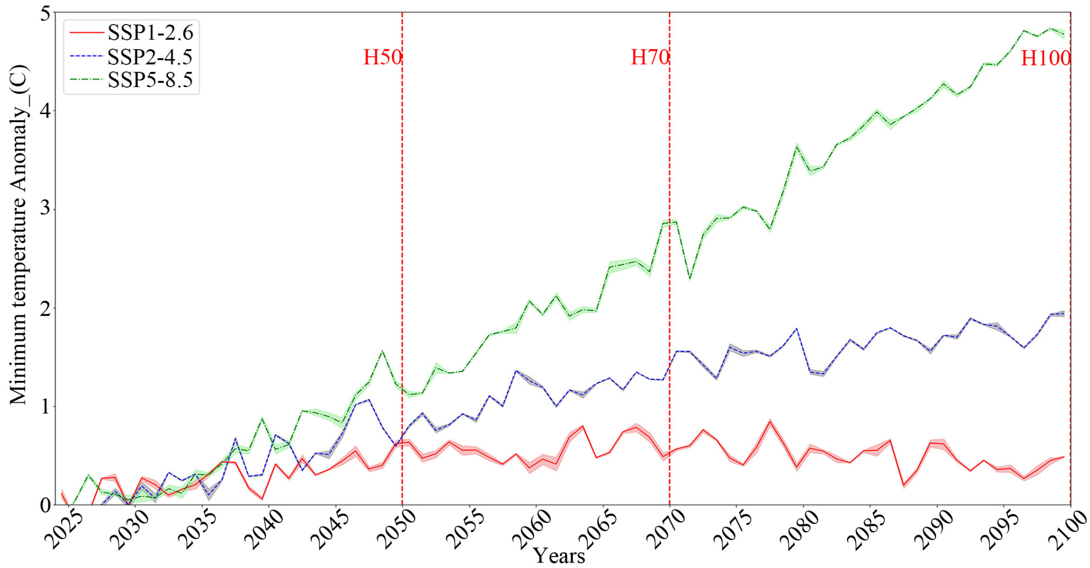


Figure 11. Inter-annual variation in projected minimum temperature for the three scenarios.

3.2.4. Expected Changes in Maximum Temperature

Analysis of the spatial distribution of projected maximum temperatures relative to the reference period (1981-2010) reveals a clear increase of 2˚C to 4˚C across all three scenarios (**Figure 12**). For SSP1-2.6, maximum temperatures are expected to rise by 2˚C for all horizons. In contrast, for the other two scenarios (SSP2-4.5 and SSP5-8.5), the increase is more pronounced, with temperatures rising by more than 4˚C from the H70 horizon onward.

An analysis of the variation in maximum temperature changes (**Figures 13(a)-(c)**) reveals convergence among the models for the SSP1-2.6 scenario, with all models predicting a minimum rise close to zero and a maximum rise exceeding 7˚C. For the other two scenarios (SSP2-4.5 and SSP5-8.5), the pattern is similar to that of SSP1-2.6, but with a larger warming amplitude: 10˚C for SSP2-4.5 and nearly 12˚C for SSP5-8.5. This highlights a high degree of variability between climate models in simulating the maximum warming amplitude.

Analysis of the inter-annual variation in maximum temperature projections from 2021 to 2100 (**Figure 14**) reveals patterns similar to those noticed for mean temperatures. The primary difference lies in the amplitude, with variations ranging from 0.7˚C to 6˚C for maximum temperatures, compared to less than 5˚C for mean temperatures. This is confirmed by several studies [4] [12], which highlight this difference in the models' ability to capture temperature amplitudes in the future, whatever the scenario.

All the above results are in line with recent studies carried out in Burkina Faso and the West African sub-region. Indeed, several studies have predicted rising rainfall and temperatures in this part of the world [30]-[32]. This suggests that phenomena such as heatwaves, floods, and droughts are likely to occur in the basin. Further studies are necessary to assess the potential impacts of these events on the basin. Regarding model uncertainties—particularly those that result in some individual models projecting cooling and decreased rainfall—several factors may explain these discrepancies. First, the West African monsoon, which is the primary driver of rainfall in Sahelian countries, remains insufficiently understood, leading to biases in precipitation modeling for the region [33]. Second, most climate models have been developed in major climate centers located in developed countries, which may limit their ability to fully capture the complex climatic realities of the Sahel. Third, the effects of aerosols—still poorly understood in the context of the Sahel [34]—may also contribute to the cooling trends projected by some models.

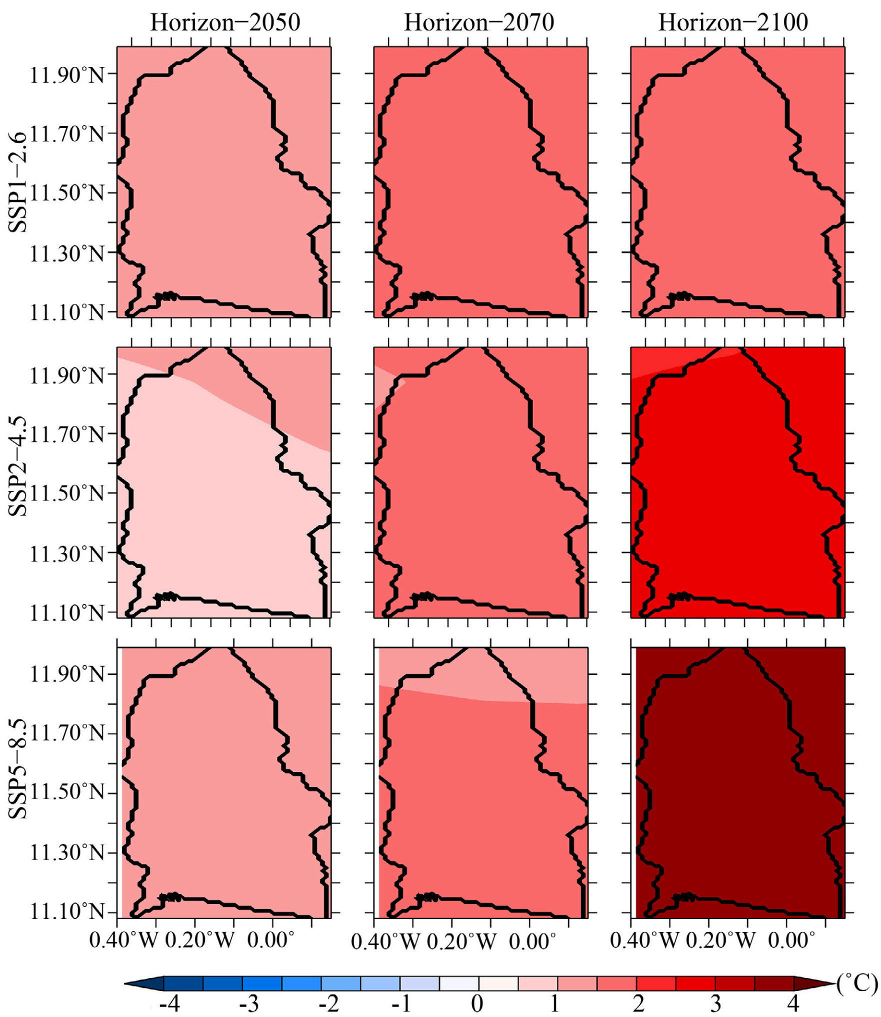


Figure 12. Average change in maximum temperature by scenarios for the time horizons 2050, 2070, and 2100.

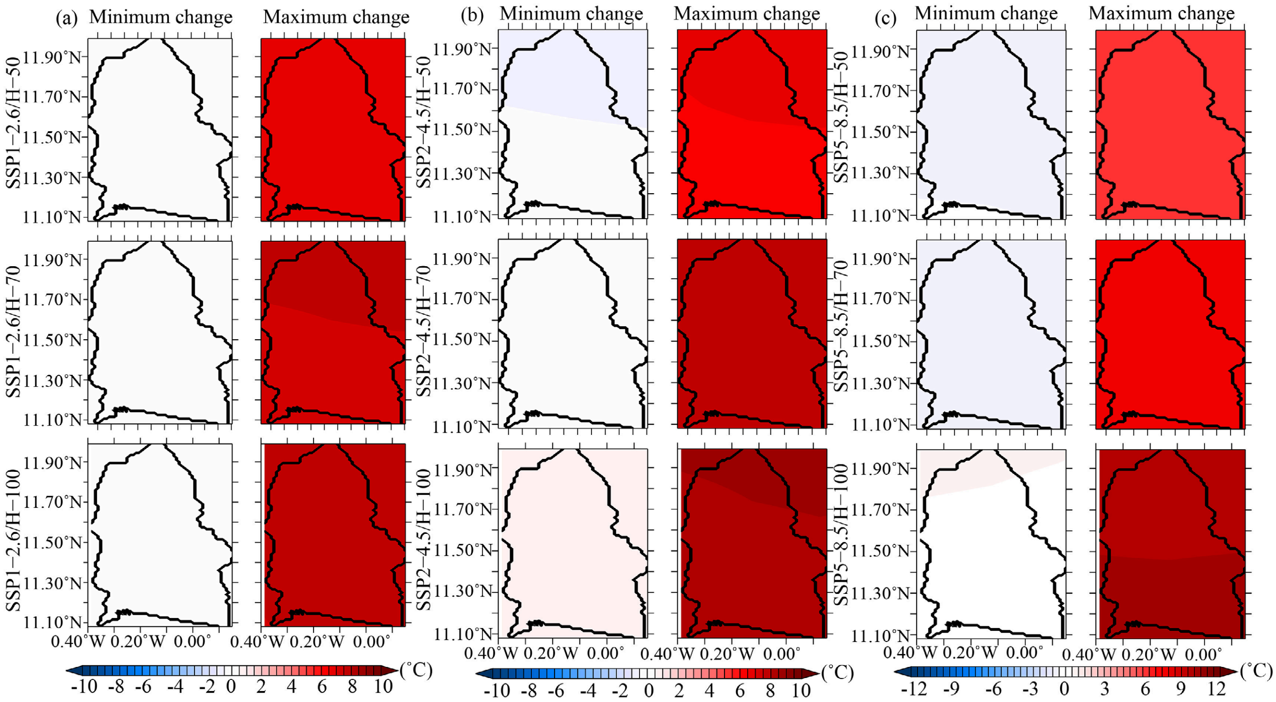


Figure 13. Minimum and maximum changes in maximum temperature for the 3 scenarios: SSP1-2.6 (a), SSP2-4.5 (b), and SSP5-8.5 (c) at time horizons H50, H70, and H100.

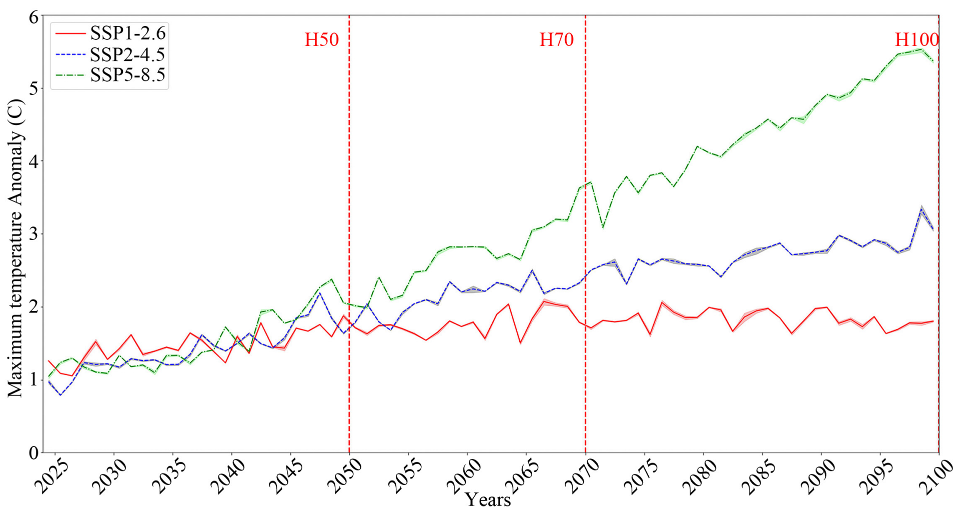


Figure 14. Inter-annual variation in projected maximum temperature for the three scenarios.

4. Conclusions

The aim of this study was to characterize the future climate of the Nouhao basin using the latest NEX-GDDP-CMIP6 data. These data were employed to assess projected changes in precipitation and temperature (mean, minimum, and maximum) under three scenarios, SSP1-2.6, SSP2-4.5, and SSP5-8.5, across three time periods: the near future (2021-2050), medium term (2041-2070), and far future (2071-2100), with reference to the 1981-2010 baseline period. Historical data from CHIRP and ERA5 were used to validate the multi-model approach.

The results indicate that, in terms of model validation, the ensemble mean effectively reproduced historical data of precipitation and temperature in the basin. As for future projections, all models predict a precipitation increase of approximately 35% by 2100. It should be noted that SSP1-2.6 and SSP2-4.5 project relatively similar climate outcomes, while SSP5-8.5 predicts the most substantial increase in precipitation and associated climate impacts. For temperature, a gradual warming trend is expected, with a rise of up to 4˚C by 2100. In the case of temperature, the projections indicate that warming increases consistently with the progression of SSP scenarios. However, significant variability between individual models was noticed. While the ensemble mean suggests an increase in precipitation, some models project a slight decrease in rainfall over the basin. Similarly, while most models predict warming, some suggest cooling trends. This variability underscores the importance of accounting for uncertainties when considering future climate projections, which can help inform adaptive strategies by addressing a broad range of possible scenarios.

Given the uncertainties, special attention should be paid to modelling and forecasting the risks of droughts and floods to better manage these extreme events. Advanced techniques such as machine learning and deep learning could be leveraged to generate high-resolution data (around 5 km) for a more comprehensive understanding of these phenomena.

Data Availability Statement

All the gridded data (in NetCDF format) used in this study can be downloaded for free:

- NEX-GDDP-CMIP6 data via https://nex-gddp-cmip6.s3.us-west-2.amazonaws.com/index.html#NEX-GDDP-CMIP6/;
- CHIRPS data are available via https://data.chc.ucsb.edu/products/CHIRPS-2.0/global_daily/netcdf/p25/.
- ERA-5 data via https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels?tab=download.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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