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Wisdom Bruce Ahiada

wisdombruce123@gmail.com

University of Energy and Natural Resources

Ebenezer K. Siabi

Earth Observation Research and Innovation Centre (EORIC)

Amos T. Kabobah

University of Energy and Natural Resources

Sarah Elikplim Siabi

University of Energy and Natural Resources

Cobbina Nana Asirifi

University of Energy and Natural Resources

Christian Amponsah

University of Energy and Natural Resources

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Wisdom Bruce Ahiada [ac*], Ebenezer K. Siabi[a,b], Amos T. Kabobah[a,c], Sarah Elikplim Siabi[a,c], Cobbina Nana Asirifi[a,c], Christian Amponsah[a]

[a]Department of Civil and Environmental Engineering, University of Energy and Natural Resources, P. O. Box 214, Sunyani, Ghana

[b]Earth Observation Research and Innovation Centre (EORIC), University of Energy and Natural Resources, P.O. Box 214, Sunyani, Ghana

[c]Regional Centre for Energy and Environmental Sustainability, University of Energy and Natural Resources, P. O. Box 214, Sunyani, Ghana

*Corresponding Author: wisdombruce123@gmail.com

ABSTRACT

Increasingly susceptible to the effects of climate change (CC), the White Volta Basin is a vital source of water for West Africa and could worsen already existing hydroclimatic issues. Consequently, CC assessment is becoming difficult in data-scarce areas, especially in the northern part of Ghana. To evaluate the CC of the basin under different climatic scenarios as described by the Shared Socioeconomic Pathways (SSPs), this study used statistically bias-corrected CMIP6 climate model outputs to estimate maximum and minimum temperature (Tmax and Tmin) variations within the Ghanaian part of the basin. Only temperature is analysed. This study employed 15 different Global Climate Models under the 6th IPCC Report's Shared Socioeconomic Pathway scenarios (SSPs) of the CMIP6 (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5), which were bias-corrected over the basin using data sourced from the Ghana Meteorological Agency stations as well as 9 virtually generated stations using ERA5 data. A weighted multi-model ensemble was subsequently developed using model performance (correlation-based weights at the GMet stations) and, for the virtual stations, model independence and performance through the ClimWIP approach. The individual bias-corrected models were evaluated against the same observations used to fit the correction (no independent validation period) using R^2, RMSE, and PBIAS, indicating goodness of fit rather than out-of-sample skill. For the bias-corrected data, R^2 ranged from 0.83 to 0.99 for Tmax and 0.91 to 0.99 for Tmin, compared with 0.00 to 0.59 for the raw data. RMSE for bias-corrected Tmax and Tmin ranged from 0.01 to 0.38 °C and 0.00 to 0.25 °C, respectively. PBIAS ranged from 0.00 to 0.48% for bias-corrected Tmax and Tmin (-16.9 to 20.0% for the raw data; positive values indicate overestimation). Under the high-emission scenario (SSP5-8.5), the projected warming could intensify pressure on water resources, agricultural productivity, ecosystem health, and overall water security (these impacts were not modelled in this study). The study revealed seasonal and spatial variations in temperature, with warming under SSP2-4.5, SSP3-7.0 and SSP5-8.5; apparent post-2060 decreases under SSP1-2.6 are probably processing artefacts and are not interpreted as cooling. The findings of the study are expected to help decisionmakers make tangible decisions in addressing SDG 11 (Sustainable Cities and

Communities), SDG 3 (Good Health and Well-being), and 13 (Climate Action) in the White Volta Basin.

Clinical trial number: not applicable.

Keywords: Global Climate Models, Shared Socioeconomic Pathways, Coupled Model Intercomparison Project, climate change, White Volta Basin

1. Introduction

Runoff, the central aspect of water resources, remains greatly responsive to climatic change. Literature maintains that temperature change reorganises runoff regimes in an elemental manner (Mensah et al., 2022).

Climate variation accentuates African poverty, famine, and stagnated economic growth, even up to the present day. The UN sees an outlook of increasing water tension, with the extreme drying in the Sahel and the southern continent.

In West Africa, temperature increase is inevitable, rendering water source planning troublesome (Abubakari et al., 2017). Extreme events, such as altered streamflow, add to water administration woes.

Upcountry in the country of Ghana, studies confirm declining Volta Basin River discharges (Sam and Dapaah, 2021). The climatic perspective reflects the rise in temperature, with the potential of reducing streamflow in key basins by upwards of 20% in the 2050s (Abubakari et al., 2017). These changes indicate water insecurity in the face of growing demand, abetted by population increase as well as by the growing agriculture sector.

In climatic influence assessment, the use of Global Circulation Models (GCMs) is inevitable, yet they are of low resolution, thus requiring downscaling at the local scale for applications (Yeboah et al., 2022). According to Sachindra et al., (2018) Statistical and dynamical downscaling schemes upscale GCMs' outputs, filling the gap in hydroclimatic forecasts. Climate uncertainty also adds to water management complexity, particularly in the presence of rising temperatures, which undermine farm productivity (Agodzo et al., 2023).

However, the White Volta Basin experiences seasonal floods, which frequently result in damage and loss of human lives (Ndakalu, 2022). Several riparian communities have been linked to health issues such as onchocerciasis and schistosomiasis (Ndakalu, 2022). This basin contains most groundwater sources with high fluoride contents. Because some communities'

wells and streams have dried up, water shortages are frequent, especially during the dry season. The limitations of research on the effects of climate change on West African water resources originate from the uncertainty around climate projection data and hydroclimatic models, as well as the lack of in-situ hydroclimatic and meteorological observations to inform models (Dembélé et al., 2022).

Also, due to the scarcity of available GMet stations and climatic data in the basin, it has, however, made downscaling very challenging, making information about the exact changes that are expected limited in this area (Mensah et al., 2022). This complicates the planning and execution of subventions. The proposed irrigation plans have not taken into account the water requirements for the various crops cultivated, nor have they taken into account potential climate differences at different sites within the catchment (Dembélé et al., 2022; Mensah et al., 2022). The basin is especially vulnerable to the effects of climate change on hydroclimatic responses because it relies on agriculture and the need for water for domestic use by the surrounding communities (Awotwi et al., 2016). Such climate-driven changes pose a threat to the delicate balance of ecosystems within the upper part of the basin as well as food security and agricultural output (Awotwi et al., 2016).

Moreover, the problem is made more difficult by the complex interactions between socioeconomic variables and climate change. Existing socioeconomic gaps, a lack of adaptive capability, and poor infrastructure for managing water resources all contribute to the basin's vulnerability (Mensah et al., 2022). There is an increasing need to comprehend and lessen the effects of climate change on hydroclimatic response because of the growing population.

Therefore, comprehensive study and adaptable strategies are critically required to address the hydroclimatic responses of climate change on the White Volta Basin. This research employs the CMhyd tool to bias-correct CMIP6 projections of maximum and minimum temperature under the Shared Socioeconomic Pathways (SSPs) for the White Volta Basin. The main objective is to use statistical bias correction and weighted multi-model ensembles to project future changes in maximum and minimum temperature under the SSPs, and to discuss their potential implications for water resources in the basin, providing climate inputs for subsequent hydroclimatic assessments. Only temperature is analysed here; runoff, floods and other hydrological responses are not simulated.

Mensah et al. (2024) applied statistical bias correction to climate scenarios in the same basin using a similar approach. The present study differs in : (i) the use of 15 CMIP6 GCMs under SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5; (ii) performance- and independence-based

(ClimWIP) weighting of the ensemble instead of a simple mean; (iii) nine ERA5-derived virtual stations supplementing the three GMet stations; (iv) any other new element].

The output of this study aims to fill the identified gap by assessing the changes in temperature (Tmax and Tmin) under the Shared Socioeconomic Pathways (SSPs) emission scenarios over the white volta using climate outputs from CMIP6 models. Analysis of the past, present, and future temperature variability and change using CMIP6 models will improve our understanding of the future climate of the basin, provide inputs for assessing its hydroclimatic responses, and allow for better anticipation of climate risks that are associated with local weather phenomena, such as droughts and floods (Mundetia et al., 2023).

Studies on climate change modelling are not often discussed within the context of sustainable development, especially how such studies can help to achieve the Sustainable Development Goals. This study, therefore, seeks to move the discussion of the findings within the sustainable development discourse (Dotse et al., 2023). Given that the effects of climate change are felt at many spatial scales and in various societal sectors, it raises important questions about how countries, including those in West Africa, can advance toward meeting sustainable development goals (SDGs) .

The risks are particularly high in countries like Ghana, where limited hydroclimatic responses are available and the economy is dependent on water resources, along with land conversion, climate change risks, and population pressure (Ali et al., 2023; Banda et al., 2022; Mundetia et al., 2023). These risks make it more difficult to achieve SDGs such as SDG 11 (Sustainable Cities and Communities), SDG 3 (Good Health and Well-being), and 13 (Climate Action) in the White Volta Basin. by the year 2030. This will also help Ghana as a country to localize the Sustainable Development Goals and develop a Sustainable Development Goals Index. In doing so, it will help in measuring the progress of regions and districts as well as country-level initiatives to achieve SDGs (Mundetia et al., 2023).

2. Materials and Methods

2.1 Study area

Geographically, with an approximate length of 885 km, the larger White Volta River Basin (9° 10'00' N, 1º15'00" W) drains Ghana, Burkina Faso, and Togo (Figure 1). Its total area is approximately 107,417 Km2. The entire Upper East Region, almost 70% of the Upper West Region, and 50% of the Northern Region make up Ghana's portion of the White Volta Basin (Awotwi et al., 2016; Mul et al., 2015). The part that is in Ghana occupies an area of roughly 47 000 km^2, or 20% of Ghana's total landmass and 44% of the White Volta Basin's overall area of coverage. The White Volta's tributaries, which run through the basin in rural areas and include both permanent and ephemeral streams, drain the basin. It starts in Burkina Faso as the Nakambe River. The Red Volta and Sissili, which originate in Burkina Faso, are tributaries of the White Volta. The majority of the population inside and outside the basin relies heavily on the surface water resources provided by the White Volta Riverine systems and streams. They serve as sources of irrigation water resources for communities living in their immediate neighbourhood. The complex network of streams in the area is more prominent in the rainy seasons, as most of the ephemeral stream channels dry out during the dry season (Abungba et al., 2022). Figure 1 illustrates the area of study.

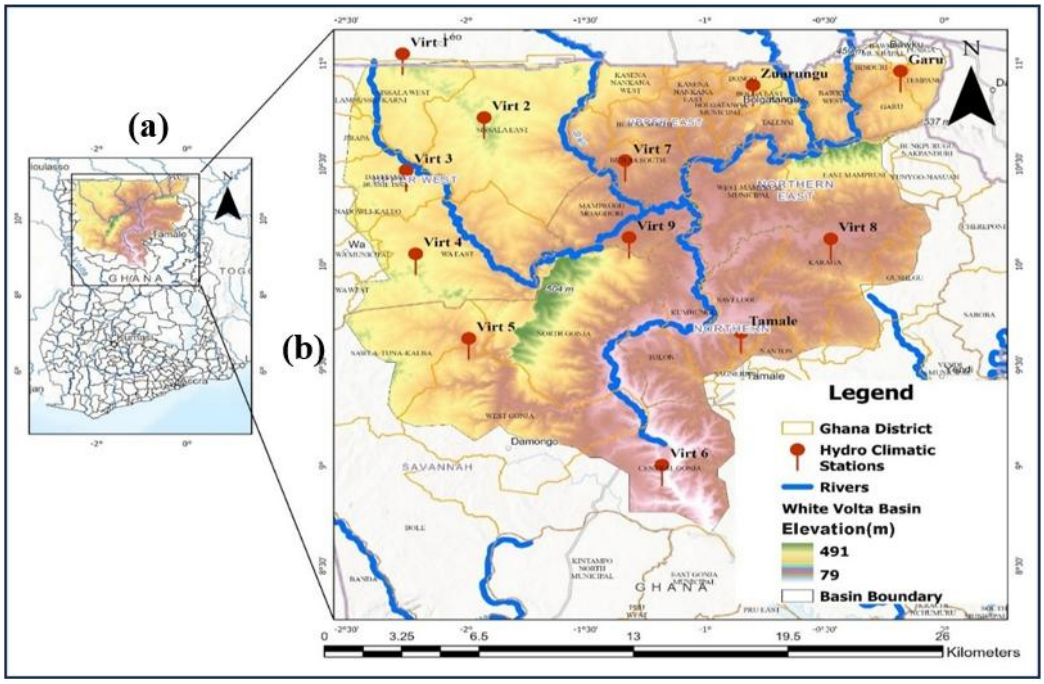

Figure 1: Area of study Virts: Virtual Stations: (a) Shows where the zoomed-in map (main map) is located nationally. (b) Shows the location of the study area (White Volta Basin) within the whole of Ghana.

2.2 Data Observed Acquisition

The Ghana Meteorological Agency (GMet) provides the Tmax and Tmin temperatures that were observed each day. The existing GMet stations, together with additional virtual stations in Ghana's WV basin, make up the baseline dataset as shown in Tables 1 and 2, whose records span 1960 to 2022 (the portion overlapping the CMIP6 historical experiment, i.e., up to 2014, was used as the baseline; Section 2.7) (Banda et al., 2022). According to Abungba et al., (2022) Insufficient hydro-climatic data is a significant constraint on water resource modelling. There are extremely few climatic stations located throughout the White Volta Basin. The accessible data are rife with gaps, even for the ones that already exist. Consequently, ERA5 datasets were utilized to complement ground-based observations (Hersbach et al., 2023). Figure 2 presents the validation of the ERA5 data against measurements from ground stations.

Table 1: Location of Hydroclimatic Stations

Station Name	Latitude (°N)	Longitude (°W)
Virtual Station1	**10.9357**	**-2.2659**
Virtual Station2	10.6189	-1.9244
Virtual Station3	10.3562	-2.2504
Virtual Station4	9.9413	-2.2107
Virtual Station5	9.5205	-1.9889
Virtual Station6	8.8908	-1.1807
Virtual Station7	10.4049	-1.3345
Virtual Station8	10.0157	-0.4747
Virtual Station9	10.0227	-1.3185

Coordinates are in decimal degrees; negative longitudes denote west of Greenwich.

Table 2: Characteristics of selected ground stations and data quality.

GMet Stations	Latitude (°N)	Longitude (°W)	% Missing Data	
			Tmax(°C)	Tmin (°C)
Garu	10.85	-0.18	0.347193	0.171625

TAMALE (New Airport)	9.55	-0.85	4.67442	3.841986
Zuarungu	10.78	-0.8	5.28169	6.01652

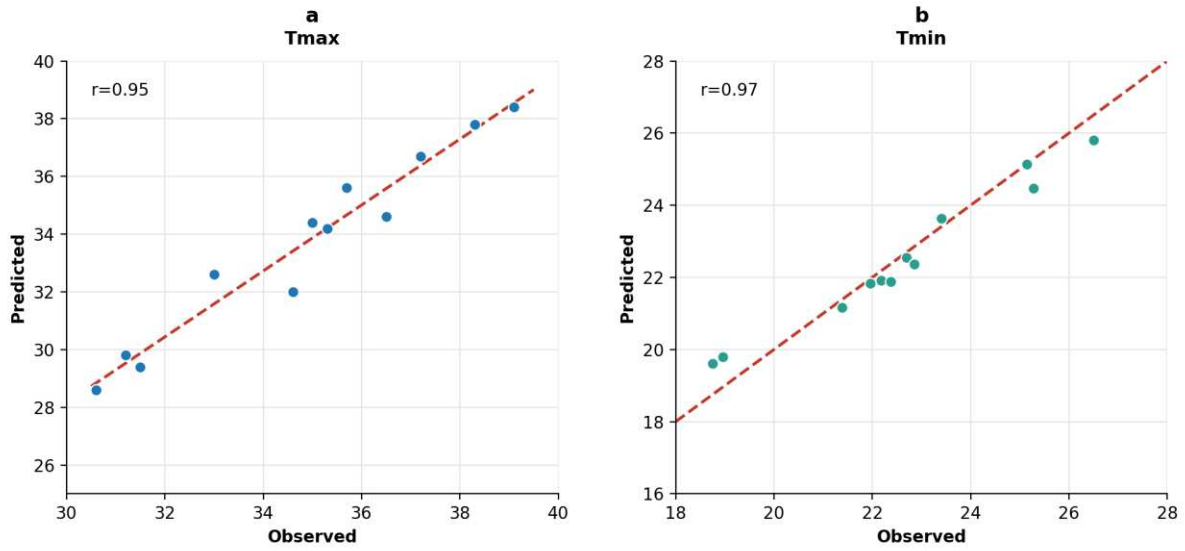

Figure 2: Validation of the ERA5 dataset against ground-station observations: (a) monthly maximum temperature (Tmax), (b) monthly minimum temperature (Tmin)

2.3 Climatic Models Acquisition and Scenarios

Diverse Global and Regional Climate Models (GCMs and RCMs) are now available to simulate temperature at a basin or local level, including the Coordinated Regional Climate Downscaling Experiment (CORDEX) climate simulation experiments (Nazeer et al., 2022) These models can help us better understand and estimate plausible future climatic conditions. In this study, CMIP6 GCM projections (Eyring et al., 2016) of minimum and maximum temperatures were used (Nazeer et al., 2022).

The dataset is based on 15 forcing GCMs, listed in Table 3, including the Max Planck Institute for Meteorology Earth System Model Low Resolution (MPI-LR)(Wu et al., 2021), Canadian Earth System Model (CanESM) (Abungba et al., 2022). The Meteorological Research Institute Earth System Model Version 2.0 (MRI-ESM2) (Yukimoto et al., 2019) and Beijing Climate Centre (BCC-CSM2) (Xin et al., 2018) among others, as illustrated in Table 3. The CMIP6 data were employed since the new scenarios, which incorporate socio-economic components of climate change, have improved resolution and accuracy over the previous version (CMIP5)

(Incoom et al., 2022; Siabi, Awafo, et al., 2023). The study considered the latest SSP scenarios created by CMIP6 of the World Climate Research Programme (WCRP) (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5). These new scenarios were taken into consideration since they show various socioeconomic developments and pathways for atmospheric concentrations of greenhouse gases (Siabi, Awafo, et al., 2023).

Future conditions in the near-to-long term (2015–2100) were compared with the baseline periods 1960–2014 and 1980–2014 for the GMet and virtual stations, respectively, to objectively evaluate future climatic changes under the various scenarios.

2.3.1 Criteria used in selecting GCMs

The choice of an appropriate ensemble of Global Climate Models (GCMs) is a cornerstone of climate change impact assessment, especially in vulnerable areas such as West Africa, where the climate is highly variable in space and time. Of the 30 CMIP6 models initially considered, the selection of 15 models was based on a multi-criteria screening (performance, resolution, data availability and ensemble diversity) aimed at optimising the credibility and utility of projections for the White Volta Basin while well capturing the spread of uncertainties in scenarios of future climates (Table 3). Model-specific scores for these criteria were not computed or tabulated; the screening relied on the published evaluations cited below and on data availability.

West African Climate Simulation performance was our first preference criterion. Numerous studies have demonstrated that while CMIP6 models overall have more skill than their CMIP5 predecessors for West African climate simulation, there are still big inter-model differences (Sultan et al., 2023). Models reported in the literature to reproduce the region's monsoon behaviour (timing of onset and withdrawal) were favoured; monsoon skill was not re-evaluated for each model in this study. The selected models were compared to observation datasets (ERA5, GMet) for their ability to simulate past temperature extremes inside the White Volta Basin.

Spatial resolution problems were of equal significance in this study’s selection. The topographically complex White Volta Basin at an elevation of 100-800 meters demands models to resolve orographic forcing. Preference was therefore given to models with a nominal resolution of about 1.5° or finer; however, several coarser models (e.g., CanESM5, MIROC-ES2L, FGOALS-g3 and MPI-ESM1-2-LR; Table 3) were retained to preserve ensemble diversity, including the spread in climate sensitivity. This selection is in agreement with

outcomes of regional climate model runs where improved simulation was realised at resolutions lower than 1.5° (Nguyen et al., 2024). The resolution requirement also supported future statistical downscaling procedures since compatibility was ensured, and the climate signal's physical integrity was maintained.

Applying required climate variables at a daily temporal resolution was another critical filter. The study required complete daily maximum and minimum temperature for all SSP scenarios. A few otherwise suitable models (e.g., TaiESM) were excluded because the wider variable set needed for follow-up hydrological work, including wind speed for potential evapotranspiration, was unavailable; potential evapotranspiration is not computed in the present temperature-only study. This strict requirement for the completeness of variables adopts AgMIP's protocol for climate impact science (Monerie et al., 2020).

Ensemble diversity was chosen carefully to adequately sample the uncertainty space of future climate projections. The ultimate selection includes models that span the range in equilibrium climate sensitivity (ECS) estimates across CMIP6, from low-sensitivity models like INM-CM4-8 (ECS ≈ 1.8°C) to high-sensitivity models like CanESM5 (ECS = 5.6°C) (Nguyen et al., 2024). This approach captures structural uncertainties within which the climate models work, but the ensemble still contains closely related pairs (CNRM-CM6-1/CNRM-ESM2-1, INM-CM4-8/INM-CM5-0 and MIROC6/MIROC-ES2L) that share parameterisations or modelling-centre heritage, so it is not fully independent. This is why independence-aware ClimWIP weighting was applied at the virtual stations, whereas the correlation-based weights at the GMet stations do not account for redundancy. Only one realisation (r1i1p1f1) of each model was used, so internal variability is not sampled, and the availability of each model under each SSP is not shown in Table 3. The resulting ensemble yields a more stable probability distribution of future climate outcomes than would be provided by the "best-performing" models alone. Skill in representing the dominant modes of West African variability (Atlantic Niño and ENSO teleconnections) was not evaluated for the selected models in this study, and interannual variability and extremes are not analysed.

This multi-faceted selection approach aligns with emerging best practice in climate model evaluation, moving beyond aggregate mean-state performance metrics to evaluate a model's ability to capture relevant physical processes (Nguyen et al., 2024). Even acknowledging that no perfect model selection protocol exists, this study’s method offers a transparent, physically driven rationale for employing the CMIP6 ensemble for this study of White Volta Basin climate

change effects. The resulting projections thus represent a considerable balance trade-off between model performance, process representation, and uncertainty sampling - worthwhile properties for generating useful climate information for regional adaptation planning.

Table 3: Selected Global Climatic Models

Model	Resolution		Variant label	Available Data
	Lat (°N)	Lon (°E)		Temperature (°C)
ACCESS-CM2	1.3	1.9	r1i1p1f1	ü
BCC-CSM2-MR	1.1	1.1	r1i1p1f1	ü
CanESM5	2.8	2.8	r1i1p1f1	ü
CNRM-CM6-1	1.4	1.4	r1i1p1f1	ü
CNRM-ESM2-1	1.4	1.4	r1i1p1f1	ü
FGOALS-g3	2	2	r1i1p1f1	ü
GFDL-ESM4	1	1.3	r1i1p1f1	ü
INM-CM4-8	1.5	2	r1i1p1f1	ü
INM-CM5-0	1.5	2	r1i1p1f1	ü
IPSL-CM6A-LR	1.3	2.5	r1i1p1f1	ü
KACE-1-0-G	1.3	1.9	r1i1p1f1	ü
MIROC6	1.4	1.4	r1i1p1f1	ü
MIROC-ES2L	2.8	2.8	r1i1p1f1	ü
MPI-ESM1-2-LR	1.9	1.9	r1i1p1f1	ü
MRI-ESM2-0	1.1	1.1	r1i1p1f1	ü

2.4 The approach of statistical bias correction

The CMhyd tool, developed to enable bias correction of simulated climate data generated from GCMs and RCMs, was employed in this study (see Figure 3) (Siabi, et al., 2023). With the assumption that the correct technique and its parameterisation for present climate conditions are also applicable to future situations, bias correction processes use a transformation algorithm to adjust climate model output. For bias correction of climate variables for diverse applications, the tool has been widely used (Arfasa et al., 2023; Kheir et al., 2023; Lanzante et al., 2018; Li et al., 2020; Nazeer et al., 2022; Rathjens et al., 2016; Siabi et al., 2021; Siabi, Phuong, et al., 2023). For statistical bias correction, the Climate Model Data for Hydrologic Modelling (CMhyd) Programme was employed. According to Rathjens et al. (2016), this tool was created to bias-correct climatic data obtained from RCMs and GCMs. Because the data from GCMs and RCMs are so coarse, bias correction is necessary. In general, the CMhyd has been used for a variety of applications (Awafo, et al., 2023). Due to its compatibility with CMIP6 data in simulating past and future climates, the CMhyd was used in the study.

Quantile mapping (QM) underlies CMhyd's approach as a statistical technique that systematically adjusts the model output distribution in response to observations. The process commences with the building of cumulative distribution functions (CDFs) of observed data and model simulations over a historical reference time frame. The temperature variables, due to their normally distributed nature, usually employ Gaussian distributions during the mapping procedure, as illustrated in Equation (1).

The actual correction is the matching of comparable quantiles between the model and observed distributions. For example, suppose a model's 95th percentile value is 20% higher than observations at any time step; the bias is systematically corrected across all time steps. This technique is particularly useful for extreme events since the biases in the tails of the distribution, most relevant to the assessments of the impacts of climate change, are specifically targeted (Padulano et al., 2025). The traditional QM approach, however, has a severe limitation - the model relationship of biases to true values is assumed to remain static over time, something increasingly disputed under non-stationarities of climatic conditions.

Temperature variables benefit from comparatively less involved handling due to their distributions being closer to symmetry. Linear scaling methods, applying additive corrections to the mean and multiplicative ones to the variance, are typically sufficient for temperature datasets (Lehner et al., 2021). This has the merit of preserving important physical correlations

in the datasets, i.e., diurnal temperature cycles and seasonal dependencies. For temperature extremes, non-parametric quantile mapping is applied by certain codes to better represent departures from the Gaussian distribution in distribution tails.

The time-invariant bias assumption is perhaps the largest weakness of the classical methods of quantile mapping. More recent methods have been developed that aim to preserve the climate change signal while correcting biases. Among the developments is the Quantile Delta Mapping (QDM), an approach whose process of correcting biases is separated from the climate change signal (Cannon et al., 2015). The technique deploys relative model future change increments but bases the absolute numbers on observed distributions to preserve the trends as the climatic model predicts.

Multivariate approaches have also been developed to address the interconnected nature of climate variables. Methods like MBCn (Multivariate Bias Correction with N-dimensional probability density function transform) attempt to preserve the physical relationships between variables, such as maximum and minimum temperature (Cannon, 2018). However, these techniques face challenges, particularly when relationships between variables may themselves change under future climate conditions.

The performance of CMhyd's techniques has been shown in multiple regional applications. These regional analyses commonly use split-sample validation approaches, wherein the approach is calibrated using one part of the historical record and assessed using an additional part, offering valuable information on the temporal stability of the corrections. No split-sample validation was carried out in this study: the metrics in Section 3.1 compare the corrected output with the same observations used to fit the correction (monthly values), so they measure goodness of fit and not out-of-sample skill or the stability of the correction under climate change.

$$f(x \mid \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} ; -\infty < x < \infty \quad \ldots\ldots\ldots\ldots\ldots (1)$$

where, x = random variable.

f = Gaussian (normal) probability density function (PDF);

μ = location parameter (mean);

σ = scale parameter (standard deviation).

For temperature, a Gaussian distribution with location parameter μ and scale parameter σ was used, as it has been confirmed as the most suitable for bias correction of temperature in previous

studies (Siabi et al., 2023). In this study, the distribution mapping method in CMhyd was therefore applied, using a Gaussian distribution for Tmax and Tmin; linear scaling, QDM and the multivariate approaches described above are presented for context only and were not applied. Distribution mapping, unlike QDM, does not explicitly preserve the model-projected change signal and may modify it (Cannon et al., 2015); the projected changes reported here should be read with this in mind.

2.5 Weighted Ensemble Mean

Rather than combining the bias-corrected GCM outputs with a simple arithmetic mean, we weighted each model's contribution to the ensemble according to its demonstrated skill over the historical period. For each station and variable, the Pearson correlation coefficient between each model's bias-corrected historical simulation and the observed series was computed over the overlapping historical record; negative correlations were set to zero, and the remaining values were normalized to sum to unity, giving each model a fixed weight. These weights were then locked and applied unchanged to the corresponding future SSP simulations of the same model, so that a model with weak historical skill at a given station carries correspondingly little influence over that station's projected future ensemble. Where a candidate model lacked sufficient historical data to compute a baseline correlation at a given station, it was assigned a weight of zero at that station rather than being dropped from the ensemble altogether.

For the virtual stations, weights were instead derived using the Climate model Weighting by Independence and Performance (ClimWIP) approach (Merrifield et al., 2019), which combines a model's historical performance with its independence from other ensemble members, so that two closely related models do not each receive full weight simply by virtue of agreeing with one another. Both weighting schemes produce a fixed, non-negative weight per model that sums to unity across the ensemble at a given station.

On any day where one or more ensemble members had no valid value for instance, where a specific model's simulation did not extend across the full future period that day's weights were renormalized to sum to unity among only the models with valid data for that day, rather than treating the missing value as a zero contribution while still counting the full weight of the missing model. This distinction matters: without renormalization, a day on which a high-weight model happened to be missing would be pulled artificially toward zero, understating both the ensemble mean and the true spread of the projection. Renormalisation also changes the ensemble composition through time and can introduce step changes if a model’s series begins

or ends; the set of contributing models should therefore be checked year by year, particularly for SSP1 Tmin.

Monthly climatologies were then computed from the resulting daily weighted-ensemble series. For Tmax and Tmin, the climatology for a given month is the arithmetic mean of the weighted ensemble across all days assigned to that month within a given period.

2.6 Metrics used for Model Validation

The study used a variety of evaluation indicators to examine how well the bias-corrected model performed. The accuracy of the bias-corrected model was assessed using the Root Mean Square Error (RMSE) as demonstrated in equation (3), the coefficient of determination (R^2) as illustrated in equation (2), and per cent bias (Pbias) as shown in equation (4). Pbias is expressed in per cent and, because it is computed as model minus observation, positive values indicate overestimation and negative values underestimation. The metrics were computed for each individual model on monthly values over the calibration period, not for the weighted ensemble. The goodness-of-fit was evaluated using RMSE, which represents the standard deviation of the differences between the modelled and observed data. As a result, decreased RMSE improves model performance.

The fit quality between the modelled and observed data was also evaluated using the R2 statistic. When R^2 gets close to 1, the performance of the model is improved (Getachew & Manjunatha, 2021)

$$R^2 = \frac{\sum_{i=1}^{N}(X_i-\overline{X})2(Y_i-\overline{Y})2}{\sum_{i=1}^{N}(X_i-\overline{X})^2\sum_{i=1}^{N}(Y_i-\overline{Y})^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Y_i - X_i)^2}{N}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

$$Pbias = 100 \text{ x } \frac{\sum_{i=1}^{N}(Y_i - X_i)}{\sum_{i=1}^{N} X_i} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

where Xi and $\overline{X}$ and Yi and $\overline{Y}$ are the observed and model monthly and average data, respectively, of the ith event in N events.

2.7 Projected change analysis

The outputs of the model for Tmax and Tmin until 2100 were compared to the reference period (1960–2014) and (1980–2014) for the observed and virtual stations, respectively. Equation 5 was used to estimate the underlying anomalies as absolute differences for Tmax and Tmin (Dembélé et al., 2022).

$$\Delta\text{future} = Q_{\text{future}} - Q_{baseline} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(5)}$$

Where;

Δ = absolute change,

Q baseline = Tmax or Tmin, for the baseline period.

Q future = Tmax or Tmin, for the future period.

The rise and fall of the variables for the future period are signified by positive and negative signals.

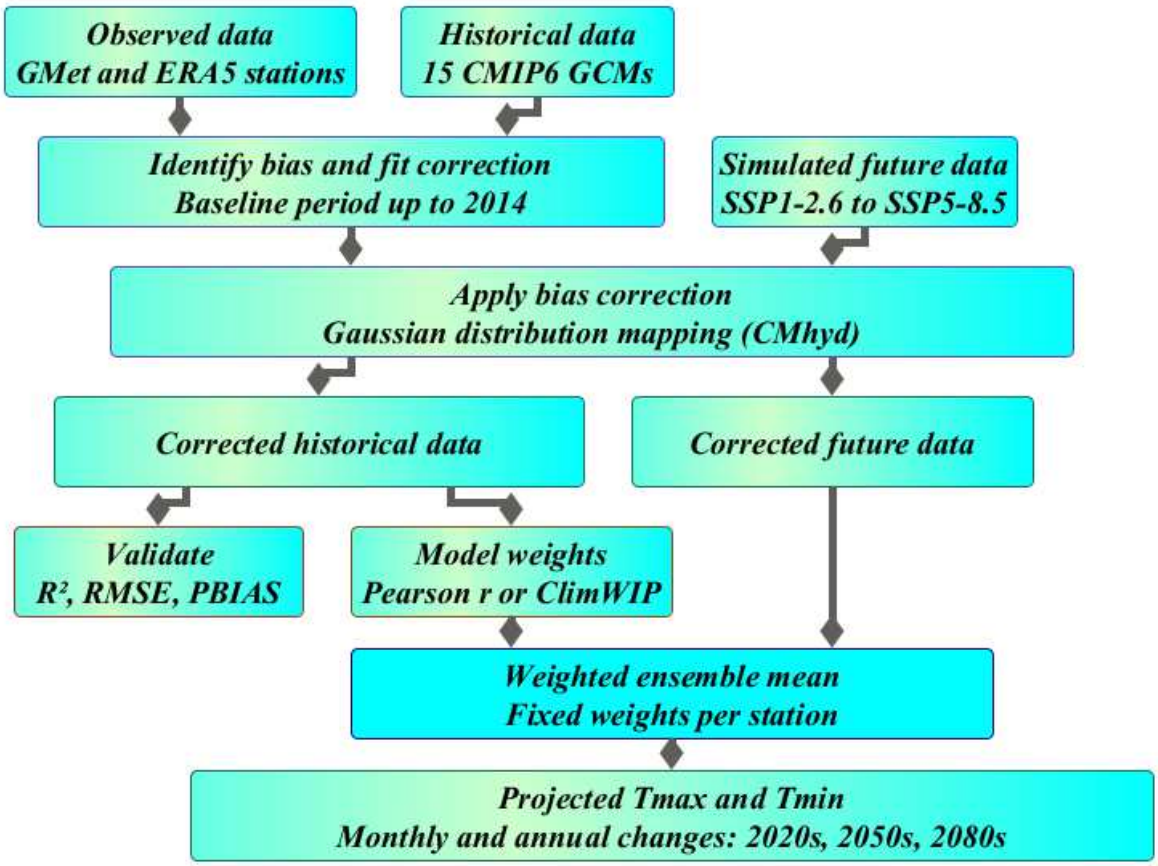

Figure 3: Framework for bias correction in CMhyd, adapted from Siabi et al., (2023)

3. RESULTS

3.1 Performance Validation of Bias-Corrected Models

The ensemble bias-corrected variables (maximum and minimum temperature) and the raw data are graphically compared in Figures 4 and 5. Figures A–C in the Appendix provide detailed data, demonstrating a realistic match between the simulated and recorded values of these variables according to the models' performance statistics. These statistics are in-sample measures of goodness of fit, computed per model on monthly values, and are not evidence of out-of-sample skill; the very small RMSE values (as low as 0.00–0.01 °C) are what is expected when a correction is evaluated against the data used to fit it.

The coefficient of determination (R^2) supports this finding. For the bias-corrected data, R^2 ranged from 0.83 to 0.99 for Tmax and from 0.91 to 0.99 for Tmin across the individual models (Appendix Figure A), compared with 0.00 to 0.59 for the raw data. For Tmax and Tmin, the bias-corrected PBIAS ranged from 0.00 to 0.48, whereas the raw PBIAS ranged from -16.9 to 20.0 (Appendix Figure C).

When the Root Mean Square Error (RMSE) was considered, the bias-corrected values ranged from 0.01 to 0.38 °C for Tmax and 0.00 to 0.25 °C for Tmin (Appendix Figure B). These figures demonstrate a significant discrepancy from the original data values, which fluctuated substantially higher. Appendix Figures A–C show that the results of using R2, RMSE, and Pbias to analyse the bias-corrected data were positive. This result agrees with Mensah et al. (2024).



Figure 4: Comparison of ensemble bias-corrected and raw Tmax relative to the baseline periods. Obs = Observed, mod = modelled. Virt = Virtual Station (a) Garu, (b) Tamale, (c) Zuarungu, (d) Virtual Station 1, (e) Virtual Station 2, (f) Virtual Station 3, (g) Virtual Station 4, (h) Virtual Station 5, (i) Virtual Station 6, (j) Virtual Station 7, (k) Virtual Station 8, and (l) Virtual Station 9.

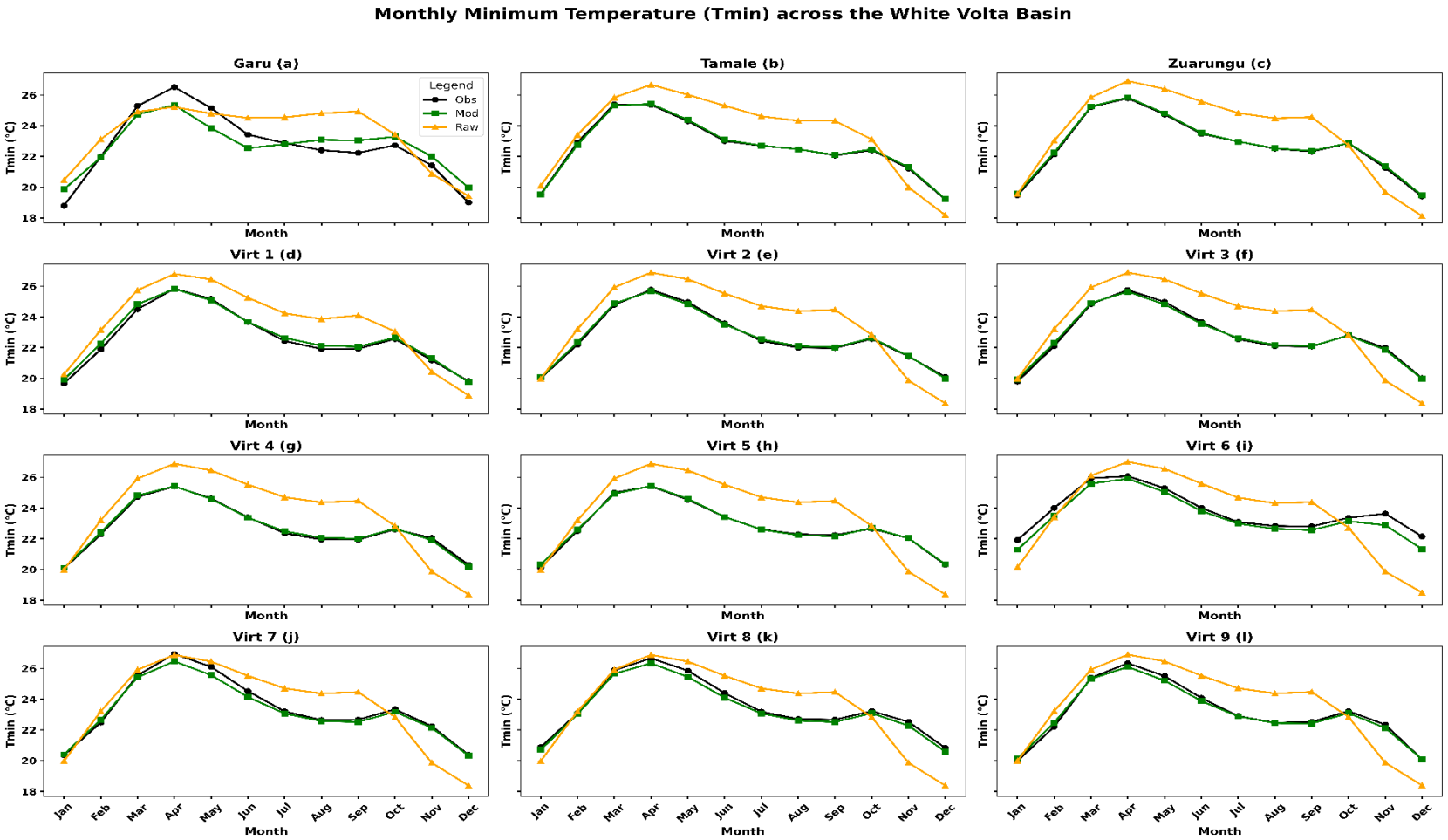

Figure 5: Comparison of ensemble bias-corrected and raw Tmin relative to the baseline periods. Obs = Observed, mod = modelled. Virt = Virtual Station (a) Garu, (b) Tamale, (c) Zuarungu, (d) Virtual Station 1, (e) Virtual Station 2, (f) Virtual Station 3, (g) Virtual Station 4, (h) Virtual Station 5, (i) Virtual Station 6, (j) Virtual Station 7, (k) Virtual Station 8, and (l) Virtual Station 9.

3.2 Projected temperature under the SSPs (1, 2, 3, and 5) in the WVB

These patterns show how temperature may change at different locations in the Ghanaian part of the White Volta Basin from past periods to the year 2100. To increase the awareness of the differences in temperature in the basin, the study took into consideration nine virtual stations in addition to three GMet stations (Garu, Tamale, and Zuarungu).

3.2.1 Projected annual ensemble mean maximum temperature trends under SSP Scenarios

The recorded historical output for Garu (Figure 6) indicates occasional variations in the highest temperature, but starting approximately 2000, a clear rising trend is seen. Observed Tmax coverage is limited (Figure 6): Garu records are sparse after about 1987, Tamale has none between about 1985 and 2013, and Zuarungu has long gaps, so the historical trends described here should be read with caution. Going forward, the maximum temperature is expected to rise continuously compared to all SSPs, with SSP5 projecting the highest increase. Under SSP5, the highest temperatures in Garu might reach close to 40°C by 2100, highlighting the implications of a world dependent on fossil fuels. The temperature rise is lower in SSP1, which represents a more sustainable future, but it is still significant, with the maximum temperature projected of about 37°C by 2100. Annual SSP1 Tmax does not fall below the observed baseline at any of the three GMet stations in Figure 6.

Tamale's temperature trends are comparable to those of Garu, while the historical data reveals a slightly elevated maximum temperature observed. The different SSP forecasts start to diverge in 2020. Under SSP5, Tamale is expected to see Tmax of about 38.5–39°C by 2100. SSP1, on the other hand, offers a more positive picture, with Tmax values that are still much greater than the existing levels but staying below 38°C. This indicates that Tamale will continue to experience the effects of climate change despite international attempts to promote sustainability. In Zuarungu, the Tmax trends are like those in Tamale and Garu, albeit with a significantly lower historical baseline. With predictions that temperatures would reach about 38.5–39°C by 2100, the rise in temperature under SSP5 is especially alarming. The rising trend is comparable, but less extreme, for the other SSPs. The Zuarungu trajectory draws attention to the pressing global issue of climate change, where even slight increases in the highest temperature may have negative impacts on the basin's availability of water, public health, and agriculture. The virtual stations (Virt 1 through Virt 9) (Figure 6), which are ERA5-derived grid locations, further highlight temperature changes in the basin. Like the three actual places, these virtual sites show constant rises in Tmax in all SSPs. These stations indicate that annual Tmax will reach about 37.5–38.5°C by 2100 under SSP5, which is a marked sign of the long-term effects of neglected climate change. These virtual station patterns highlight how consistently elevated temperatures are expected throughout the basin, indicating that no location is immune to the effects of climate change.

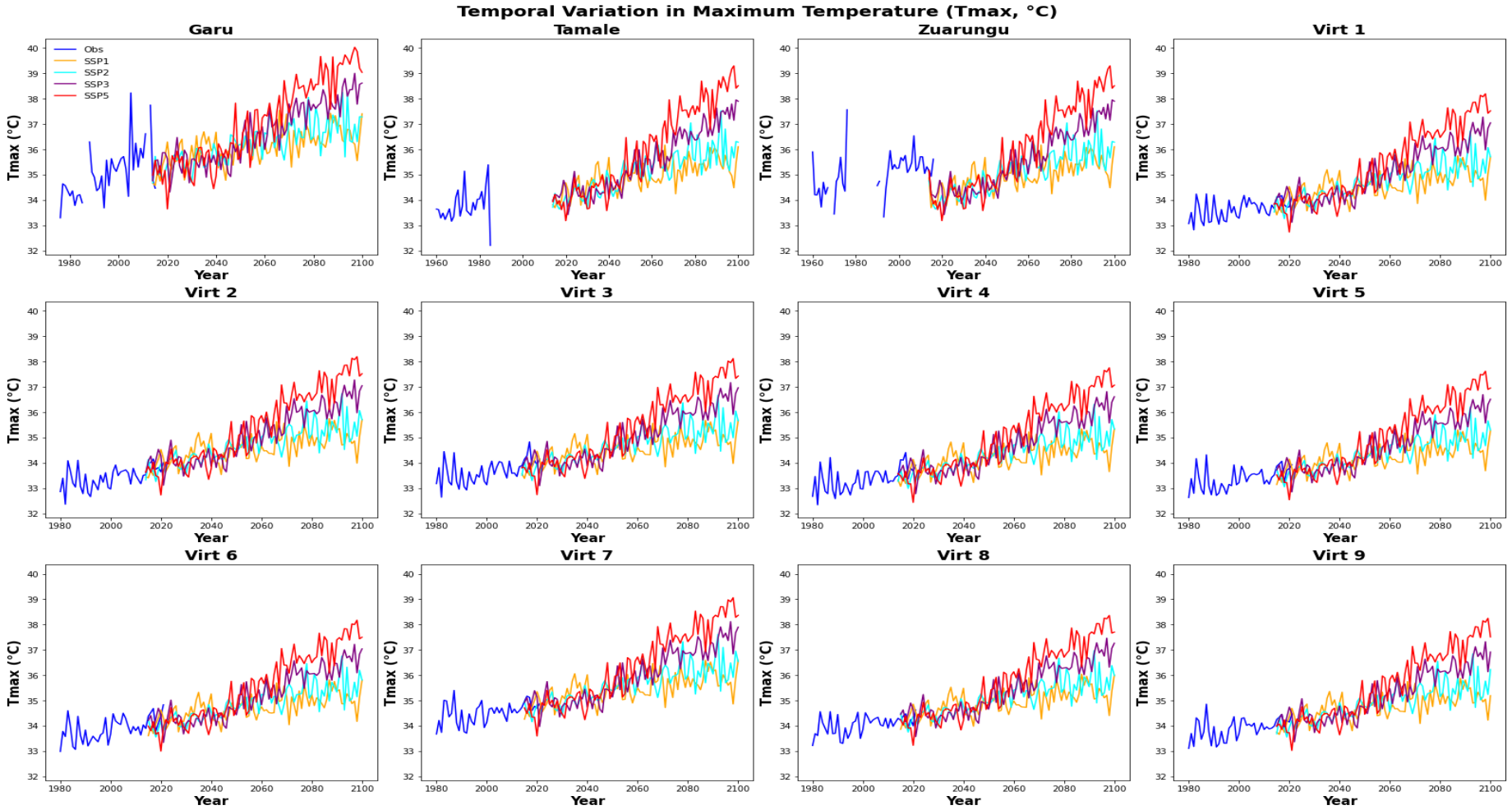

Figure 6: Variation in annual mean of daily maximum temperature (Tmax) between the period 1960 to 2100, Virt: Virtual Stations: Virtual Station 1, Virtual Station 2, Virtual Station 3, Virtual Station 4, Virtual Station 5, Virtual Station 6, Virtual Station 7, Virtual Station 8, and Virtual Station 9

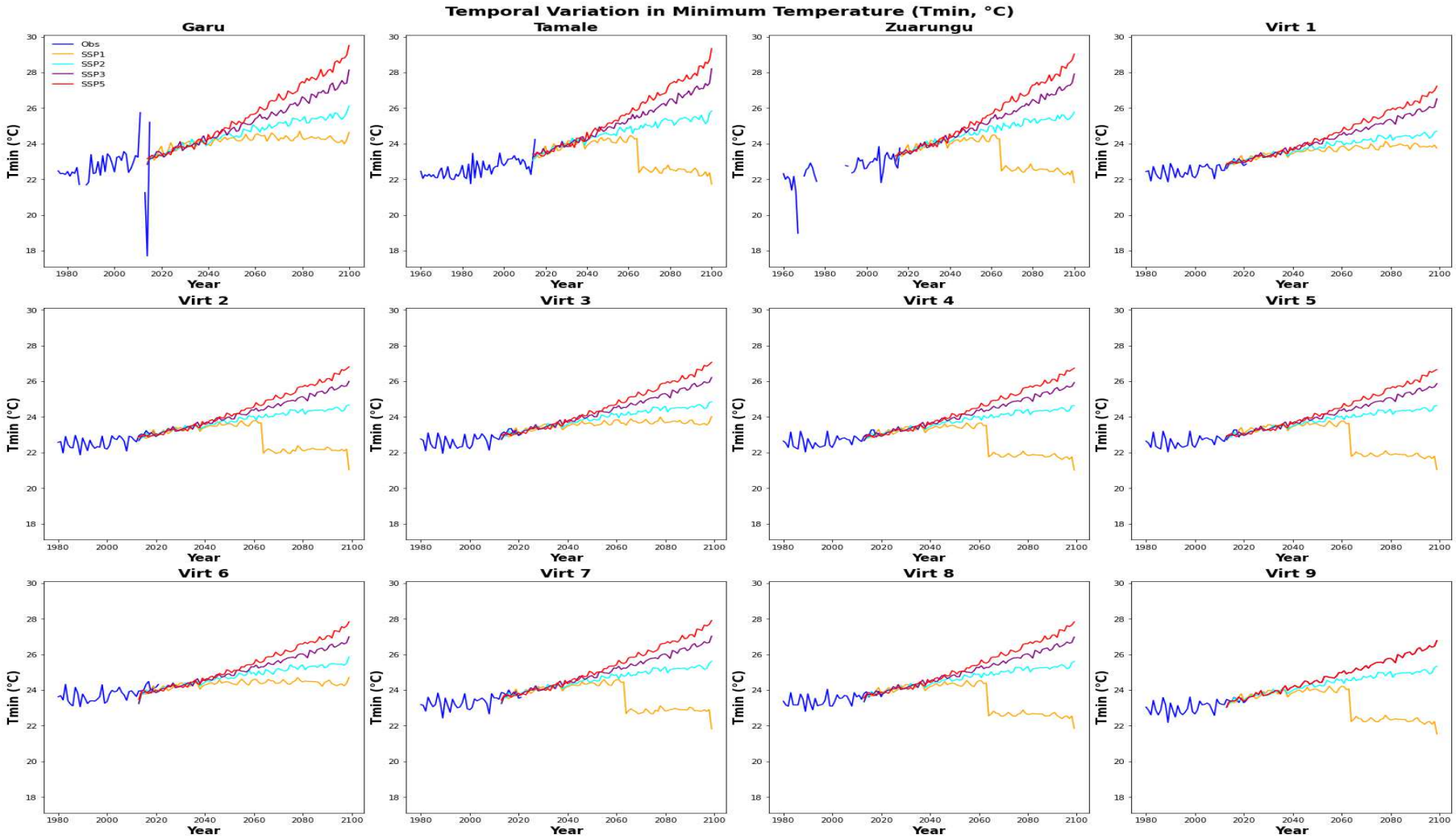

Figure 7: Variation in annual mean of daily minimum temperature (Tmin) between the period 1960 to 2100. Virt: Virtual Stations: Virtual Station 1, Virtual Station 2, Virtual Station 3, Virtual Station 4, Virtual Station 5, Virtual Station 6, Virtual Station 7, Virtual Station 8, and Virtual Station 9

3.2.2 Projected annual ensemble mean minimum temperature trends under SSP Scenarios

Observed annual Tmin (Figure 7) is broadly flat. At Garu it fluctuates between about 22 and 23.5°C from the 1980s to the early 2010s, with two isolated spikes near 2013 (about 17.7 and 25.7°C) that look like data errors and should be checked. Tamale and Zuarungu stay at about 22–23°C with no clear trend (Zuarungu has an isolated low value near 19°C in the late 1960s). At Virtual Stations 1 to 9 the ERA5-derived Tmin fluctuates around 22–23.5°C with no marked trend over 1980–2010.

Different projections under various SSPs are shown in Figure 7, starting in 2020. Though at different rates, every SSP in Garu predicts rising Tmin. From 2020 to the end of the 2080s, the Tmin stabilises at approximately 25°C under SSP1, which represents a sustainable development path with robust climate action. By comparison, SSP5 predicts a considerable increase in Tmin, with temperatures reaching about 29–30°C by 2100, assuming rapid economic expansion and a substantial reliance on fossil fuels. Minimum temperatures in SSP2 and SSP3, which are located between these two extremes, are expected to rise to approximately 26°C and 27°C, respectively, by the 2080s.

Similar trends can be seen in Tamale's Tmin forecasts. Under SSP1, Tmin stays at about 24°C until the early 2060s and then falls abruptly to about 22–23°C (see the discussion of this step below), whereas under SSP5 it rises to about 29°C by 2100. Tmin rises more moderately under SSP2 and SSP3, to about 26°C and 28°C, respectively, by 2100. The spread of roughly 3.5°C between SSP2 and SSP5 at 2100 illustrates the influence of the emission pathway on minimum temperatures in the basin. Similar trends may be seen in Zuarungu, where SSP1 stabilises at about 24°C until the early 2060s (then drops to about 22–23°C) and SSP5 rises to about 29°C by the end of the century. Although Tmin is rising under the other SSPs as well, the rate of warming is not as rapid as it is under SSP5.

Also (Figure 7), SSP1 Tmin at Virtual Station 1 stabilises at roughly 24°C, whereas SSP5 rises to about 27°C by 2100; SSP2 and SSP3 fall in between, at roughly 24.5°C and 26.5°C. At Virtual Stations 2 and 5, SSP1 Tmin follows about 23.5–24°C until the early 2060s and then drops abruptly to about 22°C, while SSP5 rises to about 27°C and SSP2 and SSP3 reach about 24.5°C and 26°C, respectively (see Figure 7).

Under SSP1, Tmin at Tamale, Zuarungu and Virtual Stations 2, 4, 5, 7, 8 and 9 shows an abrupt step decrease of about 1.5–2°C within a single year, around 2063–65, after which it stays about 2°C lower (Figure 7). No other scenario shows this feature, and it occurs at the same time at all these stations, which is the signature of a processing artefact rather than a physical response. A plausible cause is a change in the set of models contributing to the weighted ensemble, with the weights renormalised (Section 2.5). SSP1-2.6 would not be expected to cool this region below its 1960–2014 baseline, so the post-2063 SSP1 Tmin values at these stations are not interpreted as a climate signal.

In summary, the figures show a distinct rising trend in minimum temperatures for both virtual and GMet stations, with the global socioeconomic pathway selected having a major influence

on the rate and degree of heat. Tmin is predicted to stabilise at comparatively mild values under SSP1, indicating that substantial climate action can avert extreme warming. But according to SSP5, Tmin is expected to increase significantly, with annual Tmin about 3–7°C higher than under SSP1 by 2100 (the larger differences partly reflect the SSP1 step change described above), while individual monthly changes relative to the baseline can be larger (as aforementioned).

The variations in SSPs show how important decisions made at the international level will be in determining the direction of the climate in the future. Under less sustainable techniques, temperatures in places like Garu and Tamale, Zuarungu (Figure 7) are expected to rise by several degrees, which might have a substantial impact on ecosystems, agriculture, and human health. The virtual stations show broadly similar warming patterns under SSP2, SSP3 and SSP5. Ultimately, these projections show how important it will be for everyone to act on a worldwide scale to influence future climate conditions.

3.3 Mean monthly changes in temperature under multiple scenarios

3.3.1 Mean monthly changes in maximum temperature under multiple scenarios

Figures 8 to 10 show the mean monthly changes in maximum temperature (Tmax) at each station under the four SSPs. In the 2020s, the changes are small, generally between 0 and 1 °C, ranging from about −0.3 °C (Virtual Station 6, January, SSP1) to 1.7 °C (Garu, January, SSP5); Virtual Station 5 shows slight decreases (down to about −0.3 °C) in several months (Figure 8). In the 2050s, Tmax increases in almost all months under SSP2, SSP3 and SSP5, with the largest changes in May–July (up to about 2.8 °C at Garu under SSP5), whereas SSP1 shows decreases in January at most stations (down to about −3.2 °C at Virtual Station 5) (Figure 9). In the 2080s, the increases are largest under SSP5 (about 1.9–4.7 °C), followed by SSP3 (about 1.1–3.9 °C) and SSP2 (about 0.4–2.9 °C), with peaks in April–June; under SSP1 the monthly changes are mixed (Figure 10): Virtual Stations 1, 3, 6 and 7 show increases of up to about 2.1 °C, whereas the other stations show decreases of up to about −2.9 °C. These decreases are inconsistent with the annual SSP1 Tmax series in Figure 6, which stay above the baseline through 2100, and are therefore not interpreted as cooling; they should be rechecked together with the SSP1 Tmin step change (Section 3.2.2).

Across all periods, the warming is largest in April–July and, in the 2020s, in January. Garu shows the largest monthly increases of all stations, particularly in the 2080s under SSP5.

3.3.2 Mean monthly changes in minimum temperature under multiple scenarios

Tmin increases in almost every month under SSP2, SSP3 and SSP5 in all three periods (Figures 11 to 13). In the 2020s, the increases are about 0.1–1.7 °C in most months, but January stands out, with increases of about 2–6 °C across the stations, the largest at Garu under SSP5 (Figure 11). In the 2050s, the monthly increases generally range from about 0.1 to 3.8 °C, with January again showing the largest values (up to about 7.2 °C at Garu under SSP5), while SSP1 gives the smallest changes, including slight decreases in March at Virtual Stations 5 and 8 (Figure 12). In the 2080s, SSP5 gives the largest monthly increases (about 2.1–6.5 °C, highest at Garu, Tamale and Zuarungu), followed by SSP3 and SSP2 (up to about 3.9 °C). Under SSP1, the

2080s Tmin changes are mixed (Figure 13): decreases in most months at Zuarungu and Virtual Stations 2, 4, 5, 8 and 9 and in several months at Garu (down to about −1.7 °C), but increases at Tamale and Virtual Stations 1, 3, 6 and 7 (up to about 2.7 °C). The decreases at Zuarungu and Virtual Stations 2, 4, 5, 8 and 9 coincide with the SSP1 step change in Figure 7 and are treated as a likely artefact; the increase reported for Tamale and Virtual Station 7 is itself inconsistent with the step visible at those stations in Figure 7 and needs rechecking.

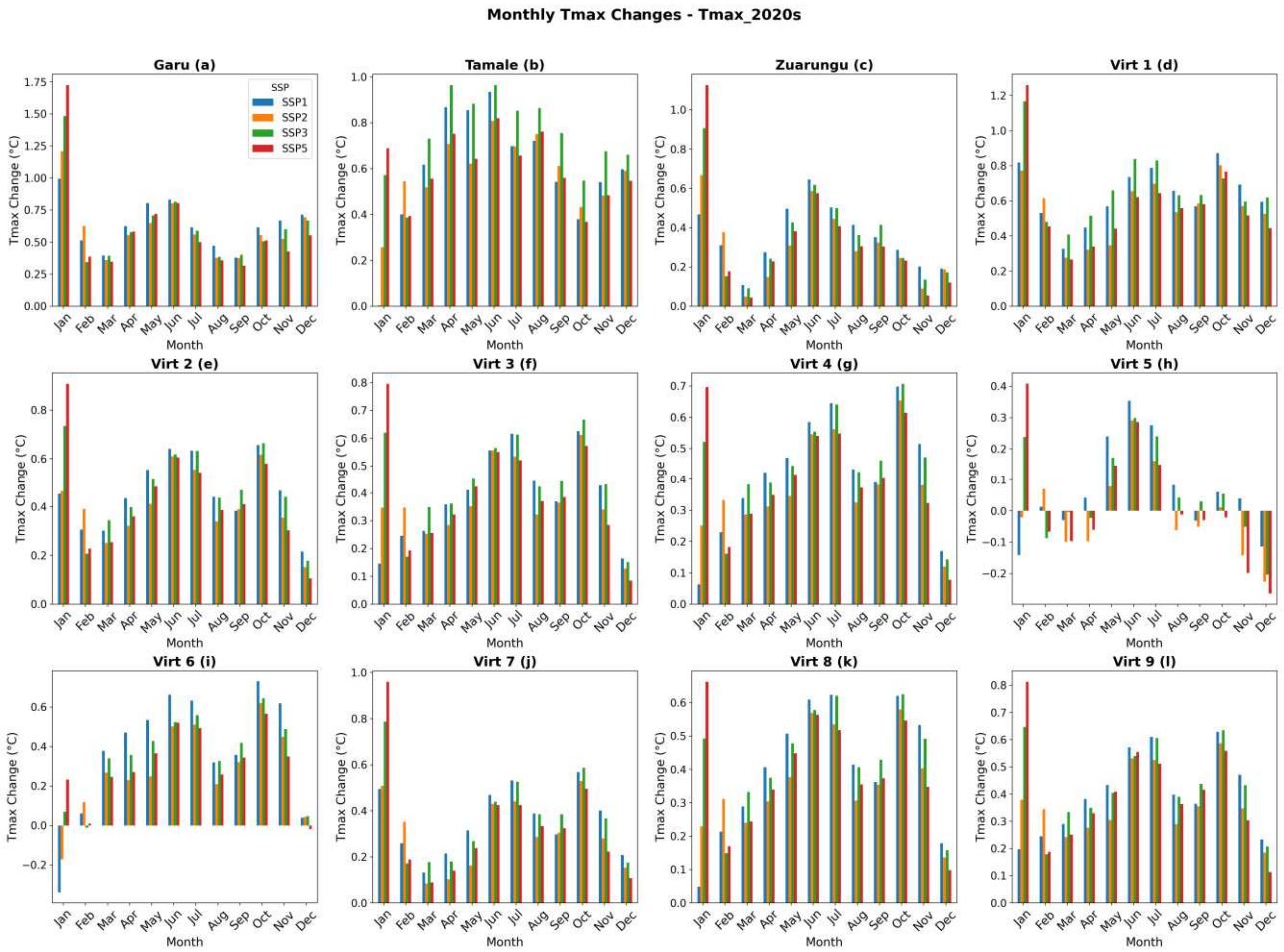

Figure 8: Monthly Maximum Temperature changes in 2020s Virts=Virtual Station (a) Garu, (b) Tamale, (c) Zuarungu, (d) Virtual Station 1, (e) Virtual Station 2, (f) Virtual Station 3, (g) Virtual Station 4, (h) Virtual Station 5, (i) Virtual Station 6, (j) Virtual Station 7, (k) Virtual Station 8, and (l) Virtual Station 9

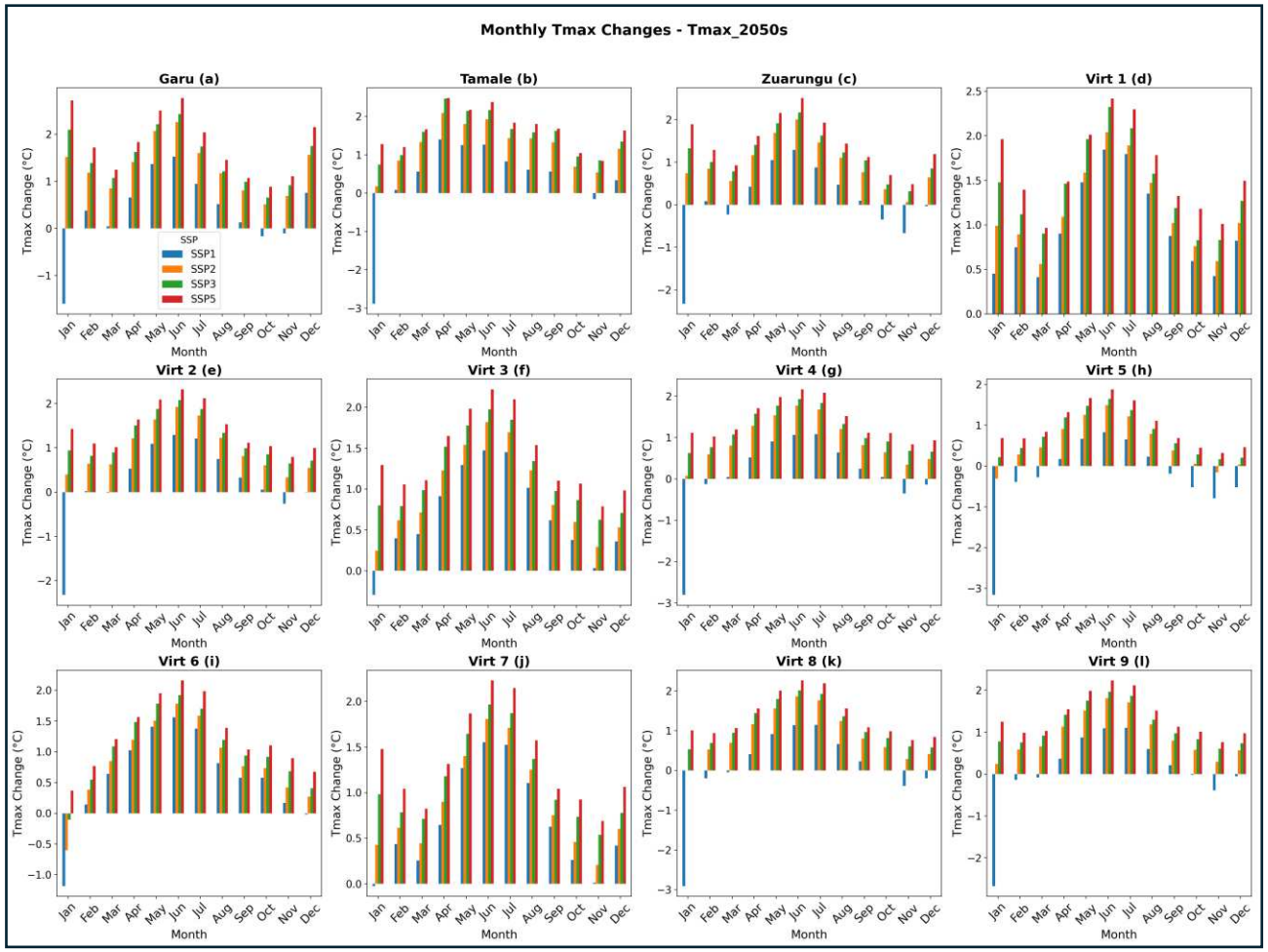

Figure 9: Monthly Maximum Temperature changes in 2050s Virts=Virtual Station (a) Garu, (b) Tamale, (c) Zuarungu, (d) Virtual Station 1, (e) Virtual Station 2, (f) Virtual Station 3, (g) Virtual Station 4, (h) Virtual Station 5, (i) Virtual Station 6, (j) Virtual Station 7, (k) Virtual Station 8, and (l) Virtual Station 9

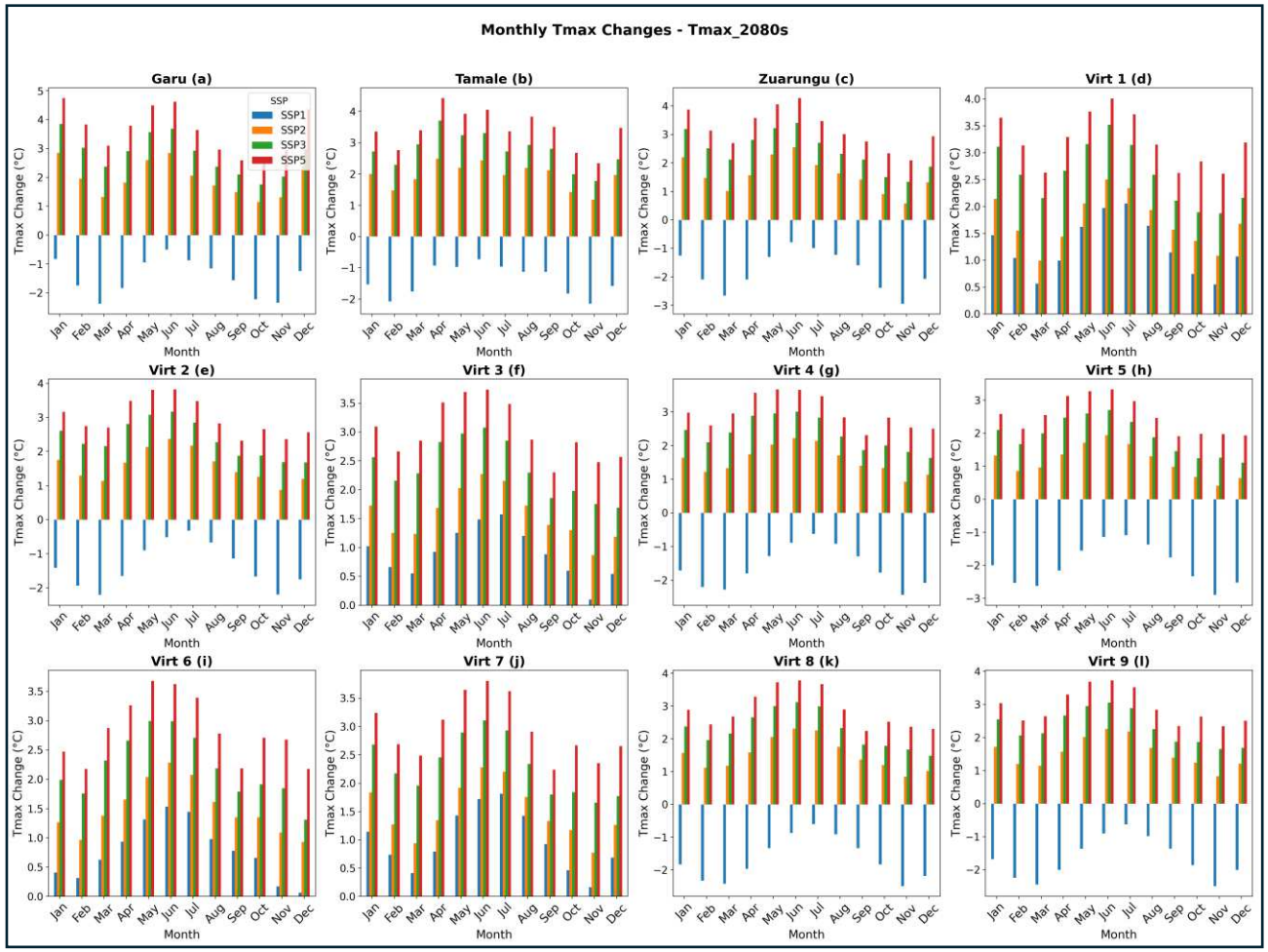

Figure 10: Monthly Maximum Temperature changes in 2080s Virts=Virtual Station (a) Garu, (b) Tamale, (c) Zuarungu, (d) Virtual Station 1, (e) Virtual Station 2, (f) Virtual Station 3, (g) Virtual Station 4, (h) Virtual Station 5, (i) Virtual Station 6, (j) Virtual Station 7, (k) Virtual Station 8, and (l) Virtual Station 9

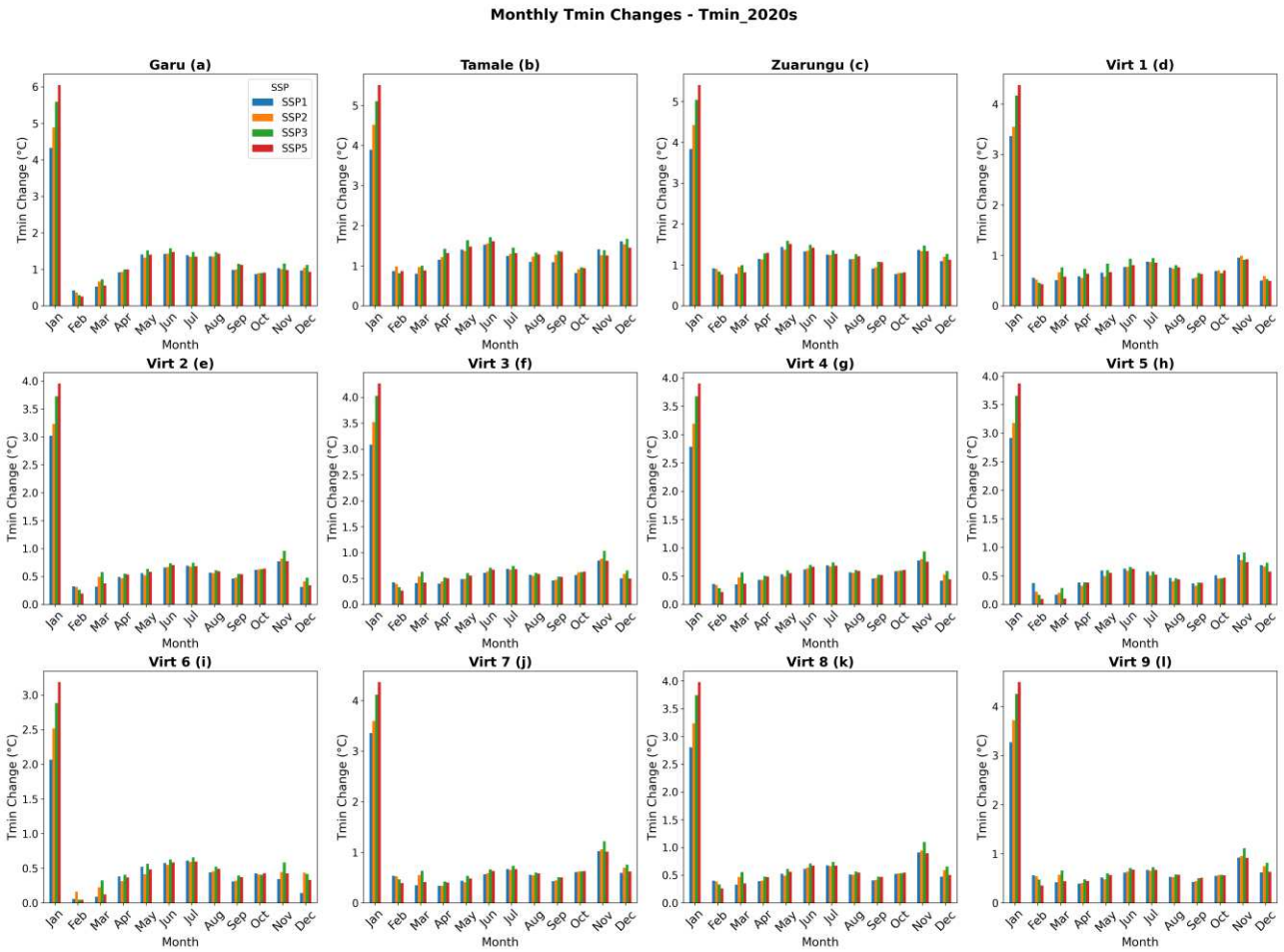

Figure 11: Monthly minimum Temperature changes in 2020s Virts=Virtual Station (a) Garu, (b) Tamale, (c) Zuarungu, (d) Virtual Station 1, (e) Virtual Station 2, (f) Virtual Station 3, (g) Virtual Station 4, (h) Virtual Station 5, (i) Virtual Station 6, (j) Virtual Station 7, (k) Virtual Station 8, and (l) Virtual Station 9.

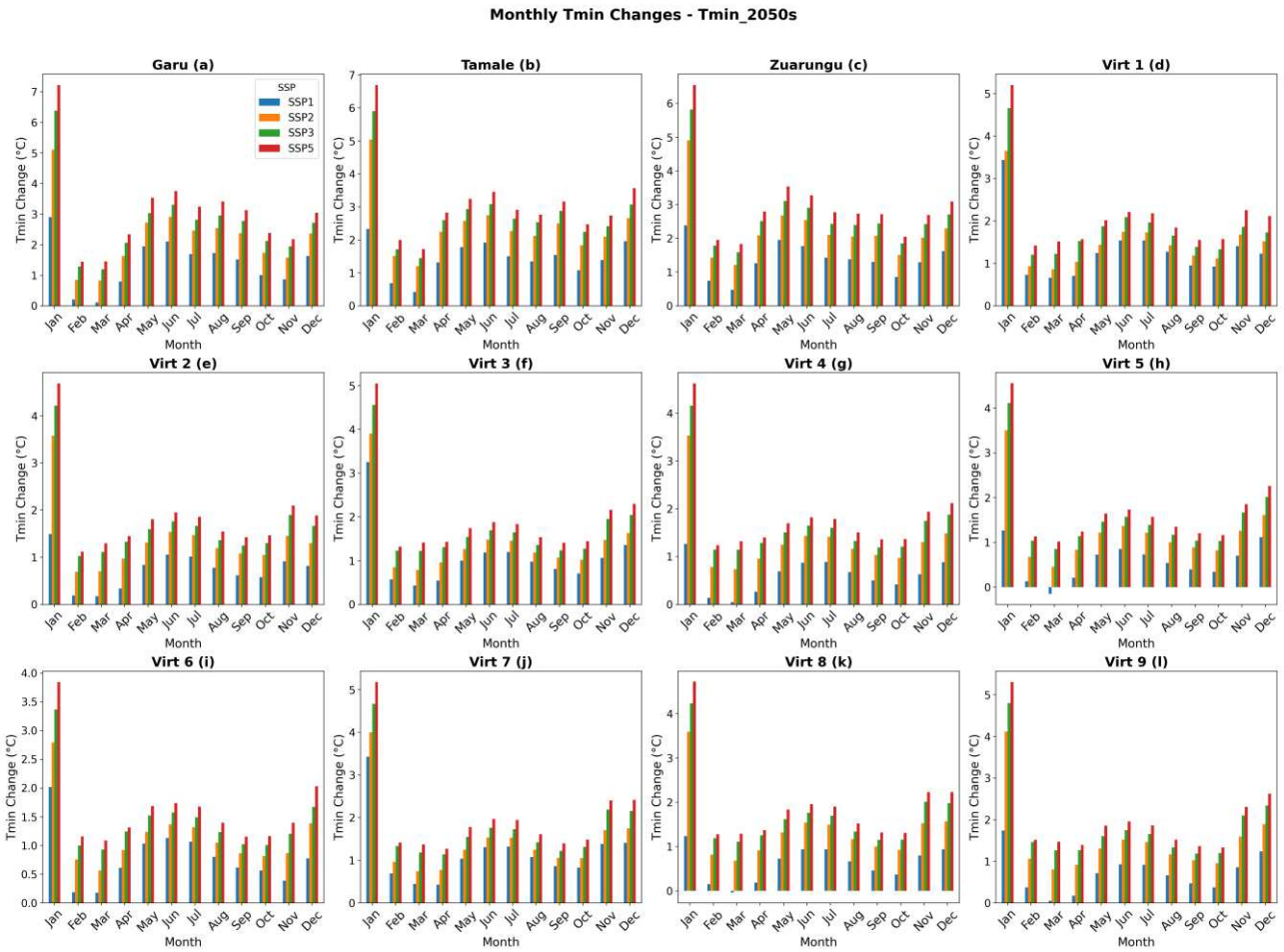

Figure 12: Monthly minimum Temperature changes in 2050s Virts=Virtual Station (a) Garu, (b) Tamale, (c) Zuarungu, (d) Virtual Station 1, (e) Virtual Station 2, (f) Virtual Station 3, (g) Virtual Station 4, (h) Virtual Station 5, (i) Virtual Station 6, (j) Virtual Station 7, (k) Virtual Station 8, and (l) Virtual Station 9

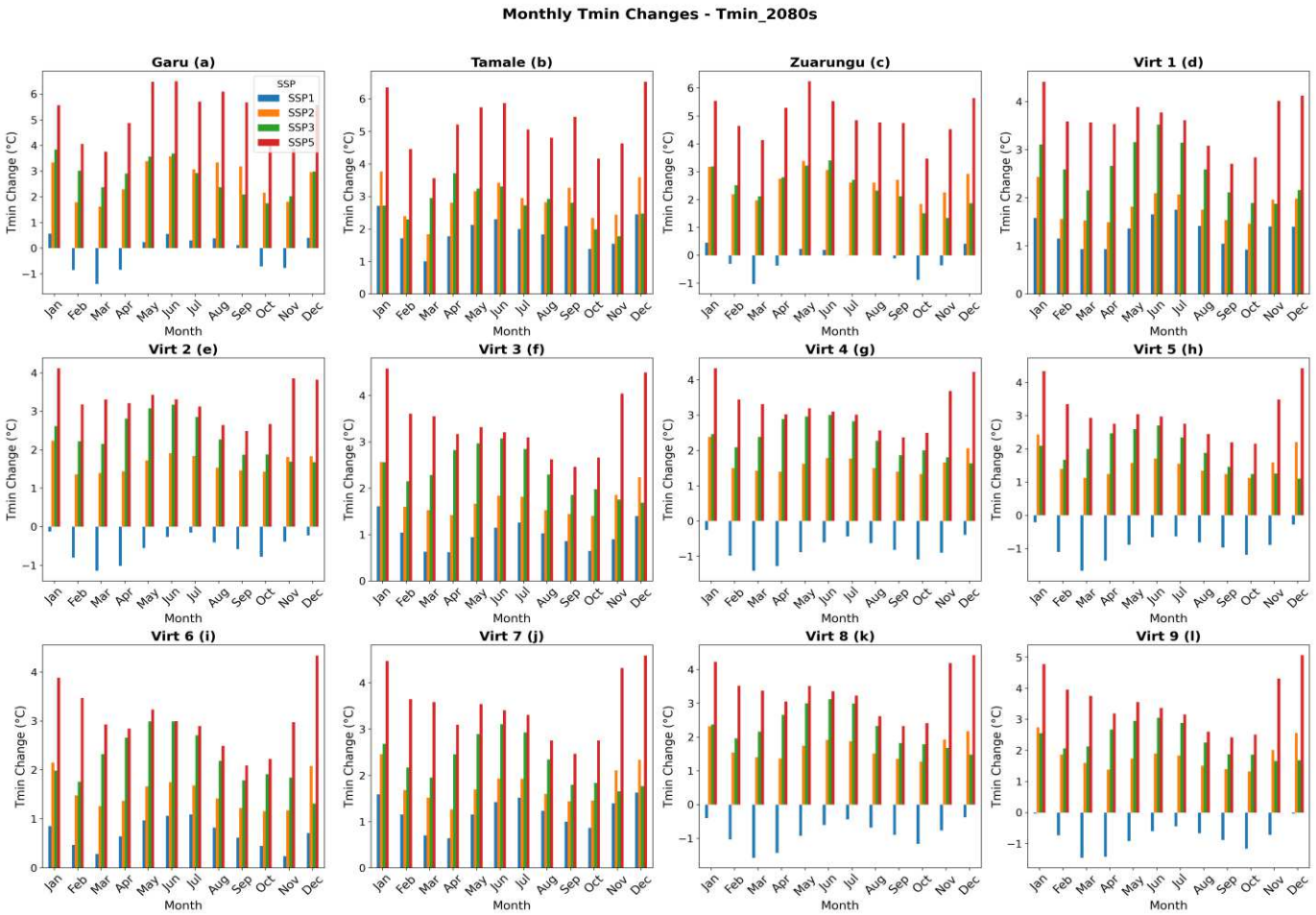

Figure 13: Monthly minimum Temperature changes in 2080s Virts=Virtual Station (a) Garu, (b) Tamale, (c) Zuarungu, (d) Virtual Station 1, (e) Virtual Station 2, (f) Virtual Station 3, (g) Virtual Station 4, (h) Virtual Station 5, (i) Virtual Station 6, (j) Virtual Station 7, (k) Virtual Station 8, and (l) Virtual Station

3.4 Spatial distribution of annual average temperature

Figures 14 and 15 show the spatial distribution of projected changes in annual mean maximum (Tmax) and minimum (Tmin) temperature relative to the baseline for each SSP in the 2020s, 2050s and 2080s. The maps interpolate only twelve station values (three GMet and nine virtual stations) by inverse-distance weighting, so they indicate broad station-to-station differences and not fine-scale spatial patterns; the GMet and virtual stations also use different baselines (1960–2014 and 1980–2014), which limits direct comparison between them, and only the Ghanaian part of the basin is covered. In the 2020s, Tmax increases by about 0.1–0.7 °C under all four SSPs, with the smallest change around Virtual Station 5 and the largest around Garu, Tamale and Virtual Station 1 (Figure 14). By the 2050s, warming increases with emission level, from about −0.2 to 1.0 °C under SSP1 to 0.7–1.3 °C under SSP2, 0.7–1.5 °C under SSP3 and 1.0–1.8 °C under SSP5. In the 2080s, Tmax rises by about 1.3–2.1 °C under SSP2, 1.8–3.0 °C under SSP3 and 2.7–3.5 °C under SSP5, with the largest increases around Garu in the north-east and around Tamale in the south-central part of the basin. Under SSP1, the 2080s pattern is mixed: Virtual Stations 1, 3, 6 and 7 still warm by about 0.7–1.3 °C, whereas Garu, Tamale, Zuarungu and Virtual Stations 2, 4, 5, 8 and 9 show decreases of up to about 1.9 °C. These Tmax decreases are not supported by the annual SSP1 Tmax series in Figure 6 and are not interpreted as cooling. Across all scenarios and periods, the smallest Tmax changes occur around Virtual Station 5 in the south-west of the basin.

Tmin increases more than Tmax in the near term (Figure 15). In the 2020s, Tmin rises by about 0.5–1.1 °C at the virtual stations and 1.4–1.7 °C at the GMet stations (Garu, Tamale and Zuarungu) under all SSPs. By the 2050s, the increases range from about 0.5–1.4 °C under SSP1, 1.1–2.3 °C under SSP2, 1.4–2.6 °C under SSP3 and 1.7–3.3 °C under SSP5. The SSP1 range for the 2050s (0.5–1.4 °C) lies below the 2020s range at the GMet stations (1.4–1.7 °C), which would imply cooling between the two periods and is a further sign that the SSP1 Tmin series needs to be reprocessed. In the 2080s, Tmin increases by about 1.7–2.9 °C under SSP2, 2.0–2.9 °C under SSP3 and 2.9–5.1 °C under SSP5, with the strongest warming around Garu, Zuarungu and Tamale. Under SSP1 in the 2080s, Tmin continues to increase at Tamale and Virtual Stations 1, 3, 6 and 7 (about 0.8–1.7 °C) but falls slightly below the baseline at Garu, Zuarungu and Virtual Stations 2, 4, 5, 8 and 9. These SSP1 decreases coincide with the step change in Figure 7 and are treated as a likely artefact; Tamale and Virtual Station 7 also show that step in Figure 7, so their reported increases need rechecking. In all periods, the GMet stations show larger Tmin increases than the virtual stations, and Virtual Station 6 in the south shows the smallest increases. Because the GMet and virtual stations use different baselines (1960–2014 versus 1980–2014), this difference may partly reflect the baselines and not a real spatial contrast.

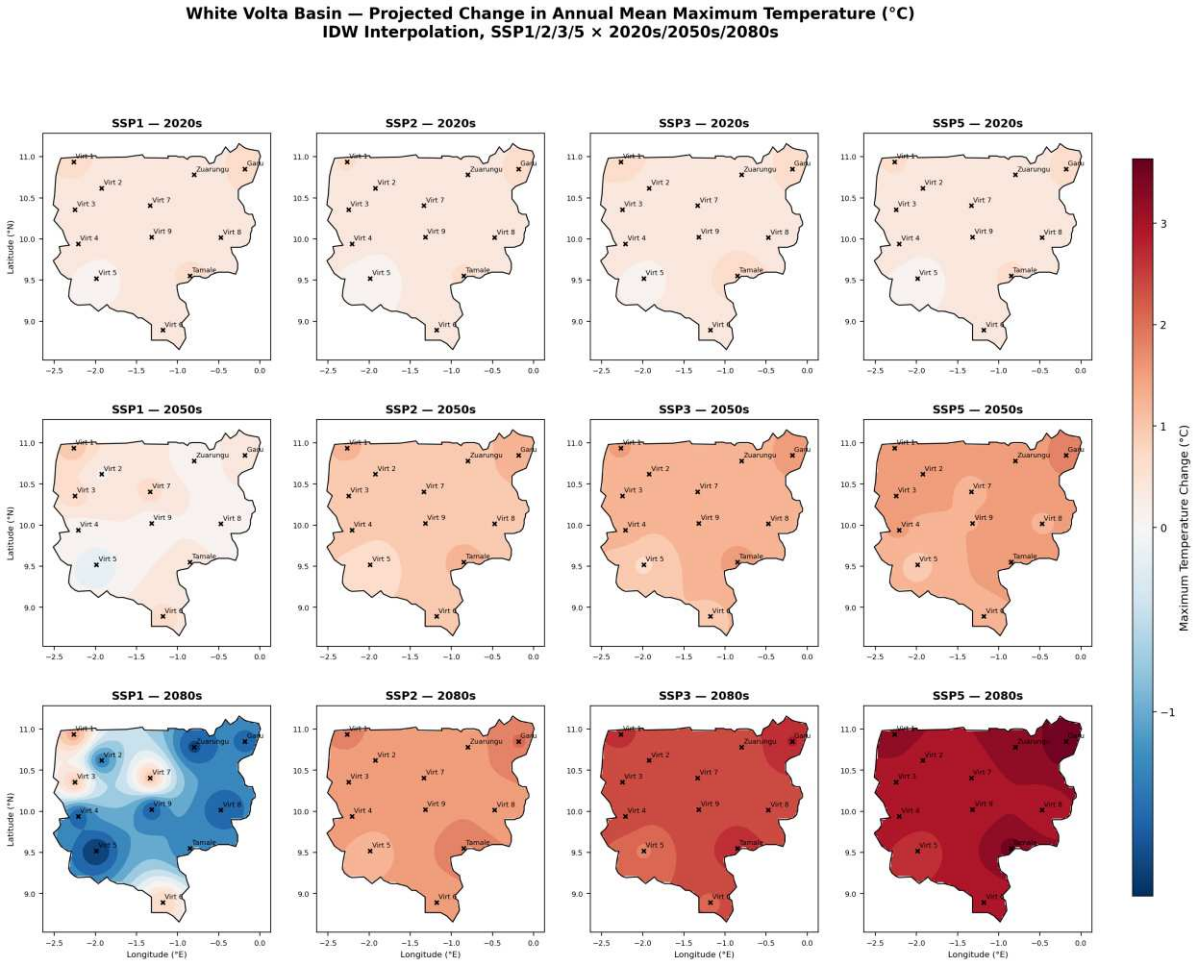

Figure 14: Spatial distribution of the change in annual mean maximum temperature (°C) across the White Volta Basin, SSP1/SSP2/SSP3/SSP5 × 2020s/2050s/2080s (IDW interpolation)

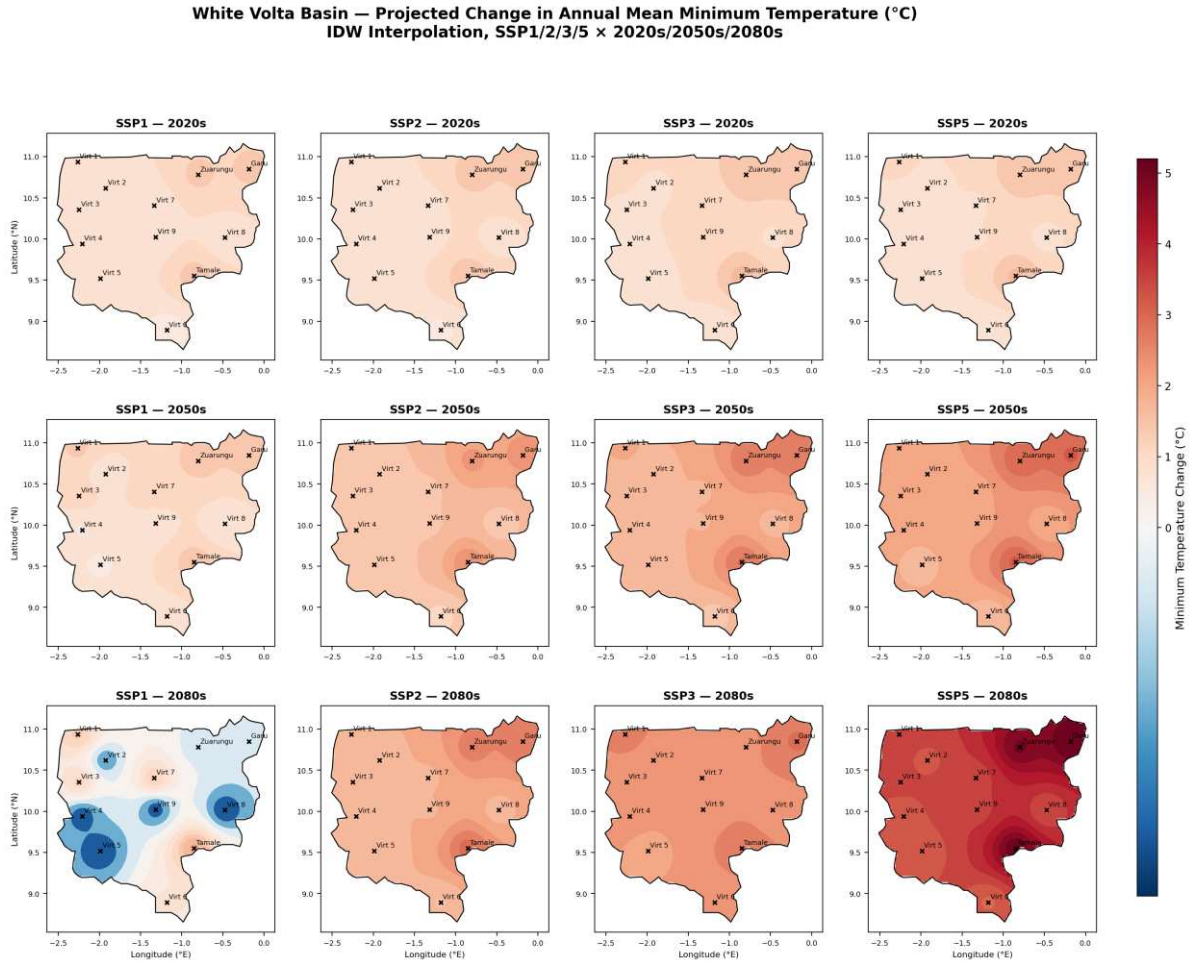

Figure 15: Spatial distribution of the change in annual mean minimum temperature (°C) across the White Volta Basin, SSP1/SSP2/SSP3/SSP5 × 2020s/2050s/2080s (IDW interpolation)

4. DISCUSSION

4.1 Metrics Performance of GCMs

The model produced a satisfactory in-sample fit overall when compared to earlier studies that used the same methodology. It is consistent with the findings of Mensah et al., 2024; Siabi et al., 2023; Yeboah et al., (2022). The ensemble bias-corrected variables perform better than the raw data, particularly when it comes to performance indicators.

According to Siabi et al., (2023) General circulation models' (GCMs') inability to accurately depict observed data may be related to the unpredictable nature of the input data. This feature of data quality has a major impact on model outputs, as seen by the discrepancy between historical and forecasted data in Figures 4 and 5. It has been observed that Tmin and Tmax are often overestimated by raw GCMs.

However, they can slightly reflect the monthly fluctuations in the empirical data. In line with Mensah et al., 2024; Siabi et al., 2023; Yeboah et al., (2022).

Based on the criteria ($R^{2,}$ RMSE, and PBIAS), an evaluation of the 12 stations revealed that they all performed better for maximum temperature and minimum temperature. The disparities discovered in the raw GCM data have been significantly reduced by applying the distribution mapping bias correction technique. However, there are still a few minor irregularities, and the RMSE and Pbias measures indicate that the stations differ from one another.

Previous research has linked unpredictability to the use of distribution mapping bias-correction techniques. Wang et al., (2023) Found that while some methods may be able to eliminate certain biases, they may also introduce new ones. Bias correction is therefore essential for effect evaluation when using raw GCMs. Moreover, previous studies have reported that CMIP6 models simulate observed climate more accurately than CMIP5 models (Incoom et al., 2022; Siabi, Awafo, et al., 2023), although a direct CMIP5 comparison was not performed in this study. However, as other recent studies have demonstrated, problems like incomplete ground station data still have a detrimental effect on model performance.

4.2 Implications of the impact of changing climate in the White Volta River Basin

According to the IPCC Sixth Assessment Report, global surface temperature in 2081–2100 is very likely to be 1.0–1.8°C higher than in 1850–1900 under the very low emissions scenario (SSP1-1.9) and 3.3–5.7°C higher under the very high emissions scenario (SSP5-8.5), with consequences for the environment (Lee, 2022). The environment, as well as socio-economic sectors like water resources, terrestrial ecosystems, coastal zones, biodiversity, agriculture, and

food security (Mensah et al., 2022), and human health (Agbosu et al., 2023), will all be impacted by climate change, according to studies on the subject.

According to the IPCC Sixth Assessment Report (Lee, 2022), for instance, climate system changes in Africa are having an additional impact on the quantity and quality of water resources. Accordingly, the White Volta Basin is not an exception. (Chen et al., 2022), since surface water and storage in rivers, lakes, and reservoirs will be impacted by the shifts linked to hotter weather (Yeboah et al., 2022). It is evident that rising temperatures pose a threat to the region's agricultural output and crop yield (Abungba et al., 2022; FAO et al., 2021; Lee, 2022; Ngaira, 2009; Siabi et al., 2021; Twumasi, 2013; Zougmoré et al., 2016).

Global mitigation efforts and local adaptation plans will be crucial in the years to come to reduce greenhouse gas emissions (Siabi, Awafo, et al., 2023). Climate-sensitive industries like hydropower are currently being impacted by climate change and its unpredictable effects on water supplies (Narkorli & Siakwa, 2023; Neumann et al., 2007; Nhemachena et al., 2020; Yeboah et al., 2022), which is making sustainable management more difficult. Given that hotter conditions are associated with increased daytime and nocturnal temperatures, animals may become more susceptible to heat stress and local water budgets (Zougmoré et al., 2016).

Crop water demand is likely to rise with increasing temperatures because of higher evapotranspiration (Incoom et al., 2022; Kabo-Bah et al., 2016), although evapotranspiration was not explicitly analysed in this study. Water supplies will be under higher stress as a result, necessitating the adoption of more drought-resistant crops or more effective irrigation techniques.

Runoff and baseflow were not modelled in this study; as a plausible implication, during dry seasons the baseflow of rivers may decrease when evapotranspiration rises alongside expected temperature increases. This influences agriculture, water supply, and hydropower production by lowering the total amount of water accessible to ecosystems and people to use.

Beyond bias correction alone, the decision to weight the multi-model ensemble rather than take a simple arithmetic mean is itself an important methodological consideration. CMIP6 models are not fully independent: many share atmospheric, land-surface, or ocean components, or trace back to a small number of modelling centres, so that an unweighted “one model, one vote” average can implicitly overrepresent a particular family of models and their shared biases (Sanderson et al., 2015). Performance-based weighting addresses a related but distinct concern: individual GCMs vary considerably in how well they reproduce observed regional climate, and a model with poor historical skill can otherwise exert as much influence on the ensemble mean and its spread as a model that is demonstrably more credible for the region (Knutti et al., 2017).

The Climate model Weighting by Independence and Performance (ClimWIP) approach adopted for the virtual station network in this study (Section 2.5; Merrifield et al., 2019) addresses both concerns jointly, down-weighting models that are either poorly performing or highly redundant with other ensemble members. Down-weighting, rather than excluding, divergent members keeps the full range of model behaviour in view while limiting the influence of outlying simulations on the projected mean. The size of this effect was not quantified here, because the weighted ensemble is not compared with an unweighted mean and individual-model results are not shown. This is the rationale for treating the weighting scheme, and not the bias correction step alone, as an important part of ensuring that the climate inputs to this White Volta Basin impact assessment are appropriately credible.

4.3 Data Gaps and Sustainability

Issues such as limited resources, spatial coverage, quality, and accessibility, and the availability of statistically bias-corrected climate data for decision-making and further study are limited in the basin and Ghana (e.g., data sharing policies) (Mamuye and Kebebewu, 2018). The sensitivity of coupled models to both direct and indirect radiative forcing of atmospheric carbon dioxide has been linked to inaccurate forecasts in West Africa (Asare-Nuamah and Botchway, 2019). However, coupled models have improved our understanding of the monsoon and atmospheric circulation in West Africa, especially in the 21st century. Chagnaud et al., (2020) emphasise that the same models indicate inconsistencies in future forecasts. In Ghana, Nkrumah et al., (2014) Also stated that inaccurate data from climate monitoring devices makes it challenging to comprehend local realities and the scope of changes. Different studies from various fields are expected to make use of the bias-corrected data. Thus, the bias-corrected projections can be used as inputs to impact studies; they are scenario-based projections, not seasonal forecasts. In addition, the statistically bias-corrected climate outputs offer a series of daily datasets that may be used to forecast a variety of parameters across the basin. Data on temperature will be made available for non-commercial study from several stations across the basin, with varied densities.

In addition, it may be critical to keep working to enhance climatic inputs for agricultural effect forecasts.

These projections are used by many institutions and foreign sectors, such as agriculture, forestry, fishing, energy, insurance, public health, water resources, recreation, transportation, health, and building. For instance, we are aware that increasing drought risk may have several

effects, such as water shortages, an early start to the wildfire season, and lower or no crop yields. This could subsequently result in higher charges for disaster relief, higher food costs, and a disturbance of statewide waterway transportation. Water resource managers can change the timing of water release from reservoirs, and farmers can change the kind of crops they grow with advanced information about drought (Ayalew et al., 2012).

Long-term climate projections can help decision-makers anticipate the consequences of warming and reduce the chance of "climate surprises." They are not seasonal forecasts: they describe forced changes under emission scenarios and say nothing about conditions in a specific season or year. The majority of agricultural activities in Ghana are the most vulnerable to climate variability as a result of climate-related events. (Acharki et al., 2023). In Ghana, for example, rice cultivation accounts for 15% of agricultural output and 45 % of the entire land used in grain production, respectively. Irrigated, lowland and upland systems are used to grow rice in the northern and southern sections of the south of Ghana. As a result, in the event of severe weather, such as prolonged drought, rice production in Ghana will decline. Rice productivity is anticipated to decline by the end of the twenty-first century as temperatures rise between the 2020s and 2080s (Kingra et al., 2019).

As a result, the unpredictability of weather and its associated fluctuations have affected crop productivity and livestock production, increasing food costs. This has led to households migrating to the south of Ghana during the dry seasons in search of fertile farmland locations to feed their families.

As envisioned by the United Nations' Agenda 2030, strategies adapted to mitigating climate change effects on sustainable crop production are thus necessary for achieving the Sustainable Development Goal (SDG) 2 (Zero Hunger), alongside SDGs 6 and 13, with the outcome targets of ending hunger and improving access to food; achieving food security and improved nutrition; and promoting sustainable agriculture and resilient agriculture by 2030 (Tong et al., 2021).

Decision-makers would benefit from the findings since they quantify the bridge between statistical methodologies and current improvements aimed at responding to and mitigating the negative effects of climate change on Ghana's sustainable crop production (Incoom et al., 2022). Improved crop and soil management to increase soil carbon storage, restoration of degraded lands, improved rice cultivation techniques, manure management, improved nitrogen fertilizer application techniques, cover cropping, mulching, conservation tillage, agroforestry, irrigation, changing cropping sequences, irrigation, as well as monitoring the basin’s and other mitigation technologies and practices will be considered (Incoom et al., 2022). By using bias-

corrected data in scenario analysis, hydropower operators may assess multiple climate scenarios and create backup plans for a range of possible futures. The efficient and sustainable management of water resources to produce electricity is encouraged by bias-corrected statistics. By implementing significant projections methods, the hydropower industry may enhance operations, adapt to changing climate conditions, and support a resilient and sustainable energy future (Mensah, 2022).

4.4 Limitations of the Study and Future Directions: Climate Sensitivity and Model Uncertainty

Climate change research, particularly studies examining future hydroclimatic extremes, is always plagued by uncertainties and limitations. While this study provides valuable information on the changes in the White Volta Basin under various SSP scenarios with CMIP6 models, certain important aspects must be acknowledged as limitations. These include uncertainties in climate sensitivity, model bias, and physical processes driving temperature changes. In addition, because the nine virtual stations were derived from ERA5, bias correction and validation at these sites are relative to the reanalysis rather than independent ground observations, so the performance metrics reported for the virtual stations reflect agreement with ERA5. Addressing these limitations is essential for guiding future research and improving the credibility of climate projections for informing policy decisions.

Further limitations concern the data and the analysis. (i) The observed records contain long gaps and apparent outliers (Figures 6 and 7) that differ from the missing-data percentages in Table 2, and no quality-control procedure is described. (ii) The performance metrics are in-sample and computed for individual models, so they do not demonstrate out-of-sample skill. (iii) Only one realisation per model was used and the spread among models is not shown, so the uncertainty around the weighted ensemble means is not quantified. (iv) The GMet and virtual stations use different baselines, and the inverse-distance-weighted maps interpolate only twelve points within a few coarse GCM grid cells, so they cannot resolve fine-scale patterns. (v) The analysis covers only the Ghanaian part of the White Volta Basin, so the results should not be generalised to the whole transboundary basin. (vi) The SSP1 Tmin series contains an abrupt step change around 2063–65 that is probably a processing artefact (Section 3.2.2), so SSP1 results after that point are unreliable.

4.4.1. Uncertainty in Climate Sensitivity Among CMIP6 Models

According to Zhu et al., (2020), one of the largest limitations of the study comes from the wide distribution of Equilibrium Climate Sensitivity (ECS) values among the selected CMIP6 models. ECS, classically defined as the long-term temperature response to CO_2 doubling, varies widely between models, with some as low as 1.8°C and as high as 5.6°C (Dong et al., 2021). This range generates substantial uncertainty in projections, particularly for high-emission scenarios like SSP5-8.5, where warmer ECS models yield more extreme warming and hydroclimatic extremes. According to Fedele et al., (2025) Climate simulations and machine learning codes are limited in standalone use due to inherent constraints, limited by structural assumptions and by data for training. Single-model projections are highly uncertain in climate science, for instance, as evidenced by CMIP6's Equilibrium Climate Sensitivity (ECS) estimates of 1.8°C–5.6°C due to variability of cloud feedback parameterisations, ocean-atmosphere coupling, and aerosol forcing, leading to divergent regional climate projections.

Similarly, machine learning codes overfit training data or miss subtle climate teleconnections and thus are limited by predictability. Ensemble techniques overcome these hardships by combining multiple models or realisations, so dependence is diminished altogether for assumed single model structures and exploring parametric uncertainties systematically by perturbing parameters with perturbed parameter ensembles (PPEs) (Ukoba et al., 2025).

Multi-model ensembles (MMEs) such as those by CMIP6 pool structural diversity by combining model codes implementing different process representations by varying and independently generated institutions, whereas emergent constraints narrow ranges of uncertainties by translating model outputs to observation data. Initial-condition ensembles, where different versions of a model are run with initially slightly perturbed conditions, distinguish internal climate variability (e.g., ENSO, Pacific Decadal Oscillation) and forced trends and thus conserve important information to evaluate extreme events. (Wang et al., 2025).

Advanced bias correction techniques, such as CDF-t and trend-preserving quantile mapping (QDM), assist in making ensembles more informative by adjusting bias and not systematically warping the climate change signal or internal variability, as evidenced by case examples such as the CRCM5 Large-Ensemble, which better projected climate over North America. Averaging across models, representing uncertainty by ensemble spread, and being robust to outliers facilitate making ensemble techniques more useful and actionable to project climate and bridge

uncertainties between climate scientists and to needs of decision makers. (Grillakis et al., 2017; Heo et al., 2019).

4.4.2 Recommendations to study limitations for Future Research

To address the limitations, this study proposes:

To improve West African climate resilience in the future through research, three major methodological improvements need priority. First, rigorous selection of models for CMIP6 ensembles using emergent constraints will filter out implausible climate sensitivity parameters, rendering projections more representative of regional variability. Second, application of advanced bias-correction techniques like Quantile Delta Mapping and multivariate methods will preserve critical climate trends and intervariable relations in downscaled products. Third, high-resolution regional climate models must investigate land-atmosphere feedback and ocean teleconnections poorly represented in global models, complemented with CO_2 physiological effects on vegetation and hydrology.

All three related breakthroughs advanced late-season modelling, improved bias correction, and process-based research will allow more reliable projections to guide adaptation responses. By bridging knowledge gaps, scientists will be able to provide policymakers with actionable tools to adapt water resources and crop and animal systems to a changing climate. Initiating such recommendations is a firm step towards climate-resilient development for West Africa, where sustainable planning is to be attained, and sound projections are required. The future of a region lies in concretely translating such developments in science into policy decisions pertinent to its prevailing climate conditions.

5. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The 21st century has seen a steady shift in climate to the new normal. It is laborious to evaluate climate change in a basin with few data, nevertheless. Maximum and minimum temperatures for the Ghanaian part of the White Volta Basin were statistically corrected for bias using 15 GCMs. The findings showed that maximum and minimum temperatures are projected to increase under SSP2-4.5, SSP3-7.0 and SSP5-8.5, with the largest increases under SSP5-8.5, whereas SSP1-2.6 gives the smallest warming. Apparent decreases under SSP1-2.6 (Tmin after about 2063, and some monthly and spatial changes) are inconsistent with the annual series, are

probably processing artefacts, and should not be read as cooling. As the temperature gets hotter, the effects of climate change on biodiversity, agricultural output, and water resources could become more pronounced (these impacts were not modelled in this study) under "business as usual" conditions. The basin's population and industry are constantly growing, yet rising water demand under a warming climate could increase pressure on ground and surface water resources. To ensure sustainable water resources in the basin, adaptation strategies for water management and governance at the local, basin-level, and regional levels will be essential.

5.2 Recommendations

The Ghanaian part of the White Volta Basin, which is part of a transboundary basin shared with Burkina Faso, faces projected warming that could add to existing pressures on agriculture and water security. Scenarios project that for various Shared Socioeconomic Pathways (SSPs), there is a concerning outlook: rising temperatures, particularly under high-emission scenarios, will exacerbate current vulnerabilities for the agro-based region. These climate alterations are arising with large data gaps, such as scarce ground-based monitoring networks and missing histories of extreme occurrences, hindering accurate climate projections and adaptation planning.

Projected warming, primarily during the principal growing seasons, could increase heat stress and crop water demand. These impacts were not modelled here and should be assessed in follow-up studies that use these temperature projections as inputs.

Overcoming these challenges requires a multi-faceted, multi-pronged approach. Firstly, plugging existing data gaps with enhanced monitoring systems is essential. That includes putting in place automated weather stations, the use of remote sensors, and the inclusion of citizen science initiatives for increased spatial coverage of climate data. These procedures should be complemented with more sophisticated climate modelling techniques, including more advanced bias correction techniques and higher resolution regional climate models with better capture of West African monsoon patterns.

Adaptation strategies must be equally inclusive. For farmland, options such as heat- and drought-tolerant crops and efficient irrigation could be evaluated against these temperature projections.

At policy levels, inclusion of climate projections within national adaptation plans is required. The Ghana National Climate Change Adaptation Strategy needs to reflect such scientific research to guide water management, infrastructure development, and agriculture planning.

Because this study covers only the Ghanaian part of the basin, transboundary data sharing and collaboration with Burkina Faso would allow the analysis to be extended to the whole White Volta Basin.

All these steps must be adopted immediately. Since climate impacts are already being seen within the basin, delay could lead to exceedingly higher future losses for humans and economies. But while such tools and know-how to get started down that path are within our reach now, by connecting science with indigenous knowledge and adaptive traditional knowledge and forging strong regional cooperation, the White Volta Basin can create resilience to cope with its changed climate future. All in all, addressing these challenges is aligned with global sustainable development targets, including SDG 11 (Sustainable Cities and Communities), SDG 3 (Good Health and Well-being)and SDG 13 (Climate Action). The case history of the White Volta Basin can just as well be applied to advantage such territories across West Africa that are vulnerable to similar climate risks. The future direction is clear: swift, collective action with a combination of scientific innovations, policy fine-tuning, infrastructure investment, and subregional cooperation offers the best hope for ensuring the basin's water future in an age of climate unpredictability.

Declarations

No funding was received either in part or in full for this study.

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The authors declare that they have no competing interests.

Consent to Participate and Consent to Publish declarations: not applicable.

Data availability: The ERA5 reanalysis data analysed during the current study are publicly available from the Copernicus Climate Change Service (C3S) Climate Data Store at https://doi.org/10.24381/cds.adbb2d47 (Hersbach et al., 2023). The CMIP6 model outputs analysed during the current study are publicly available from the Earth System Grid Federation at https://esgf-node.llnl.gov/projects/cmip6/ (Eyring et al., 2016). The observed daily temperature data from the Ghana Meteorological Agency (GMet) are not publicly available due to GMet's data-sharing policy but are available from the corresponding author on reasonable request, subject to permission from GMet. The bias-corrected datasets generated during the current study are available from the corresponding author on reasonable request.

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Appendix

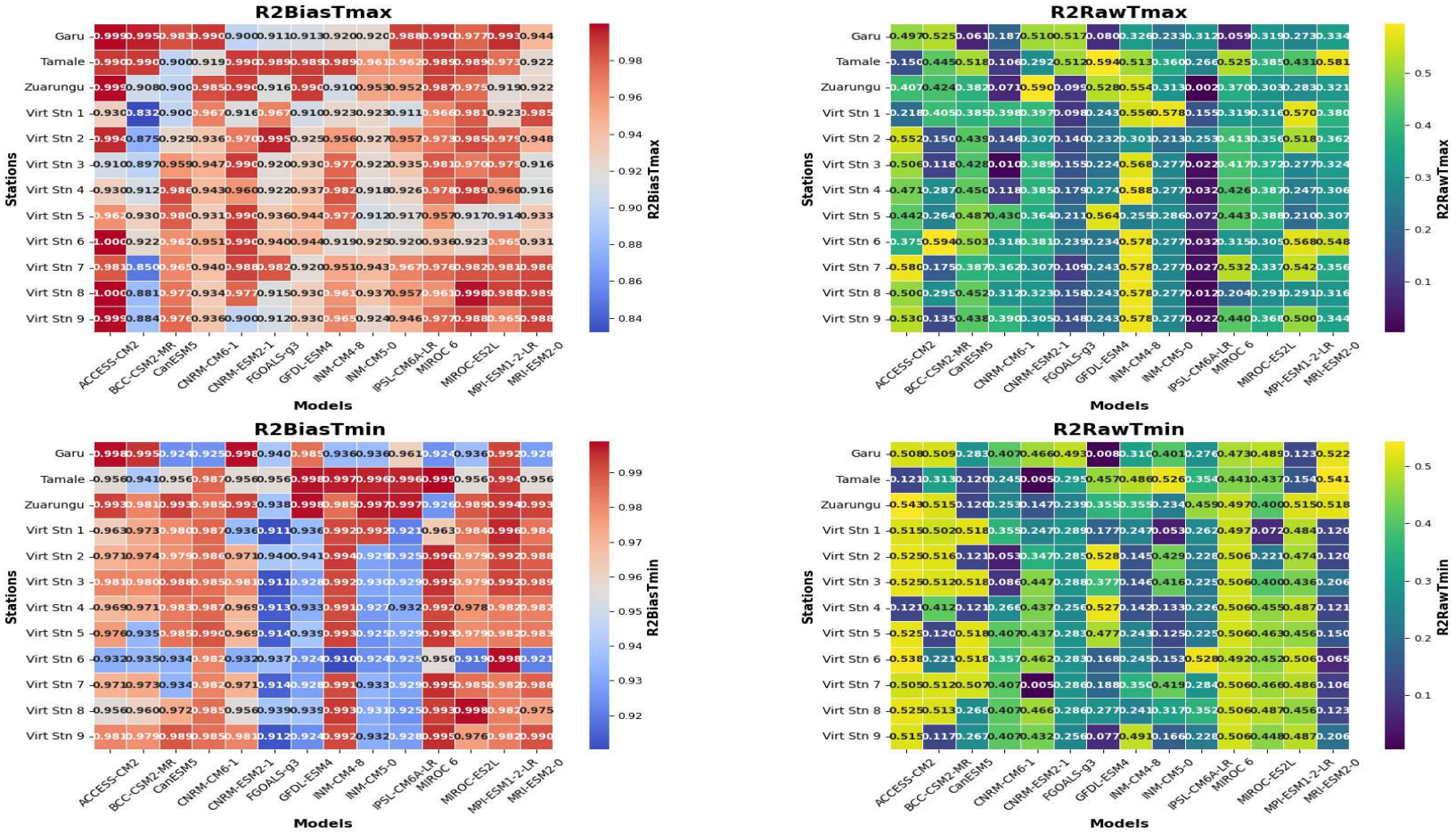

Figure A. Model performance (R^2) for Tmax and Tmin

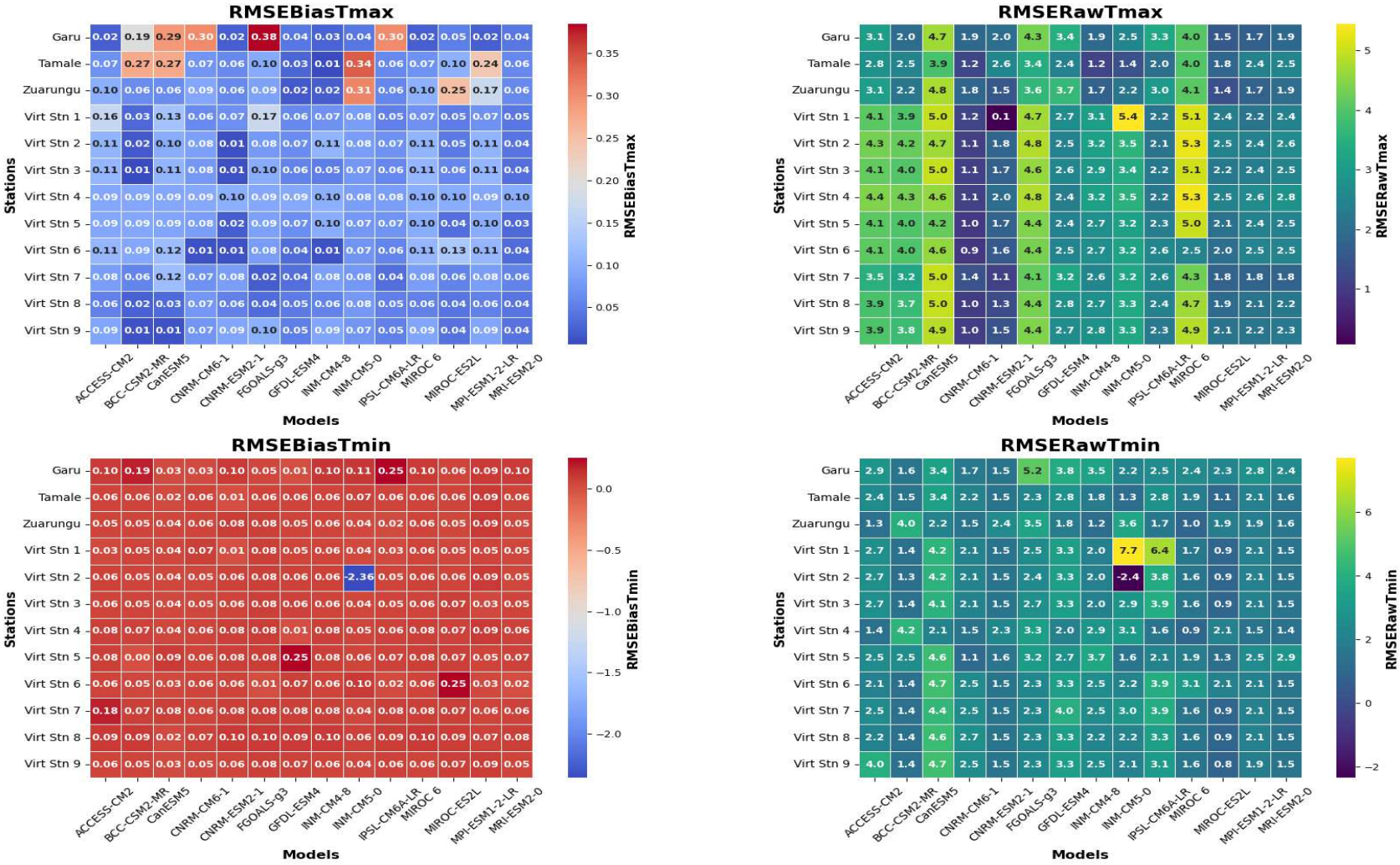

Figure B. Model performance (RMSE) for Tmax and Tmin

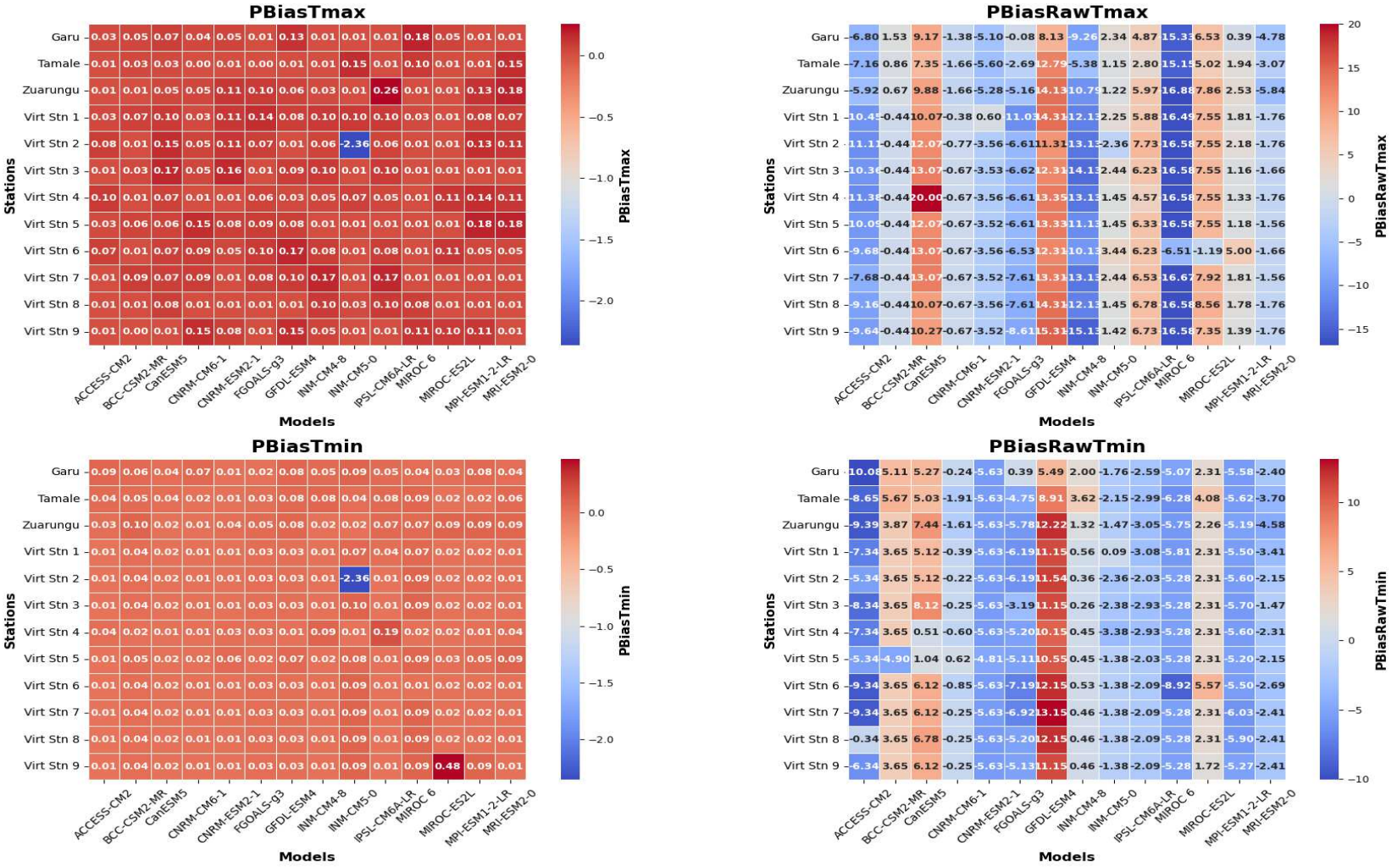

Figure C. Model performance (Pbias) for Tmax and Tmin