

RESEARCH ARTICLE



CMIP6 Multi-Model Ensemble Projections of Climate Change Impacts on Precipitation, Temperature, and Climate Extremes in the Anai Watershed, West Sumatera, Indonesia

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ABSTRACT

Climate change increasingly affects hydroclimatic conditions at the watershed scale. This study assessed the projected changes in precipitation, maximum and minimum temperatures, and climate extremes in the Anai watershed under the CMIP6 emission scenarios SSP2-4.5 and SSP5-8.5. Three CMIP6 GCMs (NorESM2-MM, NorESM2-LM, and TaiESM1) were statistically downscaled and bias-corrected with observed precipitation and temperature data using CMhyd Software. Temporal trends were evaluated using the Mann-Kendall test and Sen's slope estimator, and 14 ETCCDI indices were analyzed to characterize future climate extremes. The results showed an increase in the projected annual precipitation and temperature, particularly under a higher emission scenario. Annual precipitation is projected to increase by approximately 3.04 mm/year under SSP2-4.5 and 4.04 mm/year under SSP5-8.5 emission scenario. The maximum temperature is projected to rise at 0.01 °C (SSP2-4.5) and 0.04 °C (SSP5-8.5) while minimum temperature statistically not significant elevate under SSP 2-4.5 at 0.01 °C, and annually increase significantly under SSP5-8.5 at 0.03 °C conversely. Monthly projected precipitation and temperature tend to have similar patterns of projection compared to the historical period, with more climatic variability in the future. Furthermore, seasonal changes suggest more frequent heavy rainfall events and a decrease in cold nights in the future in the Anai watershed. These changes imply heightened risks of flooding, landslides, and heat stress, underscoring the need for climate-resilient watershed management and adaptation planning in the Anai watershed.

Introduction

The challenges posed by climate change are increasingly difficult to address [1]. This alteration notably amplifies the variability in hydrologic systems and escalates the frequency and intensity of heatwaves, flooding, and droughts [2]. Extreme climate events have proliferated globally owing to climate change, especially in relation to elevated temperatures and intense precipitation [3,4]. A standardized method is necessary for evaluating these changes because of the significant variability in their magnitude and physical drivers across various regions, especially in tropical areas with complex topography [5,6]. The expert team on climate change and indices (ETCCDI) has established an innovative framework for climate indices to categorize and standardize the assessment of climate extremes based on frequency and severity [7], which are commonly applied in observational analysis and climate projection [8–10]. Disaster mitigation planning in response to climate change events significantly depends on the analysis of prospective climate extremes, precipitation, and temperatures. Consequently, modeling regional atmospheric conditions is a critical component of climate projections [11].

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Global climate models (GCMs) are primary tools for climate modeling that provide future climate data based on socio-economic consequences. Currently, the coupled model intercomparison project phase 6 (CMIP6) from GCMs offers improved spatial resolution and parameterization of cloud microphysical processes, and the incorporation of supplementary additional Earth system processes and elements in modelling climate data [12–14]. GCMs which are based on highly sophisticated and intertwined computational processes, produce large uncertainties and biases [11], leading to the requirement of the multi-model ensemble (MME) to reduce output biases from the modeling process.

Recent studies have demonstrated the capability of CMIP6 models to simulate and project future climate change under various emission scenarios [15–18]. Most CMIP6-based applications focus on multi-model ensembles at continental, national, or large-basin scales, whereas studies conducted at the scale of medium-sized watersheds in monsoon-dominated climates remain limited, particularly in Southeast Asia and Indonesia [16–18]. In Indonesia, studies on climate change projections at the watershed scale using CMIP models remain sparse and concentrated in a few river basins, such as the Citarum, Batanghari, Pawan, and Selo Watersheds [19–22]. Furthermore, current watershed-scale studies often examine precipitation and temperature extremes individually and depend on a limited number of ETCCDI indices [23,24], highlighting a distinct gap in integrated evaluations that concurrently assess precipitation and temperature extremes using a comprehensive ETCCDI framework at the watershed level. This study aimed to analyze the impacts of climate change using CMIP6 multi-model ensembles at the medium-sized monsoon tropical watersheds of Indonesia. Focusing on the Anai watershed as a representative medium-sized, topographically complex tropical monsoon basin, this study bridges the scale gap in regional climate modelling and provides actionable, high-resolution empirical insights for localized watershed-scale adaptation planning.

Materials and Methods

Study Area

This study was conducted in the Anai watershed, West Sumatera, Indonesia (0°23'31"–0°48'04" S; 100°16'37"–100°27'58" E), covering a 703 km² area. The river originates from the mountainous peaks of Marapi, Singgalang, and Tandikek and flows westward into the Indian Ocean (Figure 1). The watershed has varied physiography, including steep slopes in the upstream area and gentle terrain in the downstream. The climatic conditions of the Anai watershed, characterized by an average annual rainfall of 3,060.65 mm and an average annual temperature of 24.07 °C, exhibit significant sensitivity to climatic variations. Consequently, employing CMIP6 multi-model projections alongside ETCCDI indices to evaluate future water resource, flood, and drought-related risks at this scale is essential.

Observed and Global Climate Model (GCM) Data

Daily observed precipitation and temperature data covering the period 1981–2013 were used as the historical baseline in this study. These data were obtained from the in-situ weather station of the Water Resource Management Authority of West Sumatera, Indonesia (Table 1). To address spatial gaps and missing values in in-situ records, the climate hazards group infrared precipitation with stations (CHIRPS) data (<https://data.chc.ucsb.edu/products/CHIRPS-2.0/> accessed on 28 August 2025) and NASA POWER modern era retrospective-analysis for research and applications (MERRA-2) dataset (<https://power.larc.nasa.gov/data-access-viewer/> accessed on 2 September 2025) datasets were integrated to complement the precipitation and temperature observations, respectively (Figure 1).

Table 1. Geographic coordinates and list of ground-based in-situ weather stations in the study region. These stations provided daily historical observed precipitation and temperature data covering the baseline period from 1981–2013. This observational network serves as the primary ground-truth baseline to complement and validate satellite/reanalysis datasets (CHIRPS and NASA POWER MERRA-2) used in the study.

Station name	Latitude (°)	Longitude (°)
Kandang	−0.51	100.33
Paraman	−0.48	100.26
Kasang	−0.77	100.31
Lubuk napar	−0.87	100.35

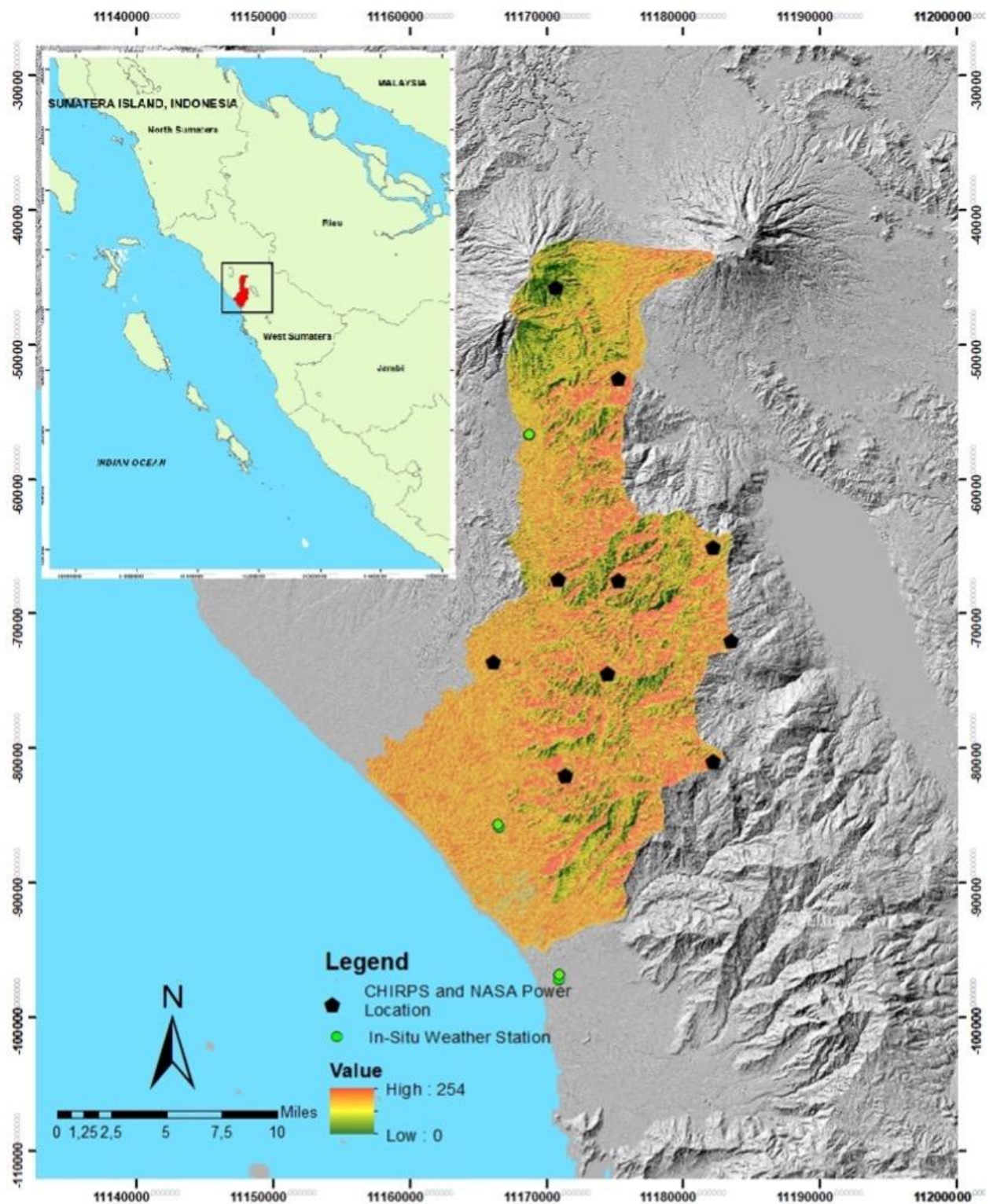


Figure 1. Geographic location, topography, and spatial distribution of meteorological data points in the Anai watershed, West Sumatra, Indonesia. The map highlights the spatial arrangement of ground-based in-situ weather monitoring stations (green circles) alongside grid-based CHIRPS and NASA POWER data extraction points (black pentagons). This spatial distribution demonstrates the alignment and coverage between satellite/reanalysis climate products and local ground observations used for baseline evaluation and hydro-climatic modeling in the watershed.

Future climate projections were derived from three GCMs in the CMIP6 framework (Table 2). The NorESM2-MM (Norwegian Earth System Model version 2 with medium atmosphere and ocean resolution) and NorESM2-LM (Norwegian Earth System Model version 2 with low atmosphere and medium ocean resolution) models showed enhanced skill in simulating regional climates, particularly in precipitation and temperature patterns [25], whereas TaiESM (Taiwan earth system model) effectively simulated tropical cyclogenesis, matching observed intensities and seasonal variability, which is crucial for understanding climate impacts in tropical regions [26]. Recent evaluation studies focusing on Southeast Asia and Indonesia have shown that GCM performance varies significantly by location and variable. Specifically, NorESM2-MM and NorESM2-LM demonstrated superior capability in representing regional atmospheric dynamics, relative humidity, and temperature variations, whereas TaiESM1 has been proven to outperformed other CMIP6 models over Southeast Asia and major Indonesian cities for precipitation and surface air temperature. Meanwhile, Norwegian models have been developed. The MME approach was used to mitigate individual model biases and uncertainties. Utilizing this high-performing three-model ensemble mitigates the systemic biases introduced by lower-ranked GCMs while effectively capturing model structural uncertainty. In this study, the historical period (1981–2013) and the projected period (2014–2100) of daily precipitation and temperature data were analyzed under two shared socioeconomic pathways (SSP) emission scenarios (SSP2-4.5 and SSP5-8.5). SSP2-4.5 represents a medium emission pathway with conditions similar to current global emissions, whereas SSP5-8.5 is characterized by rapid emissions in the future without any climate mitigation action.

Table 2. Characteristics of the CMIP6 GCMs selected for future climate projections. The table lists the three evaluated GCMs, detailing their country of origin, developing institution, spatial resolution, and specific variant labels. These high-performing models were integrated into a MME to project daily precipitation and temperature for the period 2014–2100 under SSP2-4.5 and SSP5-8.5 emission scenarios.

Model	Country	Institution	Resolution	Variant label
NorESM2-MM	Norway	Norwegian Climate Centre (NCC), Norway	1° × 1°	r1ip1f1
NorESM2-LM	Norway	Norwegian Climate Centre (NCC), Norway	1° × 1°	r1ip1f1
TaiESM1	Taiwan	Research Center for Environmental Changes, Academia Sinica, Taiwan	0.9° × 1.25°	r1ip1f1

Downscaling and Bias Correction of GCM Data

Owing to the coarse spatial resolution of GCMs, downscaling was used to increase the spatial resolution and represent regional climatic conditions [27]. Furthermore, to reduce systematic biases within the simplified physical processes of the GCM, systematic biases were analyzed. In this study, downscaling and bias correction were performed using CMhyd Software (<https://swat.tamu.edu/software/cmhyd/> accessed on 15 September 2025). This software is a python-based tool designed to integrate global climate data into a regional scale with simulated data aligned with observational records [28]. Distribution mapping (DM) was used to quantify bias correction for precipitation, while the linear scaling (LS) method was used for maximum and minimum temperatures. The choice of DM and LS methods was based on method fit assessments for temperature and precipitation in the study area. Statistical evaluation confirmed that DM was optimal for precipitation by effectively capturing extreme rainfall tails via Gamma distribution fitting, while LS performed best for temperature by removing baseline offsets in near-Gaussian distributions without the risk of overfitting.

Model Evaluation and Statistical Measures

The model performance was evaluated using statistical measures by comparing the bias-corrected GCM on the projected period results with the observed historical period data. The Kling–Gupta Efficiency (KGE), root mean square error (RMSE), percent bias (PBIAS), and RMSE–observations standard ratio (RSR) were used as evaluation metrics. These metrics were calculated as follows (Equation 1–4).

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

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Qobs_i - Qsim_i)^2} \quad (2)$$

$$PBIAS = \frac{\sum_{i=1}^n (Qobs_i - Qsim_i)}{\sum_{i=1}^n Qobs} \times 100 \quad (3)$$

$$RSR = \frac{\sqrt{\sum_{i=1}^n (Qobs_i - Qsim_i)^2}}{\sqrt{\sum_{i=1}^n (Qobs - Qobs^-)^2}} \quad (4)$$

Where, r is the correlation coefficient, α is the variability ratio, and β is the bias ratio. $Qobs$ and $Qsim$ are observed and simulated data, respectively, while $Qobs^-$ denotes the mean observation. Optimal model performance is represented by KGE values near 1, RSR and RMSE values near 0, and PBIAS within $\pm 10\%$ [29].

Mann-Kendall Trend Test

The analysis of trends in climate change was based on the application of the Mann-Kendall (MK) test to determine the direction and statistical significance of trends, followed by Sen's slope estimator (or method) to assess the magnitude (slope) of change in the climate time series. The MK test and Sen's slope estimator were employed to determine time series climate trends and their magnitudes, respectively [30]. The MK test evaluates monotonic trends at 95% confidence ($\alpha = 0.05$), and MK is known to be most effective in the presence of a non-normal distribution and/or missing values. Rstudio software was used to conduct the statistical analysis, and the specific packages used were Kendall and trend. The results are presented as an estimated trend slope (in units per year), direction of change, and degree of statistical significance for each climate variable evaluated.

ETCCDI Climate Indices

The RCLimDex package contained in RStudio was used to analyze 14 ETCCDI indices pertaining to extreme precipitation and temperature events [31]. The indices are listed in Table 3. The indices were calculated on a yearly basis and separated by emission scenario, and the trends were evaluated through linear regression analysis to assess the extent and direction of change over a given time. All trend analyses were performed in R using the ggplot2 package to produce scatter plots with fitted regression lines for each index to compare the indices and the emission scenarios.

Table 3. Description and measurement units of ETCCDI used in this study. The table details 14 climate extreme indices, categorized into precipitation along with their corresponding definitions and units of measurement. These indices were calculated on an annual basis using the RCLimDex package in RStudio to evaluate historical and future trends in extreme climatic events across the study area. This selection provides a standardized quantitative framework to assess regional changes in precipitation intensity, drought duration, and extreme temperature conditions under different emission scenarios.

Type	Index	Description	Unit
Precipitation	PRCPTOT	Annual total precipitation on wet days ($PR \geq 1$ mm)	mm
	CDD	Consecutive dry days ($PR < 1$ mm)	days
	CWD	Consecutive wet days ($PR \geq 1$ mm)	days
	R20mm	Number of very heavy precipitation days ($PR \geq 20$ mm)	days
	R95ptot	Annual total precipitation from days above 95th percentile	mm
	R99ptot	Annual total precipitation from days above 99th percentile	mm
	Rx1day	Annual maximum 1-day precipitation	mm
	Rx5day	Annual maximum consecutive 5-day precipitation	mm
	SDII	Simple daily intensity index (PRCPTOT / number of wet days)	mm/day
Temperature	TN10p	Percentage of days when TN < 10th percentile (cold nights)	%
	TN90p	Percentage of days when TN > 90th percentile (warm nights)	%
	TX10p	Percentage of days when TX < 10th percentile (cold days)	%
	TX90p	Percentage of days when TX > 90th percentile (warm days)	%

Note: PR: daily precipitation, TN: daily minimum temperature, TX: daily maximum temperature, PRCPTOT: annual total precipitation on wet days, CDD: consecutive dry days, CWD: consecutive wet days, R20mm: number of very heavy precipitation days, R95ptot: extremely wet days precipitation, R99ptot: severely wet days precipitation, Rx1day: maximum 1-day precipitation, Rx5day: maximum consecutive 5-day precipitation, SDII: simple daily intensity index, TN10p: cool nights, TN90p: warm nights, TX10p: cool days, TX90p: warm days.

Results and Discussion

Results

Model Evaluation

Thirty-three years of overlapping observed and climate model (CMIP6) data were used to evaluate the model performance. Table 4 summarizes the performance metrics for precipitation and temperature after the application of DM and LS. The evaluation results indicate a high proficiency in simulating precipitation. A KGE value near to 1 and PBIAS close to 0 suggest that the model effectively captures the correlation, variability, and mean of observed precipitation in the absence of substantial systematic bias [28]. Furthermore, the maximum and minimum temperatures showed satisfactory model evaluation results, with the KGE value exceeding 0.5 (classified as good/satisfactory performance) and the PBIAS values within 10% (classified as very good performance) [32]. These results indicate that the model captures the essential characteristics of the observed temperature data and does not exhibit a substantial systematic bias [18]. However, the high RSR value ($RSR > 0.75$), which falls into the unsatisfactory range for both precipitation and maximum-minimum temperature, indicates that the daily variability is highly uncertain owing to the high spatiotemporal heterogeneity of precipitation and temperature in tropical watersheds and the limitations in the inherent resolution of GCMs [32]. This behavior has been widely reported in the literature [32,33]. Consequently, precipitation and temperature projections were primarily interpreted in terms of long-term trends and relative changes rather than absolute daily values in this study.

Table 4. Model evaluation statistical metrics for daily precipitation and temperature simulations following bias correction. The table summarizes the performance of the climate models across four statistical indicators: KGE, RMSE, PBIAS, and RSR for precipitation, maximum temperature, and minimum temperature. These values were calculated by comparing thirty-three years of overlapping historical observed baseline data (1981–2013) with climate model outputs corrected via DM and LS.

Variable	KGE	RMSE	PBIAS	RSR
Precipitation	0.85	1.88	−0.01	0.71
Maximum temperature	0.58	0.49	1.15	0.96
Minimum temperature	0.60	0.89	4.80	0.85

Future Annual Precipitation, Maximum and Minimum Temperature Projections, and Trend Analysis

The MK test was applied to analyze the projected mean annual precipitation and temperature in the Anai watershed covering the period 2014–2098 as shown in Table 5. The annual precipitation was projected to increase by 3.04 mm/year under SSP2-4.5, with a more pronounced upward trend under SSP5-8.5, with a statistically significant increase of 4.04 mm/year. Despite the statistically significant upward trend in cumulative annual precipitation, the projected median values remained notably stable across future periods compared to the historical baseline (Figure 2a). Instead, net precipitation growth is heavily driven by an expanding spread in the 10–90% quantile range and the frequent emergence of high-value outliers during the projection period, as shown in Figure 3a. Physically, this result indicates an intensification of high-magnitude precipitation and heightened interannual precipitation variability, rather than daily or annual increases.

Table 5. MK non-parametric trend test and Sen's slope estimator for future climate projections. The table presents the statistical parameters, including MK score (S), Z-value, p-value, Sen's slope, and the level of significance (α), for mean annual precipitation, max temperature, and min temperature under SSP2-4.5 and SSP5-8.5 emission scenarios in the Anai watershed. All variables demonstrate statistically significant upward trends across both scenarios ($\alpha = 0.05$ or 0.01). These statistical results indicate a consistent warming trend and increasing long-term annual precipitation rate (3.04–4.04 mm/year), with a notably stronger magnitude observed under the high-emission SSP5-8.5 scenario.

Variable	Scenario	S	Z-value	p-value	Sen's slope	Level of significance
Precipitation	SSP2-4.5	559	2.08	0.03	3.04	$\alpha = 0.05$
	SSP5-8.5	735	2.73	0.00	4.04	$\alpha = 0.01$
Maximum temperature	SSP2-4.5	3041	11.33	0.00	0.01	$\alpha = 0.01$
	SSP5-8.5	3343	12.46	0.00	0.04	$\alpha = 0.01$
Minimum temperature	SSP2-4.5	3039	11.33	0.09	0.01	$\alpha = 0.05$

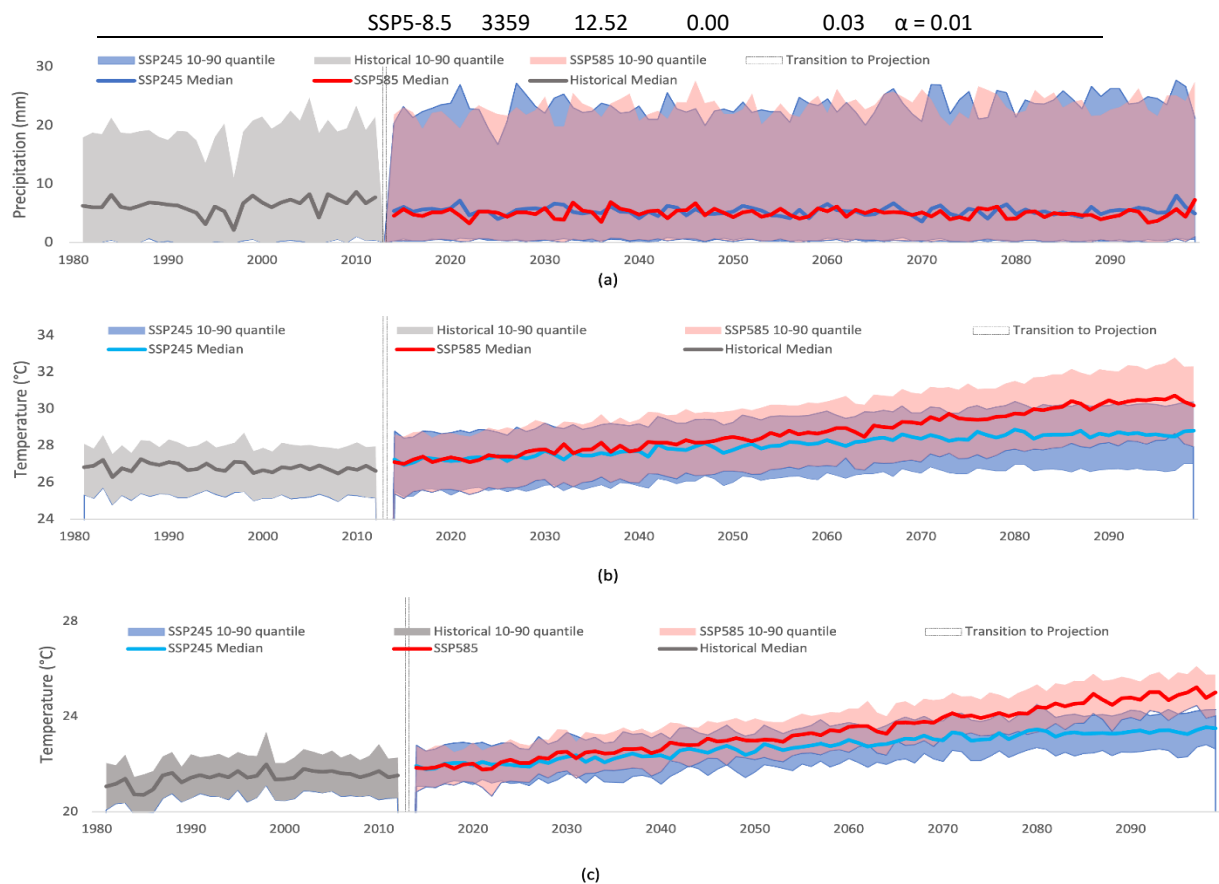


Figure 2. Historical baselines and projected future annual precipitation (a), maximum temperature (b), and minimum temperature (c) under SSP2-4.5 and SSP5-8.5 emission scenarios in the Anai watershed. The charts illustrate the annual trajectories and 10–90% quantile ranges for (a) mean precipitation (mm) and (b) temperature (°C) across the Anai watershed. While median precipitation values remain relatively stable over the projection period, temperature shows a continuous and pronounced warming trend toward 2098, particularly under SSP5-8.5. This comparison highlights an increasing interannual variability and extreme precipitation spread alongside steady regional warming over the 21st century.

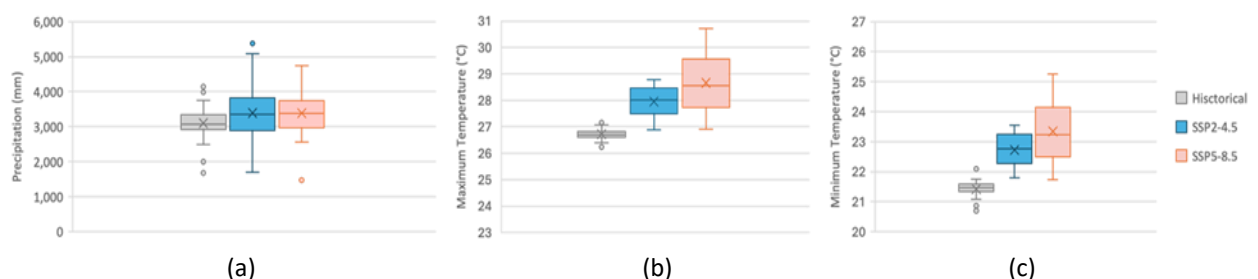


Figure 3. Interquartile range and statistical distribution of annual precipitation and temperatures across historical and projected periods. The box plots display the comparative distribution including medians (horizontal lines), means (crosses 'x'), interquartile ranges (boxes), whiskers, and outliers (circles) for (a) annual precipitation (mm), (b) annual maximum temperature (°C), and (c) annual minimum temperature (°C) comparing the Historical baseline against the projected SSP2-4.5 and SSP5-8.5 scenarios in the study region. While projected annual precipitation shows a wider spread and higher interannual variability without a drastic change in median value, both maximum and minimum temperatures exhibit a clear, pronounced upward shift in their entire distribution. This comparison underscores a robust regional warming signal, where median maximum and minimum temperatures shift significantly higher from historical baselines, particularly under the high-emission SSP5-8.5 scenario.

In contrast to precipitation, the projected annual temperatures exhibited a robust and monotonic warming signal under both climate change scenarios. Statistical analysis of the annual maximum temperature (Table 5) indicates a significant increase of 0.01 °C/year under SSP2-4.5 and 0.04 °C/year under SSP5-8.5. While an annual increase of 0.01 °C seems insignificant, it results in a considerable overall warming of approximately 0.8 °C by the end of the century under SSP2-4.5, and the 0.04 °C/year increase under SSP5-8.5 leads to a drastic cumulative warming surpassing 3.0 °C (Figure 2b). Consequently, the median annual maximum temperature gradually increased to approximately 29–30 °C under SSP2-4.5 and 30–32 °C under SSP5-8.5 from the historical period by 2100 (Figure 3b). A similar warming structure characterizes the minimum temperature (Figure 2c and 3c), where the SSP5-8.5 scenario projected a markedly significant upward trend at a rate of 0.03 °C/year. Consequently, the median annual minimum temperature is anticipated to increase from a historical period of 21 °C to approximately 25 °C by the end of the century. The synchronized upward shift in both the lower and upper thermal boundaries highlights an overall shift toward a hotter climate regime in the watershed.

Future Monthly Precipitation, Maximum and Minimum Temperature Projections, and Trend Analysis

The MME projections of monthly precipitation in the Anai watershed are shown in Figure 4. The monthly mean precipitation patterns under the two climate change scenarios exhibited a consistent trend with the historical period, with increased variability in the future (Figure 5a). Notably, the transition to the wet season is projected to experience a discernible intensification of mean precipitation, particularly in November, with approximately 600 mm. Wet intensification is characterized not only by higher mean values but also by a substantial expansion in the interquartile range (IQR) and a higher frequency of positive outliers in the projected period in November and December (Figure 5a). Physically, this demonstrates that the wet season in the future is projected to be progressively more extreme, while the dry season (June to August) tends to experience minor stable fluctuations.

According to the climate change scenarios, the maximum and minimum temperatures showed a rising tendency for all months compared to the historical period (Figures 4b and 4c). The monthly maximum and minimum temperatures are projected to increase by approximately 1.0–1.5 °C under SSP2-4.5 and by 2.0–2.5 °C under SSP5-8.5, relative to the historical mean. The broader IQR in Figure 5 reveals an increase in the maximum temperature extremes in the future, especially in April and September, which reach 32 °C under a higher emission scenario. Furthermore, the minimum temperature tended to increase in May and September to 24 °C under SSP2-4.5 and 23 °C under SSP5-8.5. The pronounced widening of thermal IQRs during these transitional periods highlights amplified intra-annual temperature variability, signaling the emergence of compound hot-and-wet extremes during seasonal transitions.

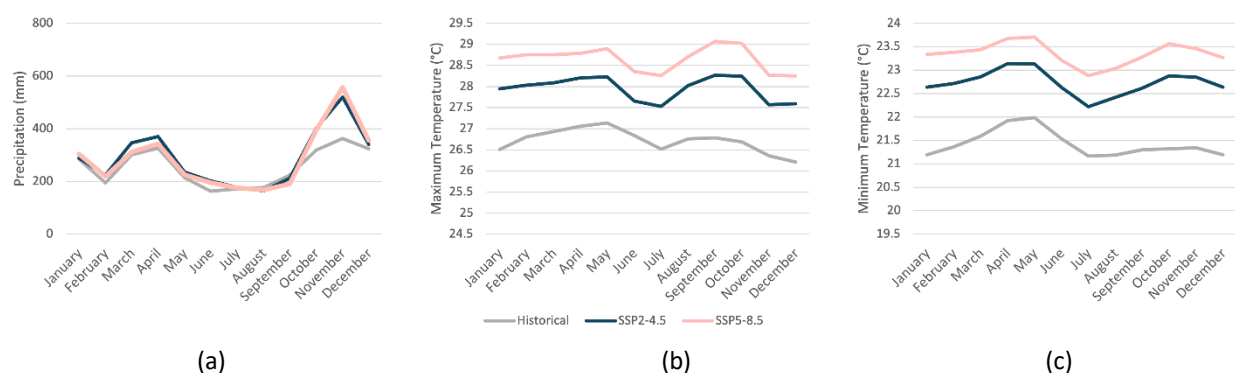


Figure 4. Historical baseline and projected monthly variability of precipitation and temperature in the study area. The line charts illustrate the monthly cycles from January to December for (a) mean monthly precipitation (mm), (b) maximum temperature (°C), and (c) minimum temperature (°C), comparing historical baseline values (grey line) with future projections under SSP2-4.5 (dark blue line) and SSP5-8.5 (pink line) scenarios. Precipitation exhibits a bimodal seasonal pattern with peak rainfall occurring in November–December, whereas both maximum and minimum temperatures show a consistent upward shift across all months under future scenarios, with the highest thermal increase projected under SSP5-8.5. This monthly comparison demonstrates the persistent seasonal distribution of rainfall alongside a year-round warming tendency across the region.

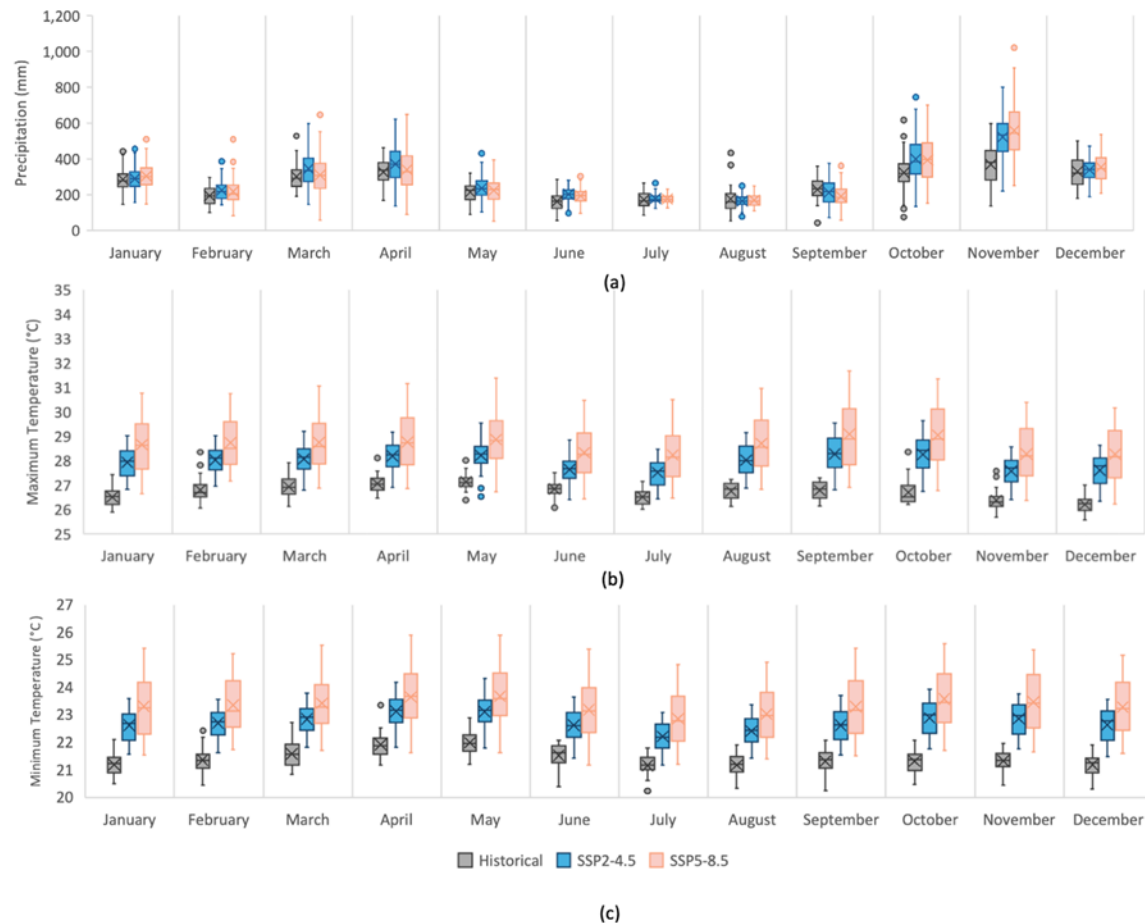


Figure 5. Interquartile range and statistical distribution of monthly precipitation and temperatures across historical and projected periods. The box plots present the monthly comparative distributions—showing median values, mean marks ('x'), IQR, whiskers, and outliers—from January to December for precipitation (mm), maximum temperature (°C), and minimum temperature (°C) in the study region. Each monthly panel compares the historical baseline (grey) against future projections under SSP2-4.5 (blue) and SSP5-8.5 (orange) scenarios. While monthly precipitation exhibits expanding interquartile ranges and increased outlier occurrences during peak wet months (November–December), both maximum and minimum temperatures project consistent, year-round upward distribution shifts across all twelve months, with the most severe thermal shifts occurring under SSP5-8.5.

Seasonal Change

The seasonal changes in precipitation and temperature were evaluated for the near future (2015–2044), mid-future (2045–2074), and far future (2074–2100) as shown in Table 6. The seasons are categorized into December–January–February (DJF), March–April–May (MAM), June–July–August (JJA), and September–October–November (SON). Seasonal change analysis indicated an increase in precipitation in the Anai watershed with different magnitudes across climate change scenarios. Rainy season II (SON) was projected to experience the most pronounced precipitation under SSP2-4.5 at 16.31% in the near future, whereas the transition period (DJF) showed the greatest increase under SSP5-8.5 by 11.55% in the mid-future. All seasons exhibited increasing change, ranging from approximately 9–15% in the near future and changes of 0.01–0.26% in the mid-future and far future under the SSP2-4.5 scenario. In contrast, the SSP5-8.5 scenario projected moderate precipitation increases of 5–9% in the near future, while by the mid-future, precipitation increases ranged from 8–12%. During the far future period, the rainy season II (SON) precipitation declines by 1.72%, whereas the other seasons exhibit substantial increases of approximately 3–10%, with the transition season showing the largest increase (10.94%). Generally, under SSP2-4.5, the dry season (JJA) is projected to experience a wetter historical period and a pronounced, earlier rainy period. However, under SSP5-8.5, a projected shift in the rainy season indicated an increase in precipitation during both the transition

(December–February) and rainy season I (March–MAM). The projections of the maximum and minimum temperatures indicated an increase across all seasons under the two climate change scenarios. The seasonal changes in the maximum and minimum temperatures followed a similar pattern, with a greater change in the minimum temperature. The rainy season (MAM) exhibited the highest temperature increase under both emission scenarios, whereas the transition season (DJF) experienced the lowest change compared to other seasons. The rainy season I (MAM) is projected to increase in maximum temperature by 12.17% and minimum temperature by 14.8% in the far future under SSP5-8.5.

Table 6. Projected percentage changes in seasonal precipitation and temperatures across future periods under climate change scenarios. The table quantifies the relative percentage shifts in precipitation, maximum temperature, and minimum temperature across four distinct seasons—Rainy Season I (MAM), Dry Season (JJA), Rainy Season II (SON), and Transition Season (DJF)—for near future, mid future, and far future periods relative to historical baselines under SSP2-4.5 and SSP5-8.5 emission scenarios. While precipitation changes exhibit seasonal variability, maximum and minimum temperatures project progressive, multi-seasonal increases that intensify significantly toward the Far Future under the high-emission SSP5-8.5 scenario.

Variable	Scenario	Future period	Rainy season I (MAM)	Dry season (JJA)	Rainy season II (SON)	Transition (DJF)
Precipitation	SSP2-4.5	Near future	9.30	15.30	16.31	13.62
		Mid future	1.02	0.09	0.05	0.09
		Far future	0.26	0.21	0.19	0.26
	SSP5-8.5	Near future	5.51	8.89	7.10	8.31
		Mid future	10.02	9.06	8.61	11.55
		Far future	6.96	3.26	-1.72	10.94
	SSP2-4.5	Near future	2.45	2.21	2.04	1.77
		Mid future	1.87	0.04	0.04	0.04
		Far future	2.61	0.06	0.06	0.06
Maximum temperature	SSP5-8.5	Near future	2.90	2.56	2.42	2.15
		Mid future	6.85	6.26	5.99	5.72
		Far future	12.17	11.32	10.92	10.33
	SSP2-4.5	Near future	3.44	3.29	3.01	2.77
		Mid future	2.33	0.03	0.02	0.02
		Far future	3.23	0.05	0.04	0.04
	SSP5-8.5	Near future	3.93	3.60	3.30	3.07
		Mid future	8.89	8.23	7.67	7.45
		Far future	14.88	13.79	13.06	12.78

Impact of Climate Change on ETCCDI Indices

The ETCCDI analysis for the Anai watershed revealed a systematic shift toward a more humid and warmer extreme climate (Figure 6). The statistical analysis results showed that the indices related to precipitation intensity, including PRCPTOT annual total wet-day precipitation (PRCPTOT), very wet days (R95ptot), and extremely wet days (R99ptot), tended to have a positive upward trend. This increase in precipitation was followed by a longer duration of precipitation, represented by the consecutive wet days (CWD) and the number of heavy precipitation days (R20mm) indices, which were projected to increase significantly. A declining trend in consecutive dry days (CDD) signifies a reduction in the duration of dry spells. However, absolute daily intensity indices, such as maximum 1-day precipitation (Rx1day), maximum 5-day precipitation (Rx5day), and the Simple Daily Intensity Index (SDII), did not exhibit statistically significant changes and instead showed relative stability or slight declines. Simultaneously, temperature-related indices showed a strong warming signal. The frequencies of cold nights (TN10p) and cold days (TX10p) are projected to decrease substantially, with the rate of decline in TN10p exceeding that of TX10p. This finding is supported by the warm night (TN90p) and warm day (TX90p) indices, which showed significant increasing trends, particularly under the high-emission SSP5-8.5 scenario.

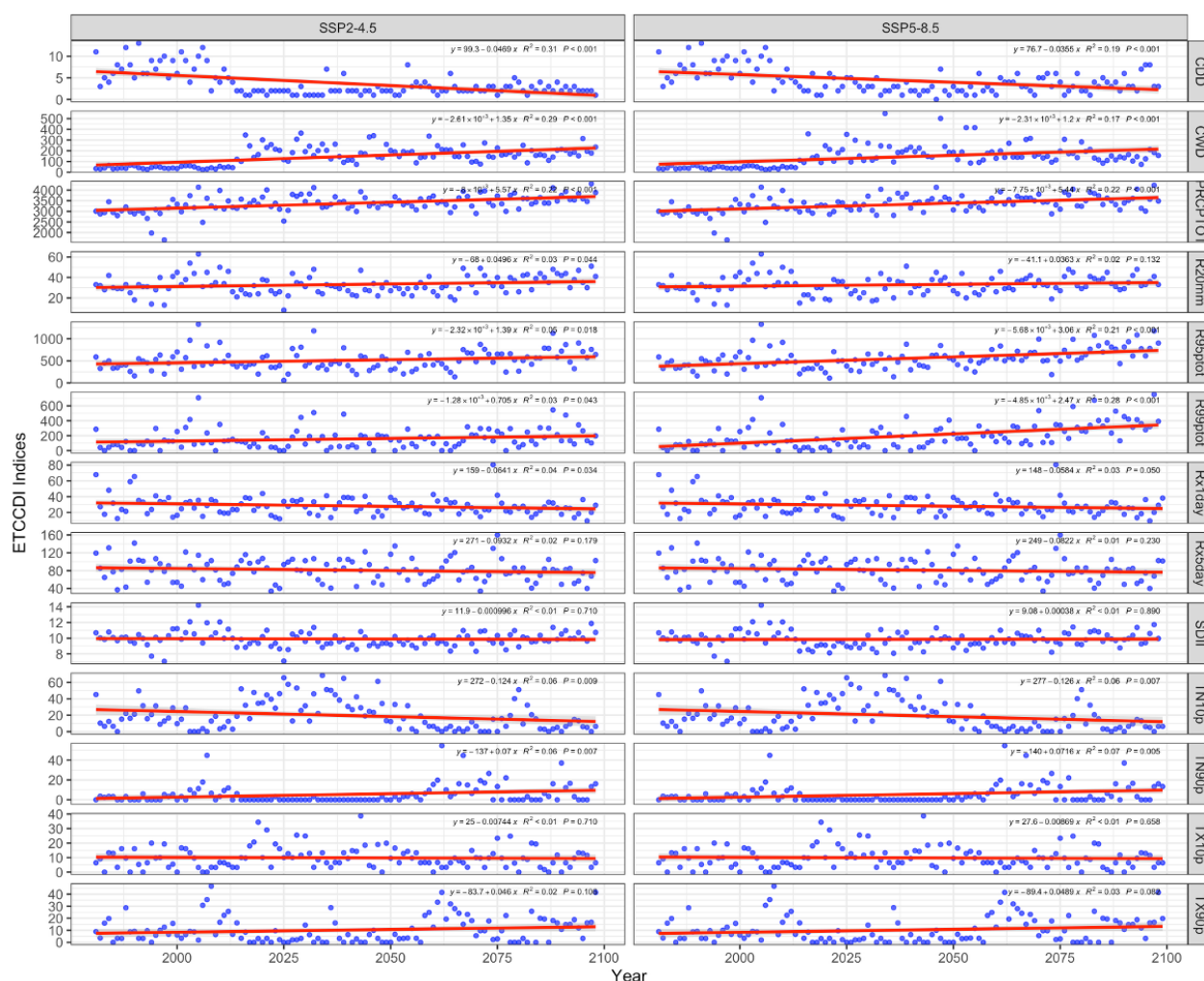


Figure 6. Projected long-term linear trends and regression analysis of extreme precipitation and temperature ETCCDI indices. The multi-panel scatter plots with fitted linear regression lines (red lines) display the annual temporal trajectory from 1981 to 2100 across 13 ETCCDI indices—comprising precipitation and temperature indices) under SSP2-4.5 (left panel) and SSP5-8.5 (right panel) scenarios. Each panel provides the fitted regression equation (y), coefficient of determination (R^2), and statistical significance level (p -value). Across both projection scenarios, dry spell duration (CDD) exhibits a statistically significant downward trend while wet spell duration (CWD), extreme precipitation amounts (R95ptot, R99ptot), and warm night frequencies (TN90p) project significant upward linear slopes ($P < 0.05$). These long-term trend lines indicate a clear shift toward heightened precipitation extremes and continuous night-time warming across the Anai watershed throughout the century.

Discussion

Climate Change Impact on Future Precipitation, Maximum and Minimum Temperature

Future climate projections in the Anai watershed are characterized by stable median annual precipitation coupled with expanding variability and a pronounced warming signal, especially under high-emission scenarios. This finding indicates a fundamental shift in the local hydrothermal dynamics in the Anai watershed, consistent with tropical monsoonal regions, where climate change tends to amplify interannual variability and extremes rather than induce large shifts in annual means [34–36]. Previous studies across Southeast Asia and other monsoonal regions have revealed similar findings, with heterogeneous trends in annual precipitation with irregularity and concentration of precipitation events [37,38]. Physically, the intensification of precipitation in the wet season is governed by the atmospheric thermodynamic response driven by the Clausius-Clapeyron relationship. The rise in temperature enhances atmospheric water content, resulting in increased cloud cover formation, which accelerates the hydrological cycle and leads to intensified precipitation [39].

The monthly analysis of precipitation patterns in this study tended to follow the Indonesian monsoon regime, which is characterized by a wet season from November to April, primarily influenced by the Asian winter monsoon [40]. Climate change notably intensifies the variability and extreme events of precipitation rather than a change in the seasonal monsoon pattern at a monthly scale in the Anai watershed. This climatic signal is coupled with an asymmetric warming pattern, where the minimum temperature increases more rapidly than the maximum temperature, indicating higher monthly warming rates driven by enhanced greenhouse forcing, increased atmospheric humidity, and greater nighttime longwave radiation trapping [34,41,42]. Increased warming during wet periods leads to accelerated evaporation rates, which influence the severity of extreme precipitation events and potentially reduce atmospheric humidity, exacerbating wet and dry extremes [43]. Consequently, the projected seasonal change in the Anai watershed tends to experience an intensification of hydroclimatic variability in the future, with an increasing precipitation rate in MAM and DJF. Asymmetric warming occurs due to a more pronounced rise in the minimum temperature compared to the maximum temperature in all seasons. The temperature increases significantly during the initial rainy season (MAM), potentially enabling the atmosphere to retain greater amounts of water vapor, resulting in increased precipitation.

The interaction of rising temperatures and changing precipitation patterns suggests a probability of more intense hydrometeorological events, including floods and landslides, as well as alterations in river dynamics. This signifies that watershed management strategies must enhance their adaptability in response to future climate projections. The upper reaches of the Anai watershed are mountainous and characterized by intensive agricultural activity. Changes in extreme precipitation during the wet season and increased drought during the dry season elevate the risk of crop failures. Smallholder farmers in vulnerable areas, particularly those dependent on rain-fed agriculture, are adversely affected by rising temperatures and extreme weather events, threatening crop productivity and food security [44]. Mitigating these risks requires hybrid adaptation frameworks that combine engineered storage with upstream nature-based solutions, such as riparian buffer restoration, slope stabilization, and soil-water conservation agriculture, to reduce erosion, curb downstream sediment transport, and protect ecosystem services [22,45,46]. To sustain regional food security, local agricultural strategies must incorporate optimized cropping calendars, heat-tolerant crop cultivars, and targeted sub-basin soil and water conservation practices [47–49].

Climate Change Impact on Extreme Indices

The ETCCDI analysis results for the Anai watershed indicate that climate change affects the frequency, intensity, and duration of extreme events. The projected increase in total annual precipitation (PRCPTOT) was primarily driven by an increase in the frequency of heavy rainfall days (R20mm) and extension of persistent wet periods (CWD), rather than by a pronounced amplification of peak daily rainfall intensity. Future extreme precipitation in the Anai watershed was projected to be more frequent and distributed over longer periods rather than concentrated into a small number of extreme periods because of the stability of SDII and Rx1day, in contrast with the significant increase in R95ptot and R99ptot. This pattern indicates that atmospheric warming under higher radiative forcing enhances moisture availability and fuels organized convective systems over multi-day periods, rather than releasing energy through isolated daily rainbursts.

This precipitation behavior is strongly coupled with the observed thermal index shifts, specifically the sharp decline in cold nights (TN10p) and the surge in warm nights (TN90p), reflecting the impact of climate change on atmospheric moisture capacity. These indices are related to reduced nighttime radiative cooling due to higher atmospheric energy levels, which support the development and persistence of the organized convective systems. The interaction between a moisture-enriched atmosphere and the complex orography of the Anai watershed likely further amplifies this response, converting thermal energy into a higher frequency of extremely wet days (R95pTOT). These extreme precipitation dynamics have severe hydrological implications for watersheds. The lengthening of persistent wet periods (CWD), combined with frequent heavy rainfall events (R20mm), will lead to progressive topsoil saturation and high antecedent moisture conditions across the upper sub-basins. In steep mountainous terrain, fully saturated soils dramatically reduce infiltration capacity, escalating surface runoff rates, triggering landsliding/slope instability, and heightening the risk of catastrophic flash floods in downstream areas. Consequently, watershed management must move beyond conventional flood defenses to incorporate slope stabilization, vegetative soil water conservation, and sub-basin-specific hazard monitoring.

Projection Uncertainties

The MME approach was employed to project changes in precipitation and climate extremes under two emission scenarios. However, the MME projection reveals inherent uncertainties. Uncertainties in this study were calculated using the 10th (P10) and 90th (P90) percentile distributions of each scenario to represent the lower and upper bounds of the projection. The uncertainty range is the difference between the 10th (P10) and 90th (P90) percentiles, which reflects the spread of projections among climate models within the MME (Table 7). A narrower range of uncertainty represents higher confidence in the robustness of project trends. Furthermore, a wider range implies greater inter-model divergence, which remains more uncertain and potentially sensitive to model-specific processes or assumptions.

Table 7. Multi-model ensemble statistical distribution and uncertainty range (10th to 90th percentiles) for projected climatic variables. The table quantifies the ensemble projected Mean, 10th percentile (P10), 90th percentile (P90), and the resulting uncertainty Range (P90 minus P10) across key climate variables (precipitation, maximum/minimum temperatures) and 12 ETCCDI indices under SSP2-4.5 and SSP5-8.5 emission scenarios. The spread between P10 and P90 illustrates the structural uncertainty and projected range of variability derived from the multi-model ensemble projections. These statistical bounds define the confidence interval for extreme climatic conditions, providing critical upper- and lower-bound thresholds for climate change adaptation and regional risk mitigation strategies in the watershed.

Variable	SSP2-4.5				SSP5-8.5			
	Mean	P10	P90	Range	Mean	P10	P90	Range
Precipitation (mm)	3,464.4	3,110.5	3,898.85	788.35	3,419.32	3,019.03	3,852.27	833.24
Maximum temperature	27.96	27.24	28.56	1.32	28.66	27.28	30.23	2.96
Minimum temperature	22.73	22.01	23.36	1.35	23.36	22.03	24.78	2.75
PRCPTOT	3,370.19	2,942.63	3,870.1	927.47	3,330.09	2,907.97	3,827.33	919.36
CDD	3.7	1	8.3	7.3	4.34	1.00	8.30	7.30
CWD	146.62	36	258.6	222.6	145.15	36.00	270.40	234.40
R20mm	33.12	22.7	45	22.3	28.32	16.03	39.03	23.00
R95ptot	511.02	264.62	783.46	518.84	81.10	48.86	113.52	64.66
R99ptot	156.26	0	302.76	302.76	556.87	294.91	854.95	560.04
Rx1day	28.32	16.03	39.03	23	198.70	40.79	408.21	367.42
Rx5day	81.1	48.86	113.52	64.66	10.22	0.00	25.07	25.07
SDII	9.89	8.84	10.98	2.14	5.41	0.00	16.14	16.14
TN10p	19.61	0	46.7	46.7	9.86	2.79	19.35	16.56
TN90p	5.41	0	16.14	16.14	19.61	0.00	46.70	46.70
TX10p	9.86	2.79	19.35	16.56	32.90	20.00	45.00	25.00

In this study, the reliability of climate projections differed across variables owing to differences in GCM resolutions, with temperature estimates demonstrating greater robustness than those of precipitation and extremes. The temperature projection displayed a relatively narrow uncertainty range, whereas the projections for precipitation and precipitation extreme indices exhibited wider ranges. This result indicates that temperature projections have stronger inter-model agreement and good confidence in the robustness of the simulated trend than precipitation, which remains more sensitive to model structural differences and underlying physical parameterizations. Furthermore, temperature projections exhibit stronger consistency among models in capturing thermodynamic responses to radiative forcing, with stable behaviour across scenarios.

Uncertainties tended to increase under SSP5-8.5, particularly for precipitation and precipitation-related indices, which means that intensified greenhouse forcing amplifies inter-modal variability in simulating precipitation processes. Finally, internal variability introduces natural chaotic noise at the daily and regional watershed scales. Recognizing these underlying drivers reveals that, while temperature projections are strongly forced and reliable, precipitation extremes remain heavily influenced by structural parameterizations and internal climate dynamics. The persistence of substantial uncertainty emphasizes the necessity of employing the MME approach to encompass the full range of potential future outcomes and support more comprehensive climate impact assessments and adaptation strategies.

Conclusions

Two climate change scenarios were employed to analyze potential future alterations in precipitation, temperature, and climate extremes in the Anai watershed using the CMIP6 MME projections. The results indicate a transition towards increased humidity in the Anai watershed. Climate variability exerted a greater influence on the Anai watershed than median alterations in annual precipitation and temperature. Heightened climate variability exacerbates extreme climatic events, with seasonal analyses indicating an extension of wet seasons and increased thermal stress during dry periods. ETCCDI analyses forecast an increase in the frequency of future precipitation extremes and a reduction in cold days and nights, heightening the risks of landslides, flooding and heat stress. Concrete watershed management strategies are essential to mitigate these risks. Flooding and landslide hazards require strict enforcement of flood zoning, dynamic reservoir operations, and upgraded early warning systems for flash floods and slope instability. Additionally, targeted watershed restoration, such as upper-slope reforestation, is vital to enhance soil infiltration and control erosion, alongside agricultural cropping calendar shifts and public health heat-stress mitigation. Overall, the results of this study have significant implications for climate impact assessments and long-term adaptation planning in the Anai watershed. These findings can be used to inform policy decisions and guide regional strategies for adapting to the effects of climate change. However, further research using higher-resolution regional climate models is required to reduce uncertainties in climate projections and enhance our understanding of the complex interactions between climatic variables and hydrological responses in tropical watersheds.

Author Contributions

YFH: Conceptualization, Formal Analysis, Funding Acquisition, Investigation, Methodology, Software, Visualization, Writing - Original Draft, Writing - Review & Editing; **FA:** Data Curation, Software, Visualization; and **EN:** Data Curation.

AI Writing Statement

When AI-assisted technologies are used in the writing process, use the following statement: During the preparation of this work, the authors used Gemini AI to refine the manuscript's English language structure and clarity. After using this tool/service, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

Conflicts of interest

There are no conflicts to declare.

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