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Projection of Climate Impact on Discharge and Energy Production of Cascade Hydroelectric Power Plant in North Sulawesi

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ABSTRACT

Background: Climate change is a major challenge for the sustainability of hydropower plants (PLTA) in tropical areas such as North Sulawesi, which are highly dependent on water availability from seasonal rainfall.
Aims & Methods: This study aims to project the water discharge and electricity production of the Tonsealama, Tanggari I, and Tanggari II hydropower plants based on the SSP2-4.5 and SSP5-8.5 climate change scenarios. Historical climate data (2014–2024) from BMKG and hydropower plant operation data (2019–2024) are used to train the prediction model using the Random Forest algorithm, with bias correction performed on the CMIP6 GCM output through a hybrid approach combining Random Forest and Delta Change.
Result: The results show a consistent decrease in discharge and energy at the three hydropower plants, especially in May, which has been the peak of the rainy season. The average annual discharge decrease reached 9%, while the decrease in electricity was recorded at 5,528.77 MWh (SSP2-4.5) and 3,053.42 MWh (SSP5-8.5) for the Tonsealama hydropower plant; 8,085.37 MWh and 12,625.98 MWh for PLTA Tanggari I; and the highest decline was experienced by PLTA Tanggari II of 18,160.42 MWh and 9,255.40 MWh. Although higher warming occurs in the SSP5-8.5 scenario, occasional extreme rainfall events partially offset the decline in energy production. These findings emphasize the importance of adaptation strategies through more flexible reservoir management, turbine operations, and integrated water resource planning to increase system resilience to future climate uncertainty.

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1. Introduction

The North Sulawesi electricity system is a rapidly growing network; in 2024, the peak daytime load of 443.9 MW grew 7.3% from 2023, and the peak nighttime load of 486.9 MW grew 7.2% from 2023. Hydroelectric Power Plants (PLTA) play an important role in this region, primarily through the Lake Tondano catchment system, which is the source for three main hydroelectric power plants: Tonsealama PLTA, Tanggari I PLTA, and Tanggari II PLTA. As a renewable energy source, hydroelectric power plants help reduce dependence on fossil fuels, but their production is highly dependent on the availability of water flow, making them vulnerable to climate variability.

Historically, rainfall changes have significantly impacted the performance of Hydroelectric Power Plants (PLTA) in North Sulawesi. One extreme example occurred in 2019 when the capacity factor of the PLTA was recorded at only around 10% due to a very drastic decrease in rainfall (PLN UP2B Sistem Minahasa, 2019). This condition raises concerns about the worsening stability of the electricity supply in the future. Similar things are also seen in Sulawesi in general (Novitasari *et al.,* 2023) and in West Java, where Perdinan *et al.* (2023) showed that rainfall and temperature variability affect the discharge and energy supply at the Saguling, Cirata, and Kracak PLTAs. These findings confirm that the risk of climate change to PLTA is a national issue that requires integrated adaptation.

The impact of declining production has also been recorded in various hydroelectric power plants in the world, such as Bagré in Burkina Faso (Yangouliba *et al.,* 2022), Sondu Miriu in Kenya (Ochieng *et al.,* 2021), and Kulekhani in Nepal (Shrestha *et al.,* 2021). These examples show that the impact of climate change on hydroelectric power plants is global and requires special attention in water resource management to ensure a sustainable electricity supply. Several studies have projected these impacts by combining global climate models (GCMs) and local hydrology, such as in the Kunhar River, Pakistan (Akbar *et al.,* 2023); Taiwan (Chiang *et al.,* 2013); and the multi-objective calibration approach proposed by Chilkoti (2019). Parkinson (2008) added that long-term energy planning must consider hydrological uncertainty not to overestimate hydroelectric power plant capacity and prevent the risk of energy supply shortages. However, most studies still focus on single power plants and rarely discuss the interactions between hydroelectric power plants in a cascade system, even though upstream-downstream operational coordination significantly impacts discharge and production stability.

This study aims to project the water discharge and energy production of Tonsealama, Tanggari I, and Tanggari II hydroelectric power plants based on the SSP2-4.5 and SSP5-8.5 scenarios using calibrated global climate data. The results are expected to provide an overview of climate change risks and become a reference for planning a more resilient North Sulawesi electricity system.

2. Methods

2.1 Study Area

This study focuses on three hydroelectric power plants in one river system in North Sulawesi—Tonsealama, Tanggari I, and Tanggari II—which form a cascade generation system where water from the upstream hydroelectric power plants flows to the downstream hydroelectric power plants. Tonsealama is located upstream, and its source is Lake Tondano, while Tanggari I and II receive flow from the previous power plants. All three are located in hilly areas with different altitudes, which affect discharge characteristics and energy potential. Because they are connected in one system, climate change or fluctuations in rainfall in the upstream will directly impact water availability in the downstream.

2.2 Data Collection

This study uses secondary data from official sources. Historical climate data (daily rainfall and temperature 2014–2024) were obtained from the Indonesian Agency for Meteorological, Climatological, and Geophysics (BMKG) North Sulawesi Climatology Station, while historical discharge and electrical energy data 2019–2024 were from PLN NP UP Minahasa as a representation of the performance of the Tonsealama, Tanggari I, and Tanggari II hydroelectric power plants. For future climate projections, Global Climate Model (GCM) CMIP6 data for the SSP2-4.5 and SSP5-8.5 scenarios from five selected models were used: CanESM5, GISS-E2-1-G, IPSL-CM6A-LR, MRI-ESM2-0, and CNRM-CM6-1. SSP2-4.5 represents the medium radiation pathway with moderate development and mitigation policies, while SSP5-8.5 describes the highest emissions with rapid economic growth and fossil fuel dominance without significant restrictions (O'Neill et al., 2016). The selection of models was based on the evaluation results of Li *et al.* (2022), which assessed suitability for the Southeast Asian region and tropical rainforest zones.

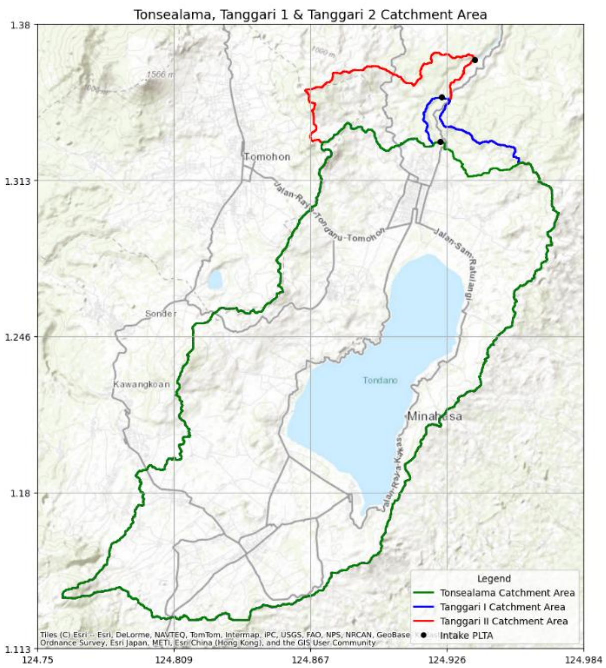

Figure 1. Map of the Tonsealama Hydroelectric Power Plant Catchment Area, Tanggari 1 and Tanggari 2.

2.3 Climate Data Bias Correction

GCM data generally has systematic bias towards local conditions, especially in tropical areas with complex topography such as North Sulawesi. Therefore, bias correction is carried out using a hybrid method that combines Random Forest Regression (baseline 2014–2024) and Delta Change (projection 2041–2100). Random Forest is calibrated with predictor variables of month, year, rainfall, and temperature from GCM, while the target is BMKG observation data. The training data is expanded using GCM data from each model as augmented data. The calibrated model improves the distribution of baseline data before Delta Change is applied. Future climate projections are calculated as the difference (temperature) or percentage change (rainfall) between the projection and the baseline, then the delta value is applied to the observation data to produce bias-corrected projections (Navarro-Racines *et al.,* 2020):

$$\Delta X_i = X_{F_i} - X_{C_i} \quad (1)$$

$$\Delta X_i = \frac{X_{F_i} - X_{C_i}}{X_{C_i}} \quad (2)$$

$X_{DCi} = X_{OBS_i} - \Delta X_i$ (3)

$X_{DCi} = X_{OBS_i} \times (1 + \Delta X_i)$ (4)

Where ΔX_i is the climate change/anomaly, X_{F_i} is the mean future climate of the model, X_{C_i} is the mean baseline of the model, X_{DCi} is the future value and X_{OBS_i} is the observed value (baseline).

2.4 Modeling of Inflow Discharge and Hydroelectric Power Plant Energy

Discharge prediction uses a machine learning approach using the Random Forest Regressor algorithm. The model is developed in three main stages referring to the method used by Obahoundje *et al.* (2024).

a. RF1-The initial model is developed using all predictor variables, namely rainfall and temperature in the relevant month, as well as lagging variables, temperature up to 6 months previously and accumulated rainfall up to 12 months previously. Discharge or energy is used as the target variable.
b. RF2 – The model is simplified by using only the five most important predictor variables based on the feature_importance attribute from the RF1 model. The variables used include current rainfall, temperature, and the most influential lagging combination on discharge or energy.
c. RF3 – Residual tuning stage, where the model is trained to predict the residuals from the RF2 results using the same variables. The residual values are then added back to the RF2 prediction results to improve the accuracy of the final model.

To reduce the risk of overfitting, hyperparameter tuning was performed using RandomizedSearchCV with a 5-fold cross-validation scheme, where the data is divided into several subsets and tested alternately on previously untrained data. This approach helps select the optimal hyperparameter combination based on the average performance in the validation set so the model is stable on new data (Bergstra & Bengio, 2012).

The model is then trained with historical data from 2019–2024 and used to predict discharge and energy in the projection period using bias-corrected climate data. Performance is evaluated using Pearson correlation, Mean Absolute Percentage Error (MAPE), and Normalized Root Mean Squared Error (nRMSE). Pearson correlation measures the linear relationship between predicted and observed discharge. Validation is done internally through cross-validation on historical data, while the projection period relies on the assumption that the pattern of discharge and climate parameter relationships remain consistent since future observation data are not yet available. Mathematically, the evaluation is done using (Obahoundje *et al.*, 2022):

$$Corr = \frac{n(\sum_{j=1}^{N} y_j \bar{y}_j) - (\sum_{j=1}^{N} y_j)(\sum_{j=1}^{N} \bar{y}_j)}{\sqrt{\left[n\sum_{j=1}^{N} y_j^2 - (\sum_{j=1}^{N} y_j)^2\right]\left[n\sum_{j=1}^{N} \bar{y}_j^2 - (\sum_{j=1}^{N} \bar{y}_j)^2\right]}} \quad (5)$$

$$MAE = \frac{1}{N}\sum_{j=1}^{N} |y_j - \bar{y}_j| \quad (6)$$

$$MAPE = \frac{100}{N}\sum_{j=1}^{N} \frac{|y_j - \bar{y}_j|}{y_j} \quad (7)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N} (y_j - \bar{y}_j)^2} \quad (8)$$

$$nRMSE = \frac{RMSE}{\sigma} \quad (9)$$

Where $Corr$ is the Pearson correlation, N is the number of samples, y_j are the observed values, $\bar{y}$ are the simulated/model values, j is the date and σ is the standard deviation.

3. Results and Discussion

3.1 Historical Climate Characteristics

The analysis of climate characteristics is based on observation data of rainfall and air temperature from 2014–2024 from the North Sulawesi Climatology Station. The interpolation and areal aggregation results show that the three hydroelectric power plant catchments—Tonsealama, Tanggari I, and Tanggari II—have uniform climate patterns (Figure 2) because they are located close together and in one hydrological system.

The seasonal rainfall pattern shows two prominent peaks in November–December and April–May, and a minimum in July–August, by the climate character Af (tropical rainforest) according to Köppen. The average monthly rainfall ranges from 100 to 350 mm, with high inter-annual variability. Air temperature is relatively stable in the range of 22.5–23.7°C, with a peak in May and a low in January–February. This temperature distribution reflects a consistent and humid tropical climate throughout the year, supporting the findings of Salim (2015) that areas with high altitudes and close distances tend to have homogeneous microclimates.

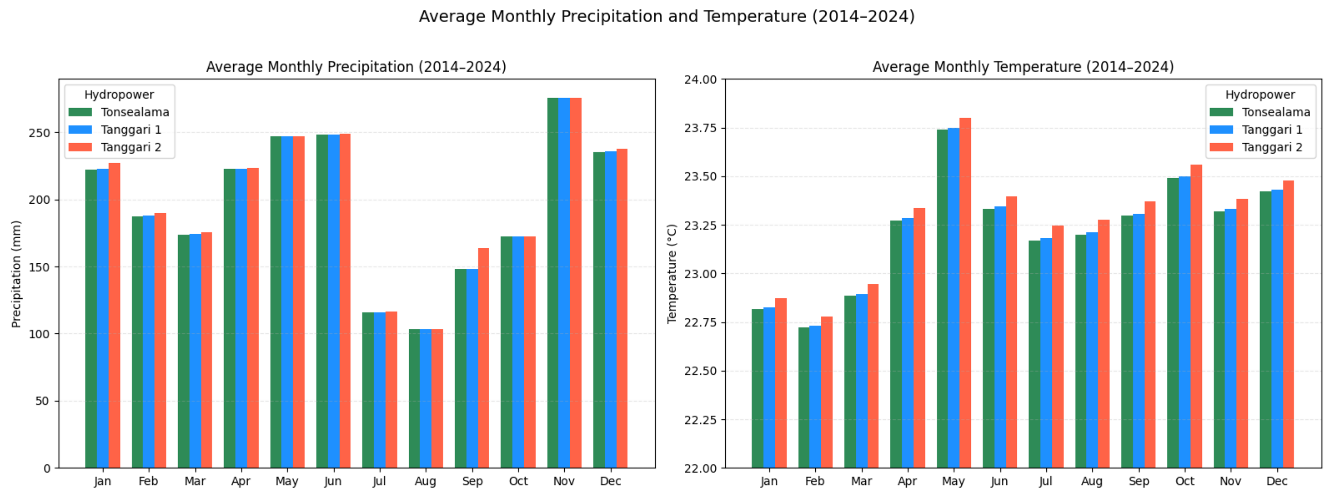

Figure 2. Average monthly rainfall and temperature per hydroelectric power plant (2014-2024).

3.2 GCM Climate Data Bias Correction

Before being used in the discharge and energy modeling, data from five GCM models were adjusted to local conditions through bias correction using Random Forest Regression trained with BMKG observation data from 2014–2024. Models were developed separately for temperature and rainfall at each hydropower plant. The evaluation results showed that this method significantly reduced the deviation between GCM and observation data, with the correlation value of observed climate data with the corrected GCM reaching 0.843–0.902 and RMSE between 44.67–55.5 mm. The correlation above 0.94 and the average error below 0.1°C indicate very good performance for temperature.

The consistency of the results across locations and scenarios proves the effectiveness of this method in capturing spatial and seasonal patterns and improving the representation of extreme events such as floods and droughts (Luo *et al.,* 2020). With a correlation approaching 0.9, climate projections are more reliable as a basis for adaptation planning, including turbine settings and mitigation of water shortages or excesses (Das *et al.,* 2022).

Table 1. Results of climate data correction evaluation

PLTA	Scenario	Rainfall			Air Temperature		
		Corr	RMSE (mm)	MAE (mm)	Corr	RMSE (°C)	MAE (°C)
Tonsealama	SSP2-4.5	0.902	44.67	34.25	0.941	0.14	0.09
Tonsealama	SSP5-8.5	0.844	55.36	40.57	0.941	0.14	0.10
Tanggari I	SSP2-4.5	0.902	44.52	34.23	0.942	0.13	0.09
Tanggari I	SSP5-8.5	0.843	55.50	40.83	0.941	0.13	0.10
Tanggari II	SSP2-4.5	0.856	46.78	34.52	0.942	0.13	0.09
Tanggari II	SSP5-8.5	0.867	45.09	34.09	0.940	0.14	0.10

3.3 Climate Change in the Study Area

The probability distribution of monthly rainfall and temperature at the three hydropower plant locations shows a consistent shift in climate patterns in the future in both SSP2-4.5 and SSP5-8.5 scenarios. Tonsealama, Tanggari I, and Tanggari II have similar distribution patterns, reflecting climate homogeneity because they are in one hydrological system (Figure 3).

Temperature projections show an increasing trend in both scenarios. In SSP2-4.5, the average temperature increases from 23–24°C (2014–2024) to 24–25°C (2041–2060), and increases again in 2081–2100. The increase is sharper in SSP5-8.5 with a peak temperature approaching 26–27°C by the end of the century, meaning the study area is projected to experience 2–3°C warming depending on the scenario. The widening distribution also indicates an increase in inter-monthly and inter-annual temperature variability. These projections are consistent with the IPCC (2023), which states that the tropics will experience significant land warming, strengthening the global hydrological cycle and increasing the risk of droughts and seasonal floods.

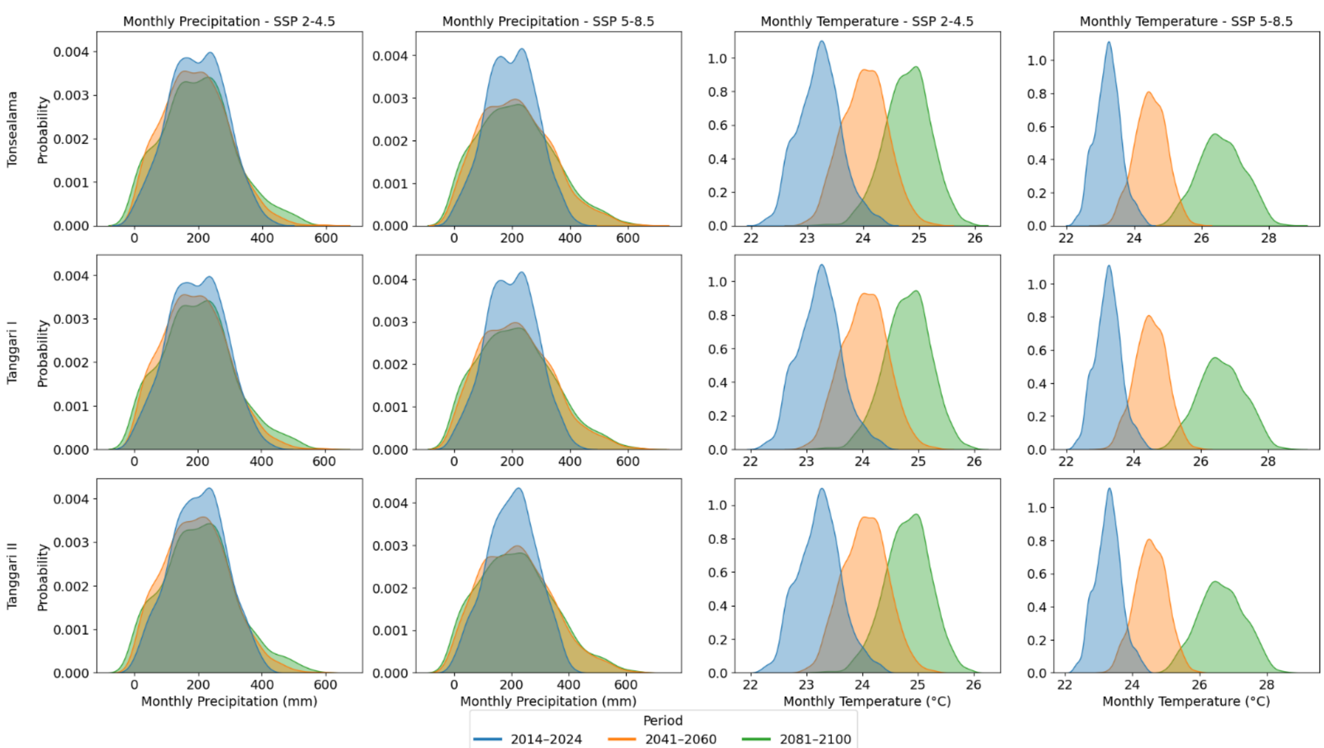

Figure 3. Monthly climate distribution per hydroelectric power plant and scenario.

The distribution of precipitation shows a more complex pattern than temperature. SSP2-4.5 shows a slight shift to lower precipitation in 2081–2100, although most of the distribution still overlaps with the baseline. In SSP5-8.5, the distribution widens and shifts to the left, indicating an increase in the frequency of low rainfall (longer dry spells) but still the potential for high rainfall in the wet season. This increase in variability strengthens the pattern of seasonal extremes—shorter heavy rainfall and longer dry spells—in line with IPCC (2023) projections that predict increasing global rainfall intensity and variability by the end of the century.

These shifts in temperature and rainfall indicate that the three hydroelectric power plants will face increasingly extreme and unstable climate conditions, especially in the high emission scenario. Although the total annual rainfall is relatively stable, its time distribution changes, so water availability is not in line with energy needs. This uncertainty has the potential to disrupt the reliability of electricity supply. Therefore, adaptation is needed through responsive water management and flexible power plant operations.

3.4 Future Discharge Prediction

3.4.1 Tonsealama Hydroelectric Power Plant

The Tonsealama hydropower discharge prediction model performs well in all scenarios and development stages. Based on Table 2, the Pearson correlation value between predicted and observed discharge ranges from 0.76–0.83, with the highest accuracy at the RF3 stage (residual tuning). MAPE decreases to about 22%, and nRMSE remains below 0.16, indicating a low error in the hydrological context. These results confirm the effectiveness of residual tuning in capturing the relationship between climate and discharge and reducing bias.

The monthly discharge projection of the Tonsealama hydropower plant (Figure 4) shows a decrease in both scenarios, especially in 2081–2100. The most significant decrease occurs in wet months such as April–May and December. However, in several months such as May, July, and August, the discharge of SSP5-8.5 is slightly higher than SSP2-4.5.

Table 2. Evaluation of random forest algorithm to predict discharge of Tonsealama Hydroelectric Power Plant.

Scenario	Stage	*Pearson Correlation*	MAPE (%)	nRMSE
SSP2-4.5	RF1 (all *lagging*)	0.774	24.3	0.164
	RF2 (*current* + 5 *lagging*)	0.762	23.7	0.168
	RF3 (*residual tuning*)	0.793	22.0	0.158
SSP5-8.5	RF1 (all *lagging*)	0.766	24.6	0.167
	RF2 (*current* + 5 *lagging*)	0.798	22.0	0.157
	RF3 (*residual tuning*)	0.830	19.7	0.145

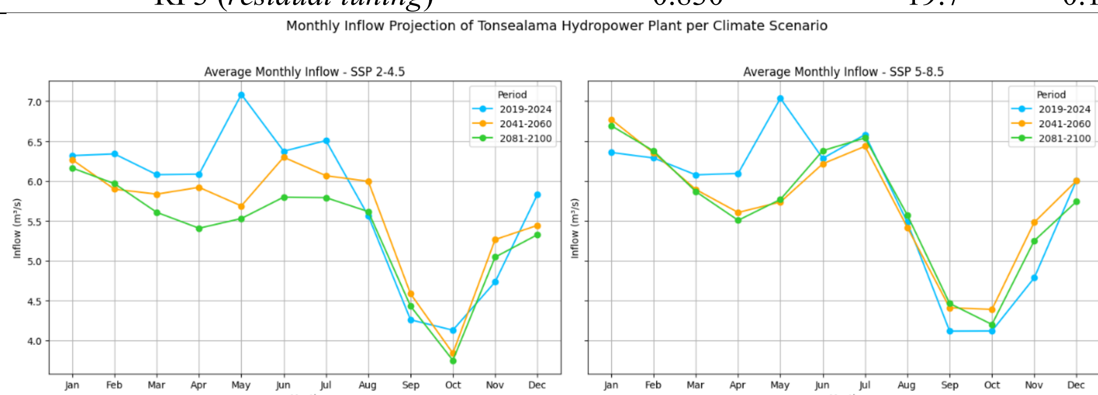

Figure 4. Monthly Discharge of Tonsealama Hydroelectric Power Plant per Period and Scenario

The rainfall distribution in the SSP5-8.5 scenario shows a rightward shift and widening of the upper tail (Figure 3), indicating an increase in extreme rainfall events (>400 mm/month), although the median remains the same. This explains the seasonal discharge spike amidst a declining or stagnant annual trend. This finding is supported by the IPCC (2023), Liang *et al.* (2022), and Hariadi *et al.* (2024), which noted an increase in extreme weather events in tropical regions, including Sulawesi. Obahoundje *et al.* (2022) also showed that combining high temperatures and extreme rainfall can increase monthly discharge variability. This condition reduces water volume and disrupts the stability of the energy supply, especially during the dry season. Therefore, high discharge fluctuations should be a concern in hydropower adaptation and operation strategies.

3.4.2 Tanggari I Hydroelectric Power Plant

The Random Forest model for PLTA Tanggari I shows consistent prediction performance with Pearson correlation between prediction results and observations reaching 0.83 at the RF3 stage in both scenarios. The residual tuning stage (RF3) improves accuracy, reducing MAPE by 19.6% and nRMSE by around 0.146 at SSP2-4.5, indicating the effectiveness of this method in correcting systematic mismatches.

Monthly discharge projections (Figure 5) show a decreasing trend from the baseline (2019–2024) to the projection periods of 2041–2060 and 2081–2100 in both scenarios. The annual average discharge is estimated to decrease from around 7.22 m^3/s to 6.72–6.73 m^3/s (SSP2-4.5) and 6.75–6.69 m^3/s (SSP5-8.5). Interestingly, although extreme rainfall increases in the SSP5-8.5 scenario, the Tanggari I hydropower plant does not show a significant surge in discharge. This is likely due to the spatially limited extreme rainfall, which does not coincide with the peak flow, and the stagnant median rainfall. As a middle power plant in the cascade system, the Tanggari I discharge is also affected by the operation of upstream hydropower plants such as Tonsealama, including water retention in the reservoir. Bakri *et al.* (2024) emphasized that the regulation in upstream hydropower plants directly impacts the water supply downstream. Overall, the decrease in discharge in Tanggari I is consistent and less responsive to extreme rainfall, so adaptation needs to focus on seasonal water management and optimization of upstream flows.

Table 3. Evaluation of random forest algorithm to predict discharge of Tanggari I Hydroelectric Power Plant

Scenario	Stage	*Pearson Correlation*	MAPE (%)	nRMSE
SSP2-4.5	RF1 (all *lagging*)	0.827	21.0	0.151
	RF2 (*current* + 5 *lagging*)	0.814	21.1	0.156
	RF3 (*residual tuning*)	0.839	19.6	0.146
SSP5-8.5	RF1 (all *lagging*)	0.824	21.1	0.152
	RF2 (*current* + 5 *lagging*)	0.796	20.9	0.162
	RF3 (*residual tuning*)	0.828	18.9	0.151

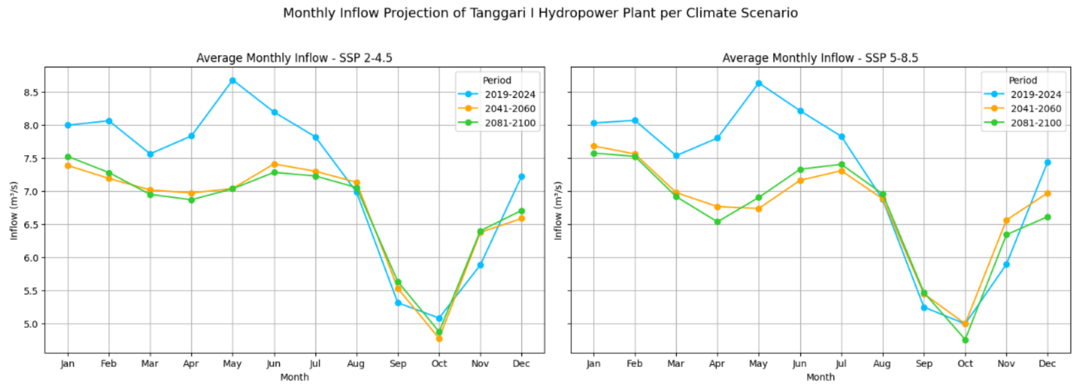

Figure 5. Monthly discharge of Tanggari I Hydroelectric Power Plant per period and scenario.

3.4.3 Tanggari II Hydroelectric Power Plant

The Random Forest model for the Tanggari II Hydroelectric Power Plant showed stable and adequate performance. The Pearson correlation between prediction and observation results reached 0.83 at the RF3 stage for the SSP2-4.5 scenario and 0.84 for SSP5-8.5. The MAPE value was successfully suppressed to around 20%, and the nRMSE was around 0.15, indicating fairly good model accuracy in predicting discharge based on climate data and lagging variables.

Table 4. Evaluation of random forest algorithm to predict discharge of Tanggari II Hydroelectric Power Plant.

Scenario	Stage	*Pearson Correlation*	MAPE (%)	nRMSE
SSP2-4.5	RF1 (all *lagging*)	0.801	23.4	0.160
	RF2 (*current* + 5 *lagging*)	0.796	22.2	0.161
	RF3 (*residual tuning*)	0.827	20.2	0.150
SSP5-8.5	RF1 (all *lagging*)	0.804	25.0	0.158
	RF2 (*current* + 5 *lagging*)	0.794	22.5	0.162
	RF3 (*residual tuning*)	0.837	20.3	0.146

The monthly discharge projections in Figure 6 show a consistent seasonal pattern. Annual discharge decreases compared to the baseline (2019–2024), but the difference is relatively moderate. In the SSP2-4.5 scenario, the annual average decreases from 9.10 m^3/s to 8.34 and 8.21 m^3/s. Interestingly, the annual discharge of SSP5-8.5 is actually higher, with an average of 8.76 m^3/s.

This difference reflects the influence of extreme rainfall on SSP5-8.5, as seen from the widening of the right tail of the rainfall distribution (Figure 3), although the peak decreases. This is in line with the IPCC (2023), Liang *et al.* (2022), and Hariadi *et al.* (2024), who reported the intensification of extreme rainfall in tropical regions. As a result, Tanggari II, as a downstream generator, can receive additional runoff from upstream, so the decrease in discharge in SSP5-8.5 is not always greater than SSP2-4.5. These findings emphasize the importance of considering spatial interactions and cascade system dynamics in assessing climate impacts on hydropower.

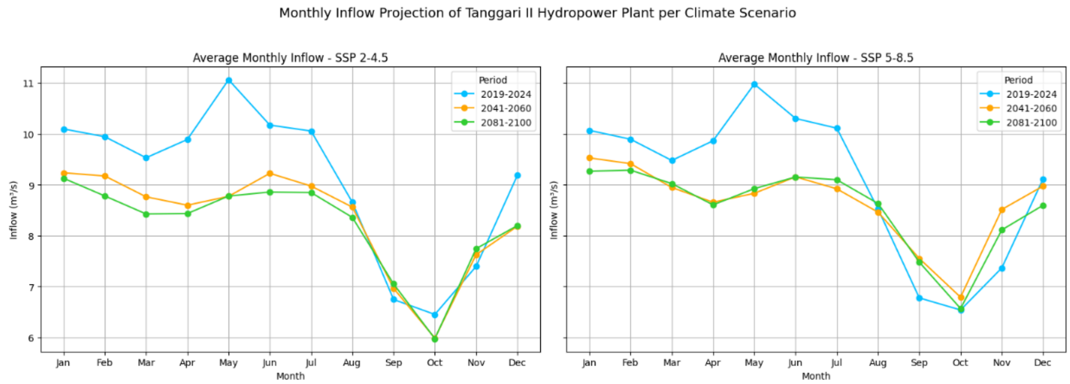

Figure 6. Monthly discharge of Tanggari II Hydroelectric Power Plant per period and scenario

3.5 Future Energy Predictions

3.5.1 Tonsealama Hydroelectric Power Plant

The Tonsealama hydropower energy prediction model was built using the Random Forest algorithm using residual tuning. The evaluation results (Table 5) showed good performance, with increased accuracy from RF1 to RF3. In RF3, the Pearson correlation between predicted and observed energy reached 0.883 (SSP2-4.5) and 0.837 (SSP5-8.5), with MAPE of 16.5–19.7% and nRMSE of 0.120–0.139. This indicates that the model is able to capture the non-linear relationship between climate and energy with acceptable accuracy.

Annual energy production projections decrease due to climate change. The decrease is calculated from the difference between predicted energy production and the 2019–2024 baseline. Table 6 shows a decrease in SSP2-4.5 of -3,065.88 MWh/year (2041–2060) and -2,462.89 MWh/year (2081–2100). SSP5-8.5, the decrease is smaller, namely -1,400.01 MWh/year, and even increases by 1,653.41 MWh/year. This shows that although SSP5-8.5 projects more extreme warming, the frequency of extreme rainfall seems to compensate for the decrease in annual discharge.

Table 5. Evaluation of random forest algorithm to predict energy production of Tonsealama Hydroelectric Power Plant

Scenario	Stage	*Pearson Correlation*	MAPE (%)	nRMSE
SSP2-4.5	RF1 (all *lagging*)	0.804	22.6	0.151
	RF2 (*current* + 5 *lagging*)	0.853	19.0	0.133
	RF3 (*residual tuning*)	0.883	16.5	0.120
SSP5-8.5	RF1 (all *lagging*)	0.779	24.3	0.159
	RF2 (*current* + 5 *lagging*)	0.803	21.9	0.152
	RF3 (*residual tuning*)	0.837	19.7	0.139

The largest monthly energy decline occurred in May, reaching -1,000 MWh in all scenarios and periods. However, SSP5-8.5 shows an increase in energy in certain months, such as November and December, to +435 MWh (Figure 7). The sharper inter-month variability in SSP5-8.5 indicates a change in seasonal patterns, affecting total production and energy supply reliability in certain seasons. This pattern is in line with IPCC (2023), Hariadi *et al.* (2024), and Obahoundje *et al.* (2022), which show that extreme rainfall can trigger seasonal production spikes even though annual production decreases. This change in time distribution poses a challenge to match supply with load. Overall, projections show that climate change is reducing the annual production of Tonsealama hydropower while changing seasonal patterns, requiring adaptations in reservoir management, turbine operations, and reserve supply.

Table 6. Decrease in energy production of Tonsealama Hydroelectric Power Plant (MWh)

Month	SSP 2-4.5		SSP 5-8.5	
	2041-2060	2081-2100	2041-2060	2081-2100
January	-323.68	-155.84	37.82	40.69
February	-117.64	-103.31	203.83	232.34
March	-383.91	-412.25	-260.42	-254.74
April	-355.10	-448.64	-469.01	-548.59
May	-972.68	-975.17	-1,060.55	-1,051.80
June	80.80	-20.81	-15.82	77.93
July	-365.97	-231.91	-208.07	-121.07
August	-145.84	-88.13	-85.33	19.25
September	-87.16	25.22	166.54	206.25
October	-208.01	-147.78	106.86	-35.78
November	119.98	254.20	435.58	235.82
December	-306.65	-158.48	-251.43	-453.71
Grand Total	-3,065.88	-2,462.89	-1,400.01	-1,653.41

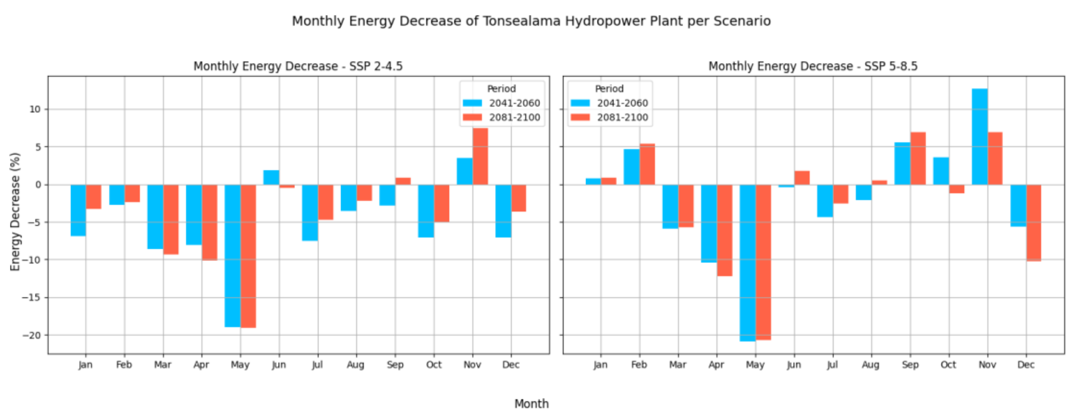

Figure 7. Percentage of monthly energy decrease of Tonsealama Hydroelectric Power Plant.

3.5.2 Tanggari I Hydroelectric Power Plant

The energy prediction model of Tanggari I hydropower plant showed good and consistent performance in both climate scenarios (Table 7). The residual tuning approach (RF3) produced a Pearson correlation between prediction and observation results of 0.873 for SSP2-4.5 and 0.838 for SSP5-8.5, with MAPE ranging from 18.1–19.1% and nRMSE ranging from 0.113–0.135, indicating the model's ability to capture non-linear patterns between climate variables and energy production.

Table 7. Evaluation of random forest algorithm to predict energy production of Tanggari I Hydroelectric Power Plant

Scenario	Stage	*Pearson Correlation*	MAPE (%)	nRMSE
SSP2-4.5	RF1 (all *lagging*)	0.856	20.1	0.120
	RF2 (*current* + 5 *lagging*)	0.854	19.5	0.120
	RF3 (*residual tuning*)	0.873	18.1	0.113
SSP5-8.5	RF1 (all *lagging*)	0.842	21.9	0.125
	RF2 (*current* + 5 *lagging*)	0.811	21.2	0.135

RF3 (*residual tuning*)	0.838	19.1	0.127

Projections show significant annual energy production declines in SSP2-4.5, up to –11.1% (2041–2060) and –9.7% (2081–2100) (Figure 8), while in SSP5-8.5 the declines are more moderate (–5.3% to –5.5%) as extreme precipitation balances losses due to high temperatures.

Table 8. Decrease in energy production of Tanggari I Hydroelectric Power Plant (MWh)

Bulan	**SSP 2-4.5**		**SSP 5-8.5**	
	2041-2060	**2081-2100**	**2041-2060**	**2081-2100**
January	-577.19	-215.05	-506.39	-594.19
February	-415.80	-38.91	-123.61	-175.57
March	-495.68	-412.94	-606.36	-699.12
April	-601.85	-687.68	-861.47	-1,060.78
May	-1,552.15	-1,606.36	-1,924.91	-1,875.65
June	-334.58	-514.42	-769.73	-697.59
July	-331.50	-152.01	-580.65	-457.06
August	253.87	313.85	-110.14	-47.52
September	99.25	272.49	-0.52	-70.29
October	-423.76	-438.05	-349.82	-482.26
November	349.59	470.09	554.70	252.93
December	-592.45	-454.15	-525.72	-914.26
Grand Total	-4,622.23	-3,463.14	-5,804.62	-6,821.36

Seasonally, the largest energy decline occurred in March-May, especially in May, which dropped by more than -1,500 MWh. Several months, such as August–September, had increased at SSP2-4.5 but were inconsistent at SSP5-8.5, which generally decreased throughout the year. This reflects unstable water redistribution due to evaporation and rainfall fluctuations, in accordance with Obahoundje *et al.* (2022), and emphasizes the need for operational adaptation through load management and water release.

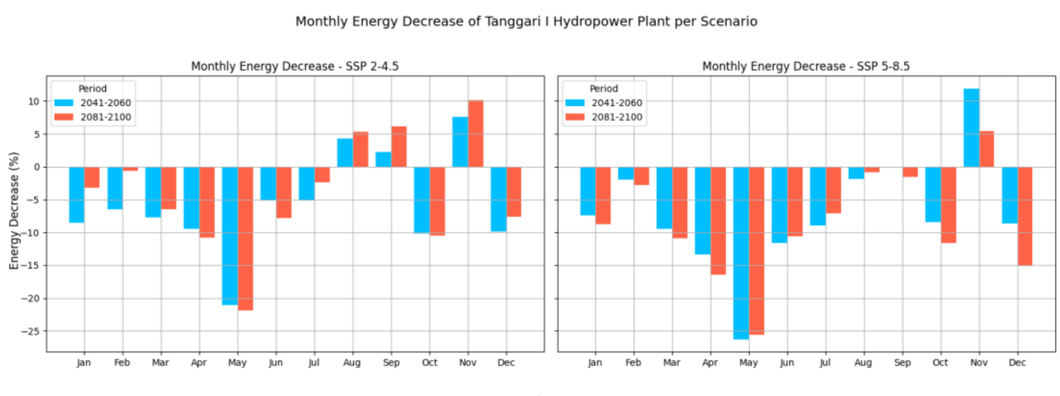

Figure 8. Percentage of monthly energy reduction of Tanggari I Hydroelectric Power Plant

3.5.3 Tanggari II Hydroelectric Power Plant

The electricity prediction model of the Tanggari II hydroelectric power plant showed quite good performance (Table 9), with the Random Forest residual tuning approach producing the highest accuracy at the RF3 stage. The Pearson correlation between the prediction and observation results was recorded at 0.888 (SSP2-4.5) and 0.875 (SSP5-8.5), while MAPE and nRMSE decreased by 17.6–17.7% and 0.113–0.137, respectively, indicating a reliable model for climate-based energy projections.

Projections show a significant decline in annual energy production of the Tanggari II hydropower plant at SSP2-4.5, namely –8,940.9 MWh/year (2041–2060) and –9,219.51 MWh/year (2081–2100) (Table 10). In contrast, at SSP5-8.5, the decline is more moderate, –4,517.95 to –4,737.46 MWh/year, because extreme rainfall helps balance losses due to high temperatures.

The largest decline occurred in April–May, exceeding -1,300 MWh/year, while October–November at SSP5-8.5 showed small fluctuations. This pattern reflects the influence of seasonal rainfall and water release from upstream. Overall, Tanggari II experienced the highest energy decline, supporting the findings of Mtilatila *et al.* (2020) that downstream power plants are more vulnerable because they depend on water supply from upstream. This decline in energy production also has the potential to affect the stability of electricity supply for the industrial and household sectors in the surrounding area, although a detailed socio-economic risk analysis has not been the focus of this study.

Table 9. Evaluation of random forest algorithm to predict energy production of Tanggari II Hydroelectric Power Plant

Scenario	Stage	*Pearson Correlation*	MAPE (%)	nRMSE
SSP2-4.5	RF1 (all *lagging*)	0,831	21,8	0,137
	RF2 (*current* + 5 *lagging*)	0,867	19,1	0,123
	RF3 (*residual tuning*)	0,888	17,6	0,113
SSP5-8.5	RF1 (all *lagging*)	0,820	22,5	0,141
	RF2 (*current* + 5 *lagging*)	0,847	19,5	0,131
	RF3 (*residual tuning*)	0,875	17,7	0,119

Table 10. Decrease in energy production of Tanggari II Hydroelectric Power Plant (MWh)

Bulan	SSP 2-4.5		SSP 5-8.5	
	2041-2060	2081-2100	2041-2060	2081-2100
January	-987,83	-1.049,05	-516,56	-449,91
February	-317,30	-674,41	8,77	16,73
March	-523,03	-889,20	-551,45	-690,66
April	-1.378,34	-1.344,50	-1.273,84	-1.360,29
May	-1.417,88	-1.396,49	-1.402,18	-1.360,27
June	-704,89	-858,97	-323,66	-66,80
July	-928,76	-792,27	-666,55	-268,31
August	-301,63	-301,02	-630,73	-562,67
September	-131,74	68,30	108,56	-147,39
October	-705,36	-758,45	190,80	-136,35
November	-234,07	-88,03	613,20	321,06
December	-1.310,06	-1.135,41	-74,30	-32,59
Grand Total	-8.940,90	-9.219,51	-4.517,95	-4.737,46

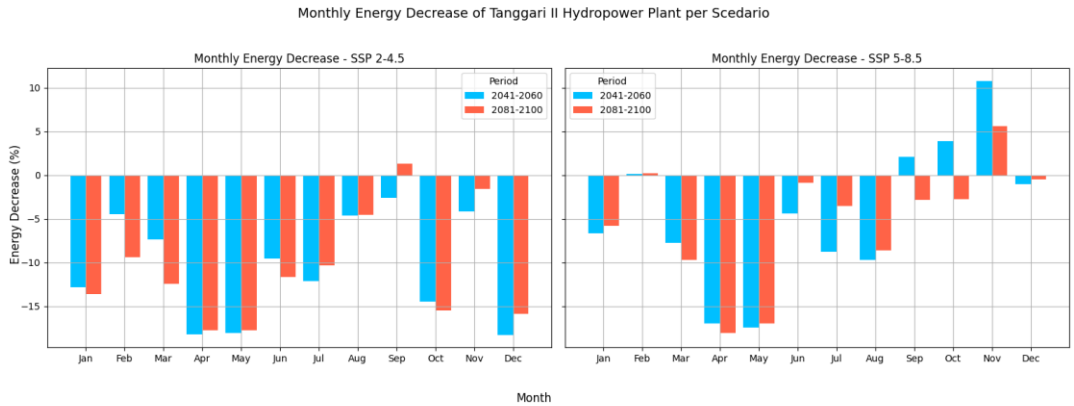

Figure 9. Percentage of monthly energy decrease of Tanggari II Hydroelectric Power Plant.

4. Conclusions

Climate change is expected to reduce water availability and energy production at the cascade hydroelectric power plants in North Sulawesi. Based on the projections of the SSP2-4.5 and SSP5-8.5 scenarios with CMIP6 GCM data, the three hydroelectric power plants (Tonsealama, Tanggari I, and Tanggari II) are projected to experience seasonal and annual discharge decreases that have a direct impact on energy production. The lowest average discharge decreases occurred in Tonsealama (1–5.1%), Tanggari I (8–9%), and Tanggari II (5–9%), with the largest monthly decrease in May, reaching around 20% in all scenarios. Regarding energy, Tonsealama decreased by around 3,000–5,500 MWh, Tanggari I 8,000–12,600 MWh, and Tanggari II experienced the highest decrease, 9,200–18,100 MWh. The Random Forest model showed good accuracy with Pearson correlation 0.76–0.88, MAPE <22%, and nRMSE <0.16, proving the effectiveness of residual tuning for discharge and energy projections. These findings emphasize the importance of an integrated adaptation strategy to maintain supply reliability, especially in the dry season. In the future, it is recommended to use long-term observation data, develop more detailed hydrological models with additional variables, and study socio-economic impacts to support appropriate adaptation policies. The results of this study are also helpful for hydropower operators to design more adaptive reservoir operations and open up opportunities for developing real-time discharge and energy prediction systems to support daily decision-making.

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6. Authors Note

The authors declare that there is no conflict of interest regarding the publication of this article. The authors also confirm that this manuscript is an original work, has not been published elsewhere, and is free from any form of plagiarism.

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