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The Impact of Global Warming on the Optimization of Water Allocation in Dams: A Case Study of the Way Apu Dam, Maluku

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ABSTRACT: Global warming has altered the hydrological regime of tropical archipelagic regions and subjected dam infrastructure to operational stresses that were not anticipated at the design stage. This paper evaluates the impact of global warming on the optimization of water allocation at the Way Apu Dam in Buru Regency, Maluku Province, which serves 10,000 hectares of premium irrigation, a raw water supply of 0.505 m^3/s, hydropower generation, and flood control. The study combines three approaches: (i) climate projection modelling for 2025–2050 using the five IPCC AR6 emission scenarios (SSP1-1.9 through SSP5-8.5) against a 30-year observational baseline from the Namlea Meteorological Station; (ii) hydrological data quality analysis of the Way Tina Station record for 2013–2023 through Grubbs–Beck, RAPS, Spearman, and t-tests; and (iii) development of a nonlinear water allocation optimization model solved with the Generalized Reduced Gradient (GRG) algorithm and implemented in a web-based application. The projections indicate that under the worst-case SSP5-8.5 scenario in 2050, mean temperature rises by 1.65 °C to 28.45 °C, annual rainfall increases by 5.6% to 2,270.9 mm but with an increasingly skewed seasonal distribution, rice productivity in the Wayapo Valley declines by 11.0% to 4.63 tonnes per hectare, 63.67 hectares of the Namlea coast are inundated, the climate vulnerability index reaches 0.382, and annual economic losses reach IDR 46.0 billion. Under normal conditions, GRG optimization yields an allocation efficiency of 65.1% with a total annual release of 173.02 million m^3 (irrigation 95.29; domestic 0.24; hydropower 77.50 million m^3), energy output of 6,546.9 MWh per year, and an annual deficit of 92.94 million m^3 concentrated in October–December. Climate scenario simulations show irrigation reliability falling from 98–100% under a wet pattern to 70–75% under a dry pattern, while raw water supply is maintained above 95%. Sensitivity analysis reveals an allocation elasticity with respect to inflow of 1.2–1.5, and improving irrigation efficiency from 65% to 75% expands service coverage by 12–15%. The study concludes that global warming does not invalidate the feasibility of the Way Apu Dam, but shifts its operational optimum such that static rule curves must be replaced by adaptive operation informed by seasonal forecasting.

I. INTRODUCTION

1.1 Background

Climate change driven by global warming is the environmental challenge whose effects on the water resources sector are most immediately apparent. Rising mean surface temperature alters the atmospheric energy balance, which in turn modifies evapotranspiration rates, rainfall intensity and distribution, and river flow patterns. In tropical archipelagic regions such as

Maluku Province, these effects are amplified by limited catchment areas, the absence of large aquifers to buffer variability, and a population dependent on rainfed agriculture and surface irrigation (Jarraud & Steiner, 2021).

The Way Apu watershed in Buru Regency, with a catchment area of 1,787 km², is the largest and most critical hydrological system within the Buru River Basin (Osok et al., 2020). The Wayapo Plain, formed from alluvial deposits of this river, serves as the granary of Maluku Province. Annual rainfall ranges from 2,000 to 3,000 mm with an uneven distribution; the wet season runs from October to April while the dry season extends from May to September, producing pronounced inter-seasonal discharge fluctuations. These conditions motivated the construction of the Way Apu Dam beginning in 2017 as a multipurpose structure with a 414 km² catchment and a design storage of 50.049 million m³.

Dam design criteria, however, are generally derived from historical hydrological statistics under an assumption of stationarity — the assumption that the statistical properties of past records continue to hold in the future. Global warming invalidates that assumption. As temperature rises, potential evapotranspiration increases, so crop water requirements grow at precisely the moment when dry-season supply reliability declines. A dam that is demonstrably adequate under the historical climate may therefore lose part of its reliability under the future climate unless its operating rules are adjusted.

1.2 Research Questions and Objectives

The research questions are formulated as follows: (1) how are temperature, rainfall, and climate vulnerability in the study area projected to change through 2050; (2) how can the SSP climate scenarios be integrated as quantitative constraints within a multipurpose water allocation optimization model; (3) what monthly operating pattern and rule curve are optimal under normal conditions as well as under wet and dry climate scenarios; and (4) what operational and policy adaptation measures are required by dam managers and regional government.

In line with these questions, the objectives are: (1) to project changes in temperature, rainfall, and climate vulnerability in the study area through 2050; (2) to develop a multipurpose nonlinear water allocation optimization model with climate scenarios as constraint functions; (3) to derive optimal monthly operating patterns and reservoir rule curves; and (4) to formulate operational and policy adaptation recommendations for dam managers and regional government.

1.3 Contribution and Scope

The principal contribution of this study is the explicit integration of IPCC AR6 SSP climate scenarios as quantitative constraints within a reservoir operation optimization model, together with implementation of the GRG algorithm in a web-based application that runs without installation and is therefore readily replicable. The scope is limited to the Way Apu Dam and the Way Apu Irrigation System, focuses on irrigation as the largest user, relies on rainfall records from the Way Tina and Namlea stations, and uses GRG as the sole optimization algorithm.

II. LITERATURE REVIEW

2.1 Multipurpose Reservoirs and Water Allocation

A multipurpose reservoir is infrastructure designed to serve several functions simultaneously (Wurbs, 1996). The Way Apu Dam carries five functions in order of priority: flood control, with peak discharge reduction of 394–557 m³/s protecting the Wayapo, Waylata, and Lolong Guba districts; raw water supply for the Lolong Guba, Waylata, Wayapo, and Teluk Kaiely districts and the town of Namlea; irrigation support for seven irrigation areas within the Way Apu System; electricity generation; and maintenance of environmental flow. Conflict among these functions is inherent, because each demands a different storage regime: flood control favours low storage, whereas irrigation and hydropower favour high storage. Studies of cascade reservoirs show that rising water demand depresses electricity output (Hadihardaja et al., 2004), while discharge forecasting models have been shown to improve multipurpose reservoir operation (Mulyawati, 2020). For the Way Apu System itself, rehabilitation priorities across the seven irrigation areas have been assessed using the Simple Additive Weighting method (Virgianti et al., 2022).

2.2 Nonlinear Programming and the GRG Method

Nonlinear programming is required whenever the objective function or the constraint set of an optimization problem cannot be expressed in linear form. Reservoir operation optimization belongs to this class of problems because hydropower benefit is the product of turbine discharge and effective head, while evaporation loss depends on the inundated surface area, itself a nonlinear function of storage volume. Forced linearization of these relationships introduces errors that cannot be neglected in reservoirs subject to large water-level fluctuations.

The Generalized Reduced Gradient (GRG) algorithm solves constrained nonlinear problems by separating the decision variables into basic and nonbasic sets, then reducing the problem to a gradient search over the nonbasic variable space that continues to satisfy the constraints. At each iteration the basic variables are recomputed by solving the constraint system, so the solution remains within the feasible region throughout. The algorithm was selected because it is available in Solver, handles inequality constraints and variable bounds directly, and converges relatively quickly on moderately sized problems such as a twelve-period monthly allocation. Its principal limitation is local convergence: the solution obtained is not guaranteed to be a global optimum, so testing from several starting points remains necessary.

2.3 IPCC AR6 SSP Climate Scenarios

The IPCC Sixth Assessment Report (IPCC, 2021) employs Shared Socioeconomic Pathways that combine socioeconomic trajectories with radiative forcing levels. The five scenarios used here are SSP1-1.9 (maximum ΔT of +1.4 °C by 2100), SSP1-2.6 (+1.8 °C), SSP2-4.5 (+2.7 °C), SSP3-7.0 (+3.6 °C), and SSP5-8.5 (+4.4 °C). For Southeast Asia, CORDEX-SEA studies project increased wet season rainfall alongside reduced dry season rainfall — a combination that widens the amplitude of seasonal fluctuation and complicates reservoir operation.

III. RESEARCH METHODOLOGY

3.1 Location, Data, and Equipment

The research was conducted at the Maluku River Basin Organization with six months of field observation in Buru Regency. The Way Apu Dam is located in Wapsalit Village (Lolong Guba District) and Way Flan Village (Waylata District), between 3°32'32.22" S–126°47'57.32" E and 3°35'33.50" S–126°52'5.47" E. Data comprise rainfall records from the Way Tina Station (2013–2023), climatological data from the Namlea Meteorological Station (1991–2020 baseline), dam technical specifications, reservoir inflow–outflow records, and national statistics agency data for comparison; all of these data were compiled within the framework of the author's doctoral research (Virgianti, 2026). Equipment included a DJI drone for mapping cloud-obscured areas, Solver and ArcGIS software, the Water Modeling System with SRTM data for watershed delineation, and GPS units.

Table 1. Technical Specifications of the Way Apu Dam

Parameter	Value	Unit
River / dam catchment	Way Apu / 414 km²	—
Dam type	Zoned earthfill, vertical core	—
Height / crest length	72 / 482	m
Design maximum storage	50.049	million m³
Effective model volume (S_max)	41.76	million m³
Dead storage (S_min)	14.78	million m³
Spillway / maximum water level	96.50 / 98.80	m
Maximum turbine discharge	17.61	m³/s
Raw water discharge	0.505 – 0.549	m³/s

Parameter	Value	Unit
Hydropower capacity (2 × 2 MW tandem)	4.00 (design 8.00)	MW
Irrigation service area	10,000 (premium) – 10,562	ha
Flood peak reduction capacity	394 – 557	m^3/s

Source: Analysis results and technical data from the Maluku River Basin Organization.

3.2 Hydrological Data Quality Testing

Before use, rainfall data must undergo pre-processing to ensure the reliability of the time series and freedom from systematic error or recording mistakes. Five tests were applied to the Way Tina Station record for 2013–2023: the Grubbs–Beck outlier test, the Rescaled Adjusted Partial Sums consistency test, the Spearman trend test, the t-test for stationarity, and a serial persistence test. Way Tina was selected because it holds the longest and most consistent record, whereas the other stations lie downstream of the catchment and are less representative of rainfall events over the contributing area.

3.3 Climate Projection Model

Climate projections were constructed deterministically from the observed baseline using the delta-change factor of each SSP scenario together with a time function f(t) representing the evolution of the climate change signal across projection years. Mean annual temperature was projected as $Tt = T_0 + \Delta T\_scenario \times f(t)$ and annual rainfall as $Pt = P_0 \times [1 + (\Delta P\%\_scenario \times f(t))/100]$, with $T_0 = 26.8$ °C and $P_0 = 2{,}150$ mm as the 1991–2020 baseline values of the Namlea Meteorological Station.

Downstream impacts were derived from these two climate variables through four modules: rice productivity, $Yt = Y_0 \times [1 - \alpha(\Delta T) - \beta(\Delta P\_anomaly)]$; the climate vulnerability index, $CVI = [(E + S) - AC]/3$, where E is weighted exposure, S is sensitivity, and AC is adaptive capacity; the inundated coastal area, $D = SLR/slope$ and $A = L \times D$; and economic loss as the sum of agricultural, coastal, and health-sector losses.

The projections were run for five SSP scenarios across five horizon years — 2025, 2030, 2035, 2045, and 2050 — yielding 25 projection points for each impact parameter. All input parameter values and their sources are presented in Table 2.

3.4 Optimization Model Formulation

The objective function is formulated as maximization of the net benefit of water allocation: Maximize Z = (Irrigation Benefit + Raw Water Benefit + Hydropower Benefit + Environmental Benefit) − (Operating Cost + Deficit Cost). In numerical implementation, this is converted into minimization of weighted quadratic deficit with irrigation weight $w_1 = 0.50$, domestic weight $w_2 = 0.35$, and hydropower weight $w_3 = 0.15$.

The model contains six constraint groups. First, mass balance: $V(t+1) = V(t) + I(t) - E(t) - R(t)$ for t = 1 to 12. Second, storage capacity: $V\_min \le V(t) \le V\_max$ with V_min = 14.78 million m^3 and V_max = 41.76 million m^3. Third, water availability, whereby total allocation cannot exceed inflow plus carry-over storage. Fourth, minimum demand: $R(t) \ge D(t) = D\_irrigation(t) + D\_domestic(t) + D\_hydropower(t)$. Fifth, climate change constraints, under which inflow and evapotranspiration are varied according to wet and dry pattern scenarios. Sixth, environmental maintenance flow, which must be sustained throughout the year.

Simulations were run with an initial storage volume $S_0 = 31.32$ million m^3, an end-of-period storage target of 60% of V_max, and a convergence tolerance $\varepsilon = 10^{-6}$. The model is implemented in a web-based application providing sequential input panels for rainfall, hydrology, irrigation demand, water balance, and GRG simulation.

3.5 Climate Model Parameters and Assumptions

All projection computations were carried out in the Buru Island Climate Change Model workbook, which contains six output modules (temperature, rainfall, rice productivity, vulnerability index, inundated area, and economic loss) alongside a single centralized assumptions sheet. All input parameters are presented in Table 2 so that the computations can be replicated and audited.

Table 2. Parameters and Assumptions of the Buru Island Climate Change Model

Parameter	Value	Unit	Source / Remarks
T_0 — baseline temperature	26.8	°C	1991–2020 mean, Namlea Station
P_0 — baseline rainfall	2,150	mm/year	1991–2020 mean
Baseline rain days	165	days/year	1991–2020 mean
VLM (vertical land motion)	−1.5	mm/year	Subsidence, requires GPS verification
Maluku regional factor	+10	%	IPCC AR6 literature
Namlea coastline length	12	km	GIS estimate
Namlea coastal slope	0.5 (1:200)	%	Topographic estimate
Y_0 — baseline rice yield	5.2	t/ha	Wayapo farmer average
Wayapo paddy area	5,700	ha	Buru Regency statistics
α — rice temperature coefficient	0.06	per °C	Requires local varietal calibration
β — rainfall coefficient	0.002	per %	Requires local varietal calibration
Grain price	5,500,000	IDR/t	2024 reference price
S — sensitivity	0.68	scale 0–1	Small island, agrarian economy
AC — adaptive capacity	0.35	scale 0–1	Limited infrastructure
w_1 / w_2 / w_3 — exposure weights	0.35 / 0.30 / 0.35	—	Temperature / rainfall / SLR
Discount rate (r)	5	%/year	Standard for environmental projects
BCR analysis period	25	years	2025–2050

Source: Assumptions & Parameters sheet, Buru Island Climate Change Model workbook.

IV. RESULTS AND DISCUSSION

4.1 Hydrological Data Validity

All five data quality tests applied to the annual maximum rainfall series at Way Tina Station for 2013–2023 ($n = 11$, $\alpha = 0.05$) returned satisfactory results, as summarized in Table 3. The Grubbs–Beck test yielded an upper bound of 96.017 mm and a lower bound of 79.036 mm, with all observations falling within that range and therefore no outliers. The Spearman test produced a rank correlation coefficient $r_s = -0.6023$ with a computed $|t|$ of 2.2634 below the critical value of 2.4906, so the hypothesis of no trend is accepted.

Table 3. Summary of Hydrological Data Quality Tests, Way Tina Station (2013–2023)

Test Method	Test Statistic	Critical Value	Result
Outlier (Grubbs–Beck)	$K_n = 2.085$	$X_H = 96.017$; $X_L = 79.036$	Satisfied
Consistency (RAPS)	$Q/\sqrt{n} = 0.9249$	$Q_{cr} = 1.303$; $R_{cr} = 1.637$	Satisfied
Absence of trend (Spearman)	$\|t\| = 2.2634$	$t_{cr} = 2.4906$	Satisfied
Stationarity (t-test)	$\|t\| = 2.1773$	$t_{cr} = 2.4906$	Satisfied
Persistence (serial)	$\|t\| = 0.8114$	$t_{cr} = 2.5656$	Satisfied

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Source: Analysis results, n = 11, a = 0.05.

The finding that the data pass the no-trend test warrants careful interpretation. An eleven-year series is too short to detect a long-term climate signal, which typically requires at least three decades. The absence of trend in annual maximum rainfall must therefore not be read as an absence of climate change, but as an indication that natural variability still dominates the change signal within that window. This is precisely why SSP-based climate projections are needed to complement the analysis of historical records.

4.2 Climate Model Computation Results, 2025–2050

The climate baseline was established from 30 years of observation (1991–2020) at the Namlea Meteorological Station following World Meteorological Organization standards: mean annual temperature 26.8 °C, annual rainfall 2,150 mm, and 165 rain days per year. The model was run for five emission scenarios across five horizon years, yielding 25 projection points for each impact parameter.

Table 4. Projected Mean Annual Temperature, Buru Island (°C)

Year	SSP1-1.9	SSP1-2.6	SSP2-4.5	SSP3-7.0	SSP5-8.5
2025	26.89	26.91	26.97	27.02	27.08
2030	26.98	27.02	27.14	27.25	27.35
2035	27.06	27.14	27.31	27.48	27.62
2045	27.24	27.36	27.64	27.92	28.18
2050	27.32	27.48	27.81	28.15	28.45

Source: Temperature Projection module; $Tt = T_0 + \Delta T\_scenario \times f(t)$*; baseline 26.8 °C.*

By 2050, the gap between the most optimistic scenario (SSP1-1.9, 27.32 °C) and the most pessimistic (SSP5-8.5, 28.45 °C) reaches 1.13 °C. This difference matters operationally because each additional degree raises reference evapotranspiration by roughly 3–5% under humid tropical conditions, translating into higher crop water requirements and greater losses from the 235.10-hectare reservoir surface.

Table 5. Projected Annual Rainfall, Buru Island (mm/year)

Year	SSP1-1.9	SSP1-2.6	SSP2-4.5	SSP3-7.0	SSP5-8.5
2025	2,154.0	2,156.7	2,160.8	2,166.1	2,170.2
2030	2,158.1	2,163.4	2,171.5	2,182.2	2,190.3
2035	2,162.1	2,170.2	2,182.2	2,198.4	2,210.5
2045	2,170.2	2,183.6	2,203.8	2,230.6	2,250.8
2050	2,174.2	2,190.3	2,214.5	2,246.8	2,270.9

Source: Rainfall Projection module; $Pt = P_0 \times [1 + (\Delta P\%\_scenario \times f(t))/100]$*; baseline 2,150 mm.*

The rainfall projection contains a paradox: the annual total rises under every scenario, reaching 2,270.9 mm under SSP5-8.5 in 2050, a 5.6% increase over the baseline. That increase, however, is the net result of higher wet season rainfall and lower dry season rainfall. For dam managers this means two opposing pressures at different times of year: greater flood risk from October to April and deeper drought risk from May to September. A rising annual total does not guarantee improved supply reliability.

Table 6. Projected Rice Productivity, Wayapo Valley (t/ha)

Year	SSP1-1.9	SSP1-2.6	SSP2-4.5	SSP3-7.0	SSP5-8.5
2025	5.17	5.16	5.14	5.12	5.10
2030	5.14	5.12	5.07	5.02	4.97
2035	5.12	5.07	4.99	4.91	4.83
2045	5.06	4.99	4.85	4.71	4.57
2050	5.03	4.95	4.78	4.61	4.63

Source: Rice Productivity module; $Yt = Y_0 \times [1 - a(\Delta T) - \beta(\Delta P\_anomaly)]$; $Y_0 = 5.2$ *t/ha.*

Rice productivity declines consistently across all scenarios, from 5.2 t/ha to 5.03 t/ha under SSP1-1.9 and to 4.63 t/ha under SSP5-8.5 in 2050, an 11.0% reduction. Applied across 5,700 hectares of paddy at a grain price of IDR 5,500,000 per tonne, this decline equates to agricultural losses of approximately IDR 17.87 billion per year. It should be noted that the SSP5-8.5 value for 2050 (4.63 t/ha) is marginally higher than the SSP3-7.0 value (4.61 t/ha), an unusual reversal of ordering that stems from the compensating β term applied to a positive rainfall anomaly; this warrants verification during further calibration.

Table 7. Projected Climate Vulnerability Index (CVI), Buru Island

Year	SSP1-1.9	SSP1-2.6	SSP2-4.5	SSP3-7.0	SSP5-8.5
2025	0.129	0.133	0.140	0.148	0.155
2030	0.149	0.156	0.170	0.185	0.201
2035	0.168	0.180	0.200	0.223	0.246
2045	0.207	0.226	0.261	0.299	0.336
2050	0.226	0.249	0.291	0.336	0.382

Source: Vulnerability Index module; $CVI = [(E + S) - AC]/3$. *Classification: <0.2 low; 0.2–0.4 moderate; 0.4–0.6 high; >0.6 very high.*

The vulnerability index rises from the low category in 2025 (0.129–0.155) to the moderate category in 2050 (0.226–0.382). The highest value of 0.382 under SSP5-8.5 in 2050 does not cross the high-category threshold, but the margin is only 0.018, so in practice the region should be treated as highly vulnerable. The structure of the index shows that Buru Island's vulnerability is driven more by high sensitivity (S = 0.68) and low adaptive capacity (AC = 0.35) than by the magnitude of climate exposure itself — implying that vulnerability is most effectively reduced through strengthening adaptive capacity rather than waiting for global emissions to fall.

Table 8. Projected Inundated Coastal Area at Namlea (hectares)

Year	SSP1-1.9	SSP1-2.6	SSP2-4.5	SSP3-7.0	SSP5-8.5
2025	7.34	8.14	9.19	10.39	12.10
2030	12.89	14.50	16.61	19.01	22.42
2035	18.46	20.86	24.02	27.62	32.74
2045	29.54	33.55	38.83	44.86	53.35
2050	35.09	39.89	46.25	53.47	63.67

Source: Inundated Area module; $D = SLR/slope$, $A = L \times D$; $L = 12{,}000$ *m, slope = 0.005.*

Table 9. Projected Total Economic Loss (IDR billion per year)

Year	SSP1-1.9	SSP1-2.6	SSP2-4.5	SSP3-7.0	SSP5-8.5
2025	10.4	10.9	11.9	12.9	13.9
2030	13.3	14.3	16.2	18.2	20.3
2035	16.1	17.7	20.6	23.6	26.7
2045	21.9	24.5	29.3	34.3	39.6
2050	24.8	27.9	33.6	39.7	46.0

Source: Economic Loss module; D_total = D_agriculture + D_coastal + D_health.

Total annual economic loss rises from IDR 13.9 billion in 2025 to IDR 46.0 billion in 2050 under SSP5-8.5, a 3.3-fold increase. Even under the most optimistic SSP1-1.9 scenario, losses still climb from IDR 10.4 billion to IDR 24.8 billion. The difference in losses between the best and worst scenarios in 2050 reaches IDR 21.2 billion per year; this figure represents, in economic terms, the value to Buru Regency of global emission mitigation efforts.

Table 10. Adaptation Strategy Priorities by Benefit-Cost Ratio

Adaptation Strategy	Estimated BCR	Priority
Adaptive rice varieties	4.20	Very high
Adaptive irrigation systems	3.50	High
Namlea sea wall	2.80	High
Coastal settlement relocation	1.20	Moderate

Source: BCR module; discount rate 5% per year, 25-year analysis period (2025–2050).

The highest adaptation priority is occupied by adaptive rice varieties (BCR 4.20), followed by adaptive irrigation systems (BCR 3.50); both are directly connected to dam water allocation management. By contrast, coastal settlement relocation at a BCR of 1.20 is only marginally viable and should be treated as a last resort. All top-ranked strategies are ecosystem-based or efficiency-based rather than reliant on structural works.

4.2.1 Note on Model Consistency

Comparison between the computation modules and the summary sheet of the workbook reveals two discrepancies requiring reconciliation before the figures are published further: the vulnerability index is 0.382 in the module but 0.397 in the summary; and total economic loss is IDR 46.0 billion in the module but IDR 44.42 billion in the summary. The inundated area module itself is consistent with an SLR of 26.53 cm rather than 30.24 cm. The values presented in all tables of this paper are those of the computation modules, because those modules contain traceable formulas and parameters whereas the summary sheet holds only final values.

4.3 Water Balance of the Way Apu Dam

Monthly water balance simulation gives a total annual inflow of 318.26 million m³ against total outflow requirements of 267.87 million m³, an aggregate annual surplus of 50.39 million m³. The annual aggregate, however, masks the principal problem: the temporal mismatch between availability and demand.

Table 11. Monthly Water Balance of the Way Apu Dam (million m³)

Month	Inflow	Irrigation	Domestic	Hydropower	Evaporation	Total Out	Surplus/Deficit
Jan	35.810	0.000	0.033	11.099	0.151	11.283	24.527
Feb	29.569	9.814	0.030	10.025	0.134	20.003	9.566
Mar	42.248	0.000	0.033	11.099	0.126	11.258	30.990

Month	Inflow	Irrigation	Domestic	Hydropower	Evaporation	Total Out	Surplus/Deficit
Apr	35.717	0.000	0.032	10.741	0.143	10.916	24.801
May	25.358	0.000	0.033	11.099	0.160	11.292	14.066
Jun	23.879	9.791	0.032	10.741	0.168	20.732	3.147
Jul	34.220	3.187	0.033	11.099	0.185	14.504	19.716
Aug	10.331	1.527	0.033	11.099	0.202	12.861	−2.530
Sep	11.742	0.000	0.032	10.741	0.185	10.958	0.784
Oct	13.010	54.994	0.033	11.099	0.160	66.286	−53.276
Nov	24.726	27.452	0.032	10.741	0.143	38.368	−13.642
Dec	31.651	28.125	0.033	11.099	0.151	39.408	−7.757
TOTAL	**318.260**	**134.890**	**0.390**	**130.680**	**1.910**	**267.870**	**50.392**

Source: Water balance program output, analysis results.

Four months record deficits: August (−2.530 million m³), October (−53.276 million m³), November (−13.642 million m³), and December (−7.757 million m³). The October deficit stands out because it coincides with the start of the planting season, when irrigation demand of 54.994 million m³ is almost four times that month's inflow of only 13.010 million m³. This constitutes a structural characteristic of the system: peak irrigation demand falls at the end of the dry season, when inflow is at its lowest. This characteristic is aggravated by global warming, since dry seasons are projected to become drier while crop water requirements rise with temperature.

4.4 GRG Optimization Results under Normal Conditions

Table 12. Optimized Monthly Operating Pattern from GRG (million m³)

Month	Inflow	S. Initial	R. Irrig.	R. Domestic	R. Hydro	R. Total	S. Final	Status
Jan	35.810	31.32	0.000	0.024	7.849	7.873	41.76	Marginal
Feb	29.569	41.76	7.105	0.022	7.090	14.217	41.76	Marginal
Mar	42.248	41.76	0.000	0.024	7.849	7.873	41.76	Marginal
Apr	35.717	41.76	0.000	0.023	7.596	7.619	41.76	Marginal
May	25.358	41.76	0.000	0.024	7.849	7.873	41.76	Marginal
Jun	23.879	41.76	7.089	0.023	7.596	14.708	41.76	Marginal
Jul	34.220	41.76	2.307	0.024	7.849	10.180	41.76	Marginal
Aug	10.331	41.76	1.106	0.024	7.849	8.978	41.76	Marginal
Sep	11.742	41.76	0.000	0.023	7.596	7.619	41.76	Marginal
Oct	13.010	41.76	37.442	0.002	0.266	37.710	16.85	Deficit
Nov	24.726	16.85	19.880	0.002	0.258	20.140	21.32	Deficit
Dec	31.651	21.32	20.363	0.024	7.849	28.235	24.59	Marginal
TOTAL	**318.260**	**—**	**95.290**	**0.240**	**77.500**	**173.020**	**24.59**	**65.1%**

Source: GRG optimization results; $S_0 = 31.32$ *million m³;* $w_1 = 0.50$*;* $w_2 = 0.35$*;* $w_3 = 0.15$*;* $\varepsilon = 10^{-6}$.

Table 13. Performance Summary of the Water Allocation Optimization Model

Performance Indicator	Value	Unit
Total allocation efficiency	**65.1 – 65.2**	**%**
Irrigation service level	71.27	%
Domestic water service level	60.64	%
Hydropower service level	58.97	%
Energy service level	65.94	%
Total annual energy output	**6,546.9**	**MWh/year**
Hydropower capacity factor	56.15	%
Total annual deficit	**92.53 – 92.94**	**million m³**
GRG iterations	300	iterations
Initial / final storage volume	31.32 / 24.59	million m³

Source: GRG optimization analysis results.

A total allocation efficiency of 65.1% with an annual deficit of 92.94 million m³ indicates that, under the demand configuration and priorities applied, the system cannot satisfy all requirements simultaneously. The irrigation service level of 71.27% exceeds the domestic level of 60.64% and the hydropower level of 58.97%, consistent with the weighting that prioritizes irrigation. It should be noted that iteration halted at the 300 limit without reaching full convergence, indicating either a flat solution surface near the optimum or a need for improved variable scaling in future work.

4.5 Performance under Wet and Dry Climate Scenarios

The wet pattern scenario sets inflow at 120–130% of the historical mean with evapotranspiration at 90–95%, while the dry pattern sets inflow at 70–80% with increased evapotranspiration. Comparative performance across the three conditions is presented in Table 15.

Table 14. Comparative Water Allocation Performance under Three Climate Conditions

Aspect	Wet Pattern	Normal	Dry Pattern	Unit
Inflow relative to historical mean	120 – 130%	100%	70 – 80%	Model constraint
Evapotranspiration	90 – 95%	100%	Increased	Model constraint
Irrigation reliability	98 – 100%	90 – 95%	70 – 75%	%
Raw water reliability	100%	> 95%	> 95%	%
Hydropower output	95 – 100%	56 – 66%	40 – 50%	% of capacity
Average storage volume	60 – 90%	40 – 80%	20 – 30%	% of S_max
Dominant operational issue	Flood control	Sector balancing	Water conservation	—

Source: Model simulation results under three climate scenarios.

Under the dry pattern, the model automatically prioritizes raw water at above 95% fulfilment while irrigation allocation is reduced to 60–70% of maximum potential with reliability falling to 70–75%. Hydropower output declines to 40–50% of design capacity. Storage tends to fall to a minimum level of 20–30% of capacity by the end of the dry season. This finding

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carries serious social implications: a 25 percentage point drop in irrigation reliability means some farmers must reduce planted area or shift planting schedules, and such decisions must be communicated well before the season begins to avoid harvest losses and social conflict.

4.5.1 Comparison of Water Allocation Patterns Before and After Global Warming Impacts

To isolate the effect of global warming on the water allocation pattern, model performance is compared across two states. The before state is the GRG-optimized allocation under the 30-year observed baseline climate (1991–2020) of the Namlea Meteorological Station, namely a mean temperature of 26.8 °C and annual rainfall of 2,150 mm with inflow at the historical average. The after state is the allocation pattern at the 2050 horizon under the highest emission scenario, SSP5-8.5, represented by the dry pattern, that is, inflow at 70–80% of the historical average with increased evapotranspiration. The comparison is presented in Table 16.

Table 15. Water Allocation Pattern Before versus After the Impact of Global Warming

Aspect	Before (baseline)	After (2050, SSP5-8.5)	Change	Unit
Mean annual temperature	26.8	28.45	+1.65	°C
Annual rainfall	2,150	2,270.9	+5.6%	mm/year
Annual reservoir inflow	318.26	222.8 – 254.6	−20 to −30%	million m³
Irrigation allocation	95.29	57.2 – 66.7	−30 to −40%	million m³
Raw (domestic) water allocation	0.240	0.240	maintained	million m³
Irrigation reliability	90 – 95	70 – 75	−20 points	%
Raw water reliability	> 95	> 95	stable	%
Hydropower output	56 – 66	40 – 50	−16 points	% of capacity
Total annual energy	6,546.9	4,665 – 5,831	−11 to −29%	MWh/year
Mean storage volume	40 – 80	20 – 30	−20 to −50 points	% S_max
Dominant operational issue	Sector balancing	Water conservation	reorientation	—
Rice productivity	5.20	4.63	−11.0%	t/ha
Annual economic loss	13.9	46.0	3.3×	IDR billion/year
Climate vulnerability index (CVI)	0.155	0.382	+0.227	index

Source: Synthesis of Tables 4, 5, 7, 8, 10, 13, 14, and 15. The before state is the GRG optimization under the 1991–2020 baseline climate; the after state is the 2050 horizon under SSP5-8.5 with a dry inflow pattern. Annual energy in the after state is derived from the hydropower output range.

The shift in allocation pattern is structural rather than a simple reduction in volume. In the before state the model divides water relatively evenly across sectors, with sector balancing as the dominant operational issue: irrigation receives 95.29 million m³, hydropower 77.50 million m³, and the deficit is concentrated in October–November. In the after state the priority order becomes hierarchical — raw water is held above 95% reliability as a non-negotiable requirement, irrigation becomes the risk-absorbing sector with reliability falling by 20 percentage points relative to normal conditions (25 percentage points if measured against the wet pattern), and hydropower becomes residual, with output declining to 40–50% of design capacity. Global warming therefore does not distribute the shortfall proportionally; it transfers almost the entire burden of scarcity to the agricultural and energy sectors.

The downstream consequences compound. The reduction in irrigation allocation coincides with a decline in rice productivity from 5.20 to 4.63 t/ha under thermal stress, so production losses arise from two sources at once: less water, and less productive plants for the same water. On the storage side, mean volume falling from the 40–80% range to 20–30% of S_max eliminates the inter-seasonal buffer, stripping the operating pattern of flexibility precisely when climate variability increases. The after-state allocation pattern therefore cannot be treated as a contracted version of the before-state pattern; it requires its own operating rules — a scenario-based rule curve, earlier announcement of cropping patterns, and acceptance that hydropower acts as a secondary water user in dry years.

4.6 Sensitivity Analysis

Table 16. Model Sensitivity to Key Parameters

Parameter Change	System Impact	Magnitude
Inflow +10%	Allocation and reliability rise across sectors	Elasticity 1.2 – 1.5
Inflow −10%	Irrigation allocation falls sharply	Elasticity 1.2 – 1.5
Irrigation efficiency 65% → 75%	Serviceable area expands	+12 – 15%
Raw water efficiency 85% → 90%	Domestic allocation can be reduced	−5 – 6%
Forest cover 62% → 50% (2035)	Weighted runoff coefficient rises	+17.3%
Forest cover 62% → 50% (2035)	Weighted Curve Number rises	+13.6%

Source: Sensitivity analysis results.

An allocation elasticity with respect to inflow of 1.2–1.5 means that every 10% reduction in inflow causes a 12–15% reduction in allocation. An elasticity above unity indicates that the system amplifies rather than dampens hydrological shocks — a characteristic directly at odds with the ideal buffering function of a reservoir. The cause is the relatively small ratio of storage to annual inflow, 41.76 million m^3 against 318.26 million m^3, roughly 13%, which leaves very limited inter-annual carry-over capacity.

Conversely, the most promising intervention pathway is efficiency. Raising irrigation efficiency from 65% to 75% through network modernization expands the serviceable area by 12–15% without additional water supply, and reducing leakage in the raw water network saves 5–6% of allocation. Efficiency acts on the demand side, so its benefits persist under dry conditions — unlike additional storage capacity, which is useful only when there is water to store.

4.7 Discussion: Management Implications

From a dam management perspective, the principal finding is that global warming shifts the operational optimum rather than invalidating the infrastructure. A static rule curve derived from historical averages will prove suboptimal: too conservative in wet years, wasting water through the spillway, and too aggressive in dry years, depleting storage before the dry season ends. Adaptive operation informed by seasonal forecasting and real-time climate monitoring is therefore required, enabling operators to adjust storage targets and allocations proactively.

From an ecosystem sustainability perspective, the model explicitly incorporates a minimum environmental flow constraint. Under normal and wet conditions this constraint can be met without sacrificing other sectors. Under extreme dry conditions, however, a genuine trade-off emerges between human demand and river ecosystem maintenance. Establishing a scientifically grounded environmental flow standard, together with its enforcement, is critical, because without regulatory protection environmental flow is the component most readily sacrificed under scarcity.

V. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

First, climate projections for 2025–2050 indicate that global warming will raise mean temperature on Buru Island by 0.53–1.65 °C depending on the emission scenario, with annual rainfall increasing by 1.1–5.6% but accompanied by a seasonal redistribution that widens the contrast between wet and dry seasons. Under SSP5-8.5 in 2050, climate vulnerability reaches a

CVI of 0.382 with economic losses of IDR 46.0 billion per year, while the adaptation strategy with the highest benefit-cost ratio is the use of adaptive rice varieties (BCR 4.20).

Second, under normal conditions the model yields an allocation efficiency of 65.1% with a total annual release of 173.02 million m³ and 6,546.9 MWh of energy, while leaving a deficit of 92.94 million m³ concentrated in October–December. System reliability is highly sensitive to climate conditions: irrigation reliability ranges from 98–100% under a wet pattern to 70–75% under a dry pattern, while raw water supply can be maintained above 95% across all scenarios.

Third, an allocation elasticity with respect to inflow of 1.2–1.5 shows that the system amplifies hydrological shocks because storage represents only about 13% of annual inflow. The most effective intervention is therefore not additional physical capacity but improved demand-side water use efficiency, which can expand service coverage by 12–15%.

Fourth, global warming does not invalidate the Way Apu Dam as strategic infrastructure, but it demands a paradigm shift in operation from fixed experience-based rules to adaptive operation grounded in modelling and climate forecasting.

5.2 Recommendations

Based on the findings, the following seven recommendations are addressed to dam managers and regional government.

- Replace the static rule curve with an adaptive operating pattern reviewed each season on the basis of climate forecasts, and recalibrate the model every two to three years using actual operational data.
- Establish real-time hydroclimatological monitoring and a geographic information system for the Way Apu watershed to improve model input accuracy and support operational decision-making.
- Formally establish a water allocation priority hierarchy for scarcity conditions, with raw water as the highest priority, followed by irrigation, environmental flow, and power generation.
- Provide early notification to farmers in seasons projected to be dry so that cropping patterns and planted areas can be adjusted before sowing.
- Modernize irrigation networks toward 80–85% efficiency and reduce raw water network leakage, as the investment offering the greatest benefit per rupiah under dry conditions.
- Implement upstream reforestation and forest conservation together with riparian vegetation restoration to restrain the rise in runoff coefficient and sustain dry season baseflow.
- Extend the research through downscaling of global climate models, more detailed rainfall-runoff modelling, and cascade operation studies should additional dams be built in the same watershed.

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