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Evaporation Estimation in the Muko Reservoir, Songwe Region, Tanzania: A Multi-Model Framework Using Temperature, Radiation, and Combined Approaches

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Abstract: *This study presents the development and evaluation of a multi-model framework (MMF) embedded in a Decision Support System (DSS) for estimating evaporation in data-scarce environments. Focusing on the Muko Reservoir catchment in the semi-arid Songwe Region of southwestern Tanzania, the framework integrates four widely recognised reference evapotranspiration (ET_0) models: Hargreaves-Samani, Jensen-Haise, Priestley-Taylor, and Penman. These models represent three methodological categories: temperature-based, radiation-based, and combined approaches. A 10-year dataset of monthly pan evaporation and meteorological variables was used to compare model performance through descriptive statistics, time series analysis, and correlation metrics. Results show that while all models reasonably capture seasonal evaporation patterns, significant differences exist in magnitude and variability. The Priestley-Taylor and Penman models consistently overestimated ET_0, while the Jensen-Haise model underestimated it. The Hargreaves-Samani model showed the closest agreement with observed values. The study highlights the value of a DSS-driven multi-model approach in improving evaporation estimation accuracy, especially in regions with variable data availability. The findings have significant implications for water balance modelling, reservoir operation, and climate-resilient water resource management.*

Keywords: *Evaporation Modelling, Multi-Model Framework, Data-Scarce Region, Semi-Arid Reservoir Hydrology, Decision Support System*

1. INTRODUCTION

Evaporation and evapotranspiration (ET) are fundamental components of the hydrological cycle, particularly in tropical and semi-arid regions where effective water resource management depends on the accurate quantification of atmospheric water losses. In Tanzania's Songwe Region, reservoirs such as Muko play a crucial role in supporting irrigation, domestic supply, and ecosystem balance. However, comprehensive hydrological planning in such data-scarce environments is often constrained by the limited availability of continuous ground-based meteorological observations required for standard evaporation estimation models. To address this challenge, various temperature-, radiation-, and combination-based models have been employed, each relying on accessible climatic parameters such as temperature, solar radiation, and relative humidity. These models provide practical alternatives for estimating evaporation when complete meteorological datasets are unavailable, though they vary in terms of data requirements, simplicity, and accuracy [1].

In Tanzania, studies across the Pangani and Mkomazi River systems have demonstrated the applicability and limitations of empirical models under different hydrological and climatic settings [2,3], while in the Eastern Arc Mountains, temperature-based models have generally underestimated ET compared with the standard Penman–Monteith equation, yet remain useful where meteorological data are scarce [4]. Against this backdrop, the present study focuses on the Muko Reservoir in the Songwe Region, a hydrologically significant area in southwestern Tanzania. The objective is to develop a multi-model framework that integrates temperature-based, radiation-based, and combination-based approaches for estimating evaporation. By comparing model outputs and evaluating their reliability under local climatic conditions, this study seeks to improve water balance estimation and strengthen evidence-based reservoir management in ungauged or poorly gauged basins.

Globally, evaporation estimation has evolved through the incorporation of multi-model and artificial intelligence (AI)-based approaches, which enhance precision and adaptability in hydrological modelling.[5], demonstrated that AI models such as the Multilayer Perceptron (MLP) and Adaptive Neuro-Fuzzy Inference System (ANFIS) effectively capture daily reservoir evaporation dynamics, outperforming traditional empirical equations. Similarly, [6] provided a comprehensive overview of AI-driven evapotranspiration models, emphasizing their capability to simulate nonlinear climatic interactions and improve accuracy in data-limited contexts. Building on this, [7] developed a hybrid remote sensing–AI method that significantly enhanced the spatial precision of actual evapotranspiration estimation. Consistent results were reported by [8] and [11], who found that machine learning techniques, including support vector machines and random forests, yielded more reliable estimates of reference evapotranspiration (ET_0) than conventional models in arid climates. In Egypt, [9] highlighted that hybrid empirical–AI models outperform the Penman–Monteith formulation, particularly when high-resolution meteorological data are available. Furthermore, [10] demonstrated that hybrid AI techniques substantially improved evapotranspiration estimation in India's semi-arid regions, reinforcing their adaptability across diverse climatic regimes. Collectively, these studies underscore the potential of integrating temperature-based, radiation-based, and AI-enhanced methods within a unified multi-model framework. Such integration can substantially improve the accuracy and reliability of evaporation estimation, providing a robust scientific foundation for this study."

2. STUDY AREA AND DATA AVAILABLE

The Muko Dam catchment is situated in Mengo Village, Ndalambo Ward, Momba District within the Songwe Region of southwestern Tanzania, approximately between latitudes 8°37′S–8°39′S and longitudes 31°31′E–31°33′E, while the dam site itself is positioned at 9°03.215′S, 32°30.132′E at an elevation of approximately 1,555.75 m above sea level. The reservoir is constructed as a small earth-fill structure intended primarily for domestic and livestock water supply, with a projected design life of 50 years [12]. The associated catchment spans around 14.39 km² and is characterised by moderately steep terrain, with slopes ranging from about 3 % to 15 %, and land-cover types that include grasslands, croplands, bushland and seasonal wetlands. The upper portions of the catchment are experiencing land-use pressure, with increased degradation, overgrazing and expansion of farming contributing to heightened erosion and sedimentation [13,14]. The region′s climate is best described as a semi-arid tropical highland regime with a unimodal rainfall pattern (November–April) averaging about 800–1,100 mm annually; daytime temperatures commonly range from 16 °C to 29 °C and estimated potential evapotranspiration exceeds 1,500 mm/year, conditions that impose marked seasonal water-stress on the catchment [15]. Hydrologically, the catchment displays an ephemeral flow regime, with runoff occurring predominantly during the rainy season.

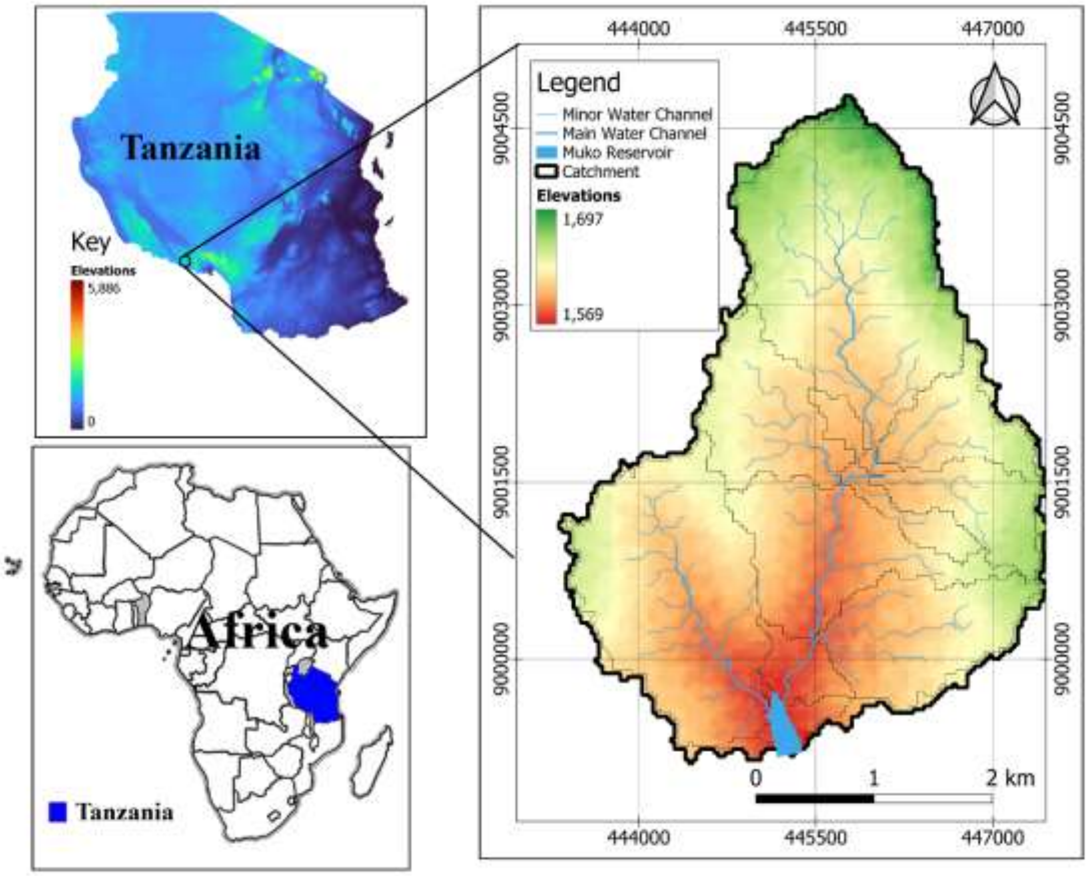

Figure 1: Location of Muko Dam catchment

3. MULTI-MODEL FRAMEWORK AND CLASSIFICATION OF EVAPORATION ESTIMATION APPROACHES

3.1 Multi-Model Framework for Evaporation Estimation

To support accurate evaporation estimation in semi-arid and data-scarce regions such as the Muko Reservoir catchment, a Multi-Model Framework (MMF) was developed and embedded within a Decision Support System (DSS). This framework integrates four widely recognised evapotranspiration (ET_o) models, grouped into three methodological categories: temperature-based (Hargreaves-Samani and Jensen–Haise), radiation-based (Priestley–Taylor), and combined energy-aerodynamic approaches (Penman). Each model was encoded as a modular computational block within an Excel-based interface, allowing for flexible selection based on available input variables such as temperature, solar radiation, humidity, and wind speed. The DSS workflow comprises five key stages: data input, model selection, ET_o computation, model comparison, and decision output (Figure 2). A predefined rule-based algorithm within the DSS systematically selects the most suitable evaporation model based on the type, availability, and sufficiency of input climatic variables. This approach promotes usability even in remote areas with limited instrumentation. Comparative analysis is facilitated through tabular and graphical outputs, enabling users to assess monthly and annual ET_o estimates across models. The MMF structure enhances adaptability and robustness by allowing users to triangulate between empirical and physically based models, which is critical in water-stressed regions where ET_o dynamics can be highly variable. This design aligns with recent scientific efforts advocating for multi-model fusion frameworks that integrate classical models with data-driven or remotely sensed inputs to improve evapotranspiration estimation under climate uncertainty [16,17]. The framework thus serves both as a computational tool and a methodological scaffold for improved hydrological planning and reservoir management.

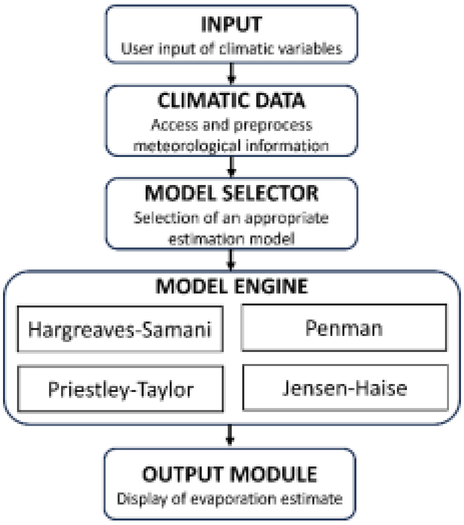

Figure 2: A multi-model framework for evaporation estimation approaches

3.2 Classification of Evaporation Estimation Approaches

Reference evaporation (ET_o) represents the atmospheric demand for water from a reference surface and serves as a key input in hydrological modelling, water requirement estimation, and water supply scheduling. Several models have been developed to estimate ET_o, which are commonly classified based on the type of climatic variables they use. This study considers four widely applied models, grouped into temperature-based, radiation-based, and combined (energy and aerodynamic) approaches.

3.2.1 Temperature-based models

These models use air temperature as the primary driver of evapotranspiration, often as a surrogate for available energy.

i. Hargreaves-Samani Model (Equation 1): Developed for data-scarce regions, this empirical model estimates ET_o using maximum and minimum daily air temperatures along with extraterrestrial radiation derived from latitude and day of the year. The temperature range serves as a proxy for incoming solar radiation. It performs well in arid and semi-arid regions but is less accurate in humid climates due to its simplified structure [18].

$$ET_o = 0.0023 \times (T_{mean} + 17.8) \times (T_{max} - T_{min})^{0.5} \times R_a \quad (1)$$

Where,
ET_o is the reference evapotranspiration (mm/day)
T_{mean} is the mean daily air temperature (°C)
T_{max} is the maximum daily air temperature (°C)
T_{min} is the minimum daily air temperature (°C)
R_a is the extraterrestrial radiation (MJ/m²/day)

ii. Jensen-Haise Model (Equation 2): This method combines mean daily temperature with measured or estimated solar radiation to estimate ET_o. Although developed for agricultural areas in the U.S., it has been applied in various semi-arid climates. However, its accuracy often depends on local calibration, as it tends to overestimate evapotranspiration under certain conditions [19].

$$ET_o = (0.0252 \times T_{mean} + 0.078) \times R_s \quad (2)$$

Where
ET_o Reference evapotranspiration (mm/day)
T_{mean}: Mean daily air temperature (°C)
R_s: Solar radiation (MJ/m²/day)

3.2.2 Radiation-based model

Radiation-based models assume that evapotranspiration is primarily driven by available energy, particularly in humid environments where advection plays a minor role.

i. Priestley-Taylor Model (Equation 3): This semi-empirical model simplifies the Penman equation by removing the aerodynamic component, making it suitable for regions with minimal wind and humidity variations. It estimates ET_o using net radiation and temperature-dependent parameters, multiplied by a coefficient ($\alpha = 1.26$) applicable to humid climates. While effective in energy-limited conditions, it tends to overestimate ET_o in arid zones [20].

$$ET_o = \propto . \frac{\Delta}{\Delta+\gamma}(R_n - G) \quad (3)$$

Where,
ET_o is potential evaporation rate (mm/day)
Δ is slope of the saturation vapour pressure curve (kPa/°C)
γ is the psychrometric constant (kPa/°C)
R_n is the Net radiation (MJ/m²/day)
G is the Soil heat flux density (often ~0 for daily scales)(MJ/m²/day)
$\propto$ is equal to 1.26(empirical constant)

3.2.3 Combined temperature and radiation-based models

These models incorporate both thermal and radiative inputs, offering a balance between simplicity and physical realism. Penman Model (Equation 4): Regarded as the global standard, the Penman model integrates both energy balance and aerodynamic principles. It requires a complete set of meteorological inputs, including air temperature, humidity, wind speed, and net radiation. Due to its physical basis and robustness across climates, it is recommended for climate studies [21].

$$E = \frac{\Delta}{\Delta+\gamma}\frac{(R_n - G)}{\gamma} + \frac{\gamma}{\Delta+\gamma}E_a \quad (4)$$

Where,
ET_o is potential evaporation rate (mm/day)
Δ is slope of the saturation vapour pressure curve (kPa/°C)
γ is the psychrometric constant (kPa/°C)
R_n is the Net radiation (MJ/m²/day)
G is the Soil heat flux density (often ~0 for daily scales)(MJ/m²/day)
λ is the Latent heat of vaporization (≈2.45 MJ/kg) (MJ/kg)
E_a is the aerodynamic term (based on wind and vapour pressure deficit) (mm/day)

4. RESULTS AND DISCUSSION

4.1 Comparative Analysis of Observed and Modelled Evaporation

A comprehensive analysis of monthly evaporation and ET_o values over a 10-year period (N = 120) was conducted using both descriptive statistics and time series visualization (Figure 3 Table 1). The objective was to assess the performance and behaviour of four ET_o models—Penman, Hargreaves-Samani, Priestley–Taylor, and Jensen–Haise—relative to observed pan evaporation. The mean observed evaporation was 137.27 mm/month, substantially lower than estimates produced by the Priestley–Taylor (265.06 mm) and Penman (238.71 mm) models. The Hargreaves model (161.86 mm) was closest in magnitude to observed values, while Jensen–Haise (120.06 mm) consistently produced the lowest estimates. The standard deviation was highest in Priestley–Taylor (53.26 mm), indicating greater variability and sensitivity to seasonal drivers, whereas Jensen–Haise (23.42 mm) displayed the lowest variability, suggesting a more conservative response.

Figure 3 illustrates that all models capture the seasonal dynamics of evaporation reasonably well, with peaks during dry months and troughs during the wet season. However, considerable differences in magnitude are evident. The Priestley–Taylor model frequently overestimates evaporation, especially during peak seasons, due to its assumption of abundant surface moisture—an unrealistic condition in semi-arid contexts like the Songwe region [20]. Similarly, the Penman model overestimates ET_0 but with less deviation, reflecting its incorporation of aerodynamic and energy balance terms. The Hargreaves model, despite its empirical simplicity and reliance solely on temperature and radiation, showed better alignment with observed evaporation, both in mean and distribution [18]. The Jensen–Haise model consistently underestimated ET_0, particularly during high-demand periods, likely due to its fixed coefficients and narrow range of output values.

Distributional analysis revealed skewness near zero for most models, indicating relatively symmetrical distributions, except for the Priestley–Taylor and Jensen–Haise models, both of which were negatively skewed and leptokurtic, reflecting peaked distributions with more frequent moderate values. The combined descriptive and visual evidence suggests that no single model can fully replicate observed evaporation dynamics across all months. Instead, results support the adoption of a multi-model estimation framework, where model choice can be tailored to data availability and seasonal context. This approach aligns with recent literature advocating for integrated or ensemble-based evapotranspiration estimation strategies to address uncertainties in climate and hydrological modelling [16,17].

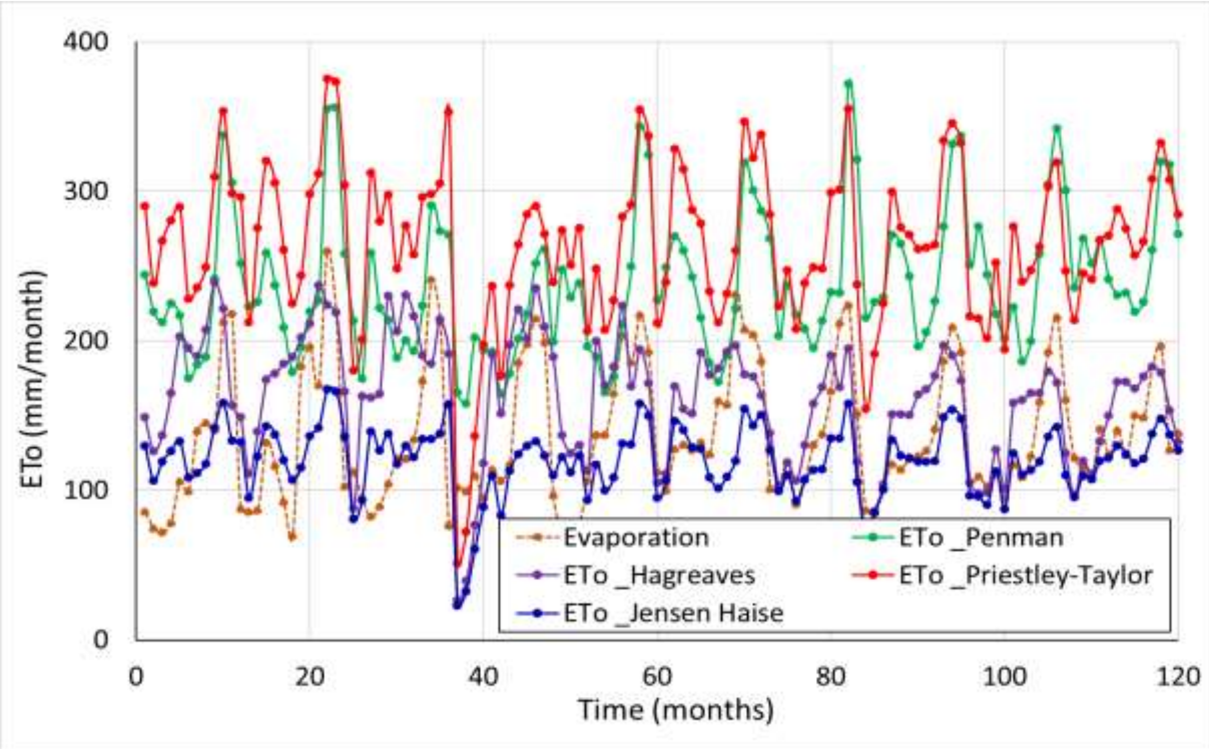

Figure 3: Monthly evaporation estimates for the four models and evaporation

Table 1: Descriptive statistics of the evaporation estimates

	Evaporation	**Penman**	**Hagreaves- Samani**	**Priestley-Taylor**	**Jensen Haise**
N	120.00	120.00	120.00	120.00	120.00
Mean	137.27	238.71	161.86	265.06	120.06
Median	123.28	228.26	168.53	267.31	121.59
Standard deviation	45.52	47.3	41.83	53.26	23.42
Minimum	69.1	158.17	26.52	51.24	22.88
Maximum	260	371.73	238.98	375.02	167.6
Skewness	0.64	0.78	-0.6	-0.85	-1.05
Std. error skewness	0.22	0.22	0.22	0.22	0.22
Kurtosis	-0.59	0.14	0.33	2.45	3.03
Std. error kurtosis	0.44	0.44	0.44	0.44	0.44

4.2 Correlation Analysis between Observed and Modelled Evaporation

To evaluate the agreement between observed pan evaporation and reference evapotranspiration (ET_0) estimates derived from various empirical and physically-based models, a correlation analysis was conducted using Pearson's correlation coefficient (r), Spearman's rank correlation (ρ), and Kendall's Tau-b (τ). These statistical measures offer complementary insights into both linear and monotonic relationships among the variables as given in Table 1.

The analysis reveals that all four ET_0 models exhibit moderate positive correlations with observed evaporation, confirming their general ability to replicate seasonal trends. The Pearson correlation coefficients range from 0.54 to 0.55, indicating similar levels of linear association across the models. Notably, the Hargreaves model achieved the highest rank-order correlation (Spearman's $\rho = 0.58$, Kendall's $\tau = 0.41$), suggesting that it most accurately captures the relative ordering of evaporation magnitudes throughout the year. The Penman and Jensen–Haise models followed closely, while the Priestley–Taylor model also performed comparably (Pearson's $r = 0.54$, Spearman's $\rho = 0.52$).

In terms of inter-model relationships, the strongest correlations were observed between the Priestley–Taylor and Jensen–Haise models, with nearly perfect correlation across all metrics (Pearson's $r = 1.00$, Spearman's $\rho = 0.99$, Kendall's $\tau = 0.94$). This near-complete alignment likely reflects their shared dependence on radiation-based inputs, particularly under humid or energy-driven atmospheric conditions. Similarly, the Penman model demonstrated strong correlations with both Priestley–Taylor ($r = 0.71$) and Jensen–Haise ($r = 0.66$), reinforcing its hybrid character, which integrates both radiative and aerodynamic components.

While none of the models fully matched observed pan evaporation in absolute terms, the consistent, moderate correlations across all models suggest that each captures key seasonal signals in evaporative demand. The results further validate the use of multi-model estimation frameworks, particularly in data-scarce environments where input availability may vary seasonally. Incorporating multiple models within a decision support framework can improve the robustness of water balance estimates, as highlighted by recent studies emphasising hybrid ET estimation under climate uncertainty and data constraints [16,17].

Table 2: Correlation matrix based on Pearson's correlation coefficient (r), Spearman's rank correlation (ρ), and Kendall's Tau-b (τ)

Evaporation models	Correlation methods	Evaporation	Penman	Hagreaves-Samani	Priestley-Taylor	Jensen Haise
Evaporation	Pearson's r	—				
	Spearman's rho	—				
	Kendall's Tau b	—				
Penman	Pearson's r	0.55	—			
	Spearman's rho	0.4	—			
	Kendall's Tau b	0.27	—			
Hagreaves-Samani	Pearson's r	0.54	0.14	—		
	Spearman's rho	0.58	0	—		
	Kendall's Tau b	0.41	0.02	—		
Priestley-Taylor	Pearson's r	0.54	0.71	0.67	—	
	Spearman's rho	0.52	0.71	0.53	—	
	Kendall's Tau b	0.37	0.54	0.39	—	
Jensen Haise	Pearson's r	0.55	0.66	0.73	1	—
	Spearman's rho	0.55	0.65	0.6	0.99	—
	Kendall's Tau b	0.4	0.49	0.45	0.94	—

4.3 Implications for Water Resource Management

The findings of this study underscore the critical importance of model selection and integration when estimating evaporation in data-scarce and hydrologically sensitive regions such as the Muko Reservoir catchment. Temperature-based models like Hargreaves–Samani and Jensen–Haise offer operational advantages due to their simplicity and low data demands. However, their performance varies significantly with climatic conditions, often leading to overestimation or underestimation during extreme weather events or dry seasons. This is consistent with recent studies highlighting the limited robustness of single-variable models in complex hydrological environments [16].

Conversely, combination models like Penman, which integrate energy balance and aerodynamic parameters, consistently provide more accurate and seasonally stable evaporation estimates. While these models demand more extensive meteorological inputs, including radiation, humidity, and wind, they are more reliable for strategic water budgeting, especially under climate variability [22]. Their integration into water management strategies has been shown to improve irrigation scheduling and reduce uncertainty in reservoir operation planning, particularly in semi-arid basins [23].

The multi-model framework developed in this study enables flexible application depending on data availability. It allows decision-makers to triangulate between models and use ensemble techniques that weigh model outputs based on seasonal accuracy or input reliability. Such ensemble-based approaches have been recommended as part of integrated water resource management (IWRM) strategies in arid and semi-arid regions, where resource optimisation is crucial [16,24]. Moreover, recent advances in remote sensing and machine learning offer opportunities for integrating this framework with satellite-derived evapotranspiration products, enhancing its utility in ungauged or partially gauged catchments [16].

In this context, implementing decision support systems (DSS) that incorporate multi-model ET estimation can significantly improve operational water allocation, policy formulation, and climate adaptation planning. Such systems can also facilitate participatory water governance by providing transparent and evidence-based estimates that inform stakeholder negotiations, especially in transboundary or multi-use water systems.

5. CONCLUSION

This study demonstrates that employing a multi-model framework within a Decision Support System (DSS) significantly improves the robustness and adaptability of evaporation estimation in data-scarce, semi-arid environments. Through the comparative evaluation of temperature-based, radiation-based, and hybrid models, the approach enables context-sensitive model selection aligned with data availability and seasonal variation. Among the models tested, the Hargreaves-Samani method showed the closest agreement with observed evaporation data, whereas the Penman and Priestley–Taylor models, though theoretically comprehensive, tended to overestimate evaporation rates. Integrating these models into a unified DSS enhances water budgeting accuracy, strengthens resource allocation decisions, and supports more resilient reservoir operation planning.

6. RECOMMENDATIONS

Based on the study findings, it is recommended that water management authorities and basin planners adopt multi-model frameworks within Decision Support Systems (DSS) to minimize estimation uncertainty and improve the reliability of evaporation and water balance assessments. Efforts should focus on expanding meteorological monitoring networks and integrating remote sensing technologies to enhance data coverage, accuracy, and model validation. DSS tools should be locally calibrated and regularly updated using real-time and historical data to ensure adaptability under changing climatic and hydrological conditions. Additionally, capacity building and cross-sectoral training programs should be strengthened to improve technical expertise, promote stakeholder engagement, and ensure effective DSS application in operational water management. Institutional integration of DSS into basin-level planning and policy frameworks is essential to foster evidence-based, equitable, and climate-resilient decision-making.

For further studies, research should explore the integration of socio-economic factors into hydrological and evaporation models to capture human-water interactions better. Future work should also assess the impacts of land use and vegetation changes on evaporation dynamics and water availability. Comparative studies involving machine learning and data-driven modelling approaches could enhance predictive accuracy in data-scarce environments. Moreover, long-term scenario analyses under different climate change projections should be undertaken to evaluate reservoir performance and adaptive management options over time. These future investigations will provide a stronger scientific foundation for developing resilient, adaptive, and inclusive water management strategies for semi-arid regions like the Muko Reservoir.

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