Development of Optimal Storage Capacity for Orle Reservoir Using Rainfall–Runoff Derived Monthly Flow Series

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Abstract - Reservoir storage determination in ungauged basins is limited by the lack of long-term stream flow records required for hydrological analysis and reservoir design. This study developed a hydrological framework for estimating the storage capacity of the proposed Orle Reservoir using rainfall–runoff derived monthly discharge data. Historical and predictive 30-year rainfall datasets, together with observed rainfall and discharge records, were used to develop a nonlinear rainfall–runoff model based on the Gauss–Newton regression algorithm, with rainfall as the predictor and discharge as the response variable. The developed model showed strong predictive performance with a coefficient of determination R^2 of 0.989, RMSE of 1.591 m^3/s, and MAE of 1.399 m^3/s, indicating close agreement between observed and predicted discharge values. The validated model was used to generate synthetic monthly discharge series for historical and predictive flow scenarios. The generated discharge data were converted into cumulative inflow volumes and analyzed using the mass curve method, yielding a gross reservoir storage capacity of approximately 1.04×10^8 m^3. Seepage and evaporation losses were evaluated using the Fakhari and Gambari seepage model and the Linarce evaporation method, producing annual losses of $7.95\times10^6 m^3$ and 3.91×10^3 m^3 respectively. After accounting for evaporation, seepage, and sedimentation losses, the effective reservoir storage capacity was estimated as approximately 9.08×10^7 m^3. The study demonstrates that integrating nonlinear rainfall–runoff modeling with mass curve analysis provides a reliable framework for reservoir storage determination and water resources planning in data-scarce regions.

Keywords - *Rainfall–runoff modeling; Reservoir storage capacity; Ungauged catchment; Gauss–Newton regression; Mass curve analysis; Synthetic discharge generation*

I. INTRODUCTION

Reliable estimation of reservoir storage capacity is essential for sustainable water resources management, particularly in regions where surface water supports domestic supply, irrigation, hydropower generation, and ecological stability [1,2]. However, reservoir design in many developing catchments is constrained by the absence of long-term hydrological records, especially streamflow data. This challenge is more severe in ungauged basins where conventional reservoir design approaches dependent on continuous discharge measurements cannot be effectively applied [3,4]. Consequently, there is an increasing need for reliable methods capable of generating streamflow estimates from available meteorological data for engineering planning and reservoir development [5, 6].

Rainfall–runoff modeling has become one of the most practical approaches for estimating river discharge in data-scarce environments. Regression-based hydrological models are particularly useful for establishing relationships between rainfall inputs and catchment response [7]. In nonlinear hydrological systems influenced by infiltration, evapotranspiration, groundwater interaction, and surface runoff processes, calibration techniques significantly improve model predictive reliability [8]. Recent advances in machine learning and hybrid hydrological approaches have further improved runoff prediction performance in ungauged watersheds [9,10]. Similarly, deep learning applications using long short-term memory networks have demonstrated improved streamflow regionalization and reservoir-regulated runoff prediction in hydrological systems [11,12]. In this study, a nonlinear regression approach based on the Gauss–Newton optimization algorithm was applied to model the rainfall–discharge relationship for River Orle.

Reservoir storage design also requires proper evaluation of inflow variability and hydrological losses. The mass curve method remains one of the most widely accepted techniques for determining reservoir storage requirements through cumulative inflow analysis [13]. However, accurate reservoir sizing must account for evaporation, seepage, and sedimentation losses, which significantly influence effective storage capacity and long-term reservoir performance [14]. Recent studies have also shown that integrated hydrological modeling and reservoir simulation improve water resources planning and flood estimation in ungauged basins [15,16].

The River Orle basin represents a typical ungauged catchment where limited hydrological data hinder conventional reservoir planning. Although historical and predictive rainfall datasets are available, continuous discharge measurements are lacking. Existing studies on reservoir development in similar environments rarely integrate predictive meteorological datasets, nonlinear rainfall–runoff modeling, synthetic discharge generation, and storage-loss assessment within a unified framework for effective reservoir sizing. This constitutes the major research gap addressed in the present study.

The aim of this study is to develop a reliable framework for determining the storage capacity of the proposed Orle Reservoir using rainfall–runoff derived monthly discharge data. Specifically, the study develops a nonlinear regression model using the Gauss–Newton method, validates the model using observed flow data, generates synthetic monthly discharge series, determines reservoir storage capacity using the mass curve method, and incorporates evaporation and seepage losses into effective storage estimation.

The novelty of the study lies in the integration of three years of observed hydrological datasets with historical and predictive rainfall datasets, nonlinear regression-based hydrological modelling, and reservoir storage analysis within a unified framework for ungauged basins. The developed methodology provides a practical and reliable tool for synthetic discharge generation, reservoir planning, and water resources development in data-limited regions.

II. METHODOLOGY

A. *Conceptual Framework*

The study adopts a sequential hydrological analytical framework to transform meteorological (rainfall) and observed discharge data inputs into reservoir design parameters for the ungauged Orle basin. The framework is structured as a data driven flow process. The schematic of the process is outlined below.

Rainfall → Regression Model → Discharge → Cumulative Flow → Storage

Historical and predictive meteorological data were obtained from the National Centre for Meteorological Research (CNRM –CM5), France. CNRM-CM5 is an atmospheric system model designed to run climate simulations [17]. The data, in conjunction with the River Orle's three years observed discharge datasets, were processed and used to develop a nonlinear rainfall–runoff regression model calibrated using the Gauss–Newton optimization technique. The validated model was subsequently used to generate synthetic monthly discharge series representing reservoir inflow conditions. The generated discharge was transformed into cumulative inflow for mass curve analysis, from which the reservoir storage capacity was determined. The estimated storage was further adjusted to account for evaporation, seepage, and sedimentation losses.

B. *Rainfall–Runoff Modelling*

Rainfall–runoff modeling was based on the assumption that a nonlinear relationship exists between rainfall and river discharge due to the combined influence of infiltration, evapotranspiration, groundwater contribution, and surface runoff processes [18] within the Orle catchment. In the model formulation, rainfall was adopted as the predictor variable, while river discharge served as the response variable.

The implementation procedure involved the following outlined steps.

- acquisition of rainfall and discharge datasets,
- validation and consistency assessment of the data,
- establishment of hydrological assumptions,
- development of nonlinear regression equations,
- estimation of monthly discharge,
- model validation
- generation of synthetic discharge series.

The rainfall datasets used in the analysis consist of mean historical and predictive monthly rainfall values derived from 30 years datasets , as presented in Table I, while the observed mean rainfall and discharge values used for model calibration are presented in Table II.

TABLE I MEAN HISTORICAL AND PREDICTIVE 30 YEARS RAINFALL VALUES

	Mean Historical Rainfall (mm)	Mean Predictive Rainfall (mm)
January	7	8
February	15	18
March	75	80
April	140	145
May	130	182
June	185	185
July	178	178
August	182	192
September	215	215
October	135	112
November	12	15
December	6	5

TABLE II MEAN FLOW AND RAINFALL DATA DERIVED FROM THE 2018, 2019 AND 2025 DISCHARGED AND RAINFALL DATA

Month	Mean Flow (m^3/s)	Mean Rainfall (mm)
January	6.850	3.24
February	8.980	15.89
March	10.230	78.78
April	14.560	143.45
May	21.368	156.23
June	31.562	188.45
July	26.590	177.57
August	35.782	187.98
September	59.356	216.46
October	10.826	130.45
November	9.125	15.00
December	6.768	2.00

C. Nonlinear Regression Model (Gauss–Newton)

The rainfall–runoff relationship was modeled using a nonlinear regression approach calibrated with the Gauss–Newton optimization algorithm [19]. The model parameters were estimated using the observed rainfall and discharge data presented in Table 2 under a 95% confidence interval.

The adopted nonlinear regression model is expressed in Equation 1.

$$Q = aR^b + c \qquad (1)$$

Where,

Q = discharge (m^3/s),

R = rainfall (mm),

a, b, and c are regression coefficients.

Validation of the model was carried out through comparison between observed and predicted discharge values.

D. Generation of Synthetic Discharge Data

The validated regression model was applied to the historical and predictive rainfall datasets in Table 1 to generate synthetic monthly discharge series for the Orle catchment. Historical, predictive, minimum, average, and maximum discharge scenarios were obtained for reservoir analysis.

E. *Reservoir Storage Determination*

Reservoir storage capacity was determined using the mass curve method based on the averaged generated synthetic discharge data in Table 5. The monthly discharge values were converted into inflow volumes using Equation 2.

$$V = Qt \qquad (2)$$

Where,
V = inflow volume (m^3),
Q = discharge ($\frac{m^3}{s}$)
t = time in seconds.

A uniform demand line was established from the annual cumulative inflow using Equation 3.

$$D = \frac{\sum v}{12} \qquad (3)$$

F. Seepage Analysis Through the Dam

Seepage through the proposed rock-filled dam with an impervious central core was analyzed using the Fakhari and Gambari seepage model. The seepage equation is given in Equation 4.

$$Q = fkh \qquad (4)$$

Where,
Q = seepage discharge (m^3/s),
f = seepage factor,
k = permeability coefficient (m/s),
h = hydraulic head (m).

$$f = (2.27 - 0.006W - 0.004h - 0.38\tan\alpha)H^{(-0.361)}\left(\frac{c}{h}\right)^{(0.3947)\tan\alpha \quad .15h-1.3591} \qquad (5)$$

$$c = b - 0.75\Delta \qquad (6)$$

Where,
α is the angle of upstream slope (degree)
W is the length of dam core crest (m)
H is the height of the core (m)

Some dams with geometric parameters similar to the projects under study were selected from the study of Fakhari and Gambari (2013) using the gross head as a guide for the implementation of Equation 3. Multi – parametric analysis was used to determine the adequate geometry to minimize seepage and enhance structural stability of the dams using the permeability of the local soil [17]. The evaluated geometric and hydraulic parameters used to implement Equation -- are presented in Table III.

TABLE III PARAMETERS USED FOR SEEPAGE ANALYSIS

Parameter	**Symbol**	**Value**
Dam height	H	28 m
Hydraulic head	h	24 m
Crest width	W	8 m
Upstream slope	θ	30°
Permeability	k	1.2×10^{-6} m/s
Seepage factor	f	0.18

G. Evaporation Loss Estimation

Reservoir evaporation losses were estimated using the Linarce evaporation model [17] based on the local meteorological parameters presented in Table IV.

TABLE IV METEOROLOGICAL PARAMETERS FOR EVAPORATION ANALYSIS

Parameter	**Symbol**	**Value**
Mean daily temperature	T	26.67 °C
Solar radiation	R_s	655.53 W/m²
Wind speed	u	1.67 m/s
Altitude	h	164 m
Dew point temperature	T_d	10 °C
Altitude correction factor	F	1.02

H. Reservoir Sedimentation Losses

Sedimentation losses were estimated by allocating a sediment storage reserve equivalent to 5% of the gross reservoir storage capacity to account for long-term deposition of suspended sediments within the reservoir. This allowance was incorporated into the storage analysis to compensate for the gradual reduction in effective storage volume during the operational life of the reservoir and to improve the long-term reliability of the reservoir system.

I. Effective Reservoir Storage Capacity

The effective reservoir storage capacity was determined by incorporating evaporation, seepage, and sedimentation losses into the gross storage estimate. The effective storage equation is given by Equation 6.

$$S_e = S_g - (V_e + V_S + V_{sed}) \qquad (7)$$

III. DISCUSSION OF RESULTS

The results obtained from the rainfall–runoff modelling, synthetic discharge generation, and reservoir storage analysis demonstrate the applicability of nonlinear hydrological modeling for reservoir design in ungauged catchments. The developed framework successfully transformed long-term meteorological data into hydrologically meaningful discharge and storage parameters suitable for the planning of the proposed Orle River Reservoir.

A. Catchment Rainfall Analysis

The rainfall analysis presented in Table 1 revealed a pronounced seasonal distribution pattern characterized by low rainfall during the dry season months from November to February and high precipitation during the wet season period from April to September. Peak rainfall values occurred in September for both historical and predictive datasets, confirming the strong influence of seasonal climatic variability on catchment hydrology. The rainfall distribution profile illustrated in Fig 1 further shows the nonlinear seasonal variation of rainfall across the hydrological year. The predictive rainfall profile generally exhibited slightly higher wet-season rainfall intensity than the historical profile, particularly during May and August, suggesting a potential increase in future runoff generation within the catchment.

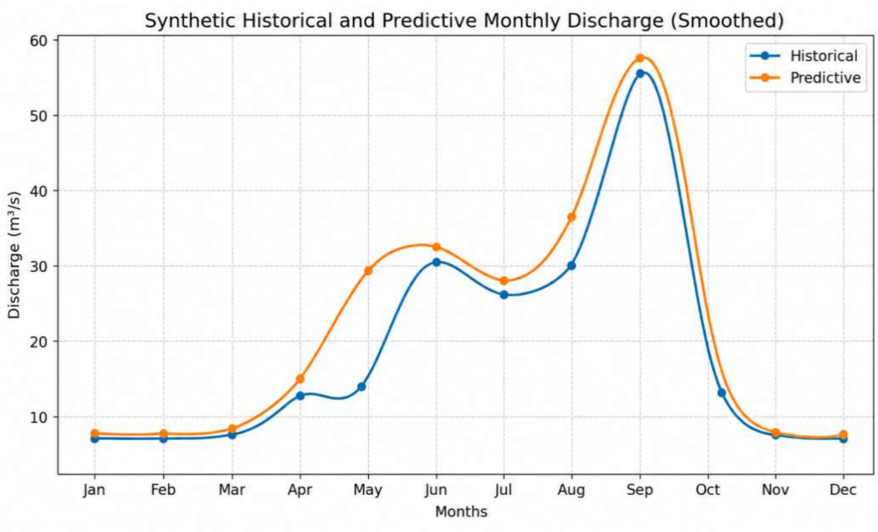

Fig. 1: Synthetic Historical and Predictive Mean Monthly Discharge

Similar seasonal rainfall variability patterns have been reported for tropical ungauged basins by [20, 16, 6] who observed that increasing rainfall intensity significantly influences runoff generation and reservoir inflow behavior in data-scarce environments.

B. Nonlinear Regression Model (Gauss–Newton) Output

The nonlinear rainfall–runoff relationship developed for the Orle basin using the Gauss–Newton regression algorithm produced strong predictive performance with a coefficient of determination (R^2) of 0.989, indicating that approximately 98.9% of the variation in discharge is sustained by rainfall input. The model performance indices are presented in Table V. The developed model was obtained as Equation 7.

$$Q = 1.89x10^{-1}\ R^{4.894} + 8.222 \qquad (7)$$

The low RMSE and MAE value confirm the adequacy of the developed model for discharge prediction.

TABLE V: STATISTICAL PERFORMANCE OF THE DEVELOPED REGRESSION MODEL

Performance Index	Value
Coefficient of Determination (R^2)	0.989
Root Mean Square Error (RMSE)	1.591 m³/s
Mean Absolute Error (MAE)	1.399 m³/s

Comparable predictive performance has been reported by [10] and [9], who demonstrated that nonlinear and hybrid rainfall–runoff models significantly improve runoff estimation accuracy in ungauged watersheds. Similarly, [22] reported that nonlinear machine-learning-based hydrological models can effectively explain runoff variability in basins with limited stream flow observations.

C. Developed Model Validation

Validation of the model was carried out through comparison between observed and predicted discharge values. The comparison between observed and predicted discharge is shown in Fig. 2

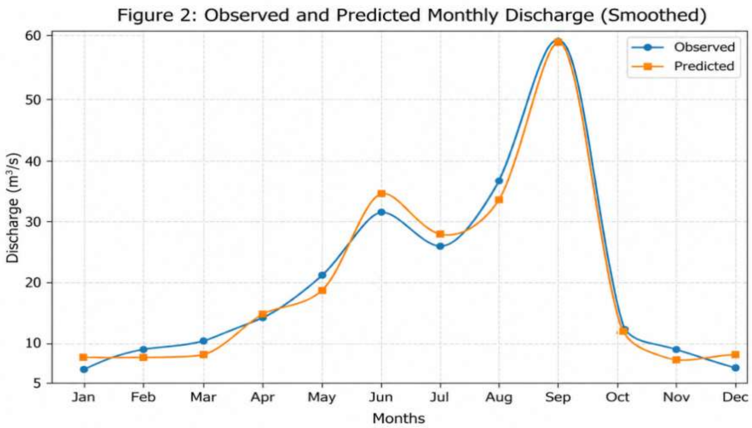

Fig. 2: Observed and Predicted Average Monthly Discharged Profile

demonstrated close agreement between measured and simulated flow values throughout the year.

Similarly, the Observed versus Predicted Correlation Plot shown in Fig. 3 confirmed the reliability of the regression model for hydrological prediction and synthetic flow generation. These results indicate that the nonlinear regression approach effectively captured the hydrological response of the Orle basin despite the absence of long-term gauging records.

Similar findings were reported by [11], who demonstrated the effectiveness of nonlinear and deep-learning approaches for stream flow regionalization in ungauged basins. Reference [15], also observed that integrated hydrological prediction models improve stream flow estimation reliability under reservoir-regulated conditions.

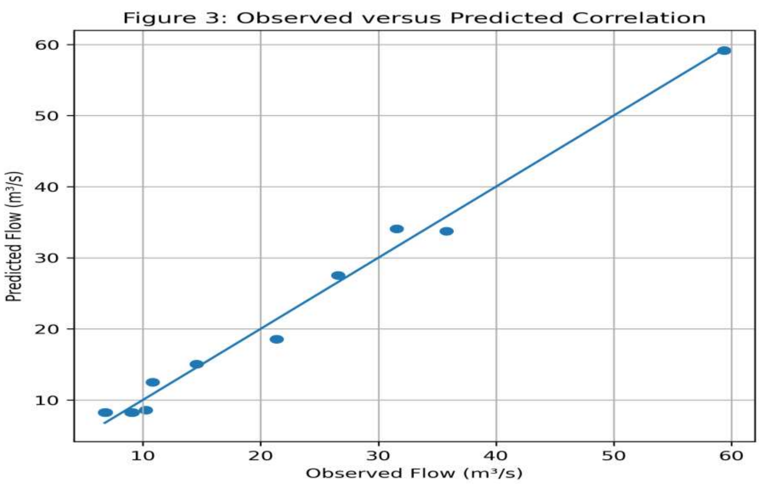

Fig. 3: Observed versus Predicted Correlation Plot

The generated synthetic discharge series plot presented in Fig. 4 showed substantial seasonal variability consistent with the rainfall distribution pattern. Peak discharge occurred in September with average flow values exceeding 57 m³/s, while dry-season discharge remained relatively low, averaging approximately 8 m³/s.

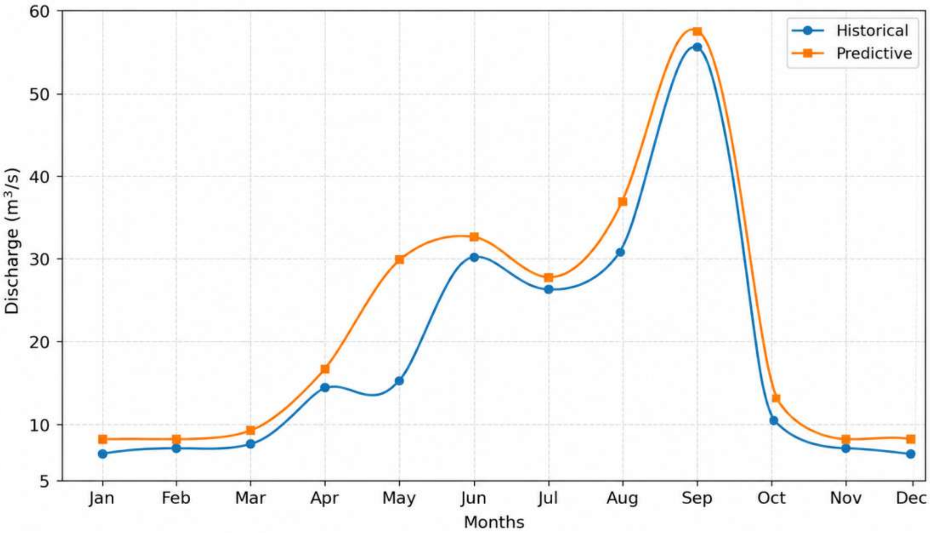

Fig. 4**:** Synthetic Historical and Predictive Discharge Plot

The plot further demonstrates the close relationship between rainfall intensity and runoff generation within the basin. Similar seasonal discharge characteristics were observed by [16] and [12], whos reported strong correlations between rainfall variability and synthetic runoff generation in reservoir-influenced ungauged basins.

The reservoir storage analysis carried out using the mass curve method showed that cumulative inflow exceeded cumulative demand during the peak rainy season, resulting in significant surplus inflow between September and November. Conversely, dry-season months exhibited cumulative deficits due to reduced inflow contributions. The cumulative inflow and deficit analysis presented in Table IV indicates that the maximum storage deficit occurred in April, yielding a required gross reservoir storage capacity of approximately 1.04×10^{8}m³.

D. The Mass Curve Inflow Analysis

TABLE VI RESERVOIR STORAGE DEFICIT ANALYSIS

Month	Cumulative Inflow (m³)	Cumulative Demand (m³)	Deficit/Surplus (m³)
January	21,311,424	51,748,632	30,437,208
February	42,622,848	103,497,264	60,874,416
March	64,807,776	155,245,896	90,438,120
April	103,221,216	206,994,528	103,773,312
May	158,210,496	258,743,160	100,532,664
June	240,703,488	310,491,792	69,788,304
July	312,670,368	362,240,424	49,570,056
August	398,908,800	413,989,056	15,080,256
September	547,884,000	465,737,688	-82,146,312
October	578,360,736	517,486,320	-60,874,416
November	599,672,160	569,234,952	-30,437,208
December	620,983,584	620,983,584	0

The relationship between cumulative inflow and uniform demand, illustrated in the Mass Curve and Demand Line Plot indicated in Fig. 5, clearly identifies the critical storage period and the point of maximum deficit used in determining reservoir capacity. The result indicates that the proposed storage capacity is sufficient to regulate seasonal inflow variability and sustain uniform water demand throughout the hydrological year. Similar applications of cumulative inflow analysis for reservoir sizing were reported by [15] and [6], who emphasized the importance of long-term synthetic discharge generation in reservoir planning under uncertain hydrological conditions.

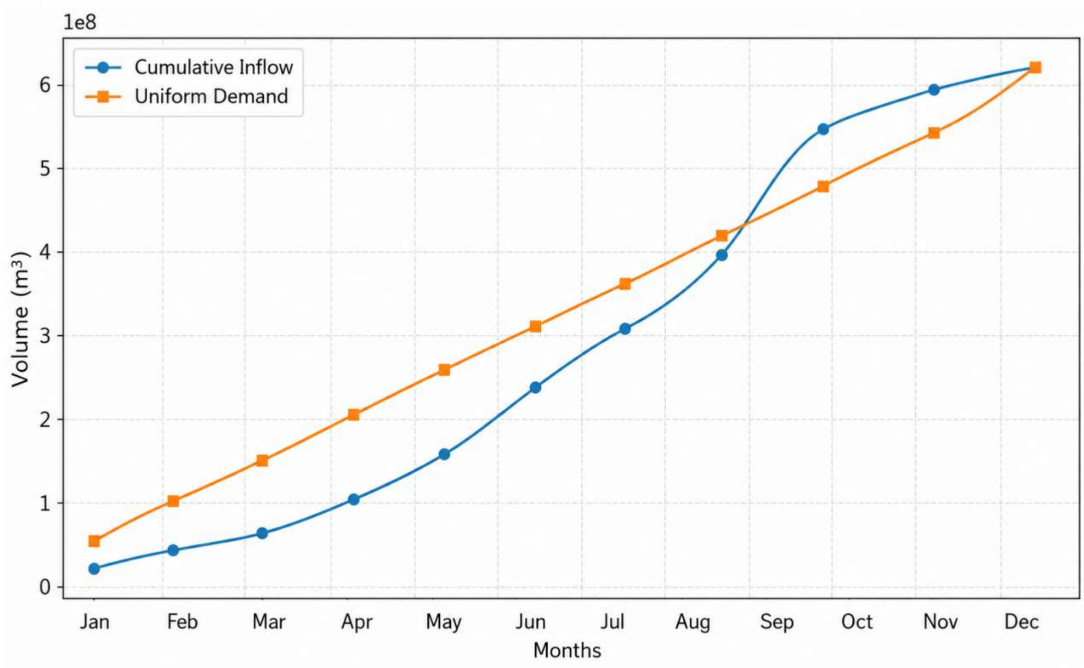

Fig. 5: Cumulative Inflow and Uniform Demand

E. *Seepage Flow Analysis*

The seepage analysis presented in Table VII showed that the proposed rock-filled dam with an impervious central core possesses satisfactory hydraulic performance. The estimated seepage discharge of 1.24×10^{-4} m^3/s is relatively small compared with the reservoir inflow, indicating effective seepage control through the selected embankment configuration.

TABLE VII SEEPAGE ANALYSIS PARAMETERS AND COMPUTED SEEPAGE DISCHARGE FOR THE PROPOSED ORLE RESERVOIR DAM

Parameter	Symbol	Unit	Value
Dam height	(H)	m	28
Hydraulic head	(h)	m	24
Crest width	(W)	m	8
Upstream slope angle	(θ)	Degree (°)	30
Soil permeability coefficient	(k)	m/s	(1.2×10^{-6})
Seepage factor	(f)	–	0.18
Estimated seepage discharge	(Q)	m^3/s	(1.24×10^{-4})
Annual seepage loss volume	(V_s)	m^3/year	(3.91×10^{3})

The result confirms the suitability of the adopted dam geometry and locally available low-permeability core materials for minimizing water losses and maintaining structural stability. Similar observations were reported by [16], who noted that proper embankment configuration and low-permeability core materials significantly reduce seepage losses in reservoir systems.

F. Evaporation Analysis

The evaporation analysis summarized in Table VIII demonstrated that reservoir surface evaporation constitutes the dominant storage loss mechanism within the system. The estimated annual evaporation loss of approximately 7.95×10^6 m³ represents a significant proportion of the reservoir water balance and highlights the importance of incorporating climatic losses into reservoir design.

TABLE VIII METEOROLOGICAL PARAMETERS AND ESTIMATED EVAPORATION LOSS FOR THE PROPOSED ORLE RESERVOIR

Parameter	Symbol	Unit	Value
Mean daily air temperature	T	°C	26.67
Incident solar radiation	R_s	W/m²	655.53
Mean wind speed	u	m/s	1.67
Reservoir site altitude	h	m	164
Mean dew point temperature	T_d	°C	10
Altitude correction factor	F	–	1.02
Estimated monthly evaporation	E	mm/month	138
Estimated annual evaporation depth	E_a	m/year	1.656
Average reservoir surface area	A	m²	4.8×10^6
Estimated annual evaporation loss volume	V_e	m³/year	7.95×10^6

This finding is consistent with the behavior of reservoirs located in tropical climatic regions where elevated temperature and solar radiation intensify evaporative demand. Similar conclusions were reported by Yu and Yang (2024) and Zhang et al. (2025), who observed that climatic variability strongly influences reservoir evaporation and long-term storage sustainability in subtropical and tropical environments.

G. Reservoir Storage Analysis

The effective storage analysis presented in Table IX showed that after accounting for evaporation, seepage, and sedimentation losses, the effective storage capacity of the Orle Reservoir was estimated as approximately 9.08×10^7m³.

TABLE IX RESERVOIR STORAGE CAPACITY COMPONENTS

Storage Component	Value
Gross storage capacity	1.04×10^8 m³
Annual evaporation loss	7.95×10^6 m³
Annual seepage loss	3.91×10^3 m³
Sedimentation reserve	5.20×10^6 m³
Effective storage capacity	9.08×10^7 m³

The relatively small difference between gross and effective storage indicates that the proposed reservoir system retains substantial live storage capacity for operational use. The effective storage obtained is considered adequate for seasonal flow regulation, dry-season water supply reliability, and long-term reservoir sustainability. Comparable results were reported by [9, 10, 22], who emphasized that integrating rainfall–runoff modeling with hydrological loss assessment significantly improves the reliability of reservoir planning and sustainable water resources management in ungauged basins.

IV. CONCLUSION

This study developed a hydrological framework for determining the storage capacity of the proposed Orle Reservoir using rainfall–runoff derived discharge data for an ungauged catchment. Historical and predictive rainfall datasets were used to establish a nonlinear rainfall–runoff relationship using the Gauss–Newton regression algorithm. The developed model produced strong predictive performance with a coefficient of determination R^2 of 0.989, confirming its reliability for discharge prediction within the Orle basin.

The validated model was used to generate synthetic discharge series for reservoir analysis. Mass curve analysis yielded a gross reservoir storage capacity of approximately 1.04×10^8m³. Further assessment showed that evaporation constituted the major storage loss component, while seepage losses remained relatively small due to the effectiveness of the proposed impervious core dam configuration. After incorporating evaporation, seepage, and sedimentation losses, the effective storage capacity of the reservoir was estimated as approximately $9.08\times10^{7}m^{3}$.

The results demonstrate that the proposed reservoir possesses adequate storage potential to regulate seasonal flow variability and sustain reliable water supply throughout the hydrological year. Overall, the integration of nonlinear rainfall–runoff modeling with mass curve analysis provides a practical and reliable approach for reservoir storage determination in ungauged basins and offers a useful framework for future water resources planning and hydrological infrastructure development in data scarce regions.

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