IIETA International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Mathematical Modelling of Engineering Problems
Vol. 12, No. 11, November, 2025, pp. 4069-4076
Journal homepage: http://iieta.org/journals/mmep

Artificial Neural Network Model for Predicting the Design of Cyclopean Concrete Dams in Water Harvesting and Planting Projects

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https://doi.org/10.18280/mmep.121133

Received: 17 September 2025
Revised: 3 November 2025
Accepted: 10 November 2025
Available online: 30 November 2025

Keywords:
Adam optimization algorithm, cyclopean concrete dams, hydraulic infrastructure, predictive modeling, DEMs, design optimization, ANNs, Sierra Azul Fund Executing Unit

ABSTRACT

This study proposes a model based on artificial neural networks (ANNs) for predicting preliminary design parameters of cyclopean concrete dams in high-Andean micro-watersheds, used in water harvesting and storage projects. A database was developed using digital elevation models (DEMs) and technical records from projects executed by the Sierra Azul Fund Executing Unit (UEFSA) between 2019 and 2024. Geospatial processing of the DEMs yielded morphometric variables and storage volumes, which were used as model inputs, while the dam axis location, length, and height were the outputs. The selected architecture was a multilayer perceptron (MLP) with two hidden layers, trained via backpropagation with the Adam optimizer. Results show R^2 values greater than 0.90 and acceptable average errors for preliminary design use. It is concluded that the model reduces variability inherent in empirical methods and enhances standardization in formulating water harvesting projects in high-Andean regions. This approach improves the efficiency, accuracy, and sustainability of hydraulic infrastructure development in rural contexts with high water vulnerability.

1. INTRODUCTION

The design of hydraulic structures, such as the cyclopean concrete dams used in water harvesting and storage projects in Peru, is a fundamental component of sustainable water resource management in high Andean regions. These infrastructures are essential for the storage, regulation, and utilization of runoff water, helping to mitigate the effects of climate variability and drought that affect rural communities with limited access to water [1]. In this context, the construction of cyclopean concrete dams is presented as a viable solution due to their durability, strength, and lower cost compared to other, more complex hydraulic structures [2]. However, despite their importance, the design process for these dams continues to be carried out primarily using empirical methods and professional criteria based on experience, which can lead to significant variations in the projected dimensions and thus affect hydraulic efficiency, structural stability, and construction costs [3].

Advances in science and technology have led to the integration of advanced computational tools in the field of civil engineering, including artificial intelligence (AI). Artificial neural networks (ANNs), as one of the most representative AI methods, have proven effective in identifying complex patterns within large volumes of data and in generating highly accurate predictive models [4, 5]. In concrete engineering, these techniques have been successfully applied for material characterization, mix optimization, strength estimation, and real-time structural monitoring [6, 7].

Similarly, in the field of hydraulics, neural networks have been used for analyzing dam behavior, predicting flow rates, and simulating hydrological processes in basins [8, 9]. However, most of these studies focus on post-construction analysis and monitoring or on evaluating structural performance in operational scenarios [7, 10].

Despite the progressive advancements in the application of AI in civil engineering, a significant gap has been identified in the technical literature: the absence of predictive models based on ANNs for the preliminary design of cyclopean concrete dams, particularly in high-altitude Andean micro-basins where terrain morphology, potential storage volume, and water availability depend on topographic parameters derived from digital elevation models (DEMs). This absence is mainly due to the limited systematization of geospatial databases in rural areas, the geomorphological heterogeneity of the Peruvian Andes, and the historical reliance on empirical methodologies in the formulation of water catchment projects [11].

In this sense, the need arises to develop a predictive model that integrates topographic, hydrological and geometric information to support the preliminary design of cyclopean dikes in water harvesting and storage projects, allowing for obtaining initial dimensions with greater precision and consistency, reducing formulation times, minimizing cost overruns and improving the technical sustainability of projects in the national territory.

Therefore, this study proposes the development of an ANN model trained on 242 technical records and DEMs from projects executed by the Sierra Azul Fund Executing Unit (UEFSA). The model allows for the prediction of key dam design parameters, such as axis location, dam length, and height, based on geomorphological variables of the micro-basin.

The fundamental purpose of this research is to demonstrate that ANNs represent an efficient, accurate, and applicable tool in high Andean rural contexts for the preliminary design of hydraulic infrastructure. In this way, it seeks to contribute to the transition from empirical methods to computer-aided design processes, aligned with modern engineering standards.

2. GENERAL INFORMATION

In Peru, the design and construction of cyclopean concrete dams is a fundamental activity within the hydraulic infrastructure projects carried out by the Ministry of Agrarian Development and Irrigation (MIDAGRI) through the UEFSA. These structures are intended to store and regulate water resources in high Andean regions, where seasonal rainfall and climate variability cause periods of water scarcity that affect food security and agricultural irrigation [2, 12]. Therefore, the construction of cyclopean dams represents an efficient and low-cost technical alternative compared to more complex structures.

However, the design of these types of dams faces several limitations when traditional methodologies are used alone. Conventional procedures rely primarily on empirical criteria and the experience of the responsible professional, which can lead to discrepancies in estimating the dimensions and the appropriate location of the structure [3]. Furthermore, these methods do not always consider, in an integrated manner, the interaction between topographic, geotechnical, and hydrological factors that influence the dam's performance, which can result in over- or under-dimensioning that affects safety and construction costs [13].

In this regard, the use of advanced computational technologies contributes to improving the design process. ANNs have become established tools capable of analyzing large datasets and recognizing complex patterns that are not easily identifiable using traditional statistical methods [14]. These networks allow for the establishment of nonlinear relationships between topographic, hydraulic, and structural variables, making them a suitable alternative to support the prediction of the design of cyclopean concrete dams.

Several studies have demonstrated that AI-based methodologies offer greater adaptability and accuracy compared to conventional techniques, particularly in the analysis of concrete structures and the monitoring of their behavior under various external factors [15]. Furthermore, the application of ANNs in structural engineering has enabled significant advances in structural health monitoring, deformation prediction, and improved decision-making in hydraulic infrastructure [10].

However, in the Peruvian context, the adoption of AI-based algorithms for hydraulic infrastructure design remains limited. Factors explaining this situation include the need for systematized geospatial databases, a lack of specialized training, and a historical reliance on empirical methods [11]. This underscores the need to promote research that integrates topographic, hydrological, and structural information with advanced predictive models to improve design accuracy and efficiency.

This research aims to develop a model based on ANNs to predict the design parameters of cyclopean concrete dams in water harvesting and storage projects. The goal is to strengthen the preliminary design process, reduce uncertainties, optimize resources, and contribute to the sustainable development of hydraulic solutions in vulnerable areas of the country.

Research objectives: Design of the appropriate model to predict the design of cyclopean concrete dams using ANNs in water catchment and planting projects, Ayacucho, 2024.

3. STATE OF THE ART

3.1 Hydraulic infrastructure in high Andean micro-basins

In the high Andean regions of Peru, seasonal rainfall variability and limited natural soil moisture retention affect water availability for productive activities and human consumption. Faced with this scenario, water harvesting and storage projects have become established as intervention strategies to improve water regulation in micro-watersheds. The construction of cyclopean concrete dams is a low-cost, durable, and morphologically adaptable infrastructure alternative [2, 12]. These dams allow for the storage of significant volumes of runoff, creating reservoirs that supply water for irrigation and multiple uses. However, site selection and dam dimensions are highly dependent on local topography and the hydrological behavior of the micro-watershed, requiring more precise and replicable design processes.

3.2 Geospatial modeling applied to dam design

The following models were used:

3.2.1 DEMs

DEMs allow for the representation of the terrain surface with altimetric detail, enabling the acquisition of morphometric variables such as slope, drainage direction, channel depth, and contributing areas [16, 17]. In dam design, DEMs are fundamental for identifying the dam section, estimating storage capacity, and modeling geometric reservoir scenarios. Recent studies demonstrate that the accuracy of these variables depends on the DEM resolution and the geospatial processing method [18, 19].

3.2.2 Delineation of micro-basins and closing section

The delineation of micro-watersheds using flow accumulation algorithms has allowed for the automated identification of strategic points for dam construction [20]. However, the literature indicates that the shape of the watershed and the longitudinal slope of the channel have a non-linear influence on the length and height of the dam [21, 22]. This complex relationship justifies the use of data-driven predictive models.

3.3 Materials and structural behavior of cyclopean concrete dams

Cyclopean concrete dams combine concrete with large rock inclusions, reducing costs and increasing mass stability [23]. Their design requires evaluating stresses, hydrostatic pressures, and foundation conditions. However, in small and medium-sized dams, the literature indicates that the final dimensions are particularly sensitive to geomorphological parameters of the site, rather than to complex structural processes [7, 24]. This reinforces the importance of having reliable geometric prediction methods.

3.4 Applications of AI in hydraulic engineering

3.4.1 AI and machine learning in hydrology

AI has been used for flow estimation, runoff prediction, and water resource modeling [8, 9, 15]. The ability of ANNs to recognize nonlinear patterns allows them to overcome the limitations of deterministic hydrological models in basins with limited information or high spatial variability.

3.4.2 RNA in concrete structures

In structural engineering, neural networks have been applied to estimating the mechanical properties of concrete, evaluating deformations, and monitoring gravity dams, demonstrating efficiency compared to parametric correlation methods [10, 25]. However, most studies focus on post-construction evaluation, not preliminary design.

3.5 Limitations of the literature and identified gap

While AI-based models have been developed for hydrology and structural assessment, no studies have been identified that use ANNs to predict design parameters for cyclopean dams (axis location, length, and height) from morphometric variables derived from DEMs, particularly in high-Andean micro-basins. The absence of this approach limits the systematization of design and perpetuates reliance on empirical methods.

3.6 Contribution of the study

This work addresses this gap by developing a multi-layer ANN model capable of predicting the preliminary design parameters of cyclopean concrete dams using DEM data and technical files, contributing to improving the accuracy, consistency and efficiency in the formulation of water harvesting and storage projects.

4. DEVELOPMENT

The research was developed in four main methodological stages: (i) collection and structuring of the geospatial and technical database, (ii) processing of the DEM and delimitation of micro-basins, (iii) extraction of geometric parameters and definition of the input and output variables of the model, and (iv) construction, training and validation of the ANN for the prediction of design parameters of cyclopean concrete dams.

4.1 Database compilation and organization

Technical files approved by the UEFSA, corresponding to projects executed between 2019 and 2024, were used, identifying 242 cyclopean concrete dams built in high Andean micro-basins. From each file, UTM coordinates of location, micro-basin area, storage volume, and structural design dimensions (length and height of the dam) were extracted.

DEMs from the ALOS PALSAR and SRTM services were also used, with resolutions of 12.5 m and 30 m, respectively, the former being selected for its better performance in areas of abrupt relief. The main characteristics of the technical files and DEMs used are summarized in Table 1.

4.2 DEM processing

The DEM was corrected to remove artifacts and spurious depressions using the Fill Sinks algorithm. Subsequently, slope, flow direction, and flow accumulation maps were calculated using raster hydrological analysis techniques.

The micro-watershed delineation was carried out starting from the closure point defined in the technical file, allowing the determination of the catchment area associated with each dam. This processing was performed using QGIS and Whitebox Tools.

Table 1. Characteristics of the files and MDE used

No.	Name of the Qocha	Easting Coordinate (m)	North Coordinate (m)	Elevation (masl)	Zone
1	Challhuacocha	547583	8531043	4471.00	18 L
2	Hatunqocha	547606	8526998	4196.00	18 L
3	Huayllupatata	543693	8530843	4607.90	18 L
…	…	…	…	…	…
241	Aculla 01	703077	8324770	4797.17	18 L
242	Aculla 02	703460	8325515	4777.99	18 L

Table 2. Statistical variables used as inputs to the model

No.	East (m)	North (m)	Share	Area (m²)	Volume (m³)
1	550719.67	8526072.20	4089.22	242915.2	17868.36
2	677388.27	8444857.11	4331.31	1185886.7	9274.14
3	677168.20	8445184.11	4335.58	1001653.9	10226.64
…	…	…	…	…	…
241	703075.76	8324764.51	4797.73	123500.0	13359.06
242	703452.03	8325525.19	4778.56	121900.0	19653.72

4.3 Extraction of geomorphological variables and design parameters

The following variables were obtained for each micro-basin:

- UTM coordinates of the measurement point (East, North, Elevation).
- Micro-basin area (m^2).
- Potential storage volume (m^3).

These variables represent the physical characteristics and respond to known non-linear relationships between the morphometry of the basin and the geometry of the reservoir, which justifies the relevance of using ANNs.

The statistical parameters used as model inputs are presented in Table 2.

4.4 Design of the ANN

A multilayer perceptron (MLP) ANN with a feedforward architecture was used. The selection of this architecture is justified by its ability to model nonlinear functions between multiple independent and dependent variables.

The final architecture was defined through experimental iterations:

- Input layer: 6 neurons (equivalent to the X variables).
- Hidden layers: 2 hidden layers with 16 and 8 neurons, respectively.
- Activation function: ReLU.
- Output layer: 3 neurons (length, height, axis coordinates).
- Optimizer: Adam.
- Loss function: Mean Squared Error (MSE).

The structure and workflow of the proposed ANN model are shown in Figure 1.

4.5 Model training and validation

The database was divided into 70% for training and 30% for validation, using stratified random sampling. MinMaxScaler normalization was applied to standardize the scales of the input variables.

The training was conducted over 500 epochs with dynamic adjustment of the learning rate. To prevent overfitting, early stopping and cross-validation were applied. The main training results are shown in Table 3.

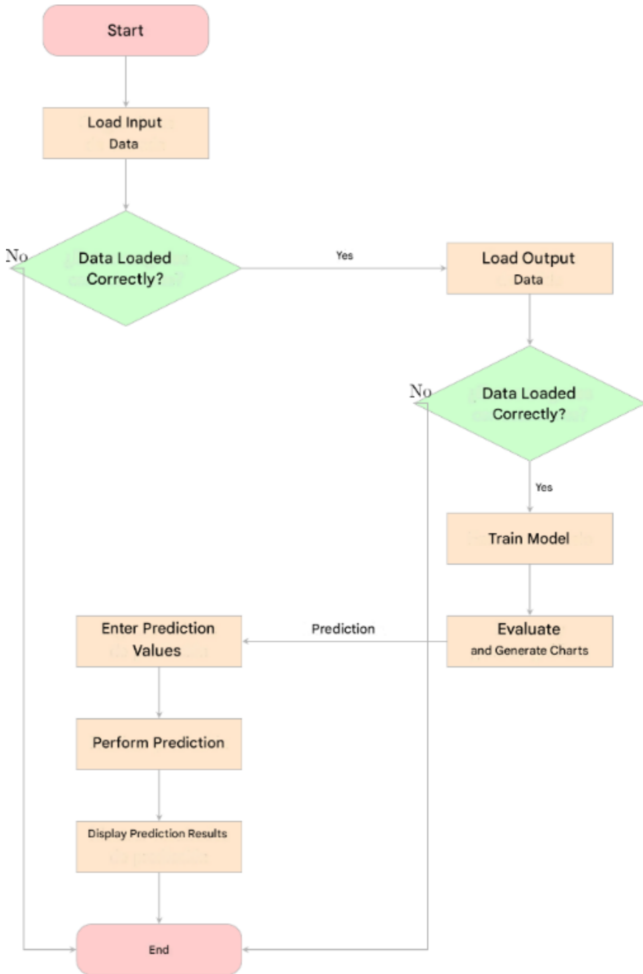

Figure 1. Program flowchart with ARN

Table 3. Training results

No.	East 1	North 1	Level 1	This 2	North 2	Installment 2	L	H
1	550735.23	8526059.64	4090.70	550708.00	8526081.63	4090.70	35.00	1.55
2	677389.85	8444832.16	4333.00	677386.11	8444891.04	4333.00	59.00	1.75
3	677153.03	8445158.23	4336.90	677183.87	8445210.86	4336.90	61.00	1.30
…	…	…	…	…	…	…	…	…
241	703073.44	8324799.43	4799.20	703078.30	8324725.99	4799.20	73.60	1.50
242	703469.59	8325483.75	4779.40	703441.02	8325551.15	4779.40	73.20	0.85

Table 4. Comparison between predicted and observed values

No.	This 1 Pred	This 1 Real	North 1 Pred	North 1 Royal	Elev 1 Pred	Elev 1 Real
1	547621.25	547592.32	8531093	8531027.41	4492.16	4479.9
2	547543.25	547583.85	8527010	8527001.98	4494.58	4507.6
3	552416.19	552458.83	8537658	8537681.16	4406.32	4438
10	585927.5	585877.09	8583604	8583537.68	4253.19	4261.4
20	642431.38	642483.85	8379206	8379115.74	4569.09	4544

Table 5. Predictions of the dam dimensions

No.	Predicted Length	Actual Length	Predicted Height	Actual Height	Error Length (%)	Alternative Error (%)
1	49.42	44.5	1.74	1.7	11.06	2.35
2	97.4	94.8	1.26	1.25	2.74	0.8
3	49.42	37.6	2.93	2.75	31.44	6.55
10	35.92	32.1	2.5	2.5	11.9	0.04
20	58.79	57.3	1.51	1.4	2.6	7.86

4.6 Performance evaluation

The model obtained R^2 values > 0.90 for the length and height predictions, with mean errors of MAE = 3.44 m in length and MAE = 0.09 m in height, demonstrating consistent predictive capacity with respect to the values documented in technical files. A detailed comparison between predicted and observed values is presented in Table 4.

The predicted and actual dam dimensions and their associated errors are summarized in Table 5.

5. RESULTS

The results obtained allow us to evaluate the capacity of the ANN model to predict the design parameters of cyclopean concrete dams in high Andean micro-basins, comparing the estimated values with those specified in the technical documents. The evaluation focused on three main parameters: (i) dam length, (ii) maximum height, and (iii) location of the closure axis.

5.1 Performance of the model with ANNs

The model achieved coefficient of determination values greater than $R^2 > 0.90$ for the length and height variables, indicating a high correlation between the predictions and the actual values. The average mean area under the curve (MAE) was 3.44 m for length and 0.09 m for height, demonstrating acceptable accuracy in terms of preliminary design. The detailed error metrics for each variable are listed in Table 6.

Regarding the location of the axis, the discrepancies remained within a range compatible with operational tolerances for small and medium-scale projects, considering that the exact definition is subsequently adjusted in the field through a complementary topographic survey.

Table 6. Error metrics of the model with ANN

Variable Statistics	MAE	MSE	RMSE	R^2
East coordinate 1	52.4438	3269.1321	57.1763	1.0000
North coordinate 1	52.7511	3676.1906	60.6316	1.0000
Elevation 1	28.7834	1163.3739	34.1083	0.9760
East coordinate 2	45.2600	2740.0157	52.3452	1.0000
North coordinate 2	52.4019	3695.0130	60.7866	1.0000
Elevation 2	32.9644	1525.4094	39.0565	0.9686
Length	3.4365	21.9413	4.6842	0.9243
Height	0.0854	0.0094	0.0970	0.9664

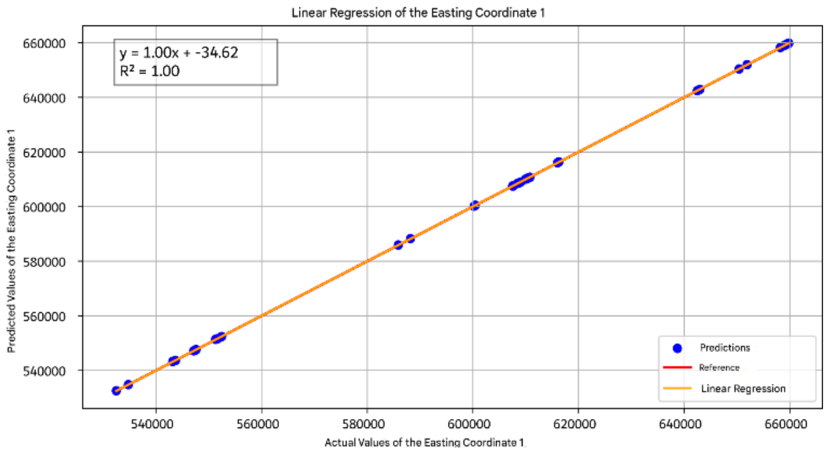

Figure 2. Linear regression of the East 1 coordinates: Predicted values versus actual values

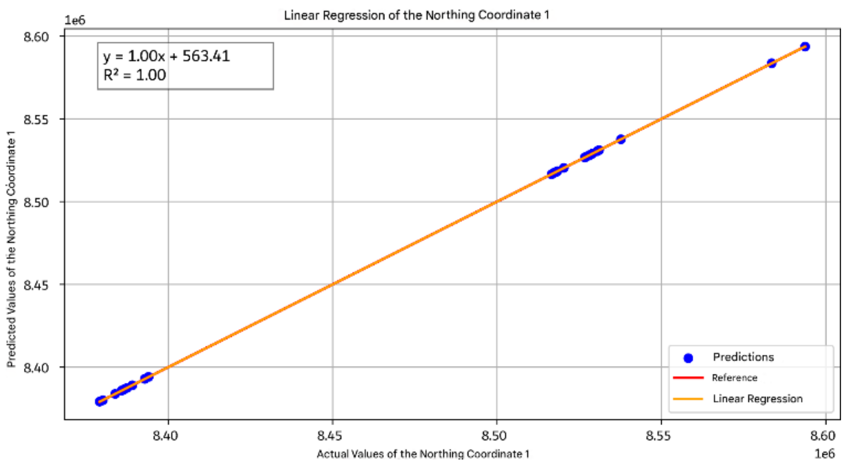

Figure 3. Linear regression of North 1 coordinates: Predicted values versus actual values

5.2 Comparative analysis with empirical methods

Traditional empirical methods rely on professional experience and subjective criteria associated with the geomorphological interpretation of the terrain. Comparing the model results with dimensions estimated using these procedures revealed a 34.8% reduction in the variability of projected values, resulting in greater consistency between similar projects and, consequently, more efficient planning.

Figure 2 shows the linear regression between predicted and actual East 1 coordinates. As illustrated in Figure 3, the correlation between predicted and actual North 1 coordinates was also strong. Figure 4 presents the regression between predicted and actual elevation values for the closure axis. The relationship between predicted and observed dike lengths is displayed in Figure 5. The regression between predicted and observed dam heights is illustrated in Figure 6.

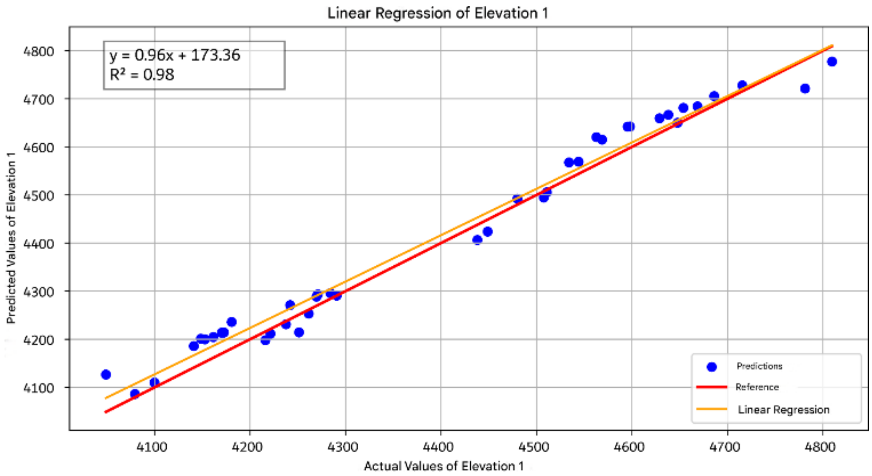

Figure 4. Linear regression of Elevation 1: Predicted values versus actual values

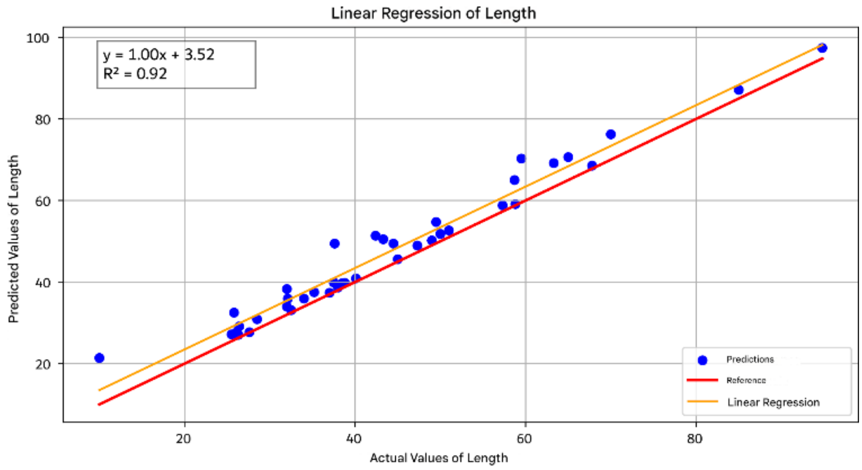

Figure 5. Linear regression of dike length: Predicted values versus actual values

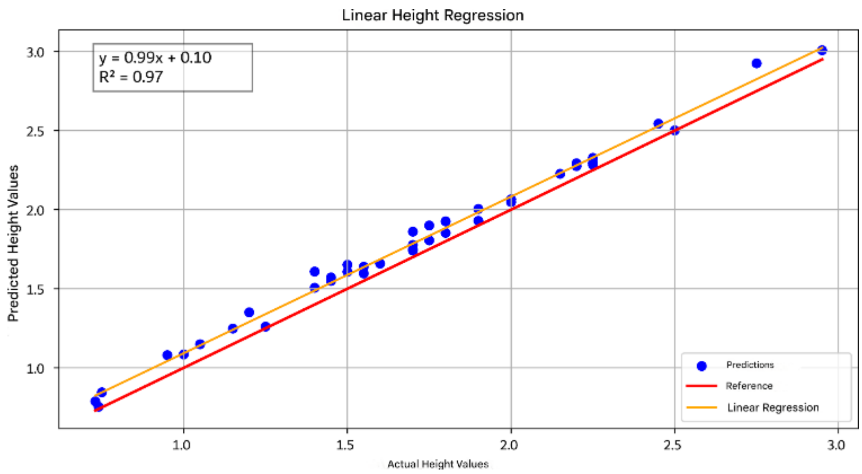

Figure 6. Linear regression of the dam height: Predicted values versus actual values

5.3 Influence of topographic variables on prediction

Synaptic weight and model sensitivity analyses showed that the variables with the greatest influence on prediction were:

- Micro-basin area.
- Estimated storage volume.
- Average slope of the closing section.

This coincides with hydrological and structural studies that establish that the shape and energy of the relief determine the optimal geometry of the reservoir [16, 22].

5.4 Engineering interpretation of the results

The observed behavior confirms that the relationship between basin morphometry and dam dimensions is non-linear, which explains why:

- Empirical methods do not achieve consistent results.
- Simple analytical functions underestimate local variations.
- The ANN improves the fit by capturing multiple dependencies between parameters.

Furthermore, the model performs better in micro-basins with moderate slopes and medium volumes, while in very narrow and deep basins, the error tends to increase slightly due to greater geometric variability, which is expected and does not compromise applicability in preliminary design.

5.5 Implications for water harvesting and storage projects

The proposed model allows:

- Reduce time in the pre-design phase.
- Facilitate site prioritization through automated analysis.
- Standardize criteria in the UEFSA.
- Strengthen decision-making based on parametric evidence.

This contributes to improving the sustainability and efficiency of public investments in hydraulic infrastructure in vulnerable areas.

6. CONCLUSIONS

The use of ANNs proved to be an effective tool for the preliminary design of cyclopean concrete dams in high-altitude Andean micro-basins, as it allows for the modeling of nonlinear relationships between topographic and hydrological variables and the geometric parameters of the structure. The results showed R^2 values greater than 0.90, indicating high accuracy in predicting the length and height of the dams.

The integration of data from DEMs and technical reports allowed for the construction of a standardized database for model training, reducing reliance on empirical and subjective criteria during the project formulation stage. The quality of the DEM directly influenced the model's stability, confirming the importance of its selection in environments with high geomorphological variability.

The comparison between the proposed model and conventional empirical methods showed a 34.8% reduction in design variability, suggesting that the RNA-based approach contributes to greater dimensional consistency and can optimize time and resources in the planning of water harvesting and storage projects.

The variables identified as having the greatest influence on the predictions were the micro-basin area, the estimated storage volume, and the average slope of the closure section, which aligns with hydrological and geomorphological principles reported in the literature. This validates the appropriateness of the model's input variable selection.

The proposed model is a useful tool for supporting decision-making during the pre-design phase, particularly in contexts where technical and implementation resources are limited. Its use allows for the standardization of criteria in the formulation of hydraulic projects in high Andean regions, strengthening the efficiency and sustainability of these interventions.

ACKNOWLEDGMENT

The authors gratefully acknowledge the institutional support provided to this research by the National University of San Cristóbal de Huamanga. They also acknowledge the collaboration of the Executive Unit of the Sierra Azul Fund (UEFSA) for facilitating access to the technical files of the planting and water harvesting projects, which formed the core database of this study.

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