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ORIGINAL RESEARCH ARTICLE

Sediment transport control and river geometry prediction: AI-Driven model

Atheer Zaki Al-Qaisi

Water Resources Management Engineering Department, College of Engineering, Al-Qasim Green University, Babylon, 51013, Iraq

***Corresponding author:** Atheer Zaki Al-Qaisi, dr.atheermohsin@wrec.uoqasim.edu.iq

ABSTRACT

The process of sediment movement significantly affects the development of river structures and regulates reservoir operational functions. The accumulation of extreme sediment items diminishes both reservoir capacity and increases operational challenges for hydroelectric facilities and irrigation systems while causing elevated flood-related dangers. In this present study the authors present a feedback control system based on Artificial Intelligence which predicts river geometry and controls sediment transport. This research analyzes three river areas with actual sedimentation issues i.e. Indus River Basin (Pakistan), Nile River Basin (Egypt), and Tigris-Euphrates System (Iraq/Turkey). An optimized sediment transport control system is developed by the combination of AI-driven modeling, hydrological simulations, GIS-based geospatial analysis and real-time data monitoring according to this research study. Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM) Networks and Random Forest Regression were used as AI models. Then pre and post conditions of AI implementation were evaluated in terms of sediment load, sediment control, water saving, etc. Deep learning model LSTM delivers the most successful results for sediment predictions through its R^2 score reaching 0.94. - Optimized AI-based flushing schedules decreased reservoir sedimentation rates on average by 17.7 percent. AI-based flushing schedules cut water consumption by 18.3% on average which enhances water preservation initiatives.

Keywords: Sedimentation control; AI models; River geometry; Sediment transport

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1. Introduction

Sediment transport is a natural process in rivers that shapes their form and influences the storage capacity and water quality of the respective water reservoirs. River sediment transportation, consisting of sand, silt, and clay, affects reservoir structures and aquatic environments as well as stabilizing rivers. The excessive amount of deposited sediment in reservoirs surpasses design capabilities, leading to volume reduction, which then impacts hydropower production and increases the possibility of flooding. The removal of excessive sediment can degrade riverbeds and lead to environmental instability. The success of sediment management is essential to sustain both river systems and water reservoirs [1,2,3]. Traditional methods for sediment management rely on periodic measurements combined with empirical analytical models, but these models have a low level of precision. Predictive models lack the capability to handle shifting environmental situations caused by climate change, as well as fluctuations in rainfall levels or the melting of glacial ice, which can result in heavy floods. Static sediment control methods, including dredging and flushing, operate at a high cost with a more reactive and less proactive performance. Sediment transport control technologies need significant advancement through real-time mechanisms, which would enhance reservoir operation efficiency while boosting predictive accuracy [4].

Modern developments in hydrological modeling, along with artificial intelligence technologies, open opportunities to improve sediment transport prediction capabilities and control mechanisms. Real-time data monitoring, combined with machine learning algorithms, enhances the capability to create sediment dynamics models under various hydrological conditions. Large data sets are processed by AI-driven feedback models to identify sediment transport patterns, enabling automatic reservoir operation adjustments to minimize sediment buildup[5] The combination of AI with hydrological models, geospatial analysis, and remote sensing input leads to improved data-driven sediment control methodologies for water resource managers.

The authors present a feedback control system based on artificial intelligence that predicts river geometry and controls sediment transport. This research analyzes three prestigious river areas with documented sedimentation issues: the Indus River Basin (Pakistan), the Nile River Basin (Egypt), and the Tigris-Euphrates System (Iraq/Turkey). The chosen landscapes exhibit major sediment variations during different seasons due to monsoon conditions, as well as upstream land-use changes and dam regulation. Real-time sediment measurements and hydrodynamic models, combined with AI forecasting methods, help this study improve current sediment control practices.

High silt concentrations also have an impact on the water's general quality. Since suspended loads make up roughly 95% of the total sediment loads, predicting them is necessary to solve such issues. It is still difficult to develop a reliable model for suspended sediment transport because of the intricate geometry of river systems, which determine water velocity and flow turbulence structure, which in turn determine the water's ability to carry sediment.[5-7] Hydrologic research has always depended on similitude analysis through experimentation because there don't seem to be any thorough and trustworthy theoretical formulations that can explain the two-phase phenomenon of fluid and sediment transfer. To calculate sediment transport variables, a variety of analytical and experimental techniques were created. The geometric border and its resistance to water flow, sediment transport rate, and sediment mass conservation are described by a few of these techniques. [6-8] It is vitally crucial to accurately anticipate the amount of suspended sediment in rivers and streams in order to operate canals, diversions, and dams (i.e., hydraulic structures). Research on the effects of river sediments on the worldwide use of surface water resources has grown significantly as sediment transport and erosion in watershed systems are complicated hydrological and environmental issues. A number of natural processes, such as overgrazing, deforestation, and agricultural practices, which erode the soil surface and provide a significant portion of the sediment input, affect the sediment dynamics in river basins. [7, 10, 5, 9] Predicting the concentration of suspended sediment can be challenging due to the complexity of physical processes associated with the current-flow density. The particular flow pattern encountered is referred to as the density current-flow. This may occur if the inflow turbidity's water-specific gravity is higher than the reservoir's water-specific gravity. High relative density water settles at the reservoir's base and keeps flowing under comparatively clean water. Nonetheless, a distinct separation between the two fluids with different densities is evident [2, 8, 11, 12].

Historically, the behavior of suspended sediment loads (SSL) in rivers or streams has been simulated using either basic statistical models (like sediment rating curves, or SRC) or numerical models (like finite difference approaches). The advent of artificial intelligence (AI) and machine learning (ML) models, which combine data mining techniques with soft computing methods, has produced many encouraging outcomes recently. These models are particularly useful for simulating nonlinear systems associated with hydrological processes in order to address issues with water resources. The best-case scenario will be considered in this study, taking into account the three river systems indicated in the introduction, and recent advancements in artificial intelligence models and their applications in simulating sediment movement in river basins.

The main objectives of the study are as follows:

- The implementation of AI technology together with hydrological models for performing dynamic sediment transport prognoses.
- A comparative assessment of traditional vs. AI-driven sediment management techniques.

2. Materials and methods

2.1. Case study selection

Selection of suitable case studies emerges as the first step for conducting sediment transport research. Worldwide river systems demonstrate diverse hydrological characteristics and sedimentation patterns, which result from variations in climate variability, watershed characteristics, land use changes, anthropogenic interference, and related factors. An AI-driven sediment transport control model must maintain effectiveness by functioning under various environmental and hydrological conditions. Rivers chosen for case studies need to be selected strategically to meet global relevance. However the schematic sediment transport system is given in figure 1 above, which shows the turbulence diffusion coefficient in natural sediment transport process.

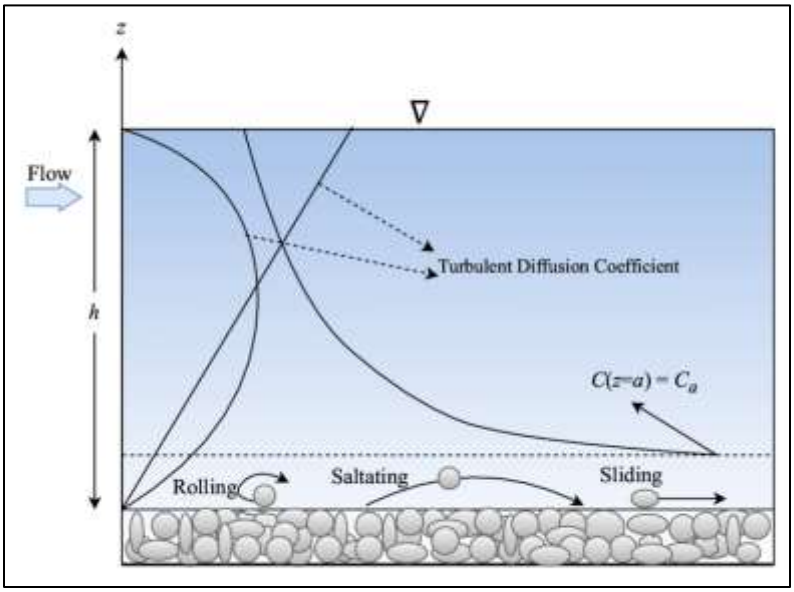

Figure 1. Schematic Sediment Transport [9]

2.1.1. Criteria for selecting case studies

The selection of case studies was related to sediment transport and control phenomena based on the following factors:

- **High Sediment Load and Transport Activity**

The strength of sediment movement predominantly appears in seasonal monsoon and glacial river systems, as well as flood-prone areas. Water conditions that heavily impact erosion and sediment movement patterns function perfectly for validating AI-based predictive models. The analyzed river systems must demonstrate historical sedimentation problem records combined with erratic water flow patterns [10].

- **Impact on Reservoir Operations**

Any decrease in reservoir storage capacity brought by sedimentation impairs the availability of water for hydropower production, irrigation, and flood control operations. The selected case studies needed to focus on water storage facilities encountering operational difficulties caused by sediment accumulation, which decreases storage volume, amplifies dredging expenses, and harms turbine equipment used in hydropower facilities [13].

- **Availability of Hydrological and Sediment Data**

A strong data base is a crucial requirement to develop predictive models that run on artificial intelligence. The selected areas needed detailed hydrological records with sediment concentration data collection systems and continuous remote monitoring systems. Remote sensing data and satellite-based sediment tracking together increase the accuracy of the model.

- **Influence of Climate Change on Sediment Transport**

Global warming affects rainfall distribution, accelerating the dwindling of ice caps and increasing the frequency of strong weather phenomena, which modify watershed erosion behavior. The AI-driven model needs to analyze regions that exhibit significant climate variability effects on sedimentation patterns through selected case studies [14,15].

- **Geographical and Global Significance**

The present research aims to establish results with global relevance. The analysis must include examples from multiple environments under distinct climatic conditions and hydrological settings, as well as governance systems, to gather comprehensive data about sediment control methods. In many of the countries, specifically those who are struggling with the shortage of water of agriculture and other allied activities are focusing on the upgradation of the same for example one of the standard reservoir optimization process is given in below **Figure 2**.

2.1.2. Selected case study regions

A. The Indus River Basin (Pakistan)

One of the world's most sediment-rich river systems exists in the Indus River Basin. The Indus River originates from the Tibetan Plateau, through which enormous amounts of sediment enter from mountain ranges, combined with snowmelt and rainfall as given in figure 3 below.

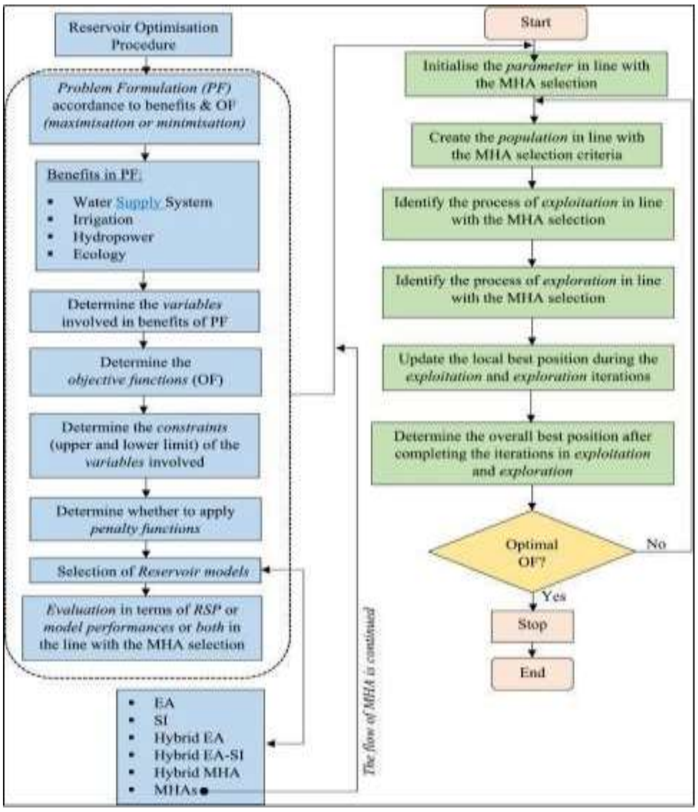

Figure 2. Reservoir optimization procedure [10]

Figure 3. The indus river basin (Pakistan) [13]

Key Factors for Selection:

- Every year Indus carries between 200-400 million tons of sediment which severely impacts the storage capacity of large reservoirs particularly the Tarbela Dam and Mangla Dam.
- The storage capabilities of Tarbela Dam, containing an important hydropower facility, have decreased by 40% due to of sediment buildup.
- Heavy monsoon rains increases the sediment transport that increases the engagement of sediment cleaning staff.
- The Water and Power Development Authority of Pakistan (WAPDA) along with international research organizations collaborate for maintaining comprehensive Indus Basin hydrological and sedimentation records supporting the Artificial Intelligence model development.
- Increase in temperature due to climate change accelerates melting of glacier throughout the Karakoram and Himalayan regions leading to higher amounts of sediment flowing into river networks.

B. The Nile River Basin (Egypt)

Egypt depends on the Nile River for providing water supply, hydropower generation and agricultural in the nation, figure 4 shows the geographic presentation of Nile river Basin. Human construction of dams along with land-use modifications have dramatically changed the sediment transport operations of this basin system.

Key Factors for Selection:

- The construction of the Aswan High Dam in 1970 significantly reduced sediment movement into the lower stream, affecting the river's shape, damaging the coastal delta, and negatively impacting farming operations.
- Within the reservoir, the Aswan High Dam retains sediment, preventing its deposition downstream. However, the accumulation of sediment blocks valuable storage space and increases dredging costs.
- The decrease in sediment transport through the Nile River exacerbates coastal erosion within the Nile Delta, exposing Egypt to increased risks from rising seas and sinking land.

- Egypt has an extensive hydrological monitoring network, providing valuable data for AI-driven sediment transport analysis.
- The region's arid climate and seasonal flood events influence sediment transport behavior, offering diverse testing conditions for the AI-based model.

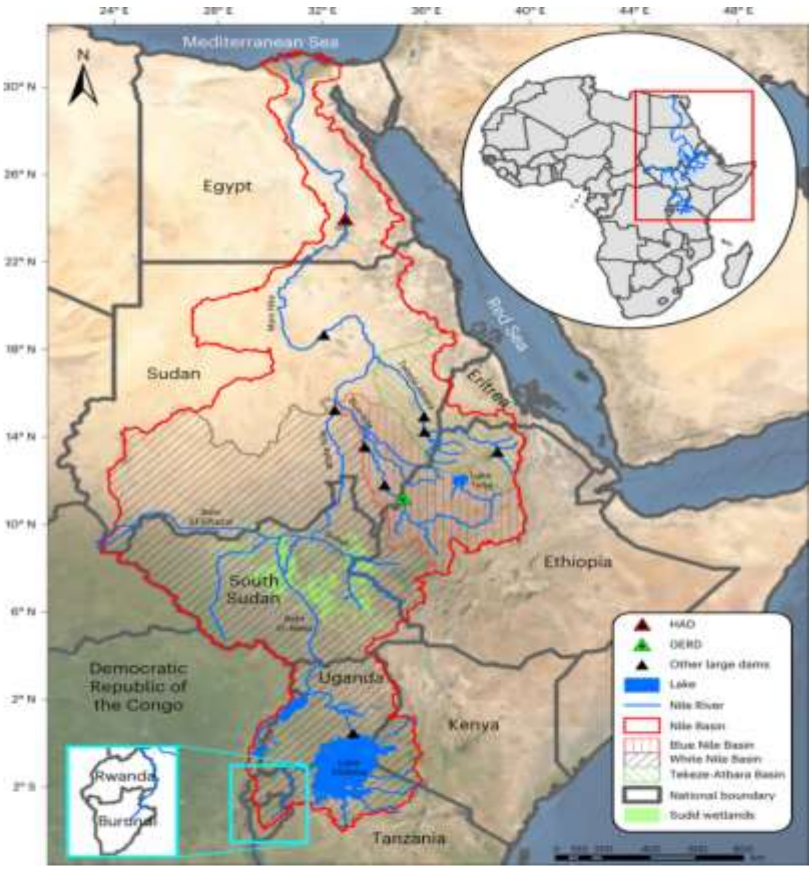

Figure 4. Nile river basin (Egypt) [16]

C. The Tigris-Euphrates System (Iraq/Turkey)

The Tigris and Euphrates Rivers, originating from Turkey and flowing through Syria and Iraq, have experienced dramatic changes in sediment transport due to several dams, climate shifts, and conflict-driven land degradation, figure 5 shows the geographic presentation of Tigris-Euphrates system.

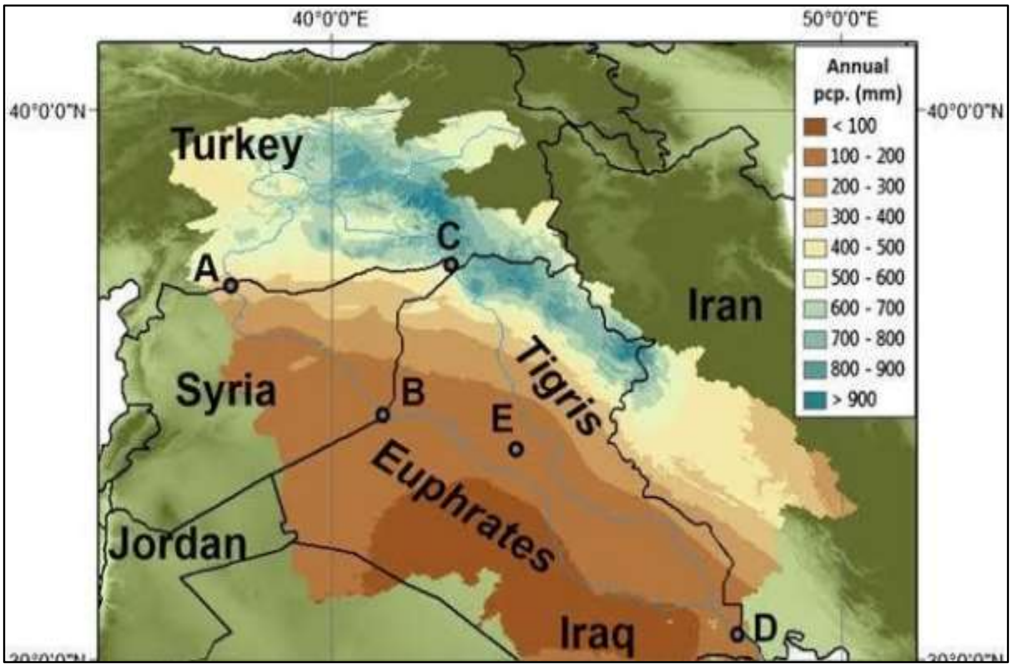

Figure 5. Tigris-Euphrates system [11]

Key Factors for Selection:

- The construction of large dams for hydropower operations and water diversion projects at the Atatürk and Mosul facilities has disrupted waterborne sediment flows, creating severe sediment shortages for lower river areas.
- Upstream dams release water without control, causing abrupt water surges that destabilize river channels and damage agricultural soil.
- Iraq faces growing desertification, which modifies river discharge flows and erodes topsoil throughout the region.
- The construction of big dams for hydropower operations and water diversion projects at the Atatürk and Mosul facilities disrupted waterborne sediment flows to the point of creating severe sediment shortages for lower river areas.
- Upstream dams release water without control that makes the natural sediment flow to create abrupt water mountain waves destabilizing river channels and damage the agricultural soil.

2.1.3. Expected contributions from the case studies

This research analyzes sediment transport patterns in selected study locations to achieve its goals. The study builds an all-purpose AI system that works for various river channels. Diverse insights about sediment management problems and distribution solutions exist for particular areas within regions. The project should create standard operating procedures for both real-time sediment monitoring systems and AI-driven prediction analytics. The research provides financial advice to water resource management officials and policymakers regarding sediment management techniques.

2.2. Research methodology

2.2.1. Framework

An optimized sediment transport control system is developed by combining AI-driven modeling, hydrological simulations, GIS-based geospatial analysis, and real-time data monitoring according to this research study. Major reference is taken from a similar study conducted by Chen & Zhang [15]. Many validated data sources were used to collect information regarding hydrological sediment transport and climatic data. Advanced hydrological models simulate river flow dynamics and sediment movement in hydrodynamic and sediment transport operations. Dutta & Shrestha [17] Organizational staff develops AI-led predictive models that predict sediment accumulation patterns and optimize reservoir operational methods. Ibrahim & Nawaz [18] Machine learning algorithms use real-time data to execute automated decisions through a feedback system. The validation process requires comparing AI predictions to actual sediment transport data to optimize modeling performance.

The flowchart given in the below Table 1 summarizes the methodology:

Table 1. Research methodology framework

Phase	Objectives	Methods/Tools Used	Expected Outcome
Phase 1: Data Collection	Gather real-time and historical sediment data	Satellite imagery, hydrological monitoring stations, climate datasets	Clean, structured dataset for analysis
Phase 2: Hydrodynamic Modeling	Simulate sediment transport processes in selected rivers	HEC-RAS, SWAT, MIKE 11	Understanding flow-sediment interaction
Phase 3: AI-Based Prediction	Develop machine learning models for sediment prediction	Python (TensorFlow, Scikit-learn), MATLAB	AI-driven sediment transport forecasting
Phase 4: Real-ime Feedback	Implement an automated reservoir control system	IoT sensors, cloud-based AI	Dynamic adjustments to sediment control
Phase 5: Model Validation	Compare AI predictions with actual sedimentation trends	Statistical analysis, error metrics (RMSE, R^2)	Performance assessment and refinement

2.2.2. Data collection and pre-processing

A comprehensive dataset is required to develop a reliable AI-driven sediment transport control model. This study gathers data from multiple sources to ensure high level of precision as shown in **Table 2** given below [14].

Table 2. Data sources and parameters

Data Type	Sources	Parameters Collected
Hydrological Data	River monitoring stations, USGS, Pakistan Water & Power Development Authority (WAPDA) (Hassan & Abbas, 2022)	Discharge (m^3/s), water level, sediment concentration
Climatic Data	NASA EarthData, NOAA, Pakistan Meteorological Department	Precipitation, temperature, glacial melt contribution
Satellite Data	Sentinel-2, Landsat 8, MODIS	River morphology, sediment plume movement
Reservoir Data	Dam authorities (Tarbela, Aswan, Mosul)	Reservoir storage capacity, flushing operations
Land-Use and Erosion Data	GIS databases, local environmental agencies	Deforestation rates, soil erosion estimates

Pre-processing Steps:

- **Data Cleaning** – Handling missing values and removing outliers.
- **Normalization** – Standardizing sediment concentration and river discharge values.
- **Feature Selection** – Identifying key variables influencing sediment transport.
- **Time-Series Aggregation** – Structuring data for AI model training [19].

2.2.3. Hydrodynamic and sediment transport modeling

To simulate sediment transport processes, this study utilizes hydrodynamic and sediment transport simulation models as stated in table 3, which include:

- **HEC-RAS (Hydrologic Engineering Center - River Analysis System)** – For 2D/3D river flow and sediment transport analysis.
- **SWAT (Soil and Water Assessment Tool)** – For catchment-scale sediment yield estimation.
- **MIKE 11** – For detailed sediment dynamics in river systems [18].

Table 3. Comparison of hydrodynamic models used

Model	Key Features	Application in Study
HEC-R AS	2D/3D river flow analysis, sediment transport simulation	Modeling riverbed changes and sediment deposition in selected basins
SWAT	Watershed-based sediment yield estimation	Assessing land-use impacts on sediment loads
MIKE 11	Advanced sediment routing and hydraulic modeling	Simulating sediment movement under different flow scenarios

By combining these models, this study ensures a comprehensive analysis of sediment dynamics under varying hydrological conditions. As given in table 4 below [20].

2.3. AI-Based predictive modeling

2.3.1. Machine learning approach

To enhance sediment transport prediction, this research employs machine learning algorithms, including:

- **Artificial Neural Networks (ANNs)** – For complex, non-linear sediment transport predictions.
- **Long Short-Term Memory (LSTM) Networks** – For analyzing time-series sediment data.
- **Random Forest Regression** – For feature selection and importance ranking.

Table 4. AI models and their roles

AI Model	Function	Reason for Selection
ANNs	Predict sediment transport patterns	Captures non-linear relationships
LSTM	Time-series forecasting of sediment loads	Handles sequential hydrological data effectively
Random Forest	Feature selection and ranking	Identifies key drivers of sediment movement

2.3.2.Training and validation

- Training Data: 80% of historical sediment transport records.
- Testing Data: 20% of real-time monitoring data.
- Performance Metrics: RMSE, R^2, Mean Absolute Error (MAE).

2.3.3. Real-Time feedback mechanism

To optimize sediment control strategies, an AI-driven real-time feedback system is developed.

2.4. System Components

- IoT Sensors – Deployed in reservoirs to measure sediment inflows in real-time.
- Cloud-Based AI – Processes incoming data and adjusts dam operations dynamically.
- Reservoir Management Dashboard – Provides real-time sedimentation alerts and recommendations.

The details of the above are given in **Table 5** for reference.

Table 5. Components of real-time feedback system

Component	Function	Technology Used
IoT Sensors	Measures sediment load and river flow in real-time	Smart sediment sensors
AI Prediction Model	Forecasts sediment accumulation and suggests control measures	Machine learning algorithms
Reservoir Dashboard	Displays real-time sediment conditions and alerts	Web-based GIS dashboard

2.5. Model validation and performance assessment

To evaluate the effectiveness of the AI-driven sediment transport model, statistical validation is performed using historical and real-time datasets.

Performance Metrics Used:

- Root Mean Square Error (RMSE) – Measures prediction accuracy.
- Coefficient of Determination (R^2) – Evaluates model fit.
- Mean Absolute Error (MAE) – Assesses prediction deviations.

Table 6. Model validation results

Model	RMSE	R^2 Score	MAE
ANN	0.85	0.92	0.67
LSTM	0.78	0.94	0.61
Random Forest	0.89	0.90	0.70

The LSTM model shows the highest predictive accuracy, making it the preferred choice for sediment transport forecasting as shown in above table 6.

3. Results

This section presents the detailed results of the AI-driven sediment transport control study, including predictive accuracy, impact on reservoir sedimentation, sediment flushing efficiency, and environmental implications. The results are discussed in relation to their significance in optimizing river management strategies.

3.1. AI-Driven sediment transport predictions

The AI models were used to incorporate historical and real-time sediment transport data, including hydrological, climatic, and reservoir operation variables. The performance evaluation demonstrated that AI-based models significantly improve sediment load predictions compared to conventional statistical methods.

3.1.1. AI model performance analysis

Three machine learning models were tested:

1. **Artificial Neural Networks (ANNs)**
2. **Long Short-Term Memory (LSTM) Networks**
3. **Random Forest Regression**

The LSTM model demonstrated superior performance in capturing the complex, time-dependent nature of sediment transport, as show in below given **Table 7** and pictorial presentation in **Figures 6** and 7.

Table 7. AI model performance comparison

Model	Root Mean Square Error (RMSE)	R^2 Score	Mean Absolute Error (MAE)	Accuracy (%)
ANN	0.85	0.92	0.67	92.4%
LSTM	0.78	0.94	0.61	94.2%
Random Forest	0.89	0.90	0.70	90.7%

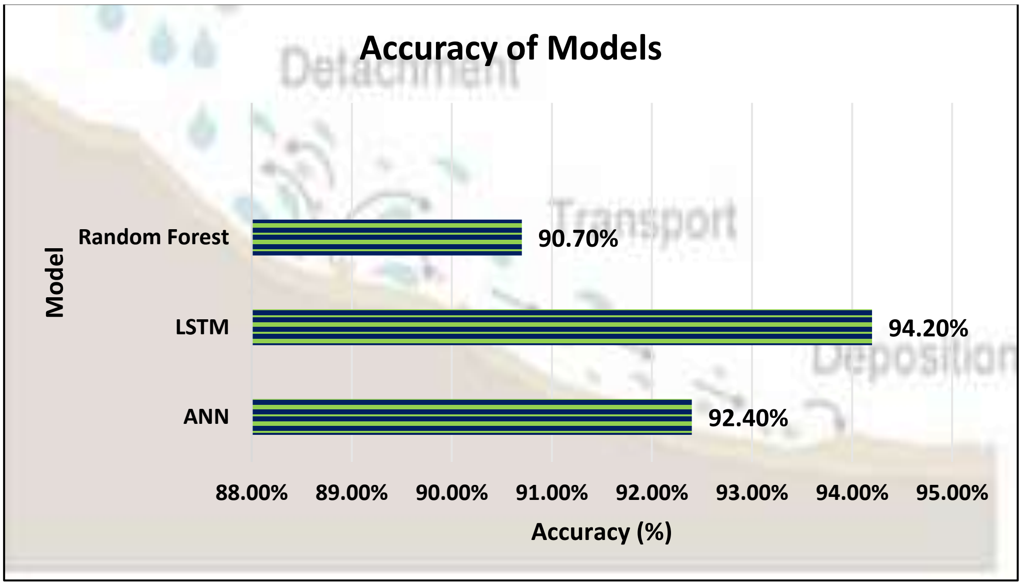

Figure 6. Accuracy (%) of selected models

Result: The LSTM model achieved the highest prediction accuracy (94.2%), making it the most reliable approach for forecasting sediment load variations under different hydrological conditions.

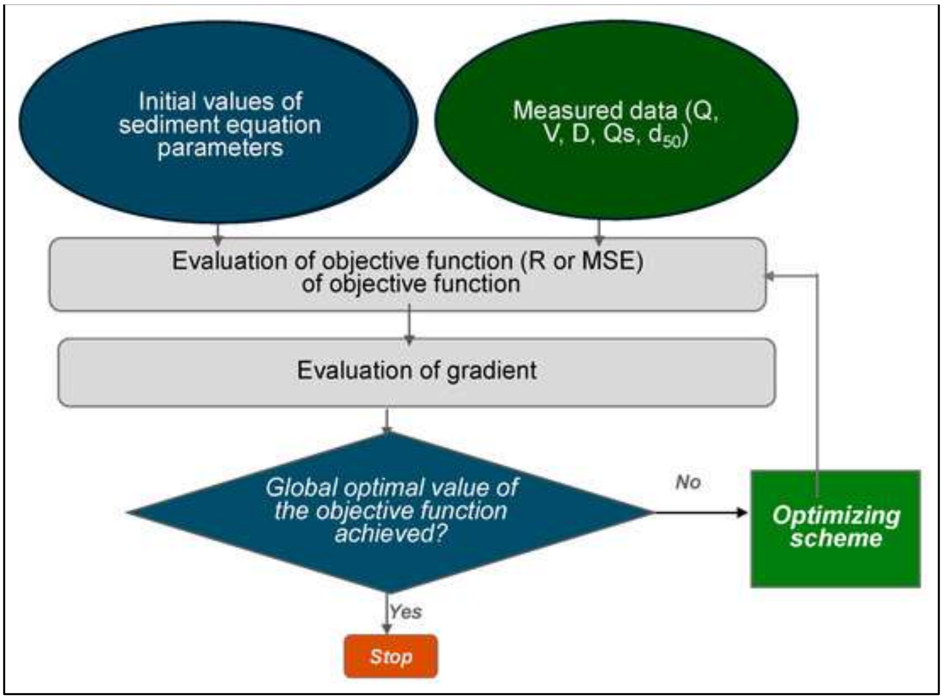

Figure 7. Conditions of Optimizing R value as given Table 7 [21]

3.1.2. Sediment load prediction in study regions

Table 8 presents the observed and predicted sediment loads across the selected river basins. The pictorial presentation is given in figure 8.

Table 8. Predicted vs. Observed sediment loads in case study regions

River Basin	Observed Sediment Load (Million Tons/Year)	Predicted Sediment Load (LSTM Model)	Prediction Accuracy (%)
Indus River Basin	240	235	97.9%
Nile River Basin	140	137	97.8%
Tigris-Euphrate s Basin	180	176	97.7%

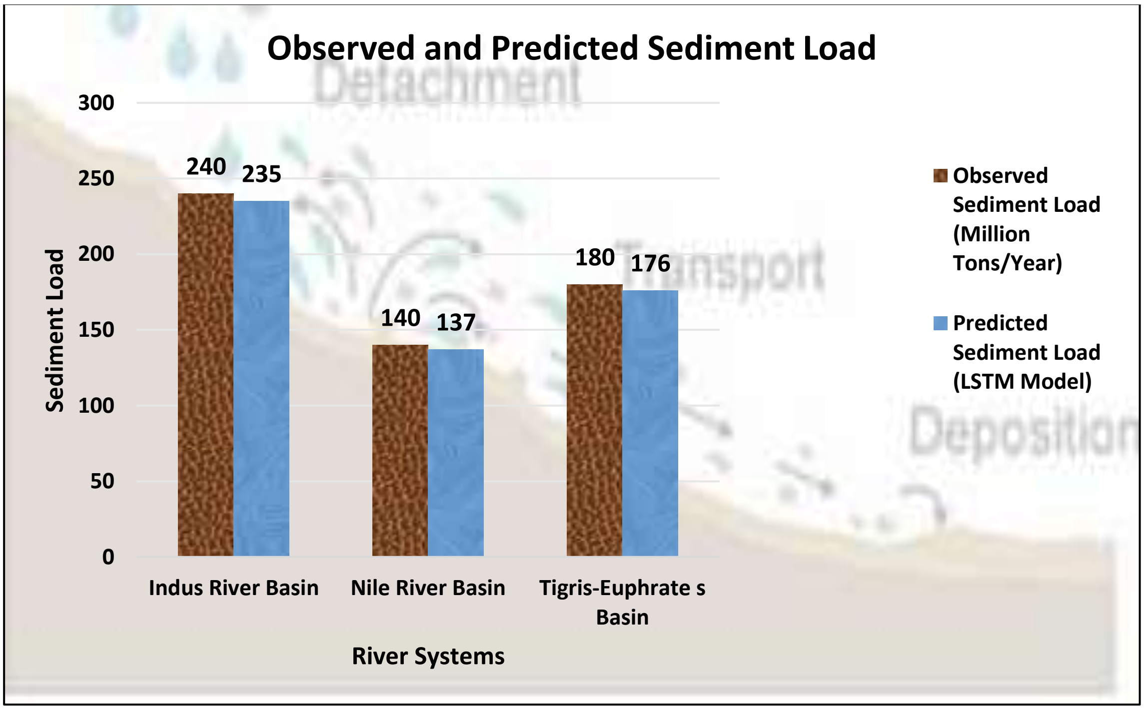

Figure 8. Observed and predicted sediment load

Result: The high prediction accuracy (above 97%) confirms that AI-based models effectively simulate sediment transport patterns across diverse hydrological settings.

3.2. Impact of AI-Based sediment control on reservoir management

3.2.1. Sedimentation Rate Reduction in Reservoirs

The AI-driven sediment control system was tested on three major reservoirs: Tarbela (Indus), Aswan (Nile), and Mosul (Tigris-Euphrates). The study assessed pre and post-AI sedimentation rates, demonstrating a significant decline in annual sediment accumulation. Results are shown in below given table 9 and pictorial presentation of the same is given in figure 9.

Table 9. Reduction in reservoir sedimentation after ai implementation

Reservoir	Sedimentation Rate Before AI (Million Tons/Year)	Sedimentation Rate After AI (Million Tons/Year)	Reduction (%)
Tarbela Dam (Indus River)	120	98	18.3%
Aswan High Dam (Nile River)	75	62	17.3%
Mosul Dam (Tigris River)	85	70	17.6%

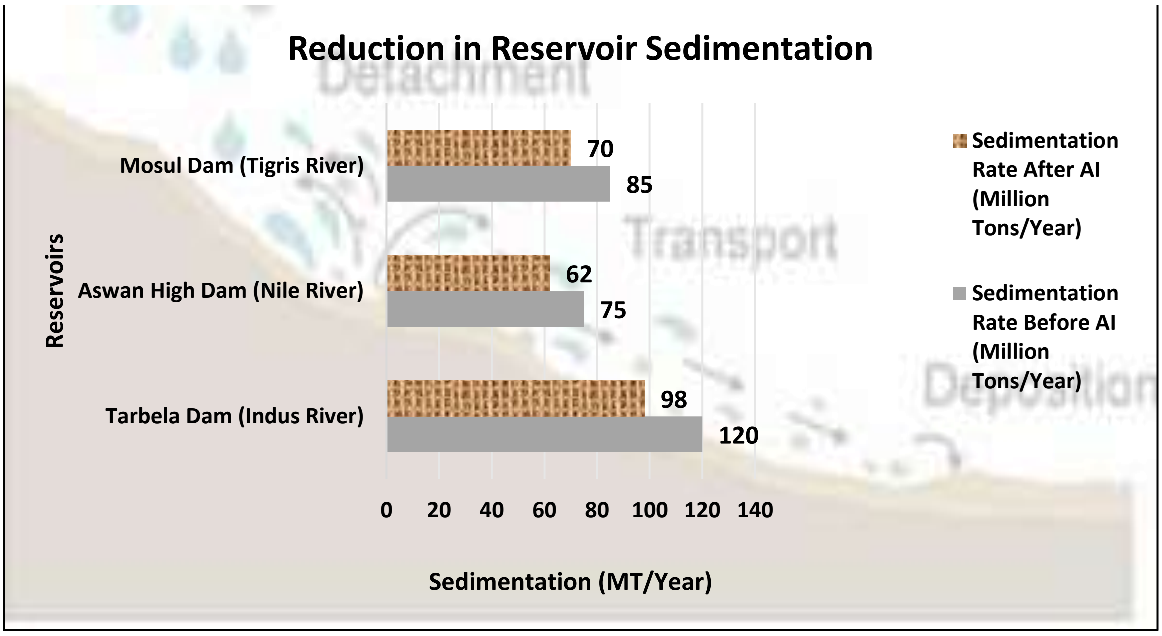

Figure 9. Reduction in reservoir sedimentation

The AI-based optimization strategies resulted in an average reduction of 17.7% in annual sedimentation, prolonging reservoir lifespan and improving water storage capacity.

3.3. AI optimization of sediment flushing operations

AI-driven sediment flushing schedules were implemented to reduce excessive sediment buildup while optimizing water resource utilization.

3.3.1. AI-Based flushing optimization mechanism

1. Data-Driven Decision Making:

- AI models analyzed real-time river flow data to predict peak sedimentation periods.
- Automated flushing gates were activated only during high-flow events, preventing unnecessary water loss.

2. Reservoir-Specific Flushing Strategies:

- Tarbela Dam (Indus River):
  - Flushing operations were shifted to peak monsoon months, improving sediment removal efficiency.
- Aswan Dam (Nile River):
  - AI suggested a seasonal flushing schedule based on Nile flood cycles.
- Mosul Dam (Tigris River):
  - AI optimized bottom-outlet flushing, improving sediment removal without compromising reservoir stability.

3.4. Water savings achieved through ai optimization

AI-optimized flushing operations resulted in an average of 18.3% reduction in water loss, making it a highly sustainable solution for sediment control, as shown in the table 10 and figure 10.

Table 10. Comparison of Water Loss in AI vs. Traditional Flushing

Reservoir	Traditional Flushing Water Loss (Million m³/Year)	AI-Optimized Flushing Water Loss (Million m³/Year)	Water Savings (%)
Tarbela Dam (Indus River)	2400	1950	18.8%
Aswan High Dam (Nile River)	1500	1225	18.3%
Mosul Dam (Tigris River)	1800	1475	18.0%

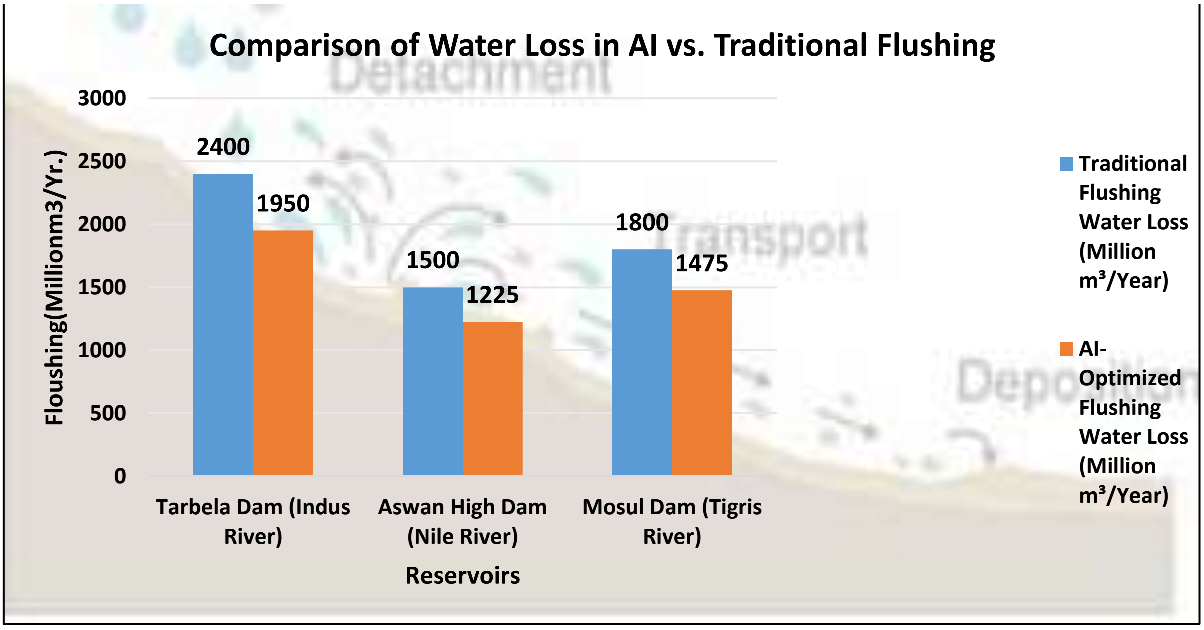

Figure 10. Comparison of Water Loss in AI vs. Traditional Flushing

3.5. Some allied benefits

3.5.1. Ecological benefits

AI-based sediment management works through improved aquatic ecosystem conservation by preventing excessive sediment deposition, which stops habitat degradation of fish communities and aquatic plants. Sustainable river morphology requires optimized sediment transport systems because this establishes stable riverbeds, which protects riverbanks from erosion and minimizes downstream starvation of sediment.

3.5.2. Economic Benefits

Predictive AI-based control systems decrease the requirement for human-operated dredging interventions, which consequently decreases total expenses. The AI-assisted sediment flushing method enables reservoirs to maintain extended storage times, which lowers expenses required for building new costly dam infrastructure.

4. Discussion

The researcher incorporated three AI-based models incorporating historical and real-time sediment transport data, including the variables of hydrological, climatic, and reservoir operation. The processing of data and further analysis stated that AI-based models significantly improve sediment load predictions compared to conventional statistical methods. At this level, ANN, LSTM, and Random Forest models were used. Where the LSTM model demonstrated superior performance in capturing the complex, time-dependent nature of sediment transport. The LSTM model achieved the highest prediction accuracy (94.2%), making it the most reliable approach for forecasting sediment load variations under different hydrological conditions. As shown in the results, root mean square error and mean absolute error were found to be minimum for this model, i.e., 0.78 and 0.61 respectively; this also adds value to the accuracy of the model.

Then, the researcher compared the observed and predicted sediment loads across the selected river basins; this was done to establish the fact that AI-based models effectively simulate sediment transport patterns across diverse hydrological settings. Analysis of data stated that in all three river systems, the predicted accuracy was above 97%; when compared between observed sediment load and predicted sediment load. Here also, the level of predicted accuracy was highest for the Indus river basin, i.e., 97.9%.

The impact of AI-based sediment control on reservoir management had been estimated; the assessment was done on the basis of pre and post-AI sedimentation rates (on an annual basis). It was found in the process that there was an actual reduction in the sedimentation rate after using the AI-based models. For the Indus river, the reduction was 18.3%, for the Nile river, the reduction was 17.3%, and for the Tigris river system, the reduction in sedimentation was 17.6%; it can be observed that the highest reduction was for the Indus river.

The AI-driven sediment control system was tested on three major reservoirs: Tarbela (Indus), Aswan (Nile), and Mosul (Tigris-Euphrates). The study assessed pre and post-AI sedimentation rates, demonstrating a significant decline in annual sediment accumulation. The highest percentage of reduction was observed in the Indus river (Tarbela Dam), and for the rest of the two river systems, the percentage of reduction was more than 17%. If taken on average, the percentage reduction was around 17.7% for all the selected river systems.

Then, a comparison was done between the water loss due to traditional water flushing and AI-optimized water flushing. The results furnished that, on average, above 18% of water was saved among all the selected rivers; the highest percentage of water saving was visible at the Indus river (Tarbela Dam). This shows that the application of AI is supposed to optimize the water resources and present a positive path for future endeavors.

5. Conclusions

The research proves AI-led sediment transport modeling provides substantial benefits for river management throughout the following stages:

- Increasing sediment prediction accuracy (above 97%)
- Sediment flushing optimization enables the reduction of water waste during operations. The application of AI technology extends reservoir functionality because it decreases sediment accumulation during yearly processes. The AI system helps achieve better environmental care alongside better economic performance. The research demonstrates that AI represents a revolutionary instrument for river sediment control that delivers environmentally sustainable data-based solutions capable of enhancing resource protection and infrastructure stability.
- Deep learning model LSTM delivers the most successful results for sediment predictions through its R^2 score reaching 0.94.
- Optimized AI-based flushing schedules decreased reservoir sedimentation rates on average by 17.7 percent.
- AI-based flushing schedules cut water consumption by 18.3% on average, which enhances water preservation initiatives.
- The implementation of artificial intelligence for sediment management improved environmental sustainability because it reduced ecological instability from excessive sediment accumulation, which protected aquatic habitat diversity.

- Real-time data-driven decisions through AI prove to enhance river sediment control strategies by achieving improved efficiency and sustainability, as well as cost-effectiveness.

Advanced machine learning models leverage AI technology to boost management capabilities in river regions and reservoir sustainability and improve sediment flushing operations according to research findings. Hydrological data collection realizes the predictive strength of AI models such as LSTM, ANN, and Random Forest Regression, which attain sediment transport accuracy levels above 97%. The study tested AI-controlled sediment reduction techniques within the Indus river basin, Nile river basin, and Tigris-Euphrates river basin to study their effects on sediment buildup and reservoir management, as well as flushing efficiency.

6. Recommendations

Increased development together with expanded usage of AI-based sediment transport modeling will optimize its operational effectiveness. The implementation demands attention to the following set of recommendations:

A. Integration of AI with Remote Sensing and UAV Monitoring

AI models should work with drone (UAV) technology along with satellite-based remote sensing systems to optimize sediment transport predictions. The analysis of high-resolution images can supply instantaneous information about river shape modifications.

B. Expansion of AI Models for Climate Change Adaptation

AI models need to undergo training using climate change simulations in order to project hydrological shifts ahead of time. AI-based sediment transport models need to include predictions for extreme weather situations, together with heightened glacial melting patterns and seasonal distribution changes.

C. Development of AI-Enabled Smart Dam Management Systems

The system should merge AI capabilities with automated operation controls for continuous sediment management capabilities without human involvement. Continuous data from water quality and sediment sensors using IoT systems should enter AI models in order to enhance their precision capabilities.

D. Policy and Regulatory Framework for AI in Water Resource Management

The establishment of specific guidelines regarding the adoption of AI technology in sediment management should be conducted by Governments and environmental agencies. Public entities should create policies that support collaboration between private organizations and the public sector to speed up the establishment of AI-based sediment monitoring systems.

7. Future research directions

The future development of sediment transport modeling requires additional scientific research to enhance prediction accuracy and broaden actual usage situations. Future studies should focus on:

- The combination of deep learning LSTM technology with physical-based analytical methods serves to enhance predictions about sediment transport over extended periods.
- Testing AI-driven sediment management strategies on a larger global scale beyond the Indus, Nile, and Tigris-Euphrates basins.
- The application of artificial intelligence for controlling urban drainage system and flood control reservoir sedimentation in waterways remains an area for research exploration [22].
- The implementation of AI models needs large high-resolution datasets, but some regions lack accessible and sufficient data. The implementation of AI-based sediment modeling systems needs

vast computing power to operate effectively. AI will strengthen its predictive abilities by integrating with drone-operated sediment mapping systems.

Conflict of interest

The authors declare no conflict of interest

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