

## Article

# Incorporating Sediment Compaction into Reservoir Sedimentation Estimates Using Machine Learning: Case Study of the Xiluodu Reservoir

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## Abstract

Hydropower is a cornerstone of global renewable energy; however, reservoir sedimentation directly undermines its benefits and operational lifespan. A critical, often overlooked, aspect of sedimentation is the compaction of fine-grained deposits, which introduces systematic discrepancies between standard siltation calculation methods. This study addresses this gap by developing a machine learning-based model to quantify sediment compaction and correct siltation estimates using the Xiluodu Hydropower Station on the Jinsha River, China, as a case study from 2014 to 2020. Based on hydrological, sediment, and fixed-section monitoring data, we applied five machine learning algorithms (Linear Regression, Neural Network, Random Forest, Gradient Boosting, and Support Vector Regression) to establish a relationship between the compaction thickness and the following key predictors: Year, Cumulative Sediment Thickness, Annual Sediment Thickness, and Distance to the Dam. The results demonstrate that the Neural Network (NN) model significantly outperforms traditional models, effectively capturing complex, nonlinear compaction dynamics with strong predictive accuracy (test  $R^2 = 0.766$ ,  $RMSE = 0.047$  m) and no significant overfitting. SHAP analysis revealed the dominant influences of consolidation time (years) and overburden stress (Cumulative Sediment Thickness), linking the model's predictions to fundamental geotechnical principles. Applying the NN model to correct for the cross-sectional volume method markedly improved its consistency with the independent sediment transport method, reducing the average relative difference from  $-33.7\%$  to  $-6.5\%$  (2016–2020). This study provides the first quantitative, continuous (198 km, 221 sections) assessment of reservoir-scale sediment compaction, confirming its widespread existence and demonstrating its critical role in the long-standing methodological discrepancies. Our study transformed compaction from an acknowledged phenomenon into a quantifiable correction, offering a novel, data-driven framework to enhance the accuracy of reservoir sedimentation assessments globally.



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**Keywords:** sediment siltation; sediment compaction; machine learning; Xiluodu Hydropower Station; siltation calculation correction; reservoir sedimentation; SHAP analysis

## 1. Introduction

Hydropower is a vital global renewable energy source that contributes approximately 16% of the world's electricity and plays a key role in the low-carbon transition of energy

systems [1,2]. Its strategic importance is underscored by its stable power supply and adaptability to grid requirements [3]. China, which accounts for 57% of the global hydropower capacity, hosts the world's largest clean energy corridor in the upper reaches of the Yangtze River, a cascade of six large reservoirs [4,5].

However, reservoir impoundment fundamentally alters river hydraulics, leading to substantial sediment deposition in the backwater area [6]. This continuous siltation encroaches upon flood control capacity, reduces regulation ability for power generation and water supply, and can hinder navigation, ultimately constraining comprehensive benefits and shortening a reservoir's designed lifespan [6,7]. This challenge is particularly acute in sediment-laden rivers like the lower Jinsha River, where the Xiluodu Reservoir is located [8,9]. Monitoring data from 2013 to 2020 indicates that cumulative siltation in the Xiluodu Reservoir reached 717 million tons, with the annual siltation rate increasing approximately sevenfold post-impoundment [10]. By 2020, it accounted for 92.5% of the total siltation in the four cascade reservoirs of the lower Jinsha River, while its average sediment discharge ratio was a mere 3.3%, far below design expectations [8,10]. This combination of high siltation intensity and low sediment throughput makes the Xiluodu Reservoir an ideal natural laboratory for studying sediment compaction, as the rapid accumulation of thick deposits amplifies the compaction signal, making it detectable within a relatively short monitoring period [8–10].

The accurate quantification of reservoir sedimentation is fundamental for scientific water-sediment regulation and sustainable reservoir management [11,12]. The two most widely used methods for this purpose are the cross-sectional volume and sediment transport method [13,14]. The volume method, which is based on periodic topographic surveys, provides the spatial distribution of siltation. The sediment transport method, which is based on the mass conservation of influx and outflux, estimates the total amount of trapped sediment. These methods have been applied globally from the Three Gorges Reservoir (Yangtze River) [15,16] to the Itaipu Dam (South America) [17] and the Xiaolangdi Reservoir (Yellow River) [18]. However, a persistent and well-documented challenge is the systematic discrepancy between the results obtained from these two independent methods, which has long been a concern in academia and engineering practice [19,20].

A primary, yet often unquantified, cause of this discrepancy is the compaction of newly deposited fine-grained sediment [18–21]. As the sediment accumulates, the increasing weight of overburden compresses the underlying layers, expels the pore water and reduces the volume. This process is well-documented in multi-sediment reservoirs like Xiaolangdi and Sanmenxia on the Yellow River, where consolidation of deposits leads to surface subsidence [18,22]. In the Three Gorges Reservoir, this compaction has even been misinterpreted as “scouring” in areas of high siltation intensity [23,24]. Ignoring compaction means the volume method measures only geometric change, systematically overestimates the mass of retained sediment when using a constant dry bulk density for conversion. This directly contributes to its divergence from the sediment transport method [19,25].

The existing quantitative studies on reservoir sediment compaction fall into two main categories. The first comprises empirical or semi-empirical formulas derived from controlled laboratory experiments that fit the time-dependent density evolution [26] or model bed-level rise using rheological approaches [27]. The second is based on the self-weight consolidation theory of soft soils, which provides a general physical framework for the process [28]. More recently, hybrid experimental–numerical approaches have been developed to directly quantify compaction from bathymetric surveys [29].

Despite these valuable contributions, existing models face three common limitations when applied to large reservoirs under routine monitoring: (1) their input variables (e.g.,

effective stress, permeability) are difficult to obtain regularly across an entire reservoir, relying on site-specific lab calibration; (2) their outputs (e.g., density profiles) are not directly compatible with the conventional siltation calculation workflow, hindering practical correction; and (3) they are typically developed for local reaches, lacking a quantitative depiction of longitudinal heterogeneity in compaction along the entire reservoir [24,26–28].

To overcome these limitations, this study proposes a novel, data-driven modeling framework based on machine learning. The innovative contributions of this study are threefold:

- **Practical Feature Engineering:** It is the first to use routinely measured cumulative Sediment Thickness, Annual Sediment Thickness, and Distance to the Dam as core predictors for compaction, directly exploiting standard fixed-section surveys without requiring additional, complex geotechnical tests.
- **Direct Integration into Engineering Practice:** The output-cross-sectional compaction thickness of the model can be directly inserted into the standard volumetric formula. This bridges the gap between the research on compaction mechanism and operational siltation correction.
- **Whole-Reservoir Spatial Quantification:** For the first time, continuous, year-by-year compaction amounts were back-analyzed at the whole-reservoir scale (198 km, 221 sections, 2014–2020), quantitatively revealing that compaction intensity decays with increasing distance from the dam and grows with cumulative sediment thickness. This study provides the first spatially explicit picture of reservoir-scale sediment compaction.

## 2. Materials and Methods

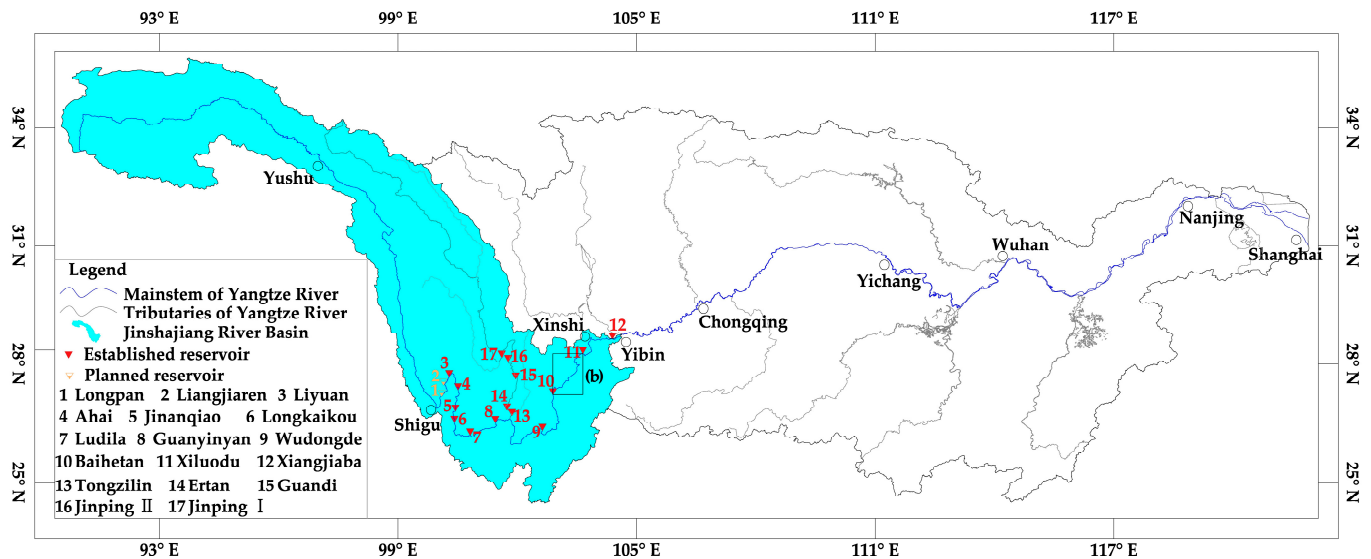
### 2.1. Study Area and Its Suitability for Compaction Research

The Xiluodu Hydropower Station is the third cascade in the development of the lower Jinsha River (Figure 1). It controls a drainage area of 454,400 km<sup>2</sup>, which is approximately 96% of that of the Jinsha River basin. The reservoir has a total storage capacity of 12.67 billion m<sup>3</sup> and a regulating storage of 6.46 billion m<sup>3</sup> [29]. Impoundment began in May 2013, and during the study period (2014–2020), the reservoir level was maintained near the normal pool level of 600 m.

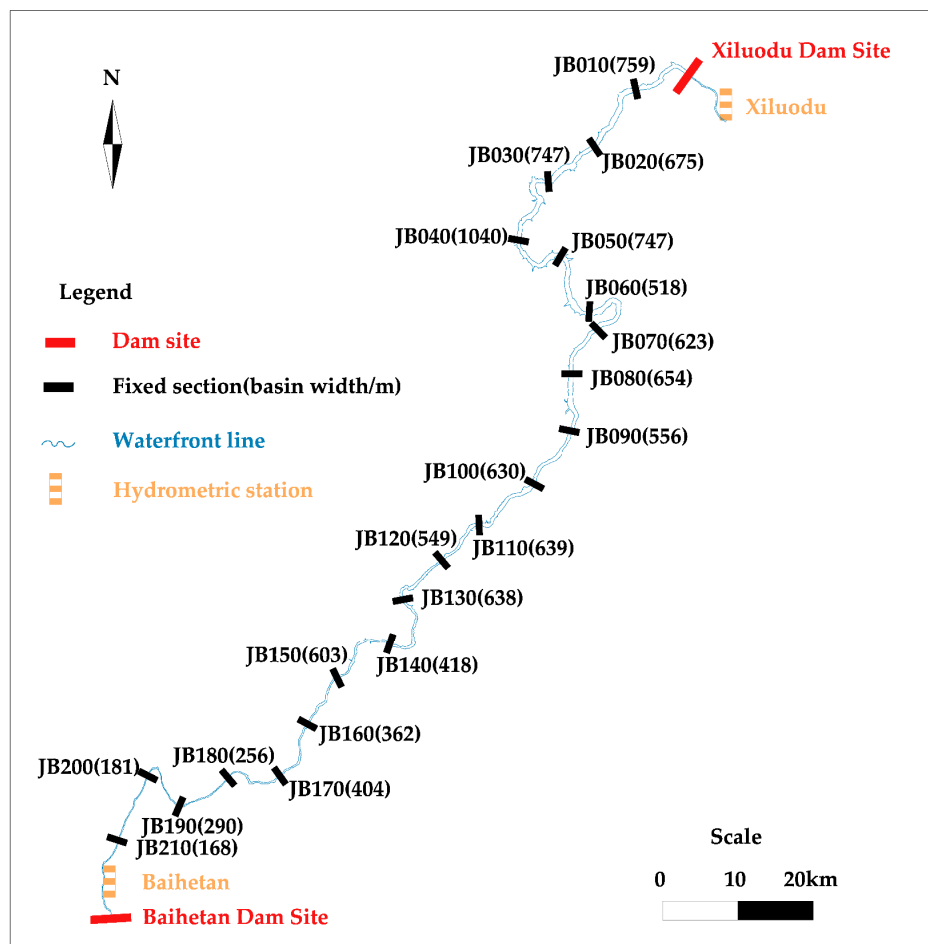
The Xiluodu Reservoir was selected as the study area because its unique combination of geological and hydrological characteristics makes it an exceptional natural laboratory for investigating sediment compaction [8,10,30].

#### 2.1.1. High Siltation Intensity and Low Sediment Throughput

The lower Jinsha River is known for its high sediment yield and complex sediment sources, which include highly erodible red beds and steep mountainous catchments [8,9]. Post-impoundment data show that cumulative siltation reached 717 million tons from 2013 to 2020, with annual siltation rates increasing approximately sevenfold compared to pre-impoundment levels [10]. Critically, the annual average sediment discharge ratio during this period was only 3.3%, which was far below pre-design expectations [10]. This combination of high siltation intensity and low sediment throughput means that the reservoir retains most of the incoming sediment, allowing compaction processes to operate on thick, rapidly accumulating depositional conditions that amplify compaction signals and make them detectable within a relatively short monitoring period [8,10].



(a)



(b)

**Figure 1.** Study area: (a) drainage areas of the Yangtze River; (b) mainstream channel of Xiluodu.

### 2.1.2. Geological and Geomorphological Attributes Conducive to Compaction Studies

The Xiluodu Reservoir exhibits several features that are particularly favorable for isolating and studying the compaction signal:

1. **Deep Canyon Morphology with Stable Confinement:** The reservoir is impounded within a deep, narrow canyon carved into the highly resistant Emeishan basalts [30–32]. The steep, massive valley walls provide rigid lateral confinement, ensuring that compaction was predominantly vertically aligned with the direction of gravitational loading. This simplifies the interpretation of elevation changes and strengthens the physical basis of the one-dimensional compaction thickness formula used in this study (Equation (4)).
2. **Competent Bedrock with Minimal Deformation:** The dam foundation and reservoir banks were composed of dense, low-permeability basalt with excellent mechanical properties [31,32]. Monitoring data confirm that reservoir-induced deformation of the bedrock (e.g., valley rebound or settlement) is negligible compared to the compaction signal [8,32]. This geological stability eliminates a potential confounding factor: changes in bed elevation can be attributed almost entirely to sediment processes rather than to deformation of the reservoir floor itself.
3. **Long, Narrow Geometry with Dense Monitoring Network:** With a mainstream back-water length of approximately 198 km and 221 fixed measurement sections, the reservoir provides an exceptionally dense spatial sampling framework for investigating how compaction varies with distance from the dam [30,32]. The longitudinal gradient in hydraulic conditions—from deep, low-velocity reaches near the dam to shallower, higher-velocity reaches upstream—creates systematic variations in sediment deposition patterns and bed material characteristics, allowing the model to learn the relationship between compaction and spatial position.

## 2.2. Data Collection and Processing

### 2.2.1. Data Sources and Institutional Provenance

All primary data used in this study were obtained from authorized hydrological and surveying institutions operating under the Changjiang Water Resources Commission (CWRC), Ministry of Water Resources, China. The specific sources are as follows:

1. **Fixed cross-section survey data (2014–2020):** Collected and provided by the Upper Changjiang River Bureau of Hydrological and Water Resources Survey (a direct subordinate institution of the CWRC Hydrological Bureau), headquartered in Chongqing, China. The surveys were conducted as part of the official reservoir sedimentation monitoring program, following industry standards (SL 257-2017) [33]. The data include pre-flood and post-flood surveys at 221 fixed sections along the 198 km mainstream of the Xiluodu Reservoir (Figure 1b).
2. **The bed material particle size distribution and dry bulk density data:** Collected during post-flood campaigns by the same bureau. Particle size analyses were conducted using standard sieve and hydrometer methods in accordance with GB/T 50159-2015 [34].
3. **Daily water and sediment series data at Baihetan Station (2014–2020)** were provided by the Upper Changjiang River Bureau of Hydrological and Water Resources Survey, which operates and maintains the Baihetan Hydrological Station as a designated inflow control station for the Xiluodu Reservoir [8,9].
4. **Daily water and sediment series data at Xiluodu Station (2014–2020)** [8] were provided by PowerChina Chengdu Engineering Corporation Limited, which operates the Xiluodu Hydrological Station in collaboration with China Three Gorges Corporation. The station serves as the official outflow control station [8–10].

### 2.2.2. Data Availability

The datasets used in this study are not publicly available because of institutional data policies, national regulations concerning sensitive infrastructure information, and the

ongoing nature of monitoring programs. However, the data are available upon reasonable request from the corresponding author, subject to institutional approval and a formal data use agreement. Details of the data are shown in Table 1.

**Table 1.** Data used in the study.

| Data Type                                       | Years     | Measurement Frequency               | Data Source                                                                                                                         |
|-------------------------------------------------|-----------|-------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------|
| Fixed cross-section data                        | 2014–2020 | Pre-flood and post-flood, once each | Bureau of Upper Yangtze River Hydrology and Water Resources Survey, Hydrological Bureau of Yangtze River Water Resources Commission |
| Bed material particle size distribution data    | 2014–2020 | Post-flood                          |                                                                                                                                     |
| Deposit dry bulk density data                   | 2016–2020 | Post-flood                          |                                                                                                                                     |
| Baihetan Station water and sediment series data | 2014–2020 | Year-round                          |                                                                                                                                     |
| Xiluodu Station water and sediment series data  | 2014–2020 | Year-round                          | Power China Chengdu Engineering Corporation Limited                                                                                 |

### 2.2.3. Measurement Accuracy and Quality Control

The accuracy of fixed cross-section topographic surveys directly affects the calculation of siltation thickness and compaction amount. Surveys were conducted using single-beam or multi-beam echo sounders. Based on repeated measurements and comparison with control points, the vertical accuracy of the surveyed bed elevations is estimated to be  $\pm 0.15$ – $0.30$  m (95% confidence interval) under typical operating conditions [35,36]. For a typical cross-section with a width of 500 m, an elevation error of  $\pm 0.2$  m translates to an area uncertainty of approximately  $\pm 100$  m<sup>2</sup>, which propagates to a volume uncertainty on the order of  $\pm 1.0 \times 10^5$  m<sup>3</sup> per reach.

For suspended sediment concentration measurements, strict quality control procedures were followed in accordance with GB/T 50159-2015 [34]. Water samples were collected using automated pumping and manual depth-integrating samplers. Sampling verticals were positioned to capture full cross-sectional variability, and samples were analyzed in accredited laboratories using the filtration-drying-weighing method (oven-dried at 105 °C). Regular inter-laboratory comparisons and replicate analyses-maintained accuracy within  $\pm 5\%$  for individual concentration measurements [37]. These measures ensured that the daily suspended sediment data were of high quality and suitable for annual load calculations.

## 2.3. Reservoir Scour-Siltation Calculation Methods

### 2.3.1. Sediment Transport Method

Based on mass conservation, the net scour-siltation amount was calculated as the difference between incoming and outgoing sediment loads during a period [38] as follows:

$$\Delta W = W_{MI} + W_{TI} - W_{MO} - W_{TO} \quad (1)$$

where  $\Delta W$  is the sediment erosion/deposition volume in the reservoir area during the calculation period (tons, deposition positive);  $W_{MI}$  is the sediment load at the main stream inflow control station (Baihetan Station) during the calculation period;  $W_{TI}$  is the sediment inflow from the reservoir area interval (between the main stream inflow station and the dam site). The interval inflow sediment in this study is relatively small and thus ignored;  $W_{MO}$  is the sediment load at the main stream outflow control station (Xiluodu Station) during the calculation period (tons);  $W_{TO}$  is the sediment distribution within the reservoir area intervals.

### 2.3.2. Cross-Sectional Volume Method

The sediment transport method yields weight, whereas the volume method yields the volume. Conversion uses the dry bulk density of deposits [39]:

$$V = \sum_{i=1}^{n-1} \frac{1}{3} (A_i + A_{i+1} + \sqrt{A_i \cdot A_{i+1}}) \Delta L_i \quad (2)$$

where  $V$  is the sediment erosion/deposition volume in the reservoir area during the calculation period ( $\text{m}^3$ , deposition positive);  $n$  is the total number of fixed cross-sections;  $A_i$ ,  $A_{i+1}$  are the measured cross-sectional areas ( $\text{m}^2$ ) of the  $i$ -th and  $i + 1$ -th cross-sections at the beginning and end of the period, respectively;  $\Delta L_i$  is the distance (m) between the  $i$ -th and  $i + 1$ -th cross-sections.

### 2.3.3. Conversion Between Mass and Volume

To compare the two methods, volume was converted to mass using the dry bulk density of deposits [40]:

$$W = \sum_{j=1}^m V_j \gamma_j \quad (3)$$

where  $W$  is the sediment erosion/deposition weight (tons);  $m$  is the number of river reaches divided for reservoir dry bulk density;  $V_j$  is the sediment erosion/deposition volume ( $\text{m}^3$ ) for the  $j$ -th reach;  $\gamma_j$  is the dry bulk density ( $\text{t}/\text{m}^3$ ) of the deposits in the  $j$ -th reach.

## 2.4. Identification and Quantification of Sediment Compaction

### 2.4.1. Identification of the Compaction Phenomenon

Analysis of fixed-section data revealed that in some sections, the post-flood bed elevation of the current year was lower than that of the previous year, despite the lack of evidence of scour. Figure 2 shows an example from section JB020, in which such a decrease was observed and interpreted as sediment compaction.

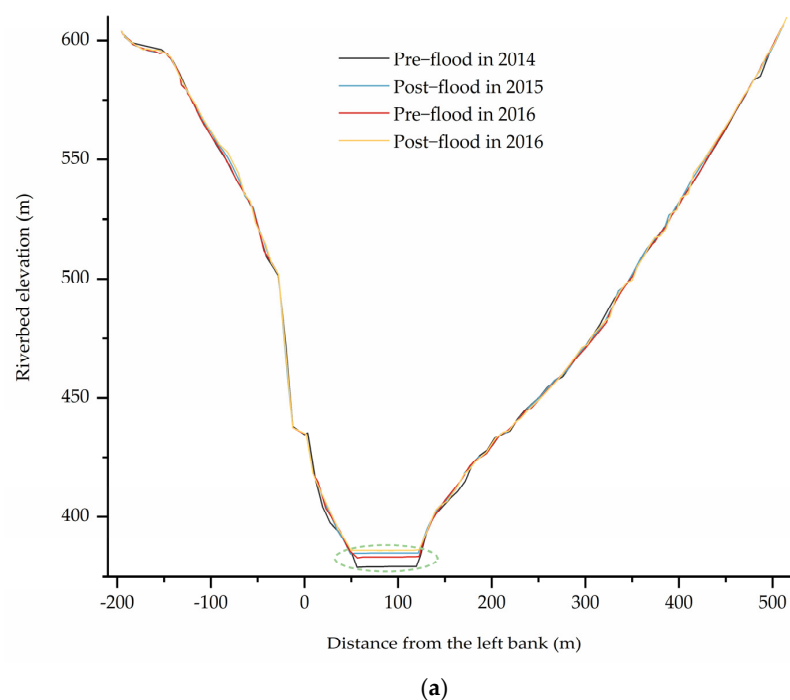


Figure 2. Cont.

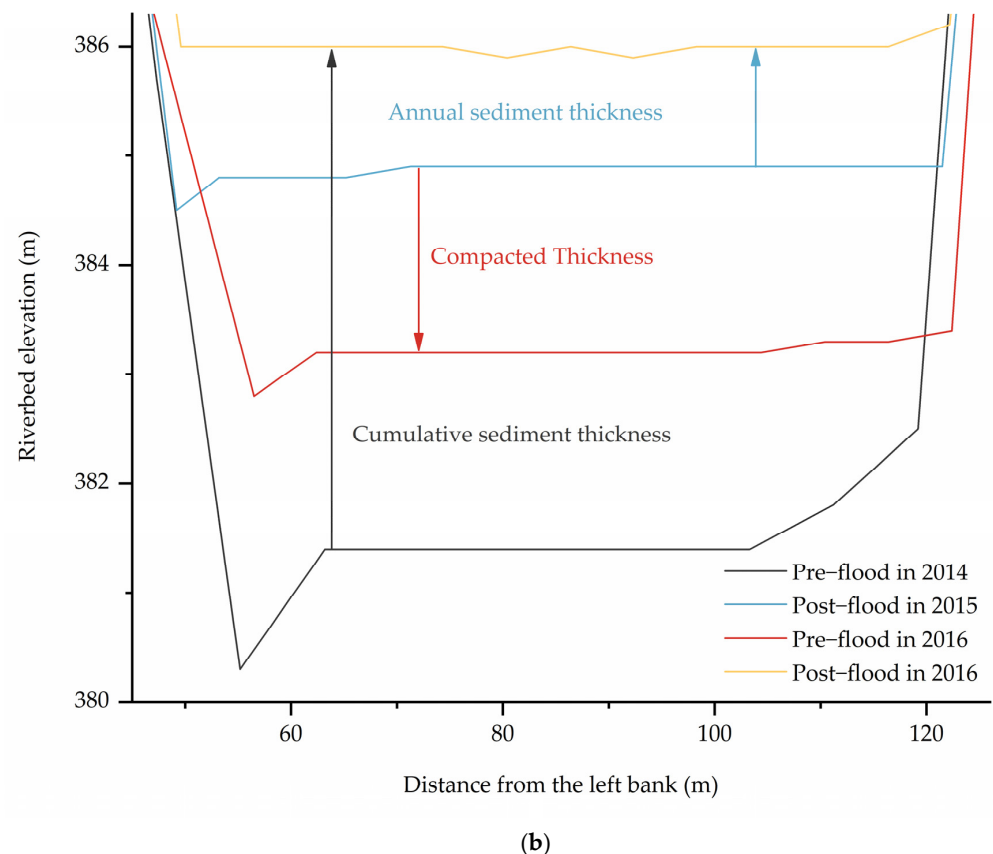


**Figure 2.** Cumulative siltation, 2016 siltation, and compaction at section JB020: (a) Overall picture; (b) Partial enlarged view of the area indicated by the dashed circle in (a). The reduction in bed elevation from post-flood 2015 to post-flood 2016, in the absence of intervening scour, indicates compaction of the 2015 deposit.

#### 2.4.2. Determination of Compaction Spatial Range

From 2014 to 2020, the Xiluodu Reservoir exhibited overall siltation, with a maximum siltation thickness of 37.1 m occurring in the middle reaches (Figure 3). Compaction was observed primarily in the fine-grained depositional zones. Figure 4 shows the longitudinal distribution of compaction thickness and corresponding sediment particle size in 2016. As the distance from the dam increased the channel narrows, flow velocity increased, bed material coarsened, and the compaction phenomenon gradually weakens until disappearing. Table 2 lists the annual upstream termination sections for compaction and the representative median particle sizes. The median particle size at the termination sections ranged from 0.013 mm to 0.090 mm, indicating that compaction mainly occurred in the fine-grained areas (silt and clay).

#### 2.4.3. Compaction Thickness and Volume Calculation

Siltation concentrates in the river thalweg. The siltation thickness and compaction thickness are calculated as follows:

$$\begin{cases} T_1 = H_2 - H_1 \\ T_2 = H_2 - H_3 \end{cases} \quad (4)$$

where  $T_1$  is the sediment siltation thickness in the thalweg,  $T_2$  is the sediment compaction thickness,  $H_2$  is the post-flood riverbed elevation in the current year,  $H_1$  is the pre-flood riverbed elevation in the current year, and  $H_3$  is the post-flood riverbed elevation of the previous year.

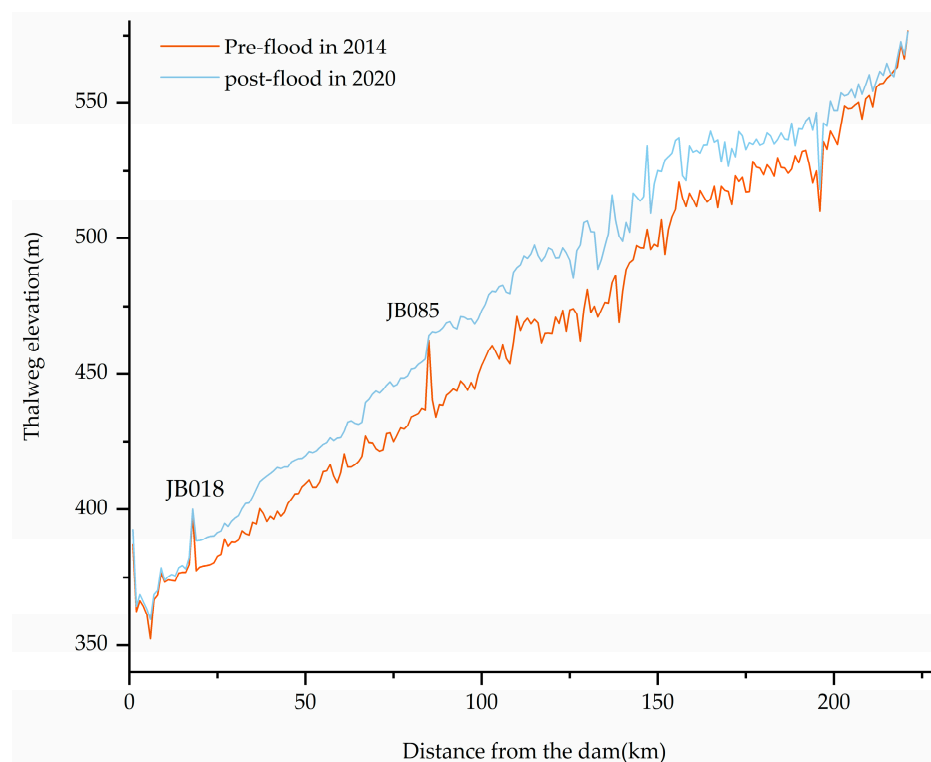


**Figure 3.** Longitudinal siltation profile of Xiluodu Reservoir, 2014–2020 (thalweg elevation change).

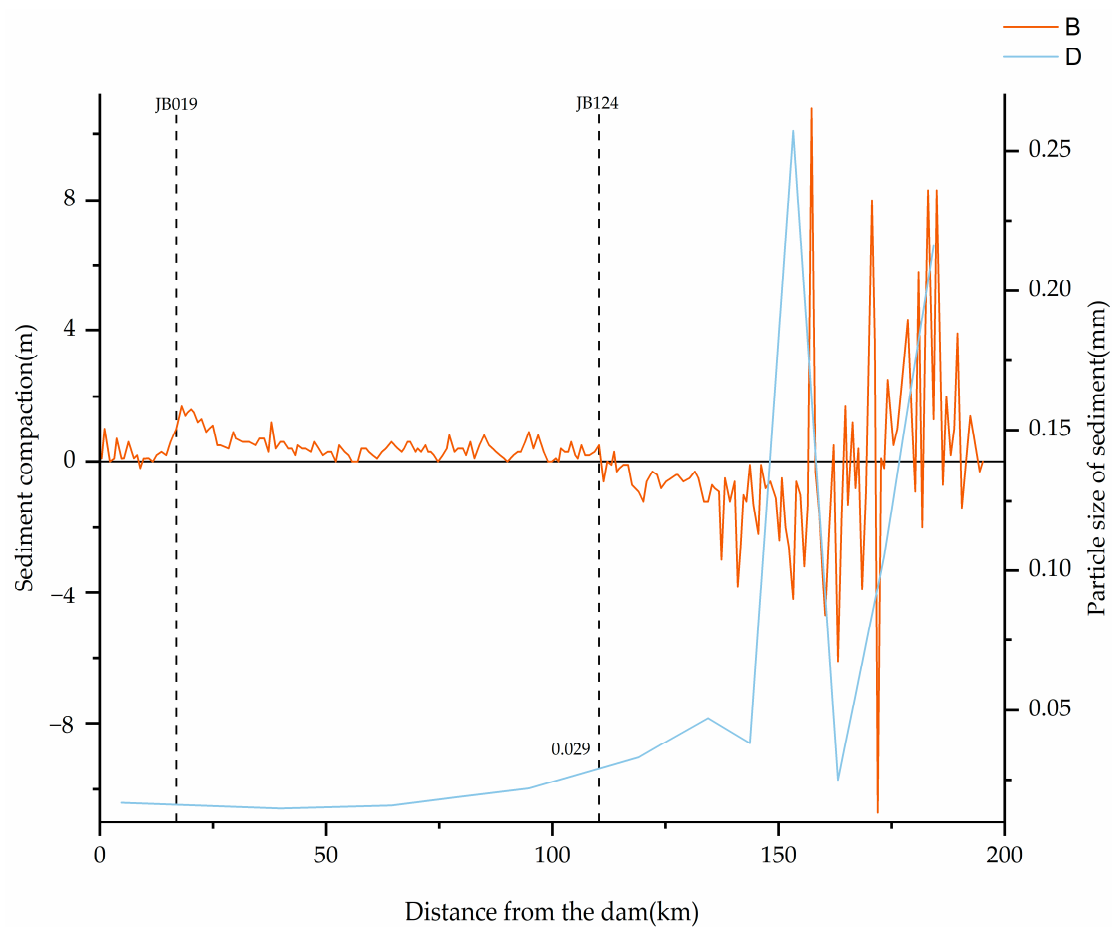


**Figure 4.** Sediment compaction situation in 2016.

**Table 2.** Annual compaction termination sections and bed material characteristics.

| Year                | 2014  | 2015  | 2016  | 2017  | 2018  | 2019  | 2020  |
|---------------------|-------|-------|-------|-------|-------|-------|-------|
| Termination Section | JB120 | JB134 | JB124 | JB124 | JB133 | JB141 | JB141 |
| Particle Size (mm)  | 0.041 | 0.013 | 0.041 | 0.029 | 0.034 | 0.090 | 0.035 |

The key assumption in Equation (4) is that a decrease in post-flood bed elevation from one year to the next, in the absence of net deposition, results from sediment compaction rather than from scour or other processes. We validate this assumption using three lines of evidence:

1. **Hydrological Evidence for Quiescent Post-Flood Conditions:** The Xiluodu Reservoir operates under a “storing clear water and releasing turbid flow” regulation scheme [8,9]. During the flood season (June–September), the pool level is lowered to facilitate sediment flushing. Following the flood season, the reservoir refills and maintains a high water level throughout the non-flood season (October–May). As shown in Figure 5, the daily average suspended sediment transport rate at the Baihetan inlet station drops to negligible levels immediately after the flood season (typically <0.1 t/s from October onward). Under these quiescent hydraulic conditions, the flow velocities are well below the threshold for sediment entrainment, rendering scour impossible [28,41].
2. **Cross-Sectional Stability During Post-Flood Periods:** We compared pre-flood and post-flood surveys from consecutive years. Analysis of all 221 fixed sections from 2014–2020 revealed that cross-sectional geometry remained essentially unchanged between consecutive post-flood and pre-flood surveys in reaches where no new deposition occurred. The mean absolute difference in bed elevation across all sections was less than 0.05 m, within the vertical measurement uncertainty ( $\pm 0.15$ – $0.30$  m). This stability confirms that the bed is not subject to erosion or large-scale morphological adjustment during the low-flow post-flood period.
3. **Exclusion of Reservoir Floor Deformation:** Reservoir floor deformation caused by tectonic activity or large-scale sediment sliding would manifest as systematic, spatially coherent changes in bed elevation across multiple sections [26]. No such patterns were observed. The elevation changes attributed to compaction are localized to depositional zones and exhibit magnitudes (0.1–1.7 m annually) consistent with geotechnical consolidation theory [28]. Furthermore, the strong correlation between compaction thickness and cumulative sediment thickness (Section 4.1) provides indirect evidence that the observed changes are physically linked to the sediment deposit itself.

The volume change due to compaction is calculated by applying the same volumetric principle to the compaction-induced area changes at each section:

$$\Delta V = \sum_{i=1}^{n-1} \frac{1}{3} \left( \Delta A_i + \Delta A_{i+1} + \sqrt{\Delta A_i \cdot \Delta A_{i+1}} \right) \Delta L_i \quad (5)$$

where  $\Delta V$  is the volume change ( $\text{m}^3$ ) due to compaction during the period;  $n$  is the total number of sections;  $\Delta A_i$  and  $\Delta A_{i+1}$  are the cross-sectional area changes ( $\text{m}^2$ ) due to compaction for sections  $i$  and  $i + 1$ , respectively.

The use of the one-dimensional cross-sectional volume method for compaction is justified by the predominantly vertical nature of consolidation in a confined canyon reservoir, the practical constraints of routine monitoring data, and the need for consistency with conventional siltation calculations [40]. While true three-dimensional variability exists, the method captures the essential volume change signal, as demonstrated by the successful correction of siltation discrepancies (Section 4.2).

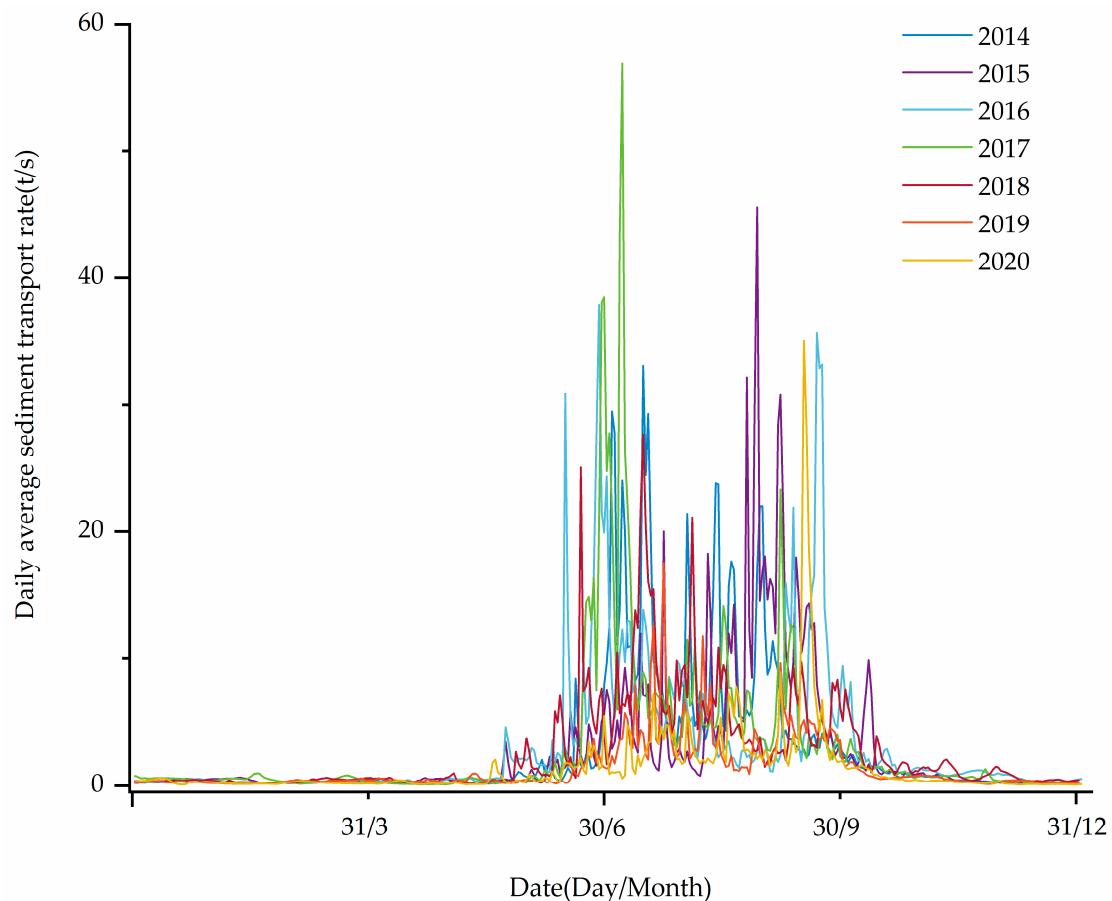


**Figure 5.** Average daily suspended sediment transport rate at Baihetan Hydrological Station from 2014 to 2020.

## 2.5. Machine Learning-Based Compaction Model

### 2.5.1. Overview

To predict compaction thickness across the entire reservoir, we developed a machine learning model using five algorithms: Linear Regression (LR), Neural Network (NN), Random Forest (RF), Gradient Boosting (GB), and Support Vector Regression (SVR) [42–46]. The technical roadmap is shown in Figure 6.

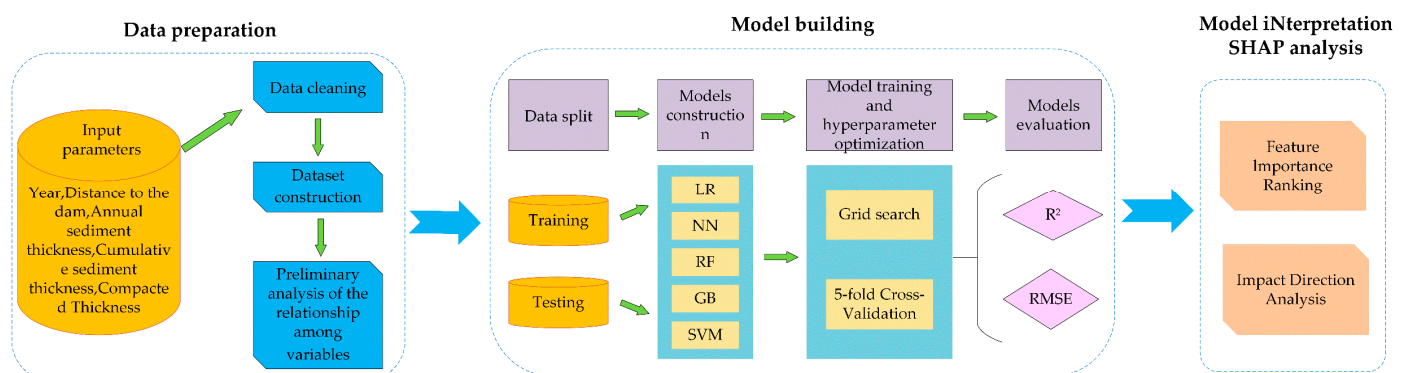


**Figure 6.** Machine learning modeling technical roadmap.

### 2.5.2. Feature Selection and Data Preparation

Within the determined annual compaction zones (Section 2.4.2), we compiled a dataset with compaction thickness as the target variable and the following features:

1. Year: Serves as a composite proxy for two interconnected physical processes: (1) consolidation time—the duration available for the sediment deposit to undergo self-weight consolidation and secondary compression; and (2) cumulative load history—each successive year adds new sediment on top of existing deposits, increasing overburden stress. These two aspects are inherently coupled in the field setting, and “Year” acts as an integrated temporal-mechanical indicator.
2. Cumulative Sediment Thickness (m): Represents the total thickness of sediment accumulated in a given section up to the current year. It is a direct proxy for the overburden stress driving consolidation.
3. Annual Sediment Thickness (m): Represents the thickness of sediment deposited in the current year. It captures the incremental load and reflects the magnitude of the flood event.
4. Distance to the Dam (km): Represents the longitudinal position along the reservoir. It serves as a proxy for hydrodynamic conditions (flow velocity, sediment transport capacity) and the resultant sediment characteristics (grain size distribution).

**Acknowledged Omission of Physical Properties:** Two physically significant variables—sediment particle size distribution and initial dry bulk density—were not included as input features. This exclusion was necessitated by fundamental technical constraints associated with deep reservoir sampling. The Xiluodu Reservoir has a maximum water depth of approximately 250 m in the near-dam reaches. Obtaining undisturbed sediment samples from such depths for particle size analysis and dry bulk density measurement presents extraordinary technical challenges [47–50]. As a result, the available measurements are spatially sparse, confined to a limited number of cross-sections (Table 1). This sparse sampling density is incompatible with our machine learning framework, which aims to continuously predict compaction thickness across all 221 sections. Including such variables would either restrict the model to a small subset or require interpolation that would introduce unacceptable uncertainty. Therefore, while fully recognizing their physical importance, we deliberately focused on features that are routinely and densely measured across the entire reservoir. Future research should prioritize the development of spatially extensive sampling campaigns to incorporate these properties.

**Data Screening and Sample Size:** The compaction thickness at each fixed cross-section is calculated according to Equation (4), and samples with negative compaction thickness are excluded. These negative or zero values do not represent the physical process of sediment compaction; they arise from either the absence of deposition (e.g., in zones upstream of the compaction termination section) or from survey noise where no compaction occurred [41,51]. Including them would introduce noise that obscures the true relationship. A total of 998 valid samples with positive compaction values were retained for model development, spanning the entire range of depositional environments and years.

Figure 7 shows the correlation heatmap between features and the target variable.

### 2.5.3. Hyperparameter Tuning and Model Evaluation

Eighty percent (80%) of the 998 samples were randomly selected as the training set and 20% as the test set. A grid search with 5-fold cross-validation of the training set was used to determine optimal hyperparameters. The configurations are listed in Table 3.

Model performance was evaluated using the coefficient of determination ( $R^2$ ), the root mean square error (RMSE), mean absolute error (MAE), and normalized RMSE ( $NRMSSE = RMSE/\text{range of observed values}$ ) [52,53]. Calculations were performed on both training and test sets to assess fit and generalization ability.

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y}_i)^2} \quad (6)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (7)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (8)$$

where  $N$  is the number of samples,  $y_i$  is the measured value,  $\hat{y}_i$  is the predicted value, and  $\bar{y}_i$  is the mean of measured values.

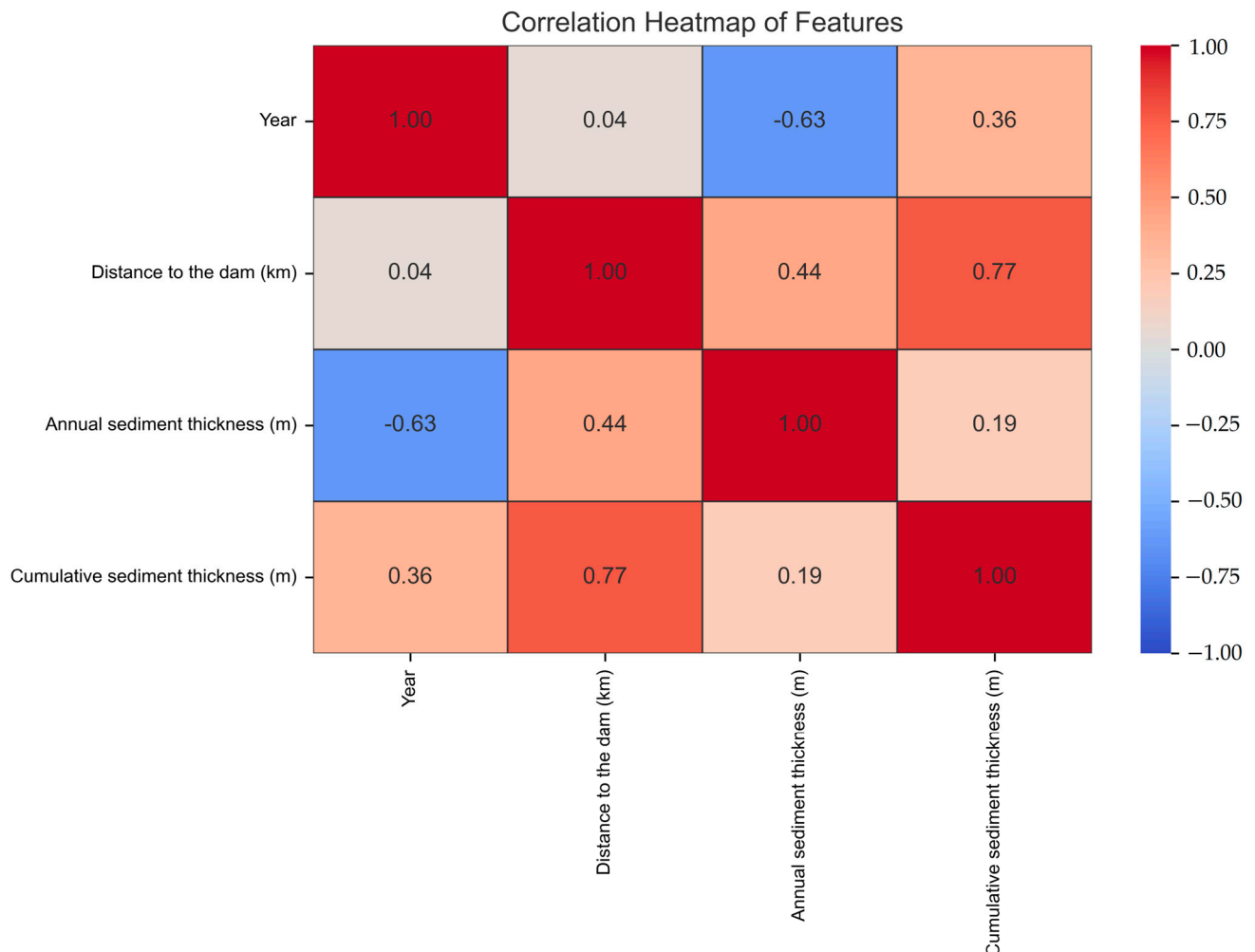


**Figure 7.** Correlation heatmap between numerical features and the target variable.

**Table 3.** Optimal hyperparameter configurations for each machine learning model.

| Model | Parameters                                                                                                                                                     |
|-------|----------------------------------------------------------------------------------------------------------------------------------------------------------------|
| LR    | Ordinary least squares, no regularization.                                                                                                                     |
| NN    | 3-layer fully connected network (3→16→8→1 neurons), ReLU activation, Adam optimizer, learning rate 0.001, batch size 32, max iterations 1000 (early stopping). |
| RF    | n_estimators = 100, max_depth = 10, min_samples_split = 2, min_samples_leaf = 1.                                                                               |
| GB    | n_estimators = 100, learning_rate = 0.1, max_depth = 8, subsample = 0.8.                                                                                       |
| SVM   | kernel = RBF, C = 10, gamma = 0.1, epsilon = 0.1.                                                                                                              |

To assess potential overfitting, we monitored the loss curve on both the training and validation sets during NN training and compared the training vs. test performance across all models.

### 3. Results

#### 3.1. Model Performance and Selection

##### 3.1.1. Performance Comparison

The Performance metrics on training and test sets for all models are listed in Table 4. The Neural Network (NN) model achieved the highest test  $R^2$  (0.766), lowest test  $RMSE$  (0.047 m), and competitive  $MAE$  (0.149 m) and  $NRMSE$  (9.2%). The low  $MAE$  indicates that the average prediction error is approximately 0.15 m, which is comparable to the vertical measurement uncertainty of the echo-sounding surveys ( $\pm 0.15$ – $0.30$  m, Section 2.2.3). An  $NRMSE$  value of 9.2% confirmed that the model predictions were accurate within approximately 9% of the full range of observed compaction thicknesses, meeting the typical benchmark for well-performing regression models in earth science applications (<10%) [54,55].

**Table 4.** Performance comparison of different machine learning models.

| Model | Train MSE | Test MSE | Train $R^2$ | Test $R^2$ | Train MAE | Test MAE | Test NRMSE (%) |
|-------|-----------|----------|-------------|------------|-----------|----------|----------------|
| LR    | 0.114     | 0.104    | 0.253       | 0.268      | 0.251     | 0.223    | 14.0           |
| RF    | 0.028     | 0.062    | 0.816       | 0.568      | 0.142     | 0.145    | 8.9            |
| NN    | 0.015     | 0.047    | 0.904       | 0.766      | 0.108     | 0.149    | 9.2            |
| GB    | 0.152     | 0.147    | −0.002      | −0.032     | 0.062     | 0.159    | 9.8            |
| SVM   | 0.598     | 0.589    | 0.246       | 0.234      | 0.187     | 0.178    | 11.1           |

Table 4 presents the performance comparison of five machine learning models. The neural network (NN) achieved the best overall performance, with the highest test  $R^2$  of 0.766 and a test  $MSE$  of 0.047, indicating strong generalization ability. Its training  $R^2$  of 0.904 reflects an excellent fit to the training data (training  $R^2$  slightly higher than test  $R^2$  is acceptable), suggesting limited overfitting. The Random Forest (RF) model also performed reasonably well, with a training  $R^2$  of 0.816 and a test  $R^2$  of 0.568, although the decrease in  $R^2$  indicated some overfitting. In contrast, the gradient boosting (GB) model exhibited very poor performance, with negative  $R^2$  values on both the training (−0.002) and test (−0.032) sets, implying that it failed to capture meaningful patterns in the data. The linear regression (LR) and support vector machine (SVM) models showed similarly low predictive power, with test  $R^2$  values of 0.268 and 0.234, respectively. Overall, the NN model emerged as the most effective model for this task, outperforming all others in terms of predictive accuracy and generalization.

These results demonstrate that the Neural Network not only achieved the highest predictive accuracy but also maintained an excellent balance between training and test performance with minimal overfitting (training  $R^2$  slightly higher than test  $R^2$ , which is acceptable). The poor performance of GB (negative  $R^2$ ) suggests it failed to learn the underlying pattern, possibly due to inappropriate hyperparameters or noise sensitivity in this dataset.

##### 3.1.2. Neural Network Training Dynamics

Figure 8 shows the loss function curve of the NN during training. The loss decreased continuously with iterations, reaching a low level after approximately 200 iterations. The smooth curve and close tracking of training and validation losses indicated stable training without abnormal oscillations or significant overfitting.

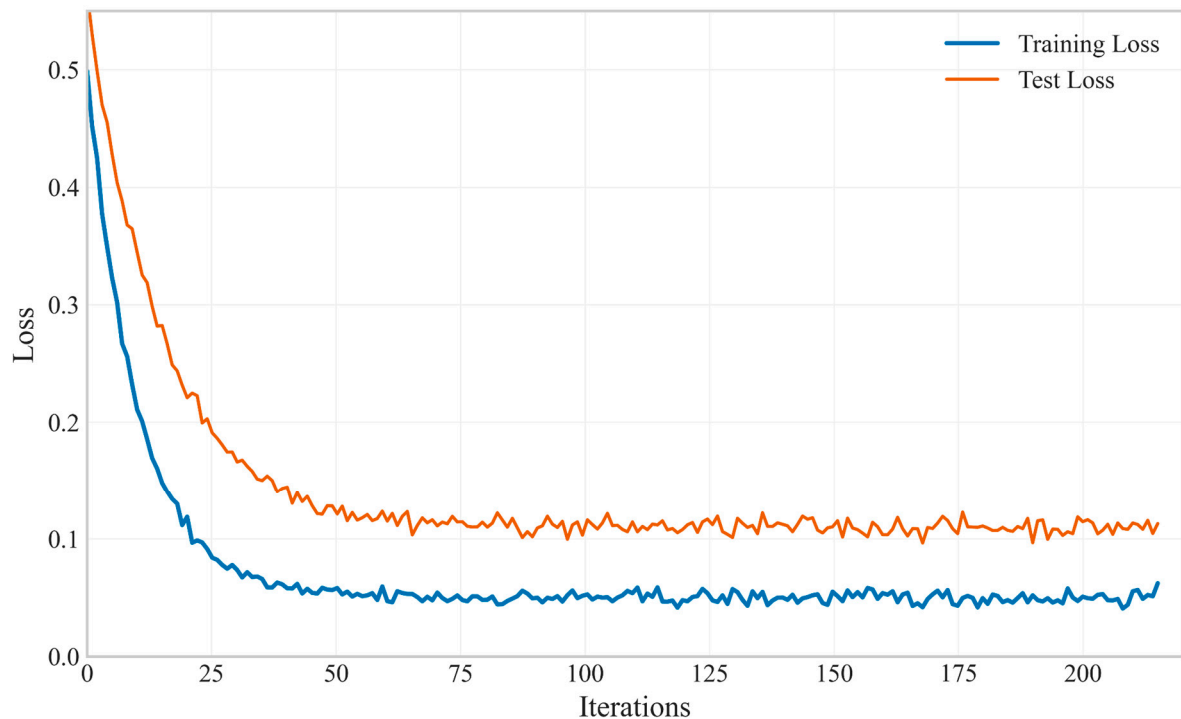


**Figure 8.** NN training and validation loss curve.

Figure 9 shows scatter plots of predicted vs. actual values for training and test sets. The data points are evenly distributed around the 1:1 line, indicating good trend-fitting capability without systematic bias. Figure 10 shows the residual histogram, which approximates a normal distribution, confirming a reasonable error structure.

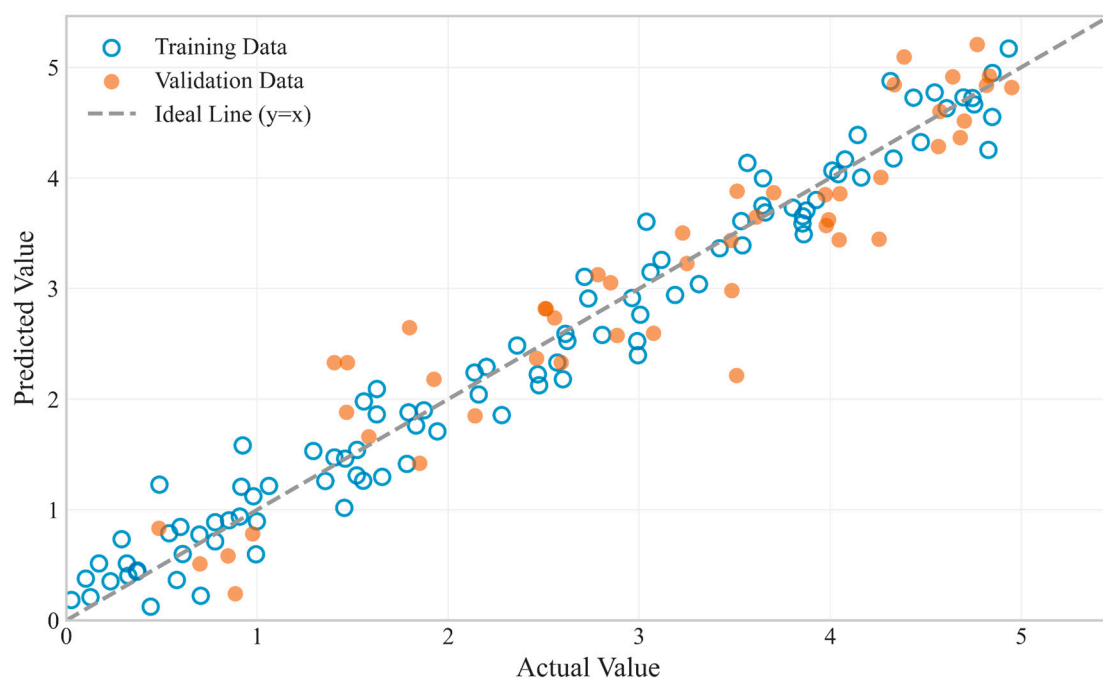


**Figure 9.** Scatter plots of predicted vs. actual compaction thickness for training set and test set.

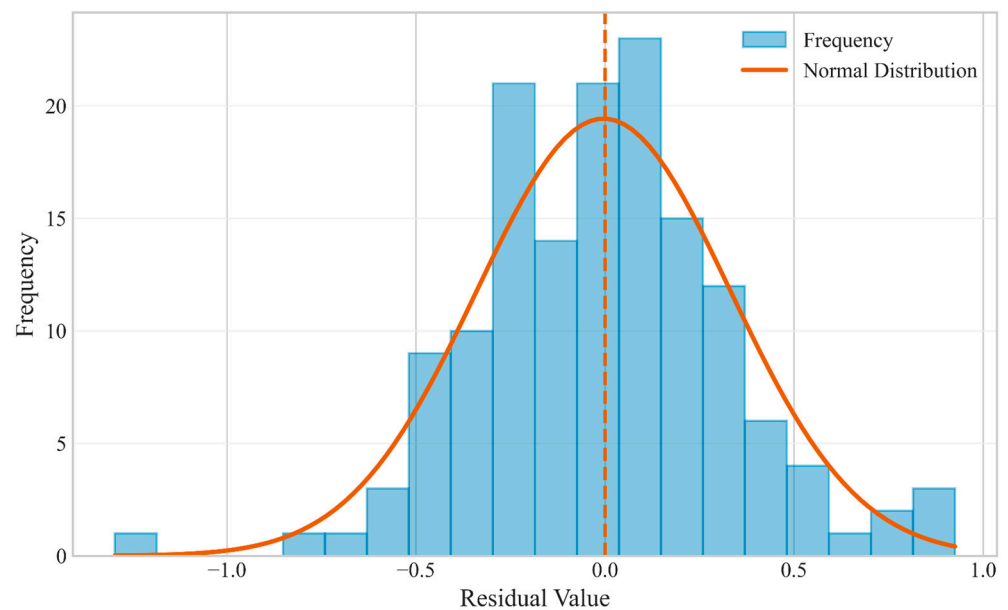


**Figure 10.** Model residual histogram.

### 3.2. Model Interpretability with SHAP Analysis

SHAP (SHapley Additive exPlanations) analysis was performed on the optimized Neural Network model to quantify the contribution of each input feature to the compaction predictions [56]. Figure 11 shows the feature importance ranking and dependence plots.

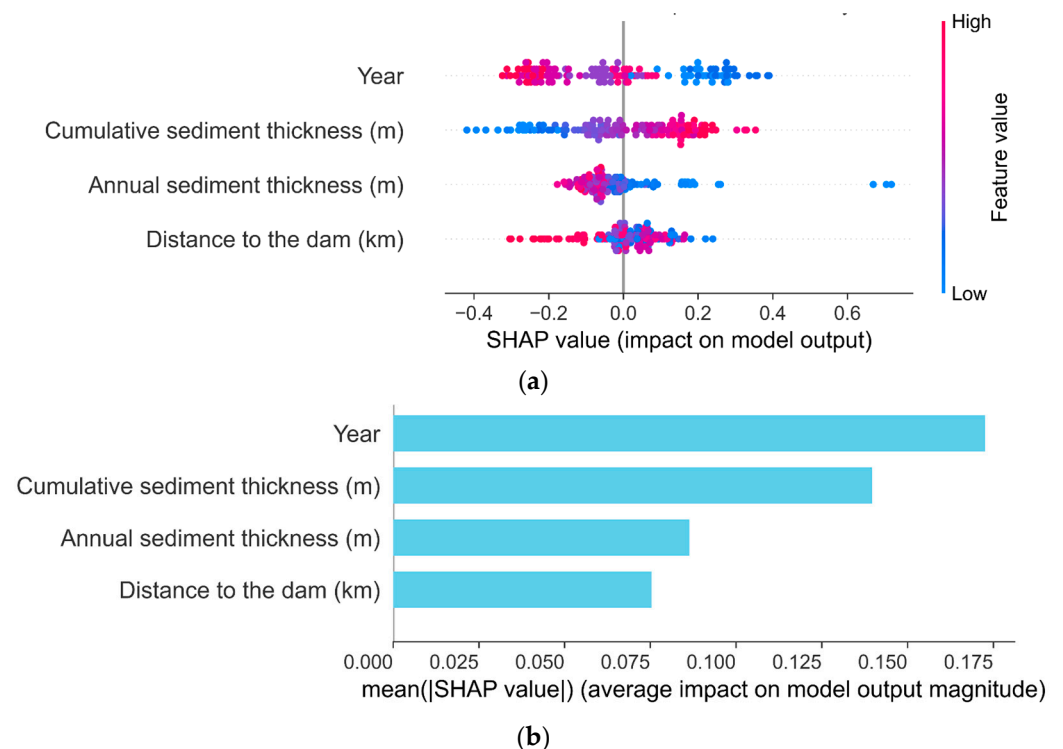


**Figure 11.** SHAP analysis results: (a) feature importance ranking (mean  $|SHAP|$ ); (b) SHAP dependence plots showing how each feature affects the model output.

The SHAP analysis reveals the following order of feature importance: Year (mean  $|SHAP| = 0.18$ ) > Cumulative Sediment Thickness (0.15) > Annual Sediment Thickness (0.08) > Distance to the Dam (0.07). This ordering provides insight into the physical drivers of compaction:

1. **Year:** The dominant influence of Year reflects the fundamental role of consolidation time and cumulative load history. The dependence plot (Figure 11b, first panel) shows a clear pattern: for early years (2014–2015), the SHAP values were positive, indicating that the model predicted higher compaction for sections with sediment from these years. In later years (2018–2020), the SHAP values became negative, indicating lower predicted compaction. This pattern aligns with consolidation theory: longer elapsed time since deposition (early years) allows more complete pore pressure dissipation and creep, leading to greater compaction [28,57]. The positive SHAP for early years, despite coarser sediment during the initial impoundment period [10,11], suggests that the consolidation time effect dominates the sediment source effect—time is so fundamental that even coarser sediments from early years show greater net compaction simply because they had years to consolidate.
2. **Cumulative Sediment Thickness:** The second-ranked importance of cumulative thickness directly represents the vertical stress history at each point. The positive SHAP relationship (greater thickness → higher SHAP values) reflects the progressive increase in effective stress as the sediment column grows, driving consolidation [58,59].
3. **Annual Sediment Thickness:** The positive SHAP for this feature captures the direct mechanical response to the current year’s load increment. Years with larger flood events deposit thicker layers that undergo immediate consolidation [40,60].
4. **Distance to the Dam:** The negative SHAP relationship (greater distance → more negative SHAP values) is directly interpretable through reservoir hydrodynamics. As distance from the dam increases: (1) flow velocity increases owing to channel narrowing, enhancing the sediment transport capacity and selectively removing fine particles [41,61]; (2) bed material coarsens (Table 2, Figure 4), shifting from fine, compressible silts to coarser, less compressible sands [15,59]; and (3) the deposition rate decreases in the fluctuating backwater zone, reducing the cumulative thickness available for compaction [37,40]. All these factors reduce compaction potential upstream.

### 3.3. Compaction Volume Calculation

Using the NN model, we predicted compaction thickness for all sections and years (2016–2020, where dry bulk density data were available for mass conversion). The resulting compaction volumes and original siltation volumes are listed in Table 5.

**Table 5.** Siltation and compaction volumes for 2016–2020 ( $10^4 \text{ m}^3$ ).

| Year              | 2016 | 2017 | 2018 | 2019 | 2020 | 2016–2020 |
|-------------------|------|------|------|------|------|-----------|
| Siltation Volume  | 6862 | 7939 | 7290 | 1577 | 3516 | 27,184    |
| Compaction Volume | 2147 | 486  | 662  | 2256 | 1193 | 6744      |

### 3.4. Correction of Reservoir Siltation Estimates

#### 3.4.1. Improvement in Method Consistency

The NN-predicted compaction volumes were used to correct the annual siltation volumes obtained from the cross-sectional volume method. The corrected siltation mass was then compared with the independent sediment transport method results (Figure 12, Table 6). This correction dramatically improved the agreement between the two methods.

The average relative difference improved from  $-33.7\%$  to  $-6.5\%$ , and the large negative bias in individual years (e.g.,  $-62\%$  in 2019) was substantially reduced. The remaining discrepancies are within the combined uncertainty bounds of the two methods (Section 3.4.3), confirming the effectiveness of the compaction correction.

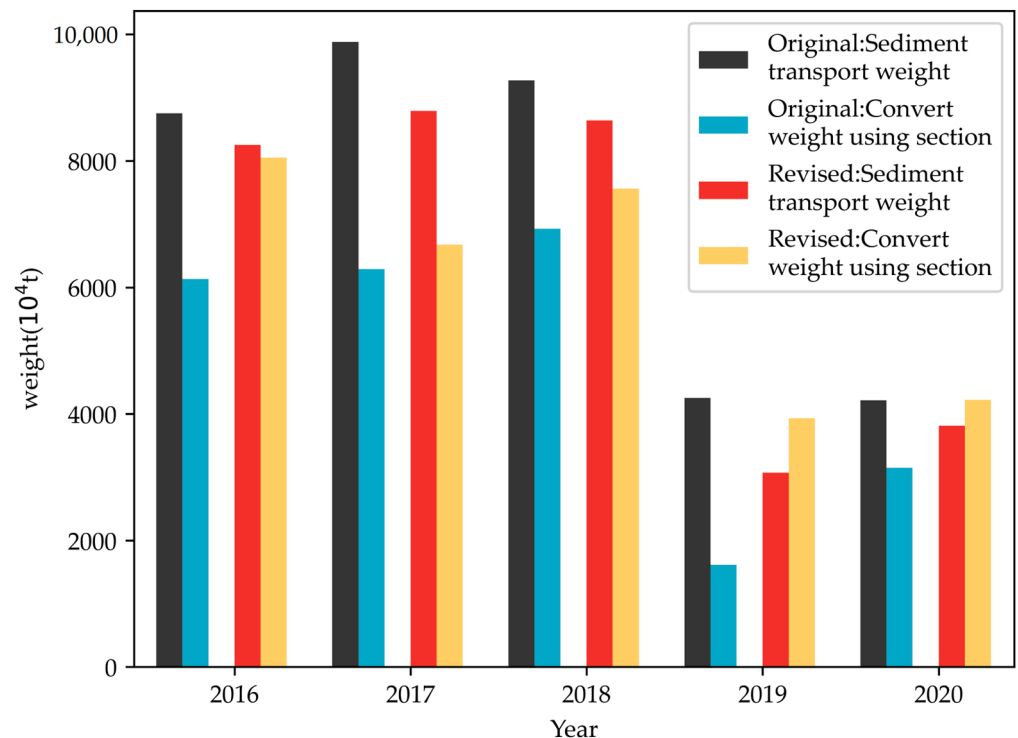


**Figure 12.** Comparison of annual siltation masses calculated by the cross-sectional volume method (before and after compaction correction) and sediment transport method.

**Table 6.** Comparison of relative differences between the two methods' results before and after compaction correction for 2016–2020 (sediment transport method as baseline).

| Year              | 2016   | 2017   | 2018   | 2019   | 2020   | 2016–2020 |
|-------------------|--------|--------|--------|--------|--------|-----------|
| Before Correction | −29.9% | −36.3% | −25.3% | −62.0% | −25.2% | −33.7%    |
| After Correction  | −2.4%  | −24.1% | −12.5% | +28.1% | +10.7% | −6.5%     |

### 3.4.2. Consideration of Uncontrolled Interval Sediment

In a further refinement, we included an estimate of sediment inflow from uncontrolled intervals between the Baihetan station and the dam using the sediment yield modulus method [62]. After including this estimated interval sediment, the corrected volume method results still showed a systematic underestimation relative to the transport method (Table 7), with an average difference of −27.1% over 2016–2020. While this represented a substantial improvement over the pre-correction difference of −47%, the persistent bias warranted discussion (Section 4.5).

**Table 7.** Comparison of relative differences between the two methods' results before and after compaction correction for 2016–2020, including uncontrolled interval sediment estimate.

| Year              | 2016   | 2017   | 2018   | 2019   | 2020   | 2016–2020 |
|-------------------|--------|--------|--------|--------|--------|-----------|
| Before Correction | −44.1% | −48%   | −39.7% | −70.7% | −42.5% | −47%      |
| After Correction  | −23.1% | −39.3% | −30.4% | −9.3%  | −16.9% | −27.1%    |

### 3.4.3. Uncertainty Assessment

The corrected results are subject to multiple sources of uncertainty:

1. **Measurement Uncertainty:** As detailed in Section 2.2.3, vertical survey errors ( $\pm 0.15$ – $0.30$  m) propagate into volume estimates. The  $\pm 0.15$  m average prediction error of the NN model (MAE) is comparable to this survey uncertainty.

2. **Model Prediction Uncertainty:** The test set *RMSE* of 0.047 m provides an estimate of the model's average prediction error for compaction thickness at individual sections. Monte Carlo simulations using bootstrap resampling of model predictions [63] indicate that the 95% confidence interval for the annual compaction volume was approximately  $\pm 12\text{--}18\%$  of the reported value.
3. **Interval Sediment Estimation Uncertainty:** The sediment yield modulus method carries substantial uncertainty ( $\pm 40\%$ ) due to spatial variability in erosion rates and incomplete coverage of small tributaries [64,65]. This contributes to the remaining systematic bias in Table 7.
4. **Combined Uncertainty:** Assuming independent errors, the total relative uncertainty in the corrected annual siltation is estimated to be on the order of  $\pm 10\text{--}15\%$  for years with significant deposition ( $> 50 \times 10^6 \text{ m}^3$ ), increasing to  $\pm 30\text{--}50\%$  for low-deposition years. The residual differences in Table 6 (e.g.,  $-2.4\%$  to  $+28.1\%$ ) are consistent with this combined uncertainty range.

## 4. Discussion

### 4.1. Physical Interpretation of the Machine Learning Model

The SHAP analysis (Section 3.2) successfully links the data-driven model to underlying physical processes. The dominance of Year highlights the importance of consolidation time in reservoir sediment compaction, a factor often underrepresented in empirical models that focus on instantaneous load. This finding aligns with classical soil mechanics, in which time-dependent secondary compression continues long after primary consolidation [28,32]. The strong influence of Cumulative Sediment Thickness confirms that compaction is driven by overburden stress, consistent with Terzaghi's principle [32]. The role of Distance to the Dam elegantly captures the integrated effect of hydrodynamics and sediment sorting along the longitudinal axis of the reservoir. This demonstrates that a well-designed machine learning model can predict and reveal the dominant physical controls in complex environmental systems.

### 4.2. Comparison with Existing Compaction Models and Added Value of the ML Approach

Compared with existing empirical formulas [26,27] and consolidation theory-based models [28,29], the machine learning framework presented here offers several distinct advantages for operational reservoir management:

1. **Data Availability:** This method relies solely on routinely collected fixed-section survey data and basic reservoir information, eliminating the need for expensive and logistically challenging laboratory tests or in situ sampling of mechanical properties.
2. **Spatial Coverage:** It is the first study to continuously map compaction thickness continuously along a 198 km reservoir, identifying the spatial extent of compaction and its relationship to bed material characteristics (Table 2).
3. **Temporal Continuity:** It quantifies compaction volumes for six consecutive hydrological years, revealing interannual variability and cumulative impact.
4. **Direct Engineering Integration:** Its output-cross-sectional area change-is fully compatible with the standard cross-sectional volume method, enabling direct correction of siltation calculations.

This approach does not replace physical understanding but rather provides a powerful tool to apply that understanding at scales not feasible with traditional models. The interpretability gained via SHAP analysis ensures that the model remains physically grounded, not a "black box".

#### 4.3. Site Specificity and Framework Transferability

It is crucial to emphasize that the trained neural network model presented here is site-specific to the Xiluodu Reservoir. The numerical relationships learned (e.g., exact weights in the network) reflect the unique geological, morphological, and operational conditions of this site and should not be directly applied to other reservoirs without recalibration. However, the methodological framework—including the feature engineering strategy (using Year, Cumulative Sediment Thickness, Annual Sediment Thickness, and Distance to the Dam), machine learning workflow, and integration of compaction corrections into the cross-sectional volume method—is designed to be transferable. For a new reservoir, the same framework can be applied by retraining the model using local monitoring data. For data-scarce reservoirs, transfer learning techniques offer a promising pathway to leverage knowledge from well-studied sites like Xiluodu [66]. Future research should prioritize multi-reservoir applications to systematically evaluate the adaptability of the framework across different morphological and sedimentological contexts.

#### 4.4. Influence of Excluded Physical Properties (Particle Size and Dry Bulk Density)

As acknowledged in Section 2.5.2, the absence of spatially distributed particle size and dry bulk density data is a limitation of the current model. These properties are known to influence compaction rates and magnitudes [67,68]. Recent advances in deep-water sediment sampling technology, such as low-disturbance corers for deep reservoirs [47,69], have made it feasible to obtain the spatially distributed physical property data required for more mechanistic modeling. Several model enhancements could be pursued using such data:

1. **Direct Inclusion as Additional Input Features:** Particle size indices (e.g.,  $D_{50}$ ) and dry bulk density could be incorporated directly, allowing the model to learn how compaction responds to sediment type and initial packing state.
2. **Two-Stage Geostatistical-ML Hybrid Framework:** Given that direct measurements may remain spatially sparse, a two-stage approach could be developed: (i) spatial interpolation of sparse physical properties using geostatistical methods [70], and (ii) a subsequent compaction model that uses both routinely measured features and interpolated properties.
3. **Physics-Informed Machine Learning (PIML):** The availability of depth-resolved stratigraphic information would enable the development of physics-informed neural networks (PINNs), where the consolidation equation serves as a physical constraint on the loss function [69,71]. This method combines the spatial coverage of data-driven methods with the physical consistency of process-based models.

These developments represent a clear pathway for future research and would not only improve prediction accuracy but also enhance the generalizability of the model to other reservoirs.

#### 4.5. Analysis of Remaining Systematic Underestimation After Interval Sediment Inclusion

Despite the substantial improvement achieved by compaction correction, a systematic underestimation of  $-27.1\%$  remains after including estimated interval sediment (Table 7). This persistent bias likely results from a combination of factors:

1. **Uncertainty in Interval Sediment Estimation:** As noted in Section 3.4.3, the sediment yield modulus method carries significant uncertainty ( $\pm 40\%$ ). If the actual interval contribution is larger than estimated (e.g., owing to unmonitored tributary flash floods or mass wasting events [72]), the sediment transport baseline would be too low, making the volume method appear negatively biased.

2. **Sediment Resuspension and Redistribution:** During flood events, previously deposited sediment can be resuspended and transported downstream, reducing net accumulation measured by the volume method while still being counted as “deposited” in the sediment transport balance [41,73]. The “storing clear water and releasing turbid flow” operation at Xiluodu may promote such resuspension in the fluctuating backwater zone [8,9].
3. **Model Error in Compaction Prediction:** The NN model explains 76.6% of the variance in compaction thickness; the remaining 23.4% unexplained variance could contribute to bias, particularly if the errors are not randomly distributed but systematic.
4. **Sediment Transport Processes:** The sediment transport method does not account for bedload transport, which can constitute 5–15% of total sediment load in gravel-bed rivers [41,74]. If this bedload is deposited in the reservoir but not measured at the outlet, the transport method would overestimate the net deposition, contributing to the apparent negative bias of the volume method. Density currents [75] could also transport fine sediments to locations not well captured by the fixed-section network.

Addressing these factors requires targeted future investigations: installation of automated gauges on major unmonitored tributaries, deployment of acoustic Doppler current profilers to monitor near-bed transport during floods, periodic bedload sampling, and application of independent methods such as radiometric dating in sediment cores to provide long-term accumulation benchmarks [76].

#### 4.6. Widespread Evidence of Sediment Compaction in Other Reservoirs

The compaction phenomenon identified in Xiluodu is not unique. Analysis of data from the Three Gorges Reservoir (Figure 13) and the Baihetan Reservoir (Figure 14) reveals similar patterns of post-flood bed elevation decrease in fine-grained depositional zones, confirming that sediment compaction is a widespread process in large reservoirs [19,24,77]. These observations underscore the general importance of accounting for compaction in reservoir sedimentation studies.

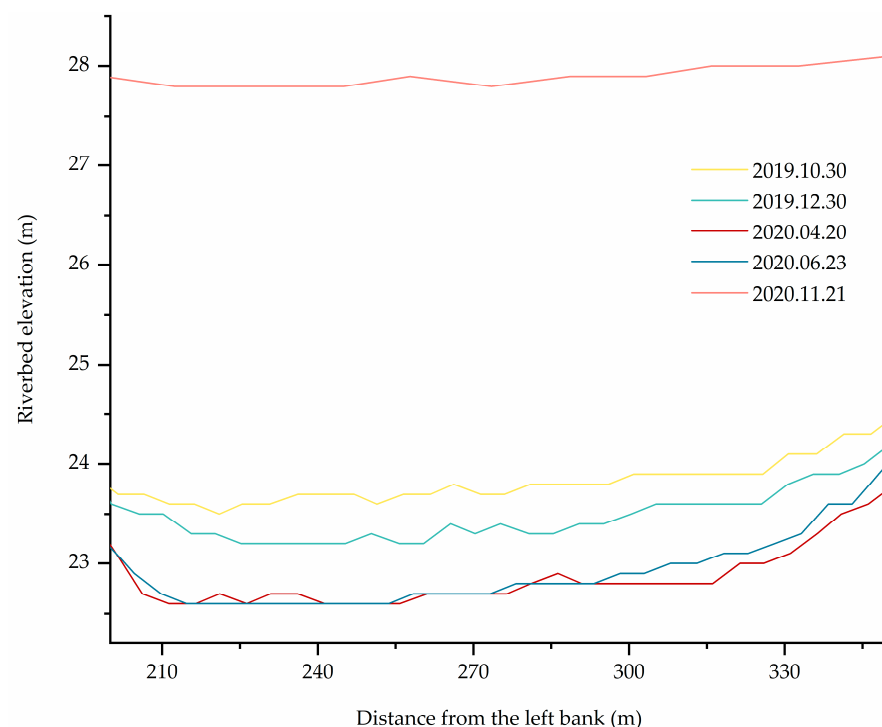


**Figure 13.** Compaction process at a typical section in the Three Gorges Reservoir area (2019–2020), showing progressive bed elevation decline between flood seasons.

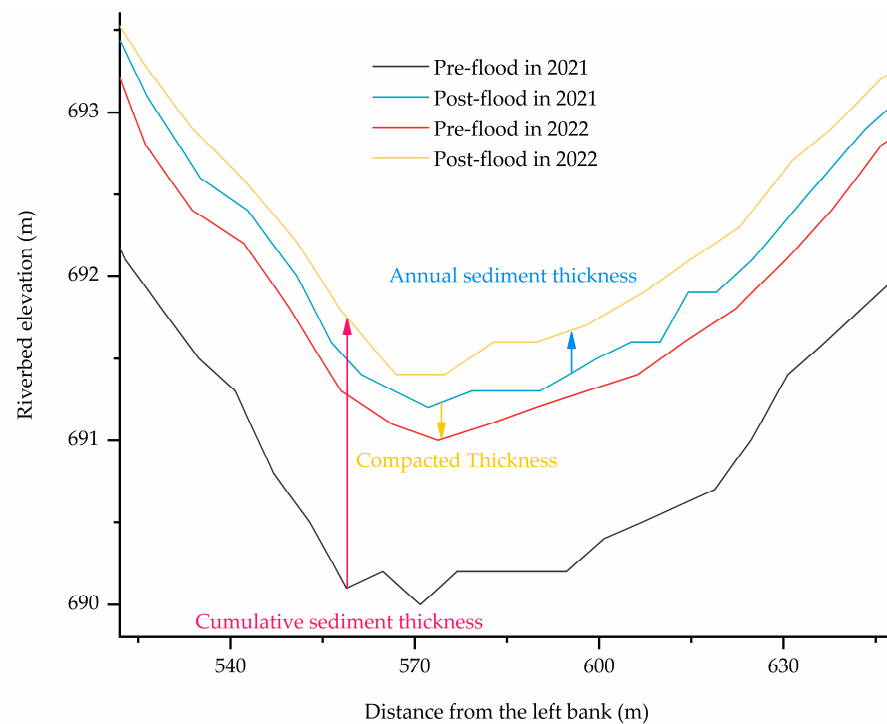


**Figure 14.** Evidence of sediment compaction at a typical section in the Baihetan Reservoir (2021–2022).

## 5. Conclusions

This study developed and validated a machine learning-based framework to quantify sediment compaction and correct reservoir siltation estimates using seven years of intensive monitoring data from the Xiluodu Reservoir. The main conclusions are as follows:

1. **Machine Learning Efficacy:** Among the five algorithms tested, the Neural Network (NN) model demonstrated superior performance in predicting sediment compaction thickness, achieving a test  $R^2$  of 0.766 and RMSE of 0.047 m. It effectively captured the complex non-linear relationships between compaction and its controlling factors without significant overfitting.
2. **Physical Interpretability:** SHAP analysis revealed the dominant physical drivers of compaction in the following order of importance: Year (representing consolidation time and cumulative load history), Cumulative Sediment Thickness (overburden stress), Annual Sediment Thickness (incremental loading), and Distance to the Dam (hydrodynamic sorting and sediment availability). This provides a quantitative link between the data-driven model and geotechnical principles.
3. **Successful Siltation Correction:** Applying the NN-predicted compaction to correct the cross-sectional volume method significantly improved its consistency with the independent sediment transport method. The average relative difference over 2016–2020 was reduced from  $-33.7\%$  to  $-6.5\%$ , confirming that neglecting sediment compaction is the primary cause of the long-standing methodological discrepancy.
4. **Quantitative Description of Compaction:** This study provides the first continuous, whole-reservoir (198 km, 221 sections, 2014–2020) quantitative assessment of sediment compaction, revealing that compaction intensity decays with distance from the dam and grows with cumulative sediment thickness. This fills a critical gap in reservoir sedimentation research by transforming compaction from an acknowledged phenomenon into a quantifiable correction.
5. **Transferable Methodological Framework:** While the trained model is site-specific to Xiluodu, the overall framework—including feature engineering, machine learning workflow, and compaction correction procedure—is designed to be transferable to other

reservoirs where similar routine monitoring data exist. This opens new avenues for improving the accuracy of sedimentation assessments globally, thereby contributing to more sustainable reservoir management.

**Author Contributions:** Conceptualization, G.F.; methodology, G.F. and X.D.; data curation, W.P. and Z.S. validation, J.L. and J.N. All authors have read and agreed to the published version of the manuscript.

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**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The datasets presented in this study are not readily available due to institutional data policies and the ongoing nature of the monitoring programs, as detailed in Section 2.2.2. Requests for access to the datasets for non-commercial scientific purposes should be directed to the corresponding author (Guozheng Feng, fengguozheng@stu.cdut.edu.cn). Data access is subject to institutional approval and signing of a formal data use agreement.

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**Conflicts of Interest:** The authors declare no conflicts of interest.

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