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Landslide Displacement Prediction Using Kernel Extreme Learning Machine with Harris Hawk Optimization Based on Variational Mode Decomposition

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Abstract: Displacement deformation prediction is critical for landslide disaster monitoring, as a good landslide displacement prediction system helps reduce property losses and casualties. Landslides in the Three Gorges Reservoir Area (TGRA) are affected by precipitation and fluctuations in reservoir water level, and displacement deformation shows a step-like curve. Landslide displacement in TGRA is related to its geology and is affected by external factors. Hence, this study proposes a novel landslide displacement prediction model based on variational mode decomposition (VMD) and a Harris Hawk optimized kernel extreme learning machine (HHO-KELM). Specifically, VMD decomposes the measured displacement into trend, periodic, and random components. Then, the influencing factors are also decomposed into periodic and random components. The feature data, with periodic and random data, are input into the training set, and the trend, periodic, and random term components are predicted by HHO-KELM, respectively. Finally, the total predicted displacement is calculated by summing the predicted values of the three components. The accuracy and effectiveness of the prediction model are tested on the Shuizhuyuan landslide in the TGRA, with the results demonstrating that the new model provides satisfactory prediction accuracy without complex parameter settings. Therefore, under the premise of VMD effectively decomposing displacement data, combined with the global optimization ability of the HHO heuristic algorithm and the fast-learning ability of KELM, HHO-KELM can be used for displacement prediction of step-like landslides in the TGRA.

Keywords: displacement prediction; kernel extreme learning machine; variational mode decomposition; three gorges reservoir area; influencing factors

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Citation: Wang, C.; Lin, G.; Zhou, C.; Guo, W.; Meng, Q. Landslide Displacement Prediction Using Kernel Extreme Learning Machine with Harris Hawk Optimization Based on Variational Mode Decomposition. *Land* **2024**, *13*, 1724. https://doi.org/10.3390/land13101724

Academic Editors: Veronica Pazzi, Stefano Morelli and Mirko Francioni

Received: 10 September 2024
Revised: 15 October 2024
Accepted: 19 October 2024
Published: 21 October 2024

1. Introduction

Landslides are one of the most common types of geological disasters in China [1–3]. Recently, the intensification of human engineering activities and increasingly severe weather landslide disasters have caused significant losses [4,5]. In the Three Gorges Reservoir Area of China, thousands of landslides are influenced by substantial mass movements due to the complex geological environment, posing a severe threat to the surrounding environment. A typical example is the Qianjiangping landslide that occurred in July 2003, causing serious casualties within a few days after the reservoir reached an elevation of 135 m. Thus, landslide displacement prediction is crucial in landslide disaster research, as an accurate displacement prediction model can reduce disaster loss and risk [6–9]. Quaternary sediments are widely distributed in the TGRA. The most significant features are loose compositions, distinct viscoelastic deformation, and high porosity, making them highly susceptible to water infiltration. Long-term studies have demonstrated that landslide deformation in the TGRA is caused by slow gravitational downslope processes that occur before the failure of the slope [10,11]. Reservoir water level and precipitation are considered the most important triggers for landslides among these factors.

Researchers have employed various mathematical models to predict landslide displacement, with the traditional approaches relying on historical experience and mathematical statistics [12]. The solution based on historical experience typically combines landslide on-site monitoring data or conducts landslide physical model experiments to predict displacement [13]. Methods based on mathematical statistics apply the gray system and probability theory to landslide displacement prediction [14,15]. With the continuous enrichment of means and types for obtaining landslide monitoring data, nonlinear and machine learning models integrating multi-source sensing information of landslides have been developed [5,16,17], flourishing the research ideas for landslide displacement prediction [18]. Although researchers have proposed various models for deformation prediction of landslide displacement, the existing models also have some shortcomings. For instance, the empirical model uses the actual monitoring data or model test data of a landslide to test the suitability of the prediction model [19,20]. However, only appropriate application scenarios can predict the displacement of landslides well. Single-factor or multi-factor models based on empirical methods often have limited prediction accuracy [21]. To a certain extent, the statistical model predicts landslide deformations with relatively complex physical mechanisms, demonstrating appealing monitoring effects for single influencing factors [15]. Nevertheless, statistical models for multiple influencing factors cannot solve the problem well. Moreover, nonlinear models, such as neural networks, have better prediction capabilities, but nonlinear models cannot solve the local minimum values due to their slow convergence speed [13]. Indeed, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) have demonstrated excellent performance in time series prediction [22–24], but their training efficiency is relatively low due to their excessive parameter cardinality.

Landslide deformation is influenced by internal and external factors presenting characteristics such as complexity, randomness, and uncertainty. The constant deformation of a landslide is closely related to its geological structure, but the short-term displacement deformation is strongly correlated with external influencing factors. Researchers have analyzed landslide monitoring data in the TGRA and found that the step-like change in displacement may strongly correlate with external precipitation and reservoir water level [4,25–27]. Therefore, the critical means for displacement prediction is to analyze the effects of internal and external factors on displacement deformation.

Displacement prediction models have progressed in recent years, but some fundamental problems must be further analyzed and solved. Firstly, researchers used various methods to decompose the original displacements into several sub-components. However, without clarifying the physical meaning of each sub-component, the correlation between components of the landslide and the decomposition factor cannot be explored. Secondly, the nonlinear characteristics of landslide displacement contain multilevel monitoring information, and some models do not adequately study the landslide deformation mechanism, leading to inaccurate prediction results. Thirdly, classical machine learning algorithms have the problem of selecting model parameters, such as back propagation (BP), Elman, and KELM. Computational efficiency can be improved by adopting trivial training methods and facilitating hyperparameter adjustment.

The purpose of this study is to propose a novel landslide displacement prediction model of VMD-HHO-KELM that considers the external influences on displacement deformation. VMD decomposes the cumulative displacement of landslides into a trend, periodic, and random terms. Then, the external influencing factors are decomposed into two subsequences characterized by periodicity and stochasticity and fused into the training set as input data. Taking a typical landslide of Shuizhuyuan in the TGRA as an example, three components are predicted separately using the HHO-KELM model, and the predicted total displacement is the sum of the three components. To validate the practicality and effectiveness of the HHO-KELM model, performance comparisons are conducted with methods such as ELM, KELM, and PSO-KELM.

2. Theory and Methodology

2.1. Variational Mode Decomposition

VMD decomposes a non-smooth signal into modal functions with different characteristics, where each modal function represents the vibration mode of the original signal in a specific frequency range [26,28]. VMD sets the number of modes according to the characteristics of the measured signal, thus overcoming the problems of maximum and minimum values in traditional empirical mode decomposition and suppressing the occurrence of mode mixing [29]. Figure 1 illustrates the VMD architecture.

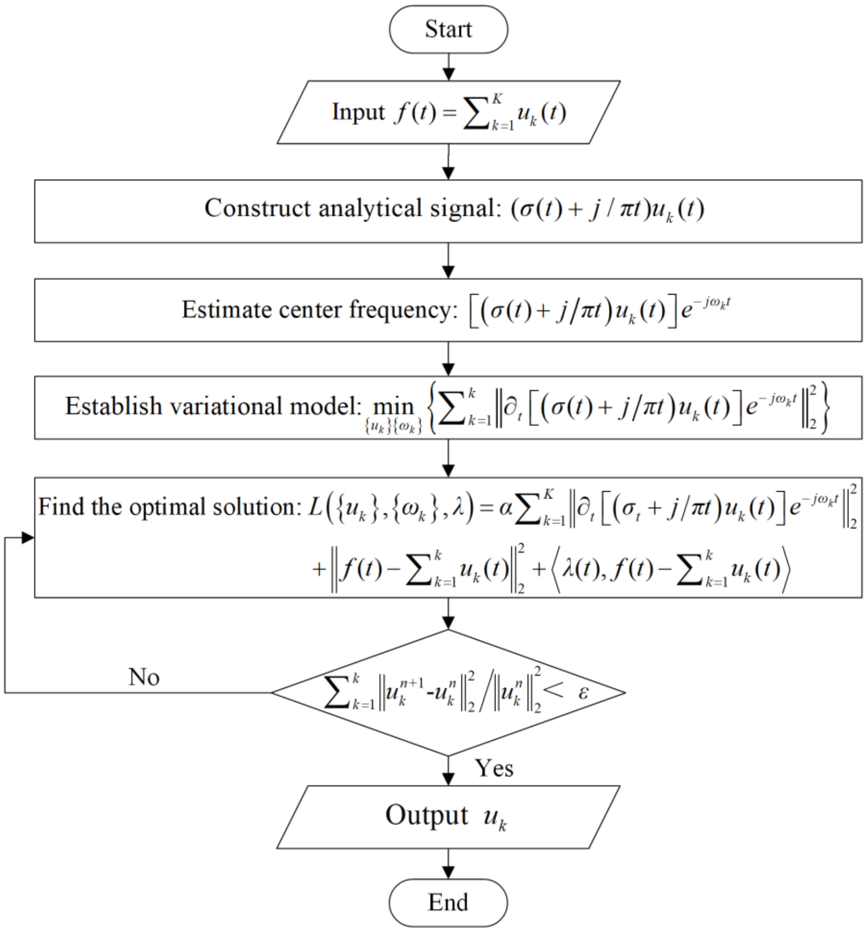

Figure 1. VMD operating principle.

2.2. Harris Hawk Optimization

HHO is a new meta-heuristic algorithm with good global search ability and adjustable parameters [30–32]. It is an intelligent algorithm that optimizes its parameters by simulating the hunting behavior of Harris hawks. HHO mainly comprises the exploration, exploration and development conversion, and development stages (Figure 2). The specific process includes the following five parts:

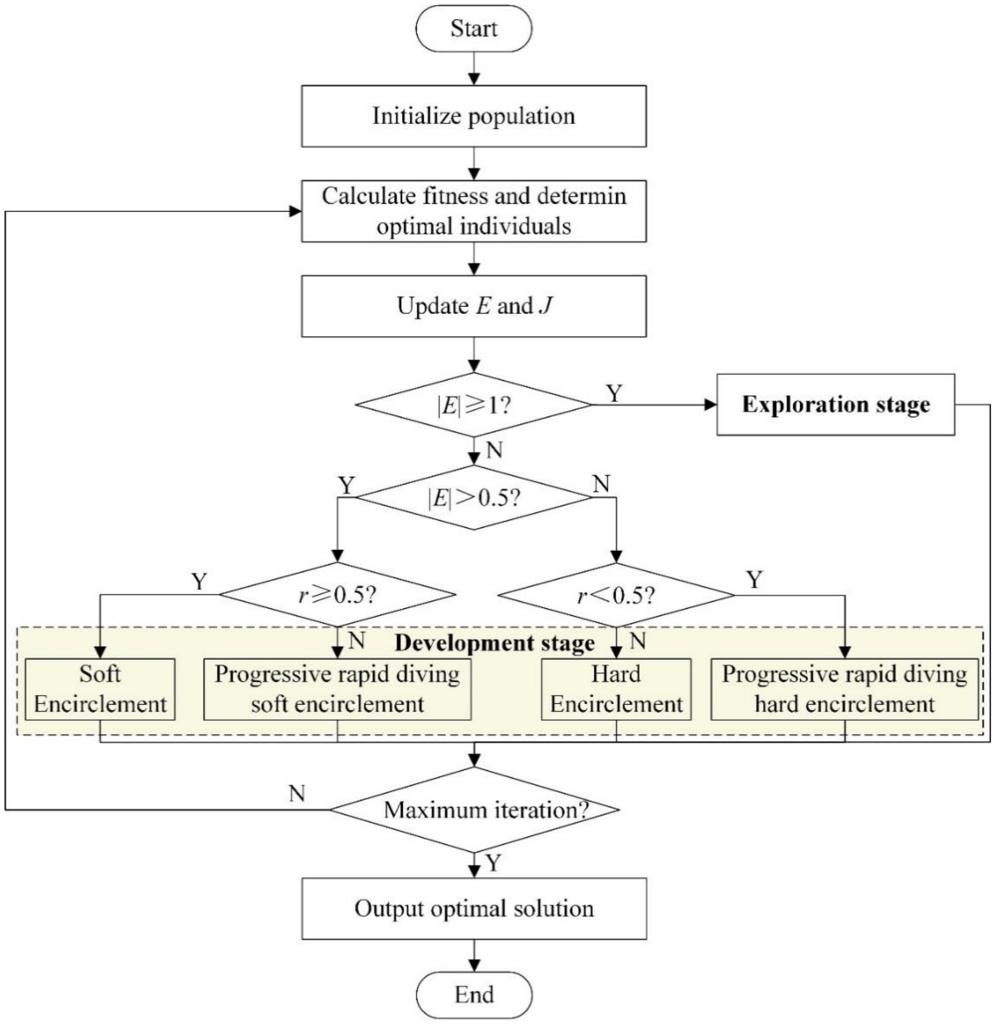

Figure 2. HHO workflow.

① Initialize the population. Determine the search space boundary and initialize the individual positions.

② Set the initial fitness. Select the optimal individual position as the current prey location.

③ Update the location. Determine the conversion during the search and development phase by calculating the escape energy E and random number J. When $|E| \geq 1$ HHO enters the search phase. The Harris Hawks algorithm uses two strategies to determine the updated position and search for prey. When $|E| < 1$ it enters the development stage and selects four different strategies to hunt prey based on the escape energy E and the random number r.

④ For each individual, calculate the fitness and update the population's optimal fitness value.

⑤ Condition judgment. The optimal value is output if the maximum iteration is satisfied. Otherwise, steps ③ and ④ are repeated.

2.3. Kernel Extreme Learning Machine

ELM is a novel hidden layer feedforward neural network with a sold nonlinear fitting ability [4,33]. Huang optimized and upgraded the *ELM* algorithm and developed KELM [34]. Precisely, in KELM, the kernel function replaced the random feature mapping of *ELM* to solve the linear system problem [25,35,36]. KELM uses orthogonal projection and ridge regression theory to introduce the regularization coefficients of C, with the output weight expressed as:

$$\beta = H^T (HH^T + I/C)^{-1} P \tag{1}$$

where β is the output weight, H is the hidden layer matrix, I is the unit matrix, and P is the predicted target vector.

The kernel matrix of the kernel function introduced in ELM is:

$$\begin{cases} \Omega_{ELM} = HH^T \\ \Omega_{i,j} = h(x_i) \cdot h(x_j) = K(x_i, x_j) \end{cases} \tag{2}$$

where x_i and x_j are the experimental input vector, and $K()$ is the kernel function.

$$K(x_i, x_j) = \exp\left(-\|x_i - x_j\| / S^2\right) \tag{3}$$

where S is the parameter of the kernel function. The KELM is expressed as:

$$\varphi(x) = [K(x, x_1); \ldots; K(x, x_N)](I/C + \Omega_{ELM})^{-1} P \tag{4}$$

2.4. Prediction Procedure

The main prediction procedure of the VMD-HHO-KELM model is illustrated in Figure 3 and involves the following steps:

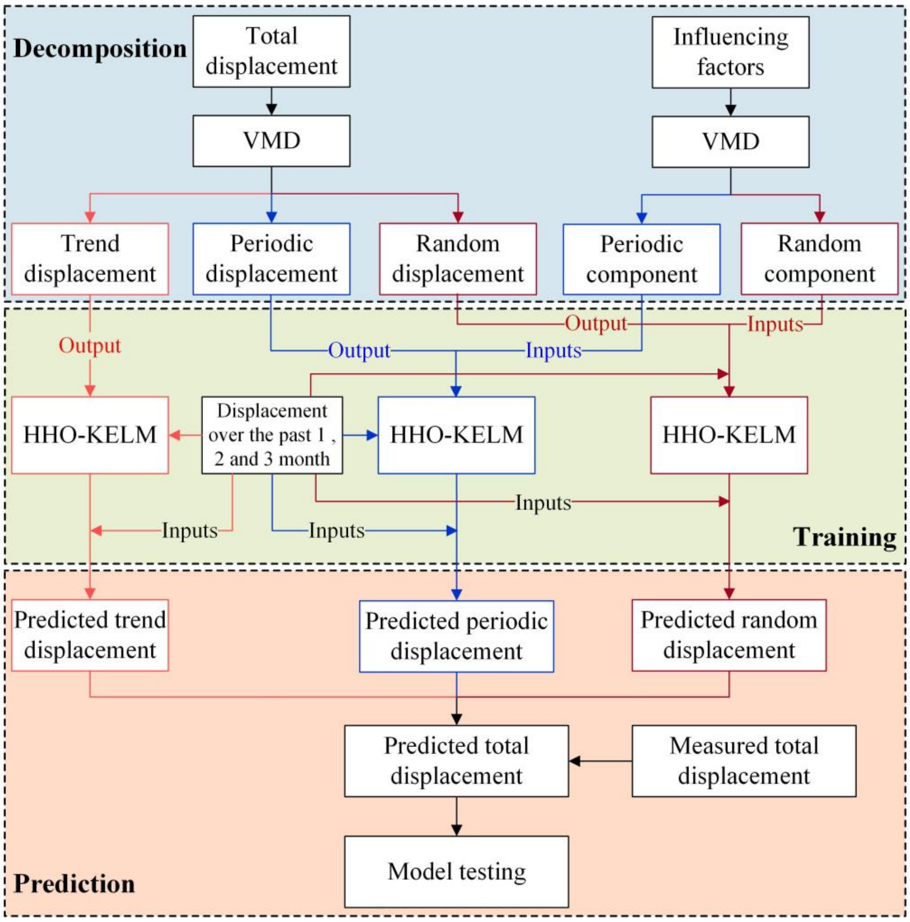

Figure 3. Workflow diagram of VMD-HHO-KELM.

① Data preprocessing. Select data from periods with distinct features as the research object and preliminary screen for influencing factors.

② Data decomposition. The measured displacement and the influencing factor are decomposed into several subsequences using VMD, respectively.

③ Dataset Integration. Integrate the data into trend, periodic, and random term datasets, respectively, and set up training and test sets.

④ Model Training The HHO-KELM predicts the periodic and random training set data trends.

⑤ Model testing and analysis. The test set data of trend, period, and random items are accumulated and summed to obtain the test set prediction data of total displacement.

2.5. Evaluation Indexes

The prediction performance of the proposed method is evaluated based on the mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE), and correlation coefficient (R^2). The four indexes are defined as follows:

$$\mathrm{MAE} = \frac{1}{M}\sum_{i=1}^{M}\left|\hat{d}_i - d_i\right| \tag{5}$$

$$\mathrm{MAPE} = \frac{100\%}{M}\sum_{i=1}^{M}\left|\frac{\hat{d}_i - d_i}{d_i}\right| \tag{6}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{M}\sum_{i=1}^{M}\left(\hat{d}_i - d_i\right)^2} \tag{7}$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{M}\left(\hat{d}_i - d_i\right)^2}{\sum_{i=1}^{M}\left(\overline{d}_i - d_i\right)^2} \tag{8}$$

where M is the number of total displacement samples, d_i and $\hat{d}_i$ are the measured and predicted value, and $\overline{d}_i$ is the average of measured value.

3. Case Study

3.1. Landslide Information

The Shuizhuyuan landslide is located in Wushan County of TGRA, at E 109°43′27.33″, N 31°00′59.37″ (Figure 4). The distance to the Wushan New Town and Three Gorges Dam is 14.82 km and 170 km, respectively. The relative height difference is about 260 m, the longitudinal length is about 800 m, the transverse width is about 360~1200 m, the area is 62×10^4 m^2, and the volume is 1850×10^4 m^3.

Figure 4. Location of the Shuizhuyuan landslide.

The study area has typical characteristics of a subtropical humid monsoon climate. The surface materials of the Shuizhuyuan landslide are loose gravelly soil with good permeability. The underlying bedrock mainly consists of mudstone and marlstone. The sliding surface has a depth of approximately 30 m. The front edge of the landslide is below the water level of the Yangtze River at 145 m, and the stability of the landslide is significantly affected by the reservoir water level (Figure 5).

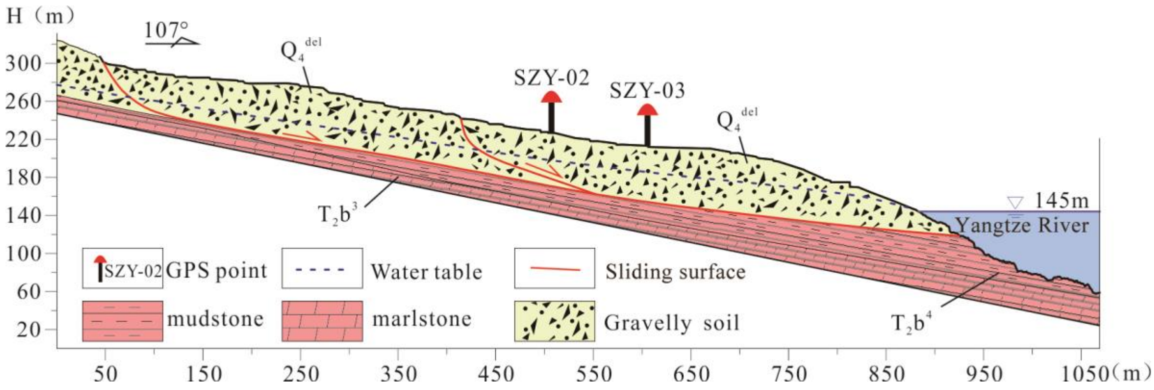

Figure 5. Geological profile of the Shuizhuyuan landslide.

3.2. Deformation Characteristic Analysis

Through on-site investigation and analysis of monitoring data, the Shuizhuyuan landslide is a large-scale soil landslide induced mainly by precipitation and reservoirs. The monitoring curve in Figure 6 highlights that the landslide had a uniform creeping slide since the deployment of automated monitoring devices in 2016.

The Shuizhuyuan landslide has a step-like deformation trend. From April to September each year, under the dual action of solid precipitation and water level decline, the landslide soil is gradually saturated with weakened slip resistance, increasing landslide displacement [25]. During the other months, the landslide deformation is stable or small due to the support of the rise of the reservoir water level.

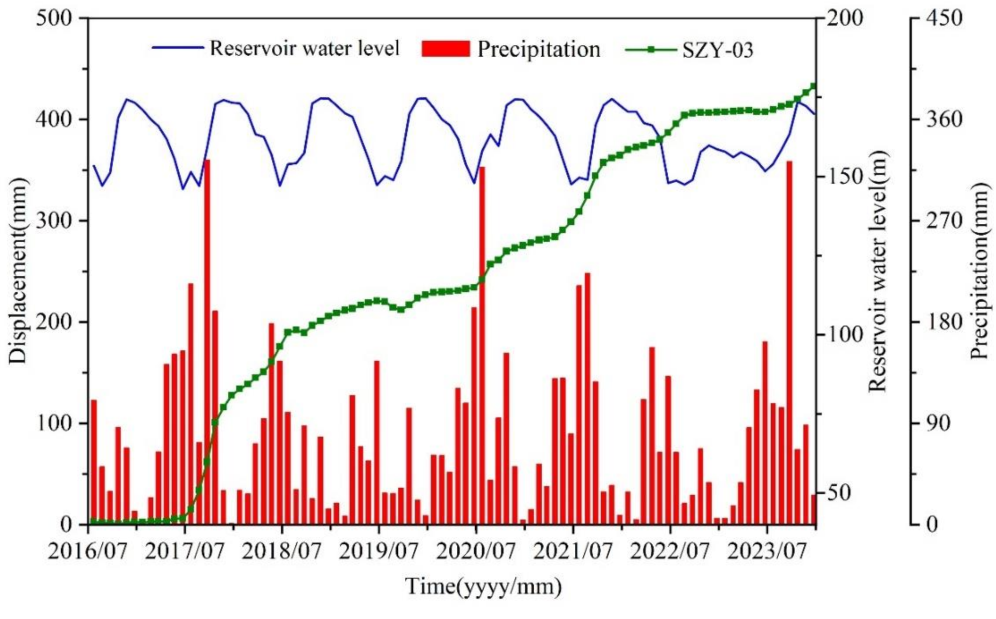

Figure 6. The monitoring data at location SZY-03 in the Shuizhuyuan landslide.

3.3. Data Processing

Considering that the cumulative displacement deformation of monitoring point three of the Shuizhuyuan landslide is the largest, SZY-03 is selected as the research object. This study primarily selects the monitoring data from SZY-03 between July 2016 and December 2023 for model construction. Seventy-eight data sets from July 2016 to December 2022 are chosen as the training set, followed by 12 data sets from January 2023 to December 2023 as the test set.

3.3.1. Data Decomposition

The number of modes must be set before applying the VMD to the landslide displacement. After several experiments, we concluded that setting $K = 3$, $\alpha = 0.3$, and $\tau = 0.3$ avoids the phenomenon of insufficient decomposition or excessive decomposition due to improper setting of the decomposition number. Figure 7 depicts the decomposition result of the displacement data.

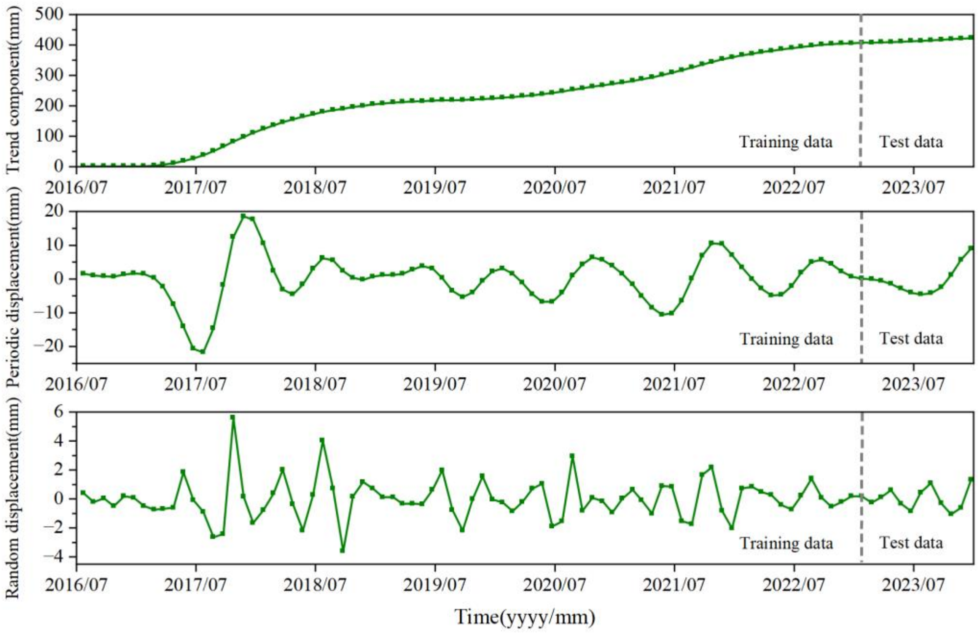

Figure 7. VMD results for displacement data. The dashed line represents the data segmentation between training data and test data.

3.3.2. Selection of Influencing Factors and Data Decomposition

Internal factors of landslides significantly impact the trend term. Specifically, changes in the rock and soil structure, internal stress, and geometric shape of landslides over time will inevitably affect the trend term. Therefore, the displacement data in the past 1, 2, and 3 months is input into the current landslide displacement deformation factor.

The periodic displacement presents small-scale fluctuation, and the influencing factors are also related to the external environment [37]. The deformation characteristics indicate that strong precipitation and periodic water level adjustments are the main factors leading to step-like displacement [38]. Additionally, continuous infiltration of precipitation weakens the landslide resistance and promotes landslide evolution. Previous studies have revealed a close relationship between accumulated precipitation in the first two months and landslide deformation [4]. In addition, Figure 6 highlights that the faster the water level drops, the greater the landslide displacement deformation [38]. Based on this analysis, this study mainly considers the influencing factors presented in Figure 8.

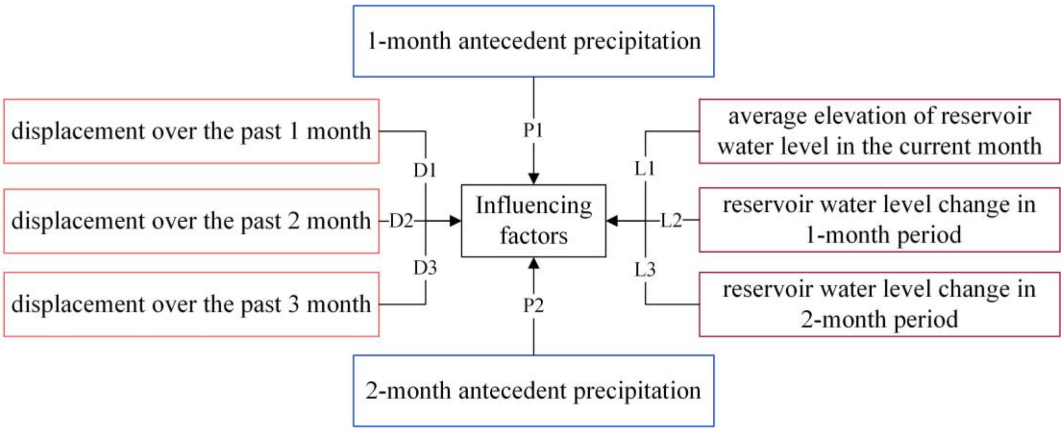

Figure 8. Influencing factors used as inputs for the modeling process.

The influencing factors do not include trend terms. Therefore, K is set to 2. Furthermore, the analysis concluded that components with ample proportions and low frequency are considered periodic. The part with a small proportion and high frequency is decomposed randomly. Figure 9 presents the decomposition results of the influencing factors.

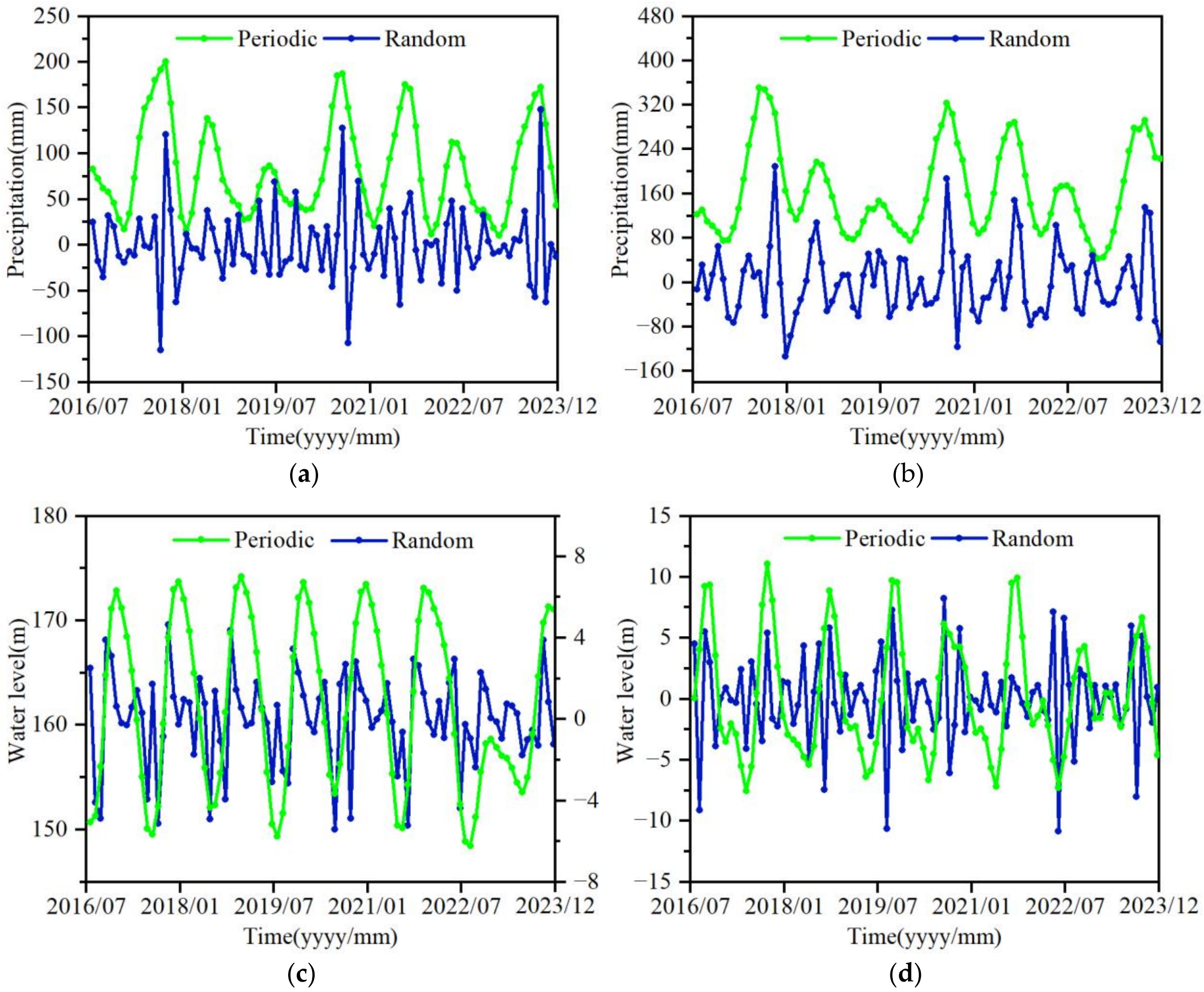

Figure 9. Decomposition of the influencing factors. (**a**) P1, (**b**) P2, (**c**) L1, (**d**) L2.

3.3.3. Correlation Analysis of the Decomposition Components and Influencing Factors

The relevance between displacement and influencing factors is further analyzed to verify the applicability of the selected influencing factors. Grey correlation degree (GRD) is an evaluation method in grey system theory that compares the correlation degree between different time series. It is applicable to the study of problems involving less data, poor information, and uncertainty. GRD determines the correlation between two variables by judging the size of the resolution coefficient. When the correlation coefficient exceeds 0.5, it can be considered to have a specific correlation coefficient [29,39]. The larger the value, the stronger the correlation coefficient.

Table 1 reports the correlation degree based on the GRD program written in MATLAB. The selected eight influencing factors strongly correlate with the periodic and the random term [9]. Therefore, choosing them as input factors to predict landslide displacement is feasible.

Table 1. GRD between each influencing factor and fluctuation displacement.

Displacement	Fluctuation Displacement			Precipitation		Reservoir Water Level		
Symbol	D1	D2	D3	P1	P2	L1	L2	L3
Periodic component	0.7512	0.7512	0.7510	0.7511	0.7511	0.7513	0.7523	0.7526
Random component	0.9966	0.9966	0.9966	0.9957	0.9961	0.6635	0.9963	0.9964

4. Results and Analysis

4.1. Trend Term Prediction

Figure 7 infers that the trend term displacement mainly depends on the change in the geological condition of the landslide, and its displacement deformation has a relatively stable and gradually increasing time series. This indicates that the Shuizhuyuan landslide is generally in a stable deformation stage during the selected monitoring period.

The prediction of the trend-term displacement of the Shuizhuyuan landslide is completed using the HHO-KELM model. In the prediction model, monthly displacements from July 2016 to December 2022 are used for training, and monthly displacements from January 2023 to December 2023 are used for testing. The displacement of trend terms from the past 1, 2, and 3 months is used as input. Through a trial-and-error process, the optimal parameters of KELM using HHO are C = 24857.246 and S = 223.352. Figure 10 infers that HHO-KELM demonstrates excellent predictive performance for trend-term displacements. The RMSE, MAE, MAPE, and R^2 are 0.1488, 0.1344, 0.0324%, and 0.9992, respectively.

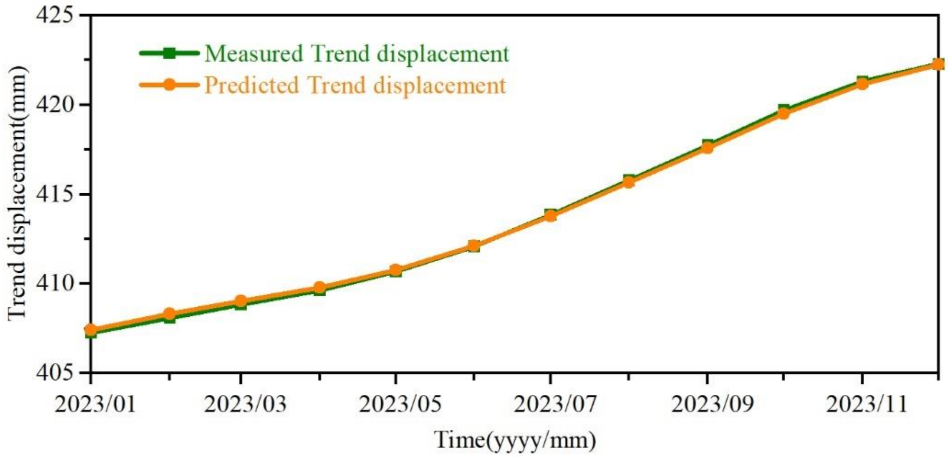

Figure 10. Predicted and measured values of the trend displacement.

4.2. Periodic Term Prediction

The periodic term of the Shuizhuyuan landslide exhibits small-scale periodic changes caused by precipitation and adjustment in the reservoir water level. In this study, the precipitation patterns in the first and second months are generally consistent with the monthly displacement (Figure 11), which can be used as inputs to capture the effect of precipitation on displacement [37]. Additionally, the periodic displacement is generally consistent with the fluctuations of the reservoir water level [40]. The deformation increases mainly during the water level decline phase (Figure 12). For example, in May 2018, the landslide deformed by 9.7 mm, and the water level dropped by 10.2 m. In June 2018, the displacement was 15.33 mm under similar precipitation conditions, and the water level dropped by 3.3 m (Figure 11). The landslide deformation shows different displacement changes with the other reservoir elevations, and therefore, water level changes and mean elevation are valid inputs to represent the effect on reservoir level adjustment (Figure 8).

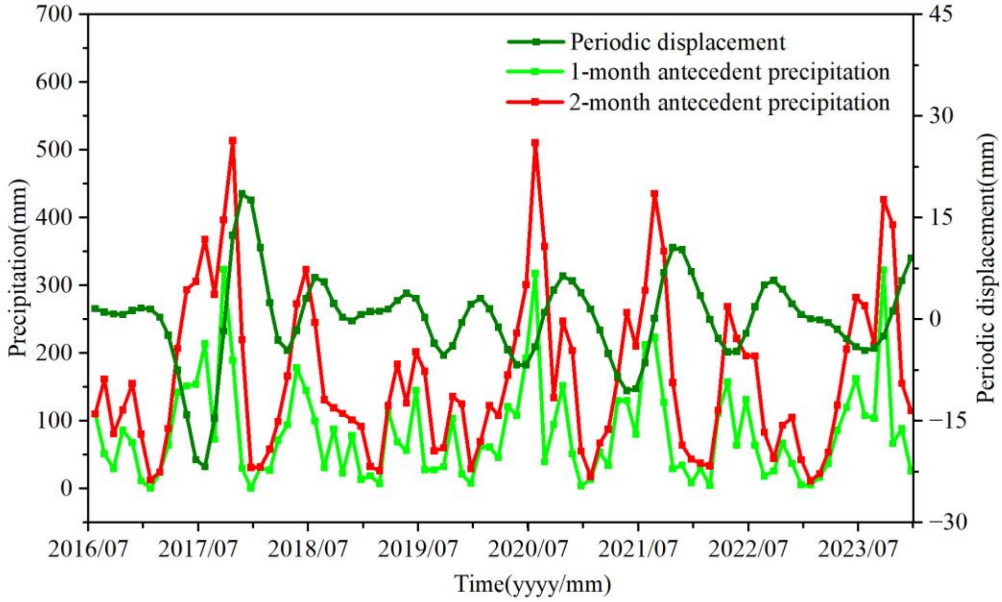

Figure 11. Relationship between early precipitation and periodic displacement.

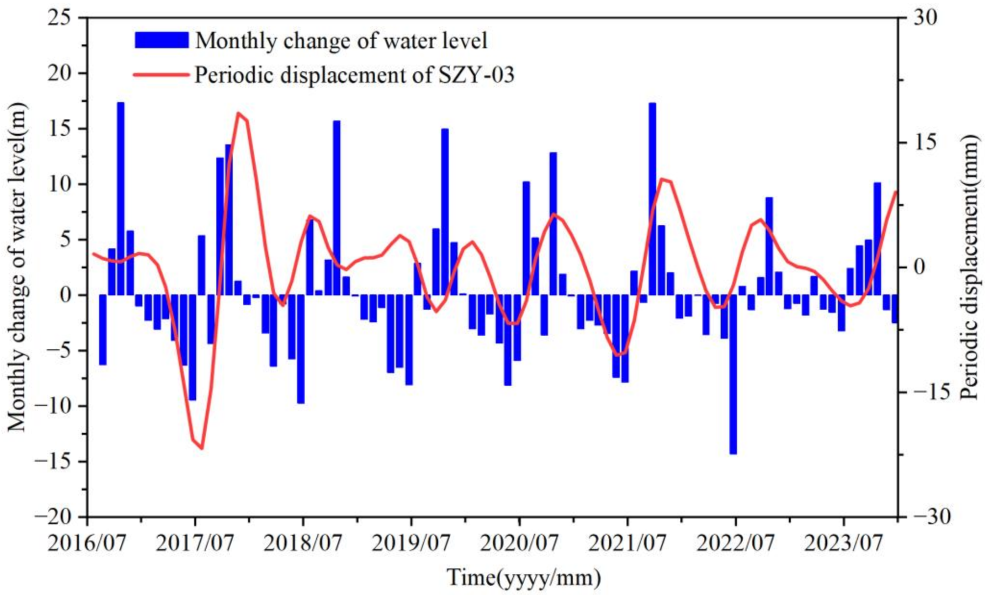

Figure 12. Comparison of monthly change of water level and periodic displacement.

Based on the deformation analysis of the Shuizhuyuan landslide, this study considers the effect of the landslide's periodic displacement and uses eight factors. Furthermore, HHO-KELM is employed to establish a periodic term prediction model. The predictive performance of HHO-KELM, PSO-KELM, KELM, and ELM periodic displacement is $C = 3000$ and $S = 10$ for HHO-KELM and $C = 343.440$ and $S = 144.422$ for PSO-KELM. According to

Figure 13 and Table 2, the predicted values of HHO-KELM and PSO-KELM in the four models are consistent with the original values. At the same time, the predictive performance of KELM and ELM is relatively general. The RMSE of the HHO-KELM in predicting periodic displacement is 0.2734, MAE is 0.2410, MAPE is 0.7565%, and R^2 is 0.9952.

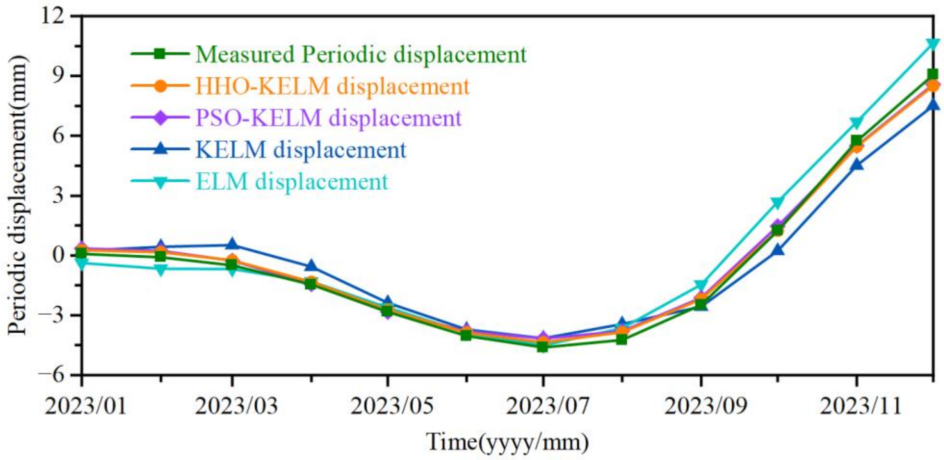

Figure 13. Predicted and measured values of the periodic displacement.

Table 2. Prediction accuracy of the periodic displacement.

Models	MAE	MAPE (%)	RMSE	R^2
HHO-KELM	0.2410	0.7565	0.2734	0.9952
PSO-KELM	0.2730	0.3087	0.3092	0.9939
KELM	0.7053	6.3479	0.8239	0.9565
ELM	0.6278	36.3613	0.8029	0.9587

4.3. Random Term Prediction

The random term components of the influencing factors are input into the HHO-KELM prediction model. Compared with the trend and periodic displacements, the random term displacement has a certain degree of randomness. Still, the fluctuation of the predicted results is within a relatively reasonable range of data error (Figure 14). In this case, HHO-KELM still shows relatively good prediction performance, with RMSE of 0.0233, MAE of 0.0175, MAPE of 0.3109%, and R^2 of 0.9989.

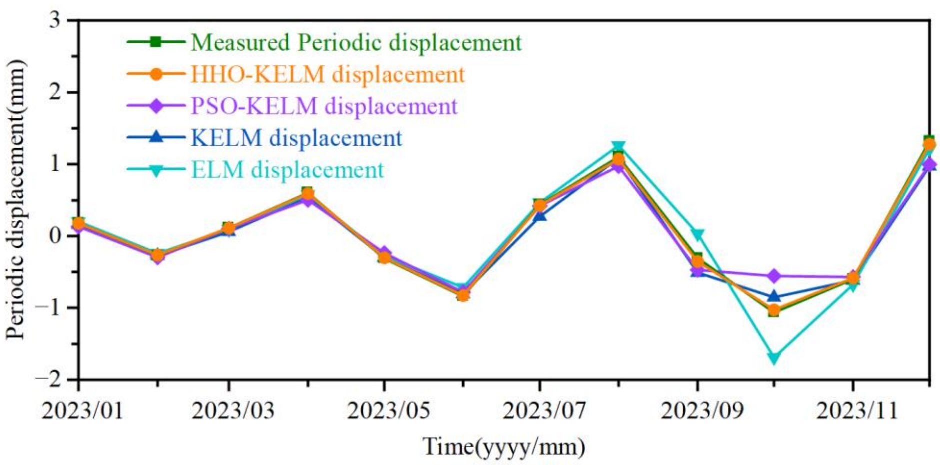

Figure 14. Predicted and measured values of the random displacement.

4.4. Total Displacement Prediction

The total predicted displacement is obtained by adding the trend, period, and random term displacements. The best agreement between the total displacement predicted by HHO-KELM and the total displacement measured is observed in Figure 15, presenting an RMSE of 0.3680, MAE of 0.3208, MAPE of 0.0773%, and R^2 of 0.9979 (Table 3).

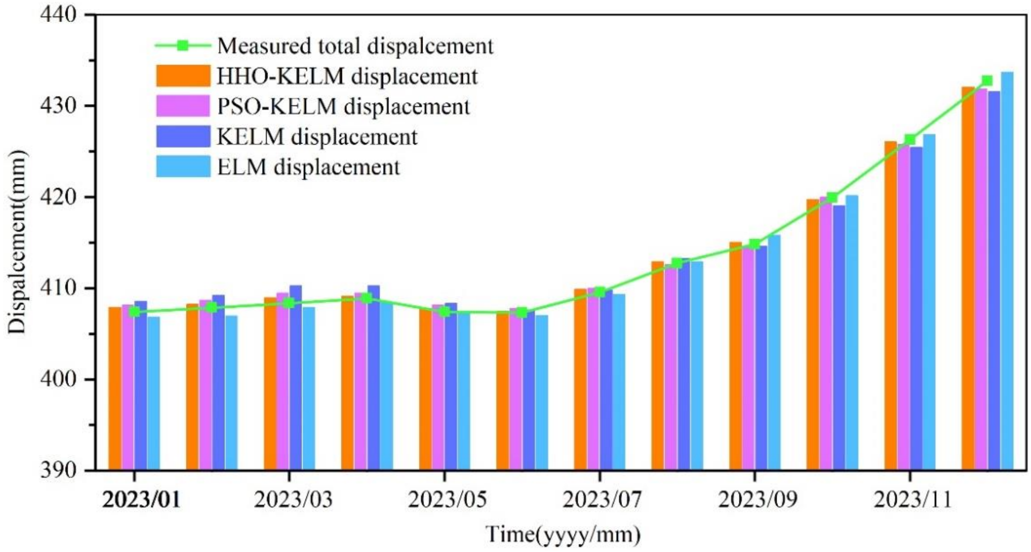

Figure 15. Predicted and measured values of the total displacement.

Table 3. Prediction accuracy of total displacement.

Models	MAE	MAPE (%)	RMSE	R^2
HHO-KELM	0.3208	0.0773	0.3680	0.9979
PSO-KELM	0.5542	0.1342	0.6324	0.9939
KELM	0.9008	0.2178	1.0338	0.9837
ELM	1.4183	0.3390	1.6995	0.9559

In addition, the HHO-KELM model exhibits good predictive performance during the step-like deformation process. In June 2017, the Shuizhuyuan landslide was severely deformed due to intense precipitation and decreased reservoir water level. Nevertheless, by considering the influencing factors, the HHO-KELM model establishes the relationship between external factors and deformation.

The four methods achieve better prediction results in most cases, but the prediction performance of KELM and ELM is not high in the critical step of the deformation period. Compared with other models, the HHO-KELM highlights that the displacement prediction considering the influencing factors is more accurate and provides better prediction results. Especially in predicting the displacement of stepped landslides, the HHO-KELM provides better prediction accuracy than other models. The main reason is that the KELM is characterized by complete coverage fitting, minor training errors, and relatively small weights. Compared to traditional gradient-based classical learning algorithms, the KELM tends to achieve the minimum training error without considering the weight.

5. Discussion

The deformation characteristics of landslides in the TGRA are closely related to various factors, mainly including their own geological structure, precipitation, and reservoir water level adjustments [4]. Through an in-depth analysis of displacement characteristics and deformation mechanisms, it was demonstrated that precipitation during the flood season and fluctuations in water level are the main influencing factors for the Shuizhuyuan landslide. Under the dual influence of these factors, the landslide shows a displacement deformation curve akin to a step-like pattern. Therefore, the prerequisite for conducting landslide displacement prediction is accurate decomposition.

Traditional methods such as EMD and EEMD have no regularity in the feature components of displacement decomposition. After decomposition, each component requires observation and analysis, followed by recombination to obtain the desired characteristic components. Recombination of these components often increases the duration of data analysis and reduces data processing efficiency. In this study, VMD can adaptively decompose the landslide displacement into characteristic components based on a predetermined number of modes. For instance, when $K = 3$, it can effectively extract trend, periodic, and random displacement components, each with a clear physical meaning. This can effectively suppress the issues of incomplete data decomposition and irregular decomposition patterns that are common in traditional methods.

Comparing models helps to validate the accuracy of the proposed method [25]. ELM is a typical representative machine learning method used for displacement prediction. Therefore, this study used ELM, KELM, and PSO-KELM models to verify the predictive performance of HHO-KELM [4,25]. As shown in Figure 15 and Table 3, the RMSE and R^2 of ELM are 1.6995 and 0.9559, respectively, indicating that ELM has the worst predictive ability. After incorporating the kernel function into the ELM, the RMSE and R^2 of the KELM are 1.0338 and 0.9837, which represents a certain improvement in the displacement prediction capability. To further improve the training efficiency of KELM, optimization algorithms are introduced to optimize the parameters of KELM. The results indicate that the RMSE and R^2 of the HHO-KELM model are 0.3680 and 0.9979, respectively, providing the best predictive outcomes among the models tested. This is mainly attributed to the global search and adaptive parameter adjustment capabilities of the HHO algorithm. Figure 15 highlights that HHO-KELM, which considers external influencing factors, achieves better landslide displacement prediction and has a very accurate displacement prediction ability, proving that the step-like displacement is affected by precipitation and reservoir water level fluctuation.

In addition, the rapid development of deep learning techniques such as multilayer perceptron (MLP) and transformer provides feasible solutions for long-term series prediction. In future research, the generalization and computational capabilities of deep learning will provide more reference options for predicting the displacement of different types of landslides.

6. Conclusions

An apparent step-like curve characterizes the Shuizhuyuan landslide in the TGRA. Under the combined effect of precipitation and reservoir water level, the deformation accelerates from April to September every year, and the landslide displacement and deformation are relatively stable for the rest of the year. Based on the analysis of the deformation characteristics, the cumulative displacement is decomposed into trend, periodic, and random term displacement through VMD.

The trend displacement is manifested as stable deformation controlled by its geological conditions, while the periodic and random displacement are affected by triggering factors and exhibit fluctuating displacement. The proposed HHO-KELM model synthesizes the characteristics of the HHO and KELM, in which KELM has high prediction efficiency. HHO can easily and quickly find suitable KELM parameters with shorter prediction runtime and better robustness. In the experiments, the HHO-KELM model with different input influencing factors is used to predict the three terms, and the total predicted displacement is obtained by adding the three terms. The predictive indicators are RMSE of 0.3680, MAE of 0.3208, MAPE of 0.0773%, and R^2 of 0.9979. This indicates that the HHO-KELM model has achieved excellent displacement prediction performance. Hence, the proposed HHO-KELM model, taking influencing factors into account, can better show the response relationship between landslide deformation and external influencing factors than PSO-KELM, KELM, and other methods. The accurate prediction of periodic displacement is an integral part of landslide displacement prediction.

Although the proposed HHO-KELM has achieved better displacement prediction results than other methods, factors such as extreme rainfall conditions and sudden drops in reservoir water level have not been fully considered, which can have a significant impact on displacement prediction performance. Considering the limitations of existing landslide monitoring data, it is insufficient to only consider the effects of precipitation and water level on displacement. More monitoring information needs to be incorporated into the model to enhance predictive capabilities. The displacement deformation of landslides varies over time, and it is important to continuously update monitoring data within the model to gradually replace existing monitoring data to enhance the accuracy of model predictions.

Therefore, thoroughly considering the response relationship between influencing factors and landslides can help improve prediction accuracy, especially in cases of step-like deformation. Overall, accurate and reliable displacement prediction can be realized at the stage of slow deformation and step-like landslide deformation by combining the background of landslide breeding and dynamic evolution theory through machine learning technology. The proposed method can be popularized and applied in the TGRA and other landslide-prone areas with step-like displacement.

Author Contributions: Conceptualization, C.W. and C.Z.; methodology, C.W., G.L. and C.Z.; software, C.W., G.L. and Q.M.; validation, G.L. and W.G.; formal analysis, C.W. and W.G.; investigation, G.L. and W.G.; resources, C.W. and C.Z.; data curation, G.L. and Q.M.; writing—original draft, C.W. and G.L.; writing—review and editing, C.Z.; visualization, C.W. and W.G.; supervision, C.Z.; project administration, C.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This study was funded by the Geological Survey Projects of China Geological Survey (No. DD20230442) and the National Key Research and Development Program of China (No. 2019YFC1509601).

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: The authors would like to express their gratitude to the Three Gorges Reservoir Geological Hazards—Chongqing Wushan Field Scientific Observation and Research Station of the Ministry of Natural Resources for providing the landslide monitoring data of Shuizhuyuan.

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

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