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ORIGINAL PAPER

Ensemble learning for landslide displacement prediction: A perspective of Bayesian optimization and comparison of different time series analysis methods

Leilei Liu[1] · Haodong Yin[1] · Ting Xiao[1] · Beibei Yang[2,3] · Suzanne Lacasse[3]

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Abstract
Precise and efficient landslide displacement prediction is crucial for improving the effectiveness of landslide warning systems. Numerous time series decomposition and machine learning (ML) methods have been proposed and applied in landslide displacement prediction. Nevertheless, most ML methods display individual biases when applied to landslide displacement datasets, and the effect of different methods for time series decomposition on prediction results has not been systematically studied. Therefore, this paper adopts four methods commonly used for time series decomposition to decompose the accumulated displacement into a trend term and a periodic term. The double exponential smoothing is utilized to predict the trend displacement. After the grey relation analysis between the periodic displacement and the external cyclical influencing factors, the ensemble algorithm is used to integrate six commonly used ML algorithms for the prediction of periodic displacement, so as to eliminate the bias of individual artificial intelligence method and enhance the accuracy and stability of prediction results. Furthermore, Bayesian optimization is employed to optimize the base-learners, ensuring the integration fairness. The typical step-like landslides (i.e., Bazimen landslide, Caojiatuo landslide) in the Three Gorges area are selected to compare the performance of different methods for time series decomposition and illustrate the effectiveness of the framework of the ensemble algorithm with the evaluation indices of mean absolute error, mean absolute percentage error and root mean square error. The prediction results indicate that the ICEEMDAN method has the best performance in displacement decomposition. In addition, the prediction results of Bayesian optimized ensemble method are more robust than those of individual ML method, facilitating more accurate and stable landslide displacement prediction and more effective reference for landslide early warning.

Keywords Displacement prediction · Machine learning · Ensemble algorithm · Bayesian Optimization · Time series decomposition

Abbreviations

Bi	Bidirectional
BPNN	Back propagation neural network
DBi	Deep bidirectional
DES	Double exponential smoothing
DTR	Decision tree regression
EEMD	Ensemble EMD
ELM	Extreme learning machine
EMD	Empirical mode decomposition
FC	Fully connected

✉ Ting Xiao
tingxiao@csu.edu.cn

Leilei Liu
csulll@foxmail.com

Haodong Yin
215012119@csu.edu.cn

Beibei Yang
yangbeibei@ytu.edu.cn

Suzanne Lacasse
suzanne.lacasse@ngi.no

1 Key Laboratory of Metallogenic Prediction of Nonferrous Metals and Geological Environment Monitoring, Ministry of Education, School of Geosciences and Info-Physics, Central South University, Changsha 410083, People's Republic of China

2 School of Civil Engineering, Yantai University, Yantai 264005, People's Republic of China

3 Norwegian Geotechnical Institute, 0806 Oslo, Norway

FOA	Fruit fly optimization algorithm
GA	Genetic algorithm
GRA	Grey relation analysis
GRU	Gate recurrent unit
GWO	Grey wolf optimizer
ICEEMDAN	Improved complete ensemble EMD with adaptive noise
IMF	Intrinsic mode functions
LSTM	Long short-term memory
MA	Moving average
ML	Machine learning
MLP	Multilayer perceptron
MFIT	Multi-feature fusion transfer learning
NARX	Nonlinear autoregressive neural network with exogenous inputs
PSO	Particle swarm optimization
RF	Random forest
RNN	Recurrent neural network
SSSC	Soft screening stopping criteria
SVR	Support vector regression
VMD	Variational mode decomposition
WA	Wavelet analysis
WMA	Weighted moving average
XGBoost	Extreme gradient boosting

Notation

Y_t	Original time series of total displacement
T_t	Time series of trend displacement
C_t	Time series of periodic displacement
M	The order of MA
$\psi_{a,b}(t)$	Successive wavelet of WA
a	The frequency factor of wavelet basis function
b	The time factor of wavelet basis function
$W_{a,b}$	Wavelet coefficients of WA
$m_1(t)$	The average envelope of the original time series Y_t
$d_1(t)$	Remaining sequence corresponding to $m_1(t)$
J	The quantity of the decomposed IMF of the Gaussian white noise of ICEEMDAN
S_t^1	The first exponential smoothing value of the t period of DES
S_t^2	The second exponential smoothing value of the t period of DES
α	Smoothing constant of DES
a_t, b_t	Model parameters of DES
Q	The number of periods predicted for the future
F_{t+Q}	Predicted value of the $t + Q$ period of DES
$\zeta_t(k)$	The correlation coefficient between the sequence of influencing factors and the displacement sequence
$C_t(k)$	The sequence of landslide displacement
$I_t(k)$	The sequence of influencing factors
ρ	The gray resolution coefficient
K	The dividing quantity of the cross-validation of ensemble algorithm
x	The parameter space of the machine learning models
$f(x)$	The objective function in the optimization process of the machine learning models

1 Introduction

Step-like landslides are a type of rainfall reservoir-induced landslide with step-like deformation characteristics, which are affected by periodic external factors (Lu et al. 2021; Zhang et al. 2021a). These landslides are widely distributed in the Three Gorges area of China and pose great potential safety hazards to the lives and property of the local people (Miao et al. 2022). As such, the disaster warning and prevention of step-like landslides are particularly important (Lin et al. 2022). Globally, landslide early warning systems are crucial for mitigating landslide hazards (Naidu et al. 2018; Fan et al. 2019). Within these systems, precise and efficient prediction of landslide displacement is essential for early detection of landslide event, understanding landslide progression, and providing reliable data for early warning initiatives (Yao et al. 2015). Hence, developing methods to accurately and efficiently predict displacement in step-like landslides holds significant value.

The methods of landslide displacement prediction have been developed over the past five decades. So far, various methods have emerged (Miao et al. 2018; Wang et al. 2023), broadly classified into four categories based on their underlying principles and modeling processes: empirical model, numerical simulation, statistical model and nonlinear prediction model. The empirical model is mainly based on the creep theory, and the rheological function describing the landslide deformation is constructed according to the physical simulation results of the laboratory creep experiment (Saito 1969; Tavenas and Leroueil 1981; Voight 1988; Li et al. 2012). The numerical simulation of the landslide is primarily using the methods like finite element or material point methods based on geometric model to calculate the deformation (Wang et al. 2016; Kardani et al. 2021), which is associated with high computational costs and low modeling efficiency (Augarde et al. 2021; Liu and Wang 2021). The statistical model predicts the displacement mainly by analyzing the statistical trend of landslide evolution (Li et al. 2012), which is constrained when considering the complexities in the landslide evolution under the influence of multiple factors (Gao et al. 2020). The nonlinear prediction model mainly predict the landslide displacement based on the nonlinear relationship between landslide displacement and influencing factors (Cao et al. 2016). Herein, due to the robust nonlinear prediction capability (Liu et al. 2021a, 2021b), the machine learning (ML) has been widely used in the field of landslide displacement prediction. (Liu et al. 2014; Li et al. 2015; Hu et al. 2021; Zhang et al. 2024). Due to the variety of linear and nonlinear factors in the evolution process of landslides, the landslide displacement is mainly composed of trend, periodic and random displacement (Zhou et al. 2016), which is influenced by different external factors. Generally, the displacement prediction process that decomposing the cumulative displacement into different components firstly and then predict them respectively is conformed to the evolution mechanism of landslide displacement, which has been widely applied in landslide displacement prediction (Yang et al. 2019). Although some studies have attempted to predict random displacement (Miao et al. 2018), the minimal impact and inherent randomness of these displacements cast doubt on the reliability of such predictions. Consequently, this paper omits consideration of random displacement terms.

The signal of cumulative displacement can be expressed as the sum of trend and periodic displacement due to the independence of different components (Du et al. 2013; Zhang et al. 2021c). The moving average (MA) technique, a conventional approach for time series decomposition in landslide displacement analysis, is simple and convenient but has limitations in processing the initial and final data points, and the smoothing order requires manual determination (Zhou et al. 2016; Zhang et al. 2021d). As spectrum analysis technology advances, wavelet analysis (WA) has gained popularity for its ability to decompose landslide displacement, although it necessitates manual selection of successive wavelet (Cai et al. 2016; Huang et al. 2016). Furthermore, empirical mode decomposition techniques, such as empirical mode decomposition (EMD), ensemble EMD (EEMD), and improved complete ensemble EMD with adaptive noise (ICEEMDAN), offer substantial versatility and reduce manual intervention based on the principle of signal decomposition. Despite their utility, EMD and EEMD sometimes exhibit issues with local oscillations and residual noise in their results (Lian et al. 2014). The ICEEMDAN method refines this by improving the noise addition in the EMD process, achieving more uniform and precise decomposition (Colominas et al. 2014). While these methods have been applied in landslide displacement decomposition, the characteristics of their decompositions, such as the number of components, vary across methods. The impact of choosing different decomposition methods on landslide displacement prediction has not been thoroughly explored and compared in the literature.

Trend displacement, indicative of the landslide's long-term internal evolutionary trend, typically follows a relatively stable developmental law. Generally, the polynomial fitting method is employed for predicting trend displacement due to its ease of operation and straightforward principle (Xu and Niu 2018; Zhang et al. 2021d). However, as polynomials are fundamentally unbounded oscillating functions, they may not be ideal for predicting monotonically increasing trend displacements. Beyond polynomial fitting, the double exponential smoothing (DES) is another viable method for predicting the landslide trend displacement (Huang et al. 2017; Xing et al. 2020). In the context of predicting periodic displacement, ML methods are increasingly being utilized, leveraging the nonlinear mapping relationship between periodic displacement and seasonal influencing factors. These methods include support vector machine, artificial neural network, decision tree regression (DTR), extreme learning machine, among other advanced technologies (Hochreiter and Schmidhuber 1997; Ma et al. 2017, 2018; Li et al. 2018, 2019; Wang et al. 2022; Xing et al. 2019). In this context, seasonal influencing factors are typically identified using methods such as grey relation analysis (GRA) (Zhang et al. 2020b). Due to variations in data characteristics and the potential for ML models to be biased, excellent performance achieved by an individual ML method on a specific sample dataset does not guarantee the same level of performance on other datasets in different research cases (Kardani et al. 2021). The predictive performance of landslide displacement varies depending on the ML method used, and there exists an individual bias associated with each method's generalization ability. In addition, to improve the prediction performance of ML algorithms, various metaheuristic algorithms are used to optimize the hyperparameters of the prediction model (Ma et al. 2022), such as genetic algorithm, artificial bee colony algorithm, particle swarm optimization algorithm and grey wolf algorithm (Li and Kong 2014; Cai et al. 2016; Zhu et al. 2018; Zhang et al. 2021b; Zeng et al. 2022). However, these algorithms often gravitate towards local optimum and may suffer from lower computational efficiency.

This paper proposes a displacement prediction model for step-like landslide based on ensemble framework, aiming to overcome the bias of individual ML model to different landslide datasets and improve the prediction accuracy and generalization ability. To highlight the effectiveness of the ensemble framework, six commonly used ML models are selected to construct the learner pool of ensemble algorithm. The Bayesian optimization method is employed to optimize the hyperparameters of base-learners in the ensemble model to ensure the fairness in the process of ensemble. In addition, four conventional techniques of time series decomposition are utilized to decompose the time series of landslide displacement, and their respective effects on landslide displacement prediction are compared. For practical application, two typical step-like landslides in the Three Gorges

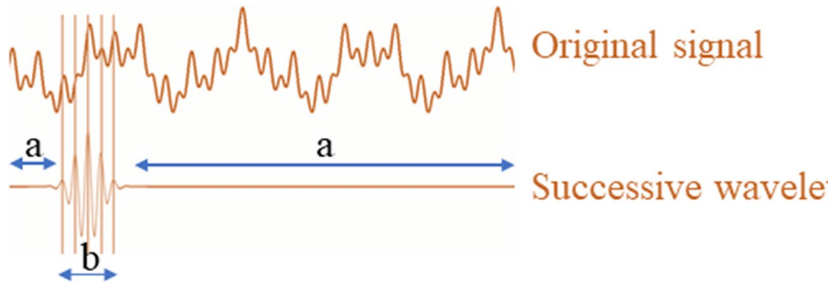


Fig. 1 Principle diagram of wavelet analysis (WA)

area, Bazimen landslide and Caojiatuo landslide, are chosen as case studies. To assess and contrast the various time series decomposition and displacement prediction methodologies, evaluation metrics such as mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE) are calculated.

2 Methodology

2.1 Decomposing the displacement time series into trend and periodic term

As the value of the random displacement is relatively small and unpredictable due to its inherent randomness, the time series of cumulative displacement are decomposed the into two components: trend displacement and periodic displacement (Lin et al. 2022; Zhou et al. 2022), as shown in Eq. (1). To analyze the influence of different time series decomposition methods on the landslide displacement prediction, the methods of MA, WA, EMD and ICEEMDAN, which are the major methods used widely in landslide displacement prediction at present, are selected to decompose the cumulative displacement of landslide.

$$Y_t = T_t + C_t \tag{1}$$

where Y_t donates the original time series of total displacement; T_t donates the time series of trend displacement; C_t donates the time series of periodic displacement.

2.1.1 Moving average

The MA method operates by sliding a fixed-size time window across the time series data. Within this window, it calculates the average value of a specified number of data points, effectively highlighting the long-term trend of the time series. This averaging approach is particularly effective at mitigating the impact of random fluctuations, making it well-suited for time series with periodic variations, such as landslide displacement. The primary formula for the MA calculation is as follows:

$$T_t = \frac{1}{M}\left(Y_{t-\frac{M-1}{2}} + \cdots + Y_{t-1} + Y_t + Y_{t+1} + \cdots + Y_{t+\frac{M-1}{2}}\right) \tag{2}$$

where M is the order of MA, which is relevant to the data frequency and the impact cycle of the external factors. Due to the annual variation of the landslide influencing factors (i.e., rainfall), the M is set to 12 to represent the time scale of one year (Yang et al. 2019; Zhang et al. 2021c).

2.1.2 Wavelet analysis

The WA method decomposes the time series of landslide displacement into components with varying frequencies. This decomposition is achieved by calculating wavelet coefficients. These coefficients are determined through the interaction between successive, artificially selected wavelets and the total displacement. In essence, each component analyzed matches the frequency of the current wavelet basis function (Huang et al. 2016). The general form of wavelet basis function utilized is as follows:

$$\int_{-\infty}^{+\infty} \psi_{a,b}(t)dt = 0 \tag{3}$$

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right), a, b \in R \tag{4}$$

where $\psi_{a,b}(t)$ donates the successive wavelet; a donates the frequency factor of wavelet basis function; b donates the time factor of wavelet basis function.

The calculation formula of wavelet coefficients is as follows:

$$W_{a,b} = \int_{-\infty}^{+\infty} Y_t \psi_{a,b}(t)dt \tag{5}$$

Figure 1 illustrates the process of continuous translation and expansion of the successive wavelet, achieved through altering parameters a and b, which in turn transforms the frequency. The wavelet coefficients, computed between the original signal and the successive wavelet, facilitate the analysis of different frequency components present in the time series of the original signal, specifically for landslide displacement.

2.1.3 EMD

The EMD method identifies all vibration modes in a time series using the characteristic time scale. Subsequently, it decomposes the complex time series into a finite number of intrinsic mode functions (IMF). These IMFs encapsulate local characteristic sequences at different frequencies from the original time series (Chen and Chou 2012; Xu and Niu 2018). The process of EMD to decompose the time series of landslide displacement is as follows:

$$m_1(t) = \frac{Y_{tmax} + Y_{tmin}}{2} \tag{6}$$

$$d_1(t) = Y_t - m_1(t) \tag{7}$$

where $m_1(t)$ donates the average envelope of the original time series; Y_{tmax} donates the fitting curve of the maximum point on the original time series (upper envelope); Y_{tmin} donates the fitting curve of the minimum point on the original time series (lower envelope); $d_1(t)$ donates the remaining sequence.

When $d_1(t)$ satisfies the stopping condition for obtaining the IMF, which means that the number of local extreme points and zero-crossing points of $d_1(t)$ are equal to 1 or the quantity gap between the two types of points is less than 1, and the average values of the upper envelope and the lower envelope at different times are equal to zero, then the $d_1(t)$ can be regarded as the first IMF obtained by the decomposition of the original time series. Otherwise, Eqs. (6) and (7) are repeated until the stopping condition is satisfied. After the first IMF is obtained, the original sequence is subtracted to obtain the first-order residual quantity, which is used to replace the original time series. The n-order modal component is obtained after repeating the steps above for n times. The IMF with the lowest frequency is regarded as the trend displacement, and the remaining IMF components are cumulated to obtain the periodic displacement.

2.1.4 ICEEMDAN

The ICEEMDAN method employs EMD to decompose Gaussian white noise, which has a zero mean, into J IMF components. These components are then added to the original landslide displacement time series for sequence reconstruction. Consequently, J time series of landslide displacement are created for decomposition. The IMF of each order is determined by calculating the mean of the IMFs derived from the decomposition of the J -times reconstructed time series. This process, including the separation of trend and periodic displacement components, is consistent with the EMD approach (Colominas et al. 2014).

2.2 Predicting the trend displacement

The DES is employed to predict the trend displacement derived from time series decomposition. This method utilizes a specialized weighted average approach, where greater weight is assigned to historical data closer to the forecast period, and less weight to data further away. The weights assigned decrease exponentially with distance from the prediction period. This characteristic makes DES particularly effective for predicting linear trend displacement (Xing et al. 2020). The primary calculation formula of DES is as follows:

$$S_t^1 = \alpha Y_{t-1} + (1-\alpha) S_{t-1}^1 \tag{8}$$

$$S_t^2 = \alpha S_t^1 + (1-\alpha) S_{t-1}^2 \tag{9}$$

where S_t^1 donates the first exponential smoothing value of the t period; S_t^2 donates the second exponential smoothing value of the t period; α donates the smoothing constant, which is set to 0.5 appropriately generally. The prediction results are given by the following formula:

$$F_{t+Q} = a_t + b_t Q \tag{10}$$

$$a_t = 2S_t^1 - S_t^2 \tag{11}$$

$$b_t = \frac{\alpha}{1-\alpha}\left(S_t^1 - S_t^2\right) \tag{12}$$

where F_{t+Q} donates the predicted value of the $t+Q$ period; Q donates the number of periods predicted for the future; a_t and b_t donate the model parameters respectively.

2.3 Predicting the periodic displacement

2.3.1 Grey relation analysis

When the base-learners of the ensemble algorithm are utilized to predict the periodic displacement, the input original data includes the periodic displacement and its external influencing factors. Herein, GRA is used to select the influencing factors closely related to the periodic displacement to improve the prediction accuracy. GRA is a multi-factor statistical analysis method. By calculating the correlation coefficient between the mother sequence (periodic displacement) and the sub-sequence (time series of influencing factors, such as rainfall, etc.) and sorting, the relation degree between the influencing factors and the periodic displacement is measured (Miao et al. 2018; Zeng et al. 2022). The correlation coefficient is calculated according to Eq. (13).

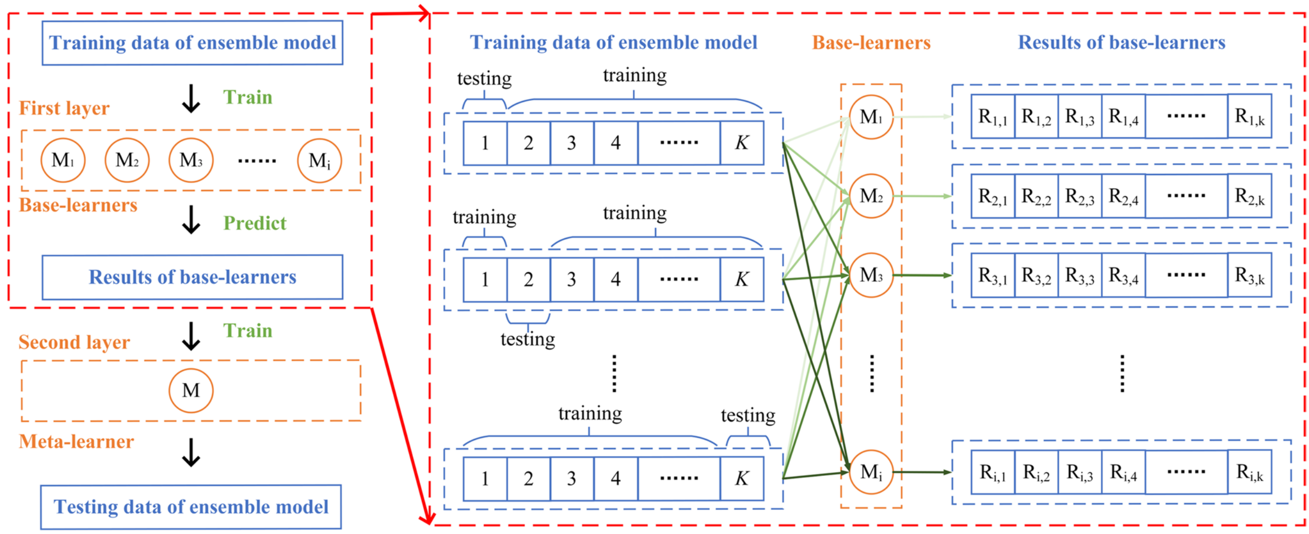


Fig. 2 The operation process of the ensemble algorithm

$$\zeta_t(k) = \frac{min_t min_k |C_t(k) - I_t(k)| + \rho max_t max_k |C_t(k) - I_t(k)|}{|C_t(k) - I_t(k)| + \rho max_t max_k |C_t(k) - I_t(k)|} \tag{13}$$

where $\zeta_t(k)$ donates the correlation coefficient between the sequence of influencing factors $I_t(k)$ at time k and the displacement sequence $C_t(k)$, which is generally between $0 \sim 1$. The relation degree increases with the growth of correlation coefficient; $min_t min_k |C_t(k) - I_t(k)|$ donates the absolute value of the second-order minimum difference between the sub-sequence and the mother sequence at time k; $max_t max_k |C_t(k) - I_t(k)|$ donates the absolute value of the second-order maximum difference between the sub-sequence and the mother sequence at time k; ρ donates the gray resolution coefficient, which is set to 0.5 appropriately generally.

2.3.2 Ensemble algorithm

The ensemble algorithm is used to predict the periodic displacement obtained by time series decomposition, which can eliminate the individual bias of different ML methods to improve the accuracy and generalization ability of the prediction model by integrating multiple individual learners, that means the overall learner is superior to the individual learner (Jena et al. 2020; Kardani et al. 2021; Rong et al. 2023). Figure 2 shows the operation process of the ensemble algorithm. The ensemble algorithm generally includes two parts: the base-learners (the first layer) and the meta-learner (the second layer). In the training process of ensemble model, the *K*-Fold cross-validation method is introduced to train the base-learners firstly. By dividing the training dataset of ensemble into K parts on average, each part is used as the testing data of each Fold, and the remaining data is used as the training data of the current Fold, then the base-learners M_i can be trained based on the training data and obtain the periodic displacement based on the testing data $M_{i,k}$. The prediction results of periodic displacement on each Fold through training and testing of one base-learner are spliced in turn to obtain a complete prediction result of periodic displacement of each base-learner on the original dataset. The prediction results of individual base-learner are used as the input features and the periodic displacement obtained by time series decomposition are used as the target output to train the meta-learner, then the training of the ensemble model is completed. In this study, we focus on the effectiveness of the ensemble framework rather than the performance of a single artificial intelligence approach. Hence, six commonly used ML regression algorithms (i.e., DTR, multilayer perceptron (MLP), random forest (RF), extreme gradient boosting (XGBoost), support vector regression (SVR) and Ridge), are selected to construct the learner pool of the ensemble algorithm.

In general, the traditional evaluation of the performance of ML model is mainly carried out by quantifying the accuracy of the prediction results of test dataset after the model training on the training set. However, the results of this performance evaluation are easily affected by the division of the training and testing dataset, while the original dataset is not fully utilized. Hence, a 5-Fold cross-validation method is used to evaluate the performance of the prediction models in this study, which shows the advantages of reducing over-fitting and fully utilizing the original dataset. The original dataset mainly incorporates the time series of periodic displacement obtained by time

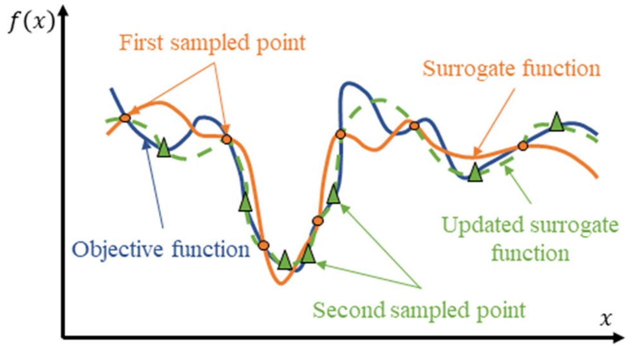


Fig. 3 The process of Bayesian optimization

series decomposition and the corresponding influence factors. After dividing the training dataset of ensemble into 5 parts on average, each part is utilized as the testing dataset of ensemble model on the current Fold, and the remaining data is used as the training dataset of ensemble model on the current Fold. Hence, the prediction results of periodic displacement on each Fold through training and testing of the ensemble model on the original dataset are spliced in turn to obtain a complete prediction result of periodic displacement. The basic process of cross-validation has been described in the training process of the base-learners above.

2.3.3 Bayesian optimization algorithm

The Bayesian optimization algorithm, recognized as one of the best methods in ML for efficiently balancing optimization efficiency and accuracy in hyperparameter tuning, is utilized in this study to optimize the hyperparameters of base-learners, aiming to ensure the fairness in model integration and enhance the modeling efficiency (Huang et al. 2022; Li and Yang 2022; Yang et al. 2022). Figure 3 shows the main process of Bayesian optimization, where x donates the parameter space of the ML models, and $f(x)$ donates the objective function. The objective function is typically a regression evaluation index such as mean square error. The optimal parameters are determined when the objective function obtains the minimum value. In this optimization process, the surrogate function is utilized to fit to the real objective function based on randomly sampled points along the x-axis. This surrogate function is continually refined by collecting more data points near the minimum value or in unsampled areas, so as to approximate the true objective function progressively. The goal is to find the optimal solution corresponding to the minimum value of the objective function, and this process is guided by the sampling function.

2.4 Flowchart of the proposed model for landslide displacement prediction

To evaluate the performance of different methods of landslide displacement prediction and time series decomposition, three indices of regression evaluation, MAE (Eq. (14)), MAPE (Eq. (15)) and RMSE (Eq. (16)) are adopted. Figure 4 shows the main process of the displacement prediction model proposed in this paper, which mainly includes three parts: time series decomposition, trend displacement prediction and periodic displacement prediction.

Part 1. Decompose the monitoring data of landslide cumulative displacement by the methods for time series decomposition to obtain the landslide periodic displacement and trend displacement.

Part 2. Predict the trend displacement by the method of DES, and the predicted trend displacement will be added to the predicted period displacement to obtain the total displacement.

Part 3. Confirm the influencing factors of landslide preliminarily by analyzing the monitoring data of landslide cumulative displacement. The GRA method is used to select the most influential factors related to the periodic displacement. The time series of these selected factors are used as inputs, while the time series of periodic displacement serves as the output for training the base-learners. The prediction results of each base-learner on the periodic displacement are obtained by cross-validation, which are used as the input of the meta-learner to establish the ensemble model. To ensure the fairness in the ensemble, Bayesian optimization is used to optimize the base-learners' parameters. The primary steps of Bayesian optimization include:

(I) Initialization of the surrogate function;
(II) Sampling using the sampling function;
(III) Training learners based on parameters from the sampled points to obtain the objective function value;
(IV) Updating the surrogate function;
(V) Repeating the above steps until the maximum number of iterations is reached.

Based on the theory of time series analysis, the predicted total displacement is obtained by adding the predicted trend and periodic displacement, and the performance of landslide displacement prediction is evaluated according to the statistical results of evaluation index.

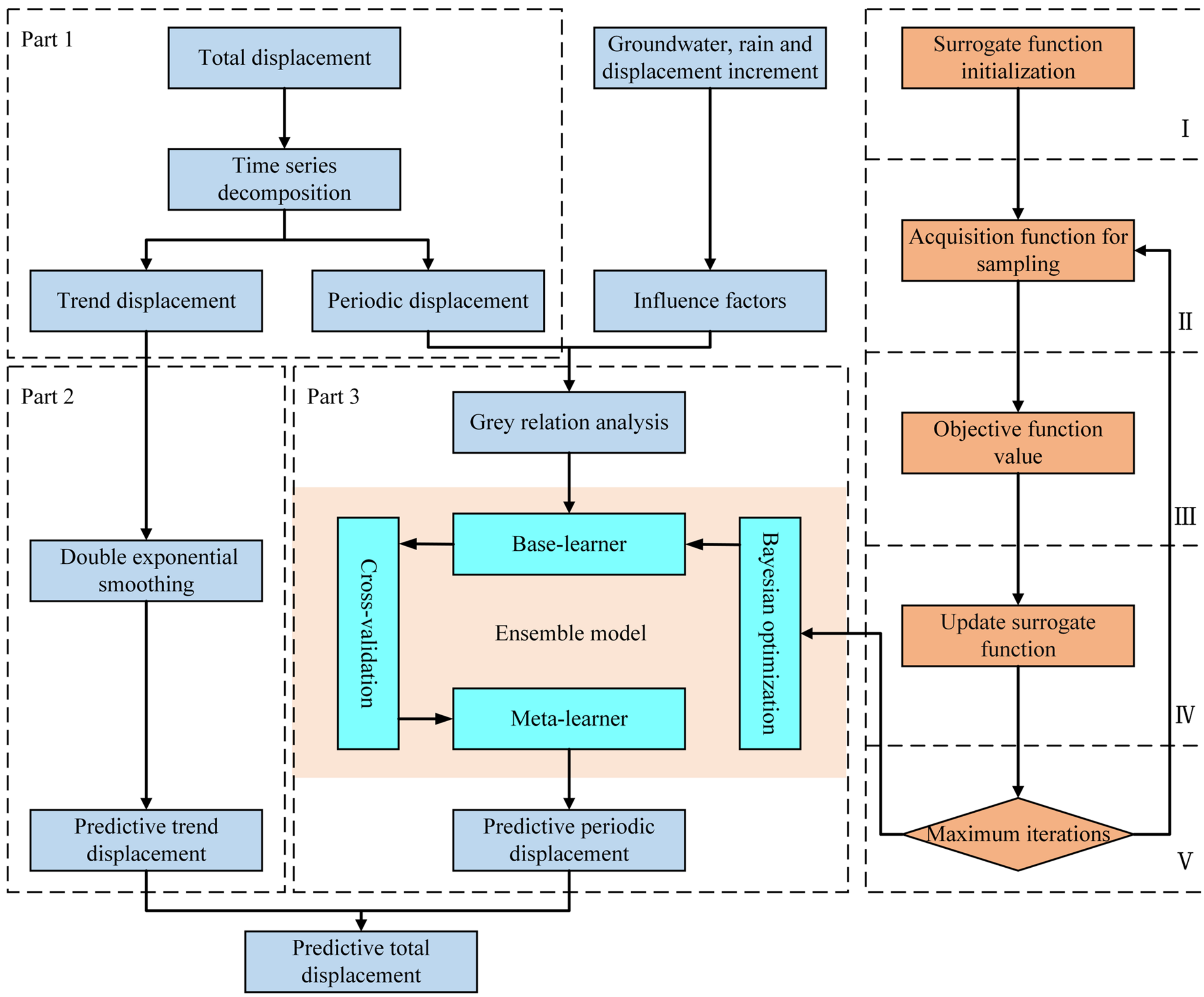


Fig. 4 Flowchart of the proposed prediction model of landslide displacement

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Y_p - Y_t\right| \tag{14}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|Y_p - Y_t\right|}{Y_t} \tag{15}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(Y_p - Y_t\right)^2}{N}} \tag{16}$$

where Y_t donates the original time series of total displacement; Y_p donates the predicted time series of total displacement, N represents the quantity of total monitoring periods.

3 Results

3.1 Case 1: Bazimen landslide

3.1.1 Geological conditions and monitoring data

The Bazimen landslide is located in Guizhou Town, Zigui County, Hubei Province, which is on the right bank of the Xiangxi River, a tributary of the northern bank of the Yangtze River. The bank slope is in north–south direction, and the landslide body is distributed at the foot of the bank slope in a dustpan shape with 139 ~ 280 m distribution elevation, the slope of the landslide body is 10 ~ 30°, and the volume of the landslide is about 2 million m^3. The types of monitoring data mainly include landslide surface displacement, rainfall and

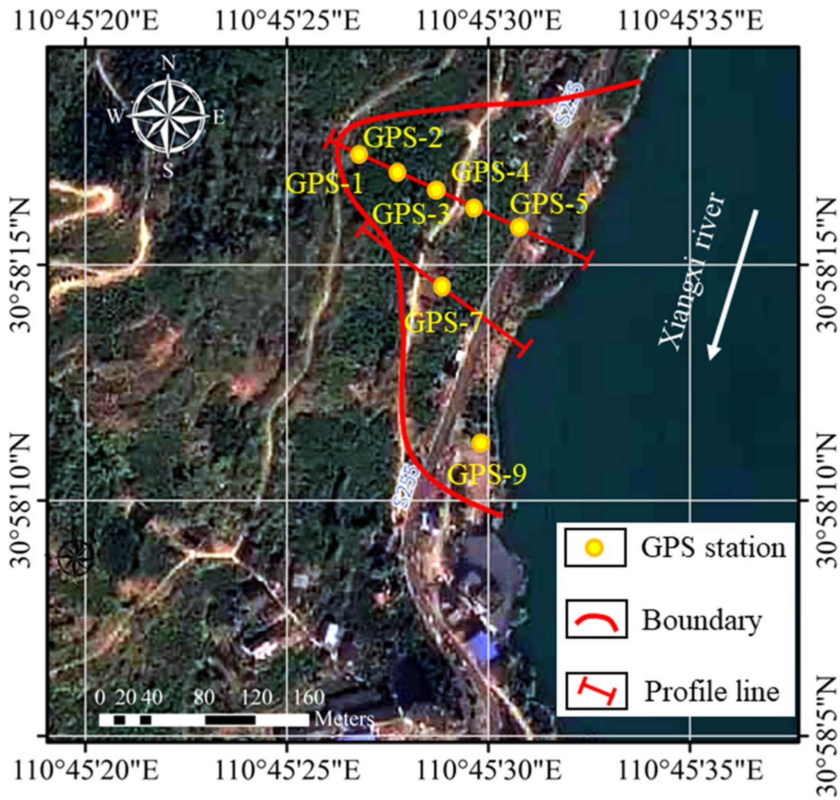


Fig. 5 The diagram of the distribution about the GPS monitoring points of surface displacement on Bazimen landslide

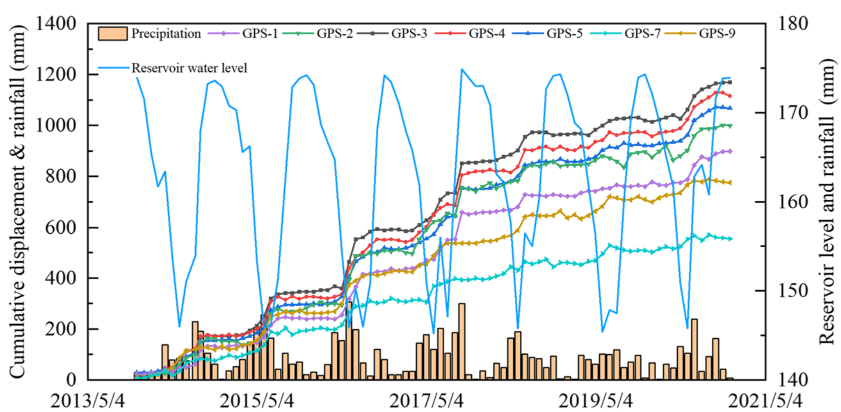


Fig. 6 Monitoring data of Bazimen landslide

reservoir water level. The distribution of GPS monitoring points of surface displacement is shown in Fig. 5.

Figure 6 displays the monitoring data for the Bazimen landslide, showing that from October 2013 to October 2020, there were multiple step-like uplifts in the landslide. Among them, a significant trend was observed where the largest uplifts in the Bazimen landslide coincided with the highest rainfall each June, with this pattern being particularly pronounced in June of 2015, 2016, and 2017. This correlation suggests a substantial relationship between the landslide deformation and both the rainfall and the fluctuations in the water level of the Three Gorges Reservoir. It is important to note that the monitoring period for the Bazimen landslide was set at one-month intervals, and thus, the displacement predictions made in this study were conducted on a monthly basis.

3.1.2 Displacement decomposition

Figure 6 indicates that among the Bazimen landslide's GPS monitoring points, GPS-3 exhibits the largest surface displacement with a pronounced step-like feature. Consequently, the monitoring data from GPS-3 is selected as the sample data for landslide displacement prediction. Various methods, including the MA, WA, EMD, and ICEEMDAN, are adopted to decompose the landslide displacement into

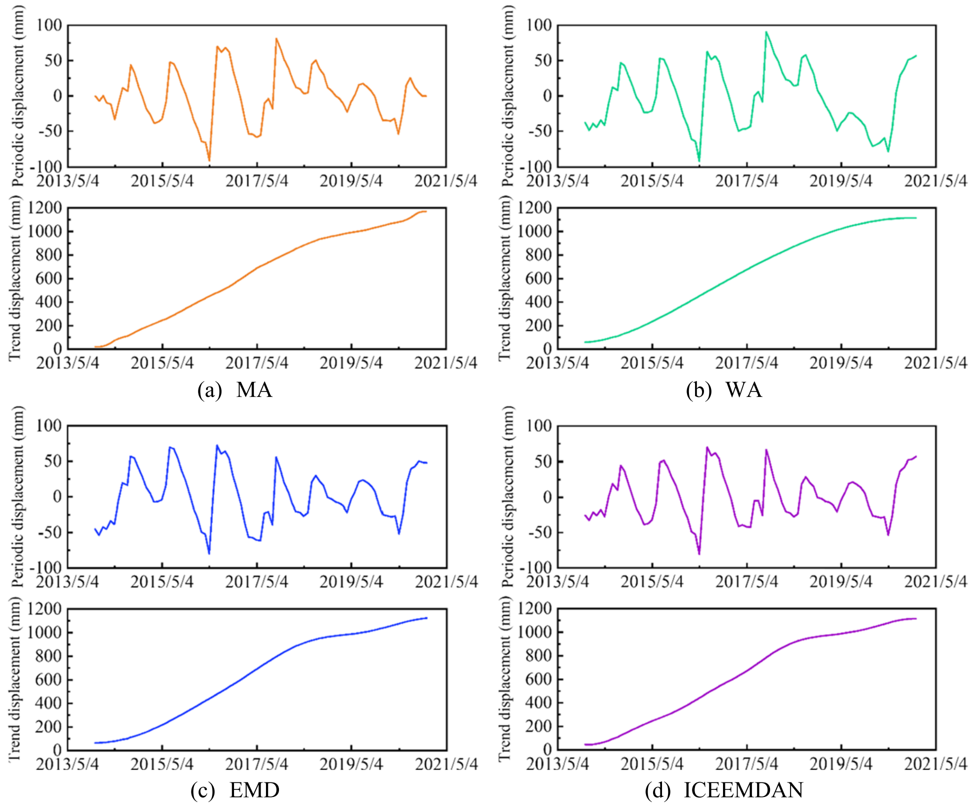


Fig. 7 Displacement decomposition of Bazimen landslide based on different methods for time series decomposition

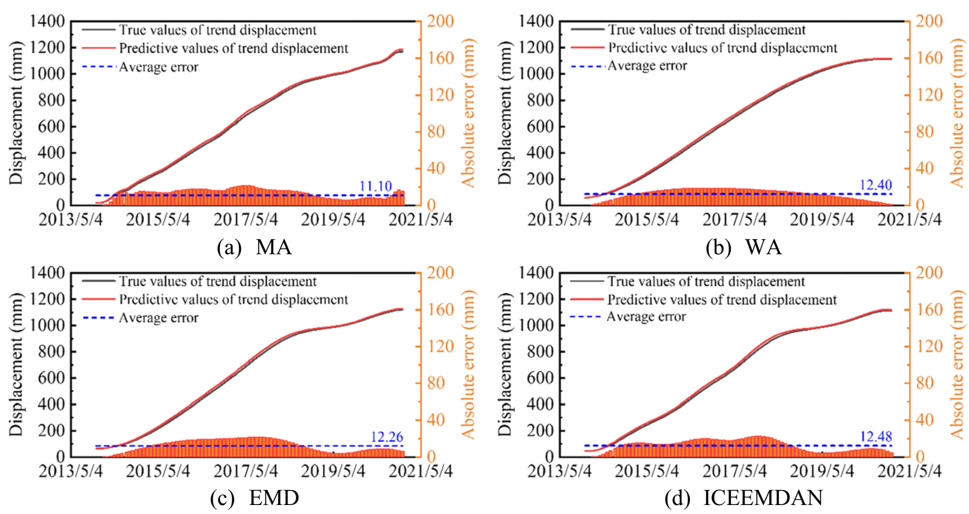


Fig. 8 Trend displacement prediction of Bazimen landslide based on different methods for time series decomposition

trend and periodic components. Figure 7 presents the decomposition results using these methods. It is observed that while the results from EMD and its improved version ICEEMDAN are similar, the trend and periodic displacements derived from other methods show differences. Notably, the trend displacement obtained through WA is the smoothest and most stable, yet this does not necessarily imply that WA's decompositions accurately reflect the actual scenario. The effectiveness of these decomposition methods needs further verification through the testing results of the total displacement prediction.

3.1.3 Trend displacement prediction

The DES method is used to predict the trend displacement derived from various time series decomposition methods. Figure 8 shows the prediction results of the trend displacement and the corresponding prediction error. It can be

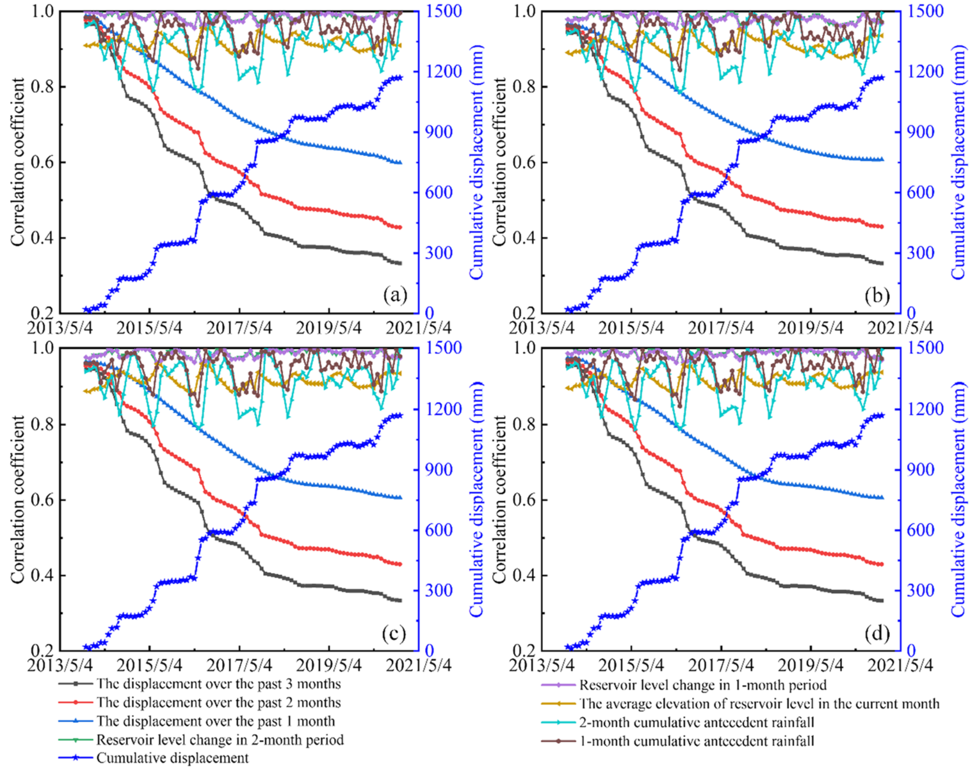


Fig. 9 The results of GRA of Bazimen landslide based on different methods for time series decomposition: (**a**) MA; (**b**) WA; (**c**) EMD; (**d**) ICEEMDAN

observed that DES effectively predicts the trend displacement, accurately reflecting the evolution characteristic of steady growth based on historical data up to the prediction point, thus offering practical significance in forecasting. Moreover, the average prediction errors for the trend displacement, derived from various time series decomposition methods, exhibit relative uniformity, predominantly between 11 to 13 mm. A noteworthy observation is that a decrease in the slope of the trend displacement curve is associated with a reduction in prediction error.

3.1.4 Periodic displacement and total displacement prediction

Determination of influencing factors The ensemble algorithm predicts the periodic displacement by extracting the nonlinear relation between the periodic displacement and seasonal influencing factors. To improve the accuracy of these predictions, it is necessary to select the influencing factors closely related to the periodic displacement (Xu and Niu 2018). Based on the Bazimen landslide monitoring data, eight influencing factors have been identified: the 1-month cumulative antecedent rainfall, the 2-month cumulative antecedent rainfall, the 3-month cumulative antecedent rainfall, the average elevation of reservoir level in the current month, reservoir level change in 1-month period, reservoir level change in 2-month period, the displacement over the past 1 month, the displacement over the past 2 months and the displacement over the past 3 months (Zhang et al. 2021d; Ma et al. 2022). The correlation coefficient between different influencing factors and the periodic displacement is calculated by the GRA method. Then, factors with high correlation coefficients are selected as inputs for the ensemble algorithm. Figure 9 illustrates the grey relational analysis process, showing the correlation between periodic displacement (obtained through different time series decomposition methods) and the selected influencing factors. A correlation coefficient closer to 1 indicates a more significant impact of the influencing factors on the periodic displacement. As depicted in Fig. 9, the correlation between past displacement and the periodic displacement decreases over time.

Table 1 presents the average values of the correlation coefficients, calculated by the GRA method, which quantify the relationship between periodic displacement and influencing factors. These coefficients range from 0.5 to 1, signifying a notable correlation between the periodic displacement, derived from diverse time series decomposition methods, and external influencing factors. Significantly, factors pertaining to rainfall and reservoir levels demonstrate a substantial impact on periodic displacement, as evidenced by higher correlation coefficients. Conversely, factors related to displacement in recent months exhibit a lesser influence, with correlation coefficients showing a decreasing trend over longer time intervals. Following the principle that a higher correlation coefficient indicates a stronger relation degree

Table 1 Calculation results of correlation coefficient between the influencing factors and the periodic displacement

Influencing factor	MA	WA	EMD	ICEEMDAN
1-month cumulative antecedent rainfall	0.951	0.947	0.951	0.950
2-month cumulative antecedent rainfall	0.909	0.906	0.910	0.908
The average elevation of reservoir level in the current month	0.915	0.913	0.916	0.914
Reservoir level change in 1-month period	0.986	0.981	0.985	0.986
Reservoir level change in 2-month period	0.987	0.982	0.986	0.987
The displacement over the past 1 month	0.750	0.746	0.748	0.747
The displacement over the past 2 months	0.619	0.615	0.617	0.616
The displacement over the past 3 months	0.537	0.533	0.535	0.534

(Miao et al. 2018; Yang et al. 2019; Zhang et al. 2020b), factors with coefficients exceeding 0.9 were selected as input features for the ensemble algorithm to forecast periodic displacement.

Periodic displacement prediction The selected influencing factors and periodic displacement are used as the original sample data for the ensemble algorithm to predict the periodic displacement. Herein, six commonly used ML algorithms are chosen to construct the learner pool of the ensemble algorithm: DTR, MLP, RF, XGBoost, SVR and Ridge. Generally, increasing the variety of base-learners in the ensemble algorithm can improve the prediction effect. Hence, all models in the learner pool are selected as the base-learners. To ensure the fairness of the ensemble, the Bayesian optimization method is used to obtain the optimal parameters of each base-learner. The prediction results from base-learners on the original sample data, validated through K-fold cross-validation, are then used as inputs for the meta-learner. Considering the need for reasonable sample division, choosing 5 as the value of K in this study. Each individual model in the learner pool is regarded as meta-learner and combined with the base-learners to establish the ensemble model. Figure 10 shows the prediction results of the periodic displacement obtained by different time series decomposition methods, based on the ensemble algorithms with various meta-learners.

According to the prediction results, it can be observed that the Bayesian optimized ensemble algorithm model has a good performance on the periodic displacement prediction of Bazimen landslide, which can correctly reflect the annual fluctuation of the periodic displacement. Among them, the prediction performance of the periodic displacement based on the ICEEMDAN method is the best compared with other methods for time series decomposition, indicating that the periodic displacement decomposed by the ICEEMDAN method are the most realistic and consistent with the actual situation.

Total displacement prediction Figure 11 shows the prediction results for the total displacement of the Bazimen landslide, achieved by various time series decomposition methods and ensemble algorithms with different meta-learners. These results represent the sum of the predicted trend displacement and periodic displacement predictions. The proposed method, combining time series decomposition and Bayesian optimized ensemble algorithm, shows excellent performance, aligning well with the step-like deformation characteristics of Bazimen landslide. Notably, the ICEEMDAN method outperforms other time series decomposition methods in predicting total displacement. Additionally, the prediction results vary significantly across local time periods when different decomposition methods are used. This variation is attributed to the significant impact of the time series decomposition results on the predictions. If there is a major discrepancy between the decomposed components (trend and periodic terms) and the actual components, the ML methods may fail to accurately map the relationship between influencing factors with seasonal fluctuations and periodic displacement. This can adversely affect displacement prediction accuracy. Therefore, selecting the most appropriate time series decomposition method is crucial for accurately predicting landslide displacement, particularly when dealing with low-frequency and simple signal scenarios.

Figure 12 shows the evaluation indices for the total displacement predictions based on various time series decomposition methods and ensemble algorithms with different meta-learners, including MAE, MAPE and RMSE.[1] The results indicate that the ensemble algorithms with different meta-learners yield relatively stable and accurate predictions, demonstrating the proposed model has better generalization ability. Among them, the ICEEMDAN method consistently shows the lowest values across all three evaluation

[1] Mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE).

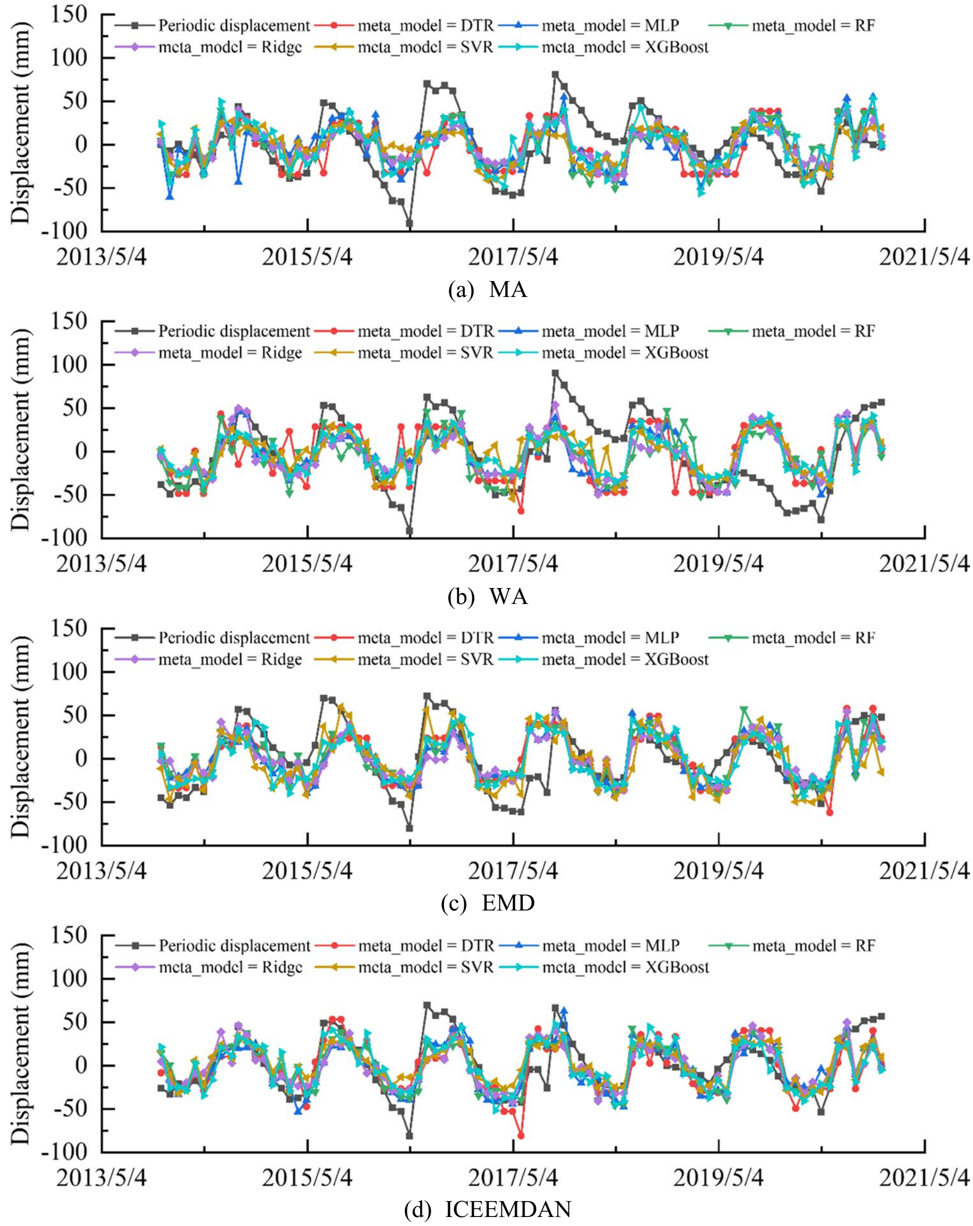


Fig. 10 Prediction of periodic displacement of Bazimen landslide based on different methods for time series decomposition

indices, suggesting its exceptional performance in landslide displacement prediction.

To further verify the advantages of the proposed method, the paired t-test is conducted based on the prediction results related to different time series decomposition. According to the paired t-test, the significance level is achieved when the p-value < 0.05, indicating that the difference of the compared time series is significant. As shown in Table 2, the most p-value related to ICEEMDAN vs. the other time series decomposition are less than 0.05, suggesting the superiority of the proposed prediction model. Besides, the significant difference between ICEEMDAN and EMD are smaller than the other pairwise comparison, which is consistent with expectations according to the results of time series decomposition in Fig. 7.

3.2 Case 2: Caojiatuo landslide

3.2.1 Geological conditions and monitoring data

The Caojiatuo landslide is located in Wushan area of Three Gorges, north bank of Yangtze River, with dustpan shape, and there are many large gullies on both sides of the landslide boundary. The landslide mainly produces sliding deformation in the direction of the Yangtze River with 187° sliding direction, and the distribution elevation is between 125 and 275 m. The length and width of the landslide are

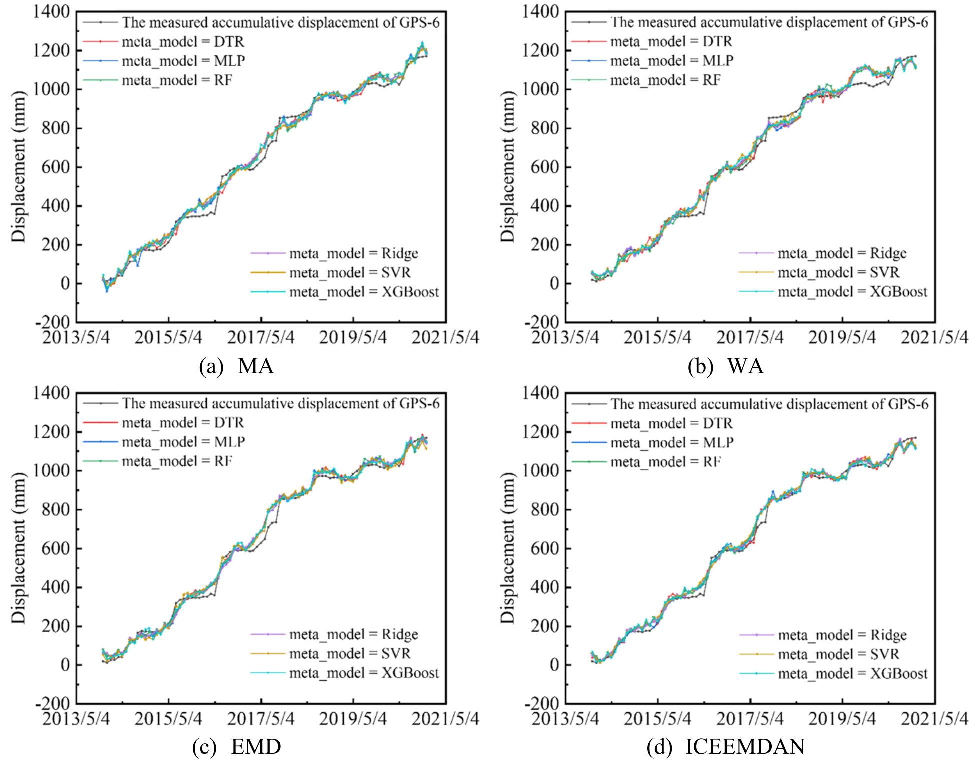


Fig. 11 Prediction of total displacement of Bazimen landslide based on different methods for time series decomposition

about 900 m and 500 m, respectively. The thickness of the sliding body is about 25 m, which belongs to the large soil landslide. The monitoring types of Caojiatuo landslide incorporate multiple monitoring points of landslide surface displacement, meteorological and hydrological. Here, the distribution of GPS monitoring points of surface displacement is shown in Fig. 13.

Figure 14 shows the displacement monitoring data of Caojiatuo landslide that from February 2007 to November 2013. It can be seen that the deformation of Caojiatuo landslide is related to the change of rainfall and reservoir water level. After the end of each water impoundment period (i.e., the reservoir water level declined to the minimum), the deformation of the landslide would uplift in the several few months, which exhibits the annual variation features of step-like deformation generally. Notably, the first large-scale deformation was observed in 2009 after the first wider fluctuation of reservoir water level. The fluctuation of reservoir water level generally affects the stability of the front edge of the landslide. With the periodic change of reservoir water level, the front edge of the landslide is constantly washed away, forming multiple local small bank collapses and constantly developing to the trailing edge and causing the Caojiatuo landslide to present the deformation characteristics as the retrogressive landslide. The displacement prediction for the Caojiatuo landslide was conducted monthly, aligned with the established monthly monitoring schedule.

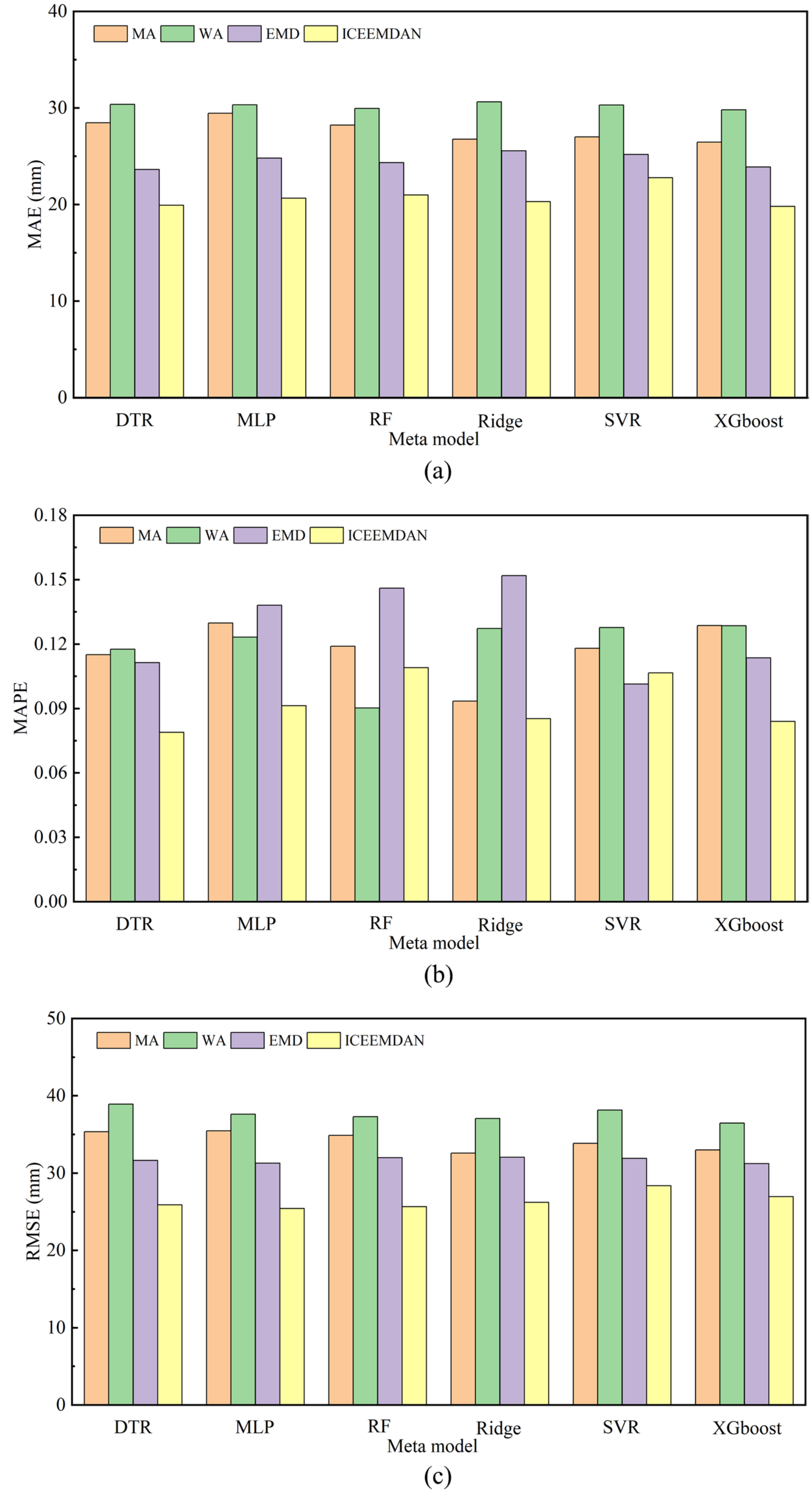
3.2.2 Displacement decomposition

The GPS-6 monitoring data is selected as the sample data for the modelling of landslide displacement prediction due to the most obvious step-like deformation characteristics, and the four methods for time series decomposition selected in this study are utilized to decompose the cumulative displacement to obtain the trend displacement and periodic displacement. Figure 15 shows the decomposition results of GPS-6 monitoring data, which indicates that the decomposition characteristics of the four methods for time series decomposition are similar to the decomposition results of Bazimen landslide. Herein, the curve of trend displacement obtained by WA is the smoothest, while the decomposition results of EMD and ICEEMDAN methods are similar. In general, the decomposition results of other methods are quite different.

3.2.3 Trend displacement prediction

Figure 16 shows the prediction results of the trend displacement of Caojiatuo landslide. The pattern of prediction errors over different time periods closely resembles that observed in the Bazimen landslide, where the prediction error diminishes as the slope of the trend displacement curve decreases. Furthermore, the prediction results show that the DES method is also suitable for the prediction of trend displacement. Although obviously

Fig. 12 Evaluation of error in total displacement prediction of Bazimen landslide based on different methods for time series decomposition



smoother than those obtained by other decomposition methods, the trend displacement results from the WA method show little difference compared to those based on the DES method.

3.2.4 Periodic displacement and total displacement prediction

Determination of influencing factors The initial influencing factors selected for the displacement prediction of Caojiatuo

Table 2 Results of the paired t-test regarding the comparison of performances of the proposed prediction model models related to Bazimen landslide based on different time series decomposition

Meta-models	Pairwise comparison	*p*-value	significance
DTR	ICEEMNAN vs. MA	0.001	Yes
	ICEEMNAN vs. WA	0.000	Yes
	ICEEMNAN vs. EMD	0.072	No
MLP	ICEEMNAN vs. MA	0.000	Yes
	ICEEMNAN vs. WA	0.001	Yes
	ICEEMNAN vs. EMD	0.017	Yes
RF	ICEEMNAN vs. MA	0.001	Yes
	ICEEMNAN vs. WA	0.001	Yes
	ICEEMNAN vs. EMD	0.056	No
Ridge	ICEEMNAN vs. MA	0.000	Yes
	ICEEMNAN vs. WA	0.000	Yes
	ICEEMNAN vs. EMD	0.001	Yes
SVR	ICEEMNAN vs. MA	0.022	Yes
	ICEEMNAN vs. WA	0.003	Yes
	ICEEMNAN vs. EMD	0.201	Yes
XGBoost	ICEEMNAN vs. MA	0.004	Yes
	ICEEMNAN vs. WA	0.000	Yes
	ICEEMNAN vs. EMD	0.032	Yes

landslide are the same as those of Bazimen landslide, owing to the similar geological similarities and deformation characteristics between the two cases. Figure 17 and Table 3 show the calculation process of GRA and the average value of the calculation results of correlation coefficient between periodic displacement and influencing factors in the different monitoring periods. Generally, the features of the calculation results of the correlation coefficient between the influencing factors and periodic displacement of Caojiatuo landslide are roughly same as that of Bazimen landslide. Notably, the correlation coefficient between cumulative rainfall and periodic displacement of Caojiatuo landslide is lower than that of Bazimen landslide. According to the calculation results in Fig. 17 and Table 3, the influencing factors with the correlation coefficient larger than 0.9 are selected as the input features of the ensemble algorithm, which are the same as those of the Bazimen landslide.

Periodic displacement prediction After the determination of the influencing factors, the prediction of periodic displacement of Caojiatuo landslide adopts the same ensemble pattern as that of the Bazimen landslide. The selected six ML algorithms in the learner

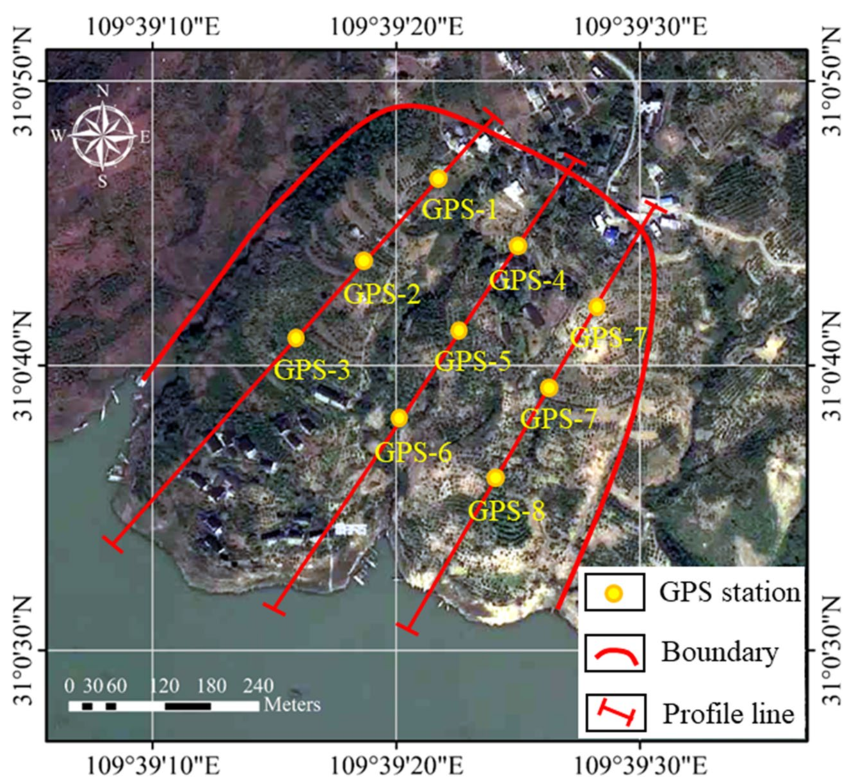


Fig. 13 The diagram of the distribution about the GPS monitoring points of surface displacement on Caojiatuo landslide

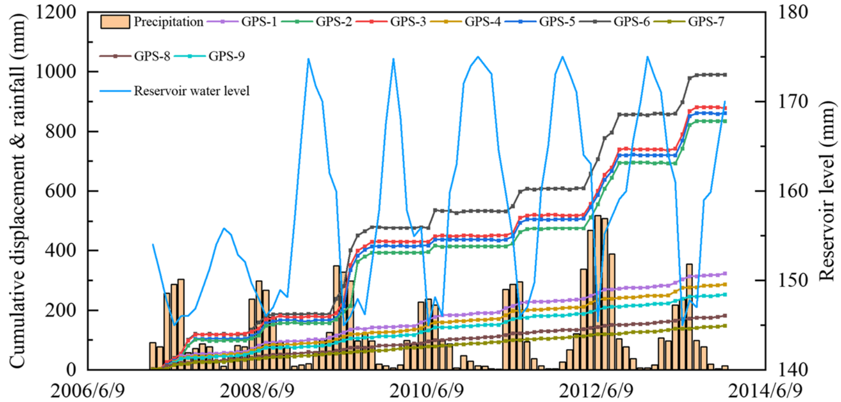


Fig. 14 Monitoring data of Caojiatuo landslide

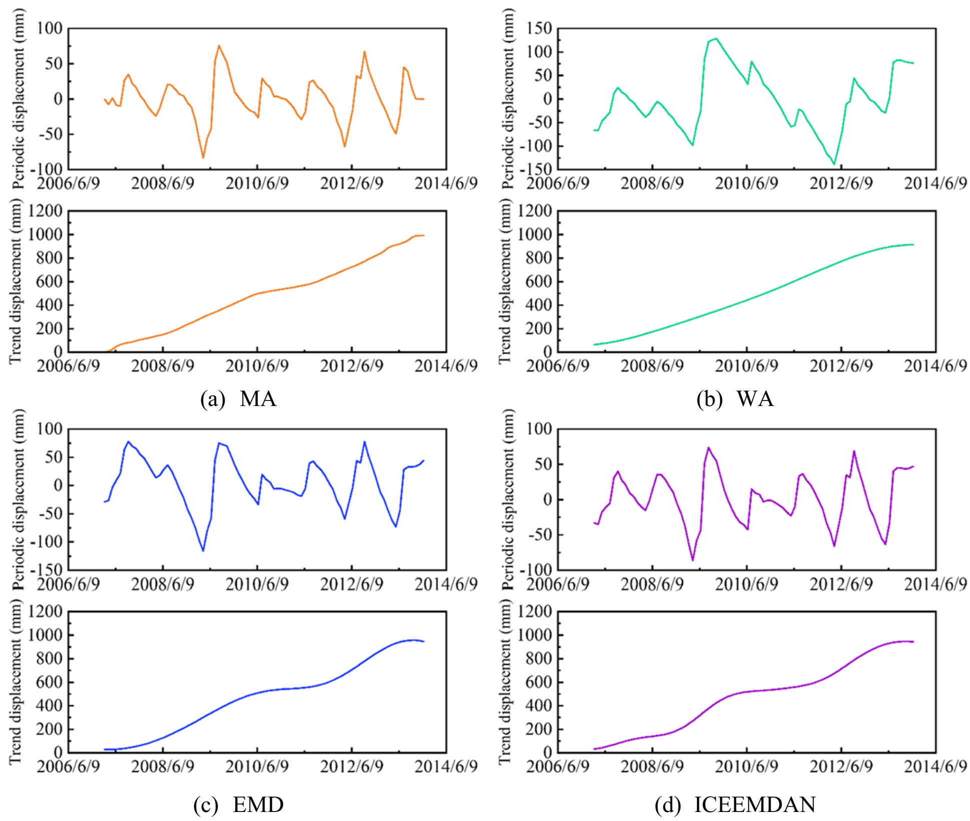


Fig. 15 Monitoring data of Caojiatuo landslide based on different methods for time series decomposition

pool are regarded as base-learners to be combined with individual ML methods (meta-learner) in the learner pool to establish the ensemble model, and the Bayesian optimization is adopted to optimize the hyperparameters of each base-learner in the ensemble model to obtain the optimal base-learner, so as to ensure the fairness of the ensemble. During the ensemble process, the prediction results of the base-learners are used as the input of the meta-learner by 5-Fold cross-validation. Using the established ensemble prediction model, the periodic displacement of Caojiatuo landslide is predicted based on the input of the influencing factors determined by GRA.

Figure 18 shows the prediction results of the periodic displacement obtained by different methods for time series decomposition of Caojiatuo landslide by the ensemble model with different meta-learners. It can be observed that the ensemble model exhibits a good performance in predicting the periodic displacement of Caojiatuo landslide, which is consistent with the seasonal fluctuation characteristics of the monitored periodic displacement. In addition, the prediction results of the periodic displacement obtained by different methods for time series decomposition are quite different. Among them, the prediction results based on the WA method produce a large prediction error when the periodic displacement changes greatly. Although the WA method can

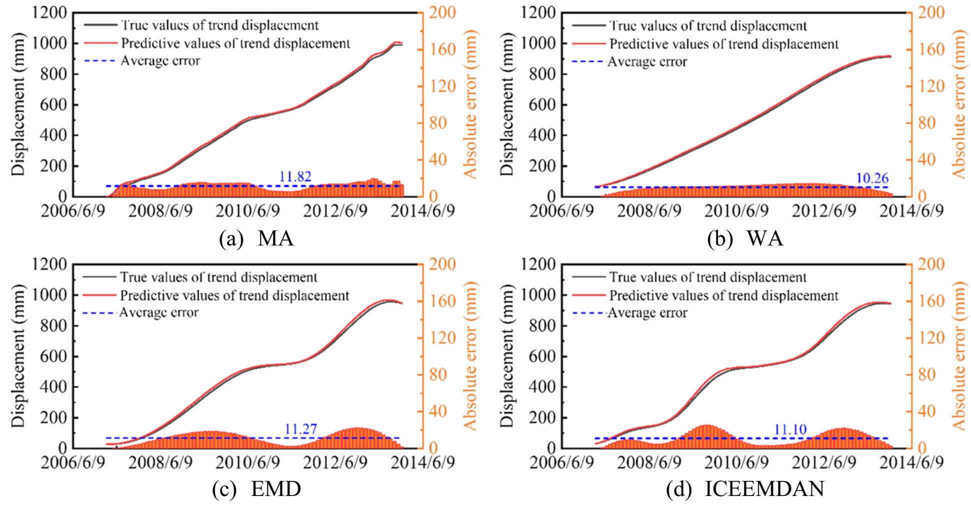


Fig. 16 Trend displacement prediction of Caojiatuo landslide based on different methods for time series decomposition

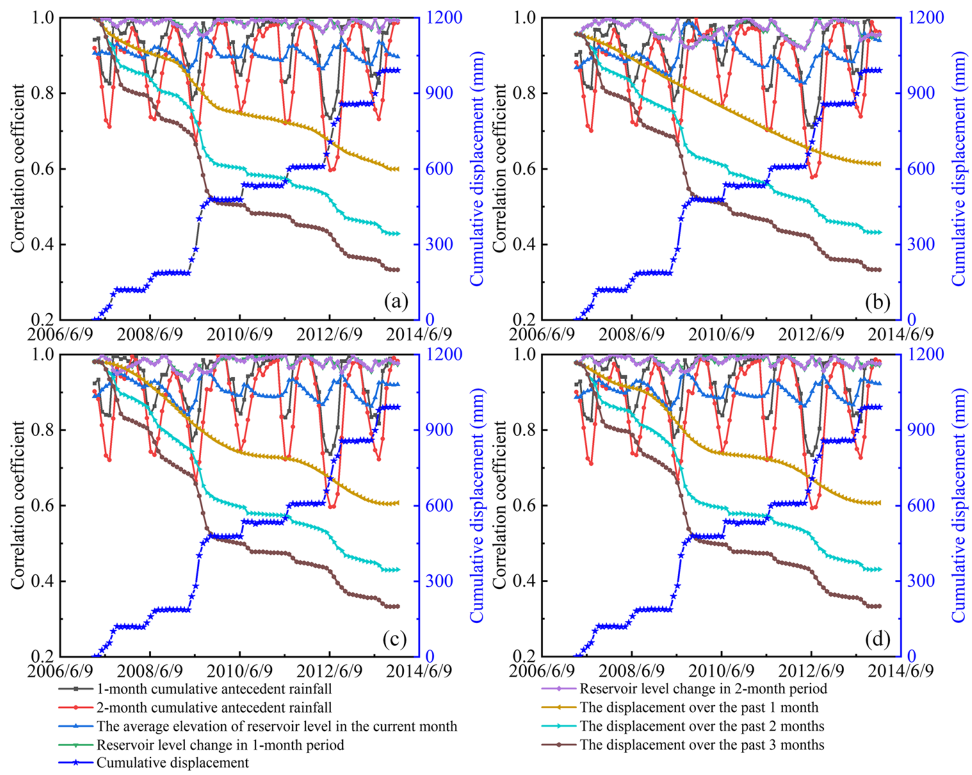


Fig. 17 The results of GRA of Caojiatuo landslide based on different methods for time series decomposition: (a) MA; (b) WA; (c) EMD; (d) ICEEMDAN

Table 3 Calculation results of correlation coefficient between the influencing factors and the periodic displacement

Influencing factor	MA	WA	EMD	ICEEMDAN
1-month cumulative antecedent rainfall	0.927	0.915	0.926	0.925
2-month cumulative antecedent rainfall	0.867	0.860	0.868	0.866
The average elevation of reservoir level in the current month	0.904	0.902	0.907	0.904
Reservoir level change in 1-month period	0.987	0.968	0.978	0.983
Reservoir level change in 2-month period	0.986	0.968	0.978	0.983
The displacement over the past 1 month	0.772	0.766	0.773	0.770
The displacement over the past 2 months	0.647	0.639	0.647	0.644
The displacement over the past 3 months	0.567	0.559	0.566	0.564

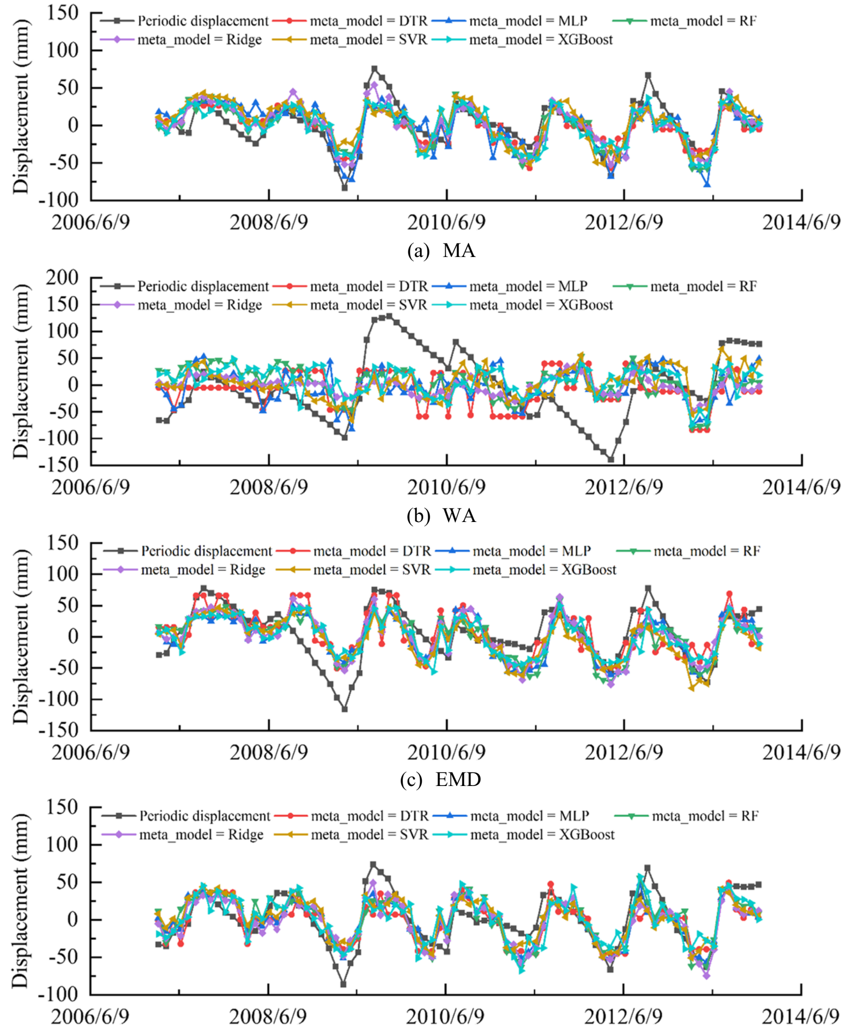


Fig. 18 Prediction of periodic displacement of Caojiatuo landslide based on different methods for time series decomposition

obtain a relatively smooth trend displacement (Fig. 16), it does not mean that the components obtained by the WA method are consistent with the actual situation, that means the effect of time series decomposition on the landslide displacement prediction needs to be evaluated according to the final predictive performance. In addition, the prediction performance based on the MA method in Caojiatuo landslide is better than the prediction performance based on the MA method in Bazimen landslide. The possible reason is due to the fact that, with the decomposition properties of the MA method, the initial and final data points of the time series of periodic displacement obtained by the MA method are always zero according to Eq. (2). When the seasonal fluctuation of landslide evolution is small, it can produce better prediction results.

Total displacement prediction The total displacement prediction results are obtained by summing the prediction results of periodic trend displacement of Caojiatuo landslide obtained by the different methods for time series decomposition (Fig. 19). It can be observed that the proposed prediction model in this paper shows a good performance in predicting the displacement of step-like landslide. In addition, the prediction results of landslide displacement based on different methods for time series decomposition are quite different. Herein, the displacement prediction results based on ICEEMDAN are the closest to the actual landslide displacement, indicating that the ICEEMDAN method is the most suitable for the decomposition of the accumulative displacement, which is the same as the displacement prediction of Bazimen landslide.

Figure 20 shows the statistical results of MAE, MAPE and RMSE[2] of total displacement predicted based

[2] Mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE).

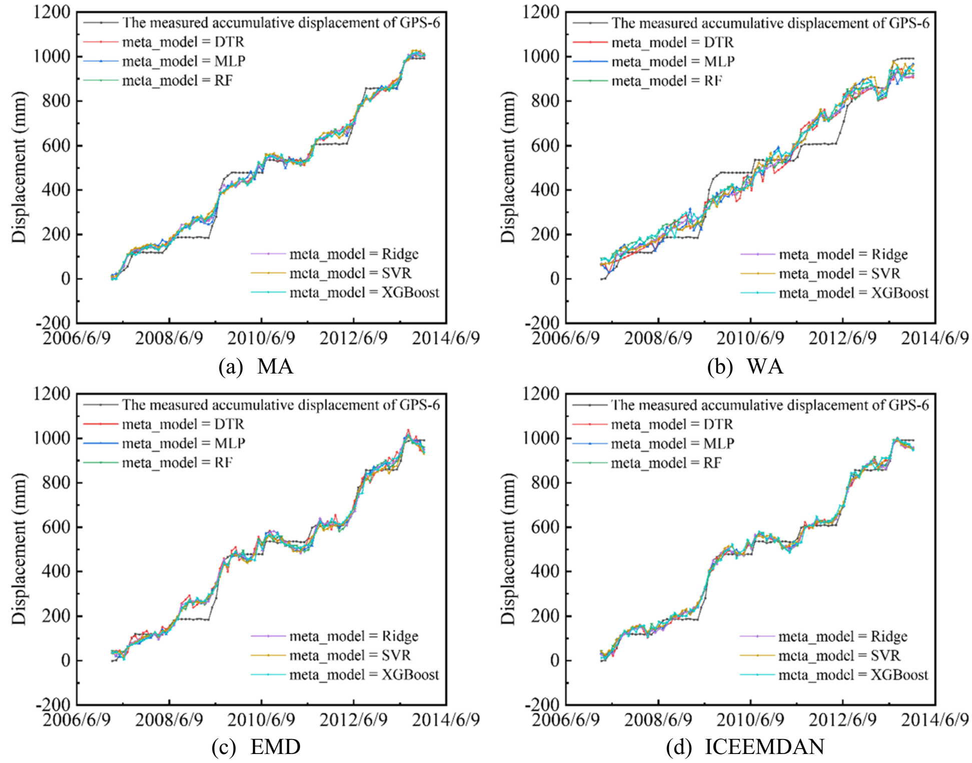


Fig. 19 Prediction of total displacement of Caojiatuo landslide based on different methods for time series decomposition

on different time series decomposition and ensemble model. Among them, the calculation results of MAPE are quite different from those of Bazimen landslide. That is because the initial displacement value of Caojiatuo landslide is close to zero. According to Eq. (15), the prediction error in the initial stage will be amplified. Hence, due to the first data of the trend displacement obtained by the MA is close to zero, the MAPE of the prediction results of landslide displacement obtained by the MA is significantly smaller than other methods for time series decomposition. In addition, according to the calculation results of MAE and RMSE shown in Fig. 20, the accuracy of the prediction results based on the ICEEMDAN method is the highest compared with the other methods for time series decomposition, which indicates that the ICEEMDAN can produce the best decomposition performance on the cumulative displacement of the step-like landslide. Furthermore, it can be seen from Table 4 that the results of the paired t-test of the prediction results of Caojiatuo landslide are similar to that of Bazimen landslide, the prediction performance based on the ICEEMDAN are significantly better than other time series decomposition, while the significant difference between ICEEMDAN and EMD are smaller than the other pairwise comparison.

4 Discussions

4.1 Comparison with individual ML models

To verify the superiority of the proposed ensemble model in estimating the individual bias of different artificial intelligence models, the prediction results of the Bazimen landslide and the Caojiatuo landslide from the optimized individual ML model and the ensemble model with the optimized base-learners are compared. It should be noted that evaluation of individual ML model is based on the fivefold cross-validation method. Figure 21 shows the statistical results of distribution range of the evaluation indices of the prediction results based on different methods for time series decomposition. It should be noted that the upper and lower bounds of each index represent the maximum and minimum values of the calculation results respectively based on different prediction models. According to the statistical results in Fig. 21, the distribution range of each evaluation index of the ensemble algorithms with the optimized base-learners is generally lower and smaller than individual optimized ML models based on Bayesian optimization, especially for the MAE and RMSE, indicating that the prediction results of the ensemble algorithm with the optimized base-learners are

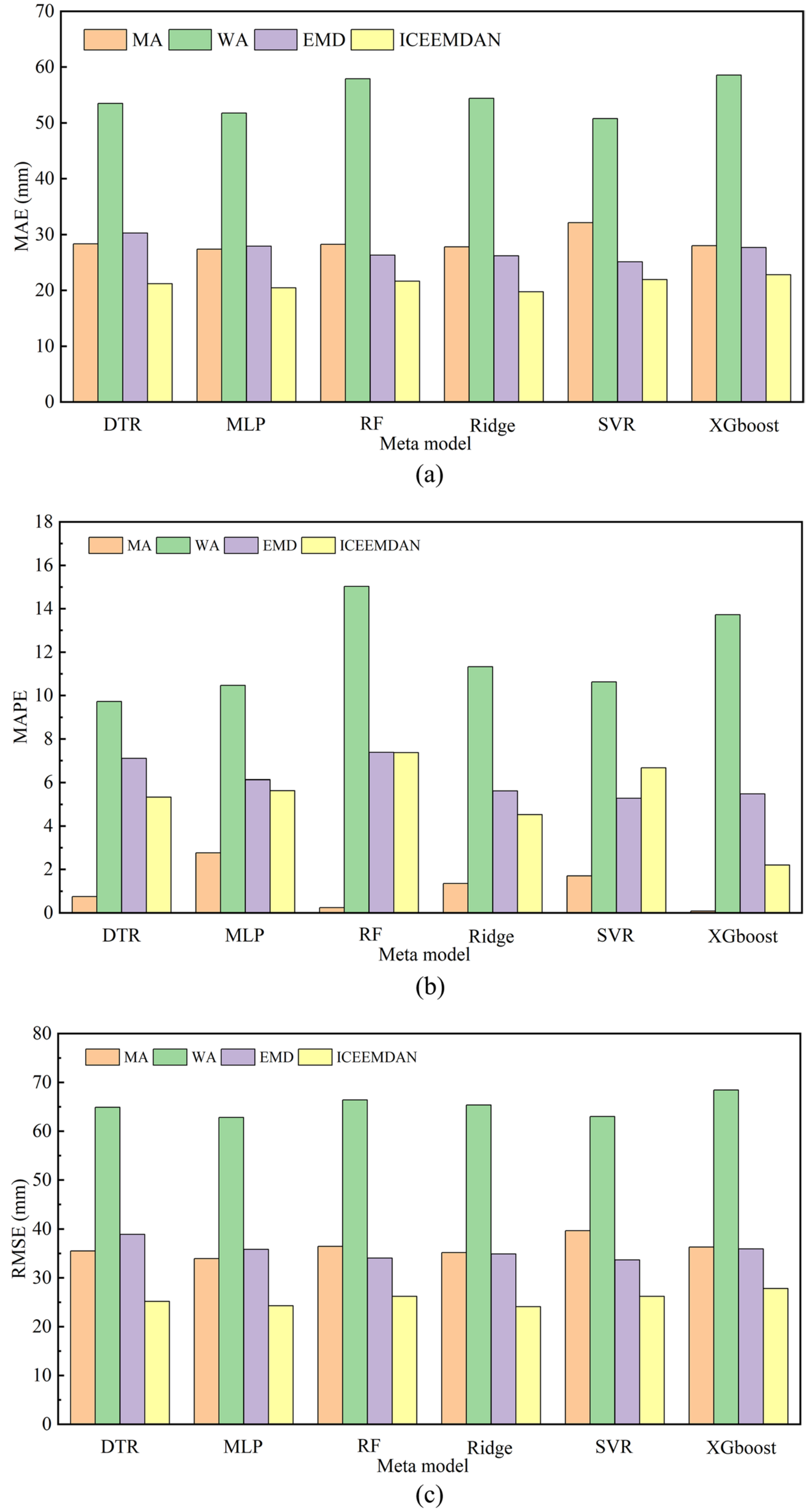


Fig. 20 Error evaluation indices of total displacement prediction of Caojiatuo landslide

more accurate and robust. In addition, due to the error amplification effect of the MAPE index in the initial and final monitoring periods when the displacement value is close to zero, the MAPE of the displacement prediction results of Caojiatuo landslide is unstable. Hence, it is necessary to select appropriate evaluation index according to the characteristics of the data itself when evaluating the accuracy of regression prediction of time series.

Table 4 Results of the paired t-test regarding the comparison of performances of the proposed prediction model models related to Caojiatuo landslide based on different time series decomposition

Meta-models	Pairwise comparison	*p*-value	significance
DTR	ICEEMNAN vs. MA	0.007	Yes
	ICEEMNAN vs. WA	0.01	Yes
	ICEEMNAN vs. EMD	0.001	Yes
MLP	ICEEMNAN vs. MA	0.005	Yes
	ICEEMNAN vs. WA	0.001	Yes
	ICEEMNAN vs. EMD	0.002	Yes
RF	ICEEMNAN vs. MA	0.016	Yes
	ICEEMNAN vs. WA	0.01	Yes
	ICEEMNAN vs. EMD	0.047	Yes
Ridge	ICEEMNAN vs. MA	0.002	Yes
	ICEEMNAN vs. WA	0.01	Yes
	ICEEMNAN vs. EMD	0.007	Yes
SVR	ICEEMNAN vs. MA	0.01	Yes
	ICEEMNAN vs. WA	0.01	Yes
	ICEEMNAN vs. EMD	0.168	Yes
XGBoost	ICEEMNAN vs. MA	0.049	Yes
	ICEEMNAN vs. WA	0.01	Yes
	ICEEMNAN vs. EMD	0.055	No

4.2 Influence of the Bayesian optimization algorithm on the proposed ensemble model

In this study, the Bayesian optimization method is used to obtain the optimal base-learners to ensure the fairness of ensemble and enhance the predictive performance, which means that the predictive performance of the base-learners will influence the final prediction results of the ensemble model. To verify the significance of the Bayesian optimization algorithm to the ensemble model, the prediction results of the two research cases based on the ensemble model with optimized base-learners and the ensemble model without optimized base-learners are compared. Figure 22 shows the distribution range of the statistical results of evaluation indices based on different methods for time series decomposition. It can be observed that the distribution range and upper limit of each evaluation index are reduced obviously after the optimization of the base-learners in the ensemble model. Although the statistical results of MAPE of the prediction results of the Caojiatuo landslide show the error amplification effect, the Bayesian optimization algorithm can improve the accuracy and robustness of ensemble model in predicting the landslide displacement. Furthermore, the focus of this paper is whether the Bayesian optimization algorithm can improve the performance of the ensemble model, rather than finding the optimal hyperparameter optimization algorithm, whereas the choice of optimization algorithm should be one of the important factors affecting the model performance. Hence, it is worthy to conduct systematic comparative studies on different types of optimization algorithms in the future.

4.3 Comparison with other studies of the step-like landslide displacement prediction of Bazimen landslide and Caojiatuo landslide

In order to eliminate the contingency inherent in a single case and enhance the persuasiveness of the conclusion, this research focuses on the Bazimen and Caojiatuo landslides, chosen for their sufficient monitoring data and typical step-like deformation characteristics. While numerous studies have investigated landslide displacement predictions for these cases, as summarized in Table 5, they predominantly emphasize the superior efficacy of deep learning methods over traditional ML models and highlight the role of hyperparameter optimization in enhancing prediction accuracy. However, these studies lack the exploration of the influence of time series decomposition on the prediction results of landslide displacement, and the individual bias of different artificial intelligence models on landslide datasets is not considered. In this study, the framework of ensemble learning is used to eliminate the individual bias of different artificial intelligence models to obtain more robust prediction results, and the prediction results of landslide displacement based on different methods of time series decomposition are analyzed. To explore the effectiveness of the framework of ensemble learning and compare the displacement prediction results of different methods of time series decomposition, six traditional ML algorithms are selected to be applied to the proposed prediction method for landslide displacement. In the future, the application of the framework of ensemble learning in deep learning can be studied, so as to establish displacement prediction models with better performance, combing them with the time series decomposition method that is more suitable for landslide deformation.

4.4 Discussion of the impact of rainfall factors on the prediction results

To comprehensively illustrate the possible impact of rainfall factors on the prediction results, the prediction results related to the Bazimen and Caojiatuo landslide with and without the input factors of rainfall are compared. Herein, the method of ICEEMDAN with the best performance is utilized to decompose the landslide accumulate displacement. The trend displacement is predicted by the double exponential smoothing, and the periodic displacement is predicted by ensemble learning with different ML models optimized by the Bayesian optimization algorithm as the meta-model. the Tables 6 and 7 present the comparison of the prediction results of the Bazimen and Caojiatuo landslides with

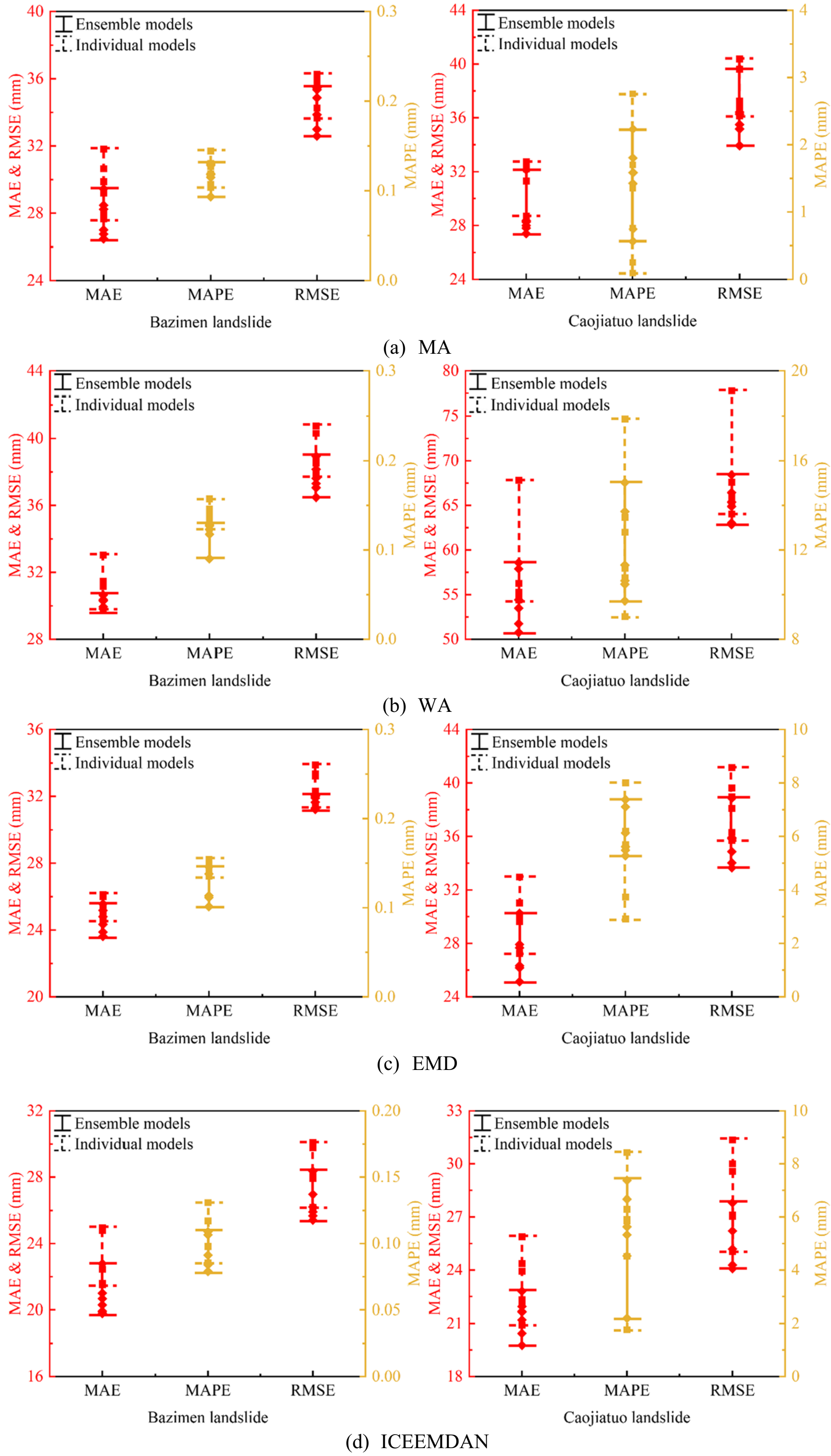


Fig. 21 The range of error indices for the predicted displacements by the ensemble and the individual ML algorithms, both based on Bayesian optimization

Fig. 22 The range of error indices of prediction results by the ensemble model with optimized base-learners by Bayesian optimization and unoptimized base-learners

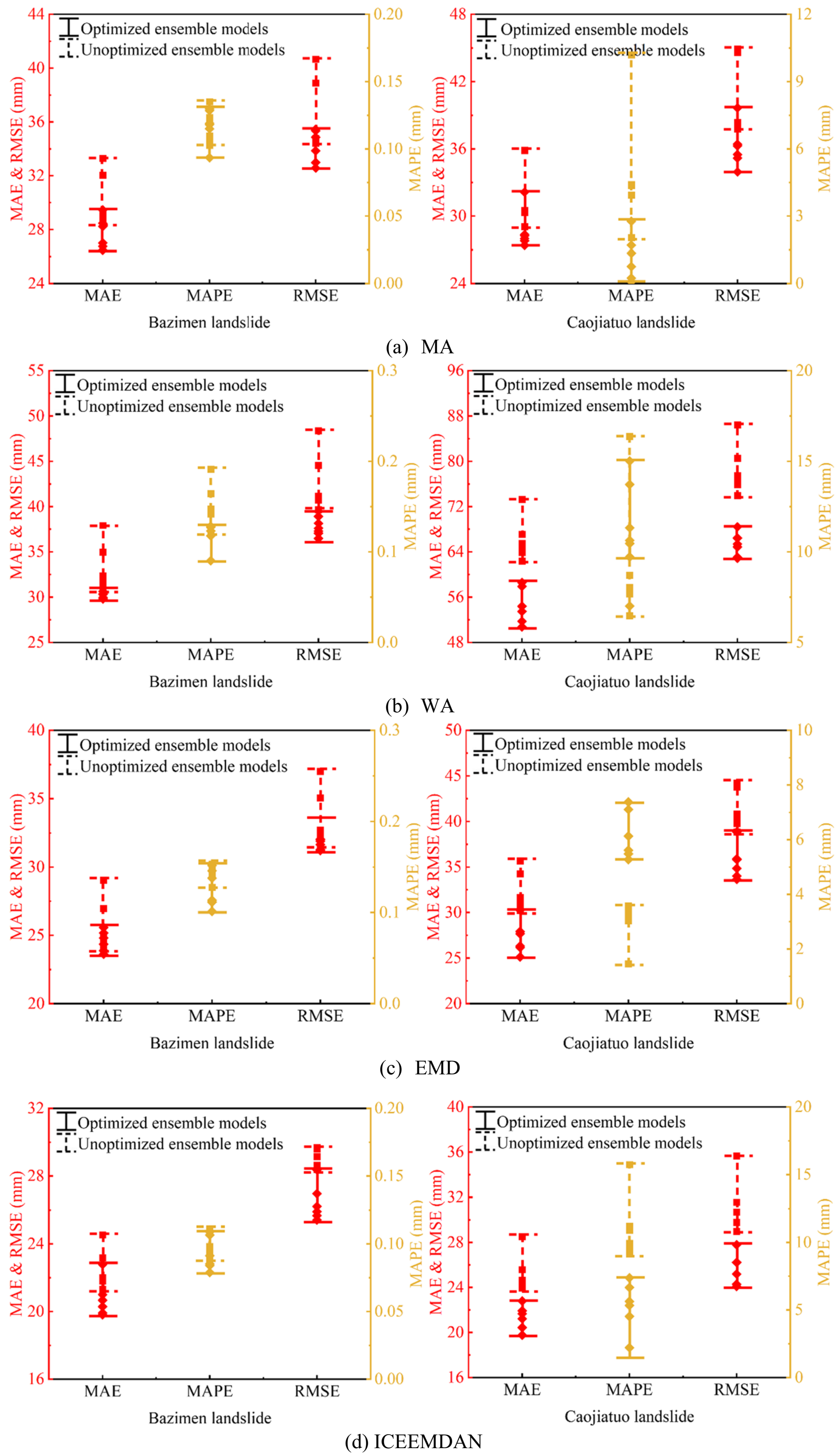


Table 5 The prediction results related to the Bazimen and Caojiatuo landslides of other studies

Landslide cases	Time series decomposition	Displacement prediction	Monitoring point	MAE	RMSE	Reference
Bazimen landslide	MA	BPNN	Z111	15.01	17.73	(Du et al. 2013)
Bazimen landslide	-	Switched prediction	Z111	12.91	25.08	(Li et al. 2015)
Bazimen landslide	MA	PSO-SVR	ZG111	13.28	25.95	(Zhou et al. 2016)
Bazimen landslide	MA	GA-SVR	ZG111	16.12	27.22	(Zhou et al. 2016)
Bazimen landslide	MA	Grid-SVR	ZG111	14.69	29.19	(Zhou et al. 2016)
Bazimen landslide	MA	SVR	ZG111	19.32	28.32	(Yang et al. 2019)
Bazimen landslide	MA	LSTM	ZG111	10.2	13.83	(Yang et al. 2019)
Bazimen landslide	-	Grey prediction model	ZG110	8.9	12.48	(Li and Wu 2021)
Bazimen landslide	-	LSSVR	ZG110	17.61	21.87	(Li and Wu 2021)
Bazimen landslide	VMD	FOA-SVR	ZG110	22.74	24.17	(Lu et al. 2021)
Bazimen landslide	VMD	Bi-LSTM	ZG110	1.18	1.36	(Zhang et al. 2021a)
Bazimen landslide	VMD	Bi-LSTM	ZG111	2.19	2.47	(Zhang et al. 2021a)
Bazimen landslide	PSO-VMD	NARX	ZG110	4.45	5.47	(Jiang et al. 2022)
Bazimen landslide	PSO-VMD	NARX	ZG111	4.87	5.93	(Jiang et al. 2022)
Bazimen landslide	WMA	LSTM-FC	ZG111	2.36	2.97	(Lin et al. 2022)
Bazimen landslide	WMA	RNN	ZG111	6.03	6.93	(Lin et al. 2022)
Bazimen landslide	WMA	GRU	ZG111	5.28	5.97	(Lin et al. 2022)
Bazimen landslide	WMA	BiLSTM	ZG111	4.64	5.14	(Lin et al. 2022)
Bazimen landslide	WMA	BiGRU	ZG111	4.68	5.34	(Lin et al. 2022)
Bazimen landslide	-	MFIT	ZG111	3.59	5.54	(Long et al. 2022)
Bazimen landslide	SSSC-EMD	DBi-LSTM	ZG111	5.11	5.32	(Zhang et al. 2022)
Caojiatuo landslide	MA	ELM	GPS-6	13.4	13.52	(Zhang et al. 2020a)
Caojiatuo landslide	MA	GWO-ELM	GPS-6	5.5	5.66	(Zhang et al. 2020a)
Caojiatuo landslide	MA	ELM	GPS-3	7.00	7.12	(Zhang et al. 2020a)
Caojiatuo landslide	MA	GWO-ELM	GPS-3	3.00	3.04	(Zhang et al. 2020a)
Caojiatuo landslide	CEEMDAN	GRU	GPS-6	3.9	4.0	(Zhang et al. 2022)
Caojiatuo landslide	CEEMDAN	SVR	GPS-6	9.7	9.9	(Zhang et al. 2022)

Table 5 (continued)

Landslide cases	Time series decomposition	Displacement prediction	Monitoring point	MAE	RMSE	Reference
Caojiatuo landslide	CEEMDAN	GRU	GPS-3	4.8	5.1	(Zhang et al. 2022)
Caojiatuo landslide	CEEMDAN	SVR	GPS-3	9.4	9.6	(Zhang et al. 2022)

Table 6 The evaluation indices of the prediction results related to the Bazimen landslide with and without the input factors of rainfall

Rainfall factors	Meta-learners	MAE	MAPE	RMSE
with	DTR	19.92	0.07	25.97
	MLP	20.67	0.09	25.41
	RF	20.99	0.10	25.67
	Ridge	20.29	0.08	26.22
	SVR	22.78	0.10	28.36
	XGBoost	19.80	0.08	26.96
without	DTR	25.75	0.11	32.50
	MLP	26.01	0.12	31.16
	RF	23.50	0.11	29.68
	Ridge	23.43	0.10	29.68
	SVR	24.57	0.12	30.07
	XGBoost	24.35	0.12	31.53

Table 7 The evaluation indices of the prediction results related to the Caojiatuo landslide with and without the input factors of rainfall

Rainfall factors	Meta-learners	MAE	MAPE	RMSE
with	DTR	21.21	5.33	25.18
	MLP	20.44	5.63	24.28
	RF	21.66	7.37	26.21
	Ridge	19.76	4.53	24.08
	SVR	21.93	6.67	26.22
	XGBoost	22.79	2.20	27.81
without	DTR	24.24	7.09	29.54
	MLP	22.65	7.06	27.25
	RF	20.20	5.51	25.64
	Ridge	21.07	7.21	25.46
	SVR	22.45	7.59	27.24
	XGBoost	25.26	6.97	30.81

and without the inputs factors of rainfall. In general, it can be observed that the accuracy of the prediction results with the rainfall factors as the input factors is higher than that without the rainfall factors as the input factors, verifying the strong correlation between the rainfall and landslide displacement. Furthermore, the difference of the prediction results with and without the rainfall factors as input of the Bazimen landslide are larger than that of the Caojiatuo landslide. The possible reason is that the regional location and geological conditions of the two landslide cases are not exactly the same, resulting in different responses of landslide deformation to rainfall.

5 Conclusions

In this paper, a novel method for predicting step-like landslide displacement based on time series decomposition and Bayesian optimized ensemble model is proposed to eliminate the individual bias of different artificial intelligence models. Additionally, a systematic comparative analysis is performed on various methods for time series decomposition. Two typical step-like landslides, namely Bazimen landslide and Caojiatuo landslide in the Three Gorges area, are selected as research cases. The main findings of this study can be summarized as follows:

(1) The evolution of landslides is a system affected by a variety of linear and nonlinear factors, which means that the deformation characteristics are usually controlled by the imposition pattern of influencing factors. According to the monitoring data of the research cases in this paper, the landslide displacement is affected by the combined action of periodic fluctuation factors, such as rainfall and reservoir water level, which cause the step-like displacement change. These deformation characteristics can provide a basis for intelligent algorithm to predict landslide displacement.

(2) The accuracy of landslide displacement prediction is influenced by the choice of time series decomposition method. For the Bazimen and Caojiatuo landslides, the MAE and RMSE of predictions based on the Bayesian optimized ensemble learning and ICEEMDAN method range between 19 mm—23 mm and 25—29 mm, respectively. This represents a decrease around 30%—60% compared to the other time series decomposition methods. Overall, the experimental results indicate that the ICEEMDAN approach is the most effective for decomposing landslide deformation monitoring data for displacement prediction purposes.

(3) The ensemble algorithm efficiently mitigates individual biases of the different ML models, enhancing

the predictive performance for landslide displacement. The distribution range of the evaluation indices of the displacement prediction results based on the ensemble framework is smaller than that of the individual ML method. Meanwhile, the ensemble framework reduces prediction errors related to the individual ML method. Besides, the Bayesian optimization technique refines the parameters of each base-learner in the ensemble algorithm, thereby improving the performance of ensemble models with smaller prediction errors, while ensuring fairness within the ensemble. Therefore, the Bayesian optimized ensemble model exhibits significant potential for landslide displacement prediction.

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Declarations

Competing interests The authors declare no competing interests.

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