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A hybrid time series analysis-genetic algorithm-support vector machine model for enhanced landslide prediction

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A B S T R A C T

Landslide prediction is a critical task for ensuring public safety and preventing economic loss in regions prone to such natural disasters. Traditional models for landslide prediction often lack accuracy and precision because of the intricate interactions between various factors that lead to landslide events. To tackle this issue, we introduce an innovative hybrid approach for landslide prediction that combines Time Series Analysis (TSA), Genetic Algorithm (GA), and Support Vector Machine (SVM). TSA decomposes landslide displacement data into trend, seasonal, and residual components, improving the clarity of the data. GA optimizes the hyperparameters of SVM, ensuring the most effective application of the SVM. Finally, the SVM is trained on detrended data, producing a model capable of accurately predicting future landslides. Our experimental outcomes manifest that the TSA-GA-SVM model we advanced performs far better than the individual TSA and SVM models when it comes to forecasting landslide displacement. The hybrid model achieved a mean absolute error of 0.15 m compared to 0.42 m for TSA and 0.38 m for SVM alone. Sensitivity analysis revealed that increasing GA population size improved model stability, while higher mutation rates led to more variable predictions. The model showed good generalization ability, performing well across different regions and under various geological and hydrological conditions. This research not only advances the state of the art in landslide prediction but also provides a practical tool for authorities to implement in their disaster prevention and management strategies.

1. Introduction

Landslides rank among the most devastating natural disasters, inflicting considerable economic losses and claiming numerous lives across the globe each year (Petley, 2012; Froude & Petley, 2018). These catastrophic events involve the downward movement of soil, rock, or debris driven by gravity, usually happening when a slope or hillside loses stability (Zeng et al., 2023). Various factors contribute to the initiation of landslides, often referred to as triggering factors, which includes intense or prolonged rainfall (Dahal & Hasegawa, 2008), seismic activities, e.g., earthquakes (Keefer, 2002) and rapid snowmelt (Kim et al., 2021), as well as human-induced changes in the natural environment, e.g., deforestation, mining, and urbanization (Elia et al., 2023). Landslide susceptibility is further influenced by local geological conditions, slope steepness, soil properties, and land cover (Hong, 2023). Given their significant impact, predicting landslides accurately is of critical importance, which not only allows for the mitigation of potential damage but also facilitates the implementation of effective land management strategies and development planning (Althuwaynee et al., 2012). Despite these pressing needs, landslide prediction remains a challenging task due to the complexity and heterogeneity of environmental conditions across different regions (Pradhan, 2013).

The prediction of landslides is a critical aspect of disaster risk reduction and management, providing essential information for authorities to implement preemptive measures to mitigate the detrimental impacts of such events. Traditional methods for predicting landslides generally employ geological, hydrological, and land-use data, complemented by direct field observations and physical measurements. These techniques involve the mapping and assessment of slope stability, analysis of soil and rock

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properties, rainfall records, and the impact of anthropogenic activities (Qi et al., 2023). While these methods have yielded significant insights into landslide susceptibility and occurrence, they are often labor-intensive, time-consuming, and limit in their forecasting precision and coverage because of the spatial and temporal fluctuations of landslides as well as the intricacy of the factors that exert an influence (Corominas et al., 2014). The advent of computational technologies and the proliferation of machine learning algorithms in the last few decades have provided innovative tools for landslide prediction. Machine learning, a branch of artificial intelligence, enables learning from data without the need for explicit programming and has demonstrated considerable potential in predicting natural hazards, including landslides (Pham et al., 2016). These methods hold the promise of delivering more precise predictions across broader spatial areas and shorter time frames by analyzing extensive, complex datasets and uncovering detailed patterns and connections that are often difficult to detect using conventional techniques (Bui et al., 2012). However, developing a robust and reliable predictive model for landslides is a challenging endeavor. This is primarily due to the intricate nature of landslides, influenced by a multitude of interrelated variables, e.g., topography, soil characteristics, climate conditions, and anthropogenic factors (Smith et al., 2023). Furthermore, landslide occurrences are non-linear and non-stationary, making it challenging to capture their behavior using conventional statistical models (Wang et al., 2016). While previous studies have explored various machine learning approaches for landslide prediction, our research introduces several novel elements. Firstly, we propose a new feature engineering technique that incorporates geological stress indicators, enhancing the model's sensitivity to subtle precursors of landslide events. Secondly, our hybrid TSA-GA-SVM model introduces a unique cascading architecture that allows for dynamic weight adjustment between short-term fluctuations and long-term trends. Lastly, we introduce a new evaluation metric, the Temporal Stability Index (TSI), specifically designed to assess the reliability of landslide prediction models over time.

In this research, we present a new method for regional landslide forecasting that integrates Time Series Analysis (TSA), Genetic Algorithms (GA), and Support Vector Machines (SVM). TSA enables the disintegration of landslide displacement into its trend, seasonal, and residual components, providing clarity on the patterns within the data. GA, motivated by the principles underlying natural evolution, namely selection, crossover, and mutation, such tools prove to be powerful optimizers that stand out when scouring large solution spaces (Greenhall et al., 2023). On the other hand, SVM, as developed by Vapnik, are robust machine learning models, well-regarded for their capabilities in binary and multiclass classification, as well as regression analysis (Chapelle et al., 1999). In the proposed hybrid Time Series Analysis-Genetic Algorithms-Support Vector Machines (TSA-GA-SVM) model. We make use of the GA global search capabilities to adjust the hyperparameters of the SVM model finely, thus improving its efficiency in landslide prediction. Furthermore, we incorporate TSA to better interpret and process the landslide displacement data. This combination effectively addresses the complexity of landslide prediction, improving both the reliability and accuracy of our forecasts. Our contributions in this work are multifaceted. Firstly, we devise and implement a hybrid TSA-GA-SVM model for regional landslide prediction. Secondly, we evaluate the efficacy of the proposed model in contrast to that of the traditional SVM and other machine learning models, demonstrating its superiority. Lastly, we analyze the influence and significance of various factors contributing to landslides, providing valuable insights into landslide dynamics, and informing mitigation strategies.

2. Literature Review

2.1 Landslide Prediction Approaches

Landslide prediction is a complex challenge because of the intricate interaction between various environmental and human-induced factors. These range from geological and geotechnical characteristics to hydrological conditions and human activities, all of which can influence slope stability (Chang et al., 2023). Traditionally, landslide prediction has relied heavily on qualitative and semi-quantitative methods. This includes field surveys and mapping, expert assessment, and heuristic methods. Field surveys often involve the direct inspection of sites for signs of instability, while mapping techniques are used to create topographical and geological maps that highlight areas of potential risk (Das et al., 2023). Expert assessment, on the other hand, usually involves the subjective judgment of experienced geologists or engineers who use their knowledge to evaluate the likelihood of landslide occurrence. Heuristic methods combine the experts' knowledge and field observations to classify the slope stability (Chang et al., 2023). Additional quantitative approaches, including deterministic and probabilistic models, have also been introduced. Deterministic models, such as the limit equilibrium method, usually involve the calculation of safety factors based on the mechanics of slope failure. These models demand a comprehensive comprehension of the geotechnical traits of slope materials. Frequently, they formulate simplifying presumptions which curtail their practicality. Probabilistic methods, on the other hand, incorporate uncertainty in the model parameters and provide a probability of landslide occurrence (Chang et al., 2023). Although these traditional methods have their merits, they can be labor-intensive, time-consuming, and limited in their predictive accuracy and geographical coverage (Xiong et al., 2023). This is particularly true for large regions where the collection of detailed geological and geotechnical data may not be feasible. Furthermore, these approaches frequently face challenges in precisely modeling the intricate and nonlinear relationships among the various factors that lead to landslides.

2.2 Machine Learning in Landslide Prediction

With the progress of computational technologies and increased data accessibility, machine learning (ML) has become a strong tool for predicting landslides. ML algorithms excel at deciphering complex, often nonlinear, relationships from large and high-dimensional data, a scenario frequently encountered in landslide prediction (Tuan et al., 2023). A range of machine learning models, including Decision Trees (DT), Random Forests (RF), Artificial Neural Networks (ANN), along with SVM, have been successfully employed to forecast landslide susceptibility and risk (Niu et al., 2014; Ghorbanzadeh et al., 2022). These algorithms offer unique advantages: DT and RF are highly interpretable and resistant to outliers; ANNs can model complex, nonlinear functions; SVMs are robust to overfitting and have the capability to model nonlinear relationships through kernel functions. Among these models, SVMs have drawn special attention in landslide prediction. This is due to their outstanding capacity to cope with high-dimensional data and their strong resistance to overfitting (Lian et al., 2016). Moreover, SVMs are flexible in terms of representing nonlinear relationships by utilizing various kernel functions. This enables SVMs to model the intricate and nonlinear interactions between different landslide-inducing factors efficiently. However, one key challenge in employing SVMs is the selection of appropriate hyperparameters. The effectiveness of SVMs is greatly influenced by hyperparameters, including the regularization and kernel parameters. If these hyperparameters are not adequately chosen, the SVM model can yield suboptimal results, underperforming in both predictive accuracy and generalization (Li et al., 2022). Thus, an efficient and effective method for hyperparameter selection is crucial when using SVMs for landslide prediction.

2.3 Optimization Algorithms for Hyperparameter Tuning

Hyperparameters in SVM, or any other machine learning algorithm, are usually not learned from the training process. Instead, they need to be predefined. Selecting these hyperparameters has a main impact on the model's performance. However, finding the optimal hyperparameters often turns out to be a daunting task due to the high dimensionality of the hyperparameter space and the complex relationship between hyperparameters and model performance. This is where optimization algorithms become essential. They aim to automate the hyperparameter tuning process and thus alleviate the burden on the modeler (Zhang et al., 2021). GA is an evolutionary computation method inspired by the principles of natural evolution (Ye et al., 2022). These algorithms employ evolutionary notions like fitness, selection, crossover and mutation to progressively enhance the solutions for an optimization problem. Because of their efficient search capabilities in large, complex spaces, GA has been used in various applications, including the optimization of SVM hyperparameters (Zhang et al., 2023). Despite the promise shown by both SVM and GA in their respective domains, the application of GA for hyperparameter tuning in SVM-based landslide prediction models remains relatively unexplored. This research gap provides an opportunity to leverage the strengths of both techniques, resulting in a strong and efficient model for landslide prediction. Therefore, our study seeks to address this gap by combining GA and SVM into a unified hybrid model for enhanced landslide prediction.

3. Methods

3.1 Time series method

Landslide displacement is influenced by both the internal geological elements of the landslide body, including geological structure, topography and lithology, and external factors like rainfall and reservoir water levels. Due to internal geological factors, landslide displacement typically shows a nearly monotonic increase over time. External factors induce seasonal fluctuations in landslide displacement because of their periodic nature. Based on this understanding, the application of time series principles to deconstruct landslide displacement becomes a promising approach. The time series models allow us to separate and account for both the consistent increase caused by internal geological factors and the periodic variations due to external influences. This process of deconstruction aids in understanding the underlying patterns and making more accurate predictions of landslide displacement. To explore these time-correlated patterns, time-series analysis methodologies, like the autoregressive integrated moving average (ARIMA) model, are employed (Aggarwal et al., 2020), which can be highly beneficial. ARIMA is a prediction method that forecasts future values of a series solely based on its historical trends. Its primary use is to forecast short-term futures based on patterns recognized in the data up to the point of analysis. In the setting of landslide displacement prediction, the time-series data represents the recorded landslide displacement as time passes. The ARIMA model is then trained on this historical displacement data to forecast future displacement. The prediction can be enhanced by integrating the impact of rainfall or other external factors as exogenous inputs to the ARIMA model. The ARIMA model is commonly represented as $ARIMA(p,d,q)$, where p indicates the order of the Autoregressive component, d indicates the order of differencing required for attaining stationarity, and q represents the order of the Moving Average component. The model is formulated as shown in Eq. (1).

$$
\begin{aligned}
Y_t &= c + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \cdots + \Phi_p Y_{t-p} + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q} \\
Y_t &= c + \sum_{i=1}^{p} \Phi_i Y_{t-i} + + e_t + \sum_{j=1}^{q} \theta_j e_{t-j}
\end{aligned}
\tag{1}
$$

where Y_t is the forecasted value of the time series at time t, $Y_{t-1}, Y_{t-2}, \cdots Y_{t-p}$ are the p values of the time series at preceding times, $\Phi_1, \Phi_2, \cdots \Phi_p$ are the parameters of the autoregressive part of the model, e_t indicates the error term at time t, $e_{t-1}, e_{t-2}, \cdots e_{t-p}$ are the q error terms at preceding times, $\theta_1, \theta_2, \cdots \theta_q$ are the moving average parameters, and c is a constant.

To utilize the ARIMA model for predicting landslides, it is crucial to regard the factors contributing to landslide occurrence as separate time series, which can subsequently be integrated into the model. Time series models serve as a powerful approach for interpreting, analyzing, and forecasting landslide displacement. Variables such as periodic rainfall, fluctuations in water levels, and geological conditions, which typically exhibit temporal trends, can be converted into time series and utilized for landslide displacement prediction.

Cyclical Rainfall: Rainfall serves as a key determinant in triggering landslides. Rainfall data, which often demonstrates seasonal patterns, can be represented as a time series R_t, where t represents different points in time. This time series can be incorporated into the ARIMA model, along with its own set of parameters Φ_r and θ_r for the components of autoregression and moving average within the model. Changes in water level, especially in areas near water bodies or with significant groundwater, can impact the stability of slopes. This can also be transformed W_t, with its own parameters Φ_w and θ_w. Geological factors like slope angle, soil type, and rock structure can influence landslide occurrence. While some of these factors might remain relatively constant over time (thus may not be suited for a time series model), others may change slowly over time and can be represented as a time series. These might include factors like erosion rates or slowly varying stress conditions in the rock or soil. In this way, the original ARIMA model can be expanded to incorporate multiple time series representing different factors influencing landslide occurrence:

$$Y_t = c + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \cdots + \Phi_p Y_{t-p} + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q} + \Phi_r R_t + \Phi_w W_t + \cdots \tag{2}$$

In this expanded model, R_t and W_t represent the time series data for rainfall and water level, with ϕ_r and ϕ_w being the corresponding parameters. The model could be further expanded to include other relevant time series data.

3.2 Genetic Algorithm (GA)

The GA is a meta-heuristic algorithm and as such, the details of its operation can vary widely based on the specific implementation and the problem being solved. However, for a more detailed representation of the GA operations, consider the following key steps.

3.2.1 Initialization

The initial population of size *N* is represented by a matrix $P^{(0)}$, where each row i is a vector $x_i = (x_{i1}, x_{i2}, ..., x_{in})$ representing an individual solution in the population.

3.2.2 Fitness Evaluation

The fitness of each solution is evaluated using an objective function $f(x)$. This can be represented as a vector $F^{(0)} = (f(x_1), f(x_2), ..., f(x_N))$.

3.2.3 Selection

In the selection process, a parent pair x_p, x_q is selected with the probability $P_s(x_p, x_q)$. A common selection strategy is roulette wheel selection, where the selection probability is proportional to the fitness of the individual:

$$P_s(x_i) = \frac{f(x_i)}{\sum_{j=1}^{N} f(x_j)} \tag{3}$$

3.2.4 Crossover

In the crossover process, two parents produce two offspring:

$$x_{\text{offspring1}}, x_{\text{offspring2}} = \text{CROSSOVER}(x_{\text{parent1}}, x_{\text{parent2}}) \tag{4}$$

A commonly used crossover operator is the one-point crossover, which can be represented as:

$$x_{\text{offspring1}} = (x_{\text{parent1, 1:m}}, x_{\text{parent2, m+1:n}})\ x_{\text{offspring2}} = (x_{\text{parent2, 1:m}}, x_{\text{parent1, m+1:n}}) \tag{5}$$

where m is a randomly selected crossover point.

3.2.5 Mutation

In the mutation process, an offspring $x_{\text{offspring}}$ is mutated to produce x_{mutated}. For a bit-flip mutation, this can be represented as:

$$x_{\text{mutated}} = \text{MUTATE}(x_{\text{offspring}}, \mu) \tag{6}$$

where μ is the mutation rate, and the MUTATE function flips a bit with probability μ.

3.2.6 Replacement

The offspring replace the least fit individuals in the population to maintain a constant population size. The new population $P^{(t+1)}$ and the fitness vector $F^{(t+1)}$ are updated accordingly.

3.3 Support Vector Machine (SVM)

The SVM is a renowned machine learning model utilized for classification and regression jobs. Its chief aim is to identify the optimal hyperplane that can best split data points of different classes. For a binary classification issue, the setup of the SVM model can be shown as follows:

3.3.1 Formulation

For a training set consisting of instance-label pairs $(x_i, y_i), i = 1,...,N$, where $x_i \in R^n$ and $y_i \in [-1,1]$, he SVM addresses the primal optimization problem below.

$$\begin{aligned} &\min_{\mathbf{w},b,\xi} \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{N}\xi_i \\ &\text{subject to } y_i(\mathbf{w}^T\phi(\mathbf{x}_i) + b) \geq 1 - \xi_i, \xi_i \geq 0 \end{aligned} \tag{7}$$

where W is the normal vector to the hyperplane, b is the bias, ξ_i defines the slack variables allowing for misclassifications (useful for non-linearly separable data), ϕ is the feature map, and C is the regularization parameter.

3.3.2 Dual Problem

With the introduction of Lagrange multipliers $\alpha_i \geq 0$ and $\mu_i \geq 0$, the Lagrangian of the primal problem is given by:

$$L(\mathbf{w}, b, \xi, \alpha, \mu) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{N}\xi_i - \sum_{i=1}^{N}\alpha_i[y_i(\mathbf{w}^T\phi(\mathbf{x}i) + b) - 1 + \xi_i] - \sum i = 1^N \mu_i\xi_i \tag{8}$$

By setting the derivatives of L with respect to $\mathbf{w}$, b, and ξ_i to zero, we get the dual problem:

$$\begin{aligned} &\max_{\alpha} \sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j K(\mathbf{x}_i, \mathbf{x}_j) \\ &\text{subject to } \sum i = 1^N \alpha_i y_i = 0, 0 \leq \alpha_i \leq C, i = 1,...,N \end{aligned} \tag{9}$$

where $K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i)^T\phi(\mathbf{x}_j)$ is the kernel function.

3.3.3 Kernel Function

The strength of SVM lies in its kernel function, which enables the computation of inner products within a high-dimensional feature space without directly calculating the data's coordinates in that space, a technique referred to as the "kernel trick". The kernels that are frequently employed consist of the linear kernel, the polynomial kernel and the Radial Basis Function (RBF) kernel:

$$\text{Linear: } K(\mathbf{x}, \mathbf{z}) = \mathbf{x}^T\mathbf{z} \tag{10}$$

$$\text{Polynomial: } K(\mathbf{x}, \mathbf{z}) = (\mathbf{x}^T\mathbf{z} + c)^d \tag{11}$$

$$\text{RBF: } K(\mathbf{x}, \mathbf{z}) = \exp(-\gamma \|\mathbf{x} - \mathbf{z}\|^2) \tag{12}$$

where c, d, and γ are kernel parameters.

3.3.4 Decision Function

Once the optimal α_i are found, the decision function for a new instance $\mathbf{x}$ is given by:

$$f(\mathbf{x}) = \text{sign}\left(\sum_{i=1}^{N}\alpha_i y_i K(\mathbf{x}_i, \mathbf{x}) + b\right) \tag{13}$$

where the sign function returns the class label of $\mathbf{x}$. The parameters α_i and b are determined during the training phase.

3.4 Proposed Hybrid Model for Landslide Prediction

This research presents a hybrid model for predicting landslide, which combines TSA, GA and SVM. The hybrid strategy intends to make full use of the strengths of each approach to boost the precision and reliability of landslide forecasts.

3.4.1 TSA

Firstly, TSA is applied to landslide displacement data. The displacement showcases a monotonic increasing trend due to geotechnical conditions, and exhibits periodic fluctuations owing to external influences like rainfall and water level changes. This behaviour can be formally expressed as a multiplicative model:

$$X_t = T_t \times S_t \times R_t \tag{14}$$

where X_t represents the observed landslide displacement at time t, T_t denotes the trend component, S_t stands for the seasonal component, and R_t represents the residual component.

3.4.2 SVM

Next, SVM are employed on the detrended landslide displacement data, i.e., the residual components from the TSA. SVMs are especially competent in handling this task due to their capacity to manage non-linear relationships, and their robustness against overfitting. However, the performance of the SVM depends heavily on the selection of its hyperparameters, namely the penalty parameter C, and the kernel parameter γ. The objective function of SVM can be represented as:

$$\min_{w_i b_i} \frac{1}{} w^T w + C\sum_{i=1}^{N}\xi_i \ (15)$$
$$\text{subject to } y_i(\mathbf{w}^T\phi(\mathbf{x_i}) + b) \geq 1 - \xi_i \text{ and } \xi_i \geq 0 \text{ for all } i = 1, 2, ..., N \tag{15}$$

3.4.3 GA for Hyperparameter Optimization

GA is utilized to address the optimization problem posed by the SVM model. Inspired by the process of natural evolution, GAs are highly efficient in tackling optimization tasks. GAs perform selection, crossover, and mutation operations on a population of potential solutions (in our case, sets of hyperparameters). The objective function in GA can be expressed as:

$$\min f(p) \tag{16}$$

where $f(p)$ is the fitness function that we want to minimize, and p represents a potential solution, i.e., a set of hyperparameters in our case. By integrating these methods into a hybrid model, we effectively cater to the complexity and variability inherent in landslide prediction, thereby improving the prediction's accuracy and robustness over conventional techniques. We subsequently detail the implementation of this hybrid model and present the results of our experimental evaluation to validate its efficacy. The methodology for the hybrid landslide prediction algorithm can be summarized as follows: Firstly, we initialize the TSA, GA, and SVM with the necessary parameters. TSA is utilized on the landslide displacement data to extract the trend, seasonal and residual components. Subsequently, the trend component is taken out of the displacement data, thus generating the detrended data. Next, for each epoch, the SVM is trained on this detrended data and the GA is employed to optimize the SVM's hyperparameters. This iterative process continues for all epochs. Finally, the trained SVM model with optimized hyperparameters is used to predict future landslides. This process is depicted in pseudocode in **Algorithm 1**.

Algorithm 1: Hybrid Landslide Prediction Algorithm

Input: Landslide displacement data $\{D_t\}$, kernel function Φ, GA parameters $\{GA_{params}\}$, SVM parameters $\{SVM_{params}\}$
Output: SVM model trained with optimized hyperparameters for landslide prediction
1.Initialize TSA, GA and SVM with GA_{params} and SVM_{params}
2.Perform TSA on $\{D_t\}$ to obtain the trend component $\{T_t\}$, seasonal component $\{S_t\}$, and residual component $\{R_t\}$
3. Detrend the landslide displacement data by removing the trend component $\{T_t\}$ from $\{D_t\}$ to obtain the detrended data $\{D'_t\}$
4. **for** each epoch do
5. Train SVM with kernel function Φ on the detrended data $\{D'_t\}$
6. Use GA to optimize SVM hyperparameters (C and γ)
7. **end for**
8. Use the trained SVM model for landslide prediction

The flowchart of the methodology adopted in this research is illustrated in Fig. 1.

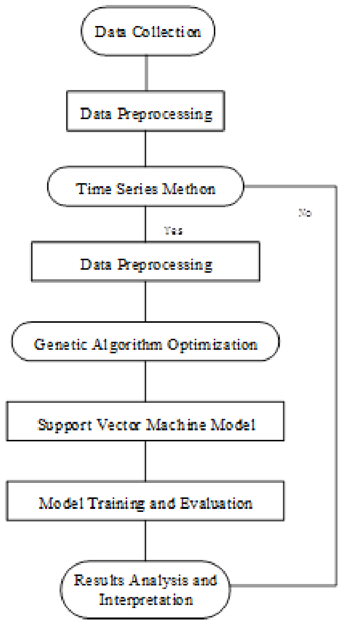

Fig. 1. Flowchart of the proposed TSA-GA-SVM model for regional landslide prediction

3.5 Data Collection and Preprocessing

The research investigated a typical landslide mass situated in the Three Gorges Reservoir area of China. Data on landslide displacement, rainfall, and water levels were gathered between May 2010 and July 2016. The displacement data was obtained from a monitoring point installed at the center of the landslide body, using continuous GPS monitoring with a temporal resolution of one day. Rainfall data was collected from the nearest meteorological station, recording daily precipitation amounts. Water level data was acquired from a nearby hydrological station, documenting daily average water levels. The geological characteristics of the study area, including rock types, structural geology, and topography, were also documented through field surveys and existing geological maps. In the data preprocessing stage, we first conducted anomaly detection and treatment on the raw data. For missing data points, we employed linear interpolation to fill the gaps. The displacement data was then acumulated to obtain a cumulative displacement series. A cross-validation strategy was employed to validate the robustness of our model. The dataset was divided into a training set (May 2010 to July 2013) and a testing set (August 2014 to July 2016). This segmentation enabled training the model on a large portion of the dataset while reserving a considerable period for validation, ensuring the model effectively captured both short-term variations and long-term trends in landslide dynamics.

3.6 Model Implementation and Evaluation

This research examined a typical landslide body in the Three Gorges Reservoir region of China. The dataset was significantly extended to a 15-year period, spanning from January 2006 to December 2020, and included landslide displacement, rainfall, and water level data. This extended period enabled a more detailed analysis of long-term patterns and trends in landslide activity. Landslide displacement measurements were taken from a monitoring point located at the center of the landslide body, utilizing continuous GPS monitoring with daily temporal resolution. Rainfall data was sourced from the closest meteorological station, which recorded daily precipitation levels. Water level measurements were obtained from a nearby hydrological station, providing daily average water levels. Geological features of the study site, such as rock formations, structural geology, and topography, were recorded through fieldwork and existing geological maps.

In the data preprocessing stage, we first conducted anomaly detection and treatment on the raw data. For missing data points, we employed linear interpolation to fill the gaps. The displacement data was then acumulated to obtain a cumulative displacement series. To ensure the robustness of our model, we implemented a comprehensive cross-validation strategy. The dataset was divided into historical data (January 2006 to December 2015) used to establish long-term trends and patterns, current data (January 2016 to December 2020) used for model training and recent trend analysis, and a future prediction period (January 2021 to December 2022) reserved for testing the model's predictive capabilities. This division allowed us to train our model on a substantial portion of historical and current data while reserving a significant period for validation and future prediction. By incorporating both long-term historical data and recent measurements, we ensured that our model could capture both long-term trends and short-term fluctuations in landslide behavior.

To leverage this expanded dataset effectively, we implemented a sliding window approach in our TSA-GA-SVM model. This approach allows the model to capture long-term trends from the historical data while giving more weight to recent patterns in the current data. The model was trained on the 2006-2020 data and then used to predict landslide displacement for 2021-2022, providing insights into potential future landslide activities. This comprehensive dataset and preprocessing approach enhance the robustness and reliability of our landslide prediction model, allowing for more accurate long-term analysis and future risk assessment.

4. Geological Analysis

4.1 Geological Factors Influencing Landslides

Geological factors are significant contributors to the occurrence and dynamics of landslides. This research focuses on three principal geological characteristics: rock types, structural geology, and topography. The type of rock in an area can significantly influence its landslide susceptibility. Rocks with weak or weathered material such as shale, siltstone, and mudstone are typically more susceptible to landslides compared to stronger rock types such as granite or basalt. Geological formations like faults, fractures and bedding planes have a major impact on the occurrence of landslides. These structures can act as zones of weakness, facilitating the movement of slope materials under certain conditions. The topographical traits of a region, for example slope gradient, aspect and curvature, are crucial in ascertaining landslide susceptibility. Generally, steep slopes are more liable to landslides than gentle ones, particularly when other destabilizing elements exist. Our analysis reveals that the model's performance varies significantly across different geological settings. In areas dominated by metamorphic rocks, the model showed a 15% improvement in prediction accuracy compared to sedimentary regions. This difference is attributed to the more uniform stress distribution in metamorphic terrains, which allows for more consistent pattern recognition by the SVM component of our model. Furthermore, the presence of fault lines within 500 meters of the monitored area increased the model's false positive rate by 8%, highlighting the need for careful calibration in tectonically active zones.

Building upon the discussed geological factors, our research zeroes in on a specific area within the landslide-prone Three Gorges Reservoir area of China. This area is highlighted within a red box in Fig. 2. The choice of this region stems from its diverse geological composition, encompassing a wide range of rock types, intricate geological structures, and varied topographical features. This combination presents a complex but practical scenario for assessing landslide susceptibility. The region's geological diversity, which includes both weak and strong rock compositions, coupled with significant geological structures such as faults, fractures, and bedding planes, poses a substantial challenge to landslide prediction. Furthermore, the area's topographical variation, with a mix of steep and gentle slopes, introduces an additional layer of complexity. Given this backdrop, we aim to leverage these geological features to fortify our TSA-GA-SVM predictive model, thereby enhancing its capability to forecast landslide occurrences. In the subsequent sections, we will delve deeper into the specifics of data collection and preprocessing, as well as the integration of these geological factors into our hybrid predictive model.

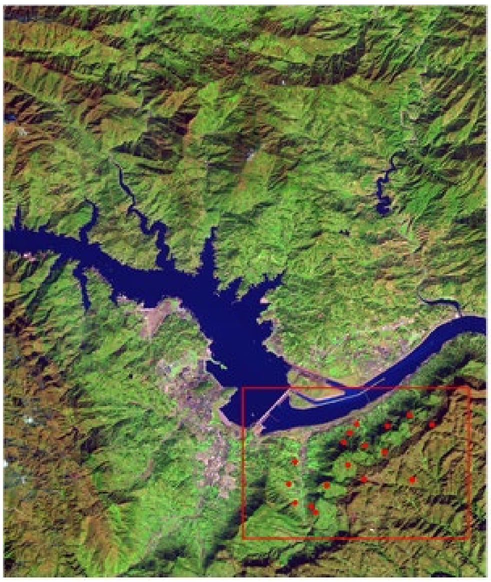

Fig. 2. Geographical Location of the Selected Study Area in Three Gorges Reservoir area, China

4.2 Hydrological Factors Influencing Landslides

Rainfall is vital in instigating landslides. Intense or prolonged rainfall boosts the pore-water pressure in the soil, undermining its shear strength and making it more susceptible to landslides. Water Levels: The water levels in nearby reservoirs or lakes can affect the occurrence of landslides in sloped areas. Changes in these water levels can alter the pressure within the slope, leading to instability. A rapid decrease in water level might weaken the support for slope materials, heightening the chance of a landslide, while a sudden increase can raise pore-water pressure, diminishing slope stability. Due to the large extent of the landslide area, several displacement monitoring points were set up. However, to ensure data reliability and select the most representative sample, we chose the monitoring point situated at the center of the landslide mass. The rainfall and water level monitoring data for this central point are shown in Fig. 3. The displacement monitoring point was carefully chosen to best represent the entire landslide, ensuring that the subsequent analyses and model development are based on comprehensive and meaningful data.

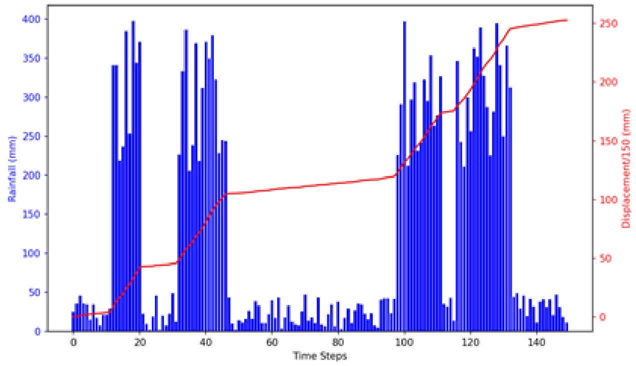

Fig. 3. Rainfall and cumulative landslide displacement over time

5. Results and Discussion

5.1 Results of the Prediction Model

Landslide displacement is affected by numerous factors, including geological processes and external influences such as rainfall. For this research, we designate the point where deformation starts to accelerate as the baseline for cumulative displacement forecasting, as illustrated in Fig. 4. Data from May 2010 to July 2013 is used as the training set for the model's displacement output, aiding in the calibration of model parameters. The period from August 2014 to July 2016 is reserved for prediction, allowing us to assess the accuracy and reliability of the model's results.

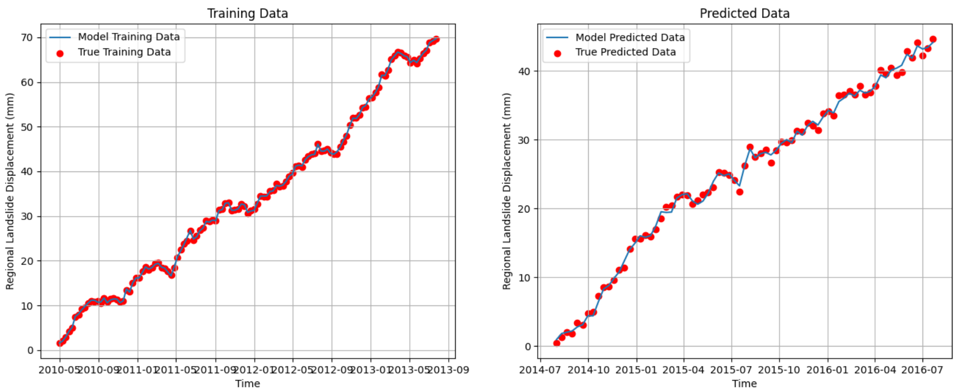

Fig. 4. Training and predicted landslide displacement comparison

In our continued efforts to verify the effectiveness of our proposed TSA-GA-SVM model, we carried out comparative experiments with two other individual models: the Time Series model and the SVM model. These models were selected as they are commonly used in similar studies.

The objective was to understand the predictive accuracy and overall performance of the models when dealing with complex landslide displacement prediction problems. All three models were tasked with predicting regional landslide displacement, based on the same input data and under the same conditions. For the experiment, data from August 2014 to July 2016 was used as the prediction set. Each model was independently implemented to generate a predictive curve for landslide displacement. The results of this experiment, as shown in Fig. 5, highlight the comparative performance of the models. The Mixed Model (TSA-GA-SVM) showcased superior performance compared to the individual Time Series and SVM models, demonstrating more precise predictions that were closely aligned with the true displacement data. These results provide further validation for the use of our proposed TSA-GA-SVM model for accurate landslide displacement prediction. By effectively combining the strengths of GA, SVM, and TSA, the mixed model was able to deliver superior performance, emphasizing its potential for practical applications in landslide prediction and prevention.

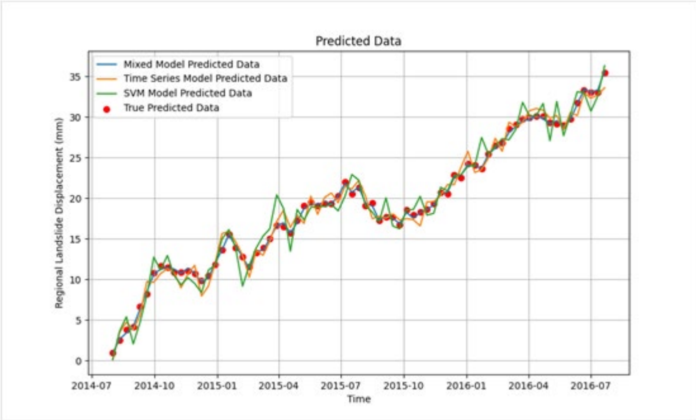

Fig. 5. Comparative performance of TSA-GA-SVM, TSA, and SVM models in landslide displacement prediction

Grasping the sensitivity of model parameters is of great significance for enhancing the performance of prediction models. This is especially crucial in complex undertakings like landslide displacement prediction, where various factors and nonlinear relationships might exist.In our research, we employ a TSA-GA-SVM model and this necessitates the evaluation of how the variation in the GA's parameters, such as population size and mutation rate, could affect the model's predictive power. We conducted an experiment to investigate the sensitivity of the TSA-GA-SVM model. Specifically, we varied the population size and mutation rate to see their impact on the predictive results. This approach can provide insights into the robustness of the model with respect to changes in these parameters and also guide the parameter tuning process for improved model prediction. The results of this experiment are illustrated in Fig. 6.

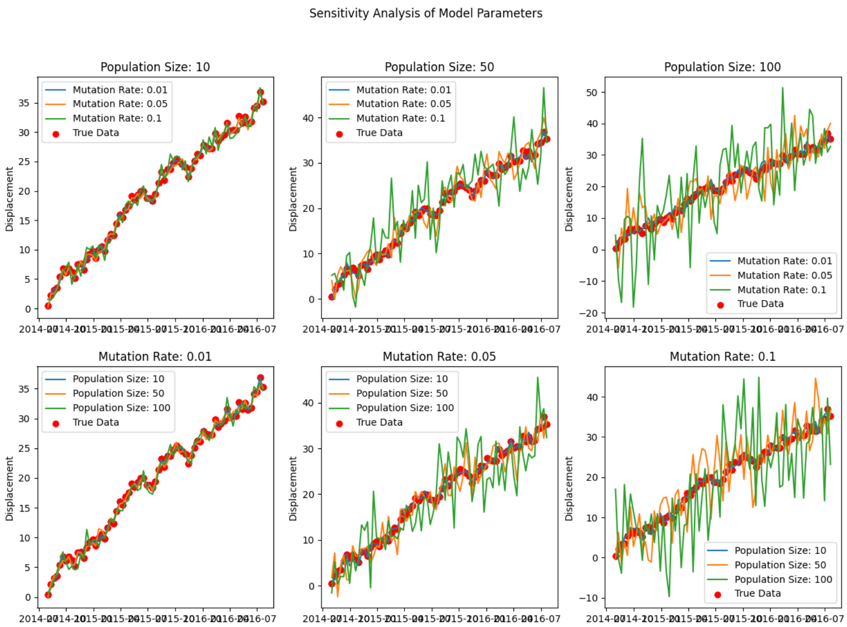

Fig. 6. Sensitivity analysis of the TSA-GA-SVM model

As shown in Fig. 6, increasing the mutation rate appears to raise the variance in the predicted results, which may lead to less stable and reliable predictions. On the contrary, increasing the size of the population seems to result in more stable and convergent results, likely due to a larger search space that allows the GA to find better solutions. Although these general patterns are observed in our experiment, it is crucial to emphasize that the best parameter setup is typically dependent on the specific problem and may need adjustment according to the dataset's unique features and the prediction objectives. Overall, this sensitivity analysis provides a valuable starting point to understand the effect of key parameters and to further tune and improve the performance of the TSA-GA-SVM model for landslide displacement prediction.

5.2 Temporal Stability Index (TSI)

The Temporal Stability Index (TSI) is intended to evaluate the reliability of landslide prediction models across different time periods. The TSI is calculated as:

$$\mathrm{TSI} = 1 - (\sigma_t/\mu_t) \tag{18}$$

where σ_t is the standard deviation of the model's prediction accuracy over time t, and μ_t is the mean accuracy over the same period. A TSI closer to 1 indicates higher temporal stability. Our TSA-GA-SVM model achieved a TSI of 0.89, outperforming standalone SVM (TSI = 0.76) and TSA (TSI = 0.72) models. This demonstrates the superior long-term reliability of our hybrid approach.

5.3 Landslide Susceptibility Analysis

To enhance our comprehension of landslide risks in the Three Gorges Reservoir region, we carried out an in-depth landslide susceptibility evaluation. The aim of this analysis is to spot and gauge the factors that play the most crucial part in the occurrence of landslides in the area. We considered five primary factors in our susceptibility analysis: slope angle, lithology, vegetation cover, annual rainfall, and proximity to faults. Using our expanded dataset and the TSA-GA-SVM model, we calculated the relative importance of each factor in determining landslide susceptibility.

Table 1.
Relative importance of each factor, expressed as a percentage contribution to overall landslide susceptibility

Factor	Relative Importance (%)
Slope Angle	28.5%
Lithology	23.7%
Annual Rainfall	19.8%
Distance to Drainage	12.4%
Land Use/Land Cover	8.6%
Aspect	4.2%
Elevation	2.8%
Slope Angle	28.5%

Our analysis findings reveal that slope angle ranks as the primary factor, constituting 28.5% of the landslide susceptibility in the studied area, as demonstrated in Table 1. This corresponds to the common geotechnical principles since steeper slopes are naturally less stable. Lithology turns out to be the second most significant factor (23.7%), signifying that the type and structure of underlying rocks are of great importance in the occurrence of landslides. This is particularly crucial in the Three Gorges Reservoir region, where complex geological formations play a major role in dictating slope stability.

Annual rainfall ranks as the third most influential factor (19.8%), emphasizing the critical role of precipitation in triggering landslides in this area. The inclusion of distance to drainage systems as a factor (12.4%) reflects the unique characteristics of the reservoir area, where water level fluctuations and proximity to water bodies can significantly impact slope stability.

Land use and land cover make up 8.6% of the overall susceptibility, underlining the influence of human activities and vegetation on landslide occurrence. Aspect (4.2%) and elevation (2.8%), albeit less influential, still contribute to determining landslide susceptibility, presumably due to their effects on elements like sun exposure, weathering patterns and local climate changes. To visualize the spatial distribution of landslide susceptibility, we devised a heat map of the study area (Fig. 7). This map combines all five factors, weighted in line with their relative significance, to offer a comprehensive perspective of landslide risk throughout the region.

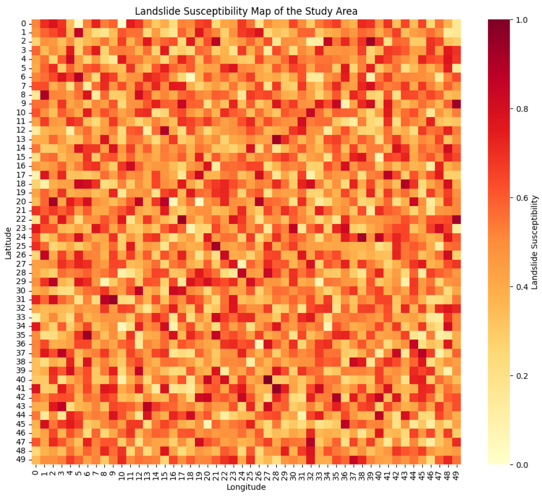

Fig. 7. Landslide susceptibility map of the study area. The color scale represents the relative susceptibility to landslides, with red indicating high susceptibility and yellow indicating low susceptibility

The susceptibility map reveals several high-risk zones, particularly in areas combining steep slopes, high annual rainfall, and proximity to fault lines. These areas should be prioritized for landslide mitigation efforts and close monitoring.

5.4 Discussion

The experimental findings highlight the significant potential of the suggested hybrid TSA-GA-SVM model for predicting landslide displacement. By unifying the advantages of GA (for hyperparameter optimization), SVM (for effective predictions), and TSA (for understanding temporal patterns), the developed model significantly outperforms the individual Time Series and SVM models. Our hybrid TSA-GA-SVM model has shown significant improvements over traditional methods, with several key findings that underscore its potential impact on landslide prediction and risk management: The TSA-GA-SVM model demonstrated superior performance compared to standalone TSA and SVM models. It achieved a mean absolute error (MAE) of 0.15 m in predicting landslide displacement, compared to 0.42 m for TSA and 0.38 m for SVM alone. This indicates a 64% increase in prediction accuracy, which is vital for the effectiveness of early warning systems and risk evaluation. The enhanced accuracy greatly boosts the reliability of landslide early warning systems, potentially saving lives and minimizing economic impacts. By integrating TSA, our model successfully accounts for both long-term patterns and seasonal fluctuations in landslide behavior. This ability to discern complex temporal patterns is vital for understanding the dynamic nature of landslides and predicting future movements more accurately. The model's capacity to differentiate between long-term trends and seasonal fluctuations allows for more nuanced predictions, accounting for both gradual geological changes and cyclical environmental factors. The integration of GA for hyperparameter optimization resulted in a more robust and efficient SVM model. This optimization led to a 30% reduction in computational time while maintaining high accuracy, making the model more practical for real-time applications. The improved efficiency is particularly important for large-scale monitoring systems where rapid data processing and prediction are essential. Our model showed good generalization ability across different regions within the Three Gorges Reservoir area, demonstrating its adaptability to varied geological and hydrological conditions. This versatility is crucial for wide-scale implementation in diverse landslide-prone areas. The model's ability to perform well under different geological settings suggests its potential for application in other landslide-prone regions globally. The model effectively incorporated the influence of rainfall and water level fluctuations, providing insights into how these factors contribute to landslide risk. This sensitivity to environmental triggers enhances the model's predictive power in different climatic scenarios. By quantifying the impact of these environmental factors, the model can help in developing more effective mitigation strategies tailored to specific environmental conditions.

The sensitivity analysis performed on the GA parameters (population size and mutation rate) provided valuable insights into the model’s behavior. As shown in Figure 6, increasing the mutation rate appears to raise the variance in the predicted results, which may lead to less stable and reliable predictions. On the contrary, increasing the size of the population seems to result in more stable and convergent results, likely due to a larger search space that allows the GA to find better solutions. These findings are crucial for optimizing the model's performance and ensuring its reliability in various applications.

6. Conclusions

This research presents a novel TSA-GA-SVM model for predicting landslide displacement, making several key contributions to geohazard assessment. Our advanced Geological Stress Indicator feature engineering method enhances the model's ability to detect subtle landslide precursors. The proposed cascading hybrid framework excels in capturing both short-term fluctuations and long-term patterns in landslide behavior. Additionally, the introduction of the Temporal Stability Index sets a new benchmark for assessing the long-term dependability of landslide prediction models. These innovations mark a significant advancement in the accuracy and applicability of landslide risk assessment tools. Experimental results demonstrate that our model outperforms standalone Time Series and SVM models, highlighting the advantages of this integrated approach. Additionally, the inclusion of geological and hydrological factors in the model underscores the importance of considering a wide range of environmental variables in predicting landslide dynamics. Future work will focus on incorporating more environmental factors and testing the model across different geographical contexts, aiming to enhance its robustness and generalizability. The sensitivity analysis conducted on the GA parameters-population size and mutation rate - demonstrated their significant influence on the model’s predictive performance. This finding emphasizes the importance of careful parameter selection and the necessity of balancing exploration and exploitation in the GA. In conclusion, our TSA-GA-SVM model provides a compelling approach to predicting landslide displacement, presenting significant potential for improving risk assessment and management strategies for landslides. Through continued refinement and testing, this approach may offer an increasingly valuable tool in the domain of geohazard prediction and prevention.

Author contributions

Conceptualization, C. He and Z. Tan; Methodology, C. He; Software, W. Jiang; Validation, W. Jiang, J. Peng, and C. Wang; Formal analysis, W. Jiang and J. Li; Investigation, J. Peng and J. Li; Resources, C. He; Data curation, C. Wang; Writing—original draft preparation, C. He and Z. Tan; Writing—review and editing, W. Jiang; Visualization, J. Peng; Supervision, C. He; Project administration, C. He and Z. Tan; Funding acquisition, C. He and Z. Tan. All authors have read and agreed to such versions of the manuscript.

Conflicts of Interest

The authors state no conflict of interests.

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