<u>Summary of the Changes to Reviewer 1's Recommendations and Comments</u>

Journal: Natural Hazards and Earth System Sciences

Ref: NHESS-2024-86R2

Title: Predicting Deep-Seated Landslide Displacement in Taiwan's Lushan Mountain through the Integration of Convolutional Neural Networks and an Age of Exploration-Inspired Optimizer

The authors appreciate the reviewer's valuable feedback. The summary of the changes based on the reviewer's recommendations & comments is listed below. All the revisions are TRACKED in the re-submitted WORD file along with marked RED COLOR for the ease of the reviewer's perusal.

Comments of the Reviewer	Authors' Summary of the Changes
I reviewed a previous version of this manuscript and suggested major revisions. The authors have taken care to address my suggestions point-by-point, and their revised manuscript reflects well the efforts of the authors to incorporate these suggestions. The results shown herein are impactful, and I appreciate the thorough investigation of models that can help guide future researchers who may undertake similar efforts. I therefore recommend publication of this work in NHESS; however, I include some additional line-by-line comments for the authors to address below:	We, the authors of this study, would like to express our sincere gratitude to the reviewer. The feedback provided in the previous round has guided our improvements. We strive to meet the expectations of both the reviewer and the NHESS journal.
1 (Title): It is a good idea to insert the country name here so people know where the Lushan mountains are located	We fully agree with the reviewer's suggestion and have added the country name to the title of this manuscript to provide readers with more detailed information about the study location. **Predicting Deep-Seated Landslide ~~Displacements~~Displacement in ~~Taiwan's~~Taiwan's Lushan Mountain through the Integration of Convolutional Neural Networks and an Age of Exploration-Inspired Optimizer**
38-44: Much improved with the added context here!	We are glad our revisions have met the reviewer's expectations in this section.
45: Should have references to support this	We have included additional references to support the assertion that 'critical factors associated with slope instability exhibit temporal variability' as requested by the reviewer. a few meters, deep-seated landslides extend deeper, often exceeding 10 meters, and can involve the movement of underlying bedrock (Lin et al., 2013). Predicting these events is challenging and costly (Thai Pham et al., 2019). Therefore, extensive efforts have been made to predict such disasters throughout history (Corominas and Moya, 2008; David and Raymond, 1989; Aleotti and Chowdhury, 1999). One method that has been employed involves thoroughly examining the physical and geological characteristics of the mountainous areas at risk of landslides (Cotecchia et al., 2020). Furthermore, the level of
49: There are much older references than these, e.g., Iverson and Major (1985) and references therein	We acknowledge the value of the reference recommended by the reviewer, which provides an excellent explanation for the argument in question.

	Notably, this reference was conducted some time ago, indicating that the argument has been widely accepted within the academic community for quite some time. Consequently, we have incorporated this reference as a citation in the relevant section. method that has been employed involves thoroughly examining the physical and geological characteristics of the mountainous areas at risk of landslides (Cotecchia et al., 2020). Furthermore, the level of groundwater has been shown by numerous studies in the past to influence the mechanisms behind landslide formation significantly (Miao and Wang, 2023; Preisig, 2020; Iverson and Major, 1987).
63: It is not mentioned what the constraints are of traditional machine-learning models	We have added a discussion on the limitations of machine learning in this section, as suggested by the reviewer. One of the most effective solutions for constructing models to predict time series data involves applying data-driven techniques. The advancement of computational capabilities has driven the widespread adoption of data-driven machine-learning models over physics-based models. This shift is based on the premise that the data used for slope monitoring originates from nonlinear systems (Zhou et al., 2018). However, a ~~major~~significant drawback of traditional machine learning models ~~such as Random Forest and Support Vector Machine~~, such as Random Forest and Support Vector Machines, is their difficulty ~~in~~ handling spatiotemporal data. These models struggle to capture the sequential relationships necessary for landslide prediction, resulting in lower performance (Zhang et al., 2022a; Tehrani et al., 2022).
73: A term to use throughout the manuscript would be "deep-seated landslide displacement"	We fully concur with the reviewer's insight and have consistently utilized the term 'deep-seated landslide displacement' throughout this study. substantial effectiveness. Consequently, the fine-tuning of hyperparameters represents a potent avenue for elevating the efficiency of AI models in research focused on predicting ~~deep-seated displacement~~deep-seated landslide ~~s~~displacement. Leveraging the effective methodologies mentioned above, this study employs AI models optimized by an innovative metaheuristic optimization algorithm to predict ~~deep-seated displacement~~deep-seated landslide displacement on the northern slope of Lushan Mountain in Ren'ai Township, Nantou County, Taiwan. The geological characteristics of this area have undergone extensive research (Wang et al., 2015; 1) To analyze the application of machine learning and deep learning methods to time series data to forecast short-term, deep-seated ~~slope~~ landslide ~~displacements~~displacement across the Lushan Mountain area. 2) To identify the optimal model and hyperparameters for accurately forecasting ~~deep-seated displacement~~deep-seated landslide ~~s~~displacement in the study area. 3) To evaluate the role of metaheuristic optimization algorithms in fine-tuning the hyperparameters of AI models. **2. Literature Review** **2.1 Groundwater Levels and the Forecasting of ~~Deep-Seated Displacement~~Deep-seated ~~landslide sdisplacement~~Landslide Displacement** Our research aims to adopt a novel approach compared to previous landslide studies at Lushan Mountain by utilizing AI models and metaheuristic optimization algorithms. This research will utilize ~~weather conditions~~temperature, humidity, and groundwater levels as input data~~s~~ for AI models to predict ~~deep-seated displacement~~deep-seated landslide displacement, thus aiding in landslide forecasting in this region. **~~3.8~~3.5 Age of Exploration-Inspired Optimizer** This study employs a range of AI models to forecast ~~deep-seated displacement~~deep-seated landslide displacement in mountainous regions. To enhance the prediction accuracy of these AI models, the study **~~3.9.2~~4.2 Data Collection ~~and Preprocessing~~** In this study, hourly data of ~~deep-seated displacement~~deep-seated landslide displacement and groundwater level were collected by the Department of Civil Engineering, College of Science and Technology, at the National Chi Nan University research group over eight years from July 2009 to June Based on the collected data, analyses have examined the correlation between groundwater levels and ~~deep-seated displacement~~deep-seated landslide displacement at Lushan Mountain. To observe this correlation, graphs illustrating the precipitation of recorded heavy rainfall (Figure 7A), variations in displacement (Figure 7B and Figure 7C), and groundwater levels (Figure 7D) over time have been plotted. June 17, 2012, totaling 1029 mm over 219 hours (as indicated in Table 2 and Figure 7A). The abnormal rise in groundwater levels led to~~caused a structural alteration in the area's soil~~ increased pore water pressure,~~,~~ ~~consequently amplifying~~ which triggered ~~deep-seated displacement~~deep-seated landslide displacement at both stations, namely E_2 and SAA, as evidenced in Figure 7B and Figure 7C.

Similar events occurred in November 2017. Heavy rainfall totaling 638.5 mm over 178 hours during this period also caused a sudden alteration in groundwater levels, resulting in significant ~~deep-seated displacement~~deep-seated landslide displacement. Through comparison, it is apparent that there were up to 13 instances of anomalous heavy rainfall during the study period. However, not every example of heavy

In addition to groundwater level data, weather factors such as temperature and humidity are also utilized as input data for the prediction model. This study includes temperature as an input variable for AI models to predict ~~deep-seated displacement~~deep-seated landslide displacement due to its impact on soil structure. Elevated temperatures can cause thermal expansion of soil particles, which can increase pore

Table 3 displays the input and output variables for AI models to predict ~~deep-seated displacement~~deep-seated landslide displacement at Lushan Mountain. Two datasets will be generated: one for predicting displacement at the E_2 station and another for indicating displacement at the SAA station.

Table 3. Input and output variables of a model predicting ~~deep-seated displacement~~deep-seated landslide displacement.

	Attributes group	Attributes	Variable ID	Dataset of E_2 station	Dataset of SAA station
Output variables	~~Deep-seated displacement~~Deep-seated landslide displacement measures	Displacement extensometer at station E_2 (mm)	Y1	✓	-
		Displacement extensometer at station SAA (mm)	Y2	-	✓

Predicting ~~deep-seated displacement~~deep-seated landslide displacement at Lushan Mountain is undoubtedly highly challenging, given that such landslides depend on numerous factors. Therefore, multiple methods will be employed simultaneously to identify the optimal AI model for prediction. These

In addition to the numerical AI models, this study employs individual CNN models for predicting ~~deep-seated displacement~~deep-seated landslide displacement. Subsequently, similar to the approach above, the best CNN model with the highest displacement prediction capability will be fine-tuned by the

~~4.2.1~~5.2.1 Numerical Models~~AI Models~~

a. Machine Learning Models

Initially, single machine learning models will be employed to predict ~~deep-seated displacement~~deep-seated landslide displacement. In this phase, machine learning models will utilize default hyperparameters, as detailed in the research of Chou and Nguyen (2023). The prediction results of these models at both E-

74: Would insert the country name here as well

We have included information regarding the country Taiwan to enhance the reader's understanding of the study's geographical context.

by an innovative metaheuristic optimization algorithm to predict ~~deep-seated displacement~~deep-seated landslide displacement on the northern slope of Lushan Mountain in Ren'ai Township, Nantou County, Taiwan. The geological characteristics of this area have undergone extensive research (Wang et al., 2015; Lin et al., 2020). Previous studies have identified varying depths of the shear plane. Specifically, Lin et

131: Specify which atmospheric variables will be used instead of the term "weather conditions"

Specifying the variables related to weather conditions undoubtedly enriches the information presented and enhances the clarity and comprehensibility of this study for readers. Accordingly, we have incorporated this information following the reviewer's suggestion.

Our research aims to adopt a novel approach compared to previous landslide studies at Lushan Mountain by utilizing AI models and metaheuristic optimization algorithms. This research will utilize ~~weather conditions~~temperature, humidity, and groundwater levels as input datas for AI models to predict ~~deep-seated displacement~~deep-seated landslide displacement, thus aiding in landslide forecasting in this region.

134 (Fig. 1): Why is the orange layer filled in on the second panel and not the first? Why not the upper layer too? Additionally, water tables typically include an inverted triangle denoting their position.

We have revised Figure 1 to ensure color consistency between the images on the left and right. In the right image, only the water layer is filled with color, while the soil and rock layers remain uncolored. Additionally, we have added an inverted triangle symbol to mark the location of the groundwater.

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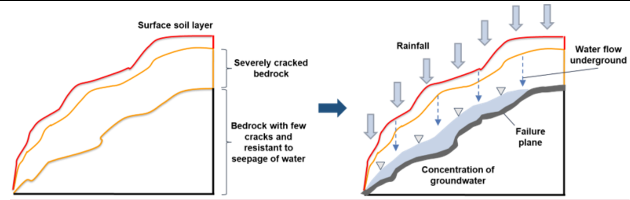
<tr><td></td><td>

Figure 1. Schematic illustration showing the effects of groundwater on deep-seated slope failure.</td></tr>
<tr><td>149: change to “physically based” from “physical-based”</td><td>We have made the changes as per the reviewer's suggestion.

Moreover, physically~~-~~ based numerical and laboratory modeling methods are also gaining traction in landslide research. These methods aim to maintain forecasts using various data types while reducing</td></tr>
<tr><td>164-171: There is a deep literature on this subject and I encourage the authors to include some more fundamental contributions to slope stability analysis here. It does not need to be a substantially longer paragraph as that is not the focus of this work. However, some more foundational work should be briefly referenced.</td><td>In response to the reviewer's request, we have included additional citations of studies that employ stability analysis in landslide assessments.

Stability analysis is another commonly used method related to physics, which evaluates the forces acting on ~~a~~ slope behavior. Fu and Liao (2010) presented a technique for implementing the non-linear Hoek-Brown shear strength reduction, determining the correlation between normal and shear stress based on the Hoek-Brown criterion. Subsequently, the micro-units (microscopic components of the rock mass) instantaneous friction angle and cohesive strength under specific stress conditions are calculated. Although this approach effectively addresses cost and labor issues, it still heavily relies on the researcher's assumptions and is limited by the ability to utilize only a small portion of data from the research area. Additionally, there are several other limitations. For instance, Mebrahtu et al. (2022) indicated that stability analyses become less reliable in ~~scenarios involving seismic loads~~seismic load scenarios. Safaei et al. (2011) also noted that stability analysis necessitates a substantial amount of detailed input data obtained from laboratory tests and field measurements, thereby limiting the areas that can be effectively assessed.</td></tr>
<tr><td>172-180: I’m not sure I understand this paragraph. Why are AI models better suited to incorporation of new data than, say, deterministic models? I think the advantage may be that most deterministic modeling requires some knowledge of physics to predict displacement, which can be exceedingly complex in a large landslide, and these kinds of models rarely can achieve predictive success of a few percent.</td><td>We greatly appreciate the reviewer's suggestion, which allowed us to revise this section for greater clarity. We have updated the passage to explain why conventional methods were not used, as they require users to have specialized knowledge in physics and demand specific types of input data, making them less flexible compared to AI models. Therefore, given the advantages of AI models, they will be utilized in this study.

~~However, in landslide studies, monitoring data is constantly updated, generating large volumes daily with a temporal relationship (Peternel et al., 2022; Corominas et al., 2014).~~ As previously mentioned, using conventional methods ~~pose~~poses significant challenges, as their application requires a deep understanding of both the physics involved and the complex behavior of soil~~in landslide research presents numerous challenges whenever data changes or gets updated~~. In addition, ~~conventional~~traditional methods require specific types of input data, highlighting the rigidity and lack of flexibility inherent in these approaches (Safaei et al., 2011). In contrast, AI models can overcome these difficulties by automatically learning to identify ~~connections~~ mapping functions between input and output data, eliminating ~~the need for users to have~~users needing specialized knowledge of soil behavior and physics. Additionally, AI models can be updated to incorporate new input variables, offering flexibility to leverage available data based on real-world conditions~~. AI models can be updated to incorporate additional input variables and handle increasing amounts of data flexibly in response to real-world conditions~~. Therefore, AI models will be utilized in this research instead of conventional methods.</td></tr>
<tr><td>184-186: There is somewhat of a disconnect here because the Margarint et al. paper does not appear to utilize AI, it just presents an analysis using a standard logistic regression model. The preceding sentence should therefore be changed, or a more appropriate example should be provided.</td><td>Based on the reviewer's comment, we reference a different citation that employs AI models in landslide research to align better with the core content of this section.</td></tr>
</table>

	In studies employing machine learning and deep learning models for landslide research, a plethora of research utilizes discrete data to train AI models to predict the probability of landslides or to construct maps depicting landslide susceptibility. For instance, ~~Margarint et al. (2013) employed a logistic regression model to predict landslides based on discrete data in four regions of Romania. The logistic regression model yielded promising predictions, with an AUC value (area under the curve) ranging between 0.851 and 0.94 for the validation dataset~~ Pradhan and Lee (2010) used Geographic Information System (GIS), remote sensing, and a neural network model to analyze landslide susceptibility in Cameron Highlands, Malaysia. Ten factors, including topographic slope and drainage distance, were processed to generate a susceptibility map. The model achieved 83% accuracy in predicting landslide locations. ~~Subsequently, these results were utilized to construct a map of landslide susceptibility in the study area.~~ In a similar study, Pham et al. (2016) used multiple AI models, including support vector machines (SVM), logistic regression (LR), Fisher's linear discriminant analysis (FLDA), Bayesian network (BN), and naïve Bayes (NB), for landslide susceptibility assessment in a region within the Uttarakhand state of India. The SVM model yielded the best prediction results among the models used.
474-477: The DBSCAN algorithm is not mentioned previously to this point and thus it is confusing. Furthermore, Equations 13 and 14 do not exist in the manuscript. Some additional prior explanation is needed here.	To explain the AEIO algorithm in this study, we have added citations and a description of the DBSCAN algorithm. We hope this addition will enhance the reader's understanding of the algorithm. The strength of the AEIO algorithm lies in its ability to develop specific strategies for particles based on their positions, enabling faster convergence to the optimal point~~. Using~~, using density-based spatial clustering of applications with noise (DBSCAN) for particle clustering. DBSCAN is an unsupervised clustering method that organizes data points by their spatial closeness in high-dimensional spaces (Ester et al., 1996). This algorithm is particularly effective at detecting clusters of different shapes and densities. It relies on two primary parameters: ε (the radius of the neighborhood) and MinPts (the minimum number of points required to form a dense area). Clusters are created by locating neighboring points ~~that have enough surrounding points, while those points~~ with enough surrounding points, while those that do not belong to any cluster are classified as noise or outliers. Using the DBSCAN algorithm, ~~t~~ the AEIO determines whether particles are in favorable or unfavorable positions, reminiscent of explorers during the Age of Exploration. The proximity (within clusters) allows explorers to gather information and move toward optimal locations, thereby enhancing Additionally, we have rechecked the numbering of the equations and made necessary corrections to ensure their accuracy. The exploratory steps in the AEIO algorithm begin by classifying positions using the DBSCAN algorithm. Subsequently, the explorers update the crowd control mechanism according to equations (9~~13~~) and (10~~14~~), and move according to various strategies defined by equations (4~~8~~), (6~~10~~), (7~~11~~), and (8~~12~~). This process is conducted iteratively until the maximum number of iterations is reached. We have also updated the numbering of the equations in the flowchart to facilitate easier tracking for the readers.

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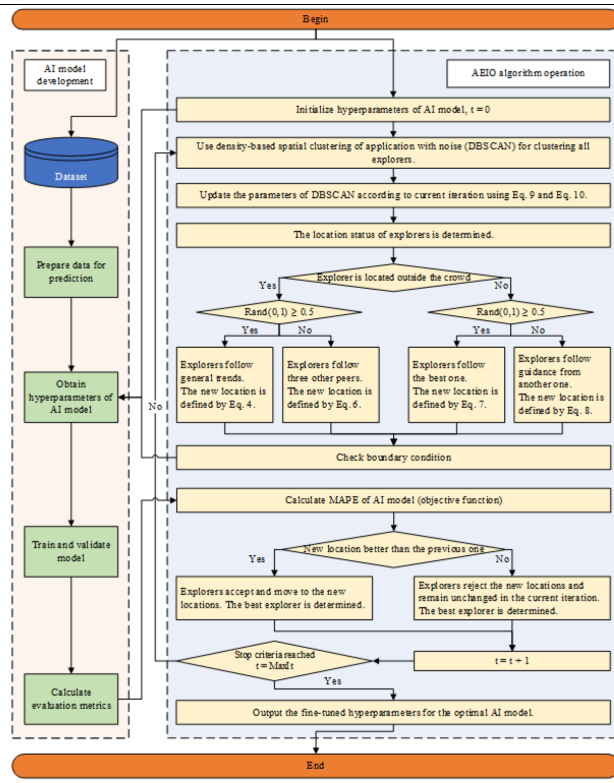

Figure 4. Flowchart of the fine-tuning process of AI models by the AEIO algorithm.
Figure 4. Flowchart of the fine-tuning process of AI models by the AEIO algorithm.
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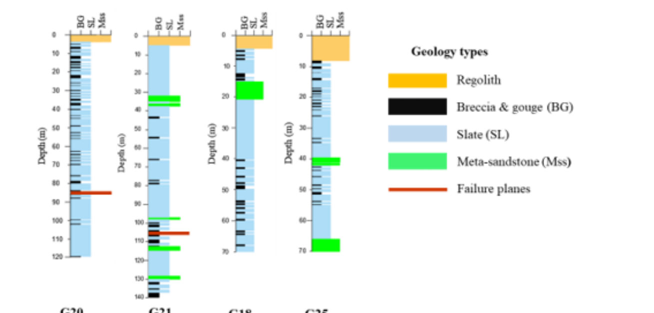
<td>490 (Fig. 6): It would be useful to have the approximate failure plane depths measured for G20 and G21 shown graphically here.</td>
<td>
Incorporating the location of the failure plane is undoubtedly essential, as it provides readers with a clearer understanding of the geological conditions in the area. Therefore, we have included this information in Figure 6.


Figure 6. Illustration of geological drilling survey.
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<td>494: I think the term “youthful” is too colloquial here</td>
<td>
We agree with the reviewer's suggestion and will replace 'youthful' with 'incipient.' This term is more academically appropriate and accurately reflects the geological conditions of the area, where many valleys are in the early stages of formation.
The current study focuses on the northern slope of the Lushan hot spring in Ren'ai Township, Nantou County, Taiwan (Figure 5), with Nenggao Mountain to the east, Hehuan Peaks to the north, Zhuoshe Mountain to the south, and Puli Basins to the west. The terrain features rugged mountain ranges, ~~youthful~~ incipient valleys, and notable river erosion (Lee and Chi, 2011). Lushan Hot Springs is located below the hill, and the main access roads for nearby settlements and hot spring sites include Provincial Highway 14 and County Highway 87.
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<td>514-521: I don’t think my previous comment regarding the definition of “cleavages” was sufficiently addressed here. Please specify what this term means in this context, or utilize a different term throughout</td>
<td>This revision has replaced the term 'cleavage' with 'fracture.'

Previous research has detected signs of brittle deformation in the area. These indications include chevron folds within fracture~~cleavage~~s, visible cracks, and intricate jigsaw puzzle-like patterns at the head of the rock formations. Overturned and flexural toppling fracture~~cleavage~~s are prevalent toward~~s~~ the toe of the slope. Additionally, kink bands are observable on fractures recently undergoing flexural folding along the eastern boundary. Notably, horizontal fracture~~cleavage~~s near the toe region also ~~exhibitexhibits~~exhibit inter-fracture~~cleavage~~ gouges. Further details on this geological information can be found in the study by Lin et al. (2020). These instances highlight the potential for significant geological changes and landslide risk in this region.</td>
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<td>546 (Fig. 7): This is much improved from the previous figure, although there is an issue now in that the timing does not appear to line up between the plots. For example, the large displacement in 2012 appears to come before the rise in water levels in (D).</td>
<td>The synchronization of events across all four charts is vital, highlighting the interrelationship within the dataset used in this study. This alignment forms a solid basis for selecting input variables for the AI models. We have carefully fine-tuned the data to ensure that the events in all four charts are precisely aligned.

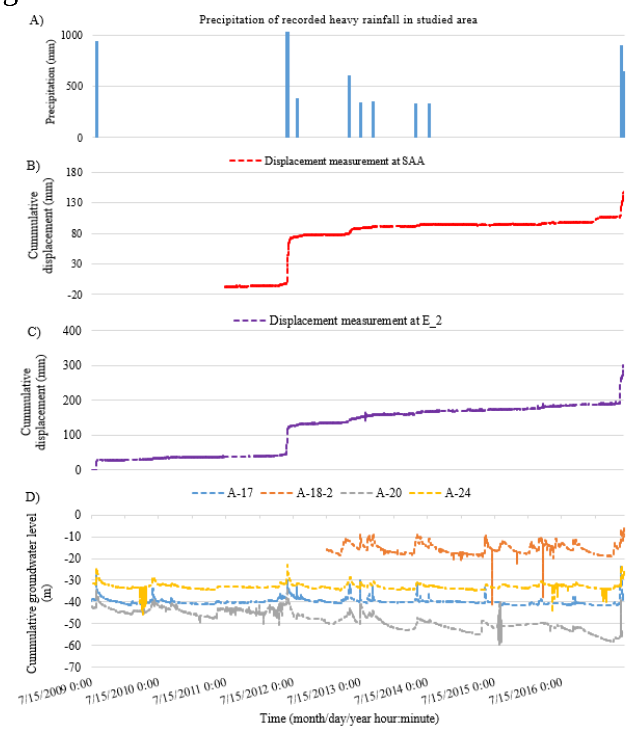

Figure 7. Unified timeline visualization of data in this study.
A) Precipitation of recorded heavy rainfall in the studied area; B) Measured displacements from extensometer SAA C) Measured displacements from extensometer E_2; D) Groundwater levels at stations A-17, A-18-2, A-20, and A-24.</td>
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<td>554-556: Did a previous study show specifically that a structural alteration in soil took place? Also, the failure plane is well below the “soil” depth and the landslide displacement should be insensitive to the soil present at the landslide surface. I recommend re-writing to say that, based on the temporal association of rapid displacement with a rapid rise in groundwater levels, it could be inferred that enhanced pore water pressure lead to the onset of motion.</td>
<td>In previous studies on the landslide in Lushan Mountain, Taiwan, other authors did not specifically demonstrate that a structural alteration in the soil occurred. Therefore, based on the reviewer's analysis in this comment, we have revised our explanation to state that enhanced pore water pressure led to motion onset.

The graphs above show that the displacement values at both stations often exhibit significant increases coinciding with periods of pronounced fluctuations in groundwater levels. Specifically, in June 2012, there was a notable surge in groundwater levels attributed to heavy rainfall from June 8, 2012, to</td>
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<td>June 17, 2012, totaling 1029 mm over 219 hours (as indicated in Table 2 and Figure 7A). The abnormal rise in groundwater levels led tocaused a structural alteration in the area's soil increased pore water pressure,; consequently amplifying which triggered deep-seated displacementdeep-seated landslide displacement at both stations, namely E_2 and SAA, as evidenced in Figure 7B and Figure 7C.</td>
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<td>616: “Deep-seated landslide displacement”</td>
<td>We have revised the terminology in this section and throughout the manuscript to 'deep-seated landslide displacement' per the reviewer's suggestion.

4.5.Model Establishment and Analysis Results
4.15.1 Model Establishment
Predicting deep-seated displacementdeep-seated landslide displacement at Lushan Mountain is undoubtedly highly challenging, given that such landslides depend on numerous factors. Therefore, multiple methods will be employed simultaneously to identify the optimal AI model for prediction. These</td>
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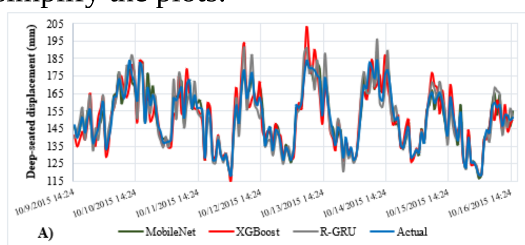
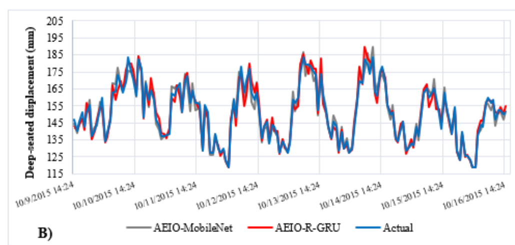
<td>776 (Fig. 10). Why are the descriptions at (a) and (b) above the introduction to Fig. 10? Second, in panel (a) there are a bunch of confusing floating dots that fall below the main plot and cover the legend. Third, the dots in general are distracting because it is difficult to see the subtle differences in each time series. I would remove the dots and just show lines for each model.</td>
<td>For the issues identified in Figure 10, we have made several revisions per the reviewer's suggestions. These revisions include the following:
- Move the descriptions of charts A and B below the introduction of Figure 10.
- The floating dots appearing in the main plot and covering the legend are due to an error during the PDF export process. We will ensure this issue does not occur in the subsequent sections.
- Remove the dots on each line to avoid confusion and simplify the plots.



a) Prediction results of deep-seated displacementdeep-seated landslide displacement by single AI models.



b) Prediction results of deep-seated displacementdeep-seated landslide displacement by AI models optimized using the AEIO algorithm.
Figure 10. Graph comparing the real and predicted deep-seated displacementdeep-seated landslide displacement: -A) Prediction results of deep-seated landslide displacement by single AI models; - B) Prediction results of deep-seated landslide displacement by AI models optimized using the AEIO algorithm.</td>
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<td>783: This is not entirely fair as there are a number of studies now that use AI to forecast landslide displacement as a function of environmental variables.</td>
<td>Other studies have indeed employed AI models to forecast landslide displacement, and claiming this approach as entirely novel is inaccurate. Consequently, we have made several revisions in this part. At the beginning of Section 4.3 (Discussion), we concisely summarized the study's</td>
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	objectives and removed any misleading information to ensure clarity for the readers. **~~4.4~~5.3 Discussion** This study focuses~~centers~~ on landslides in Lushan Mountain, Taiwan, ~~with the aim of developing~~intending to develop models to predict deep-seated landslide displacement for both 1-day and 7-day forecasts. These predictive models utilize input data such as ~~groundwater levels, temperature, and humidity in the region~~the region's groundwater levels, temperature, and humidity. ~~,~~Accurately~~adopting a fundamentally different approach than previous research. While past studies primarily focused on constructing AI models for classification, calculating the probability of landslide occurrences, and generating landslide susceptibility maps (Balogun et al., 2021; Hakim et al., 2022; Jaafari et al., 2022), our study is oriented towards predicting displacement to provide warnings about potential landslide hazards.~~ ~~As utilized in our calculations,~~ computing ~~deep seated displacement~~deep-seated landslide displacement offers several benefits. Firstly, ~~understanding internal displacements~~it provides ~~accurate~~ timely information for engineers to assess the resilience of structures and infrastructure in at-risk areas, facilitating the issuance of sensible warnings. Secondly, forecasting ~~deep seated displacement~~deep-seated landslide displacement offers insights into the severity of the disaster, aiding in effective evacuation and rescue planning.
826: I would specify that this study addresses the persistent threat of large, slow-moving landslides.	We are very grateful to the reviewer for this suggestion, which helped clarify the type of landslide most relevant to our study. We have made the necessary revisions in line with the reviewer's recommendation. **~~5.~~6. Conclusion** This study addresses the persistent threat of large, slow-moving landslides, a primary concern due to their severe impact on lives and property. Employing various AI models, such as machine learning, time