

Dear Anonymous Referee #3:

First of all, we would like to express our sincere appreciation of your very constructive comments and suggestion.

Next, in a sequence, we would like to respond to comments in a point to point manner so that hopefully all the questions can be answered or clarified. All the answers and responses are in red.

This paper proposes a new data-driven approach for real-time and site-specific analysis of landslide stability changing regularities based on a multi-attribute entropy analysis of deformation states from the aspect of landslide system. This approach was applied to different landslide and presented interesting results and could provide better information on site-specific landslide activity.

Thanks for your encouraging words.

Still, several revisions may help to improve the overall quality of the work.

Firstly, the advantages and the limitations of existing methods seems too brief to emphasize the meaning and emergency of the proposed approach. The processes of the model is complex, please organize this part clearly. I suggest that the methods should be divided into several subsections. This method named “the proposed joint clustering method combining k-means and cloud model” should be refined. The part of “materials and results” should be correspondence with the part of “methods”.

Thanks for your kind suggestion. Firstly, a detailed introduction to these methods (Saito’s method, LEM and FEM) has been added, including their advantages and the limitations. Given that several methods are involved in this approach, we have tried our best to divide it into two near-independent parts, respectively the definition and the multi-attribute entropy analysis of deformation states. Too much sub-section may undermine the integrity of the content. The method name “the proposed joint clustering method combining k-means and cloud model” may be too long but it expresses apparently the essential factors of this method. K-means and cloud model complement each other, together form the core of the joint clustering. Sorry, we have not figure out a better alternative. Any suggestions and advices on this issue are always welcome.

Saito’s method is an empirical forecast model and is suitable for the prediction of sliding tendency and then the failure time. Based on homogeneous soil creep theory and displacement curve, it divides displacement creep curves into three stages: deceleration creep, stable creep and accelerating creep, and establishes a differential equation for accelerating creep. The physical basis of Saito’s method helped it to successfully forecast a landslide that occurred in Japan in December 1960, but also makes it strongly dependent on field observations. LEM is a kind of calculation method to evaluate landslide stability based on mechanical balance principle. By assuming a potential sliding surface and slicing the sliding body on the potential sliding surface firstly, LEM calculates the shear resistance and the shear force of each slice along the potential sliding surface and defines their ratio as the safety factor to describe landslide stability. LEM is simple and can directly analyse landslide stability under limit condition without geotechnical constitutive analysis. However, this neglect of geotechnical constitutive characteristic also restricts it to a static mechanics evaluation model that is incapable to evaluate the changing regularities of landslide stability. In the meanwhile, LEM involves too many physical parameters such as cohesive strength and friction angle, which makes it greatly limited in landslide forecast and early warning. As a typical numerical simulation method, FEM subdivides a large problem into smaller, simpler parts that are called finite elements. The

simple equations that model these finite elements are then assembled into a larger system of equations that models the entire problem. FEM then uses variational methods from the calculus of variations to approximate a solution by minimizing an associated error function. In landslide stability analysis, FEM can not only satisfy the static equilibrium condition and the geotechnical constitutive characteristic, but also adapt to the discontinuity and heterogeneity of the rock mass. However, FEM is quite sensitive to various involved parameters and the computation will increase greatly to get more accurate results. If parameters and boundaries are precisely determined, LEM and FEM can provide results with high reliability. [Has been added in "Introduction"]

Secondly, in the "Deformation state definition based on K-means combined with Cloud Model", a better explanation why deformation rate and acceleration are selected to define deformation states may be necessary. How the displacement data was chosen because it is quite common for a landslide to have multiple displacement monitoring points at present.

Thanks for your kind advice.

1) Why we only select one typical displacement data:

Nowadays, one landslide may be monitored by multiple monitors with multiple sensors and various data can be obtained such as surface displacement, deep displacement, pore pressure, water content and so on. There is no doubt that all these monitoring data contain the information about landslide state and much more comprehensive landslide state can be obtained if all these monitoring data are utilized. However, this comprehensive monitoring data is not yet common. And thus a traditional operation, selecting one typical displacement data of GPS, is adopted for generality and simplicity. Research of multi-monitoring and multi-sensor data fusion has been carried.

2) why deformation rate and acceleration are selected to define deformation states

The essence of this problem is how to determine the deformation features of displacement monitoring data. While defining deformation states, deformation velocity and acceleration are selected because they are considered to represent the landslide deformation characteristics well on the assumption that displacement is monitored monthly. At this time scale, the monitoring error of GPS can be ignored compared to landslide actual deformation. However, as the time resolution of displacement monitoring data increases, the impact of monitoring errors will be greater. In this case, landslide deformation features may not be deformation velocity and acceleration but determined by some feature extraction methods. Neglecting the consideration of monitoring error, the method is capable to monitoring data with higher time resolution and corresponding feature extraction methods are under study.

Thirdly, in the "materials and results" section, only monthly displacement data was used and it seems not very consistent with "real-time" in the title. Since for now monthly monitoring displacement is mainly adopted in most studies, "monthly stability" may be more appropriate for the title. In the meanwhile, the discussion on the process of other monitoring frequency data needs to be added.

Thanks for your kind suggestion. The doubt about data selection has been explained in the former question. Simply speaking, this approach is capable to monitoring data with high time resolution. But for generality and simplicity, monthly monitoring data is selected in this paper on the consideration that it is the most adopted data for now.

Finally, “Discussion” and “Conclusion” present several repetitions and need a better description. Meanwhile, the English written of this paper should be modified carefully again.

Thanks for your constructive suggestion. We have merged and rephrased the “Discussion” and “Conclusion”. The revised “Discussion and conclusion” section is as follows.

Under the guidance of dynamic state system and based on the relationship of displacement monitoring data, deformation state and landslide stability, a state fusion entropy approach is proposed to conduct a real-time and site-specific analysis of landslide stability changing regularities. A joint clustering method combining K-means and cloud model is firstly proposed to investigate landslide deformation states, and then a multi-attribute entropy analysis follows to estimate landslide instability. Furthermore, a historical maximum index is introduced for landslide early warning. To verify the effectiveness of this approach, Xintan landslide is selected as a detailed case and four other landslides in the Three Gorges Reservoir area as brief cases. Taking Xintan landslide as an example, cumulative state fusion entropy mainly fluctuated around zero in the initial deformation stage and uniform deformation stage, but an obvious fluctuant increasing tendency appeared after Xintan landslide entered accelerative deformation stage. In the meanwhile, a thorough collection of the macroscopic proofs also suggested that historical maxima are highly consistent with landslide macroscopic deformation behaviors.

Compared with traditional safety factor, state fusion entropy evaluates the landslide instability, and is capable to indicate its extent and changing regularities. Compared with simulation methods for landslide stability analysis, this approach takes displacement monitoring data as the basis of landslide stability analysis, and thus is prone to real-time stability analysis. Compared with direct judgment from deformation velocity and acceleration, this approach analyse landslide deformation states by a data-driven model, avoiding the disunity of individual engineering geology experience, ensuring its applicability to the geological conditions of different landslides.

However, several issues also need to be clarified. The landslide stability changing regularities are obtained by comparing current stability with the past stability and thus it is meaningless to compare the state fusion entropy of different landslides. In addition, if displacement monitoring data only covers one evolutionary stage, cumulative state fusion entropy may not present the fluctuant increasing trend but a relatively simple curve with only a few historical maxima. For now, the state fusion entropy is designed without the function of forecasting but it still offers helps for landslide stability analysis and further the early warning. Cumulative state fusion entropy reflects the overall instability of landslide and its changing forms (fluctuation around zero type and fluctuant increasing type) also do help to judge landslide evolutionary stages and deformation tendency. Besides, the historical maximum index indicates the renewal of the most dangerous state of the landslide and may server as a new clue for landslide early warning. But this new clue should not be exaggerated to such an extent that other clues can all be replaced. Once historical maximum is renewed frequently, other clues such as macro cracks should also be taken into account to fully determine landslide early warning level.