Response to Review Comments

Title: **The assessment of earthquake-triggered landslides susceptibility with considering coseismic ground deformation**

First of all, the authors are grateful to the reviewer, who offered many constructive suggestions to enhance the manuscript. With this reply we hope to provide detail answers to the comments of the reviewers. This is done in a point-by-point fashion below.

Responses to the Comments Raised by Reviewer #2

1. In this manuscript, authors present the results of statistical analyses done to the distribution of landslides induced by the Mid-Niigata earthquake (2004), Mw 6.8. Three different statistical methods (logistic regression, Artificial Neural Network and Support Vector Machine) are applied to landslide inventory at two different scales: regional and near field. In this last case, coseismic ground deformation is considered as an influencing factor in the susceptibility analysis. From the analyses, the ANN method gives the best results. The objective of the paper is to analyze the importance of the coseismic ground deformation to explain landslide distribution and the benefits of using it when preparing susceptibility maps.

The paper is properly organized and most of figures and tables are of interest.

Authors' reply:

Many thanks for your positive comments and valuable time to improve the manuscript.

2. Regarding the main objective of the paper, I miss a reflection by the authors about the true usefulness of the parameter in question in the preparation of susceptibility maps. As the authors point out in the Introduction, these maps constitute the main tool that our society has to establish the areas prone to suffer seismic-induced landslides, and thus define an appropriate use (or restrict their occupation) of the territory. However, the parameter that constitutes the center of the article, the coseismic ground deformation, is a parameter that can only be evaluated afterwards, that is, once the earthquake has occurred. So what real use does it have? Personally, I see this parameter, as well as the distance to the surface of rupture, useful for subsequent studies, to explain why instabilities have occurred in certain contexts or areas, but not to predict their occurrence. In fact, the difference in AUC when considering/not considering this parameter is less than 5%.

Authors' reply:

Many thanks for your useful comments. The landslide susceptibility is defined as the likelihood of a landslide occurring in an area on the basis of the local terrain and environmental conditions (Reichenbach et al., (2018). Susceptibility measures the degree to which a local terrain can affect the **future slope movements.** In other words, it is an estimate of "where" landslides are **likely to occur.** So, the main objective of landslide susceptibility in this study is to provide planners or decision makers with the foreknowledge of landslides regions and reducing the effects of landslides which trigger by **future earthquake**. The foundation of landslides susceptibility is based on the assumption that future landslides would be more likely to occur under similar conditions to those of the existed landslides. It means the influencing factors should be derived afterwards the earthquake occurrence (landslides occurrence), especially like the influencing factors concerning the seismology. As the seismic influencing factors only could be obtained after the earthquake. For example, the PGA is the maximum change of ground shaking velocity recorded by seismometers during an earthquake and it has been commonly used in the assessment of landslide susceptibility ((Cao et al., 2019; Sangeeta et al., 2020; Bai et al., 2012; Tian et al., 2019; Xu and Xu, 2013; Xu et al., 2013; Li et al., 2013; Umar et al., 2014; Xu et al., 2012). The coseismic ground deformation is also a kind of seismic influencing factors.

In addition, the coseismic ground deformation will help to reveal the hidden subsurface damage. It should be noted that not all deformation will direct lead the landslides.

However, the area with large coseismic surface deformation often indicates that the movement of the rock mass may be further developed and the integrity of rock mass is reduced, which renders slopes prone to landslip in future earthquakes again. Zhao et al., (2012) explored the localized coseismic deformation in Kizawa (a small village), Japan after the earthquake. The results showed the calculated coseismic deformation in Kizawa is relatively larger, but the landslides are sparse. However, after a detail investigation, it found that the underground structures such as tunnels and wells were severely damaged. The road alignment of the Kizawa tunnel, which was buried 30 m beneath the ground surface, was shifted sideways 1-1.5 m to east-to-southeast direction. Furthermore, two irrigation well were dislocated at 30 m and 20 m, beneath the ground, respectively. Therefore, it is highly possible that the ground underwent some subsurface damage at locations where the large coseismic deformation. Although the deformation did not form the landslides at these locations in the 2004 Mid-Niigata earthquake, as there were accumulated deformation within the rock and soil, the landslide will easily occur in the next earthquake event. According to the comments above, the coseismic ground deformation should be regarded as a useful influencing factor in the assessment of landslides susceptibility.

Then, in order to evaluate the effects of the coseismic ground deformation on the assessment of landslides susceptibility, the Analysis of Variance method (ANOVA) has been utilized to evaluate the predictive capability of used conditional factors. The factors with higher variance values indicate a higher contribution to landslide models and vice versa. The predictive capability of eight landslide affecting factors was shown in Table 1.

Table 1. Predictive importance of different influencing factors

Number	Influencing factor	Predictive importance
1	Lithology	0.213
2	Slope	0.207
3	PGA	0.169
4	Curvature	0.125
5	Coseismic ground deformation	0.093

6	Elevation	0.086
7	Slope aspect	0.057
8	Distance to roads	0.048

From Table1, it could be found the coseismic ground deformation ranked fifth place among the eight factors. The importance of coseismic surface deformation is higher than the elevation, aspect and distance from the road. Reichenbach et al., (2018) critically review the statistically based landslide susceptibility assessment literature by systematically searching for and then compiling an extensive database of 565 peer-review articles from 1983 to 2016. The results showed that elevation, aspect and distance from the road are commonly chosen as influencing factors in the assessment of landslides susceptibility. It means the coseismic ground deformation should be regarded as an important factor in the assessment of landslides susceptibility.

The AUC is a commonly used indices to evaluate the model prediction performance. At present, there are no unanimous standards to assess the increment of AUC. This means it is still debated that how much increment of AUC will be regarded as significant improvement. Most studies just considered the larger value of AUC means the better performances of the model. For example, Pham et al., (2016) conducted a comparative study of five different machine learning methods for landslide susceptibility assessment. The increment of AUC value for different models was about 0.045 (0.910-0.955). Yilmaz (2010) made a comparison of landslide susceptibility mapping methods. The increment AUC value for different models was 0.019 (0.827-0.846). Pham et al., (2017a) made a comparative study of sequential minimal optimization-based support vector machines, vote feature intervals, and logistic regression in landslide susceptibility assessment. The increment of AUC value for different models was 0.044 (0.812-0.856). Pham et al., (2017b) used the hybrid integration of multilayer perceptron neural networks and machine learning ensembles for landslide susceptibility assessment. The increment of AUC value for different models was 0.01 (0.876-0.886). Aghdam et al., 2017 conducted the landslide susceptibility assessment using a novel hybrid model of statistical bivariate methods (FR and WOE) and adaptive neuro-fuzzy inference system

(ANFIS). The increment of AUC value for different models was 0.03 (0.82-0.85). Tsangaratos and Ilia (2016) conducted the landslide susceptibility mapping using the certainty factor method, the Iterative Dichotomizer version 3 algorithm, the J48 algorithm and the modified Iterative Dichotomizer version 3 model. The validation results showed that AUC values for these models varied from 0.7766 to 0.8035. Xu et al., 2012 made a comparison of different models for susceptibility mapping of earthquake triggered landslides related with the 2008 Wenchuan earthquake in China. The results showed that the AUC values for the models varied from 0.7253 to 0.801. So, comparing the increment of AUC values in this study with above mentioned similar studies, it may be concluded that the increasing of AUC is relatively significant.

Reference

1. Pham, B.T., Pradhan, B., Bui, D.T., Prakash, I., Dholakia, M.B. 2016. A comparative study of different machine learning methods for landslide susceptibility assessment: A case study of Uttarakhand area (India). Environmental Modelling & Software. 84, 240-250

2. Yilmaz, I., 2010. Comparison of landslide susceptibility mapping methodologies for Koyulhisar, Turkey: conditional probability, logistic regression, artificial neural networks, and support vector machine. Environmental Earth Sciences, 61(4): 821-836.

3. Pham, B.T., Bui, D.T., Prakash, I., Long, H.N. and Dholakia, M.B., 2017a. A comparative study of sequential minimal optimization-based support vector machines, vote feature intervals, and logistic regression in landslide susceptibility assessment using GIS. Environmental Earth Sciences, 76(10): 371.

4. Pham, B.T., Bui, D.T., Prakash, I., Prakash, I. and Dholakia, M.B., 2017b. Hybrid integration of Multilayer Perceptron Neural Networks and machine learning ensembles for landslide susceptibility assessment at Himalayan area (India) using GIS. Catena 149, 52–63

5. Aghdam, I.N., Pradhan, B., Panahi, M., 2017. Landslide susceptibility assessment using a novel hybrid model of statistical bivariate methods (FR and WOE) and adaptive neuro-fuzzy inference system (ANFIS) at southern Zagros Mountains in Iran. Environmental Earth Sciences, 76: 237.

6. Tsangaratos, P., Ilia, L., 2016. Landslide susceptibility mapping using a modified decision tree classifier in the Xanthi Perfection, Greece. Landslides, 13:305–320.

7. Xu, C., Xu, X., Dai, F. and Saraf, A.K., 2012. Comparison of different models for susceptibility mapping of earthquake triggered landslides related with the 2008 Wenchuan earthquake in China. Computers & Geosciences, 46(3): 317-329.

8. Zhao, Y., Konagai, K. and Fujita. T., 2012. Multi-scale Decomposition of Co-seismic Deformation *from High Resolution DEMs: a Case Study of the 2004 Mid-Niigata Earthquake. Acta Geologica Sinica(English Edition), 86(4): 1013-1021.*

9. Reichenbach, P., Rossi, M., Malamud, D.B., Mihir, M. and Guzzetti, F., 2018. A review of statistically-based landslide susceptibility models. Earth-Scienc Reviews, 180: 60-91.

10. Cao, J., Zhang, Z., Wang, C.Z., Liu, J.F., Zhang, L.L., 2019. Susceptibility assessment of landslides triggered by earthquakes in the Western Sichuan Plateau. Catena, 175, 63-76.

11. Sangeeta, Maheshwari, B.K., Kanungo, D.P. GIS-based pre- and post-earthquake landslide susceptibility zonation with reference to 1999 Chamoli earthquake. Journal of Earth System Science 129, 55.

12. Bai, S.B., Wang, J., Zhang, Z.G., Cheng, C., 2012. Combined landslide susceptibility mapping after Wenchuan earthquake at the Zhouqu segment in the Bailongjiang Basin, China. Catena, 99, 18-25.

13. Tian, Y.Y., Xu, C., Hong, H.Y., Zhou, Q., Wang, D., 2019. Mapping earthquake-triggered landslide susceptibility by use of artificial neural network (ANN) models: an example of the 2013 Minxian (China) Mw 5.9 event. Geomatics, Natural Hazards and Risk, 10,1-25.

14. Xu, C., Xu, X., 2013. Controlling parameter analyses and hazard mapping for earthquake-triggered landslides: an example from a square region in Beichuan County, Sichuan Province, China. Arabian Journal of Geosciences 6, 3827–3839.

15. Xu, C., Xu, X., Yu, G., 2013. Landslides triggered by slipping-fault-generated earthquake on a plateau: an example of the 14 April 2010, Ms 7.1, Yushu, China earthquake. Landslides 10, 421–431

16. Li, W.L., Huang, R.Q., Tang, C., Xu, Q., Westen, C.V., 2013. Co-seismic Landslide Inventory and Susceptibility Mapping in the 2008 Wenchuan Earthquake Disaster Area, China. Journal of Mountain Science. 10(3), 339-354.

17. Umar, Z., Pradhan, B., Ahmad, A., Jebur, M.N., Tehrany, M.S., 2014. Earthquake induced landslide susceptibility mapping using an integrated ensemble frequency ratio and logistic regression models in West Sumatera Province, Indonesia. Catena, 118, 124-135.

18. Xu, C., Xu, X., Dai, F. and Saraf, A.K., 2012. Comparison of different models for susceptibility mapping of earthquake triggered landslides related with the 2008 Wenchuan earthquake in China. Computers & Geosciences, 46(3): 317-329.