Author Responses Addressing Review from Referee #2 for **"Transfer learning for landslide susceptibility modelling using domain adaptation and case-based reasoning"** *by* **Wang et al.**

For these responses, we address each Referee comment (RC) individually and include our response below it. The Referee Comments are numbered and use a black font, while the Author Responses (AR) use a red font.

This paper evaluates the performance of different transfer algorithms for LSM including case-based reasoning (CBR) and domain adaptation (DA). The study is very interesting, relevant and suitable for GMD. However, the following issues should be carefully addressed before publication:

AR0.0: We want to thank Referee #2 for the helpful comments and suggestions. We have done our best to address each of the comments below.

RC1. The problem is very well characterized and the objectives clearly established.

AR1: Thanks for the comment.

RC2. Authors should explain strategies they have adopted to select non-landslide points from landslide points randomly. What are the criteria and the distance they have set as thresholds for considering non-landslide regions, especially when they have a low-resolution dataset?

AR2: Thanks for the comment.

Following previous work such as Goetz et al. (2011) and Brock et al. (2020), the landslides and non-landslides are selected using simple random sampling and the non-landslide samples are grid cells that did not identify as the landslide. Moreover, because landslides cover a small portion of the entire area, a random sampling of grid cells that do not relate to mapped landslide locations is reasonable to summarize the characteristics of landslide-free zones for the purpose of statistical analyses (Blahut et al., 2010; Goetz et al., 2015; Steger and Glade, 2017).

In our study, one grid cell was selected as one sample point. When the area size of a landslide is less than the area size of a single grid cell, the landslide is removed. We also added the following sentence in *Section 2.3*:

"At the same time, landslides that are smaller than one grid cell were excluded in our study."

Reference:

1. Goetz, J. N., Guthrie, R. H., & Brenning, A. (2011). Integrating physical and empirical landslide susceptibility models using generalized additive models. Geomorphology, 129(3-4), 376-386.

2. Brock, J., Schratz, P., Petschko, H., Muenchow, J., Micu, M., & Brenning, A. (2020). The performance of landslide susceptibility models critically depends on the quality of digital elevation models. Geomatics, Natural Hazards and Risk, 11(1), 1075-1092.

3. Blahut, J., Van Westen, C. J., & Sterlacchini, S. (2010). Analysis of landslide inventories for accurate prediction of debris-flow source areas. Geomorphology, 119(1-2), 36-51.

4. Goetz, J. N., Brenning, A., Petschko, H., & Leopold, P. (2015). Evaluating machine learning and statistical prediction techniques for landslide susceptibility modeling. Computers & geosciences, 81, 1-11.

5. Steger, S., & Glade, T. (2017, May). The challenge of "trivial areas" in statistical landslide susceptibility modelling. In Workshop on World Landslide Forum (pp. 803-808). Springer, Cham.

RC3. What is the spatial and temporal resolution of the rainfall dataset? How did the authors handle the spatial resolution difference between the rainfall dataset and DTM-derived parameters? Considering rainfall data's dynamic characteristics, how could authors relate the other statistic parameters (topographic condition, etc.) to dynamic parameters and predict and produce a reliable landslide inventory? How do authors handle the spatio-temporal characteristics of landslide events in the different regions?

AR3: Thanks for the comment.

We're looking at susceptibility as a static variable and that the potential incorporation of rainfall is a topic for future work that might apply transfer learning beyond the context of landslide susceptibility.

For handle the spatio-temporal characteristics of landslide events in the different regions, Yate et al. (2018) in *TREE* journal pointed out that environmental differences are a key factor for successful model transfer, while spatial and temporal separation may have little effect on model transfer. We considered the environmental characteristics of different regions that have an important influence on the landslide assessment, such as slope, elevation, etc. By comparing the similarity between these characteristics, we can relate landslide events in different regions. Meanwhile, we also delineated in *Discussion*:

"Although the study areas cover a wide range of climates with different land cover types and landslide process types, our set of source areas is by no means complete and the results may therefore not be fully representative for the performances that might be achieved at a global scale. Future work should therefore broaden the database of source areas."

Reference:

1. Yates, K. L., Bouchet, P. J., Caley, M. J., Mengersen, K., Randin, C. F., Parnell, S., ... & Sequeira, A. M. (2018). Outstanding challenges in the transferability of ecological models. Trends in ecology & evolution, 33(10), 790-802.

RC4. The methodology's major limitation is the different types of mass movements! I want to ask how the author handled and incorporated the geometric differences of different mass movements (landslides) into the models to correctly predict the different types of mass movements, especially knowing that each landslide type has its own geometric and physical characteristics.

AR4: Thanks for the comment. This is a really good point. We also discussed it in *Section 4.2*,

"These similarity attributes do not explicitly account for landslide type, which is an important factor to consider when landslide susceptibility modelling (Huang and Zhao, 2018). However, geologic attributes and terrain attributes such as slope angle, may work together as a suitable surrogate to anticipate the most likely landslide types given little to no landslide data in the target area. Landslide type information is also difficult to collect and is often lacking in landslide inventories (Mezaal and Pradhan, 2018). Prior information on unseen areas or integrating expert experience may be helpful in formulating landslide types for transfer learning."

Also, for example, according to the Wieczorek and Jäger (1996) and Zinko et al., 2005, different types of mass movements may depend on the lithology and groundwater and soil moisture conditions in relation to topography. These attributes could also be used for predicting the different types of mass movements. Predicting the landslide type for model transferring is a challenge and still needed to do further research. But we would like to point out that although our study cannot clearly predict landslide types, by identifying landslide types that are common between source and target areas, we can reduce the burden of collecting and labeling data and give a quick landslide susceptibility map that can help decision makers develop basic preventive measures.

Reference:

1. Wieczorek, G. F., & Jäger, S. (1996). Triggering mechanisms and depositional rates of postglacial slope-movement processes in the Yosemite Valley, California. Geomorphology, 15(1), 17-31.

2. Zinko, U., Seibert, J., Dynesius, M., & Nilsson, C. (2005). Plant species numbers predicted by a topography-based groundwater flow index. Ecosystems, 8(4), 430-441.

RC5. Finally, why authors just contended the simple Logistic GAM for implementing the DA algorithm while more robust algorithms exist for solving the non-linearity relationship of the input parameter and also considering the binary case of the classification

AR5: Thanks for the comment.

According to Goetz's and Brock's publications, we can find GAM can obtain good results in terms of predictive performance in landslide assessment compared to several other statistical and machine-learning algorithms. Furthermore, GAM can adjust the degree of non-linearity (or effective degrees of freedom) for each variable using an inner generalized cross-validation, which can save the time and effort of the calibrating parameters (Wood, 2017). Otherwise, GAM allows for a separate interpretation of additive effects in terms of odds ratios and variable importance, which some existing robust or state-of-the-art algorithms may not be able to do.

But there is research value in considering other state-of-the-art algorithms for implementing the DA.

Reference:

1. Goetz, J. N., Guthrie, R. H., and Brenning, A.: Integrating physical and empirical landslide susceptibility models using generalized additive models, Geomorphology, 129, 376-386, https://doi.org/10.1016/j.geomorph.2011.03.001, 2011.

2. Goetz, J. N., Brenning, A., Petschko, H., and Leopold, P.: Evaluating machine learning and statistical prediction techniques for landslide susceptibility modeling, Computers & Geosciences, 81, 1-11, https://doi.org/10.1016/j.cageo.2015.04.007, 2015.

3. Brock, J., Schratz, P., Petschko, H., Muenchow, J., Micu, M., & Brenning, A. (2020). The performance of landslide susceptibility models critically depends on the quality of digital elevation models. Geomatics, Natural Hazards and Risk, 11(1), 1075-1092.

4. Wood S. 2017. Generalized additive models: an introduction with R. 2nd ed. Chapman and Hall/CRC. London (UK)