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

We would like to thank the editor and the reviewers for their thorough revisions and the thoughtful comments they provided. We have made extensive changes in order to incorporate recent publications related to transfer learning and deep learning in both the introduction and the discussion, and an English native speaker carefully revised and improved the language. We therefore hope that the editor will be satisfied with the changes made in the revised manuscript.

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

Dear authors:

Thank you for participating in the Interactive Discussion. You revised the paper to make it more consistent with the arguments of the referee. As GMD's editor, you'll notice that one referee rated the scientific significance as "Fair" and the scientific quality as "Poor." Numerous technical aspects have been raised and must be thoroughly addressed. Several additional comments follow, which I recommend you consider before publishing.

AR0.0: We want to thank Editor for the comments. We have done our best to address each of the comments below.

EC1: This paper's motivation is unconvincing. Except for comparing and combining two transfer learning strategies for landslide susceptibility modeling, case-based reasoning (CBR) and domain adaptation (DA), the authors have not provided any new methods or made substantive improvements to the existing models. One of the innovations could result from evaluating the potential of transfer learning for landslide susceptibility modeling using CBR and DA techniques to reduce the burden of data collection and labeling. However, as far as I am aware, the following key related works have been proposed in recent years (but are not limited to):

1. Wang, H., Wang, L., and Zhang, L.: Transfer learning improves landslide susceptibility assessment, Gondwana Research, 1-17, https://doi.org/10.1016/j.gr.2022.07.008, 2022.
2. Xu, Q., Ouyang, C., Jiang, T., Yuan, X., Fan, X., and Cheng, D.: MFFENet and ADANet: a robust deep transfer learning method and its application in high precision and fast cross-scene recognition of earthquake-induced landslides, Landslides, 19(7), 1617-1647, 2022.
3. Ai, X., Sun, B., and Chen, X.: Construction of small sample seismic landslide susceptibility evaluation model based on Transfer Learning: a case study of Jiuzhaigou earthquake, Bulletin of Engineering Geology and the Environment, 81(3), 116, https://doi.org/10.1007/s10064-022-02601-6, 2022.
4. Qin, S., Guo, X., Sun, J., Qiao, S., Zhang, L., Yao, J., Cheng, Q., and Zhang, Y.: Landslide detection from open satellite imagery using distant domain transfer learning, Remote Sensing, 13(17), 3383, https://doi.org/10.3390/rs13173383, 2021.
5. Liu, D., Li, J., and Fan, F.: Classification of landslides on the southeastern Tibet Plateau based on transfer learning and limited labelled datasets, Remote Sensing Letters, 12(3), 286-295, 2021.
6. Zhu, Q., Chen, L., Hu, H., Pirasteh, S., Li, H., and Xie, X.: Unsupervised Feature Learning to Improve Transferability of Landslide Susceptibility Representations, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13, 3917-3930, 2020.

7. Lu, H., Ma, L., Fu, X., Liu, C., Wang, Z., Tang, M. and Li, N.: Landslides information extraction using object-oriented image analysis paradigm based on deep learning and transfer learning, Remote Sensing, 12(5), 752, https://doi.org/10.3390/rs12050752, 2020.

The author should give a broad discussion on these transfer learning methods applied to landslide susceptibility modelling. And then, the necessity and novelty of this work should be demonstrated by analyzing and summarizing the advantages and disadvantages of these transfer learning methods.

AR1: Thanks for the comments and providing the references. It is helpful for us to clarify the research value of our study. Our response is divided into two parts, the first part is the response to the comment (Part 1) and the second part is the phrases we added to the manuscript (Part 2).

Part 1:

We would like to kindly point out that the long list of recent transfer learning publications also shows that this is a very active research topic, that is, transfer learning techniques have not been fully explored in landslide susceptibility modelling.

In the field of landslide assessment research, environmental characteristics are extremely important for landslide modeling, prediction of landslide susceptibility in unknown areas, and interpretation of final results. As Yates et al. (2018) point out in their article:

"Environmental dissimilarity is what matters most for successful transfers, for which spatio-temporal distances might only occasionally be good surrogates."

However, when we read the articles above and other related papers, we can easily find that they considered target and source areas with similar environmental characteristics/data distribution, which are inconsistent with realistic landslide assessments. For example, Wang et al. conducted a transfer learning study only for the region of Hong Kong; Xu et al. specified the landslide triggered by earthquakes; Ai et al. implemented landslide model transfer only for Sichuan Province; Liu et al. studied only the south-eastern Tibet Plateau; Zhu et al. studied the Chongqing region; Lu et al. studied only the region located in Sichuan. In contrast, our work explores the use of model transfer using data from different parts of the globe.

Hence, it is of great importance to research applying model transfer with data from different regions and data sources around the globe, which is one of our study motivations and innovations. Also, we have further pointed this out in the Discussion.

"Until now, model transfer in landslide modelling have usually relied on a homogeneous availability of data and a strong model generalization to avoid local overfitting and allow the application of a model in an adjacent target region (Goetz et al., 2011; Wenger and Olden, 2012; Petschko et al., 2014; Bordoni et al., 2020). Although this approach has been identified as a robust method for regional susceptibility modelling, its model transferability is often limited to nearby locations that have the same feature space and a nearly identical data distribution. "

Meanwhile, in general, data spatial resolution affects model fit and prediction. Previous work using transfer learning for landslide assessments only uses the same spatial resolution data for achieving landslide model transfer. However, as our work demonstrates, we do not necessarily need to be bound to data with similar spatial resolution. For example, we found that even though a source area had a different resolution than the target area, the model transfer performance was still great (target area: Burgenland in Austria with a 10 m resolution, source area: Modena in

Italy with a 25 m resolution). Thus, evaluating different spatial resolution for landslide model transfer is also one of our study motivations and innovations. We also pointed it out in the manuscript:

"We evaluate the performance of transferred susceptibility models using DA, CBR and a combined CBR-DA technique, as well as the sensitivity of these methods to spatial resolution."

Otherwise, most studies have been conducted based on a single source area, while our paper discusses the case of single and multiple source areas and proposes the use of similarity between source and target areas as weight values to combine landslide models obtained from multiple source areas. Thus, the experiment and the obtained results further improve the comprehension of landslide model transfer studies.

Part 2:

We have extended the Introduction to demonstrate recent transfer learning methods (Line 47):

"For example, Wang et al. (2022) combined deep learning and transfer learning for landslide assessments in Hong Kong and obtained good prediction results. Xu et al. (2022) demonstrated landslide model transfers for regions with earthquake-induced landslides. Qin et al. (2020) applied distant domain transfer learning for landslide detection in the city of Shenzhen, Guangdong province, China. However, these studies required training samples from the target region, which may lead to problems, such as the timing of sample acquisition, and whether the selected sample can correctly characterize the entire region. Thus, unsupervised transfer learning is highly attractive in landslide assessments. Zhu et al. (2020) proposed unsupervised feature learning and improved landslide susceptibility model transfer performance in Chongqing, China. These studies were based on landslide data and predictors from the same or adjacent areas with the same spatial resolution as the target area: i.e., their environmental characteristics and data distributions were highly similar, which may not always be the case. It is therefore necessary to find more suitable landslide transfer-learning methods without the limitation of scale and spatial resolution."

Reference:

1. Wang, H., Wang, L., and Zhang, L.: Transfer learning improves landslide susceptibility assessment, Gondwana Research, 1-17, https://doi.org/10.1016/j.gr.2022.07.008, 2022.

2. Xu, Q., Ouyang, C., Jiang, T., Yuan, X., Fan, X., and Cheng, D.: MFFENet and ADANet: a robust deep transfer learning method and its application in high precision and fast cross scene recognition of earthquake induced landslides, Landslides, 19(7), 1617-1647, 2022.

3. Qin, S., Guo, X., Sun, J., Qiao, S., Zhang, L., Yao, J., Cheng, Q., and Zhang, Y.: Landslide detection from open satellite imagery using distant domain transfer learning, Remote Sensing, 13(17), 3383, https://doi.org/10.3390/rs13173383, 2021.

4. Zhu, Q., Chen, L., Hu, H., Pirasteh, S., Li, H., and Xie, X.: Unsupervised Feature Learning to Improve Transferability of Landslide Susceptibility Representations, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13, 3917-3930, 2020.

We broaden our Discussion (Line 435) for the potential of the novel methods in landslide assessment, the content is as following:

"4.4 The potential of the novel methods for landslide assessment

Deep learning is getting more and more popular in the study of landslide model transfer. For example, Ai et al. (2022) proposed a supervised method by combining deep learning and transfer learning for landslide susceptibility modelling. Liu et al. (2021) performed landslide classification using VGG-19 and transfer learning based on limited data from the unseen area. Lu et al. (2020) mapped landslides based on deep learning and transfer learning. These studies show that deep learning is a potential method in landslide model transfer studies, although they are limited to a regional scale or require training data from the target area.

Combining CBR with deep learning could be a worthy unsupervised method in landslide assessments. By calculating similarities between the target area and source areas and selecting related source areas, deep learning can directly use them to train landslide models for the target area, which might avoid the need for tuning hyperparameters."

Reference:

1. Ai, X., Sun, B., and Chen, X.: Construction of small sample seismic landslide susceptibility evaluation model based on Transfer Learning: a case study of Jiuzhaigou earthquake, Bulletin of Engineering Geology and the Environment, 81(3), 116, https://doi.org/10.1007/s10064-022-02601-6, 2022.

2. Liu, D., Li, J., and Fan, F.: Classification of landslides on the southeastern Tibet Plateau based on transfer learning and limited labelled datasets, Remote Sensing Letters, 12(3), 286-295, 2021.

3. Lu, H., Ma, L., Fu, X., Liu, C., Wang, Z., Tang, M. and Li, N.: Landslides information extraction using object-oriented image analysis paradigm based on deep learning and transfer learning, Remote Sensing, 12(5), 752, https://doi.org/10.3390/rs12050752, 2020.

EC2: More detailed information, such as novelty, valuable results, and the major limitation of the methodology, should be included in the conclusion. The authors should also suggest several future research directions.

AR2: Thanks for the comment. The Conclusion has been reconstructed to provide more detailed information based on the editor's comments (Line 446):

"The aim of our study was to examine the performances of geographically informed case-based reasoning (CBR) and unsupervised domain adaptation (DA) in geographically transferring knowledge for landslide susceptibility modelling in "new" target areas without landslide inventory data. We extended the study of landslide model transfers to a larger global scale and considered the effect of different spatial resolutions on landslide model transfer. In addition, different scenarios (single source area and multiple source areas) were considered, which made methods and results much closer to practical applications in the real world. Moreover, in the multi-source scenario, we proposed a method to combine multiple landslide models based on environmental similarity. Our comparative study revealed that CBR strategies with a single source area and multiple related source areas were robust and effective in developing highly transferable landslide susceptibility models without requiring prior knowledge of landslides in the target area. In particular, single-source CBR was the most effective method for performing model transfer to the target area in most situations. Its performance was also very close to that obtained by models trained with data from the target area itself. CBR similarity criteria in our study are still preliminary, and data sets used in our study might not be enough for an application at a global scale, which should therefore be considered in future research.

Overall, the findings of this paper demonstrated that the proposed transfer leaning approaches can alleviate the burden of collecting and labelling data, resulting in a more expedited preparation of landslide susceptibility maps for large and data-scarce regions. By calculating the similarity between data and region characteristics, trained models can directly be used for the new task, especially in situations that require rapid model development, such as emergency situations. We also suggest that novel methods such as deep learning may also benefit greatly for landslide model transfer studies."

EC3: Throughout the paper, English writing should be greatly improved. Some sentences are too complex, and the correct meaning cannot be extracted. Line 25: "Landslide susceptibility refers to..., and to estimating the likely location of future landslides," for example, but there are many more. I strongly advise the authors to to go over and revise their manuscript.

AR3: Thanks for the comment. We have tried our best to correct and improve our English writing. We also had the paper reviewed and corrected carefully by a (Canadian) English native speaker. There are many revisions (more than 200) in the revised manuscript, and here are some examples of the revisions. All line numbers were based on the revised manuscript with tracking.

1. We changed Line 24: "Landslide susceptibility refers to..., and to estimating the likely location of future landslides," to Line 27 "These models are typically data-driven and rely heavily on terrain characteristics to capture conditions that can lead to landslide occurrence.".
2. We reconstructed Line 57 "Transfer learning techniques such as domain adaptation (DA) and case-based reasoning (CBR) have been developed to select the best data and corresponding models from source areas for predicting in a spatially and or temporally distinct target area." to
   "Transfer learning techniques such as domain adaptation (DA) and case-based reasoning (CBR) are emerging techniques to tackle the challenge of model transfer. In general, they have been developed to select the most suitable data and corresponding models from source areas with similar data characteristics for predicting to a distinct target area in space and time."
3. Line 122 "the problem part for formalizing" to "the challenge of formalizing"
4. Line 149 "A latent feature space is defined in which the source and target areas have the same distribution, and as a consequence, classifiers trained on labelled data from source areas are likely to perform well in the target area" to "At first, a latent feature space is defined in which the source and target areas have the same distribution;, and as a consequence, classifiers trained on labelled data from source areas are likely to perform well in the corresponding target area".
5. Line 287 "The distribution trend it displayed implied that single-source DA to some extent improved performances" to "This distribution trend implied to some extent that single-source DA improved performances".