Response to Reviewers

March 2025

Dear Dr. Wenbin Xu,

We would like to sincerely thank you and the reviewers for the constructive feedback on our manuscript entitled **"Application of Neural Networks for Estimating Coseismic Slip Distribution Using Synthetic GNSS Data."** We appreciate the opportunity to address the comments and further improve our work. Below, we provide a detailed response to each point raised by the reviewers and summarize the corresponding changes made to the manuscript.

Reviewer A

Computation efficiency

Reviewer's comment: The extremely fast computation time is impressive. However, it relies heavily on pre-computation and dense training. If the model cannot be directly applied to other megathrust earthquakes, this should be discussed.

Response: We appreciate this observation. We have added a discussion in the Conclusion section highlighting that while the model achieves fast computation, its applicability is inherently limited by the GNSS station distribution used for training. Extending the model to other megathrust earthquakes would require a broader dataset that includes more complex rupture patterns and data from additional GNSS stations.

Applicability to complex megathrust events

Reviewer's comment: The manuscript focuses on single-asperity earthquakes like Illapel. A discussion about its applicability to multi-asperity events would strengthen the study.

Response: We expanded the Conclusion section to clarify that the model was trained exclusively on single-asperity events, making it well-suited for similar ruptures. We acknowledge that applying it to multi-asperity events would necessitate a more diverse training dataset. Future work will focus on incorporating synthetic cases with more realistic rupture patterns.

Minor points

- **Line 22: Add year for the Illapel earthquake** Added 2015 to specify the year of the Illapel earthquake.

- **Lines 55-64: In this paragraph, the authors summarized various applications and advances in the use of Machine Learning (ML) and Deep Learning (DL) in seismic sciences. However, some important contributions are omitted, such as studies on earthquake magnitude estimation (J.-T. Lin et al., 2021) and coseismic slip distribution prediction (Cui et al., 2023).** Incorporated the suggested citations.

- **Line 82: Revised to "associated with slip distributions of synthetic earthquakes"** Corrected.

- **Line 85: Does "daily" mean the continuous GNSS data?:** Clarified that "daily" refers to continuous GNSS data.

- **Revised to "The solution of equation (2) can be written as"** Corrected.

- **The labels in figures, except for Figure 2, are difficult to read. Could you please use a large font size to improve clarity? In addition, the black arrows are hard to distinguish the background slip distribution. Using a bright color for arrows would improve clarity** Adjusted font sizes for readability and changed the arrow colors from black to red and from red to yellow for improved visibility.

Reviewer B

- **Abstract, include results from hyperparameter exploration and data conditions:** The Abstract was updated to briefly summarize the model's performance concerning hyperparameters and data conditions.

- **Abstract, add some discussion points:** Discussion points related to the comparison with the RLS method were added.

- **All figures are fuzzy and unclear:** The resolution of the figures was improved, font sizes were increased, and arrow colors were adjusted for better clarity.

- **Introduction, why do we need to propose a novel approach to estimate coseismic slip? The structure of introduction needs to be rewritten to make the content more logical. For example, line 60, "in this study..." should start in a new paragraph:** The study's motivation was explained, highlighting the advantages of neural networks over traditional inversion methods. The Introduction was restructured by separating the part starting with "in this study..." and adding a justification for proposing this novel approach.

- **Line 63, what is the model and how is the model got:** An explanation was added in the introduction, clarifying that our model consists of a neural network trained to infer the slip distribution from surface GNSS displacements. The training involves generating a diverse set of synthetic earthquake scenarios to capture a wide range of slip behaviors.

- **Line 69, in the whole manuscript, the "model" and the "neural network" are confused:** In the introduction, the distinction was clarified by explaining that the neural network, once trained, functions as a predictive model for coseismic slip estimations.

- **2.1 Synthetic GNSS data, the content of this section is not only the GNSS data. Rename the title:** The title was changed to "Synthetic Earthquake Data" to better reflect the content.
- **Line 84, give the detailed information about the synthetic dataset** Details on how the synthetic dataset properties were randomly generated were added. Additionally, a new figure has been included to provide more detailed insights into the synthetic earthquake data. This figure illustrates the configuration used and two examples of synthetic earthquake scenarios with varying slip distributions
- **Line 98, give the purpose of employing or representing the Least Squares Inversion:** It was clarified that the least squares method is used to compare with the proposed model.
- **Line 139, how does this study build the model. Try to give more details about the model building process:** A more detailed explanation in the Neural Netwroks section of the model building process was added, stating that we use a neural network as the predictive model to estimate earthquake slip distributions. The network is trained to learn the relationship between surface crustal displacements recorded at GNSS sites and their causative fault slip distributions.
- **2.3 Artificial Neural Networks, the content and logicality of this section are confused:** The structure and content of Section 2.3 were reorganized for better clarity.
- **Line 190-191, what are the expected and anticipated results? Do these mean the real-world results:** It was clarified that the expected results correspond to real-world measurements.
- **Line 193, the GNSS horizontal accuracy is significantly higher than the vertical one. Explain why the average residual of the horizontal component is 3.5 cm, while for the vertical component it is 1.6 cm:** It was explained in the conclusion that the larger magnitudes of the horizontal components pose a greater challenge for the model, resulting in higher residuals compared to the vertical component.
- **Line 239, explain the possible reasons for the discrepancy:** It was suggested that the discrepancy may be due to the distribution of GNSS stations, with a higher density of stations in the north providing better constraints for the model.
- **Conclusion, there is no point related to hyperparameters and data conditions in the conclusion:** A general summary of the impact of hyperparameters and data conditions was added to the Conclusion.

Additional Changes

Neural Networks Section A reference to the additional activation functions tested was added, and the reader is referred to the supplementary material for further details. .

Least Squares Inversion Section A clarification on the application of the positivity constraint in the least squares inversion was included.

We appreciate the reviewers insightful comments, which have strengthened the manuscript. Additionally, we have acknowledged the reviewers' efforts in the Acknowledgements section, as suggested.

We hope the revised manuscript meets the journal's standards, and we look forward to your feedback.

Sincerely,
Valentina Inzunza et al.