



Scan for abstract

Advances in the Identification of Geological Discontinuities in Boreholes with Deep Learning

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1 Introduction

Geological discontinuities define and impact rock mass behaviour. Manually collecting this information is time-consuming, labor-intensive, and subjective. A faster, standardized, and automated approach is needed.

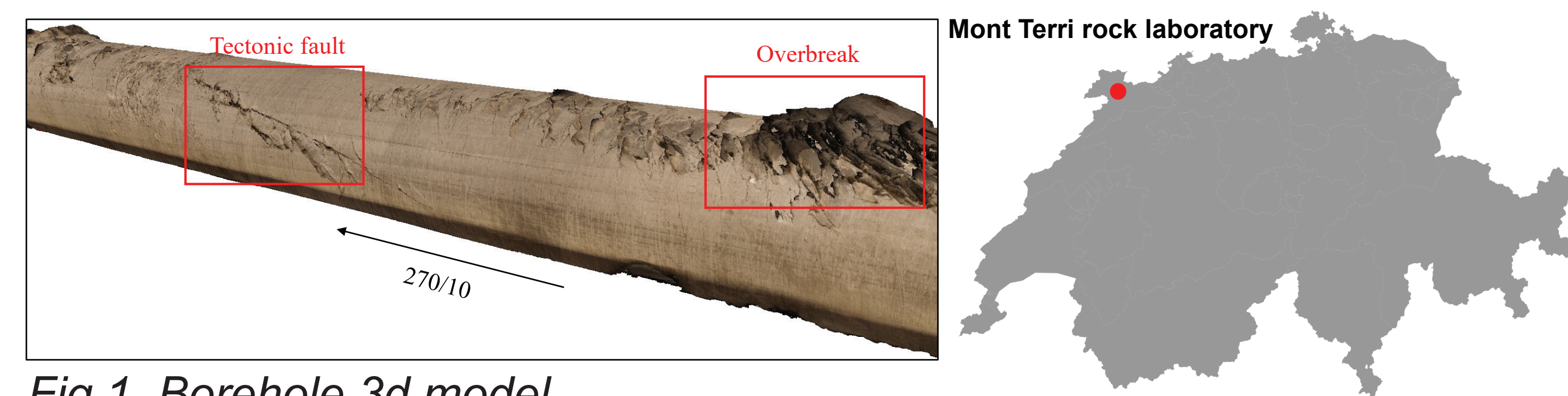


Fig 1. Borehole 3d model.

2 Research Goal

Develop a deep learning model for pixelwise identification of various geological structures.

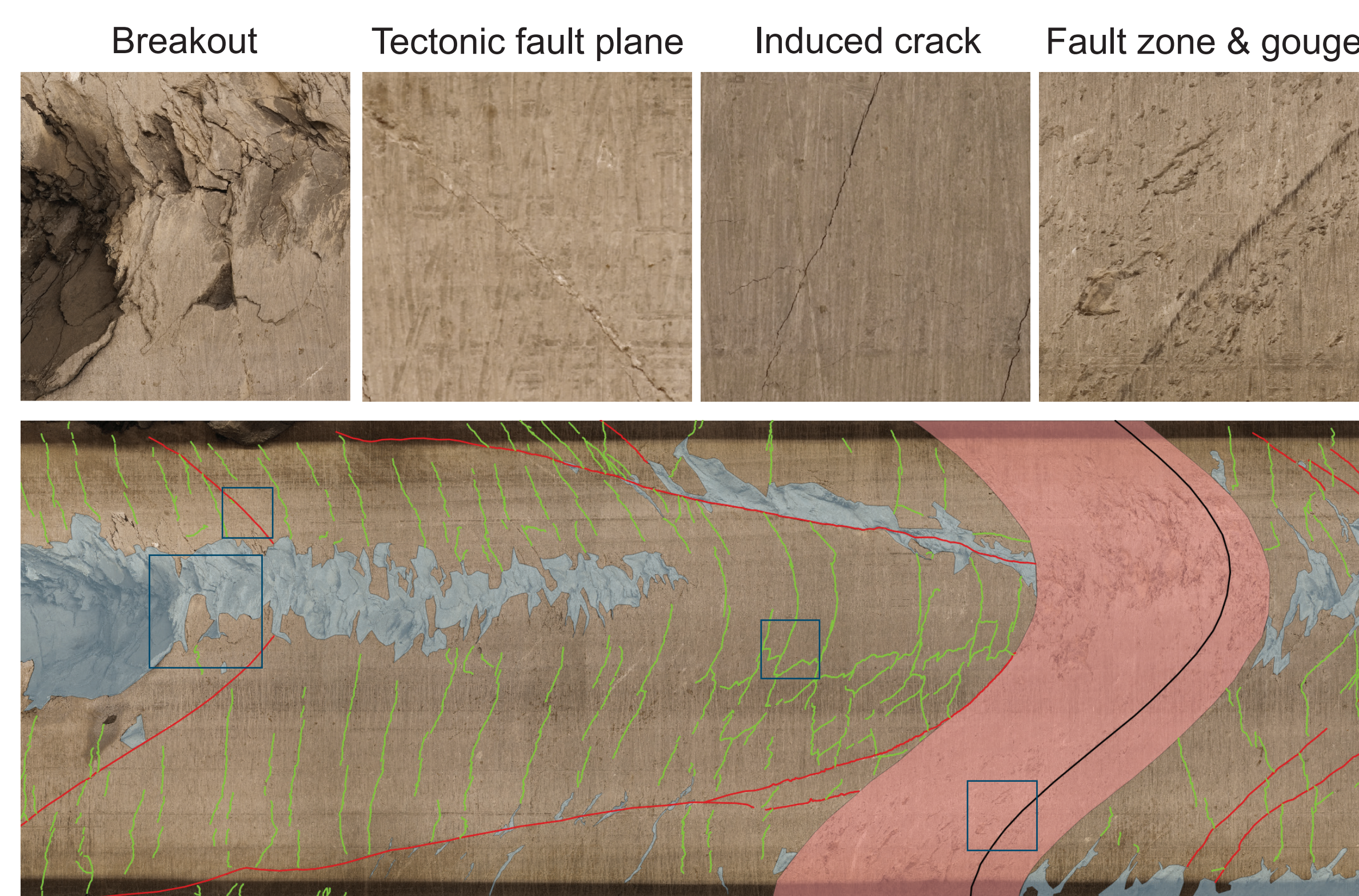


Fig 2. Example of our manual labeling used as ground truth to train the model. Red: tectonic fault plane; Green: induced crack; Blue: breakout; Pink: fault zone; Black: fault gouge.

3 Insights & Implications

Does the model see what geologists see? And how confident is it?

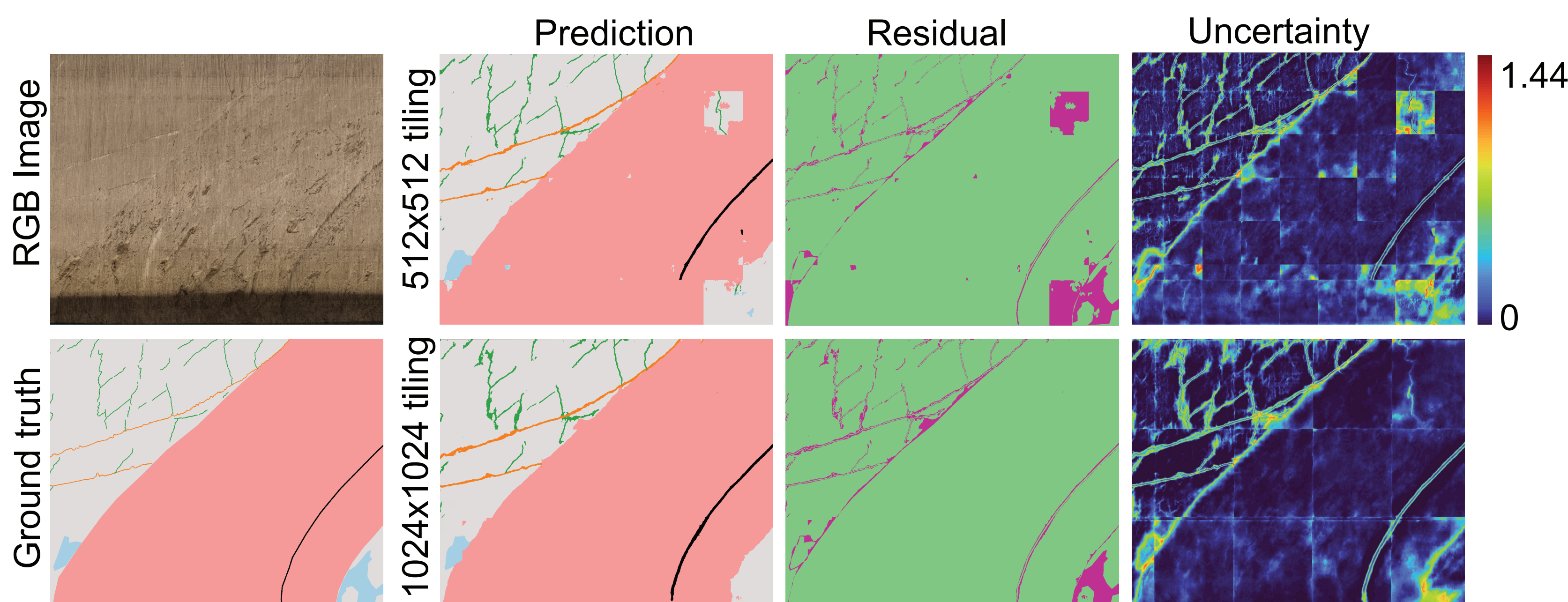


Fig 7. Comparison of multi-scale model predictions using different tile sizes. Prediction: Output from the trained model. Residual: Differences between manual labels and model predictions, green area indicates agreement, magenta area indicates disagreement. Uncertainty: Pixel-wise confidence of the model, brighter colors represent higher uncertainty.

3 Methods

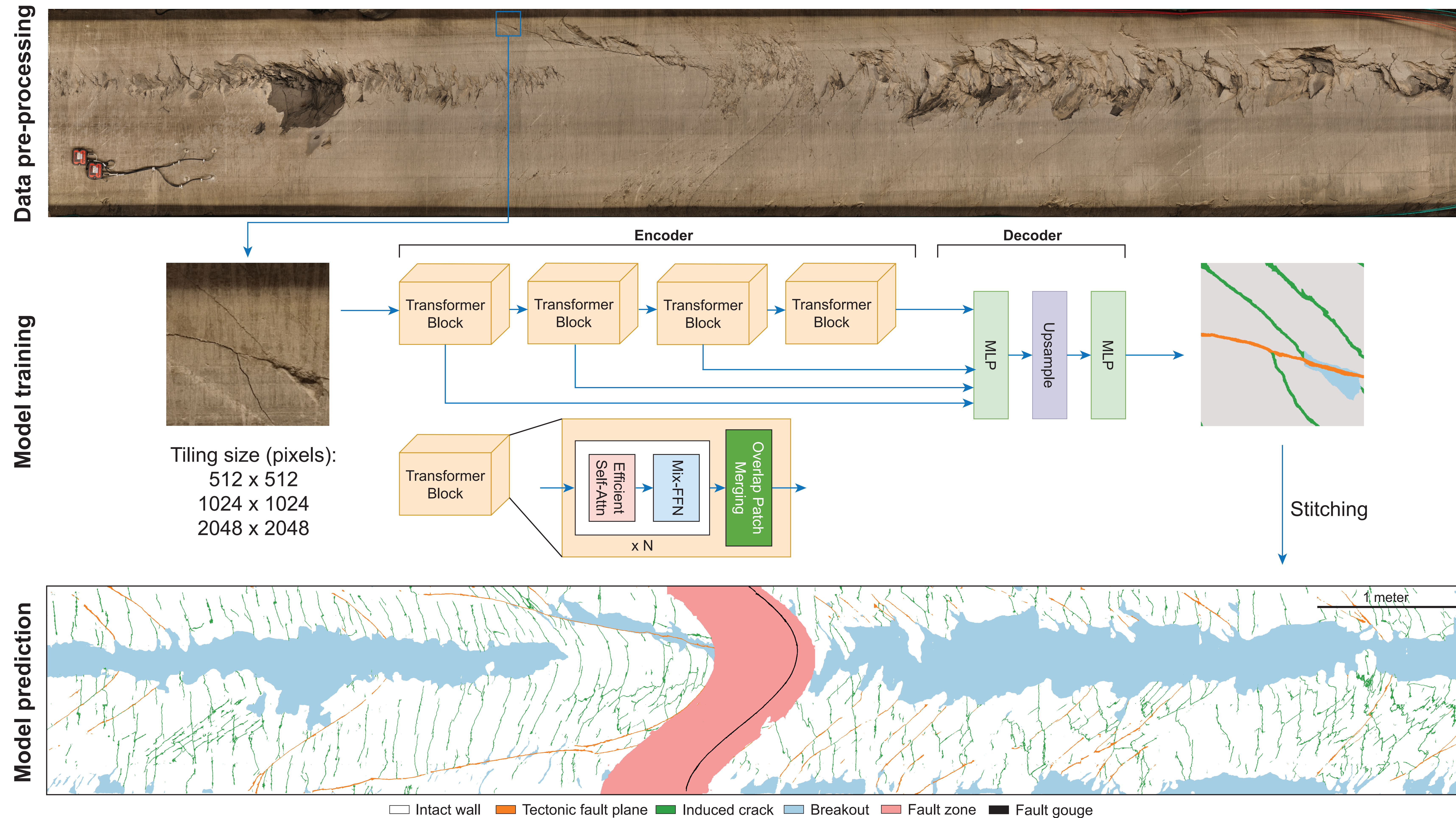


Fig 3. Workflow of semantic segmentation on borehole imagery. The original borehole image has the size of 48436 x 7091 pixels. Due to computational limitations, it is divided into smaller tiles for model inference. The predictions from each tile are then stitched together to reconstruct the full segmentation map.

4 Results

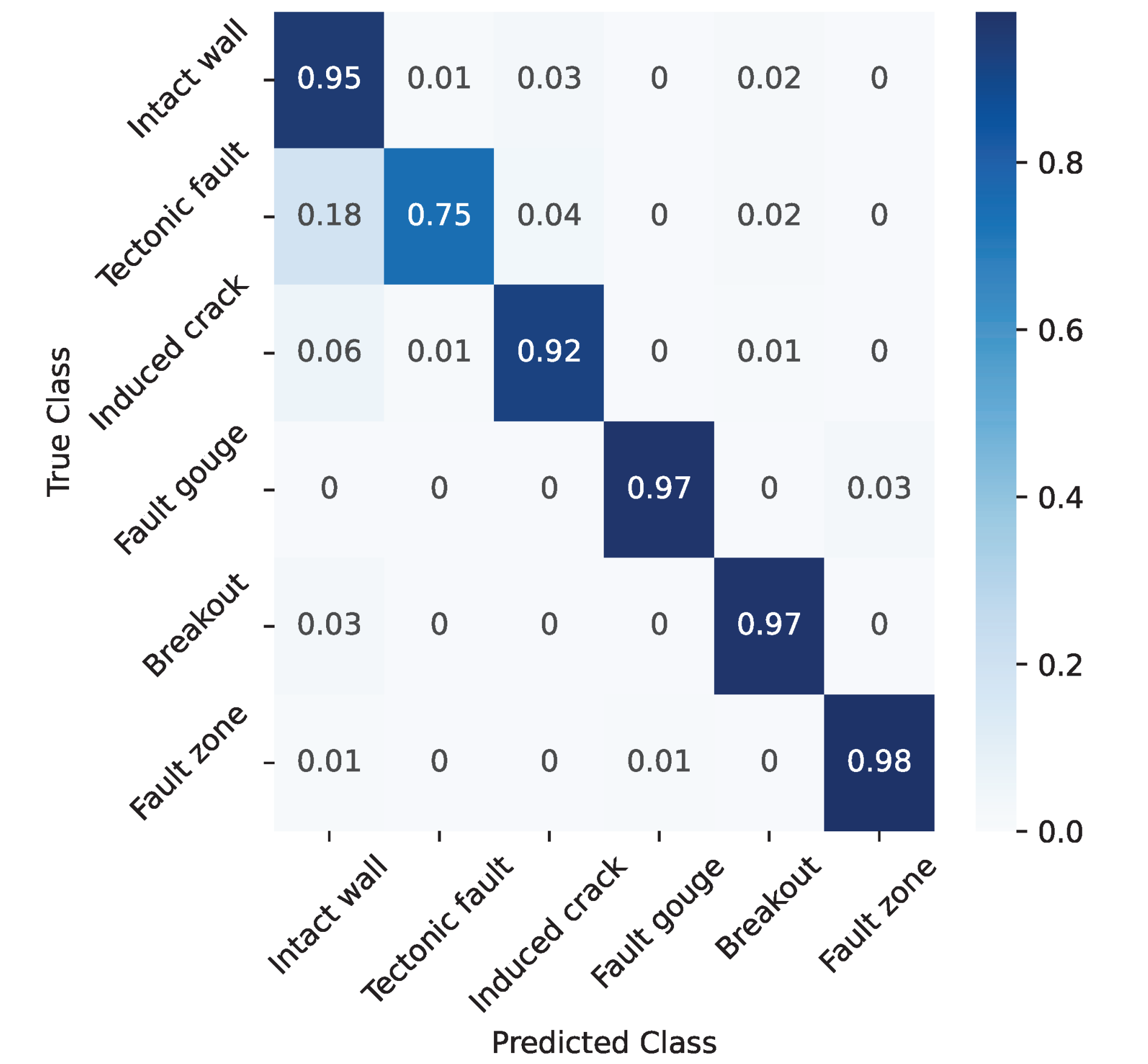


Fig 5. Confusion matrix of the prediction.

- Intact wall shows high recall.
- Tectonic faults tend to be misclassified as intact wall.

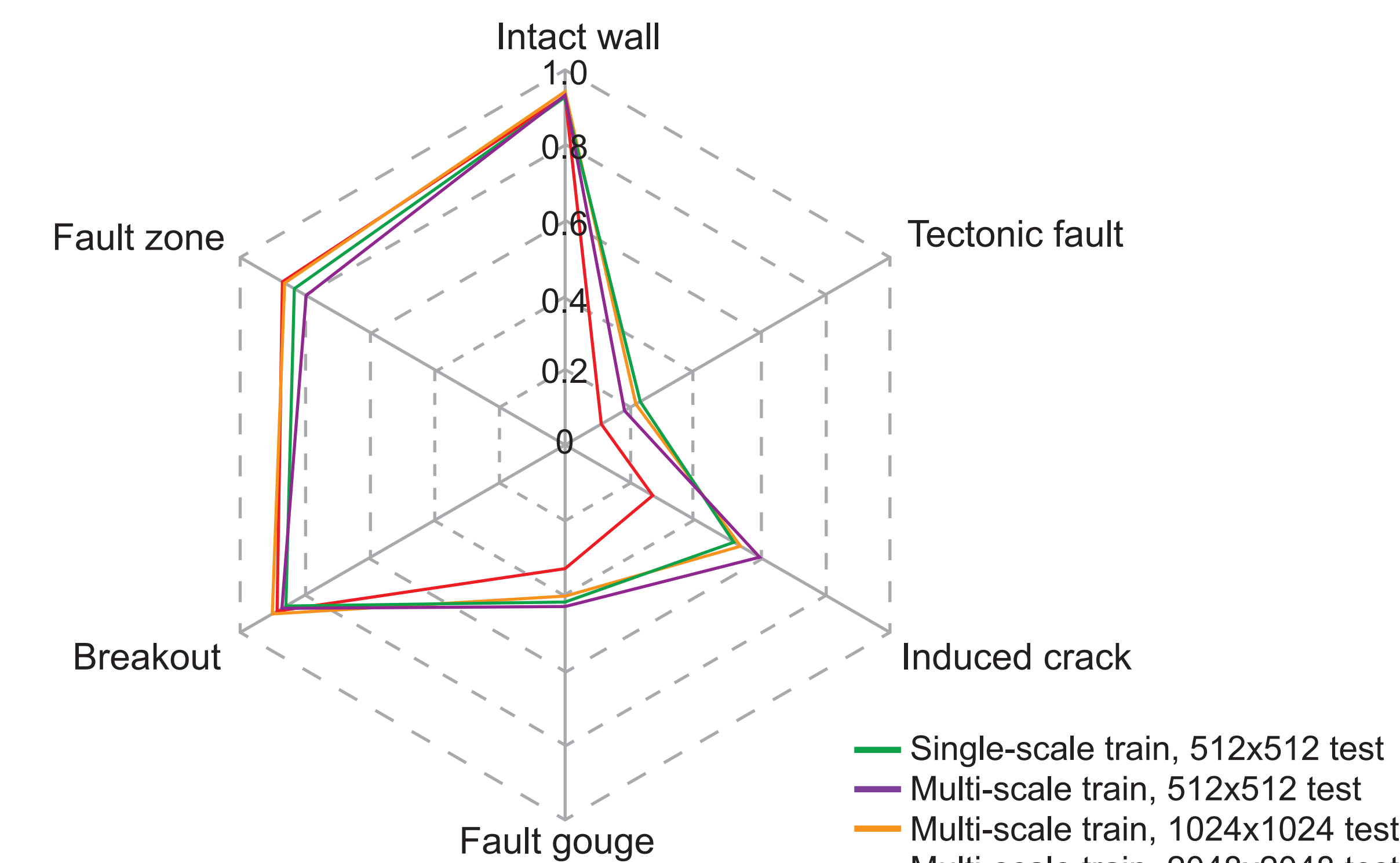


Fig 6. Intersection over Union (IOU) score per class over different tiling size for training and testing.

- Larger tiles capture fault zones better, smaller tiles improve crack detection.

6 Main Takeaways

1. Tiling size is critical in training and prediction.
2. Class imbalance can hinder performance but is addressable through good training strategies.
3. Deep learning models offer efficient, consistent segmentation and can reveal features missed in manual labeling.
4. Future study will focus on generalization to various geological settings (e.g., typical borehole images / 3D tunnel faces data).

Quantifying borehole damage

- For breakout: calculate the total breakout area from the predicted mask.
- For induced crack: skeletonize all the induced cracks, and then calculate the total length of the skeleton.



Fig 8. Skeletonize of the prediction. The left one is the original image. The middle one is the prediction from our model. The right one is the skeleton of induced cracks.

Can deep learning contribute to monitoring rock mass behaviour?

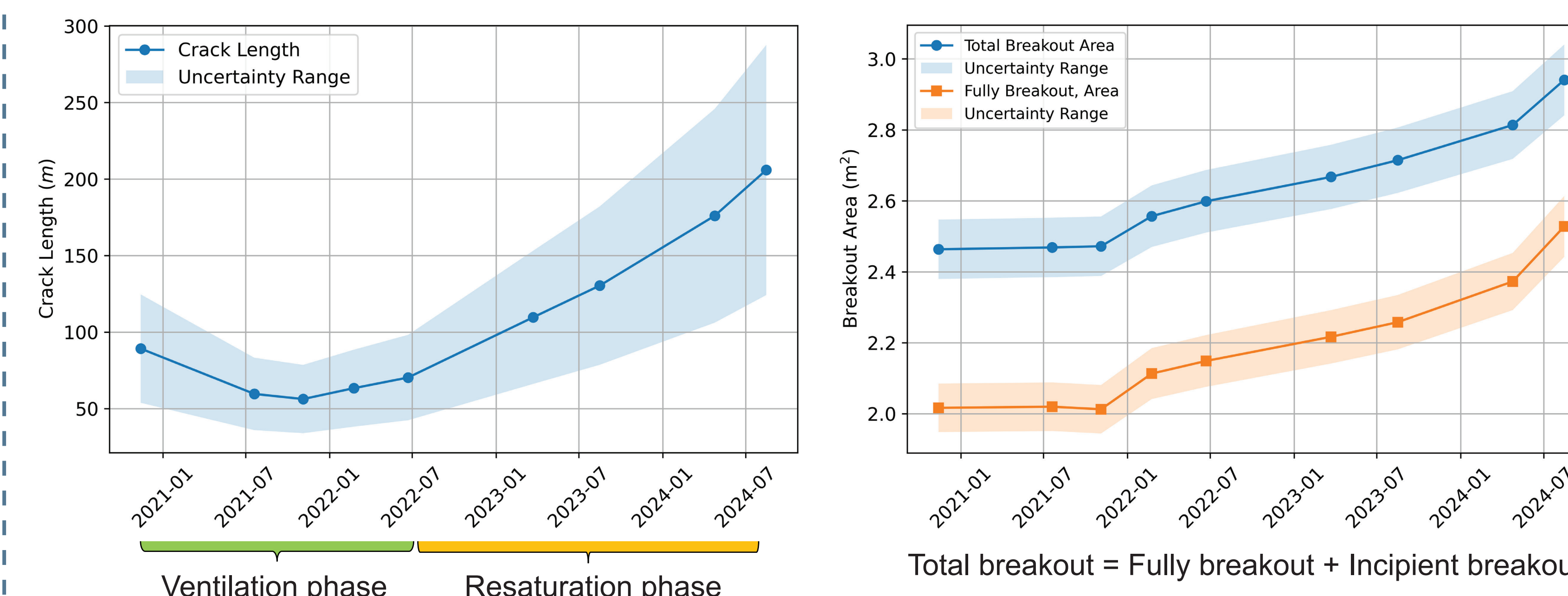


Fig 9. Temporal evolution of induced cracks and breakouts. The left plot shows the total lengths of induced cracks over time. The right plot illustrates the evolution of breakout areas. Fully developed breakouts refer to regions with clear volume loss, while incipient breakouts are visibly disturbed areas that may experience volume loss in the future.

Reference

- [1] Xie, E., Wang, W., Yu, Z., Anandkumar, A., Alvarez, J. M., & Luo, P. (2021). SegFormer: Simple and efficient design for semantic segmentation with transformers. *Advances in neural information processing systems*, 34, 12077-12090.
 [2] Wang, R., Ziegler, M., Volpi, M., Manconi, A. (2025). Advanced Identification of Geological Discontinuities with Deep Learning. In submission.