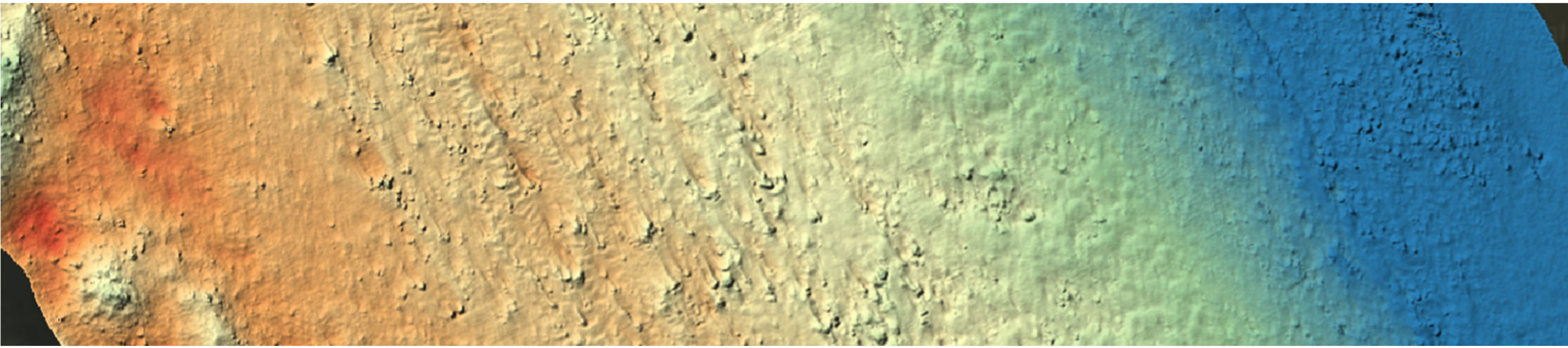
# “AI-Driven Detection of Quartzite Blocks in the River Rhine Using CNN U-Net with Backscatter and Bathymetric Data”

By

Eric Idun



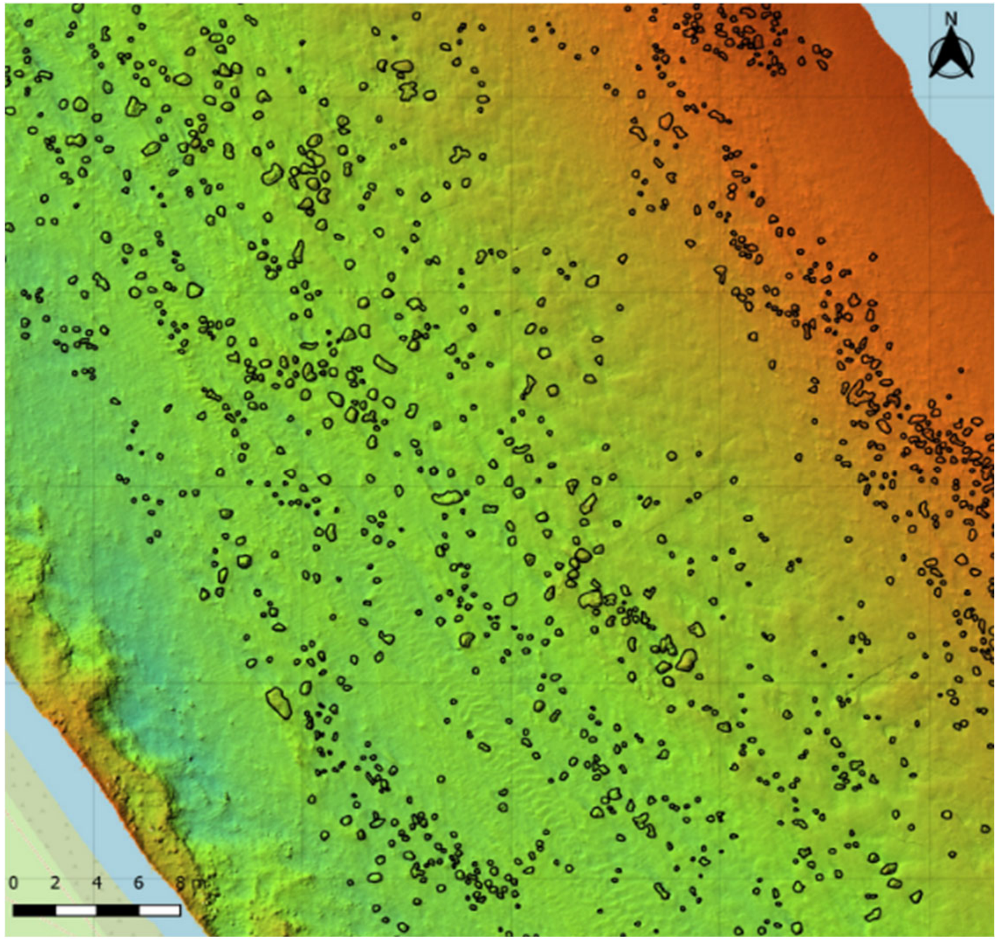
**Motivation**

Methodology

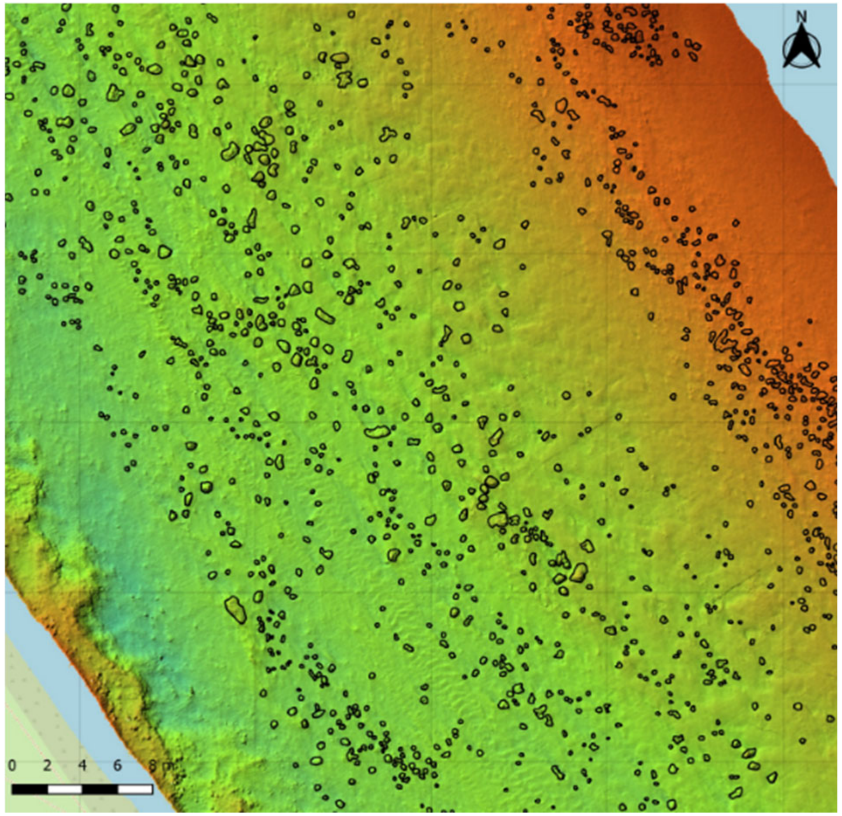
Results

Conclusion

Bibliography




# Motivation





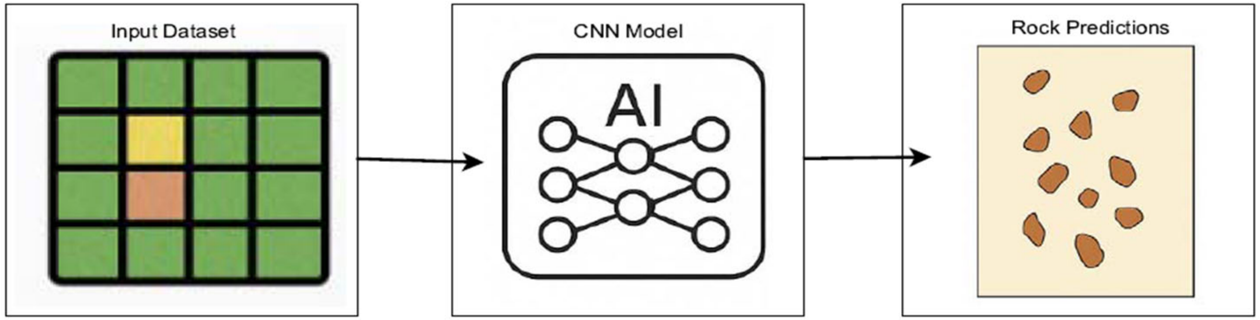

Motivation

- ✓ Explores the effectiveness of AI in enhancing the detection of quartzite blocks in the River Rhine using bathymetric and backscatter data.
- ✓ This will help reduce time and cost, ensure the safe passage of vessels and reduce the likelihood of accidents.
- ✓ It aims to evaluate the differences in detection rates and properties between manual and AI-based detection methods and Determine which data combination offers the best performance for rock detection.

The research will address the following questions:

- ✓ • How can CNNs improve the accuracy of quartzite block detection in the River Rhine?
- ✓ • What are the benefits of integrating bathymetric and backscatter data, along with their statistical derivatives, for detecting geological features?
- ✓ • Which dataset combinations yield the optimal performance for the model?

# Research Questions




- Study area
- Data acquisition
- Data processing
- Manual digitising of rocks
- Dataset pre-processing and Preparation

- Model structure
- Training setup

- Model performance
- Detection results
- Comparison with manual mapping

# Workflow

# Study Area

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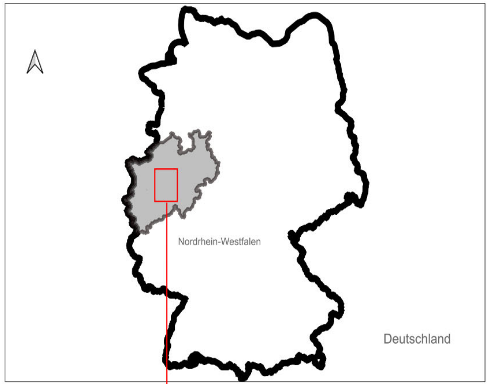
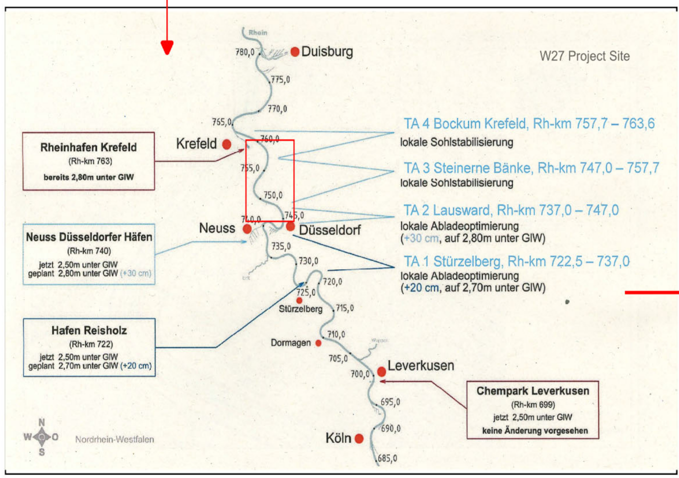
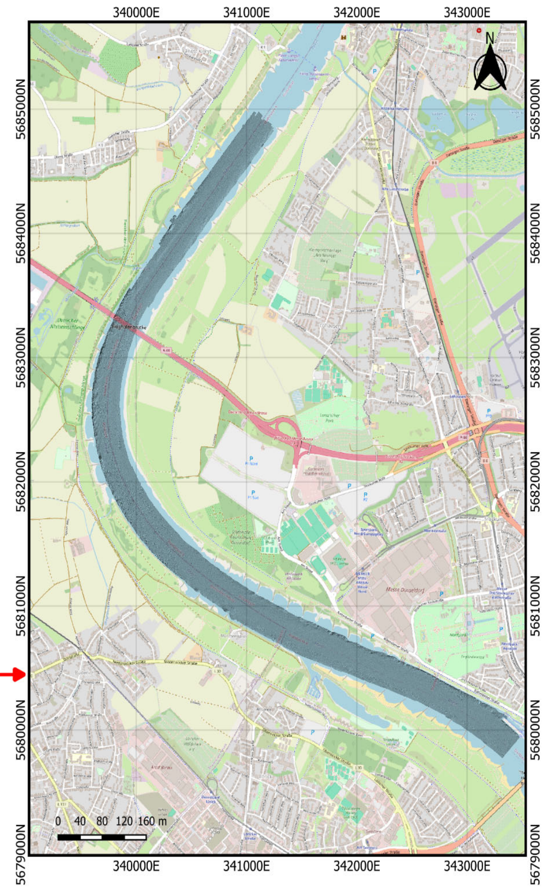
**Study Area**



## Data Acquisition

| Equipment | Software |
|---|---|
| AML-3 LGR Sound Velocity Profiler | AML Software |
| Kongsberg EM2040P MKII MBES | Kongsberg SIS / Qinsy |

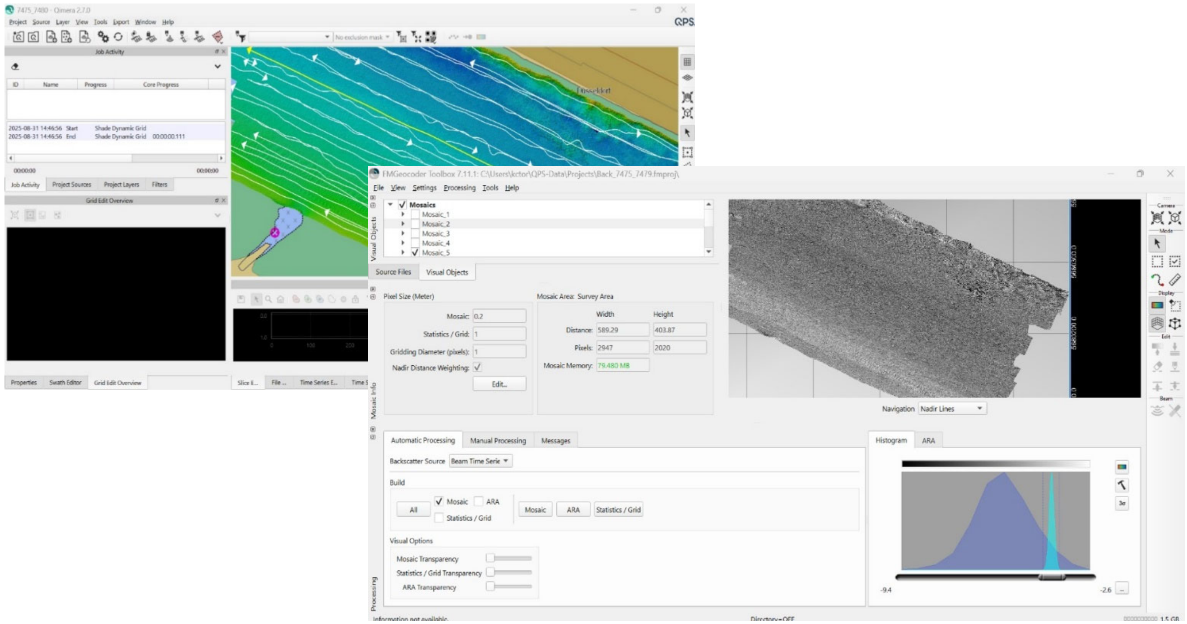
DVocean

MBES

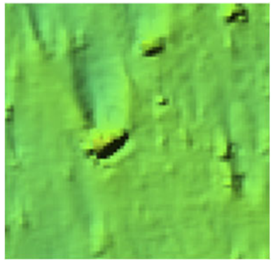
SVP

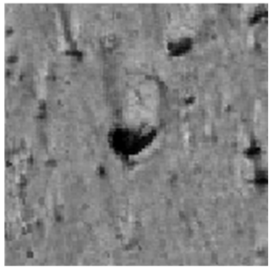
## Data Processing

| Data | Software |
|---|---|
| MBES Bathymetry | QPS Qimera , Fledermaus |
| MBES Backscatter | FMGT |
| Maps | QGIS |

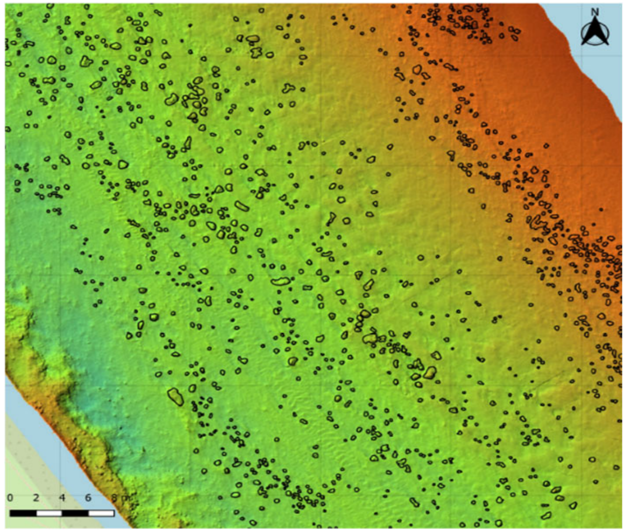


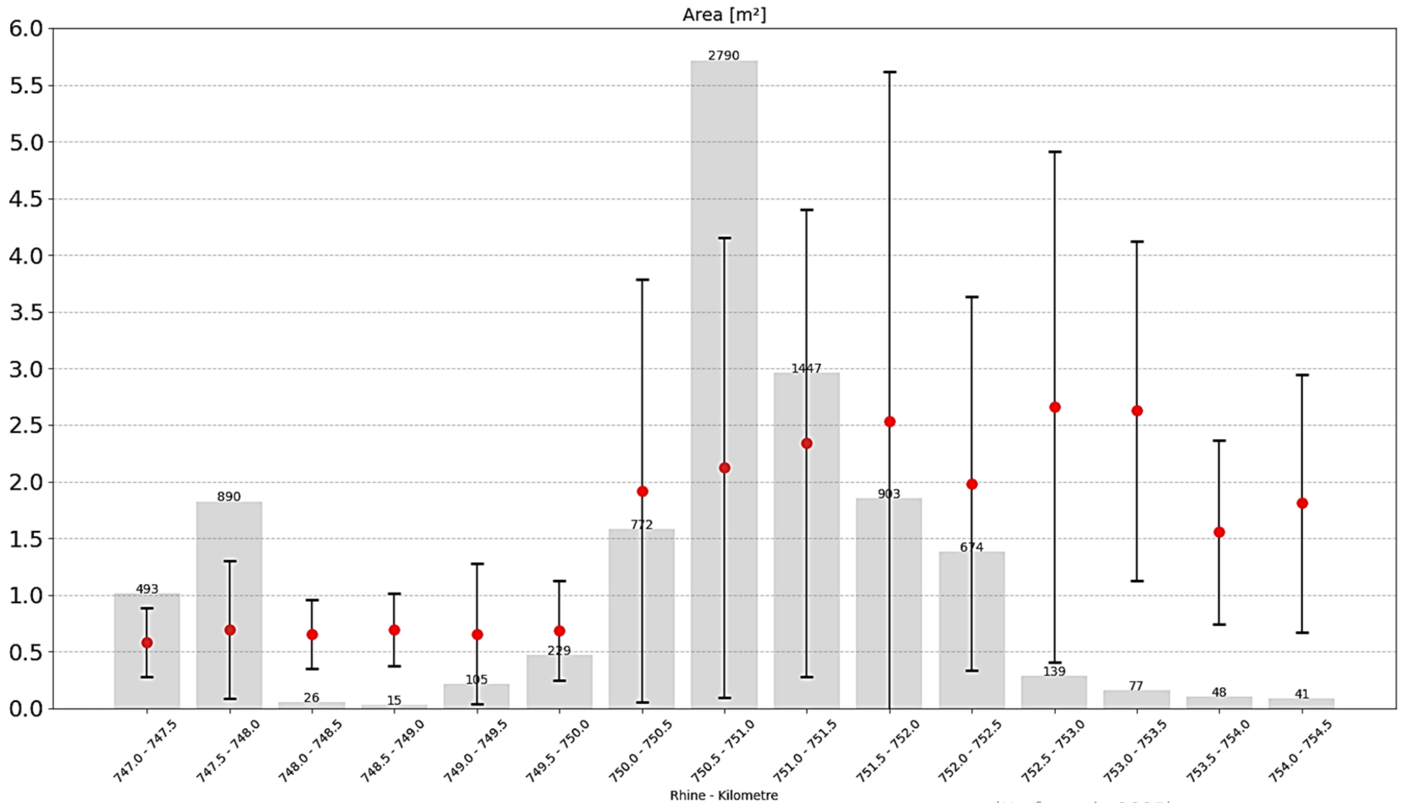
# Manual Digitising of Rocks





scour marks or depressions



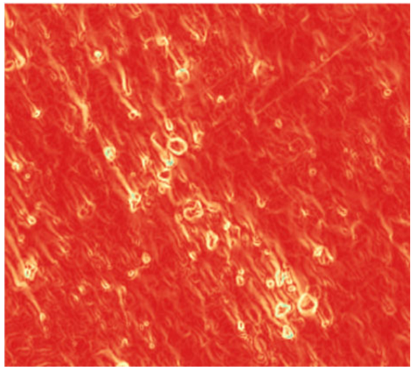



(Kraft et al., 2025)

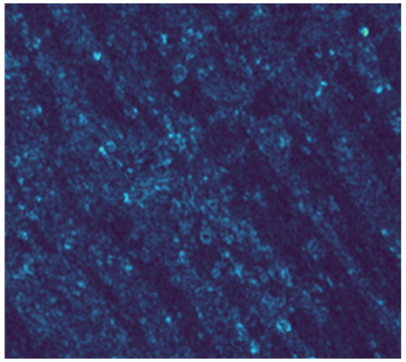
## Dataset Pre-processing and Preparation - Derivatives

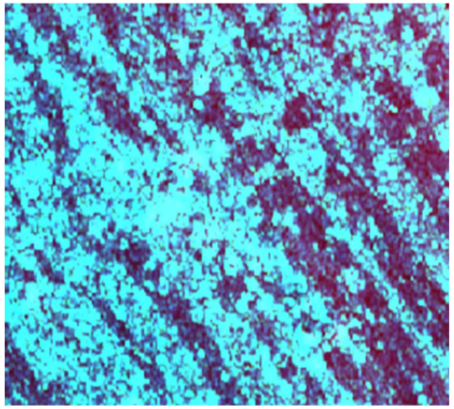
| Bathymetric Derivatives | Backscatter Derivatives |
|---|---|
| Curvature | Contrast |
| Slope | Dissimilarity |
| Roughness | Homogeneity |

clearly visible rocks



limited rock visibility

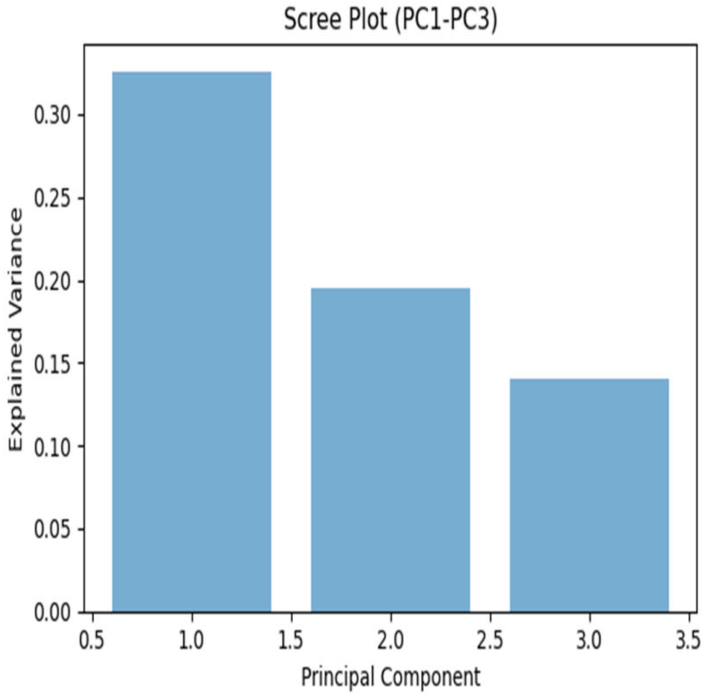


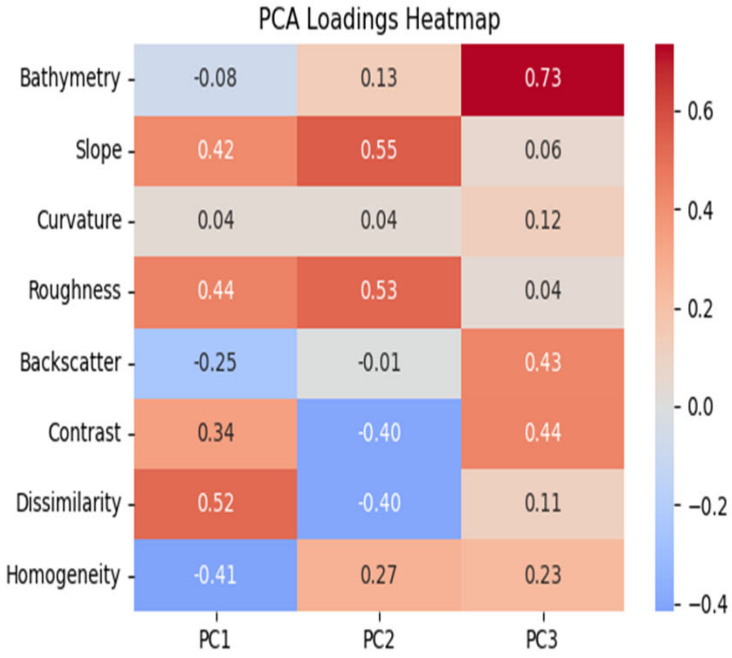


feature combination composite image

## Dataset Pre-processing and Preparation – PCA based selection

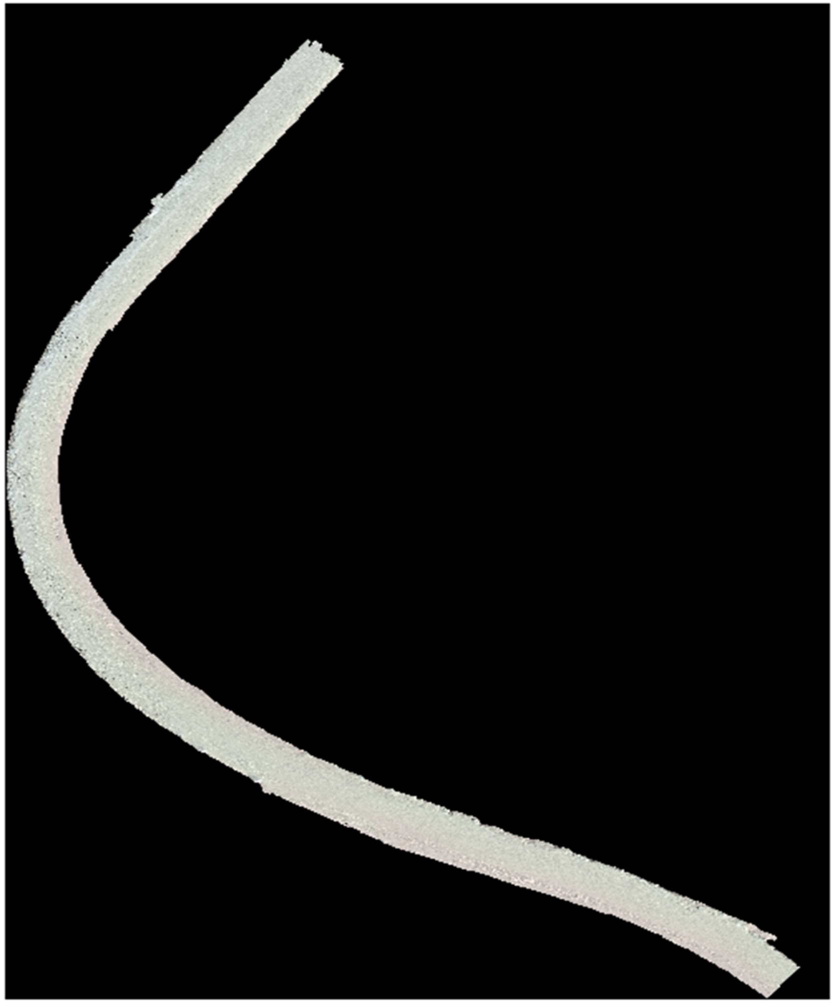
- ✓ The first composite comprises Slope, Roughness, and Backscatter. Slope describes large-scale gradients, while Roughness reflects micro-topographic complexity. Backscatter contributes unique radiometric information.
- ✓ The second composite includes Bathymetry, Dissimilarity, and Contrast. Bathymetry captures geomorphological variation. Dissimilarity measures local pixel variability. Contrast emphasise edge transitions and textural sharpness.



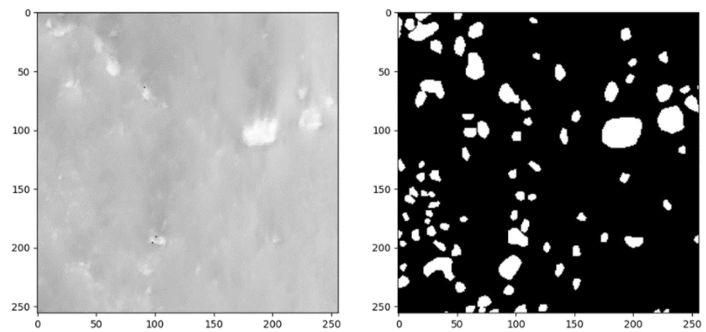
## Dataset Pre-processing and Preparation - Mask Generation and Tiling

- ✓ Measurements were rescaled to a normalised range between 0 and 1.
- ✓ No-data values were handled by assigning a common placeholder value of NaN to all null or invalid measurements.
- ✓ Shapefile annotations were converted into rasterised binary masks with rock areas assigned a value of 1, with all background pixels set to 0.
- ✓ A tile size of 256 × 256 pixels was chosen to preserve geological details while minimising the inclusion of no-data regions.

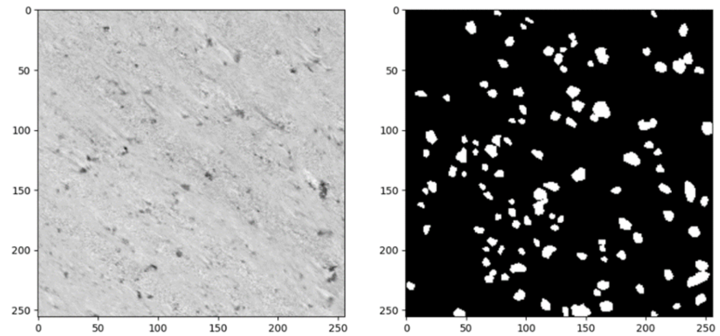


## Dataset Pre-processing and Preparation – Input Dataset

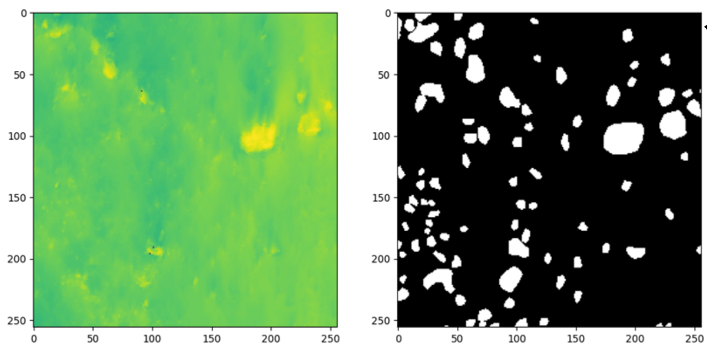
| ID | Dataset | Training | Validation | Test | Total Tiles | Channel |
|---|---|---|---|---|---|---|
| Ba | Bathymetry | 279 | 163 | 23 | 465 | Single band image |
| Bs | Backscatter | 281 | 164 | 24 | 469 | |
| BCD | Bathymetry + Contrast + Dissimilarity | 253 | 148 | 21 | 422 | Three band image |
| BsRS | Backscatter + Roughness + Slope | 259 | 151 | 21 | 431 | |



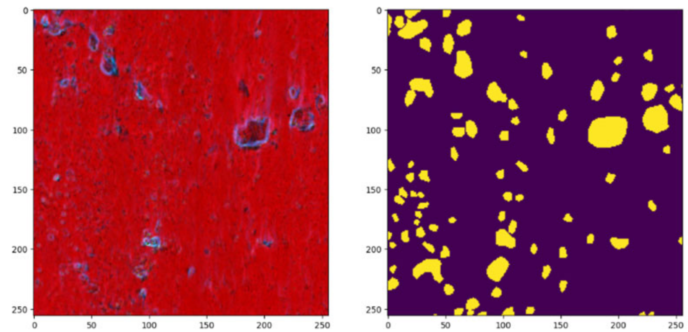
✓ Ba



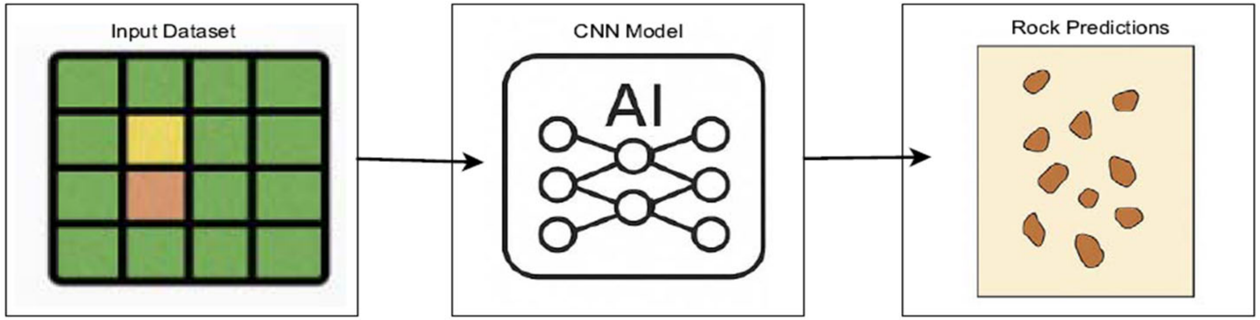
✓ Bs



✓ BCD



✓ BsRS

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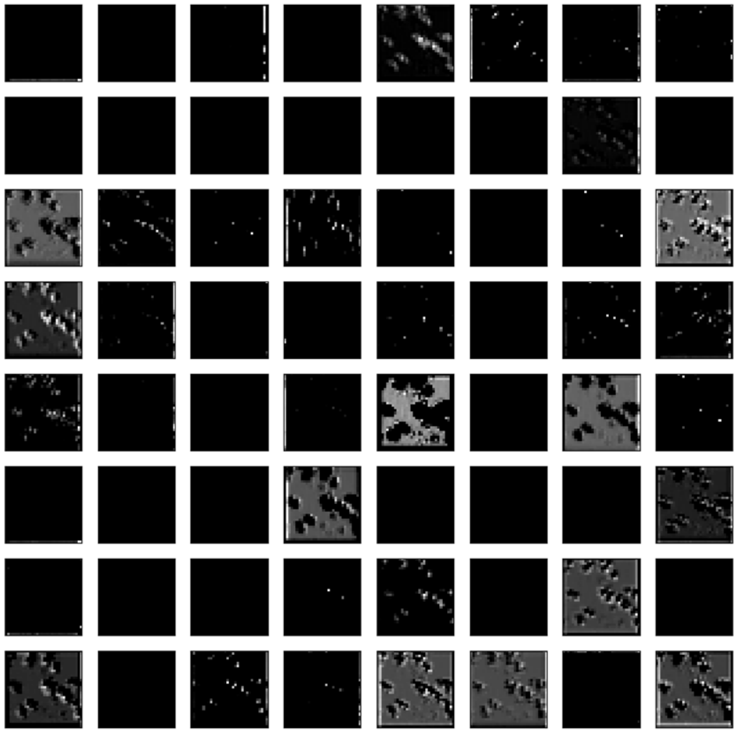
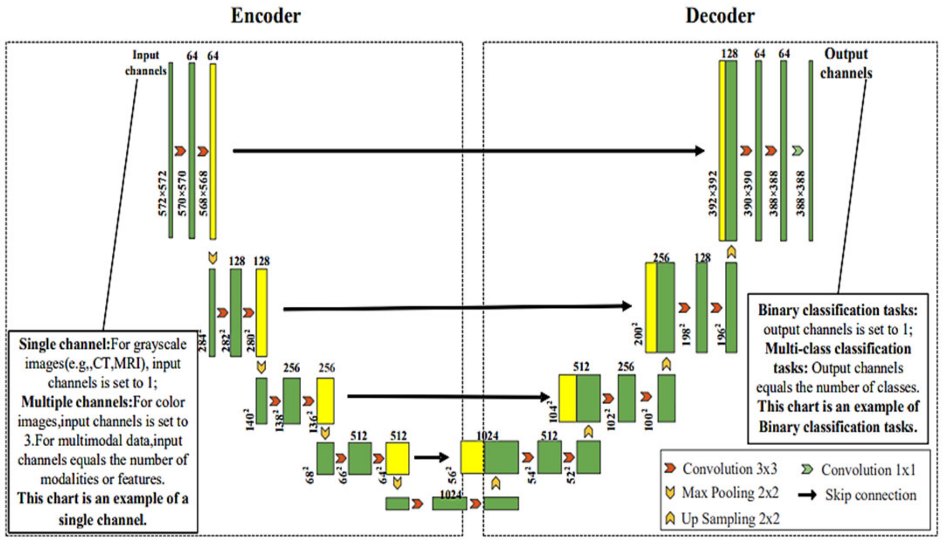
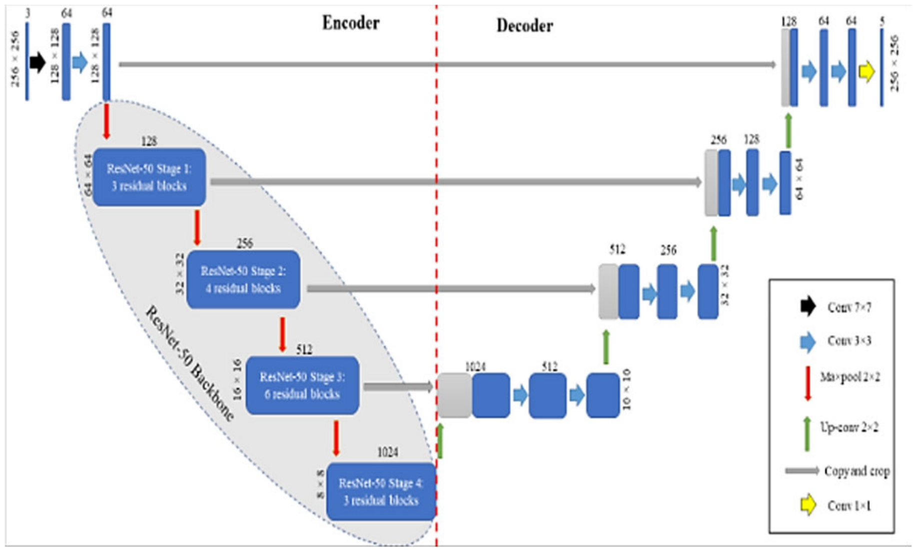
# Workflow

# U-Net model Architecture





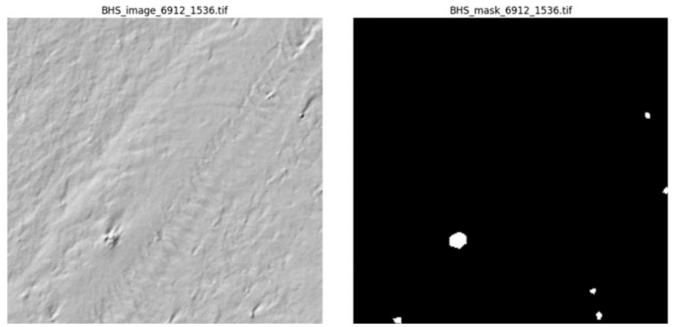

(Jiangtao et al., 2025)

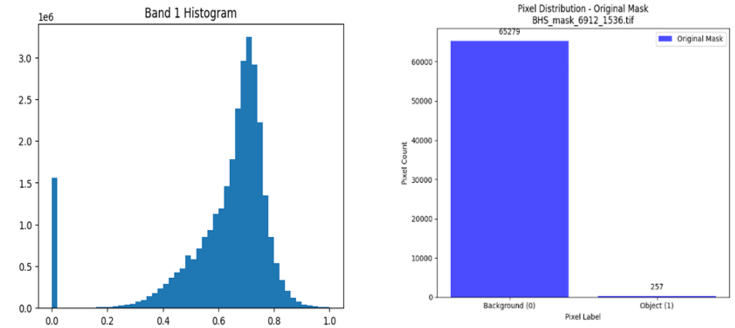


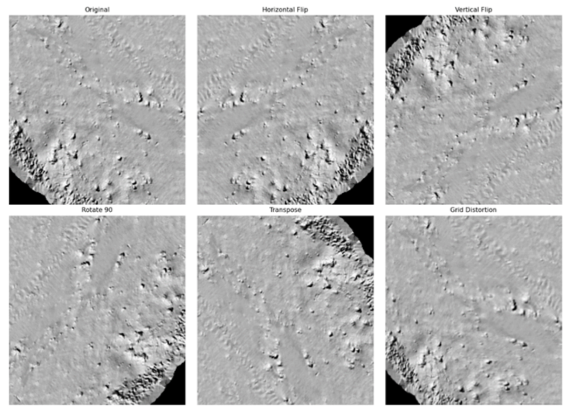

(Manos et al., 2022)

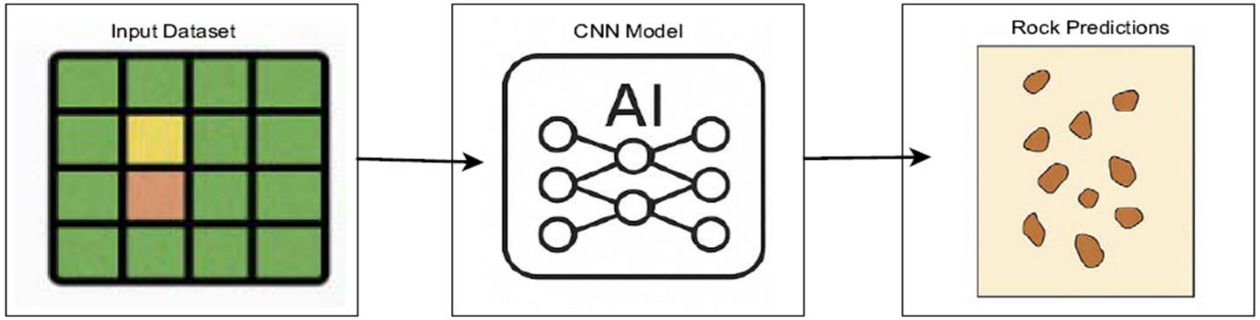
## Training and Validation Setup – Data Handling

- ✓ Visual inspections of randomly selected image-mask pairs to confirm proper spatial alignment.
- ✓ Pixel value distribution histograms to identify inconsistencies, outliers, or other anomalies across the dataset.
- ✓ Address class imbalance by calculating sample weights to reduce bias toward the dominant background class.
- ✓ Data augmentation techniques (vertical and horizontal flips, Rotation, Transpose and Grid distortion) to improve the model's ability to generalise and perform well on unseen data by generating modified versions of the existing images and masks.



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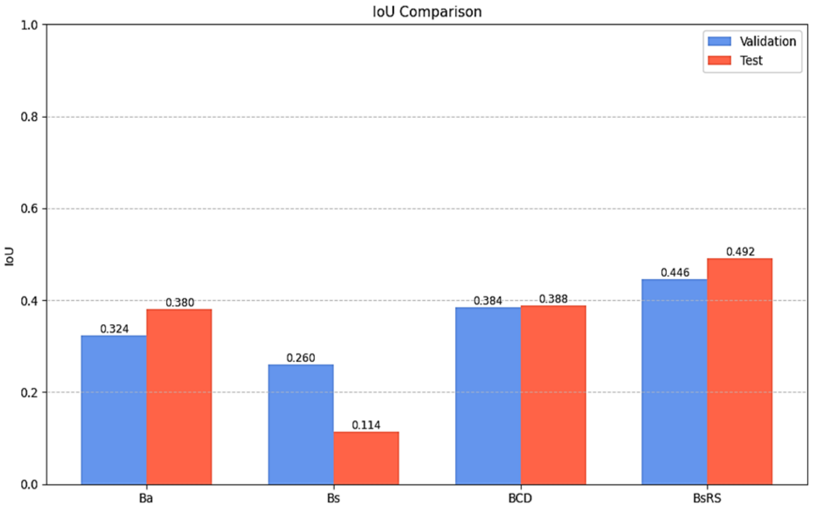
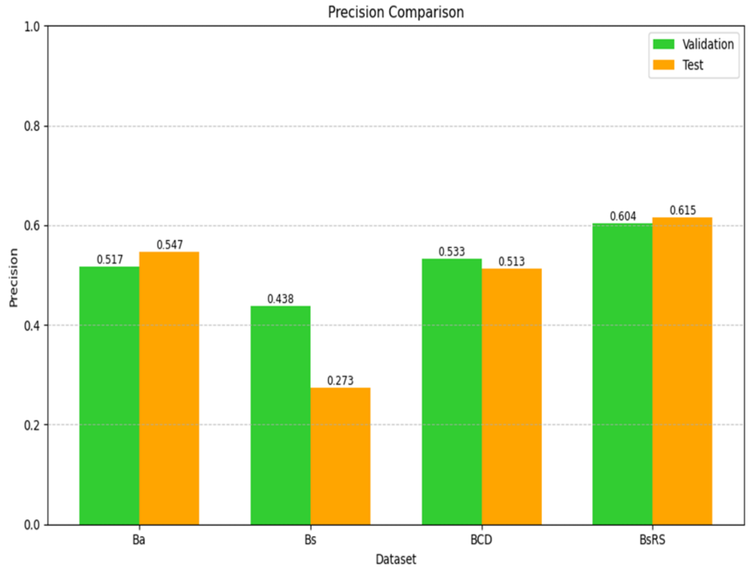
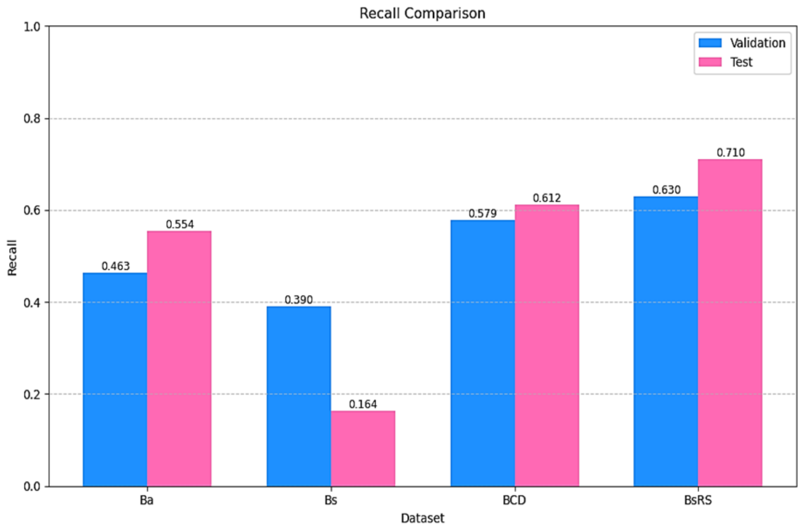
# Workflow

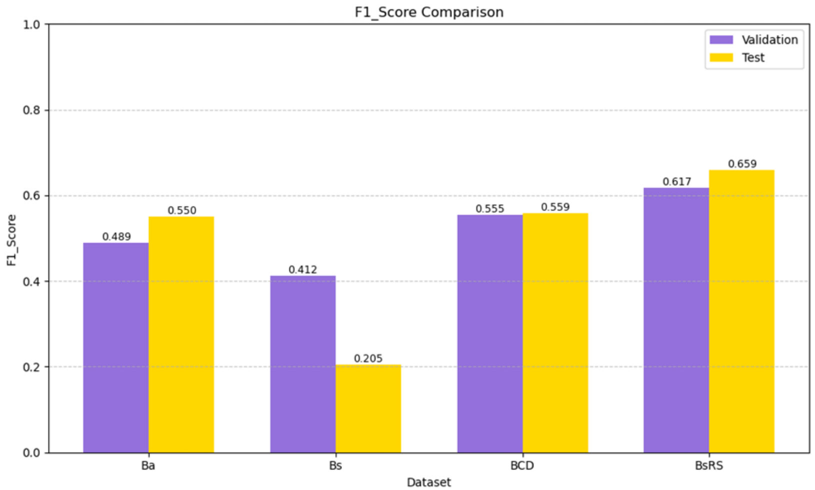
# Model Performance – Evaluation metrics




- ✓ IoU represents how much the predicted rock region aligns with the ground truth rock area.
- ✓ Precision measures how many of the pixels labelled as rock by the model are truly rock pixels.
- ✓ Recall measures how many true rock pixels were successfully detected by the model
- ✓ F1-score reflects overall model accuracy by balancing false positives and false negatives.

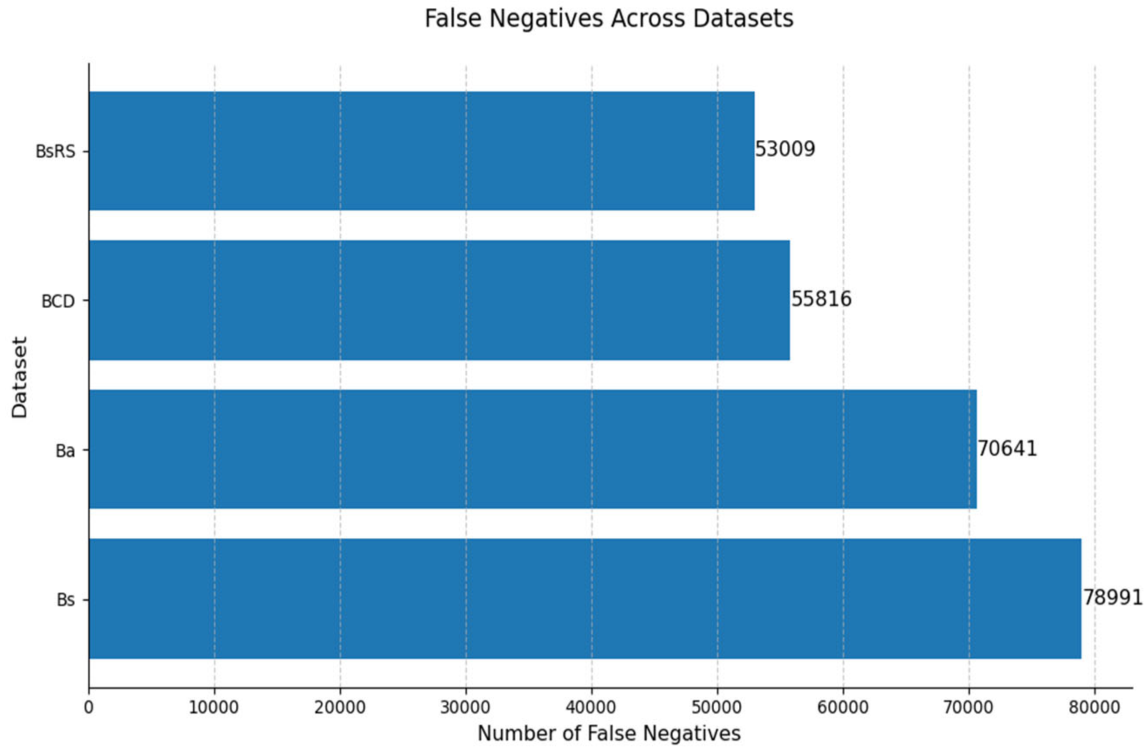


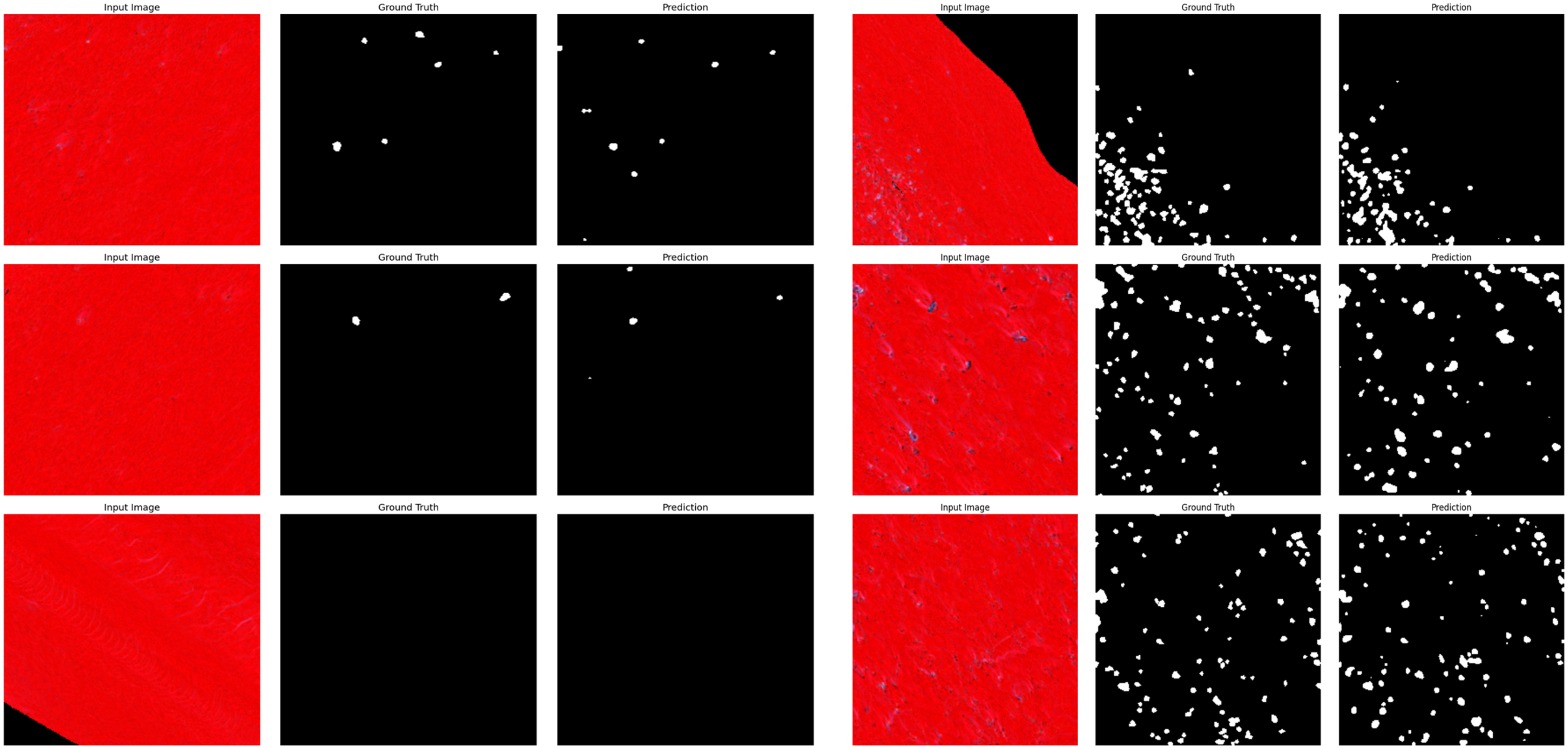
# Model Performance – Evaluation metrics

➢ Insights into model errors

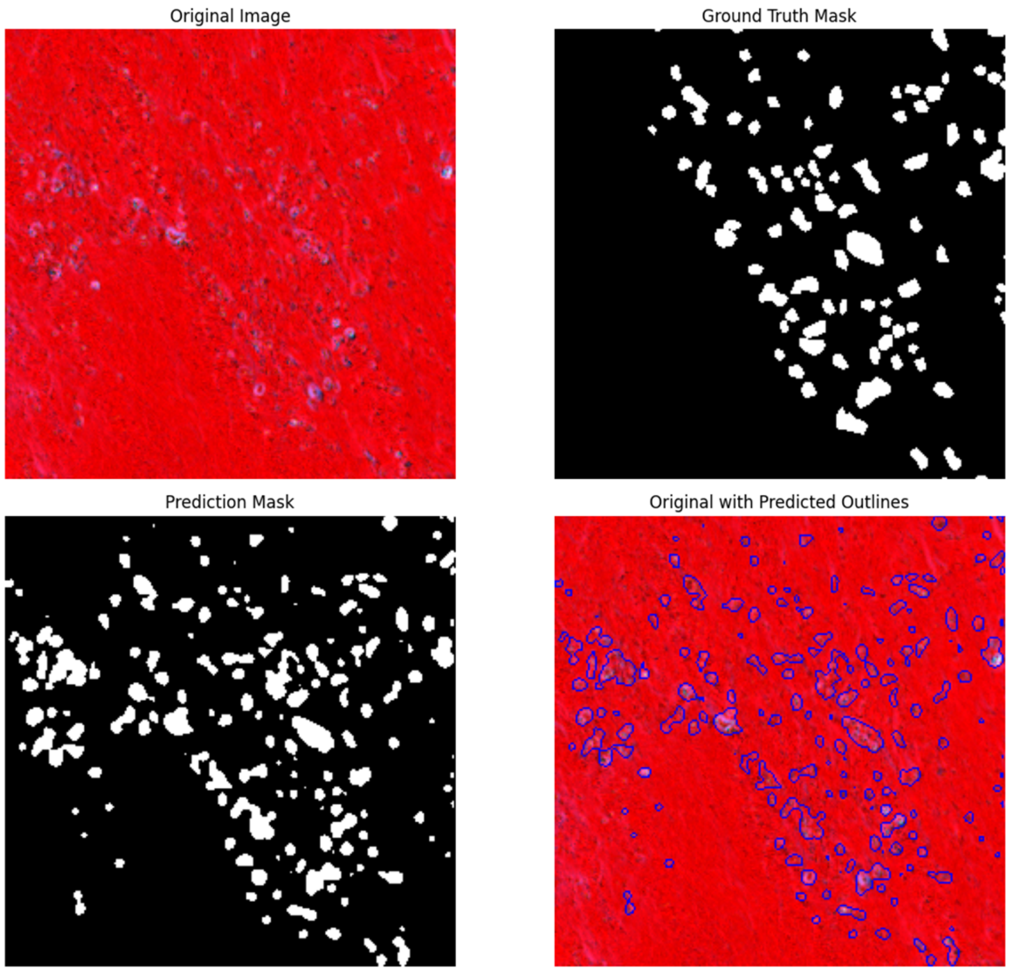
✓ When a model incorrectly labels a pixel that actually represents a rock as background, it can lead to underestimating how difficult the terrain is.

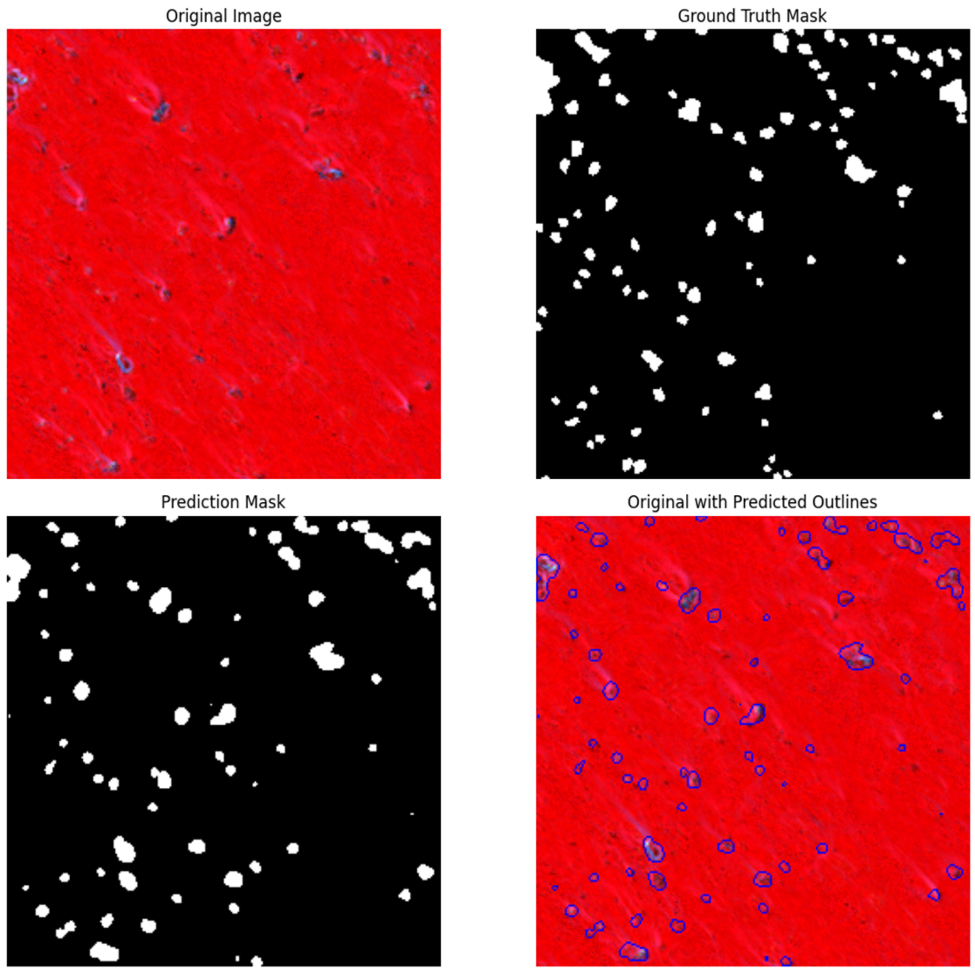


# Detection Results - BsRS



# Detection Results - BsRS

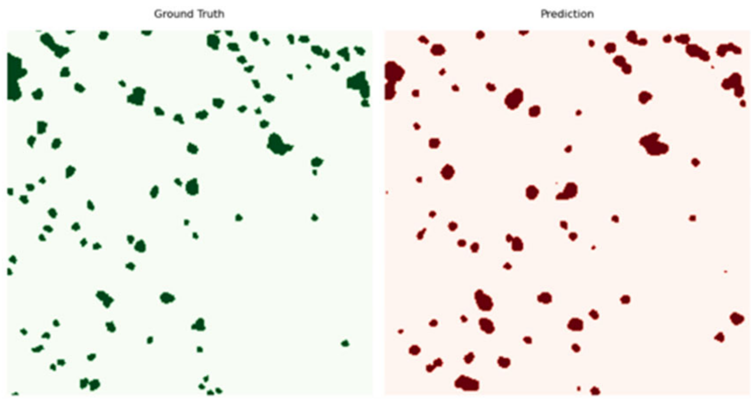


# Comparison with Manual Mapping

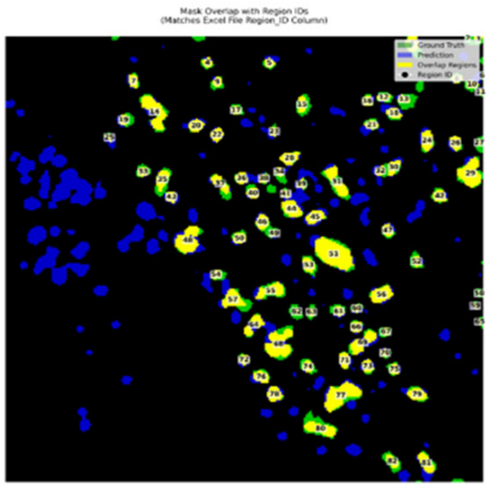
Test Image 1


Test Image 2




- ✓ How similar are the rock sizes detected by the model compared to those identified manually?
- ✓ Does the model tend to overestimate or underestimate rock sizes?

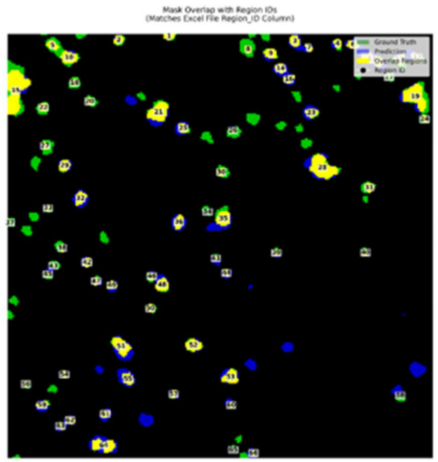
- ✓ Size of individual rock segments were analysed using scatter plots and Bland-Altman plots to assess the level of agreement between the model and manual mapping.



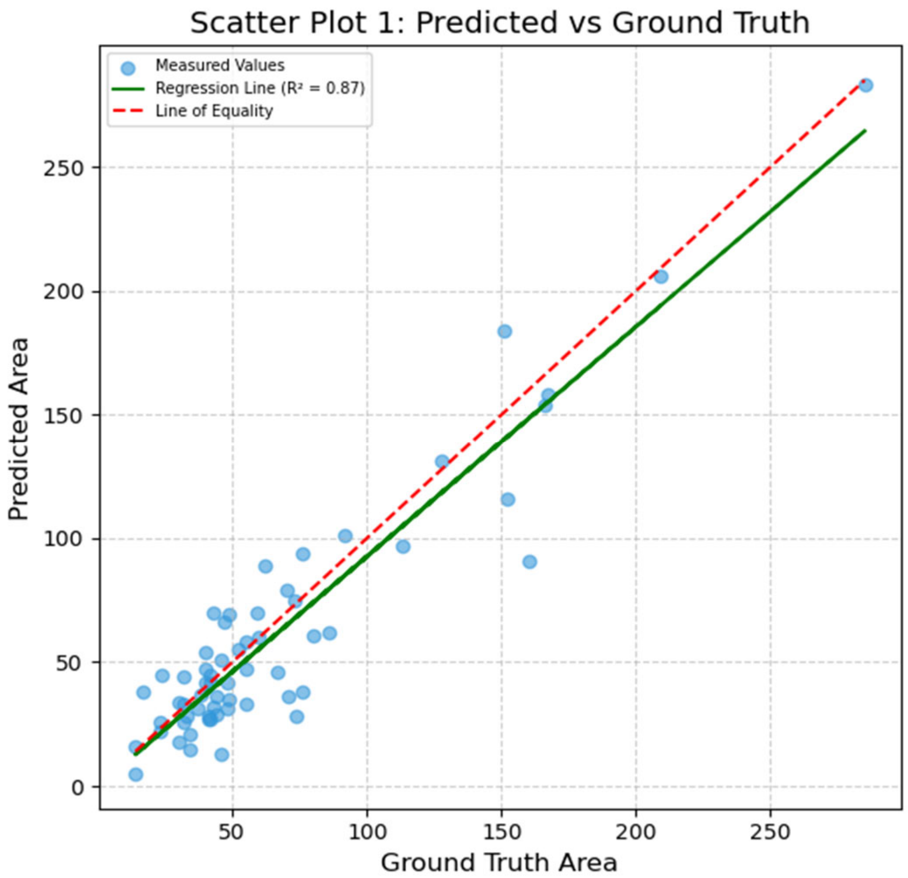

Ground truth

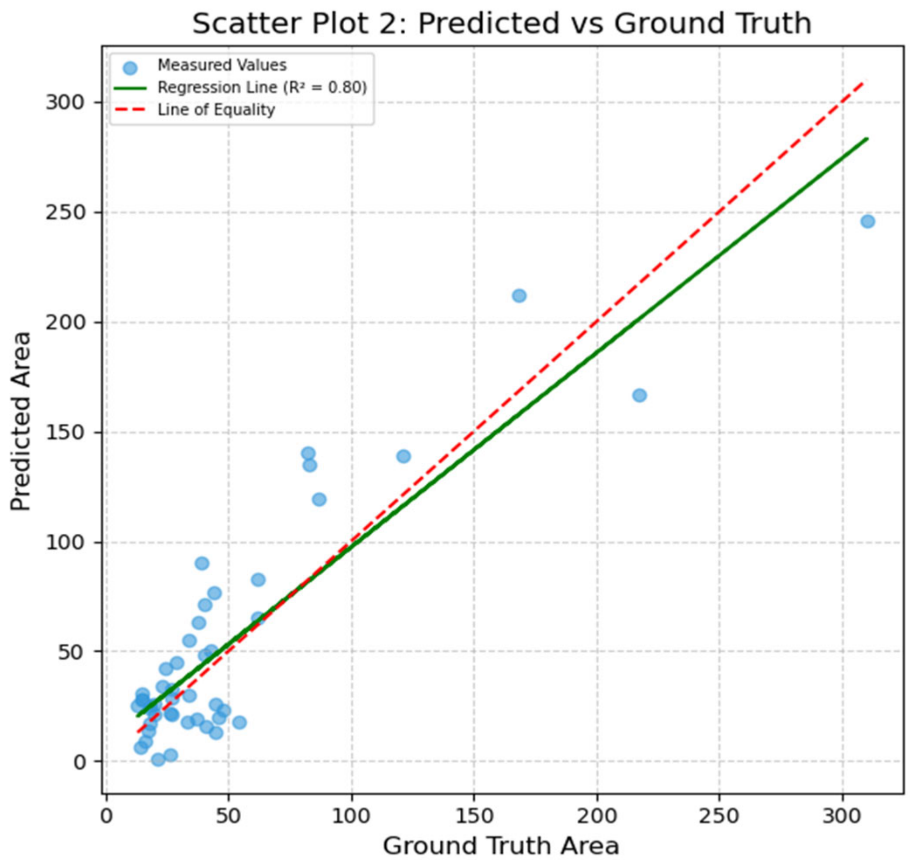
Prediction

Overlap



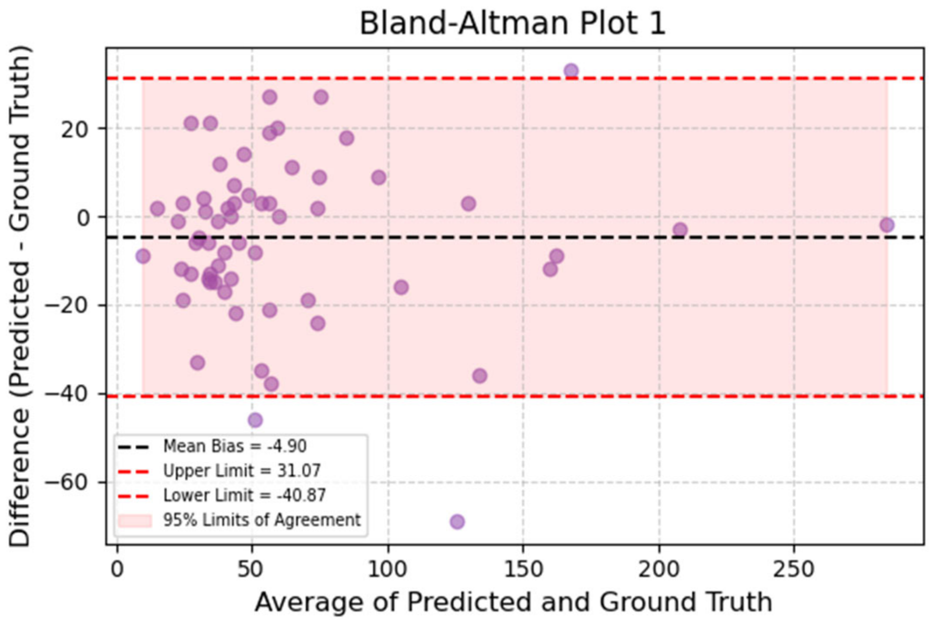
## Comparison with Manual Mapping - Scatter Plot Analysis

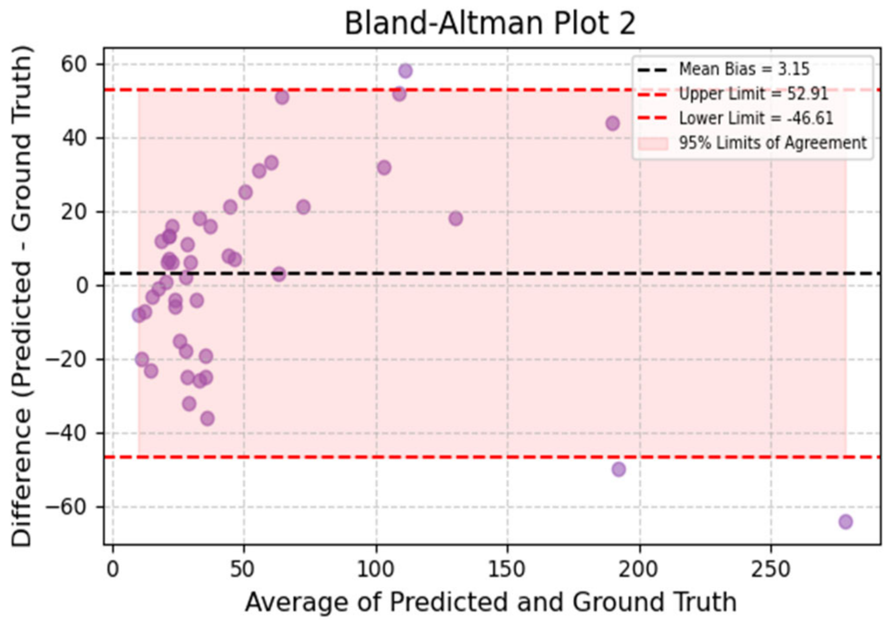



✓ Area in pixel units

## Comparison with Manual Mapping - Bland-Altman Plot Analysis




- ✓ Area in pixel units

Motivation

Methodology

Results

**Conclusion**

Bibliography

- ✓ The dataset, which comprised a little over 400 image tiles per variant, was relatively small. Even though this provided a foundation for initial experimentation, it is relatively small compared to the data volumes typically required for training deep learning models with strong generalisation capability.
- ✓ Study was confined to a single segment of the Rhine, restricting the model’s exposure to varying geological, sedimentary, and acoustic conditions.
- ✓ The manual annotations were produced by non-experienced annotators, which may have introduced inconsistencies, particularly in acoustically noisy or ambiguous regions. A broader datasets with expert-verified labels will be essential to improve model robustness and reduce annotation-related noise.

## Limitation

- ✓ The BsRS model, in particular, outperformed both simpler and less integrated approaches, confirming the importance of combining bathymetry, backscatter, and other data sources to create a rich feature space for machine learning applications.
- ✓ The results showed strong alignment between model predictions and manual annotations, with some instances of superior detection capability.
- ✓ Although further improvements are required, especially with respect to increasing performance metrics, and generalisability, the approach developed in this study represents a significant step toward in automating fluvial hazard detection.

Kraft, M., Hollman, N., Torres, K., Idun, E., Heffner, E., Walter, A. L., & Sternberg, H. (2025). Detection of quartzite blocks in the River Rhine: Development of semi-automatic and automatic approaches for the detection of boulders. *Journal of Applied Hydrography*(130), 30–33. https://doi.org/10.23784/HN130-04

Zhang, Z [Zhongheng], & Castelló, A. (2017). Principal components analysis in clinical studies. Annals of Translational Medicine, 5(17), 351. https://doi.org/10.21037/atm.2017.07.12

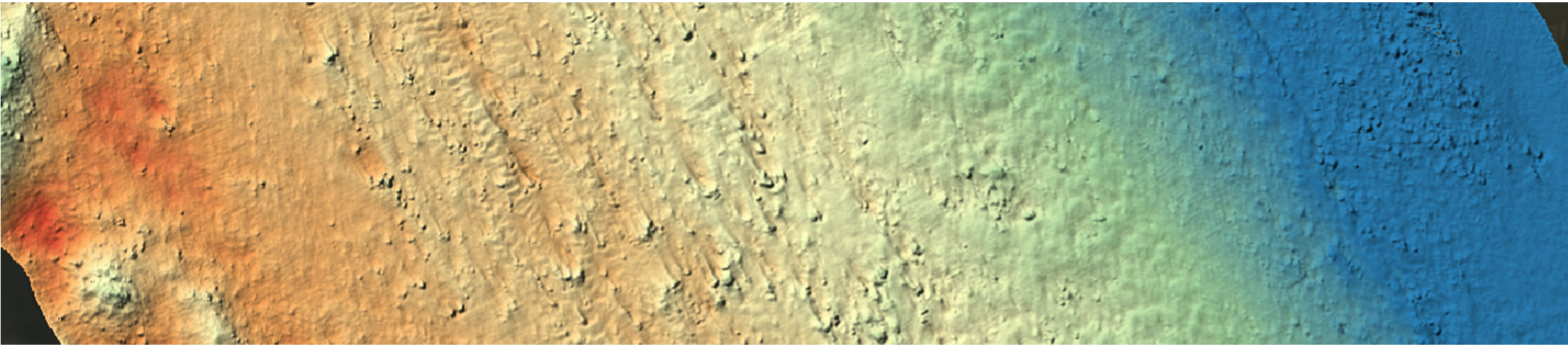
Jiangtao, W., Ruhaiyem, N. I. R., & Panpan, F. (2025, February 9). A Comprehensive Review of U-Net and Its Variants: Advances and Applications in Medical Image Segmentation. http://arxiv.org/pdf/2502.06895 https://doi.org/10.48550/arXiv.2502.06895

Manos, E., Witharana, C., Udawalpola, M. R., Hasan, A., & Liljedahl, A. K. (2022). Convolutional Neural Networks for Automated Built Infrastructure Detection in the Arctic Using Sub-Meter Spatial Resolution Satellite Imagery. Remote Sensing, 14(11), 2719. https://doi.org/10.3390/rs14112719

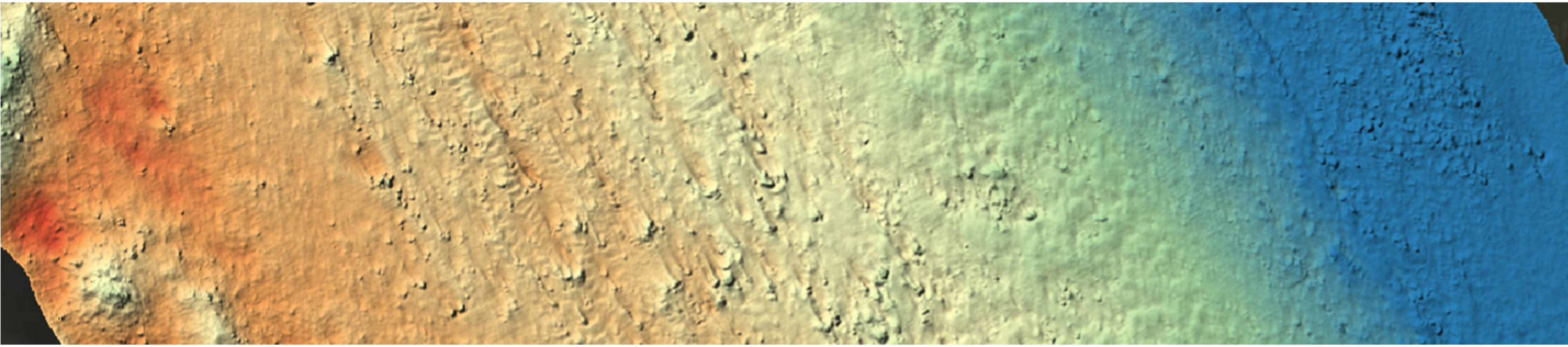
Miller, C., Portlock, T., Nyaga, D. M., & O'Sullivan, J. M. (2024). A review of model evaluation metrics for machine learning in genetics and genomics. Frontiers in Bioinformatics, 4, 1457619. https://doi.org/10.3389/fbinf.2024.1457619

Terven, J., Cordova-Esparza, D.-M., Romero-González, J.-A., Ramírez-Pedraza, A., & Chávez-Urbiola, E. A. (2025). A comprehensive survey of loss functions and metrics in deep learning. Artificial Intelligence Review, 58(7). https://doi.org/10.1007/s10462-025-11198-7

Nemavhola, A., Chibaya, C., & Viriri, S. (2025). A Systematic Review of CNN Architectures, Databases, Performance Metrics, and Applications in Face Recognition. Information, 16(2), 107. https://doi.org/10.3390/info16020107



Thank you



# Thank you

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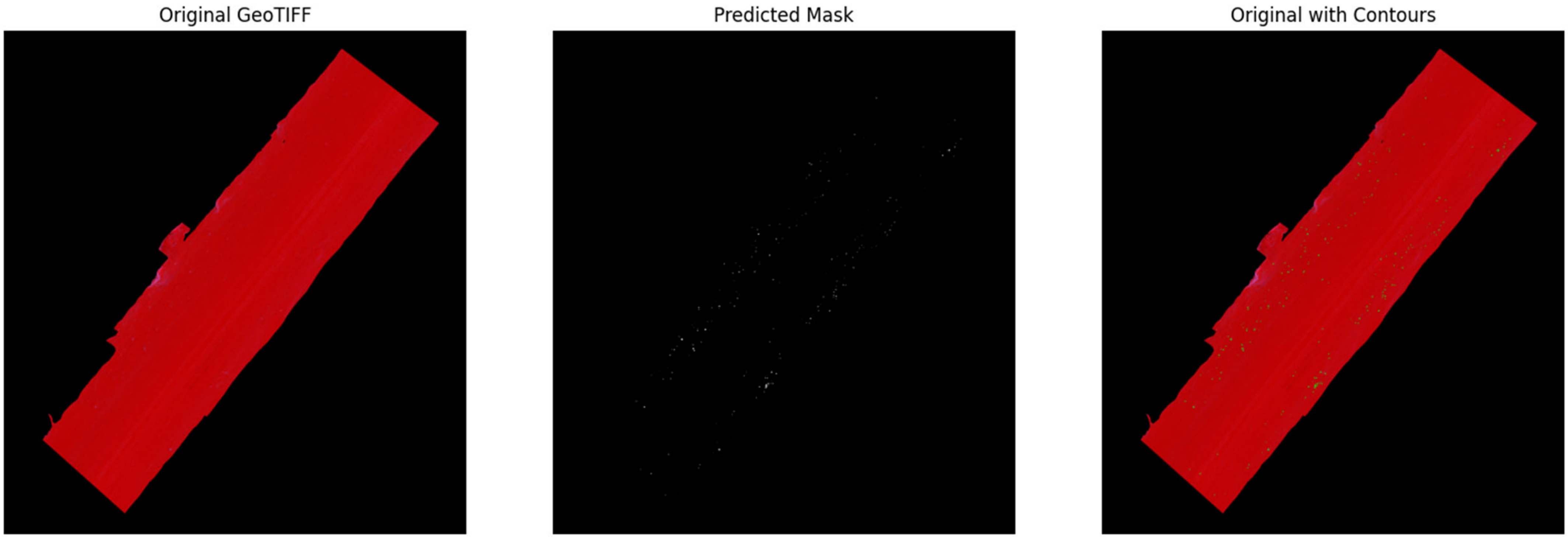
Original GeoTIFF
Predicted Mask
Original with Contours