GENERATIVE ADVERSARIAL NETWORKS AS A NOVEL APPROACH FOR TECTONIC FAULT AND FRACTURE EXTRACTION IN HIGH-RESOLUTION SATELLITE AND AIRBORNE OPTICAL IMAGES

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Natural fractures & faults form dense, complex networks of curvilinear traces at ground surface

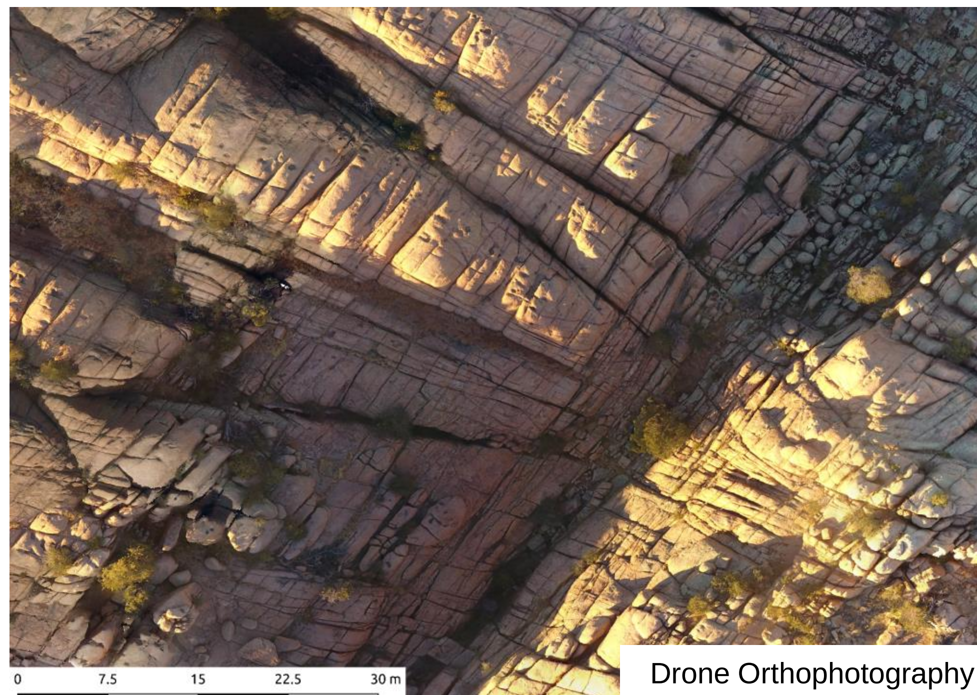
- Fractures and Faults are ubiquitous on Earth
- Responsible for earthquakes, landslides, reservoir fracturing, etc.
- Form dense complex networks
- Fault planes generally intersect ground surface, forming complex networks of curvilinear traces
- Mapping of fault traces commonly done manually at ground surface or in remote images – **But very time consuming**

→ Need to develop a fast, reliable and accurate automatic mapping method: DEEP LEARNING

Valley of Fire, Nevada

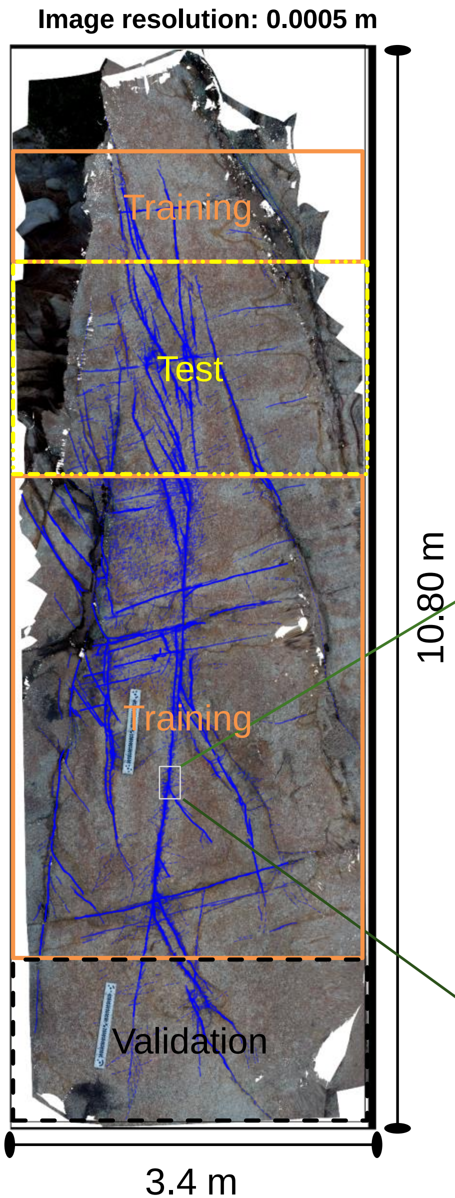
Field photogrammetry *(photo courtesy of I. Manighetti)*

Granite Dells, Arizona



Ground truth: optical images + manual fault maps

Example of a fault site in Granite Dells, Arizona

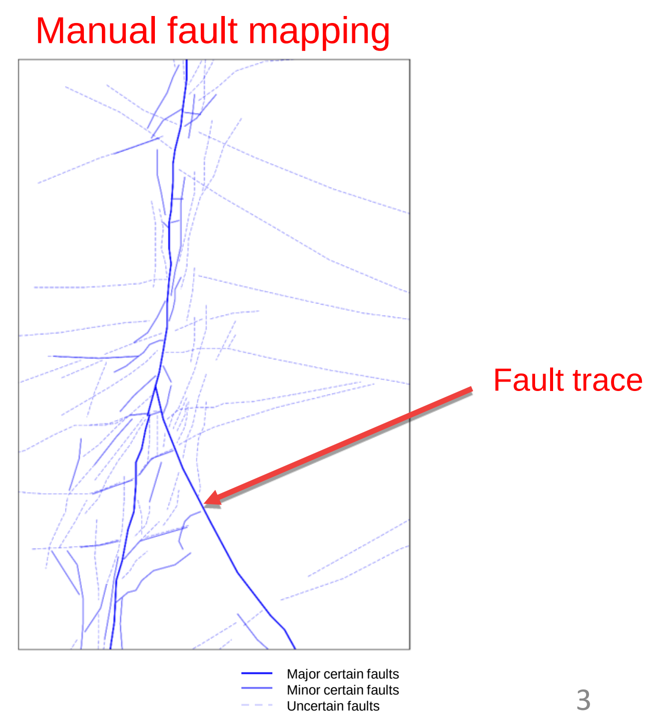


Ground truth:

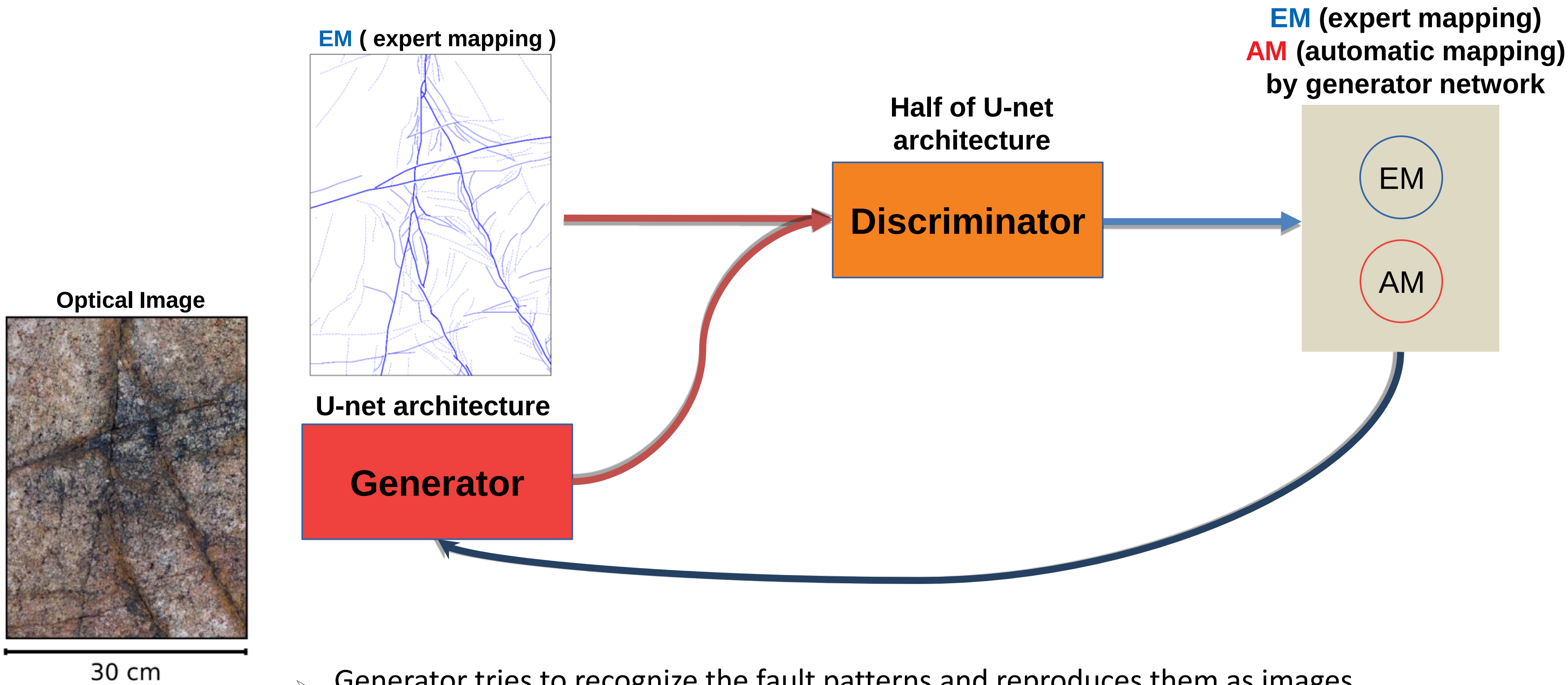
- Red, Green and Blue bands of georeferenced optical image
- Expert manual fault mapping

Approach:

- Actual thickness of fault traces (i.e., several pixels) represented with a Gaussian distribution function
- Binary approach, “fault – not a fault”
- 3840 images used for training

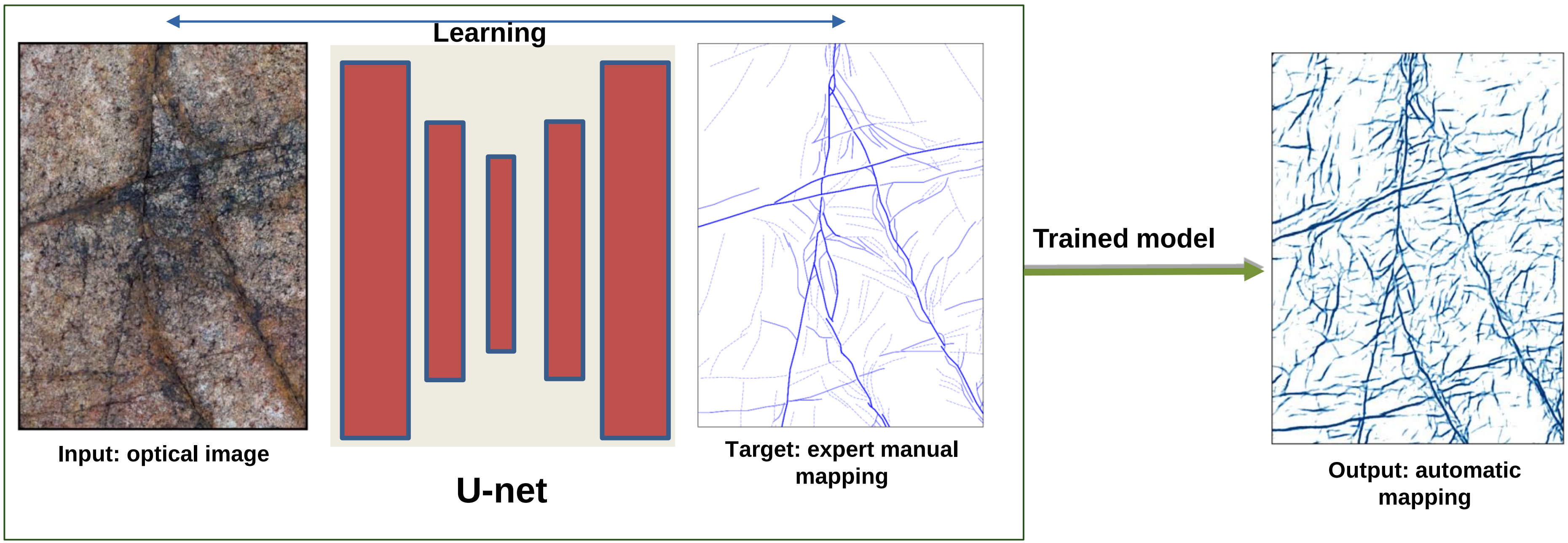


Testing Generative Adversarial Network (GAN) to map faults and fractures



- Generator tries to recognize the fault patterns and reproduces them as images
- Generator minimizes the difference between its synthetic fault images and the expert fault mapping
- Discriminator discriminates the expert and the synthetic mapping
- Based on the Discriminator feedback, the Generator network learns to map the faults more accurately

Testing CNN U-Net to map faults and fractures



- **Training stage:** the model learns from expert manual mapping how faults look like in optical image
- **Validation stage:** verifying model efficiency
- **Test stage:** Calculation of model accuracy

→ **Each stage = different images**

Network fed with different images in each training stage

Results: automatic fault extraction with GAN

Manual fault traces

1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0
0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0
0.0	0.0	0.0	1.0	1.0	0.0	0.0	0.0

Network output

1.0	0.4	0.1	0.3	0.0	0.5	0.5	0.5
0.5	0.9	0.1	0.3	0.5	0.4	0.9	0.3
0.3	0.2	0.5	0.1	0.4	0.8	0.1	0.1
0.2	0.3	0.2	0.7	0.8	0.4	0.4	0.6

Probability of being fault > 0.5

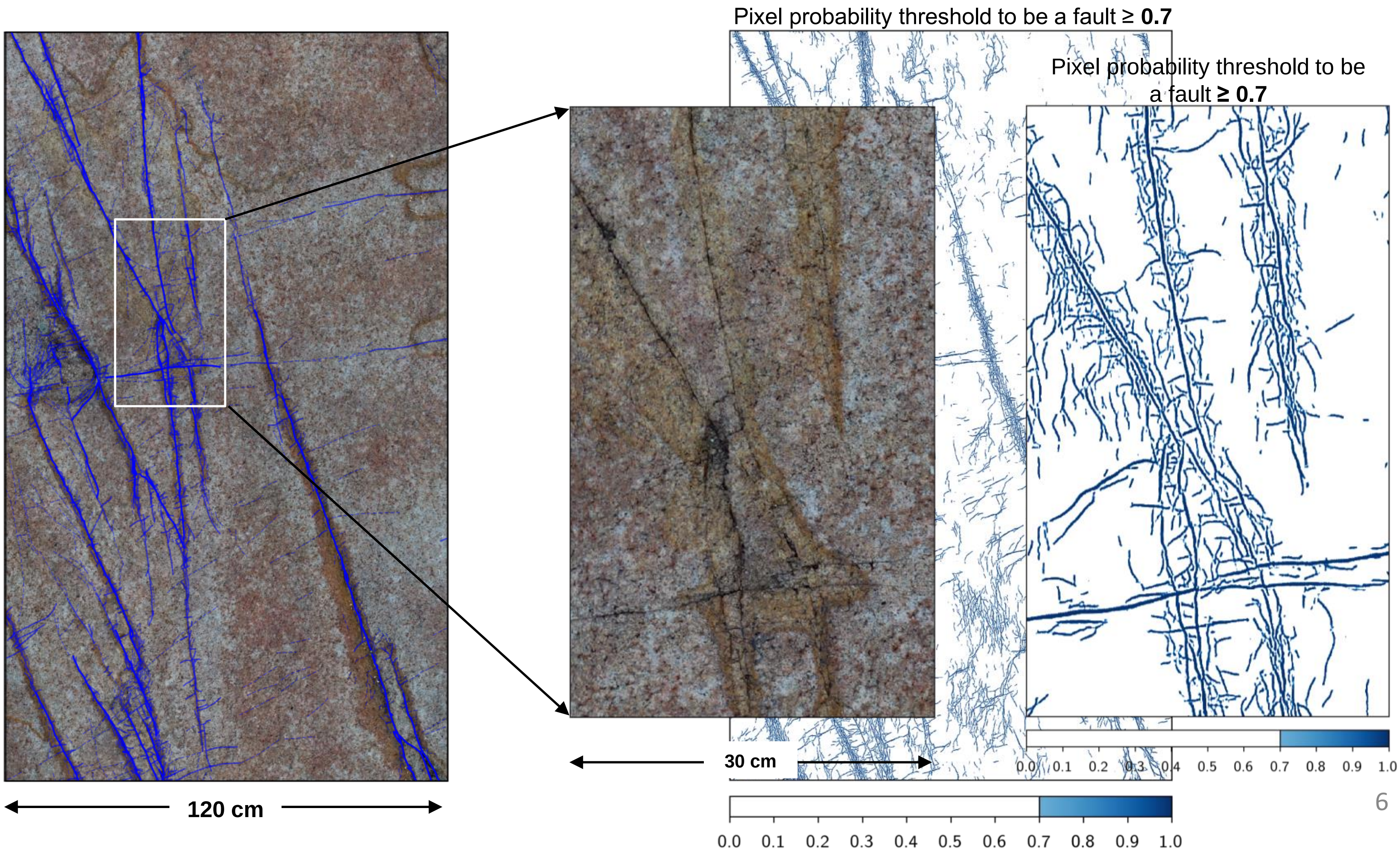
Probability > 0.5

1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0
0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
0.0	0.0	0.0	1.0	1.0	0.0	0.0	1.0

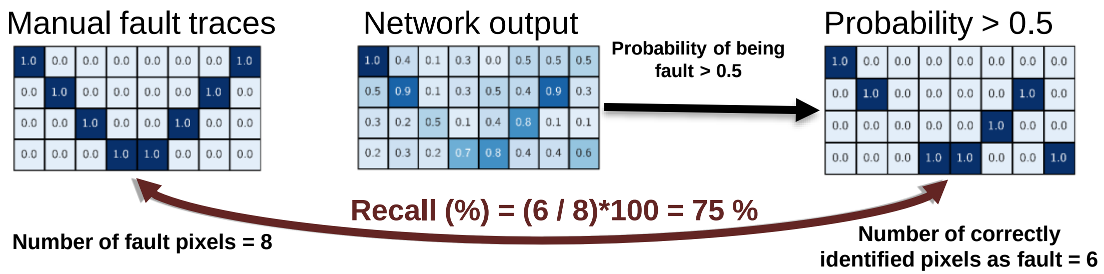
Number of fault pixels = 8

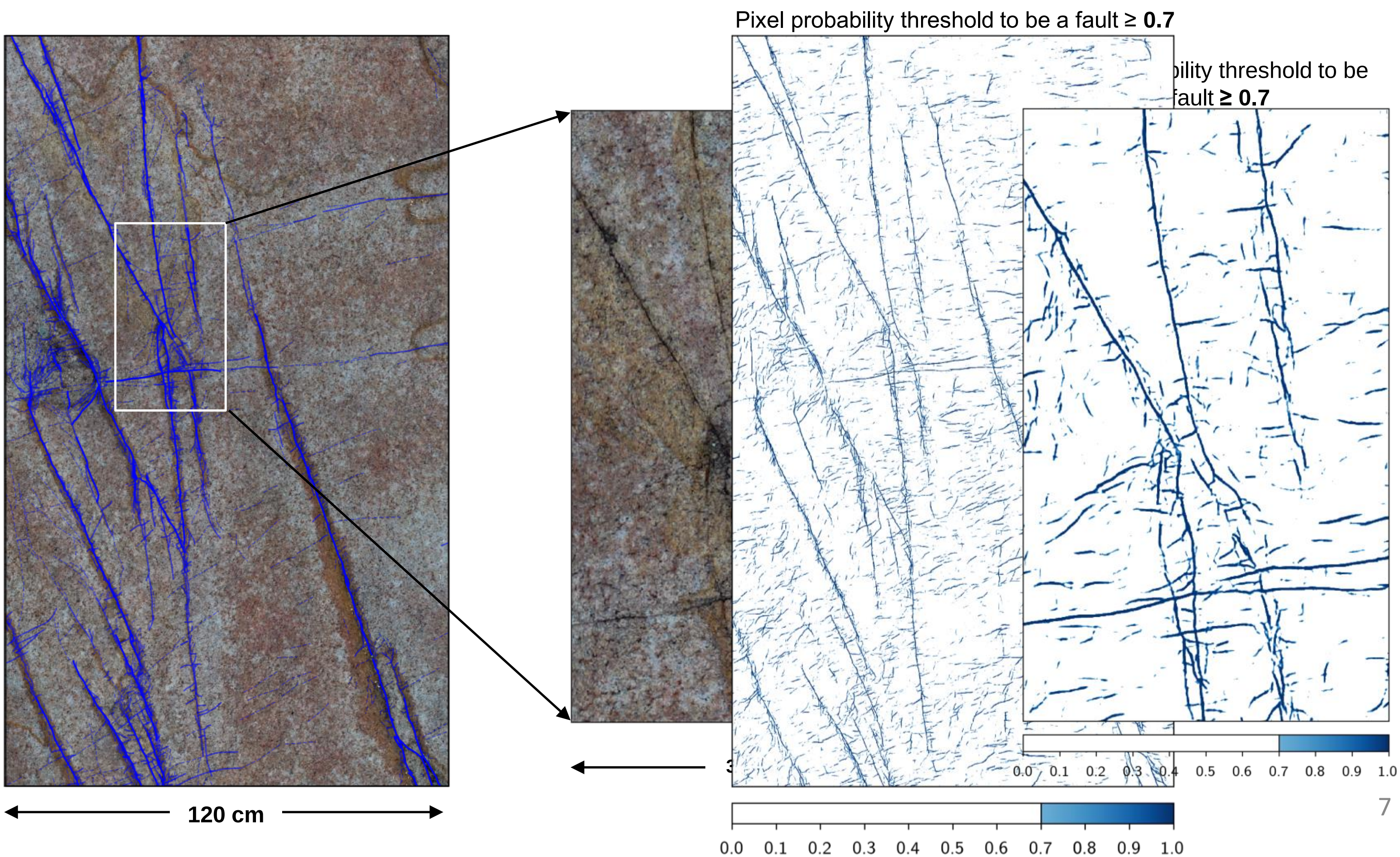
Recall (%) = (6 / 8)*100 = 75 %

Number of pixels correctly identified as fault = 6



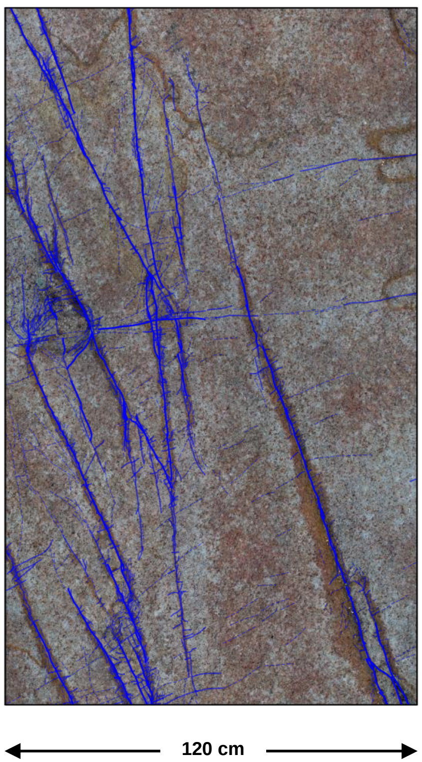
Results: automatic fault extraction with U-net

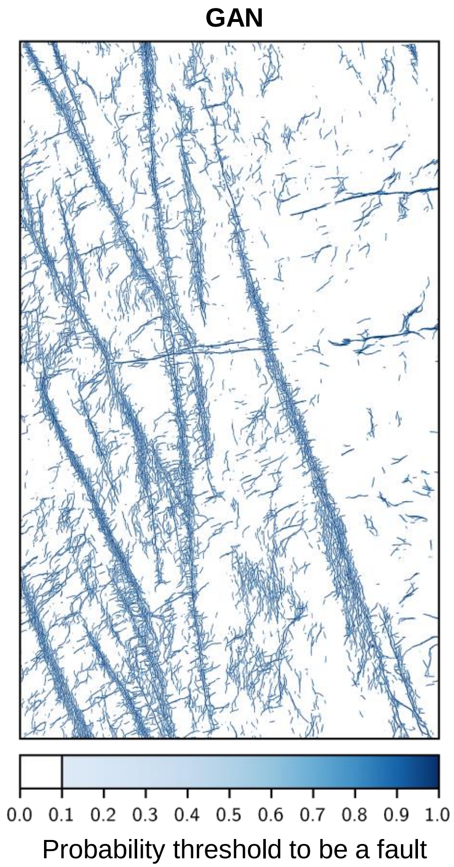


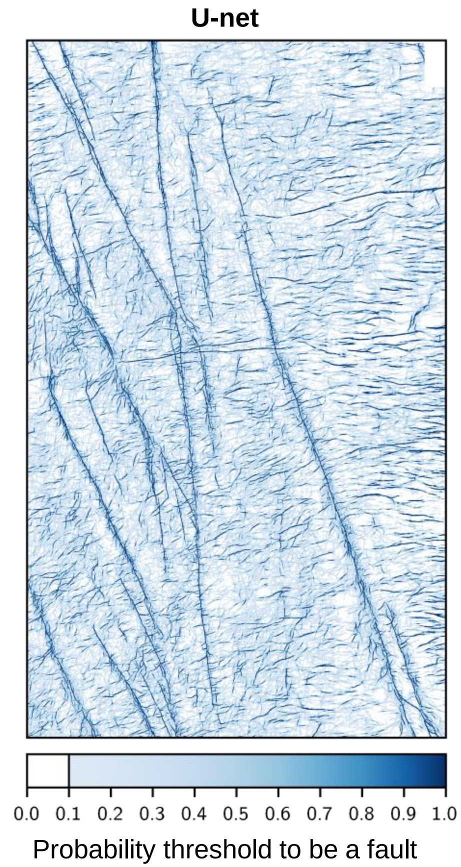


Results: comparison between U-net and GAN

GAN	➢ High GPU memory ➢ Longer training time (RTX 2080-11 GB, ~48 h) ➢ High probability values for identified faults ➢ More appropriate for fault pattern simulation
U-net	➢ High GPU memory ➢ Shorter training time(RTX 2080-11 GB, ~24 h) ➢ Different probability values for identified faults ➢ More appropriate for fault identification

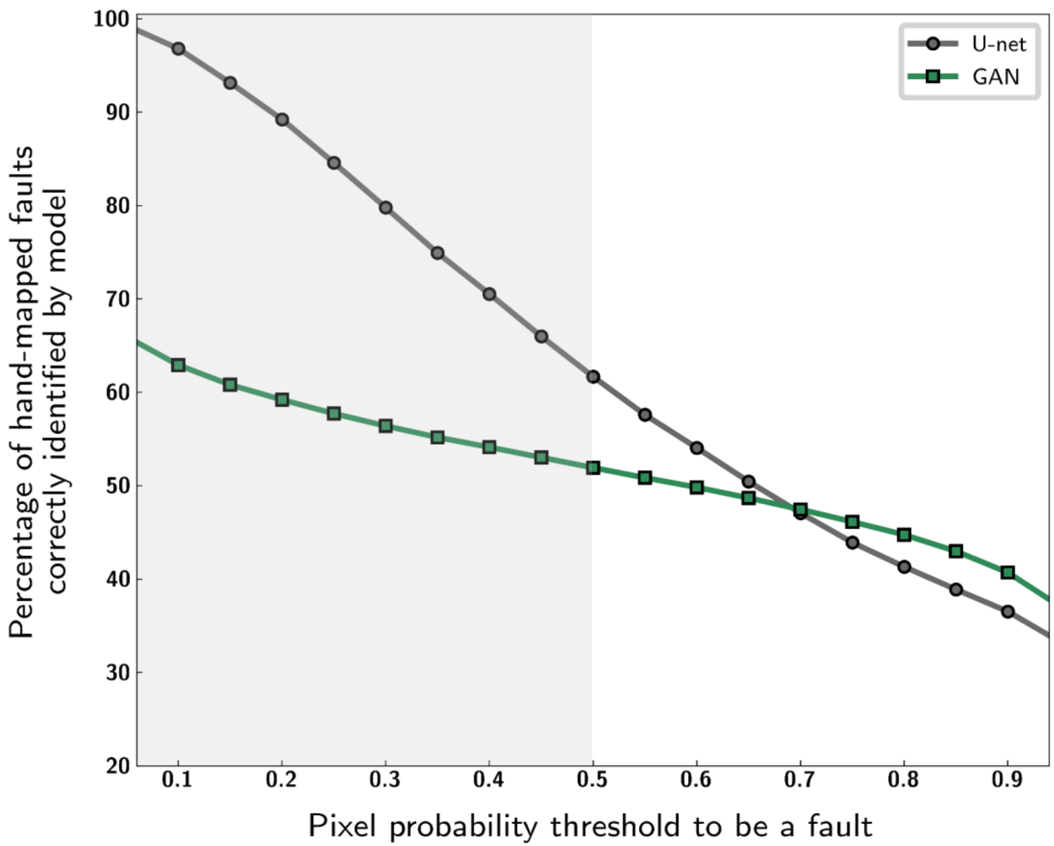






Results: comparison between U-net and GAN

GAN	➢ High GPU memory ➢ Longer training time (RTX 2080-11 GB, ~48 h) ➢ All identified faults with high probability ➢ More appropriate for fault pattern simulation	**U-net**	➢ High GPU memory ➢ Shorter training time(RTX 2080-11 GB, ~24 h) ➢ Different probability values for identified faults ➢ More appropriate for fault identification



Conclusions

- **U-net more appropriate for fault mapping in optical images**
- With U-net, **more than 60% of the hand-mapped faults are correctly identified**
- Although trained with a small dataset, the model has **good generalization ability**: it well predicts faults in unseen parts of the image

Perspectives

- **Examine further the generalization ability** of the models (use model to extract faults from different image types and resolutions, including satellite and aerial images)
- **Predict the hierarchy of the faults:** major faults, minor faults, more uncertain faults
- Convert the predicted probabilities into **vector lines for statistical analysis of fault networks** : lengths, densities, azimuths, cross-cutting relations, etc.
- **Quantitative description of fault networks**, useful for rock mechanics and earthquake physics