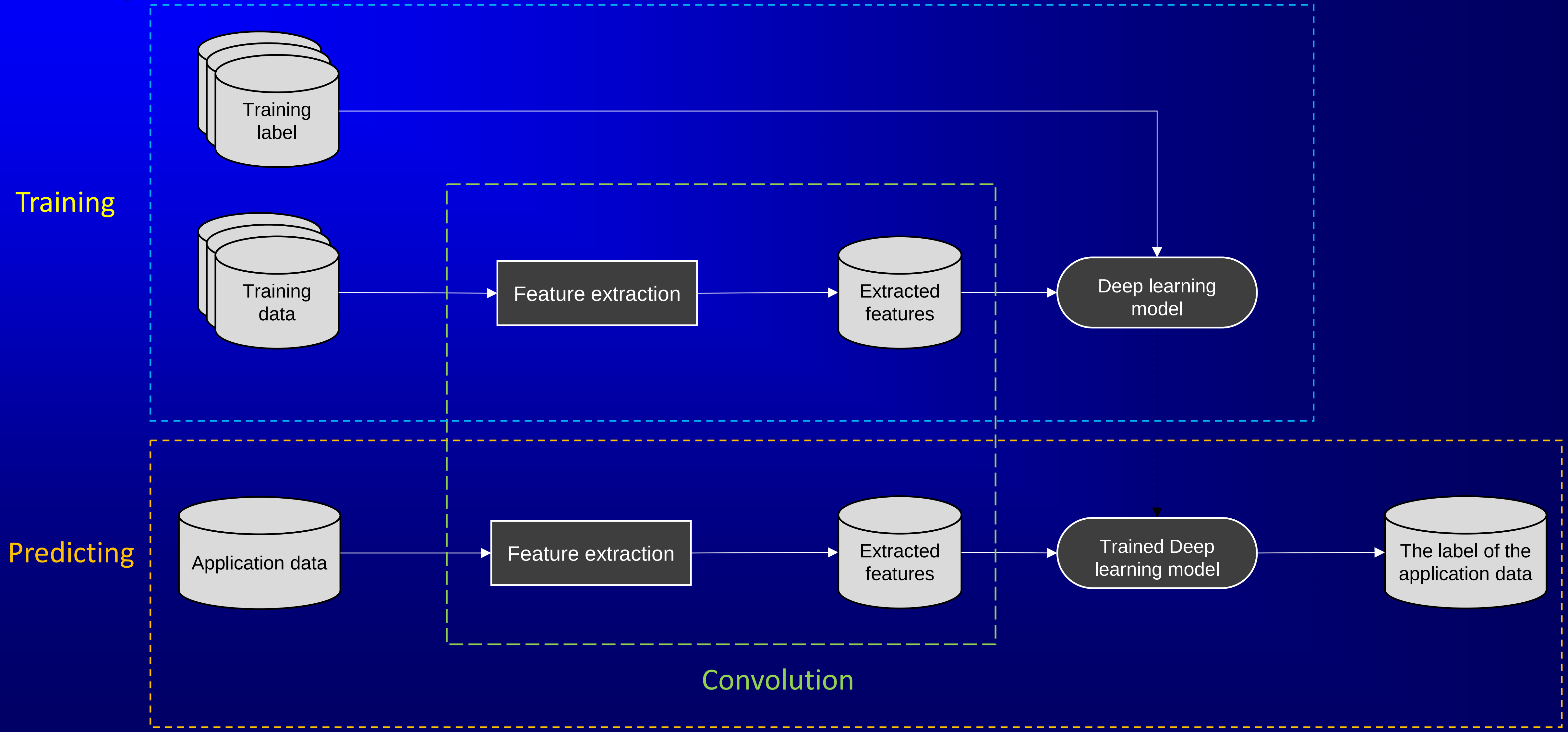
Seismic Attributes - from Interactive Interpretation to Machine Learning

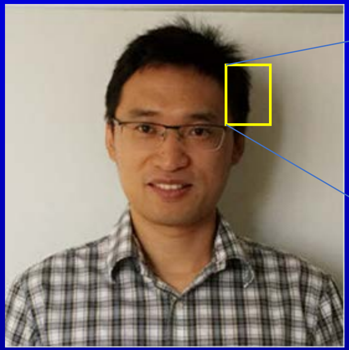
Jie Qi and Kurt J. Marfurt
(The University of Oklahoma)

Deep Learning and CNN fault detection

A deep learning workflow



Convolutional Neural networks



1	0	1	2	0
2	4	4	4	4
1	4	0	4	1
4	4	2	4	1
0	0	0	1	2

*

0	1	0
0	1	0
0	1	0

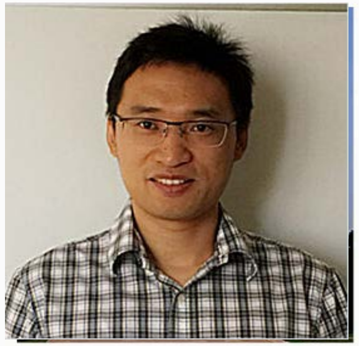
=

8	5	10
12	6	12
8	2	9

Age?

Sharpen:

0	0	0	0	0
0	0	-1	0	0
0	-1	5	-1	0
0	0	-1	0	0
0	0	0	0	0

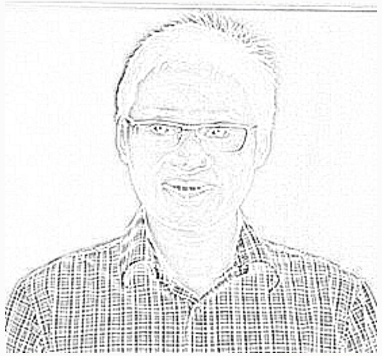


Blur:

0	0	0	0	0
0	1	1	1	0
0	1	1	1	0
0	1	1	1	0
0	0	0	0	0

Edge Detect:

	0	1	0	
	1	-4	1	
	0	1	0	

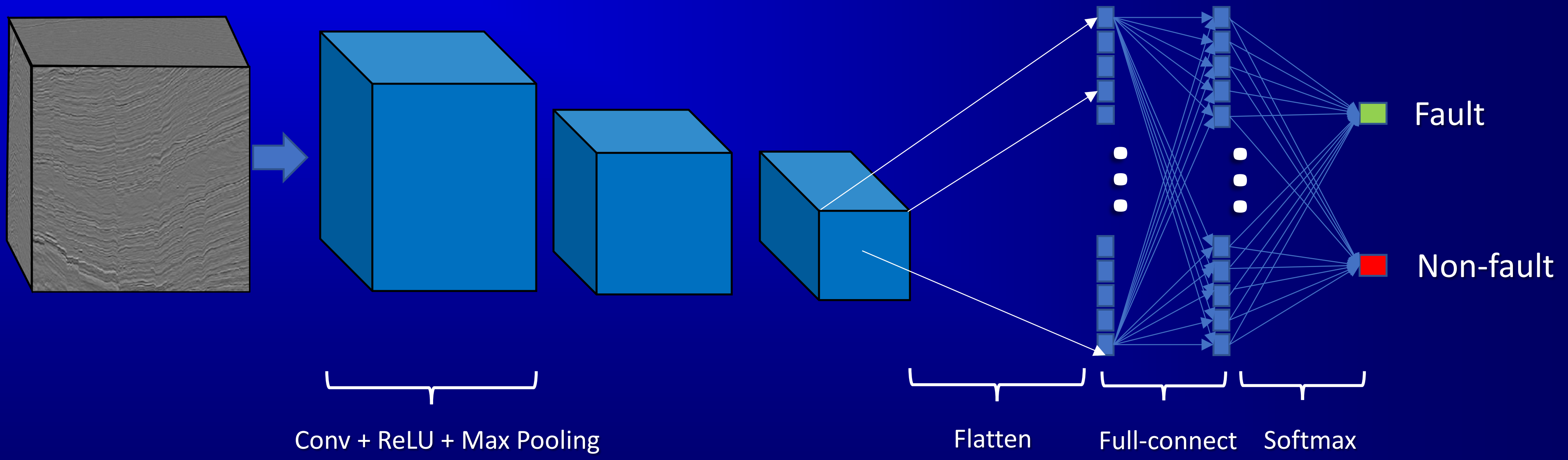


https://www.superdatascience.com/blogs/the-ultimate-guide-to-convolutional-neural-networks-cnn

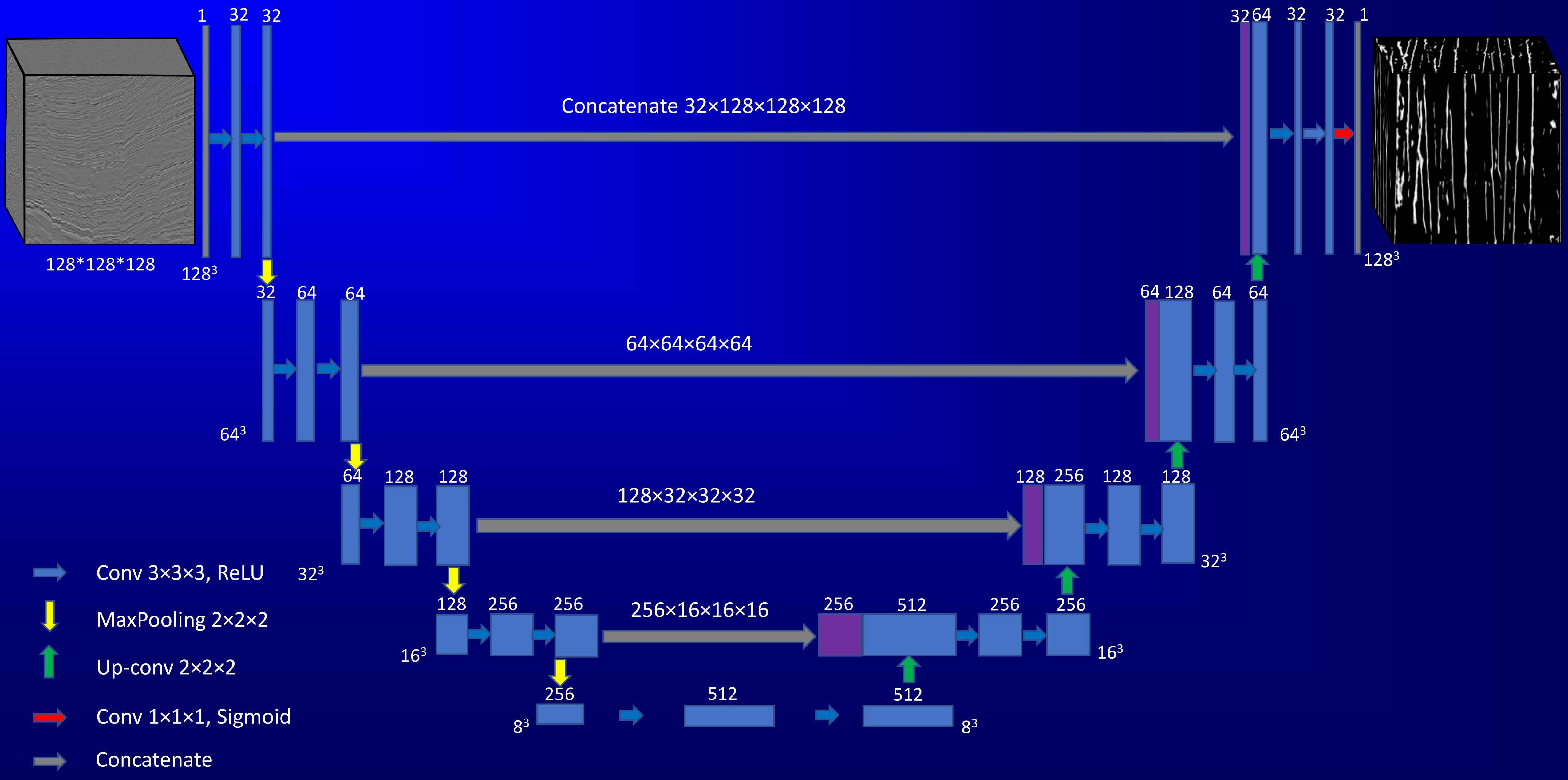
CNN workflow

- Generate training seismic images and label images
- Build a convolutional neural network model
- Train and validate the model with training seismic images and label images
- Feed the application seismic data to the model for prediction

Typical architecture of a CNN model



The U-Net

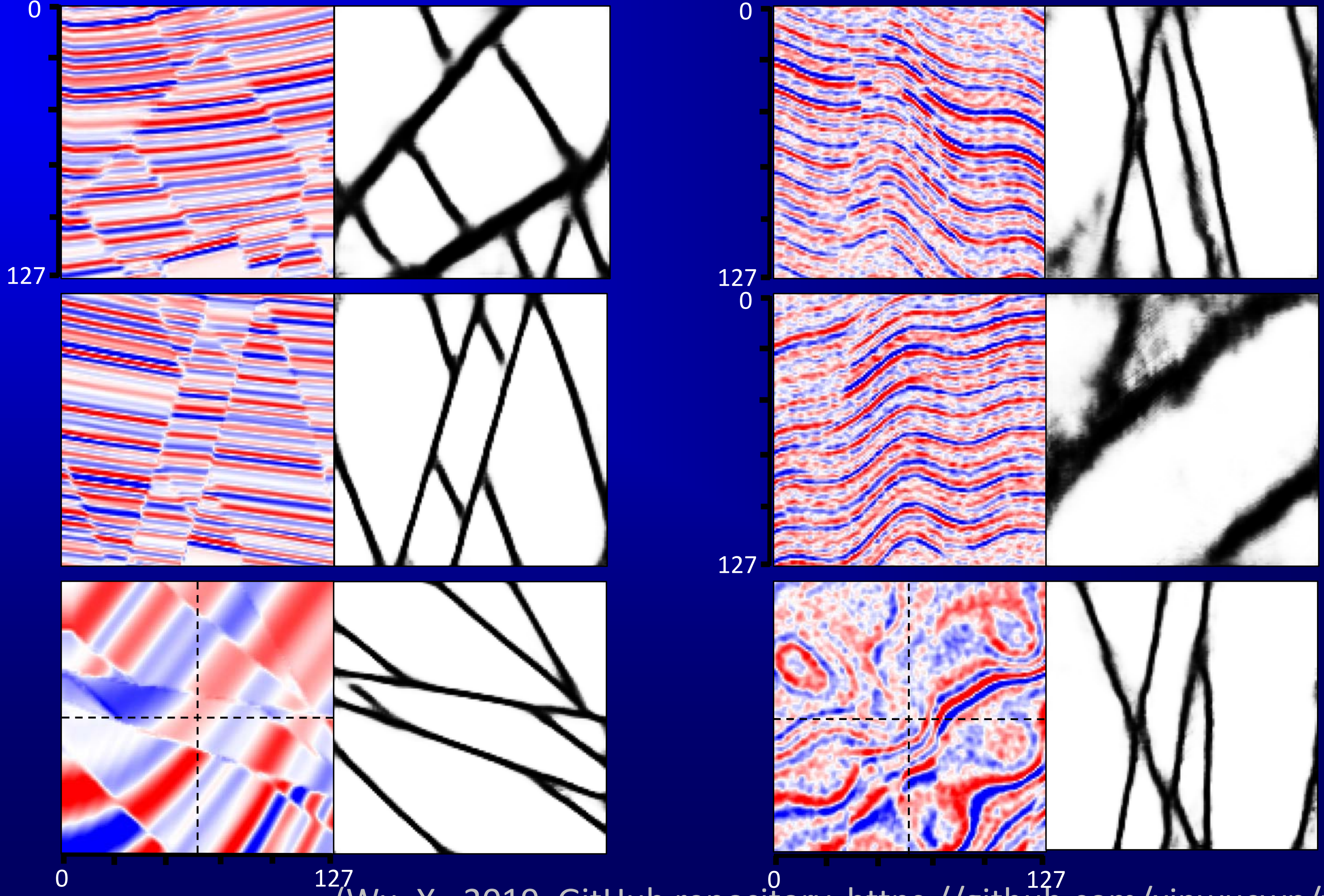


1
32
32
128*128*128
128^3
Concatenate 32×128×128×128
32
64
32
32
1
128^3
32
64
64
64^3
64×64×64×64
64
128
64
64
64^3
64
128
128
32^3
128×32×32×32
128
256
128
128
32^3
128
256
256
16^3
256×16×16×16
256
512
256
256
16^3
256
8^3
512
512
8^3
Conv 3×3×3, ReLU
MaxPooling 2×2×2
Up-conv 2×2×2
Conv 1×1×1, Sigmoid
Concatenate

U-Net architecture

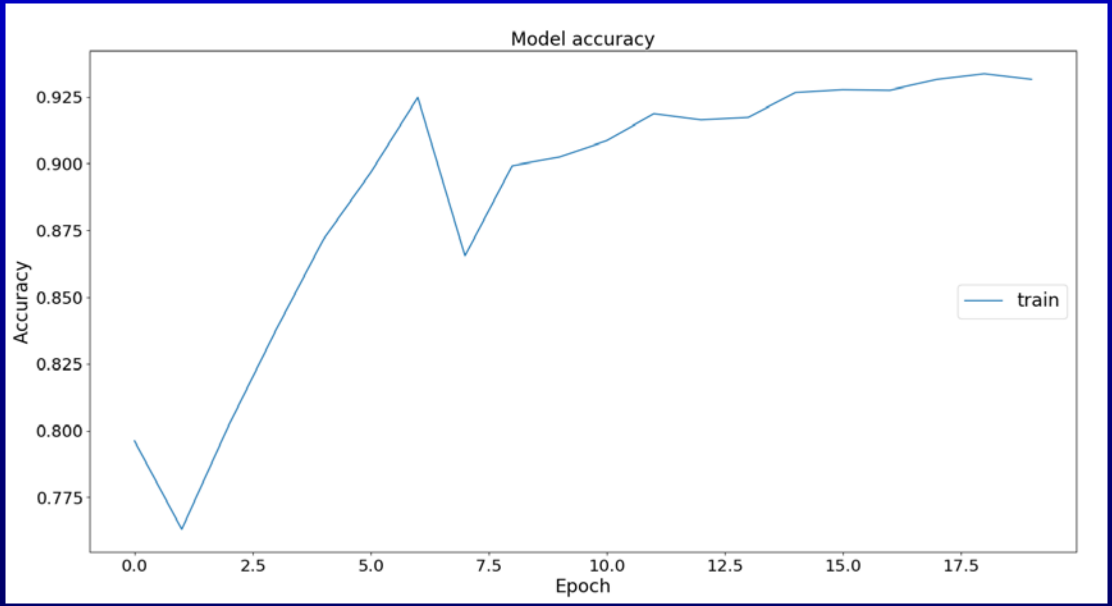
- Consists of a contracting path (capture features) and an expansive path (localization);
- A fully convolutional network without any fully connected layers;
- Increases the resolution of the output by supplying successive layers;
- Allows to input the full context;
- Needs to extrapolate the context at the border region.

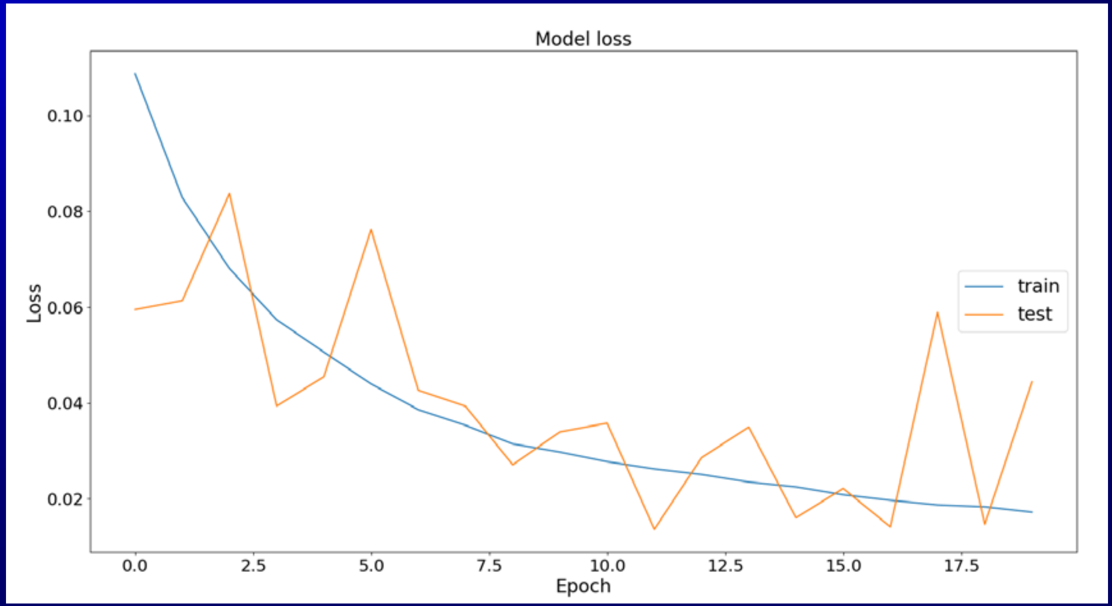
Training volumes



(Wu, X., 2019, GitHub repository, https://github.com/xinwucwp/faultSeg)

Training and validation





Application to steep normal faults (an easy problem)

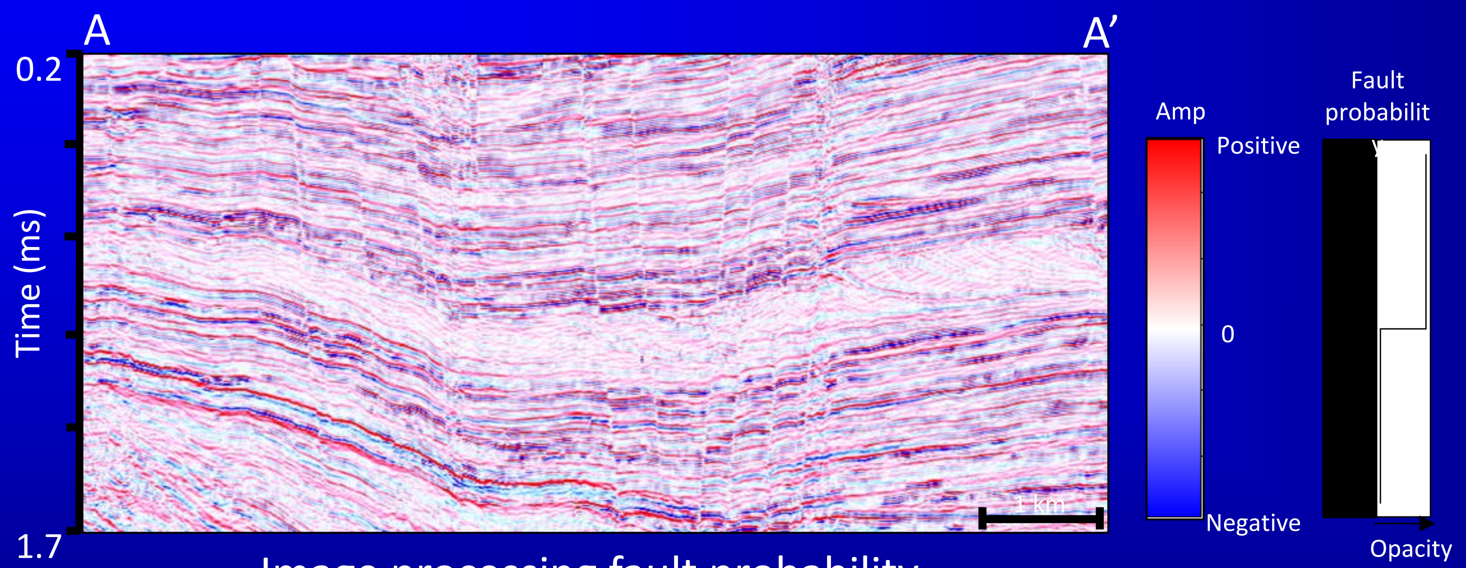
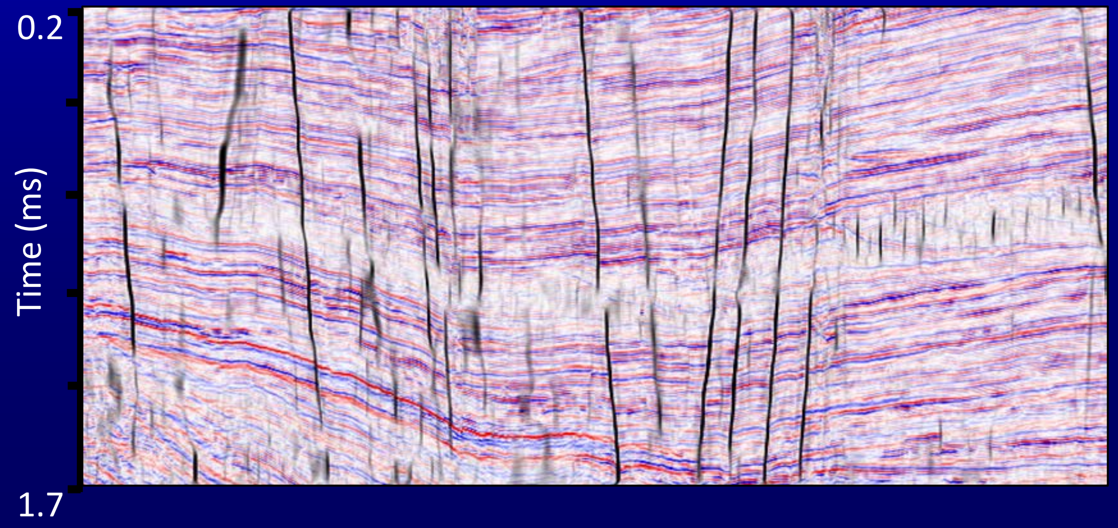
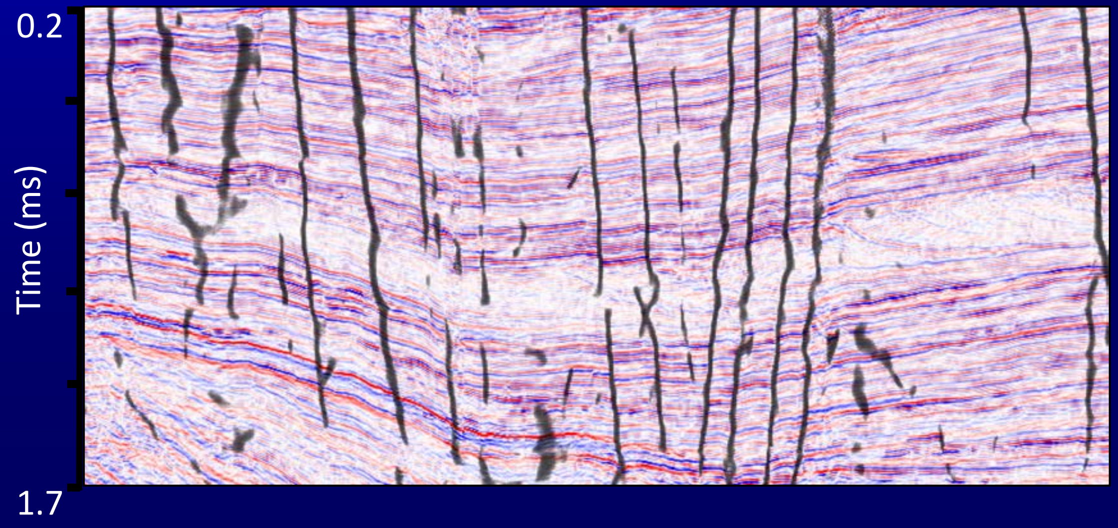


Image processing fault probability



CNN fault probability



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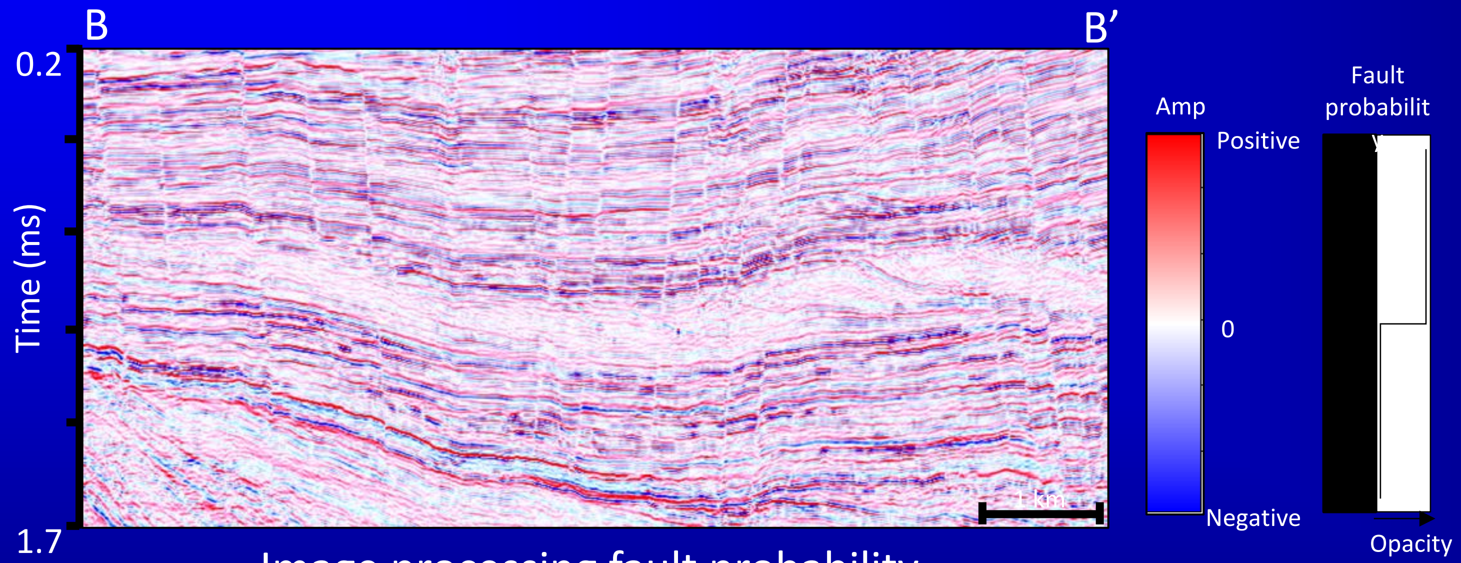
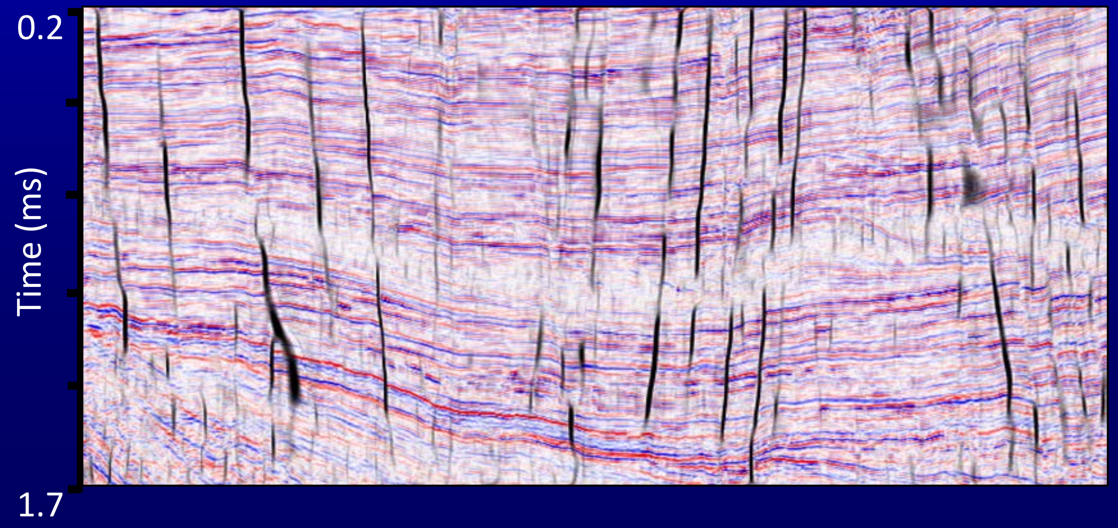
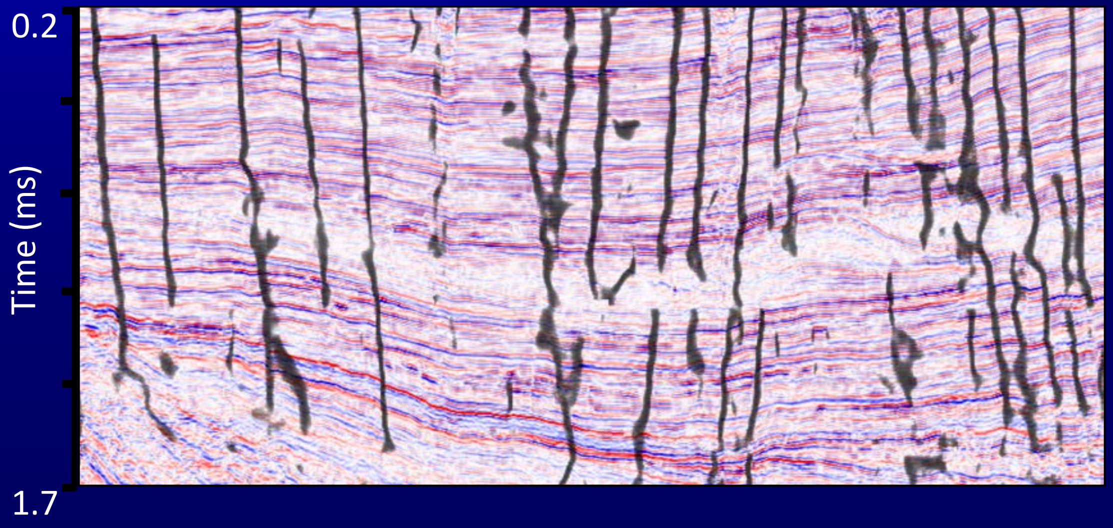


Image processing fault probability



CNN fault probability



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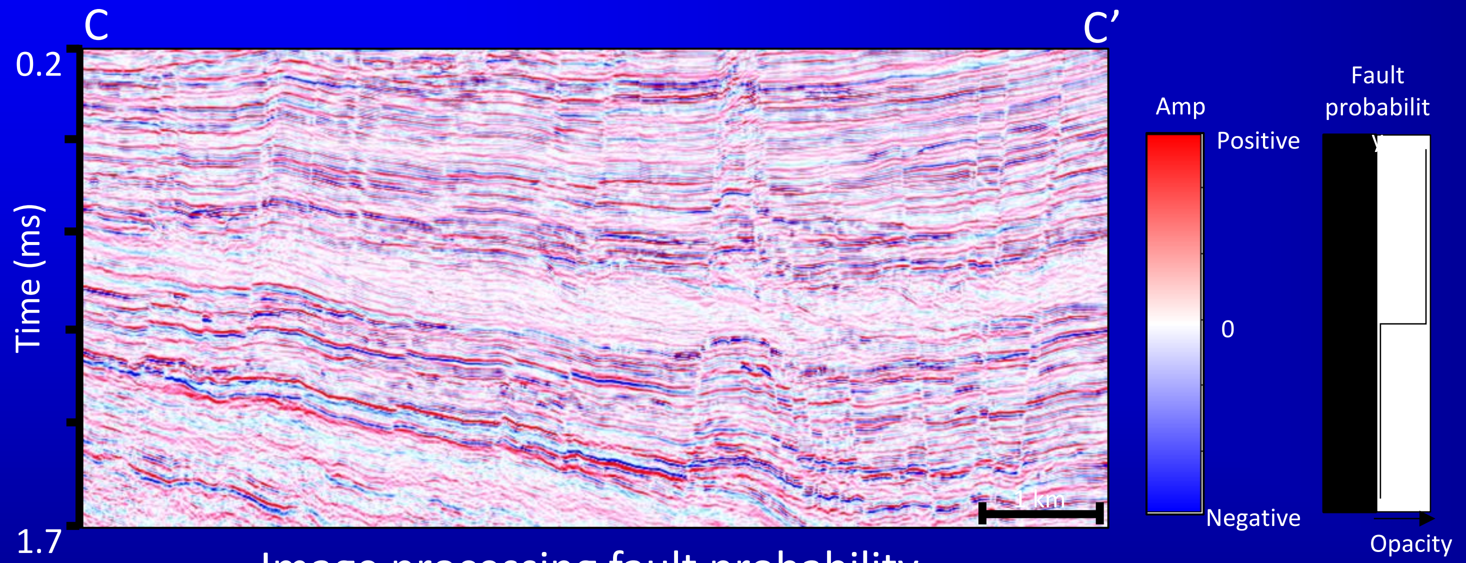
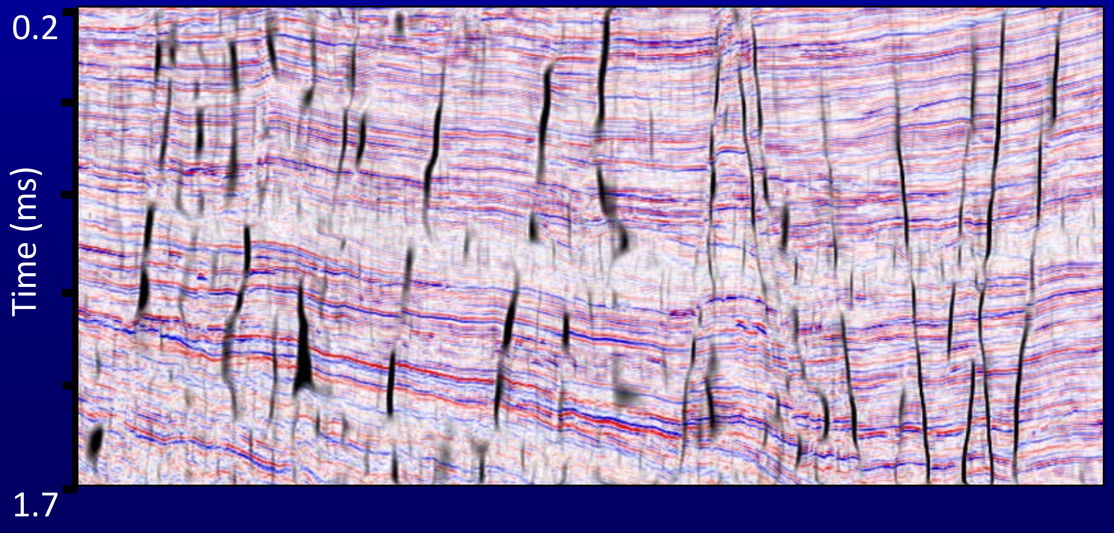
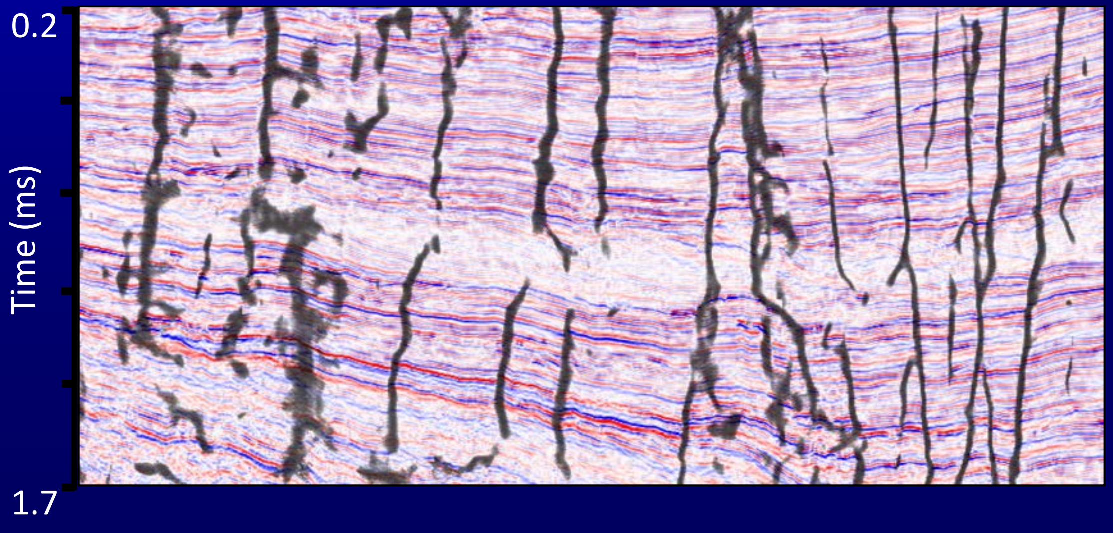


Image processing fault probability



CNN fault probability



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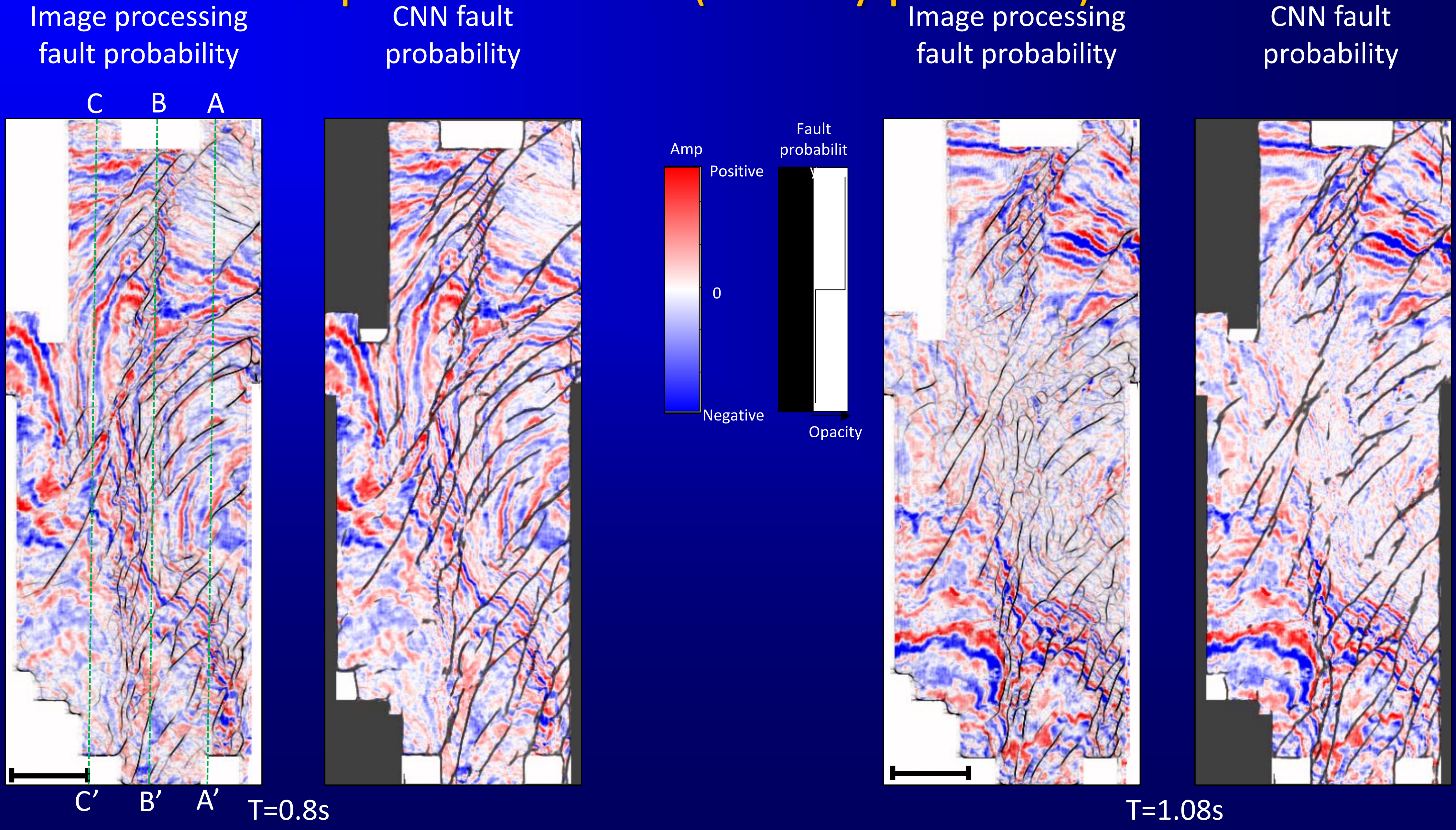
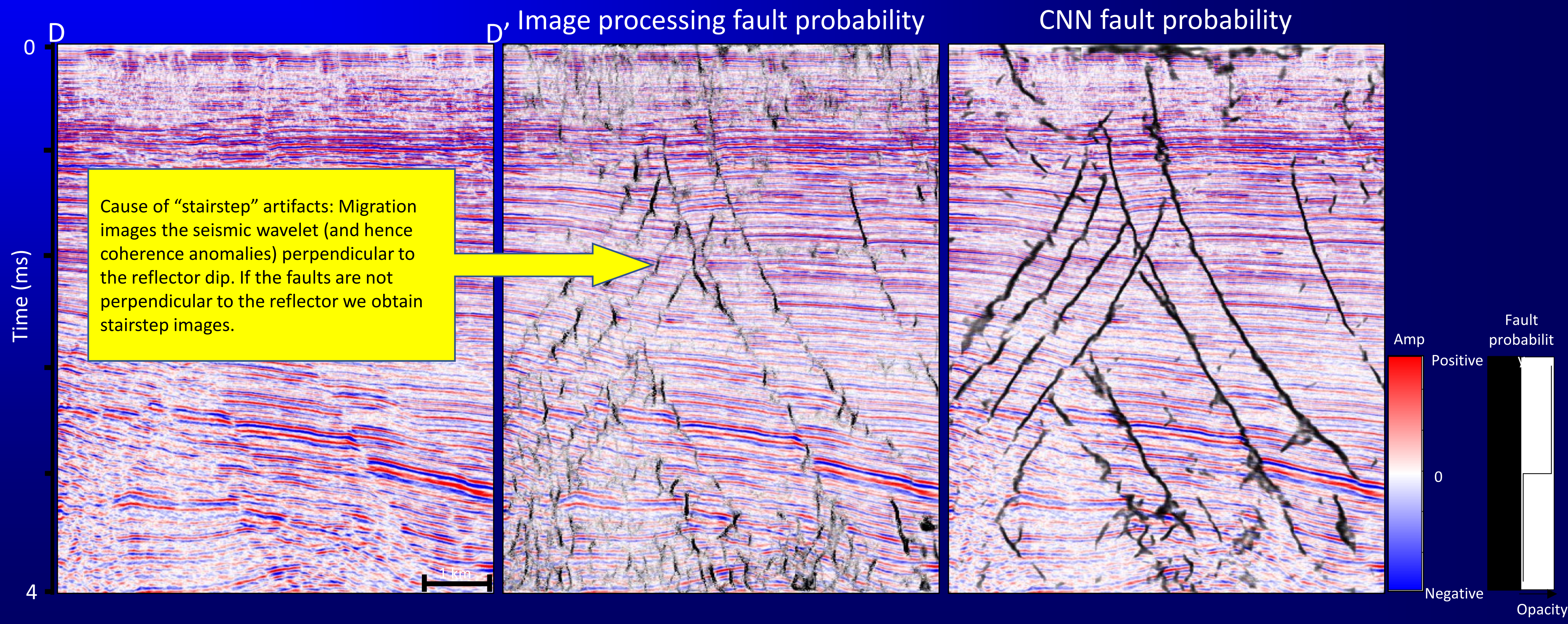


Application to moderate angle faults (an intermediate problem)



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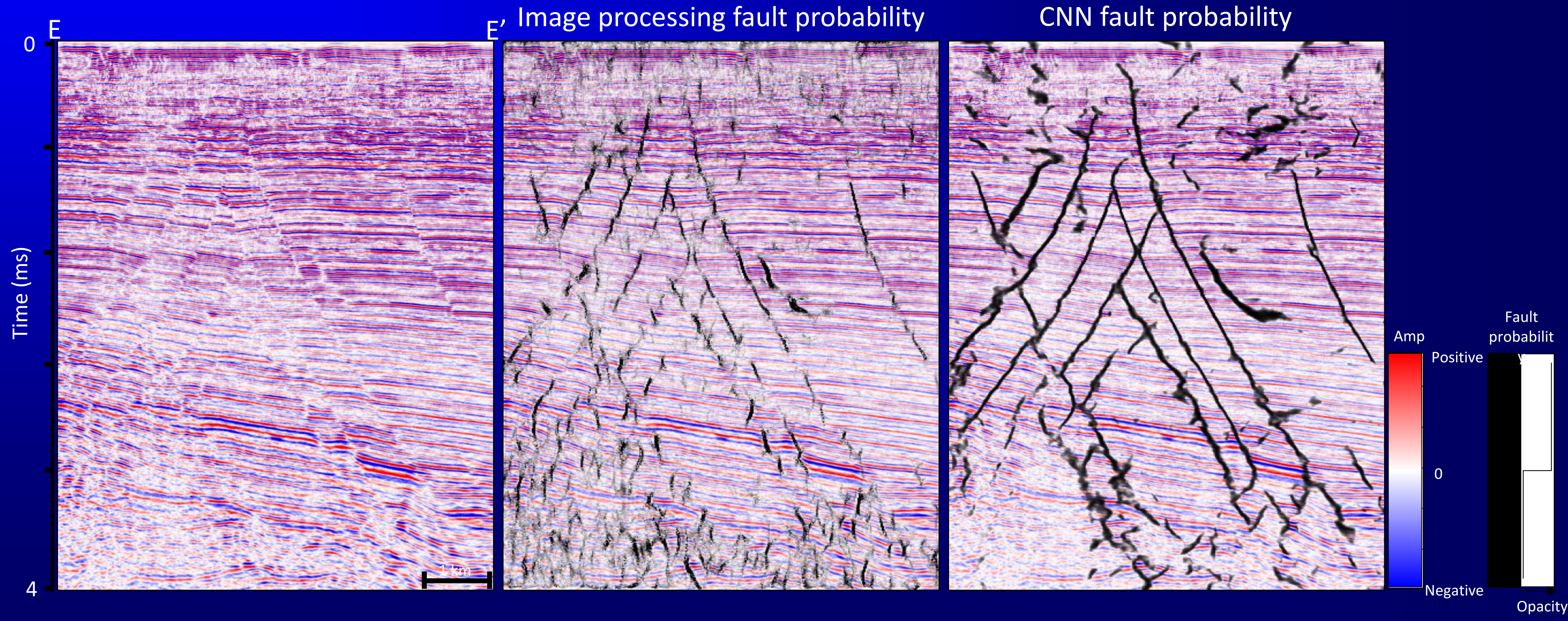

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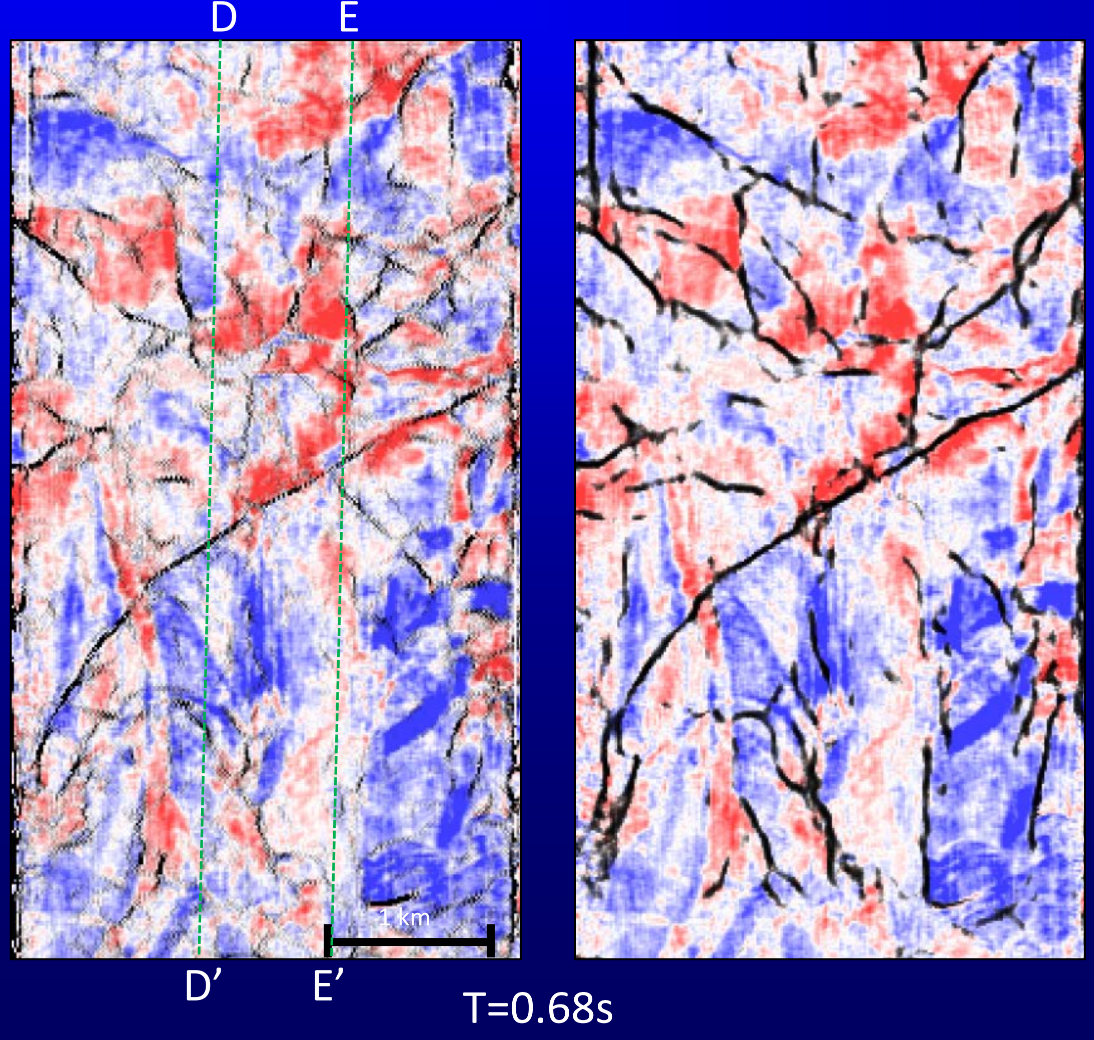
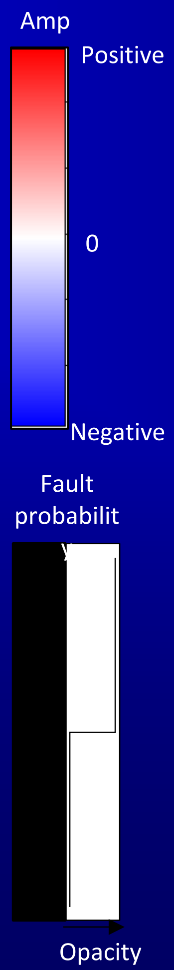
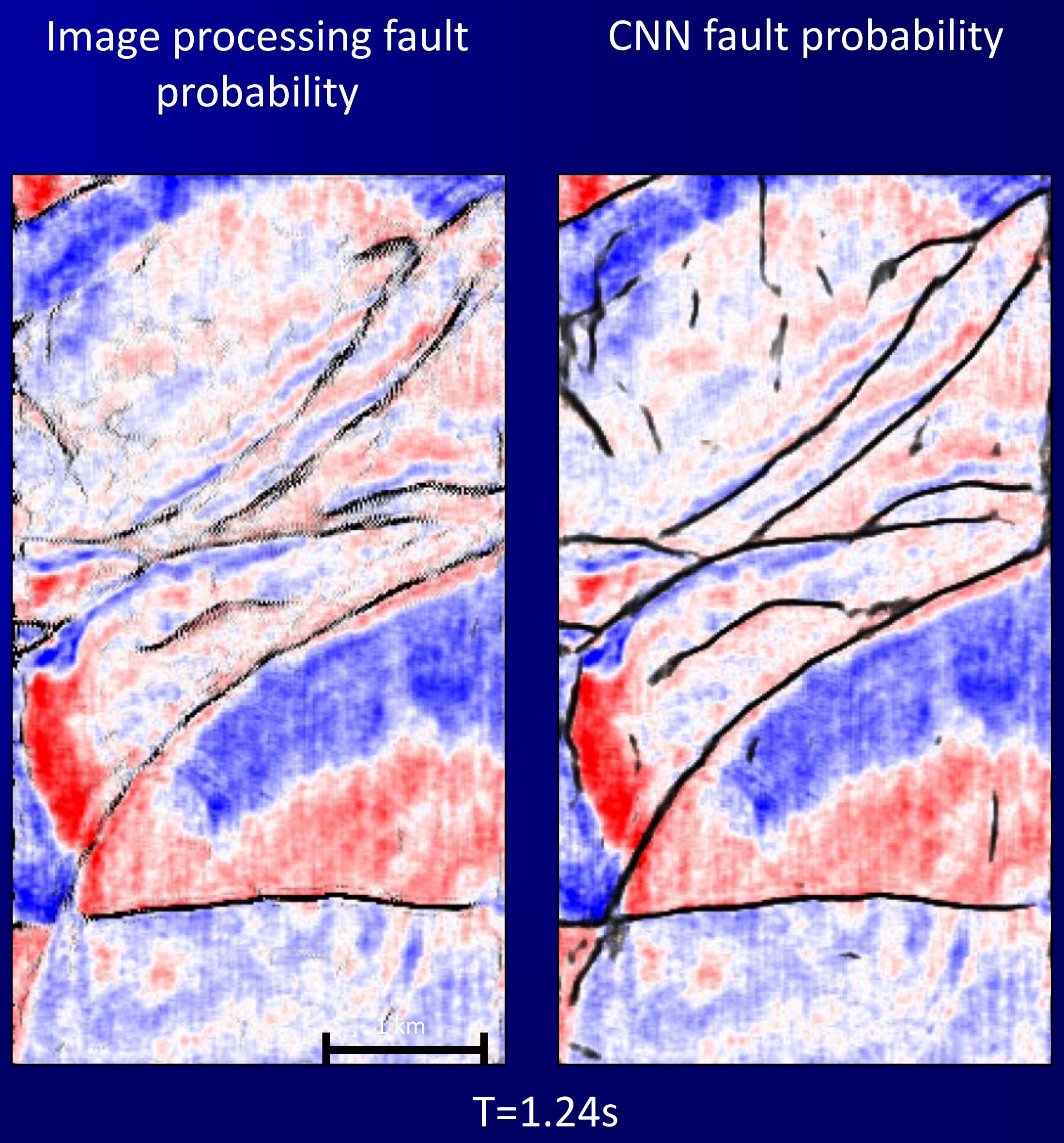
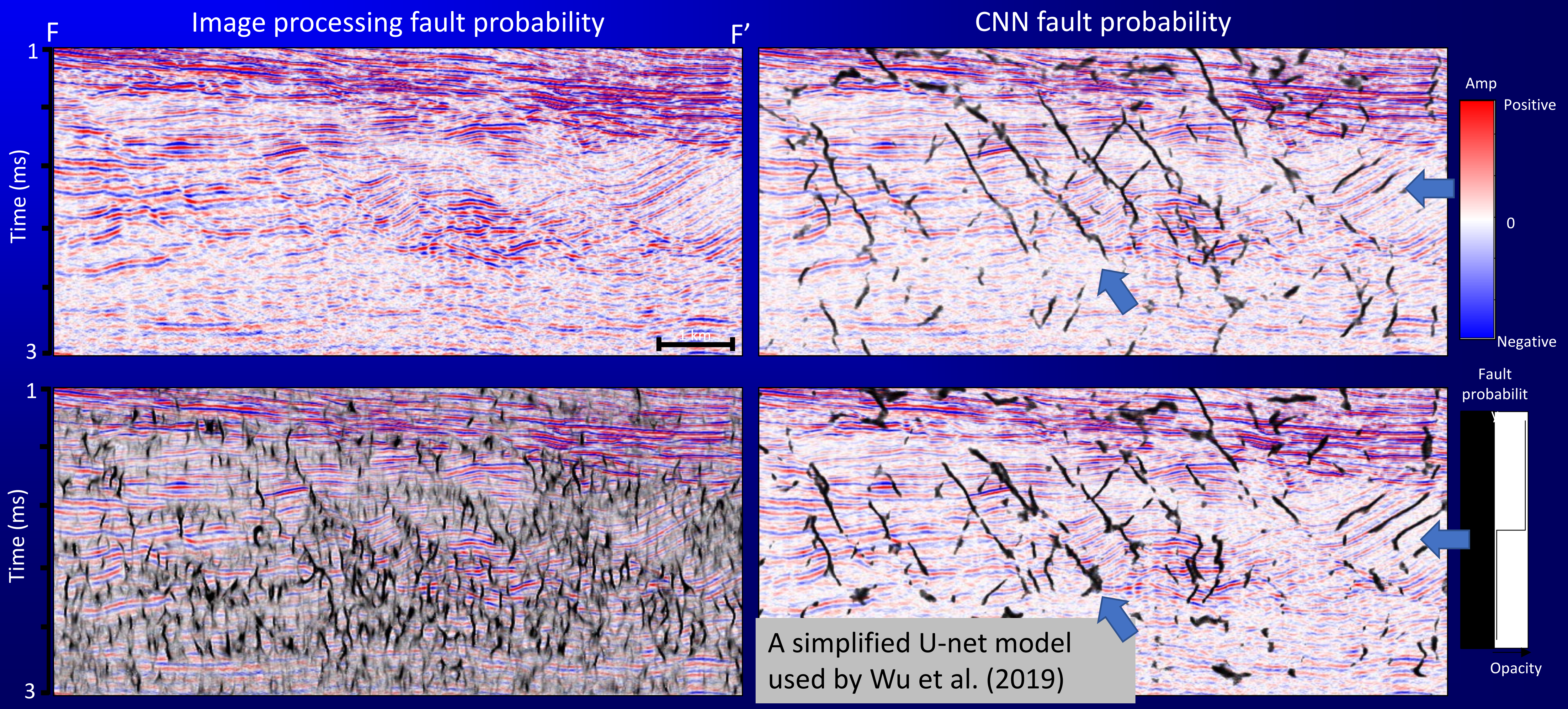






Application to listric faults (a difficult problem)



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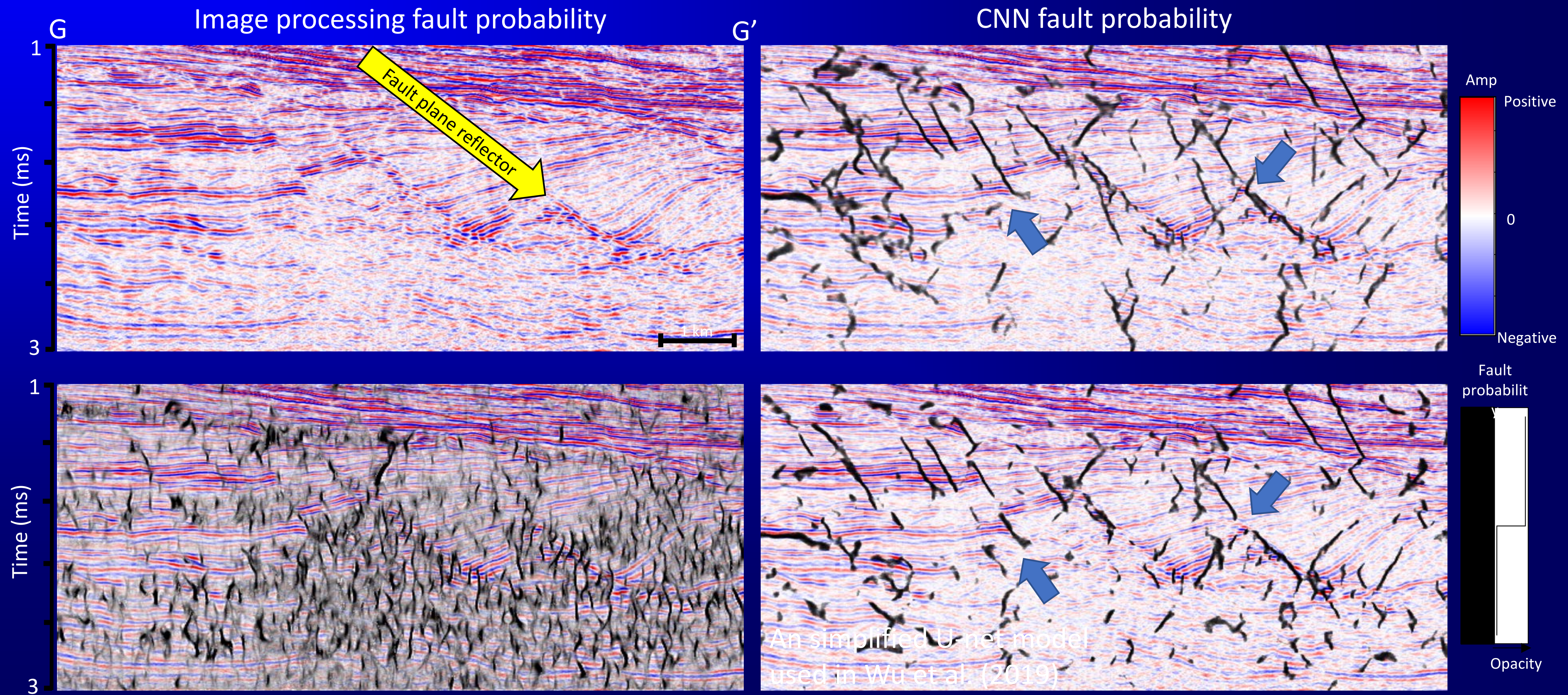


Application to listric faults (a difficult problem)

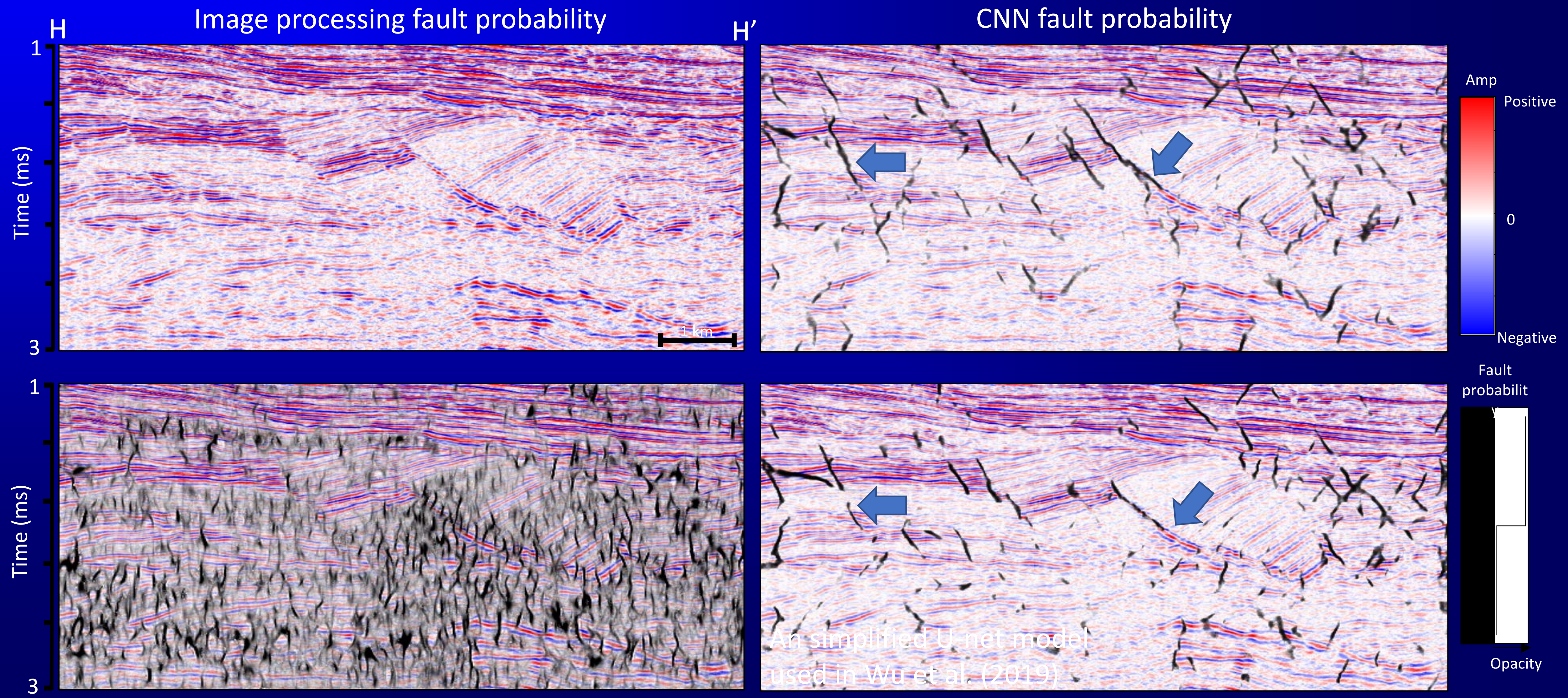
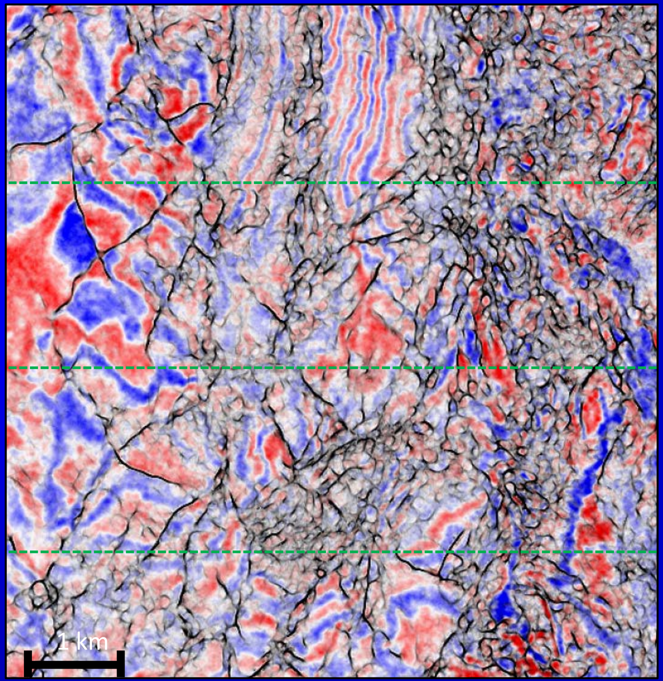


Image processing fault probability

T= 1.52s

H H'
G G'
F F'



CNN fault probability

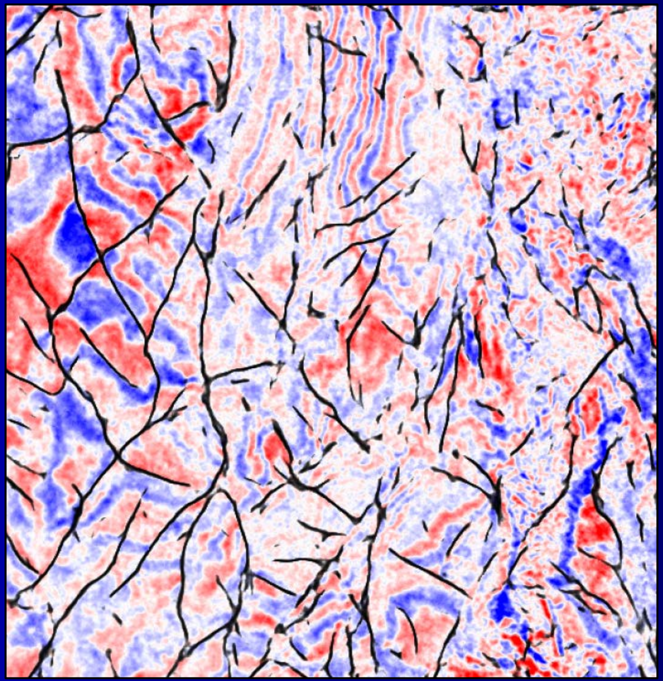
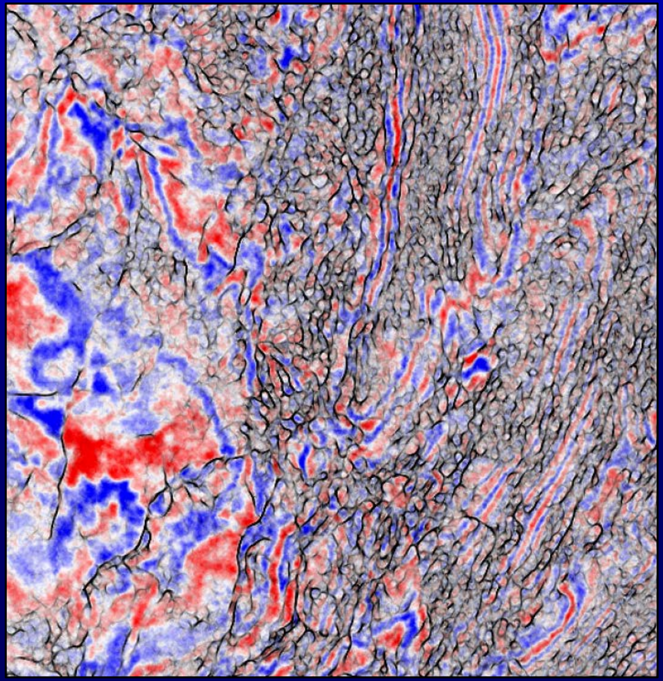
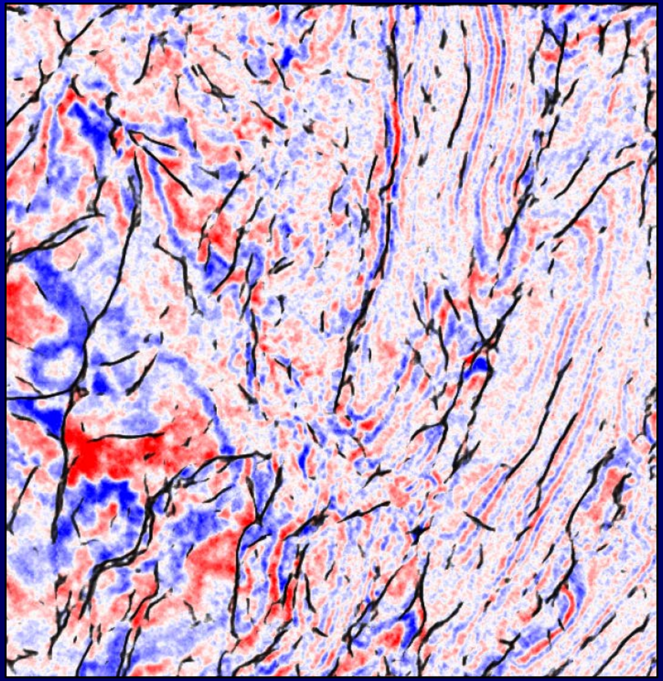


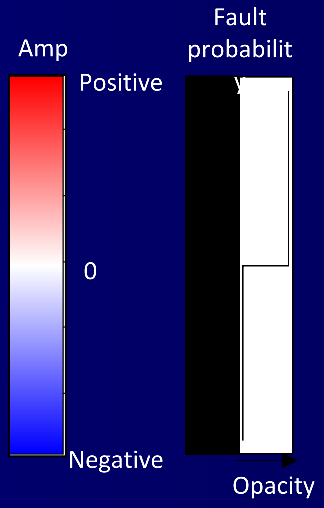
Image processing fault probability

T= 2s



CNN fault probability





Conclusions

- The U-Net architecture CNN performs well on fault detection without any human-computer interactive work;
- The CNN model trained by the synthetic training volumes can be applied to different data;
- The computation cost on training a CNN model is high, but extremely low on data prediction;
- The CNN method was trained only to be sensitive to faults, resulting in two classes – a fault, and not-a-fault;
- The CNN method does better than image processing in detecting faults with shallower dips, including those represented by fault-plane reflections;
- CNN images do not generate stair-step artifacts.

Future plans

- Generate more complex models for CNN training;
- Allow the CNN model to be trained by cropped 3D real data volumes;
- Allow interpreters to select synthetic or real data to train a new model;

References

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