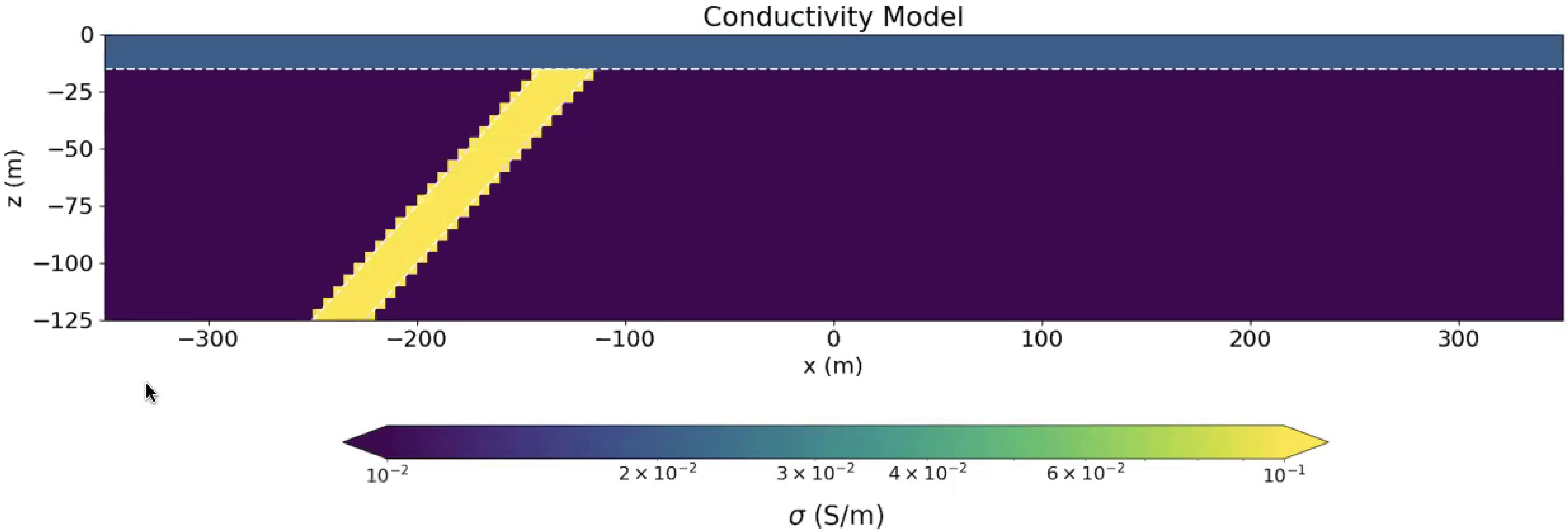
Leveraging Convolutional Neural Networks for implicit regularization in DC resistivity inversions (DIP-Inv)

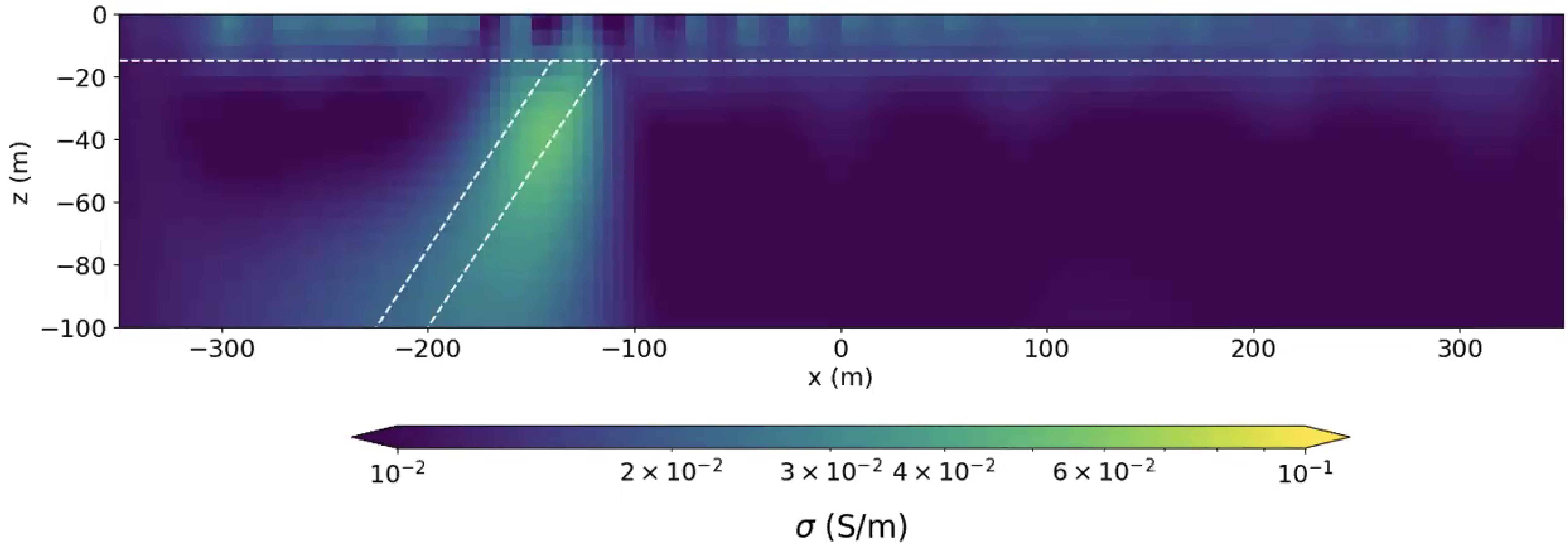
Anran Xu and Lindsey J. Heagy

December 11-15, 2023

2D DC resistivity inversion



L2 Norm Inversion

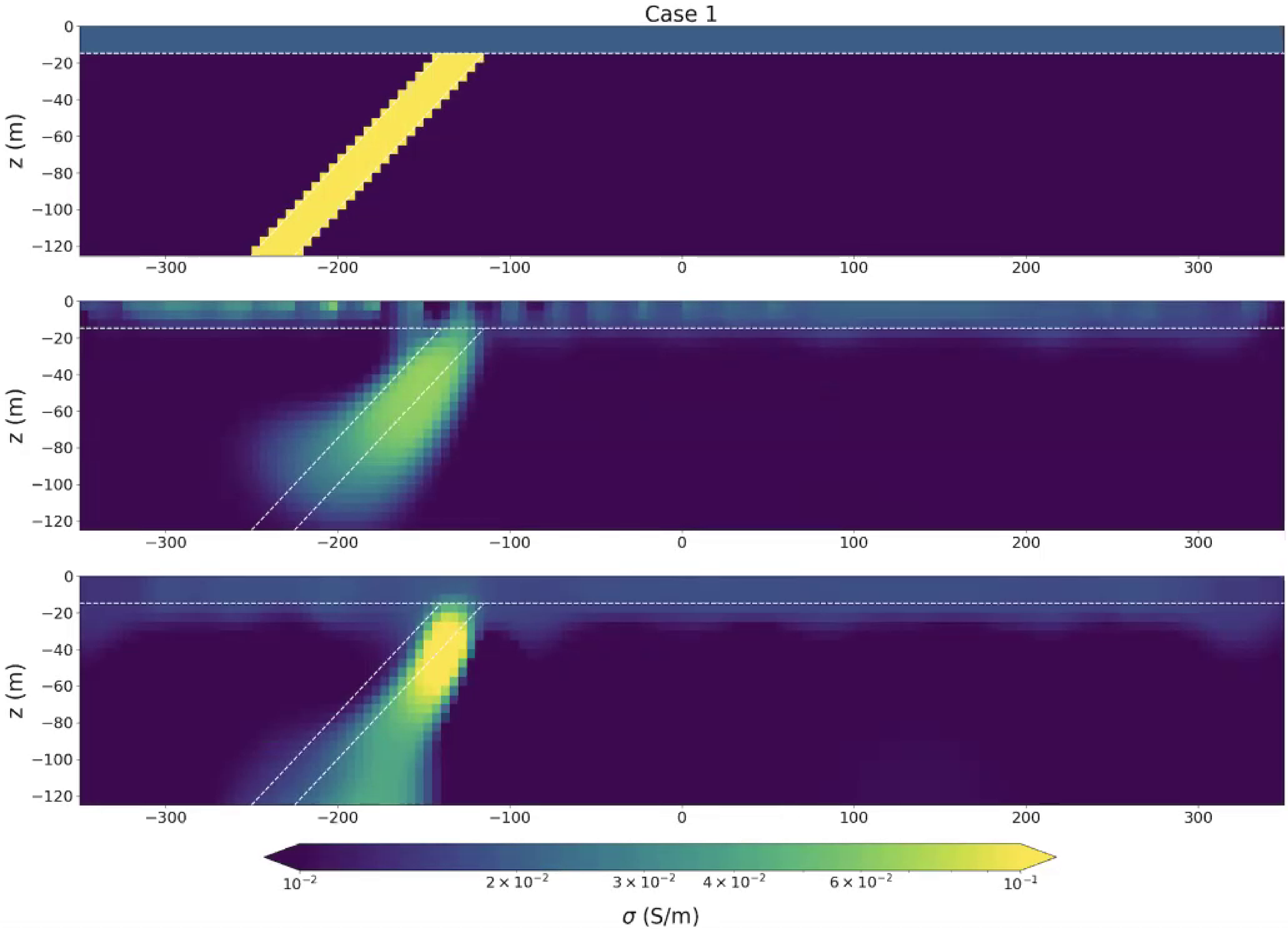


Sparse Norm Inversion

True Model

Predicted model (without sensitivity weighting)

Predicted model (with sensitivity weighting)



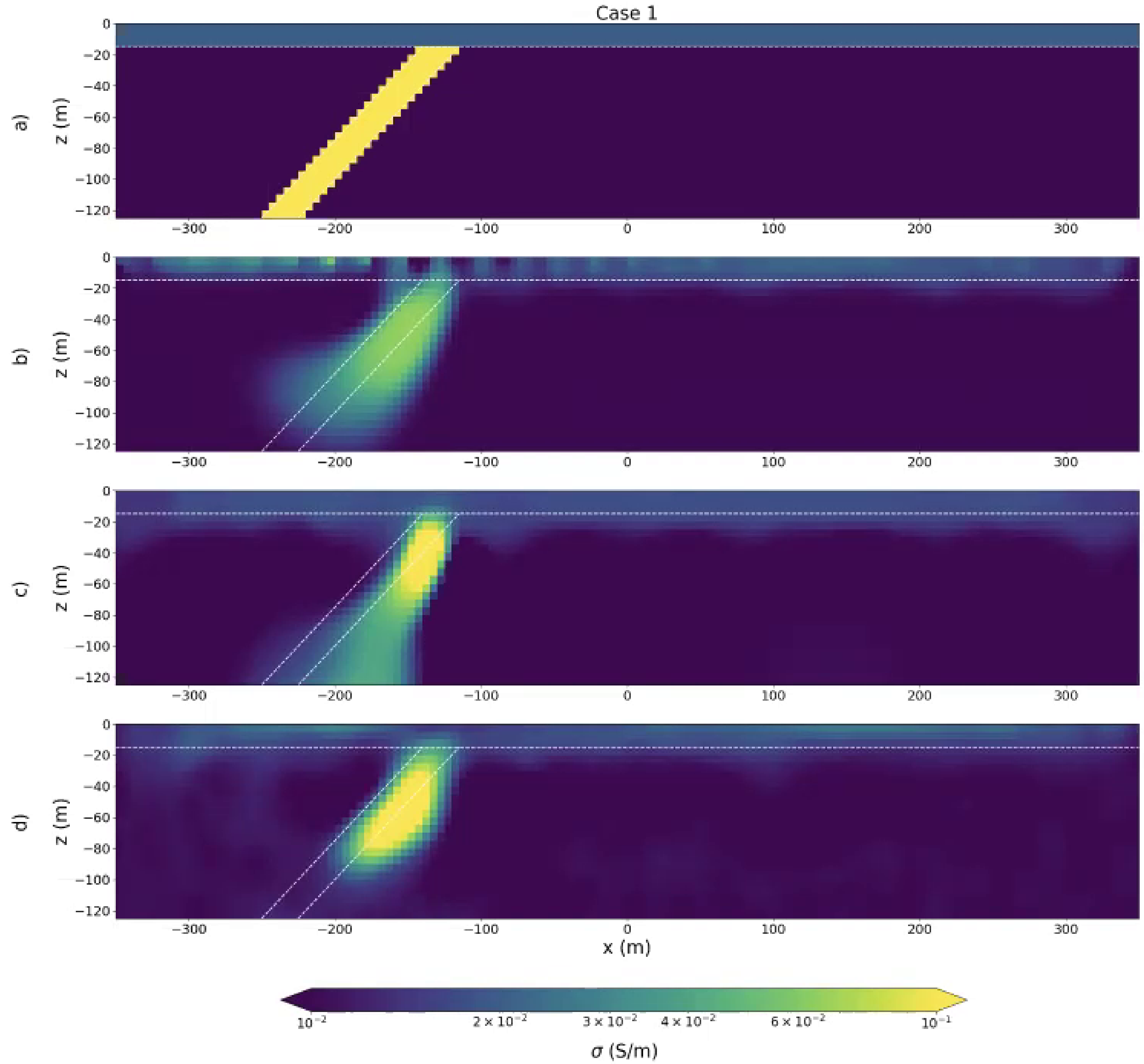
Deep Image Prior Inversion (DIP-Inv) Result

True Model

Predicted model (without sensitivity weighting)

Predicted model (with sensitivity weighting)

Predicted model (DIP-Inv)



Outline

1. Background: Concept of Deep Image Prior (DIP)

2. Motivation: Are the prior statistics implicitly included in the Convolutional Neural Network (CNN) useful for geophysical inversion?

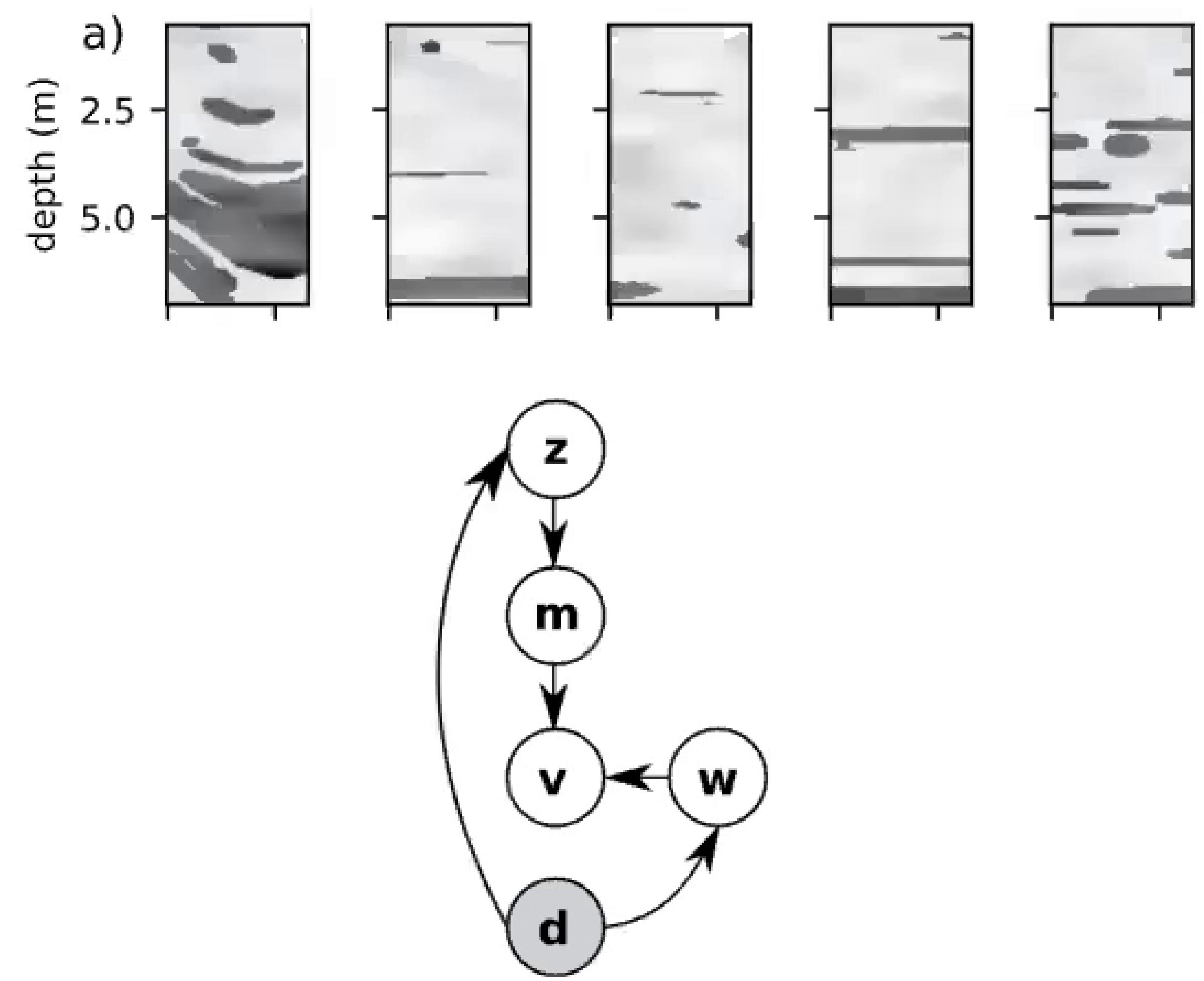
3. Proposed pipeline: Difference between the conventional method and the DIP-Inv

4. Results

Regularization in Geophysical inversion

<u>Explicit regularization:</u>

- Tikhonov regularization
- Parametric inversions
- Using neural networks in a supervised manner
- …



Lopez-Alvis, J., Nguyen, F., Looms, M. C., & Hermans, T. (2022). Geophysical inversion using a variational autoencoder to model an assembled spatial prior uncertainty. Journal of Geophysical Research: Solid Earth, 127, e2021JB022581. https://doi. org/10.1029/2021JB022581

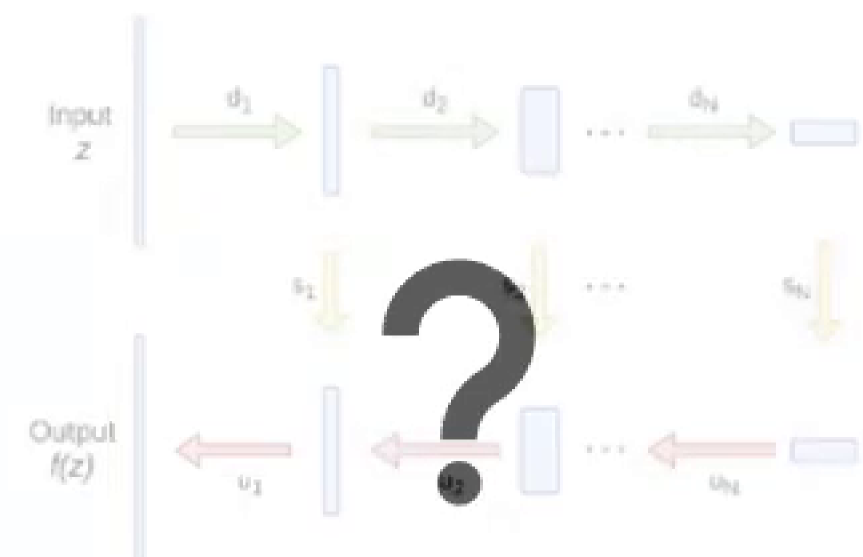
Regularization in Geophysical inversion

<u>Explicit regularization:</u>

- Tikhonov regularization
- Parametric inversions
- Using neural networks in a supervised manner
- …

Prior statistics → Regularization

<u>Implicit regularization:</u>

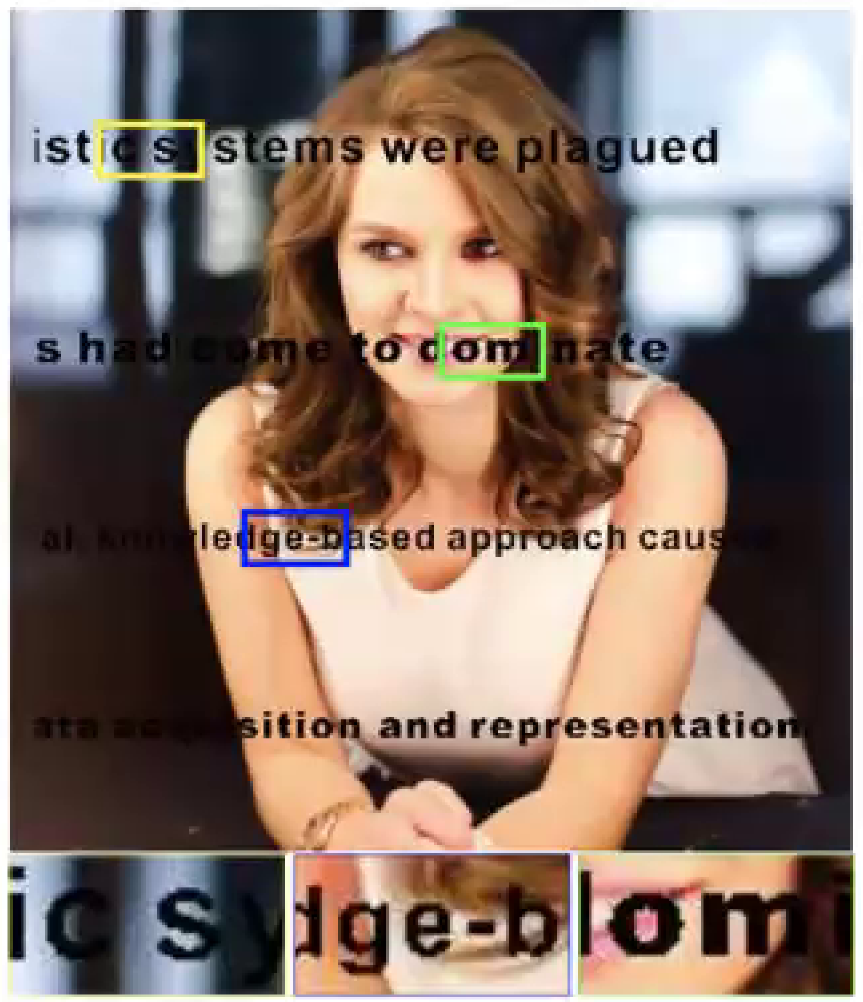


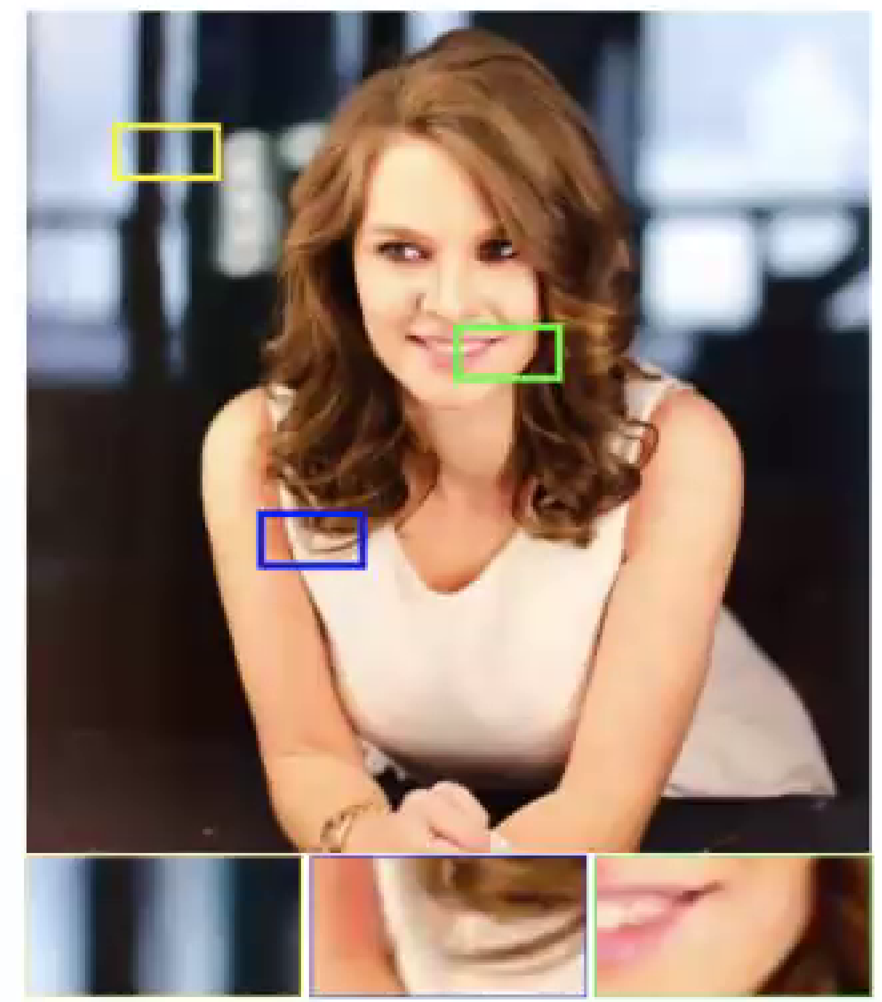
Dmitry Ulyanov, Andrea Vedaldi, and Victor Lempitsky, (2017), "Deep Image Prior," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 9446-9454.

DIP (Deep image prior)

- **training set free**
- **unsupervised learning**

- Inverse Problems in Computer Vision (CV)





DIP result

Dmitry Ulyanov, Andrea Vedaldi, and Victor Lempitsky, (2017), “Deep Image Prior,” Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 9446-9454.

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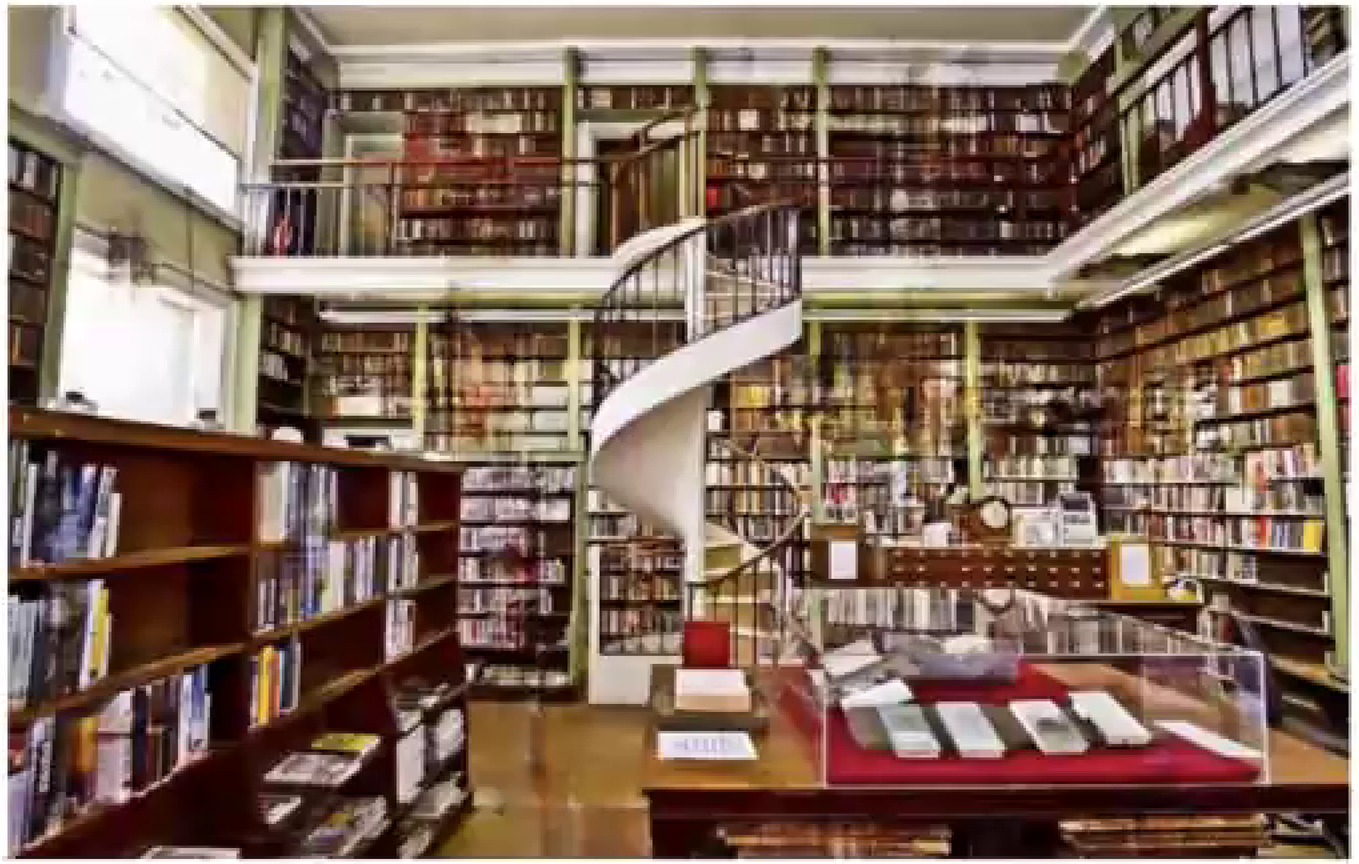

DIP result

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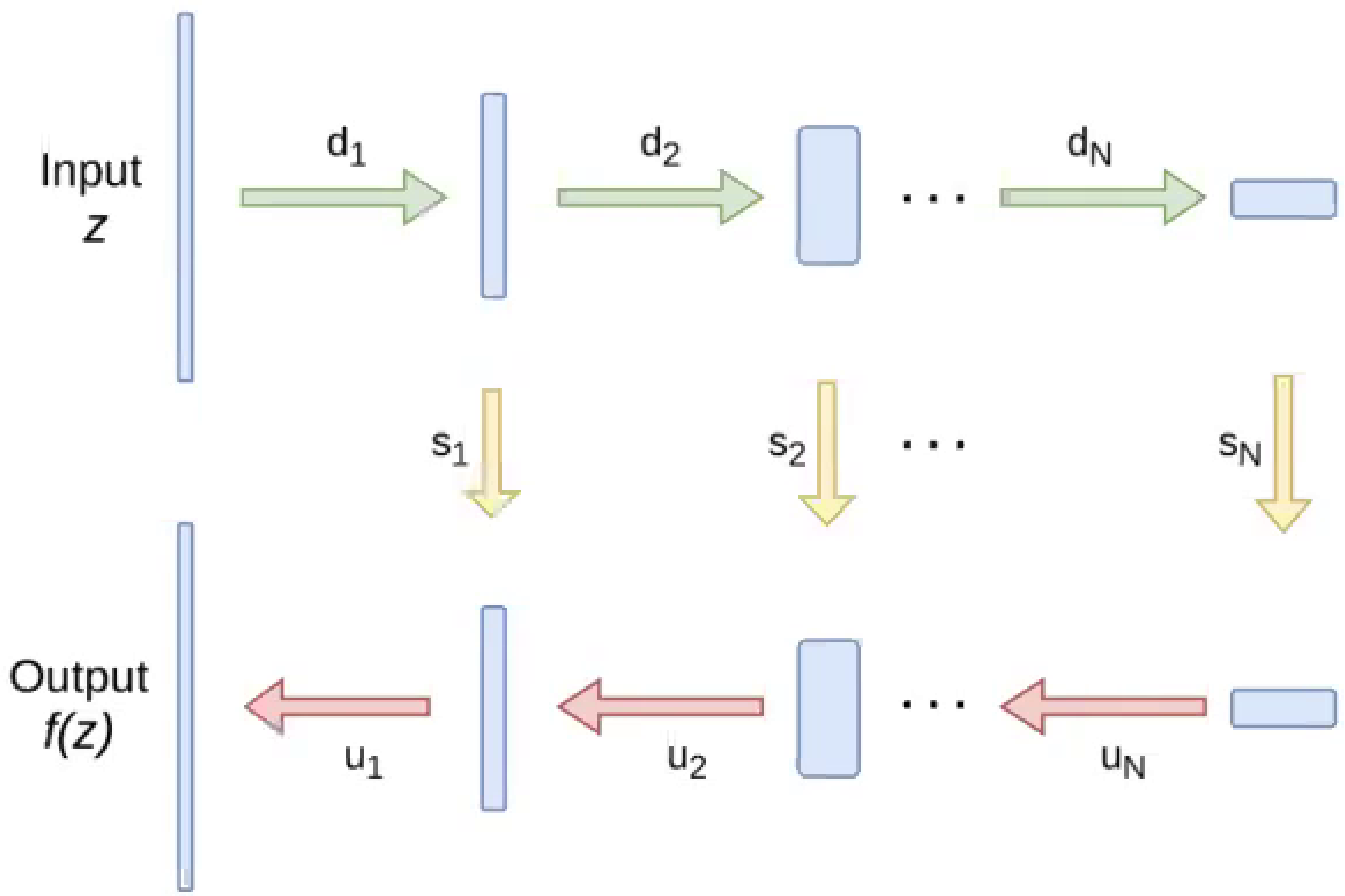
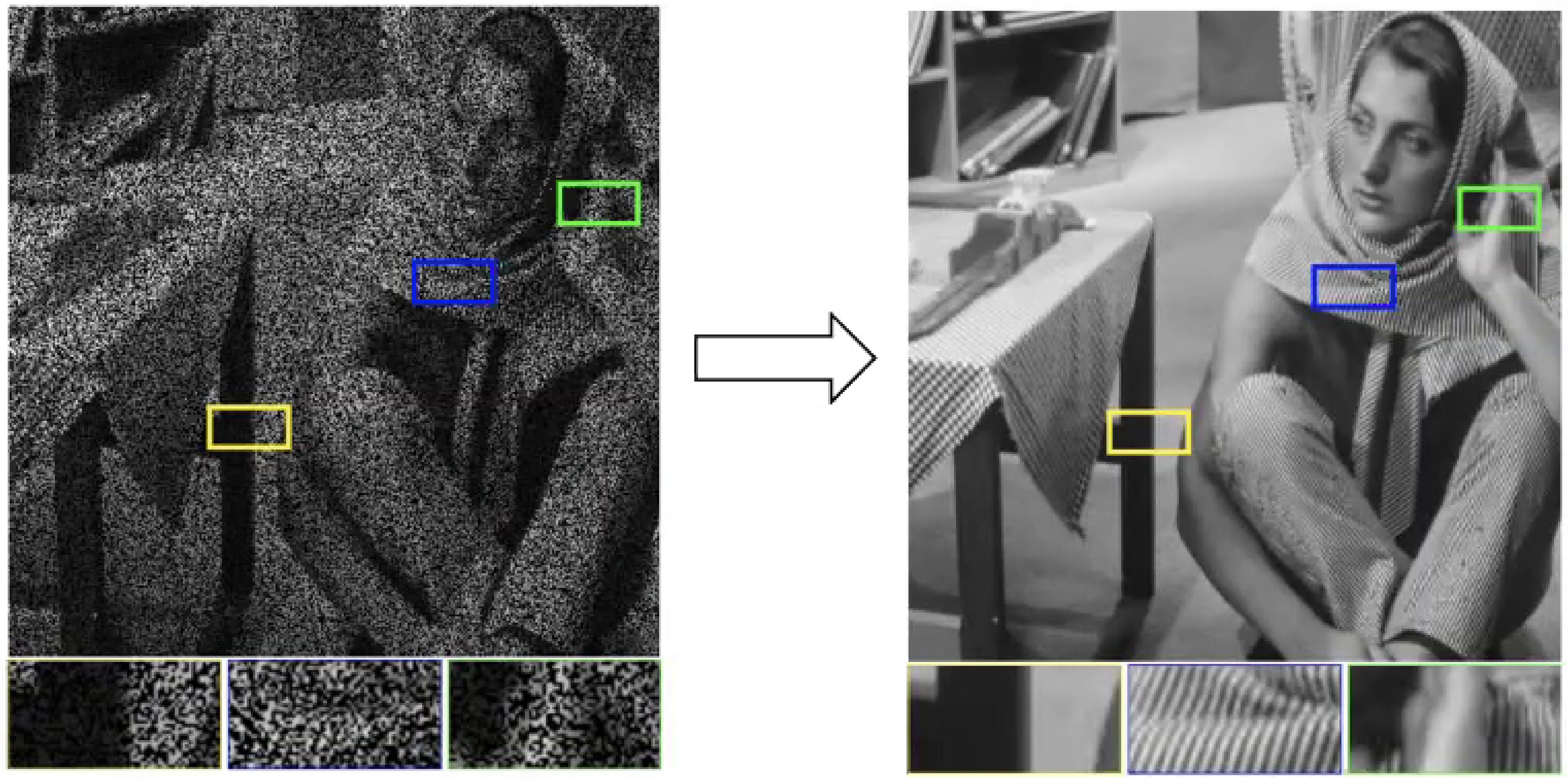
DIP (Deep image prior)

- **training set free**
- **unsupervised learning**

Solving inverse problems by learning self-similarity:

$$\min_{\theta} \|f_\theta(z) - x_0\|^2 \qquad \text{z: input; } x_0\text{: corrupted image}$$





Dmitry Ulyanov, Andrea Vedaldi, and Victor Lempitsky, (2017), "Deep Image Prior," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 9446-9454.

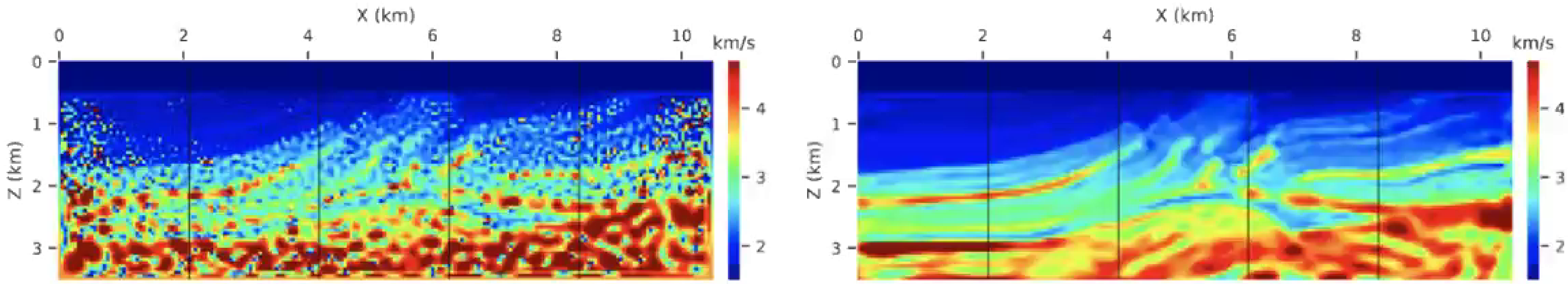
Key information from DIP in CV

- Structure of a generator network is sufficient to capture a great deal of low-level image statistics before any learning.

- Structure of the network imposes a strong prior (regularization effect)!

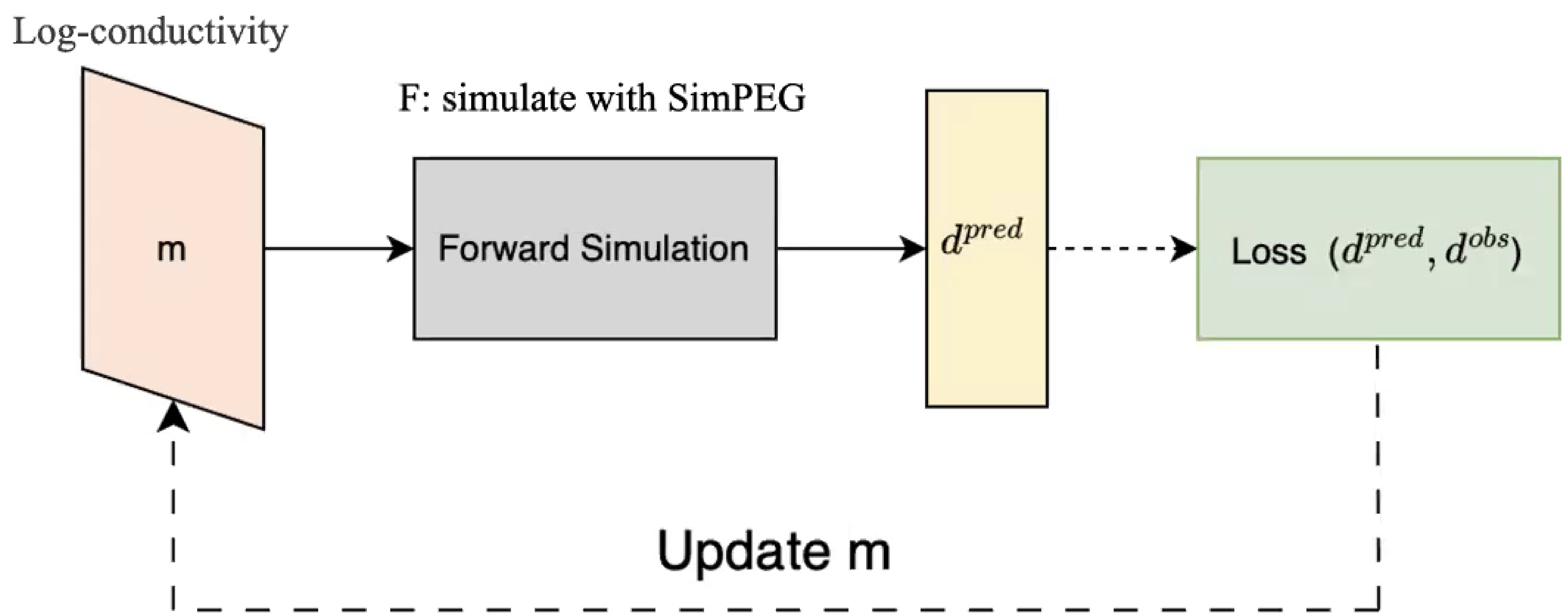
Motivation

- Will it work in Geophysical inversion?
- Demonstrated potential in seismic FWI



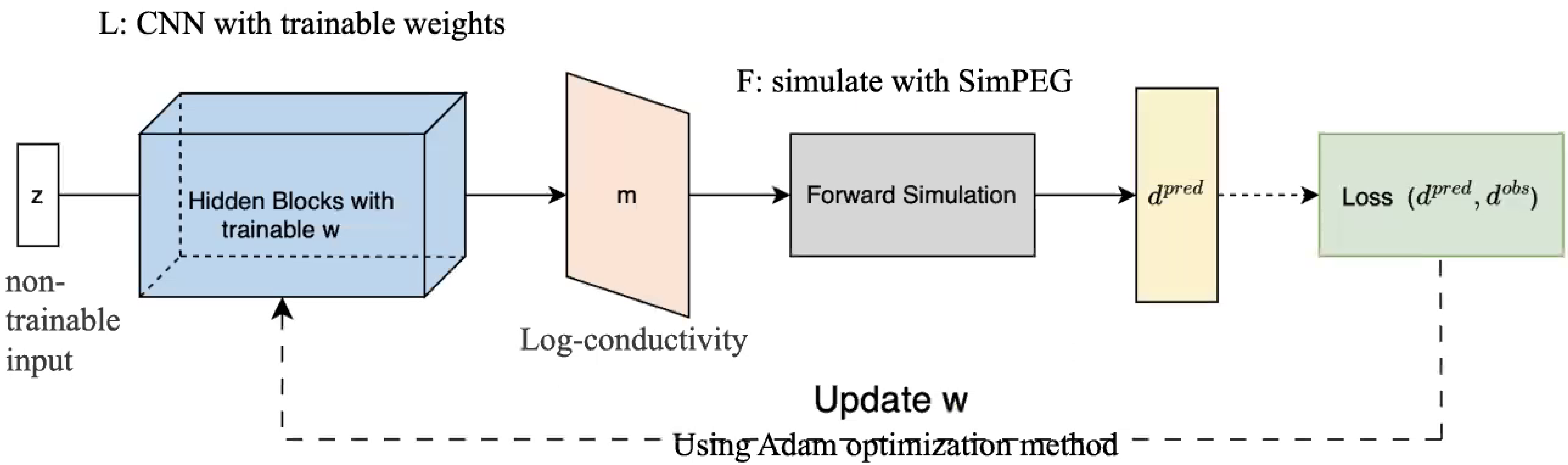
Weiqiang Zhu, Kailai Xu, Eric Darve, Biondo Biondi, and Gregory C. Beroza, (2022), "Integrating deep neural networks with full-waveform inversion: Reparameterization, regularization, and uncertainty quantification," *GEOPHYSICS* 87: R93-R109.

3. Proposed Pipeline



Conventional inversion:

$$\min_m \left(\phi_d(m) + \beta\phi_m(m)\right) = \min_m \left(\left| W_d \left(F(m) - d^{obs} \right) \right|^2 + \beta \left(\alpha_s \left| W_s \left(m - m_{ref} \right) \right|^p + \alpha_x |W_x(m)|^q + \alpha_z |W_z(m)|^q \right) \right)$$



Conventional inversion:

$$\min_m \left(\phi_d(m) + \beta\phi_m(m)\right) = \min_m \left(\left|W_d\left(F(m) - d^{obs}\right)\right|^2 + \beta\left(\alpha_s\left|W_s(m - m_{ref})\right|^p + \alpha_x |W_x(m)|^q + \alpha_z |W_z(m)|^q\right)\right)$$

DIP-Inv inversion :

$$\min_w (1-\beta)\left(W_d\left(F\left(L_w(z)\right) - d^{obs}\right)\right)^2 + \beta\left(L_w(z) - m_{ref}\right)^1$$

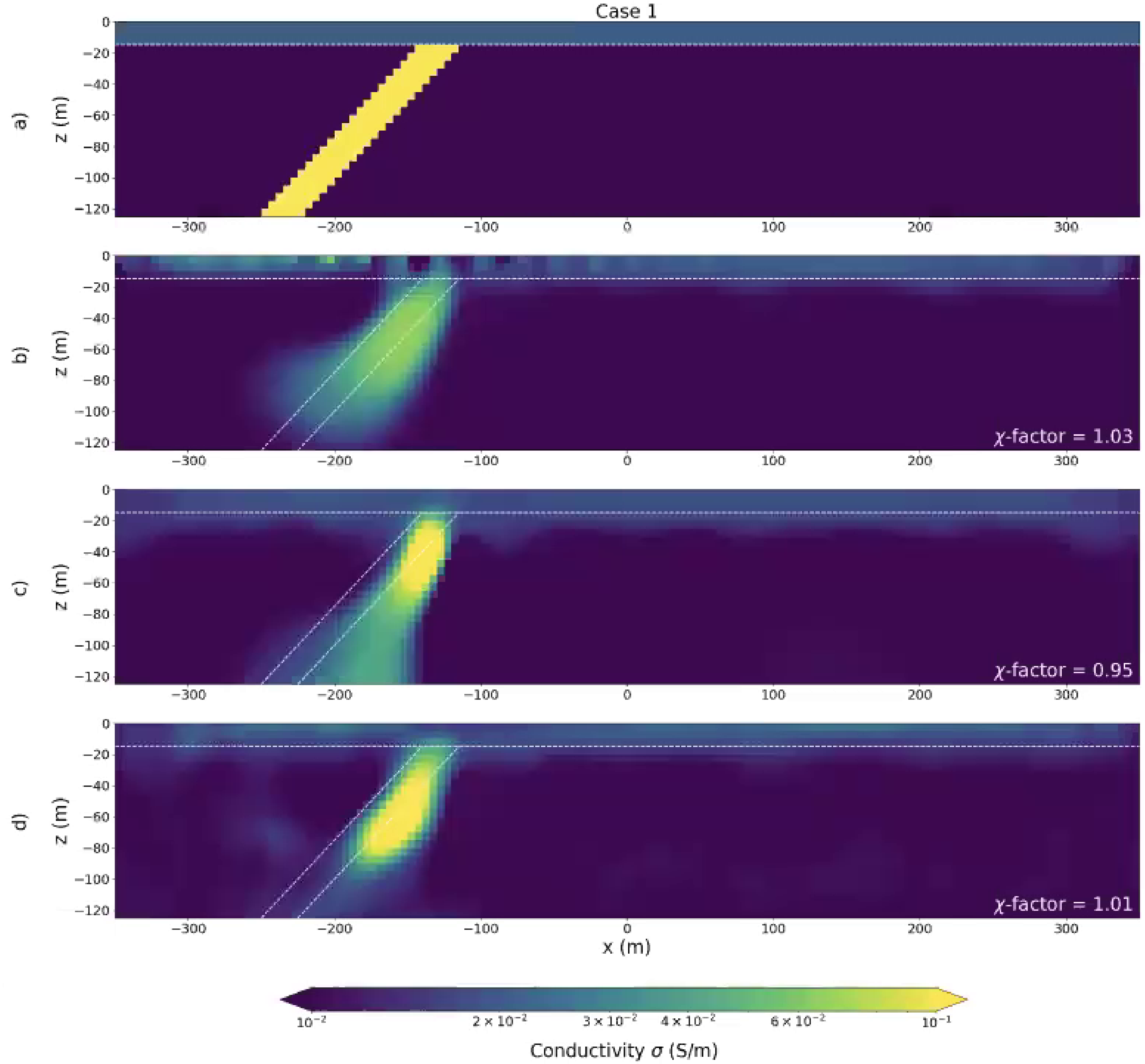
Results: Dipole-Dipole survey in 2D DCR inversion

True Model

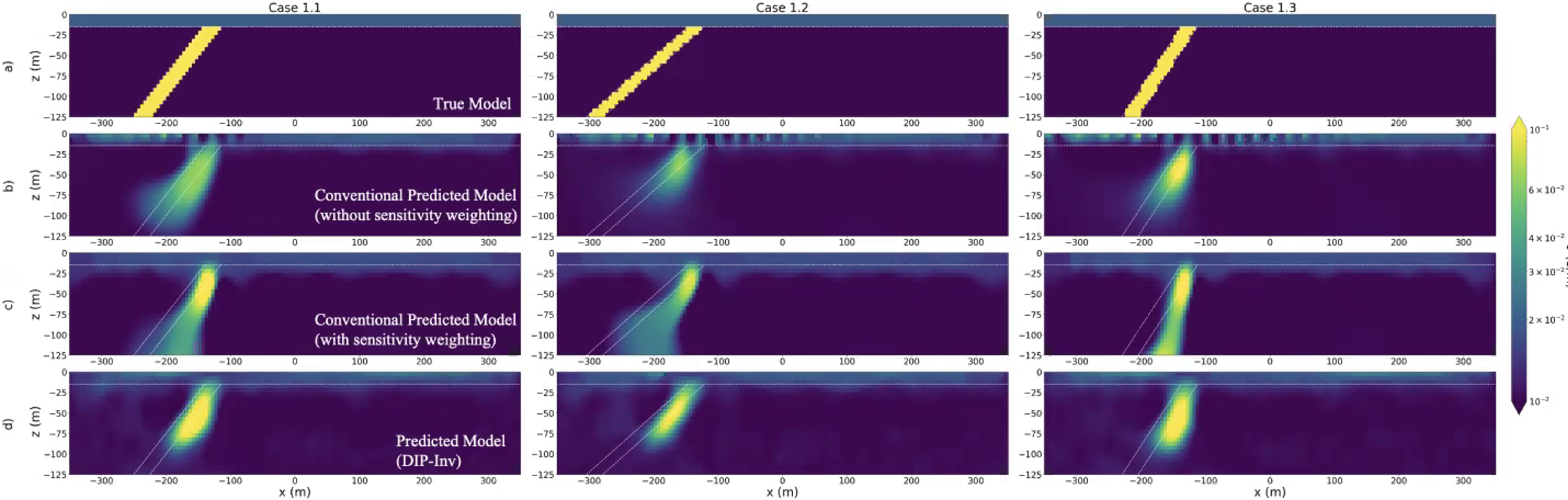
Predicted model (without sensitivity weighting)

Predicted model (with sensitivity Weighting)

Predicted model (DIP-Inv)

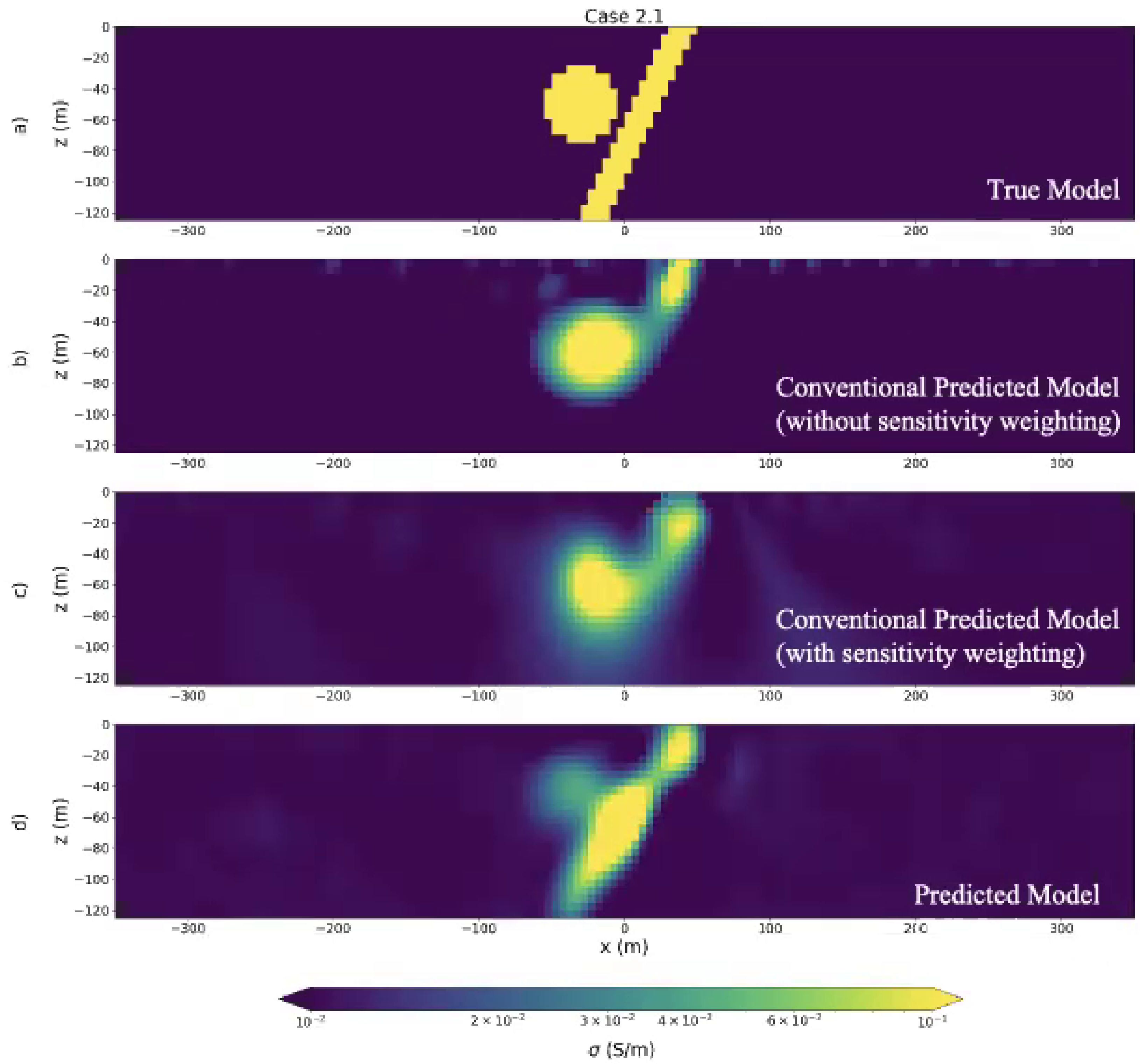


Results: Dipole-Dipole survey in 2D DCR inversion



The DIP-Inv method performs better than the conventional method in terms of the dip angle recovery and the recovery of the top layer.

Results: Dipole-Dipole survey in 2D DCR inversion

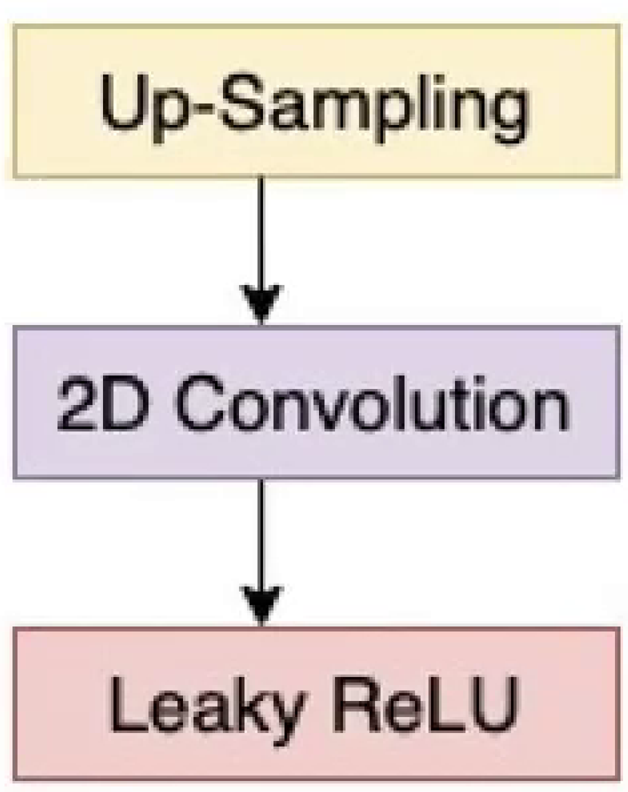


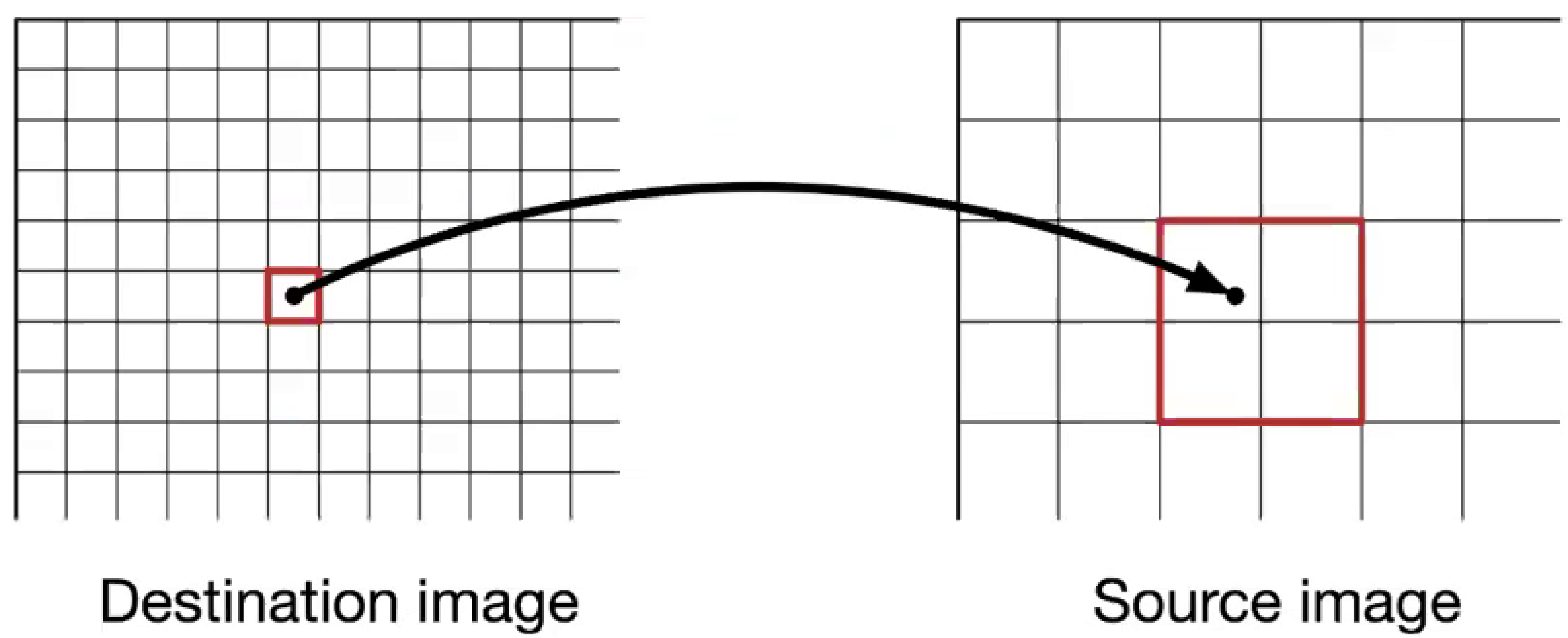
The DIP-Inv method performs better than the conventional method in terms of distinguishing two closed-placed compact targets.

Further Discussion

- The observed implicit regularization effect is partly from the bi-linear upsampling Operator.

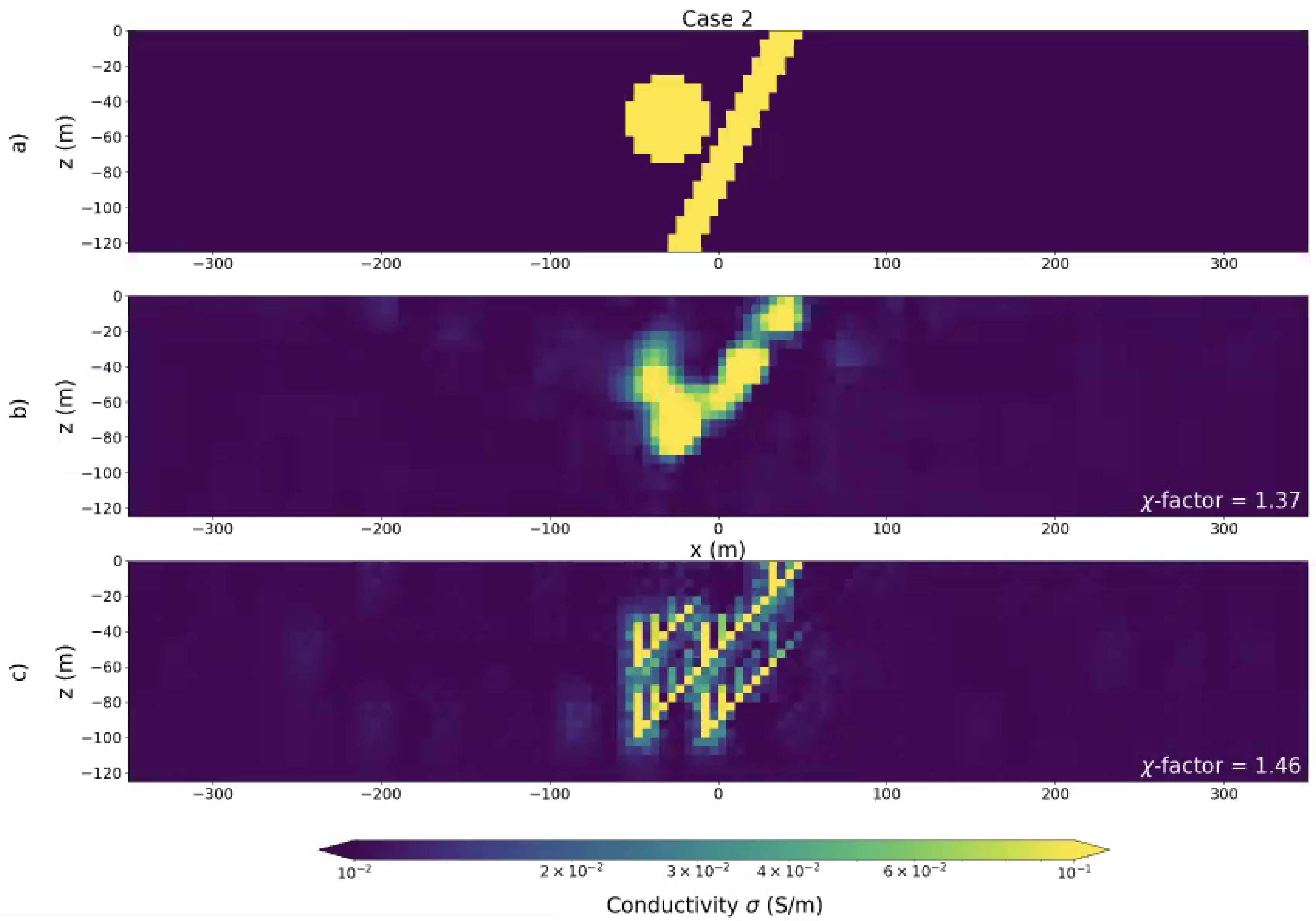
- The output value of the bi-linear interpolation in each pixel is a (distance-based) weighted sum of the surrounding pixels.



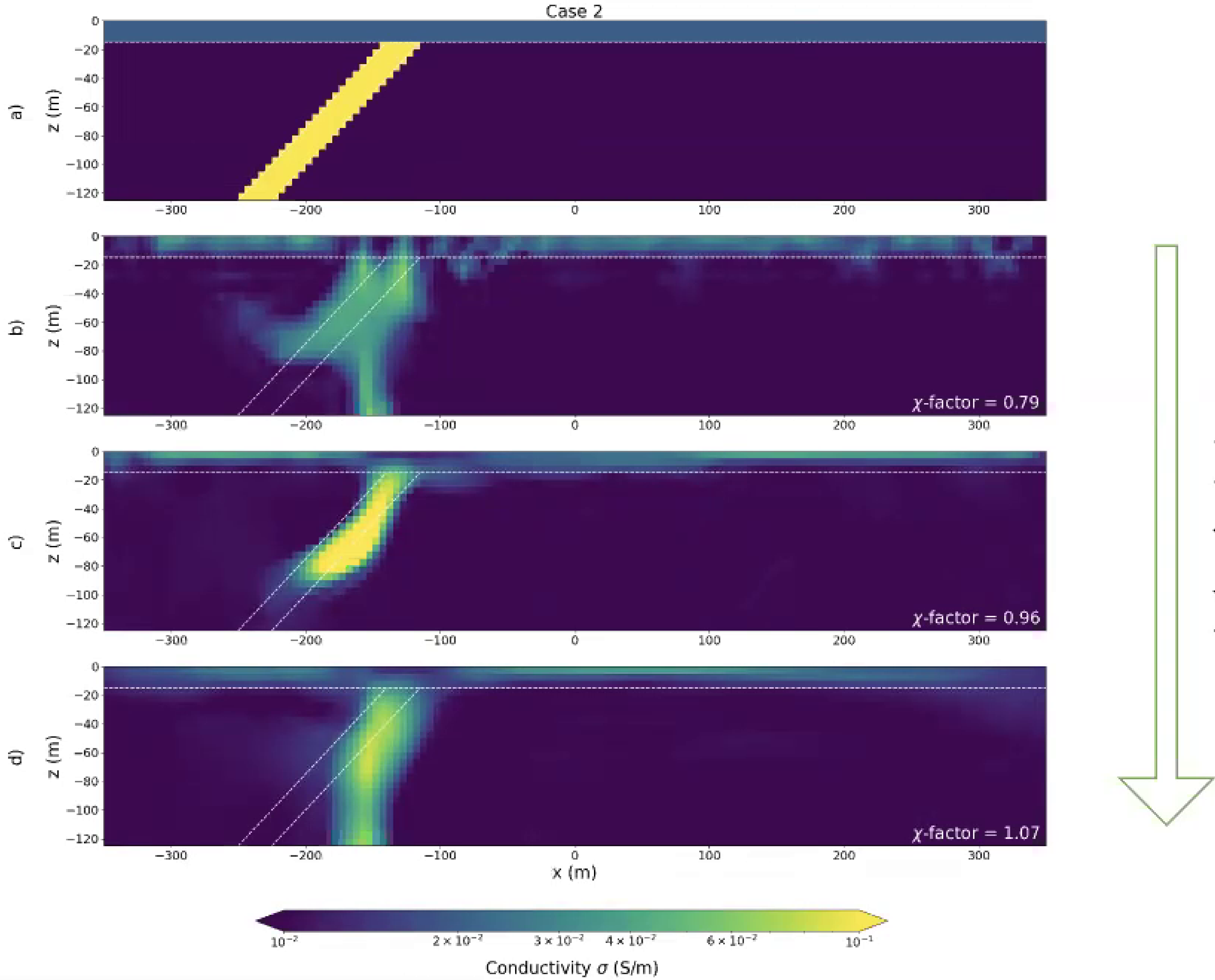


https://machinethink.net/blog/coreml-upsampling/

Replace Bi-linear by Nearest or ConvTranspose



Choice of architecture



Increasing the number of hidden layers

Conclusions & Future research

DIP-Inv: uses CNN for implicit regularization

- Training data free

Promising results for dipping, compact targets

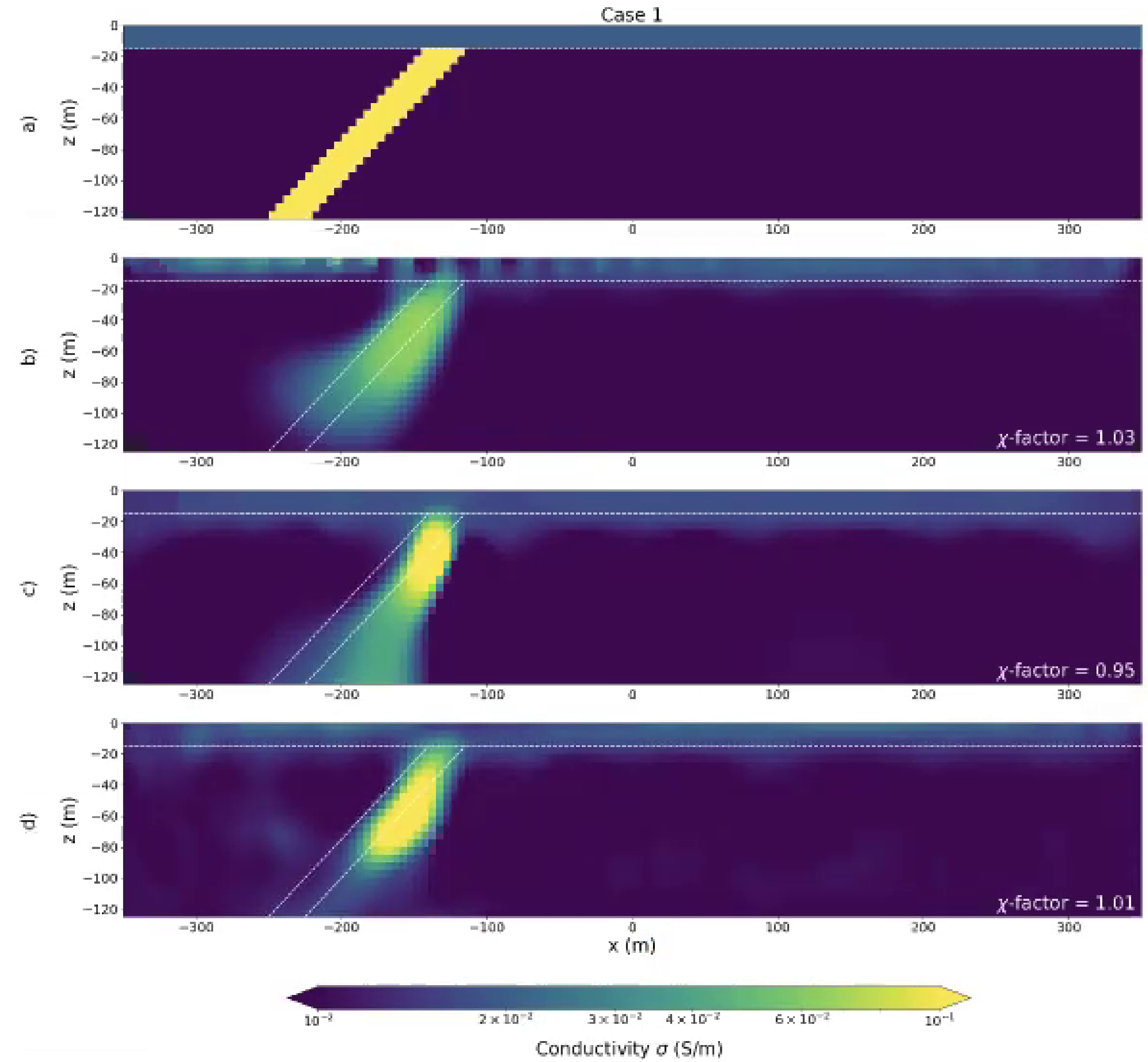
- Smoothness in conventional inversions promote axes-aligned structures

Connect SimPEG & PyTorch

- Approach can be adapted to other physics

Future research

- requires many iterations
- lots to explore: network architectures, …



Thanks!

Please come to our session on Wednesday, 13 December 2023; 14:10-15:40 PST, at MC, eLightning Theater V, Hall D –South

Information about the preprints the codes for reproducing the results can be found on the iPoster.