Modern seismic signal processing, imaging, and full-waveform inversion algorithms for efficient resource exploration and production

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UQÀM Département des sciences de la Terre et de l'atmosphère
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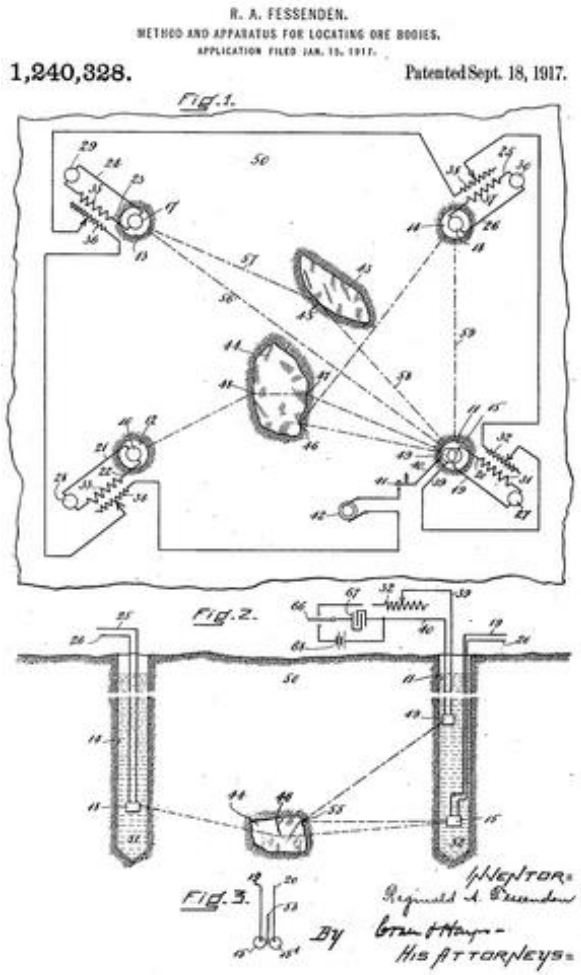
Domaines d'expertise

- Apprentissage automatique
- Géophysique
- Optimisation mathématique
- Sismologie
- Subsurface terrestre
- Traitement du signal

What is Geophysics?

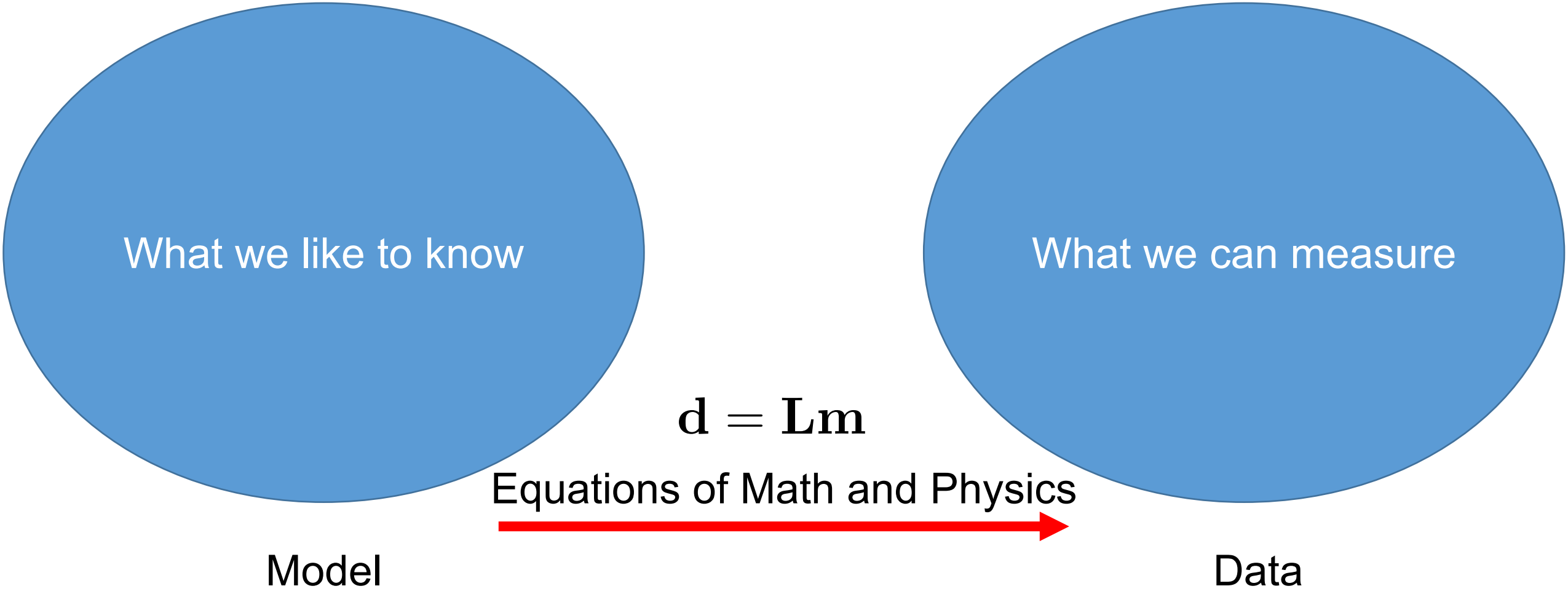
Reginald Aubrey Fessenden (1866-1932)



Indirect and non-destructive imaging of subsurface structure

(Wikipedia)

Geophysics and Sensing

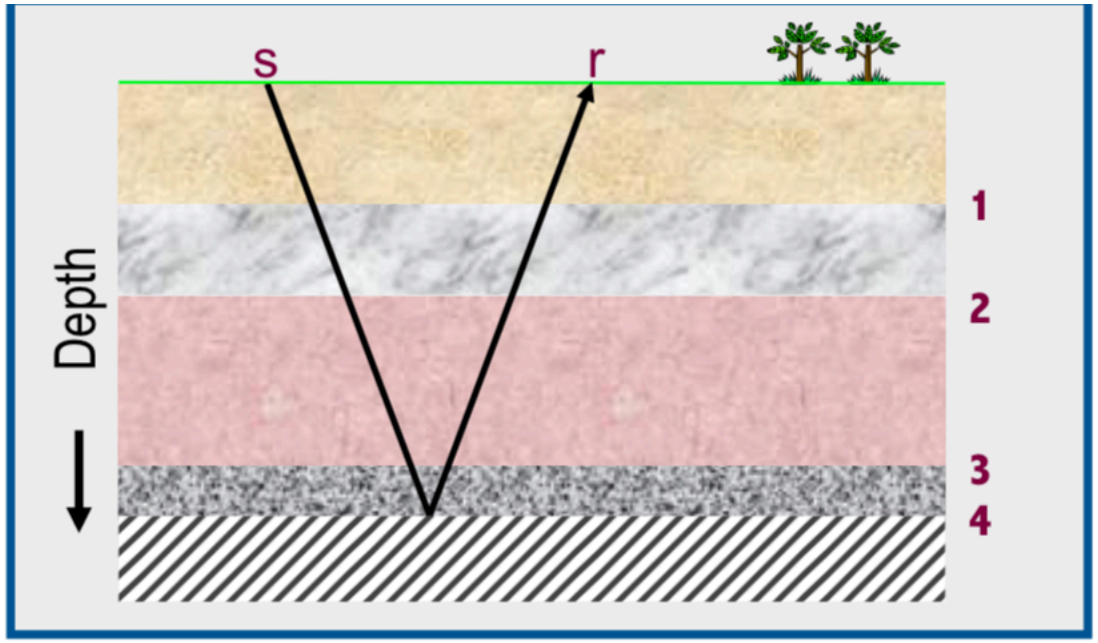


Geophysics and Sensing

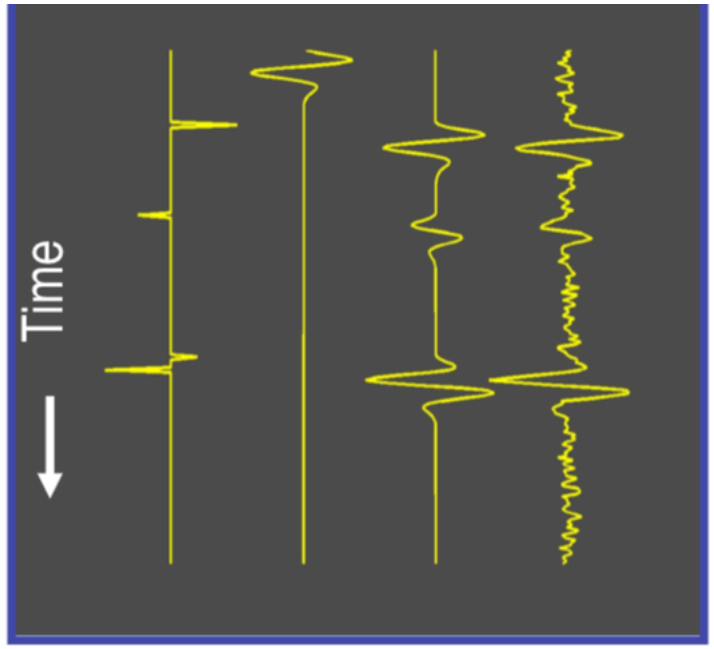
Data (What we can measure)	Model (What we like to know)	Method (Course)
Gravity anomalies	Density	Potential Field Methods
Electrical potential	Resistivity	Potential Field Methods
Electrical and Magnetic Fields	Electrical conductivity	EM/MT Methods
Magnetic Fields	Susceptibility	Potential Field Methods
Traveltime and Amplitudes of Seismic Waves	Velocities	Seismic Methods

Seismic Sensing

Model



Data



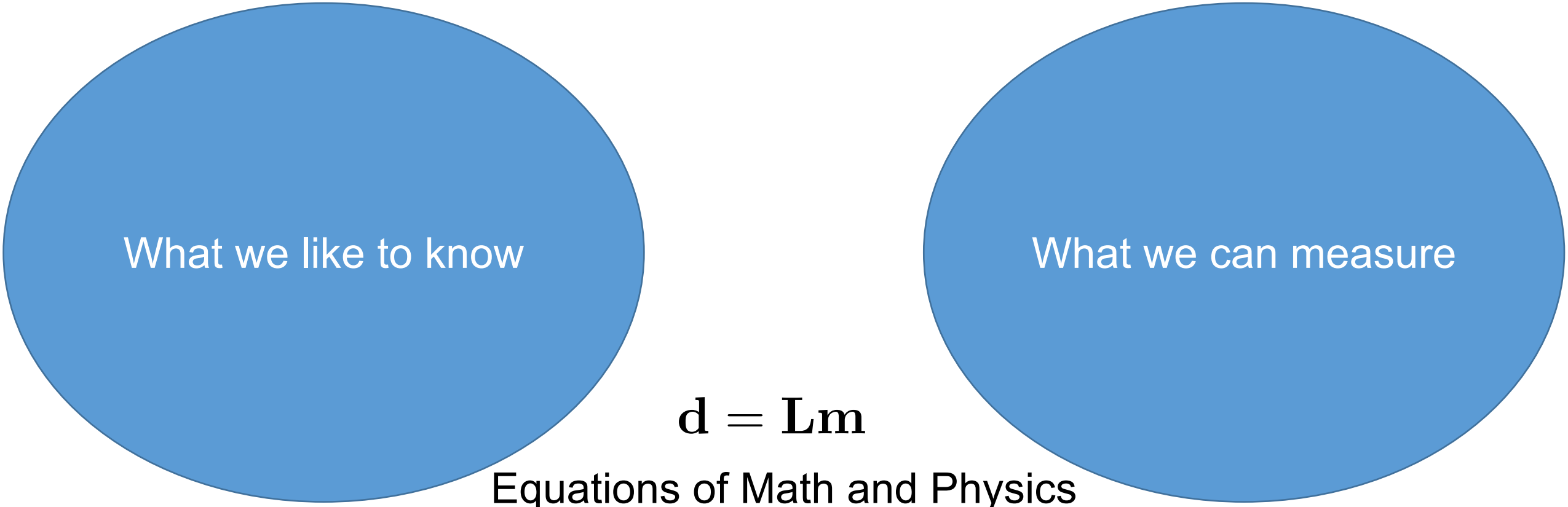
$r \quad W \quad d_0 \quad d$

$$d(t) = \int w(\tau - t) r(\tau) d\tau + n(t)$$

$$d = d_0 + n$$

$$= Wr + n$$

Geophysics and Sensing



$$\mathbf{d} = \mathbf{L}\mathbf{m}$$

Equations of Math and Physics

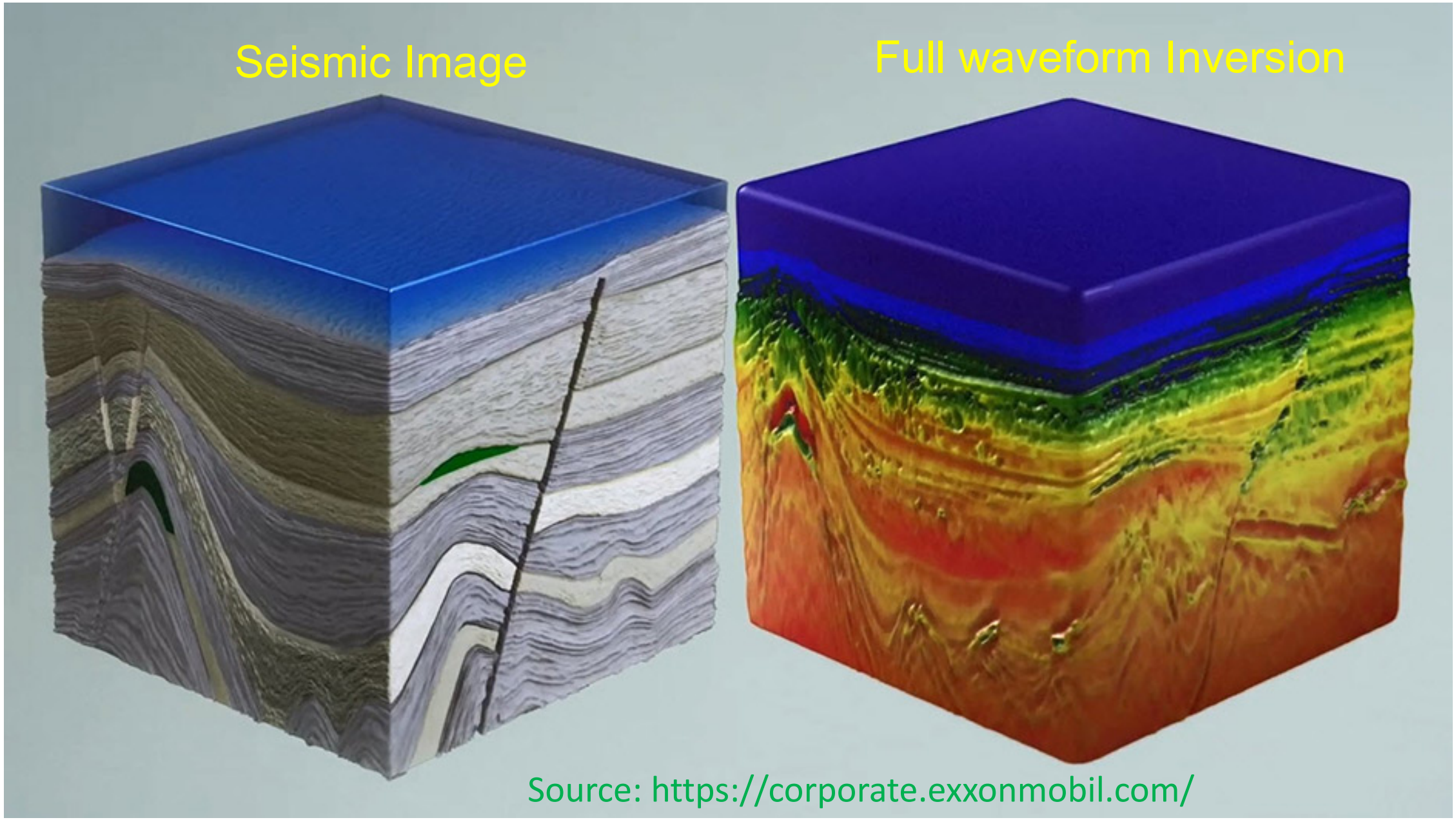
Model

Data

Inverse Theory

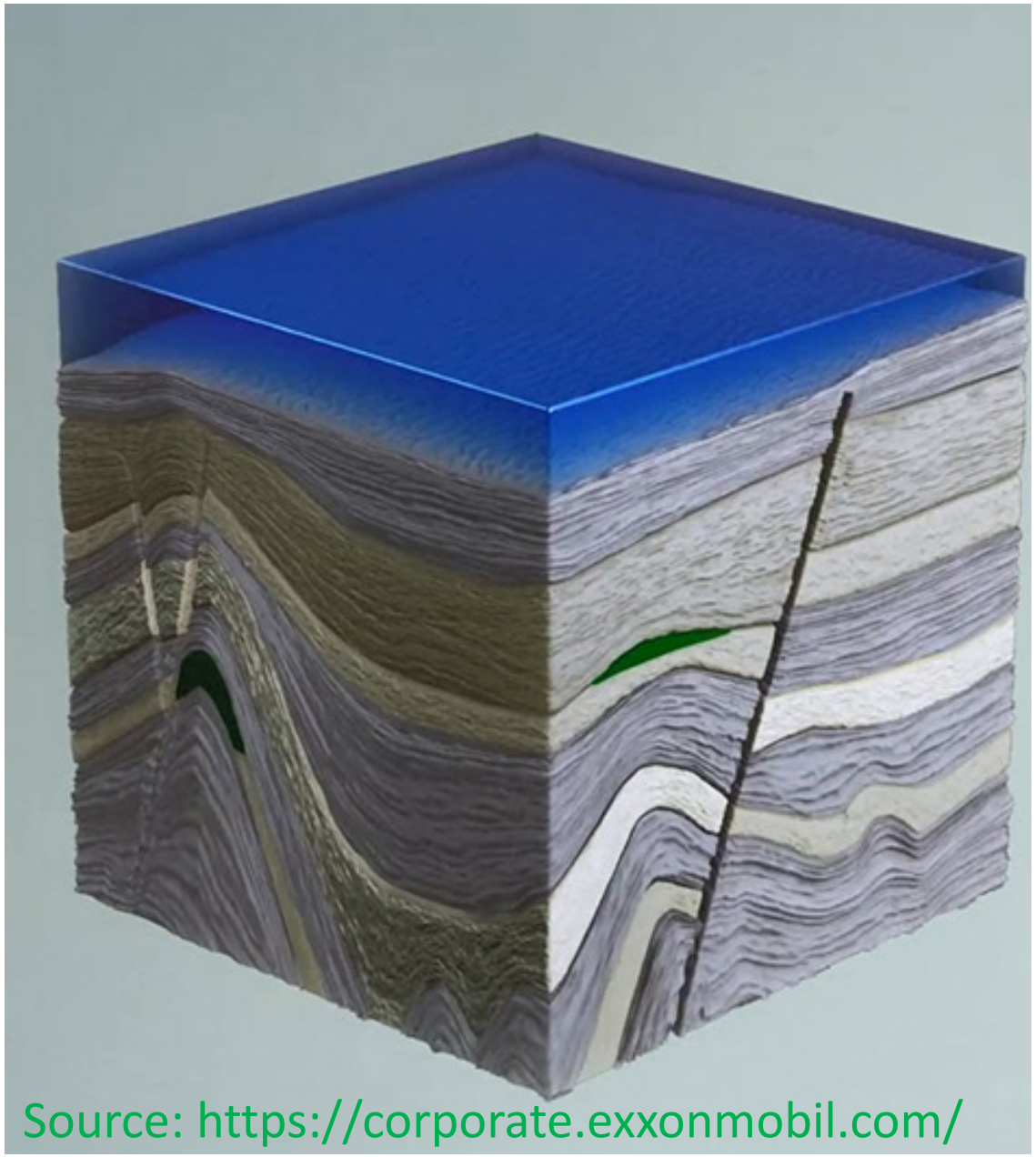
$$\mathbf{m} = \mathbf{L}^{-1}\mathbf{d}$$

What we like to know



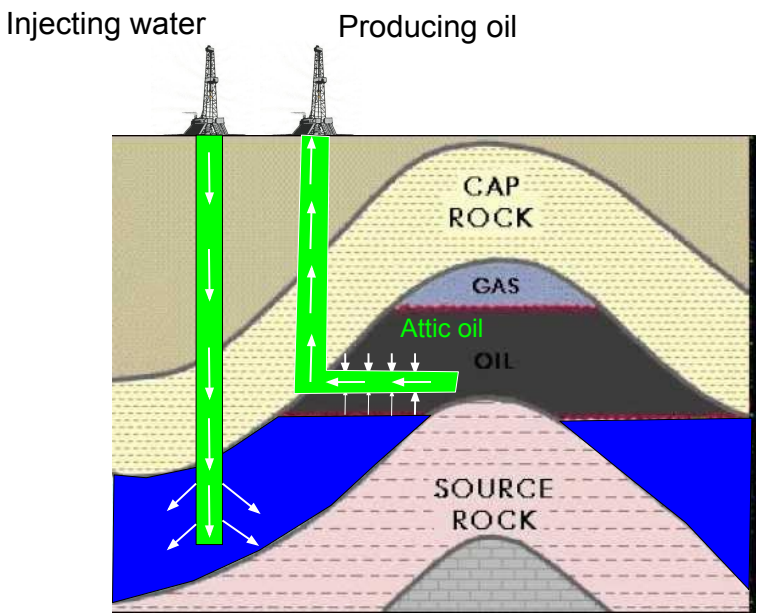
Source: https://corporate.exxonmobil.com/

Seismic imaging

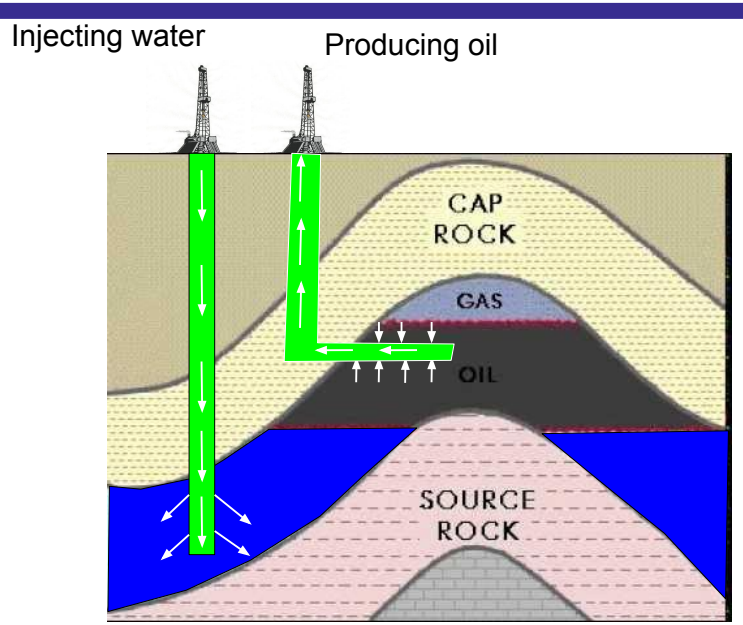


Source: https://corporate.exxonmobil.com/

Importance of Reduced Uncertainty in Imaging



Scenario A: Imaging with high uncertainties



Scenario B: Imaging with less uncertainties

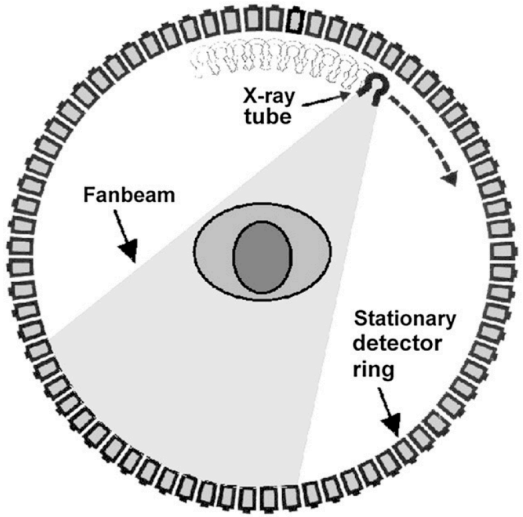
Added value of Scenario B with respect to Scenario A ($ saved):
Reports from Chemali, 2011 (distinguished SPE lecture).

- ✓ Statoil Hydro Troll field: $2.4 B (Based on OTC-17110).
- ✓ Chevron Alba (John Hampson) $225 M of additional production in 3 wells.

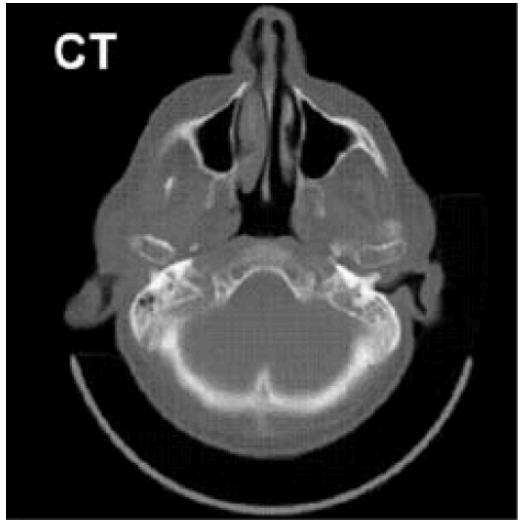
Uncertainties of depth imaging

CT scan

Goldman, 2007

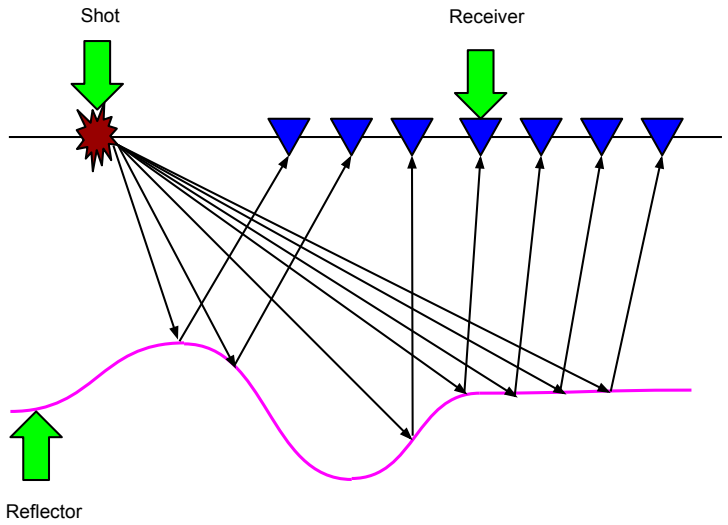


Greenspan, 2008

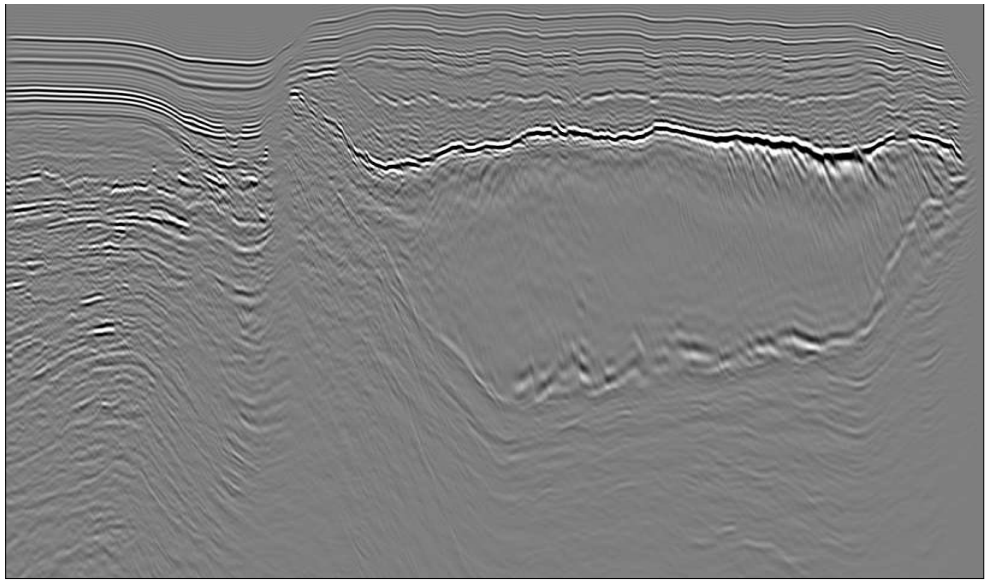


Surface seismic

Kazemi Nojadeh, 2017

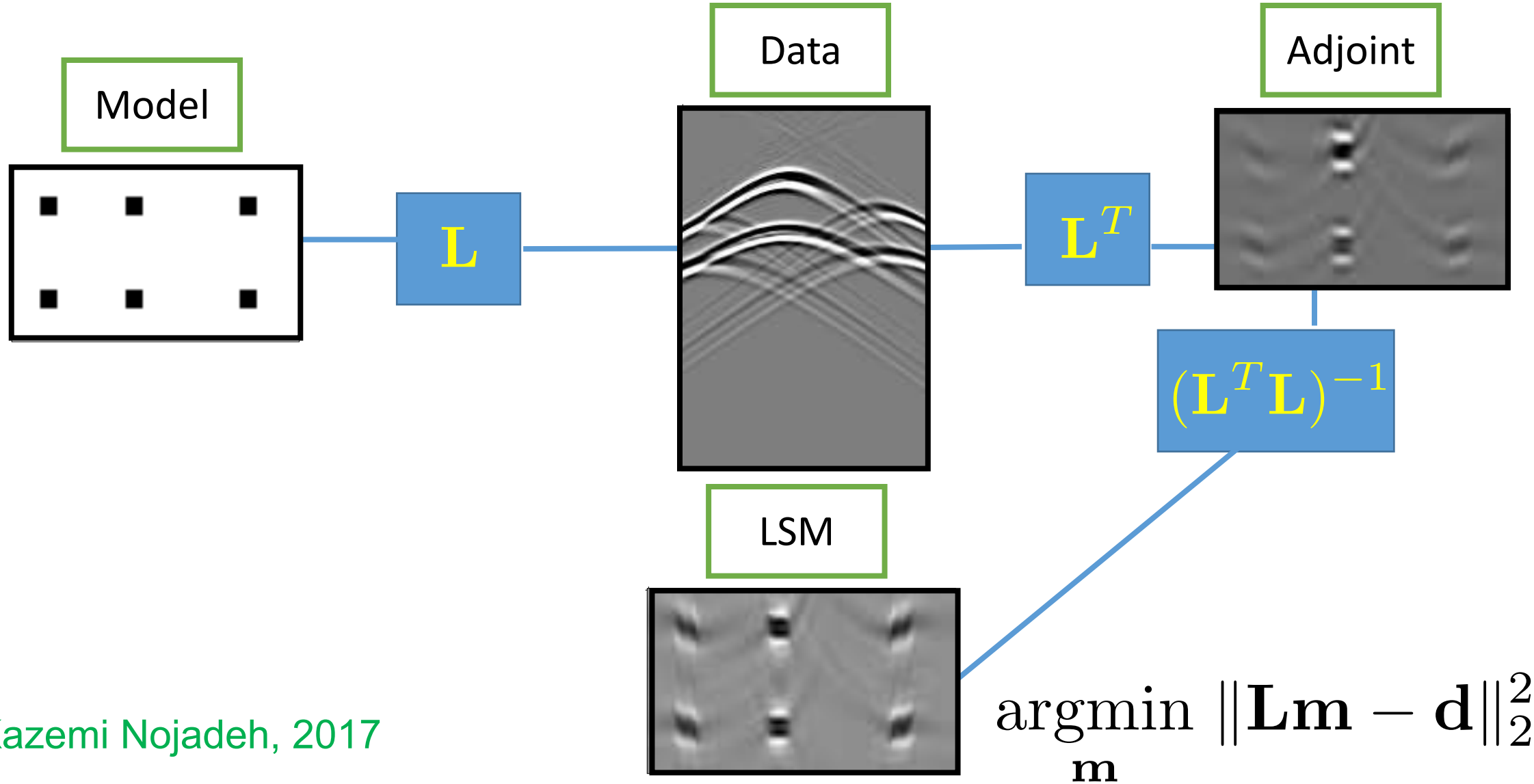


Kazemi, 2018



Least-squares imaging of surface and seismic-while-drilling datasets

Improving illumination with LSM

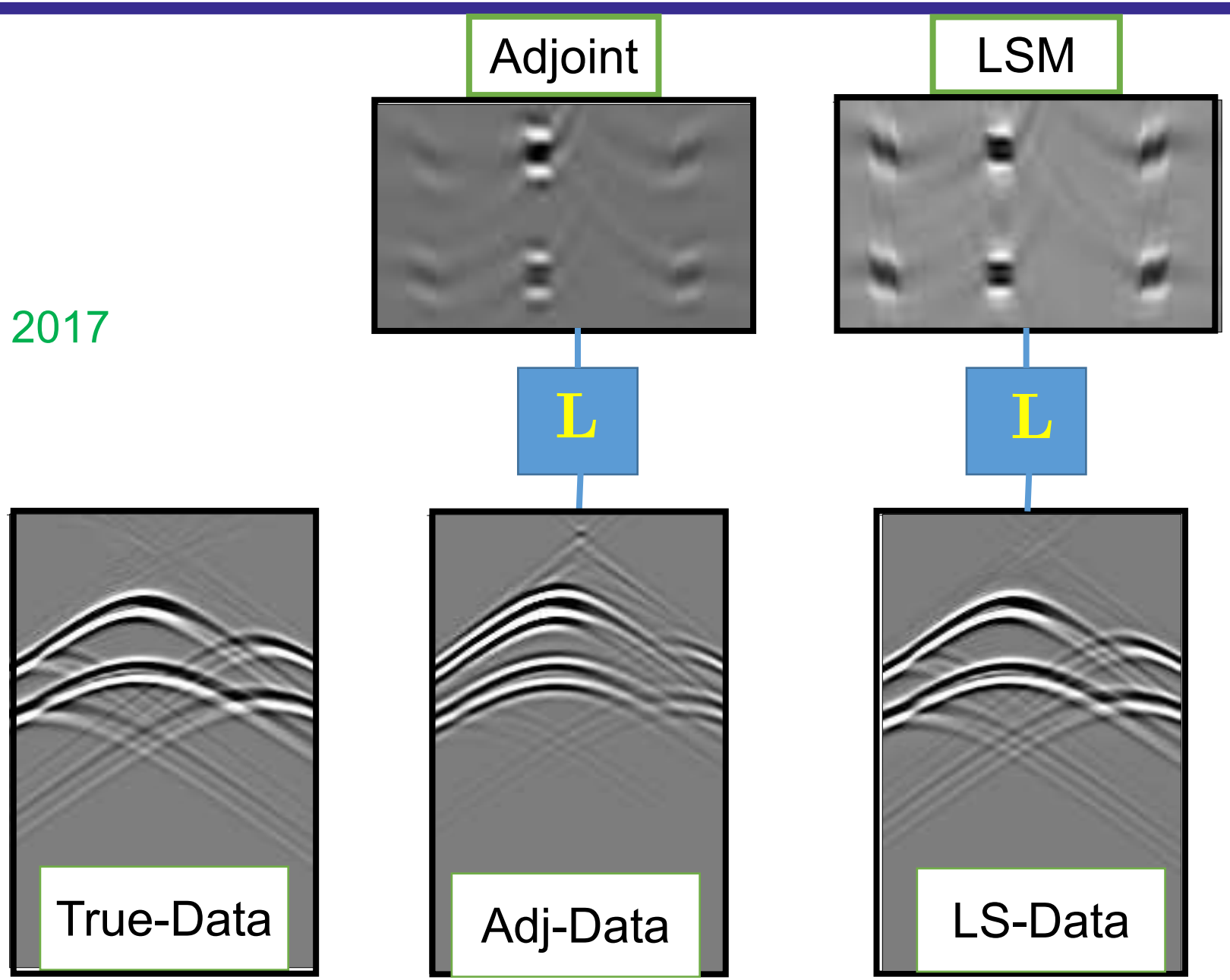


$$\underset{\mathbf{m}}{\operatorname{argmin}} \|\mathbf{Lm} - \mathbf{d}\|_2^2$$

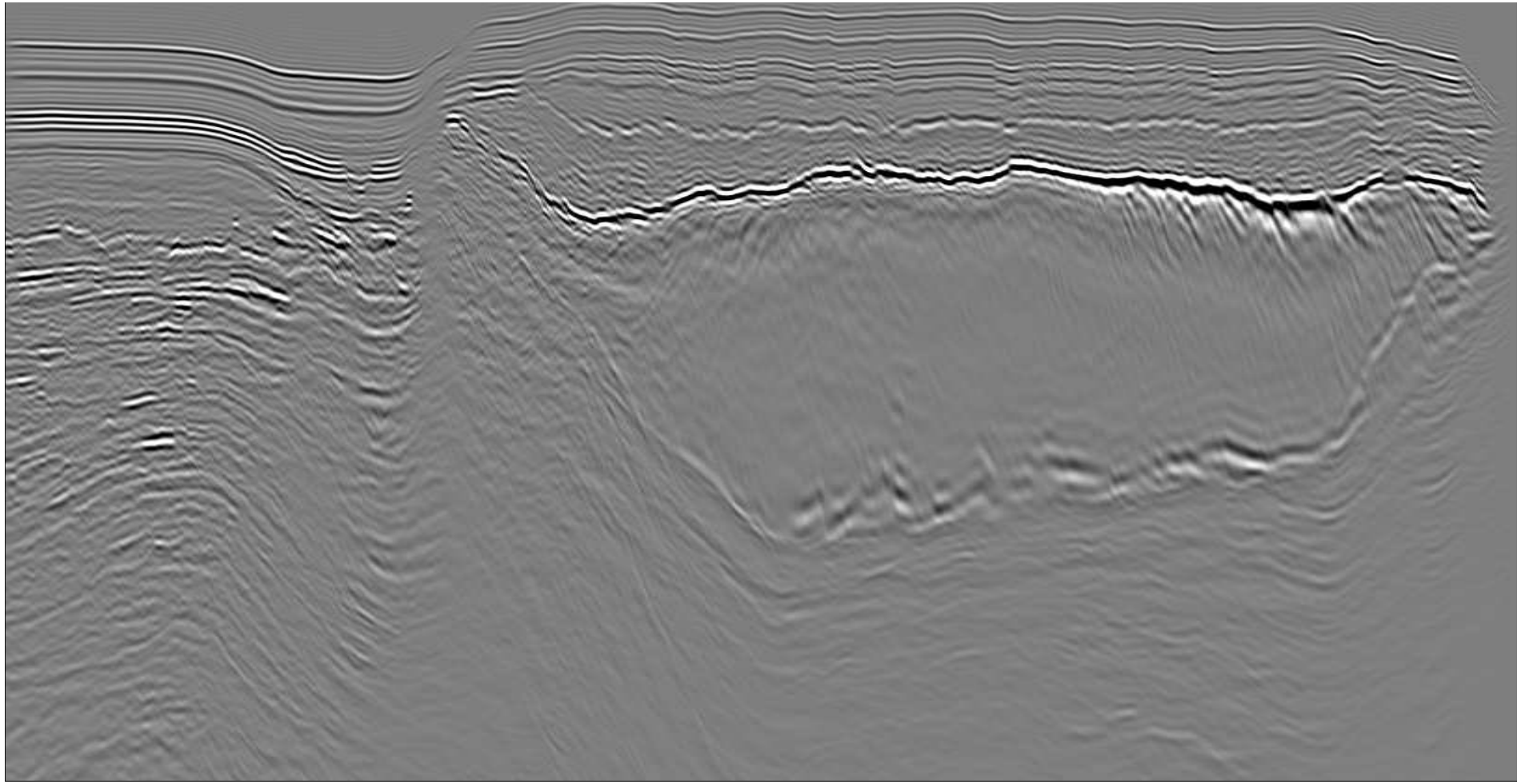
Kazemi Nojadeh, 2017

Improving data fitting with LSM

Kazemi Nojadeh, 2017

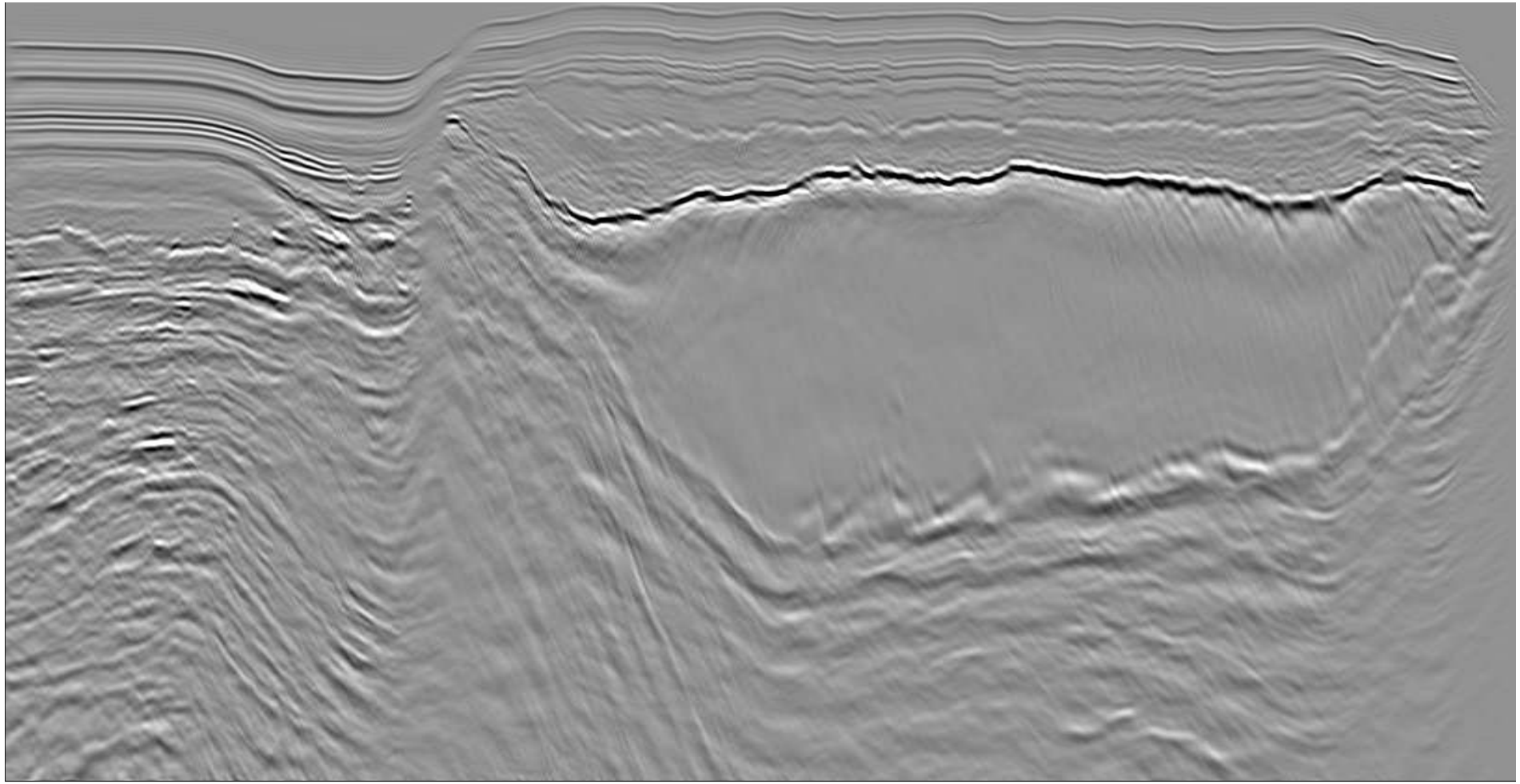


Inversion (LSM) vs. Adjoint migration



Adjoint migration of Gulf of Mexico dataset, Kazemi, 2019.

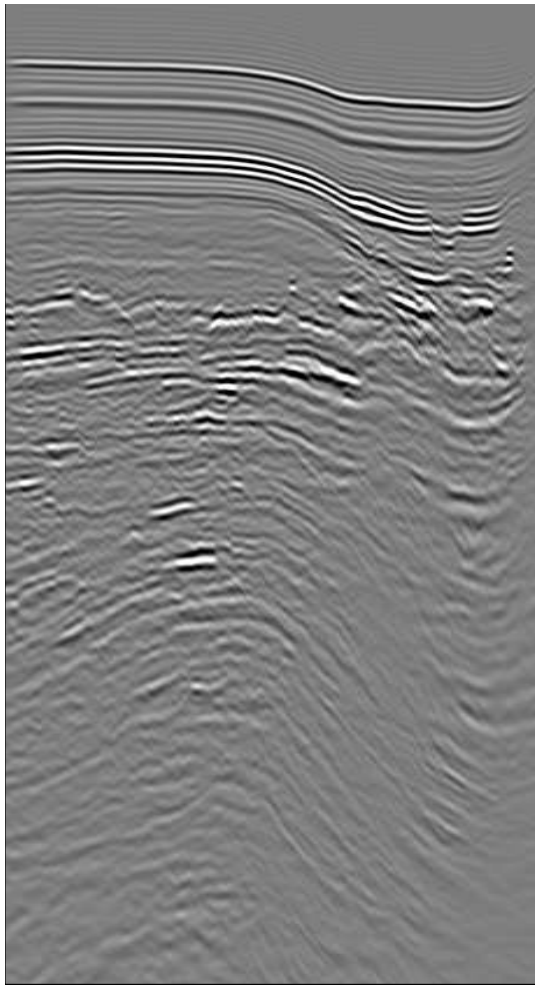
Inversion (LSM) vs. Adjoint migration



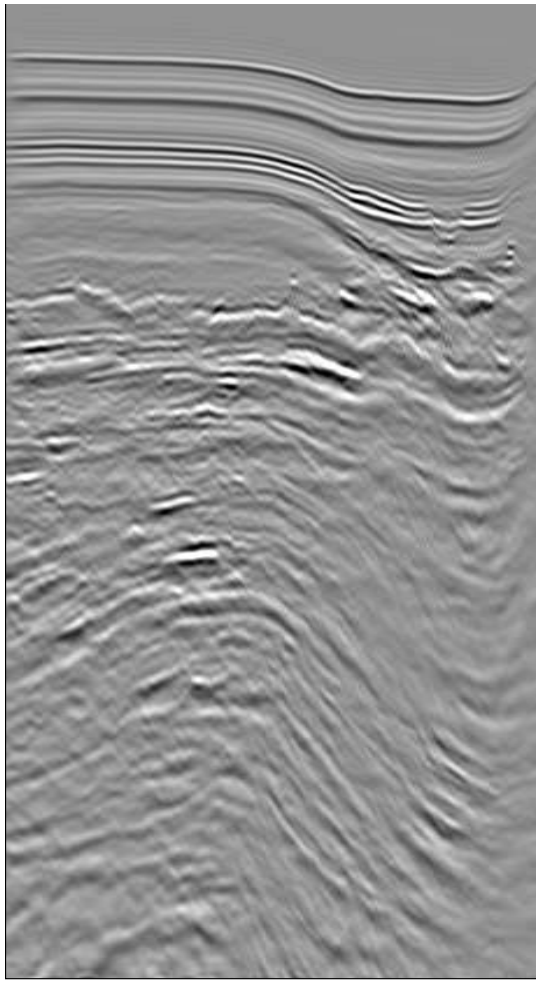
LS migration of Gulf of Mexico dataset, Kazemi, 2019.

Inversion (LSM) vs. Adjoint migration

Adjoint



Least squares



Adjoint vs. LS migration of Gulf of Mexico dataset

Pros and cons of least squares migration

Inversion (LSM):

Merits:

Balanced amplitudes

Attenuated artifacts

Better resolution

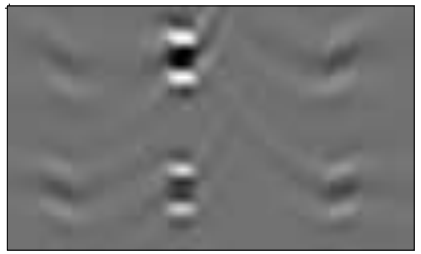
Reduced acquisition footprint

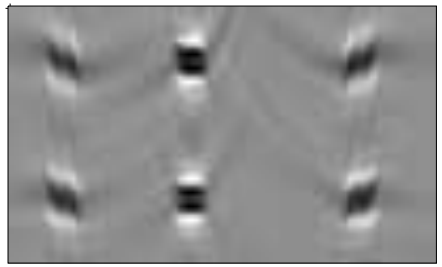
Demerits:

Computational time

Null space of the operator

Migration

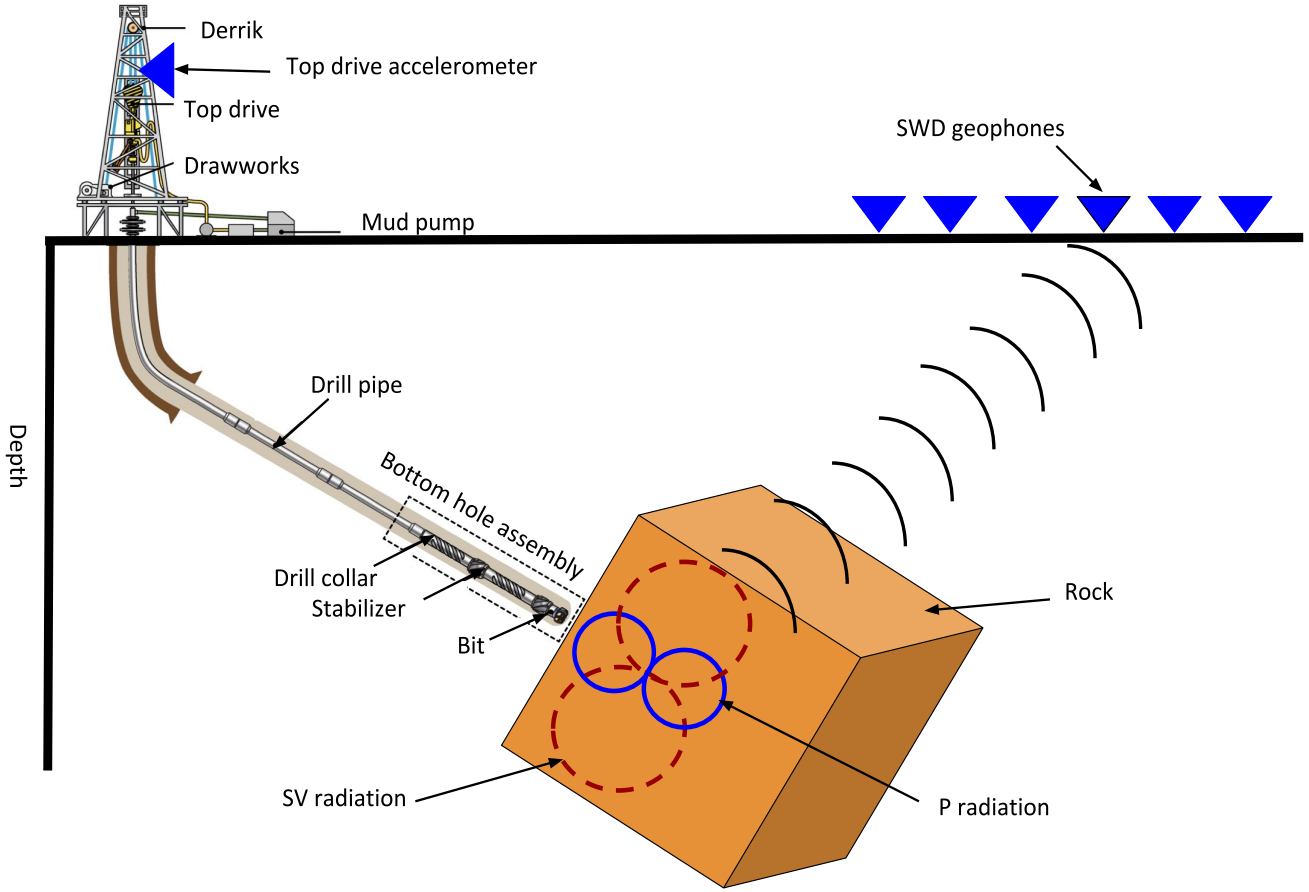




Kazemi Nojadeh, 2017

Geophysicists make safe and efficient drilling possible

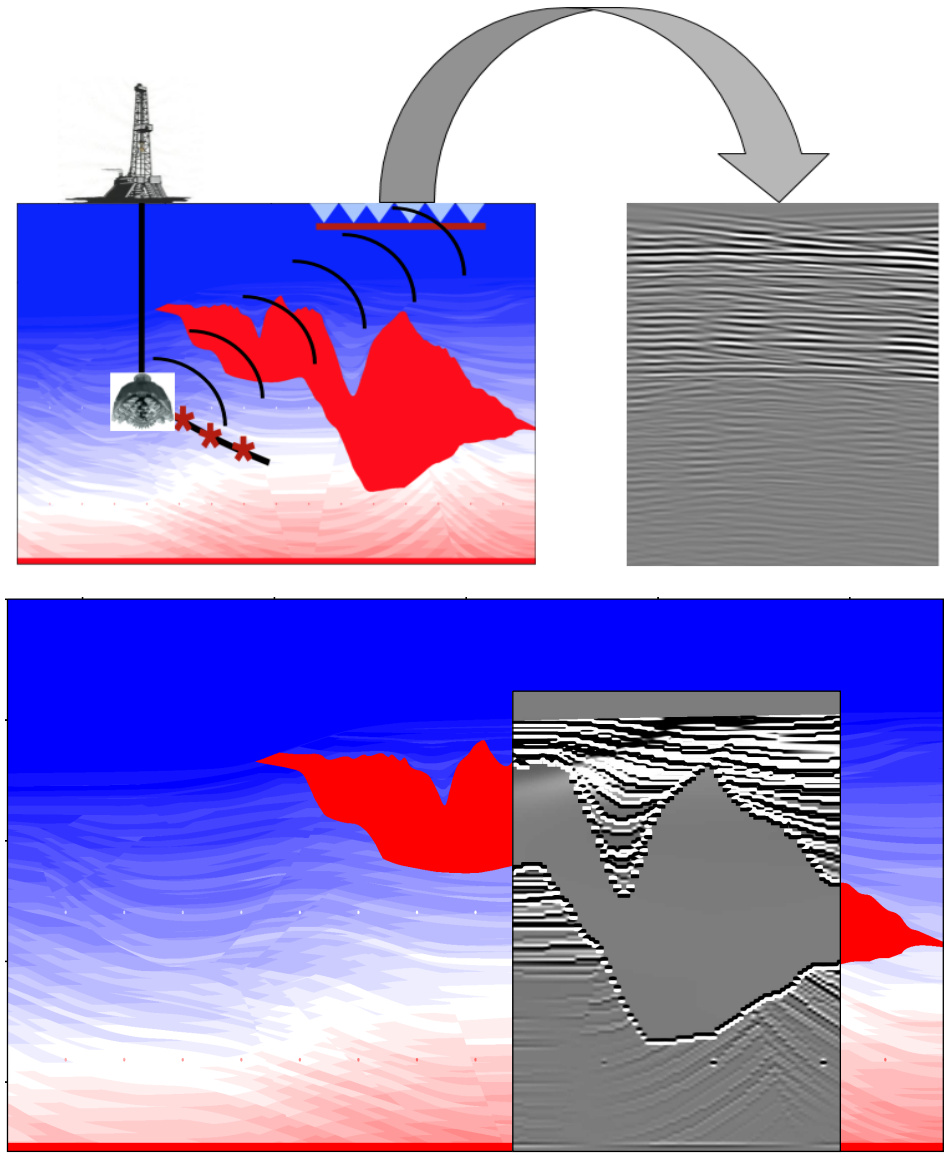
Drilling



Kazemi , Nejadi, et al., 2020, Energy Report

Auriol, Kazemi, et al., 2021, Mechanical systems and signal processing

Subsurface monitoring



Towards uniform illumination

Proposal:

- Add new sources and receivers with different configurations.
- Seismic-while-drilling acquisition can add new insight about the subsurface.
- Seismic-while-drilling will help to reduce the null space of the migration operator.

Added value of SWD data

- ❑ Geosteering
- ❑ Optimized well placement
- ❑ Interactive decision making for drilling
- ❑ Reducing the drilling risks
- ❑ Reducing uncertainties- improving illumination

Joint least squares migration

Joint data

$$\underset{\sim}{\mathbf{d}} = \begin{bmatrix} \mathbf{d}_{SURF} \\ \mathbf{d}_{SWD} \end{bmatrix}$$

Joint forward operator

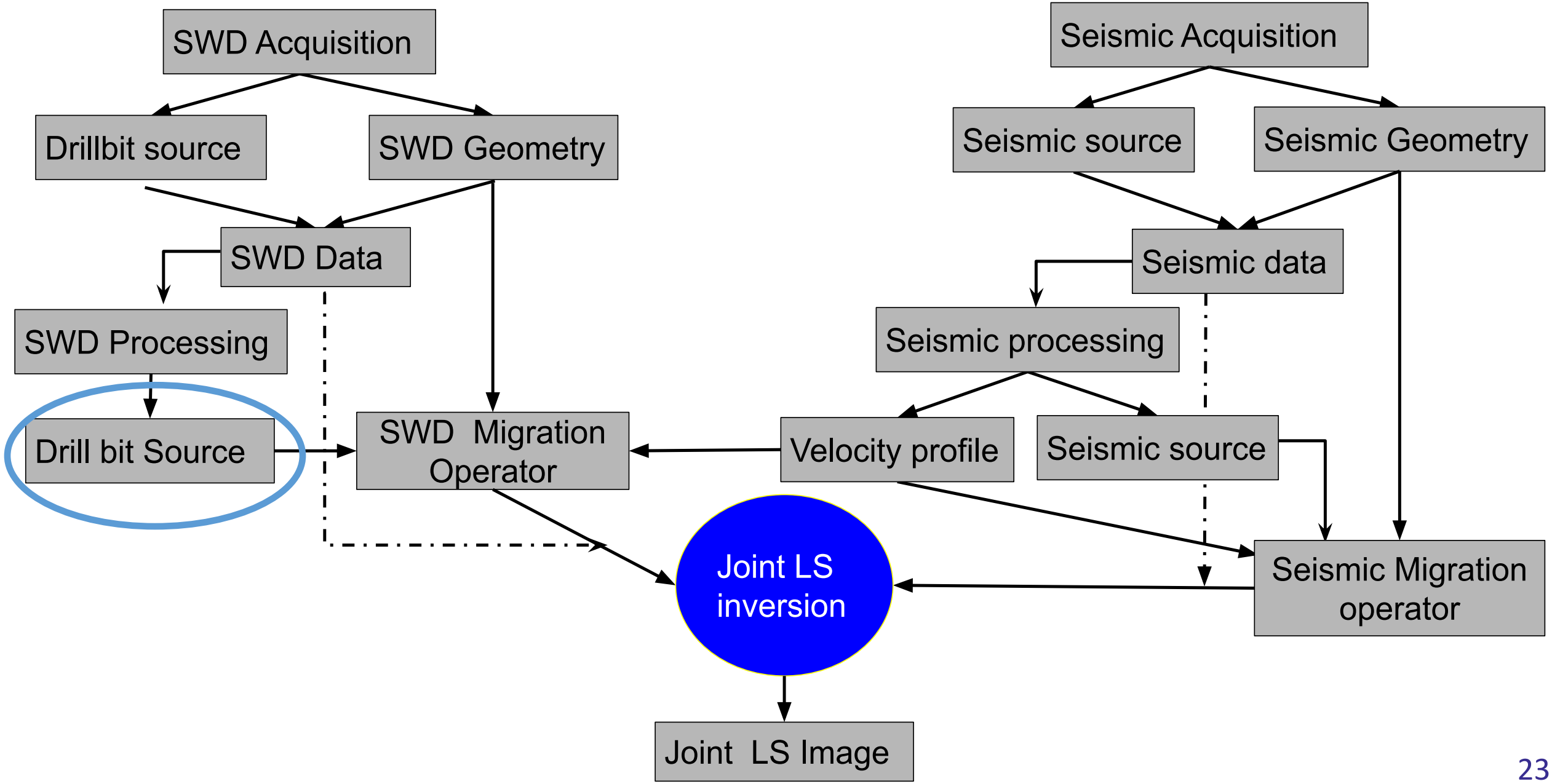
$$\underset{\sim}{\mathbf{L}} = \begin{bmatrix} \mathbf{L}_{SURF} \\ \mathbf{L}_{SWD} \end{bmatrix}$$

Joint least-squares minimization

$$\mathbf{m}_{LS}^{Joint} = \underset{\mathbf{m}}{\operatorname{argmin}} \, \|\underset{\sim}{\mathbf{L}}\mathbf{m} - \underset{\sim}{\mathbf{d}}\|_2^2 + \mu \|\mathbf{D}\mathbf{m}\|_2^2$$

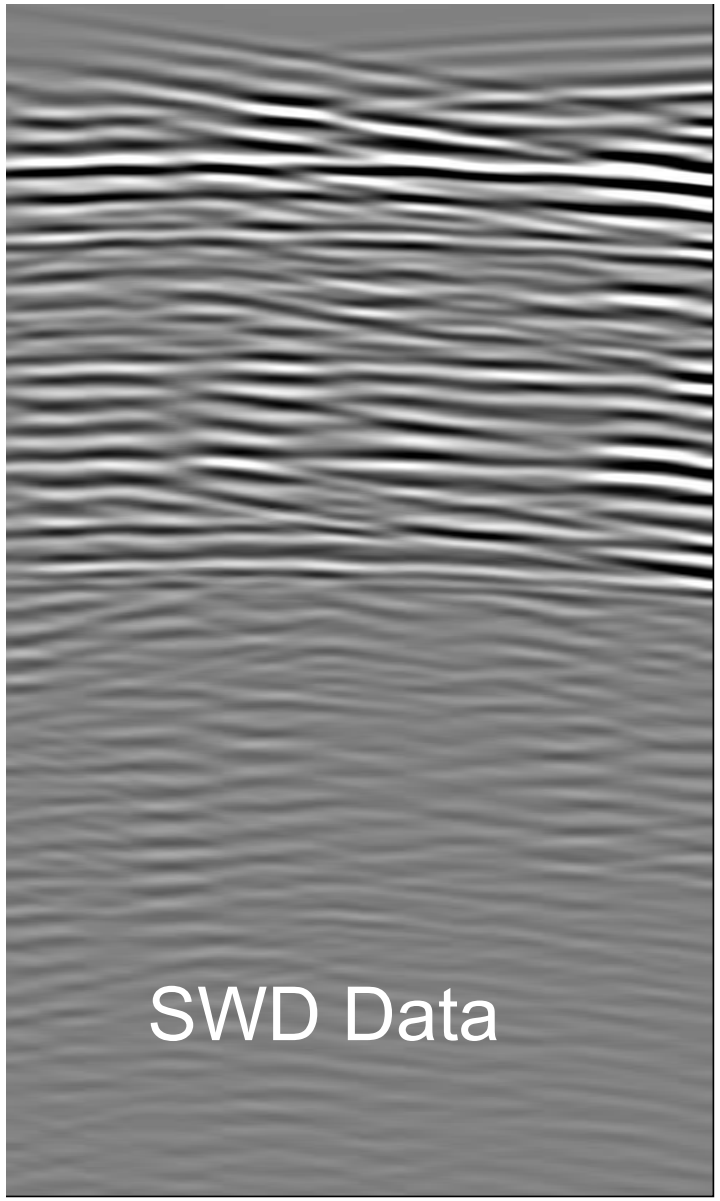
$$\underset{\sim}{\mathbf{L}}^T \underset{\sim}{\mathbf{L}} \approx \mathbf{I}$$

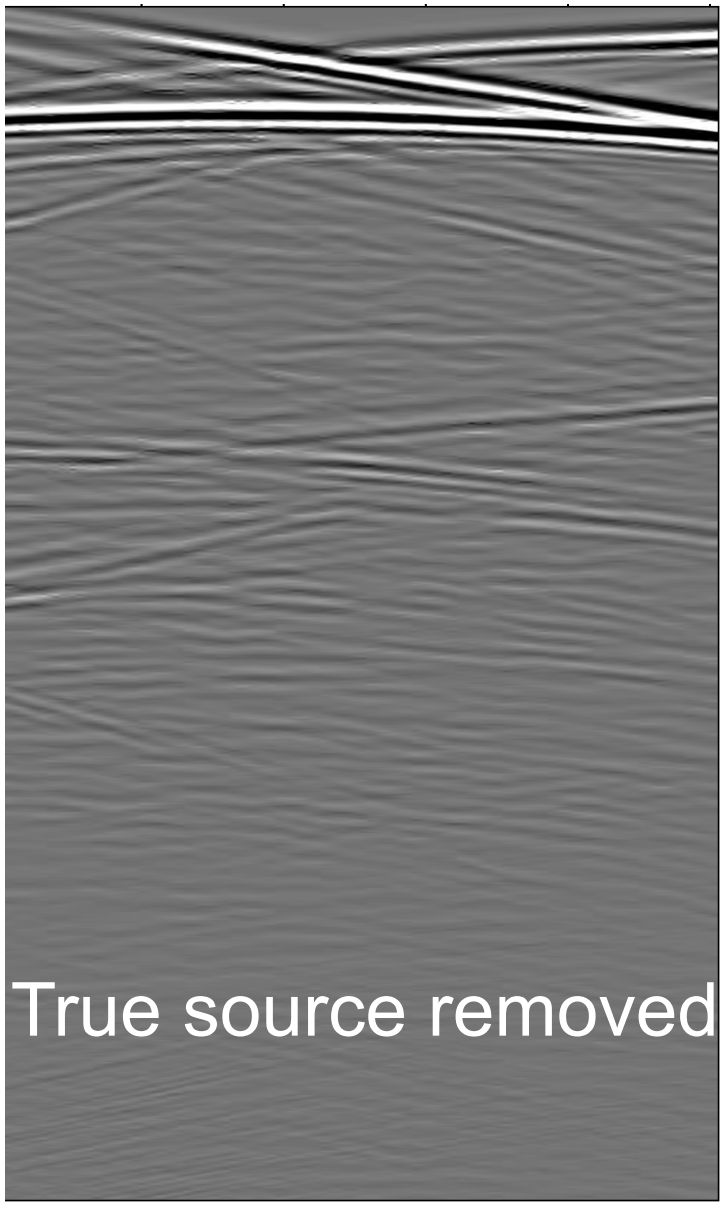
Joint least-squares migration workflow

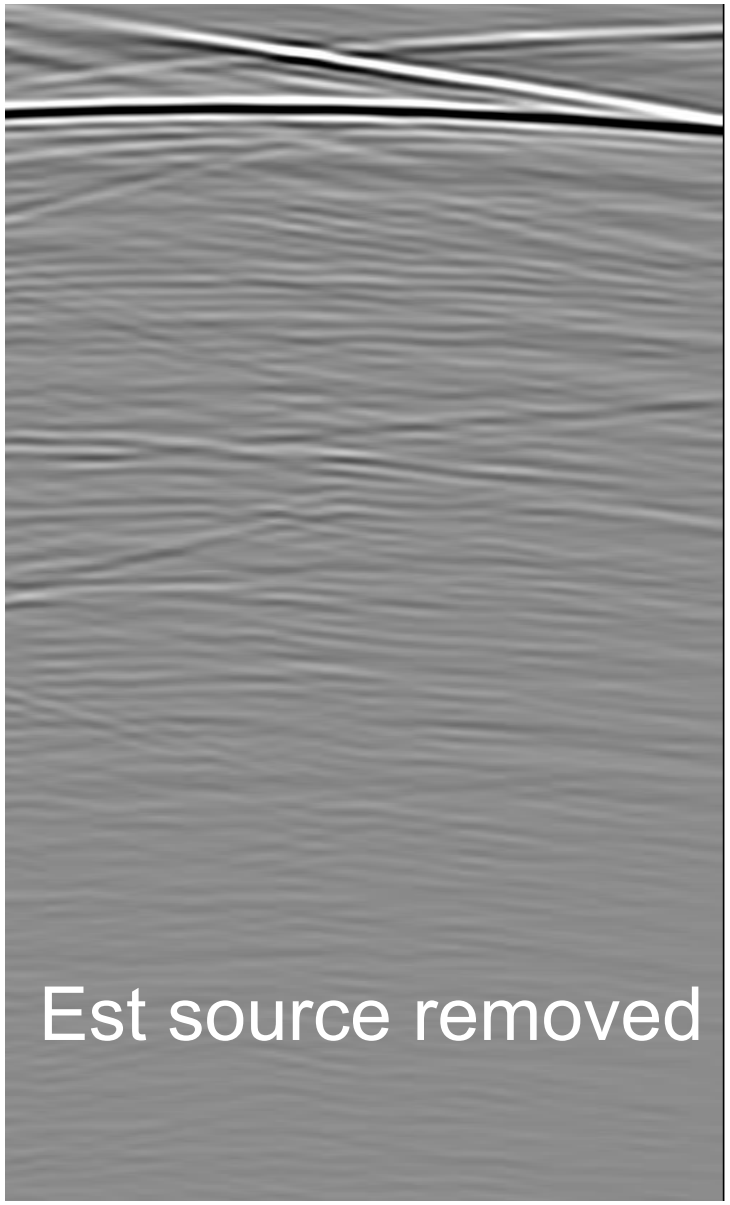


SWD source signature estimation

Kazemi and Sacchi, 2014



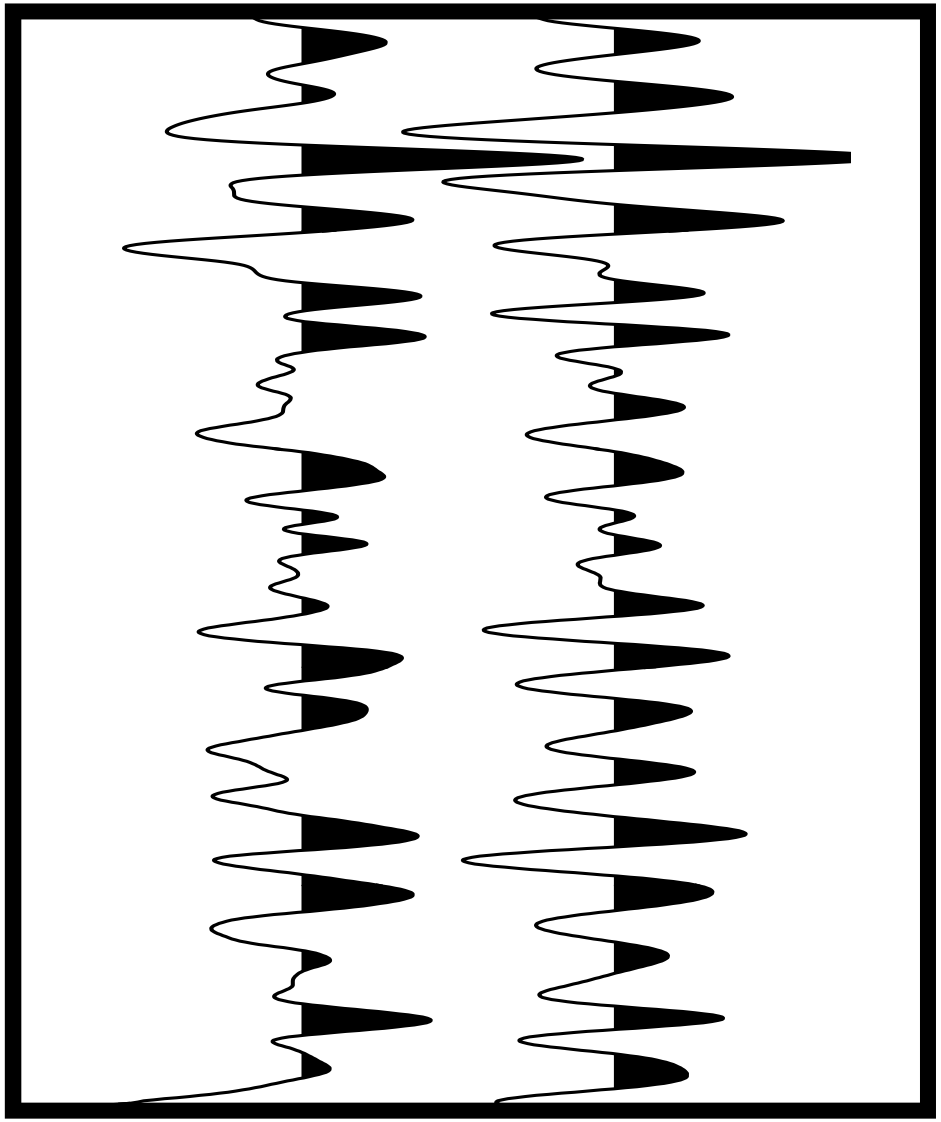




SWD source signature estimation

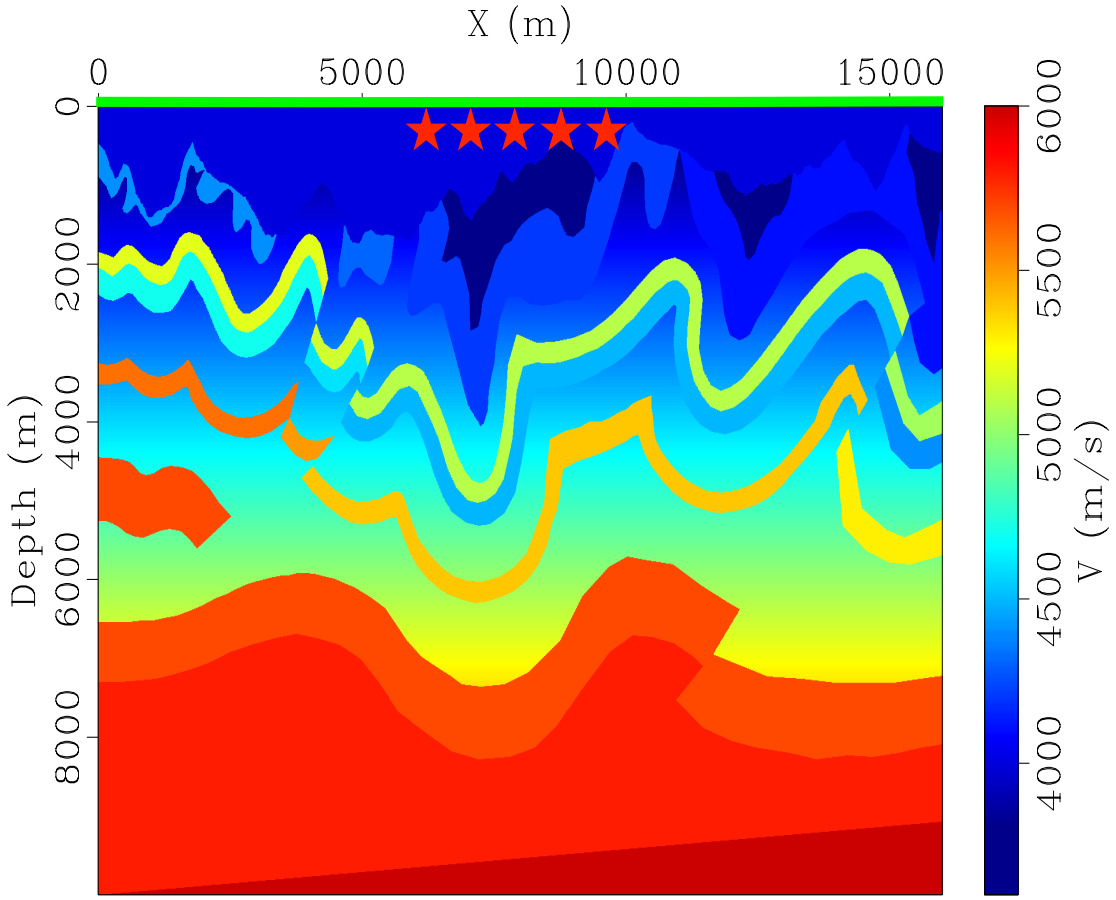
Original Estimated

NCC=0.88

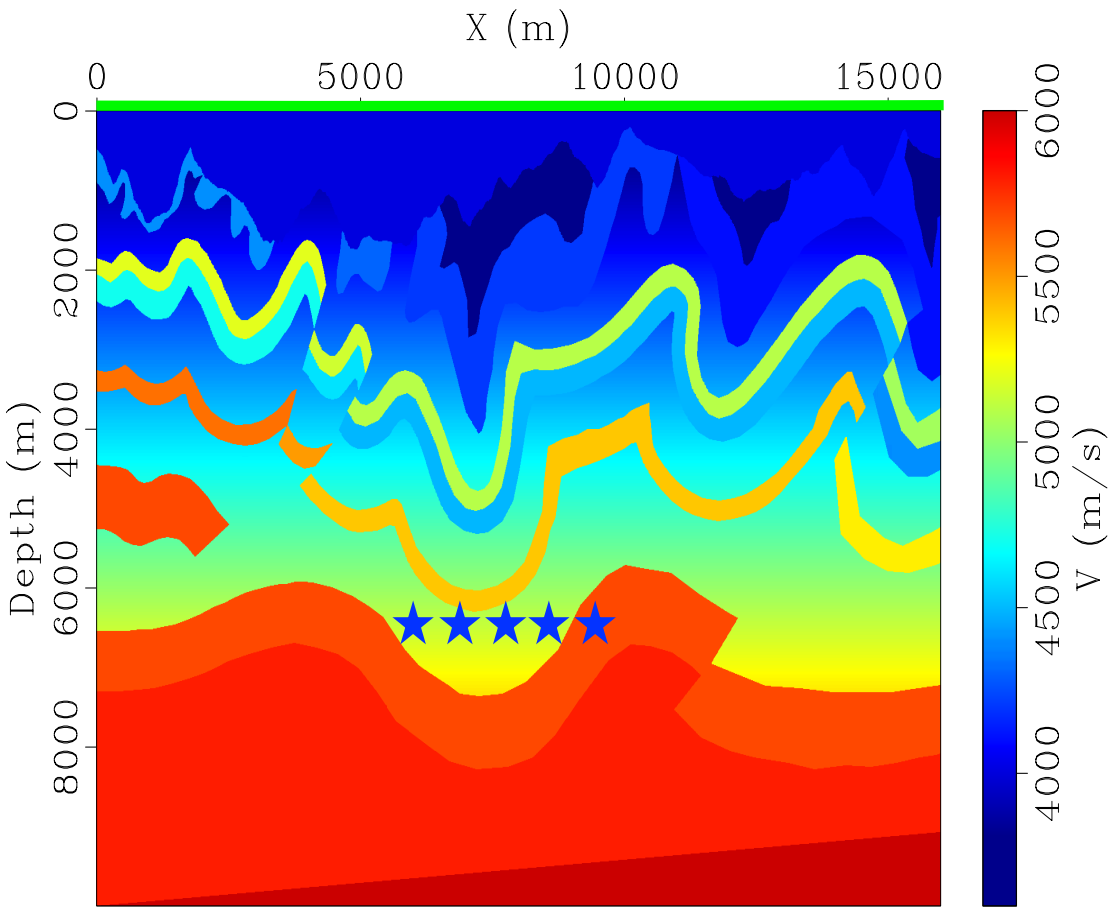


Surface and SWD acquisition on BP model

Model representing the foothills of the Canadian Rockies

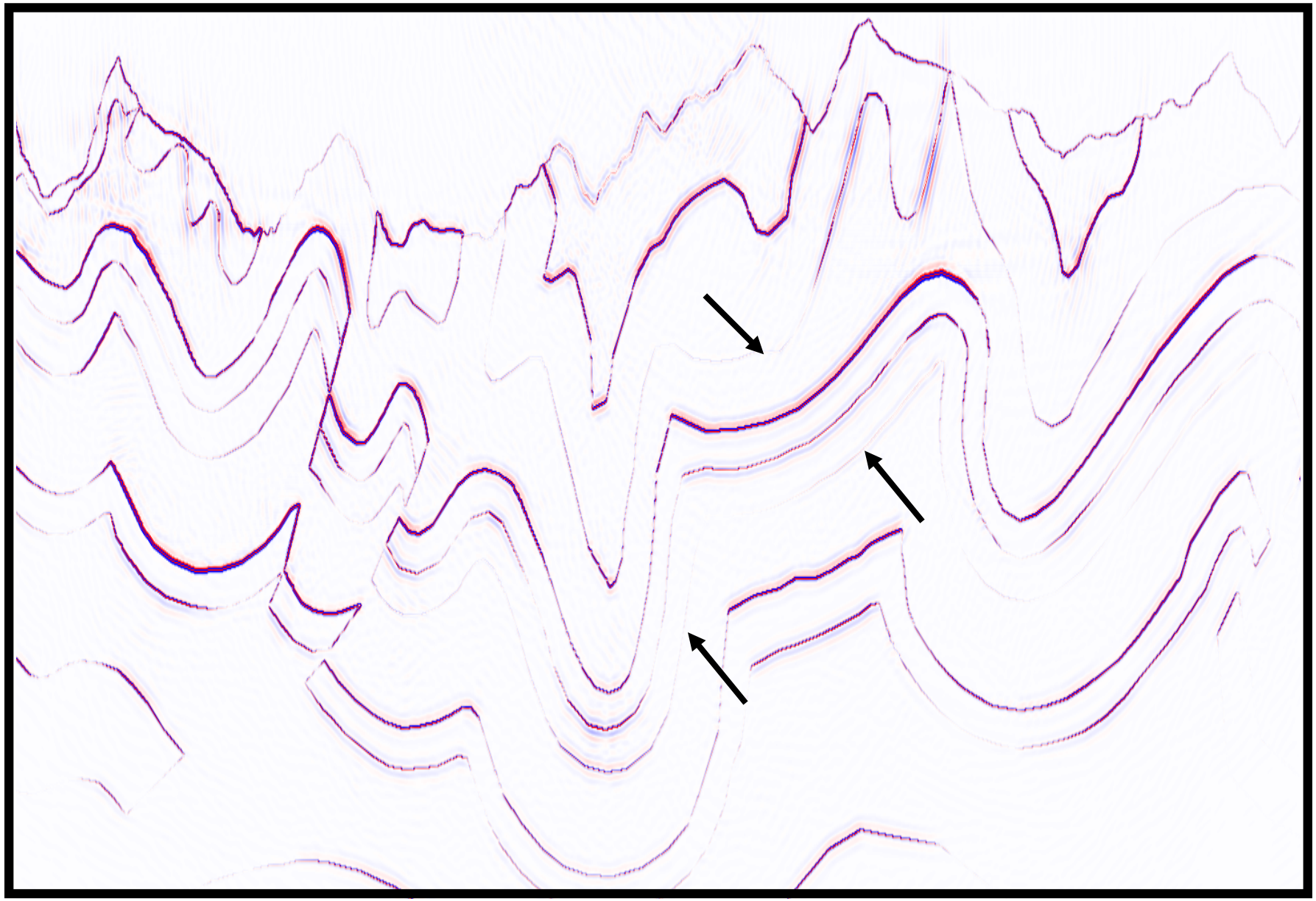


Surface seismic Geometry

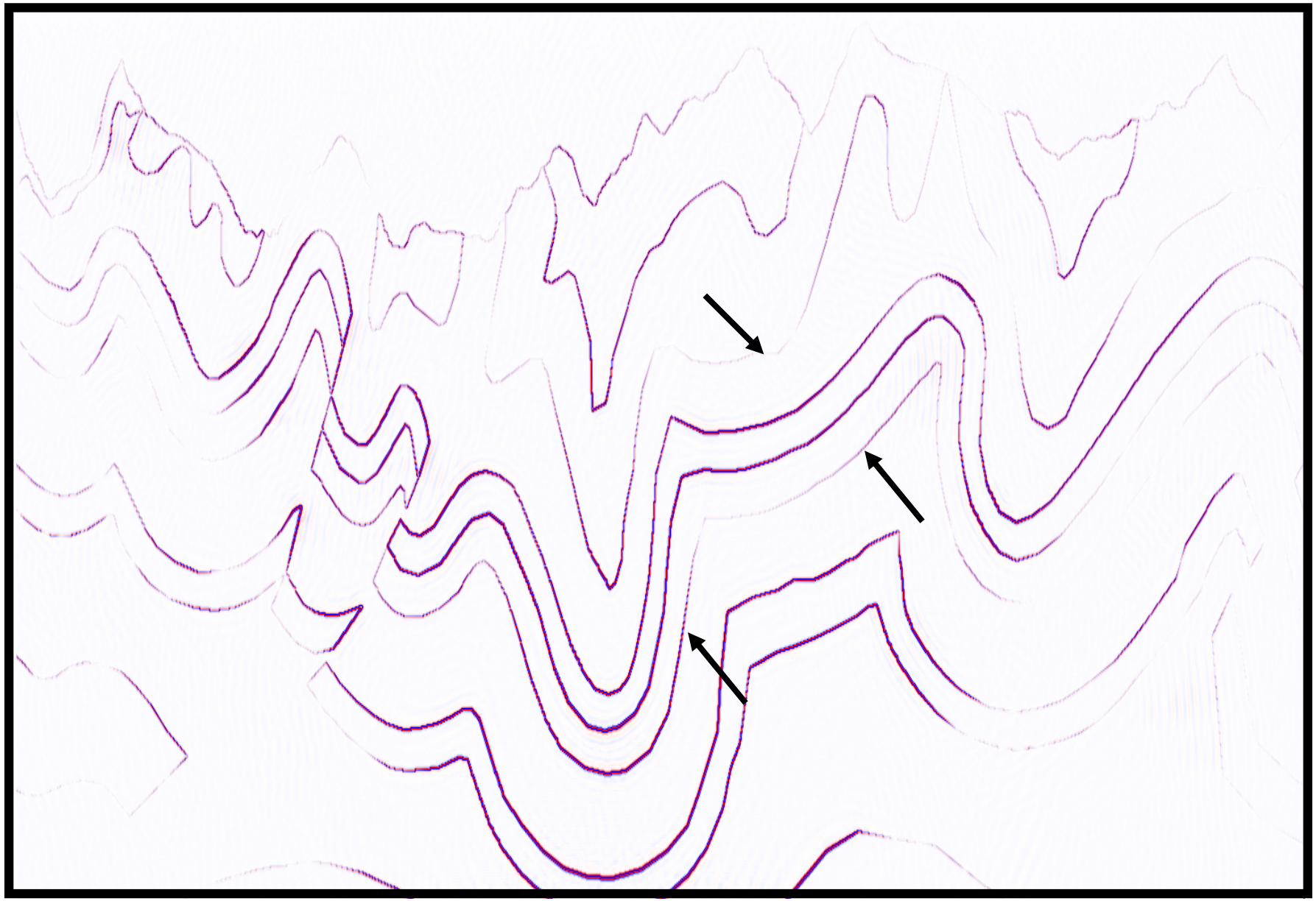


SWD seismic Geometry

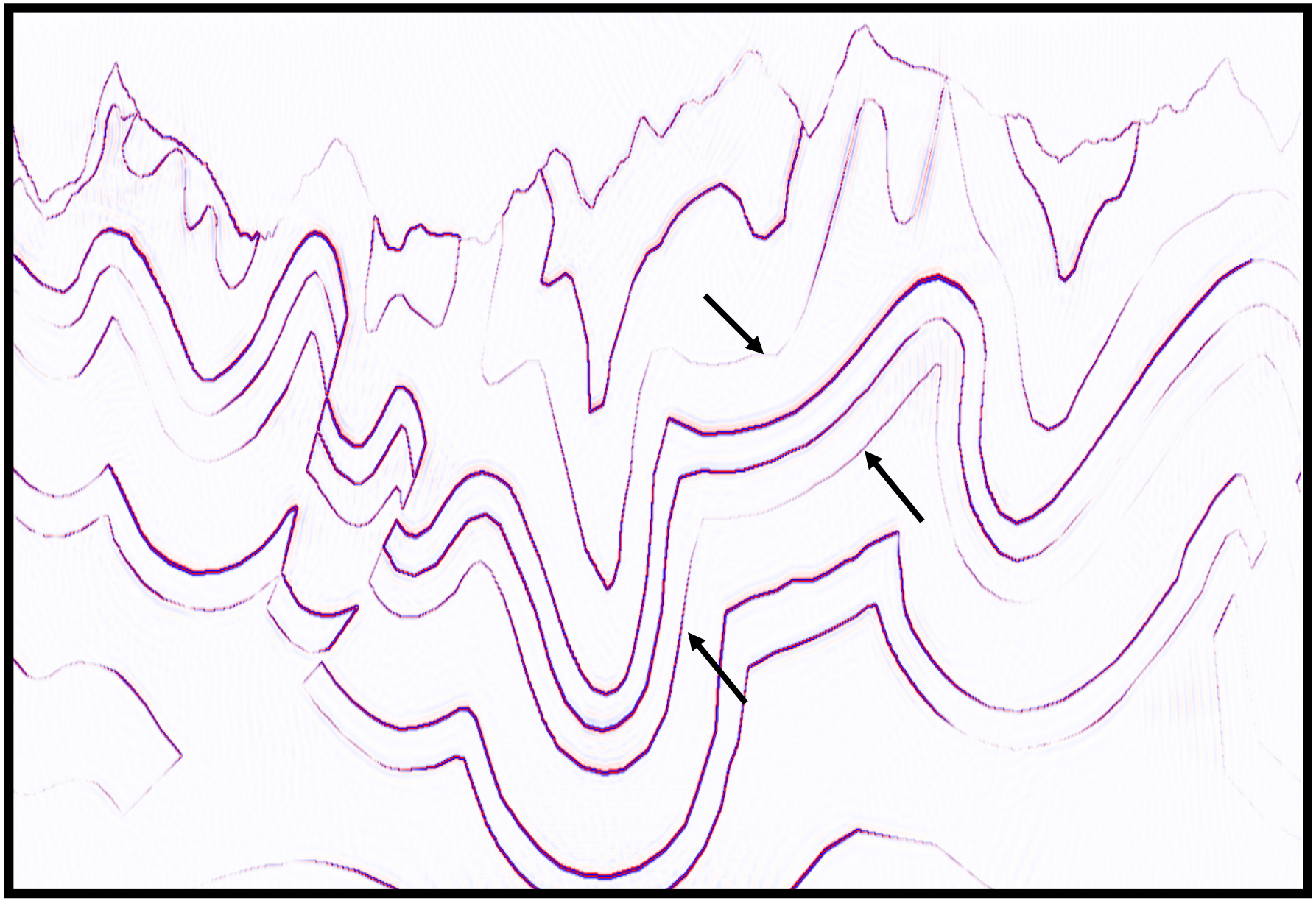
LSRTM of surface seismic data



LSRTM of SWD data

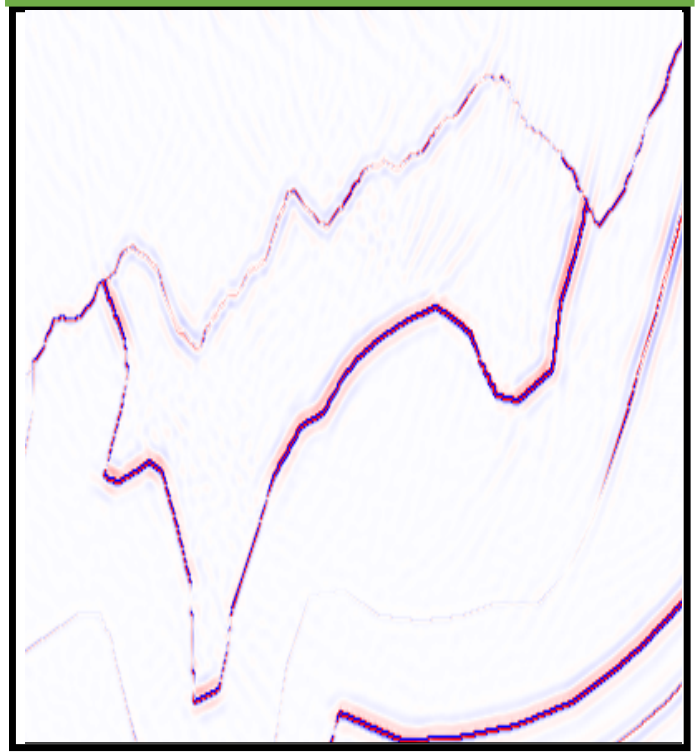


Joint LS-RTM of surface seismic and SWD data

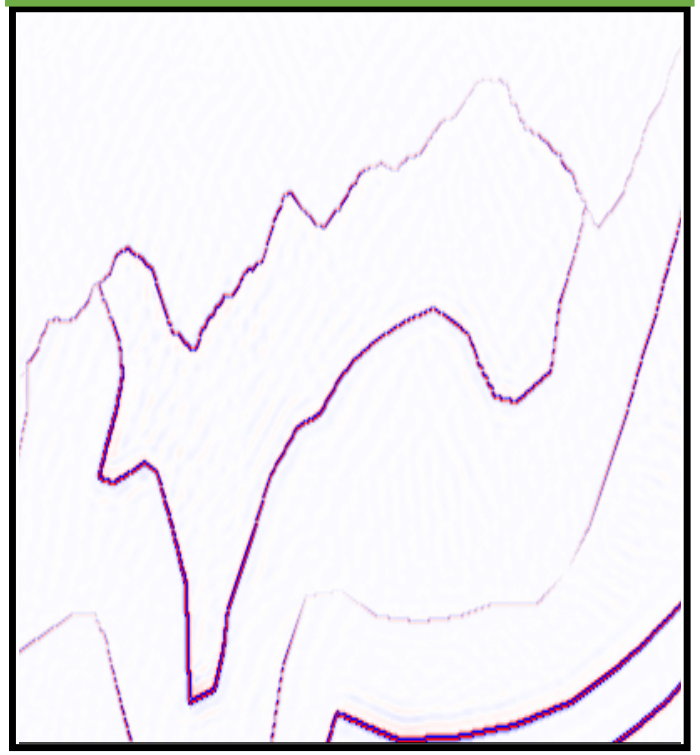


Zoomed version: Shallow part

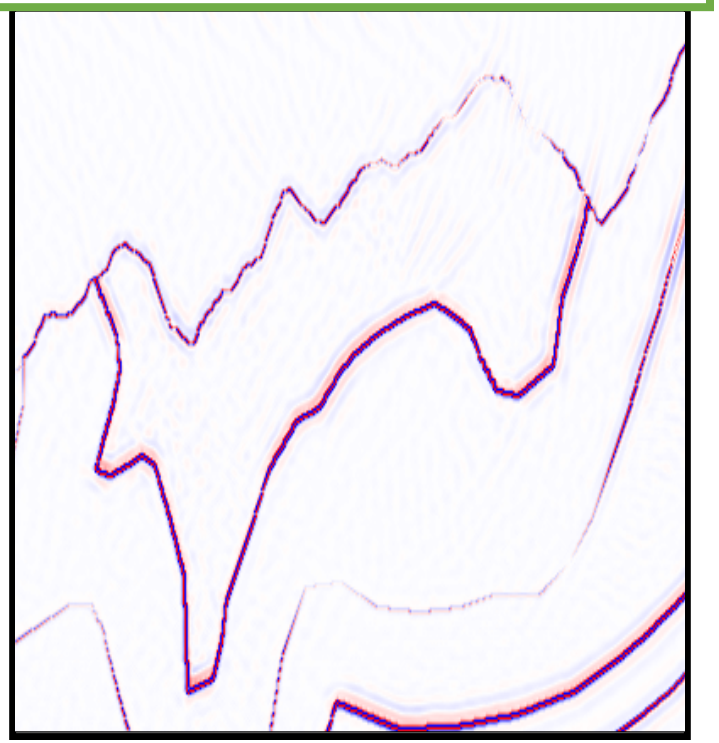
Surface migration



SWD migration

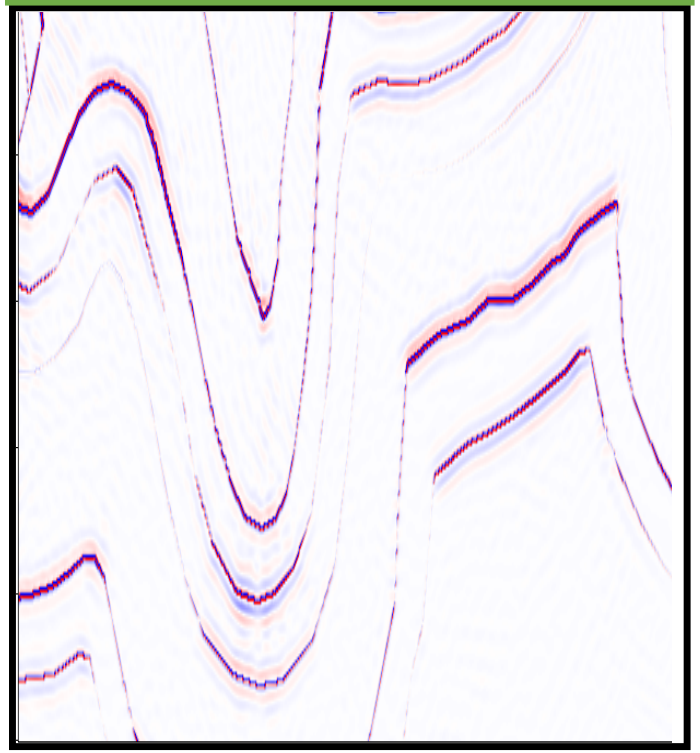


Surface+SWD migration

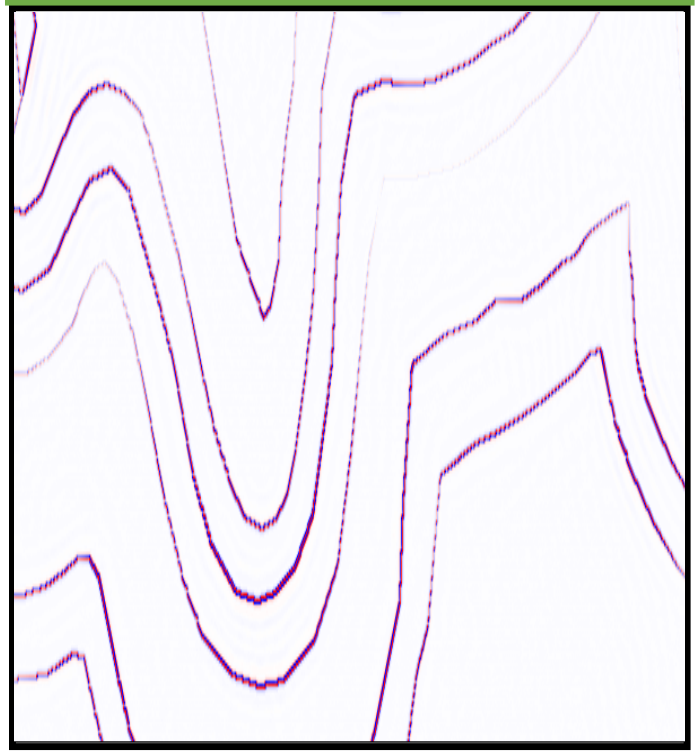


Zoomed version: Deeper part

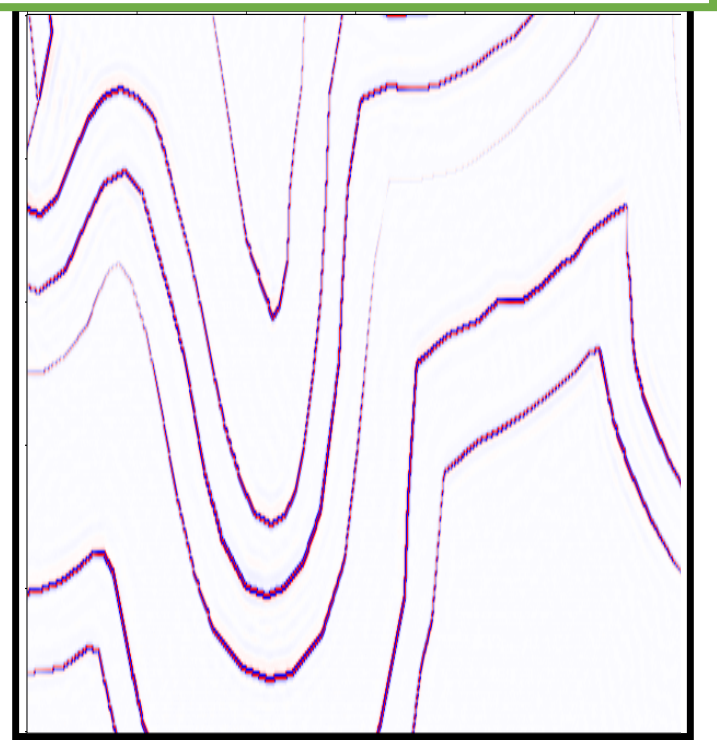
Surface migration



SWD migration

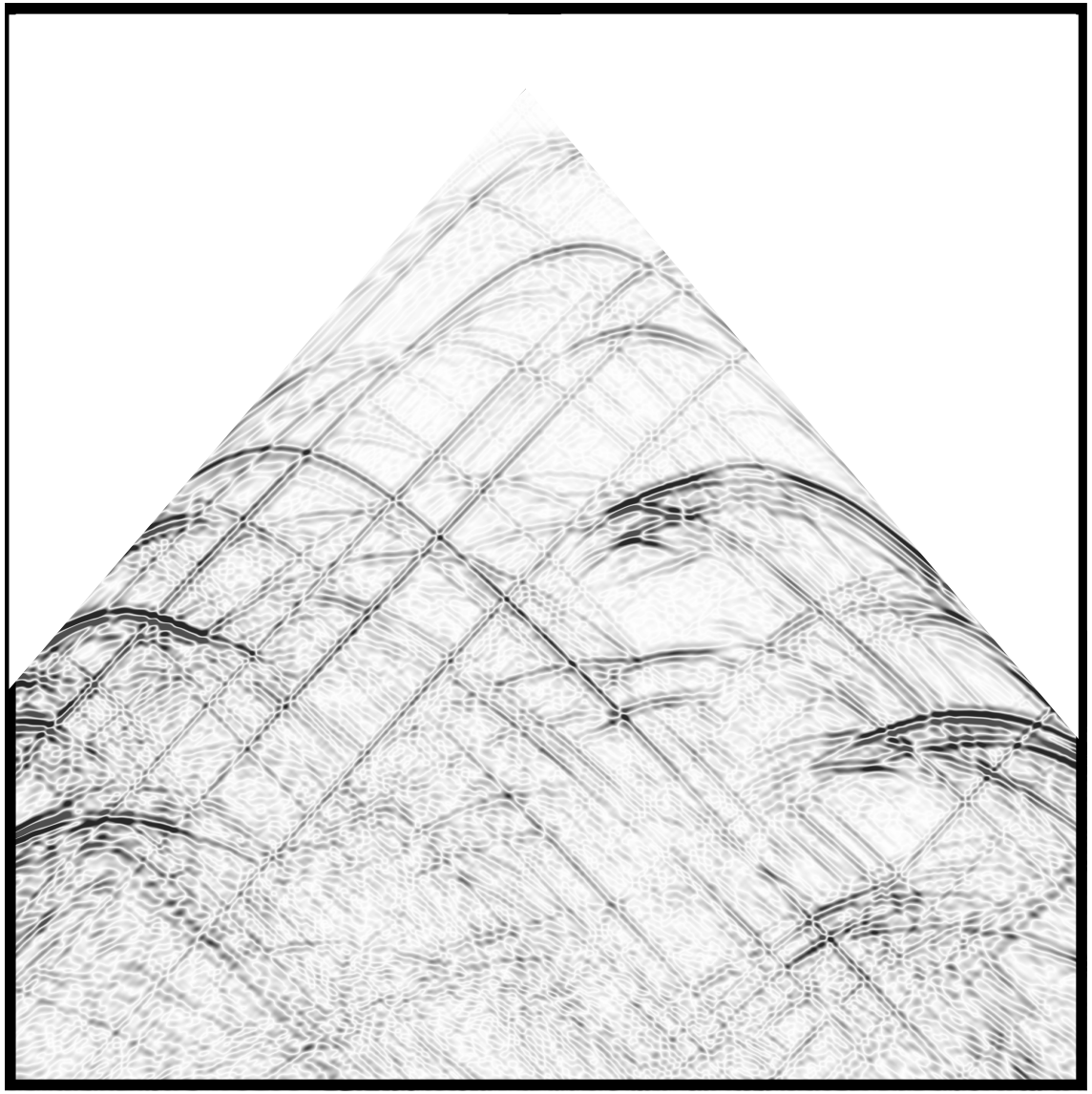


Surface+SWD migration

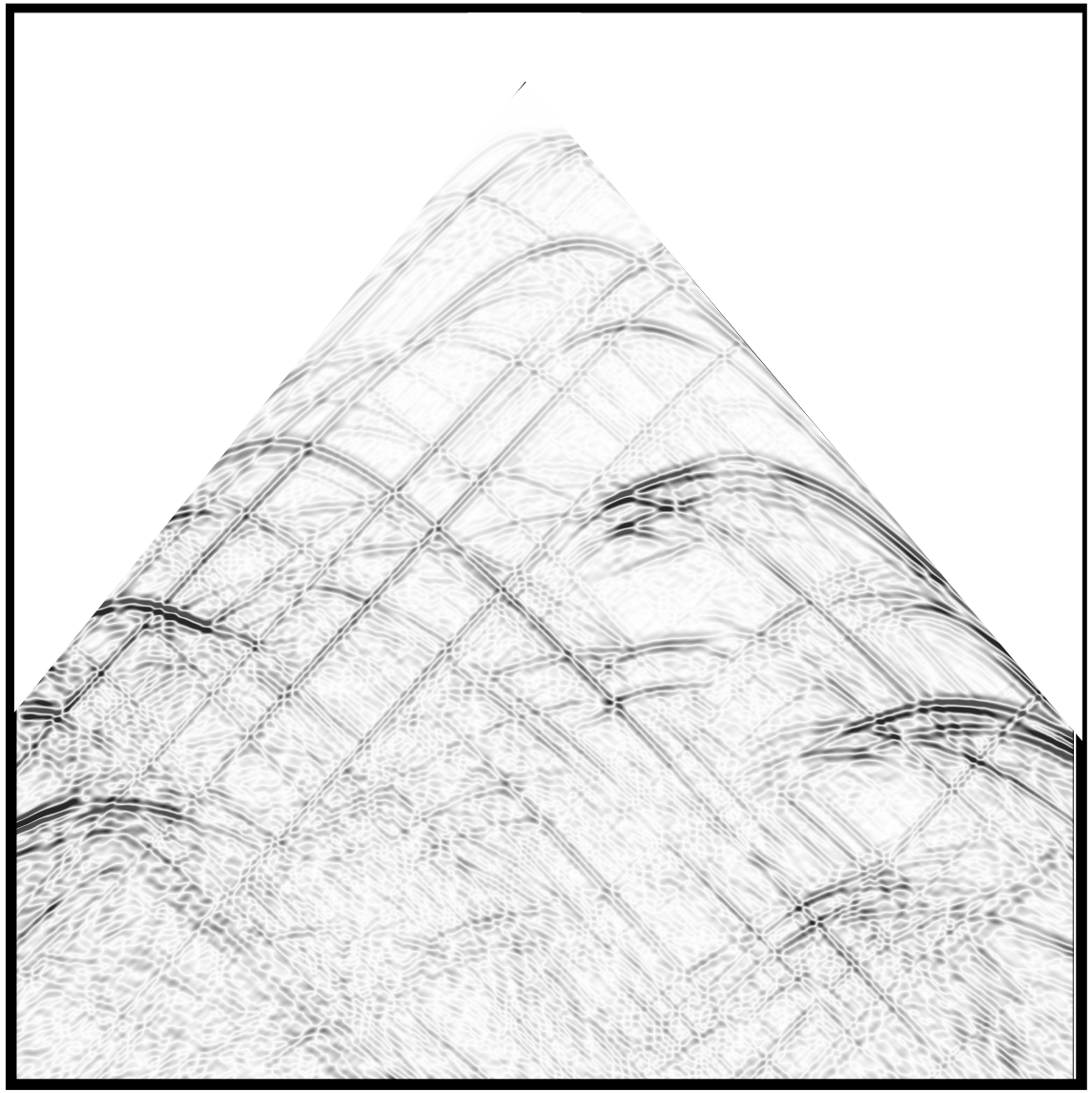


Fitting the data- Surface seismic

True data

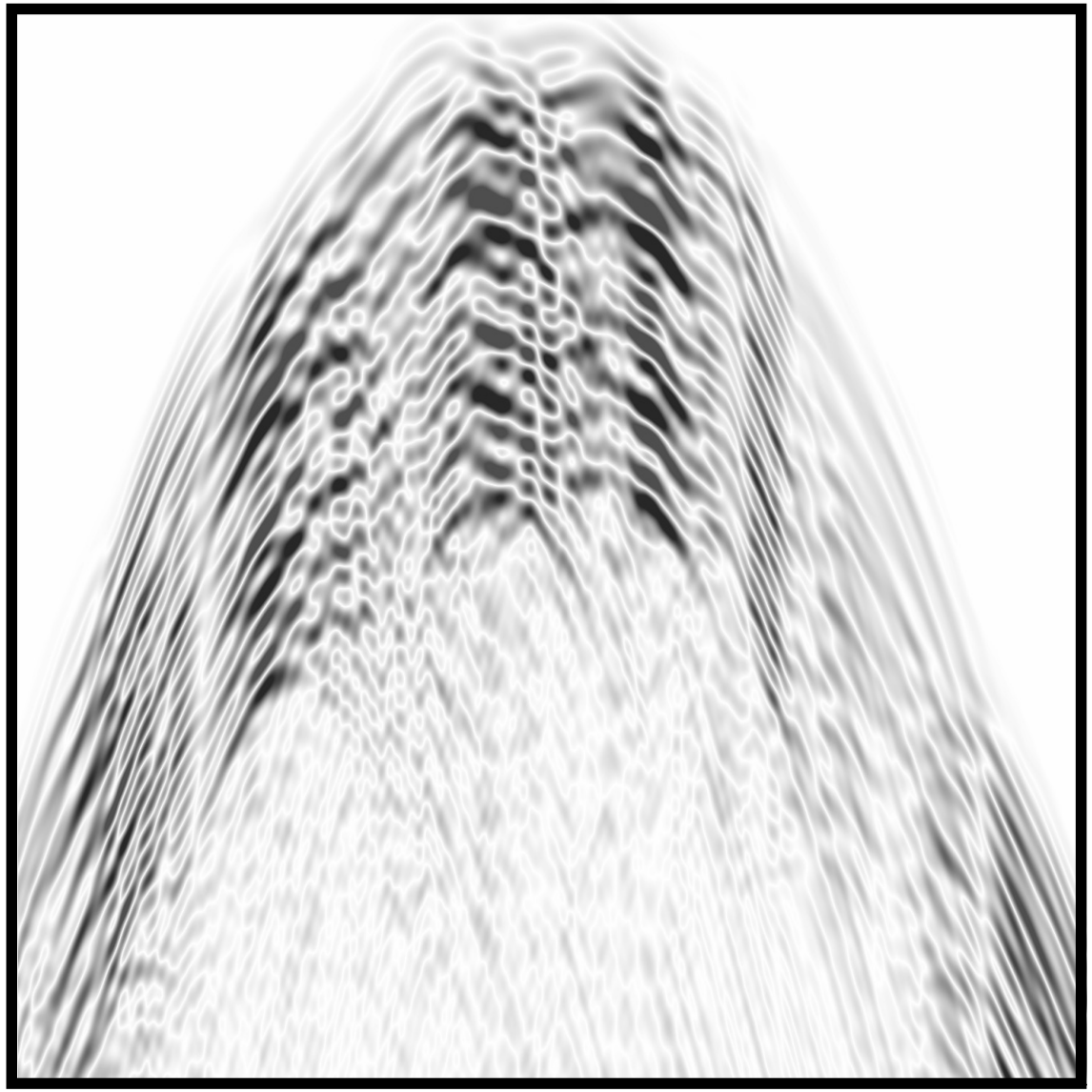


Predicted data

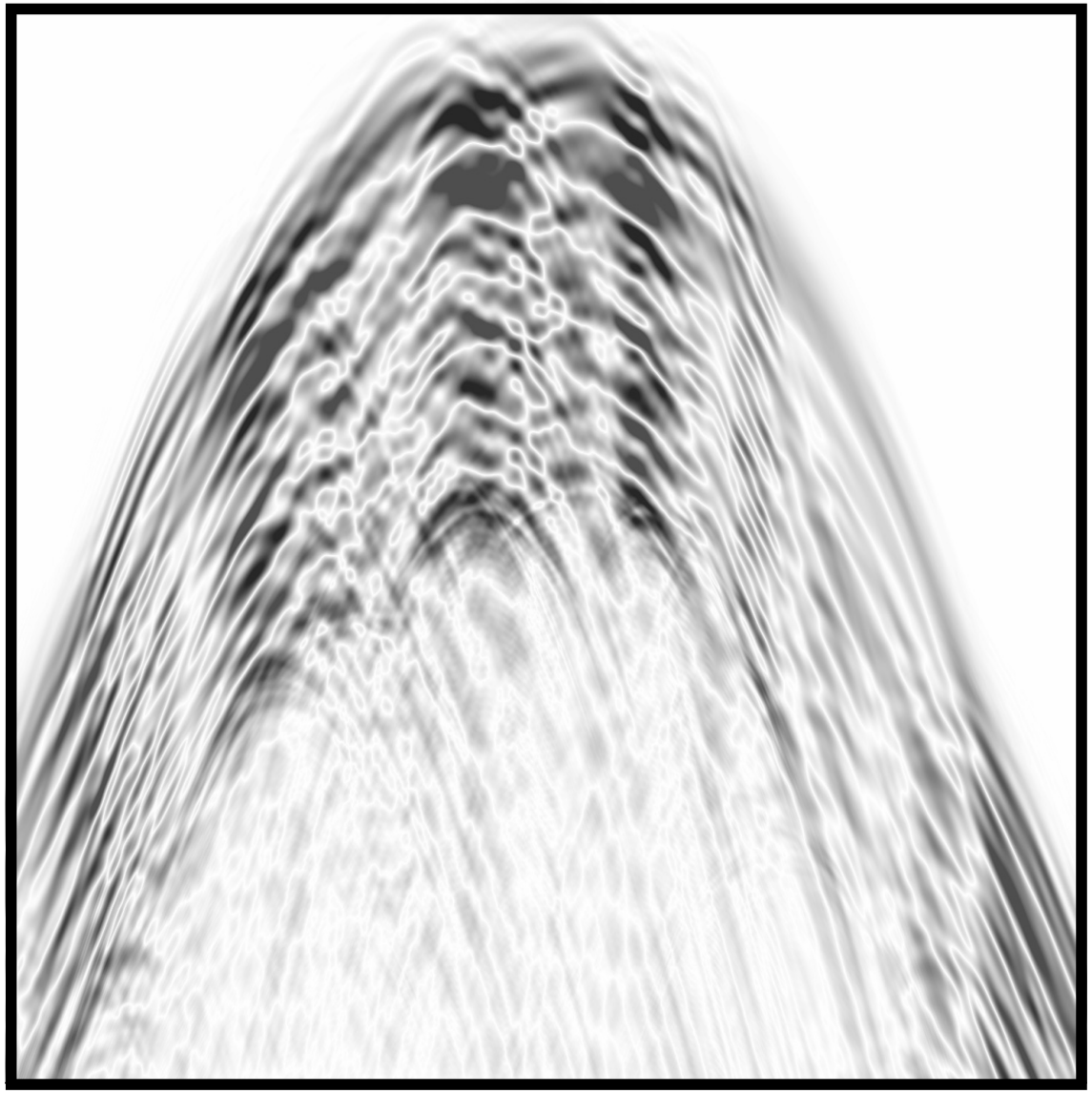


Fitting the data- SWD

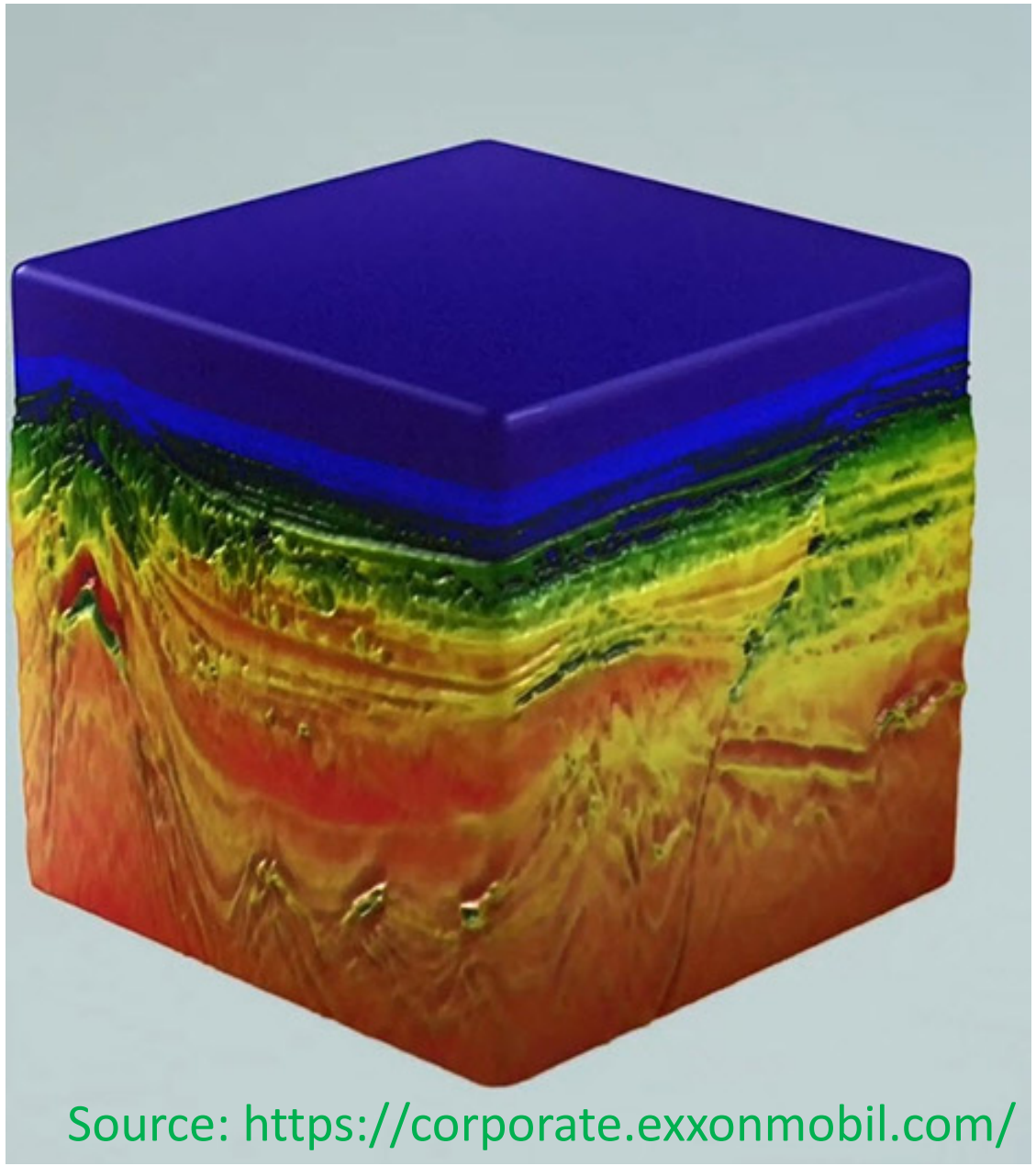
True data



Predicted data



Full-waveform inversion



Full-Waveform Inversion of Surface Seismic and Seismic-While-Drilling Datasets

Full Waveform Inversion- Data Modeling

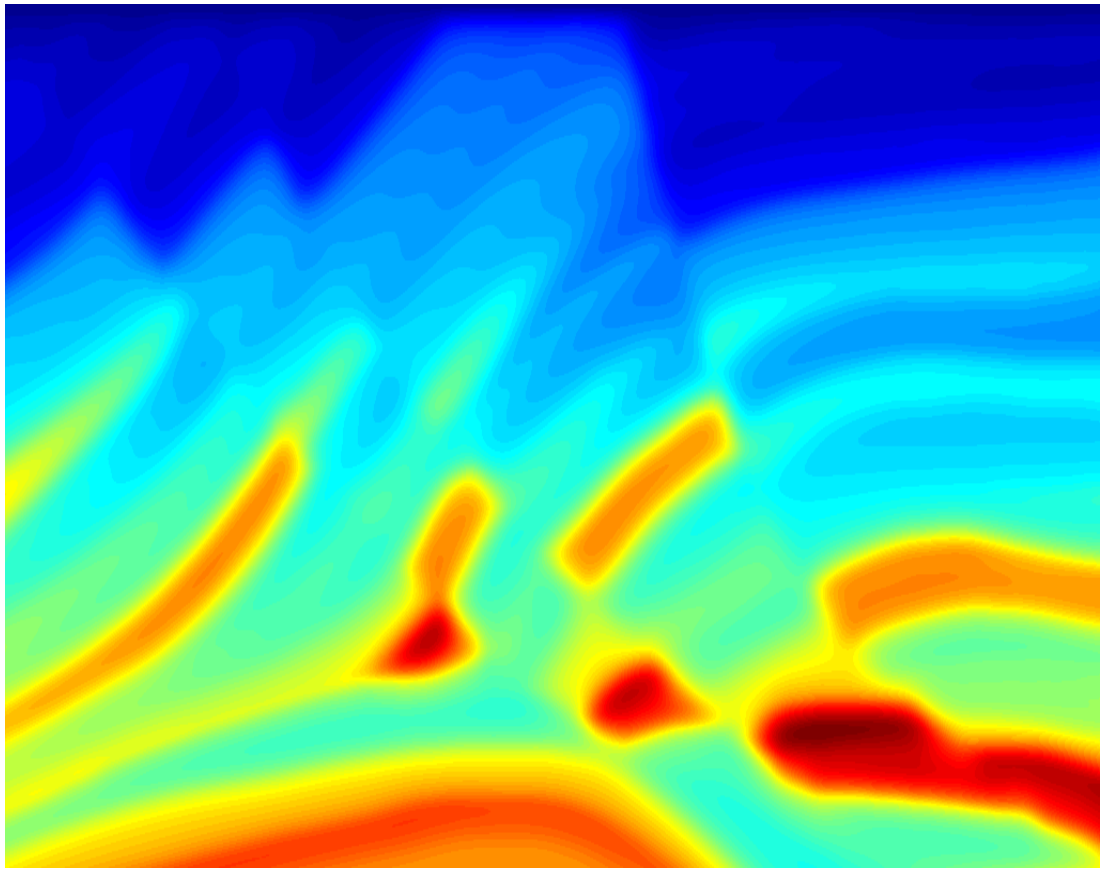
$$\mathbf{M}(\mathbf{x})\frac{\partial^2 \mathbf{u}(\mathbf{x},t)}{\partial t^2} + \mathbf{S}(\mathbf{x})\frac{\partial \mathbf{u}(\mathbf{x},t)}{\partial t} + \mathbf{D}\ \mathbf{u}(\mathbf{x},t) = \mathbf{F}(\mathbf{x},t)$$

$$\left[-\omega^2\mathbf{M}(\mathbf{x}) + j\omega\mathbf{S}(\mathbf{x}) + \mathbf{D}(\mathbf{x})\right]\ \mathbf{u}(\mathbf{x},\omega) = \mathbf{F}(\mathbf{x},\omega)$$

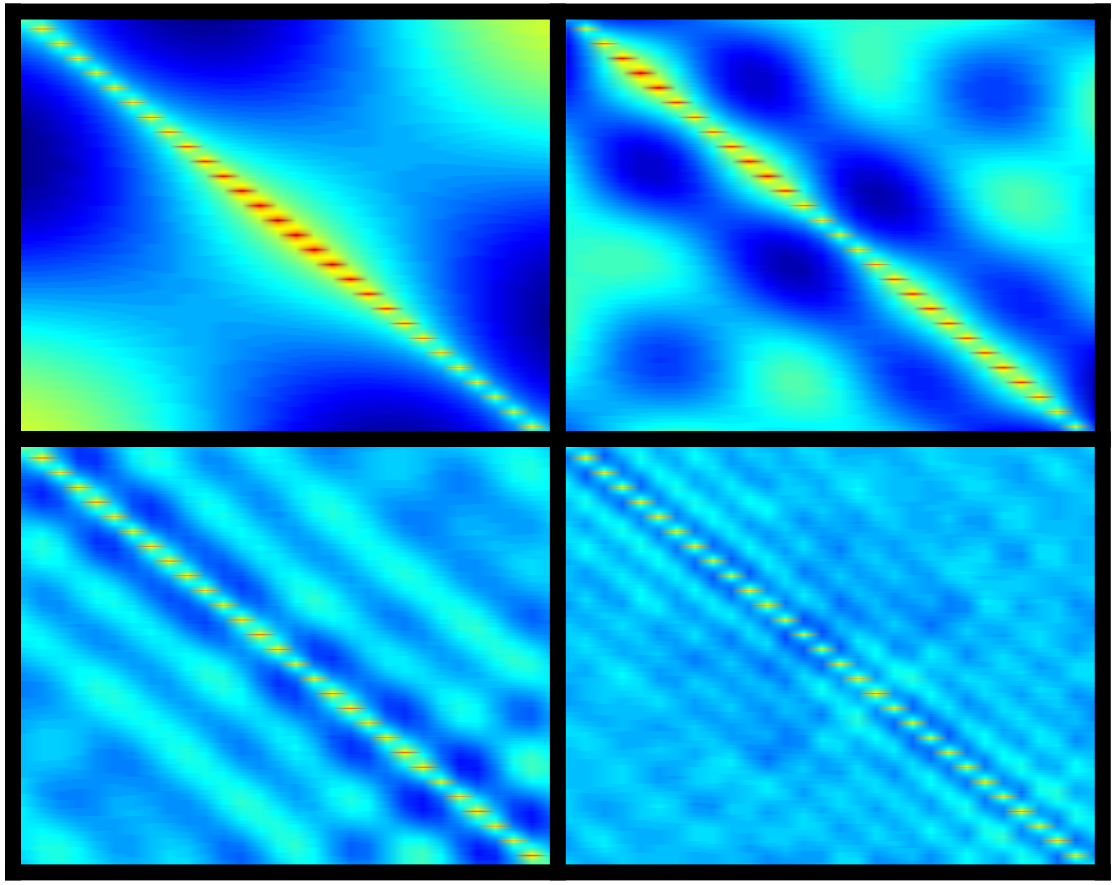
$$\mathbf{B}(\mathbf{x},\omega)\ \mathbf{u}(\mathbf{x},\omega) = \mathbf{F}(\mathbf{x},\omega)$$

$$\mathbf{u} = \mathbf{L}(\mathbf{m})$$

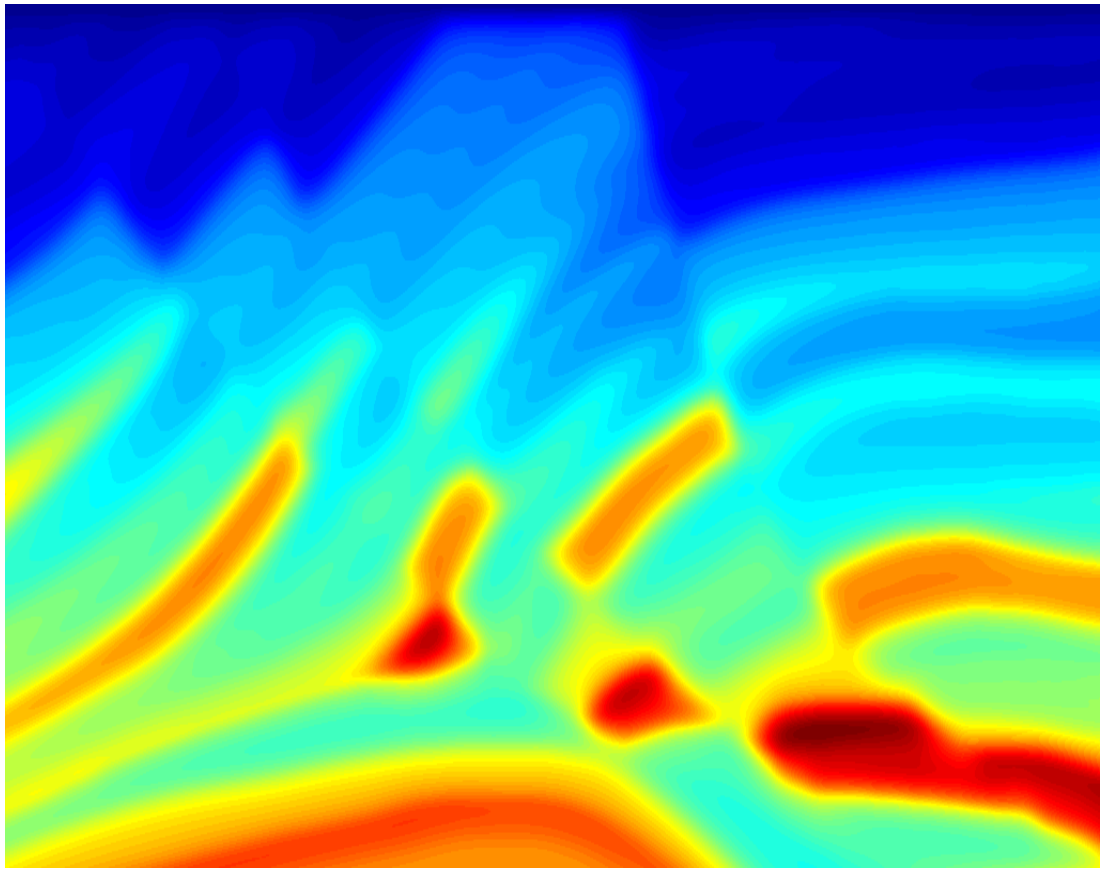
Data Modeling



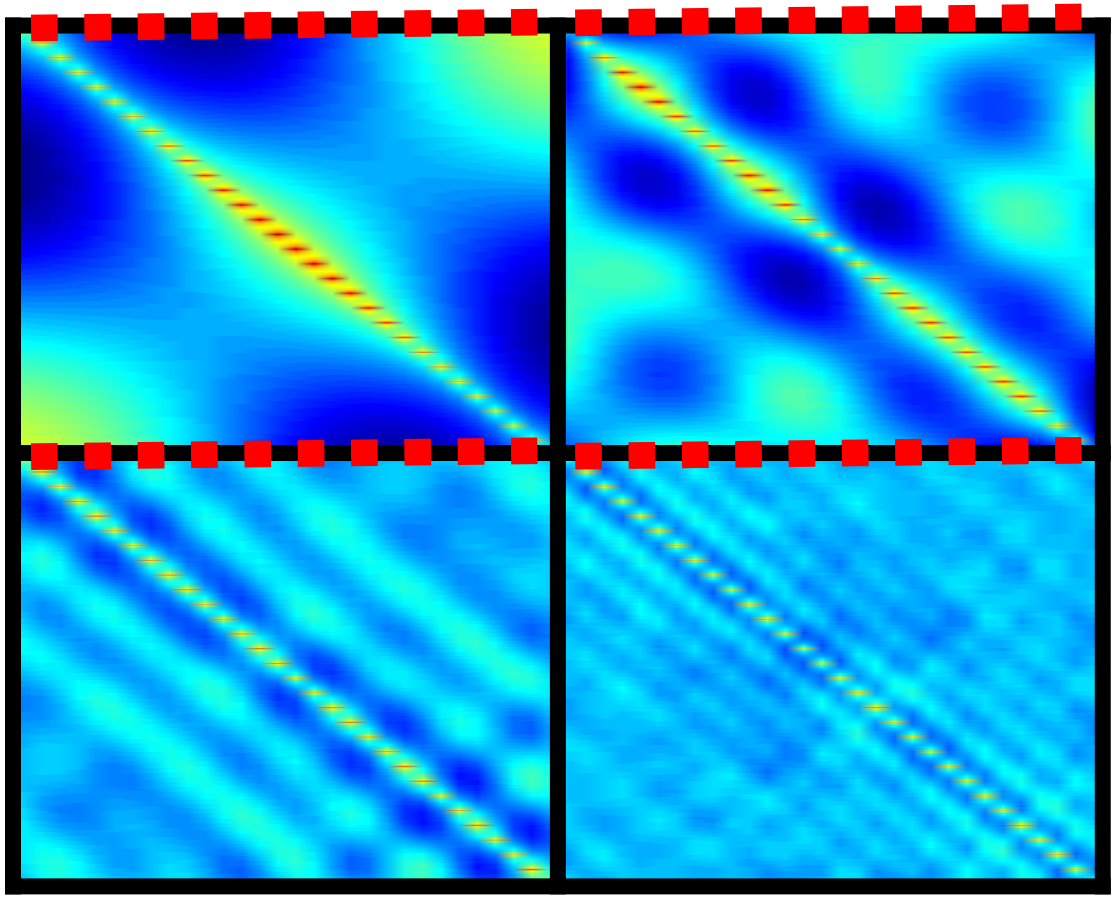
$\Longrightarrow$



Full Waveform Inversion



$\Longleftarrow$



Full Waveform Inversion

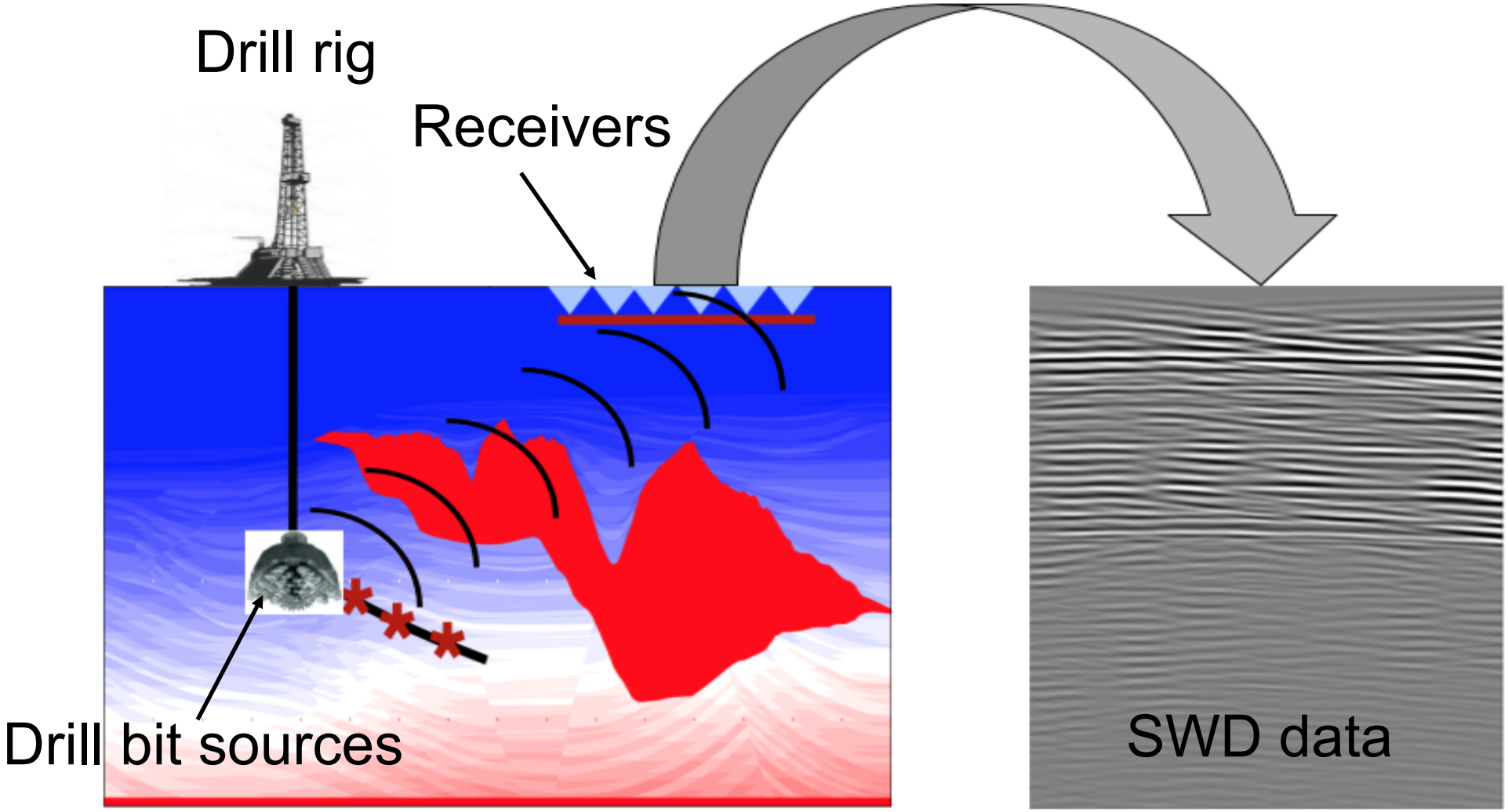
Match the recorded wave field at the surface $\mathbf{u}_{obs}$ with the modeled data $\mathbf{u}_{cal}$ by solving

$$J = \|\mathbf{u}_{obs} - \mathbf{S}\mathbf{L}(\mathbf{m})\|_2^2 + \alpha\|\mathbf{m}\|_2^2$$

Full Waveform Inversion (ill posed)

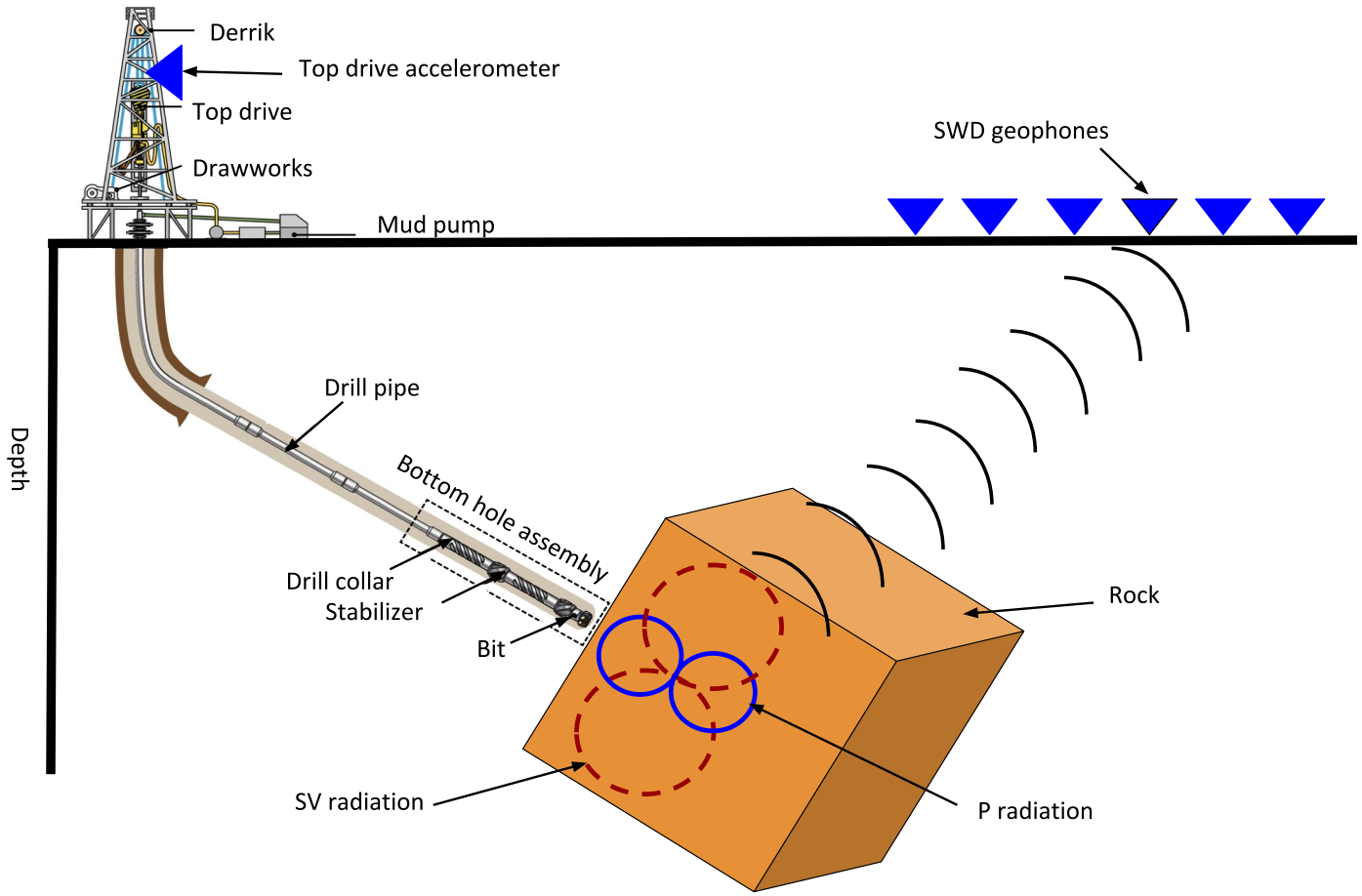
- Changing cost function: Envelope, Beat tone, etc.
- Changing cost function to a better behaved one with less local minima could improve, to some extent, the cycle skipping issue
- Still problem is ill-posed
- Null space issue (shadow zone, surface acquisition geometry, poor illumination)
- Ideally, we need to have sources everywhere in the subsurface to make the FWI problem well-posed
- Seismic-while-drilling data improves subsurface illumination and reduces null space

SWD Acquisition

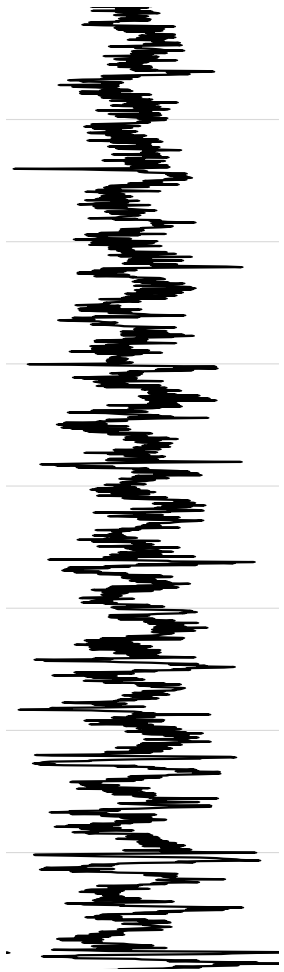


Drill bit- rock Interaction- Directional Drilling

SWD radiation patterns

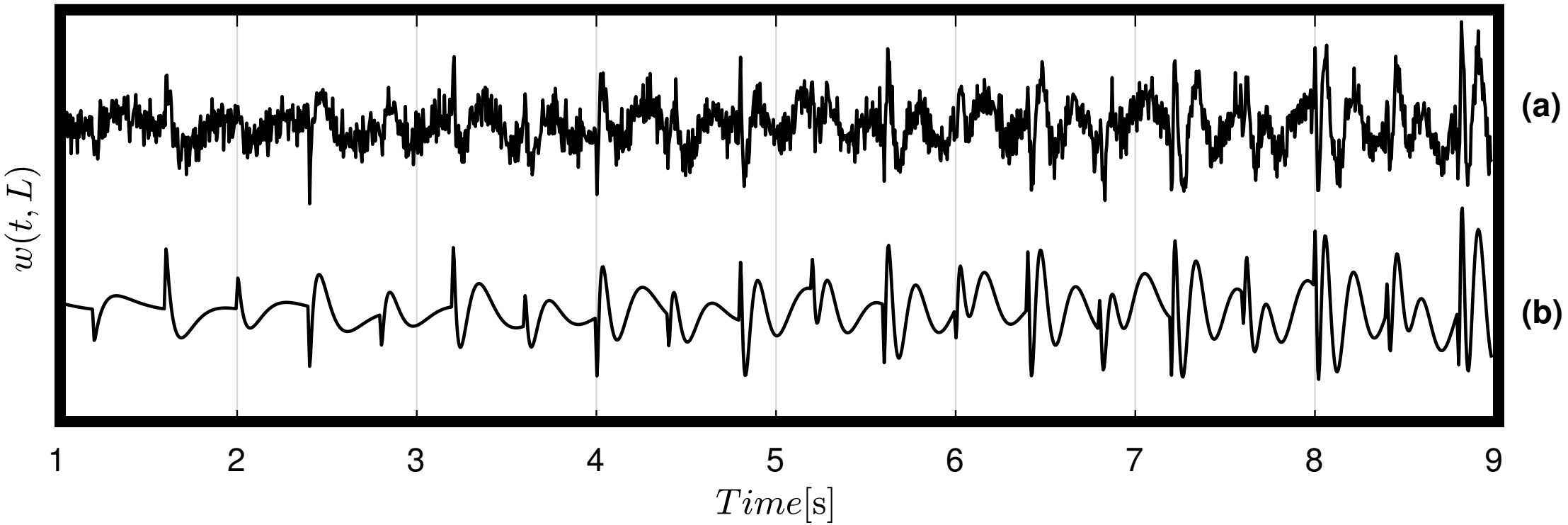


Auriol, et al, 2021



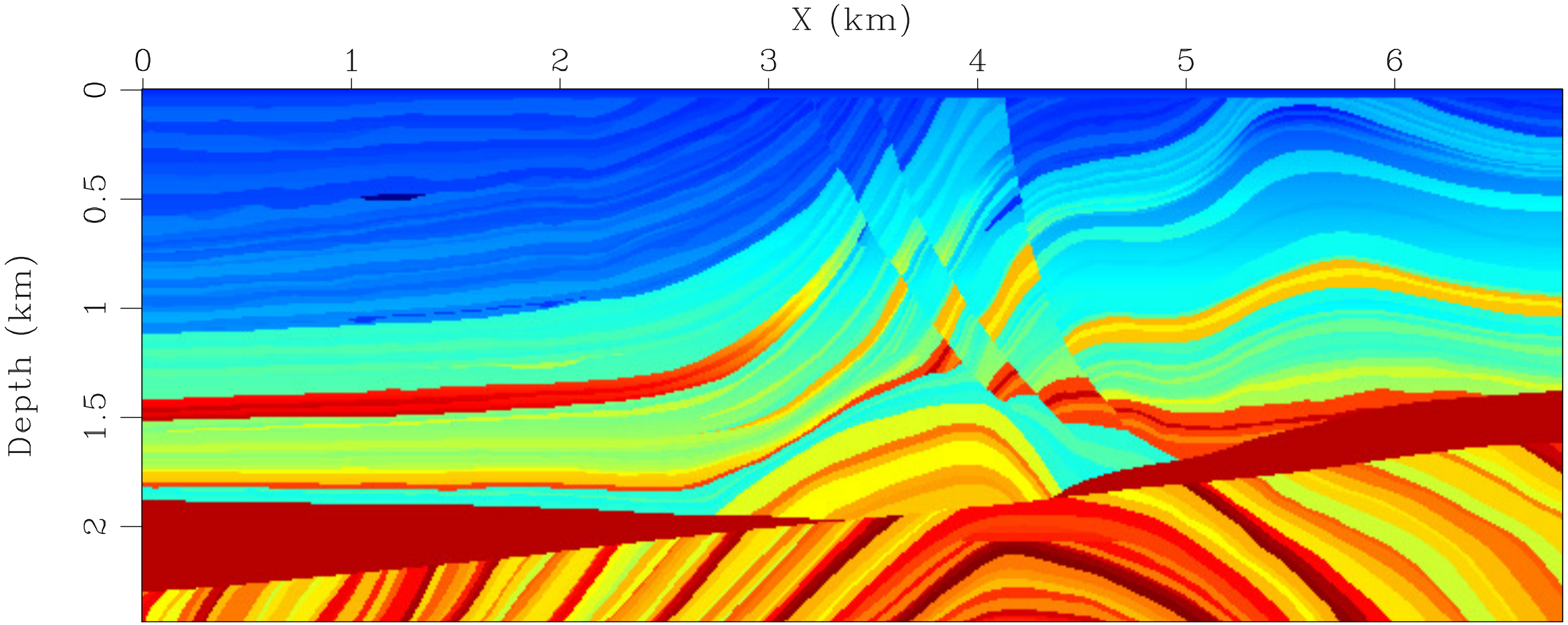
Simulated Drill-bit Source Waveform

SWD Source Signature Modeling

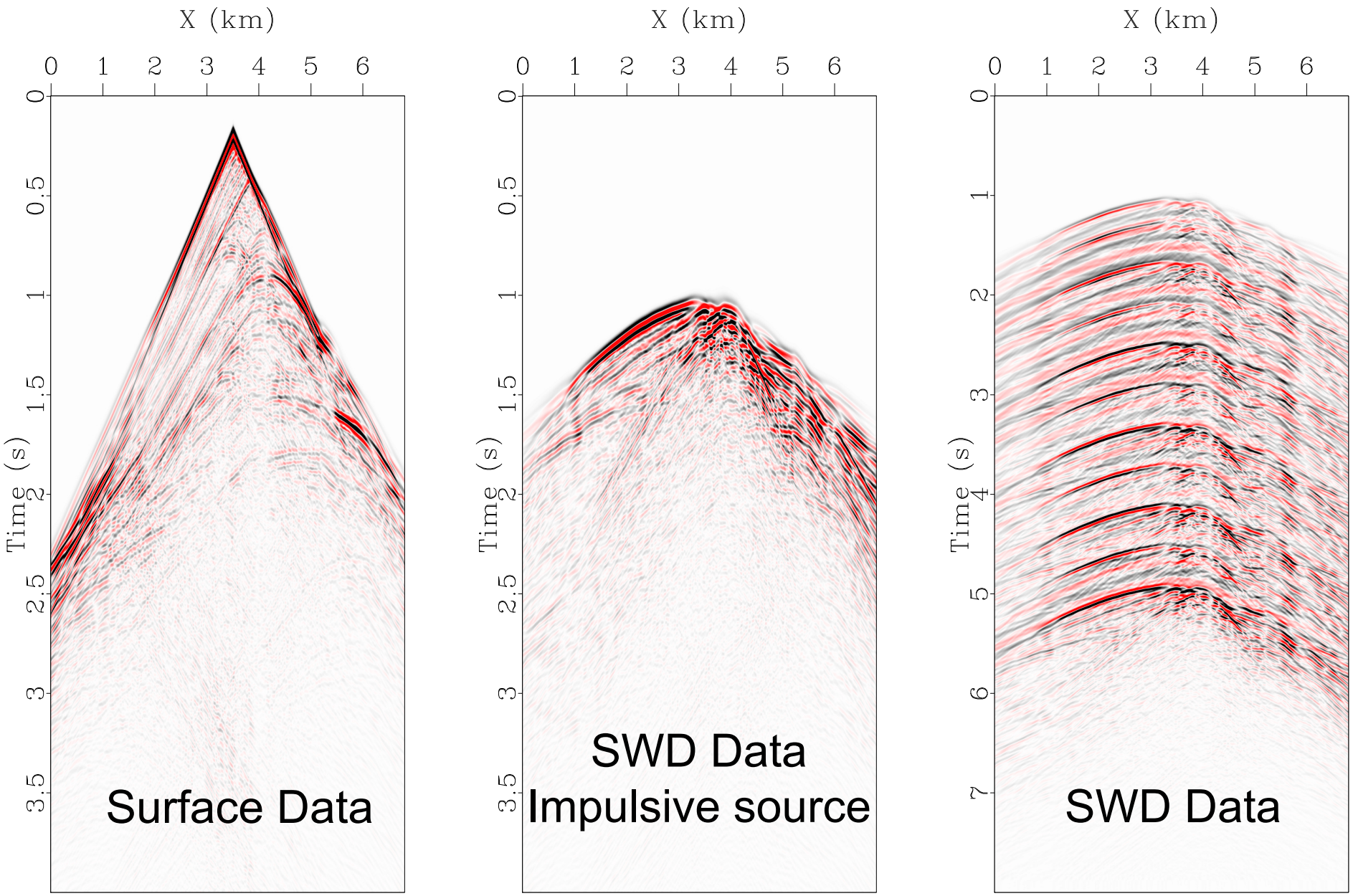


(a)Original (b)Estimated

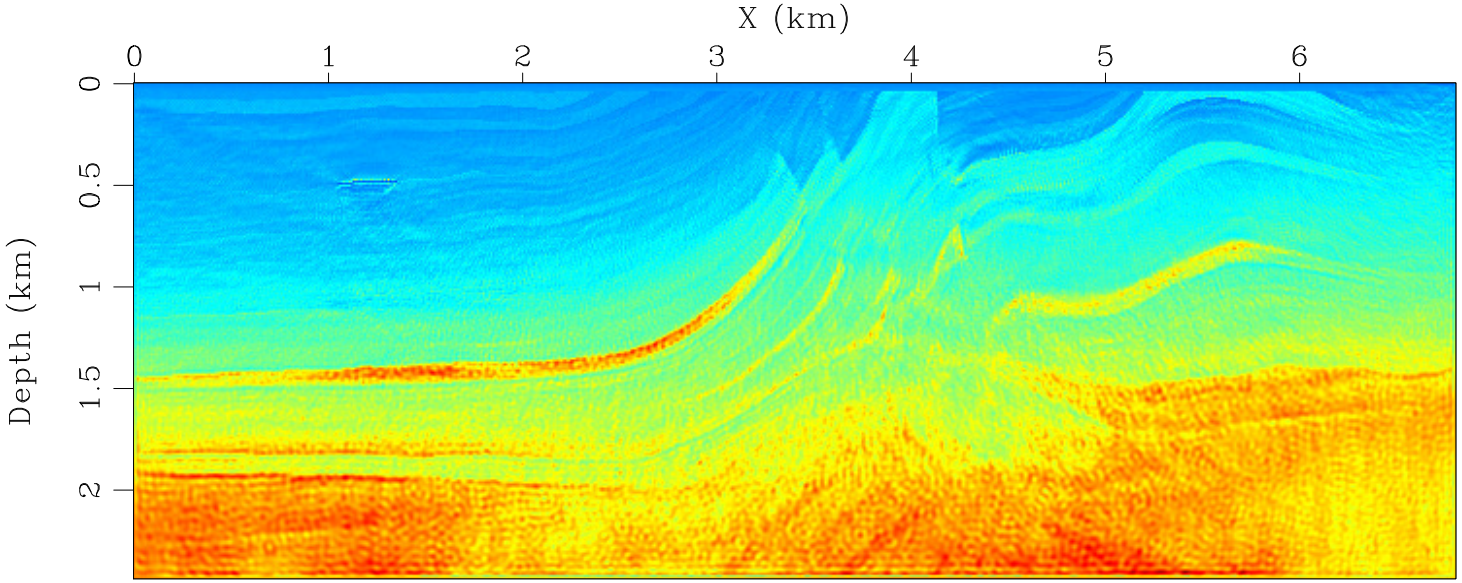
Full Waveform Inversion- Examples

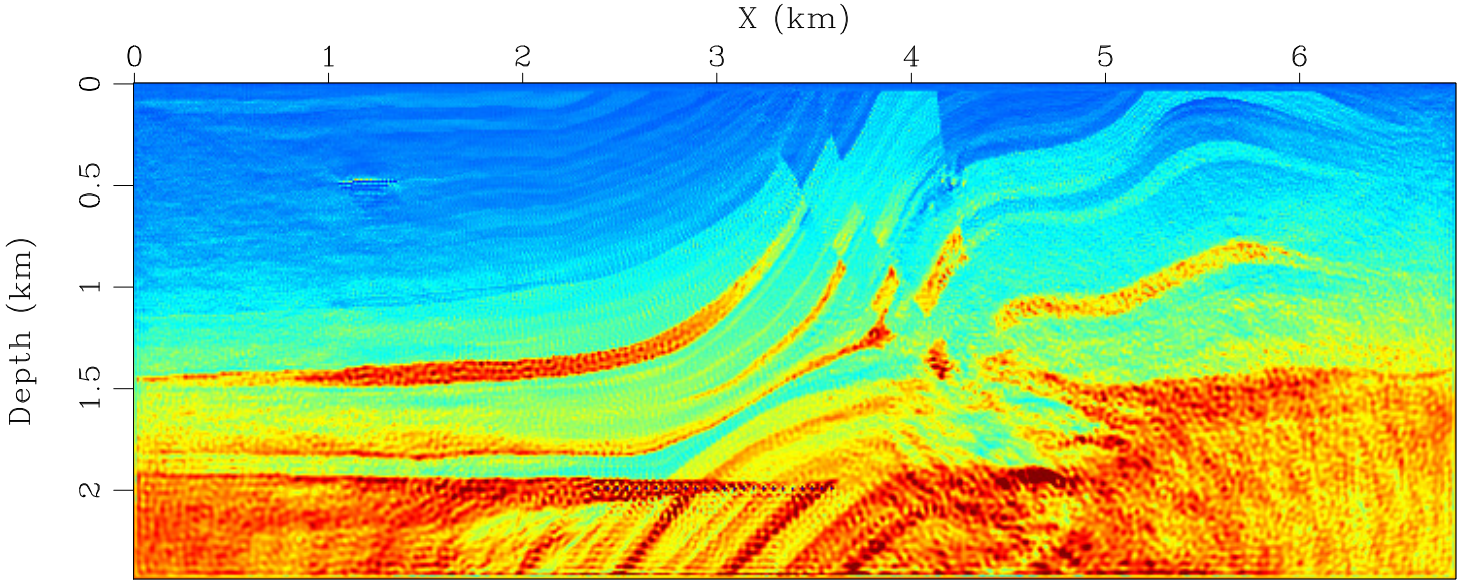


Surface and SWD Data Differences

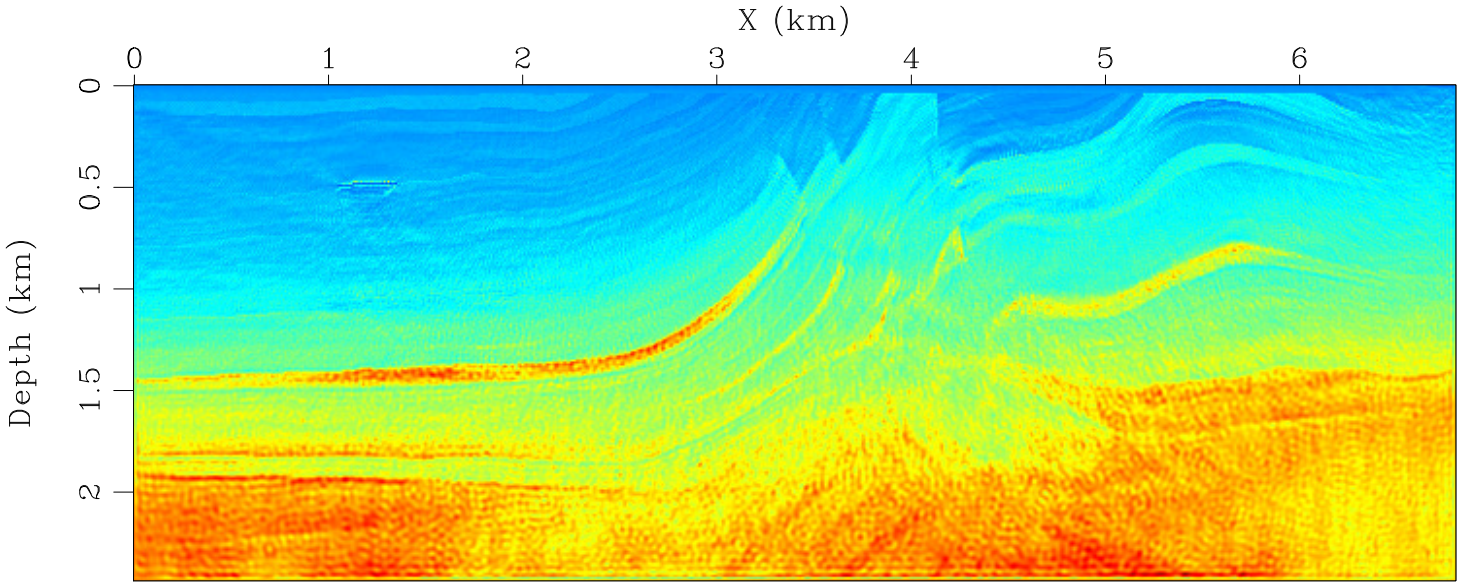


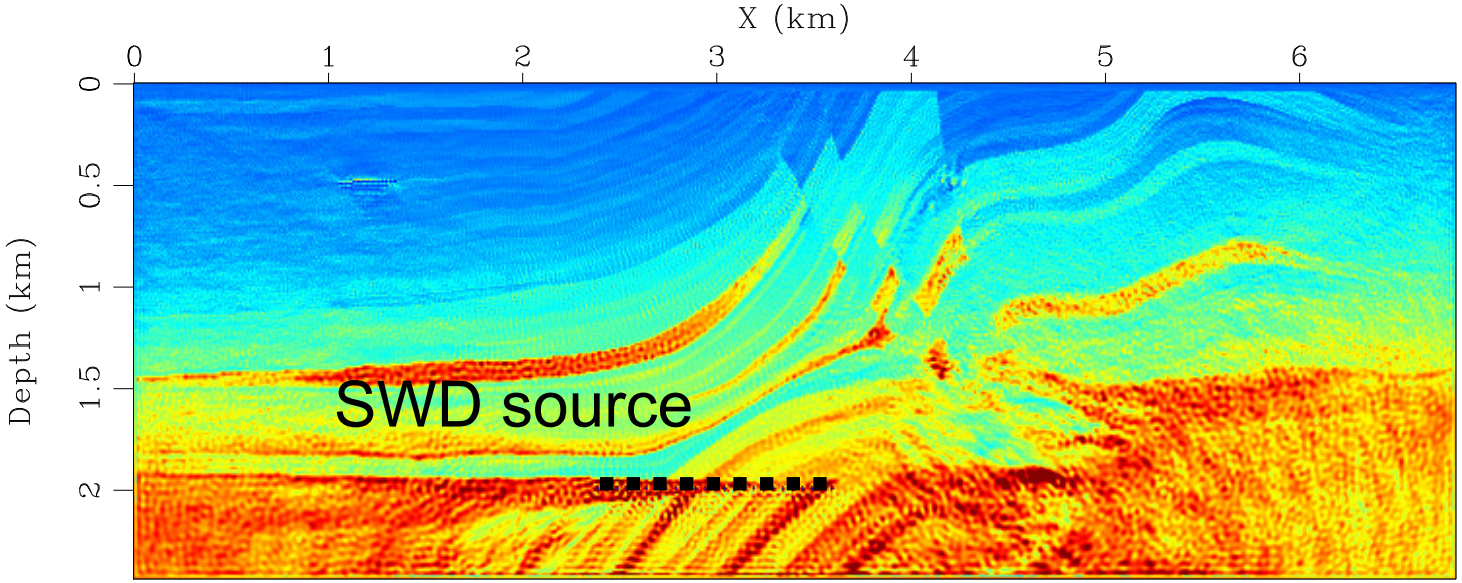
Full Waveform Inversion- Results



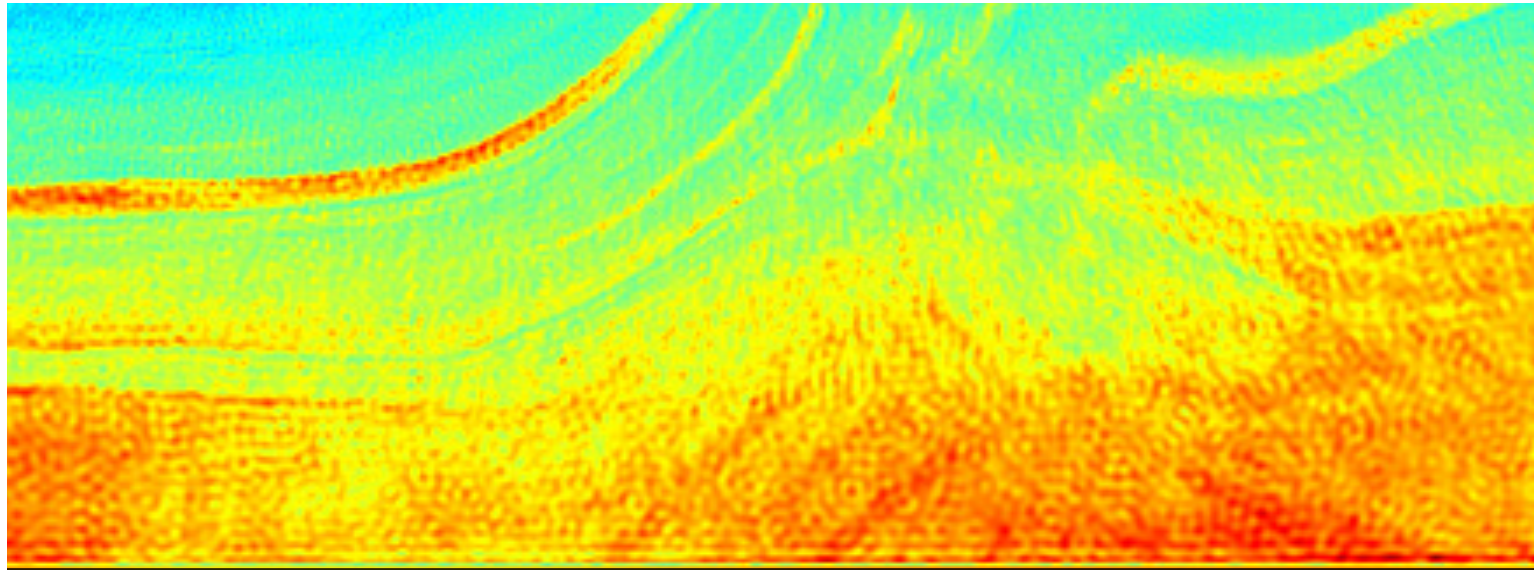


Full Waveform Inversion- Results

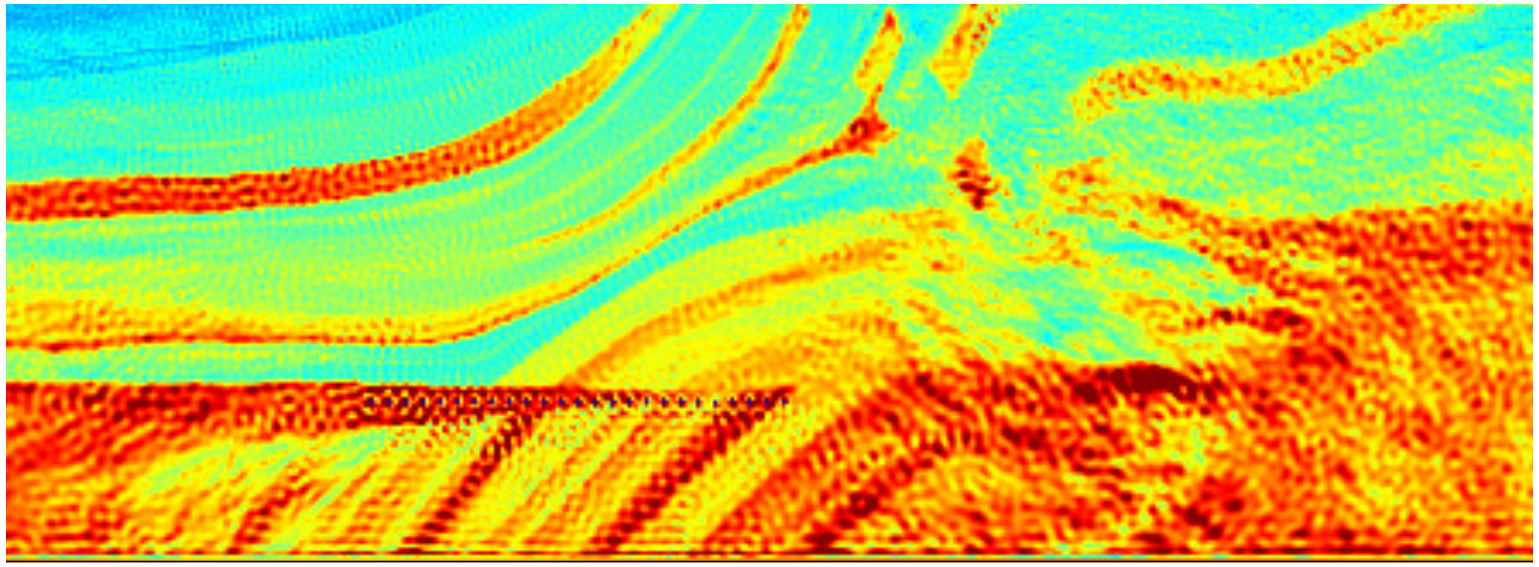




Full Waveform Inversion- Results



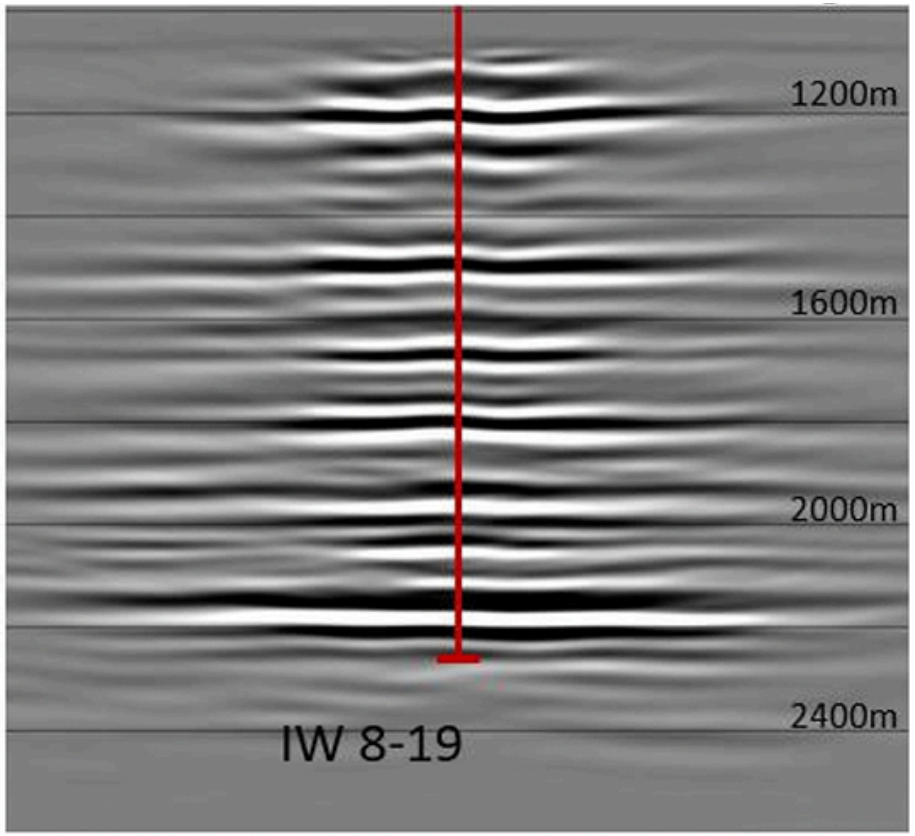
Conventional FWI



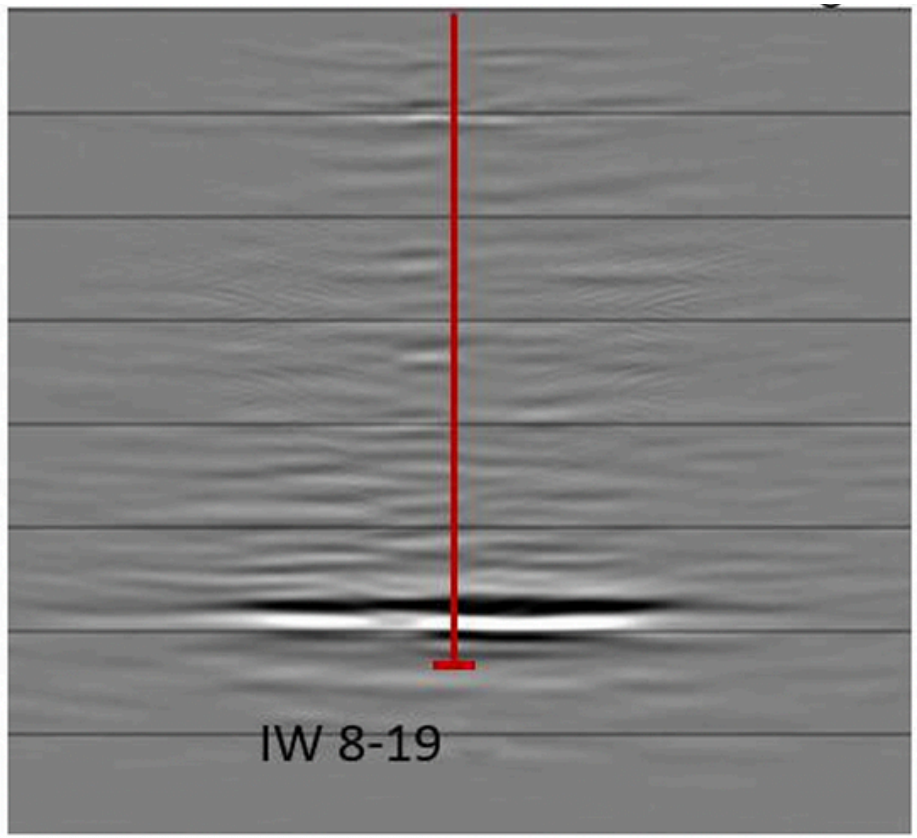
Successive FWI
Surface+SWD

DAS VSP at Quest Site, Alberta, CCS project, Shell

Base line



Monitoring line



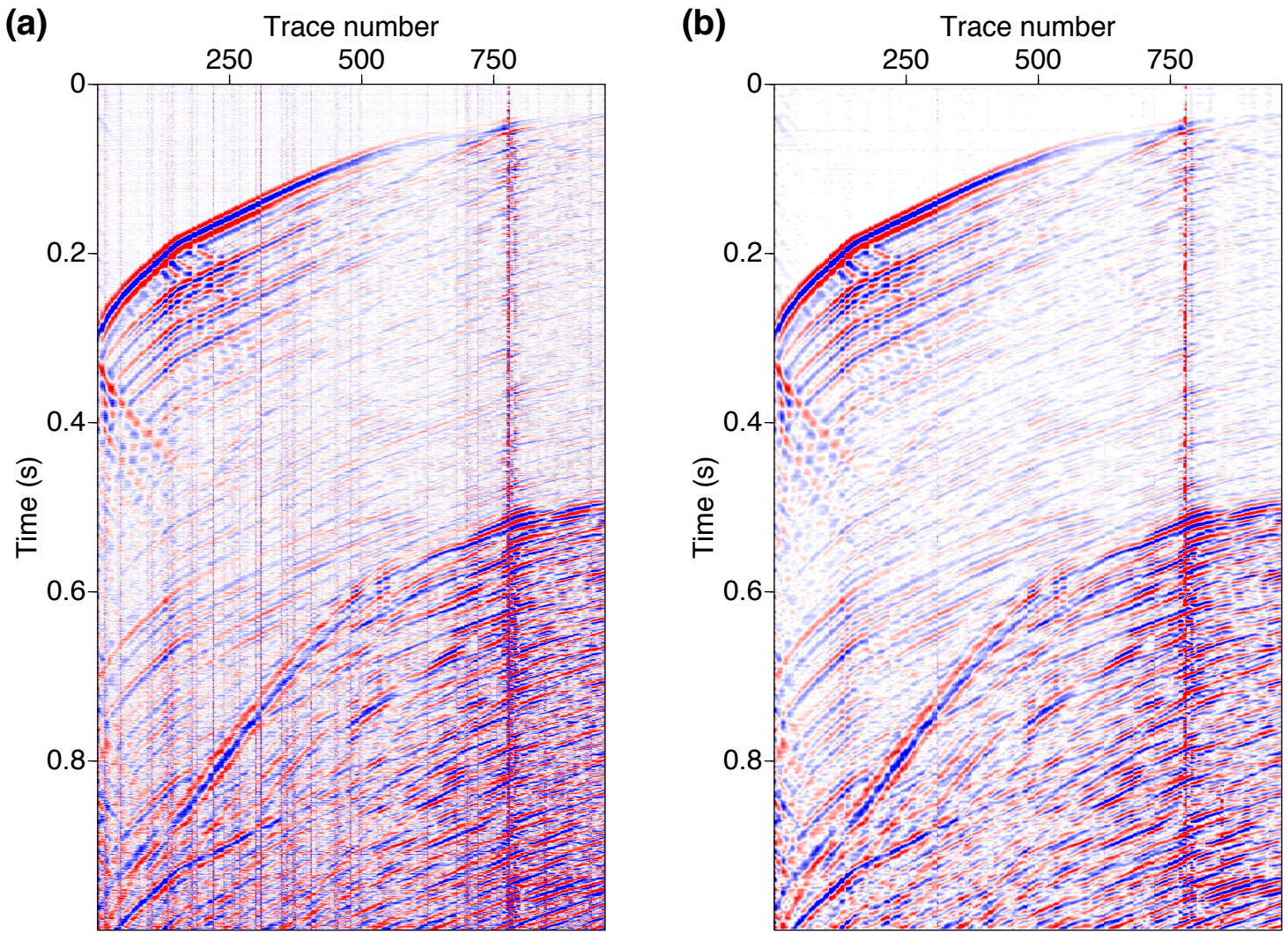
Maturing DAS VSP as an Onshore CCUS monitoring technology at the Quest CCS Facility

Jonathan Hopkins[1], Albena Mateeva[2], Stephen Harvey[1], Denis Kiyashchenko[2], Yuting Duan[2]
[1]Shell Canada Limited, [2]Shell International Exploration and Production Inc.

DAS noise suppression FORGE Geothermal DAS data

Noise types for DAS data:

- Cultural
- Environmental
- Common mode
- Fading
- Coupling

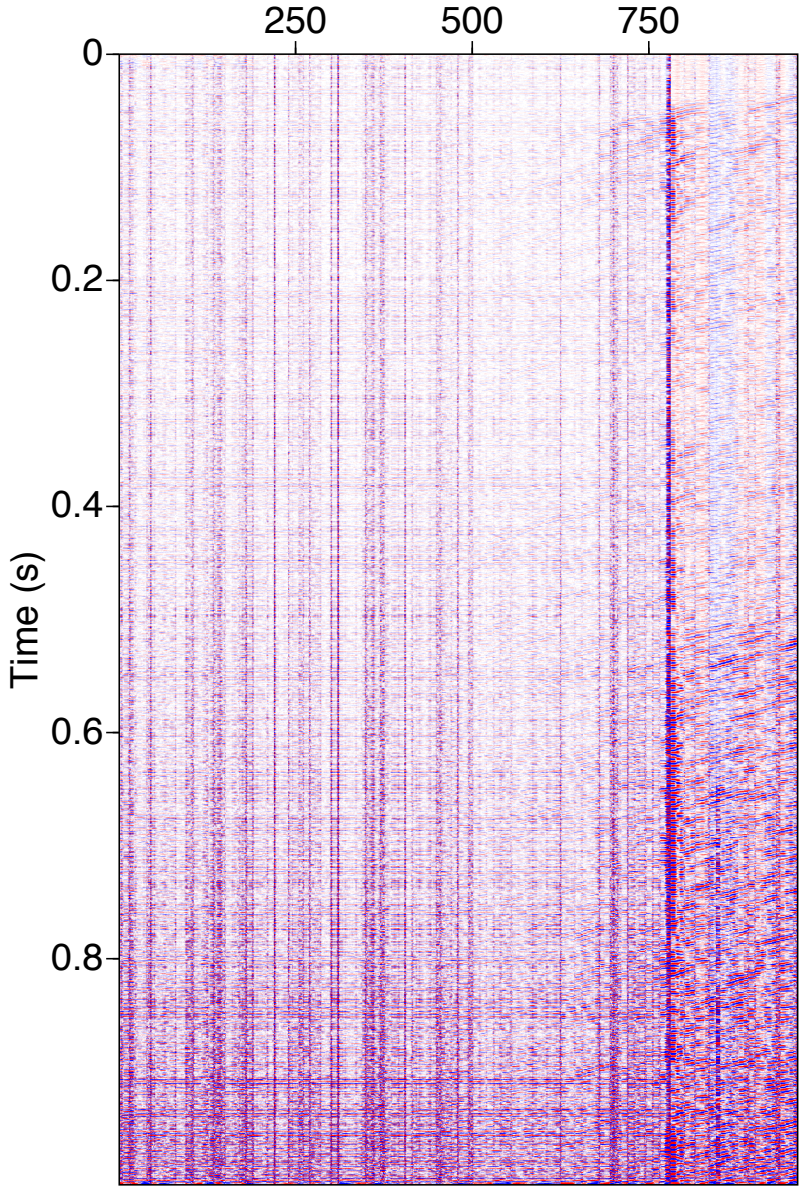


Kazemi, 2023, EAGE

Estimated noise panel for FORGE Geothermal DAS data

After processing of Das data, we can:

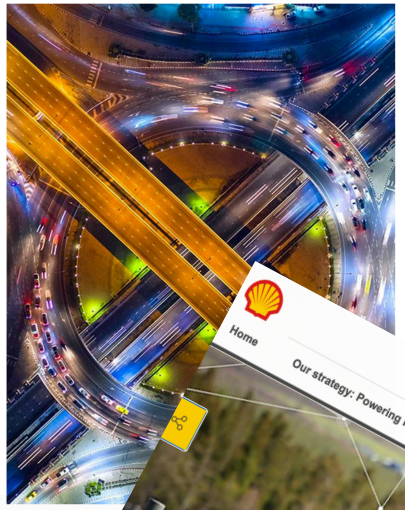
- Estimate subsurface images for monitoring Carbon storage
- Monitor and prevent leakages
- Adjust injection and production rates to optimize efficiency and insure caprock integrity
- Prevent risks and environmental disasters- polluting fresh waters, contaminating surface, inducing seismicity



Digital Transformation in the Headlines

Baker Hughes

Featured Capabilities | Products & Services | Company



The power of Artificial Intelligence

The energy industry is changing, and operators are tasked with delivering new levels of productivity, efficiency, and safety. We believe Artificial Intelligence, machine learning, and deep learning technologies will help operators understand massive data sets in order to predict problems before they occur, resulting in daily improvements that lead to big picture outcomes.

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Suncor accelerates digital transformation journey through strategic alliance with Microsoft

CALGARY, Alberta, Nov. 12, 2019 (GLOBE NEWSWIRE) -- Suncor today announced a multi-year strategic alliance with Microsoft Canada as a part of the company's effort to further accelerate its digital transformation journey. Suncor has selected Microsoft as its str cloud provider, tapping into the full range of Microsoft's cl solutions to empower a connected and collaborative upgrade data centres, and increase analytics ca

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Toward A Digitally Inspired Sustainable Economy

By ICTC-CTIC | 2 February 2022 | No Comments

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DIGITAL TRANSFORMATION IN ENERGY INDUSTRY

Digital technologies are transforming our lives in ways that were unimaginable even a decade ago. This digital transformation of the energy industry is improving efficiency and safety, and it is facilitating the increased use of renewable energy.

We are at a tipping point of exponential technological advancement. In the coming years, the internet of things will consist of a trillion sensors, all generating and sharing data. Machine learning and artificial intelligence are no longer science fiction; they are already automating and optimising operations. Digital technologies are driving cost efficiency, providing new revenue

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Digital transformation, accelerated

How to move forward in the midst of a global crisis

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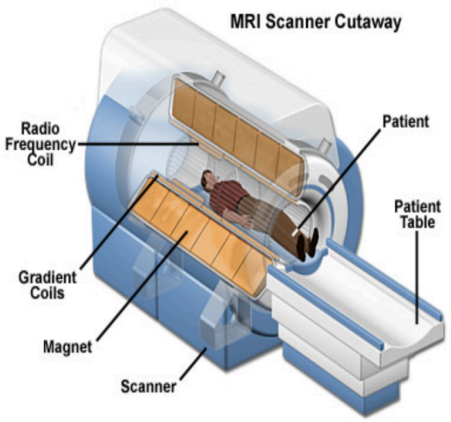
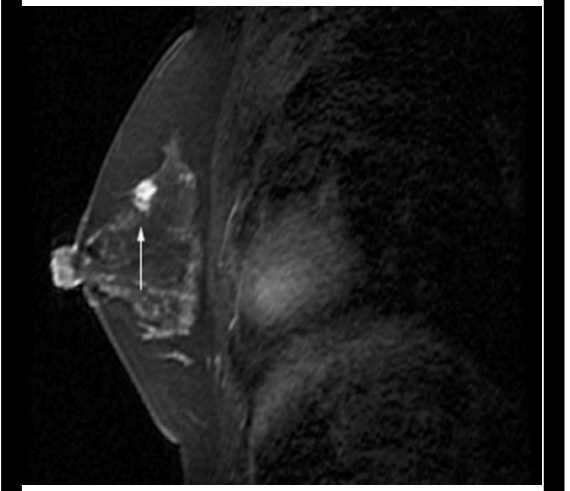
Domain Similarities

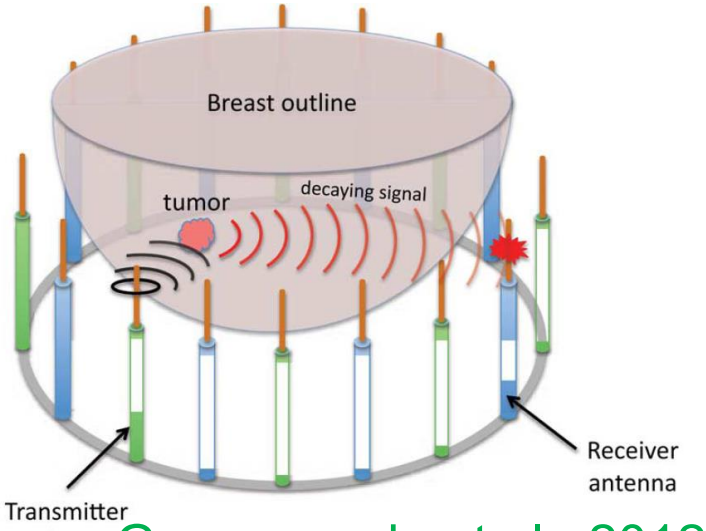
MR Imaging





Lehman and Schnall, 2005

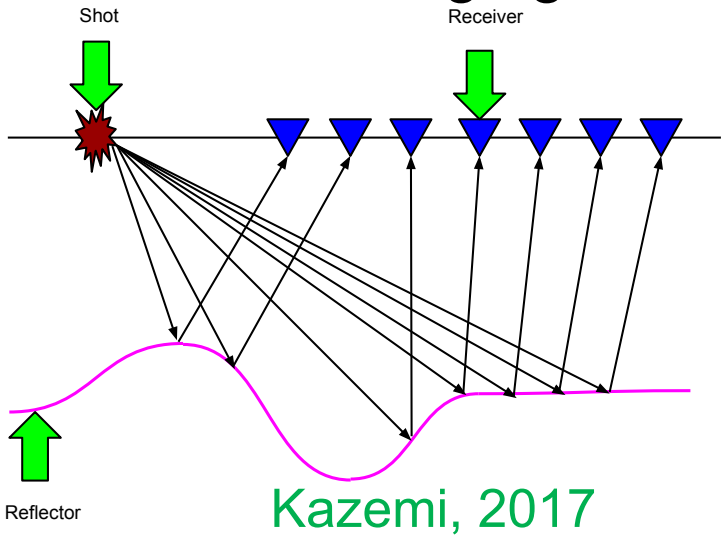
Microwave Breast Imaging



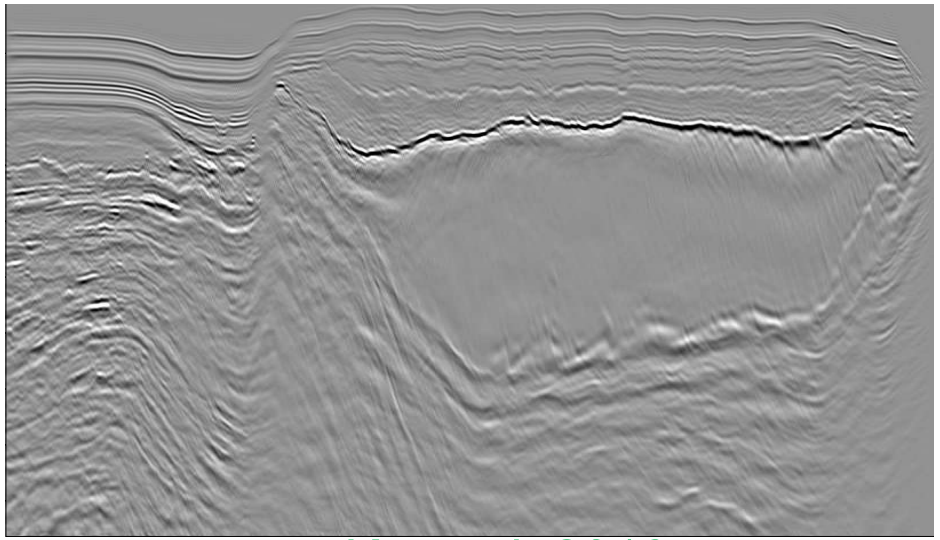
Grzegorczyk, et al., 2012

Kazemi and Fear, 2023

Seismic Imaging

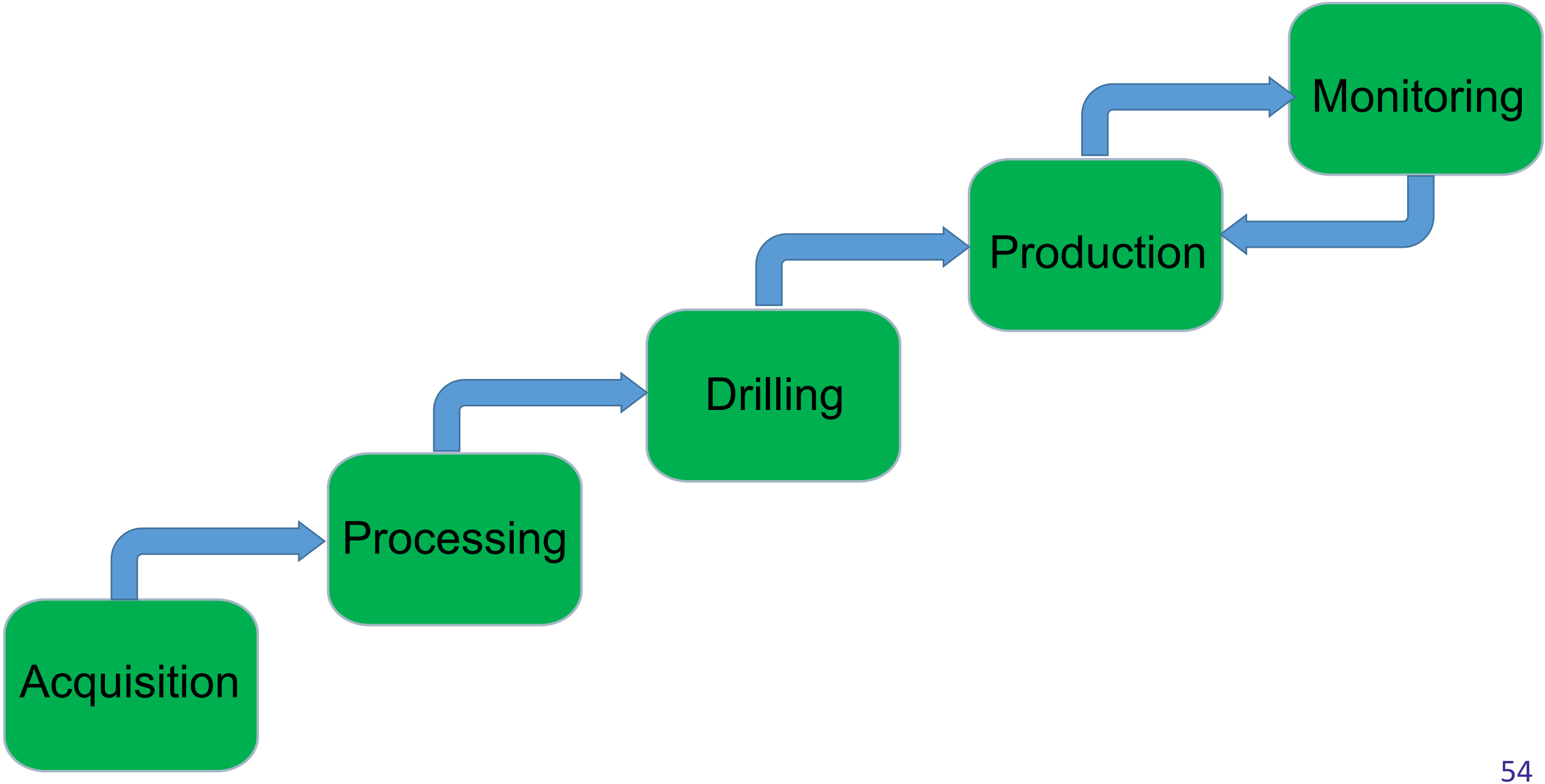


Kazemi, 2017

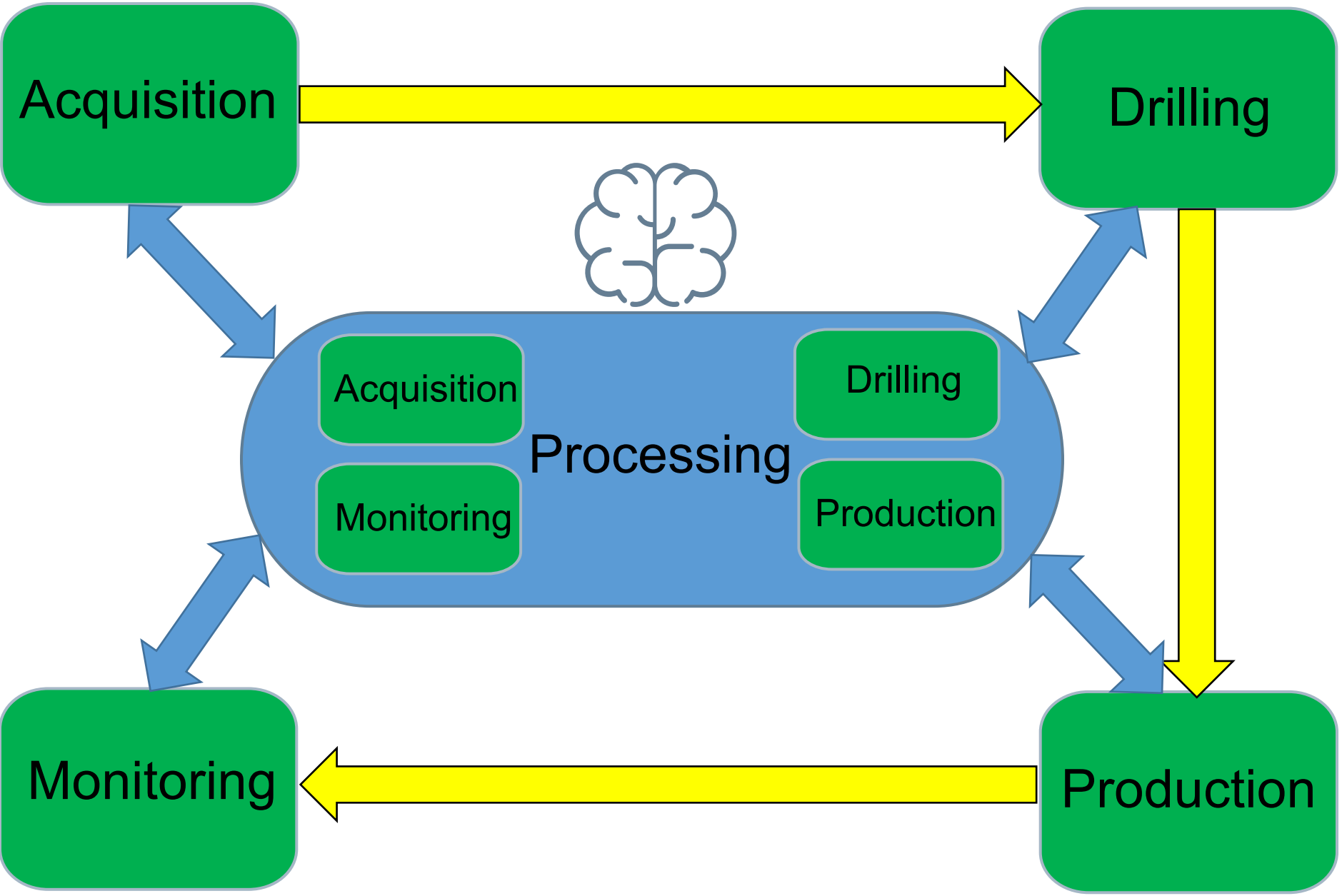


Kazemi, 2019

Energy Industry before Digital Transformation



Energy Industry after Digital Transformation



Millions and millions of sensors

Cloud and Edge computing

Real-time decision making

Efficient and safe resource production

Cyber-security

Intelligent and ethical data processing

Machine learning in signal processing

ML-based Denoising of Seismic datasets with Domain Adapted DnCNN

Compressive Sensing Recovery of Seismic data using ML-based RED

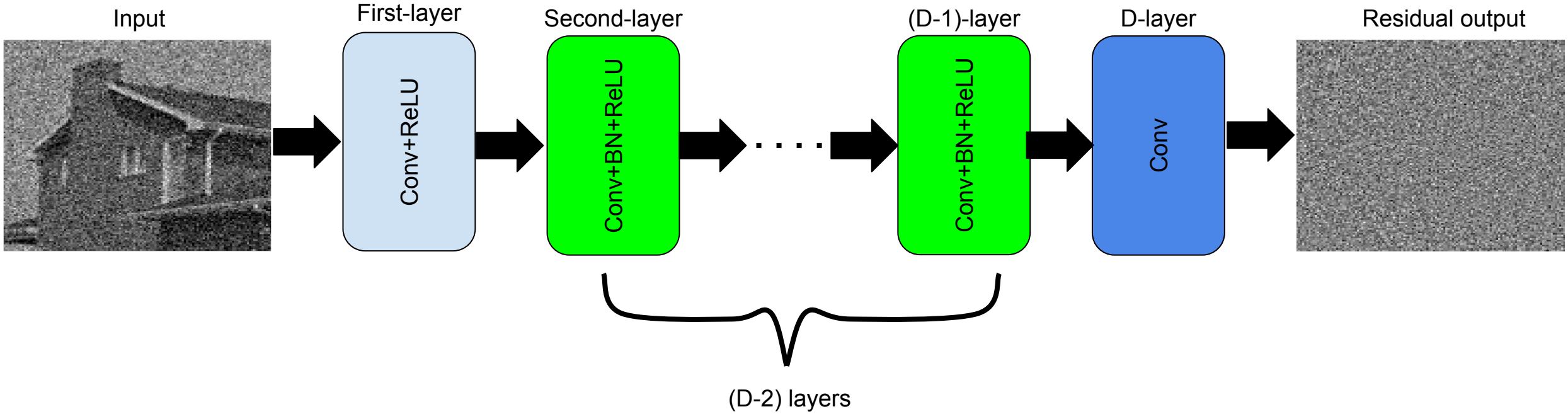
Generalization issues in ML

- ❑ Big datasets (labeled)
- ❑ High-performance Computing
- ❑ Over-parameterization, and proper algorithms

Compared to natural-image domain, in Seismic

- we do not have comprehensive/labeled dataset for training and
- most of us work in Classical regime for ML model building

Feed-forward Denoising Convolutional Neural Networks (DnCNN)



- DnCNN is a residual learning method
- network learns to remove the latent clean image, hidden in the layers of the network
- predict the noise component as a residual output

How DnCNN works?

$$\mathbf{d} = \mathbf{s} + \mathbf{n}$$

$$\mathcal{L}(\mathbf{d}) \approx \mathbf{n}, \quad \text{and} \quad \mathbf{s} \approx \mathbf{d} - \mathcal{L}(\mathbf{d})$$

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} \quad \frac{1}{2N} \sum_{j=1}^{N} \|\mathcal{L}(\mathbf{d}_j; \Theta) - (\mathbf{d}_j - \mathbf{s}_j)\|_F^2$$

DnCNN for Seismic domain

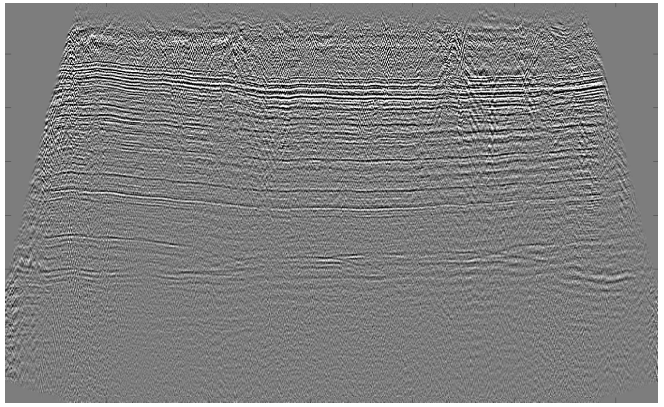
Due to lack of comprehensively labeled seismic data

- We need to explore Domain adaptation techniques
- Domain adaptation is a sub-class of Transfer Learning

Domain adaptation is where the labeled data is available in the source domain (natural image) but not in the target domain (seismic).

Seismic Domain Adaptation

$$\mathbf{d} = \mathbf{d}^{+} - \{-\mathbf{d}\}^{+}$$



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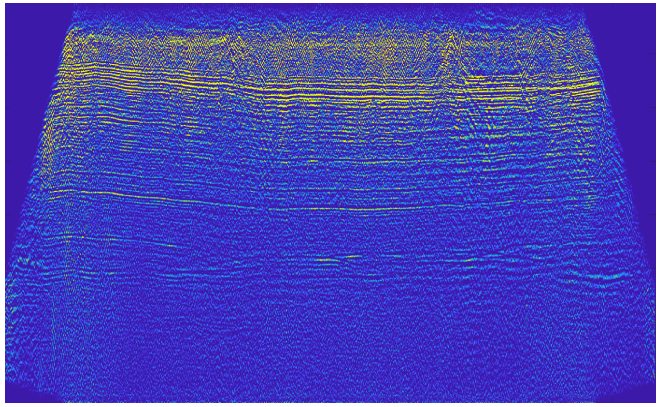

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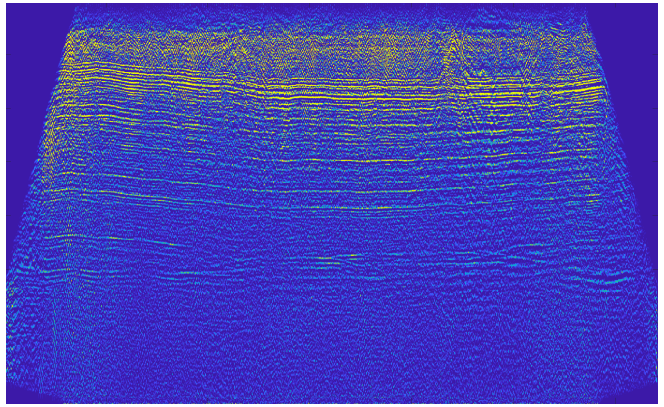
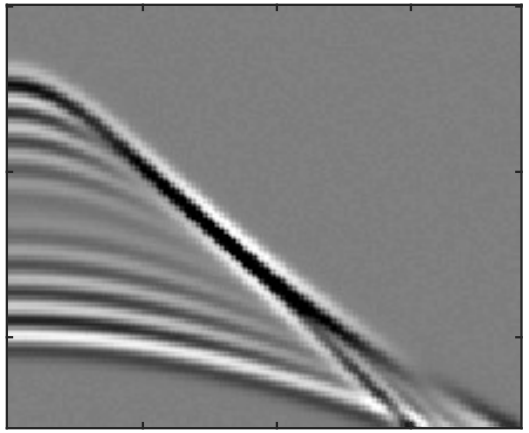


Seismic domain adaptation of natural-imaged learned DnCNN

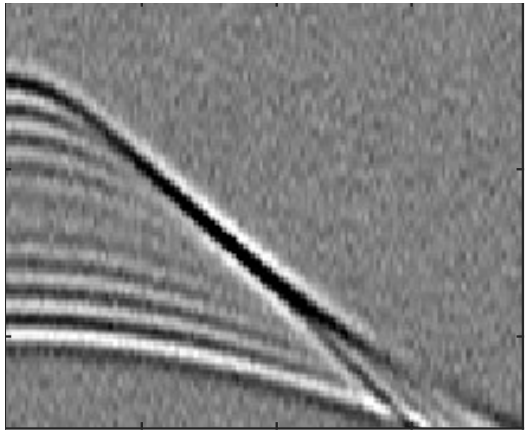
$$\mathcal{L}_{da}(\mathbf{d}) = \mathcal{L}(\mathbf{d}^{+}) - \mathcal{L}(\{-\mathbf{d}\}^{+})$$

Kazemi et al., 2021, CSEG

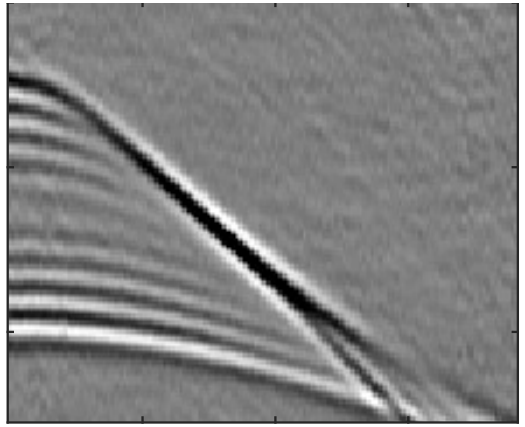
Seismic Noise Suppression (SNR=2)



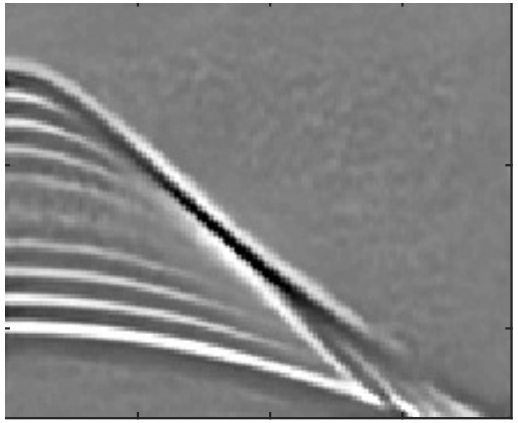
Clean data



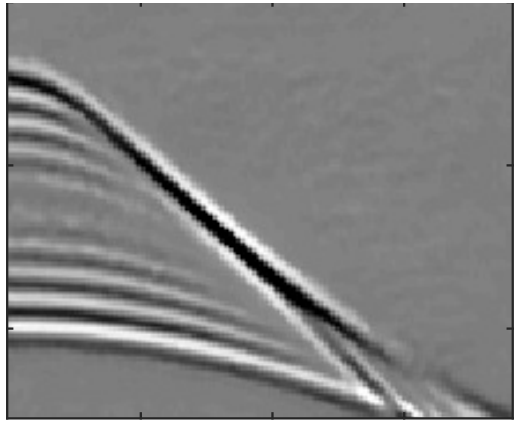
Noisy data



Fx- deconvolution



DnCNN

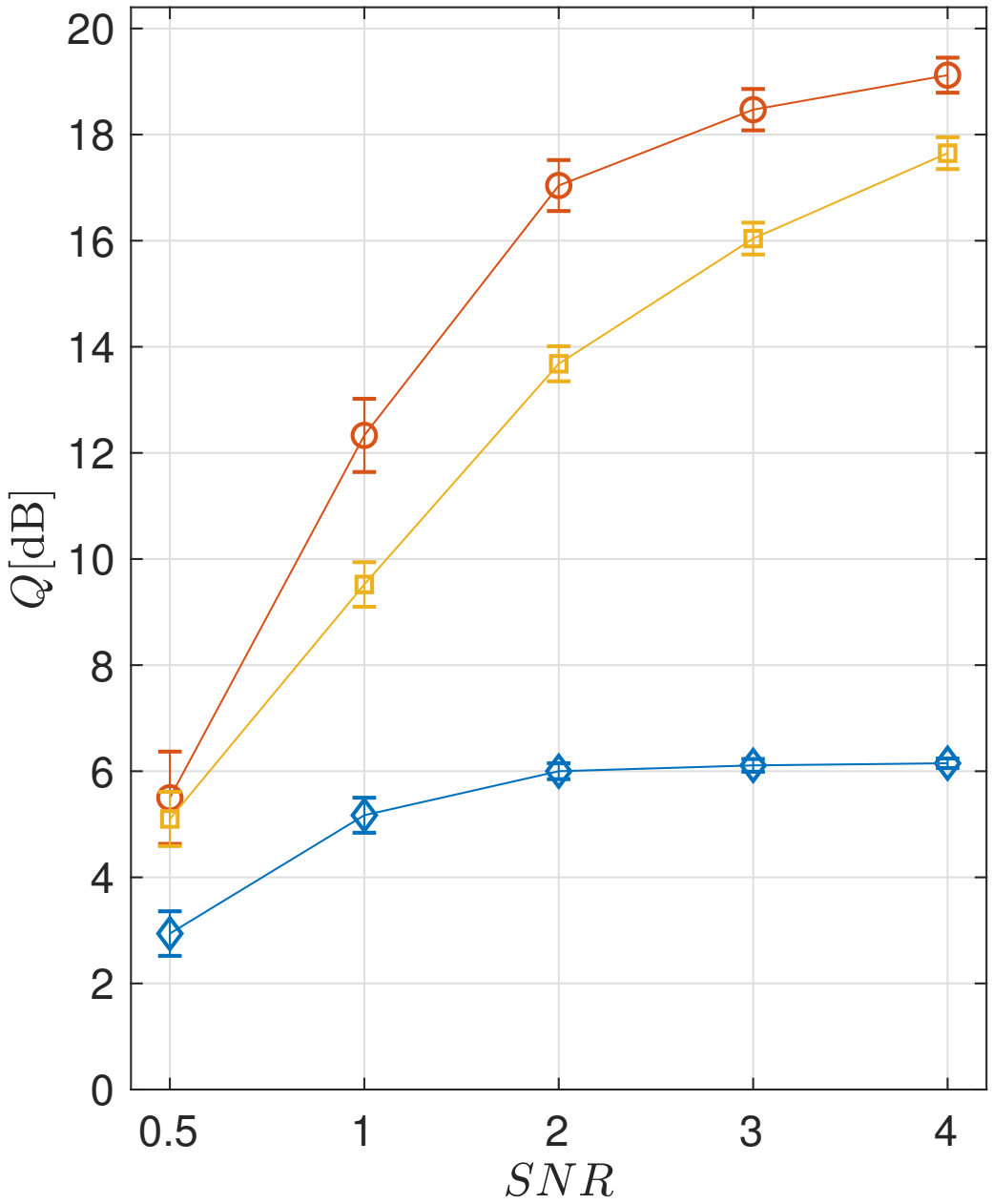


Seismic- Adapted DnCNN

Method	Q [db]
Fx-Deconvolution	13.71
DnCNN	5.99
Seismic-Adapted DnCNN	17.41

$$Q = 10 \log \frac{\|\mathbf{s}^{true}\|_2^2}{\|\mathbf{s}^{est} - \mathbf{s}^{true}\|_2^2}$$

Seismic Noise Suppression- Sensitivity analysis

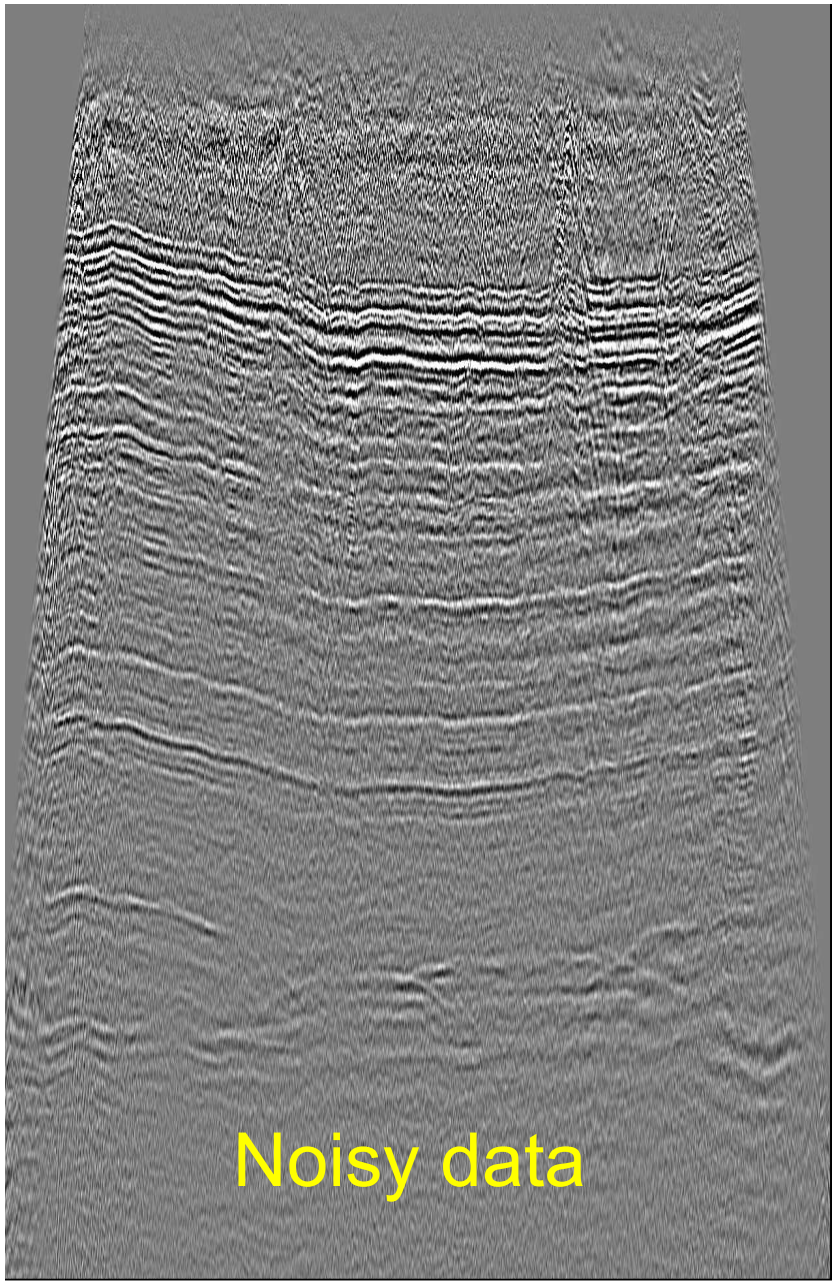


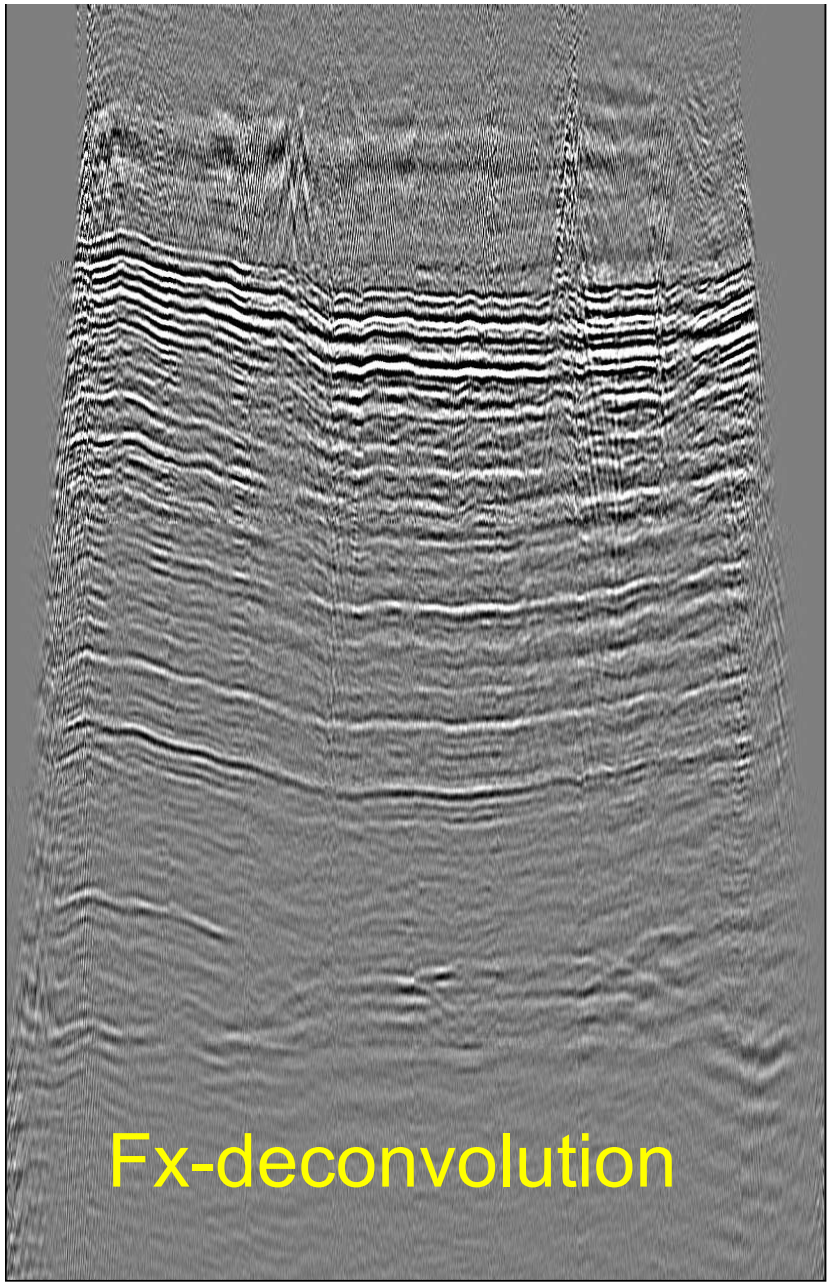
Seismic-Adapted DnCNN

Fx-deconvolution

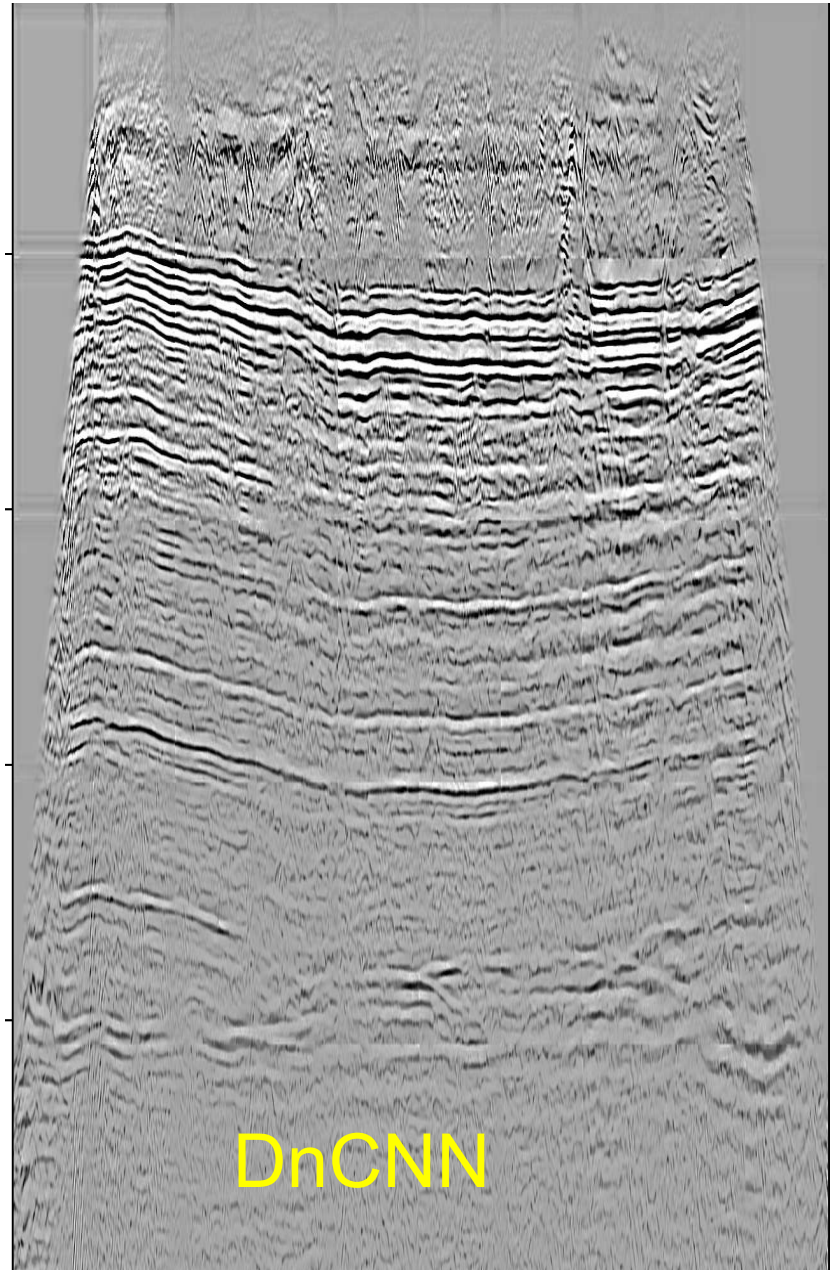
DnCNN

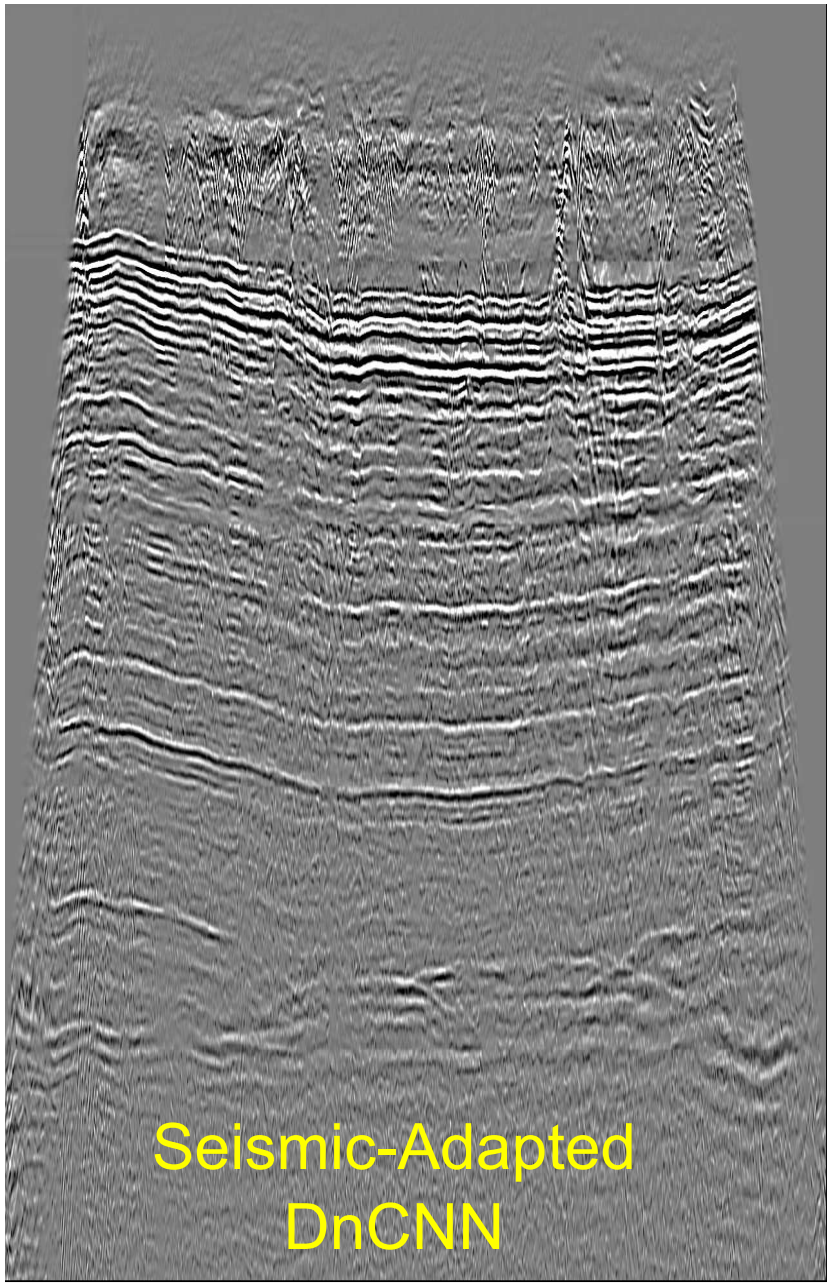
Seismic Noise Suppression- Real data



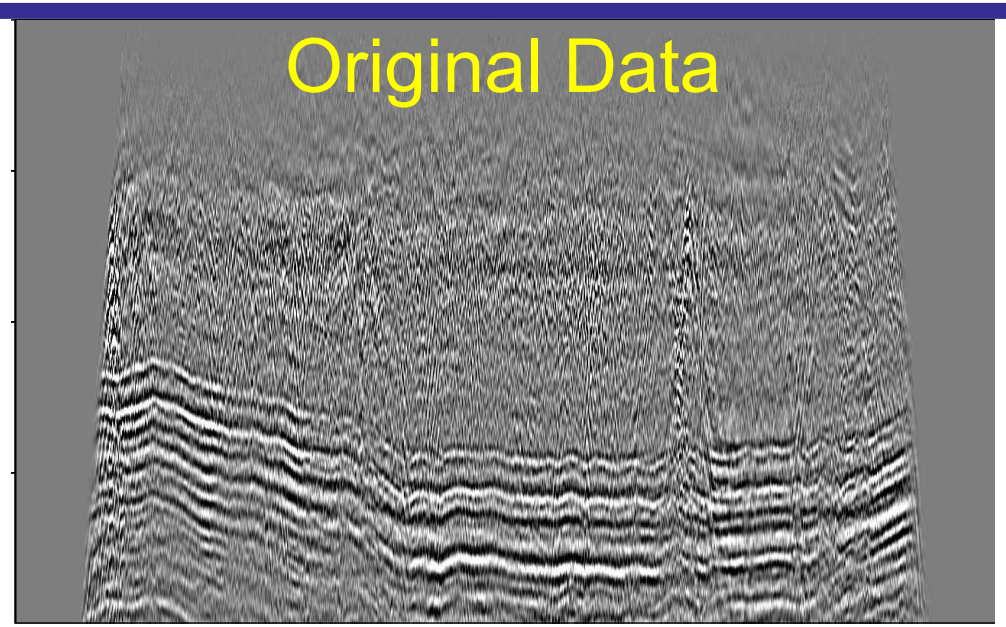


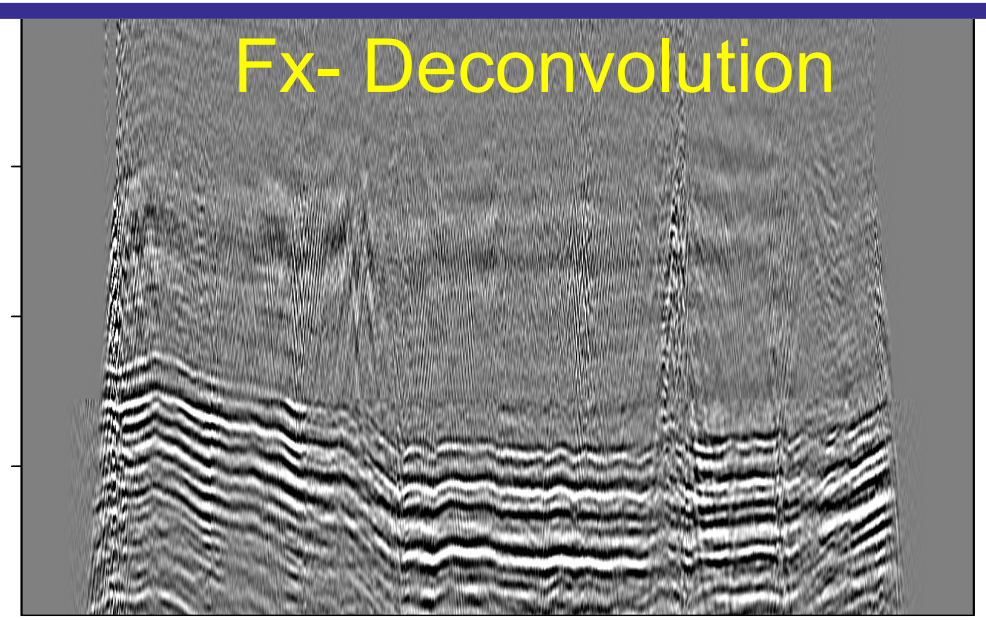
Seismic Noise Suppression- Real data

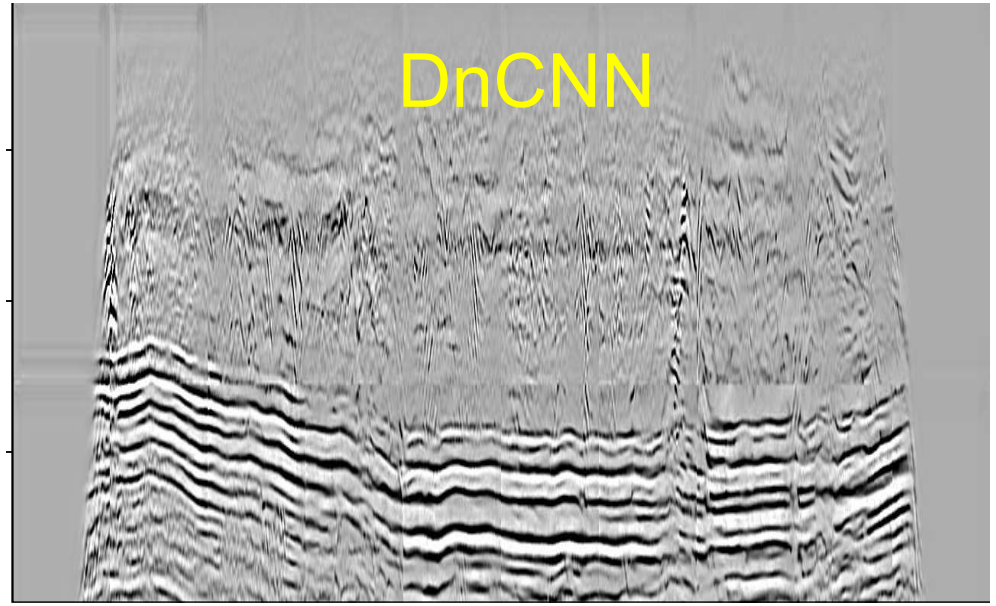


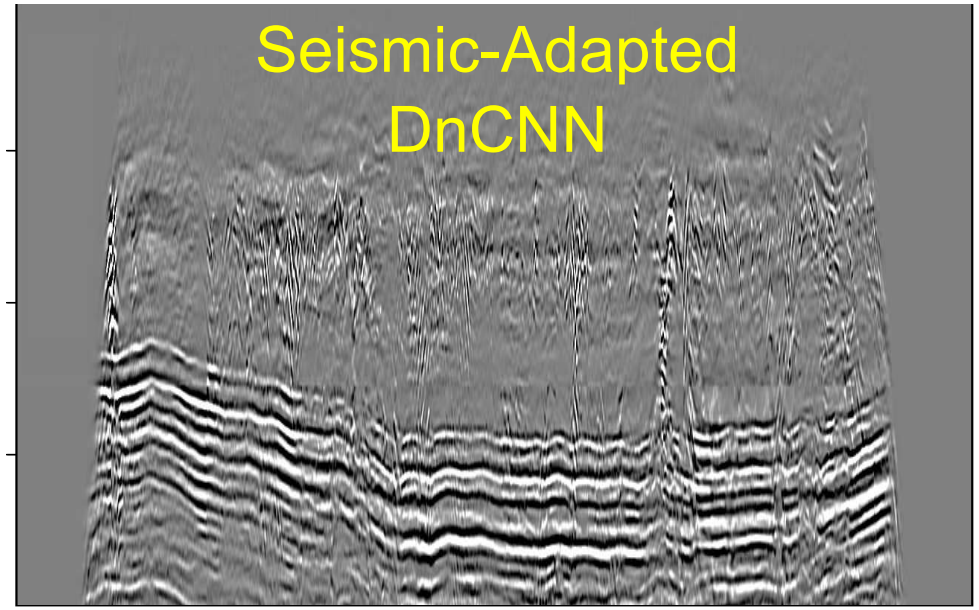


Seismic Noise Suppression- Real data (zoomed)

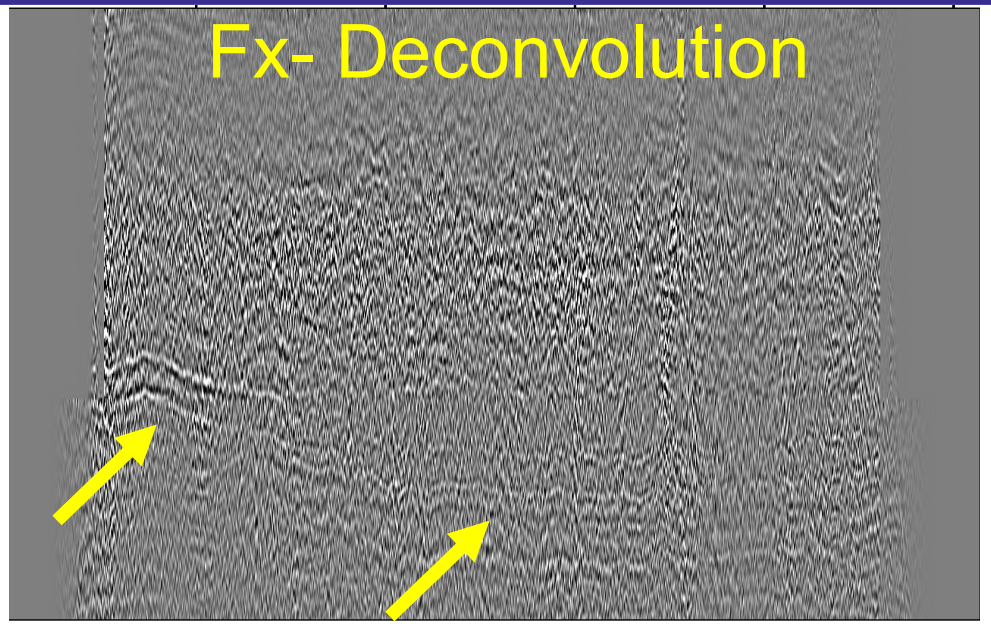


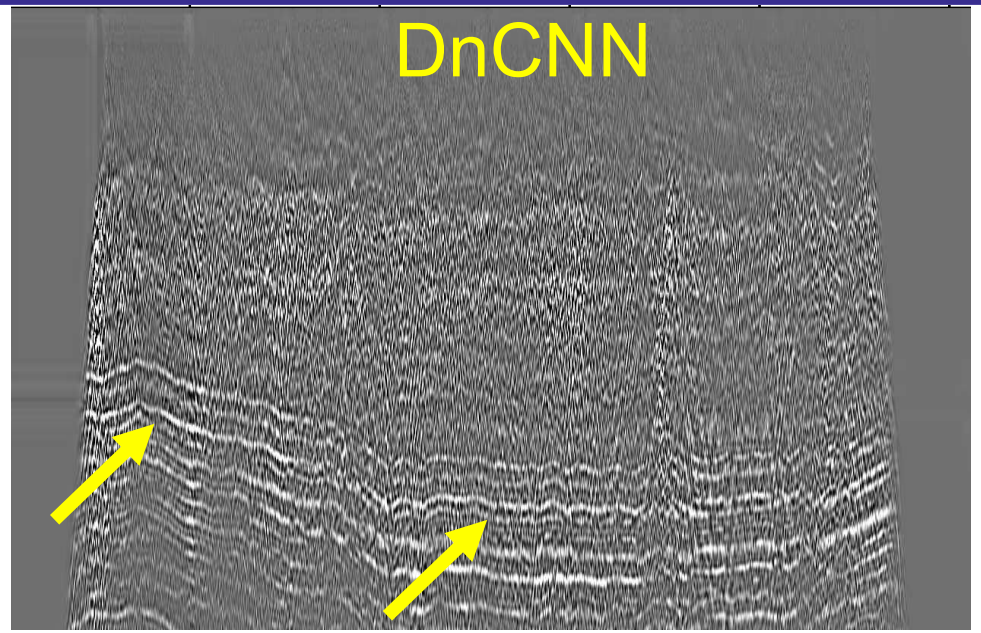


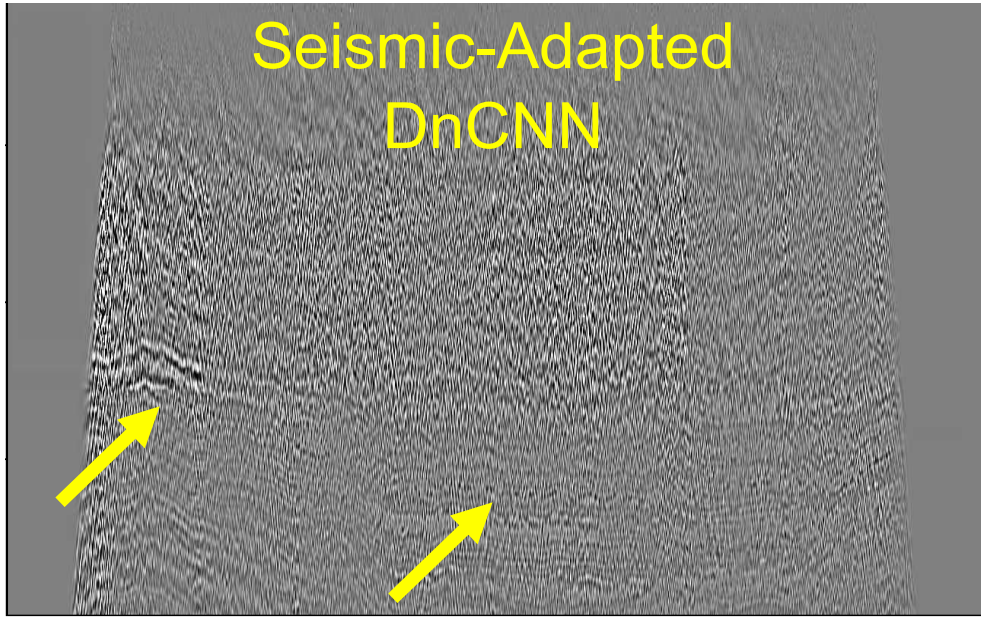




Seismic Noise Suppression- Real data (residual)







General problem of interest

$$\hat{\mathbf{s}} = \underset{\mathbf{s}}{\operatorname{argmin}} \quad f(\mathbf{s}; \mathbf{y}) + \lambda \mathcal{R}(\mathbf{s})$$

Regularization by denoising- RED

To build a general and efficient denoising regularizer we assume

- noise component is orthogonal to clean signal
- denoising operators can be modeled as the action of an input-dependent pseudo-linear operator on input (Milanifar 2012)

Milanfar, P. [2012] A tour of modern image filtering: New insights and methods, both practical and theoretical. *IEEE signal processing magazine*, 30(1), 106–128.

Compressive sensing recovery with ML-based RED

Compressive Sensing Recovery of Seismic data using ML-based RED

- Incorporate ML-based denoisers in Regularization by De-noising workflows ($\mathcal{R}(\mathbf{s})$)

- Change generic cost function to compressive sensing recovery with ML-based RED

Compressive sensing recovery with ML-based RED

APG algorithm

Require: $\mathbf{y}_c$, $\mathscr{D}(\cdot)$, $\mathbf{A}_c$, λ, $\mathbf{v}^0 = \mathscr{D}(\mathbf{A}_c^*\mathbf{y}_c)$, $L > 0$, $\mathbf{s}^0 = \mathbf{v}^0$, $t_0 = 1$, $k = 1$

While not converged

1: $\mathbf{s}^k = \underset{\mathbf{s}}{\operatorname{argmin}} \quad \|\mathbf{y}_c - \mathbf{A}_c\mathbf{s}\|_2^2 + \lambda L \|\mathbf{s} - \mathbf{v}^{k-1}\|_2^2$

2: $t_k = \frac{1+\sqrt{1+4t_{k-1}^2}}{2}$

3: $\mathbf{z}^k = \mathbf{s}^k - \frac{1-t_{k-1}}{t_k}(\mathbf{s}^k - \mathbf{s}^{k-1})$

4: $\mathbf{v}^k = \frac{1}{L}\mathscr{D}(\mathbf{z}^k) - (\frac{1-L}{L})\mathbf{z}^k$

5: $k \leftarrow k+1$

If converged $\quad \mathbf{s} \leftarrow \mathbf{s}^k$

$$\mathbf{y}_c = \mathbf{A}_c\mathbf{s} + \mathbf{n}$$

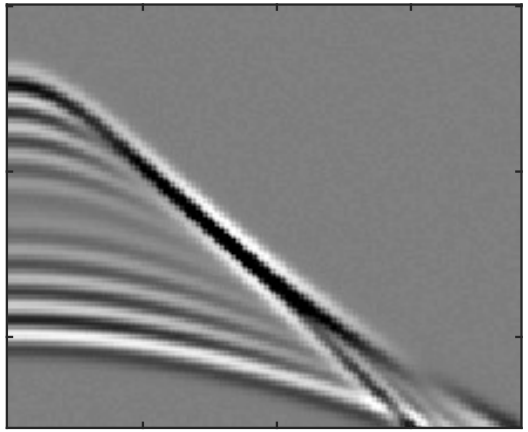
$$\hat{\mathbf{s}} = \underset{\mathbf{s}}{\operatorname{argmin}} \quad \|\mathbf{y}_c - \mathbf{A}_c\mathbf{s}\|_2^2 + \lambda\, \mathbf{s}^T(\mathbf{s} - \mathcal{D}(\mathbf{s}))$$

where $\mathcal{D}(\mathbf{s}) = \mathbf{s} - \mathcal{L}(\mathbf{s})$, and
$\mathcal{L}(\cdot)$ is seismic-adapted DnCNN operator

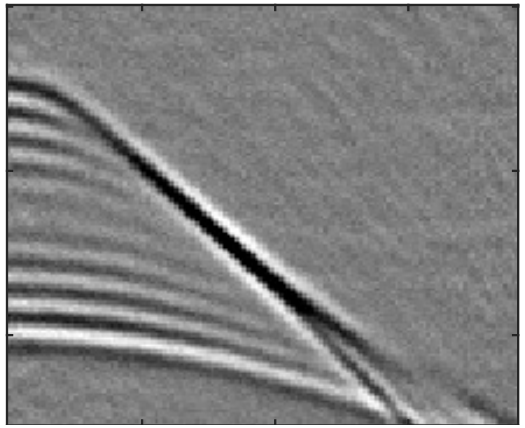
Sparse projection matrix with a randomized discrete cosine transform

N.Ailon and B.Chazelle, The fast Johnson–Lindenstrauss transform and approximate nearest neighbors, *SIAM Journal on computing*, vol. 39, no. 1, pp. 302–322, 2009.

CS with RED (noise free data with 50% compression)

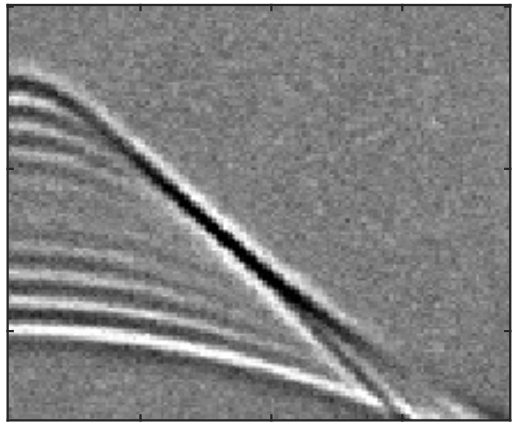


Clean data

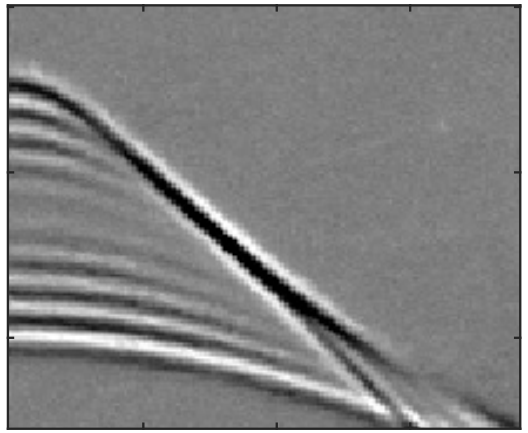


Fx- deconvolution

Method	Q [db]
Fx-Deconvolution	11.33
DnCNN	7.58
Seismic-Adapted DnCNN	14.96



DnCNN

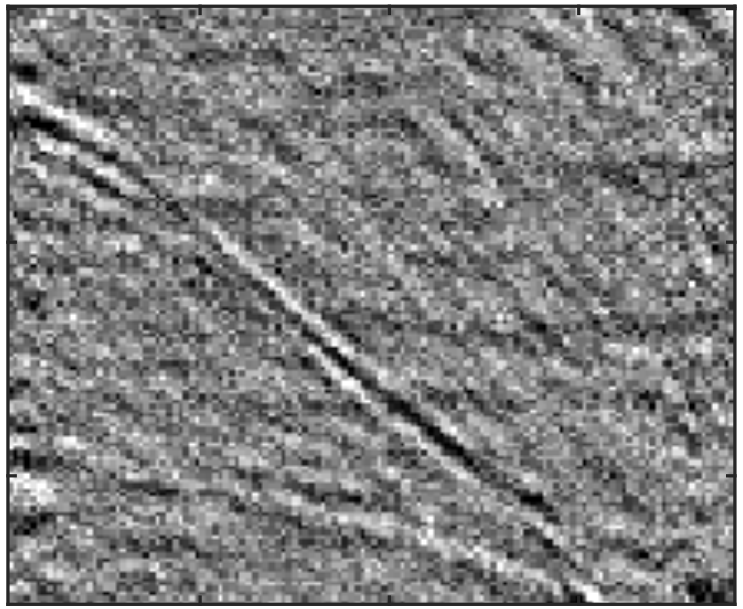


Seismic- Adapted DnCNN

$$Q = 10 \log \frac{\|\mathbf{s}^{true}\|_2^2}{\|\mathbf{s}^{est} - \mathbf{s}^{true}\|_2^2}$$

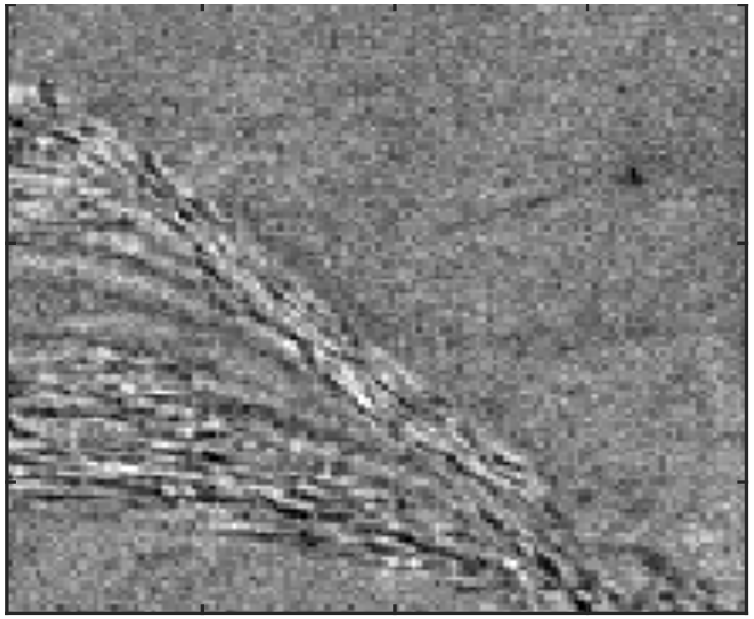
Kazemi, 2021, EAGE

CS with RED (noise free data with 50% compression)- Residuals



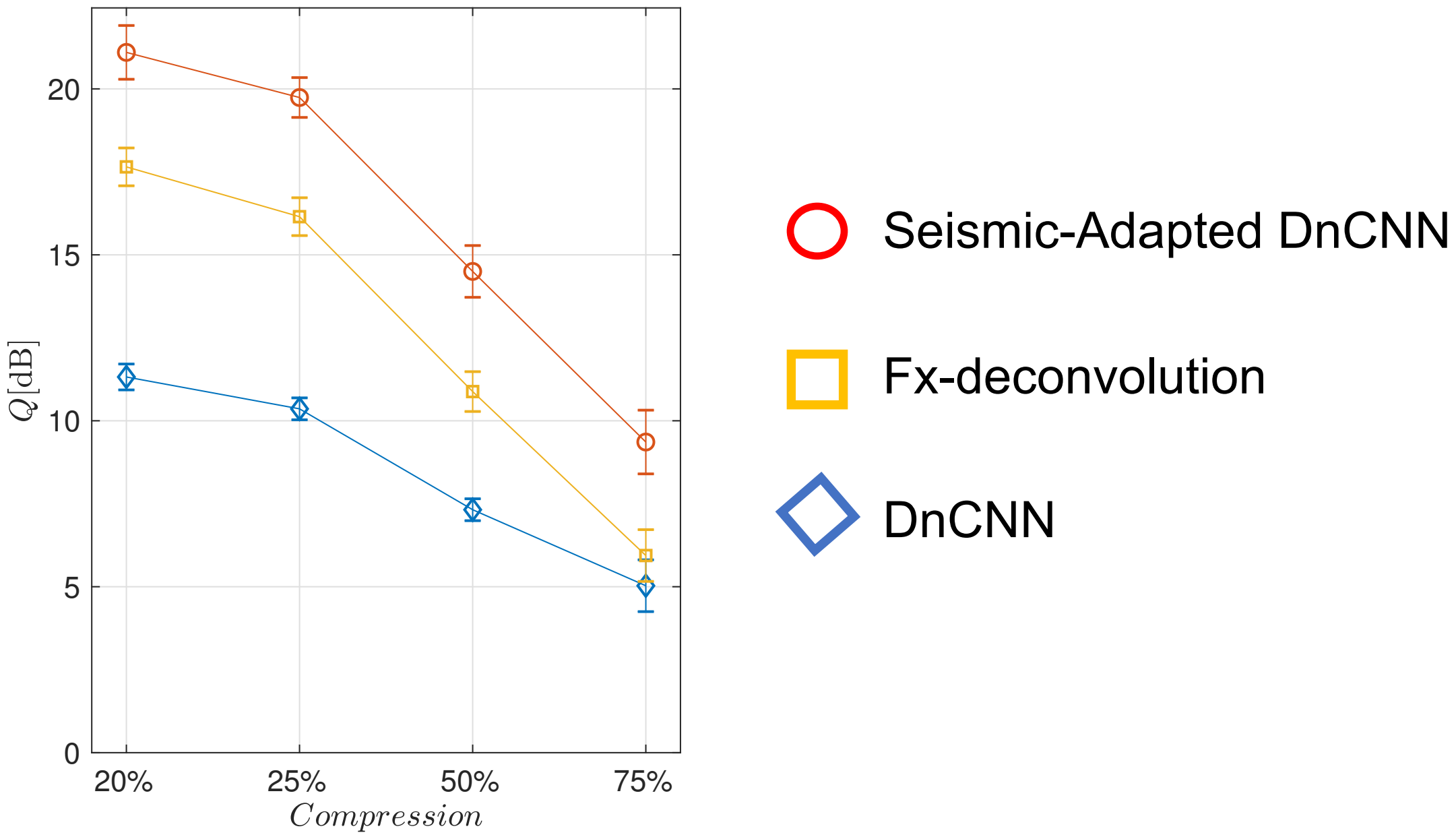
Fx- deconvolution

DnCNN

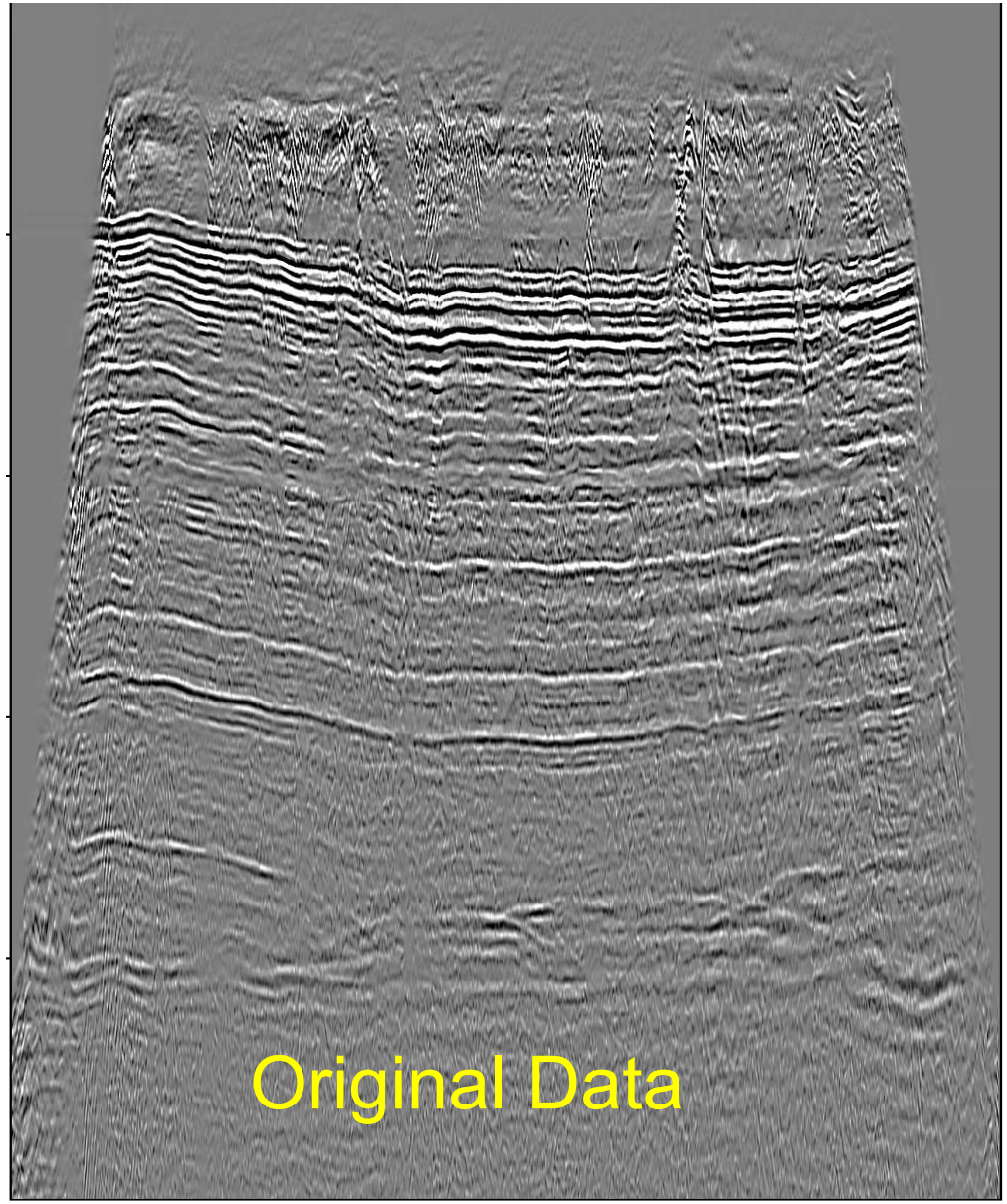


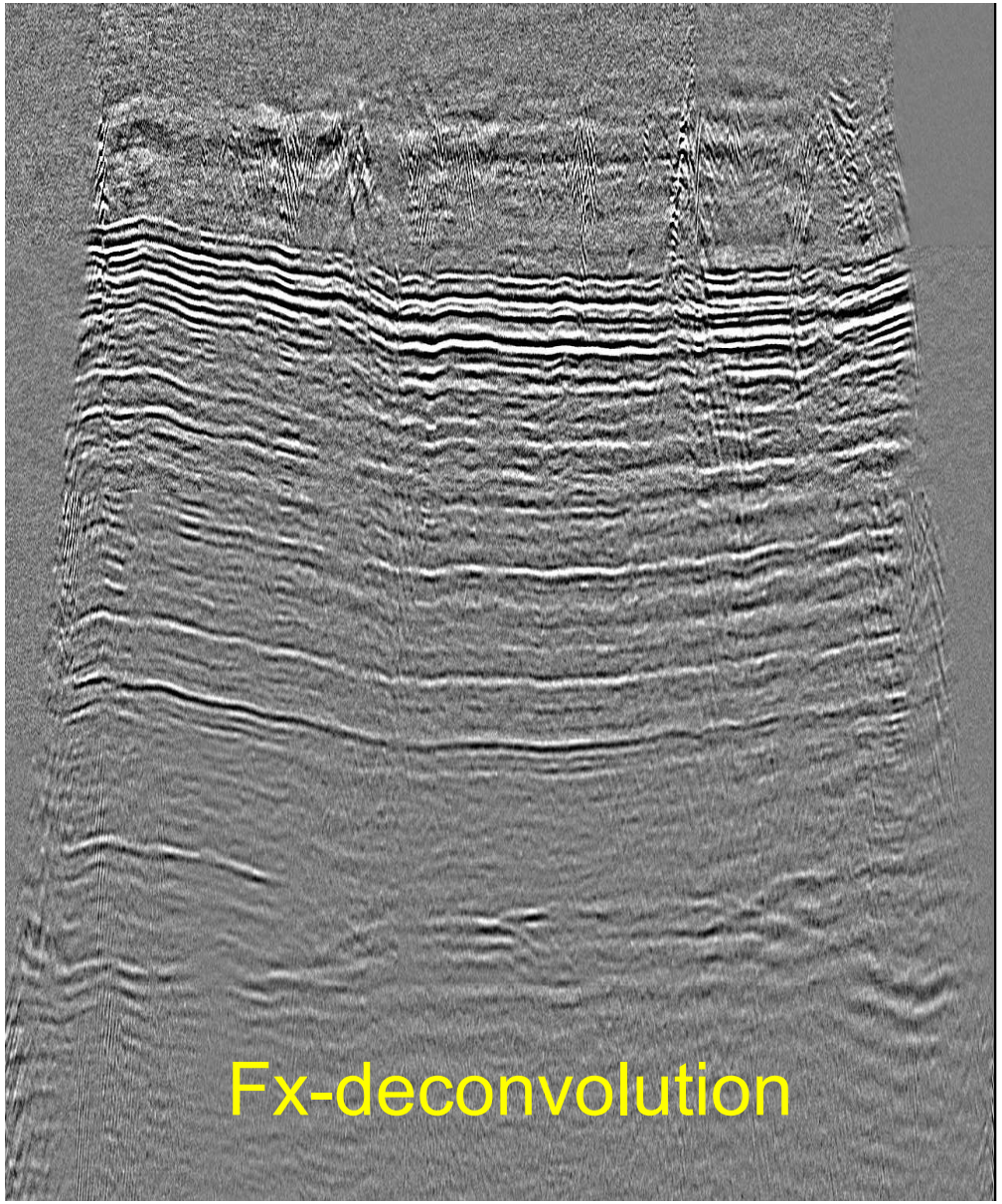
Seismic- Adapted DnCNN

CS with RED- Sensitivity analysis

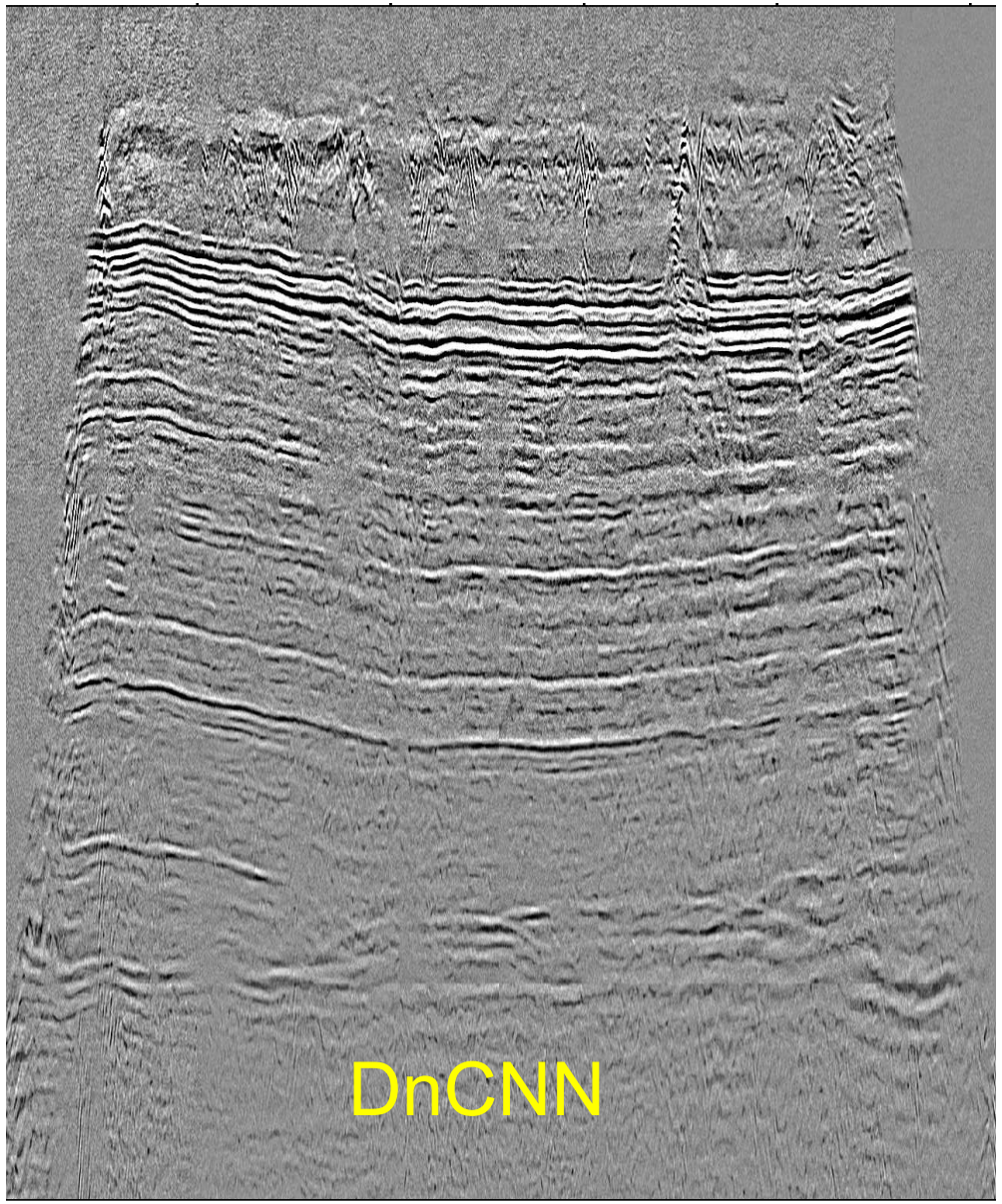


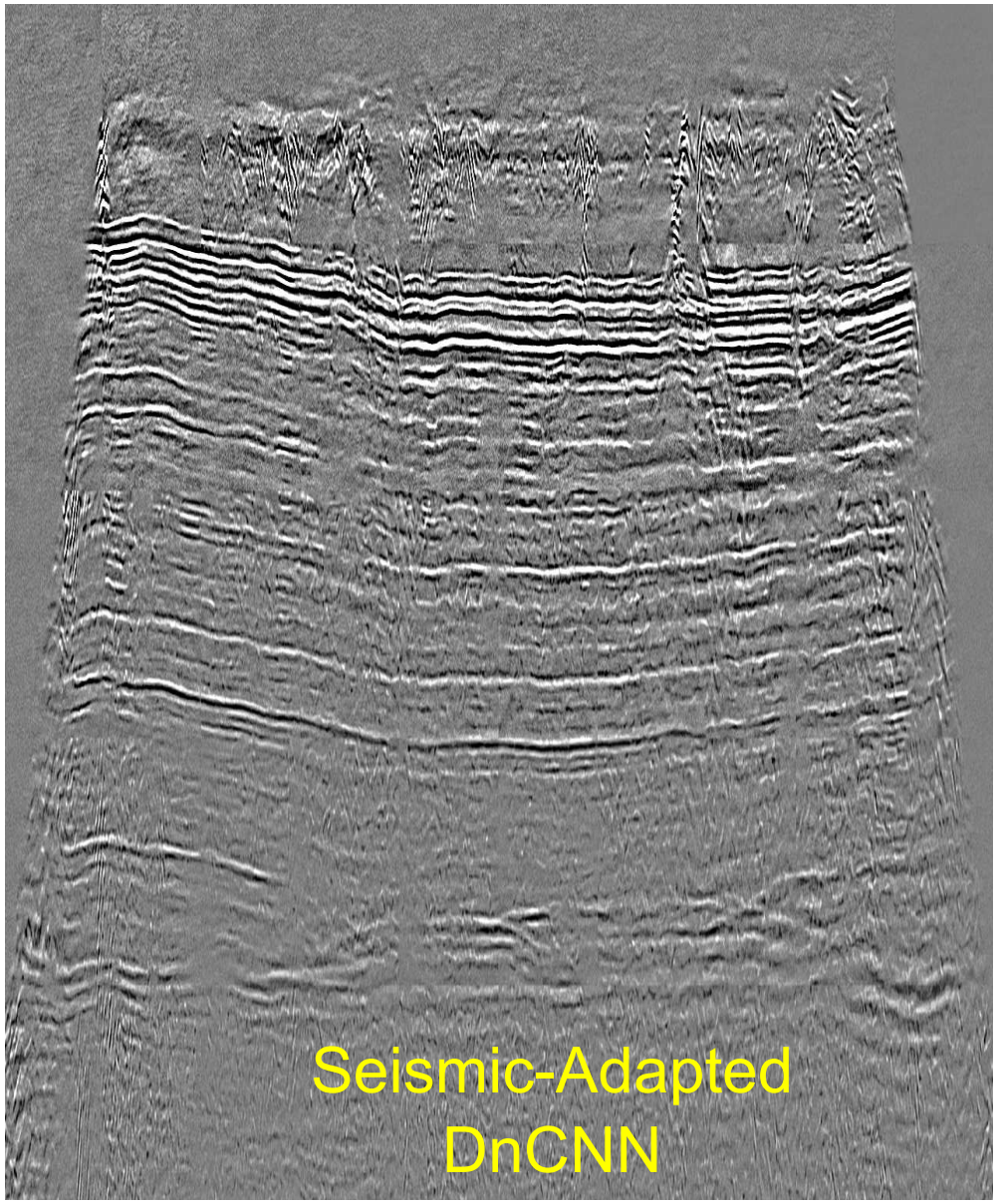
CS with RED (50% compression) Real data



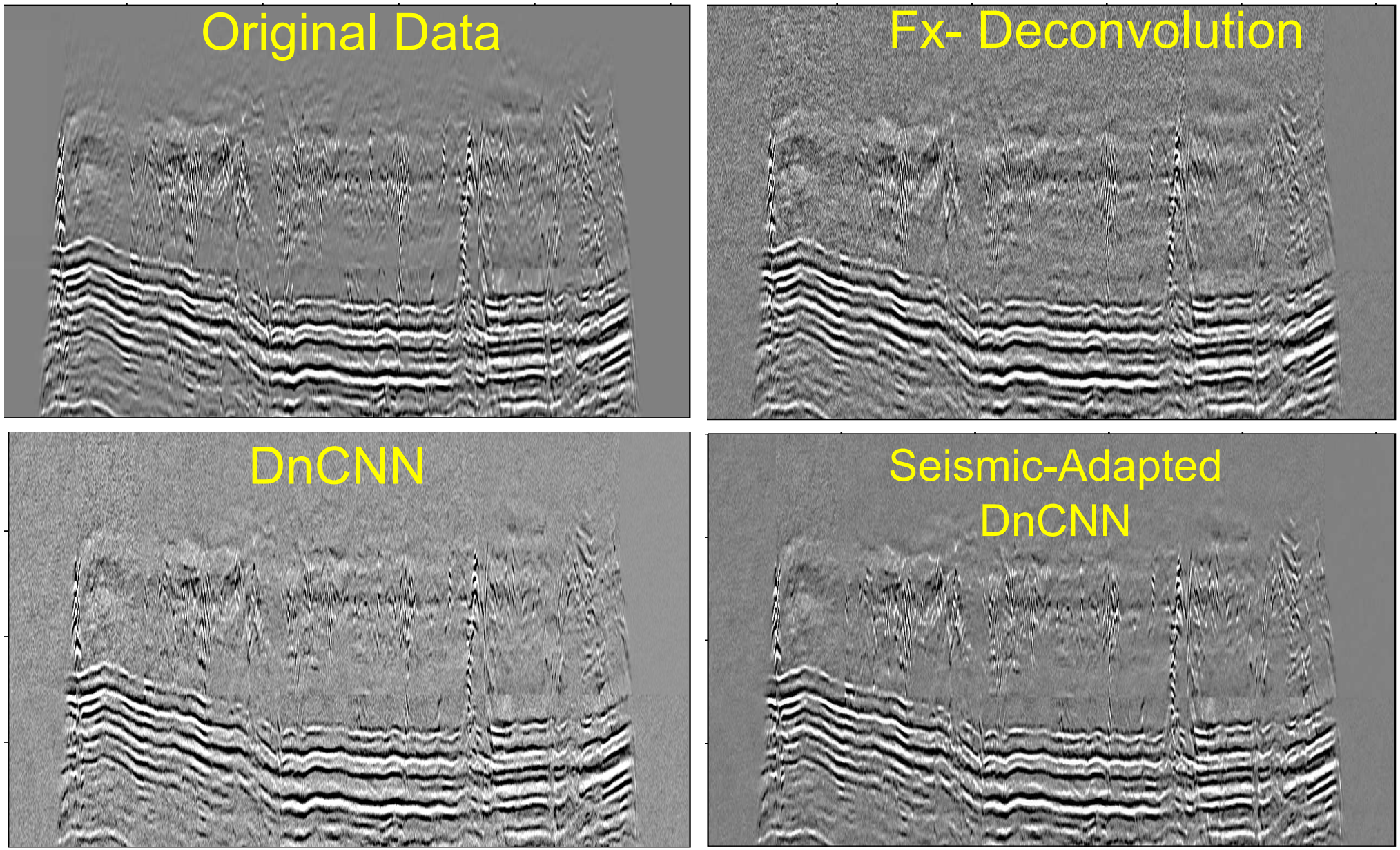


CS with RED (50% compression) Real data





Seismic Noise Suppression- Real data (zoomed)



Machine learning in drilling automation

Why drilling automation matters

Risk

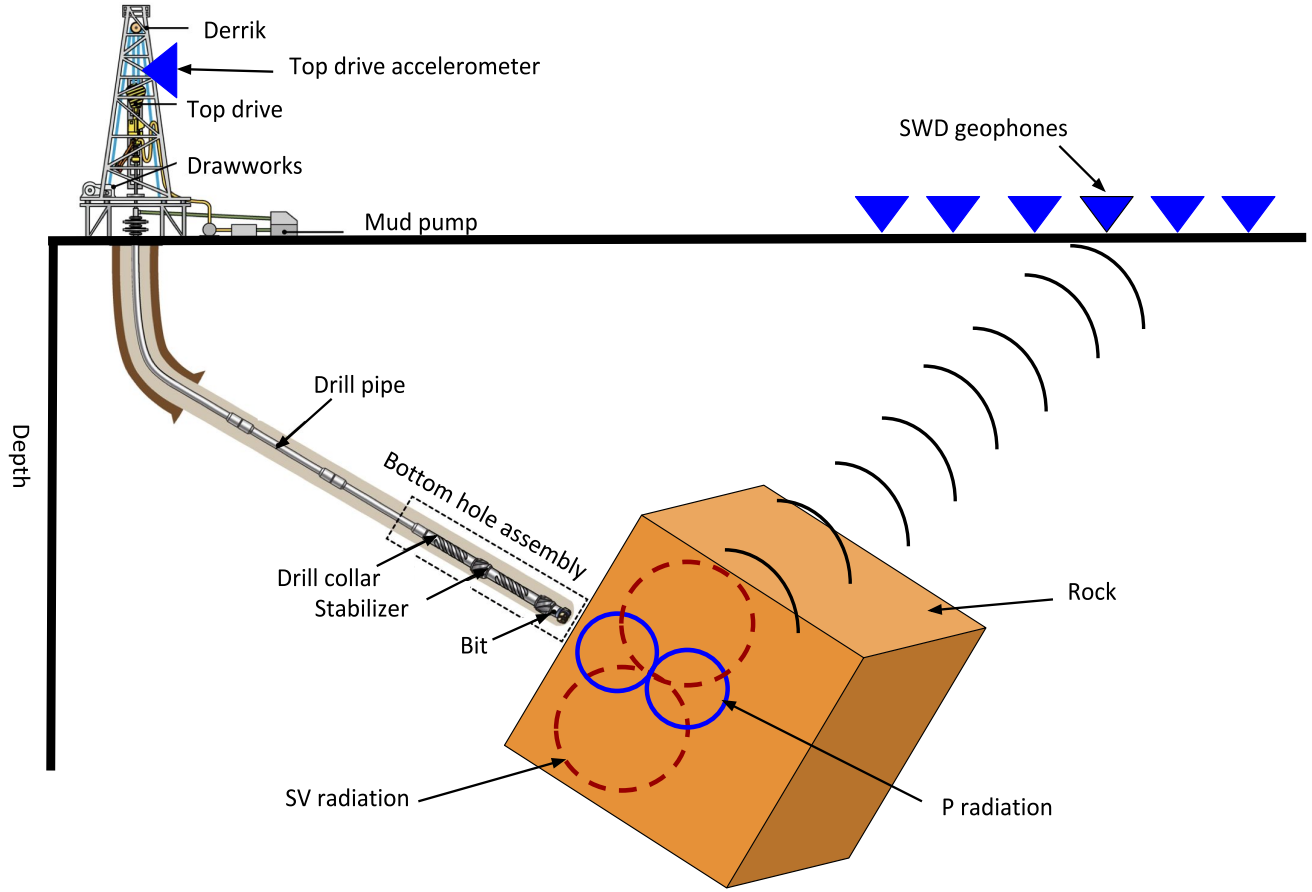
Cost

Kazemi , et al., US & CA Patent, 2021

Deepwater Horizon disaster (2010)

How it works? What is the role of ML?

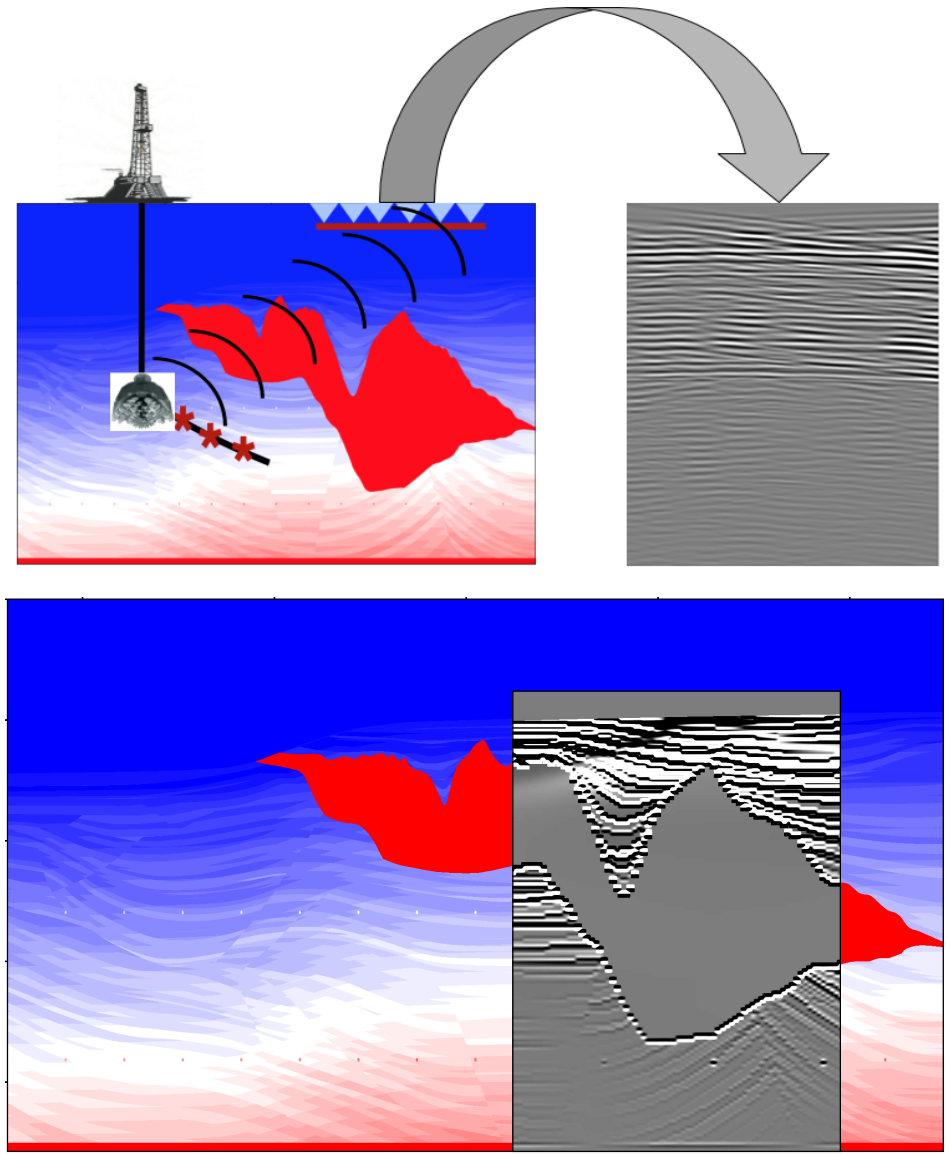
Drilling automation



Kazemi , Nejadi, et al., 2020, Energy Report

Auriol, Kazemi, et al., 2021, Mechanical systems and signal processing

Subsurface monitoring



Machine learning in drilling automation

Machine learning algorithms for

1) Estimating the mechanical properties of rocks

2) Estimating friction parameters in the drill string

Estimating mechanical properties of rocks while drilling

Objective:

1) Reduce non-productive time
2) Increase Rate of Penetration (ROP)
3) Reduce drill string dynamics
4) Increase safety
5) Design control flows to damp the harmful drill string vibrations

Tools:

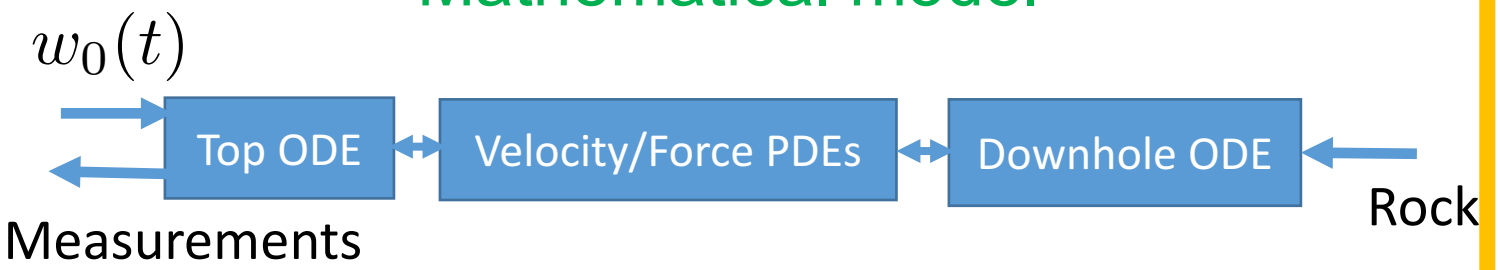
1) Design an observer based on Riemann invariants and Backstepping approach with top-drive measurements

Requirements:

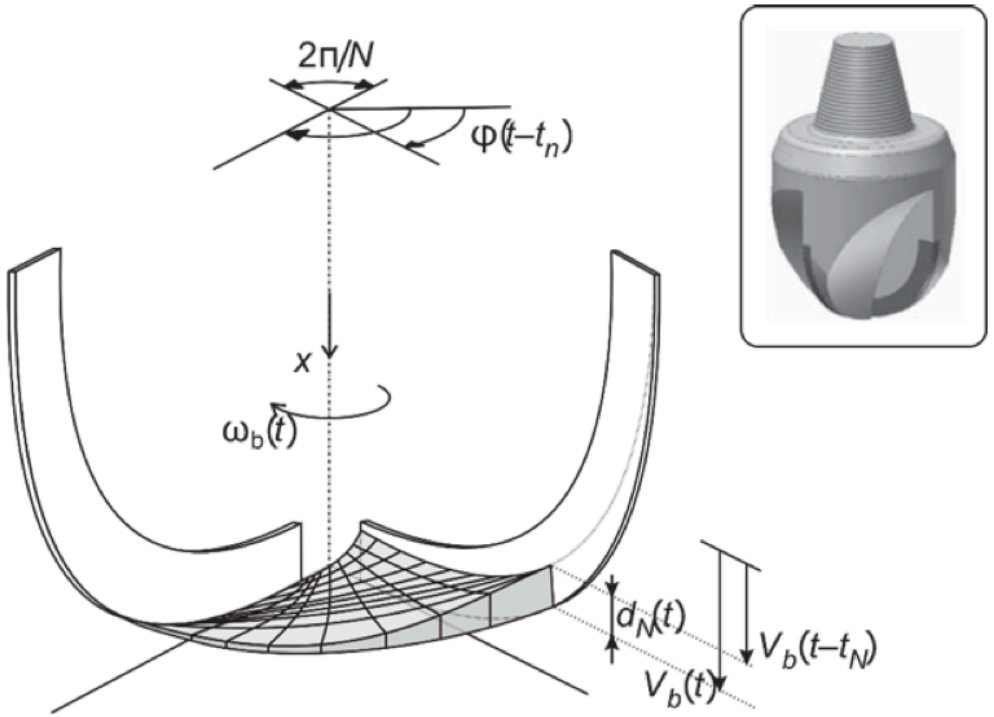
1) Physical parameters of the drilling system
2) Nature of the drilled rock

Mathematical model of drilling system

Mathematical model



Drill bit-rock interaction



The intrinsic specific energy of rock ϵ, is necessary for designing the observer

Observer Design

Inputs:

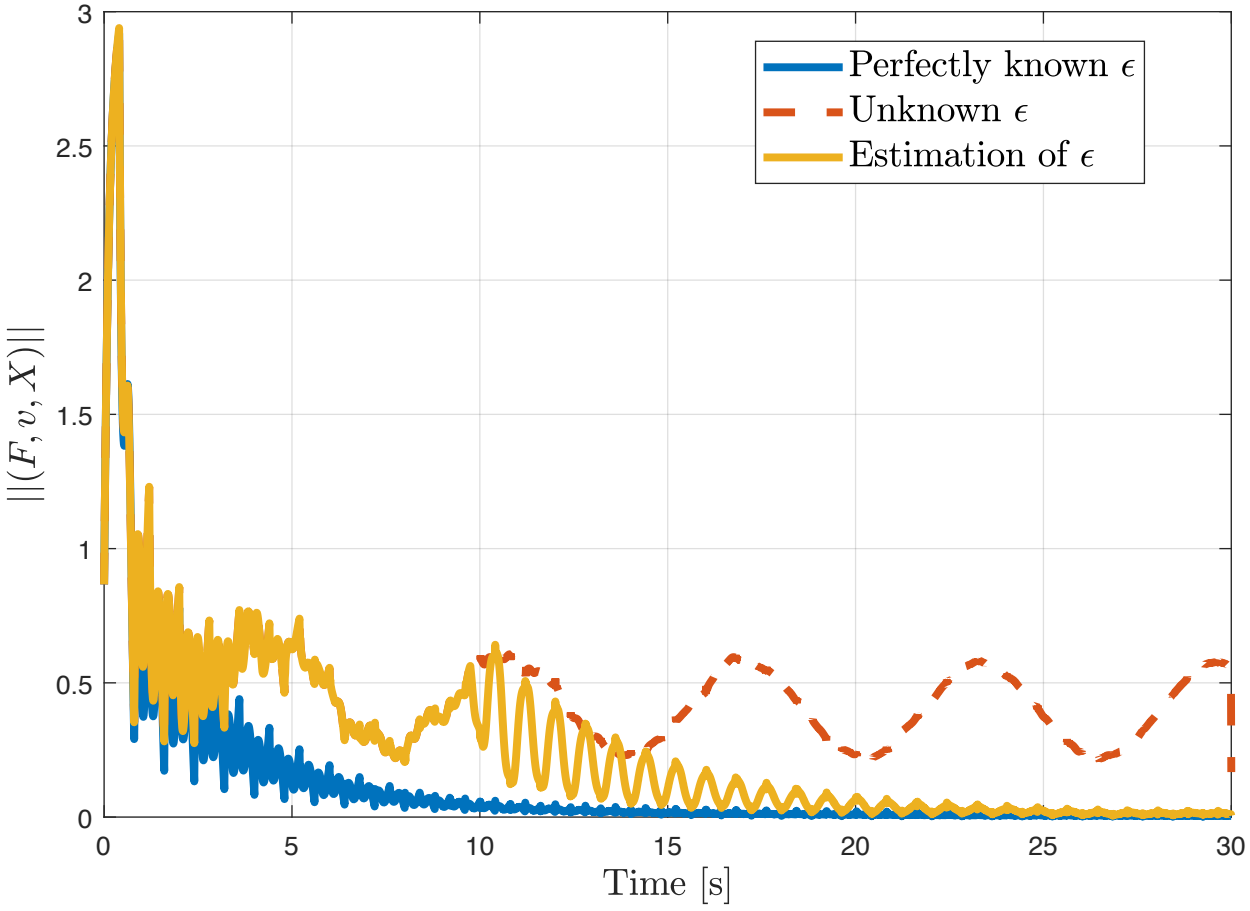
1) Mathematical model
2) Top-side velocity and force values
3) Intrinsic specific energy of rock ϵ

Design an observer based on

1) Inputs
2) Riemann invariants and
3) Backstepping method

Auriol, Kazemi et al., 2019
American Control Conference

Auriol, Kazemi et al., 2020
IEEE Trans. Geoscience and remote sensing



Machine learning for estimating ϵ

Attribute selection:

Inputs are time series and outputs are scaler values

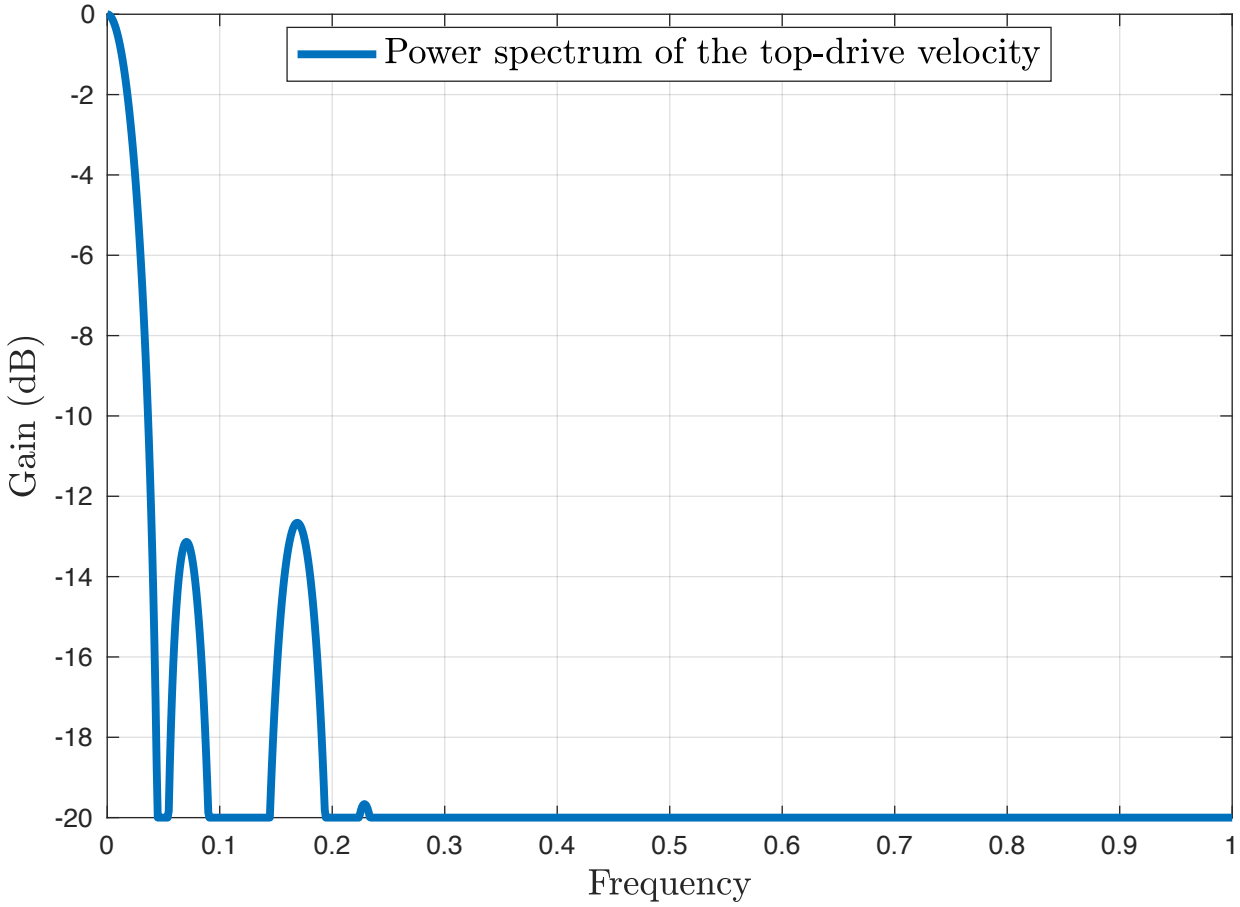
Can we reduce input parameters?

Observation:

ϵ changes the dominant frequencies and their corresponding amplitudes

Correlation:

ϵ is correlated with first and second dominant frequencies of top-drive force



Machine learning for estimating ϵ

Supervised learning with cross validation

1) Simulate 10000 inputs with randomly selected values of ϵ
2) Calculate attributes (first and second dominant frequencies and their coefficients)
3) Design a neural network for a regression problem to match attributes to ϵ (sklearn.neural_network.MLPRegressor: 50 hidden layers, a BFGS solver for weight optimization, and an adaptive learning rate)
4) Divide library to training and test and use cross validation for generalizability
5) Train the network
6) Use the network on new attributes to predict ϵ

Machine learning for estimating ϵ

Performance of machine learned operator in estimating the ϵ

Rock	Real ϵ		Machine Learning
Unconsolidated sands	11	Mean	9.7
		Stand. Dev.	2
Sedimentary Rocks	57	Mean	60.9
		Stand. Dev.	3.3
Metamorphic Rocks	175	Mean	184
		Stand. Dev.	17.8

Pros:

It is fast- helps real time decision making

Only requires measurements at the surface

Drawbacks:

Model dependency- needs real world data for training

Not general enough to handle different geometries, boundary conditions, etc.

Estimating friction parameters in drilling

Frictions:

Characterize the interaction between the drill pipe and the wellbore walls (Coulomb source terms) within the curving wellbore

Importance:

1) Design the next generation of stick-slip mitigation controllers
2) Develop real-time wellbore monitoring tools
3) Enable effective toolface control for directional drilling

Can machine learning operator learn to predict static and kinematic friction parameters for different well geometries and depths?

Machine learning for estimating friction parameters

Attribute selection:

Inputs are time series and outputs are scaler values

Can we reduce input parameters, and include geometry of wells in neural network?

Observations:

Friction parameters change with top-side torque and angular velocity

There is coupling between static and kinematic friction parameters

Correlation:

Friction parameters are correlated with first and second dominant frequencies of top-side torque measurements

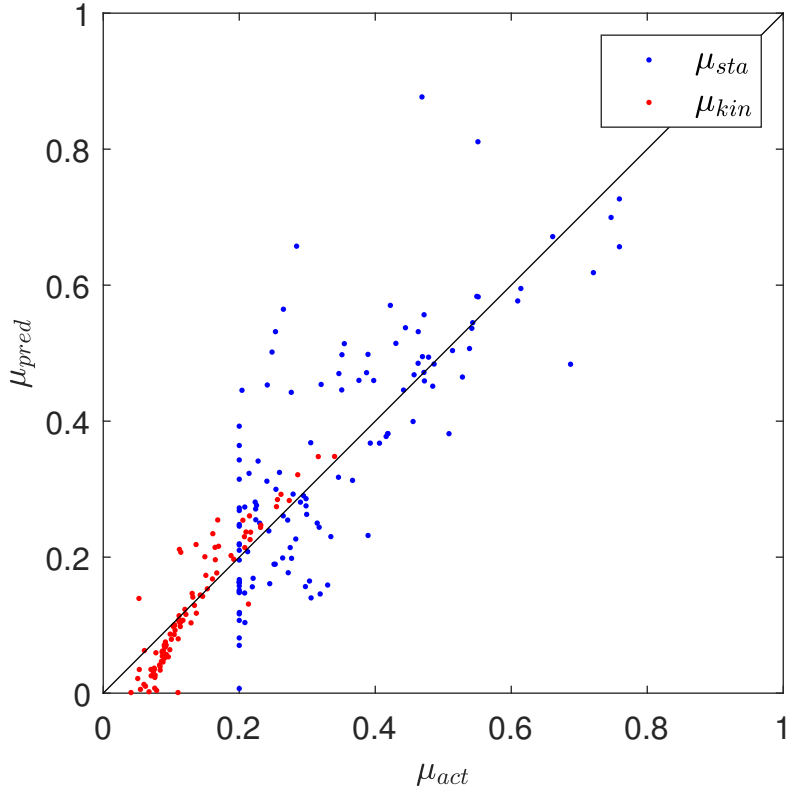
Machine learning for estimating friction parameters

Supervised learning with cross validation

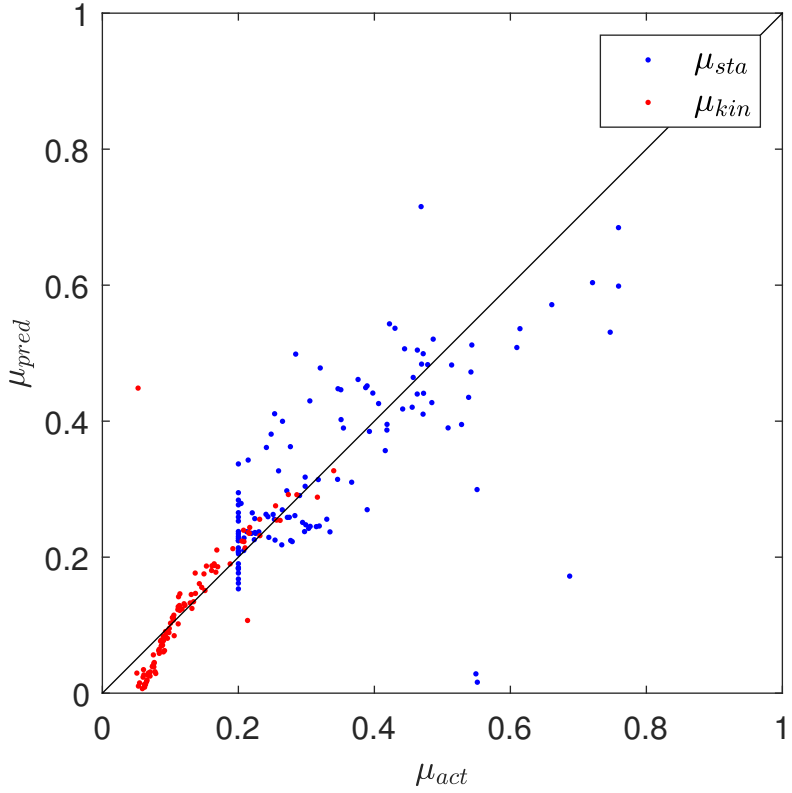
1) Simulate 10000 top-drive torque measurements with randomly selected values of frictions and different well geometries and length of drilling system
2) Calculate attributes (first and second dominant frequencies and their coefficients)
3) Design a neural network for a regression problem to match attributes to friction parameters (sklearn.neural_network.MLPRegressor: 150 hidden layers, ADAM solver for weight optimization, and an fixed learning rate)
4) Divide library to training and test and use cross validation for generalizability
5) Train the network
6) Use the network on new attributes to predict friction parameters

Machine learning for estimating friction parameters

Performance of machine learned operator in predicting static and kinematic frictions



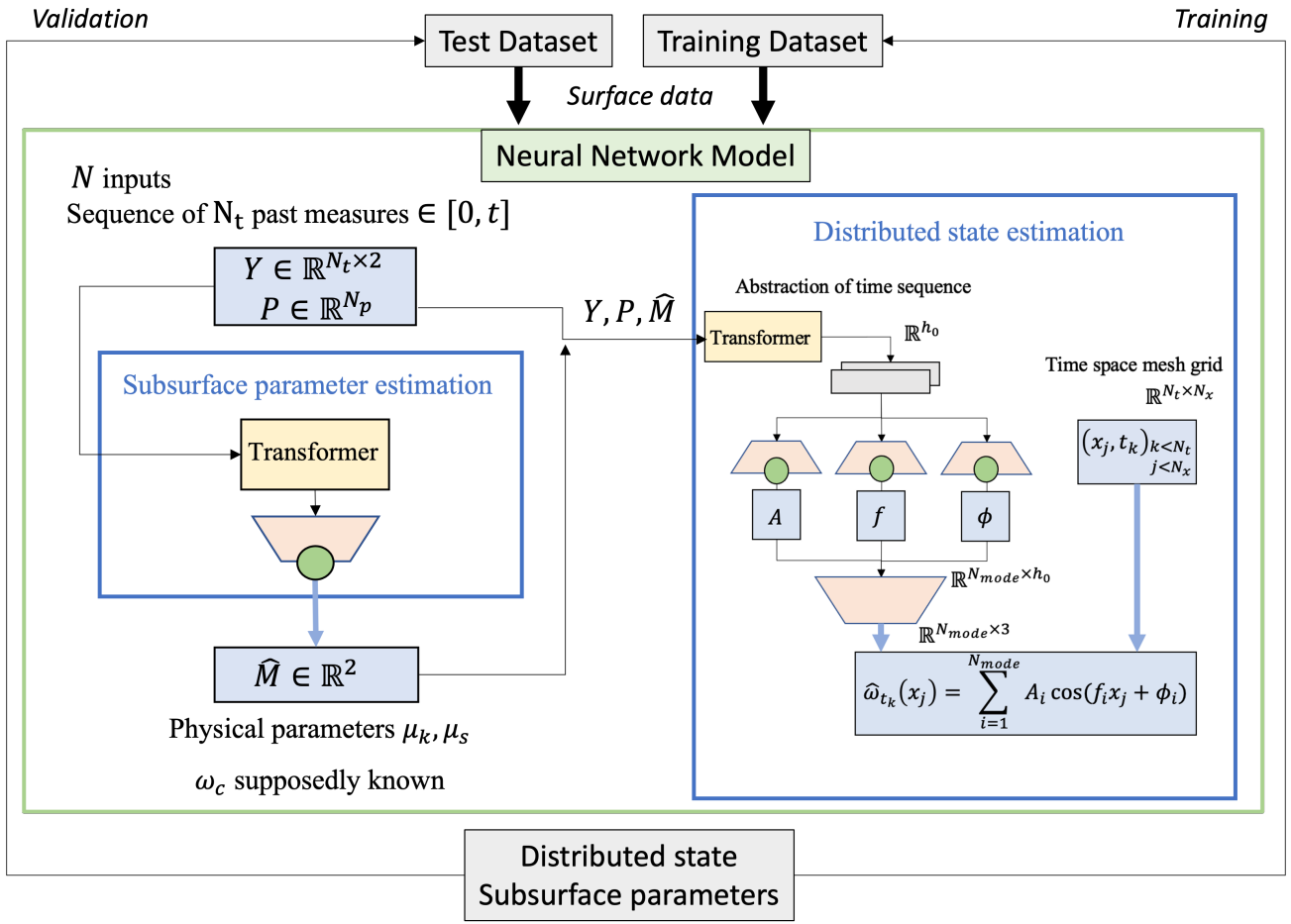
Depth range of test data NOT covered in the of training data



Depth range of test data covered in the of training data

Transformer-based dual architecture network

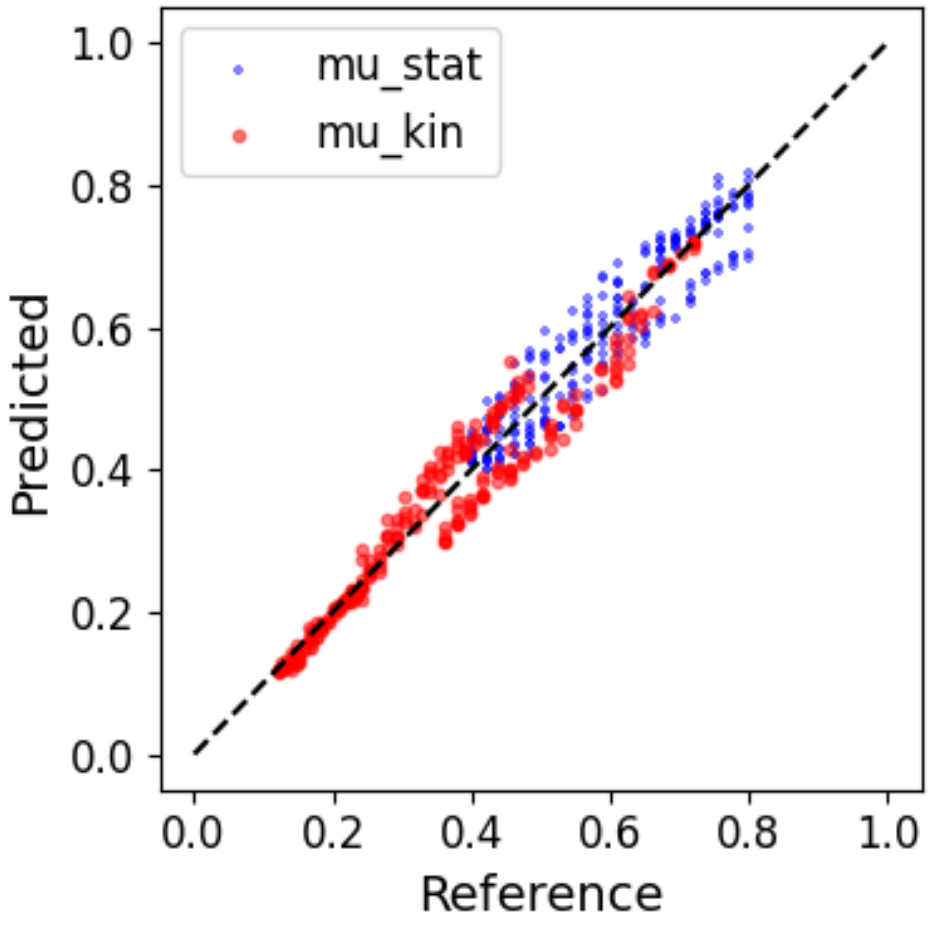
$M = (\mu_k, \mu_s) \in \mathbb{R}^2$, P : physical (known) parameters, Y: measurement.



Detailed view of the neural network architecture.

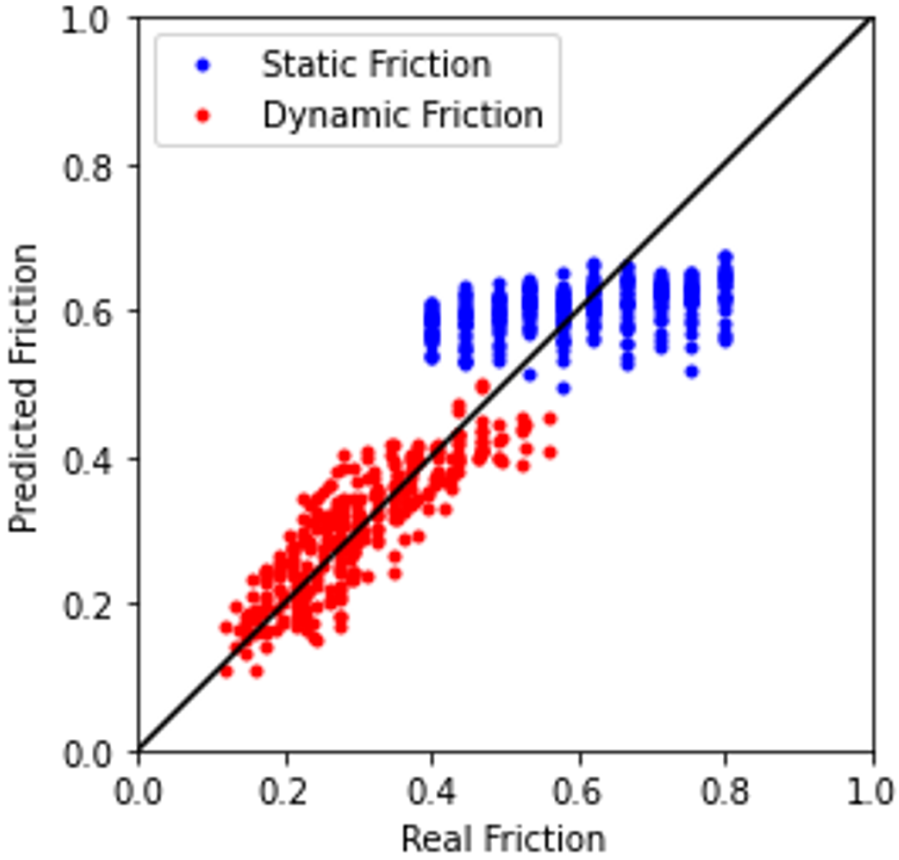
Physics guided friction parameter estimation

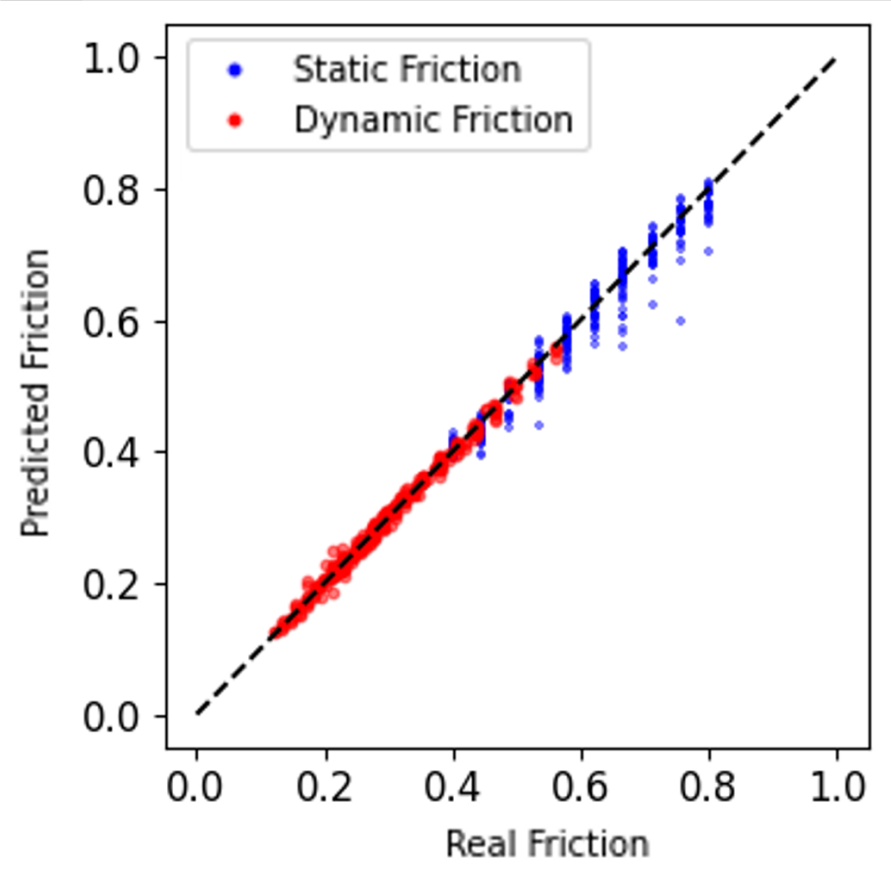
- Input: measurement Y, physical parameters P.
- We want to minimize $\mathcal{L}_{L_2}(\theta) = \frac{1}{N_b}\sum_{i=1}^{N_b} \|M - T_\theta(Y)\|_2^2$.



Estimation of (μ_k, μ_s) using physics guided dual network.

Performance of data driven and physics guided networks





Estimation of (μ_k, μ_s) using a RNN (left) and the transformer approach (right).

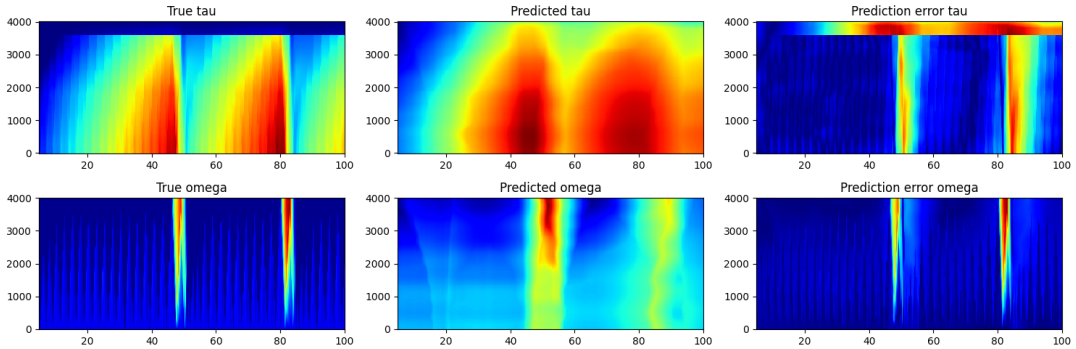
State estimation: Physics guided network

- Input: measurement Y, physical parameters P, and **estimated friction parameters** $\hat{M}$.
- We want to minimize $\mathcal{L}(\Theta) = \mathcal{L}_{\mathcal{D}}(\Theta) + \mathcal{L}_{\text{PDE}}(\Theta) + \mathcal{L}_{\text{BC}}(\Theta)$.

$$\mathcal{L}_{\mathcal{D}}(\Theta) = \frac{1}{N_x}\frac{1}{N_t}\frac{1}{N_b}\sum_{i=1}^{N_b}\sum_{j=1}^{N_x}\sum_{k=1}^{N_t}\|X(t_k,x_j) - S_{Y,\Theta}(t_k,x_j)\|_2^2, \quad \textbf{State}$$

$$\mathcal{L}_{\text{PDE}}(\Theta) = \frac{1}{N_x}\frac{1}{N_t}\frac{1}{N_b}\sum_{i=1}^{N_b}\sum_{j=1}^{N_x}\sum_{k=1}^{N_t}\|\mathcal{O}(f_{Y,\Theta}(t_k,x_j))\|_2^2, \quad \textbf{PDE}$$

$$\mathcal{L}_{\text{BC}}(\Theta) = \frac{1}{N_t}\frac{1}{N_b}\sum_{i=1}^{N_b}\sum_{k=1}^{N_t}\|\mathcal{B}(S_{Y,\Theta}(t_k))\|_2^2 + |\hat{\tau}(t_k,L)|^2, \quad \textbf{BC}$$



Example of a prediction for a sample of the validation set after training.

Machine learning for estimating friction parameters

Performance of machine learned operator in predicting static and kinematic frictions

Pros:

Reliable, and easy to implement
Estimation of static and kinematic frictions

Fast algorithm (once properly trained)

Drawbacks:

Requires thousands of training points
Lacks generalizability

Depends on the initial conditions of the system

Concluding remarks

Uncertainties of depth imaging are discussed.

Poor subsurface illumination inherent in seismic imaging is shown to be one of the major sources of uncertainties.

Seismic-While-Drilling imaging combined with surface seismic improved subsurface illumination.

It is shown that estimating SWD source signature is an important step for prestack depth imaging of SWD data.

A multichannel blind deconvolution technique is used to estimate the SWD source signature.

Joint inversion of the SWD and surface seismic data are developed.

Concluding remarks

FWI is an ill-posed and nonlinear problem

FWI requires low and high frequencies in data, proper initial model (local optimization), and efficient solvers

Uncertainties in FWI due to lack of low frequencies in the data, can result in sub-optimal production and reduce productivity of the reservoir

Seismic-while-drilling data is complimentary to surface seismic data and it compensates for lack of low frequencies in FWI problem

Successive inversion of surface seismic and SWD data gives FWI results with less uncertainties

Concluding remarks

To generalize machine-learned operators, we need to be in the modern interpolation regime.

Compressively labeled data for seismic applications does not exist.

We need to use domain adaptation (Transfer learning) techniques to transfer the better-learned operator from the source domain to the target domain

We developed a simple post-processing strategy to adapt a natural image-learned operator for suppressing noise in seismic data.

We incorporated the domain-adapted operator into optimization algorithms for compressive sensing recovery of seismic data.

Concluding remarks

Mathematical modeling of drill string dynamics is possible

Observer design is necessary for controlling and monitoring drilling performance

Estimating friction parameters and nature of the rocks in near-real-time resulted in designing a reliable observer, improving performance, and increasing the safety of drilling

Machine learning provided near real-time estimate of friction parameters and mechanical properties of rocks

The applicability of the machine learning algorithms in the field remained an open question.

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