Wavefield-reconstruction inversion with source estimation and minimum smoothness constraint
- application to the Chevron 2014 dataset

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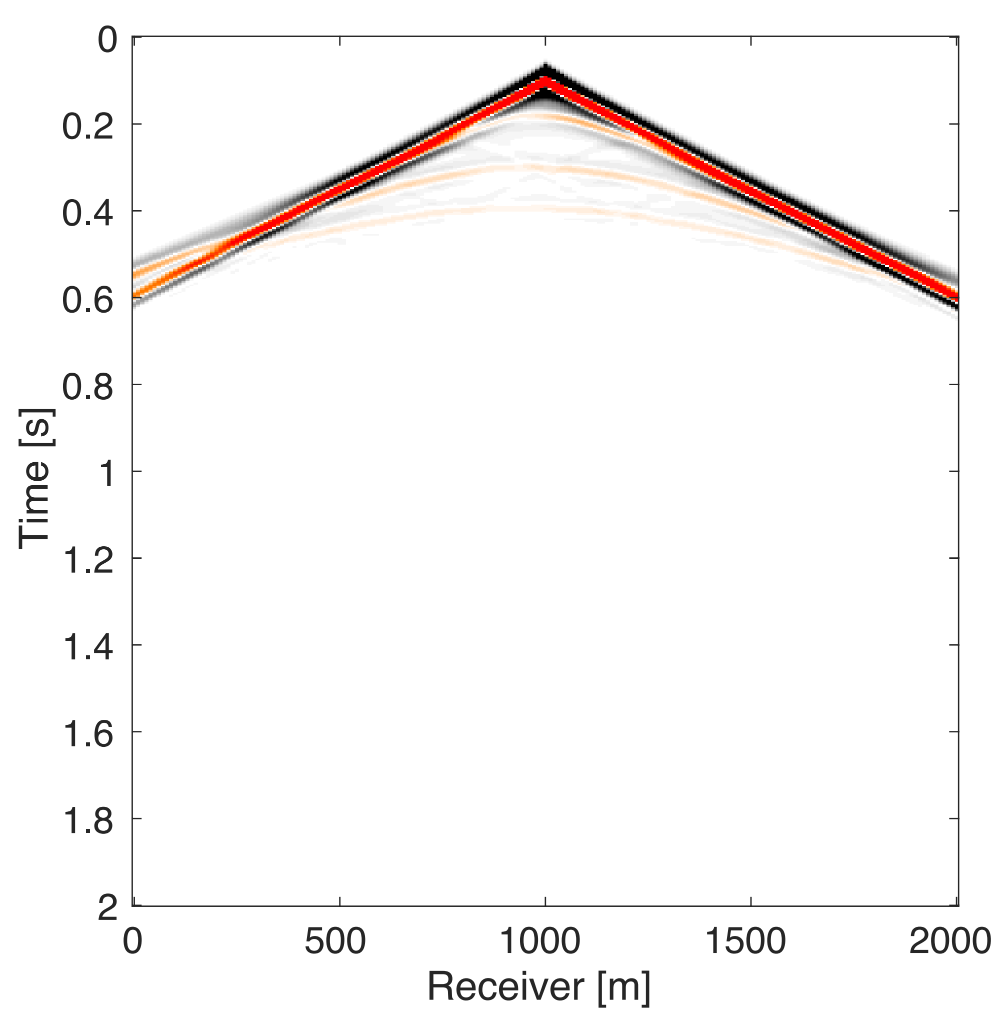
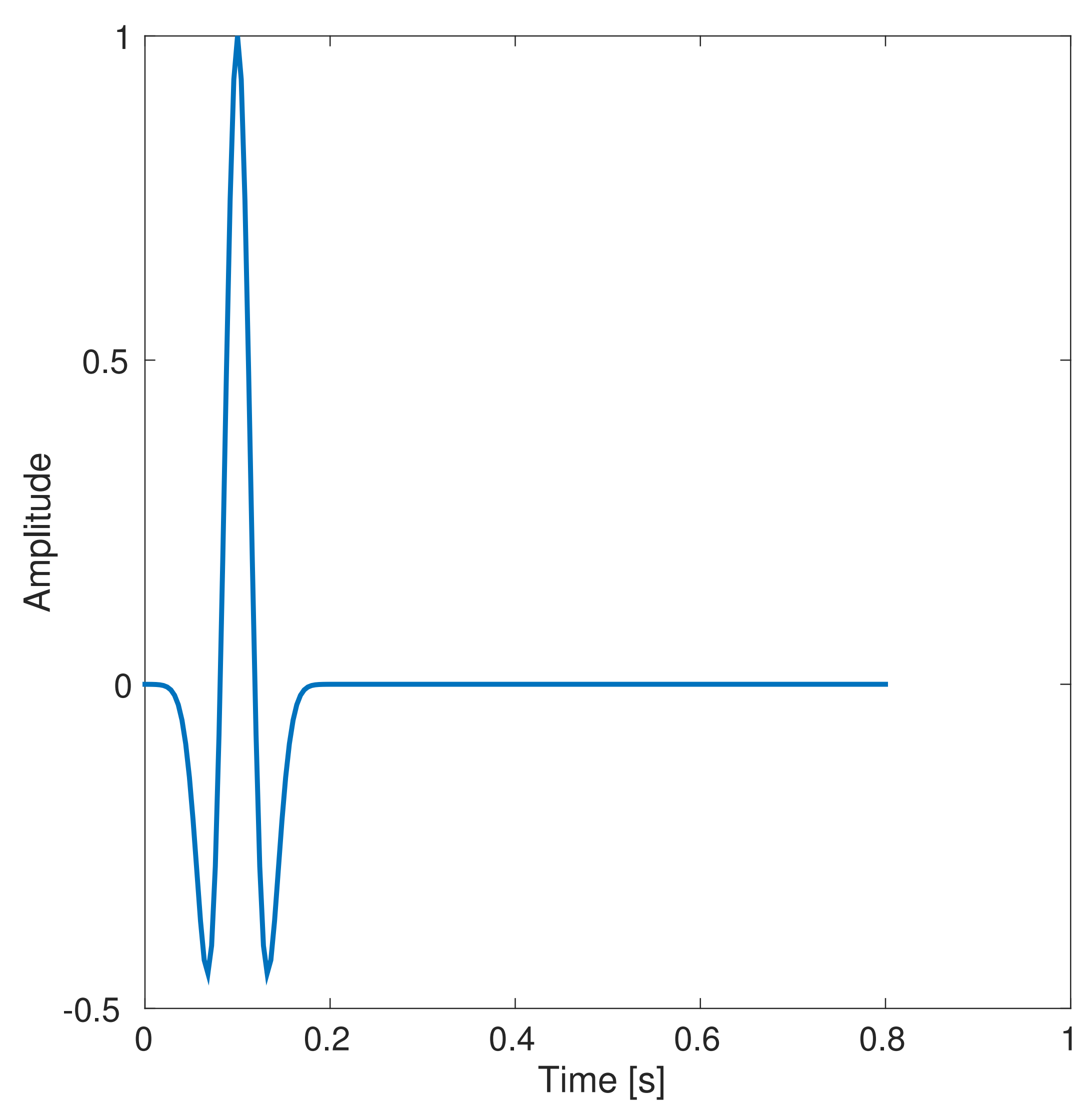
SLIM
University of British Columbia

Motivation



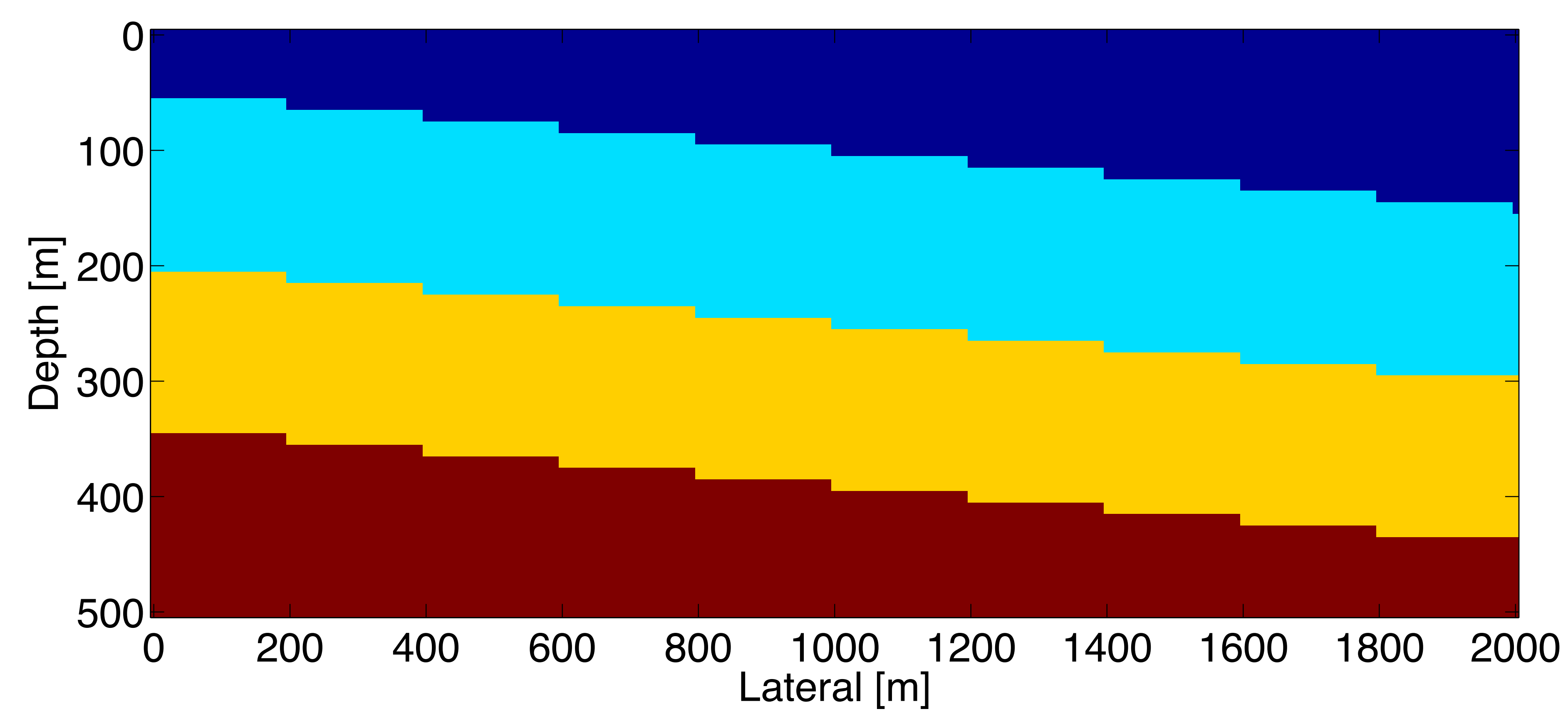
Data

=



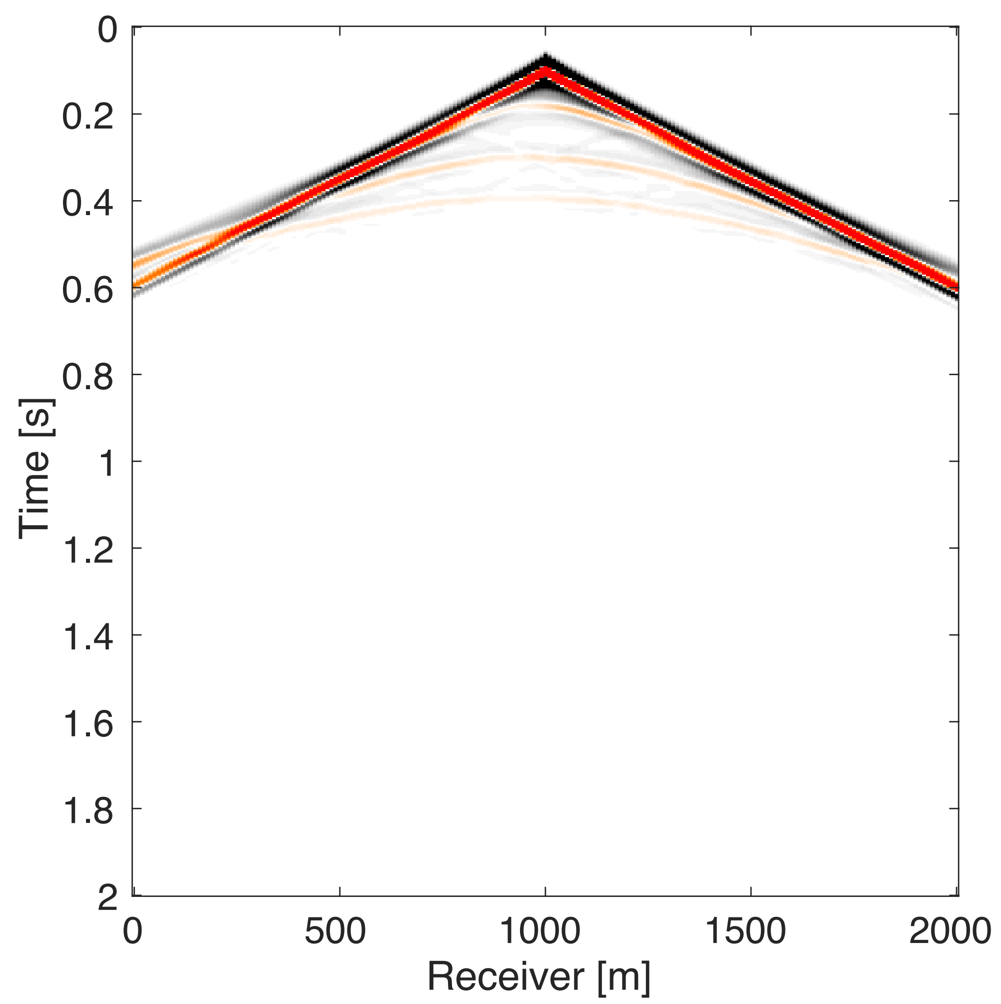
Source wavelet

*



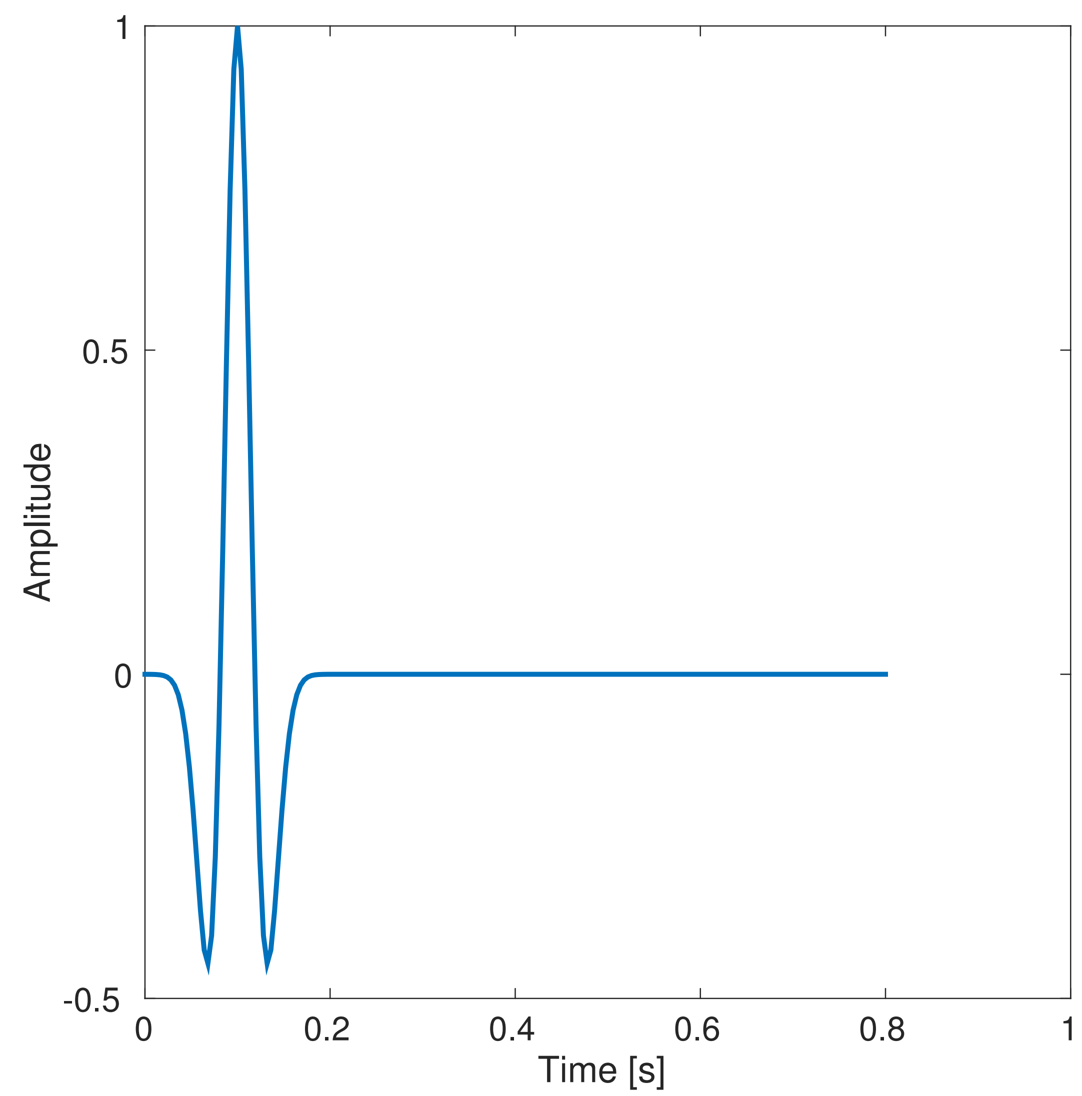
Velocity model

Motivation

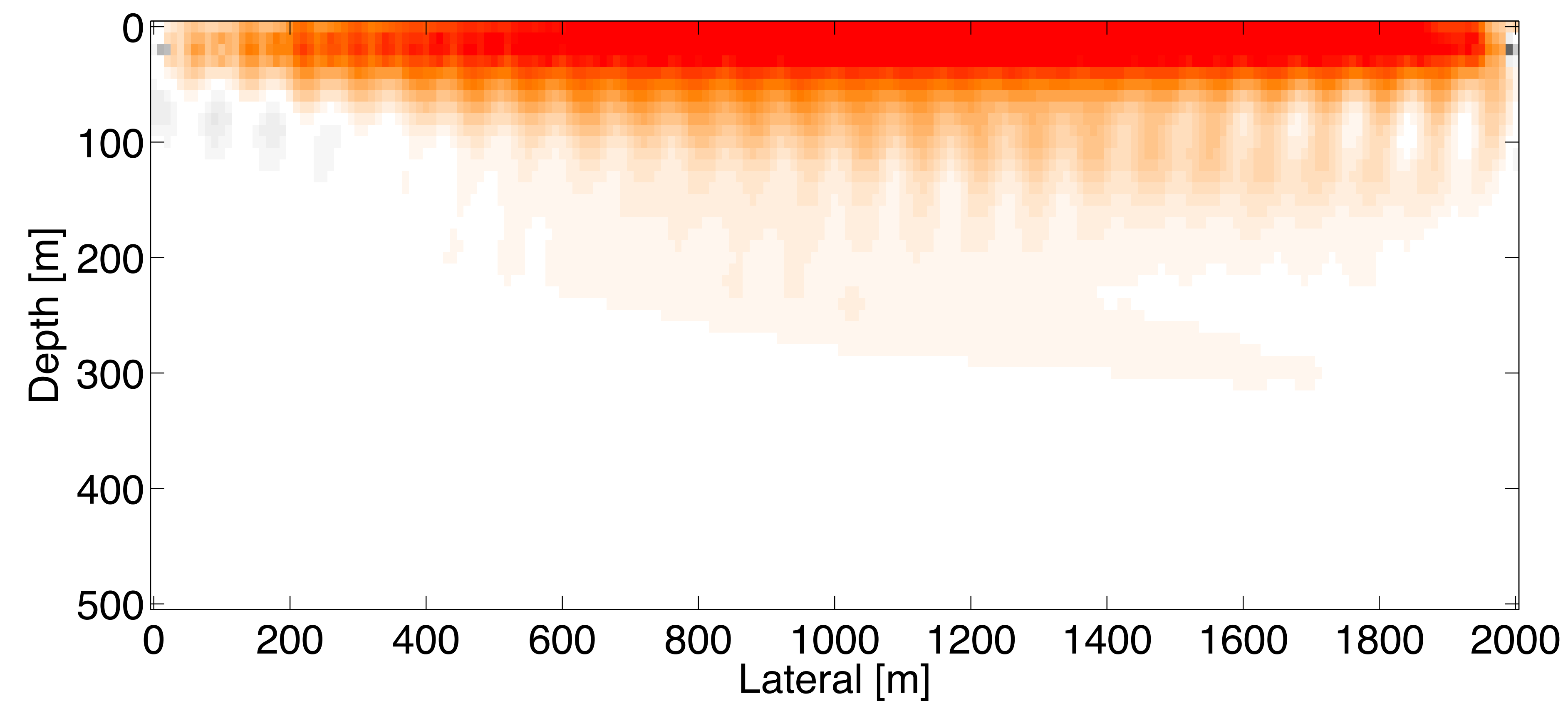


Data

+

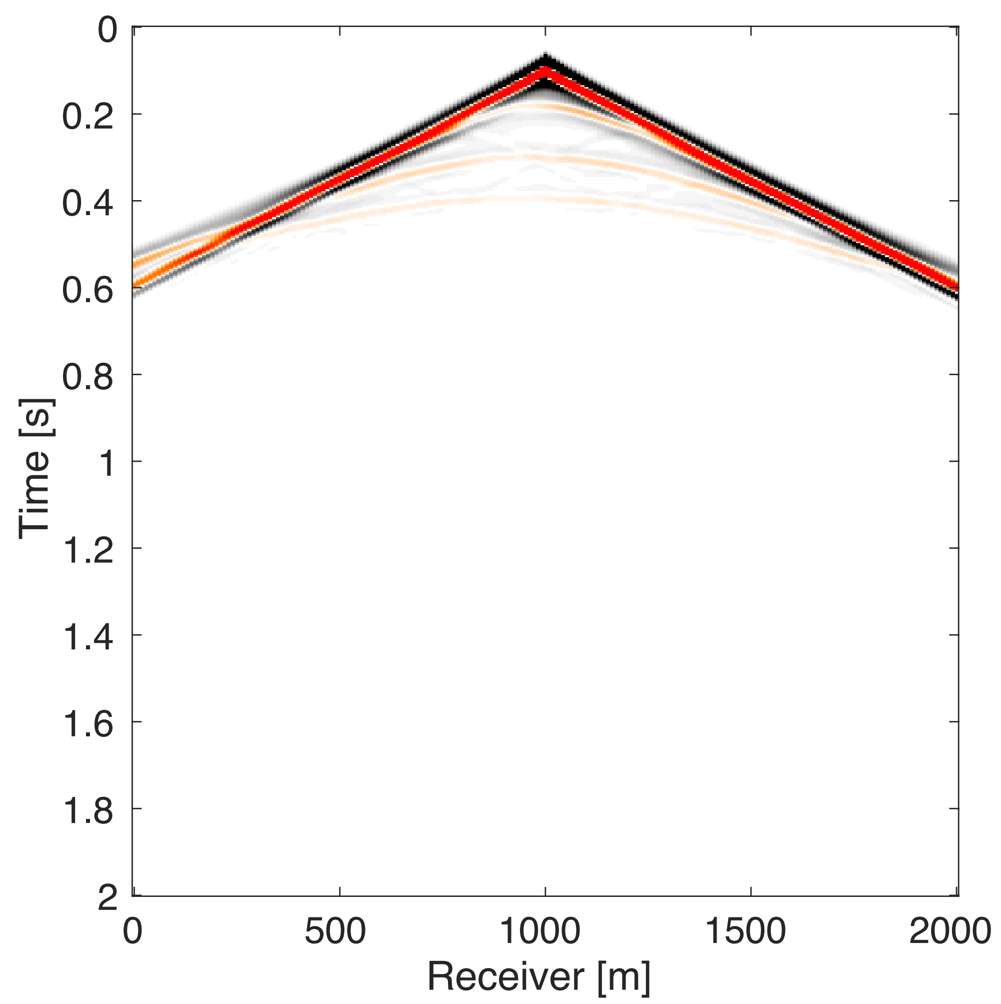


Correct source wavelet



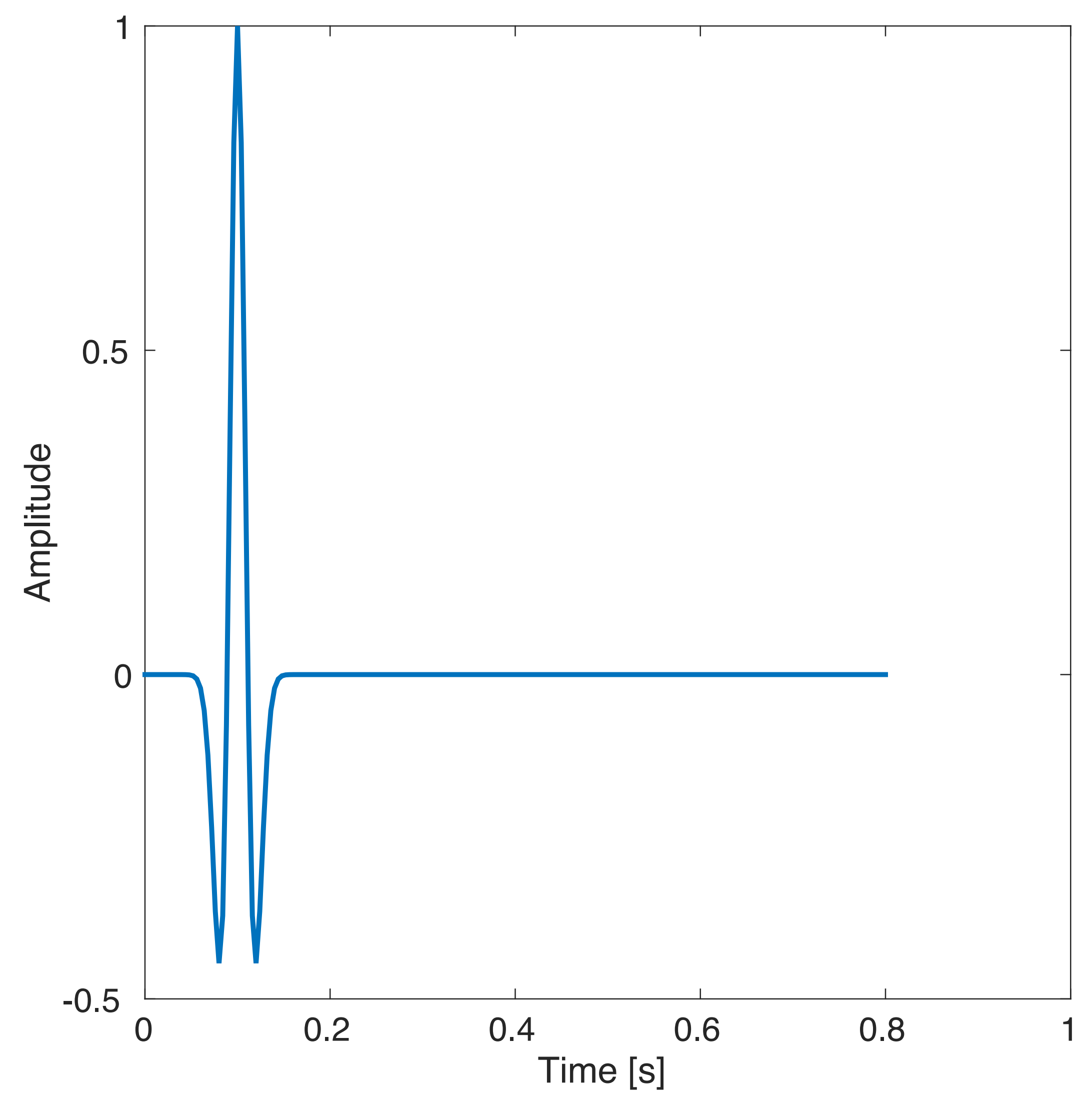
Correct gradient

Motivation



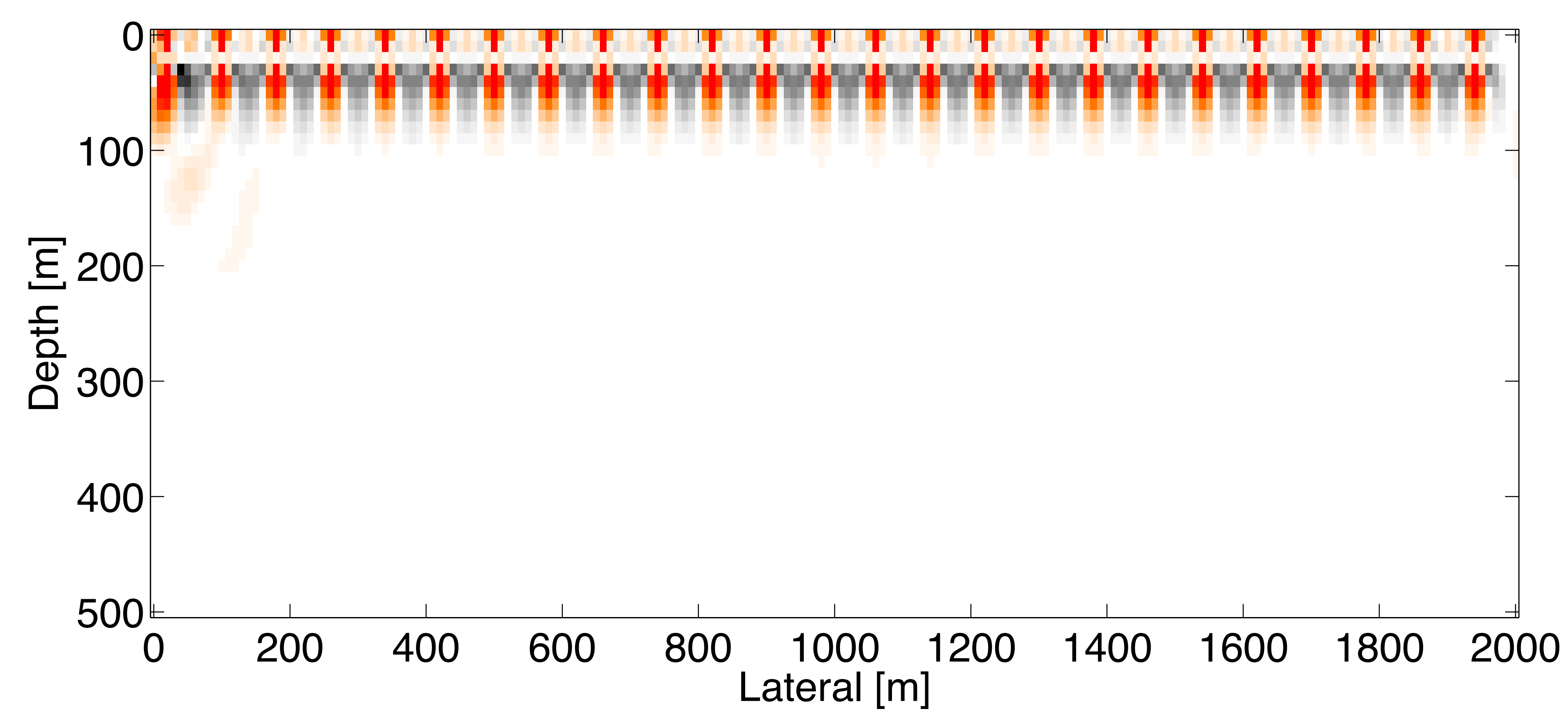
Data

+



Wrong source wavelet

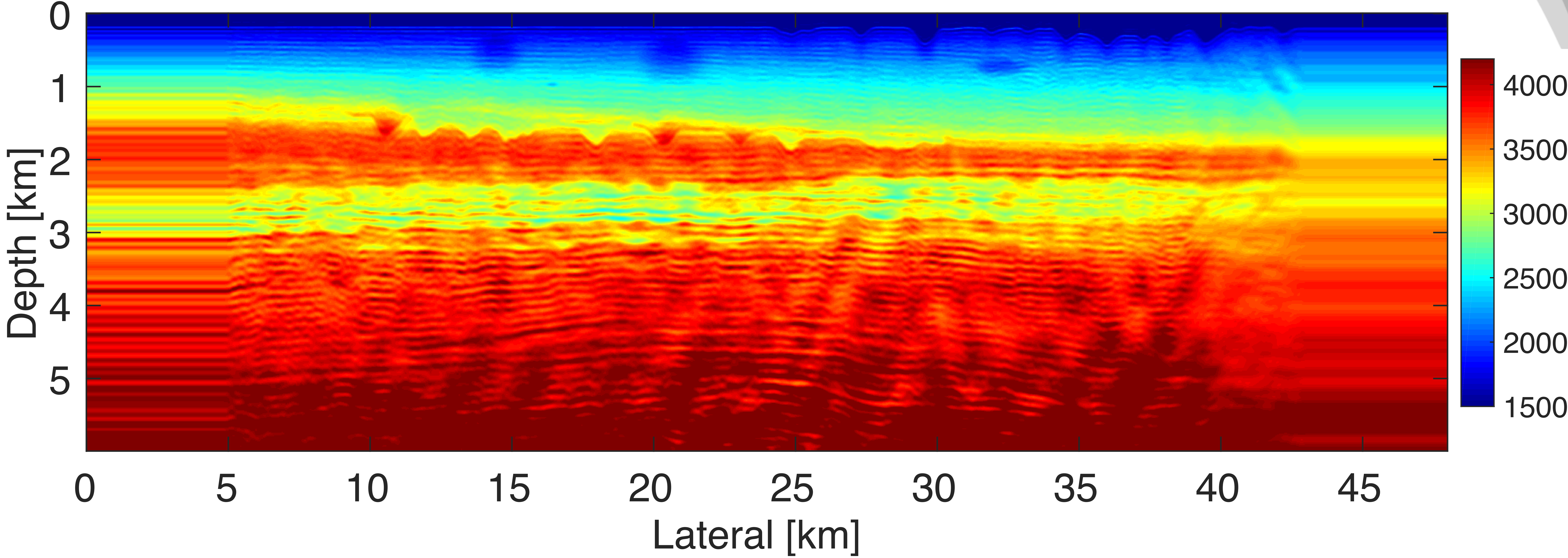
→



Wrong gradient

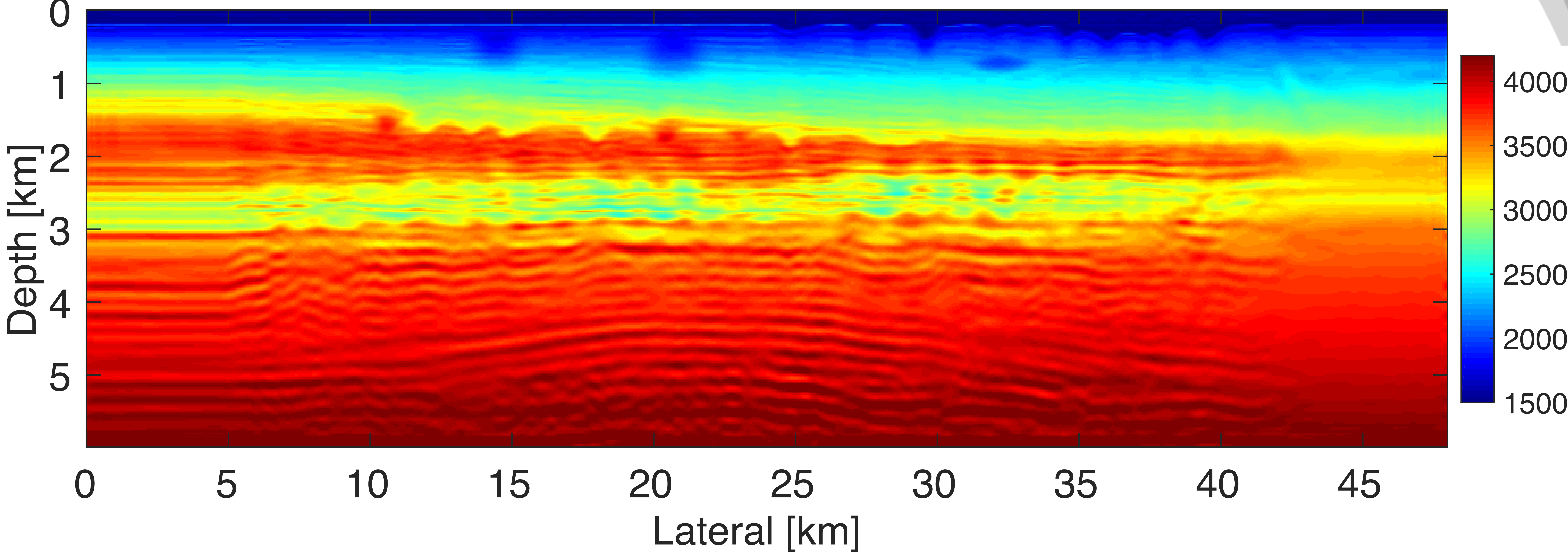
Chevron blind test data

— Wavefield-reconstruction inversion with source estimation (presented in the EAGE 2015)



Chevron blind test data

— Wavefield-reconstruction inversion with source estimation and minimum smoothness constraint



[Tarantola, 1984]

[J. Virieux and S. Operto, 2009]

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Full-waveform inversion

Original problem:

$$\underset{\mathbf{u},\mathbf{m}}{\text{minimize}} \sum_{k,l} \|\mathbf{P}_k \mathbf{u}_{k,l} - \mathbf{d}_{k,l}\|_2^2$$

$$\text{subject to } \mathbf{A}_{k,l}(\mathbf{m})\mathbf{u}_{k,l} = \mathbf{q}_{k,l},$$

where,

$\mathbf{u}_{k,l}$ – Wavefield of the kth shot at lth frequency

$\mathbf{d}_{k,l}$ – Observed data of the kth shot at lth frequency

$\mathbf{q}_{k,l}$ – Source of the kth shot at lth frequency

$\mathbf{A}_{k,l}$ – Helmholtz of the kth shot at lth frequency

$\mathbf{P}_k$ – Receiver projection operator of the kth shot

$\mathbf{m}$ – Squared-slowness

[Tarantola, 1984]

[J. Virieux and S. Operto, 2009]

Full-waveform inversion

Reduced/adjoint-state method:

$$\underset{\mathbf{m}}{\text{minimize}} \sum_{k,l} \|\mathbf{P}_k \mathbf{A}_{k,l}(\mathbf{m})^{-1}\mathbf{q}_{k,l} - \mathbf{d}_{k,l}\|_2^2$$

with the gradient given by

$$\mathbf{g} = \sum_{k,l} \mathbf{u}_{k,l}^* \frac{\partial \mathbf{A}_{k,l}^*}{\partial \mathbf{m}} \mathbf{v}_{k,l}$$

$$\mathbf{u}_{k,l} = \mathbf{A}_{k,l}(\mathbf{m})^{-1}\mathbf{q}_{k,l}$$

$$\mathbf{v}_{k,l} = \mathbf{A}_{k,l}^{-*}(\mathbf{m})\mathbf{P}_k^*\mathbf{r}_{k,l}$$

$$\mathbf{r}_{k,l} = \mathbf{P}_k \mathbf{A}_{k,l}(\mathbf{m})^{-1}\mathbf{q}_{k,l} - \mathbf{d}_{k,l}$$

2 PDE solves are required !

[van Leeuwen, T and Herrmann, F J , 2013]
[Peters, B, Herrmann, F J and van Leeuwen, T, 2014]
[Golub, G H and Pereyra, V , 1973]

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Wavefield-reconstruction inversion

Joint optimization problem:

$$\underset{\mathbf{u},\mathbf{m}}{\text{minimize}} \sum_{k,l} \|\mathbf{P}_k \mathbf{u}_{k,l} - \mathbf{d}_{k,l}\|_2^2 + \lambda^2 \|\mathbf{A}_{k,l}(\mathbf{m})\mathbf{u}_{k,l} - \mathbf{q}_{k,l}\|_2^2$$

Eliminate $\mathbf{u}$ w/ variable projection:

$$\overline{\mathbf{u}} = \arg\min_{\mathbf{u}} \sum_{k,l} \|\mathbf{P}_k \mathbf{u}_{k,l} - \mathbf{d}_{k,l}\|_2^2 + \lambda^2 \|\mathbf{A}_{k,l}(\mathbf{m})\mathbf{u}_{k,l} - \mathbf{q}_{k,l}\|_2^2$$

[van Leeuwen, T and Herrmann, F J , 2013]

[Golub, G and Pereyra, V, 1973]

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Wavefield-reconstruction inversion

Corresponds to solving the following augmented system:

$$\begin{pmatrix} \lambda \mathbf{A}_{k,l} \\ \mathbf{P}_k \end{pmatrix} \overline{\mathbf{u}}_{k,l} = \begin{pmatrix} \lambda \mathbf{q}_{k,l} \\ \mathbf{d}_{k,l} \end{pmatrix}$$

with the gradient

1 augmented system solves is required !

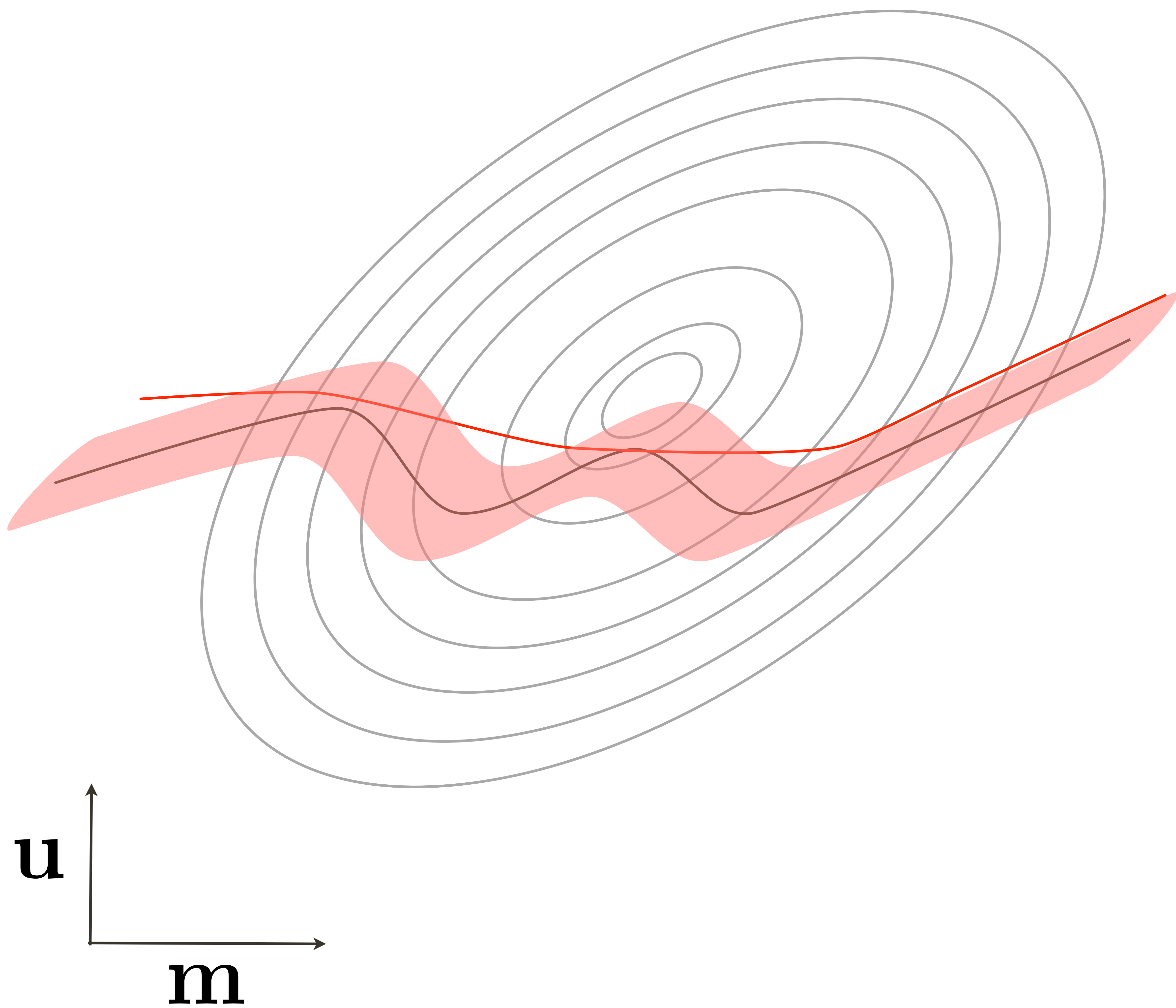
$$\mathbf{g} = \sum_{k,l} \overline{\mathbf{u}}_{k,l}^{*} \frac{\partial \mathbf{A}_{k,l}^{*}}{\partial \mathbf{m}} \overline{\mathbf{v}}_{k,l}$$

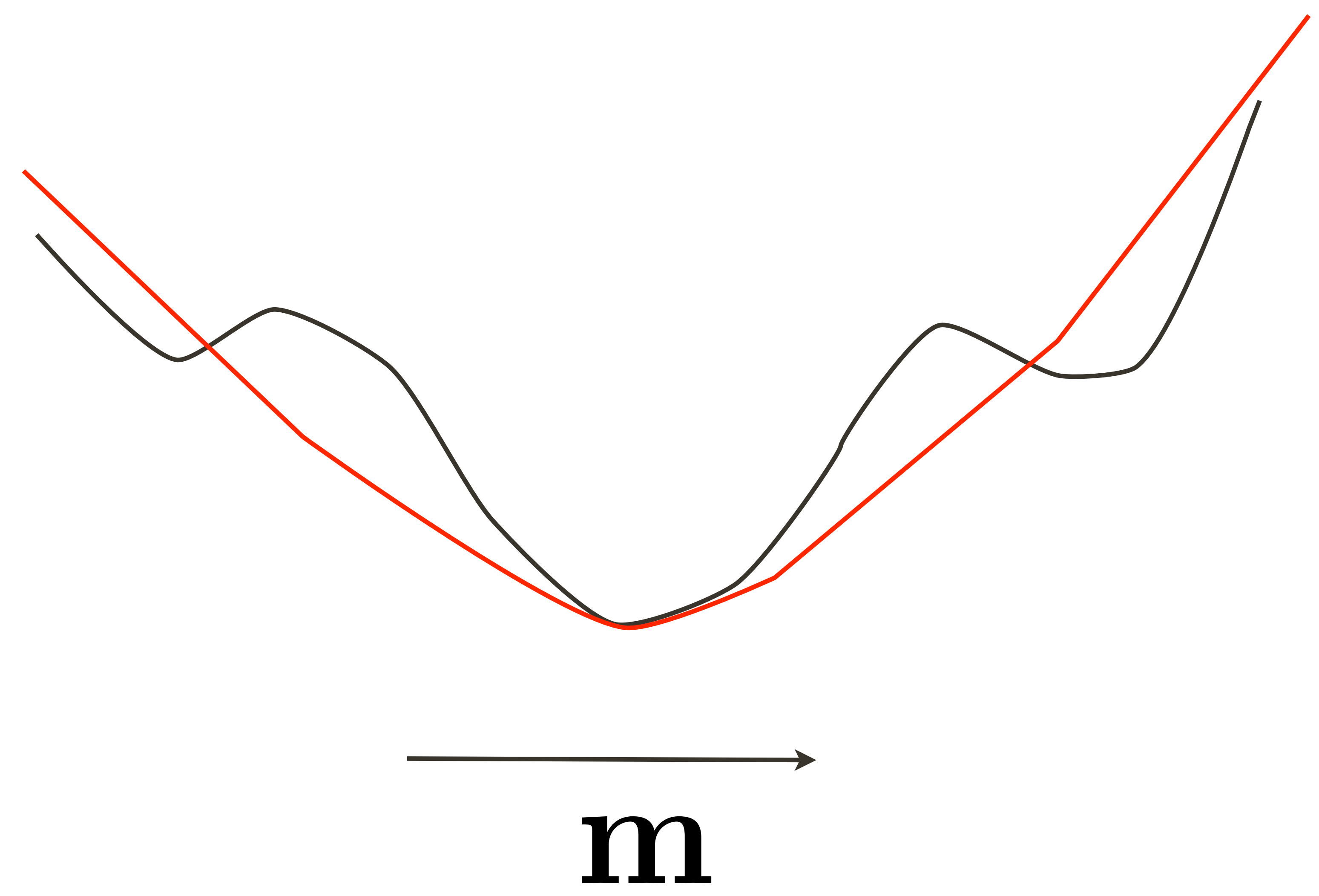
$$\overline{\mathbf{v}}_{k,l} = \mathbf{A}_{k,l}(\mathbf{m}) \overline{\mathbf{u}}_{k,l} - \mathbf{q}_{k,l}$$

WRI vs. FWI

[van Leeuwen, T and Herrmann, F J , 2013]

[Peters, B, Herrmann, F J and van Leeuwen, T, 2014]

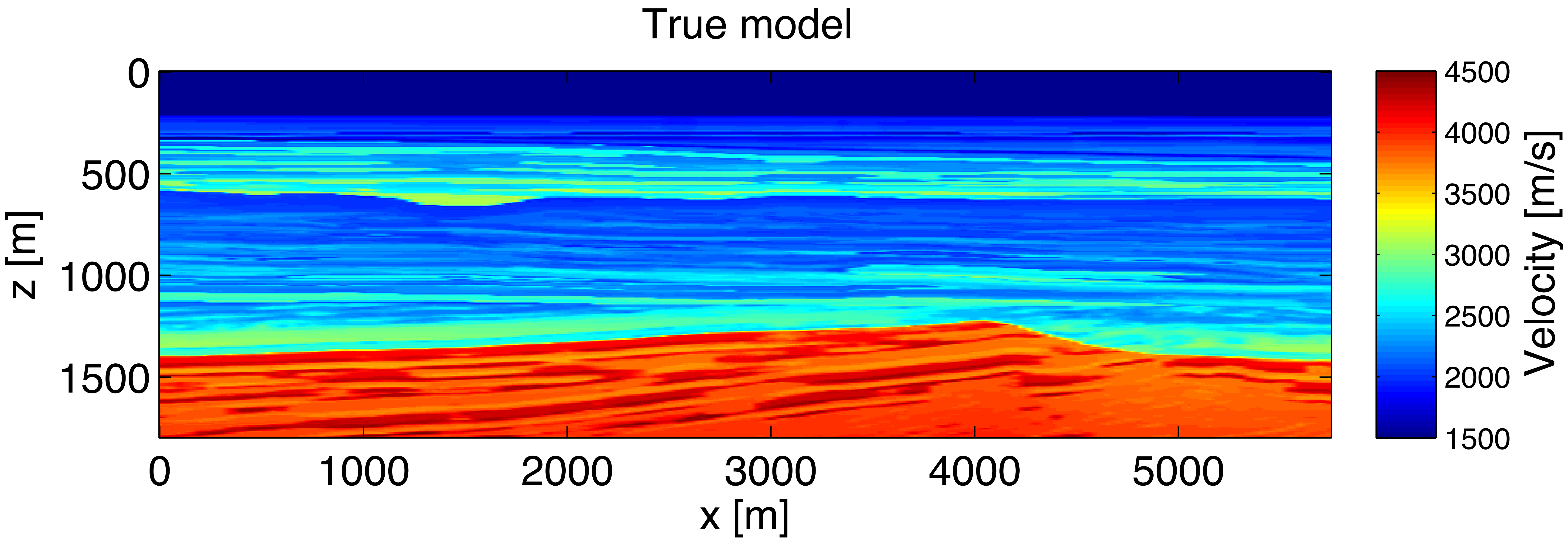


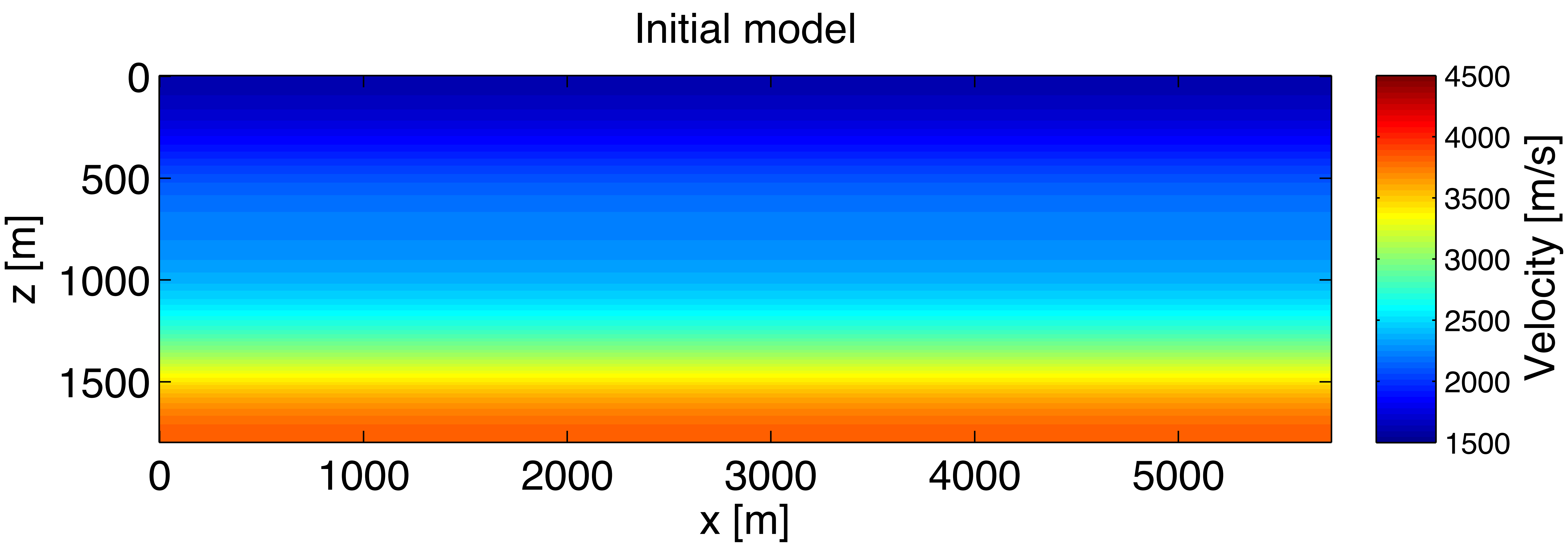


True & initial model

[van Leeuwen, T and Herrmann, F J , 2013]

[Peters, B, Herrmann, F J and van Leeuwen, T, 2014]

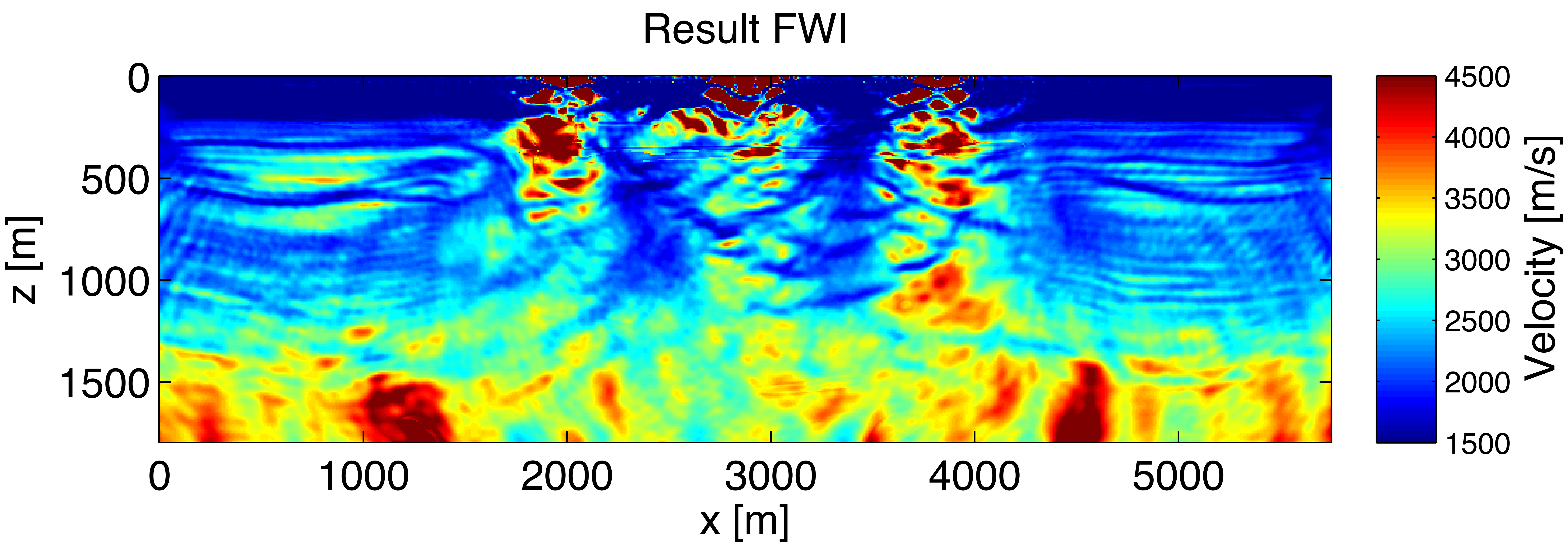


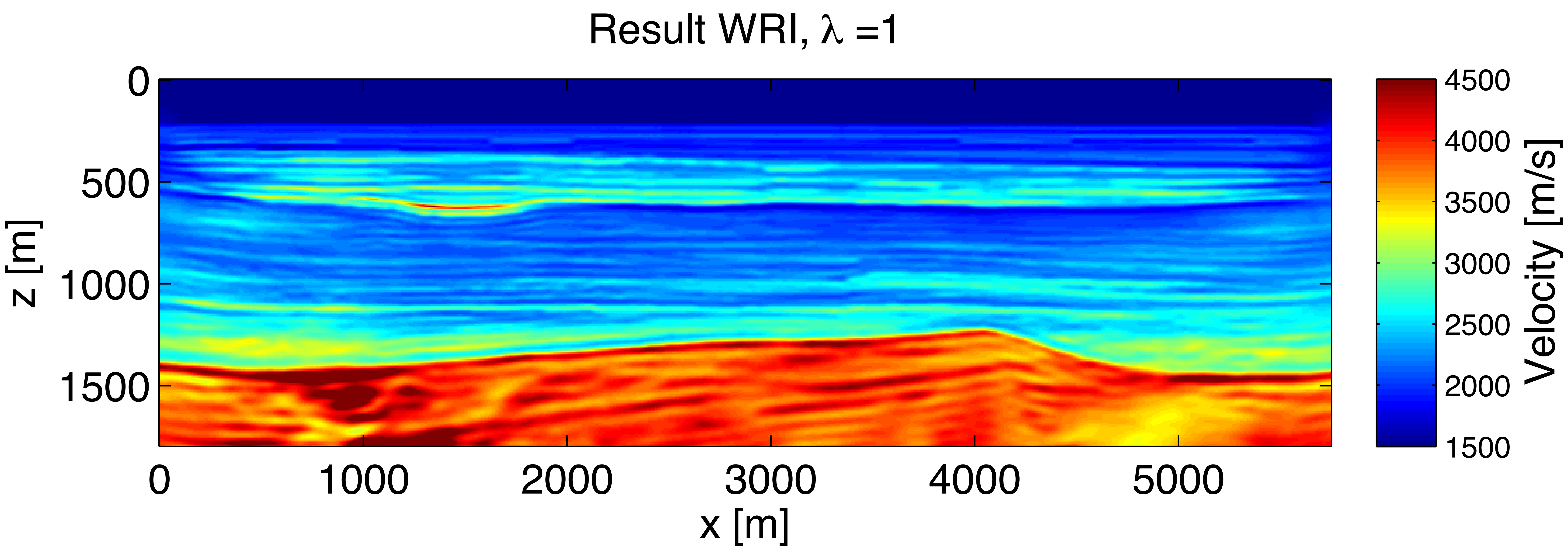


FWI vs WRI

[van Leeuwen, T and Herrmann, F J , 2013]

[Peters, B, Herrmann, F J and van Leeuwen, T, 2014]





WRI with source estimation

Triple parameters optimization problem:

$$\underset{\mathbf{u},\mathbf{m},\alpha}{\text{minimize}} \sum_{k,l} \|\mathbf{P}_k \mathbf{u}_{k,l} - \mathbf{d}_{k,l}\|_2^2 + \lambda^2 \|\mathbf{A}_{k,l}(\mathbf{m})\mathbf{u}_{k,l} - \alpha_{k,l}\mathbf{e}_{k,l}\|_2^2$$

[Aravkin, A Y, van Leeuwen, T, Calandra, H, and Herrmann, F J, 2012]

[Li, M, Rickett, J, and Abubakar, A, 2013]

SLIM

FWI with source estimation

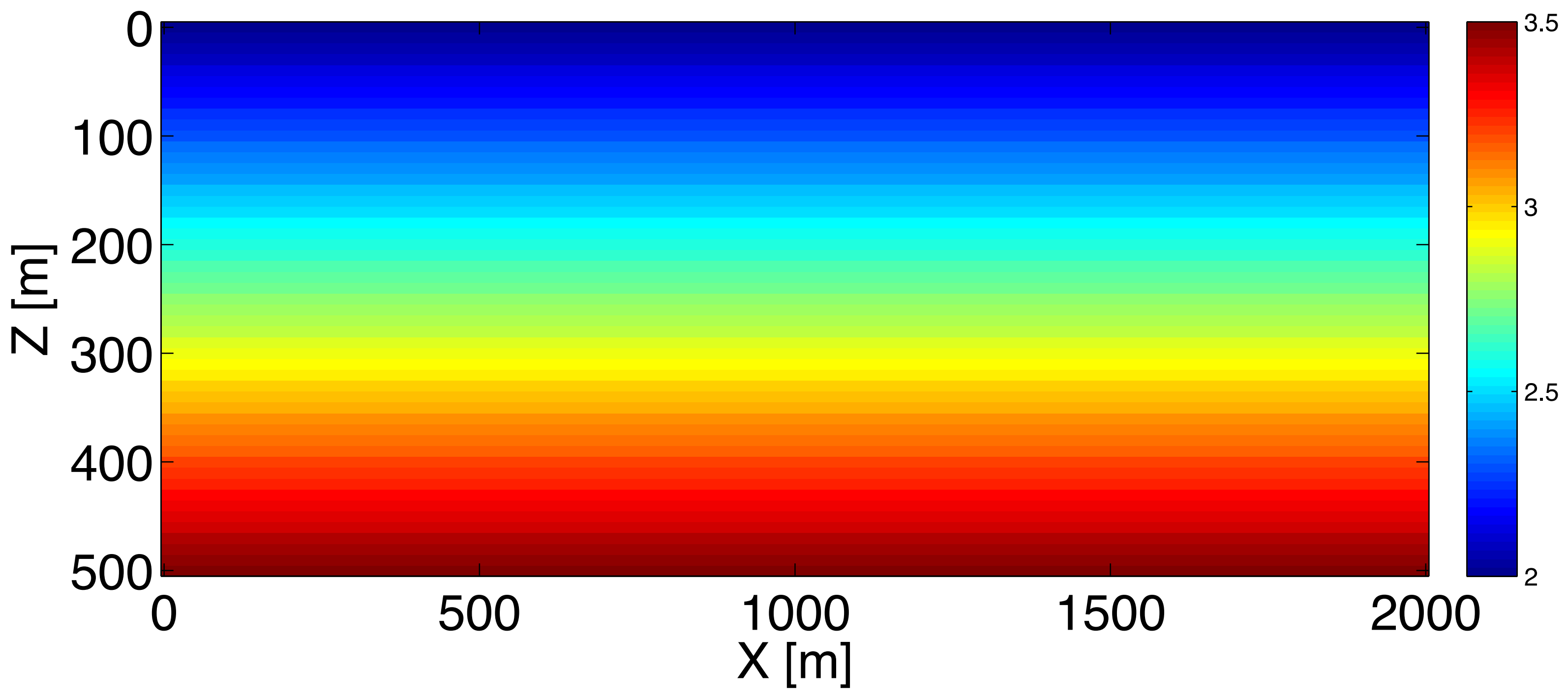
Joint optimization problem:

$$\underset{\mathbf{m},\alpha}{\text{minimize}} \sum_{k,l} \|\mathbf{P}_k \mathbf{A}_{k,l}(\mathbf{m})^{-1} \alpha_{k,l} \mathbf{e}_{k,l} - \mathbf{d}_{k,l}\|_2^2$$

Eliminate α w/ variable projection:

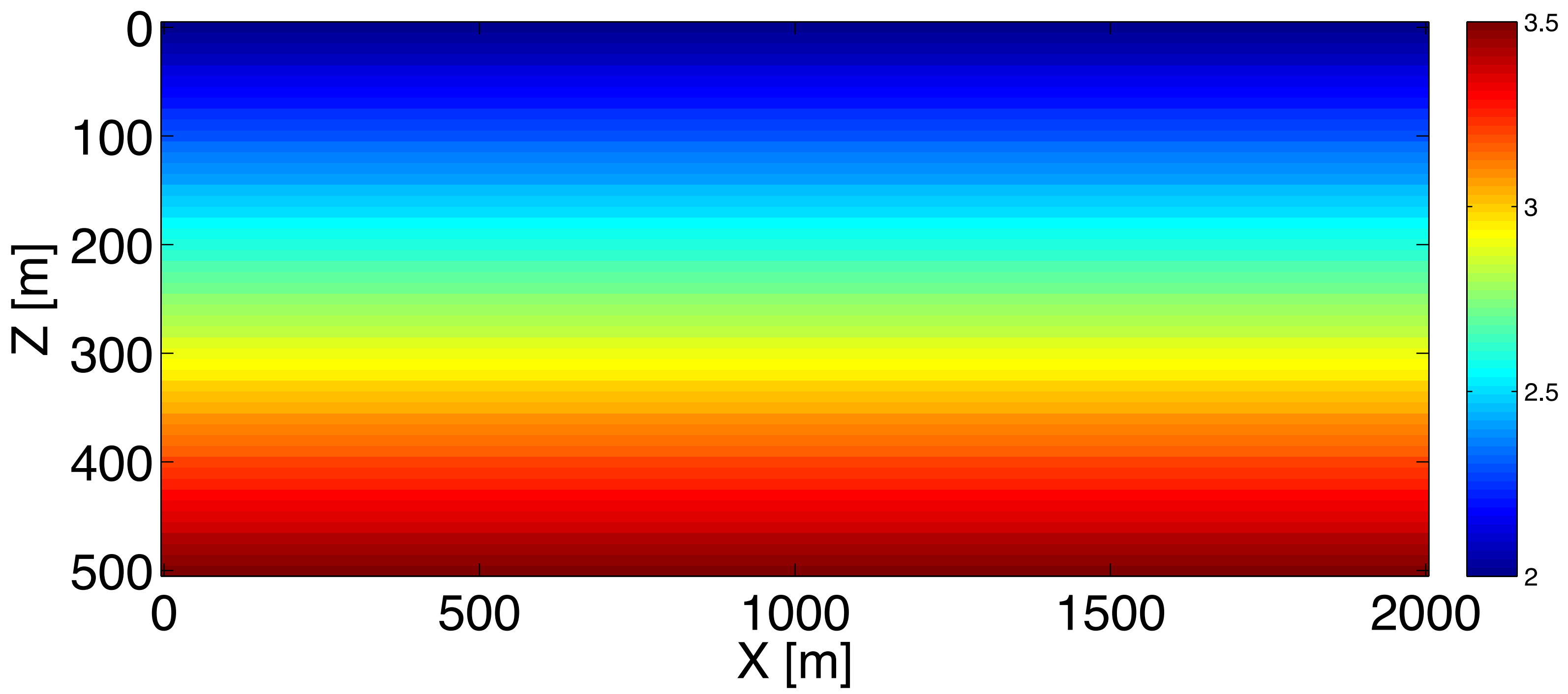
$$\overline{\alpha} = \arg\min_{\alpha} \sum_{k,l} \|\mathbf{P}_k \mathbf{A}_{k,l}(\mathbf{m})^{-1} \alpha_{k,l} \mathbf{e}_{k,l} - \mathbf{d}_{k,l}\|_2^2$$

FWI with source estimation



$\mathbf{m}$

FWI with source estimation

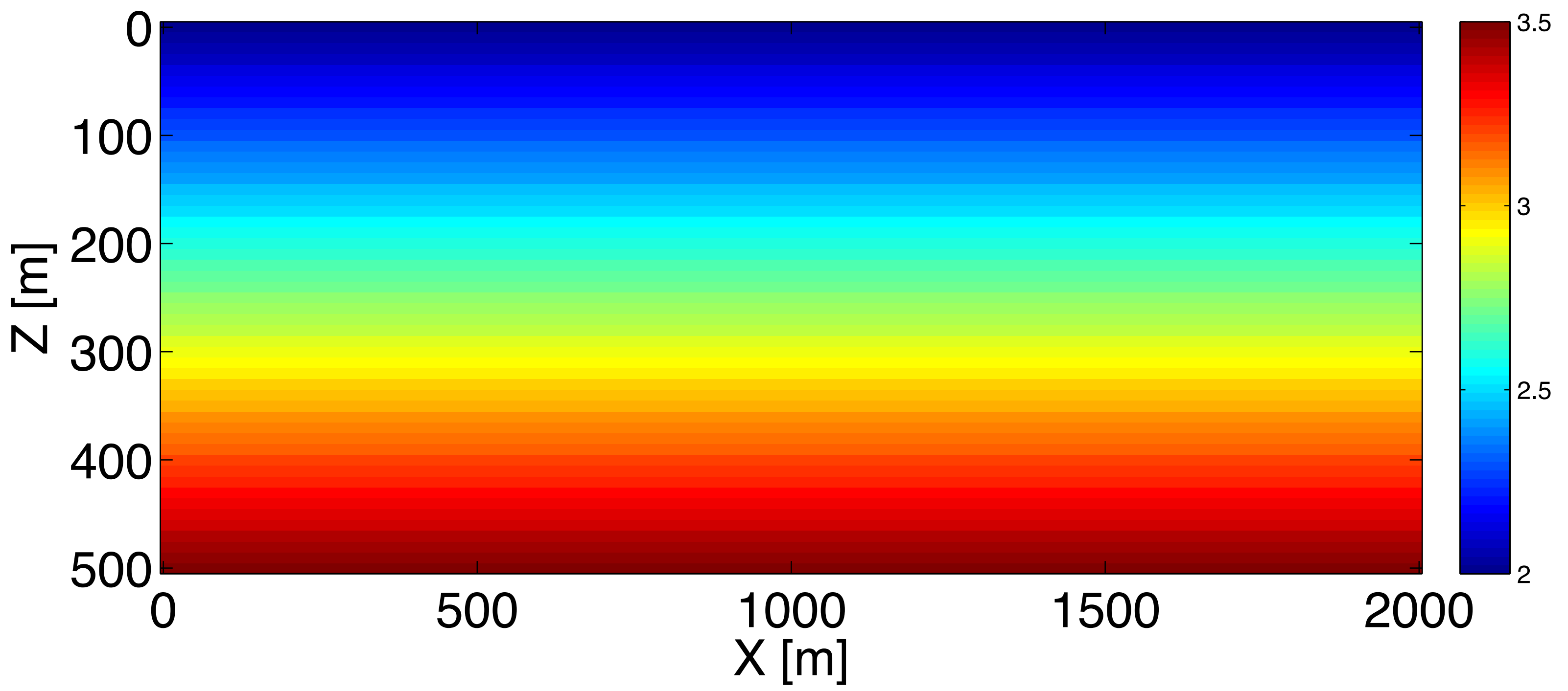


$$\mathbf{m}$$

$$\mathbf{u} = \mathbf{A}(\mathbf{m})^{-1}\mathbf{e}$$

$$\mathbf{d_{pred}} = \mathbf{P}\mathbf{u}$$

FWI with source estimation



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$$\mathbf{u} = \mathbf{A}(\mathbf{m})^{-1}\mathbf{e}$$

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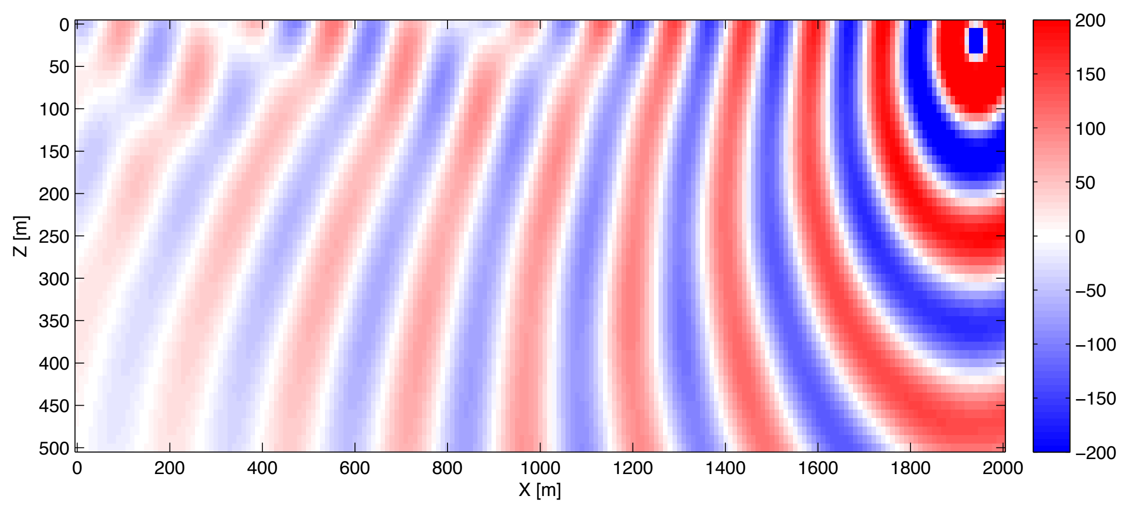
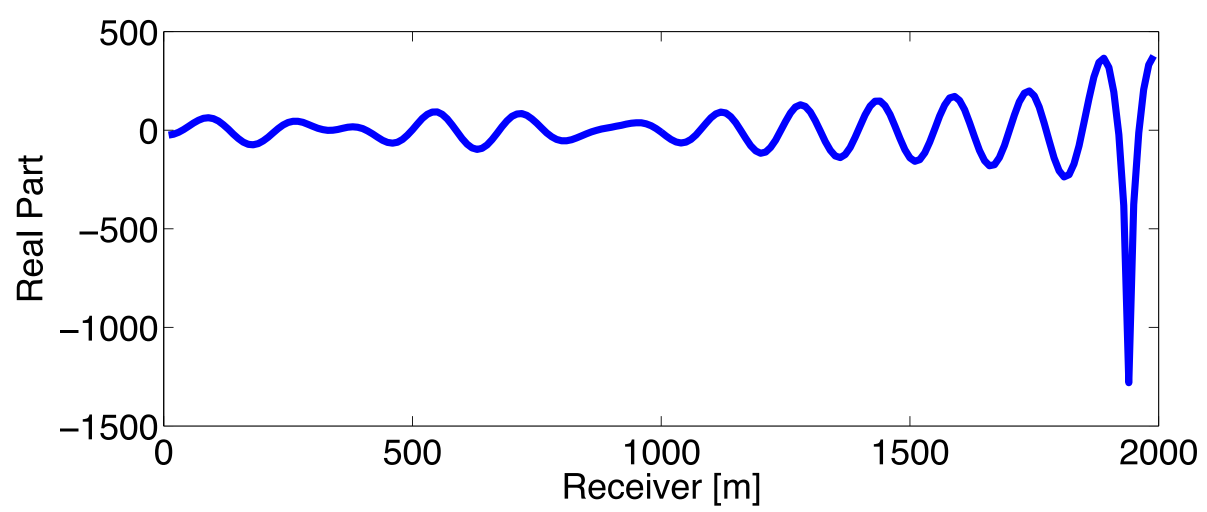
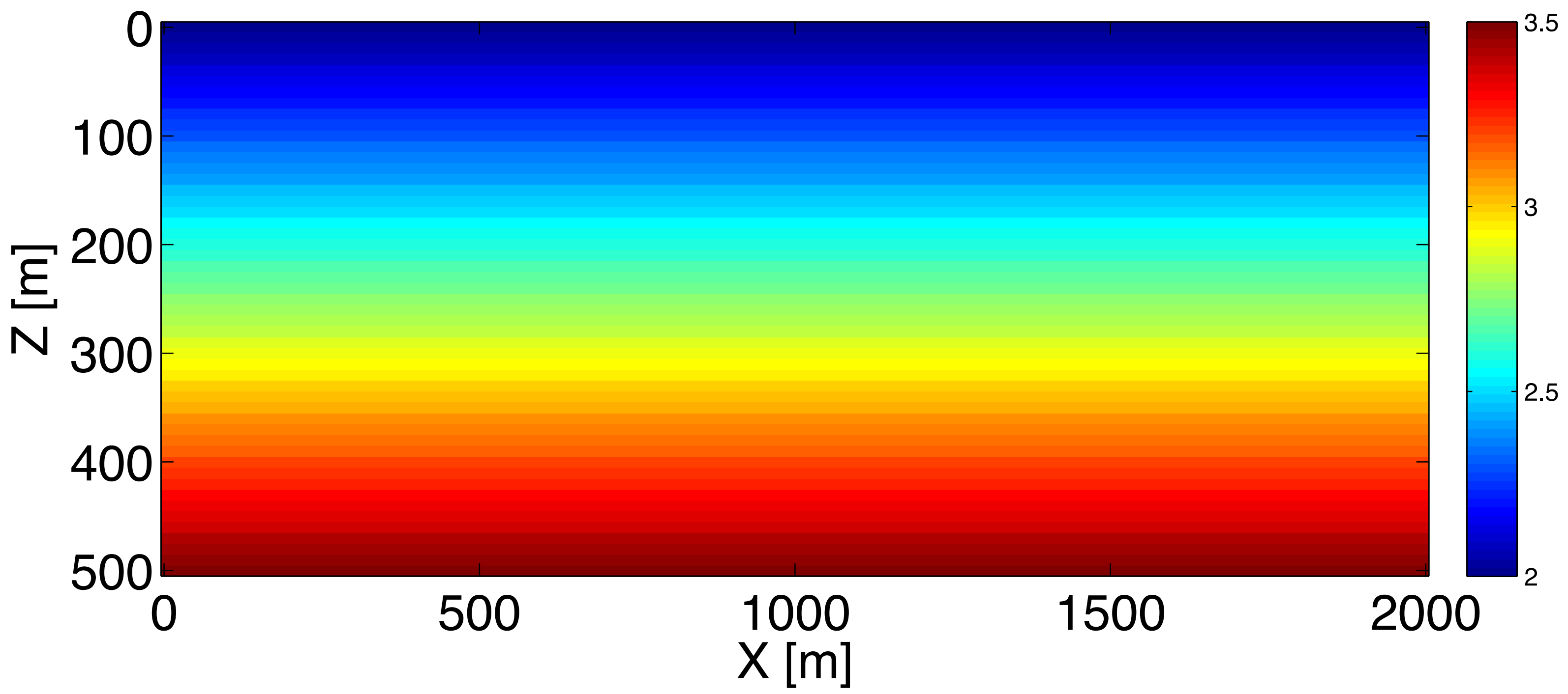


$$\mathbf{u}$$



$$\mathbf{d_{pred}}$$

FWI with source estimation



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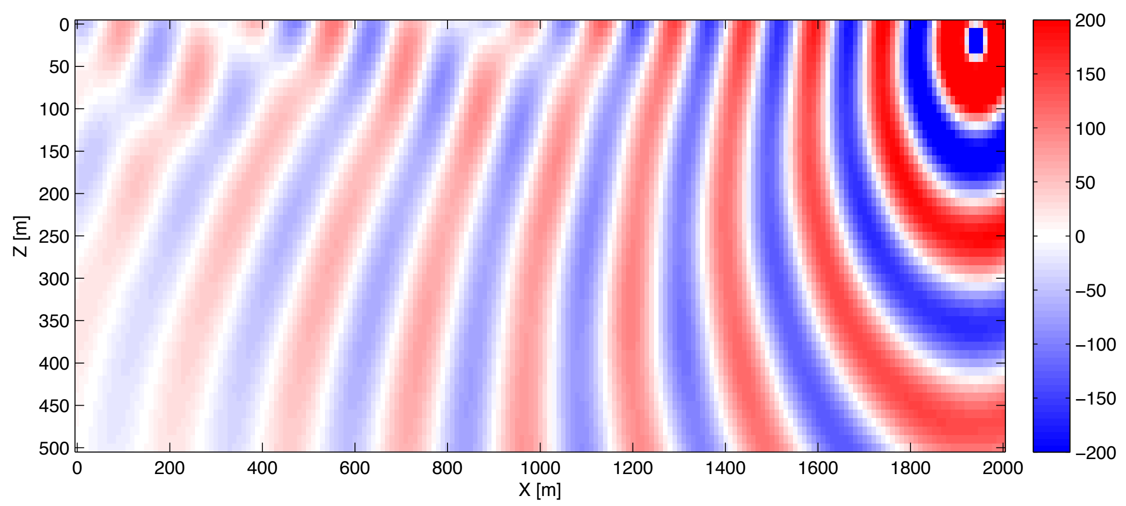
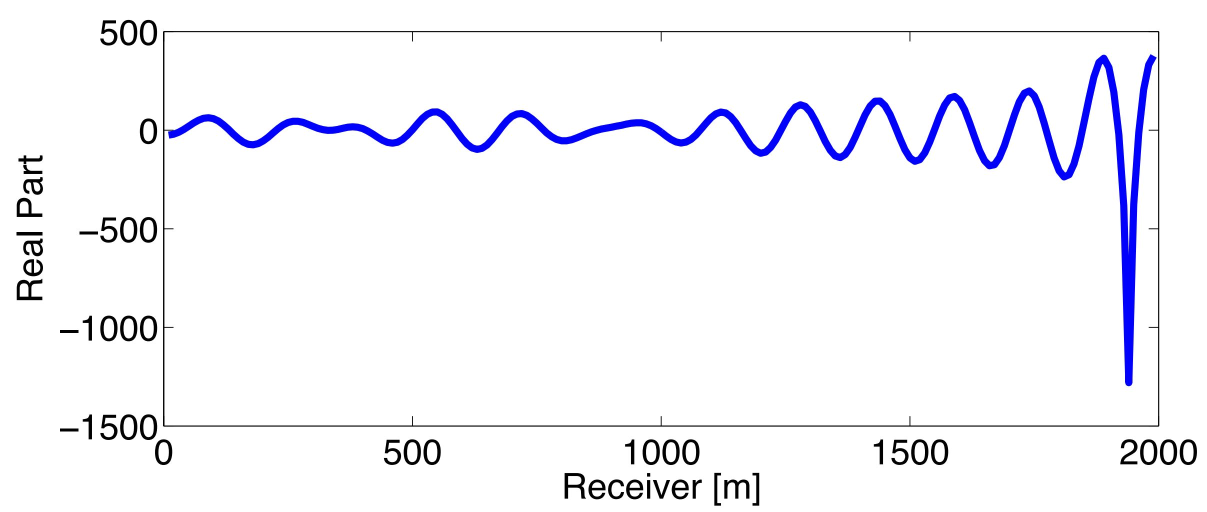
$$\mathbf{u} = \mathbf{A}(\mathbf{m})^{-1}\mathbf{e}$$

$$\mathbf{d_{pred}} = \mathbf{Pu}$$

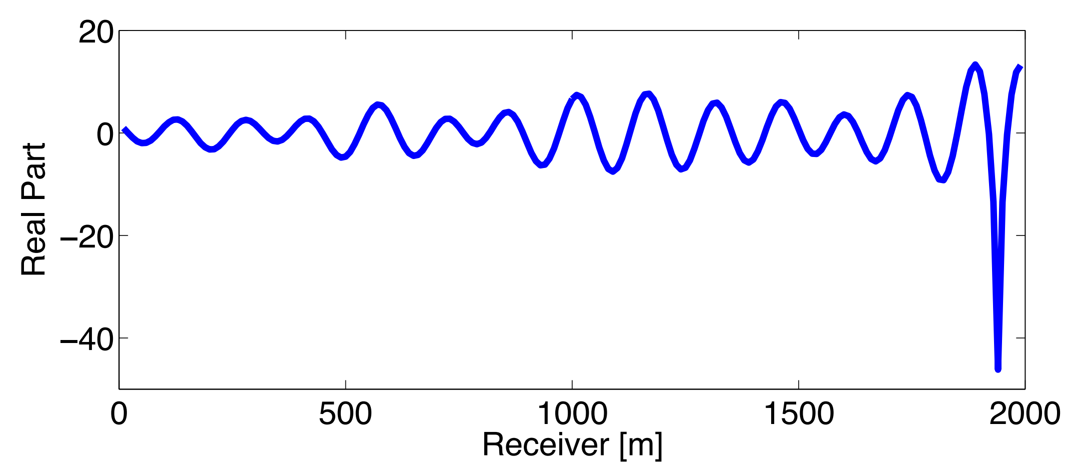


$$\mathbf{u}$$

$$\overline{\alpha} = \frac{\mathbf{d_{pred}^T d_{obs}}}{\mathbf{d_{pred}^T d_{pred}}}$$

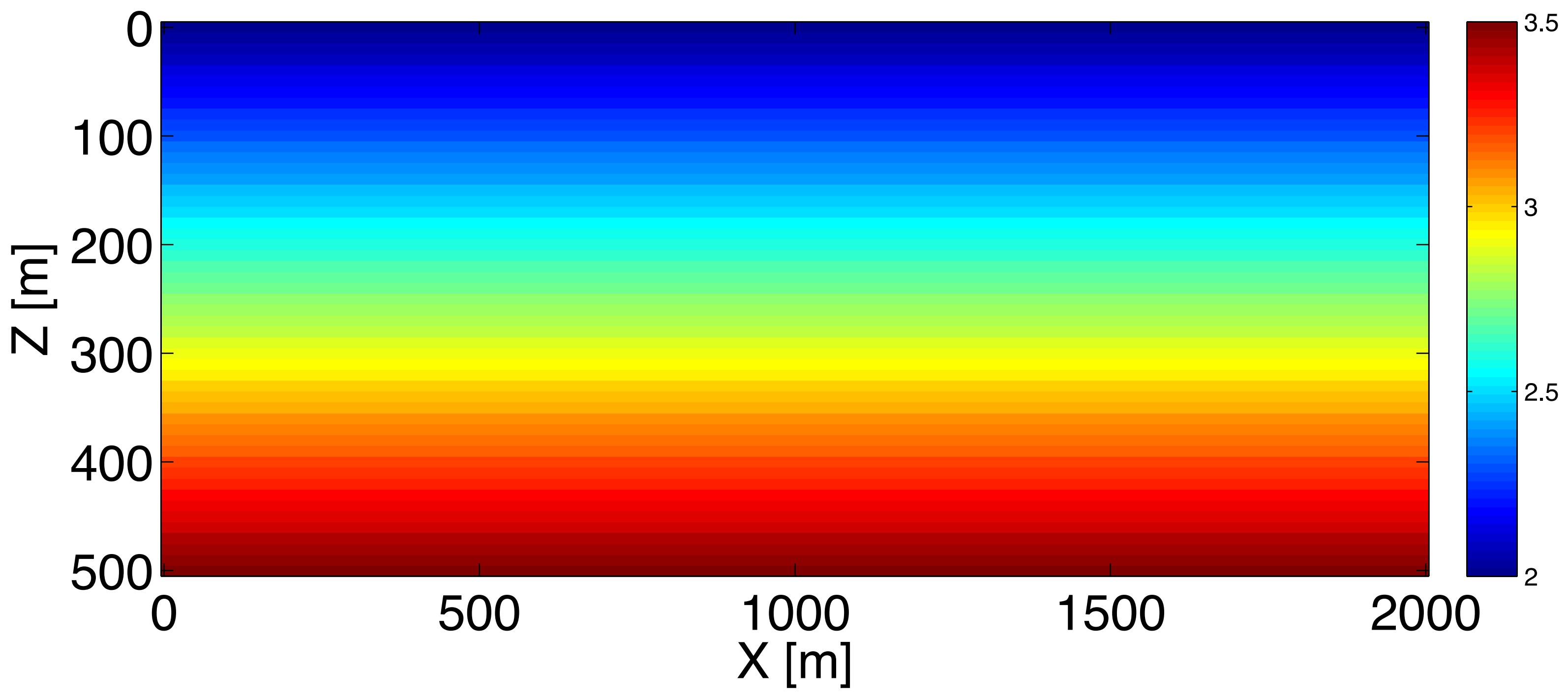


$$\mathbf{d_{pred}}$$



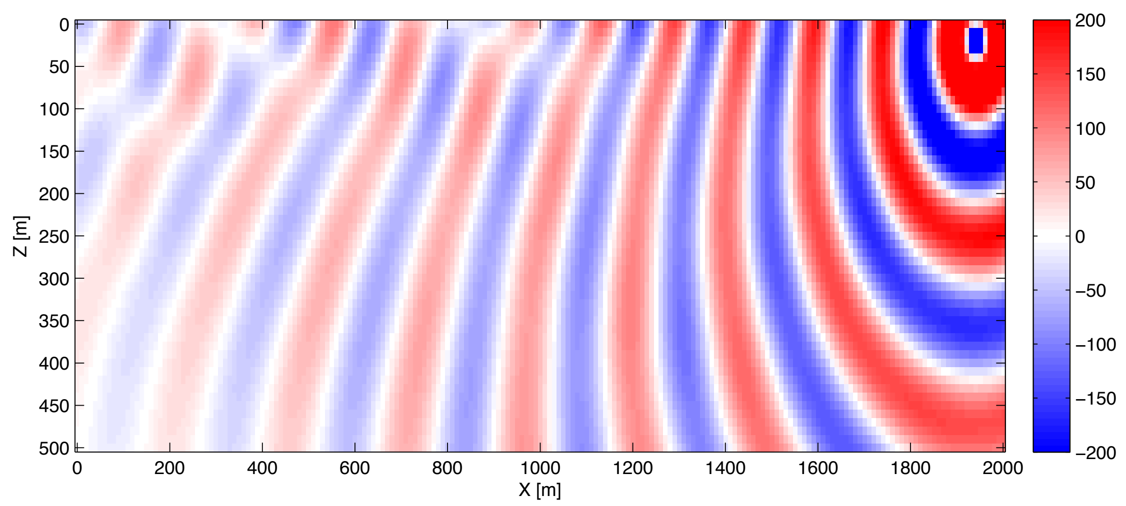
$$\mathbf{d_{obs}}$$

FWI with source estimation



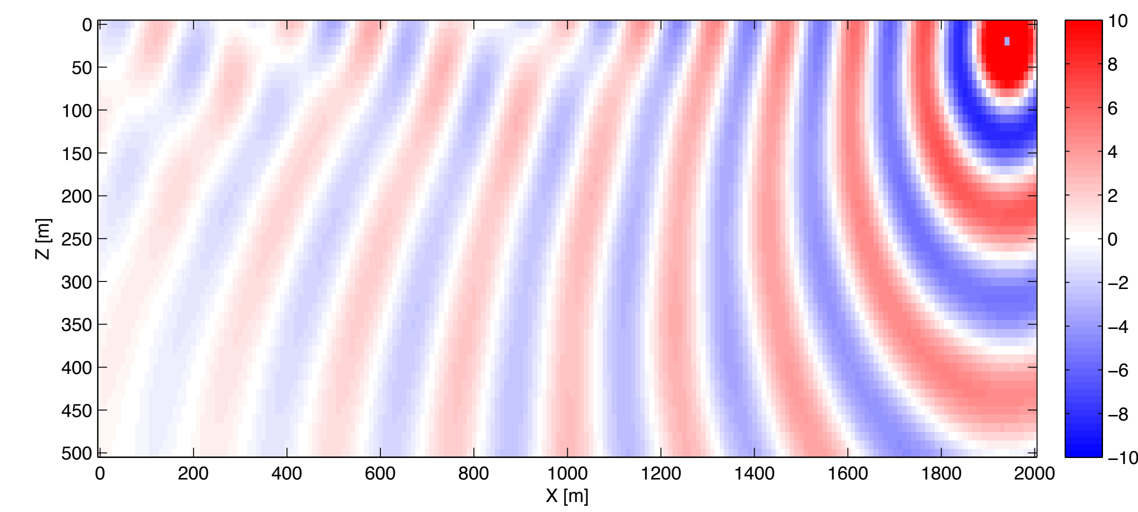
$\mathbf{m}$

$$\mathbf{u} = \mathbf{A}(\mathbf{m})^{-1}\mathbf{e}$$
$$\mathbf{d_{pred}} = \mathbf{P}\mathbf{u}$$

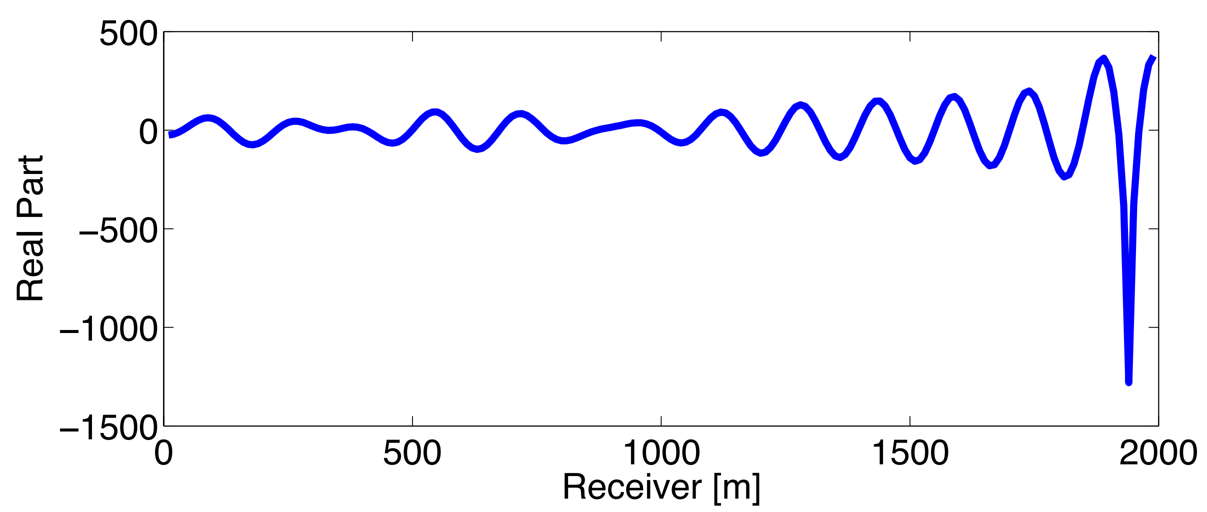


$\mathbf{u}$

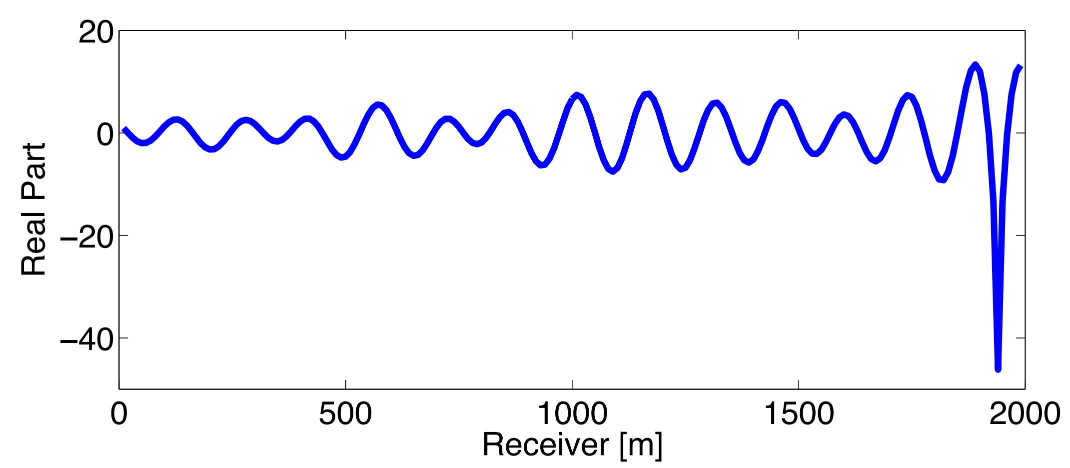
$$\overline{\alpha} = \frac{\mathbf{d_{pred}^T}\mathbf{d_{obs}}}{\mathbf{d_{pred}^T}\mathbf{d_{pred}}}$$



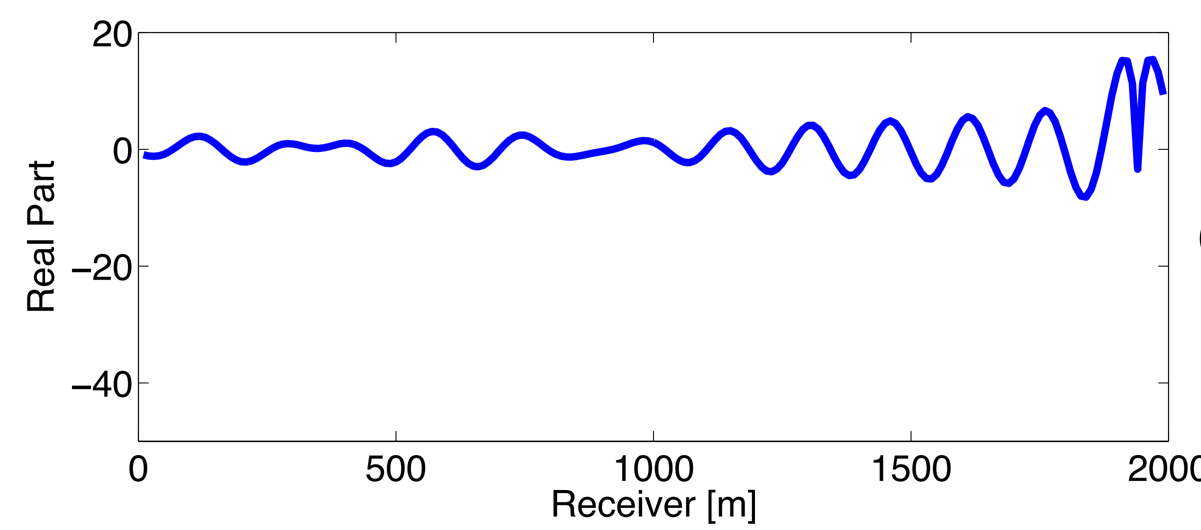
$\tilde{\mathbf{u}}$



$\mathbf{d_{pred}}$

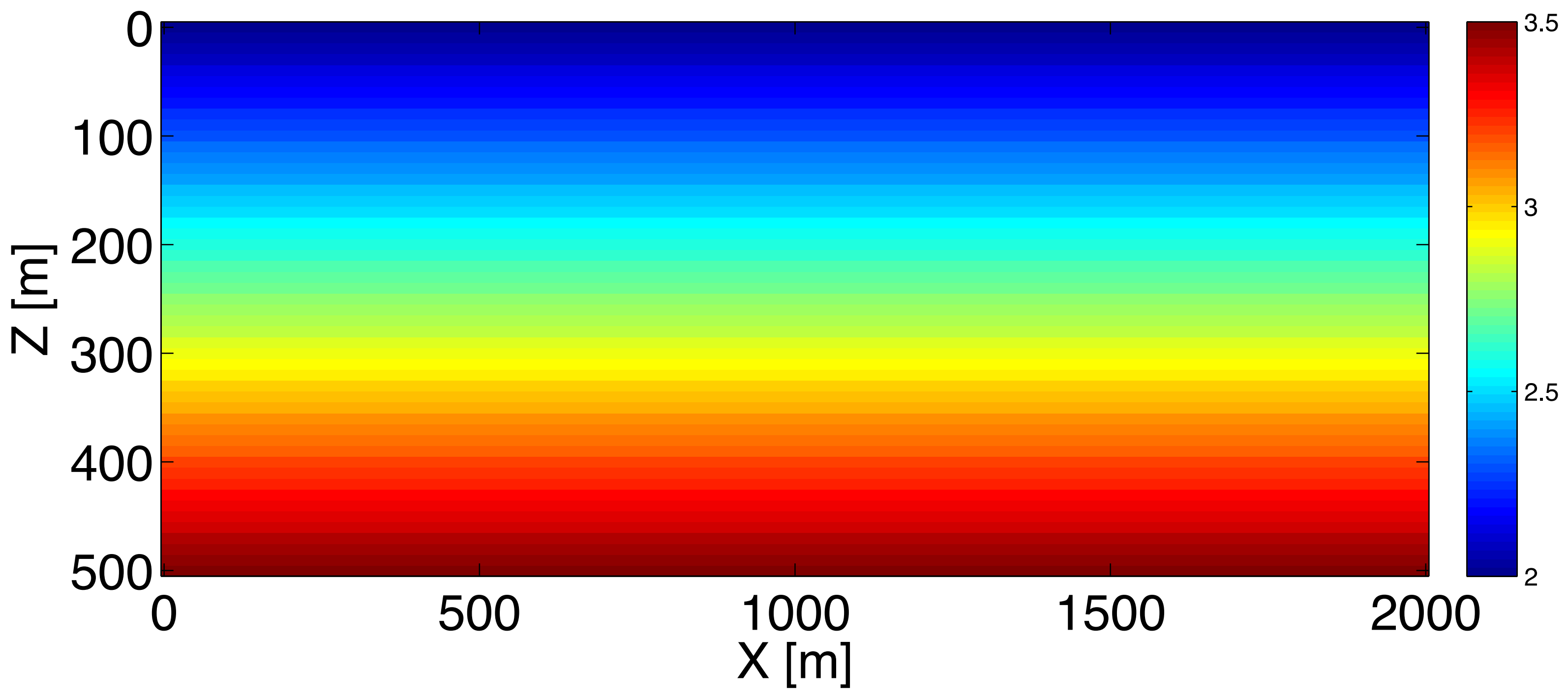


$\mathbf{d_{obs}}$

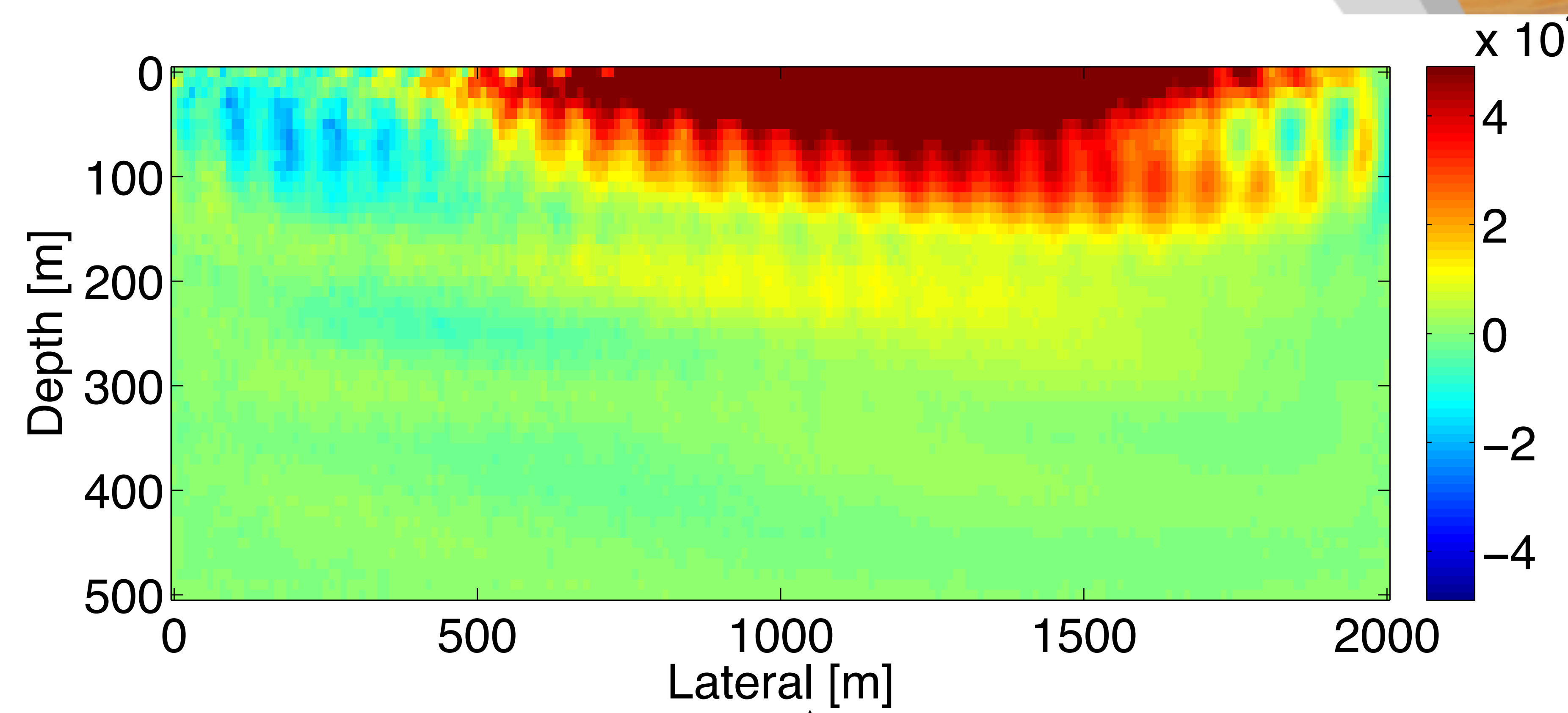


$\tilde{\mathbf{d}}_{\mathbf{pred}}$

FWI with source estimation



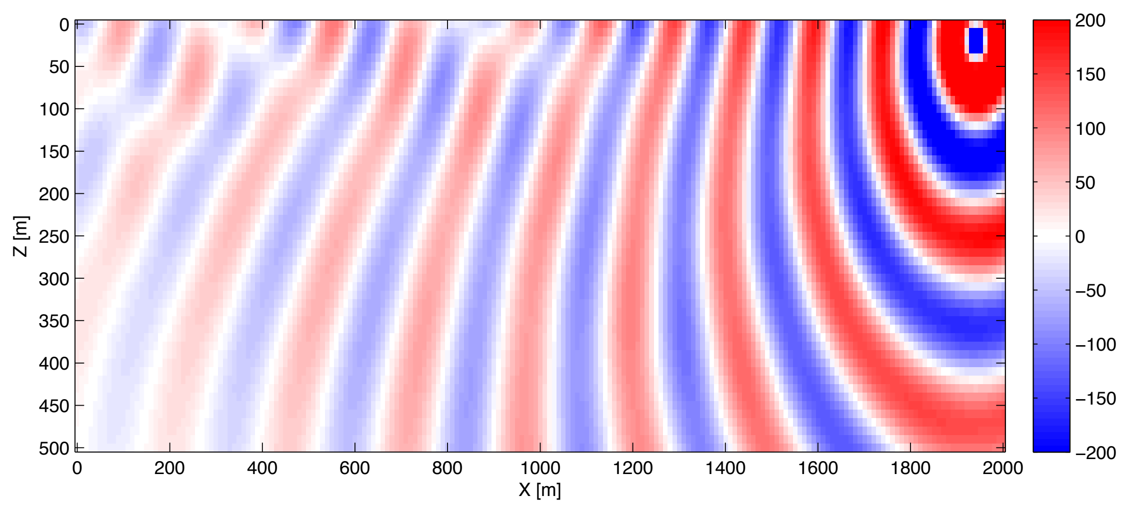
$$\mathbf{m}$$



$$\mathbf{g}$$

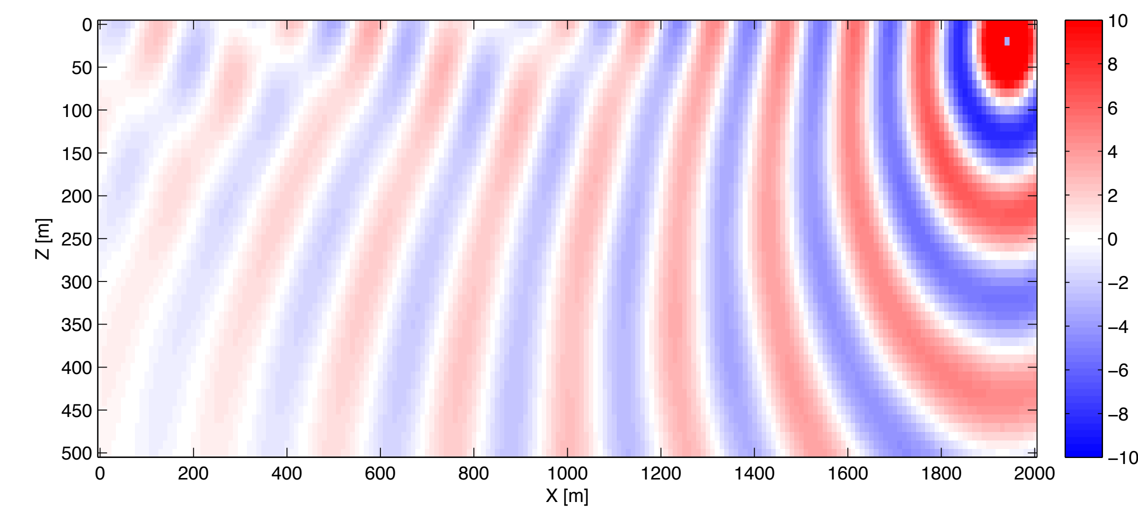
$$\mathbf{u} = \mathbf{A}(\mathbf{m})^{-1}\mathbf{e}$$

$$\mathbf{d_{pred}} = \mathbf{P}\mathbf{u}$$

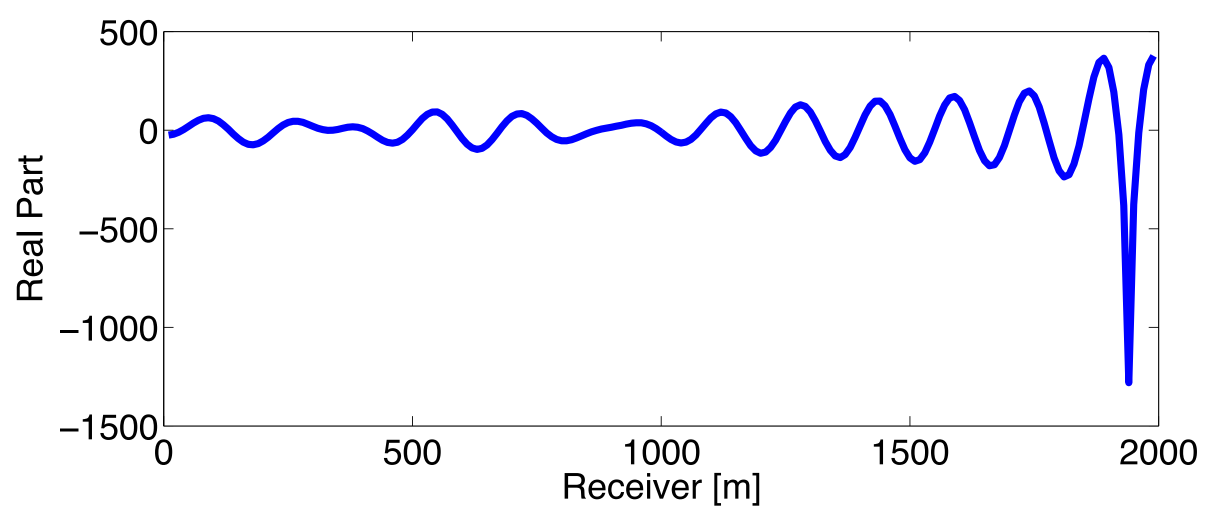


$$\mathbf{u}$$

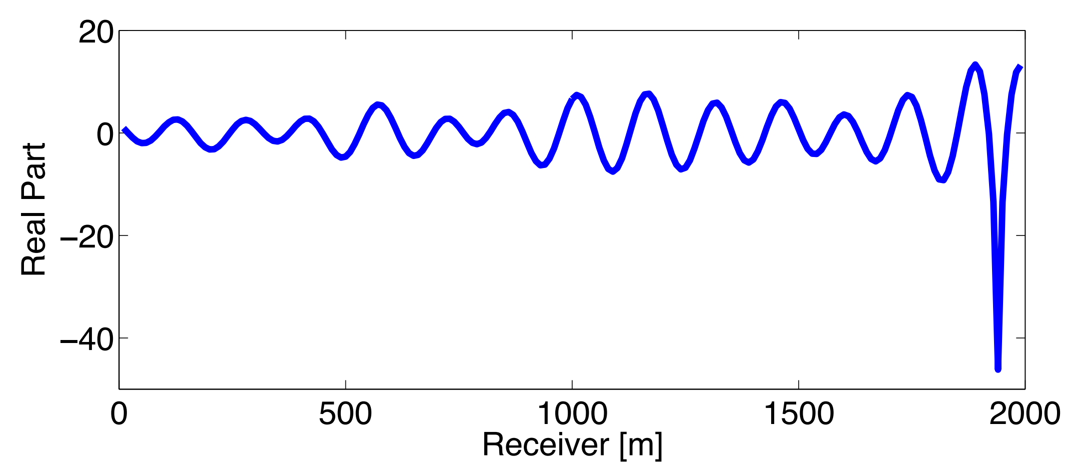
$$\overline{\alpha} = \frac{\mathbf{d_{pred}^T}\mathbf{d_{obs}}}{\mathbf{d_{pred}^T}\mathbf{d_{pred}}}$$



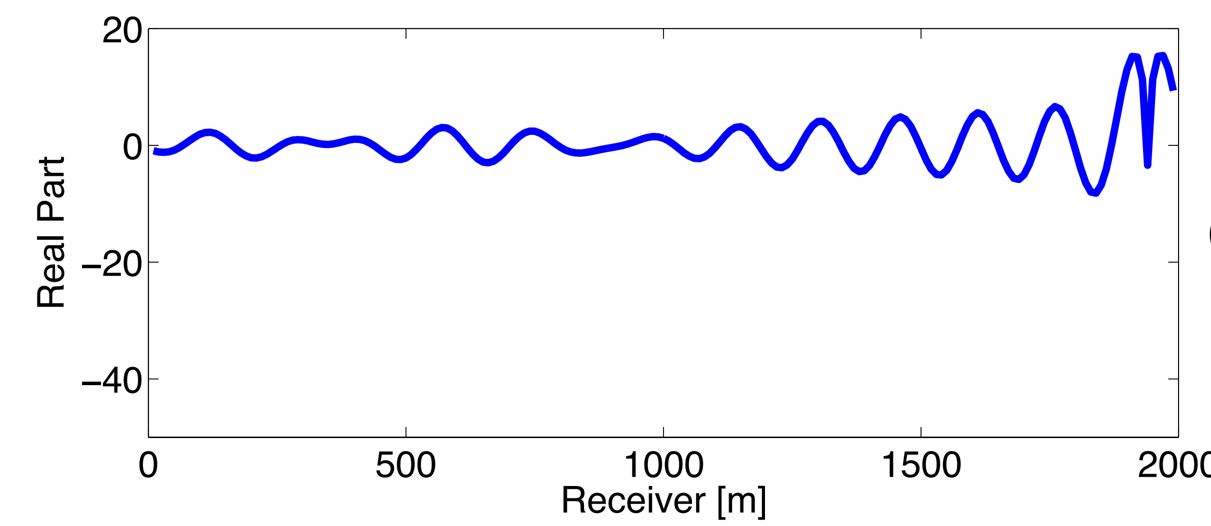
$$\tilde{\mathbf{u}}$$



$$\mathbf{d_{pred}}$$

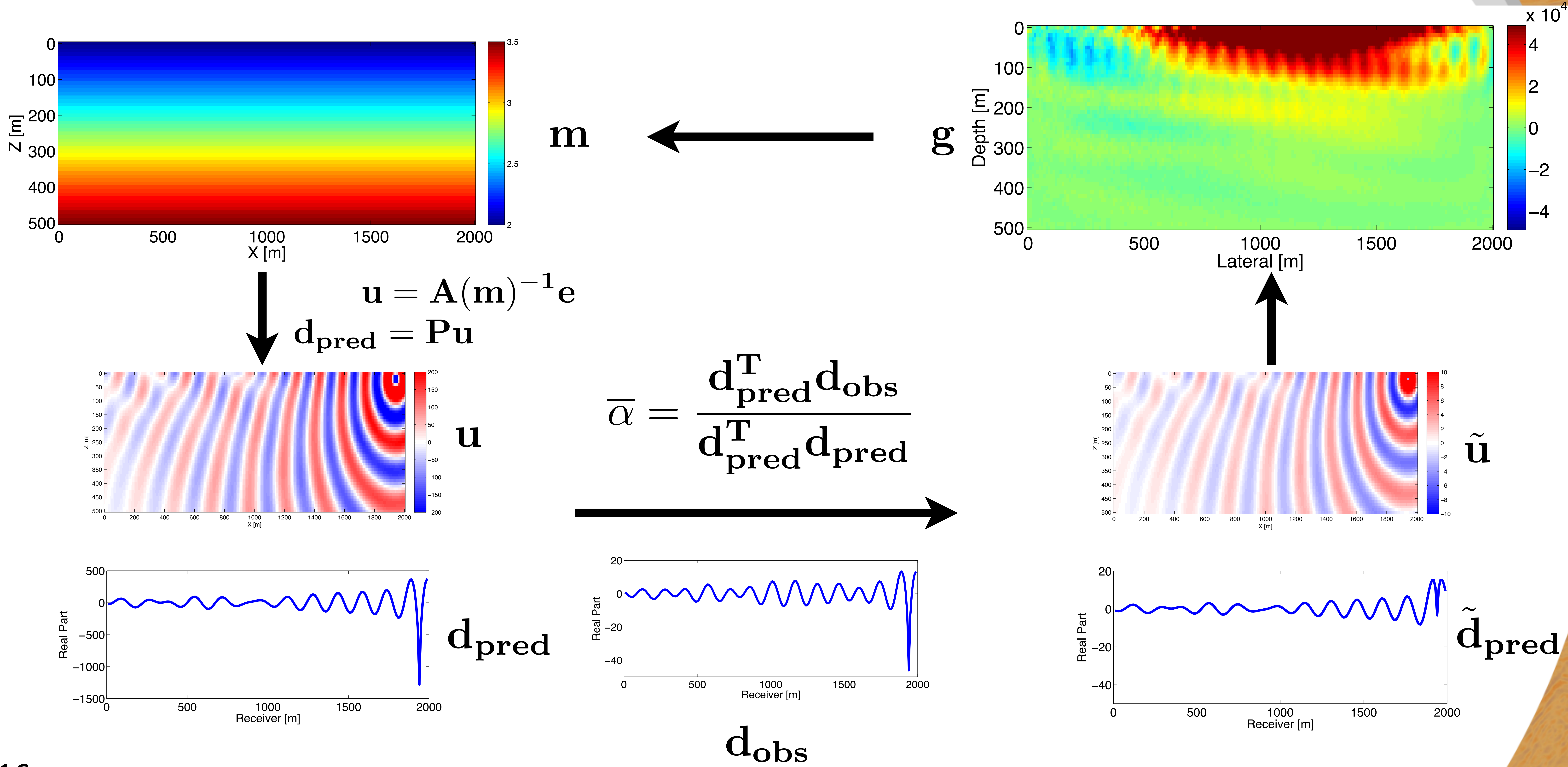


$$\mathbf{d_{obs}}$$



$$\tilde{\mathbf{d}}_{\mathbf{pred}}$$

FWI with source estimation



WRI with source estimation

Triple parameters optimization problem:

$$\underset{\mathbf{u},\mathbf{m},\alpha}{\text{minimize}} \sum_{k,l} \|\mathbf{P}_k \mathbf{u}_{k,l} - \mathbf{d}_{k,l}\|_2^2 + \lambda^2 \|\mathbf{A}_{k,l}(\mathbf{m})\mathbf{u}_{k,l} - \alpha_{k,l}\mathbf{e}_{k,l}\|_2^2$$

WRI with source estimation

Triple parameters optimization problem:

$$\underset{\mathbf{u},\mathbf{m},\alpha}{\text{minimize}} \sum_{k,l} \|\mathbf{P}_k \mathbf{u}_{k,l} - \mathbf{d}_{k,l}\|_2^2 + \lambda^2 \|\mathbf{A}_{k,l}(\mathbf{m})\mathbf{u}_{k,l} - \alpha_{k,l}\mathbf{e}_{k,l}\|_2^2$$

Eliminate $\mathbf{u}$ and α jointly w/ variable projection:

$$[\overline{\mathbf{u}}, \overline{\alpha}] = \arg\min_{\mathbf{u},\alpha} \sum_{k,l} \|\mathbf{P}_k \mathbf{u}_{k,l} - \mathbf{d}_{k,l}\|_2^2 + \lambda^2 \|\mathbf{A}_{k,l}(\mathbf{m})\mathbf{u}_{k,l} - \alpha_{k,l}\mathbf{e}_{k,l}\|_2^2$$

WRI with source estimation

Corresponds to solving the following augmented system:

$$\begin{pmatrix} \lambda \mathbf{A}_{k,l} & -\lambda \mathbf{e}_{k,l} \\ \mathbf{P}_k & 0 \end{pmatrix} \begin{pmatrix} \overline{\mathbf{u}}_{k,l} \\ \overline{\alpha}_{k,l} \end{pmatrix} = \begin{pmatrix} 0 \\ \mathbf{d}_{k,l} \end{pmatrix}$$

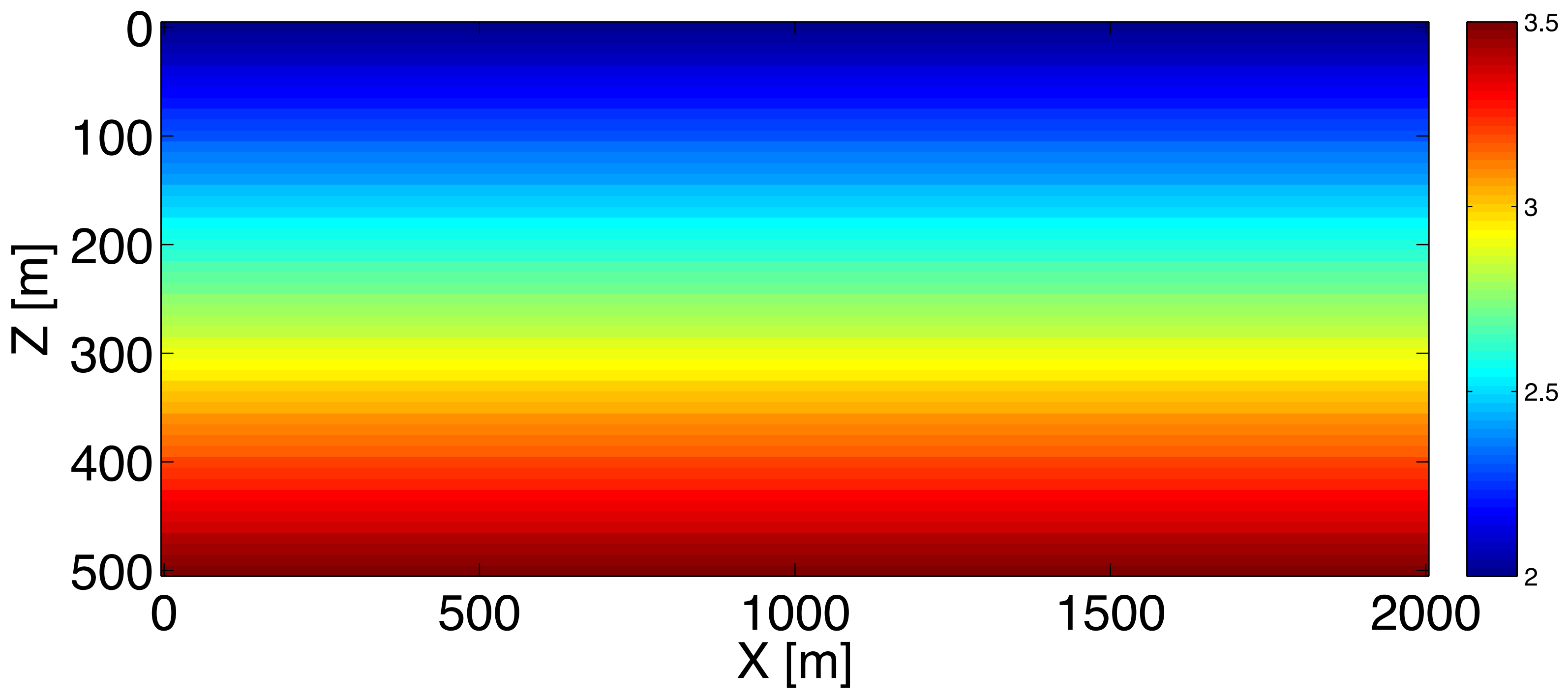
Cf. original augmented system:

Full column rank!

No additional computational cost!

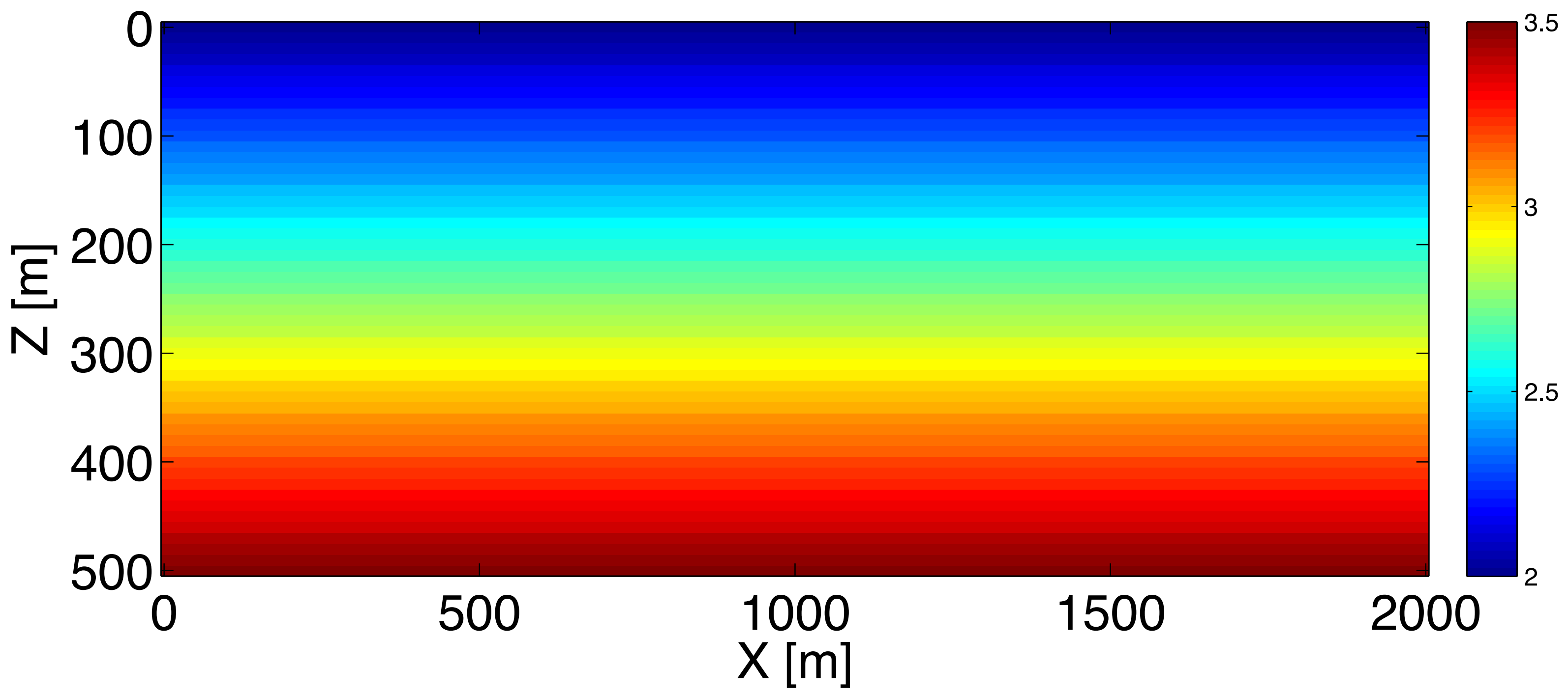
$$\begin{pmatrix} \lambda \mathbf{A}_{k,l} \\ \mathbf{P}_k \end{pmatrix} \overline{\mathbf{u}}_{k,l} = \begin{pmatrix} \lambda \mathbf{q}_{k,l} \\ \mathbf{d}_{k,l} \end{pmatrix}$$

WRI with source estimation

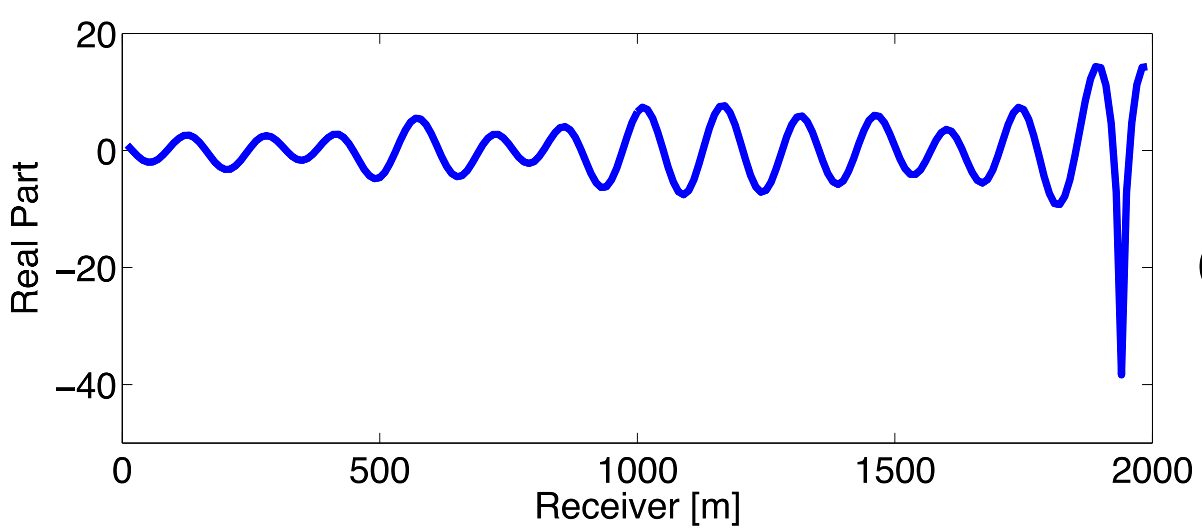


$\mathbf{m}$

WRI with source estimation



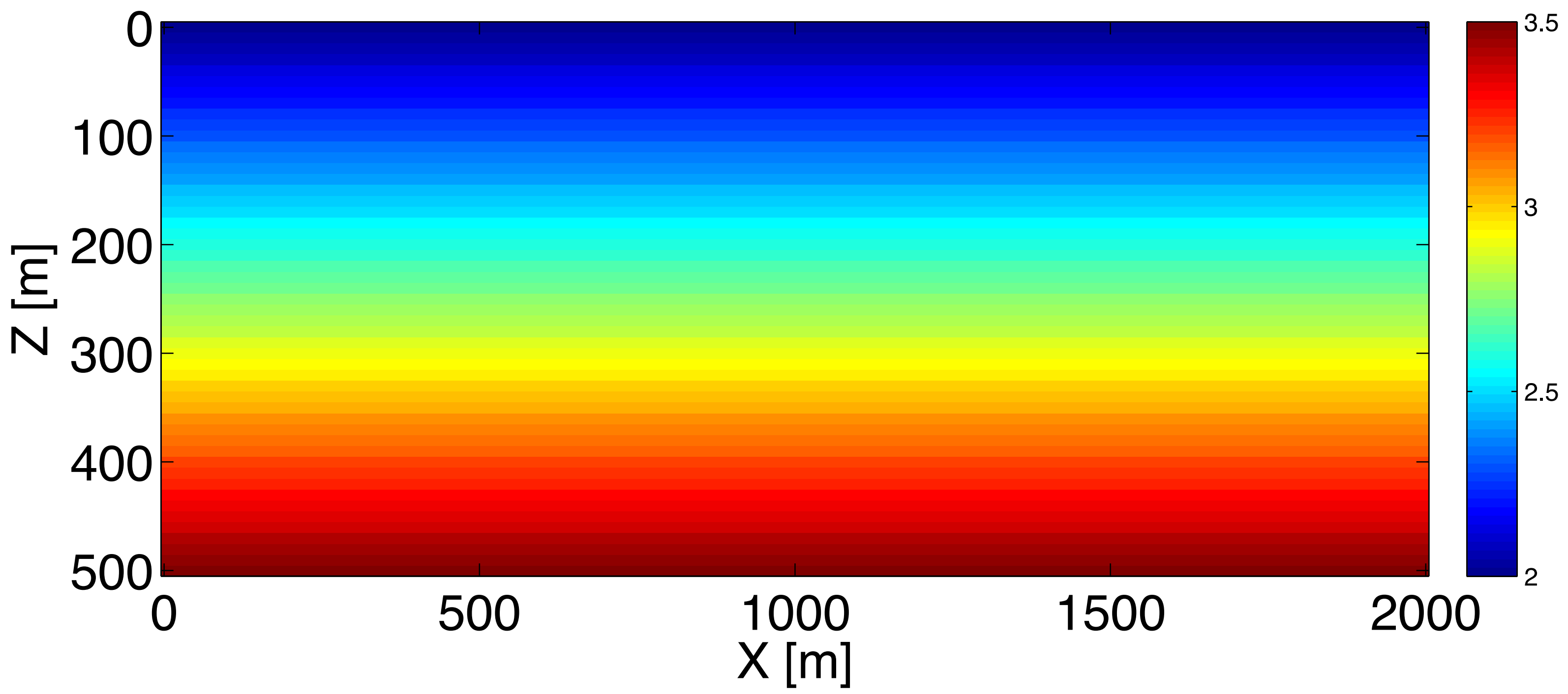
$\mathbf{m}$



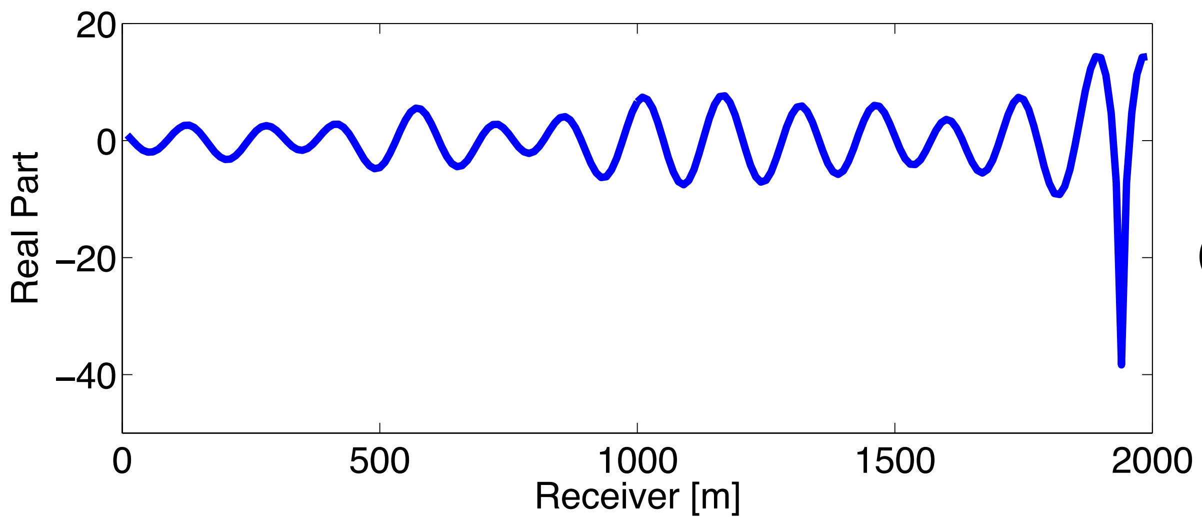
$\mathbf{d_{obs}}$

$$\begin{pmatrix} \lambda \mathbf{A} & -\lambda \mathbf{e} \\ \mathbf{P} & 0 \end{pmatrix} \begin{pmatrix} \overline{\mathbf{u}} \\ \overline{\alpha} \end{pmatrix} = \begin{pmatrix} 0 \\ \mathbf{d_{obs}} \end{pmatrix}$$

WRI with source estimation



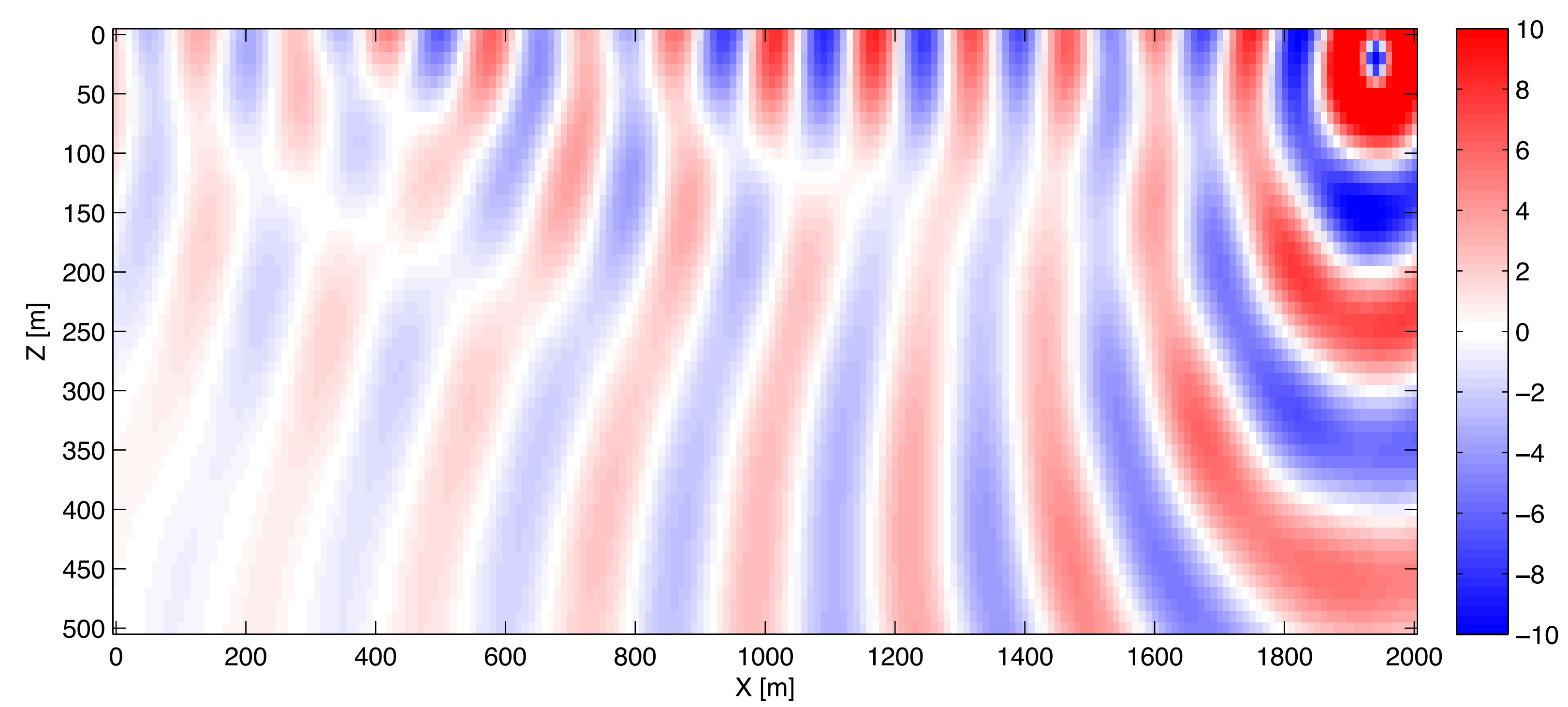
$\mathbf{m}$



$\mathbf{d_{obs}}$

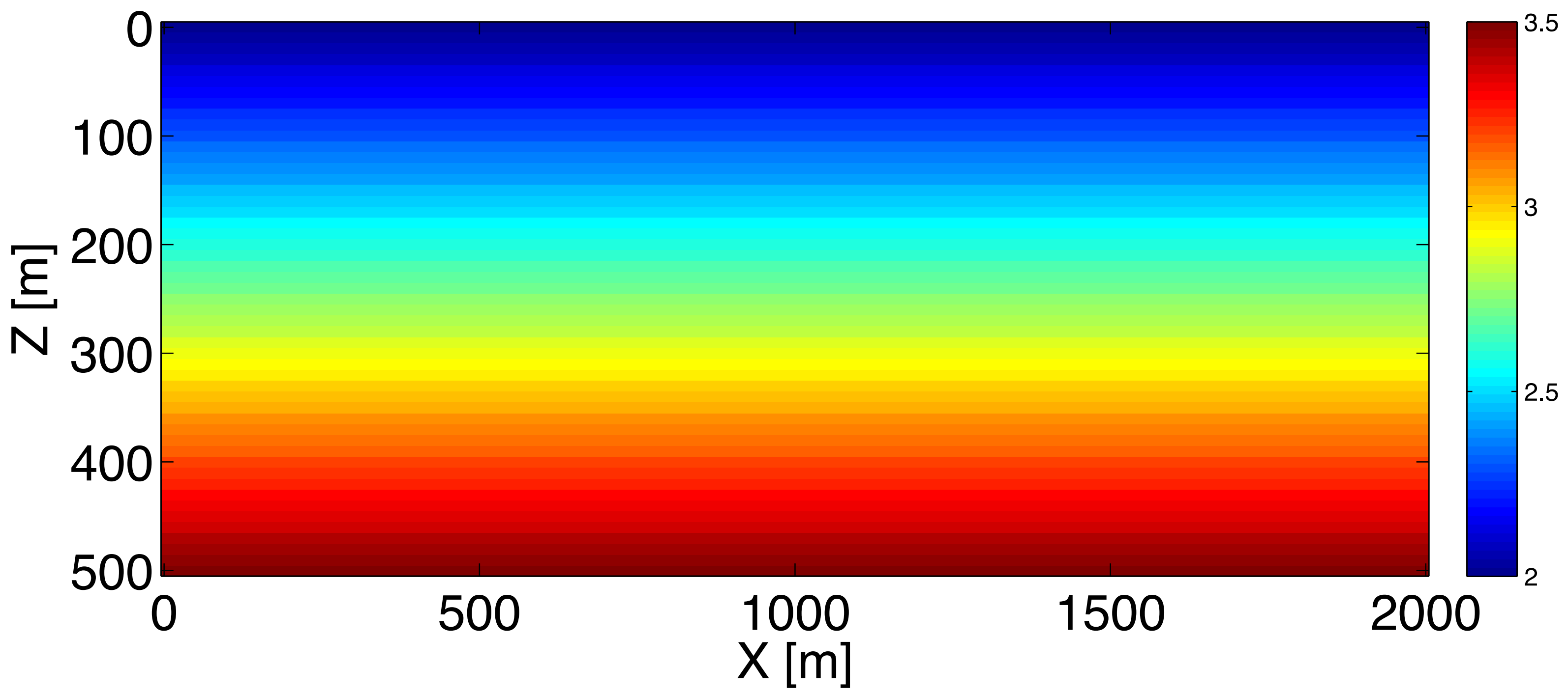
$$\begin{pmatrix} \lambda\mathbf{A} & -\lambda\mathbf{e} \\ \mathbf{P} & 0 \end{pmatrix} \begin{pmatrix} \overline{\mathbf{u}} \\ \overline{\alpha} \end{pmatrix} = \begin{pmatrix} 0 \\ \mathbf{d_{obs}} \end{pmatrix}$$

$\overline{\alpha}$ **and**

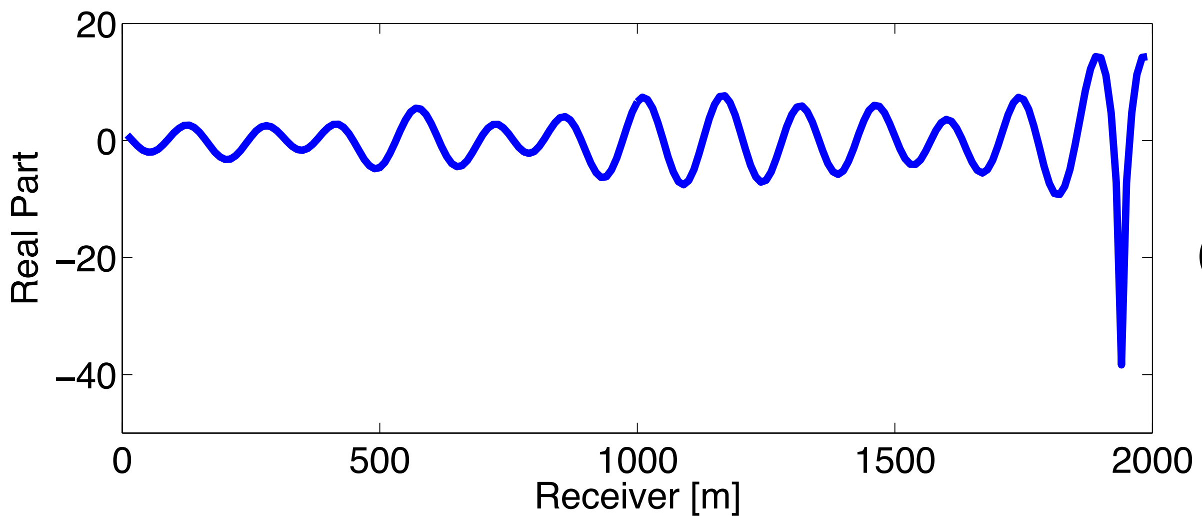


$\overline{\mathbf{u}}$

WRI with source estimation



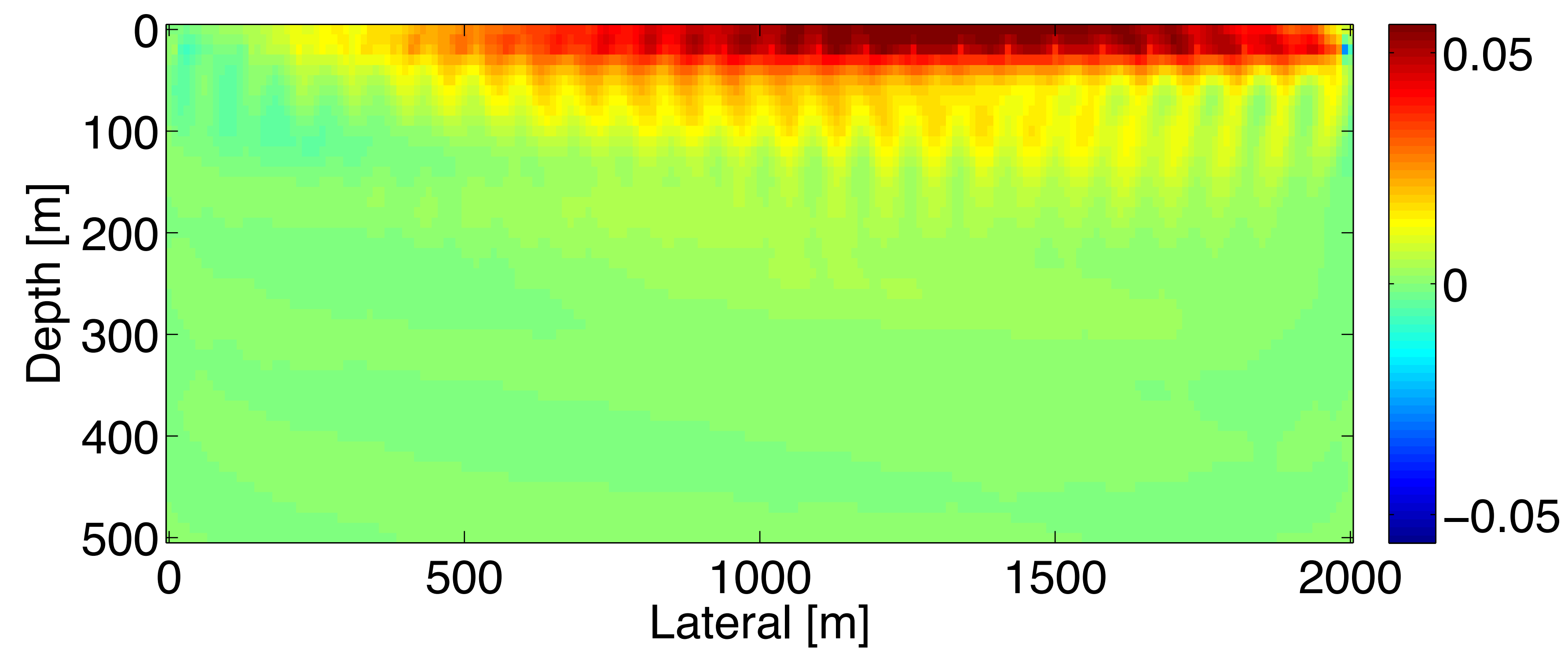
$\mathbf{m}$



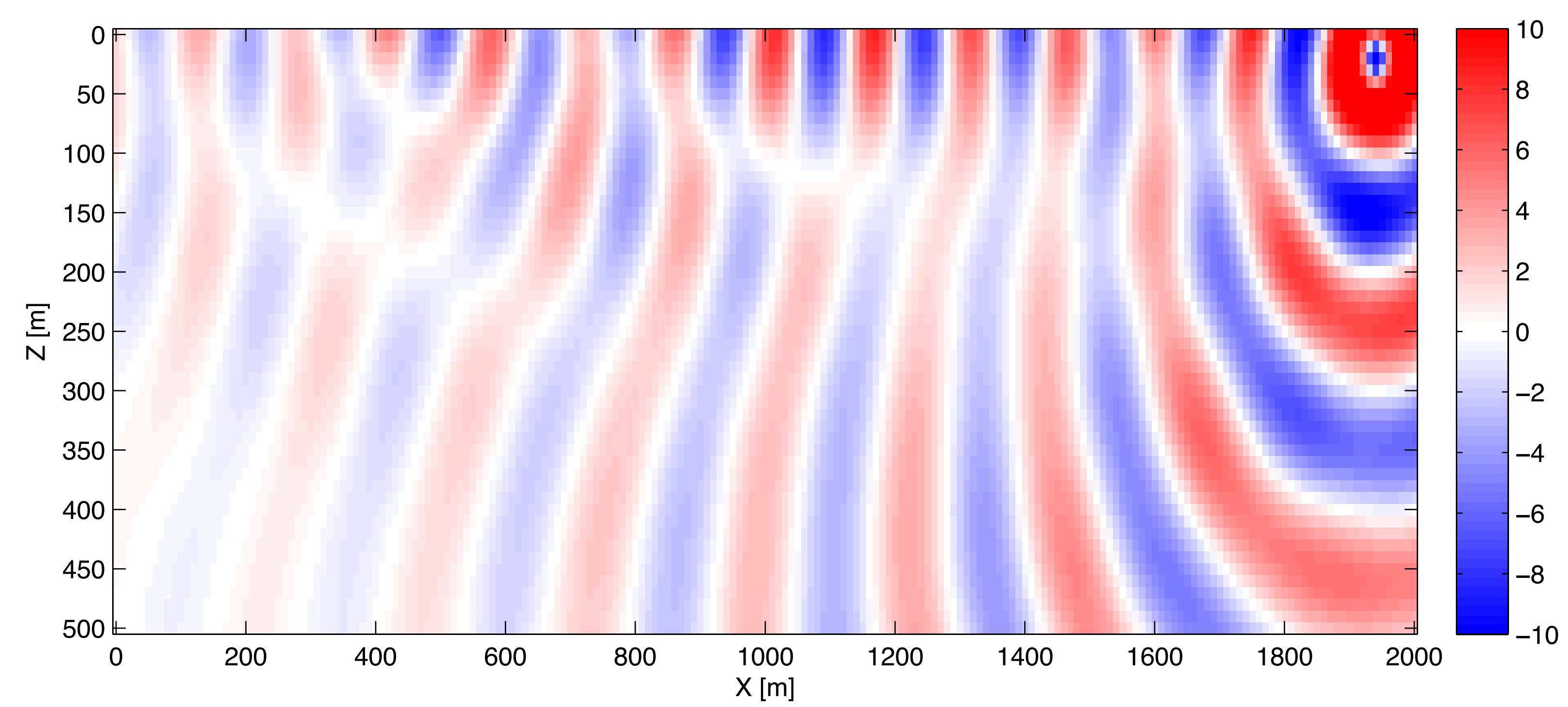
$\mathbf{d_{obs}}$

$$\begin{pmatrix} \lambda \mathbf{A} & -\lambda \mathbf{e} \\ \mathbf{P} & 0 \end{pmatrix} \begin{pmatrix} \overline{\mathbf{u}} \\ \overline{\alpha} \end{pmatrix} = \begin{pmatrix} 0 \\ \mathbf{d_{obs}} \end{pmatrix}$$

$\mathbf{g}$

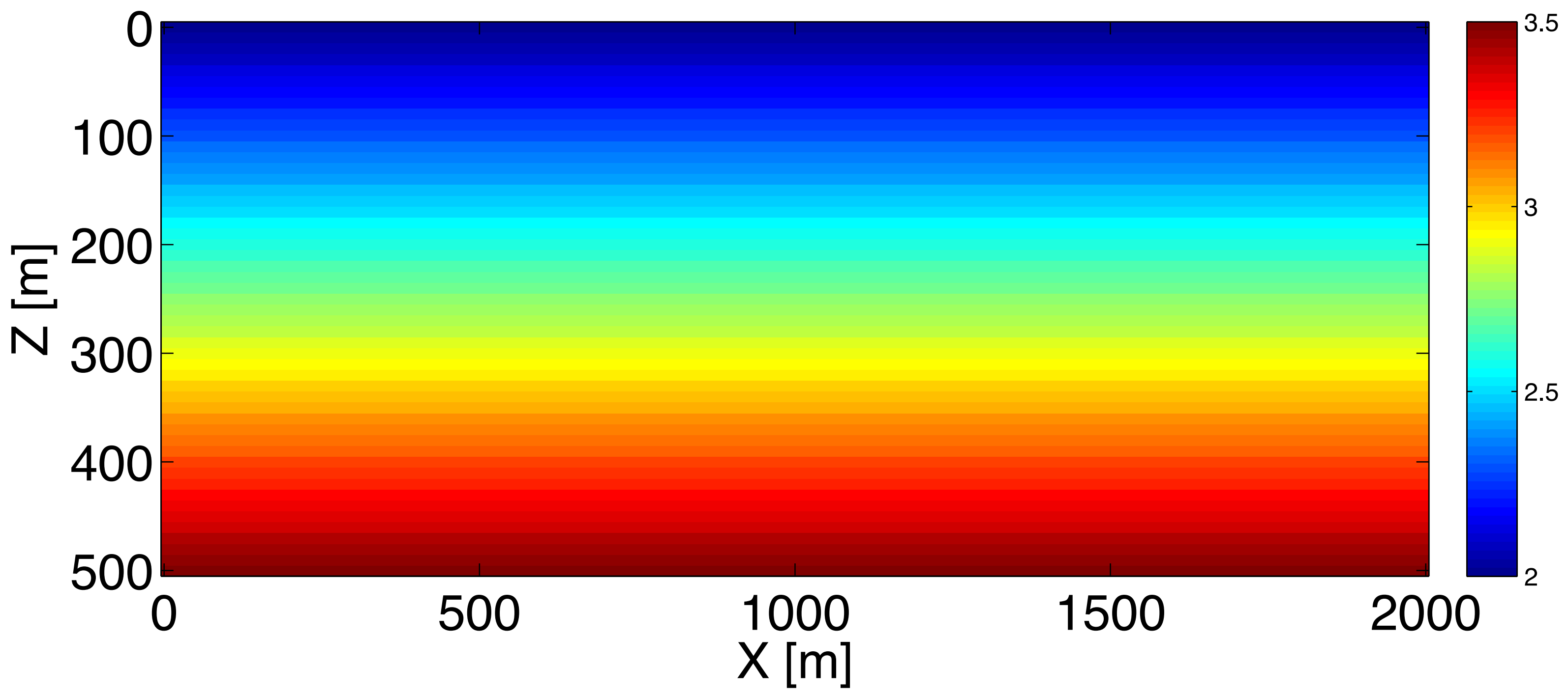


$\overline{\alpha}$ **and**



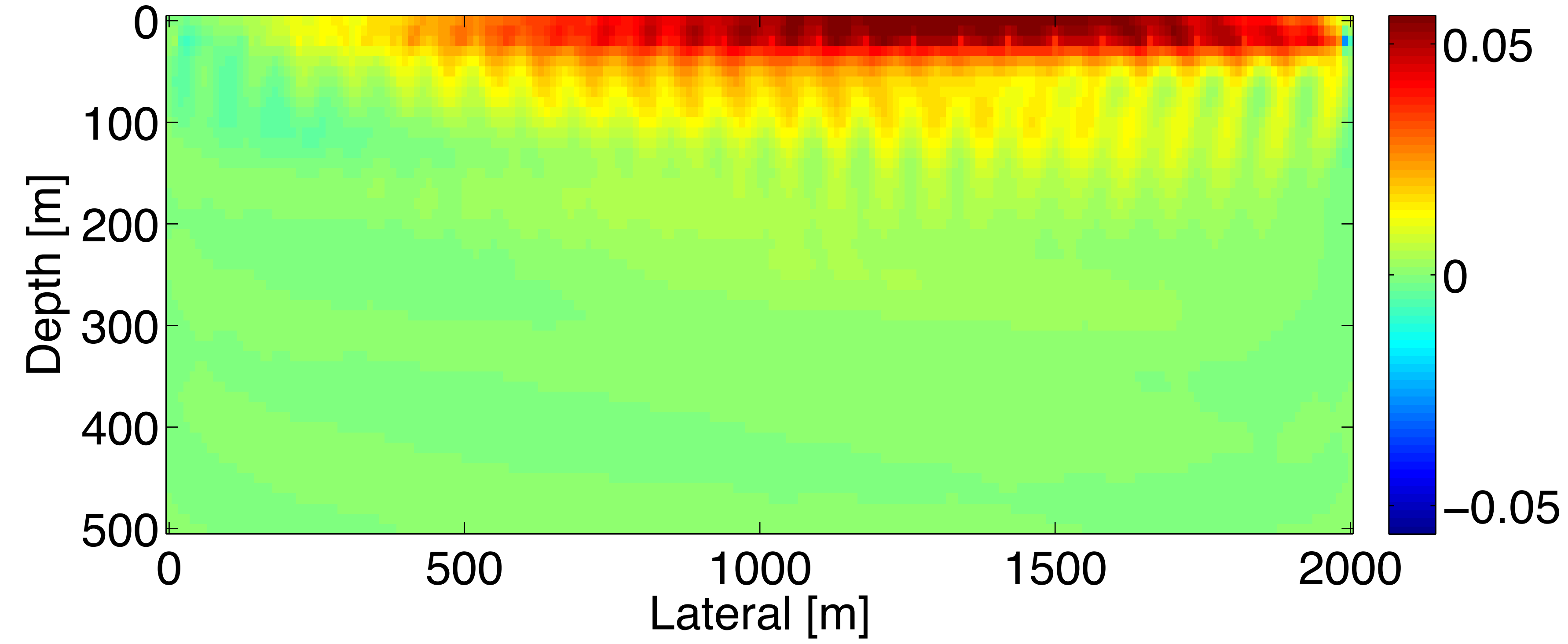
$\overline{\mathbf{u}}$

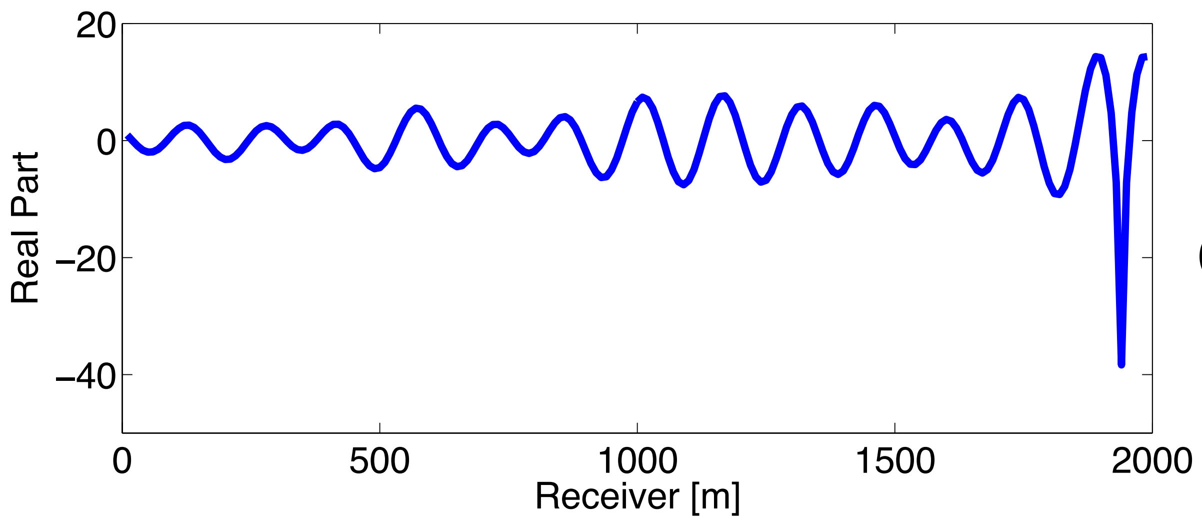
WRI with source estimation



$\mathbf{m}$

$\mathbf{g}$

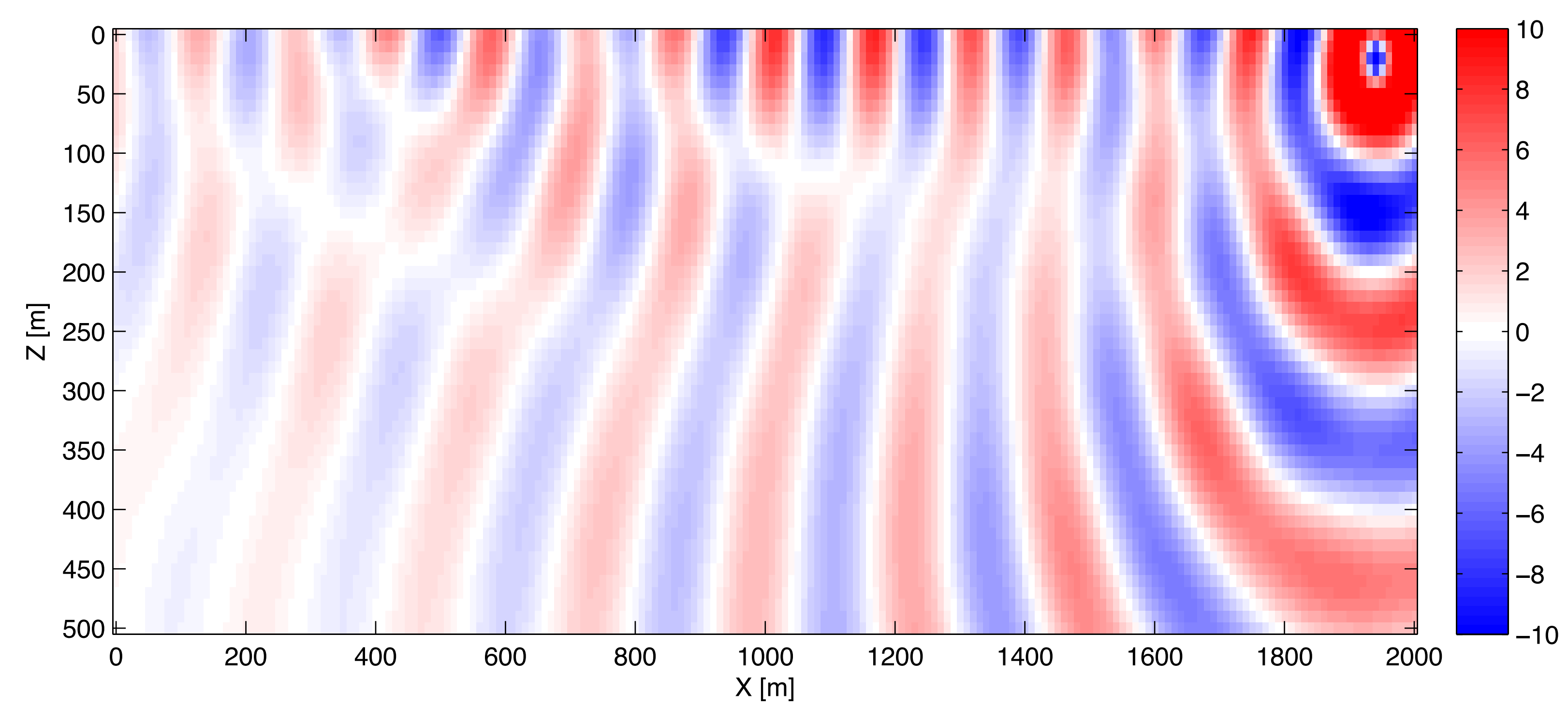




$\mathbf{d_{obs}}$

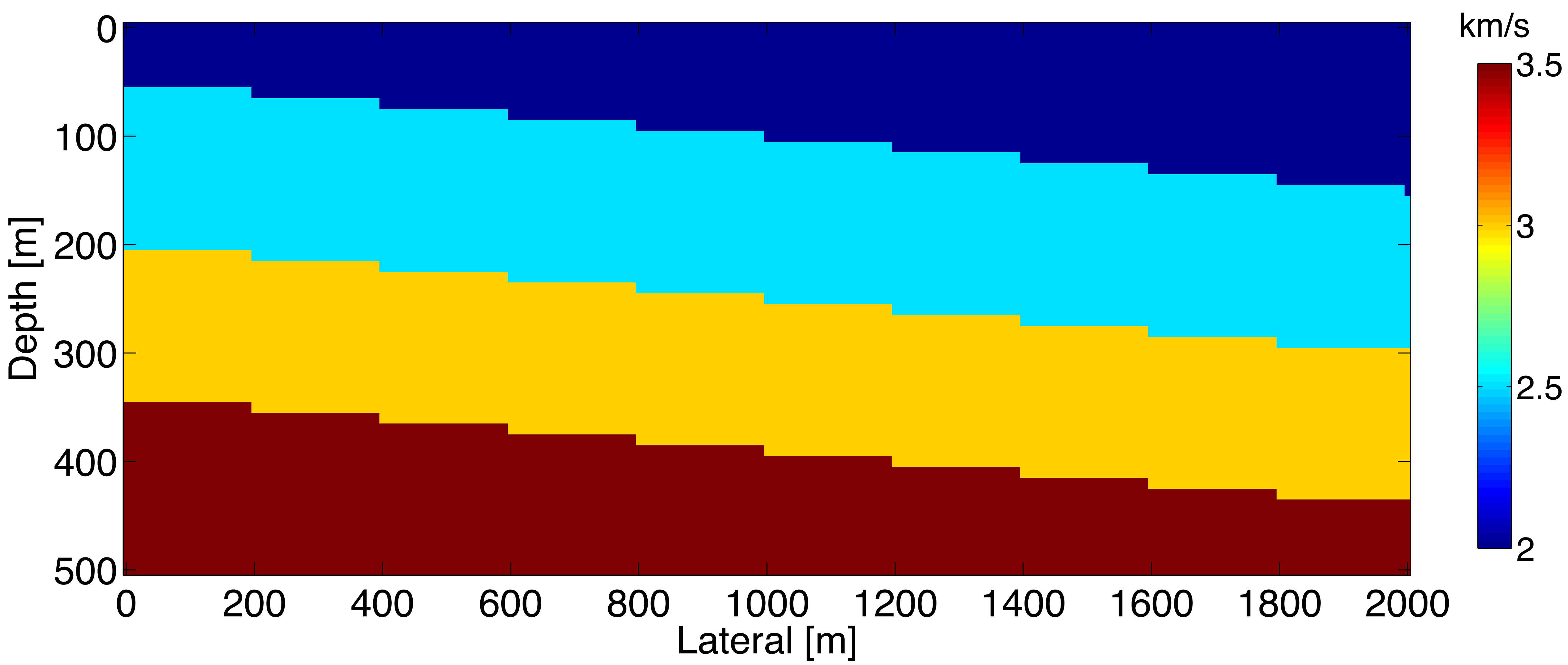
$$\begin{pmatrix} \lambda \mathbf{A} & -\lambda \mathbf{e} \\ \mathbf{P} & 0 \end{pmatrix} \begin{pmatrix} \overline{\mathbf{u}} \\ \overline{\alpha} \end{pmatrix} = \begin{pmatrix} 0 \\ \mathbf{d_{obs}} \end{pmatrix}$$

$\overline{\alpha}$ **and**

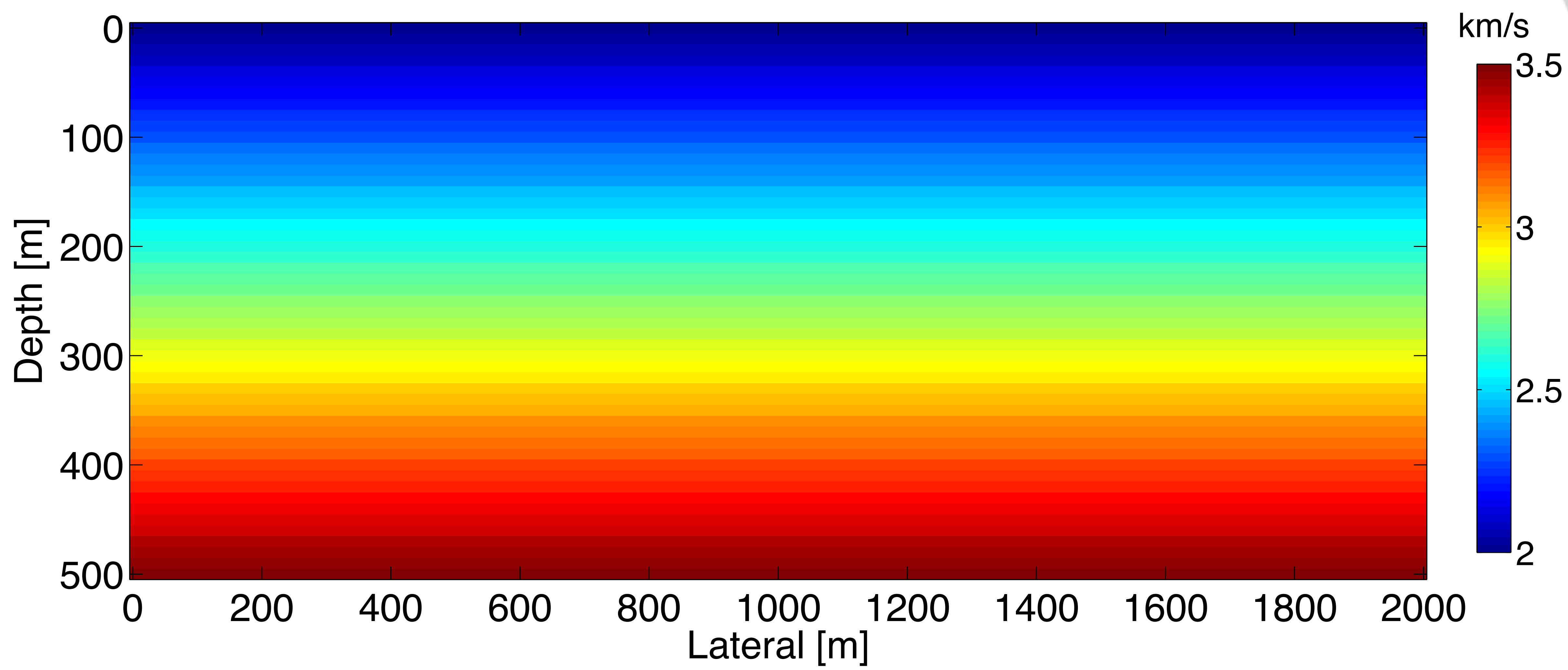


$\overline{\mathbf{u}}$

Synthetic example

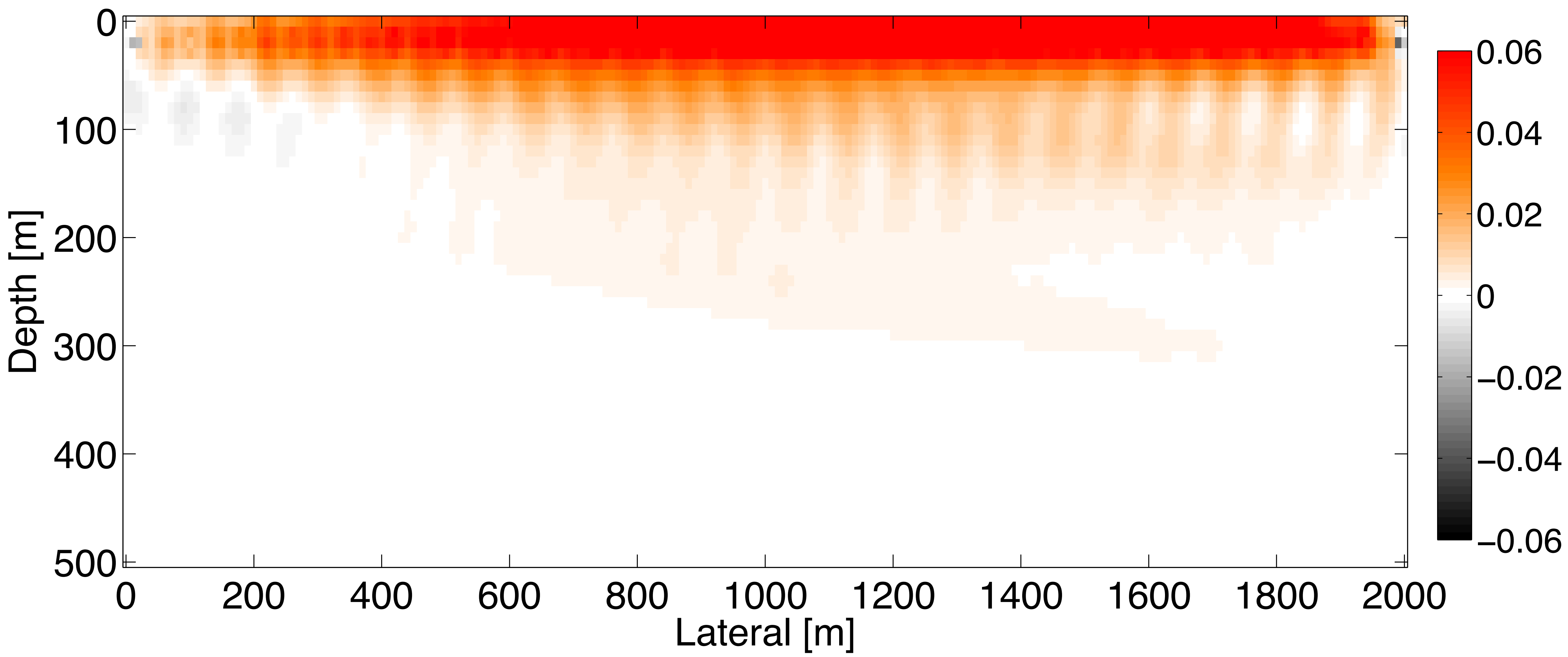


True Model

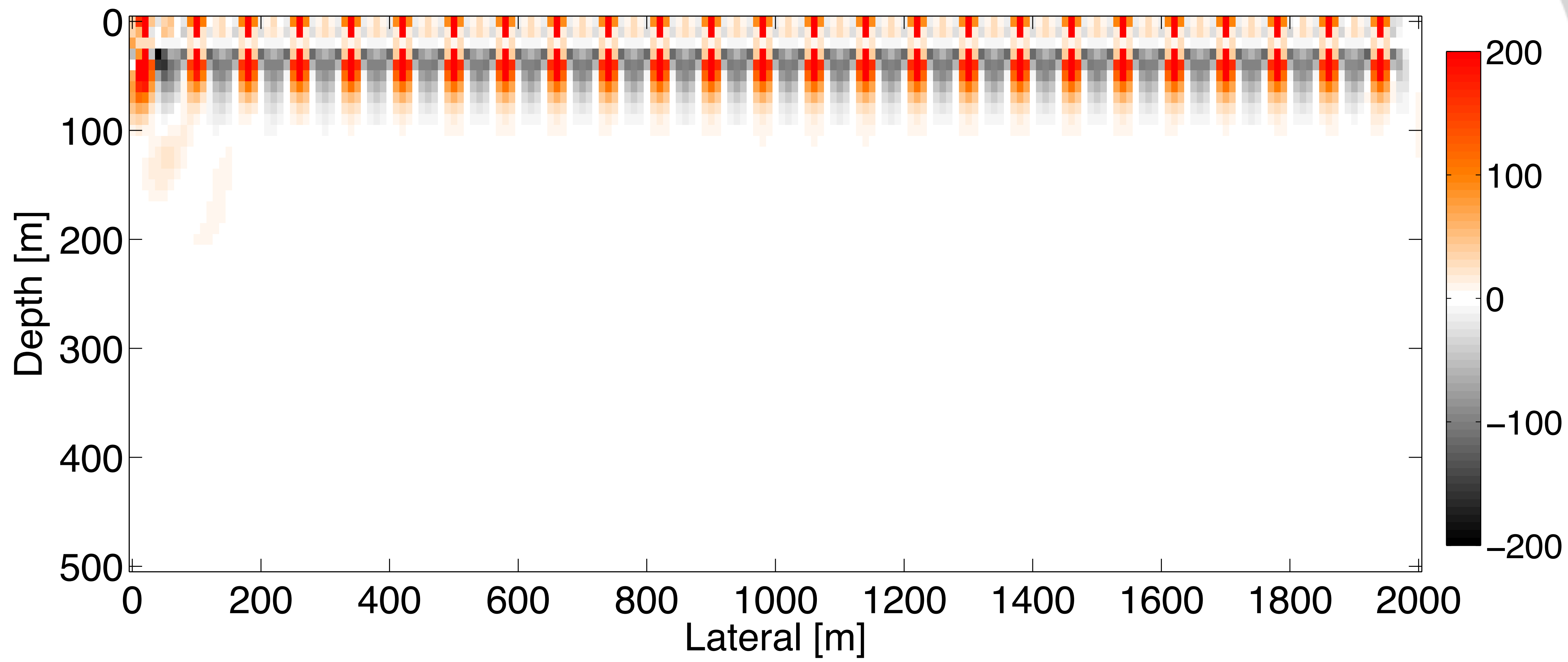


Initial Model

Gradient comparison

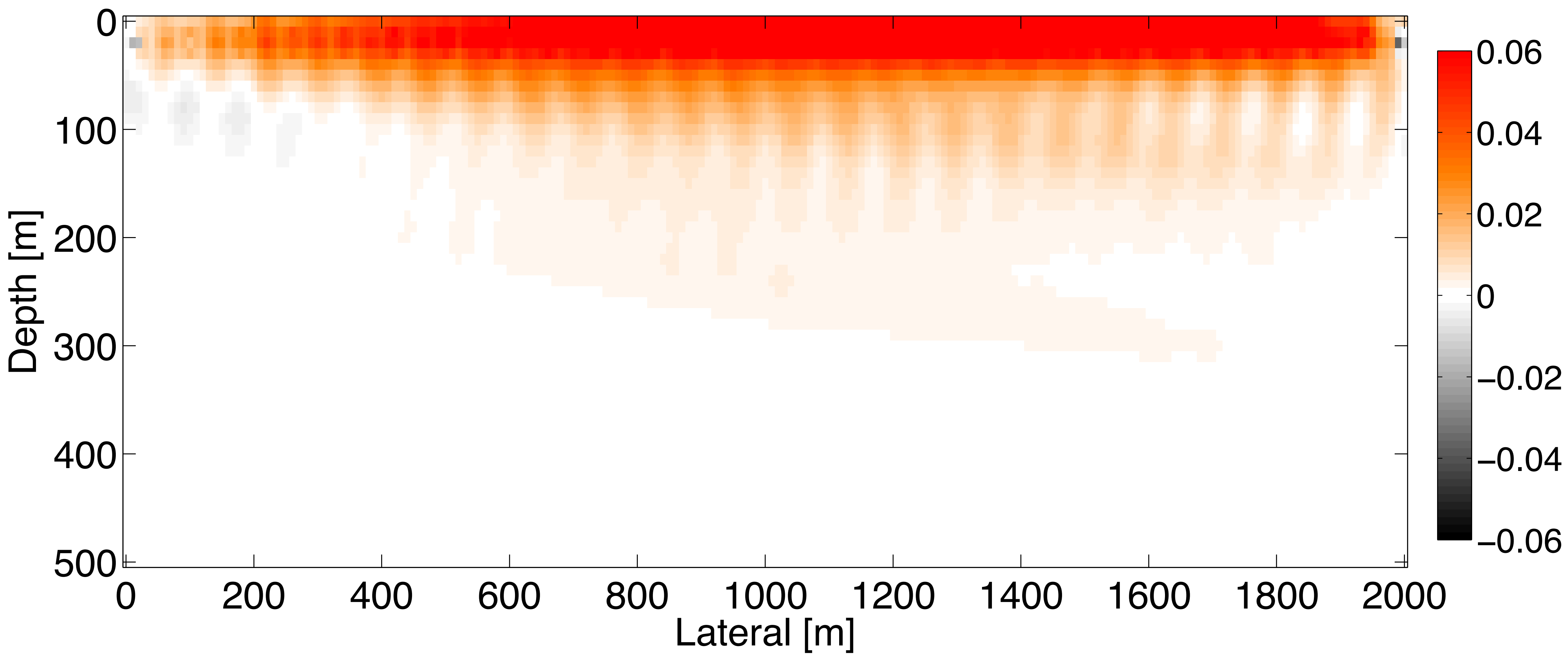


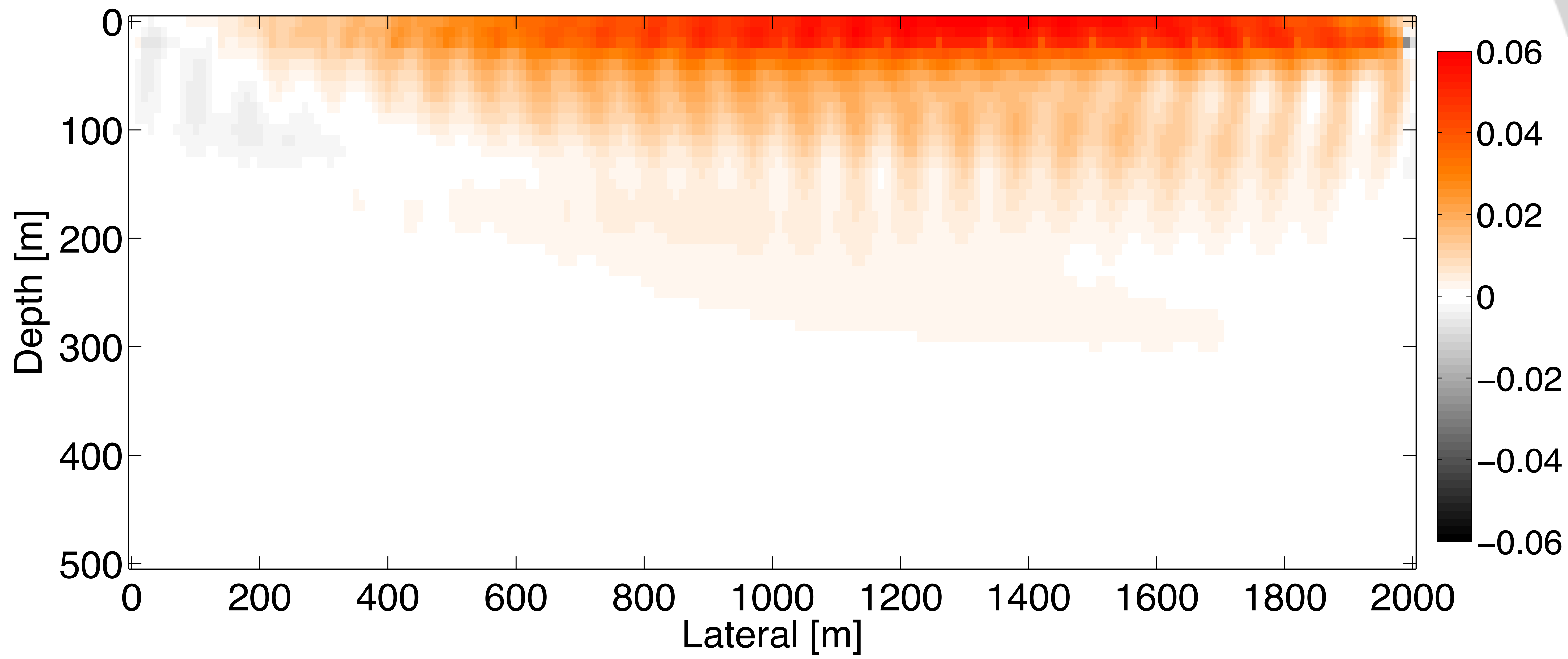
Gradient with true source wavelet



Gradient with wrong source wavelet

Gradient comparison

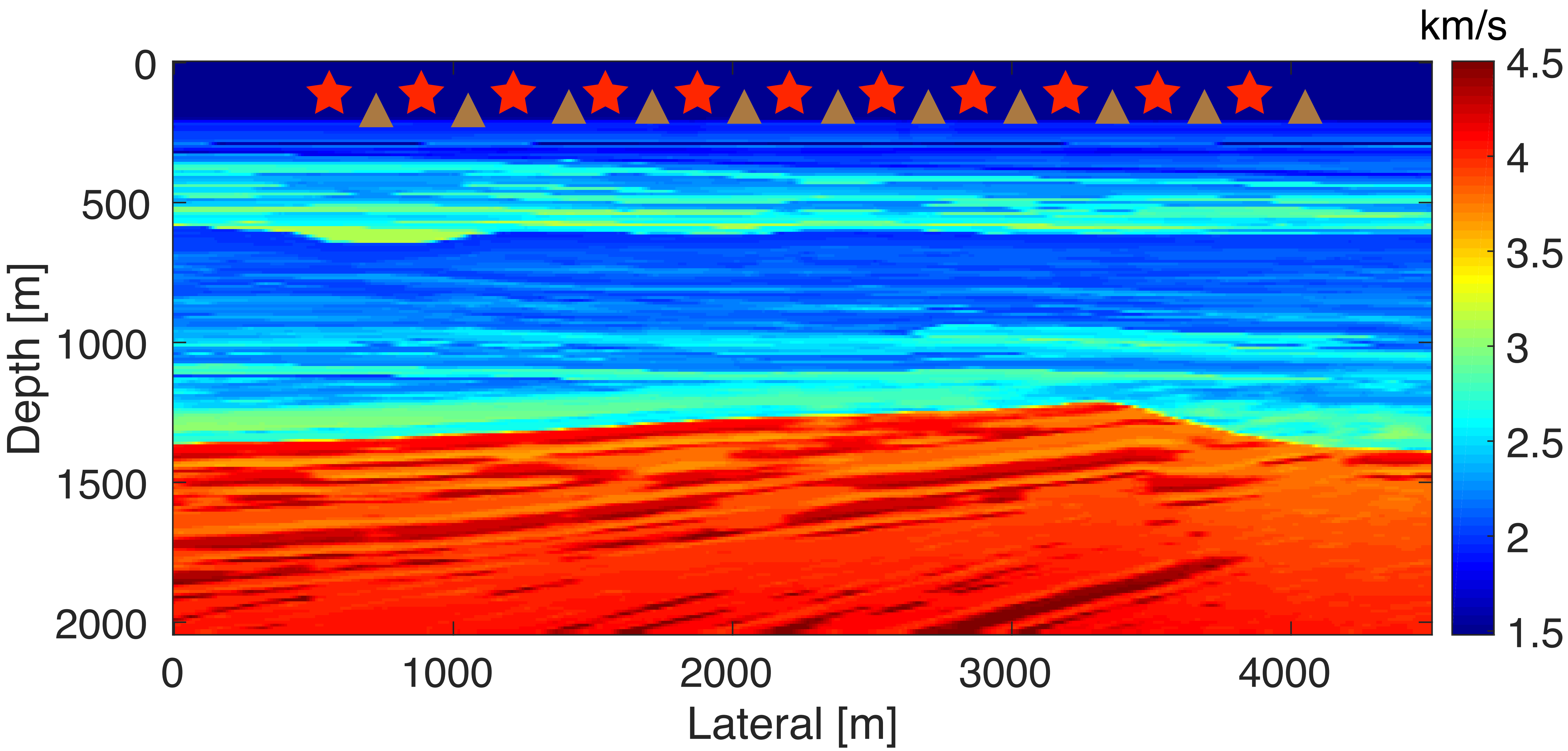




Gradient with true source wavelet

Gradient with estimated source wavelet

BG model



Modeling information:

Model size: 2000m x 4500m

Source spacing: 50m

Receiver spacing: 10m

Fixed spread 4.5km

Frequency : 2~31 Hz

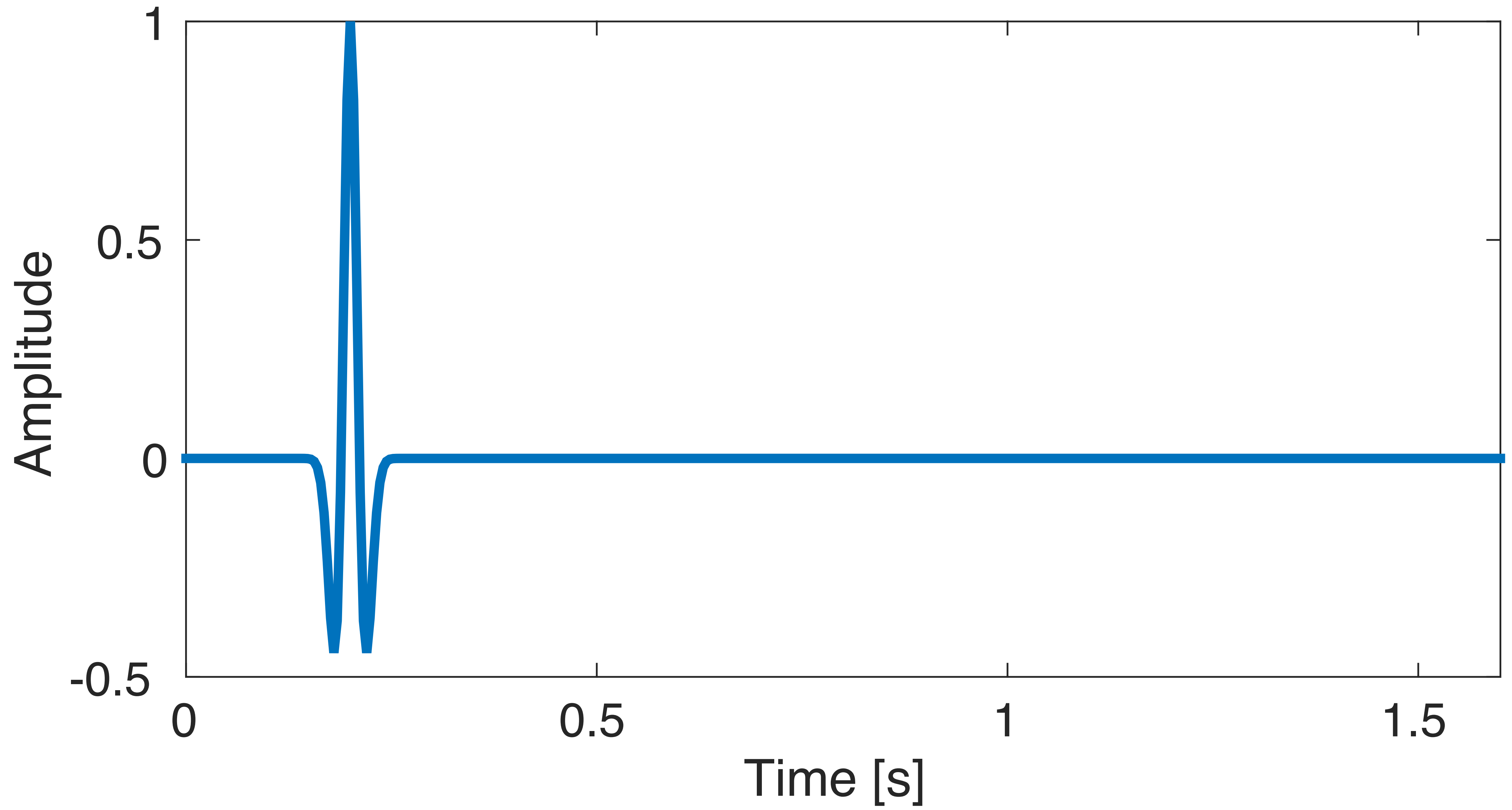
Inversion information:

Optimization Solver: Gauss-Newton

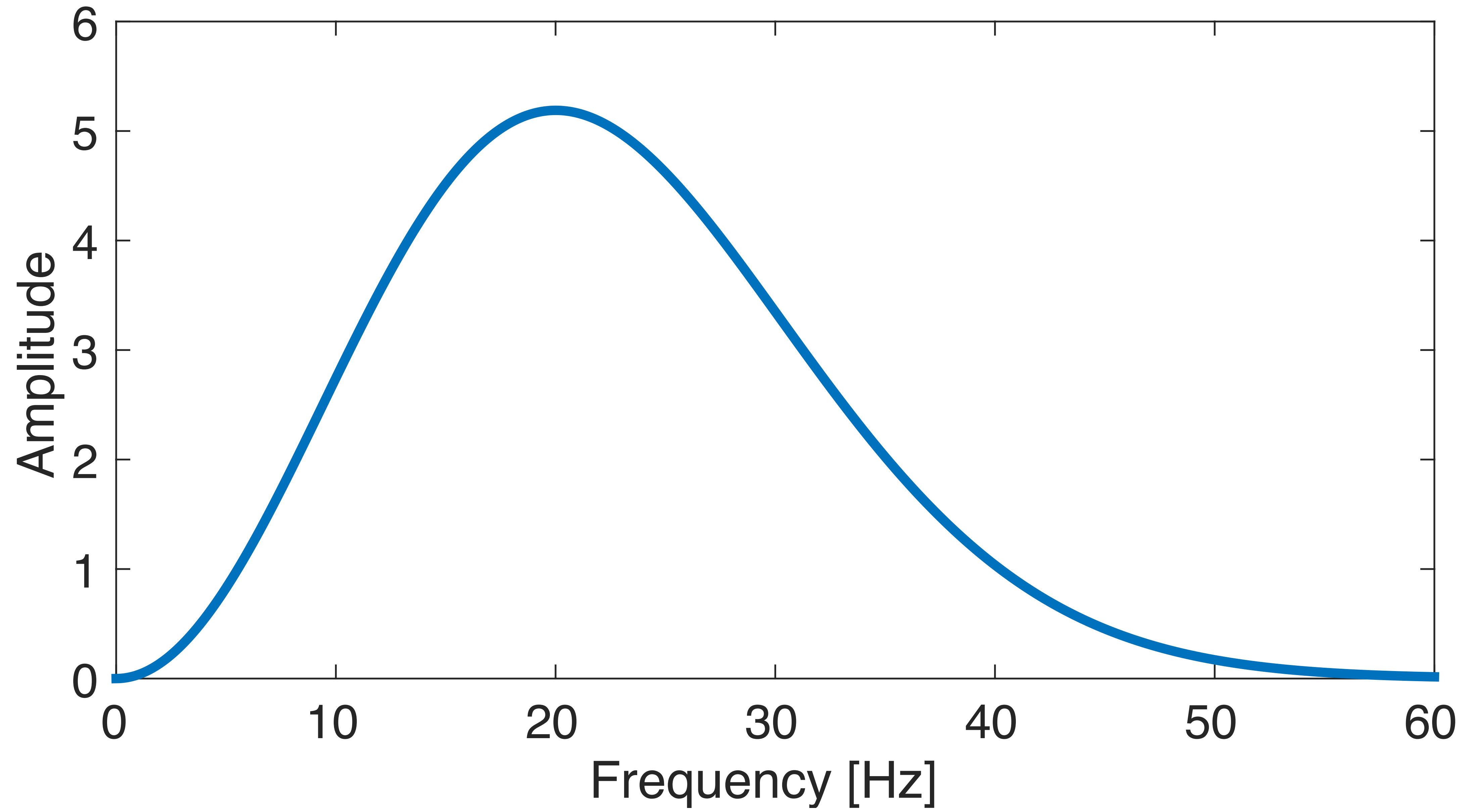
Iterations per frequency band: 21

Batch size: 15

Source wavelet

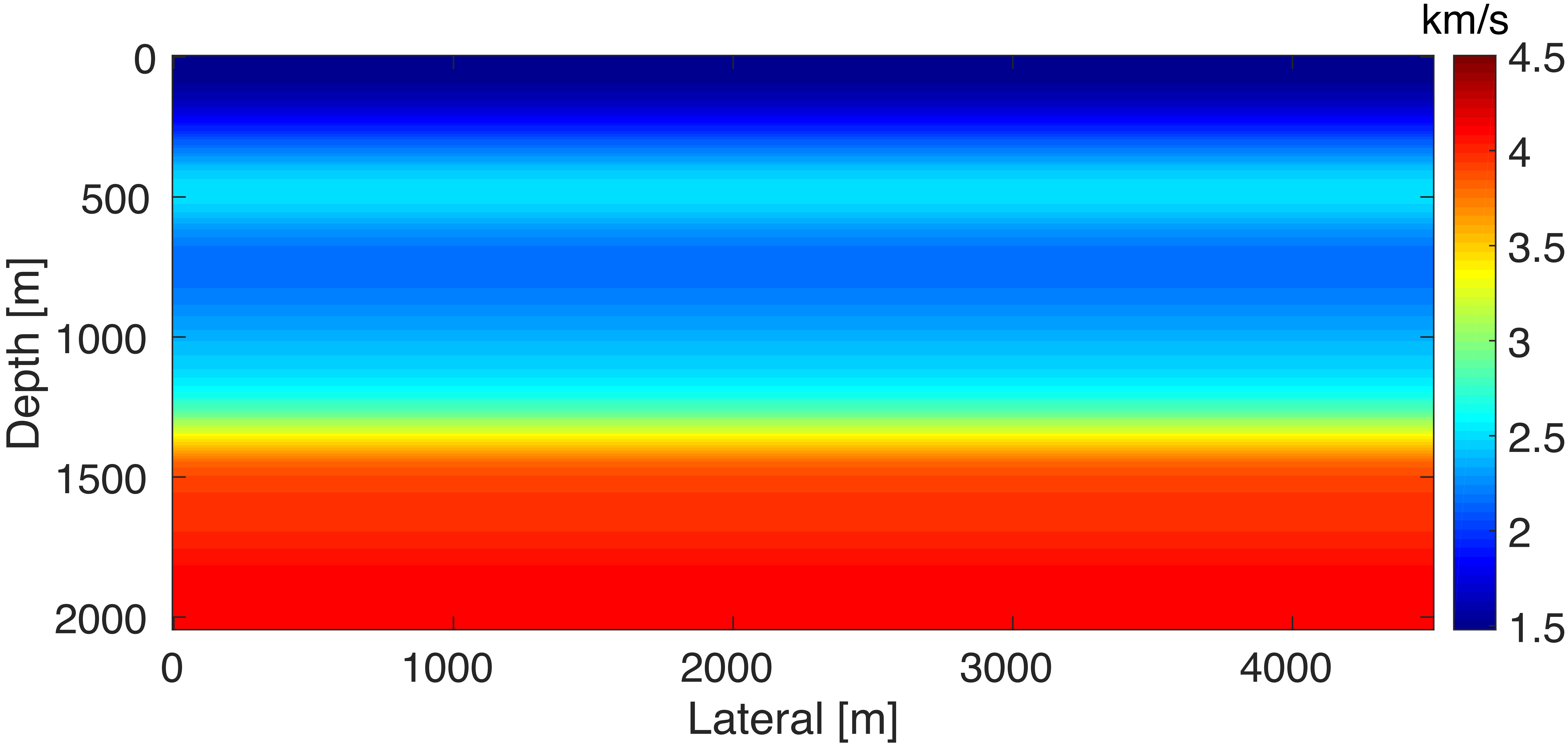


Source Wavelet

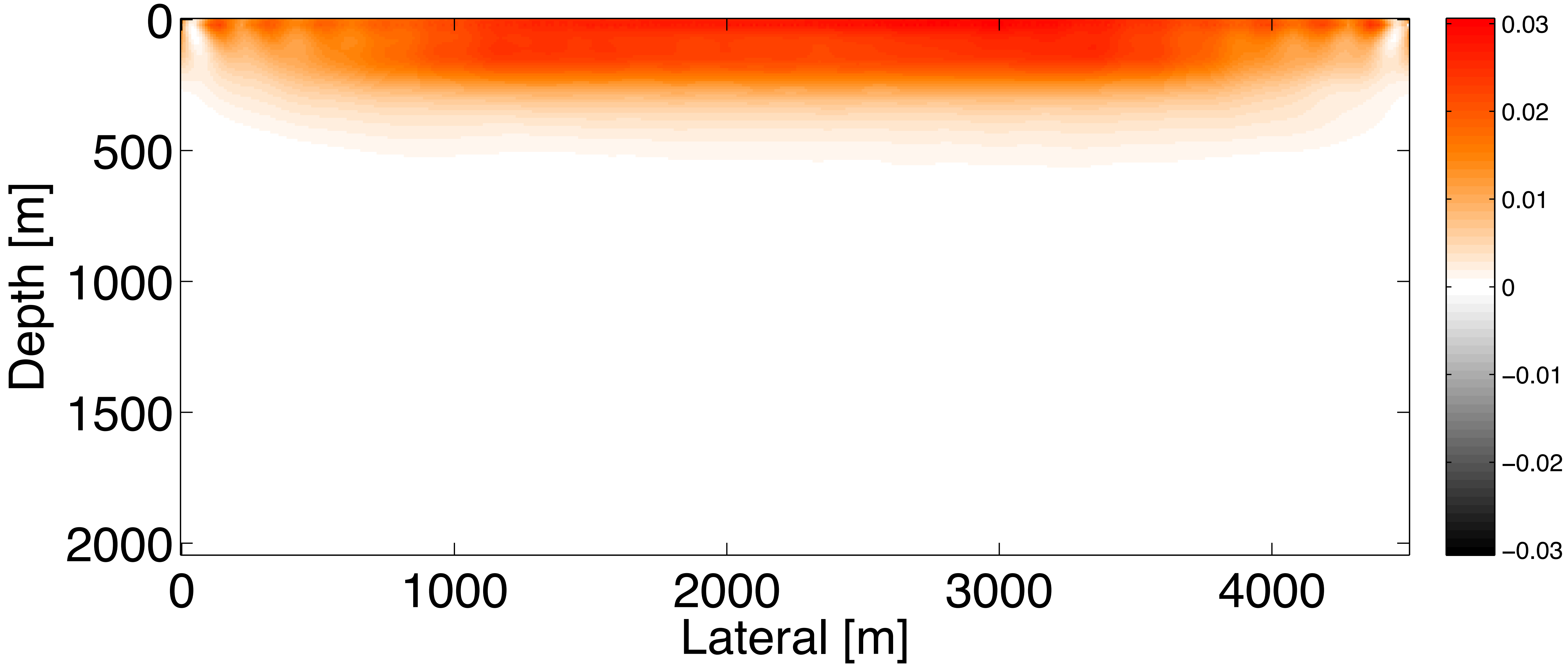


Spectrum

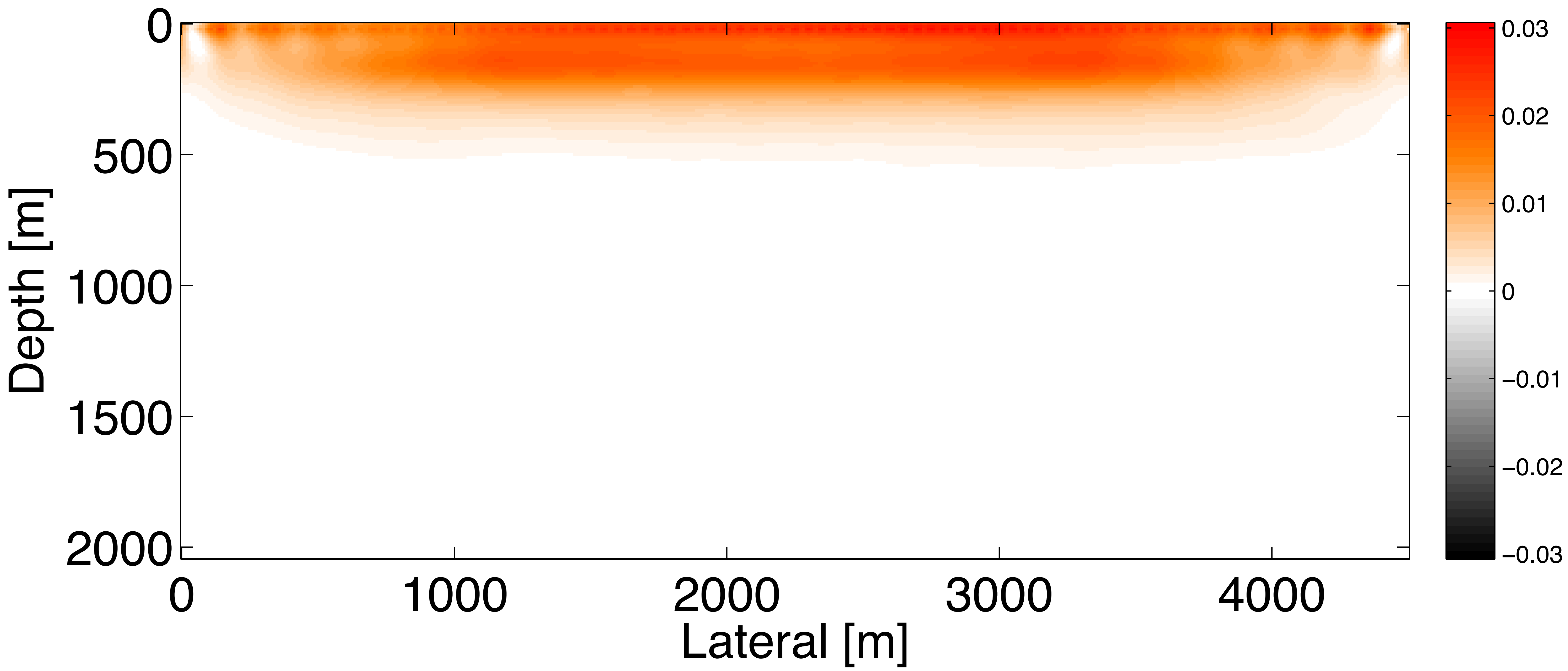
Initial model



First gradient comparison

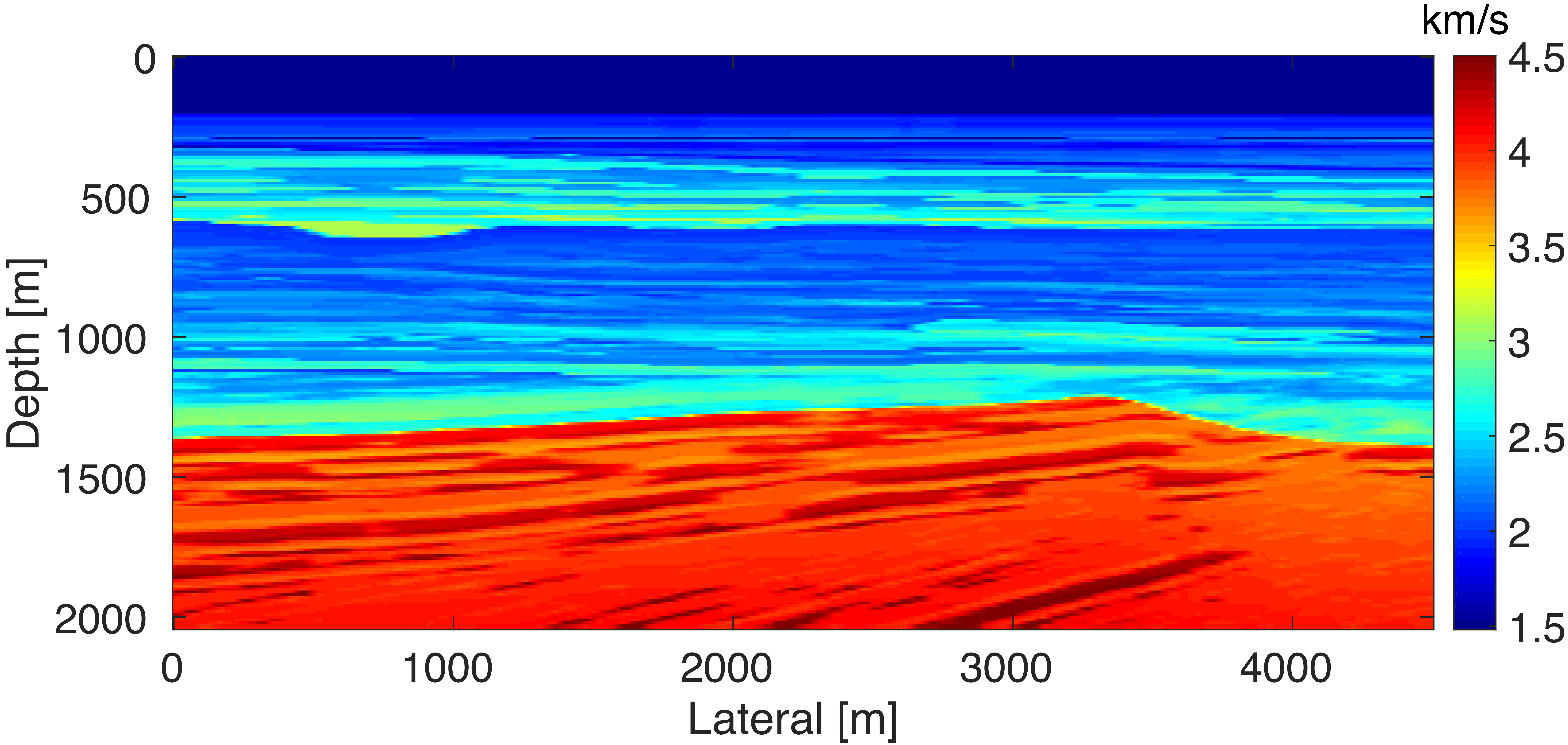


Gradient with true source wavelet

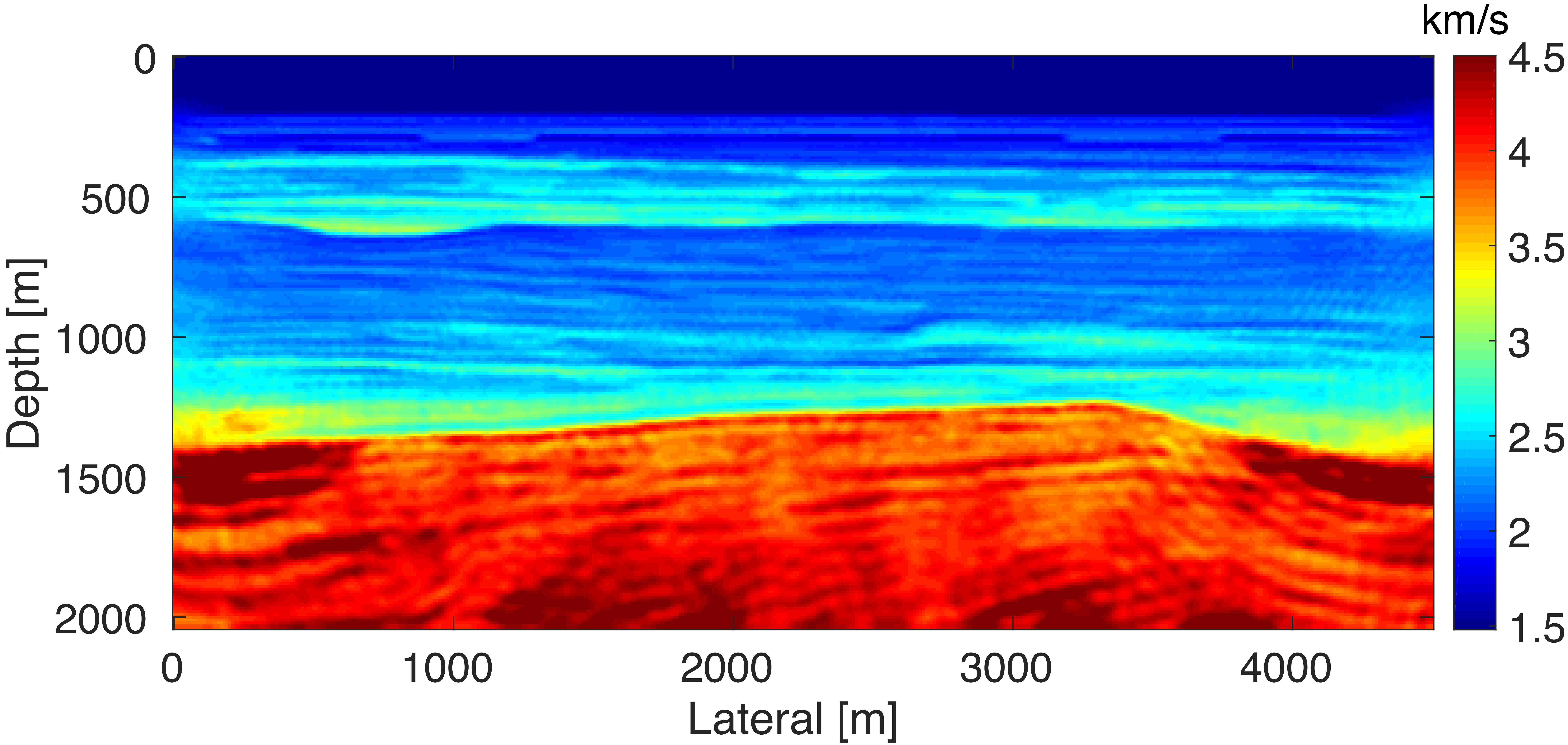


Gradient with estimated source wavelet

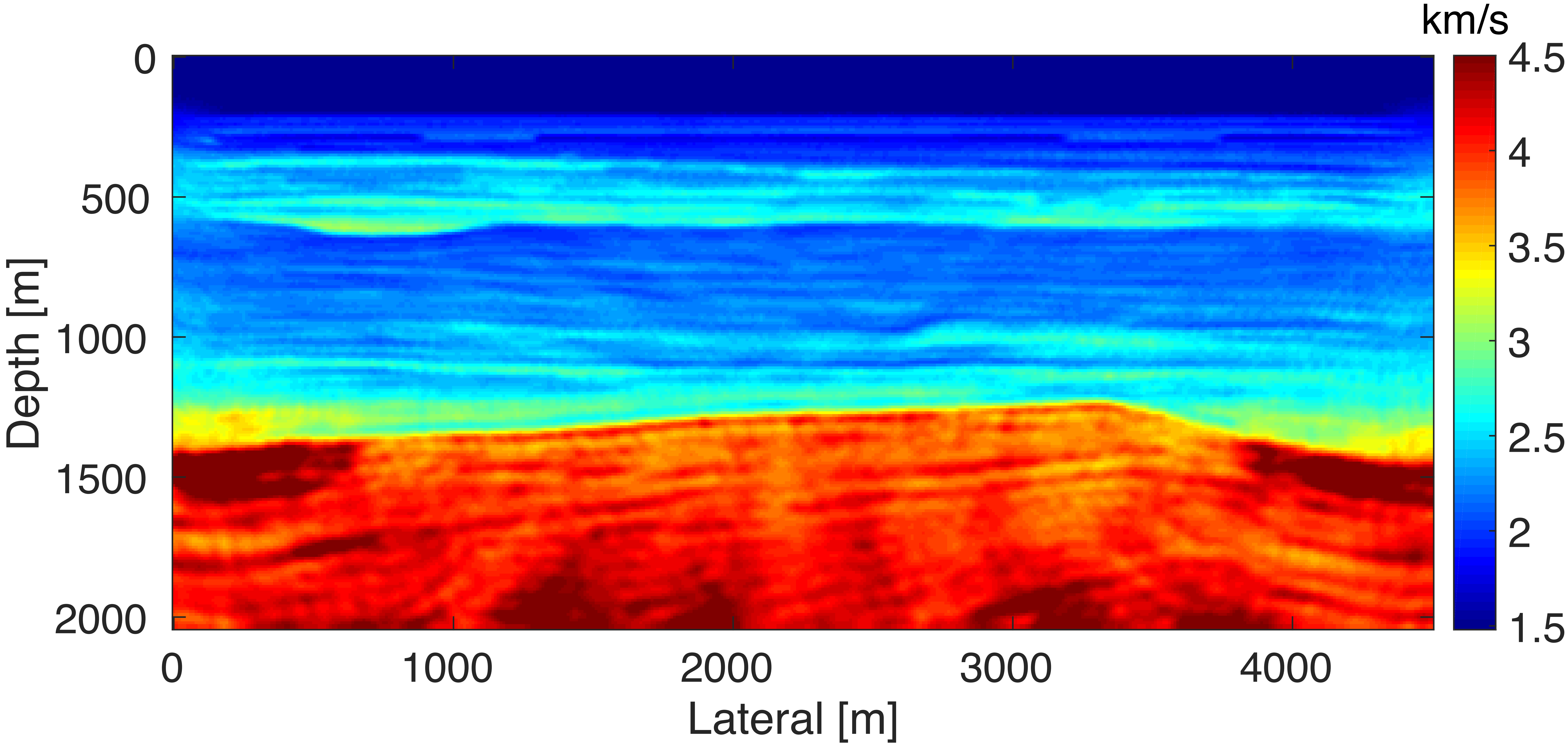
True model


km/s
4.5
4
3.5
3
2.5
2
1.5
0
500
1000
1500
2000
Depth [m]
0
1000
2000
3000
4000
Lateral [m]

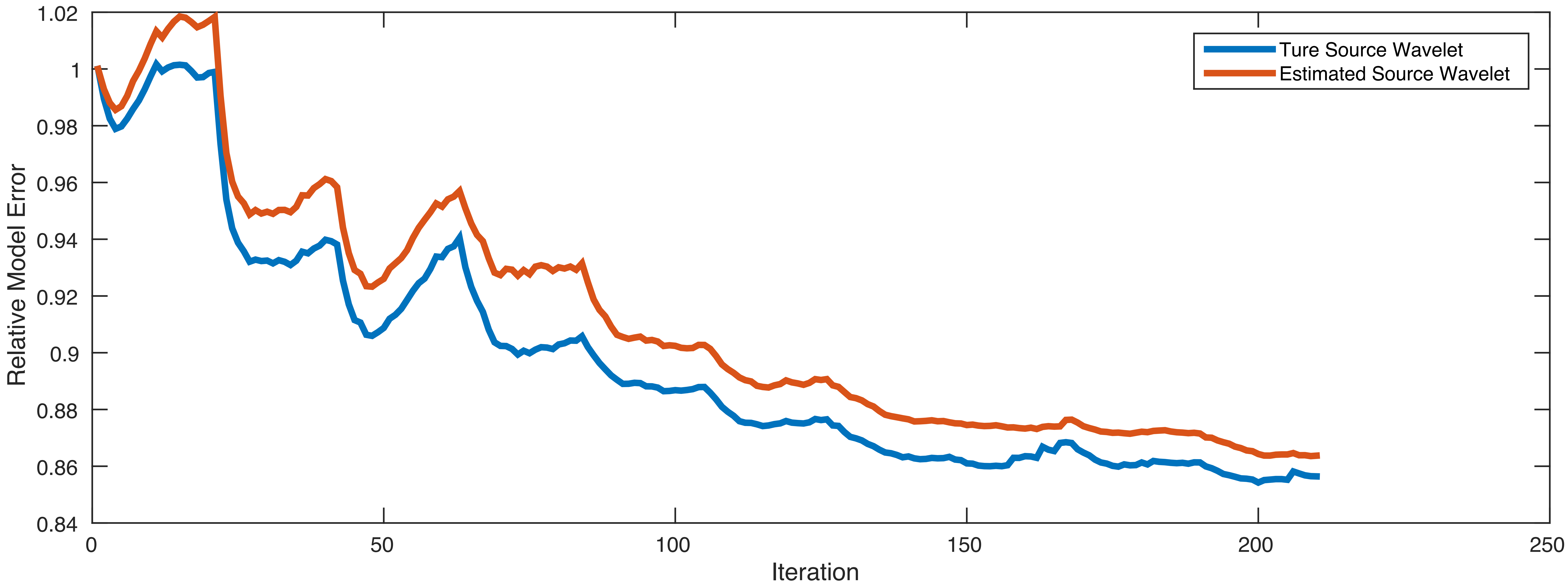
Result with true source wavelet



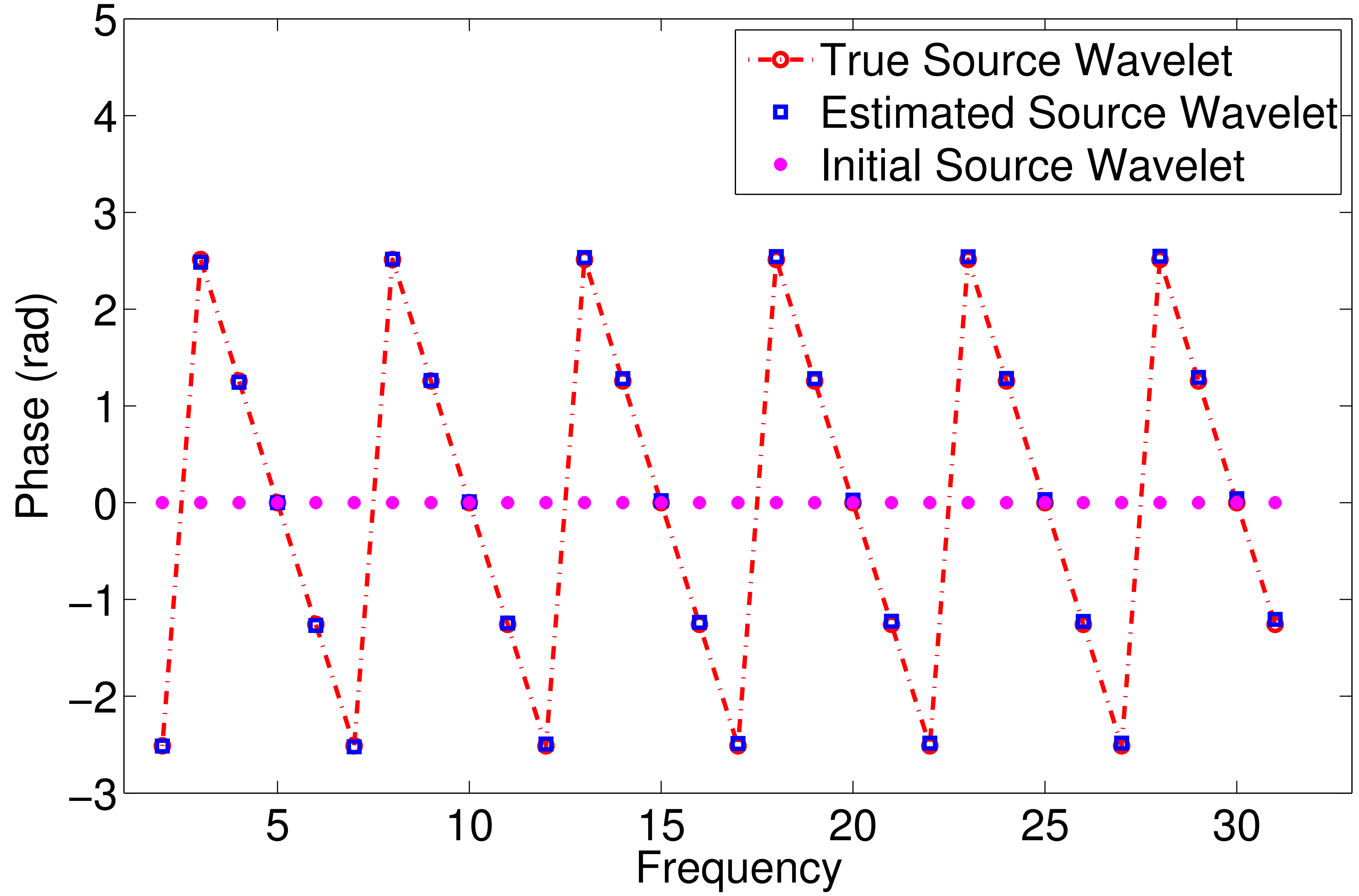
Result with estimated source wavelet



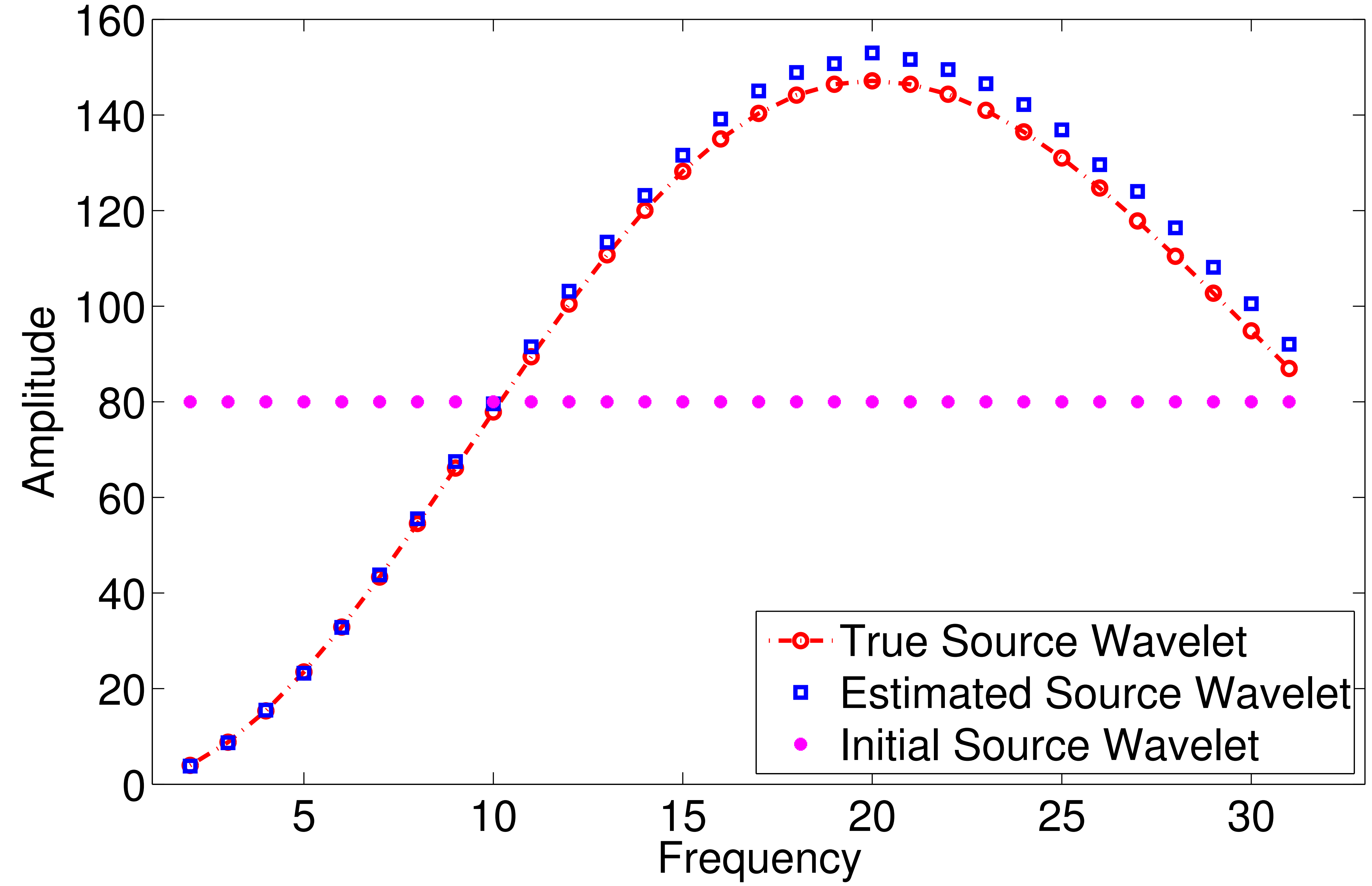
Relative model-error comparison



Source wavelet comparison

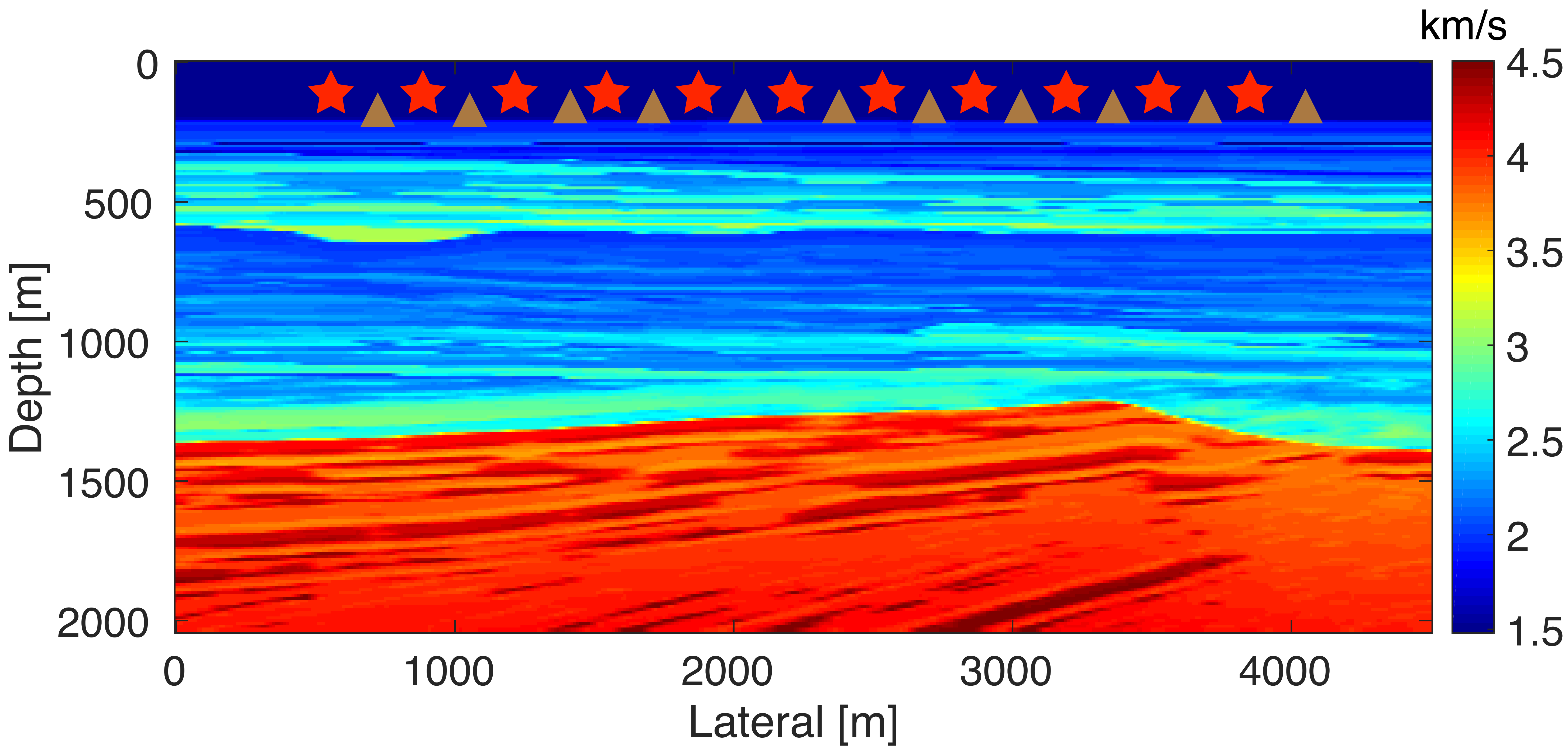


Phase



Amplitude

BG model



Modeling information:

Model size: 2000m x 4500m

Source spacing: 50m

Receiver spacing: 10m

Fixed spread 4.5km

Non-inversion crime example

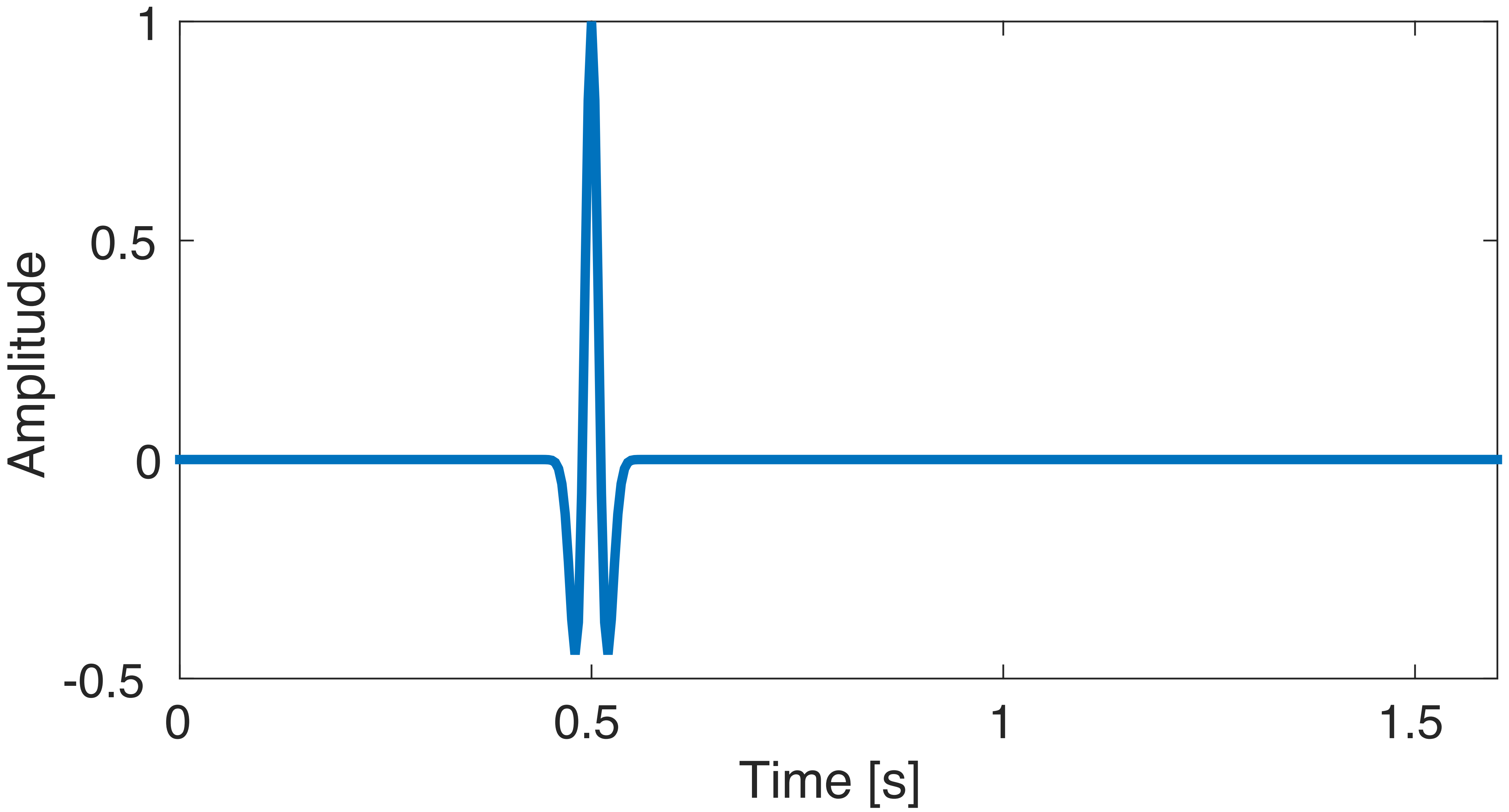
Observed Data information:

- Time domain data by iWAVE
- Grid size: 5m
- Source wavelet: 20Hz Ricker wavelet

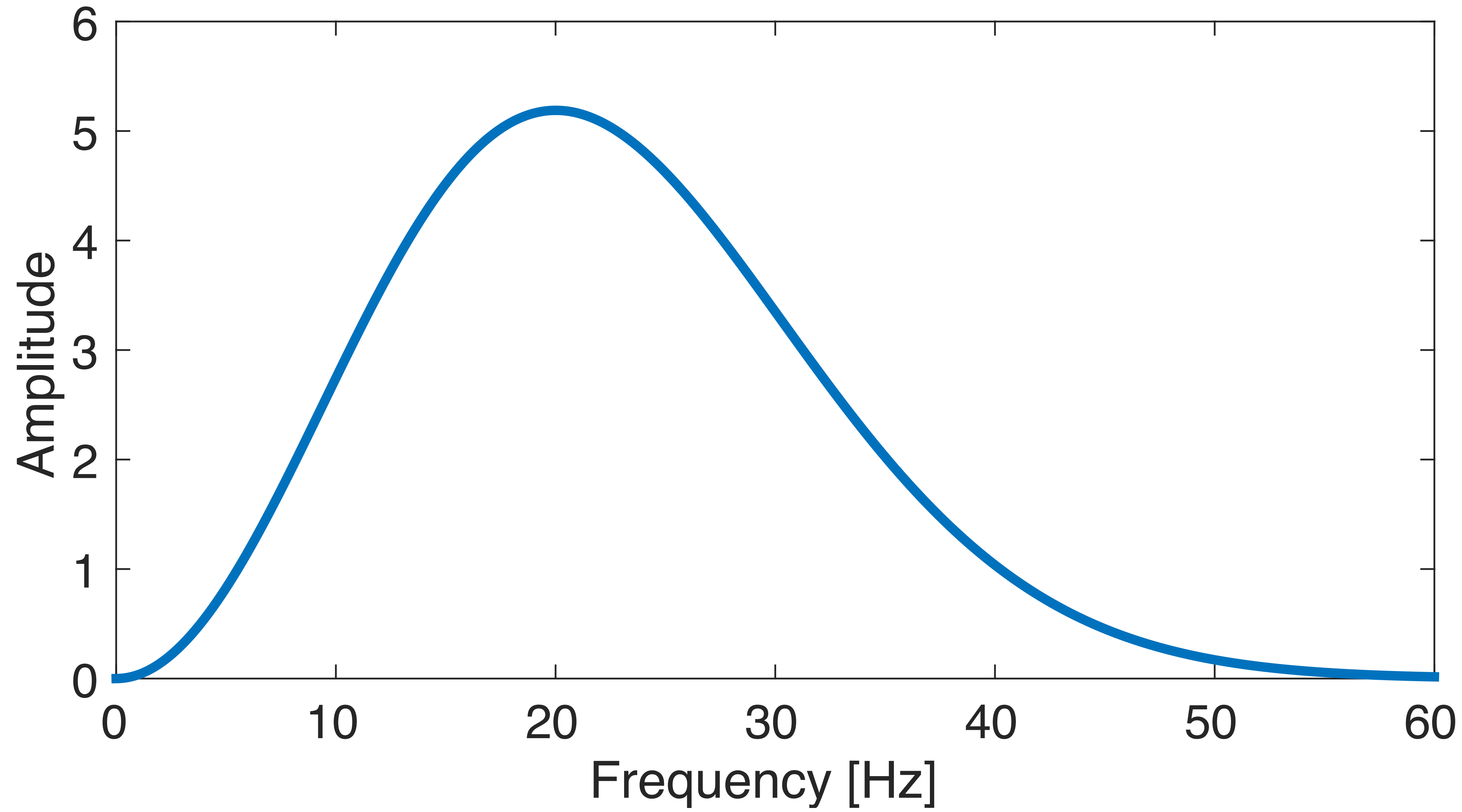
Inversion strategy:

- Frequency: 2-29Hz
- Grid size: 10m (2-20 Hz), and 6m (20-29 Hz)
- Gauss-Newton method with 20 iterations per frequency band

Source wavelet

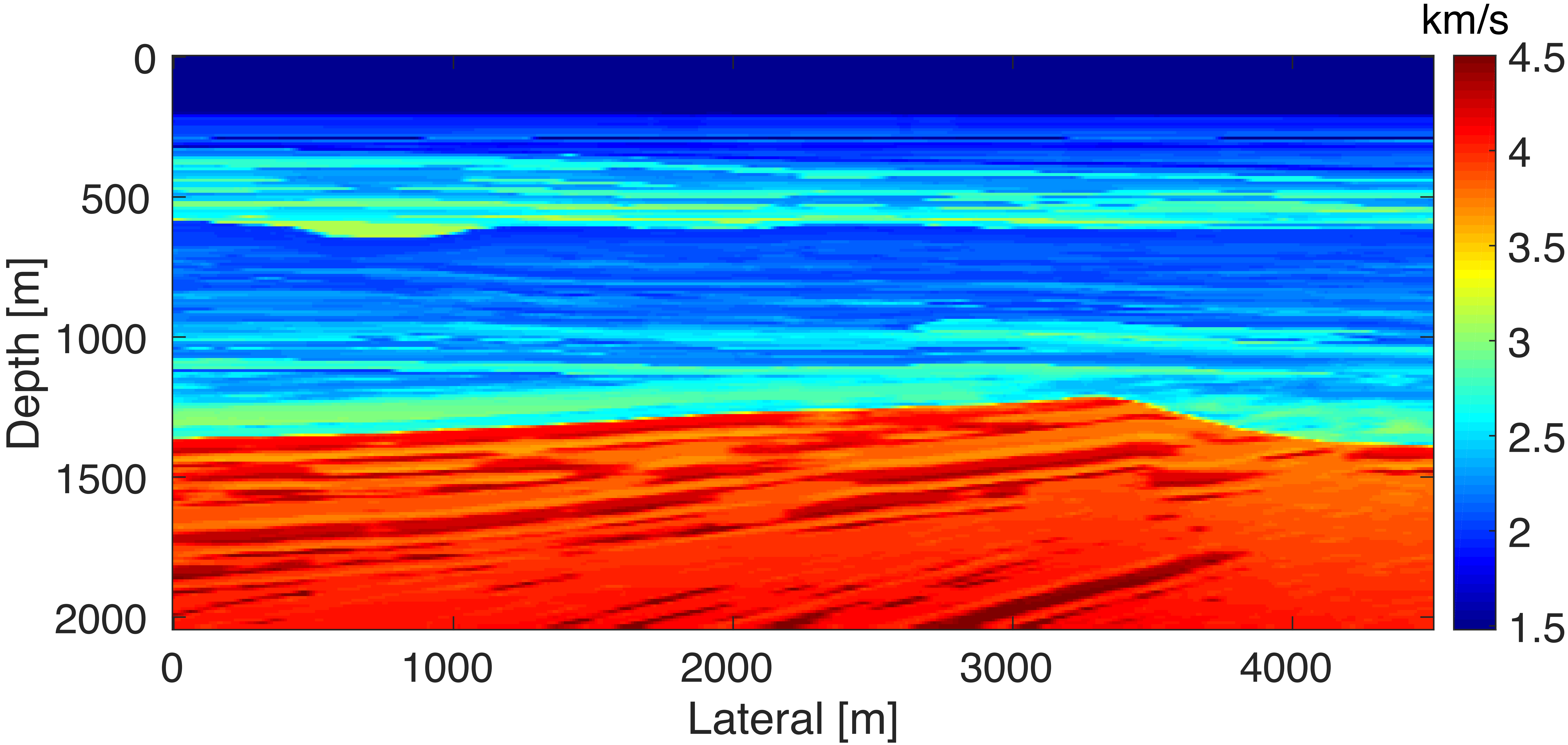


Source wavelet



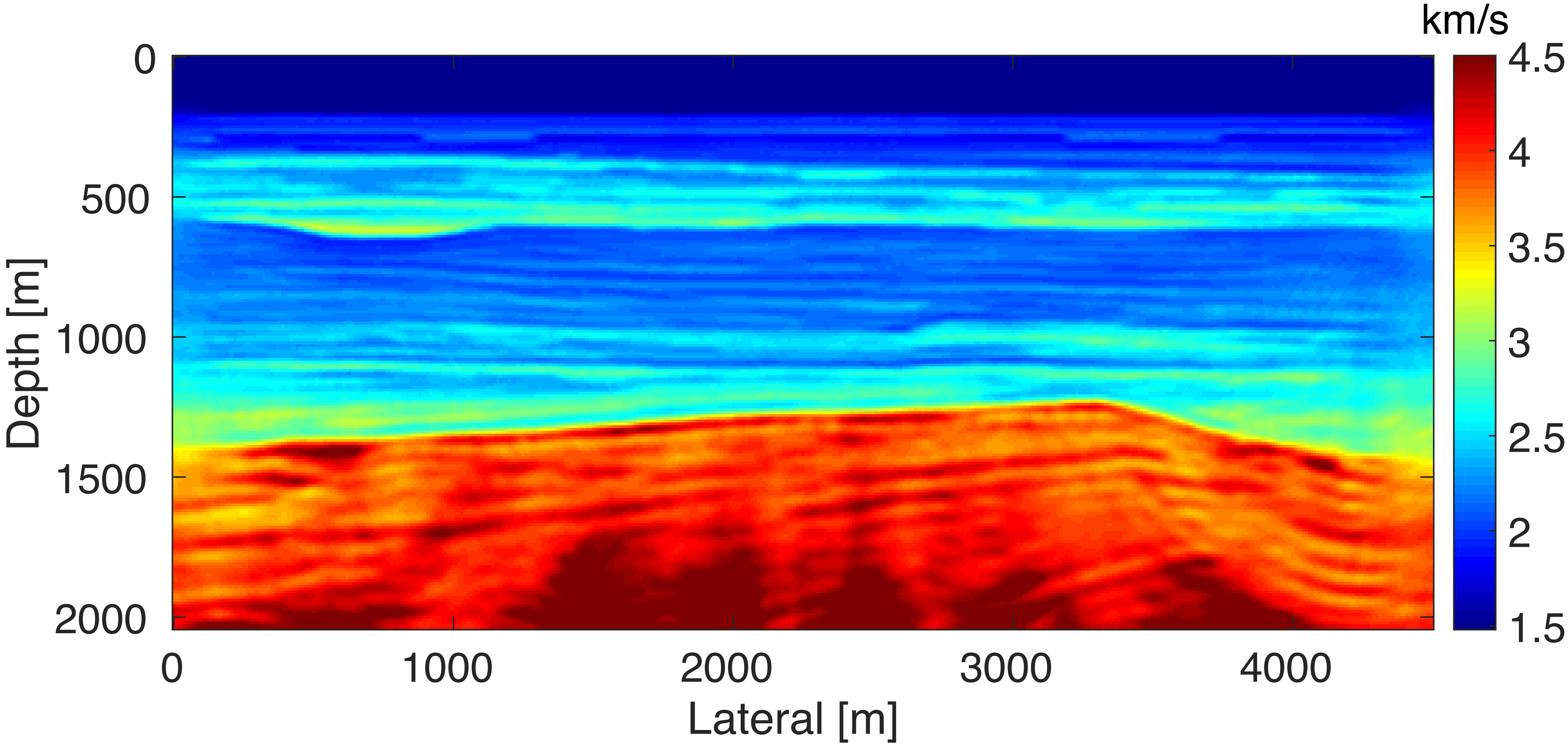
Spectrum

True model

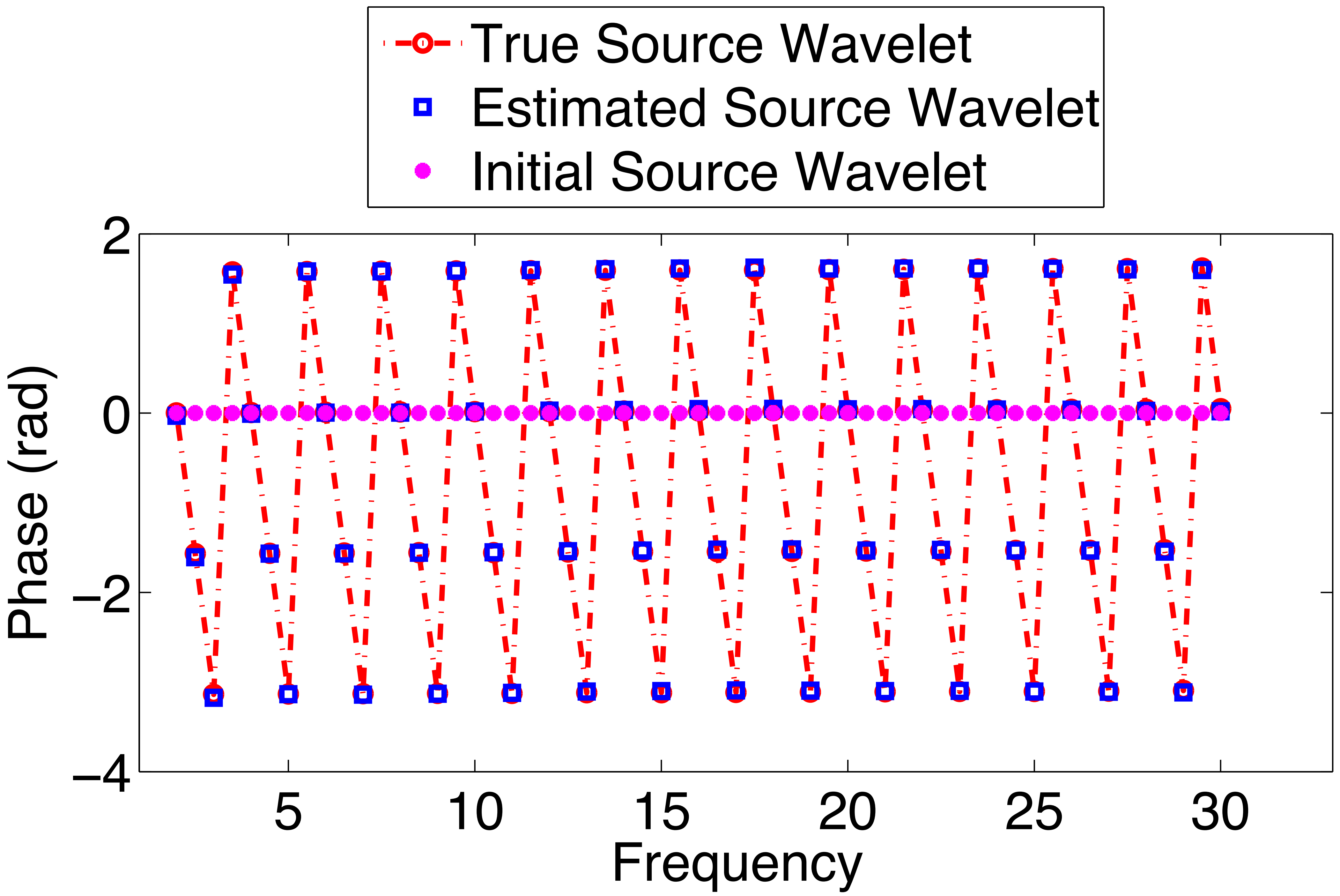


km/s
0
500
1000
1500
2000
Depth [m]
0
1000
2000
3000
4000
Lateral [m]
4.5
4
3.5
3
2.5
2
1.5

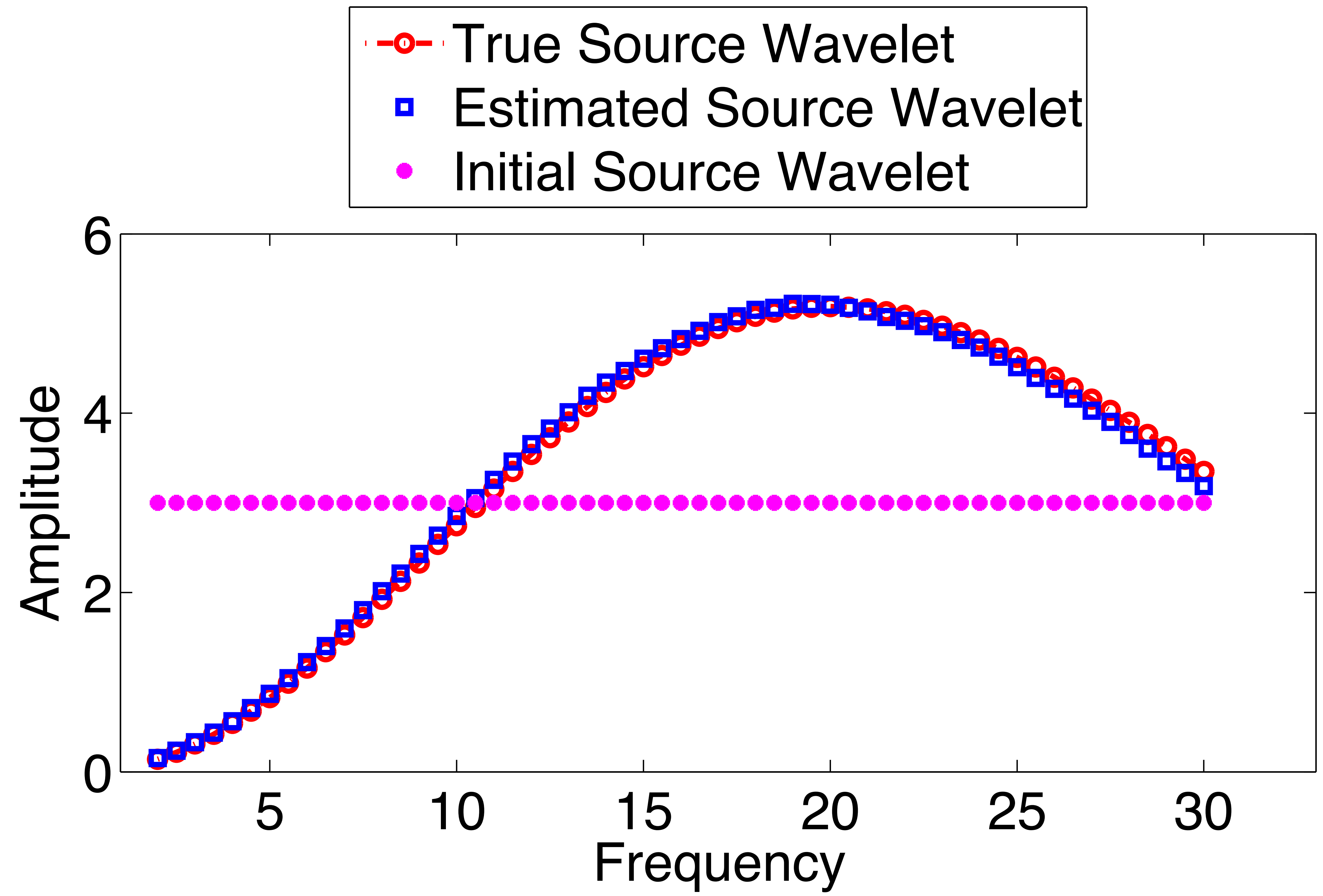
Inversion result



Source wavelet comparison

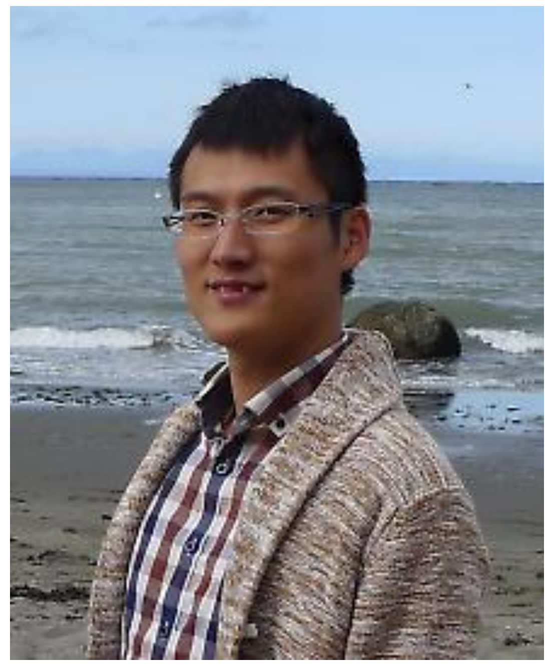


Phase

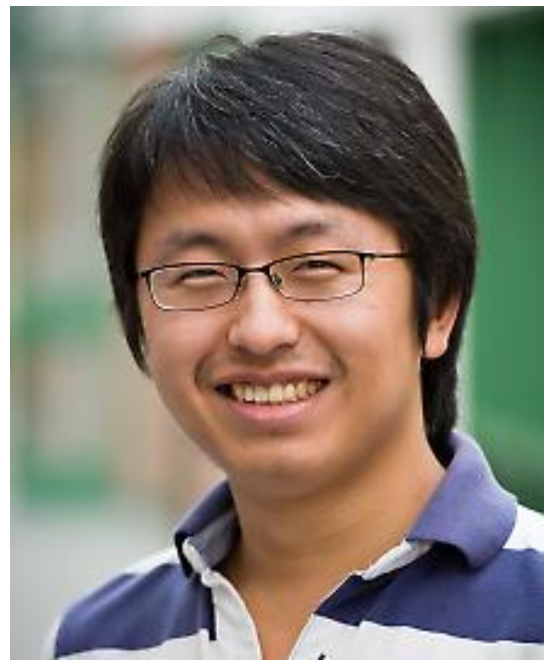


Amplitude

Chevron blind test data



Zhilong Fang



Xiang Li

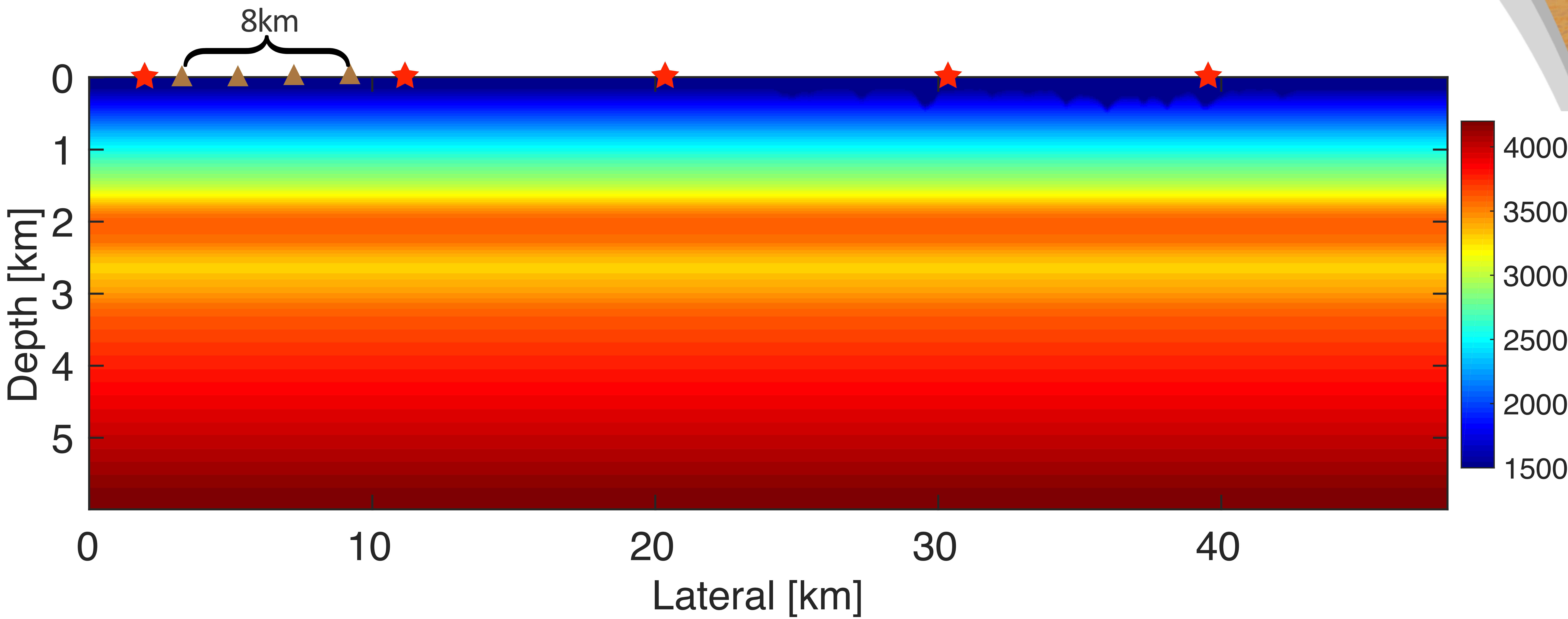
Bas Peters

Brendan Smithyman

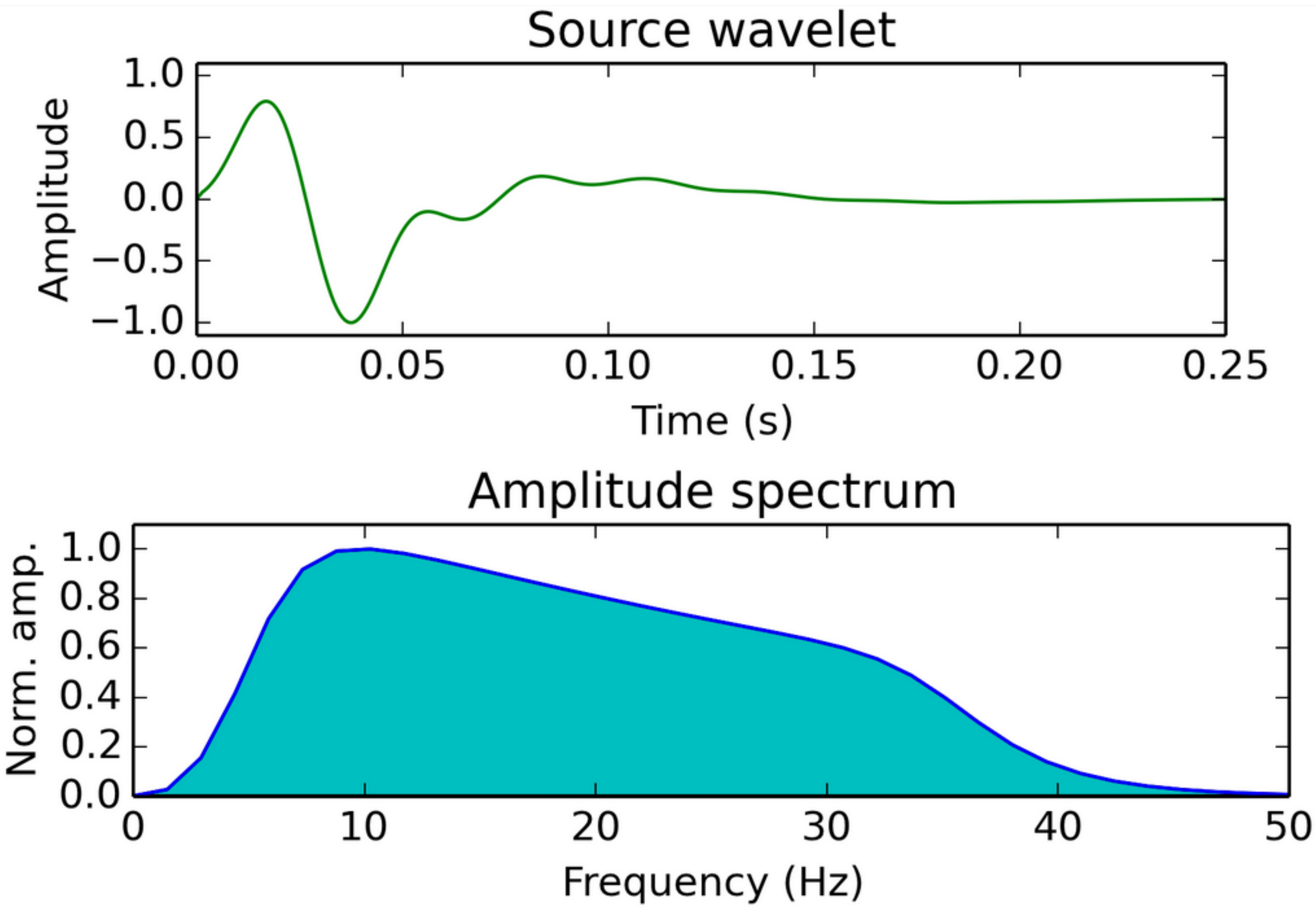
Mengmeng Yang

Felix J. Herrmann

Chevron blind test data



Chevron blind test data



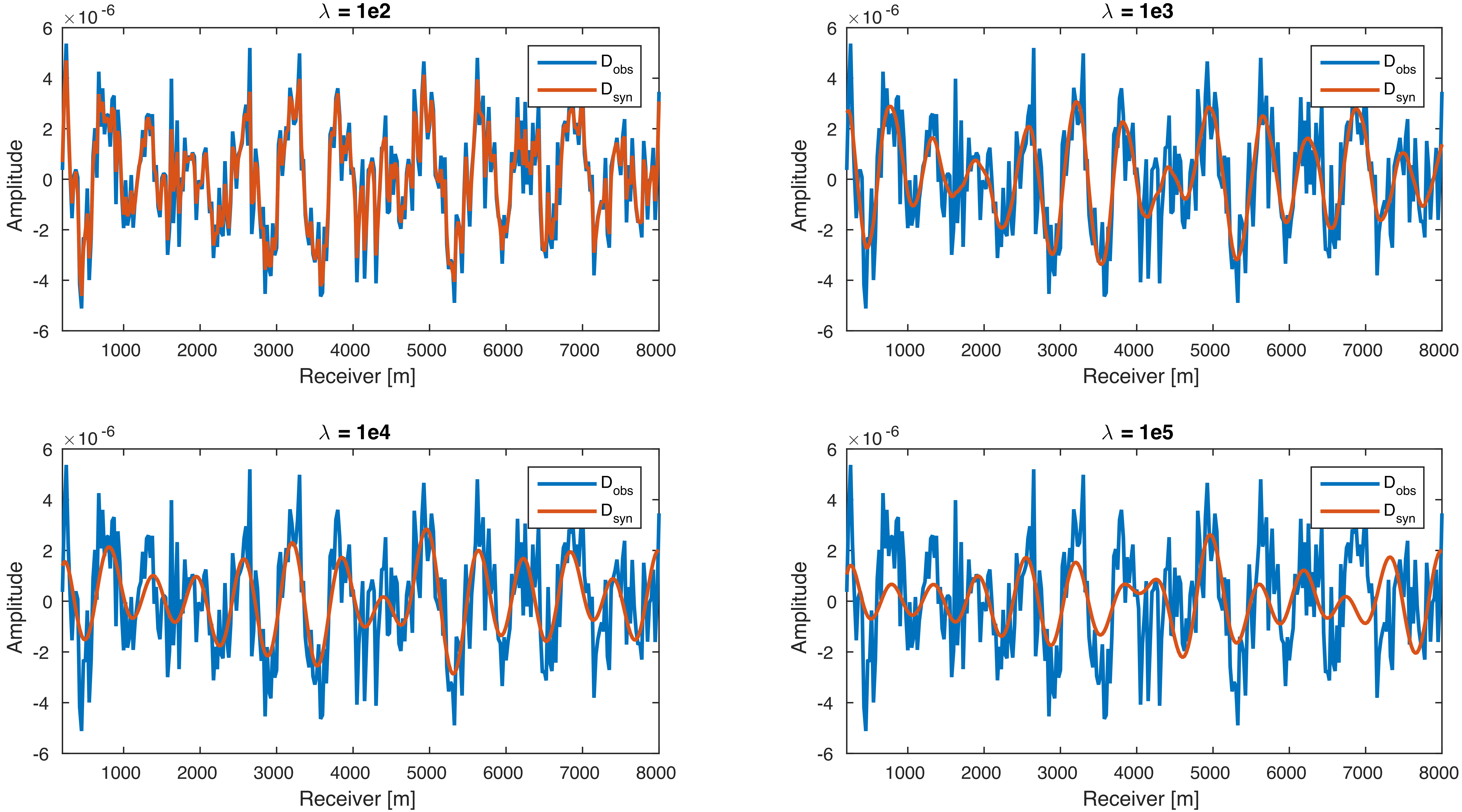
SLIM

Chevron blind test data

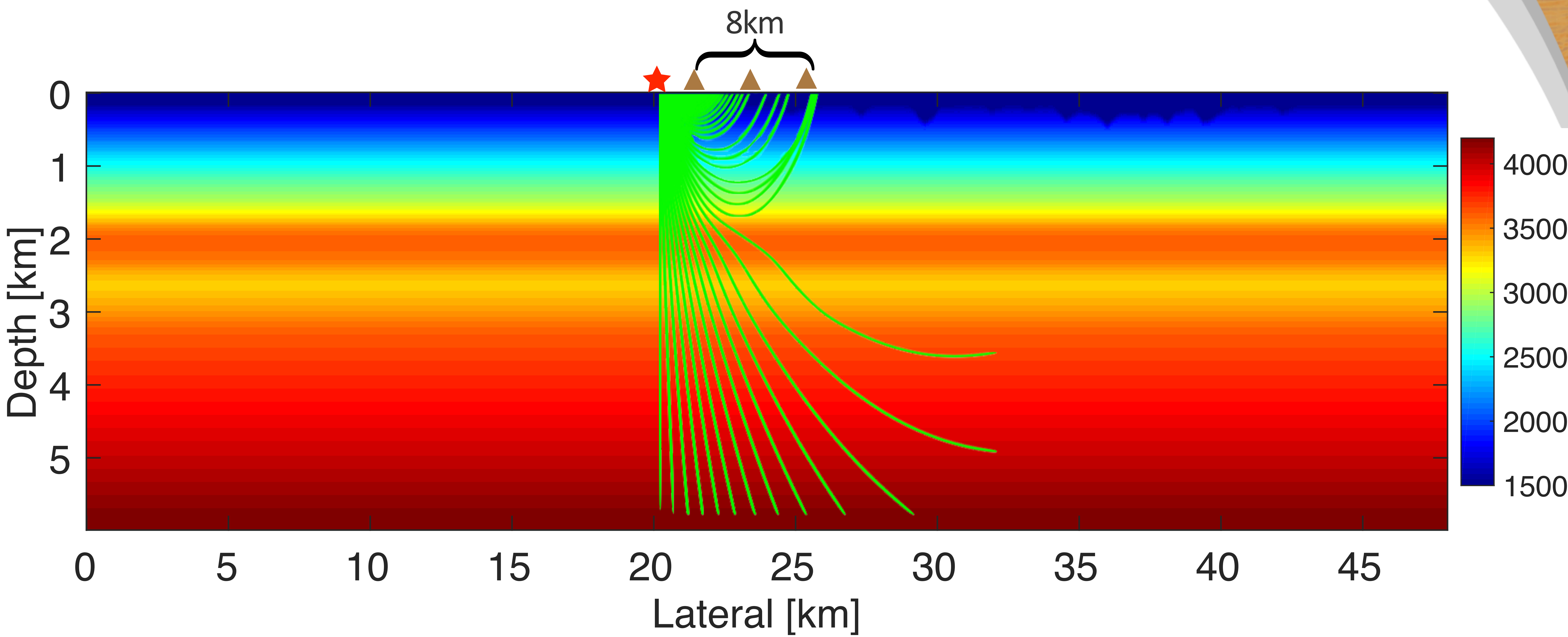
Data-set information:

1. 1600 shots: ds = 25 m, Source depth = 15 m;
2. 321 hydrophone recs/shot: dr = 25 m, Receiver depth = 15 m;
3. Maximum offset = 8000 m;
4. Record time = 8.0 s, sample rate 4 ms;
5. Vp water = constant = 1510 m/s;
6. With free surface multiples present in the data;
7. Isotropic Elastic.

Data comparison
— 3 Hz Data of 800th shot



Initial model



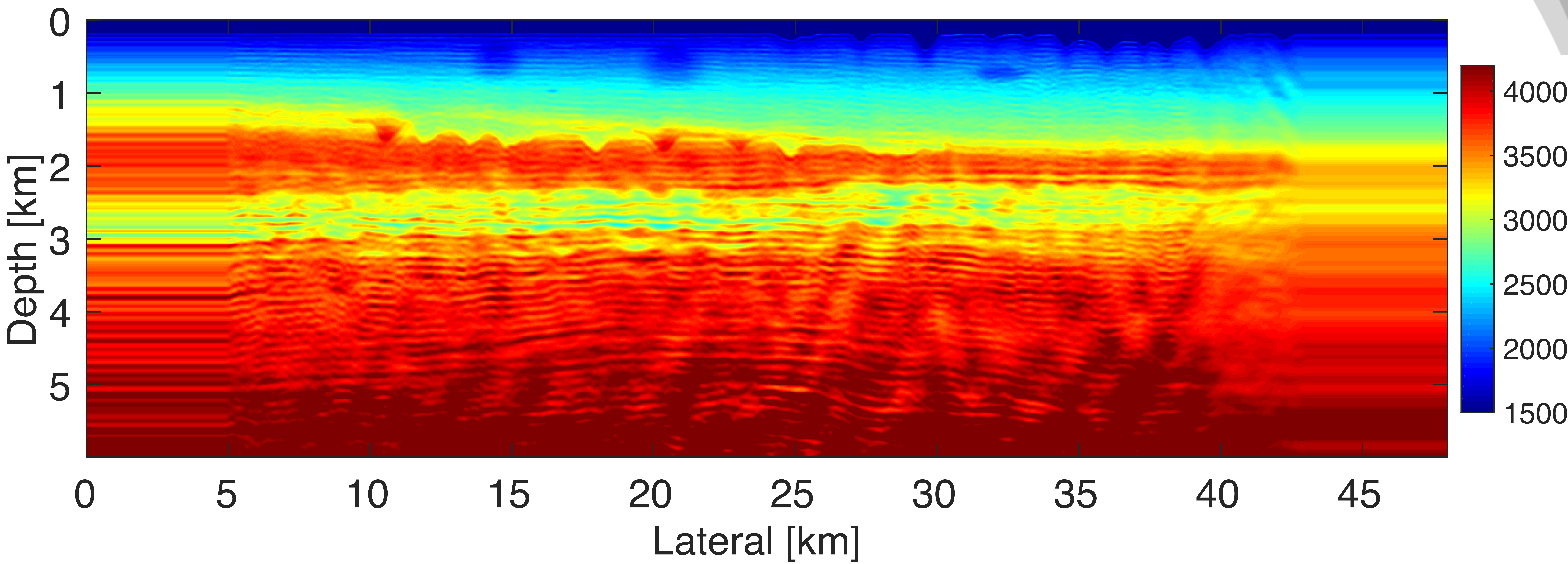
SLIM

Chevron blind test data

Inversion strategy:

1. Frequency domain WRI with Source estimation;
2. Frequency bands: [3:0.2:5]Hz, [3:0.2:7]Hz, [3:0.2:9]Hz, [3:0.2:11]Hz, [3:0.2:15]Hz;
3. Batch sizes of random frequency subsets: 3, 6, 10, 10, 15;
4. Batch size of random source subsets: 300;
5. Optimization solver: l-BFGS with 20 iterations per frequency band;
6. 4 passes of WRI at frequency 3-11 Hz and 1 pass to 15 Hz;
7. Grid size: 20m for 3-11Hz and 12m for 3-15Hz;
8. No pre-processing !!!

Inversion result



WRI with minimum smoothness constraint

$$\underset{\mathbf{u}(\mathbf{m}),\mathbf{m},\alpha(\mathbf{m})}{\text{minimize}} \sum_{k,l} \|\mathbf{P}_k \mathbf{u}_{k,l} - \mathbf{d}_{k,l}\|_2^2 + \lambda^2 \|\mathbf{A}_{k,l}(\mathbf{m})\mathbf{u}_{k,l} - \alpha_{k,l}\mathbf{e}_{k,l}\|_2^2$$

SLIM

WRI with minimum smoothness constraint

$$\underset{\mathbf{u}(\mathbf{m}),\mathbf{m},\alpha(\mathbf{m})}{\text{minimize}} \sum_{k,l} \|\mathbf{P}_k \mathbf{u}_{k,l} - \mathbf{d}_{k,l}\|_2^2 + \lambda^2 \|\mathbf{A}_{k,l}(\mathbf{m})\mathbf{u}_{k,l} - \alpha_{k,l}\mathbf{e}_{k,l}\|_2^2$$

$$\text{suject to} \quad \mathbf{m} \in \mathcal{C}_1 \bigcap \mathcal{C}_2$$

$$\mathcal{C}_1 \equiv \{\mathbf{m} \mid \mathbf{b}_l \leq \mathbf{m} \leq \mathbf{b}_u\}$$

$$\mathcal{C}_2 \equiv \{\mathbf{m} \mid E^* F^* (I - S) F E \mathbf{m} = 0\}$$

[B. Smithyman, et al 2015]

SLIM

WRI with minimum smoothness constraint

$$\underset{\mathbf{u}(\mathbf{m}),\mathbf{m},\alpha(\mathbf{m})}{\text{minimize}} \sum_{k,l} \|\mathbf{P}_k \mathbf{u}_{k,l} - \mathbf{d}_{k,l}\|_2^2 + \lambda^2 \|\mathbf{A}_{k,l}(\mathbf{m})\mathbf{u}_{k,l} - \alpha_{k,l}\mathbf{e}_{k,l}\|_2^2$$

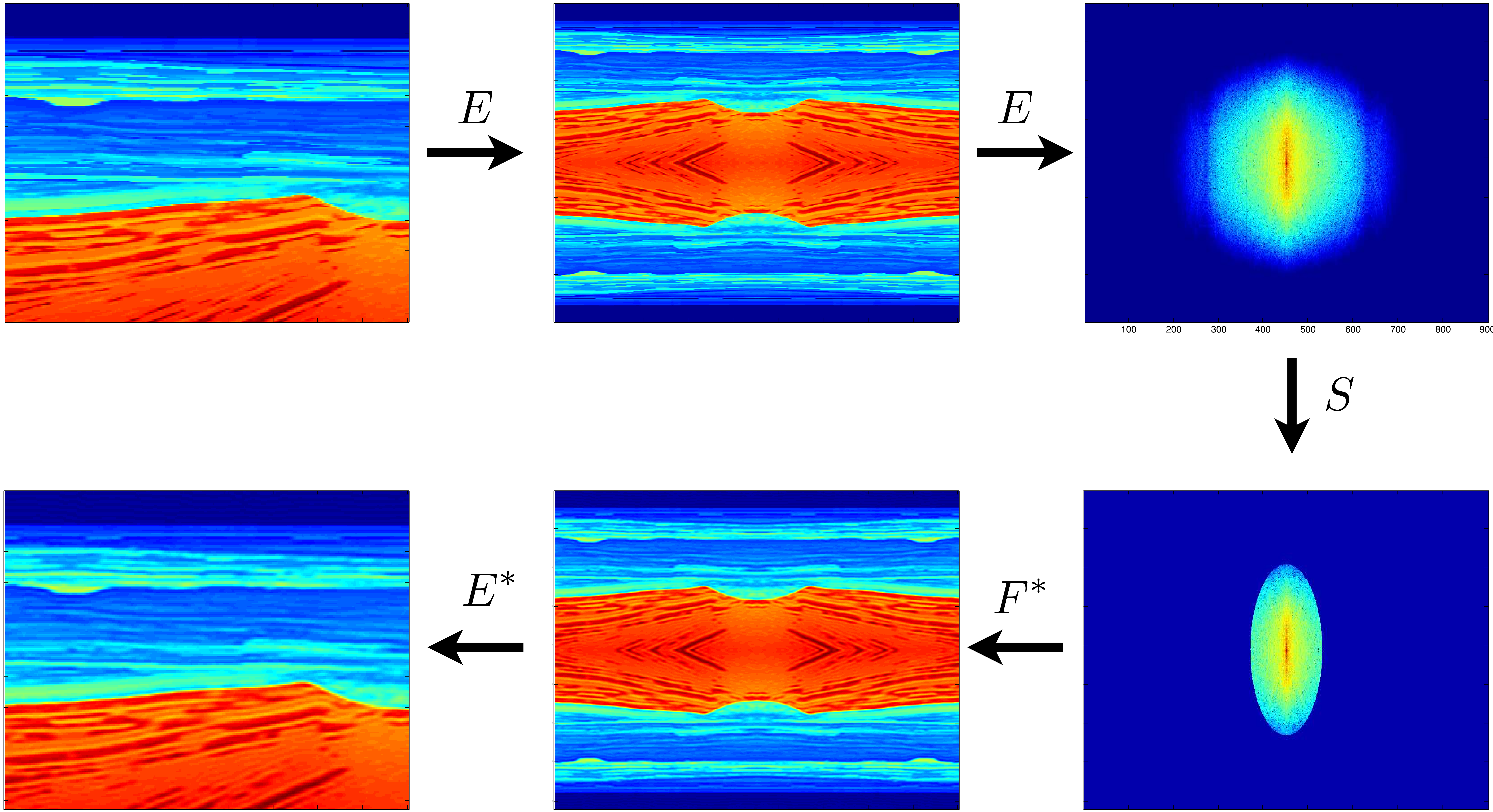
$$\text{suject to} \quad \mathbf{m} \in \mathcal{C}_1 \bigcap \mathcal{C}_2$$

$$\mathcal{C}_1 \equiv \{\mathbf{m} \mid \mathbf{b}_l \leq \mathbf{m} \leq \mathbf{b}_u\}$$

$$\mathcal{C}_2 \equiv \{\mathbf{m} \mid E^* F^* (I - S) F E \mathbf{m} = 0\}$$

1. 2D mirror extension of the model (to avoid periodic boundaries)
2. 2D DFT
3. Remove coefficients outside ellipse (highest spatial frequencies)
4. 2D inverse DFT

WRI with minimum smoothness constraint

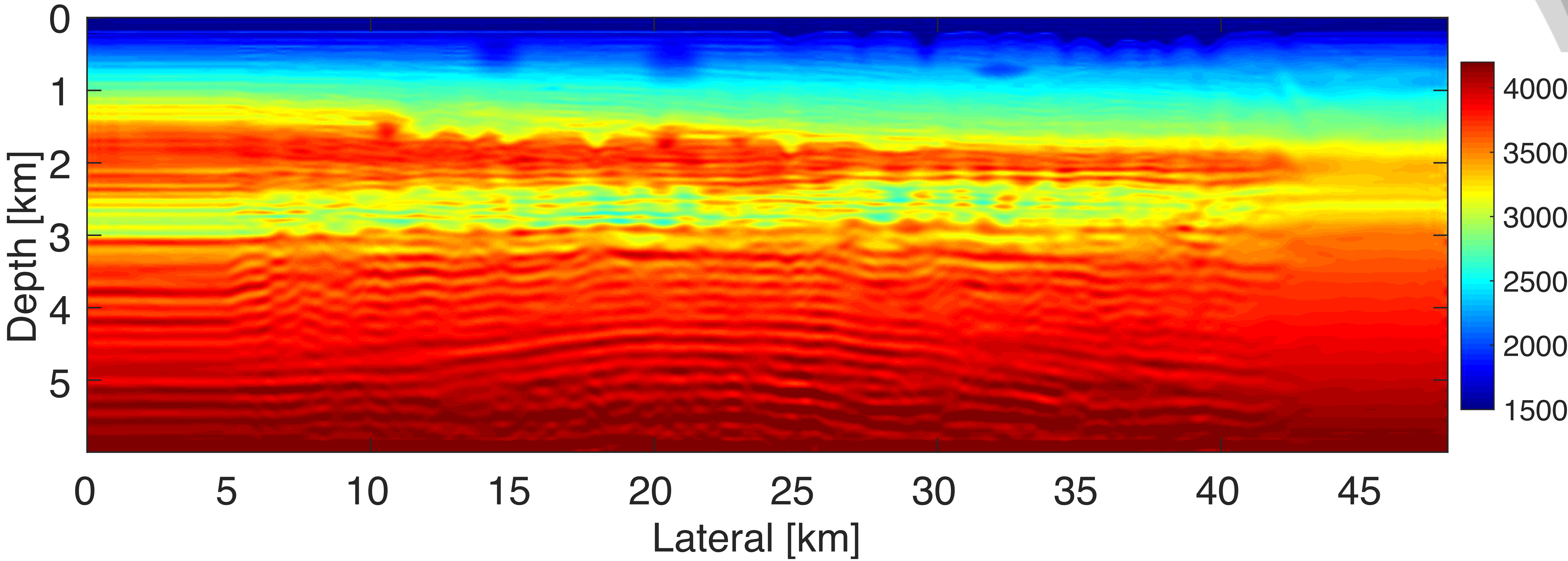


Chevron blind test data

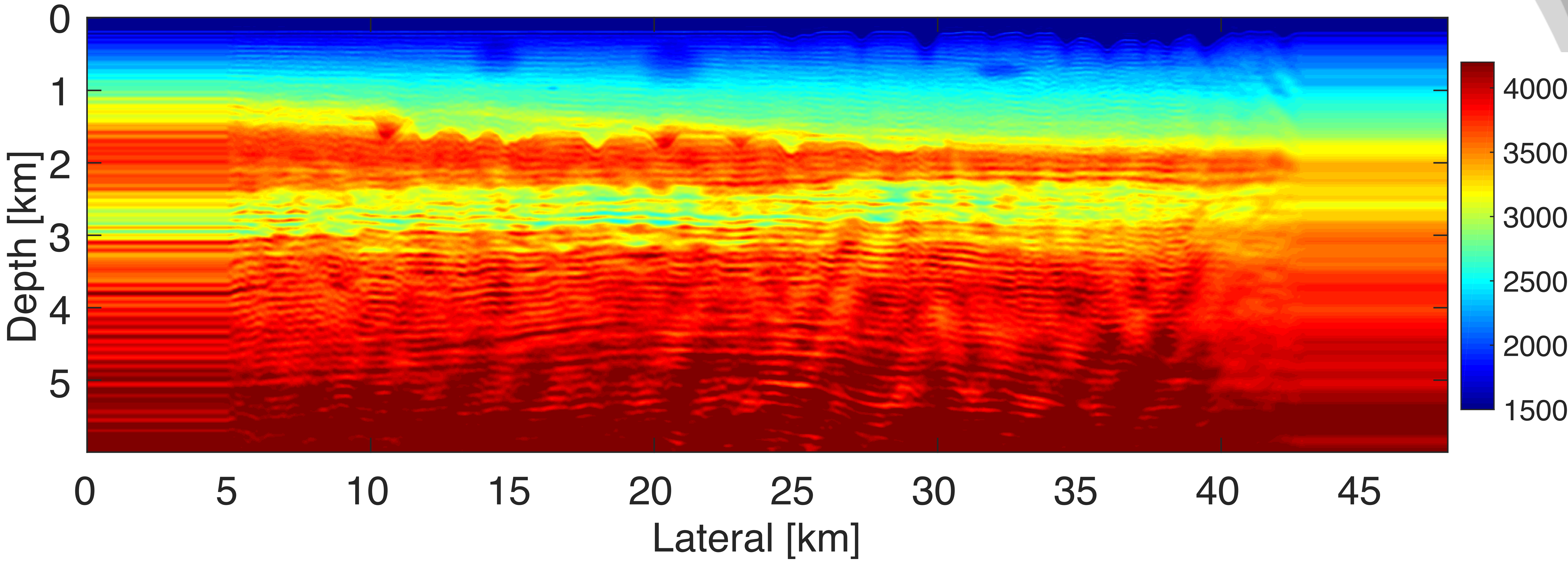
Inversion strategy:

1. Frequency domain WRI with Source estimation and smoothness constraint;
2. Frequency bands: [3:0.2:5]Hz, [3:0.2:7]Hz, [3:0.2:9]Hz, [3:0.2:11]Hz;
3. Batch sizes of random frequency subsets: 3, 6, 10, 10;
4. Batch size of random source subsets: 300;
5. Optimization solver: PQN with 20 iterations per frequency band;
6. 2passes of WRI from frequency 3-11 Hz;
7. Grid size: 20m;
8. No pre-processing !!!

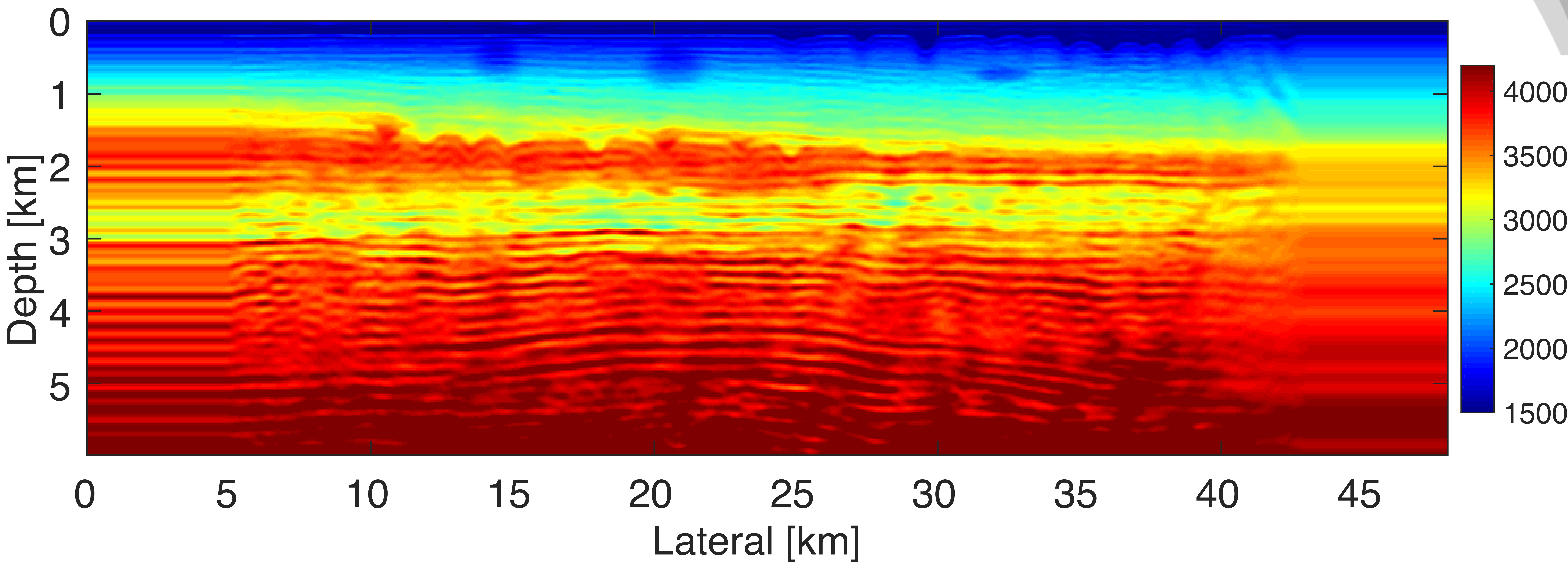
Inversion result



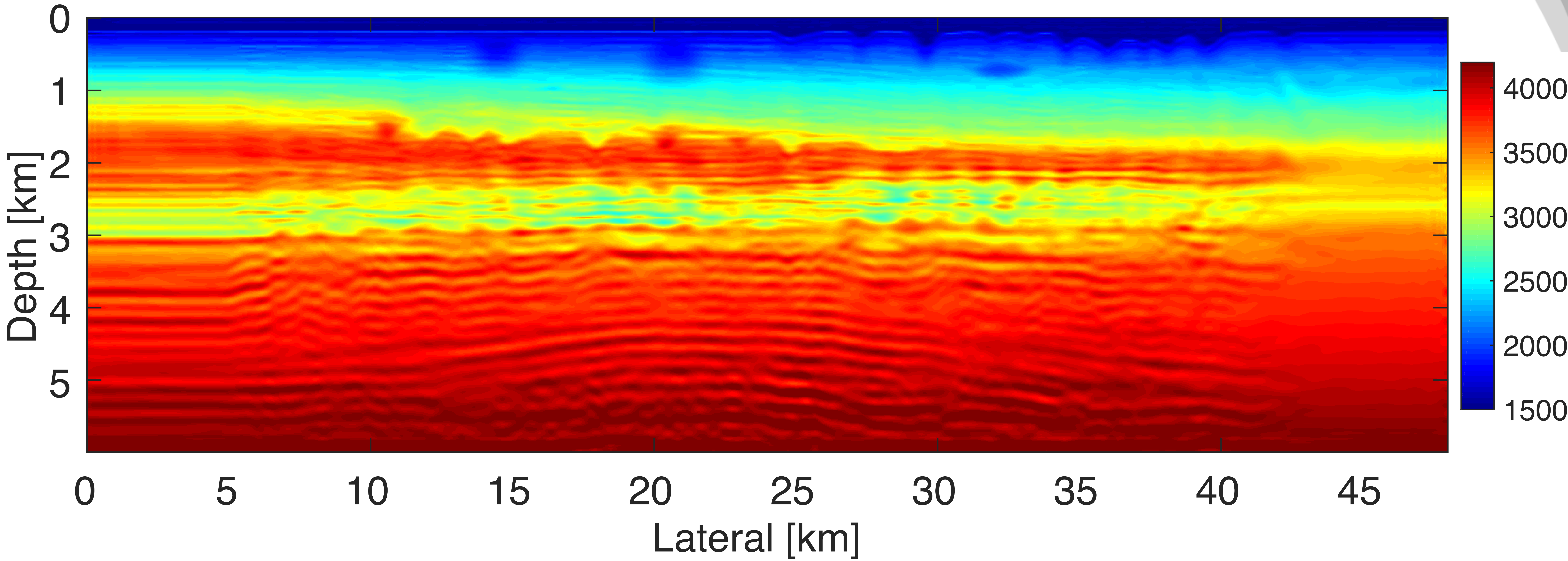
Inversion result (presented in EAGE 2015)



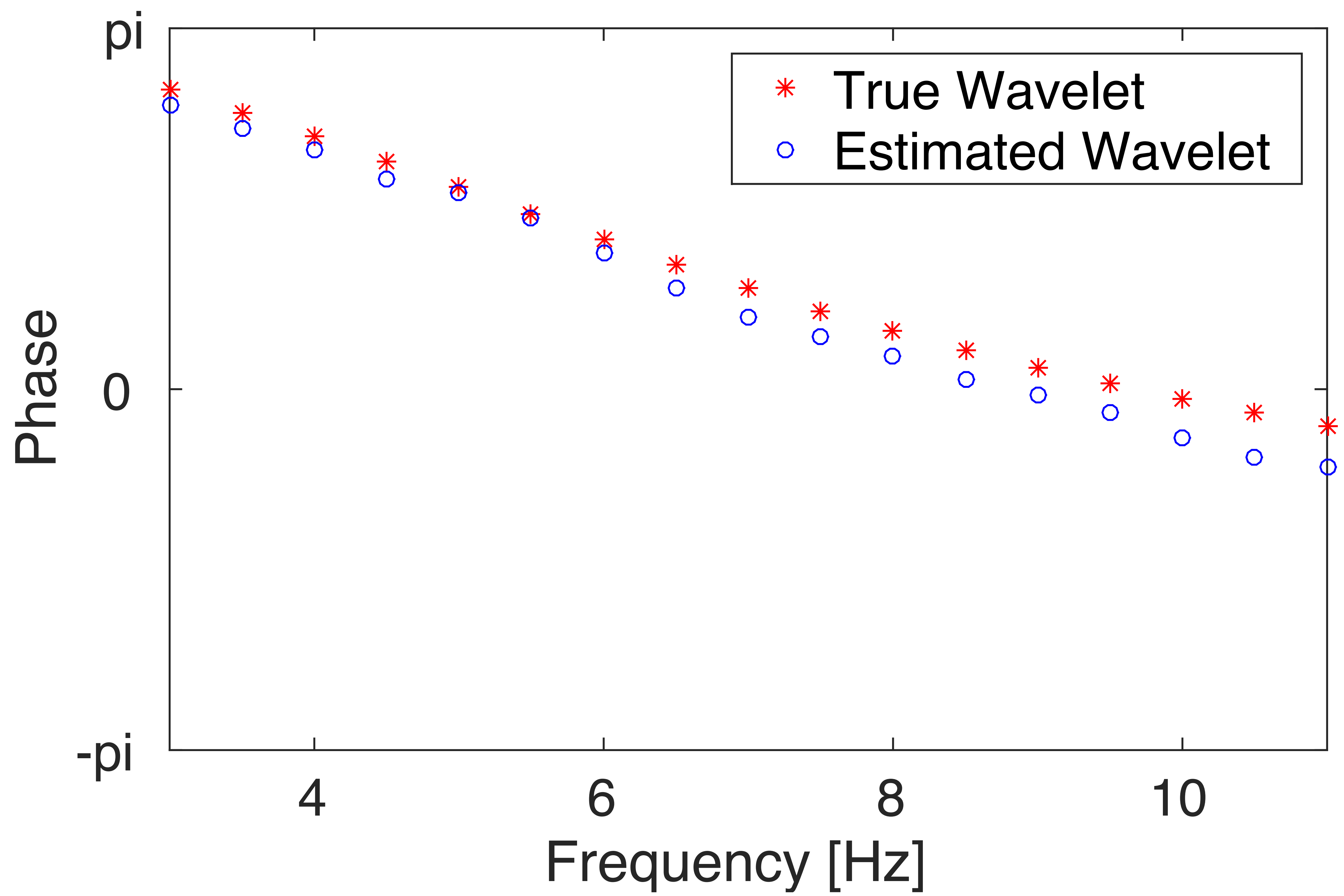
Inversion result
(without minimum smoothness constraint)



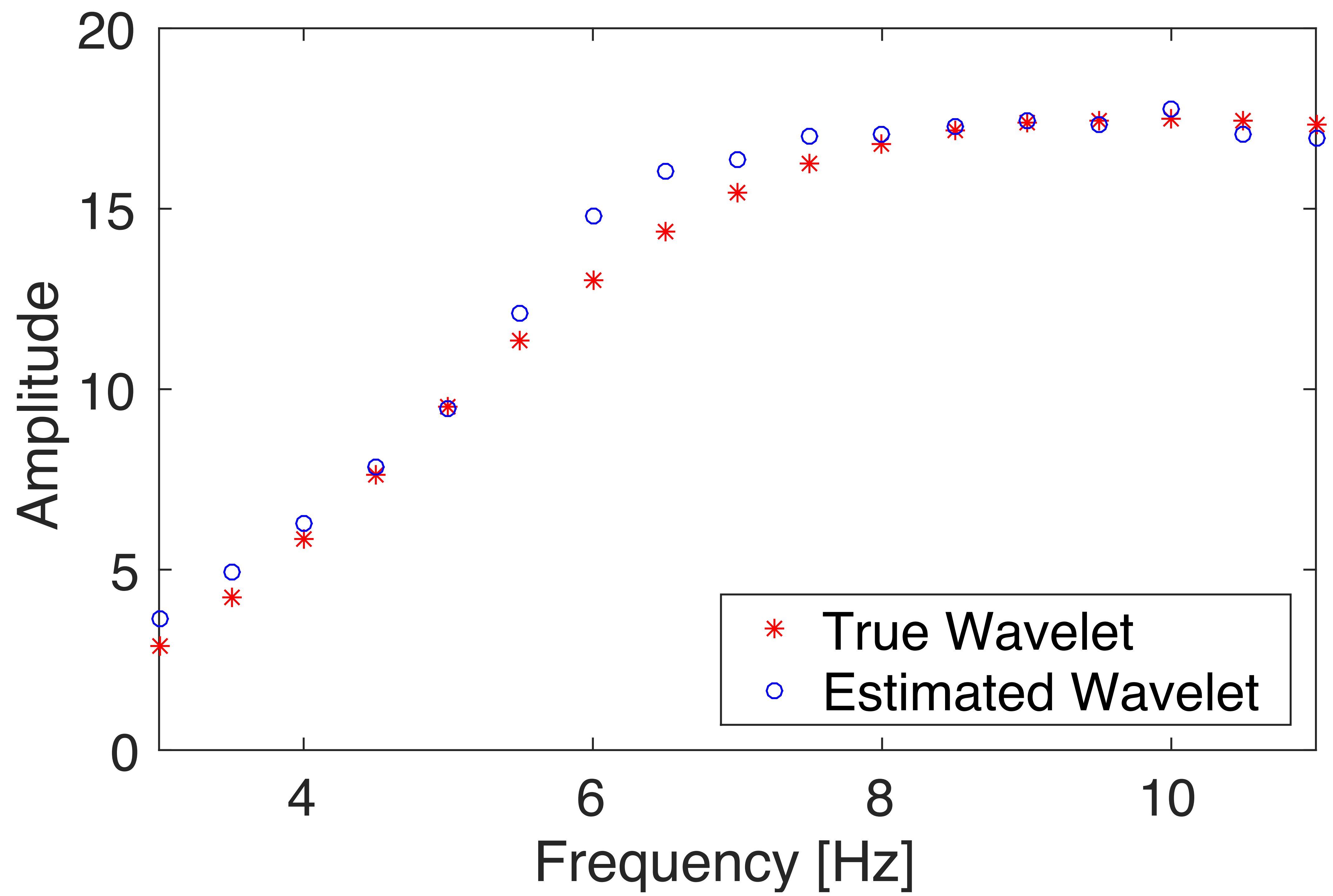
Inversion result (with minimum smoothness constraint)



Source wavelet comparison

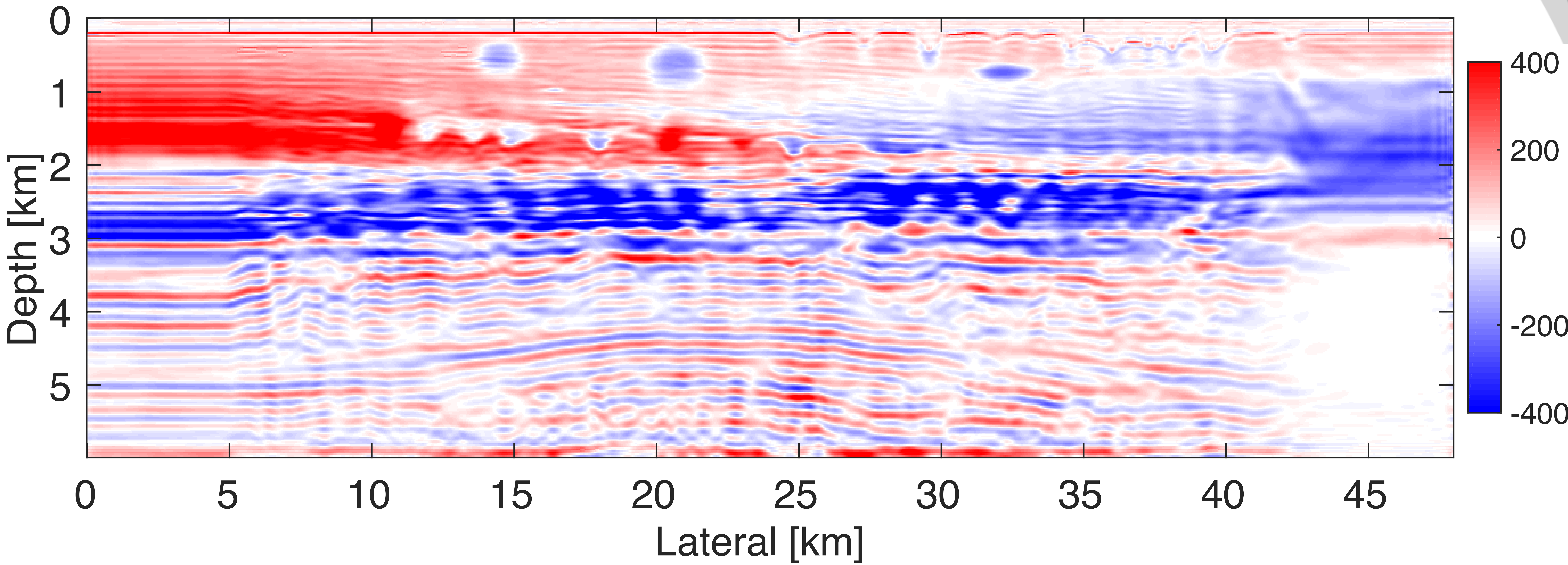


Phase

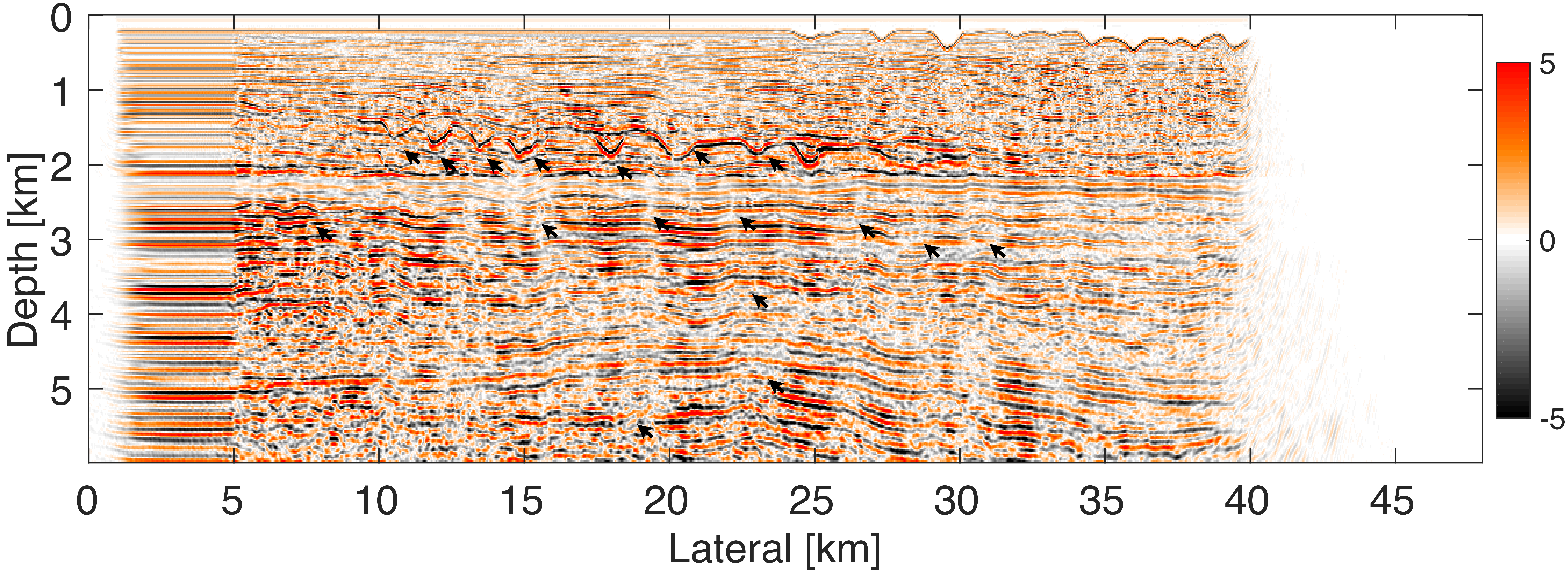


Amplitude

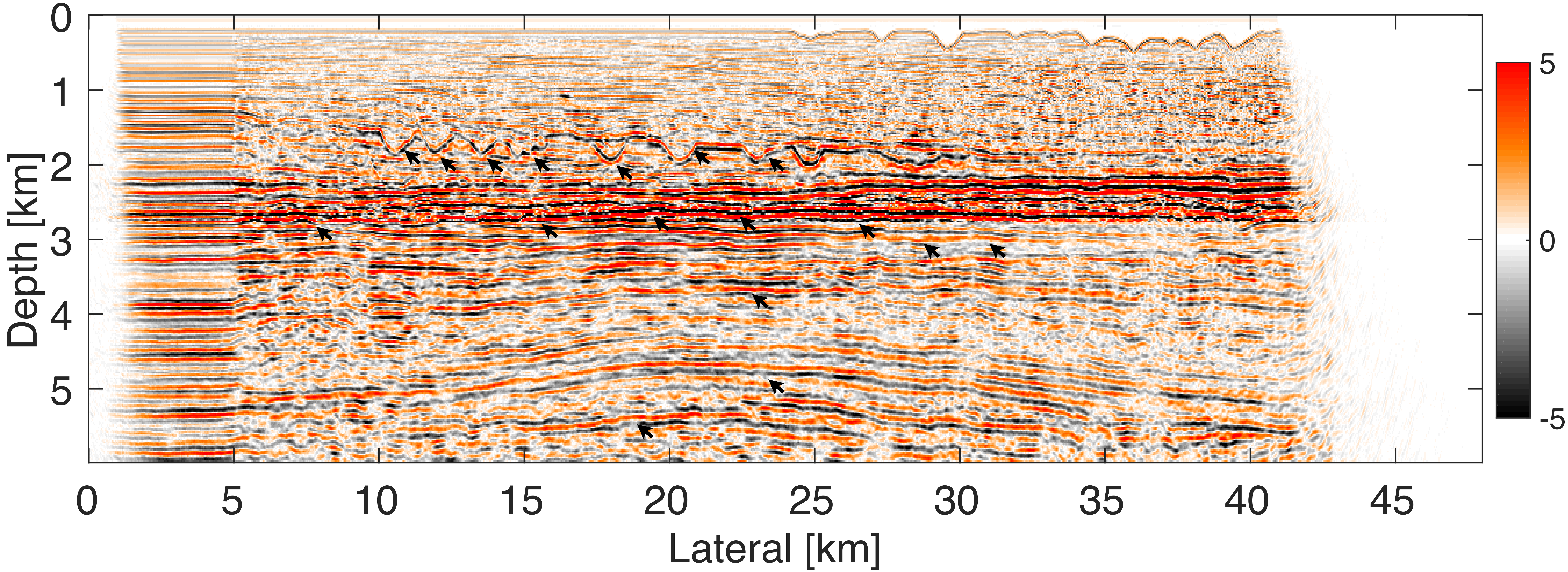
Model update



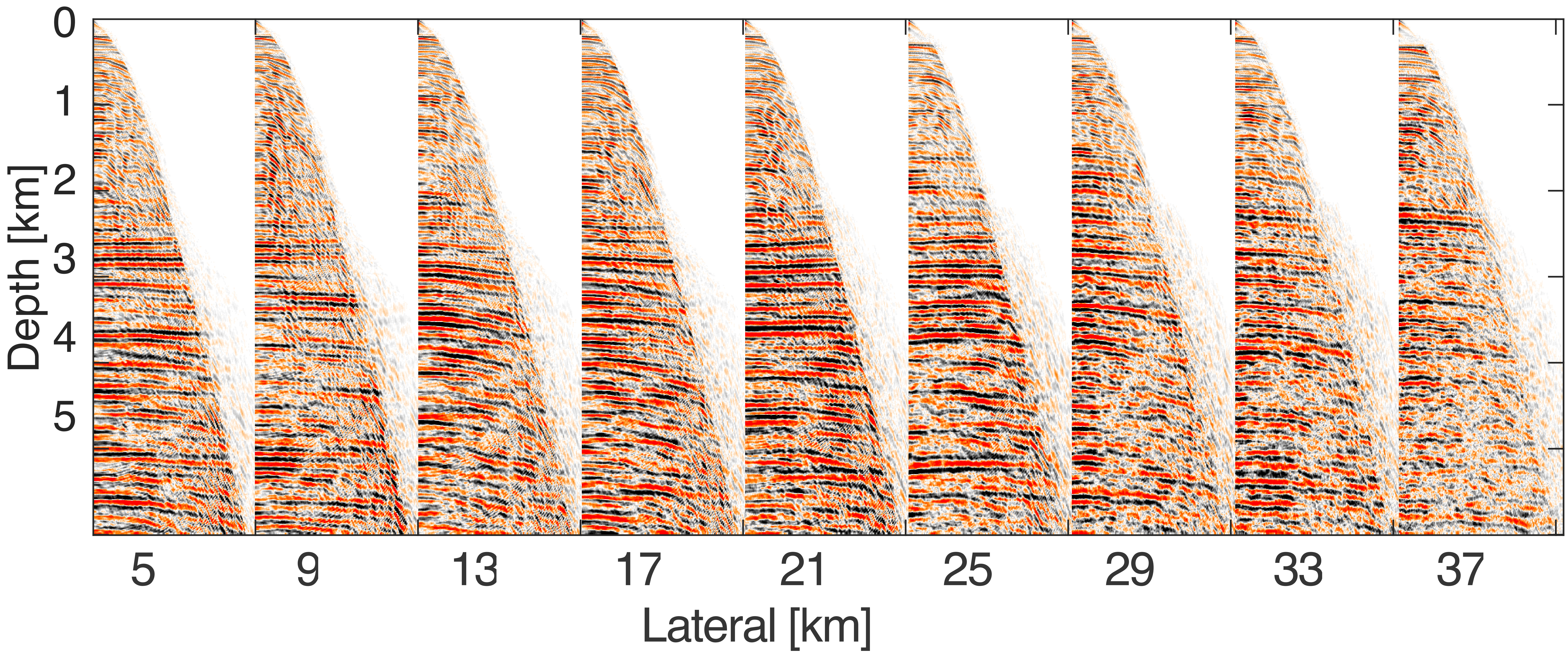
Kirchhoff migration
—Initial model



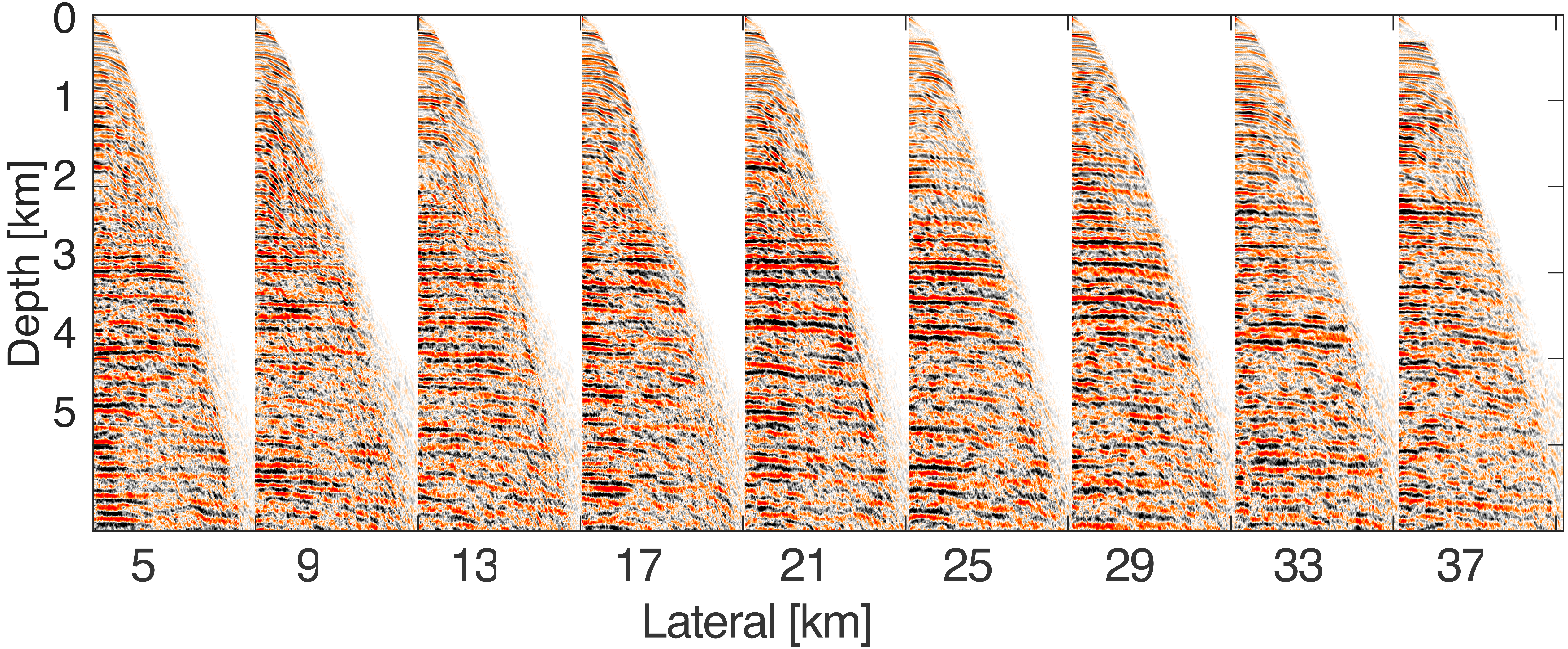
Kirchhoff migration
—Inversion result



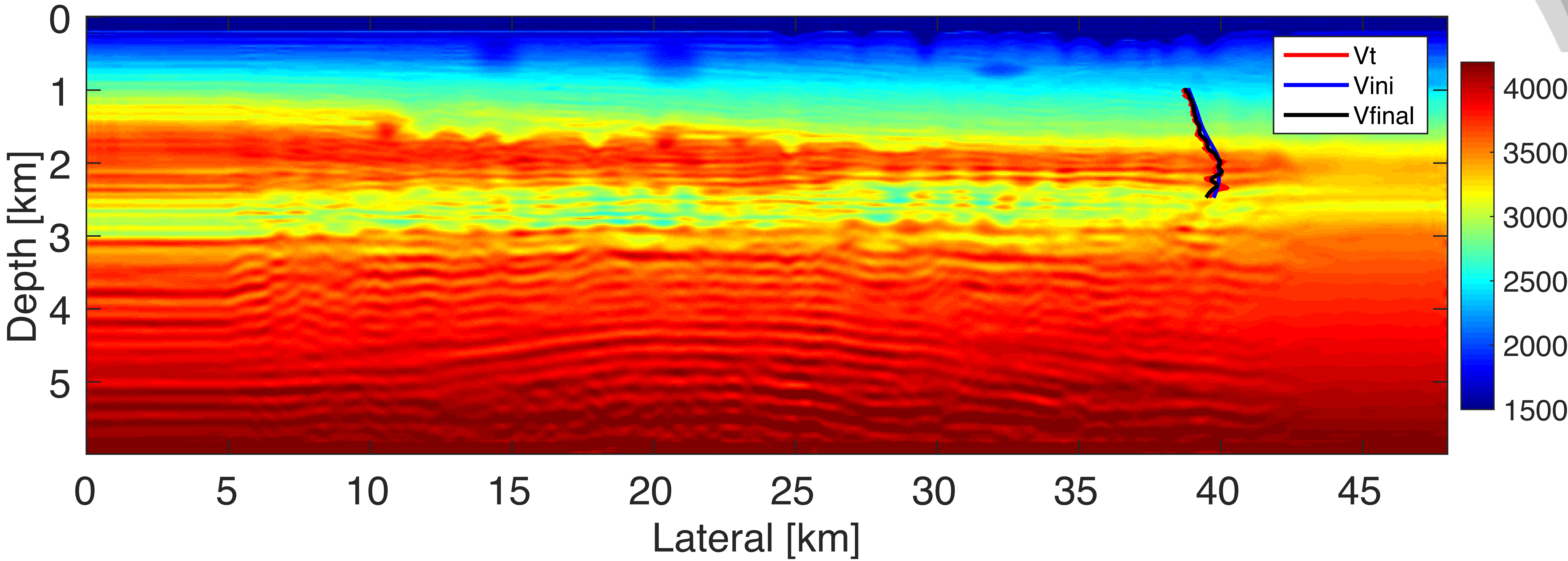
Common Image Gather
—Initial model



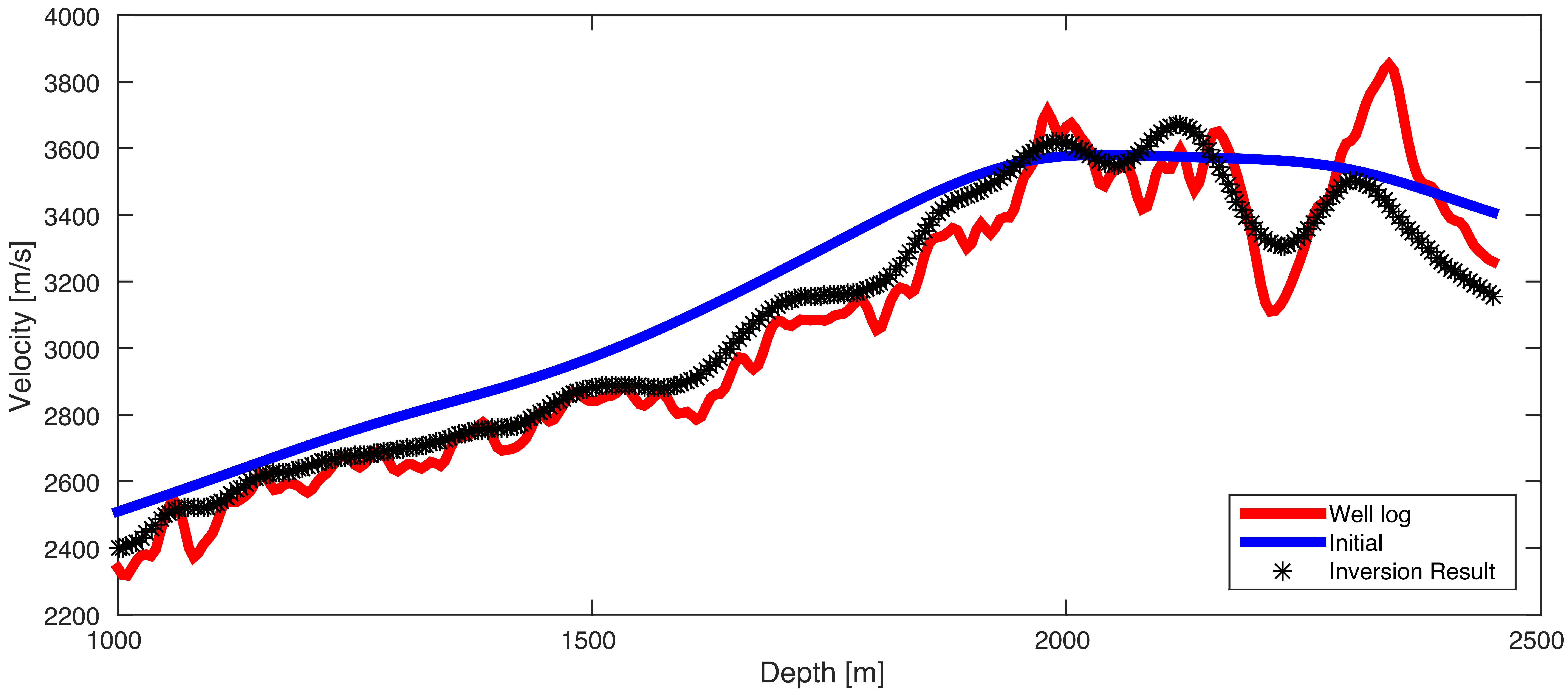
Common Image Gather
—Inversion result



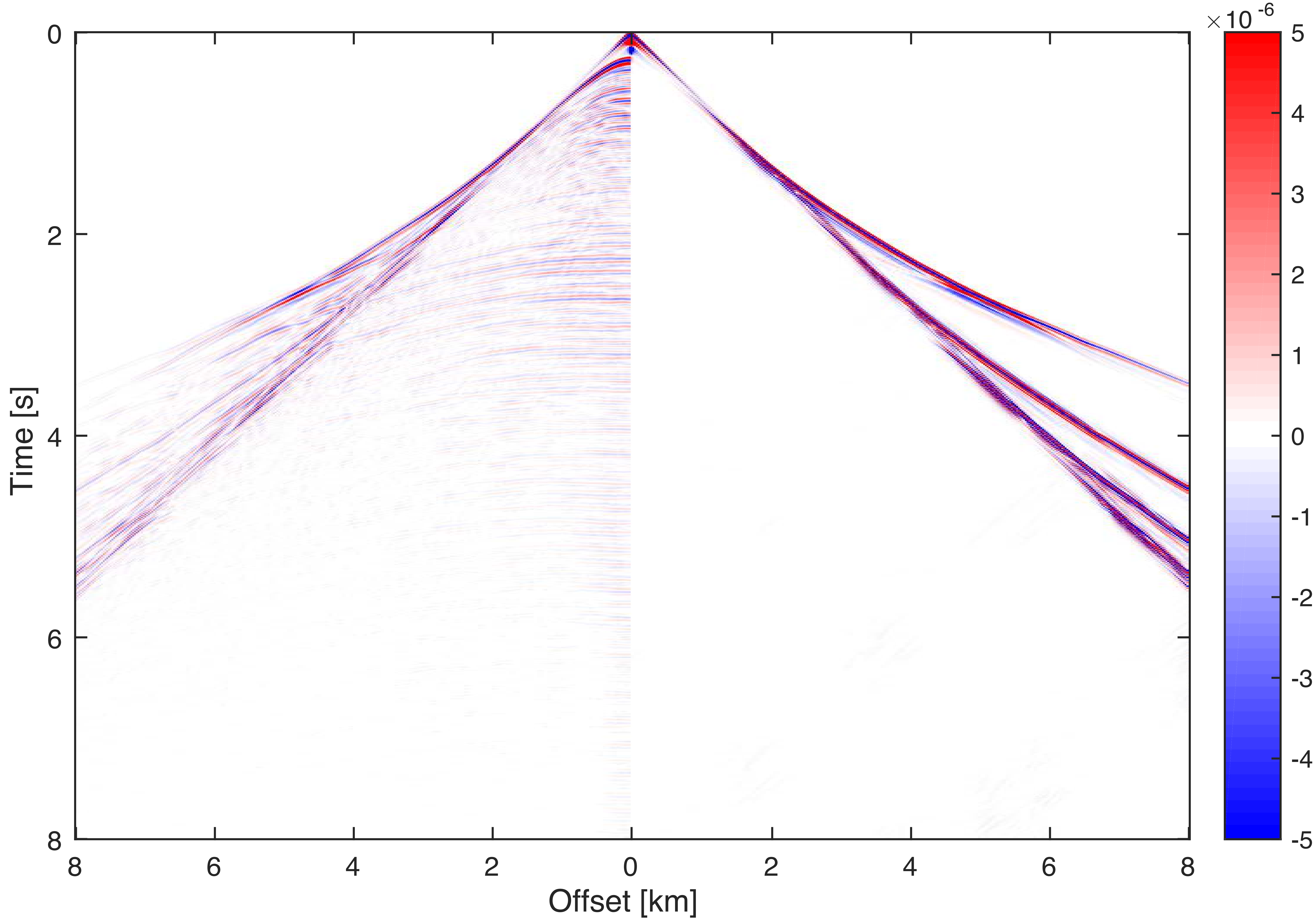
Well-log comparison



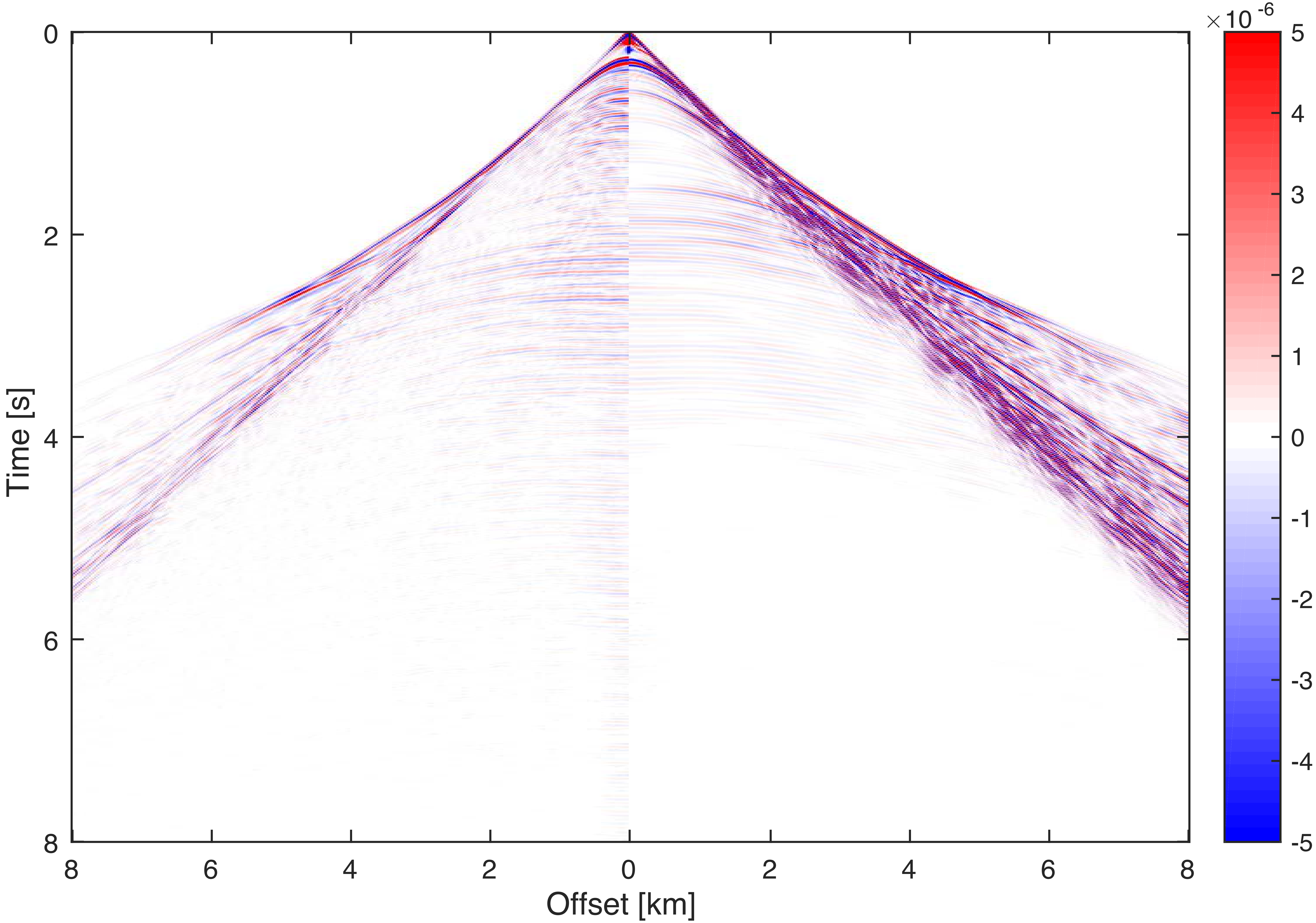
Well-log comparison



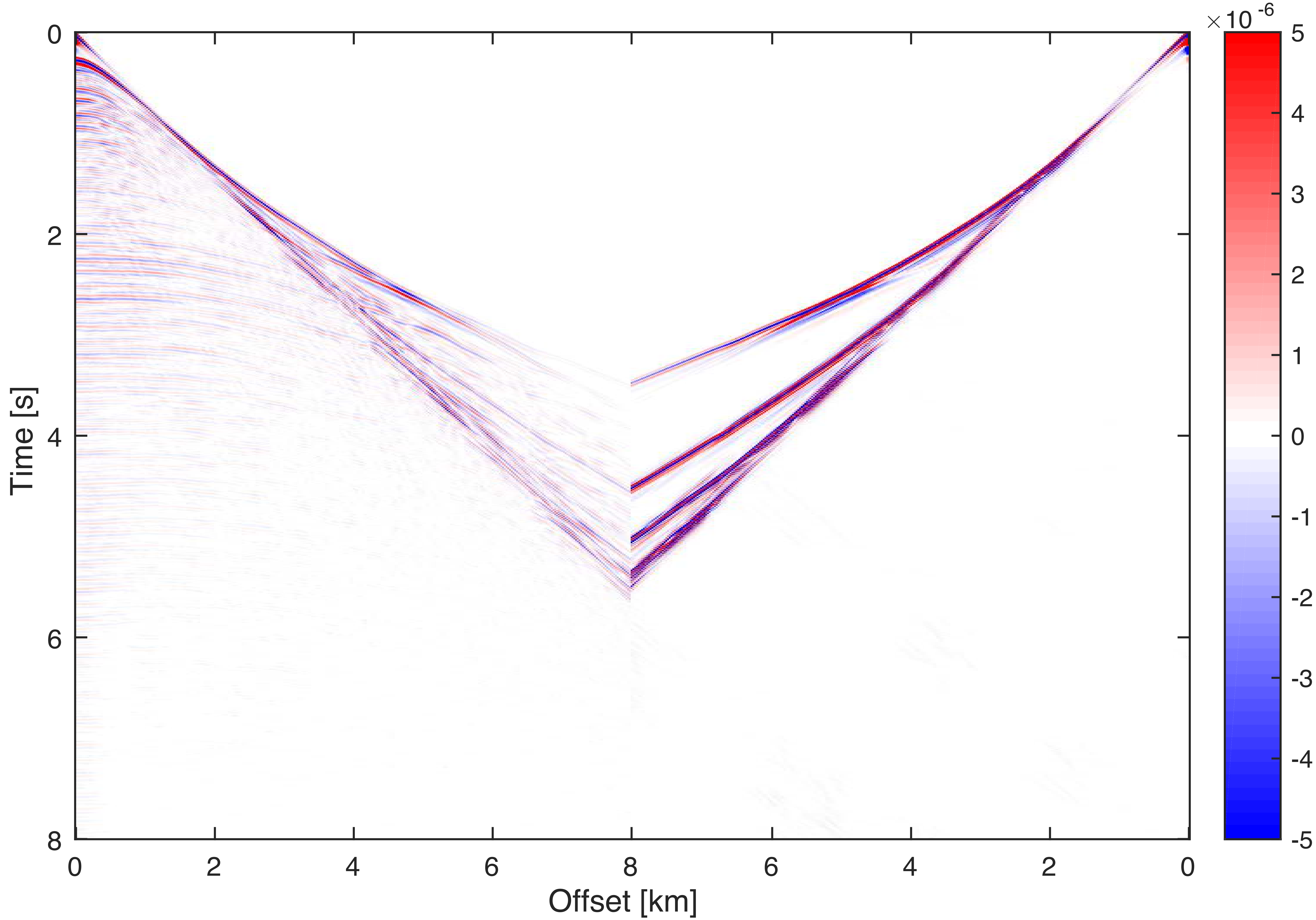
Shot record comparison—— Initial model



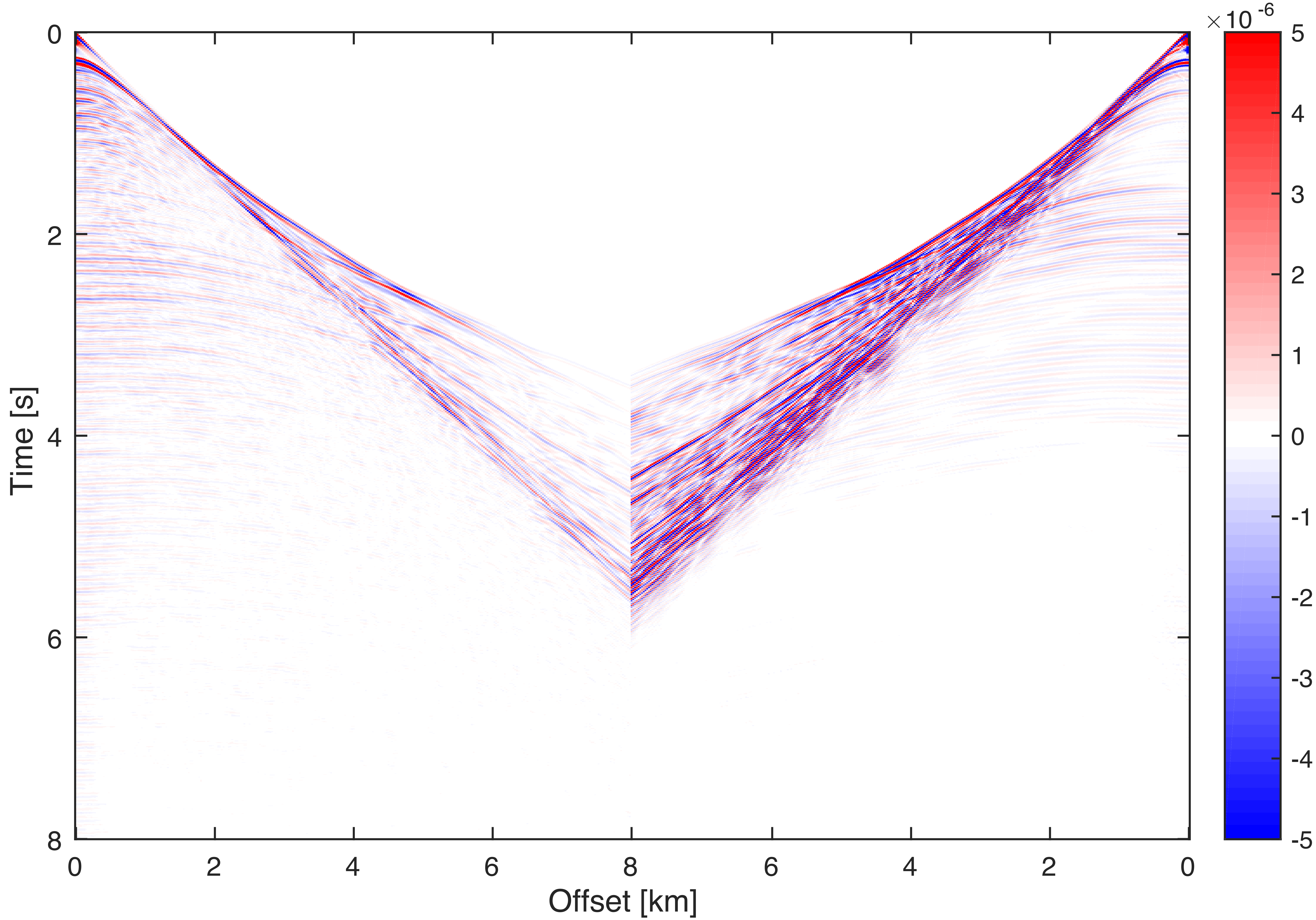
Shot record comparison—— Inversion result



Shot record comparison—— Initial model



Shot record comparison—— Inversion result



SLIM

Conclusions

1. Using the variable projection method, we can estimate the source wavelet for the WRI.
    - Synthetic BG model

2. Source estimation enhances the robustness of WRI for field seismic data.
    - Chevron blind test data

3.Minimum smoothness constraint can remove artifacts in the inversion result and improve its quality.

SLIM

Future work

1. Use other constraint such as minimum L1 norm and TV norm constraint.

2. Study the effect of different λ to the final result.

Acknowledgements

Thank you for your attention !!

SINBAD

NSERC CRSNG

This work was in part financially supported by the Natural Sciences and Engineering Research Council of Canada via the Collaborative Research and Development Grant DNOISEII (375142--08). This research was carried out as part of the SINBAD II project which is supported by the following organizations: BG Group, BGP, CGG, Chevron, ConocoPhillips, DownUnder GeoSolutions, Hess, Petrobras, PGS, Schlumberger, Sub Salt Solutions and Woodside