

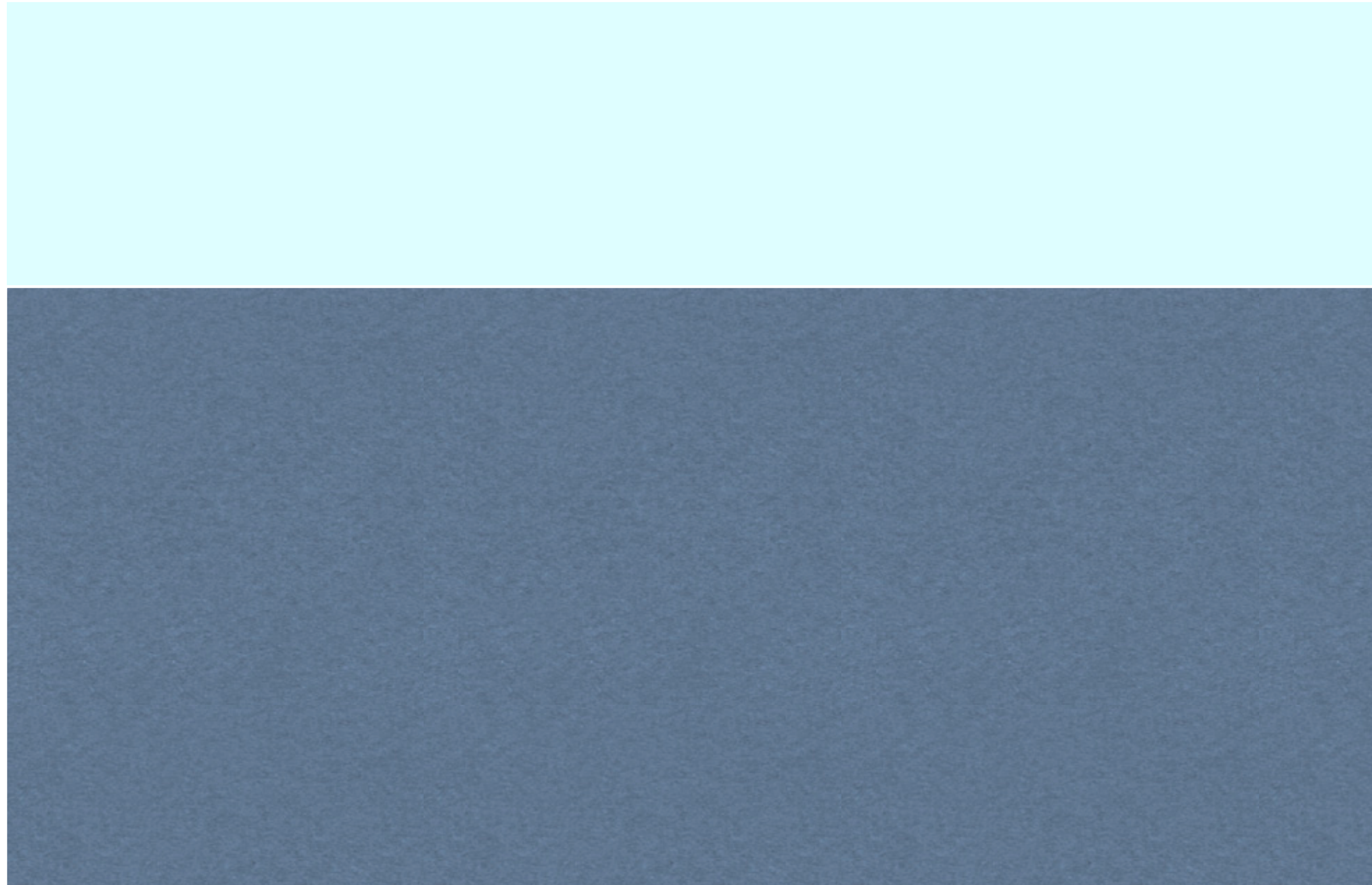
Sparsity-promoting joint microseismic source collocation and source-time function estimation

Shashin Sharan, Rongrong Wang, Tristan van Leeuwen and Felix J. Herrmann

SEG 2016

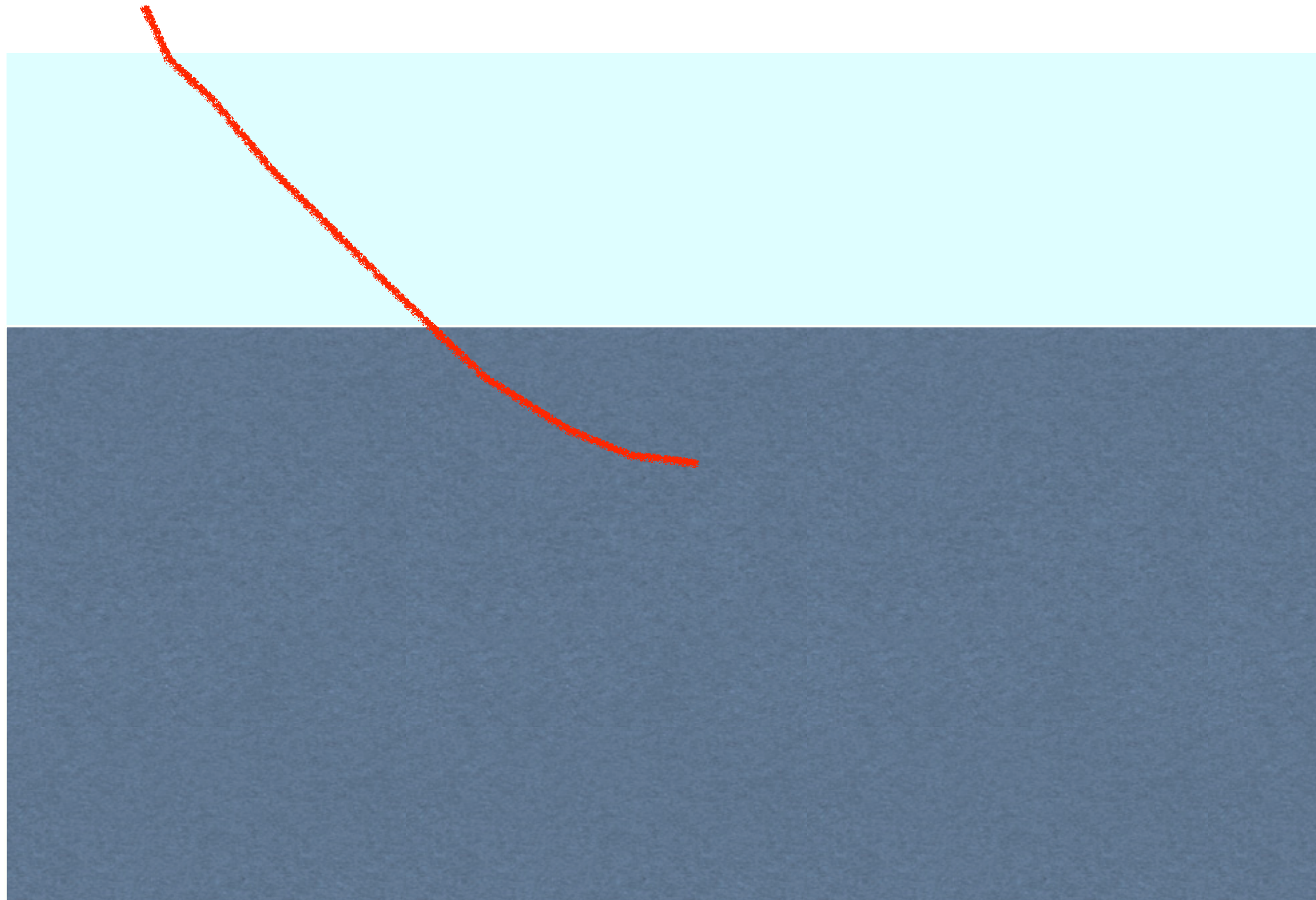


Motivation



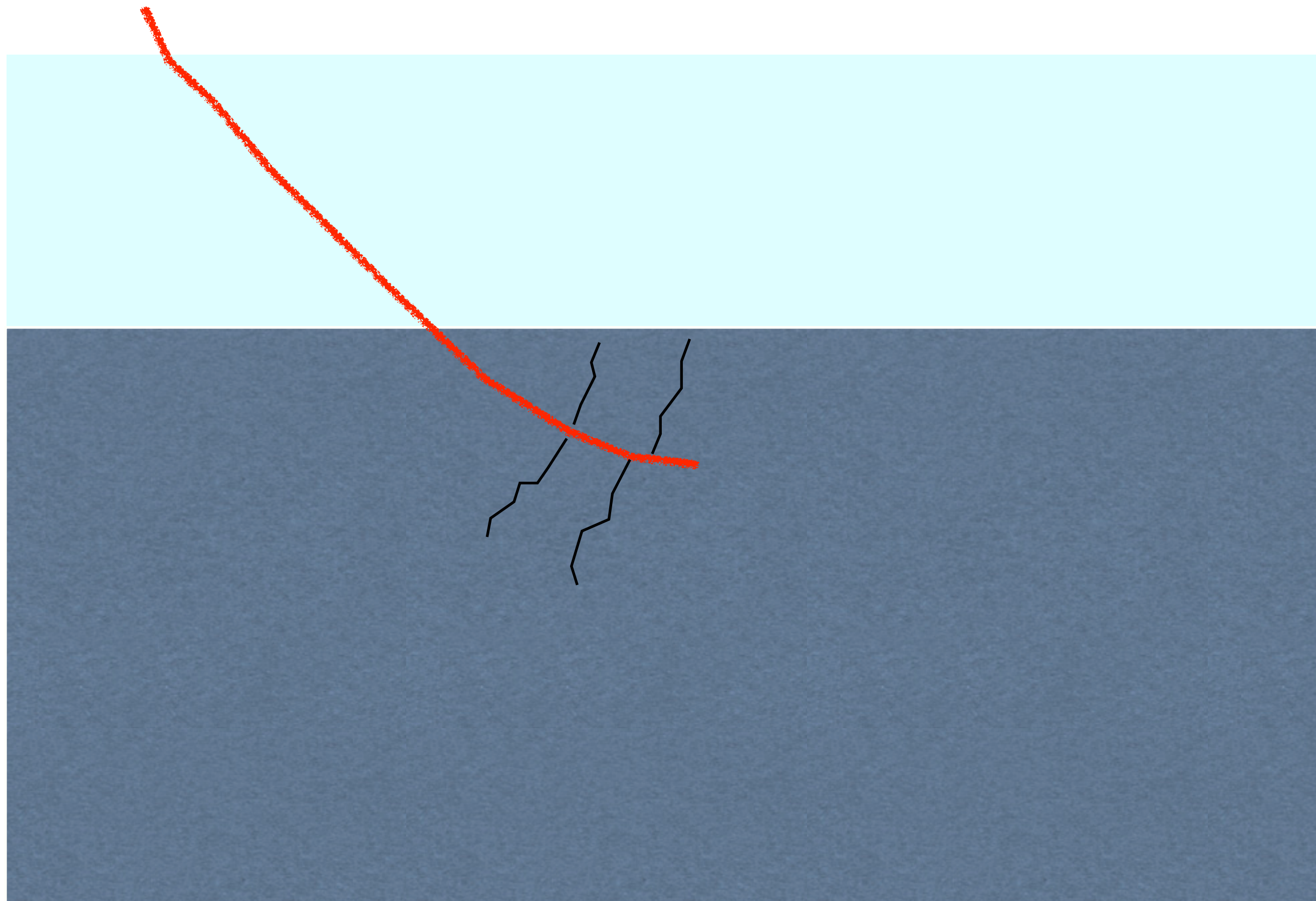
**Unconventional
Reservoir Schematic**

Motivation



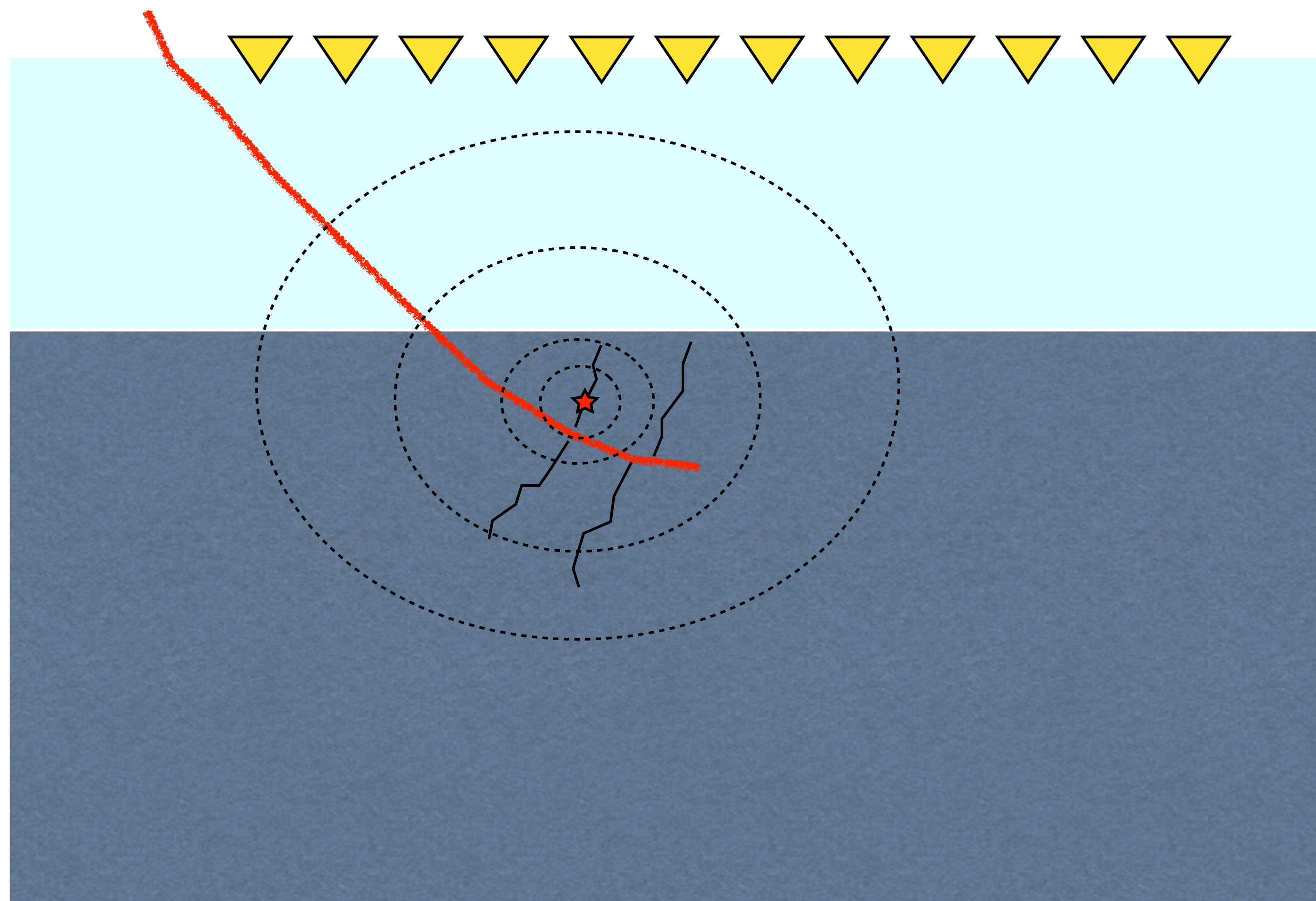
**Unconventional
Reservoir Schematic**

Motivation



**Unconventional
Reservoir Schematic**

Motivation



**Unconventional
Reservoir Schematic**

Motivation behind microseismic imaging

Microseismic benefits

- ▶ Locating fracture at far distance from treatment well
- ▶ Tracer based and sonic log based method fails at far distances

Hazard prevention

- ▶ Activation of pre-existing faults
- ▶ Interference of fractures with wells

Motivation behind microseismic imaging

Reservoir evaluation

Source attribute estimation

- ▶ Moment tensor orientation
- ▶ Origin time
- ▶ Spectral properties of sources

Objectives

Super-resolution via sparsity promotion and “lifting”

Simultaneous estimation of the location of microseismic events and their source time functions

Pre-existing methods

Based on travel-time picking:

- ▶ estimate the origin time
- ▶ estimate the location
- ▶ time consuming
- ▶ no source time function

Pre-existing methods

Imaging based

- ▶ estimates origin time
- ▶ estimates the location

Geometric-mean RTM

- ▶ based on cross-correlation imaging condition
- ▶ wave equation solve for each receiver

Pre-existing methods

Hybrid imaging condition

- ▶ Computationally less intensive
- ▶ Requires grouping of neighboring receivers
- ▶ Lower resolution
- ▶ Receiver group length determination not trivial

FWI based method

$$\underset{\mathbf{f} \in \mathbb{R}^{n_x}, \mathbf{w} \in \mathbb{R}^{n_t}}{\text{minimize}} \quad \|\mathcal{F}[\mathbf{m}](\mathbf{f}\mathbf{w}^T) - \mathbf{d}\|$$

*where $\mathcal{F}[\mathbf{m}] = \mathcal{PA}[\mathbf{m}]^{-1}$ is the forward modelling operator

$\mathbf{f}$ and $\mathbf{w}$ are the spatial and temporal component of source

Merits:

- ▶ alternating estimation approach
- ▶ good estimation when either spatial or temporal components are known

FWI based method

$$\underset{\mathbf{f} \in \mathbb{R}^{n_x}, \mathbf{w} \in \mathbb{R}^{n_t}}{\text{minimize}} \quad \|\mathcal{F}[\mathbf{m}](\mathbf{f}\mathbf{w}^T) - \mathbf{d}\|$$

*where $\mathcal{F}[\mathbf{m}] = \mathcal{PA}[\mathbf{m}]^{-1}$ is the forward modelling operator

$\mathbf{f}$ and $\mathbf{w}$ are the spatial and temporal component of source

Limitations:

- ▶ poor estimation when both source location & source time function unknown
- ▶ assumes prior knowledge on number of sources

Our method w/ sparsity promotion

Estimates complete source wavefield

- ▶ space
- ▶ time

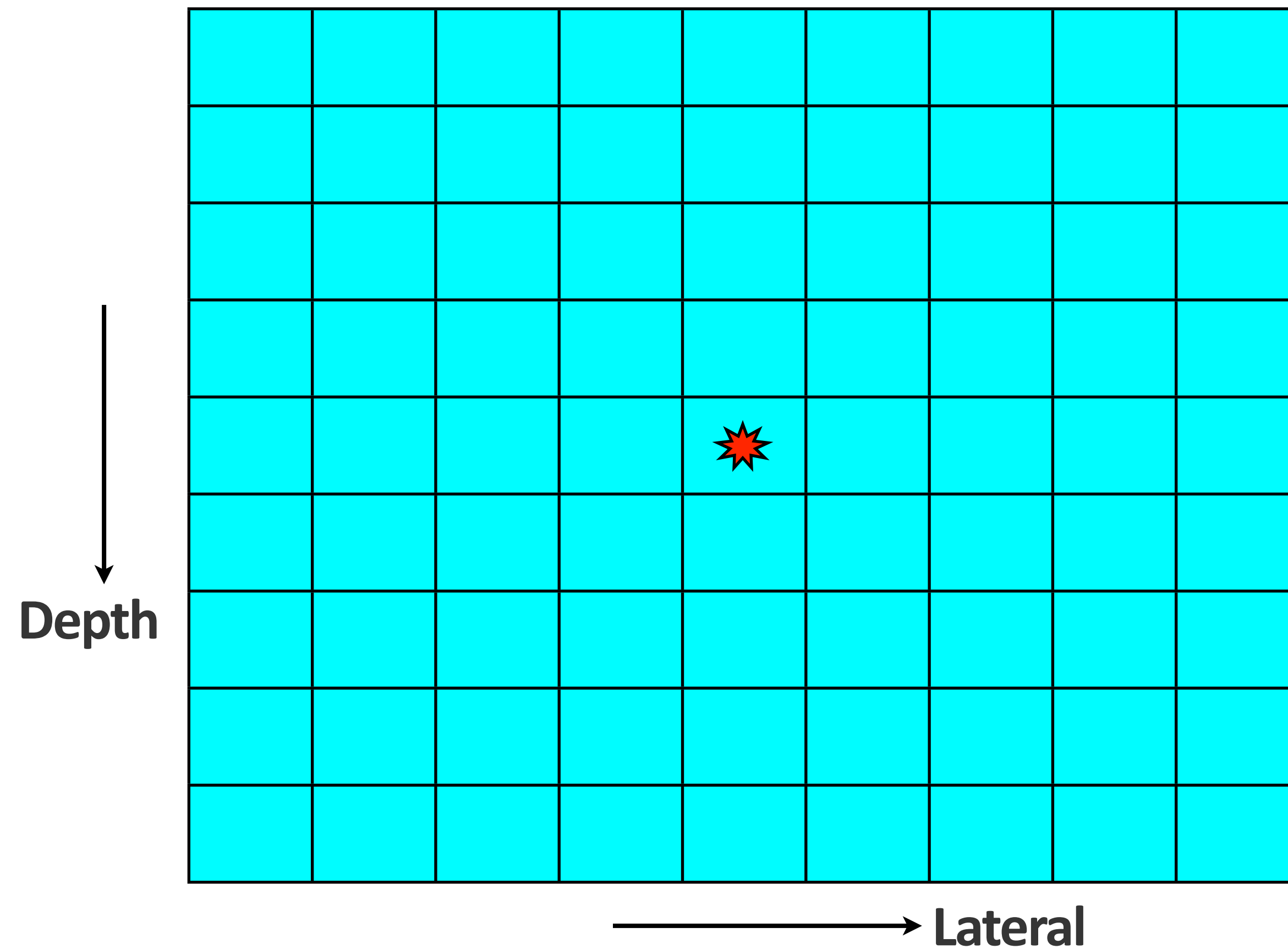
Simultaneous estimation

- ▶ source directivity pattern
- ▶ microseismic event location
- ▶ source time function
- ▶ source origin time

Our method w/ sparsity promotion

Assumptions:

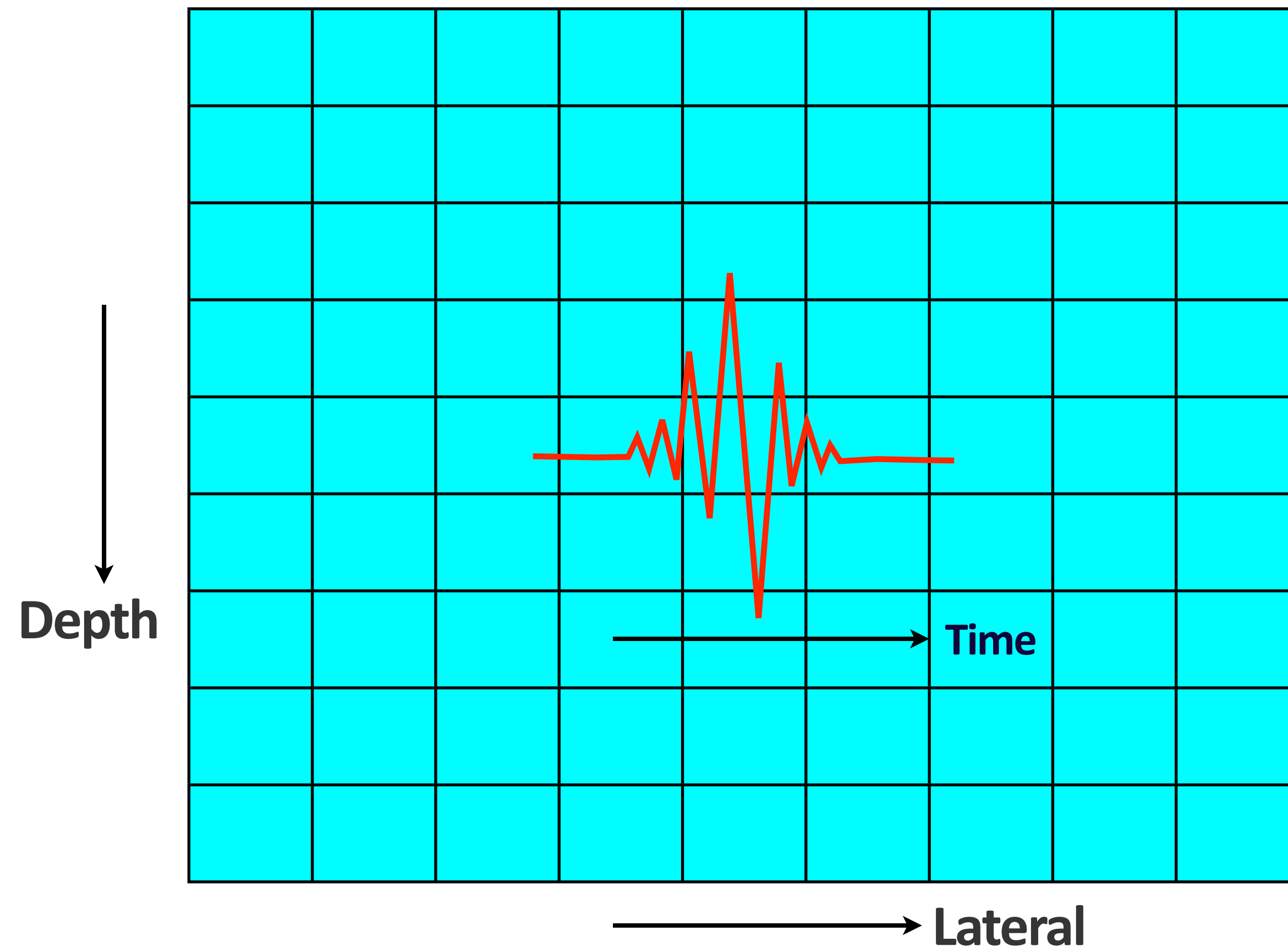
- ▶ localized in space



Our method w/ sparsity promotion

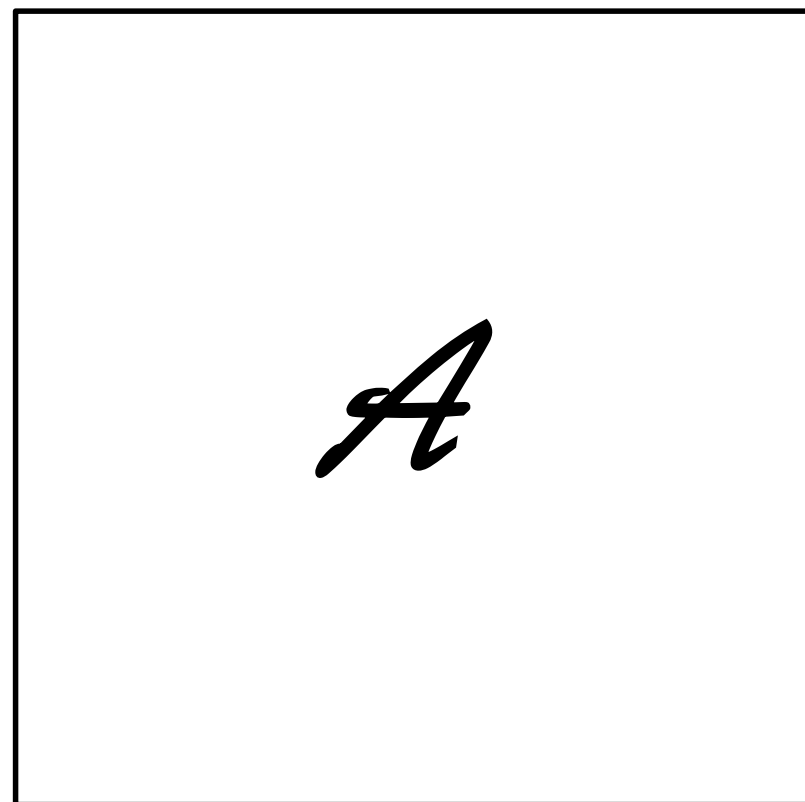
Assumptions:

- ▶ localized in space
- ▶ finite energy along time

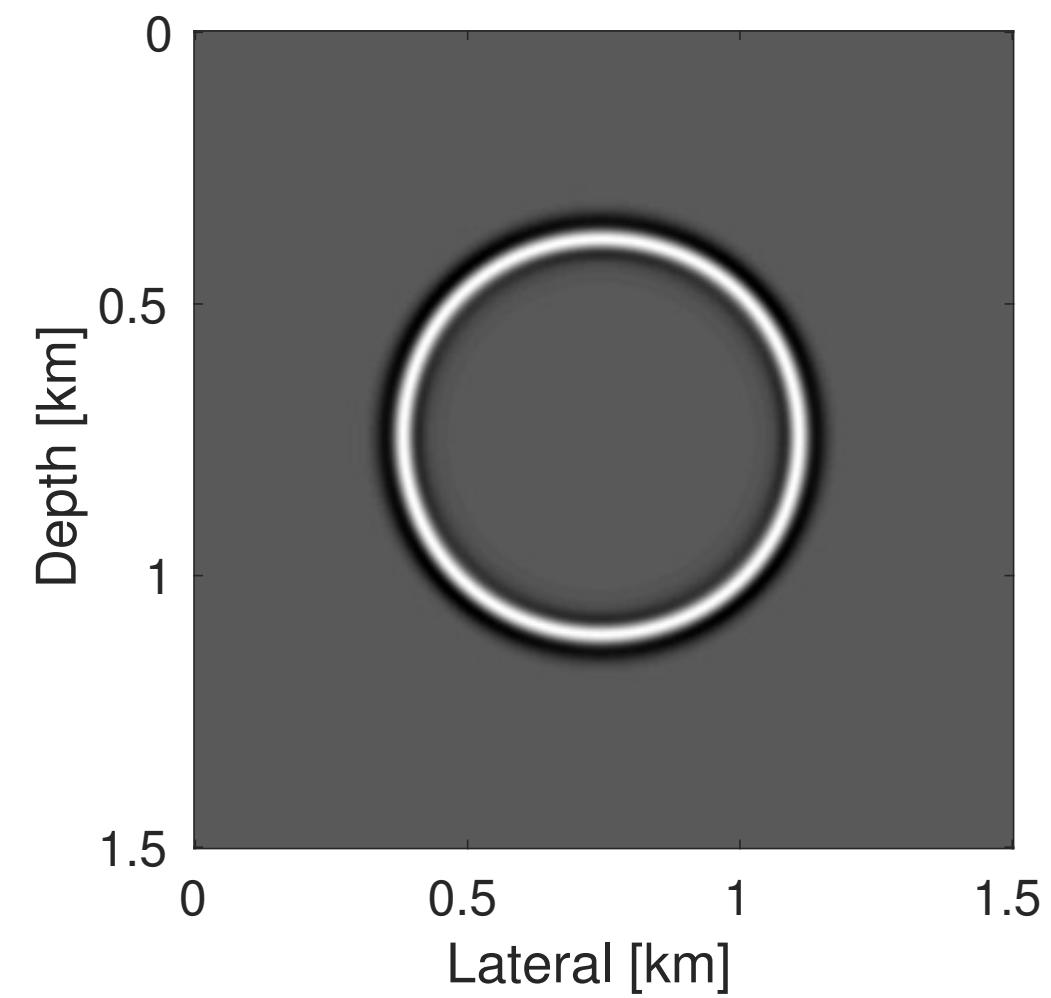


Co-sparsity property of wave equation

Time-stepping operator

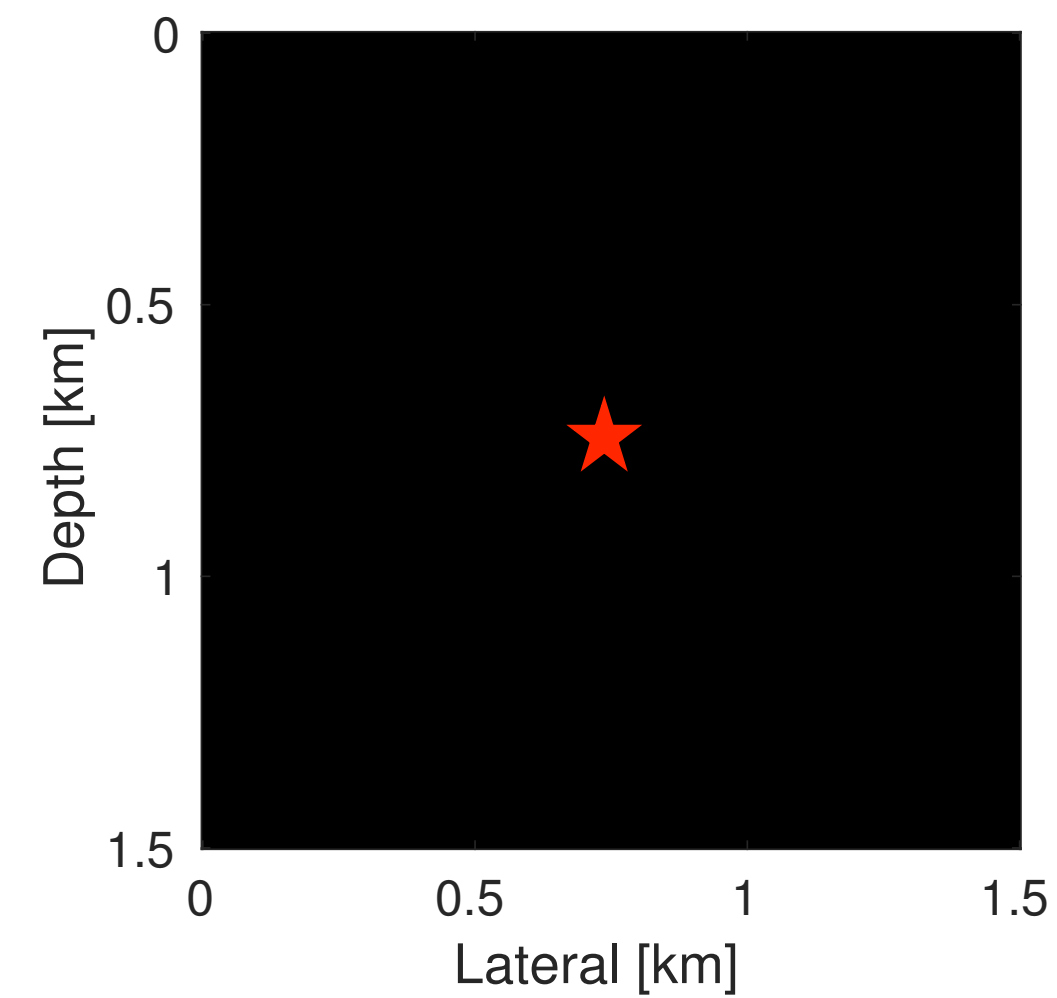


Wavefield

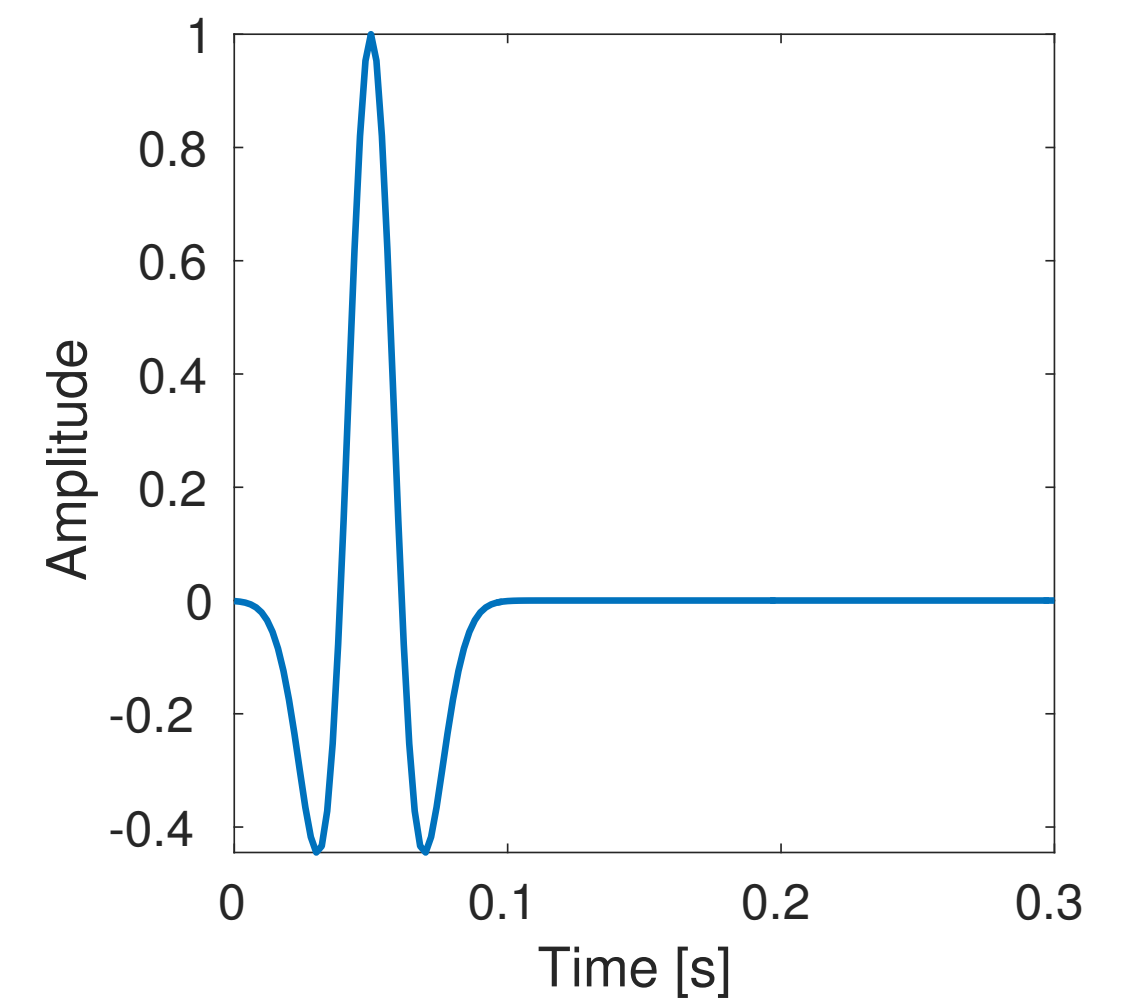


=

Source



Source time function



$$\mathcal{A}[\mathbf{m}](\mathbf{u}) = \mathbf{q}$$

Problem statement

$$\begin{aligned} & \underset{\mathbf{u}}{\text{minimize}} \quad \|\mathcal{A}[\mathbf{m}](\mathbf{u})\|_{2,1} \\ & \text{subject to} \quad \|\mathcal{P}(\mathbf{u}) - \mathbf{d}\|_2^2 \leq \epsilon \end{aligned}$$

Problem statement

**Time stepping
operator**


$$\begin{aligned} & \underset{\mathbf{u}}{\text{minimize}} \quad \|\mathcal{A}[\mathbf{m}](\mathbf{u})\|_{2,1} \\ & \text{subject to} \quad \|\mathcal{P}(\mathbf{u}) - \mathbf{d}\|_2^2 \leq \epsilon \end{aligned}$$

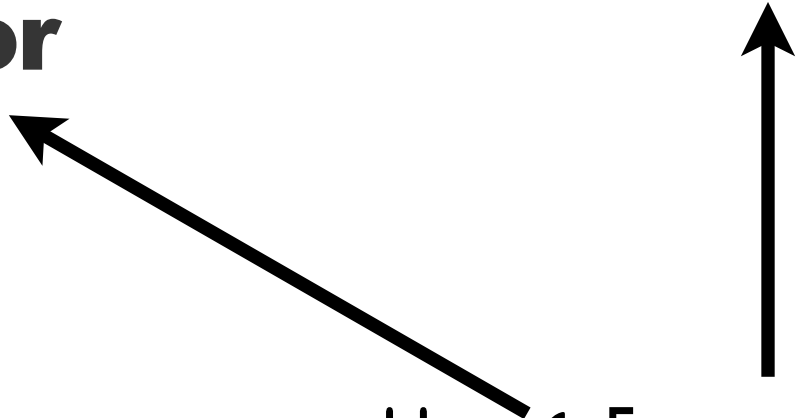
Problem statement

Time stepping operator

Slowness square

minimize $\|\mathcal{A}[\mathbf{m}](\mathbf{u})\|_{2,1}$

subject to $\|\mathcal{P}(\mathbf{u}) - \mathbf{d}\|_2^2 \leq \epsilon$

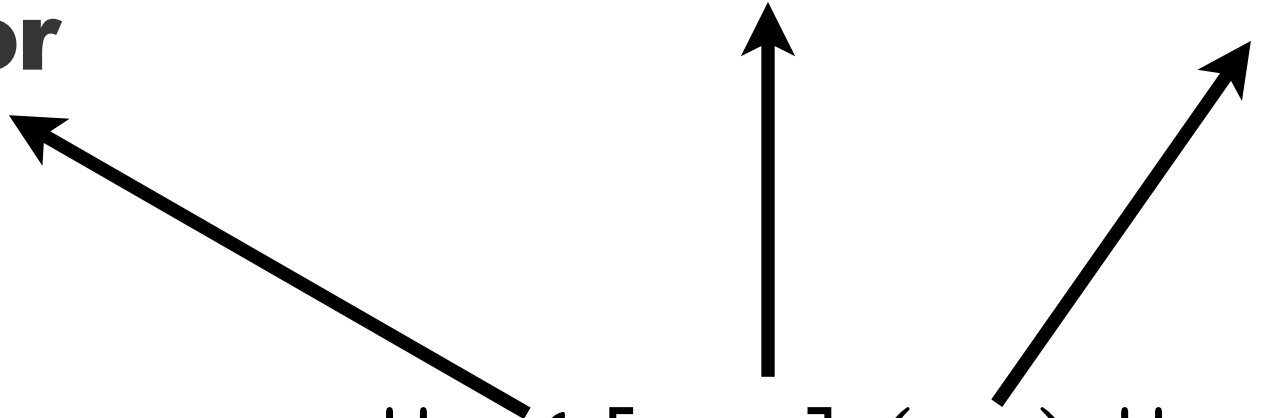


Problem statement

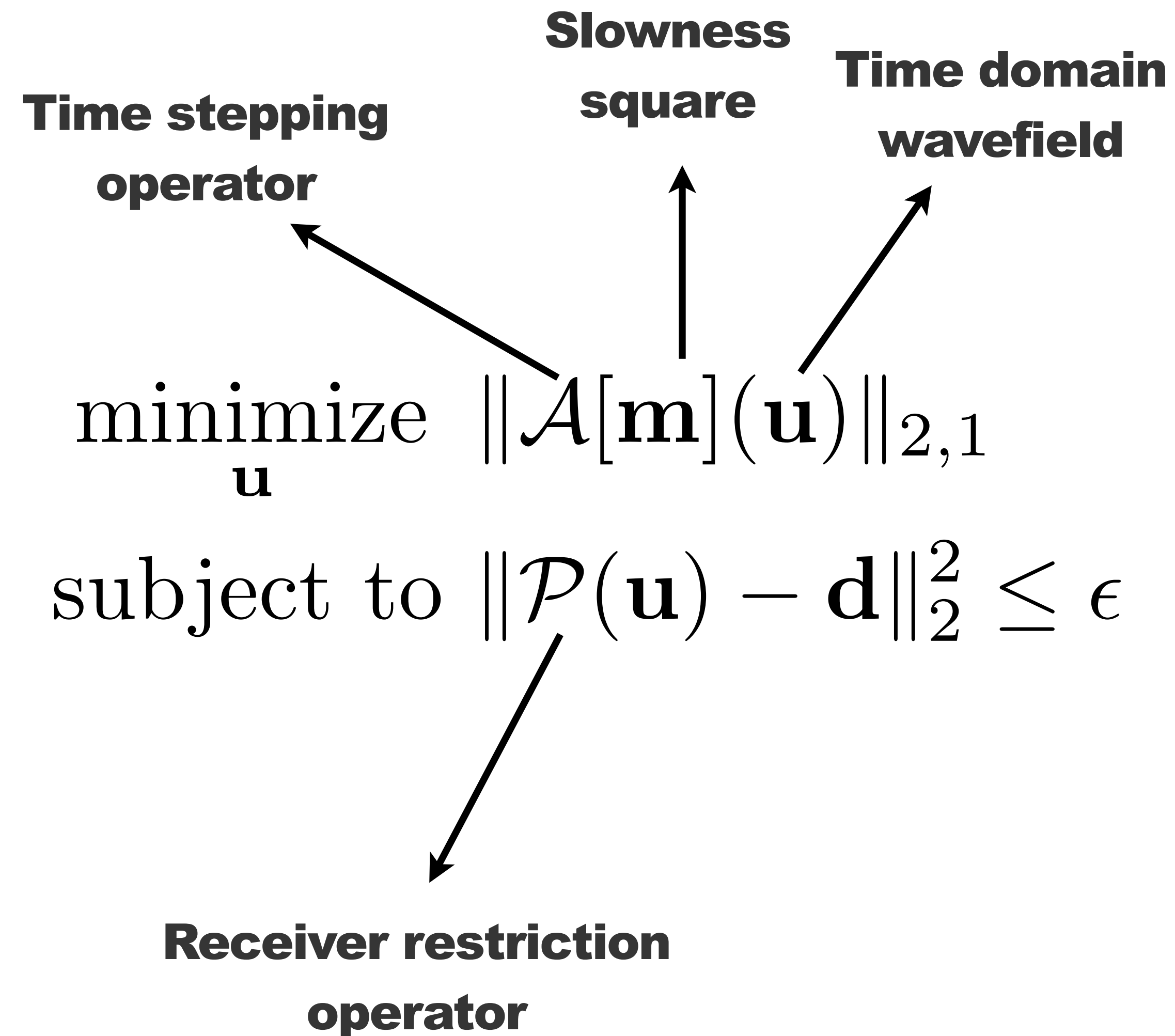
Time stepping operator **Slowness square** **Time domain wavefield**

minimize $\|\mathcal{A}[\mathbf{m}](\mathbf{u})\|_{2,1}$

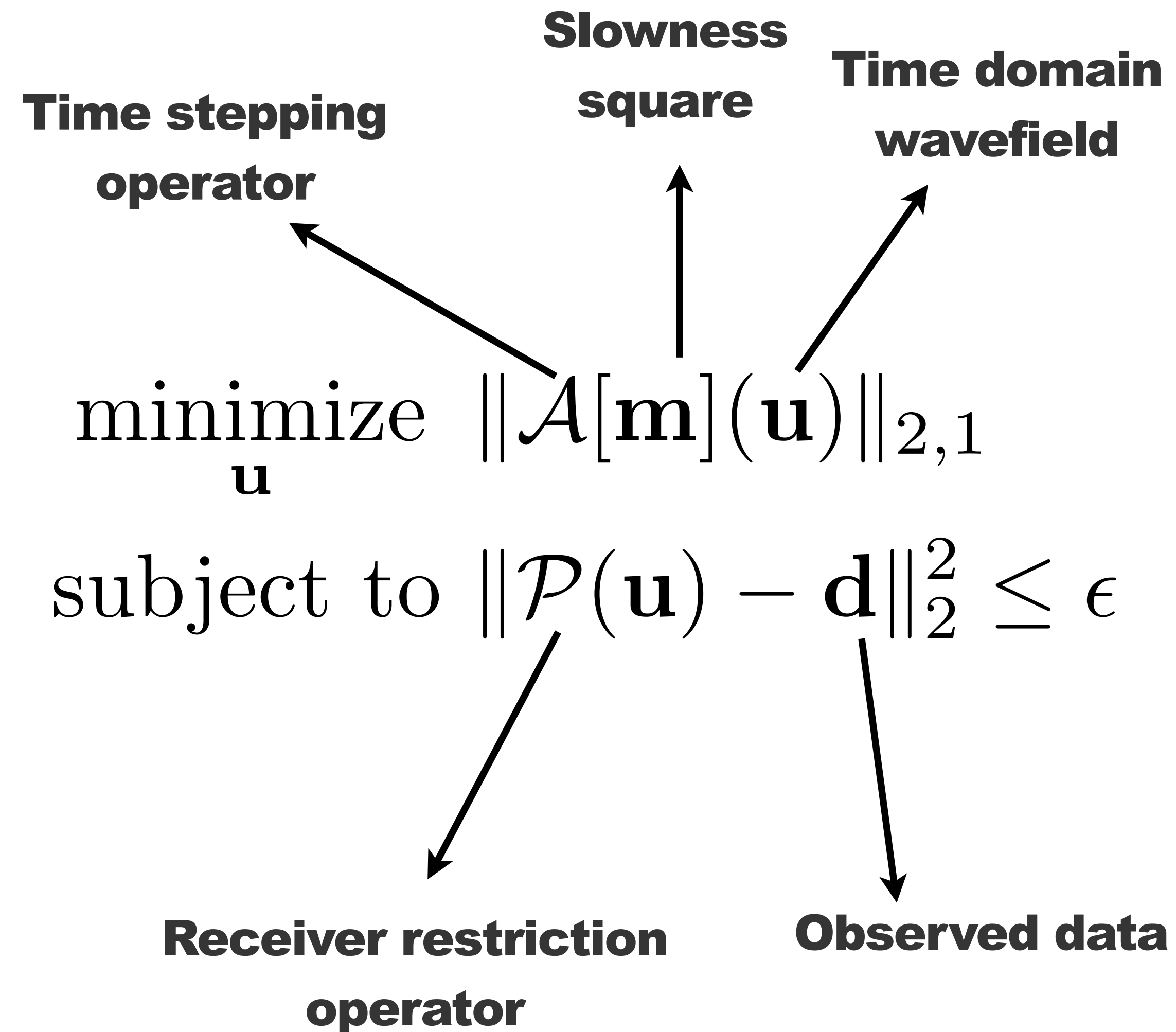
subject to $\|\mathcal{P}(\mathbf{u}) - \mathbf{d}\|_2^2 \leq \epsilon$



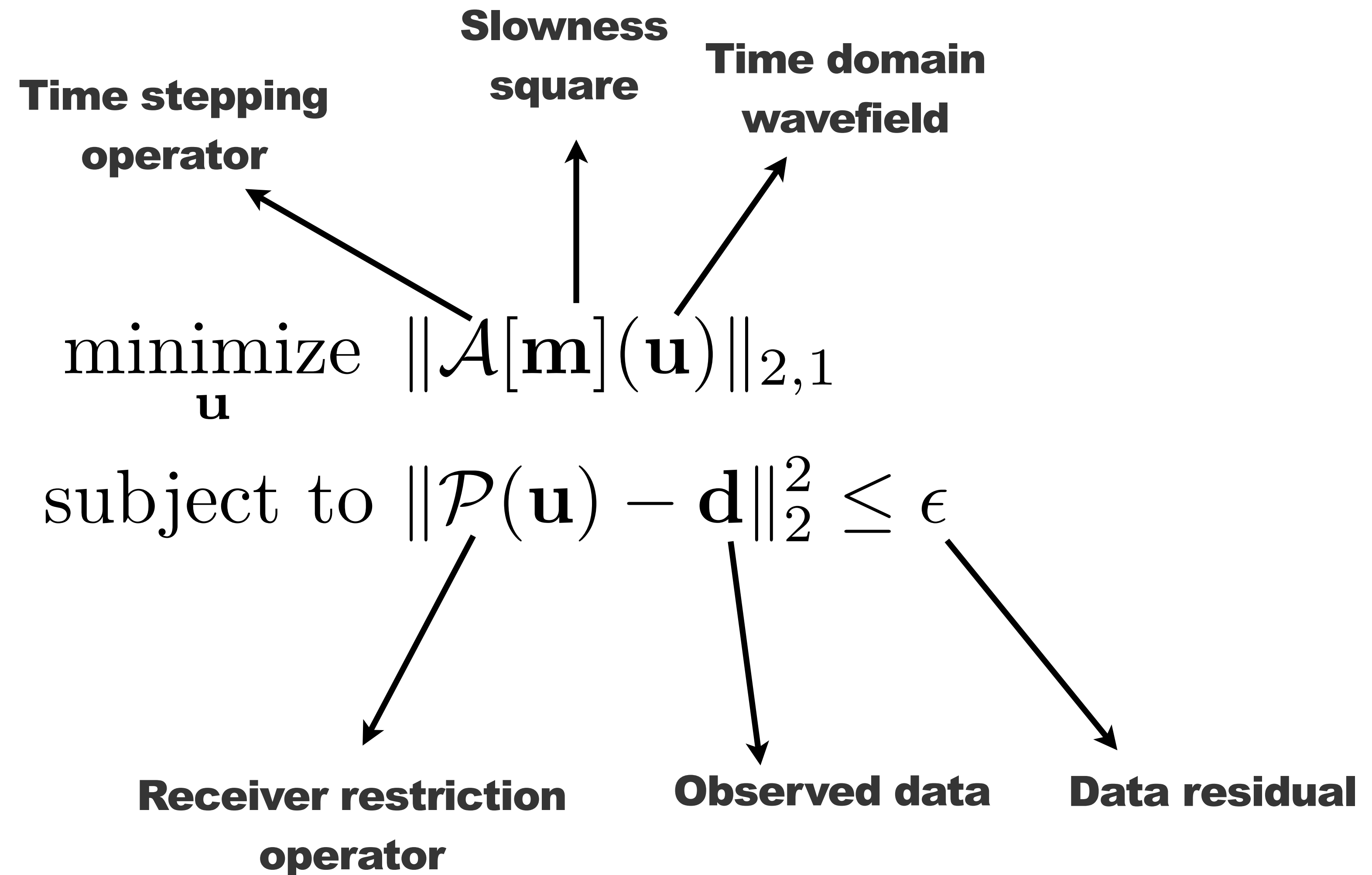
Problem statement



Problem statement



Problem statement



Our method w/ sparsity promotion

$$\begin{aligned} & \underset{\mathbf{u}}{\text{minimize}} \quad \|\mathcal{A}[\mathbf{m}](\mathbf{u})\|_{2,1} \\ & \text{subject to} \quad \|\mathcal{P}(\mathbf{u}) - \mathbf{d}\|_2^2 \leq \epsilon \end{aligned}$$

- ✓ Does not require separable structure of source term into spatial & temporal components
- ✓ Does not require prior information on number of sources
- ✓ Simultaneously estimates location/directivity pattern & source origin/source time function

Method

Made more tractable by change of variable $\mathcal{A}[\mathbf{m}](\mathbf{u}) = \mathbf{Q}$

So we have

$$\begin{aligned} & \underset{\mathbf{Q}}{\text{minimize}} \quad \|\mathbf{Q}\|_{2,1} \\ & \text{subject to} \quad \|\mathcal{F}[\mathbf{m}](\mathbf{Q}) - \mathbf{d}\|_2^2 \leq \epsilon \end{aligned}$$

Similar to classic Basis Pursuit Denoising (BPDN) Problem!

Modified Linearized Bregman

$$\begin{aligned} & \underset{\mathbf{Q}}{\text{minimize}} \quad \lambda \|\mathbf{Q}\|_{2,1} + \frac{1}{2} \|\mathbf{Q}\|_F^2 \\ & \text{subject to} \quad \|\mathcal{F}[\mathbf{m}](\mathbf{Q}) - \mathbf{d}\|_2^2 \leq \epsilon \end{aligned}$$

*where $\|\cdot\|_F$ is the Frobenius norm

- ▶ Recent successful application
- ▶ Three-step algorithm simple to implement
- ▶ Solves slightly relaxed version of original Basis Pursuit Denoising problem

Modified Linearized Bregman

$$\begin{aligned} & \underset{\mathbf{Q}}{\text{minimize}} \quad \lambda \|\mathbf{Q}\|_{2,1} + \frac{1}{2} \|\mathbf{Q}\|_F^2 \\ & \text{subject to} \quad \|\mathcal{F}[\mathbf{m}](\mathbf{Q}) - \mathbf{d}\|_2^2 \leq \epsilon \end{aligned}$$

*where $\|\cdot\|_F$ is the Frobenius norm

- ▶ Choice of λ controls trade off between sparsity & Frobenius norm
- ▶ $\lambda \uparrow \infty$ corresponds to solving original BPDN problem

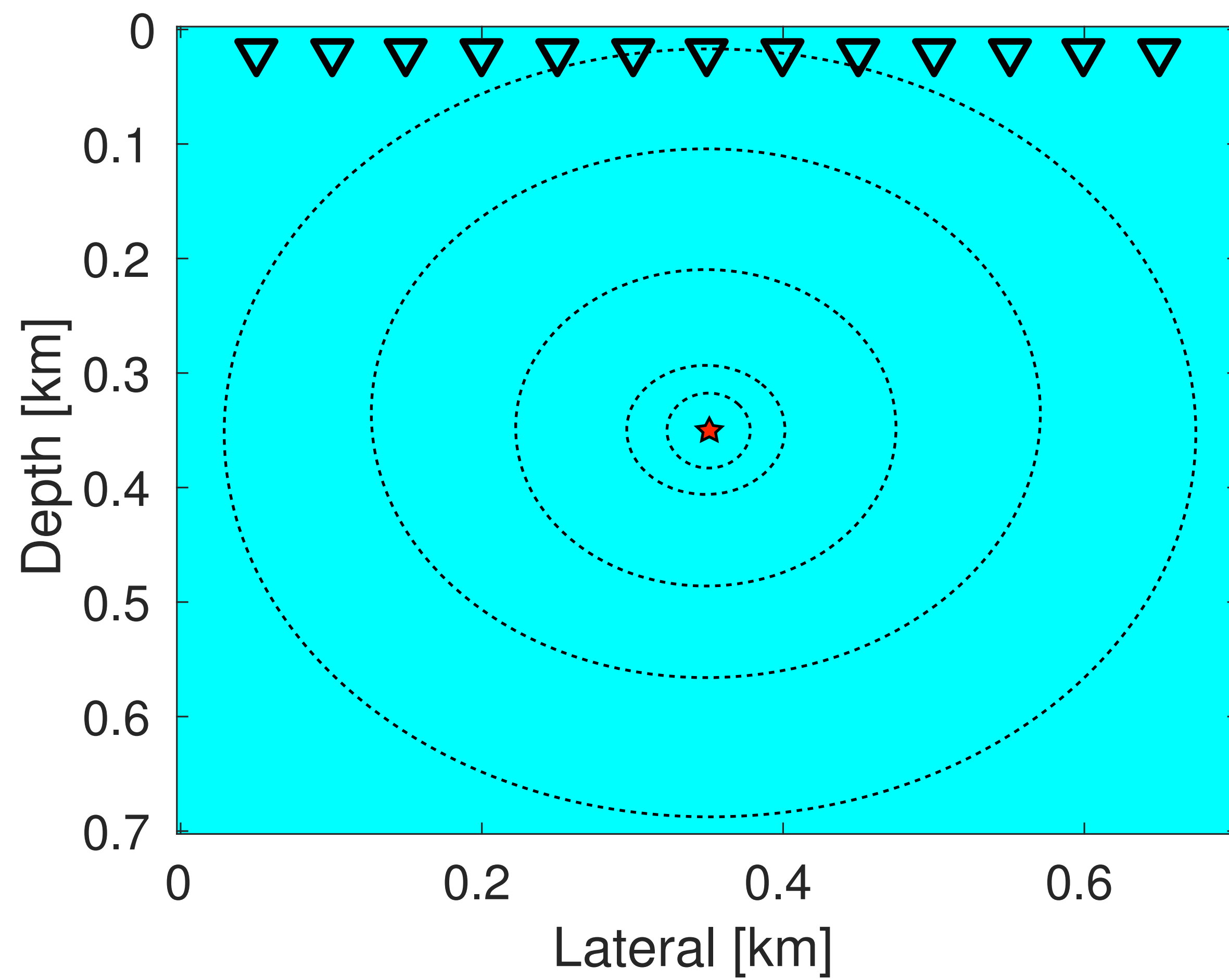
Algorithm

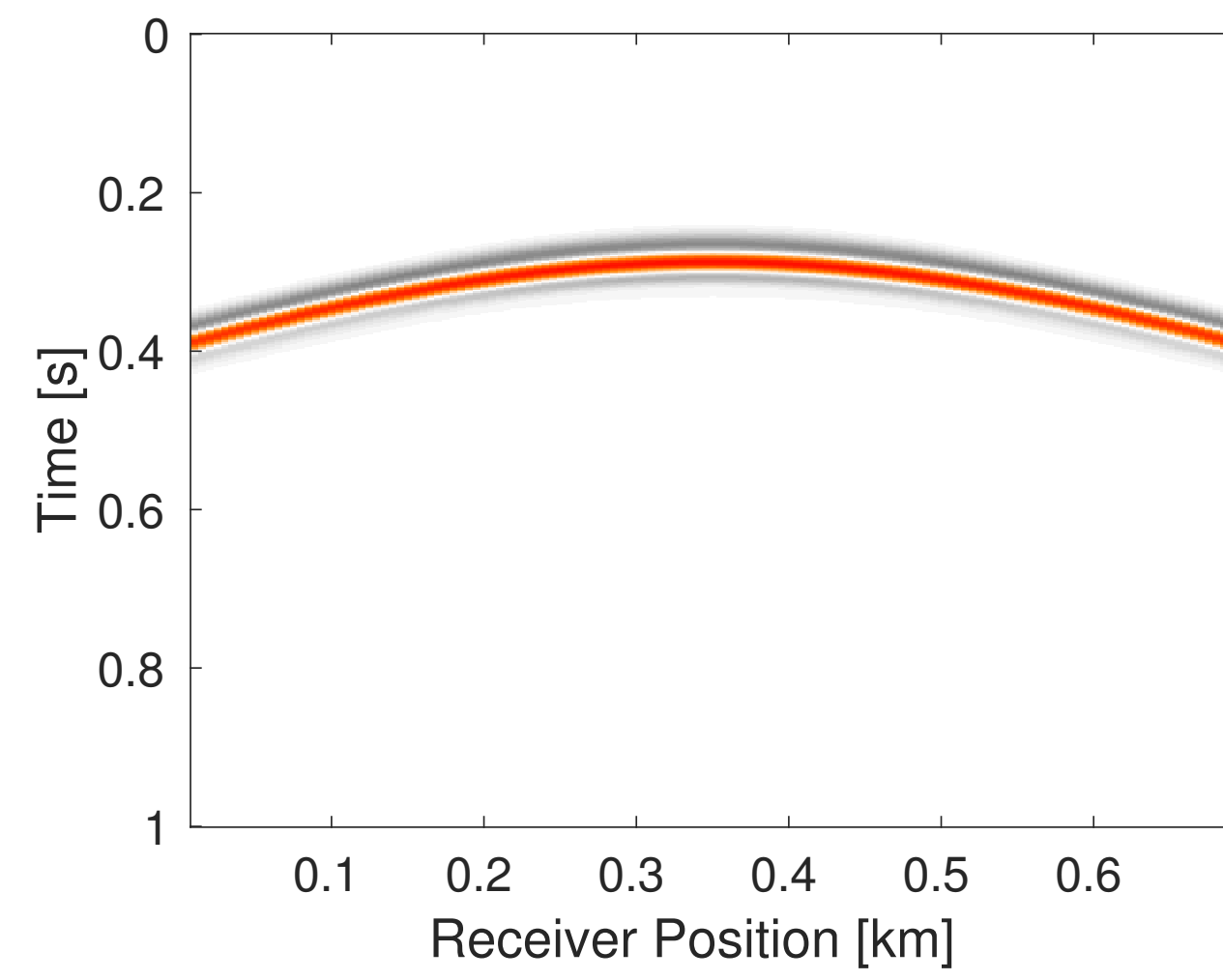
1. **for** $k = 0, 1, \dots$
2. $\mathbf{V}_k = \mathcal{F}^T[\mathbf{m}](\Pi_\epsilon(\mathcal{F}[\mathbf{m}](\mathbf{Q}_k) - \mathbf{d}))$ //adjoint solve
3. $\mathbf{Z}_{k+1} = \mathbf{Z}_k - t_k \mathbf{V}_k$ //auxiliary variable update
4. $\mathbf{Q}_{k+1} = \text{Prox}_{\lambda \|\cdot\|_{2,1}}(\mathbf{Z}_{k+1})$ //sparsity promotion
5. **end**

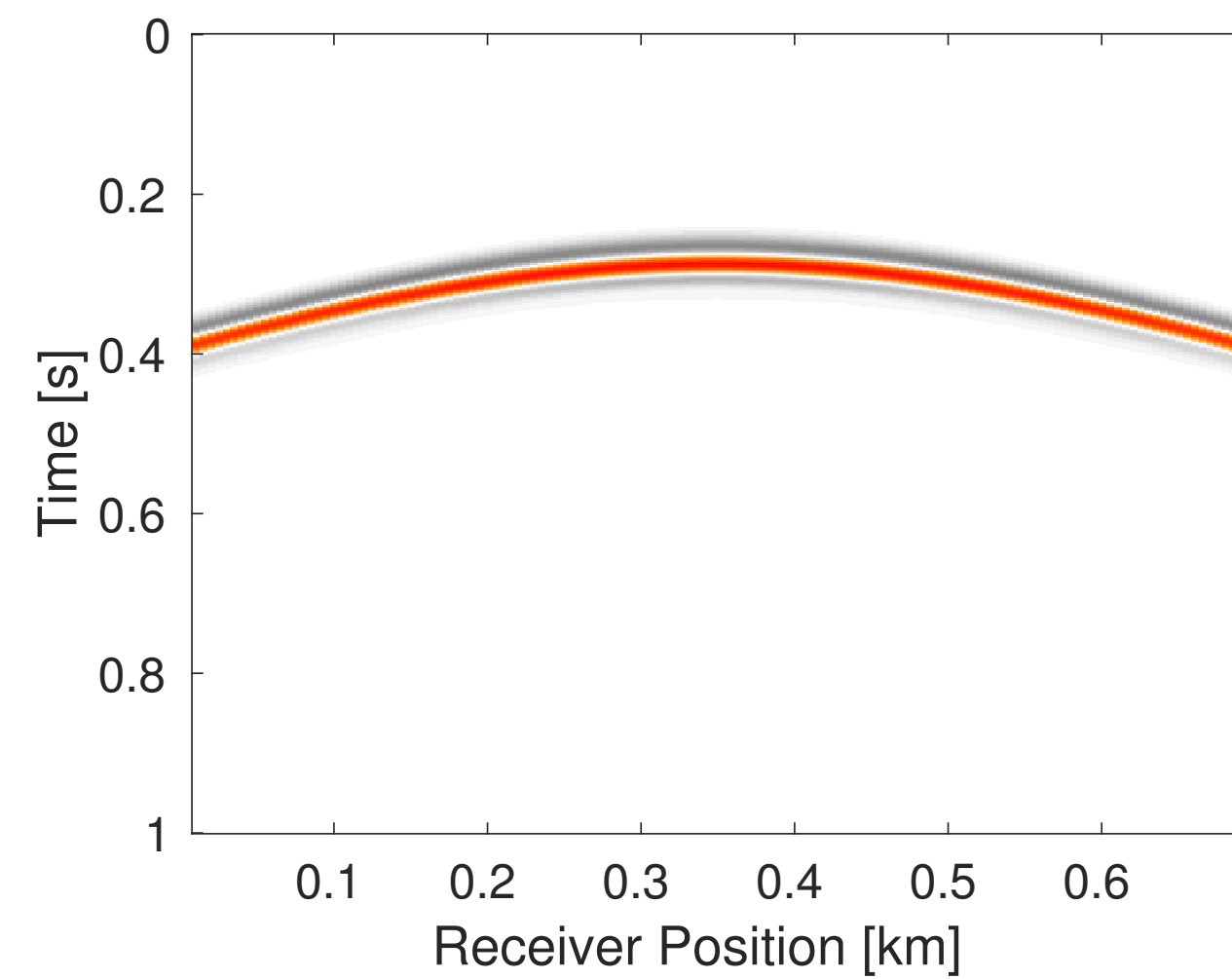
*where $t_k = \frac{\|\mathcal{F}(\mathbf{m})\mathbf{Q}_k - \mathbf{d}\|^2}{\|\mathcal{F}(\mathbf{m})^T(\mathcal{F}(\mathbf{m})\mathbf{Q}_k - \mathbf{d})\|^2}$ is the dynamic step length

* $\text{Prox}_{\lambda \|\cdot\|_{2,1}}(c) := \arg \min_b \lambda \|b\|_{2,1} + \frac{1}{2} \|c - b\|_F^2$ is the proximal mapping of the ℓ_{21} norm

* $\Pi_\epsilon(\mathbf{x}) = \max\{0, 1 - \frac{\epsilon}{\|\mathbf{x}\|}\} \cdot (\mathbf{x})$ the projection on to ℓ_2 norm ball



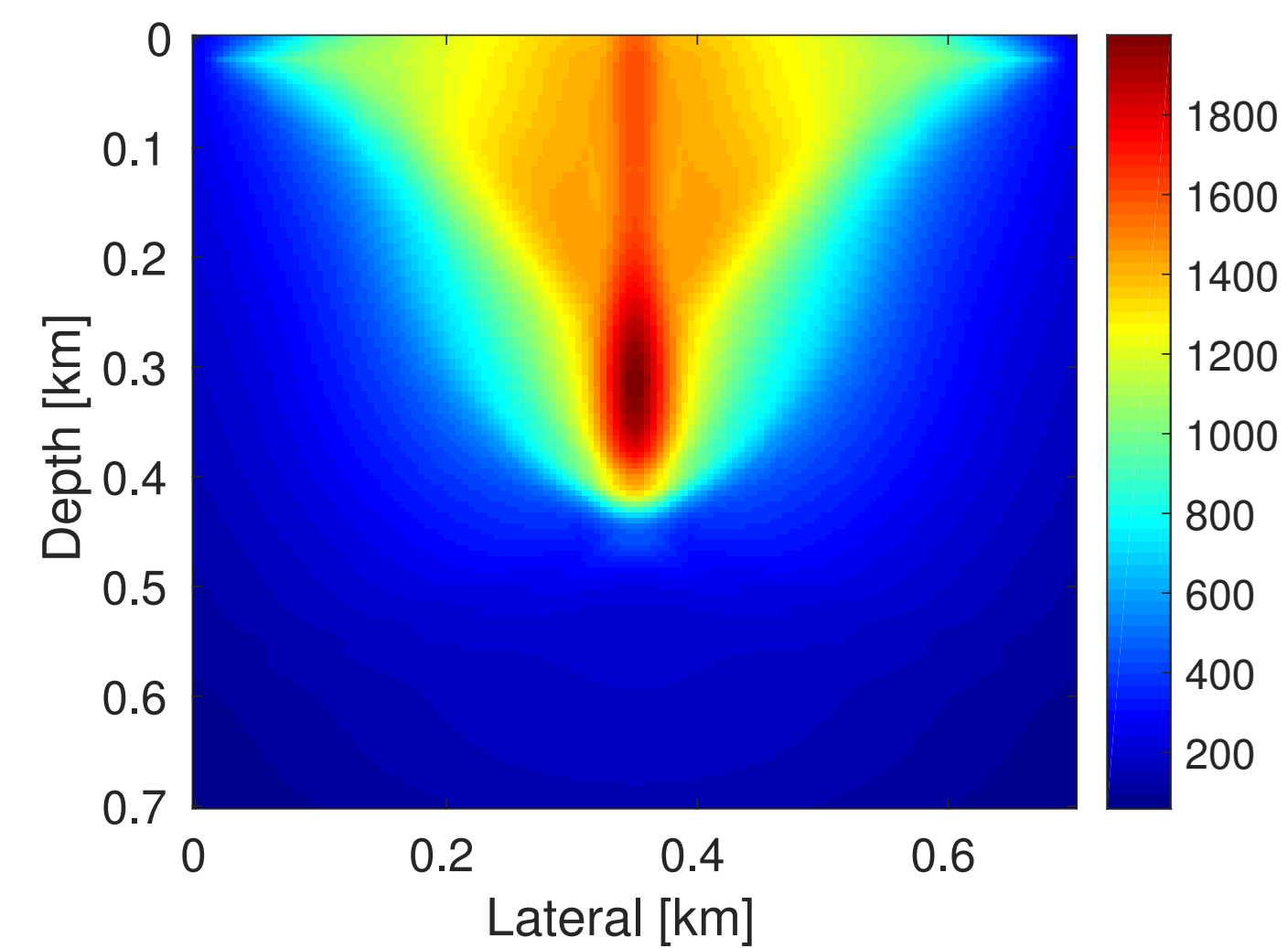


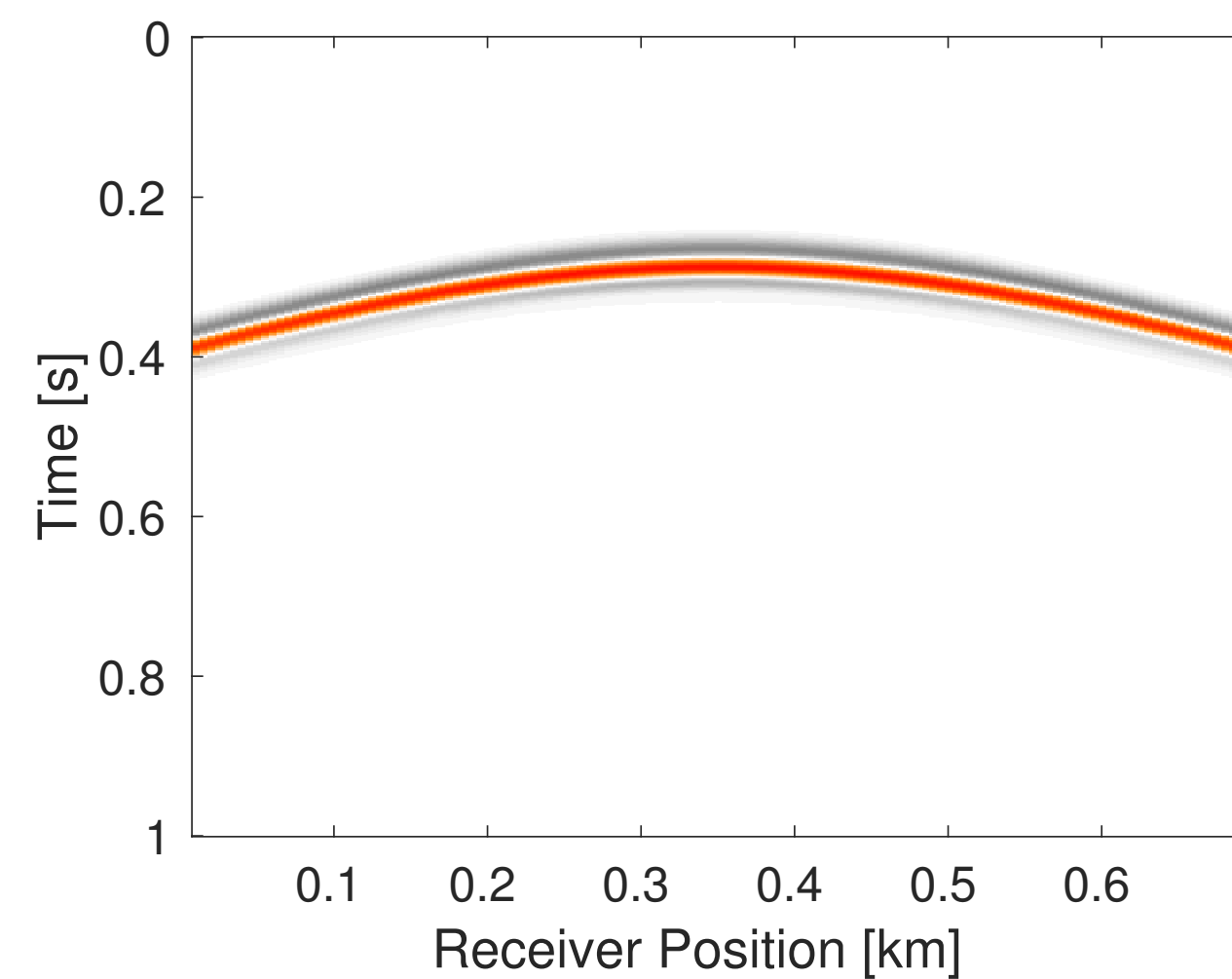


$$\mathbf{V}_1 = \mathcal{F}^T[\mathbf{m}](\Pi_\epsilon(\mathcal{F}(\mathbf{Q}_0) - \mathbf{d}))$$



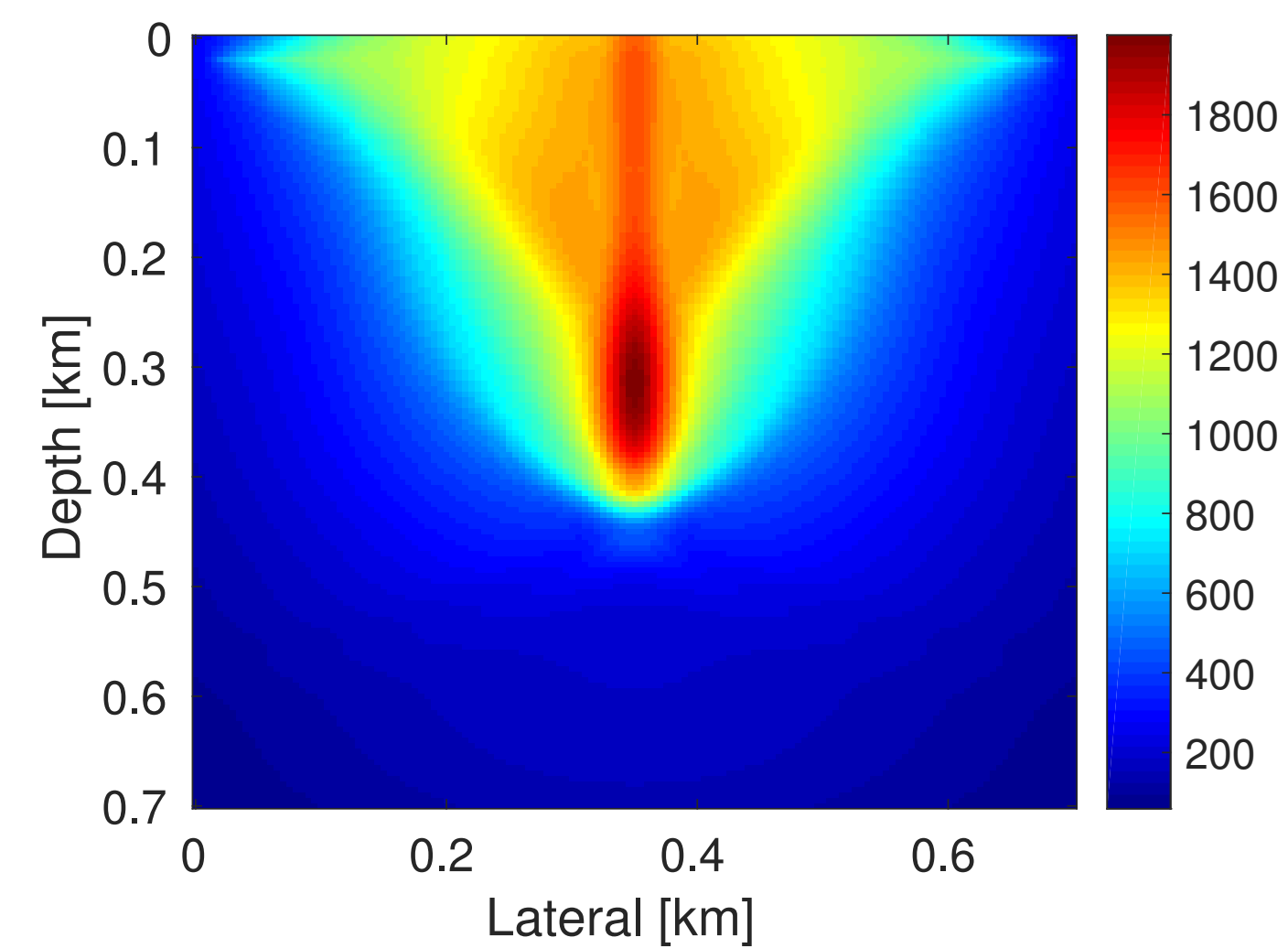
Adjoint solve





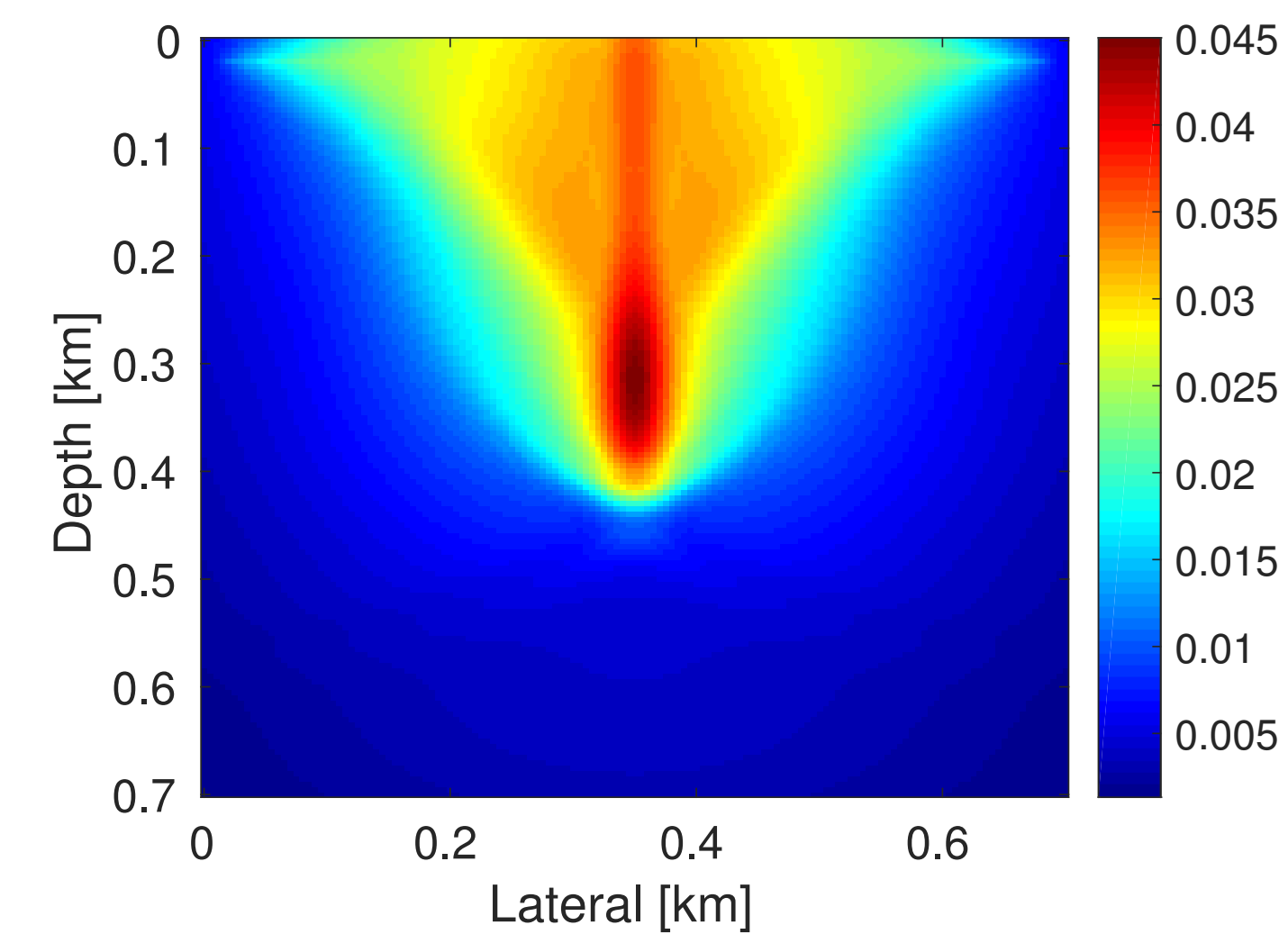
$$\mathbf{V}_1 = \mathcal{F}^T[\mathbf{m}](\Pi_\epsilon(\mathcal{F}(\mathbf{Q}_0) - \mathbf{d}))$$

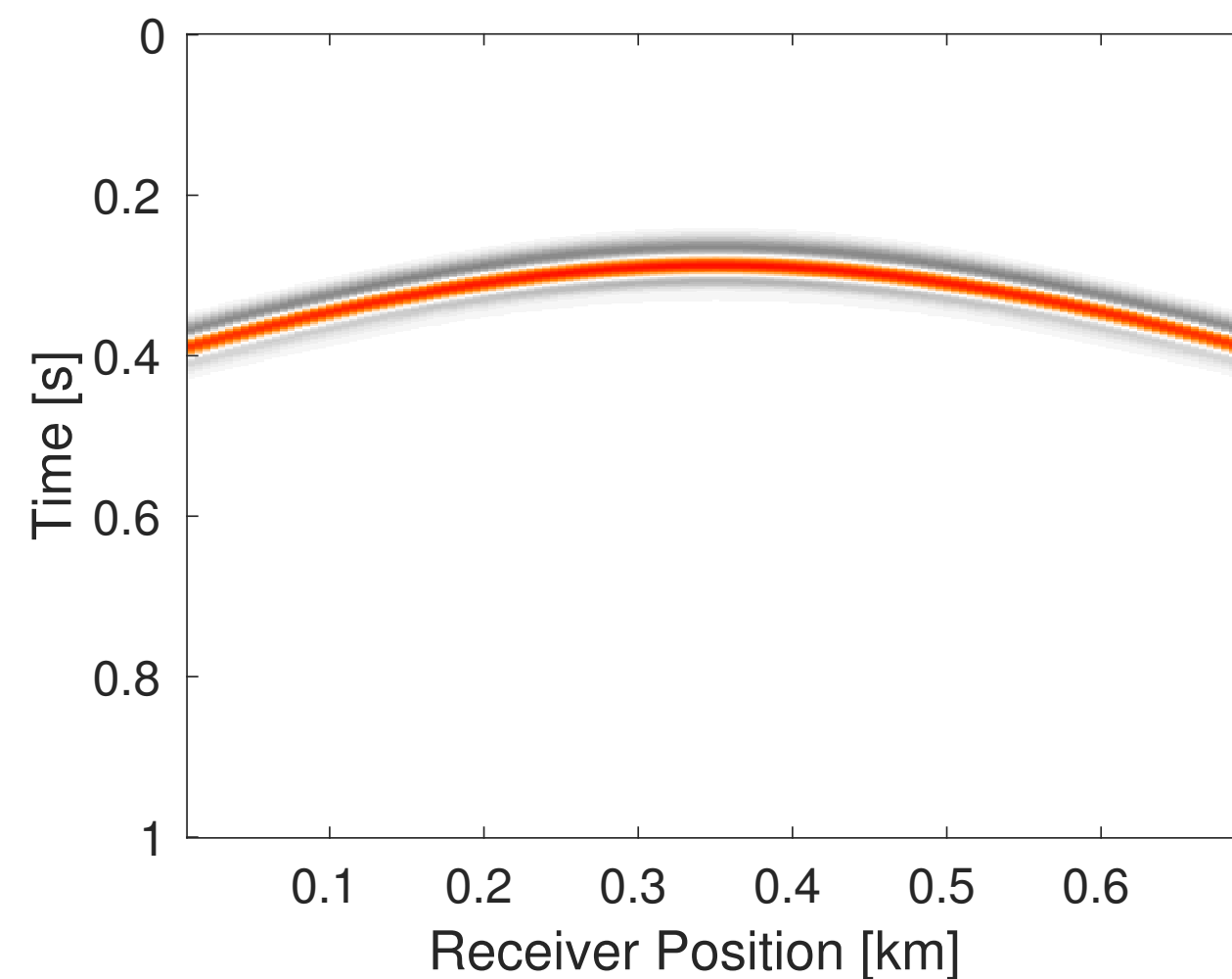
Adjoint solve



**Auxiliary variable
update**

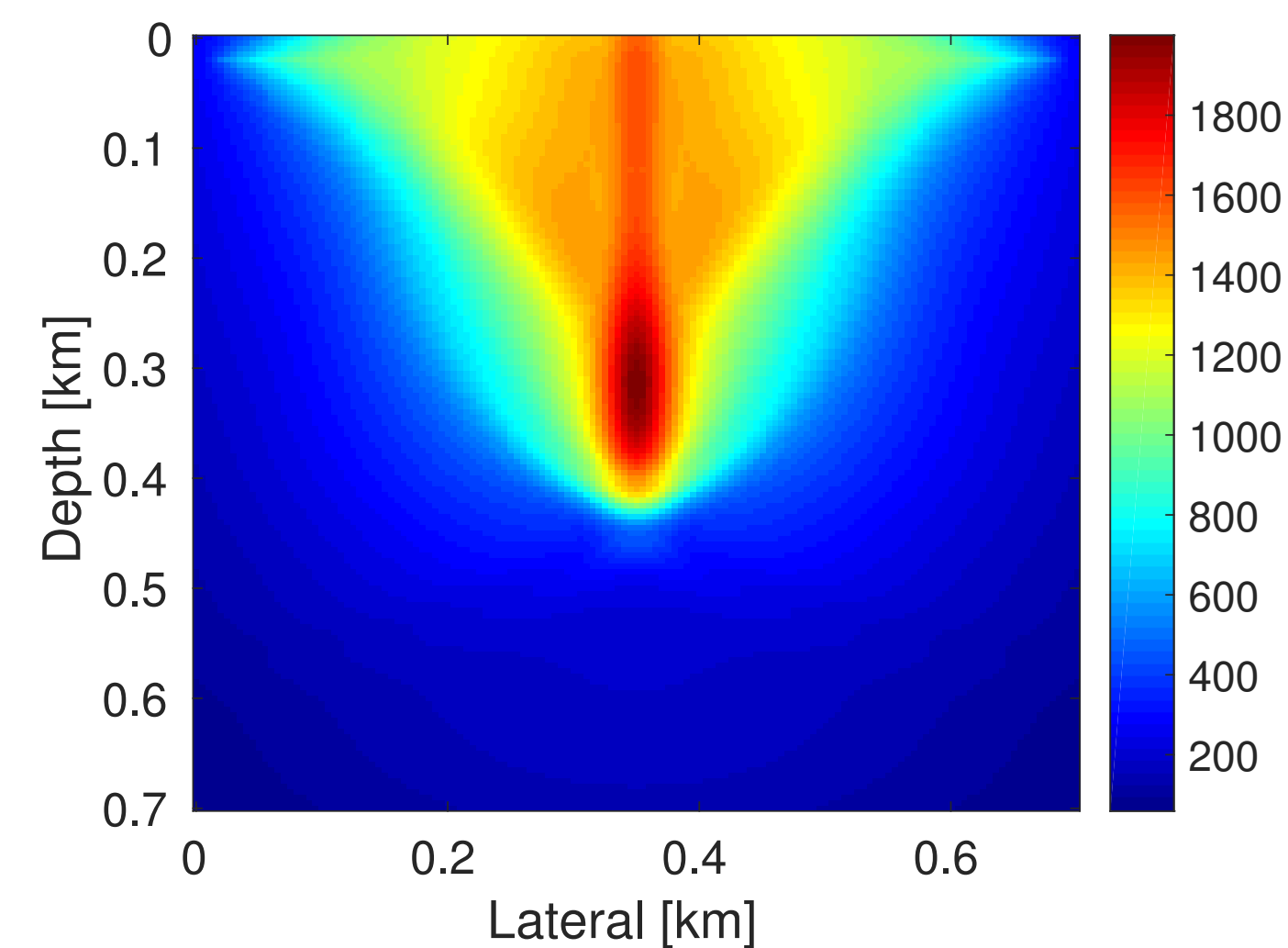
$$\mathbf{Z}_1 = \mathbf{Z}_0 - t_1 \mathbf{V}_1$$





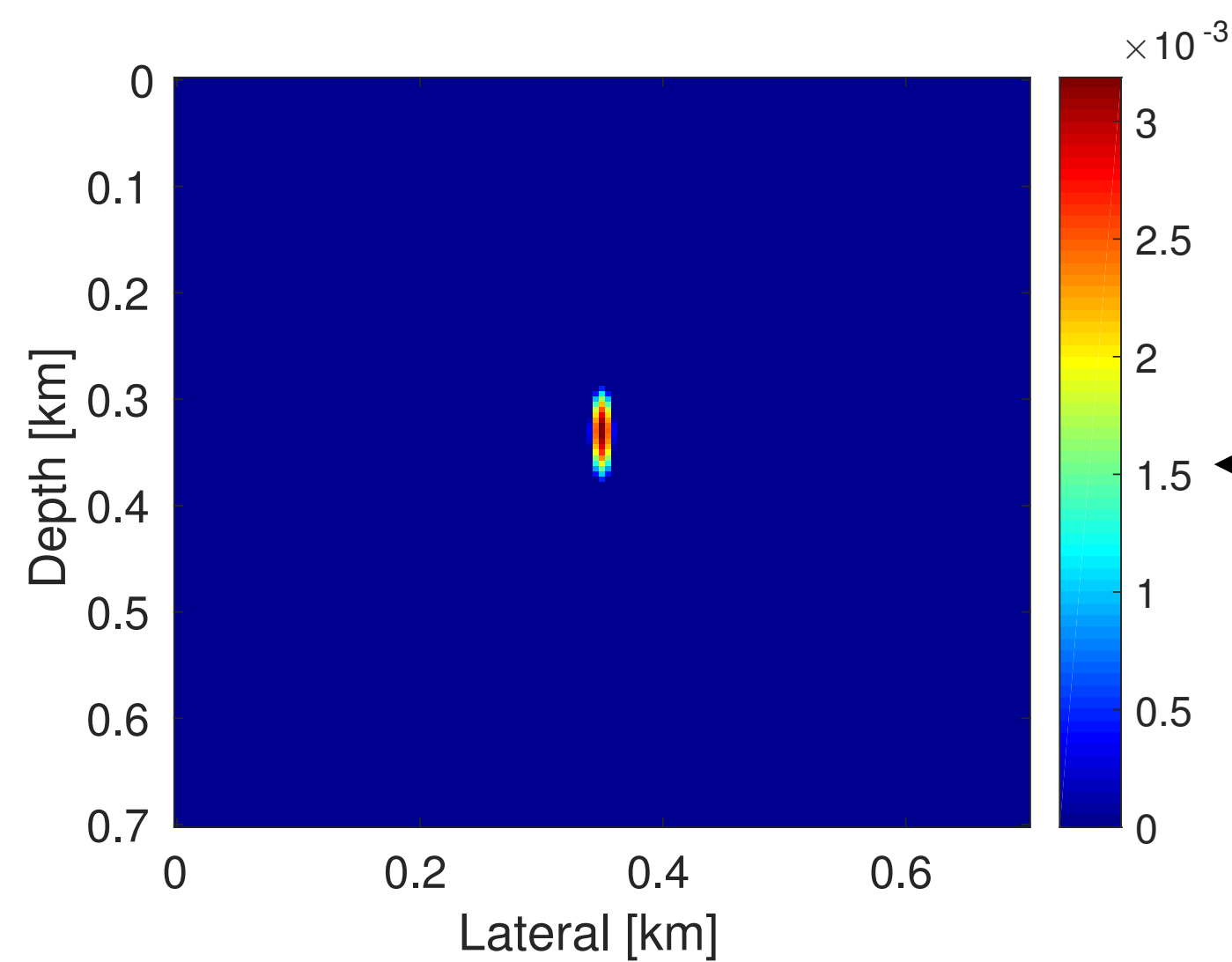
$$\mathbf{V}_1 = \mathcal{F}^T[\mathbf{m}](\Pi_\epsilon(\mathcal{F}(\mathbf{Q}_0) - \mathbf{d}))$$

Adjoint solve



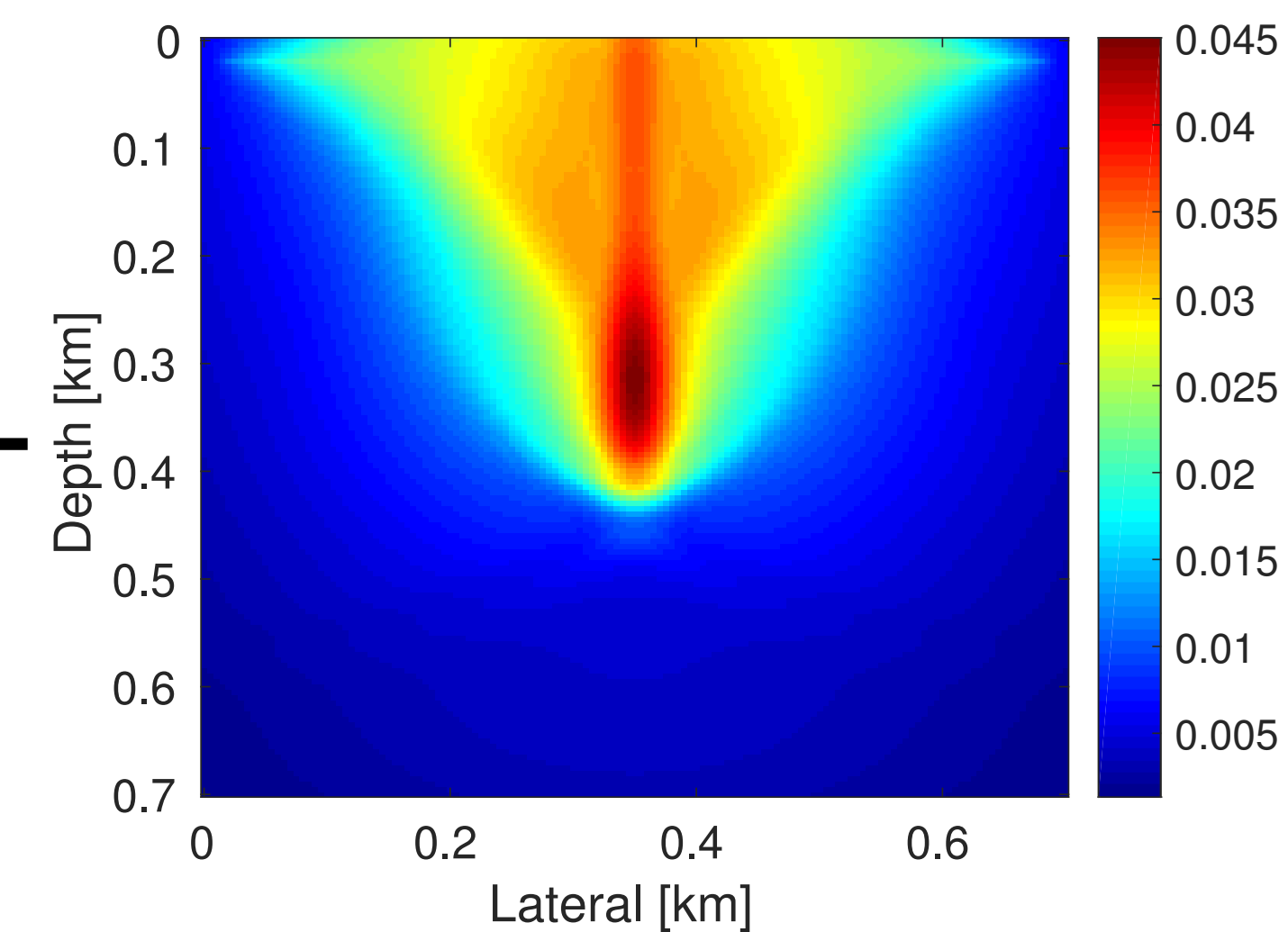
**Auxiliary variable
update**

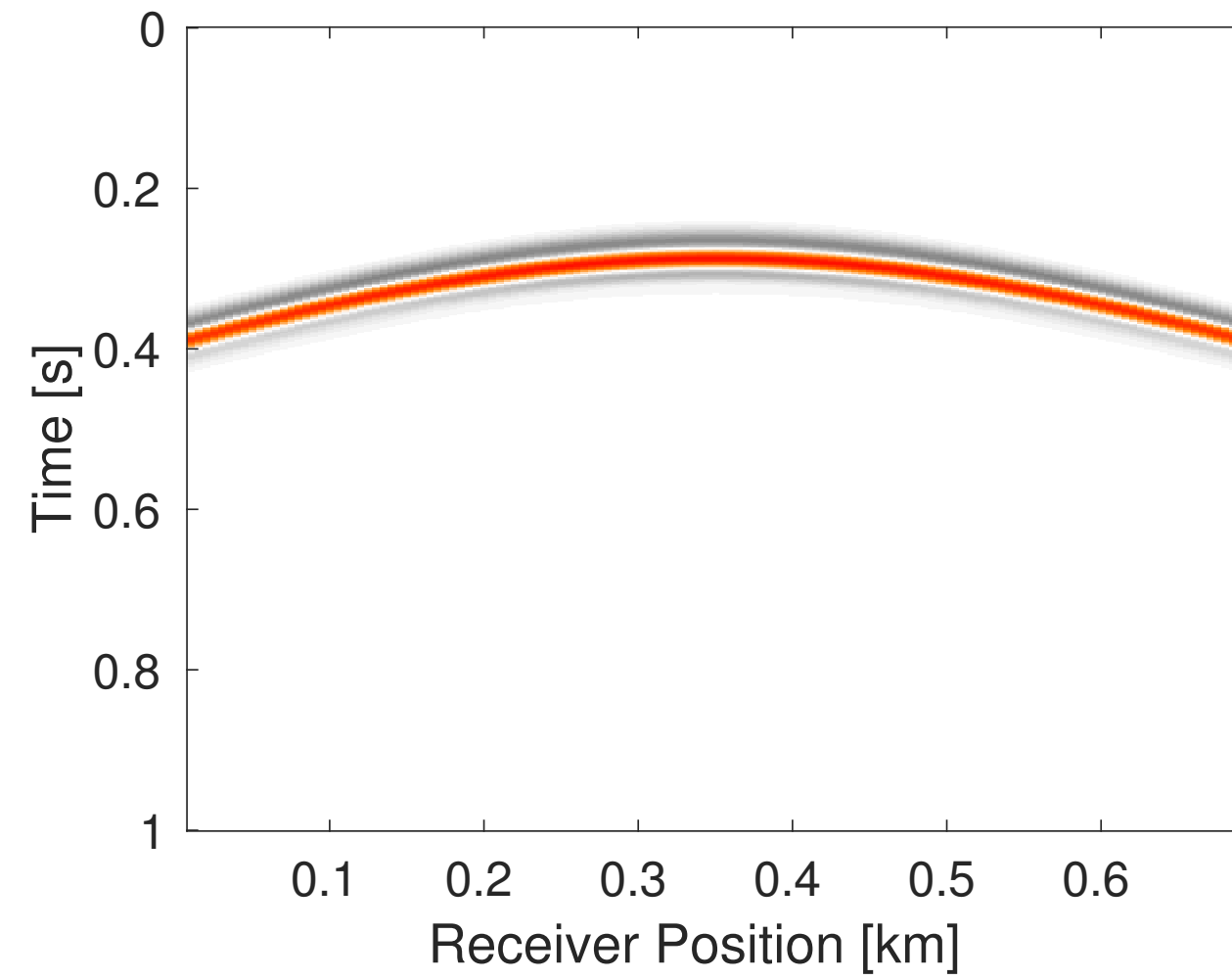
$$\mathbf{Z}_1 = \mathbf{Z}_0 - t_1 \mathbf{V}_1$$



$$\mathbf{Q}_1 = \text{Prox}_{\lambda \|\cdot\|_{2,1}}(\mathbf{Z}_1)$$

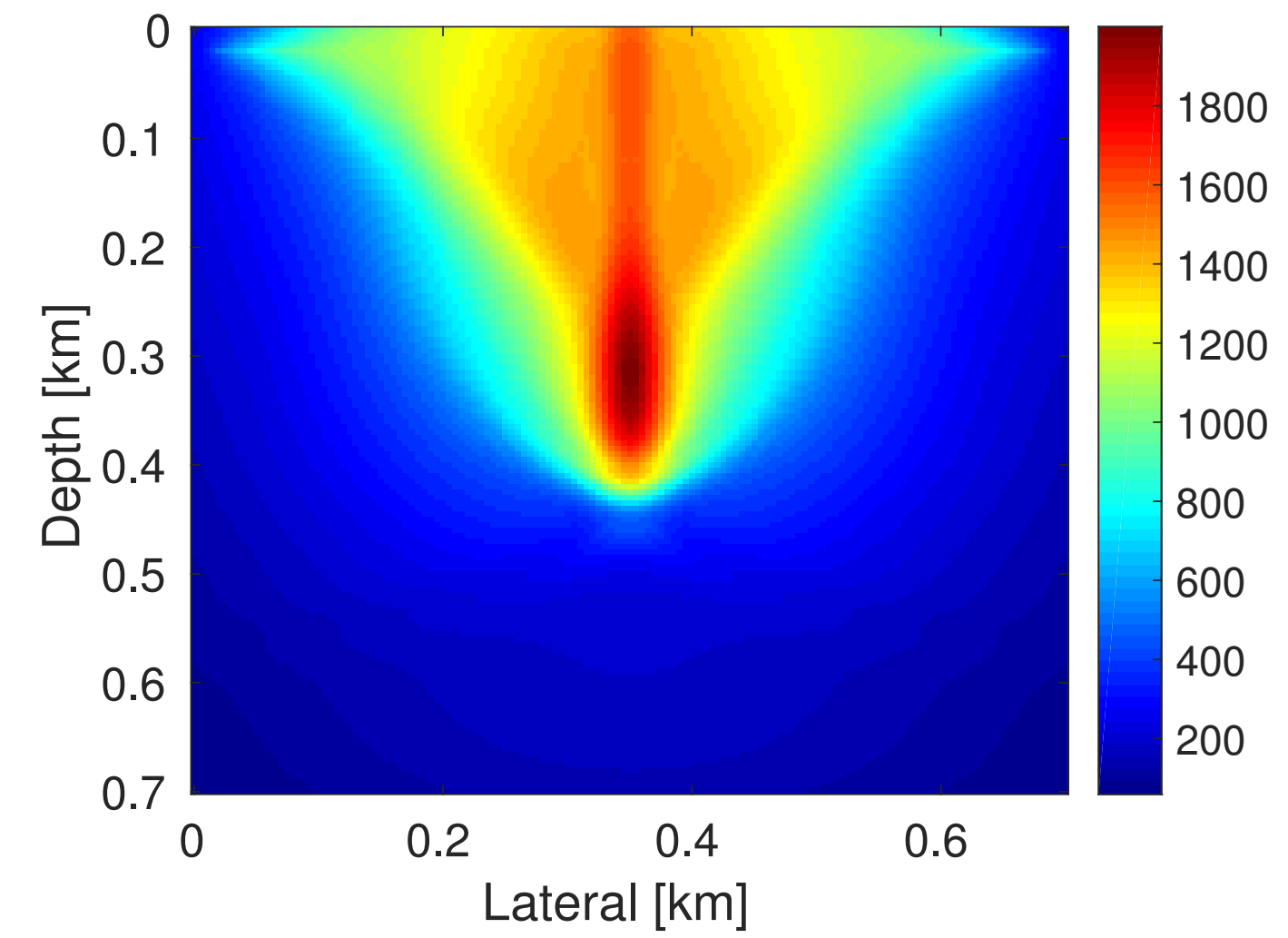
Sparsity promotion





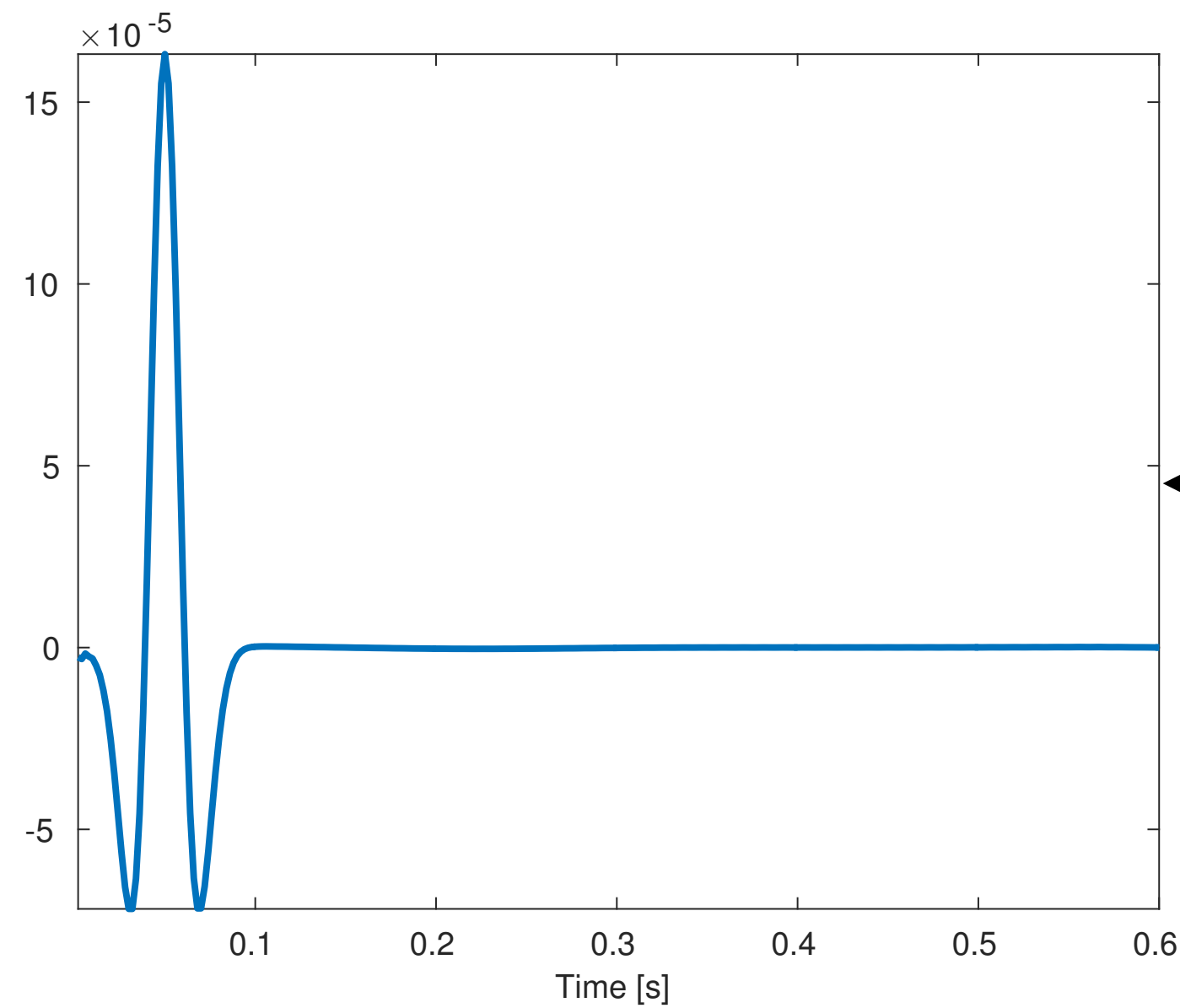
$$\mathbf{V}_1 = \mathcal{F}^T[\mathbf{m}](\Pi_\epsilon(\mathcal{F}(\mathbf{Q}_0) - \mathbf{d}))$$

Adjoint solve



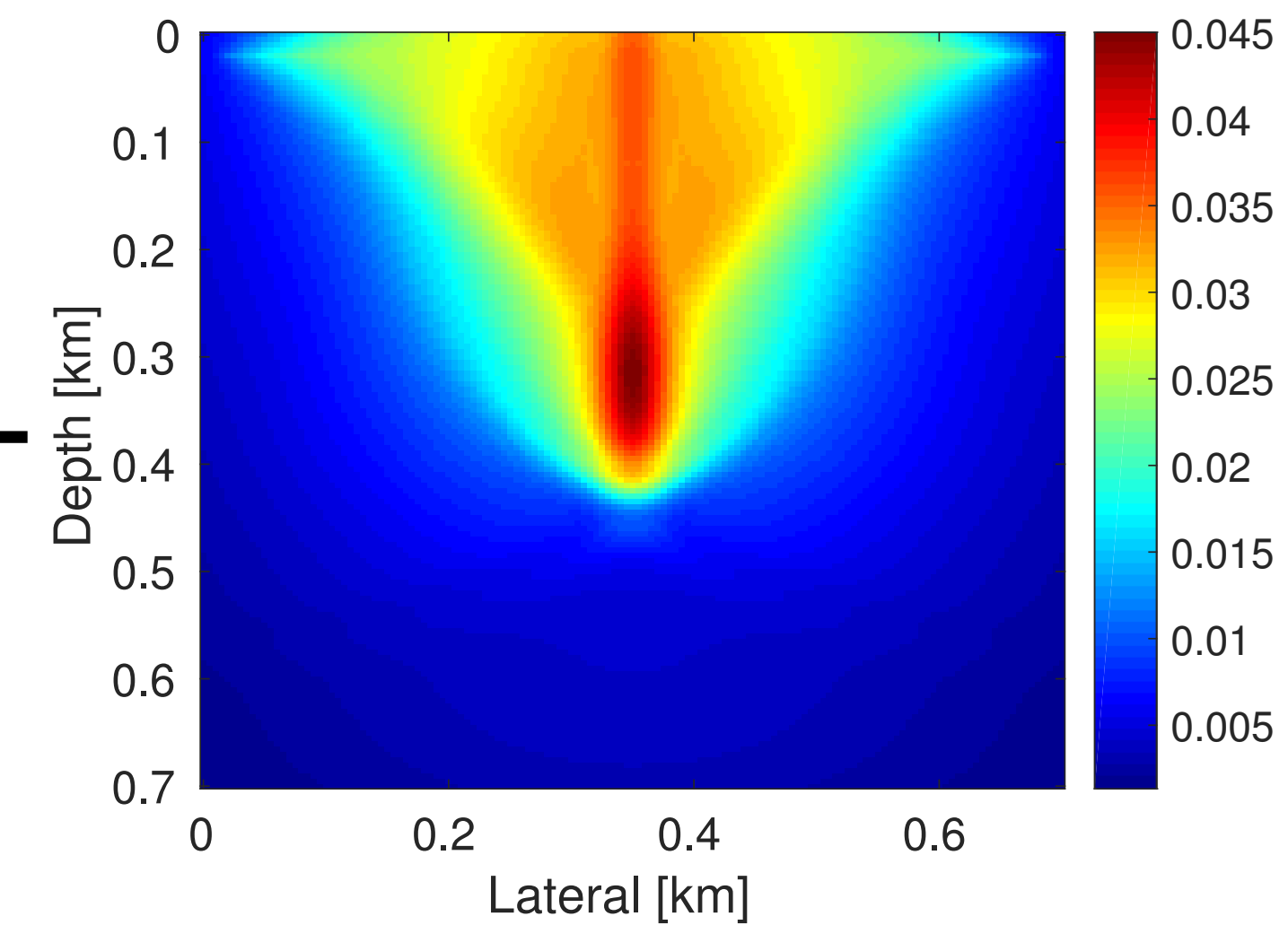
**Auxiliary variable
update**

$$\mathbf{Z}_1 = \mathbf{Z}_0 - t_1 \mathbf{V}_1$$



$$\mathbf{Q}_1 = \text{Prox}_{\lambda \|\cdot\|_{2,1}}(\mathbf{Z}_1)$$

Sparsity promotion



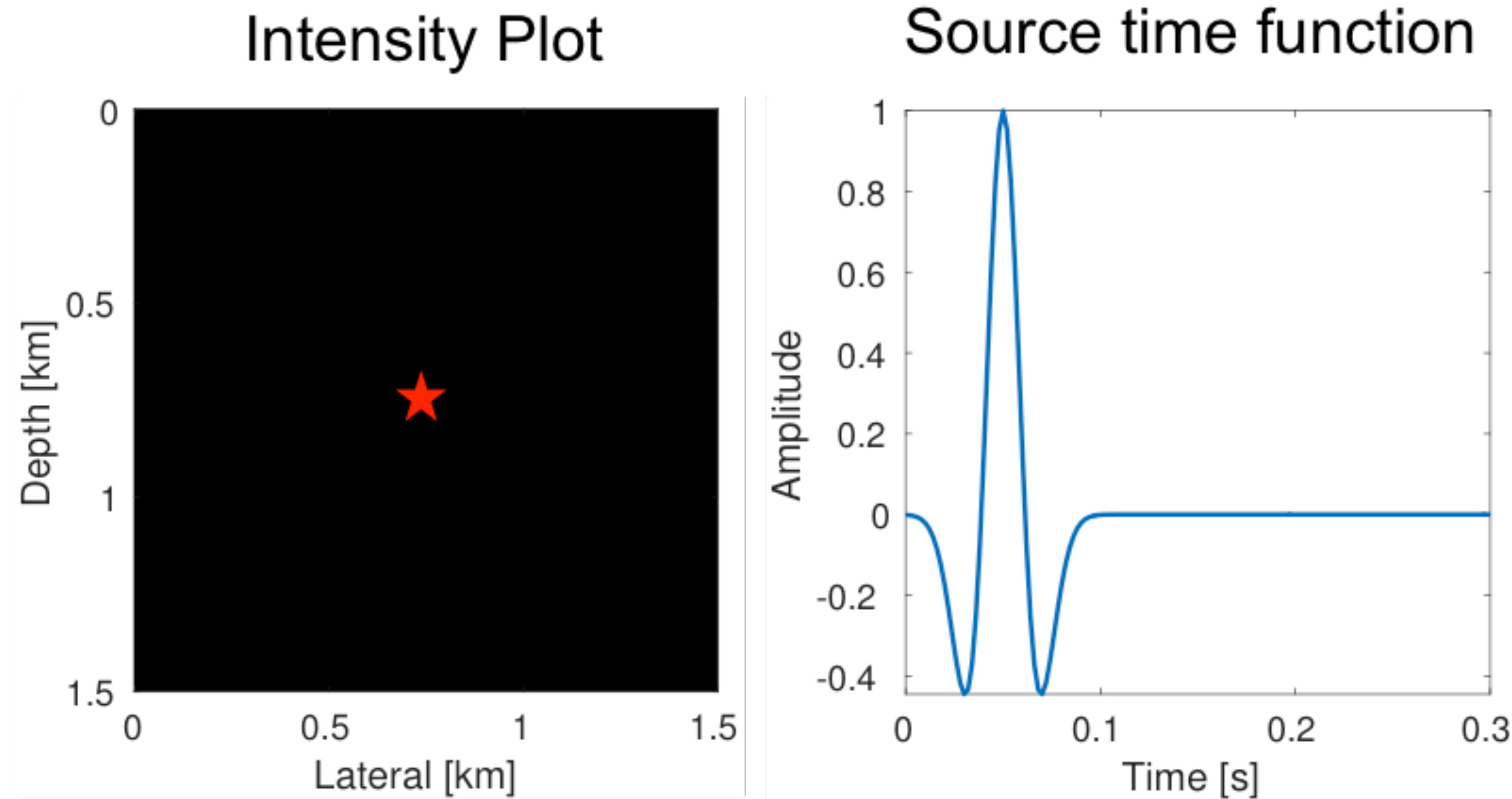
Location and source time function estimation

Source location: estimated as outlier in intensity plot

$$I(\mathbf{x}) = \sum_t | \mathbf{Q}(\mathbf{x}, t) |$$

Source time function: temporal variation of wavefield at estimated source location

Source location & source time function



Schematic showing source location as outlier and corresponding source time function

Case study

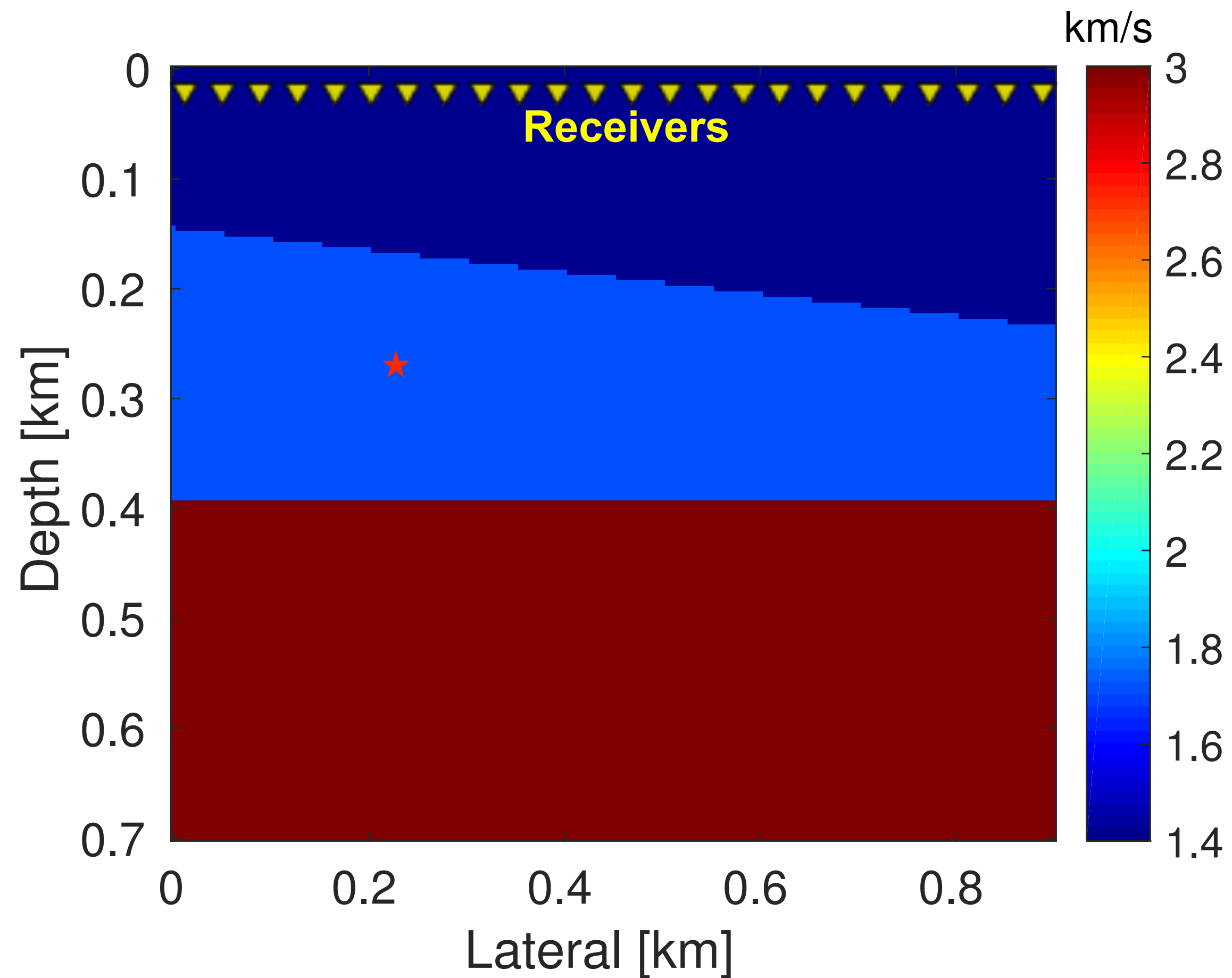
Case study 1: True velocity experiment

Assumptions:

- ▶ access to true velocity model
- ▶ noise-free data

Both can be relaxed...

Experimental setup



Modeling information:

Model size: 0.9 km x 0.7 km

Grid spacing: 10m

Receiver spacing: 10m

Source depth: 0.27 km

Source lateral position: 0.25 km

Wavelet: Ricker wavelet

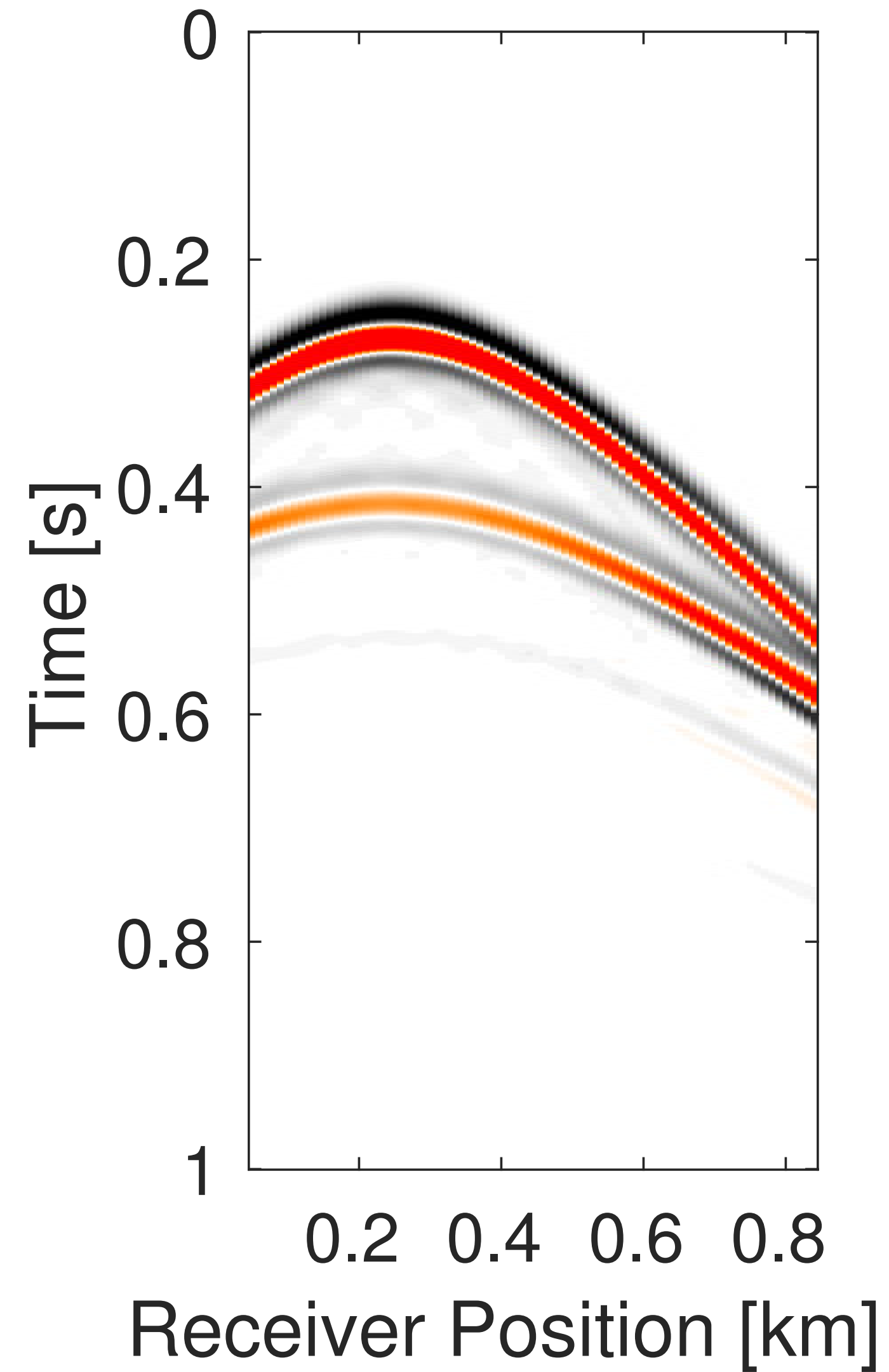
Receiver depth: 20m

Fixed spread: 0.88km

Sampling interval: 1 ms

Recording length: 1s

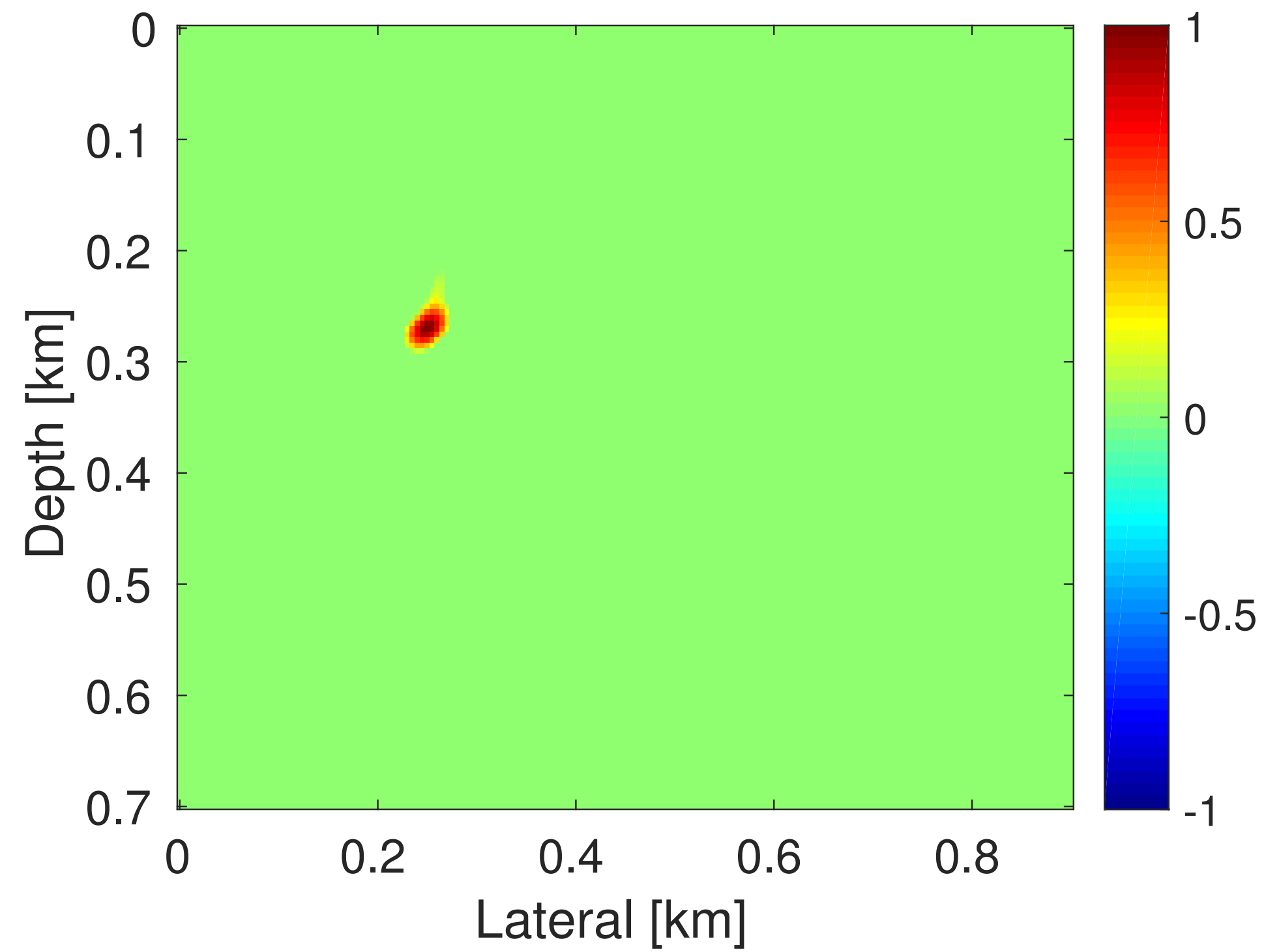
Peak frequency : 20 Hz



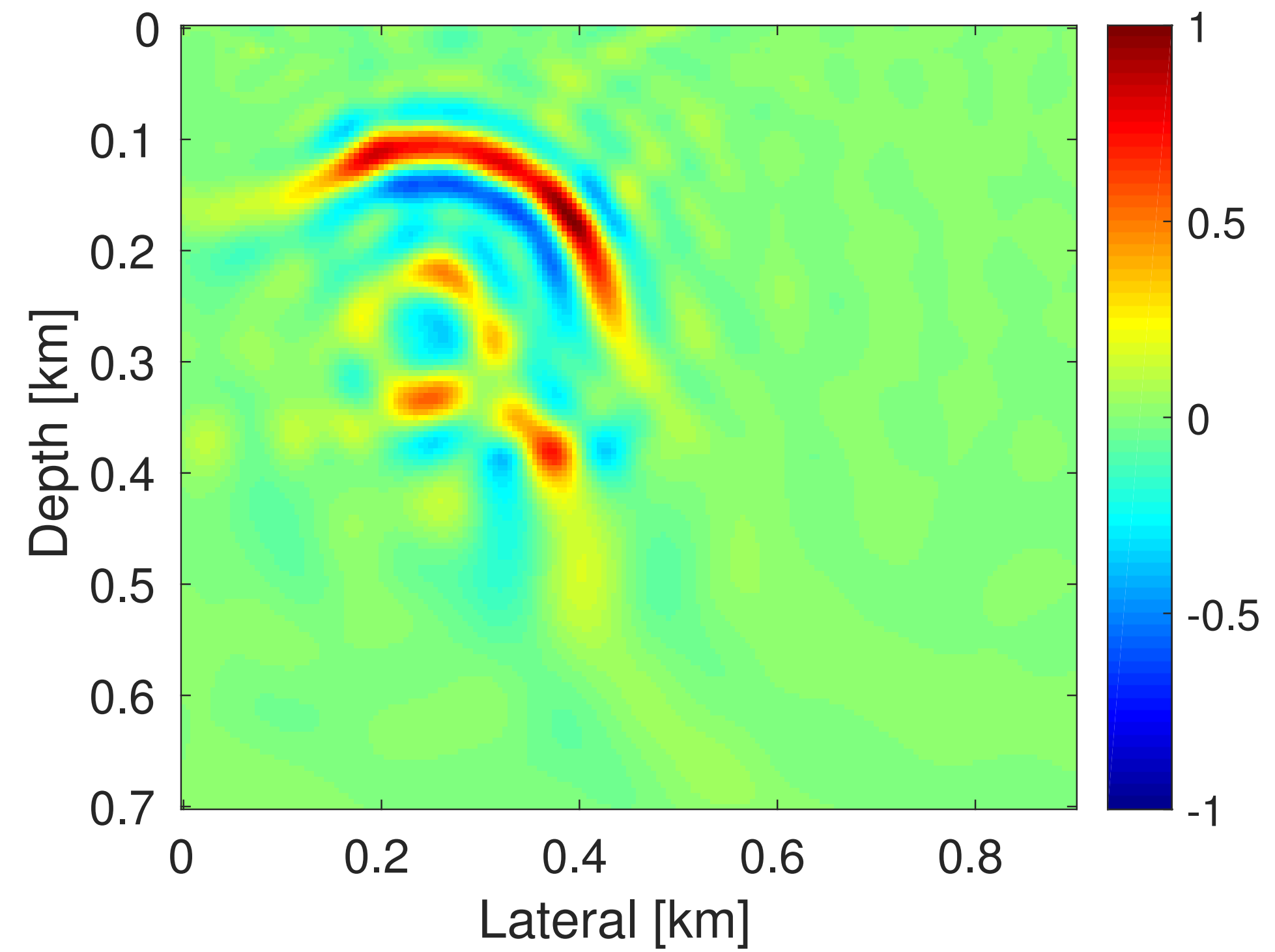
Synthetic microseismic data

**Data is simulated using
finite difference time
stepping code**

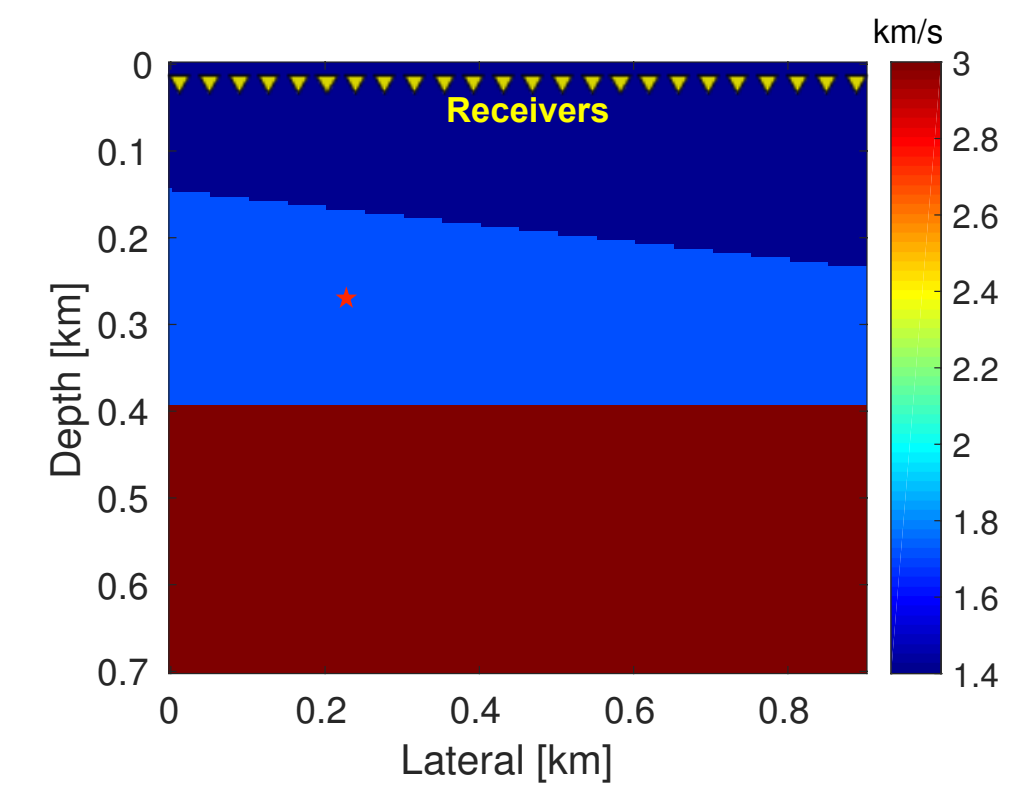
Estimated source location



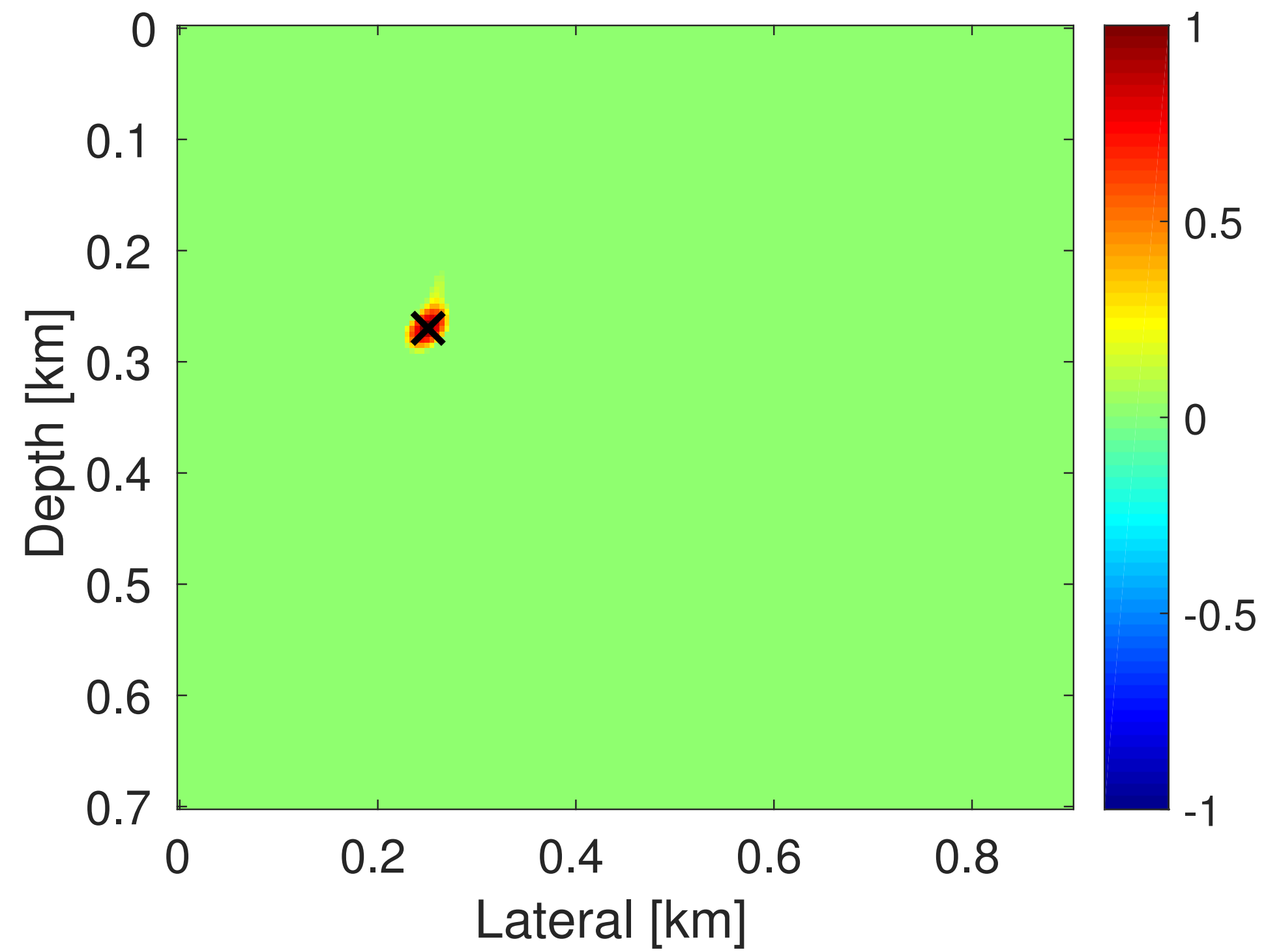
Sparsity-promoting method



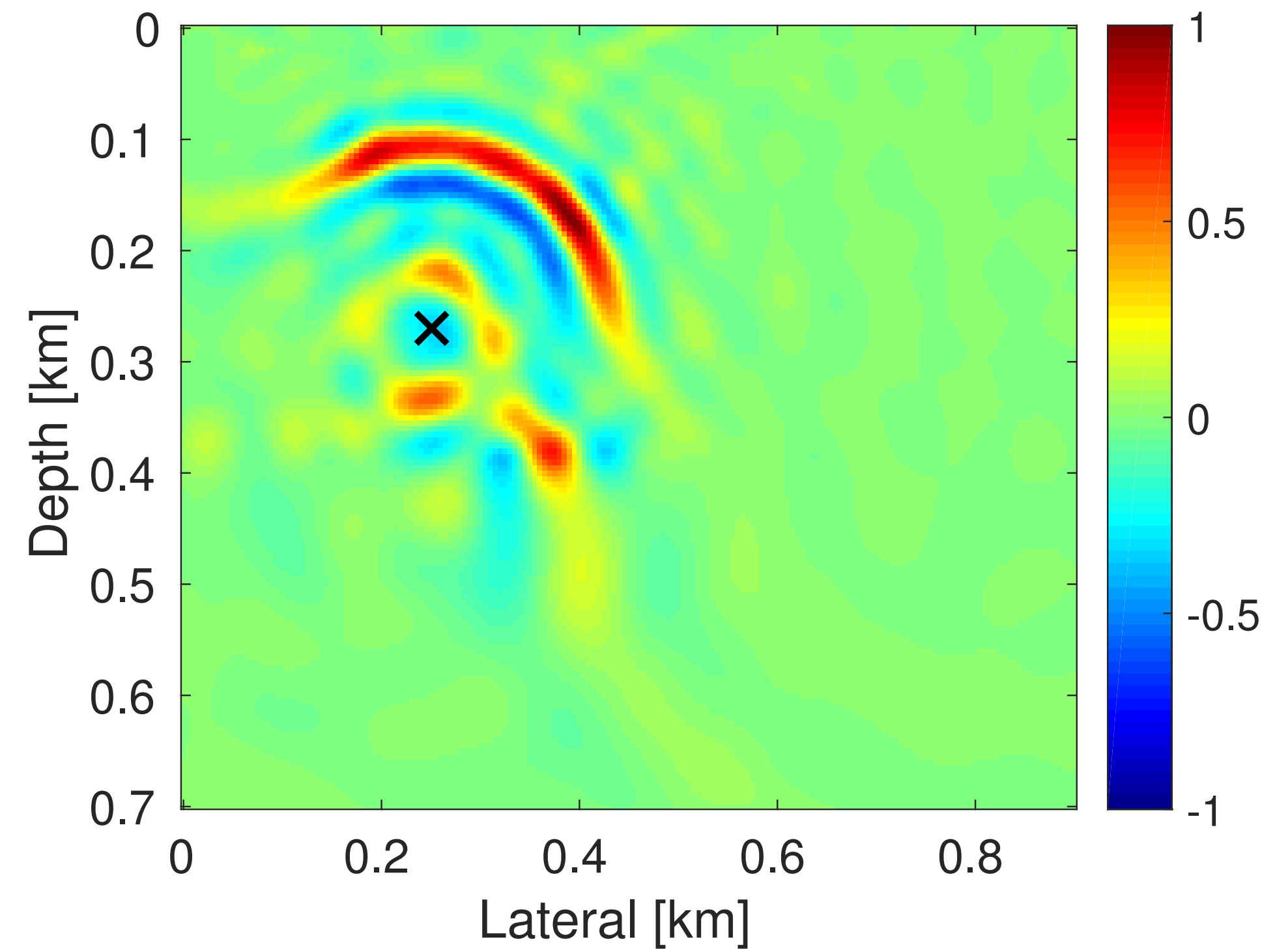
FWI



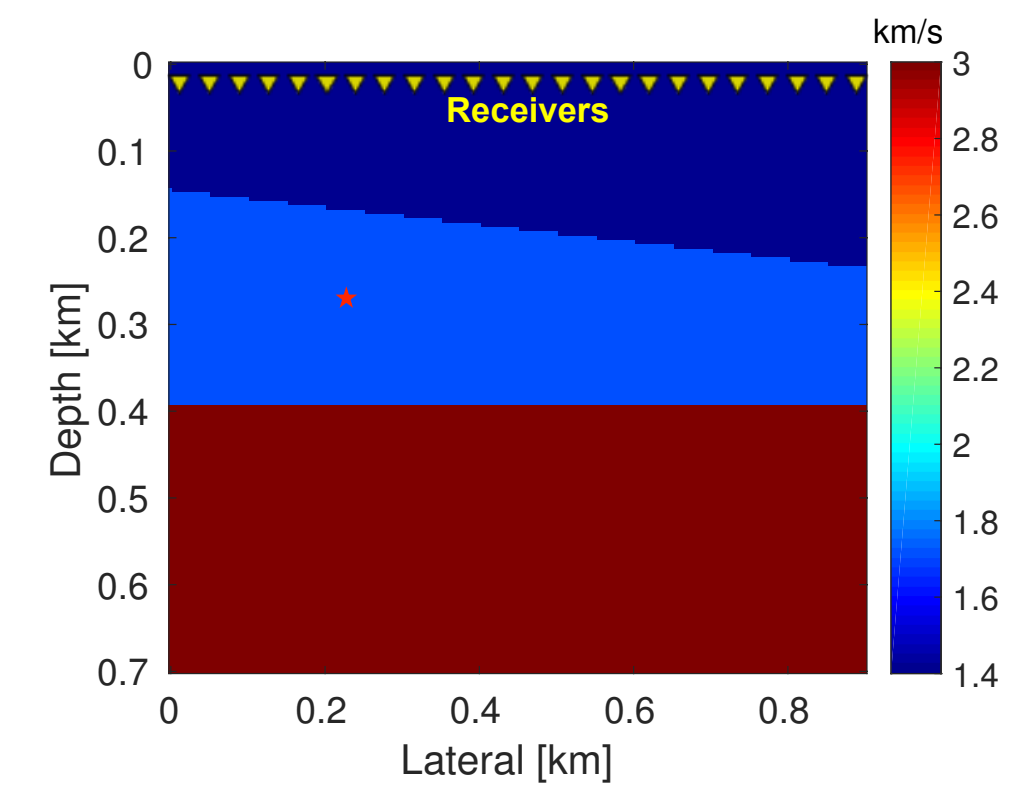
Estimated source location



Sparsity-promoting method

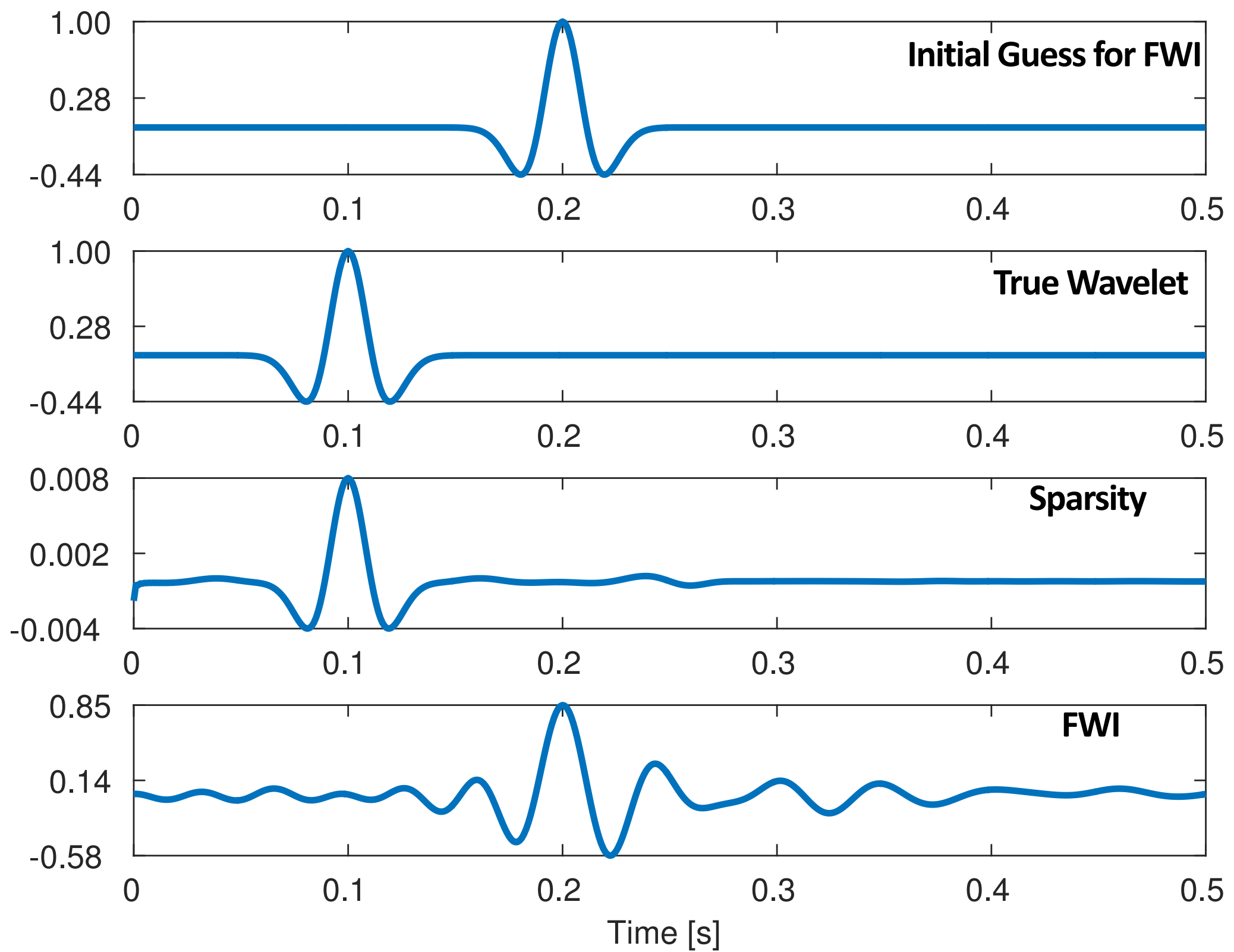


FWI

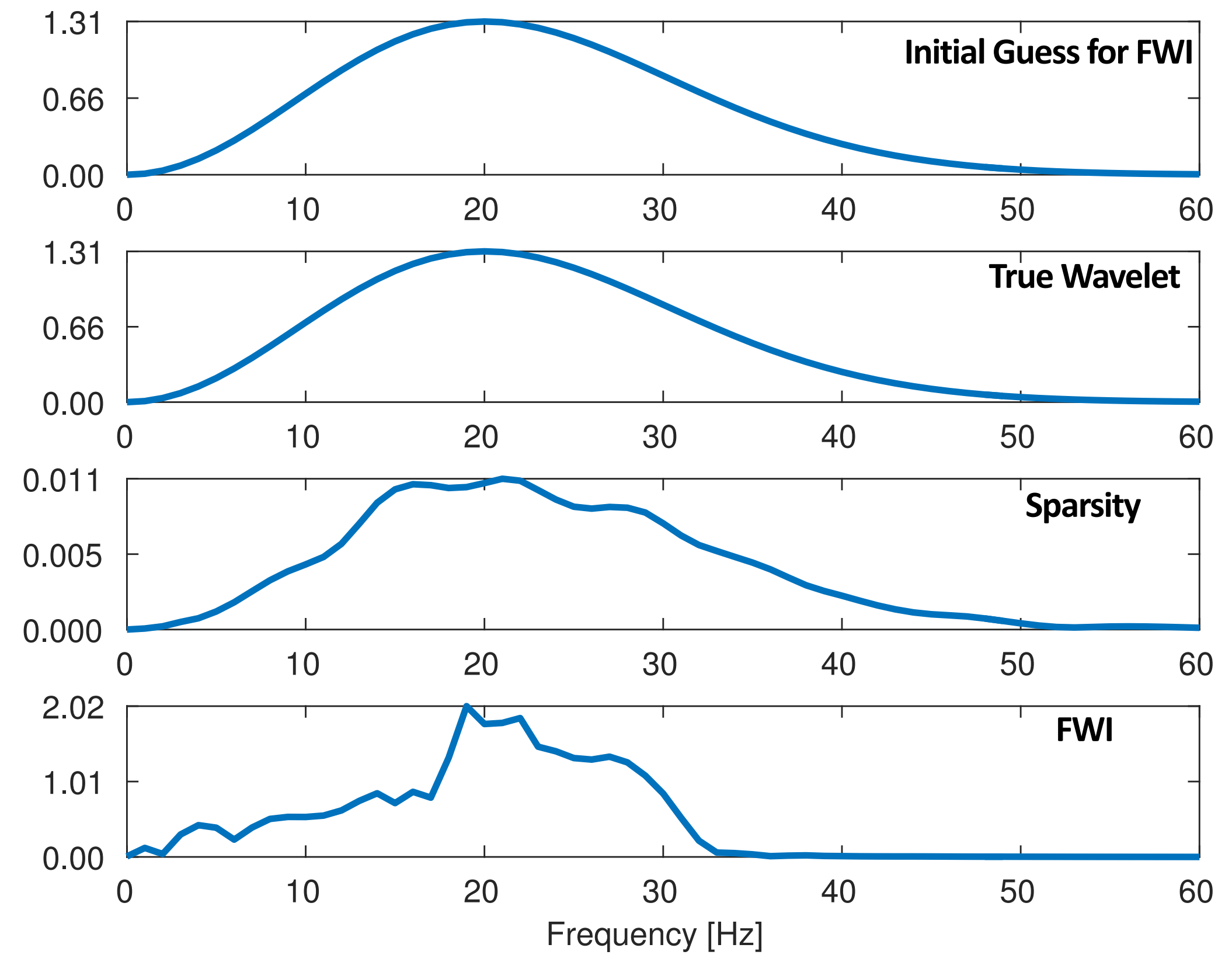


Wavelet comparison

Wavelet



Spectrum



Case study 2: Multiple source experiment

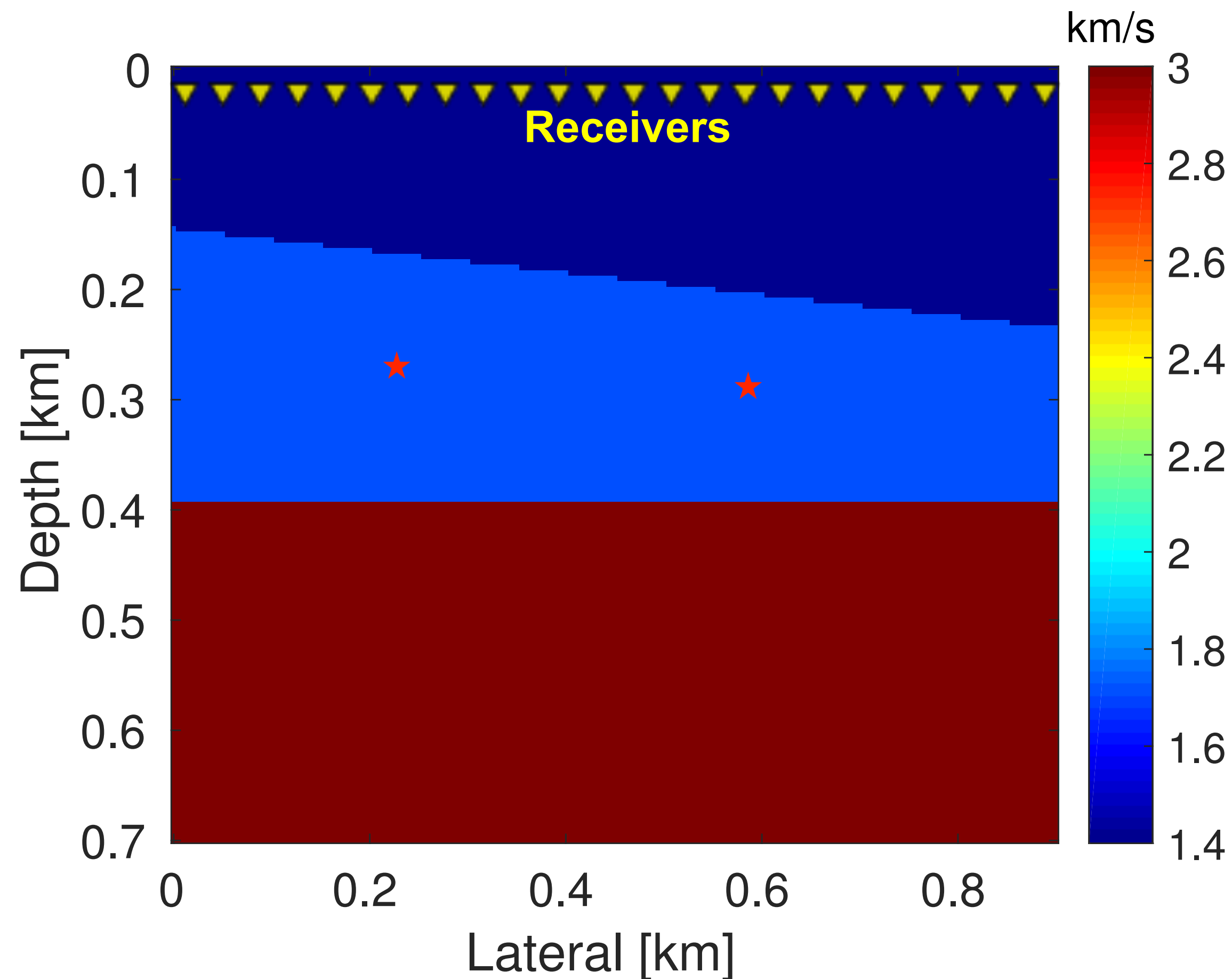
Assumptions:

- ▶ access to smooth background velocity model
- ▶ noisy data (bandwidth limited random noise up to 45 Hz)

Sources are activating at

- ▶ different source origin times
- ▶ different dominating frequencies

Experimental setup



Modeling information:

Model size: 0.9 km x 0.7 km

Grid spacing: 10m

Receiver spacing: 10m

Source 1 depth: 0.27 km

Source 1 lateral position: 0.25 km

Source 2 depth: 0.60 km

Source 2 lateral position: 0.28 km

Receiver depth: 20m

Fixed spread: 0.88km

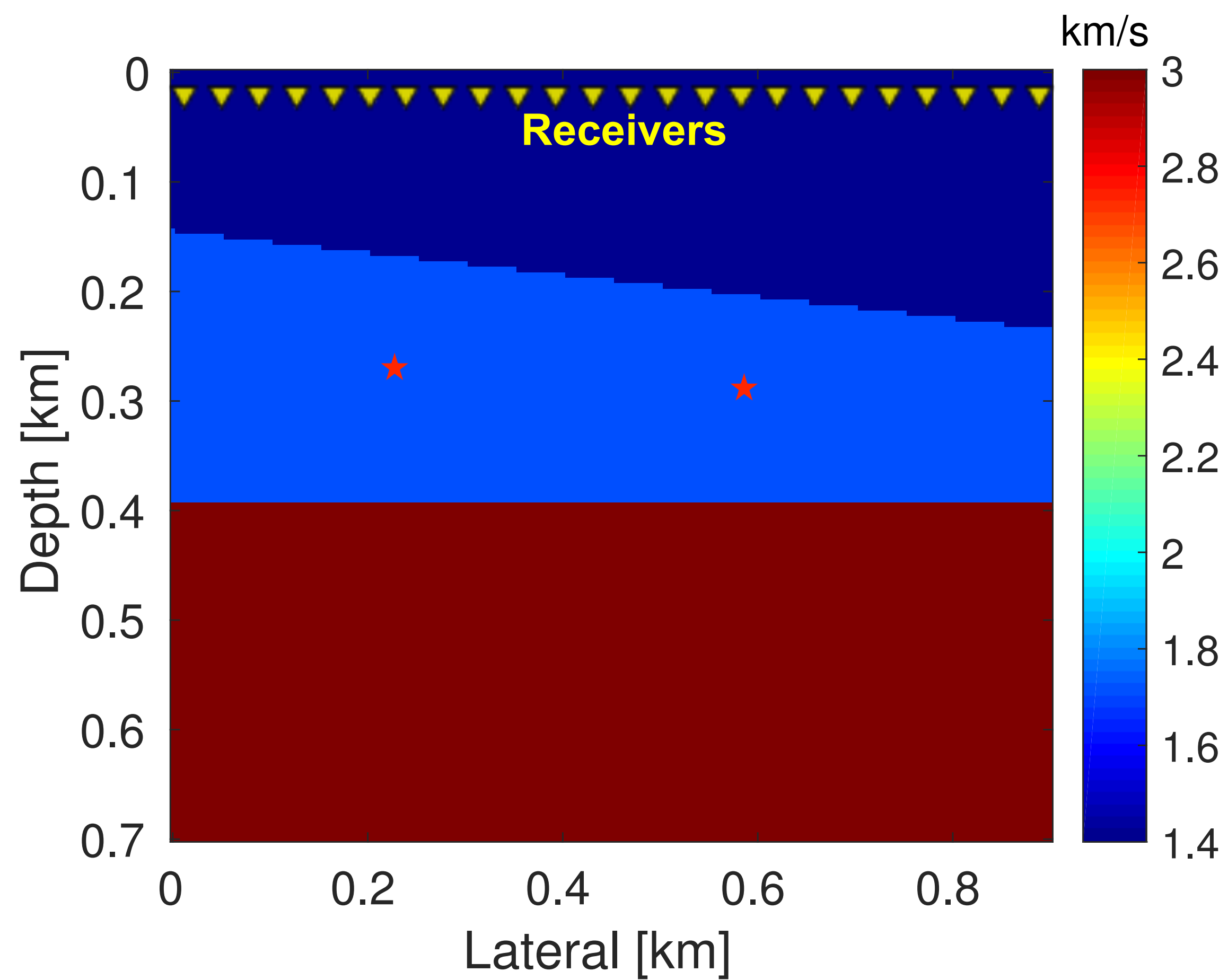
Sampling interval: 1 ms

Recording length: 1s

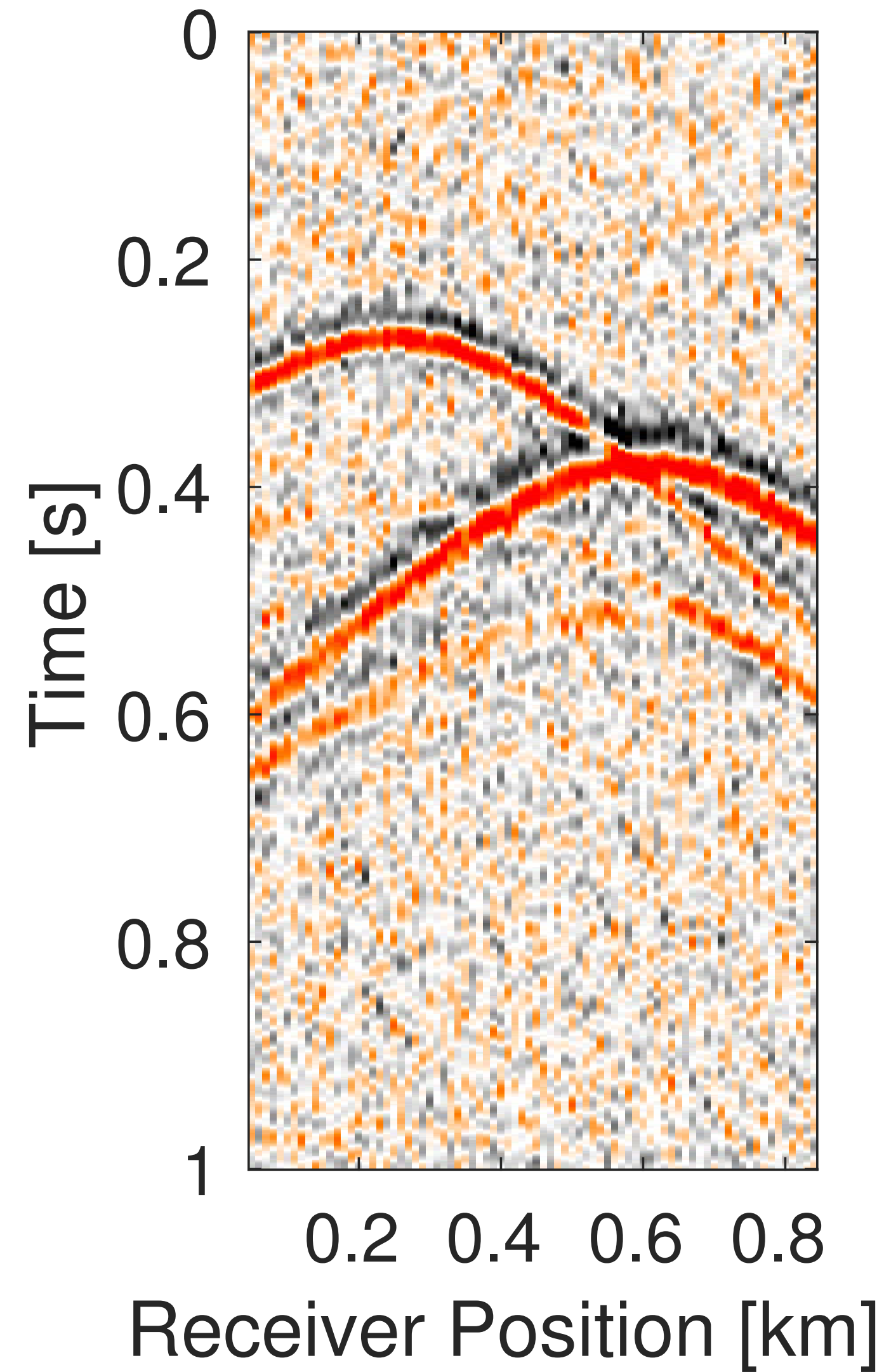
Source 1 Peak frequency : 20 Hz

Source 1 Peak frequency : 15 Hz

Experimental setup



Dominant wavelength: 113 m

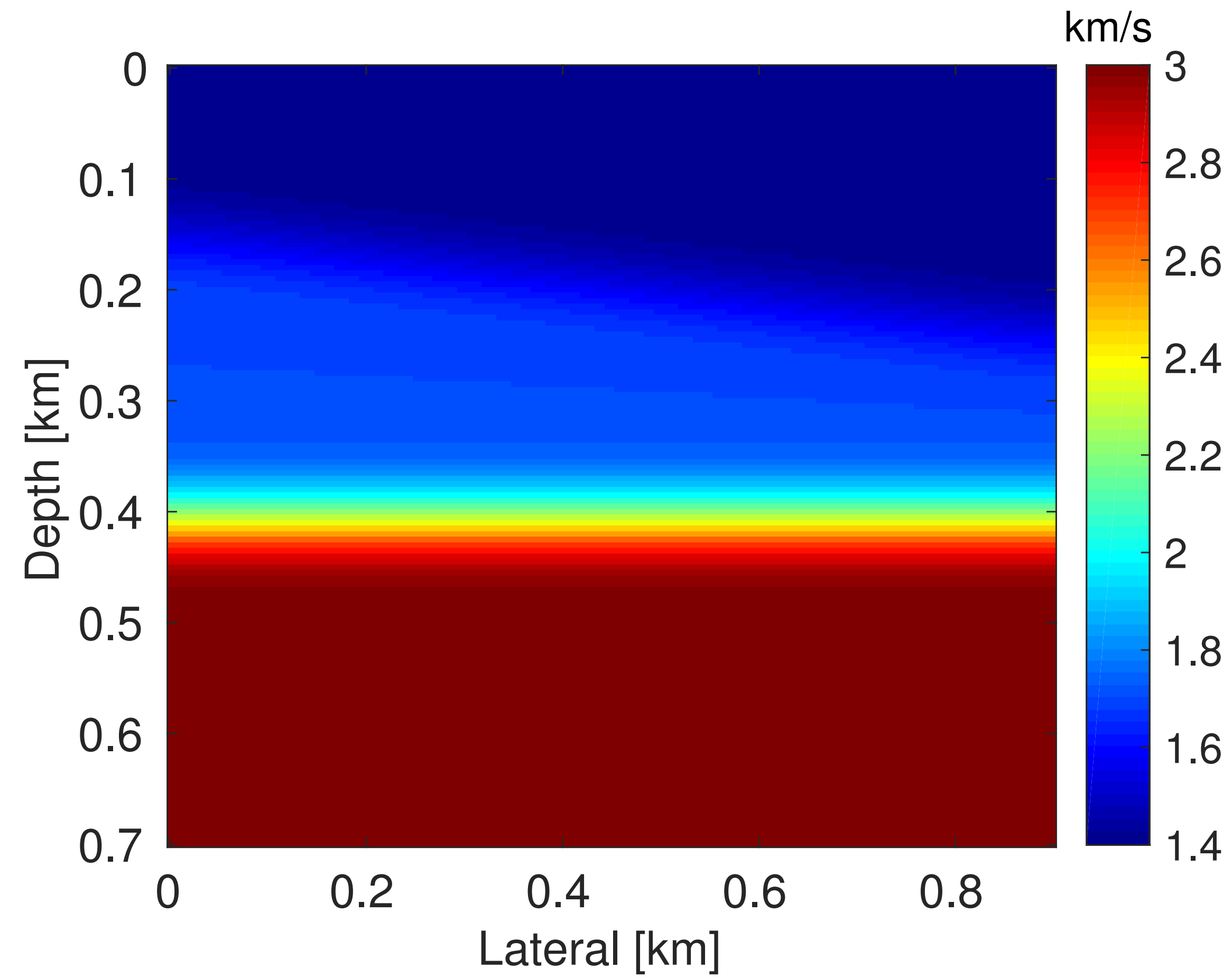


Observed microseismic data, SNR = 0.34

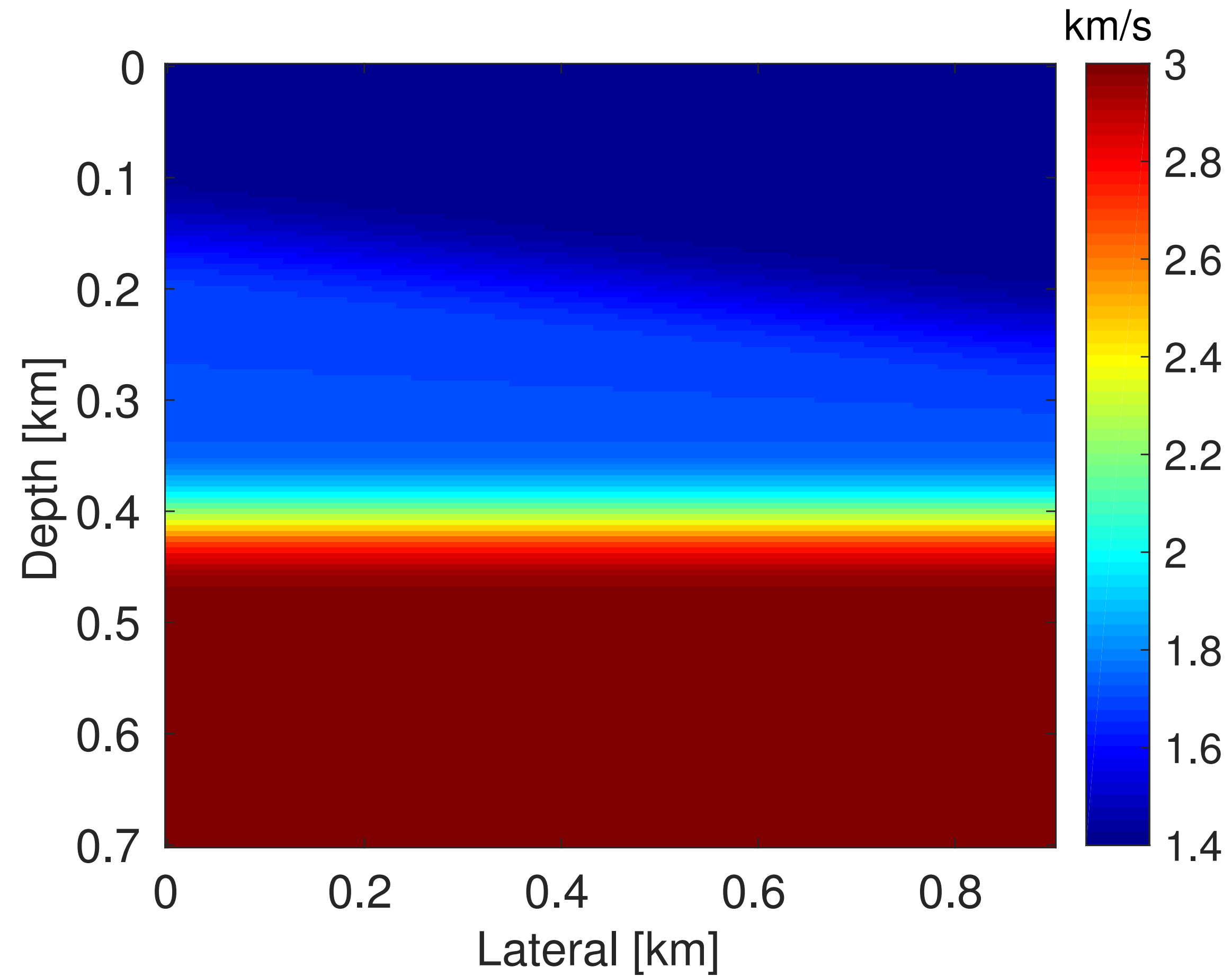
**Data is simulated using
finite difference time
stepping code**

**Data is contaminated with
low frequency random
noise (up to 45 Hz)**

Smooth velocity model

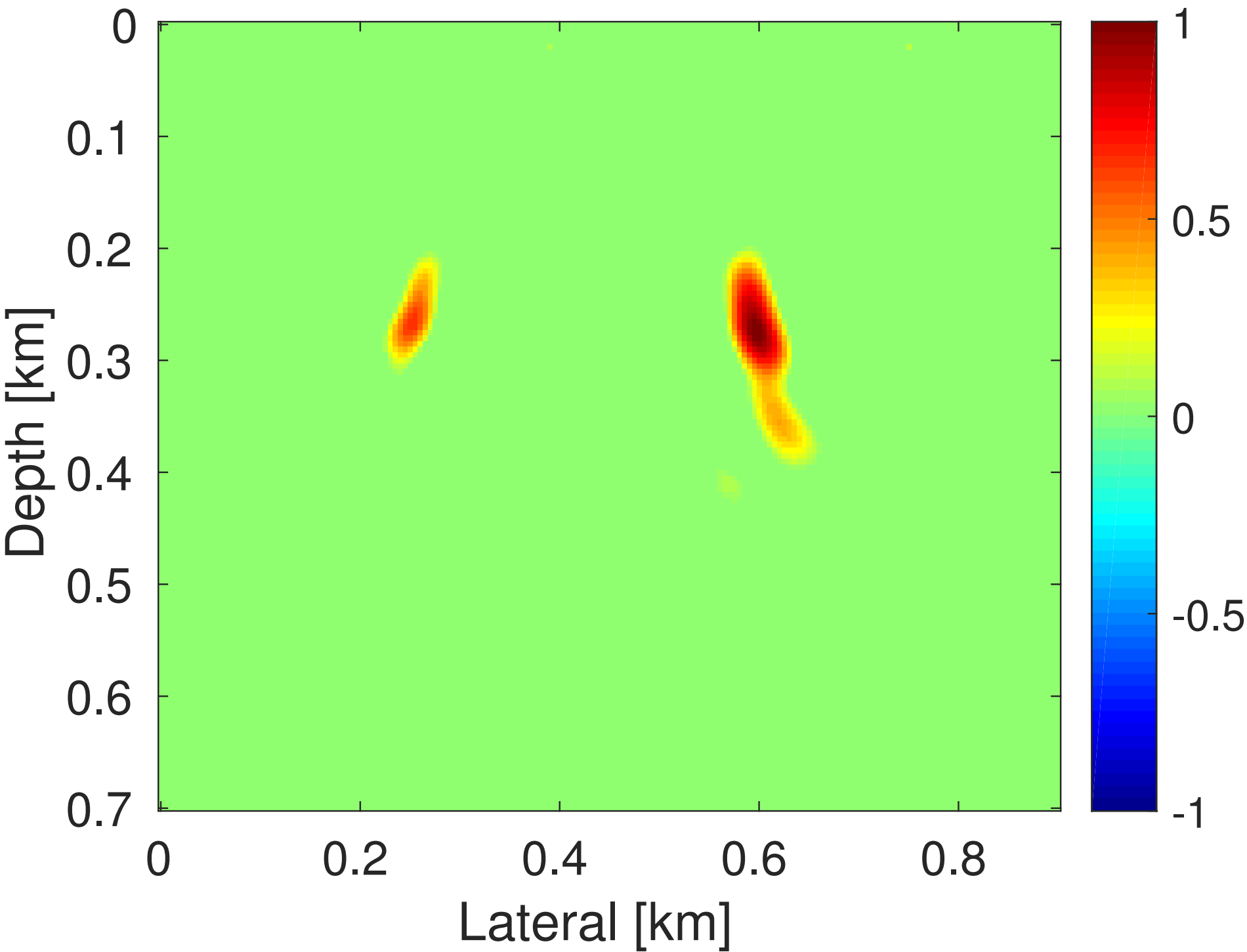
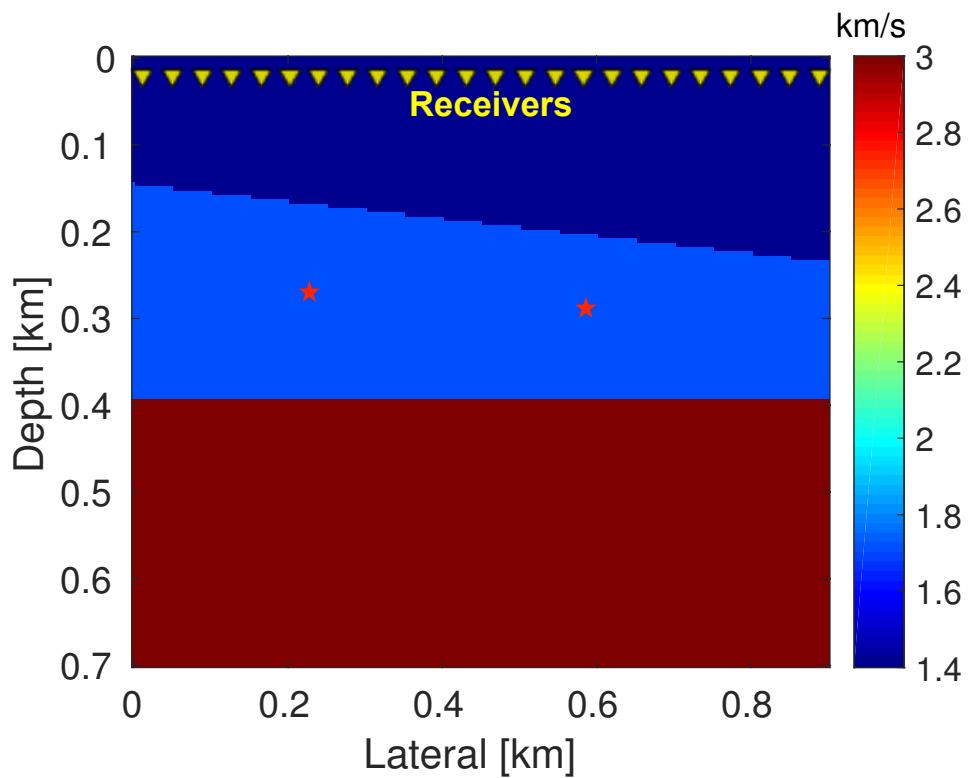


Smooth velocity model

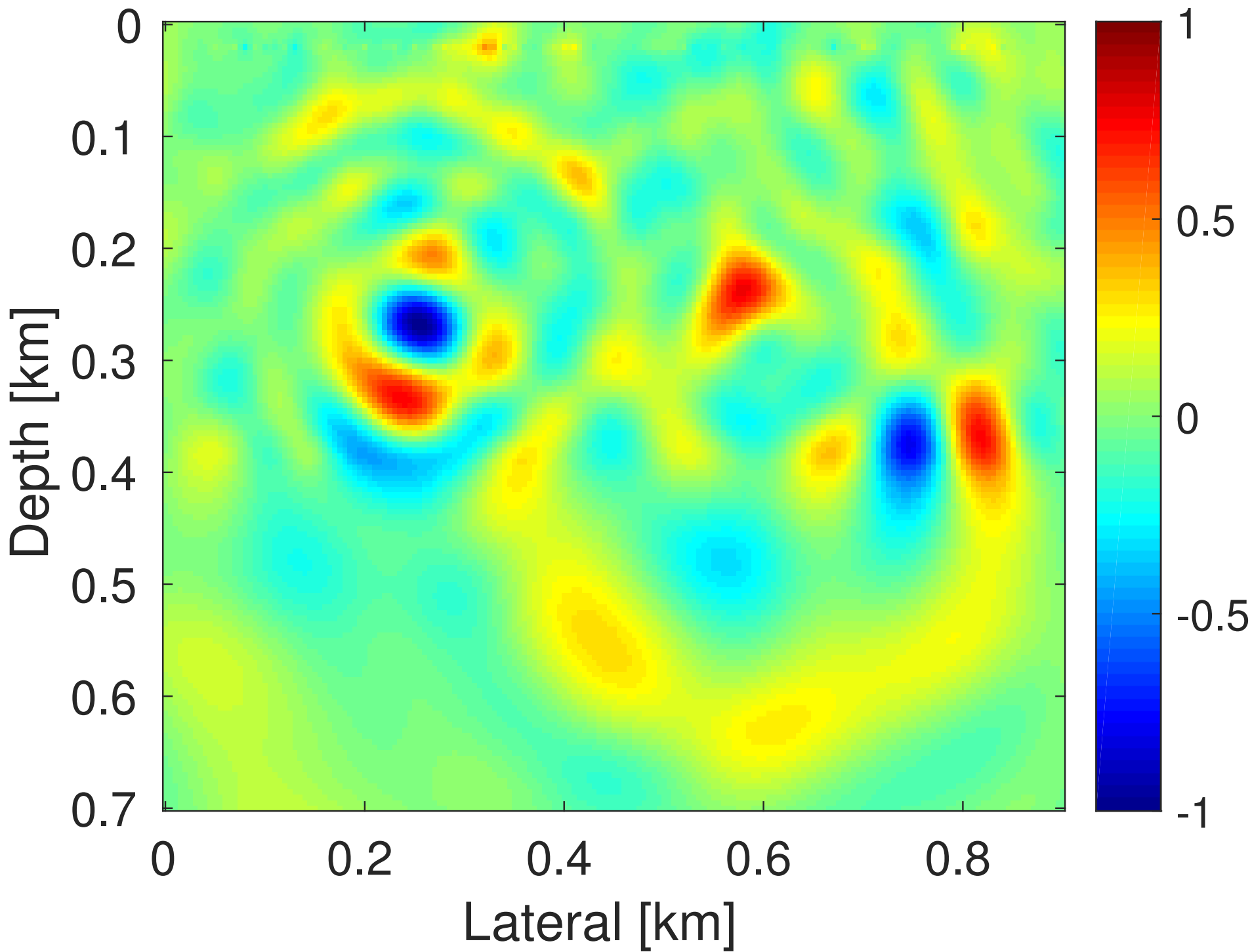


Used for joint microseismic source location & source time function estimation

Estimated source location

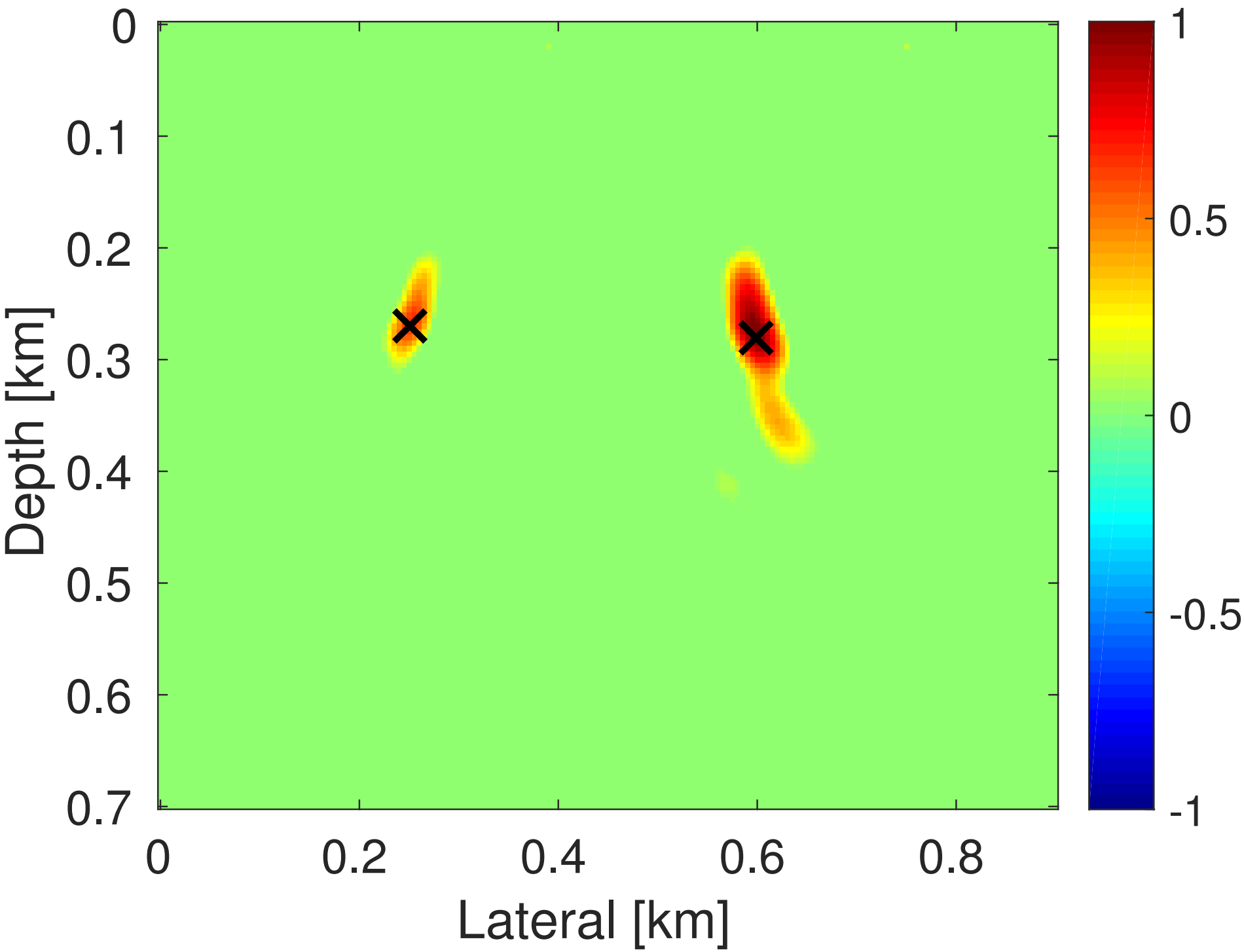
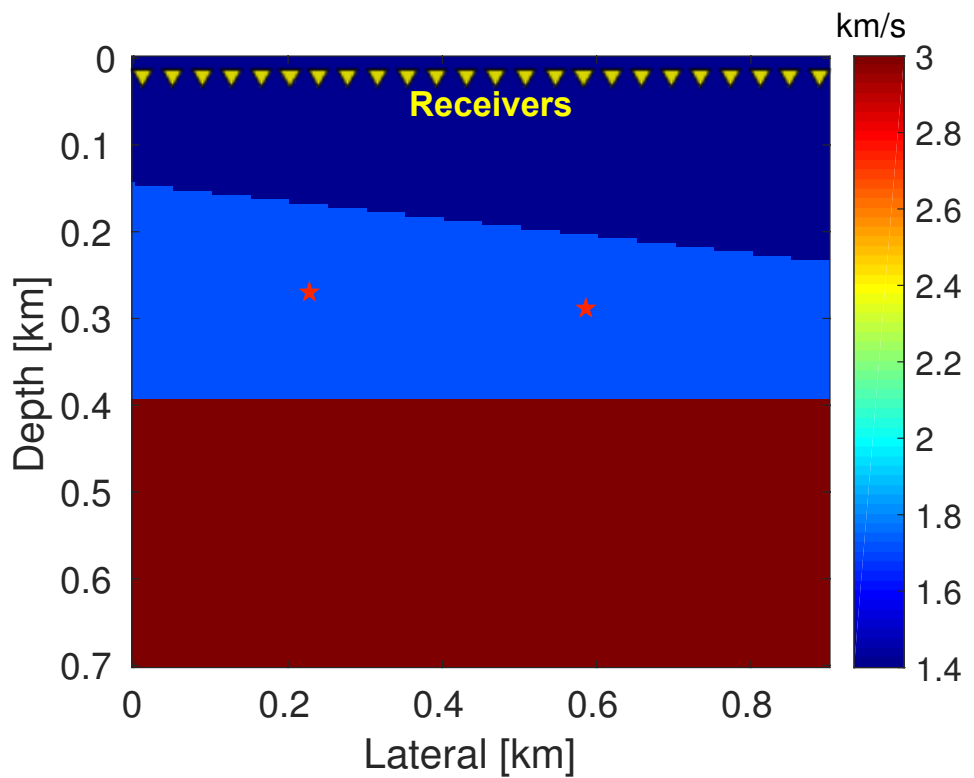


Sparsity-promoting method

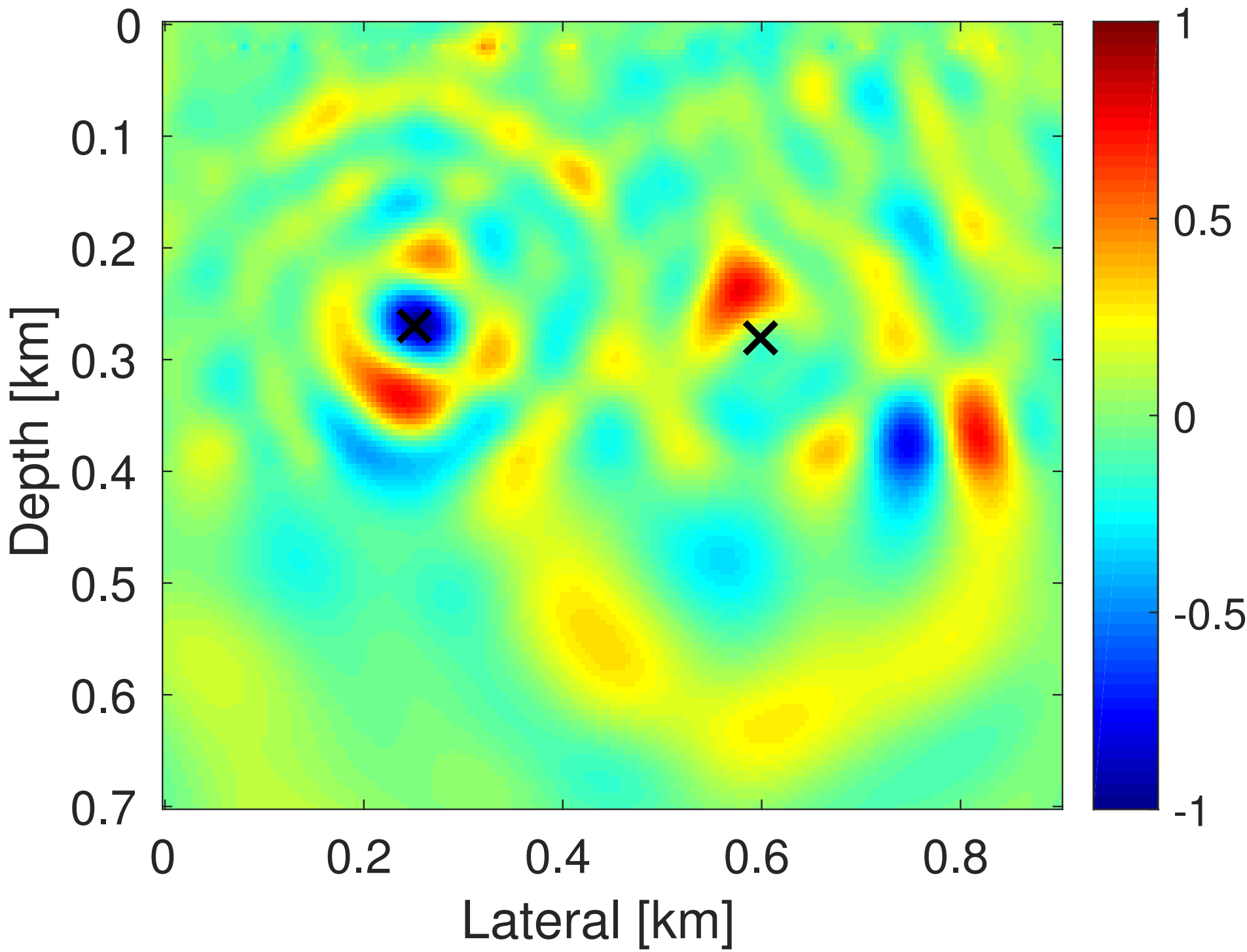


FWI

Estimated source location



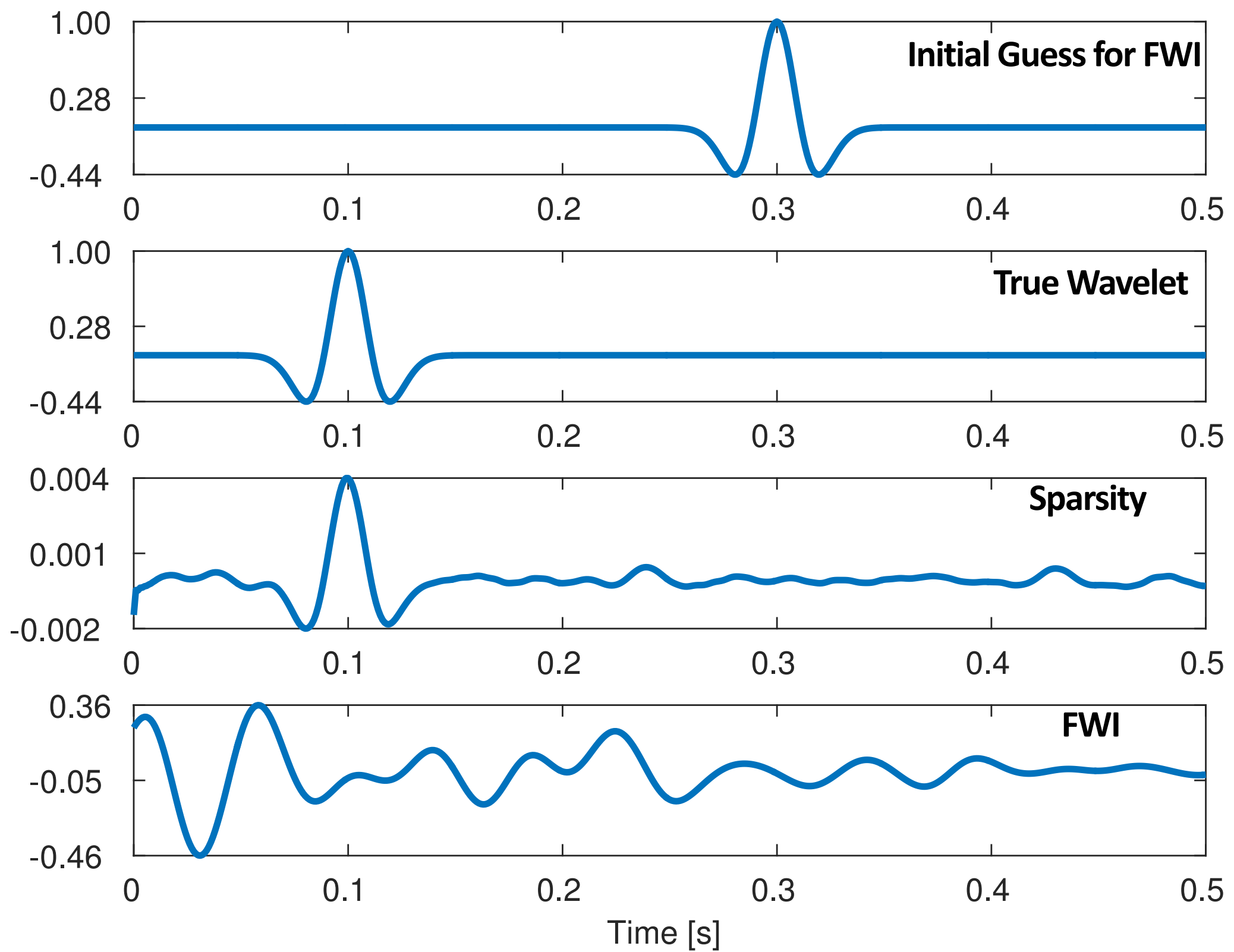
Sparsity-promoting method



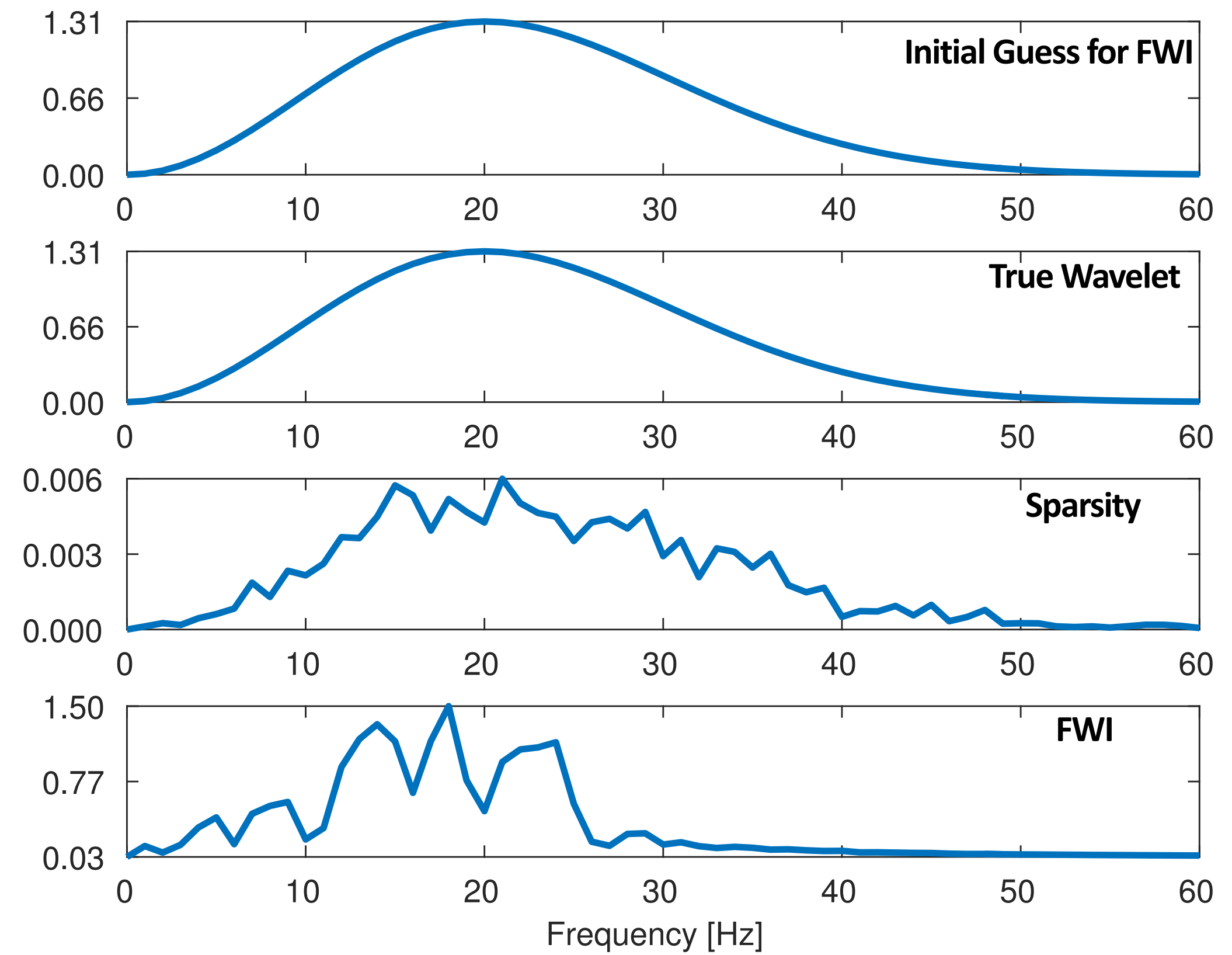
FWI

Location 1

Wavelet

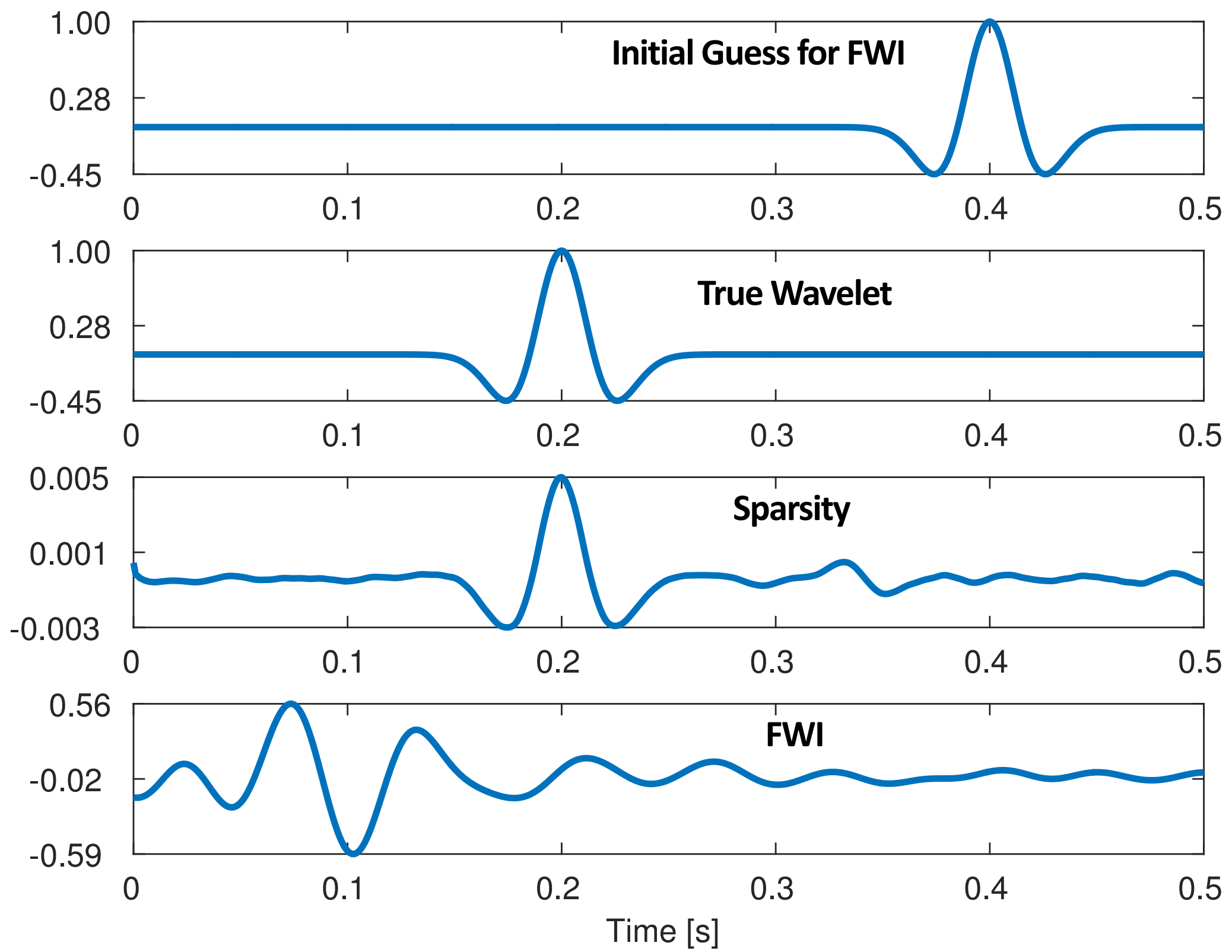


Spectrum

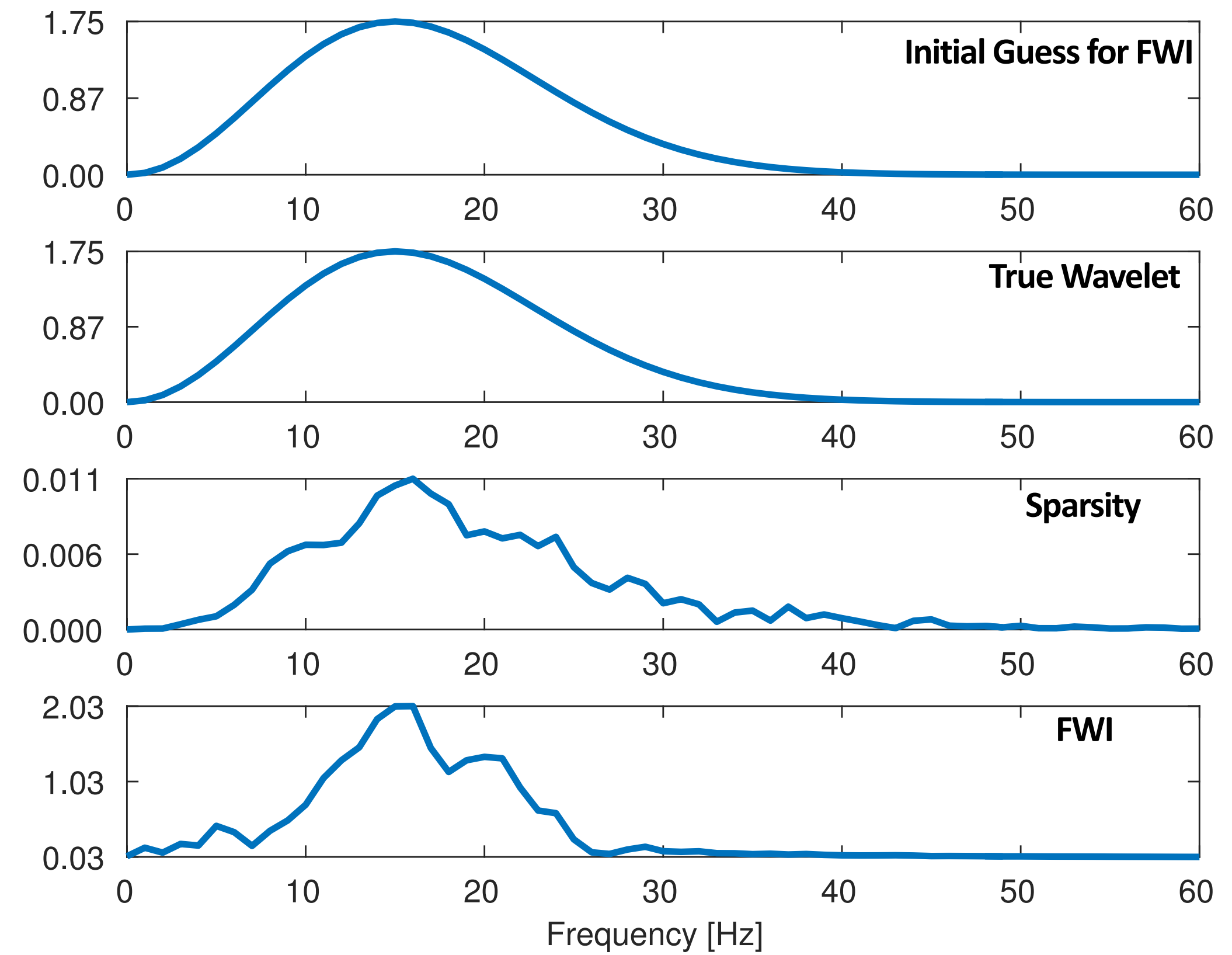


Location 2

Wavelet



Spectrum



Extension to BG compass model

Objective

- ▶ to show the ability of our method in realistic geological setting

Extension to BG compass model

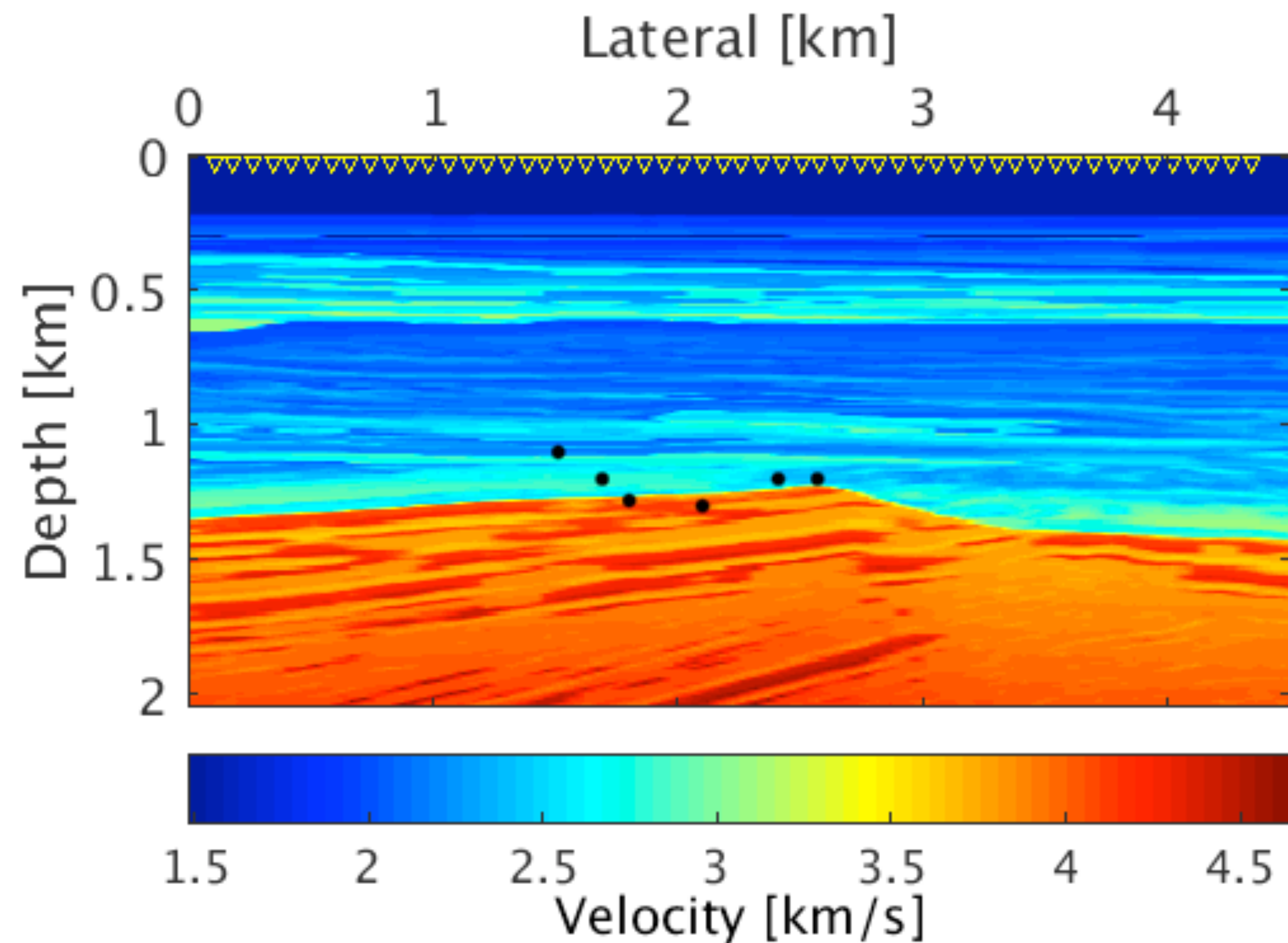
Objective

- ▶ to show the ability of our method in realistic geological setting

Assumptions

- ▶ access to smooth background velocity model
- ▶ noisy data (bandwidth limited random noise up to 45 Hz)

Experimental setup



BG Compass velocity model

Modeling information:

Model size: 2.04 km x 4.50 km

Grid spacing: 10m

Total number of sources: 6

Receiver spacing: 20m

Receiver depth: 20m

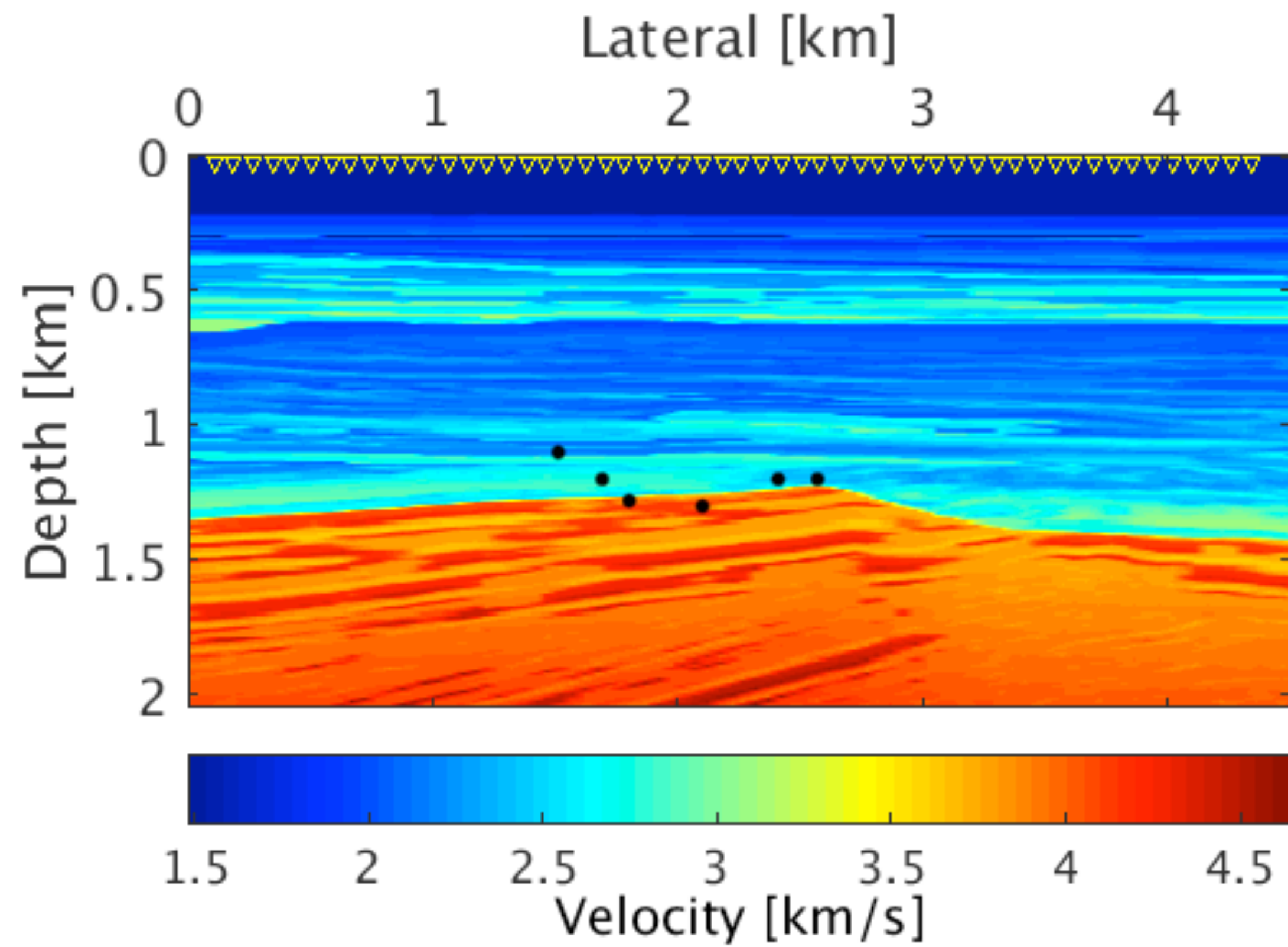
Fixed spread: 4.30 km

Sampling interval: 1 ms

Recording length: 2.5 s

Peak frequency : 15 Hz & 10 Hz

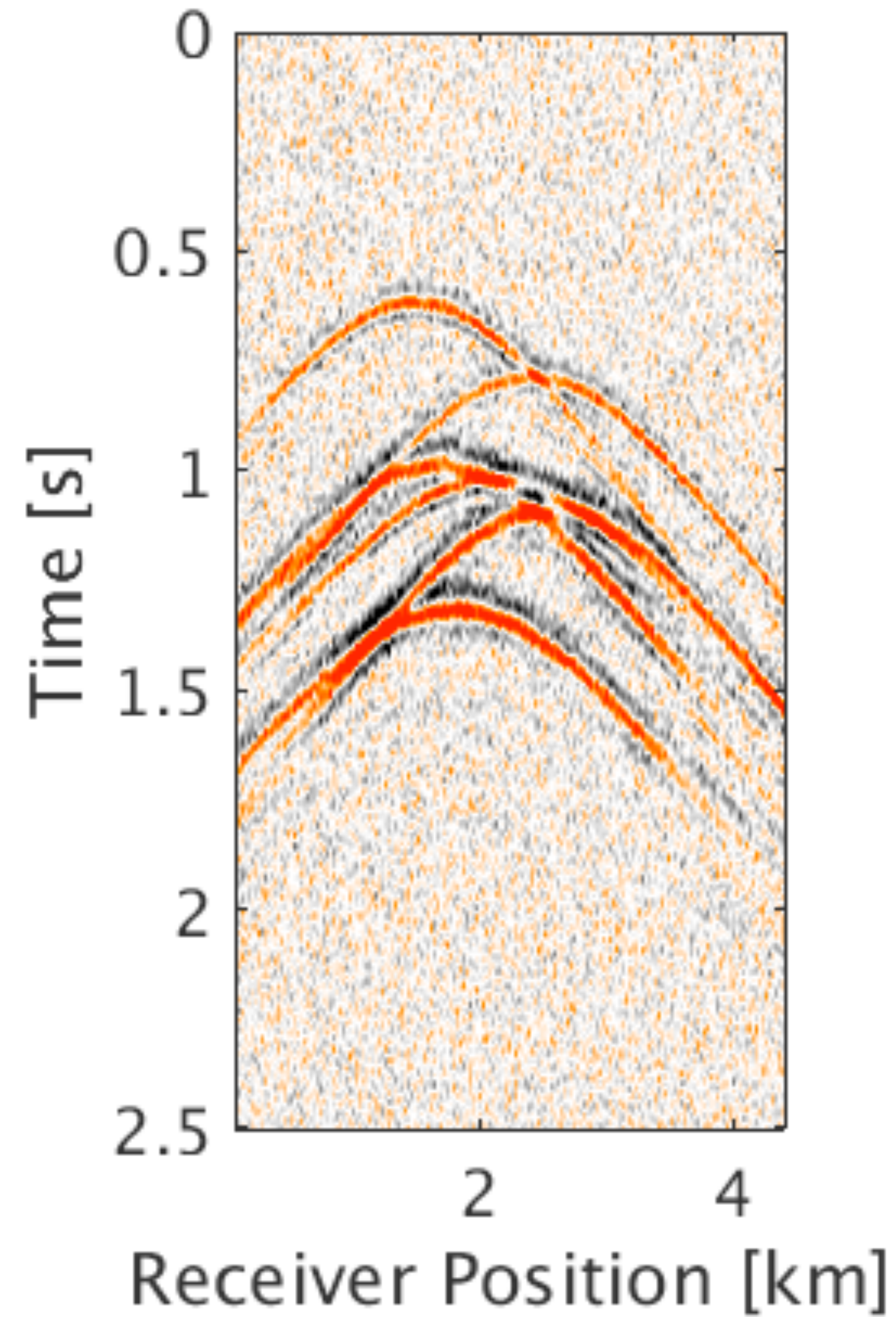
Experimental setup



BG Compass velocity model

Dominant wavelength: 420 m

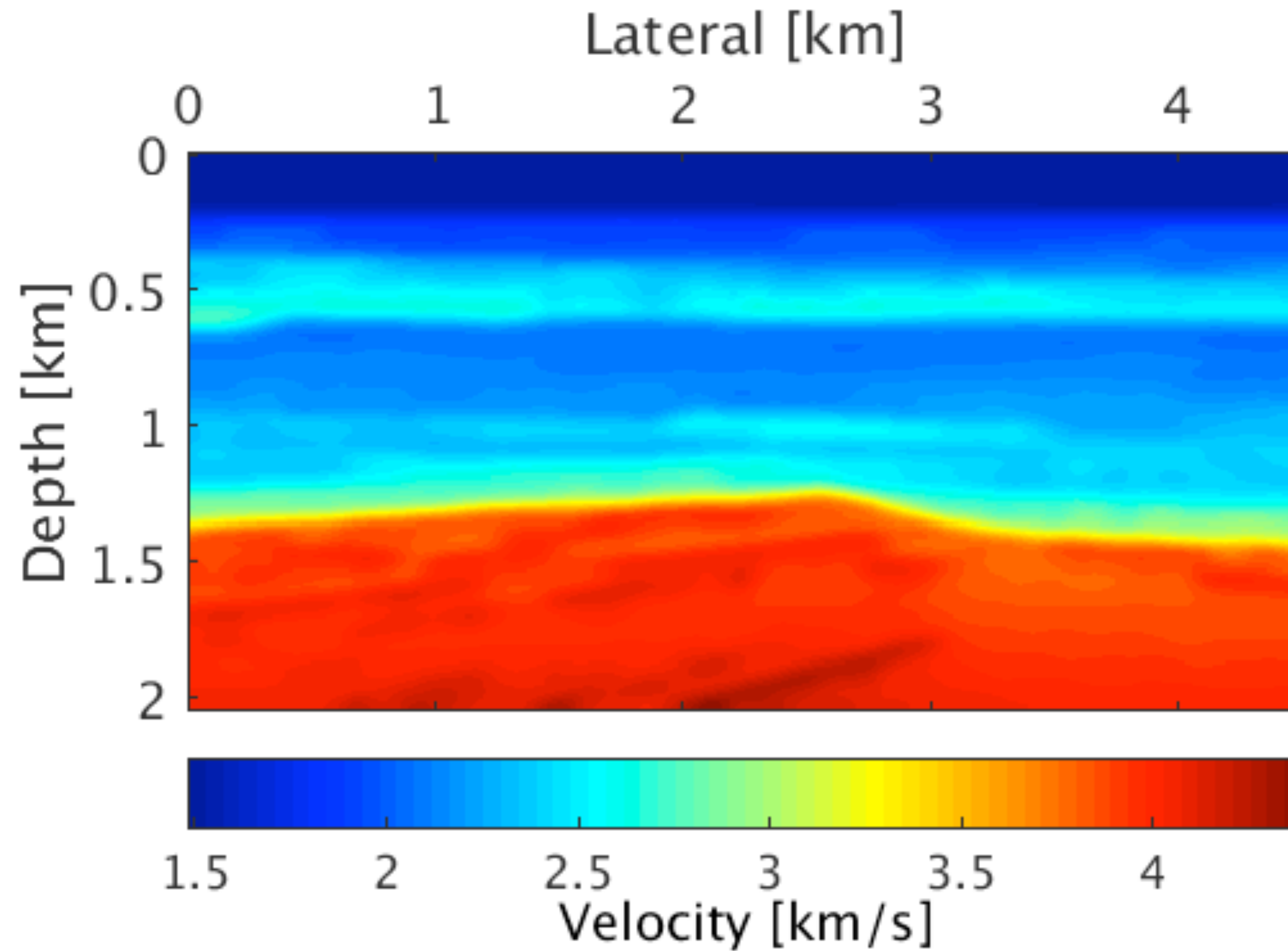
Observed microseismic data



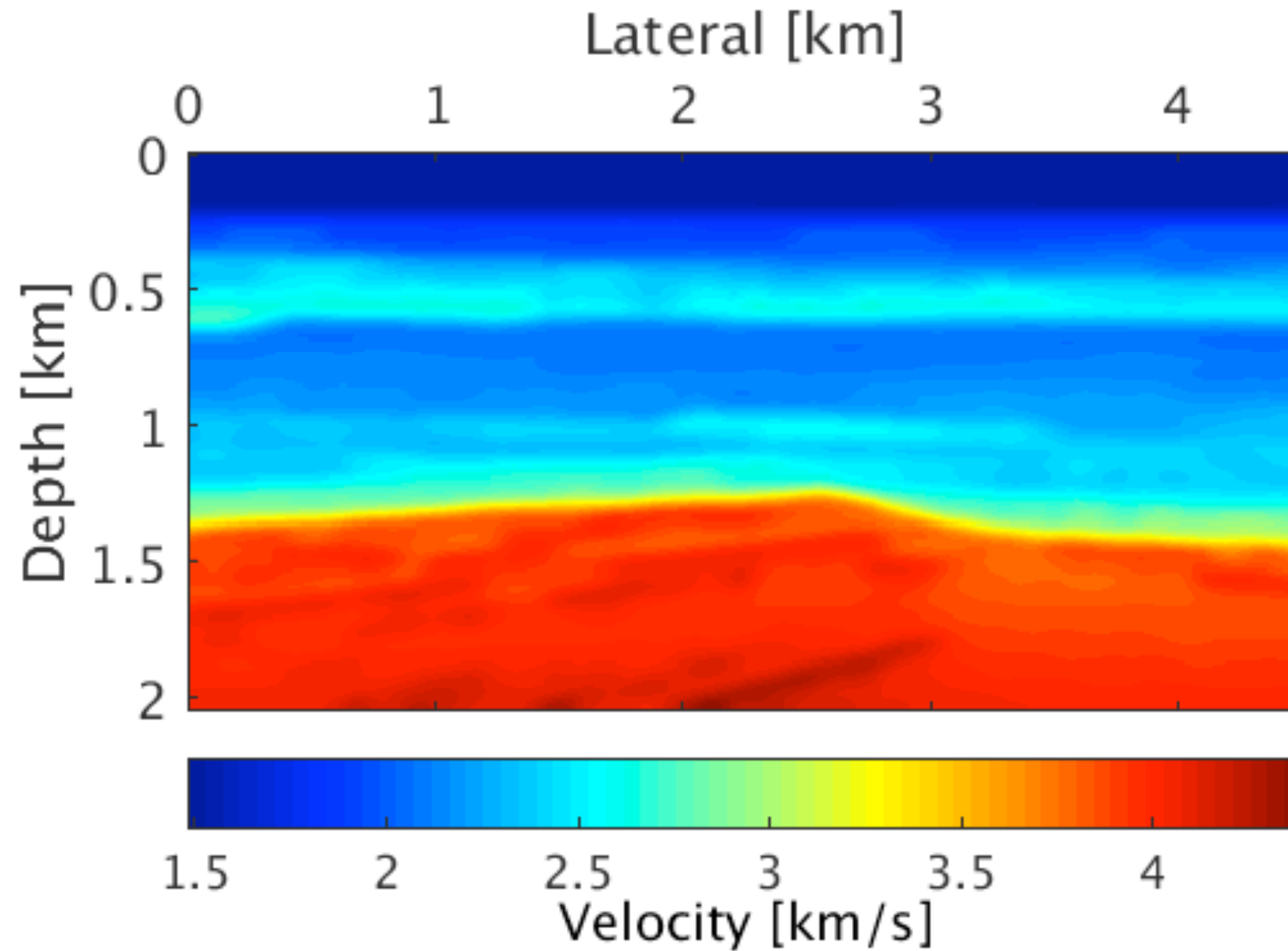
Data is contaminated with low frequency random noise (up to 45 Hz)

Noisy microseismic data, SNR = 2.83

Smooth velocity model

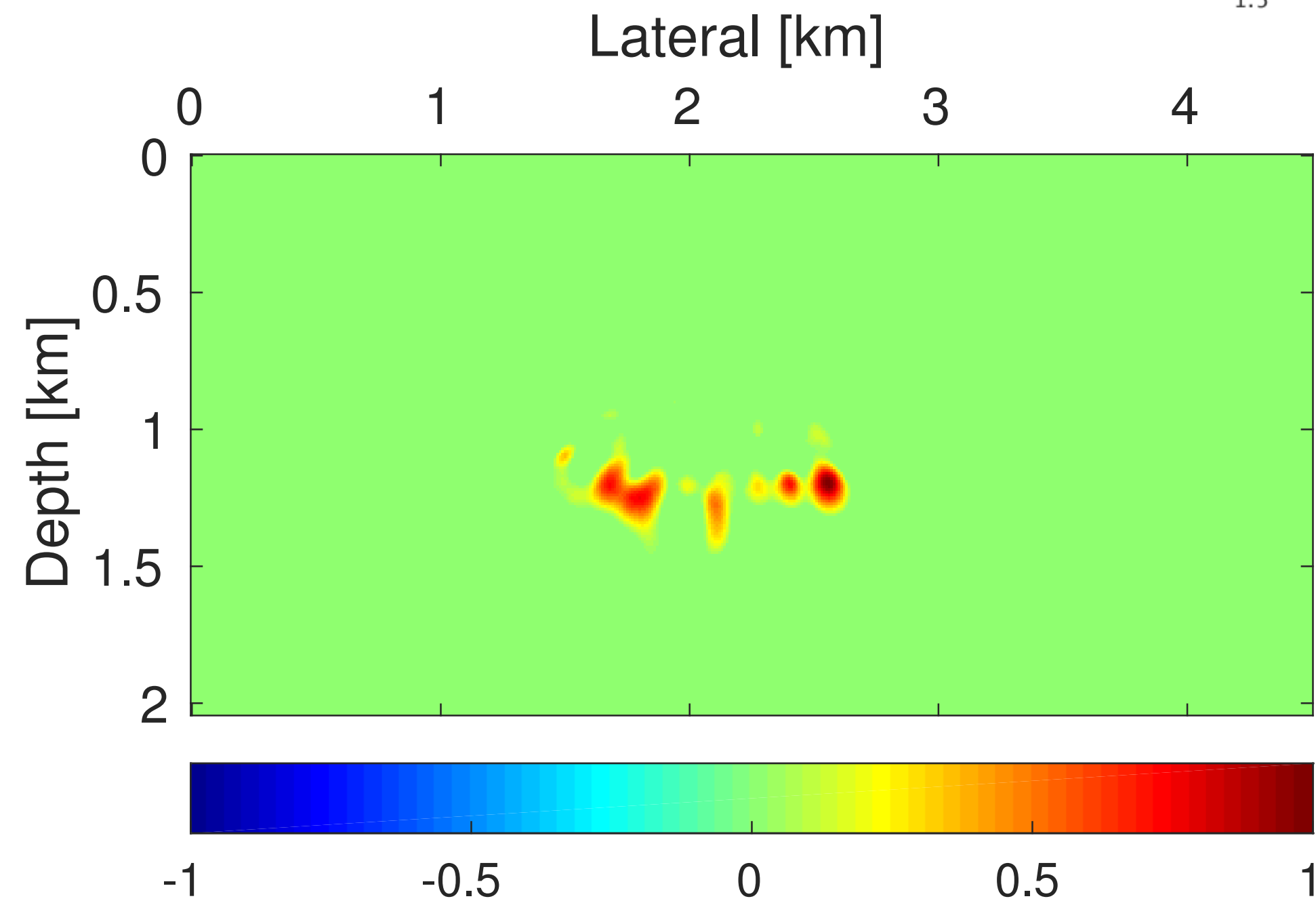
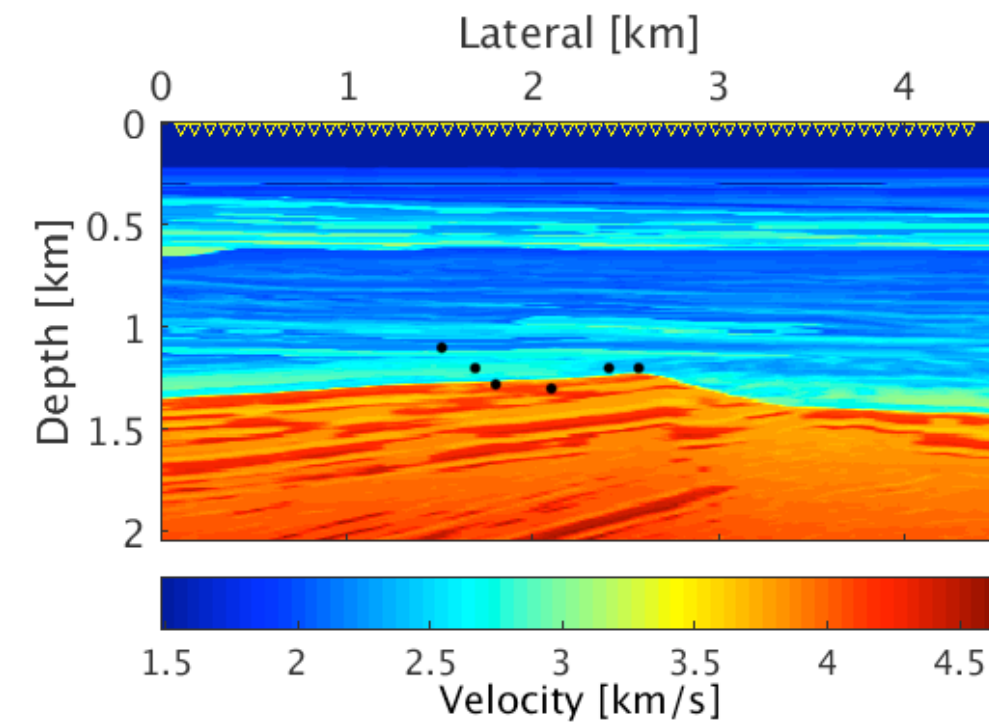


Smooth velocity model

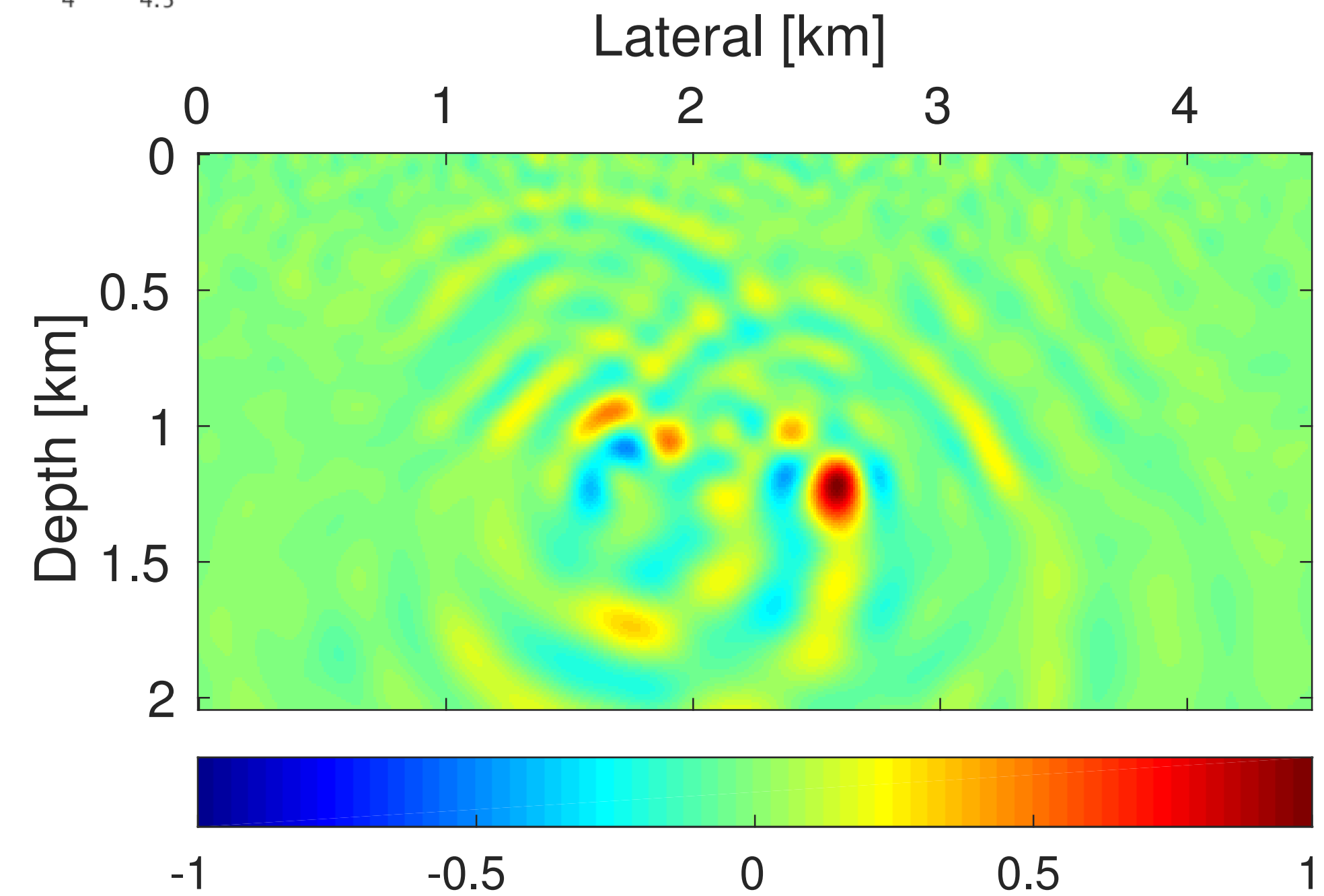


Used for joint microseismic source location and source time function estimation

Estimated Source location (From noisy data)

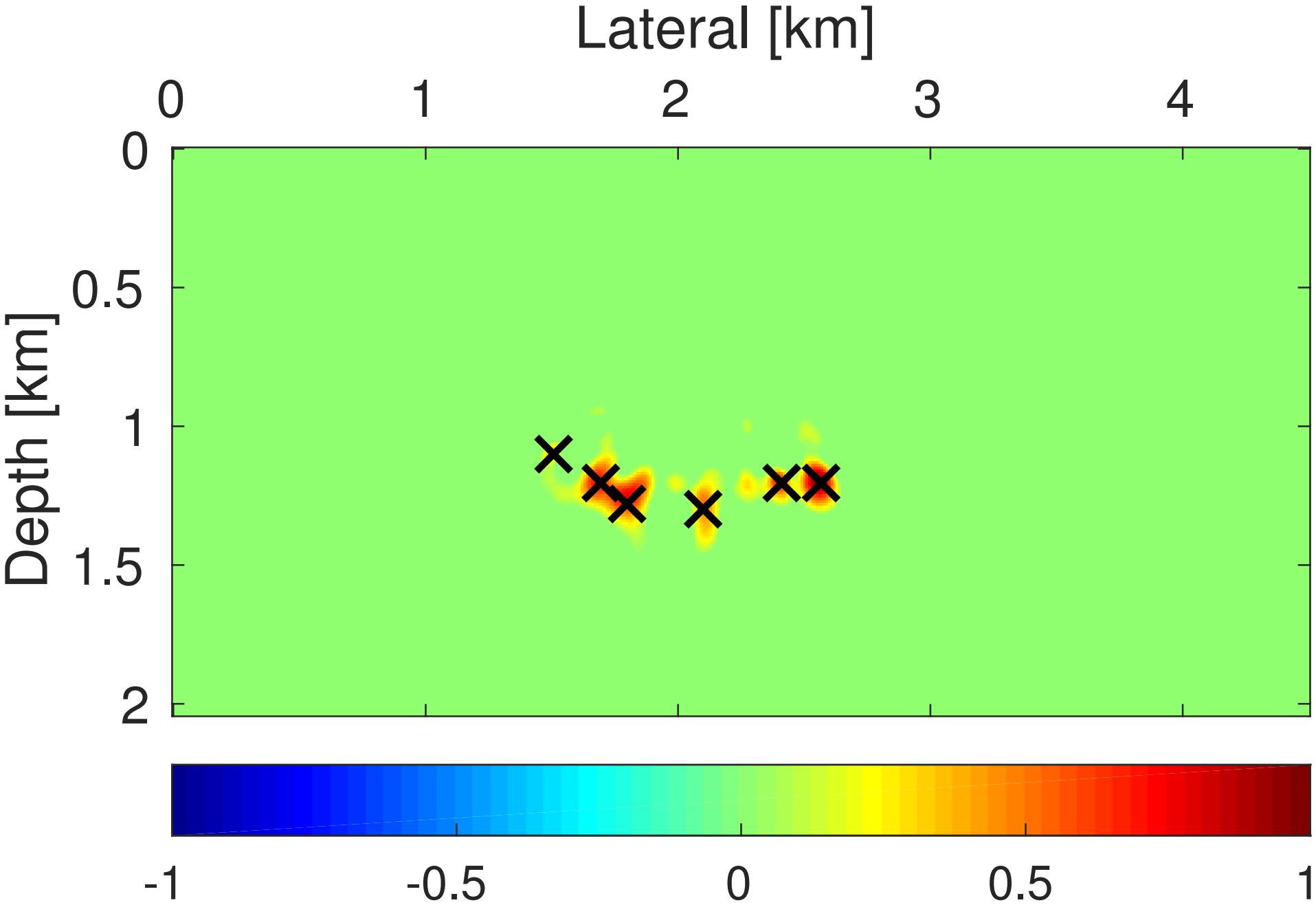
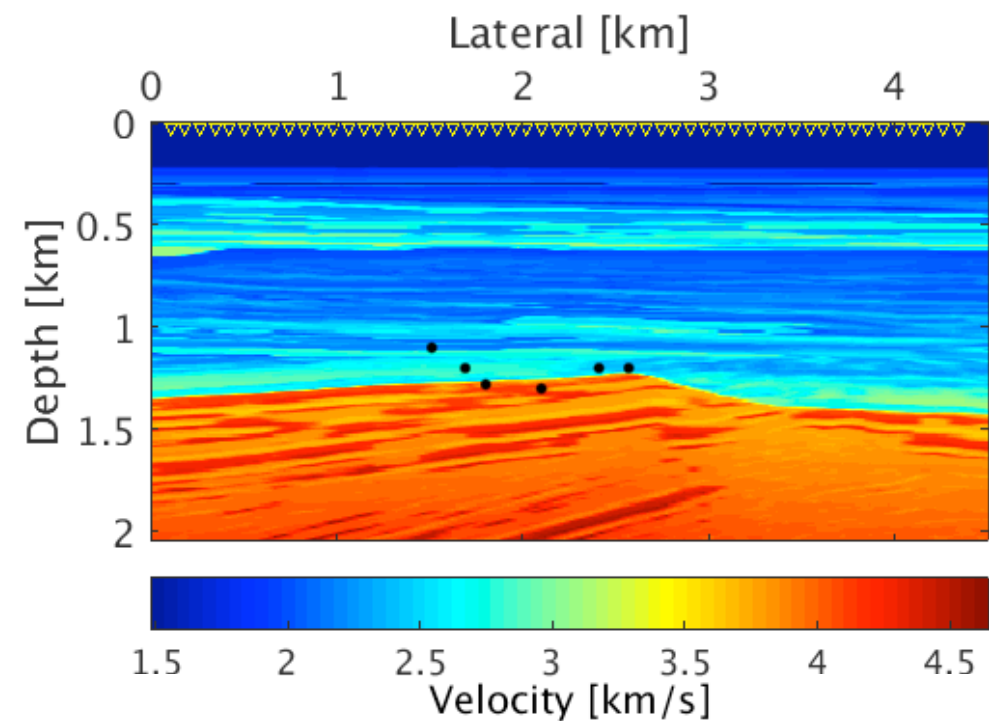


Sparsity-promoting method

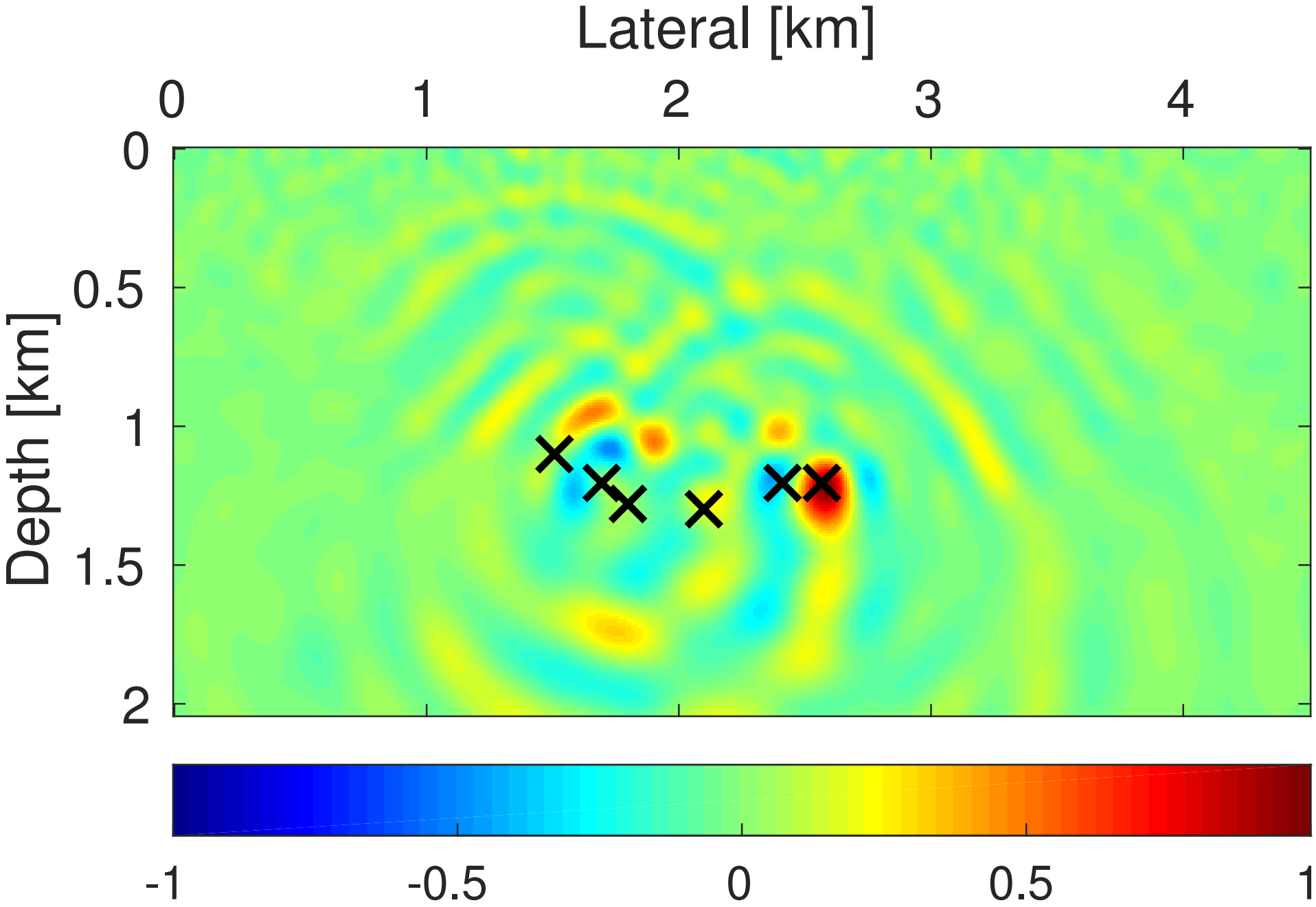


FWI

Estimated Source location (From noisy data)

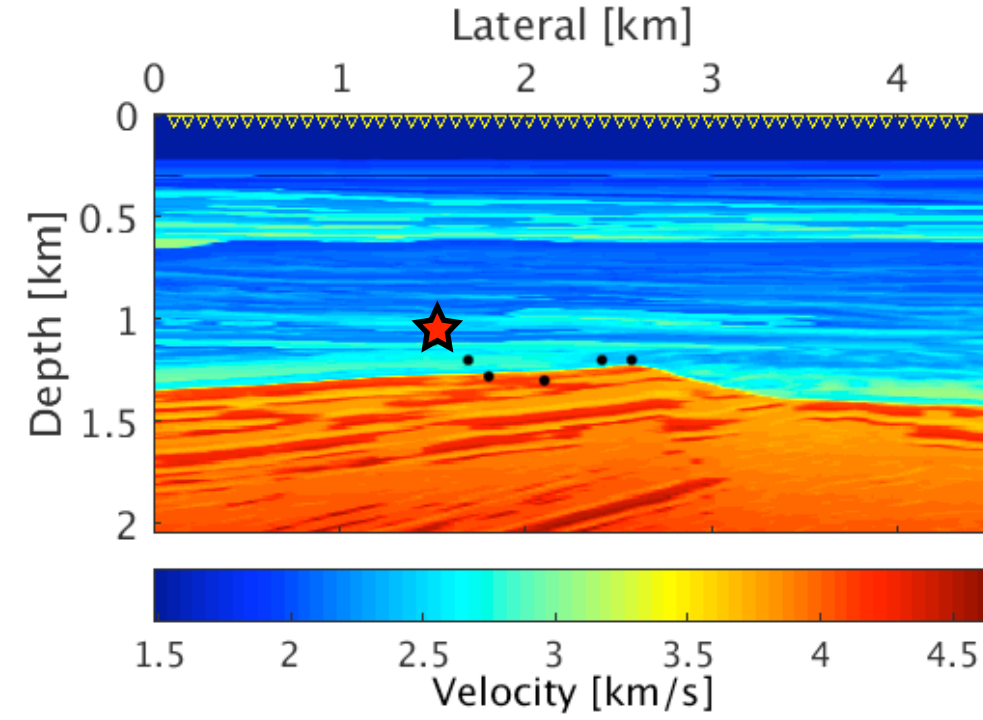


Sparsity-promoting method



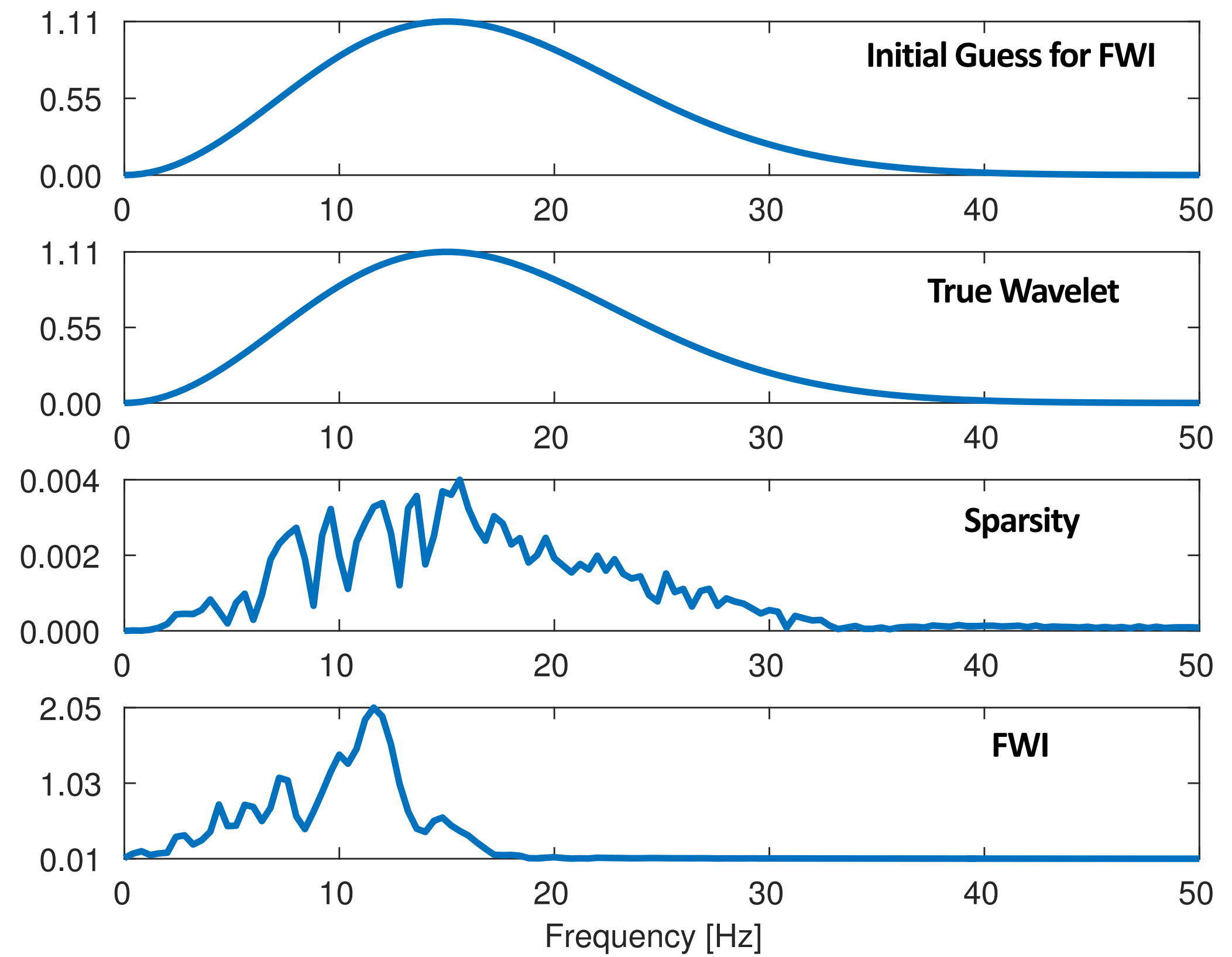
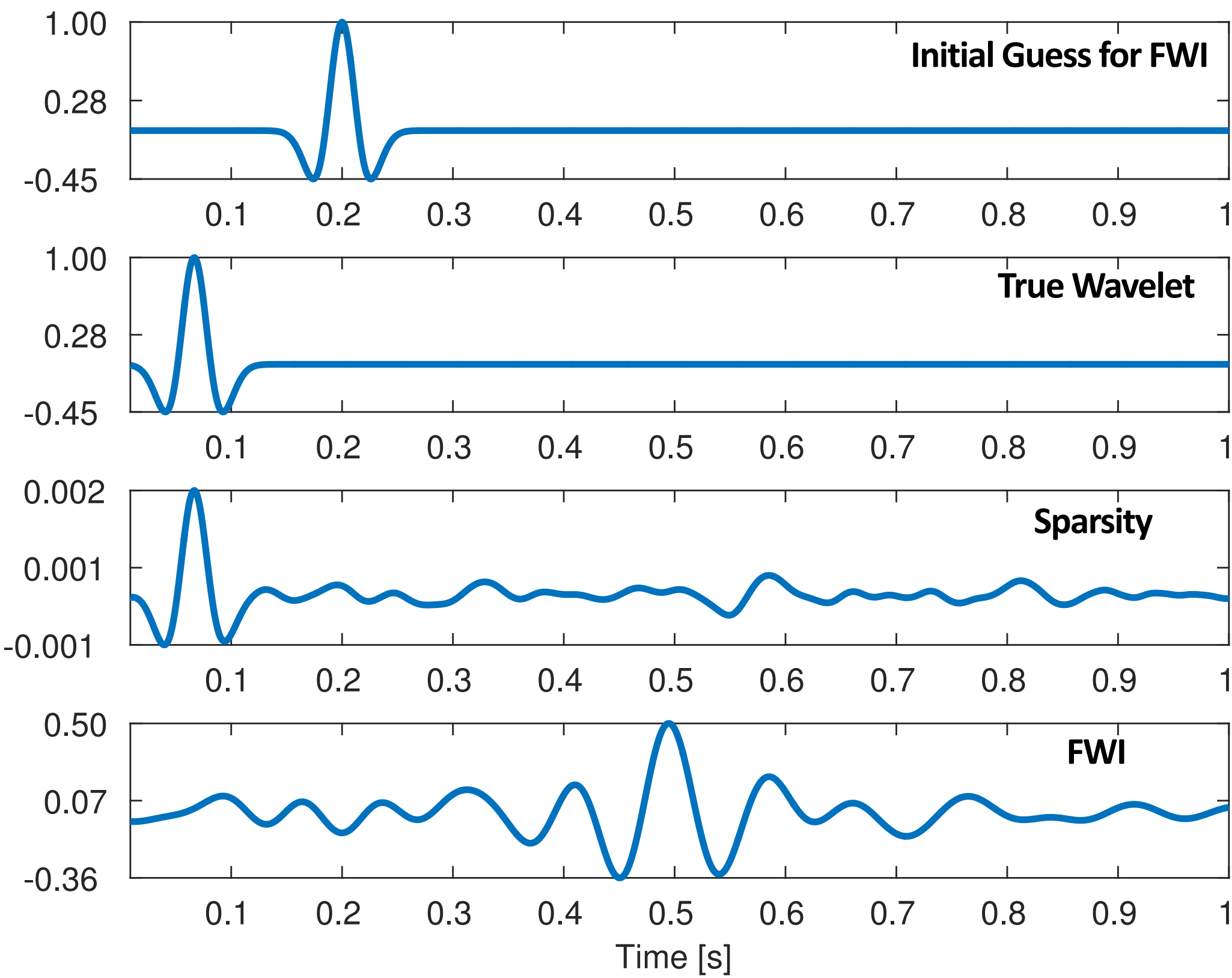
FWI

Location 1

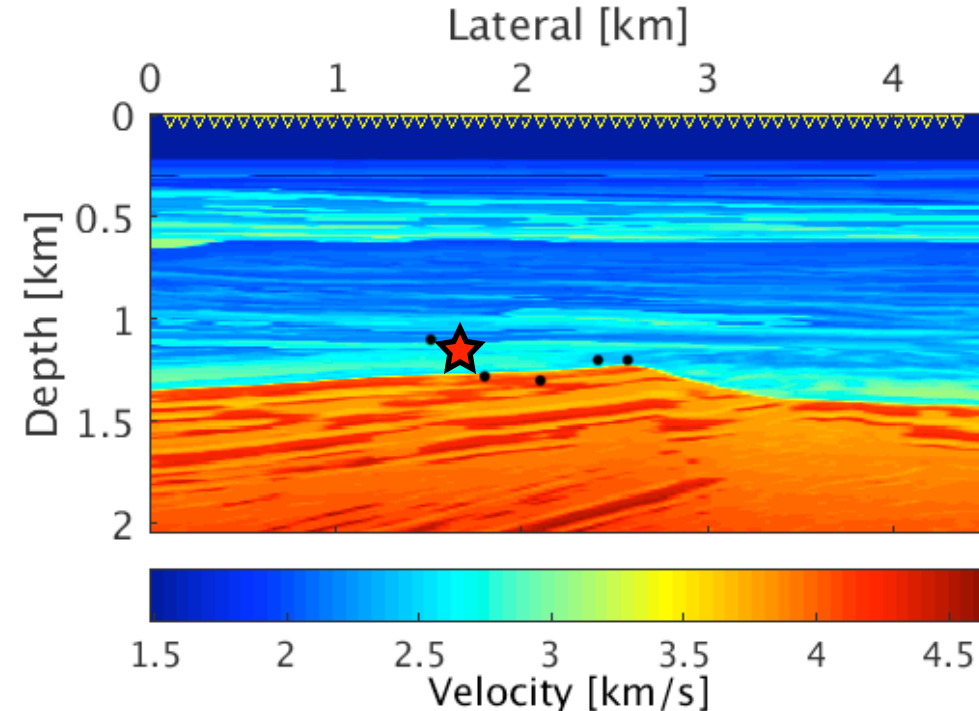


Wavelet

Spectrum

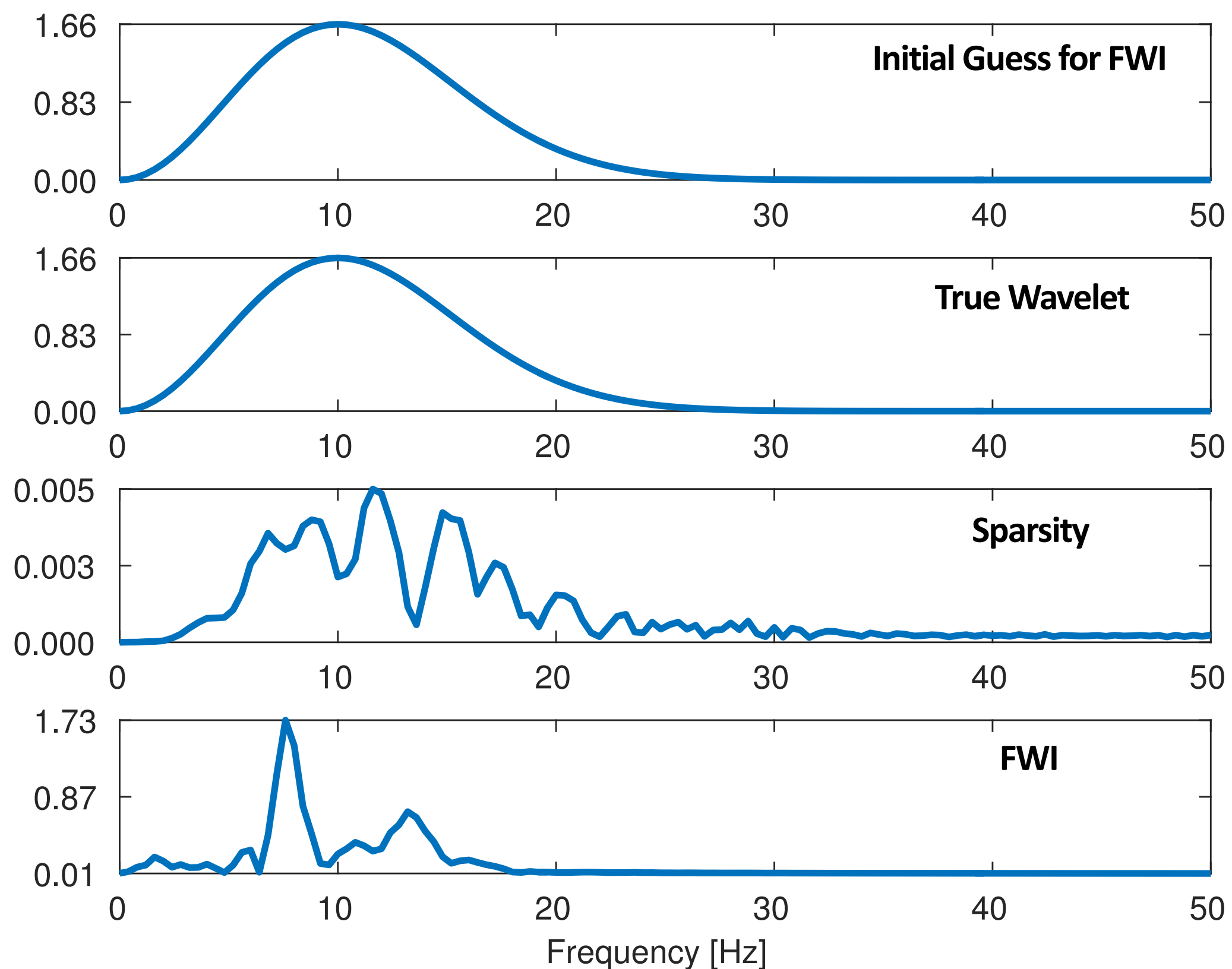
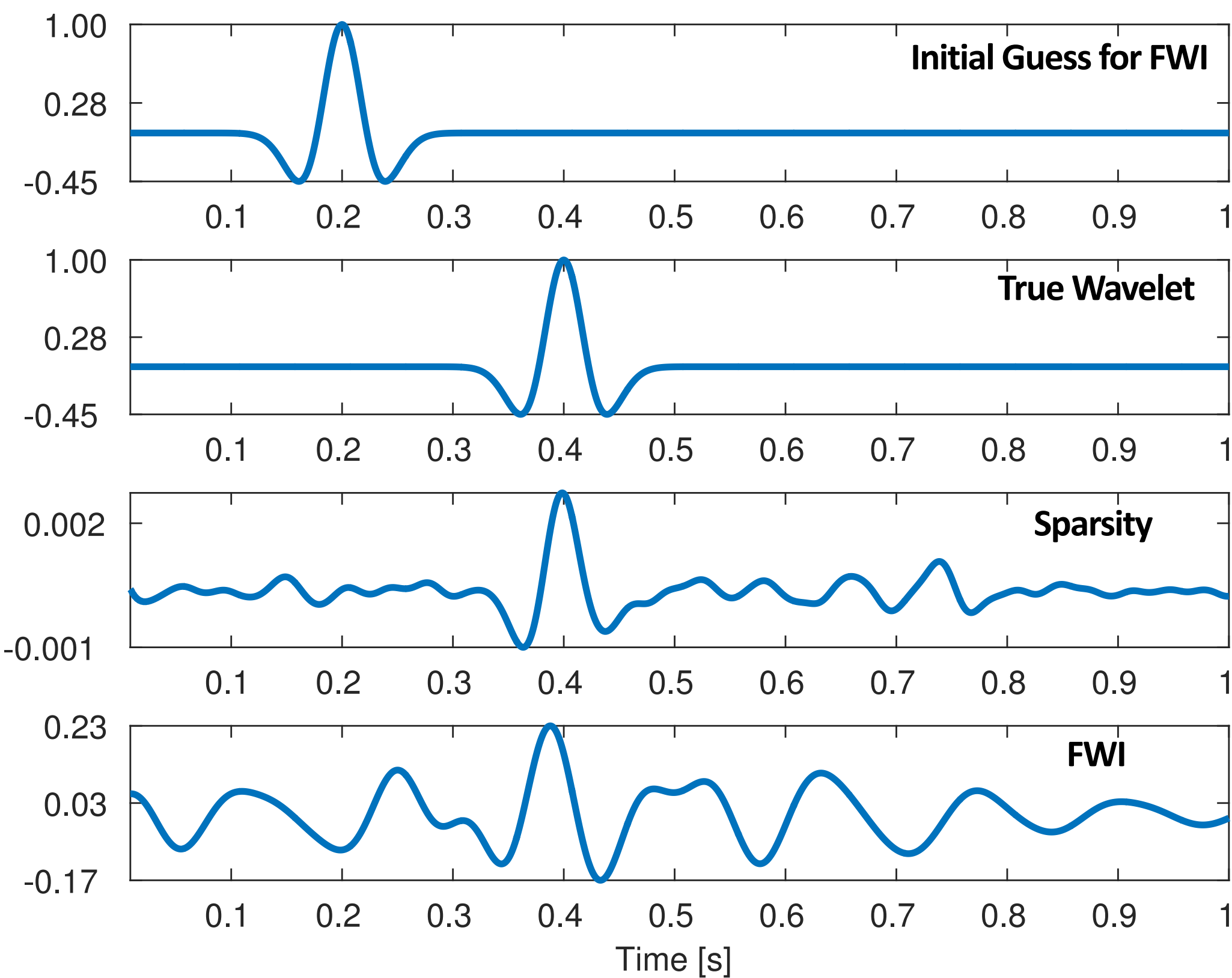


Location 2

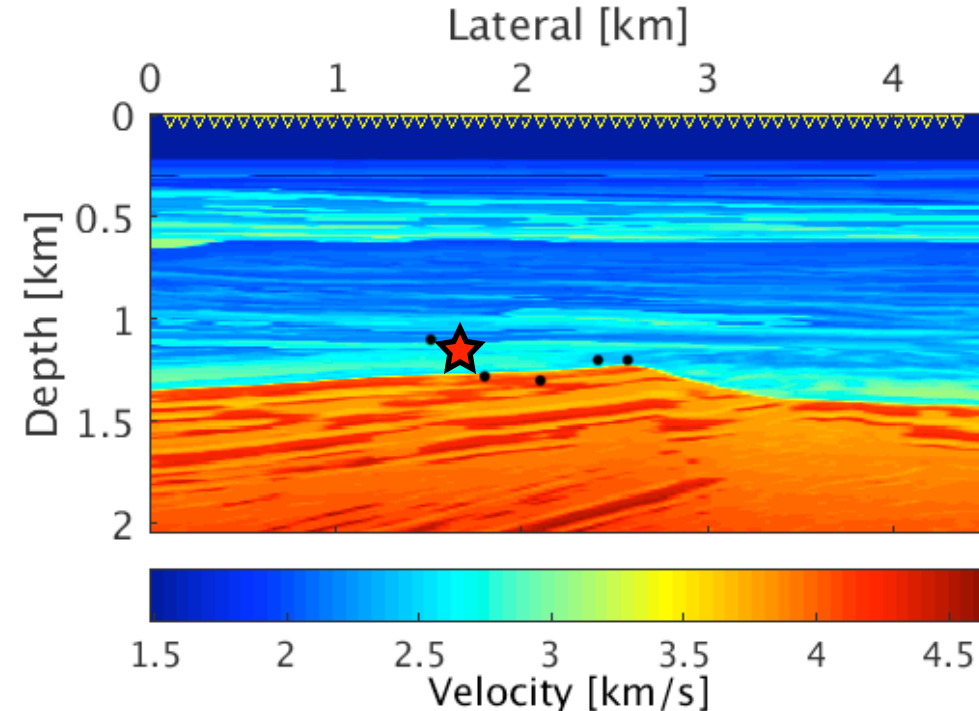


Wavelet

Spectrum

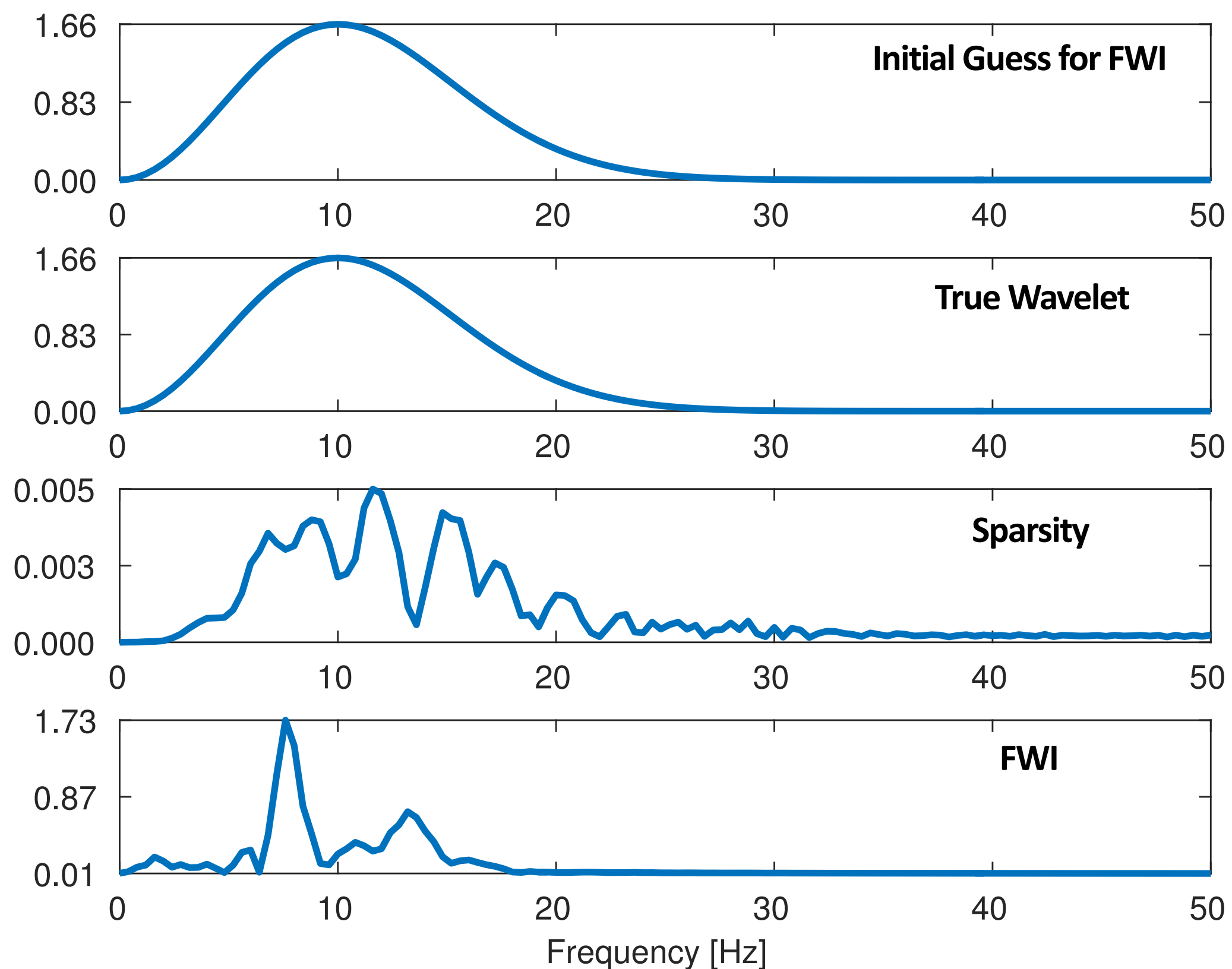
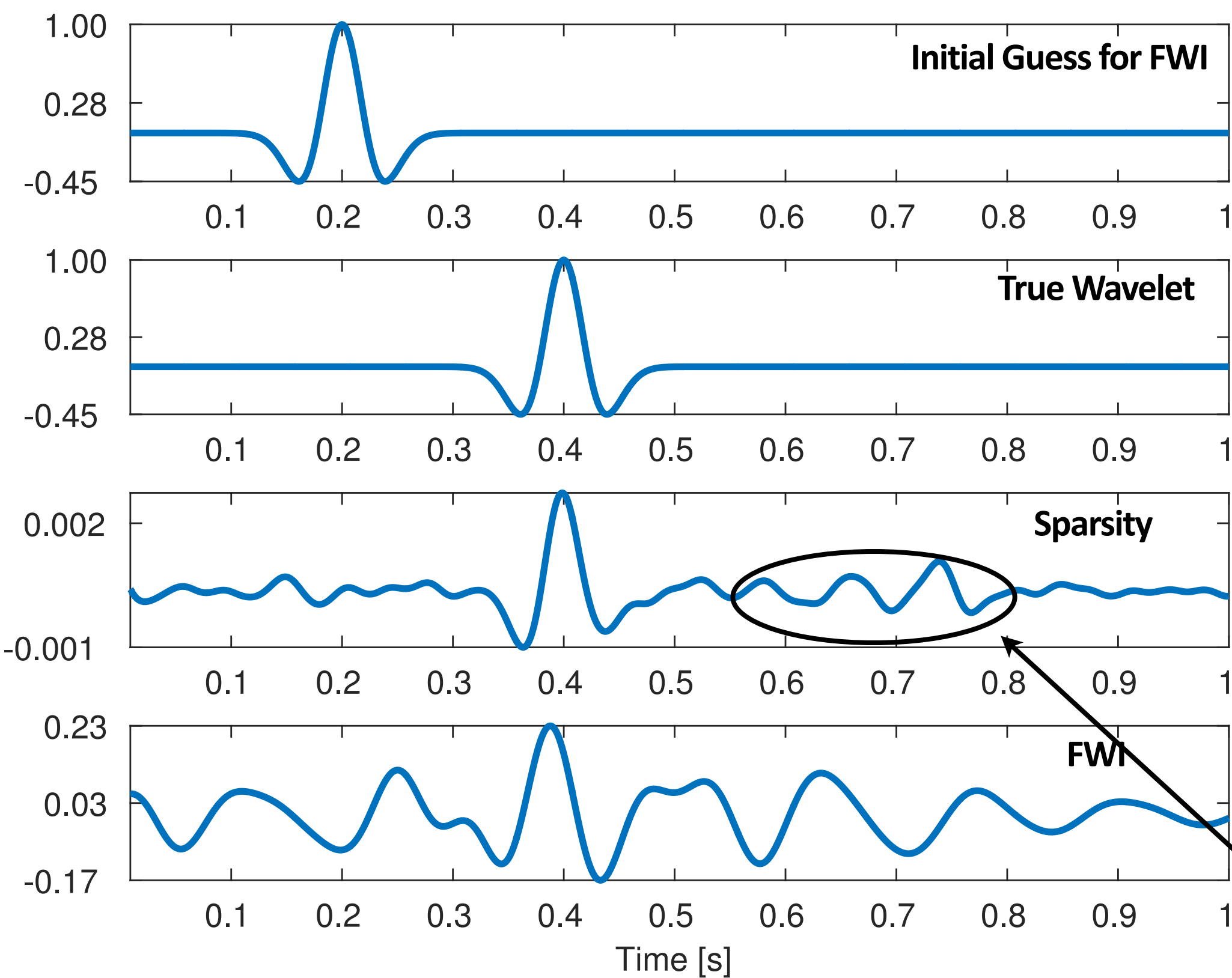


Location 2



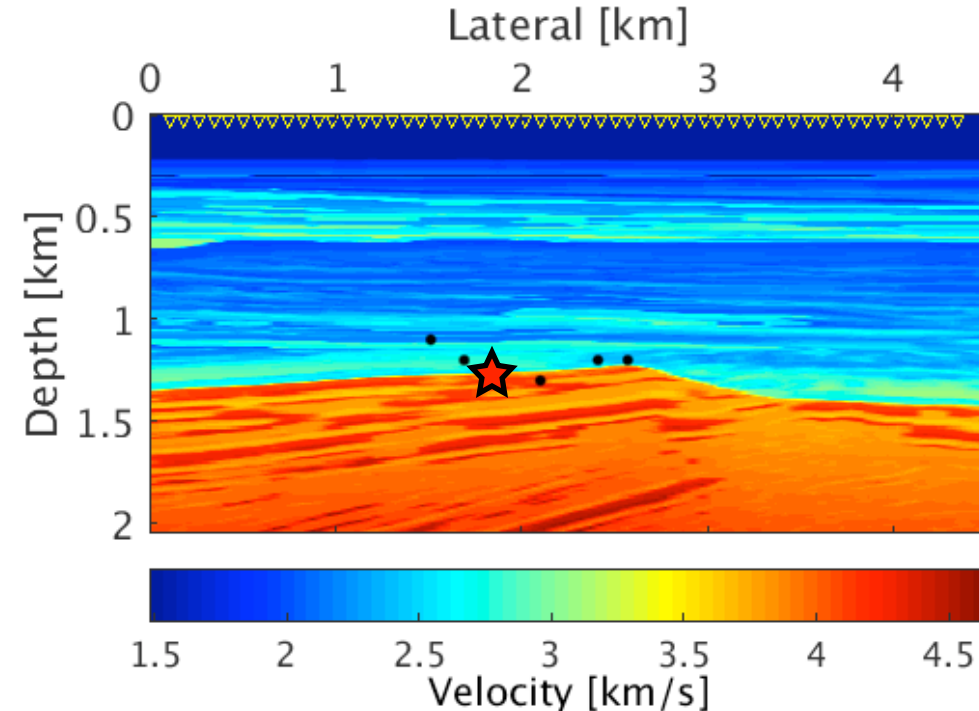
Wavelet

Spectrum



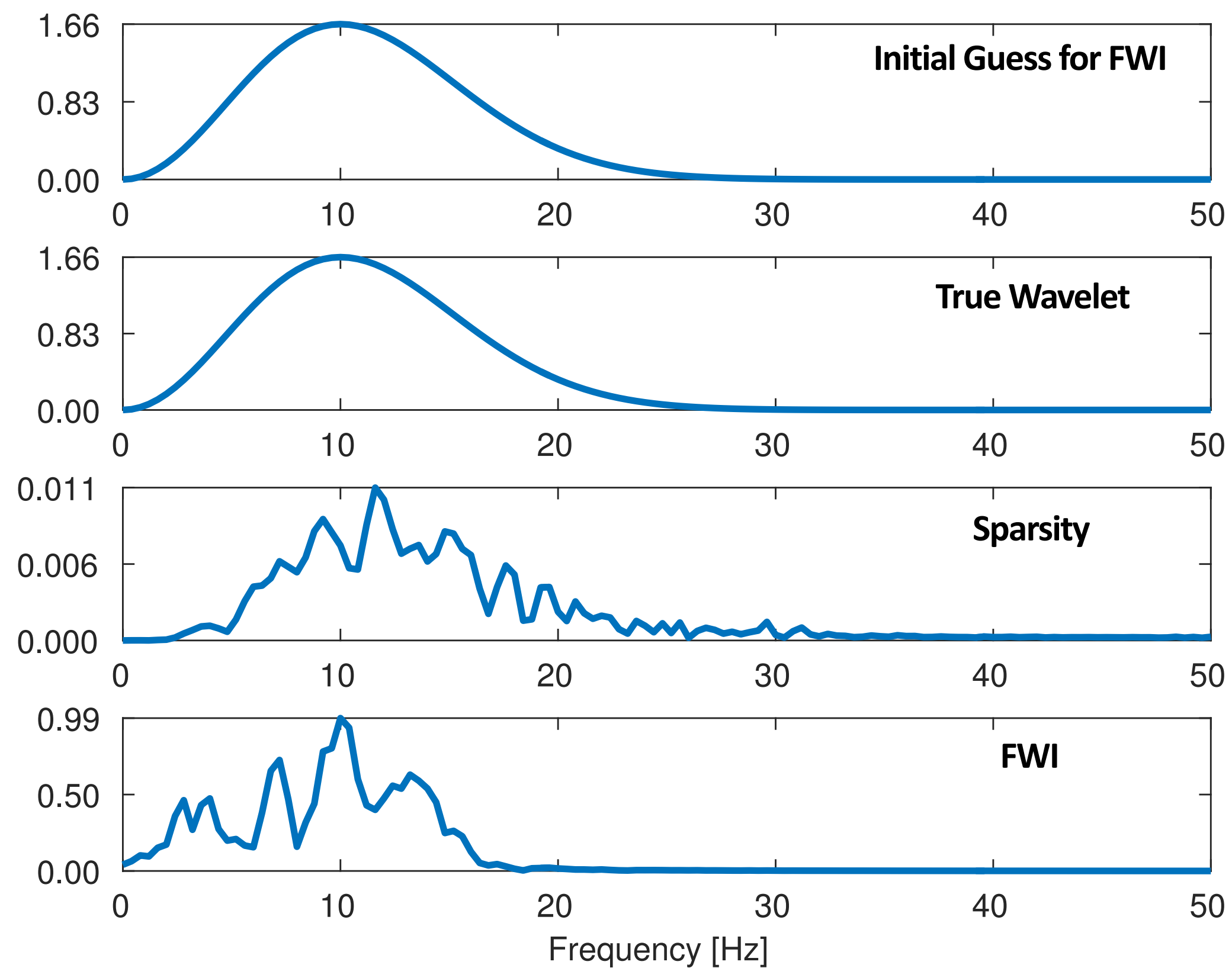
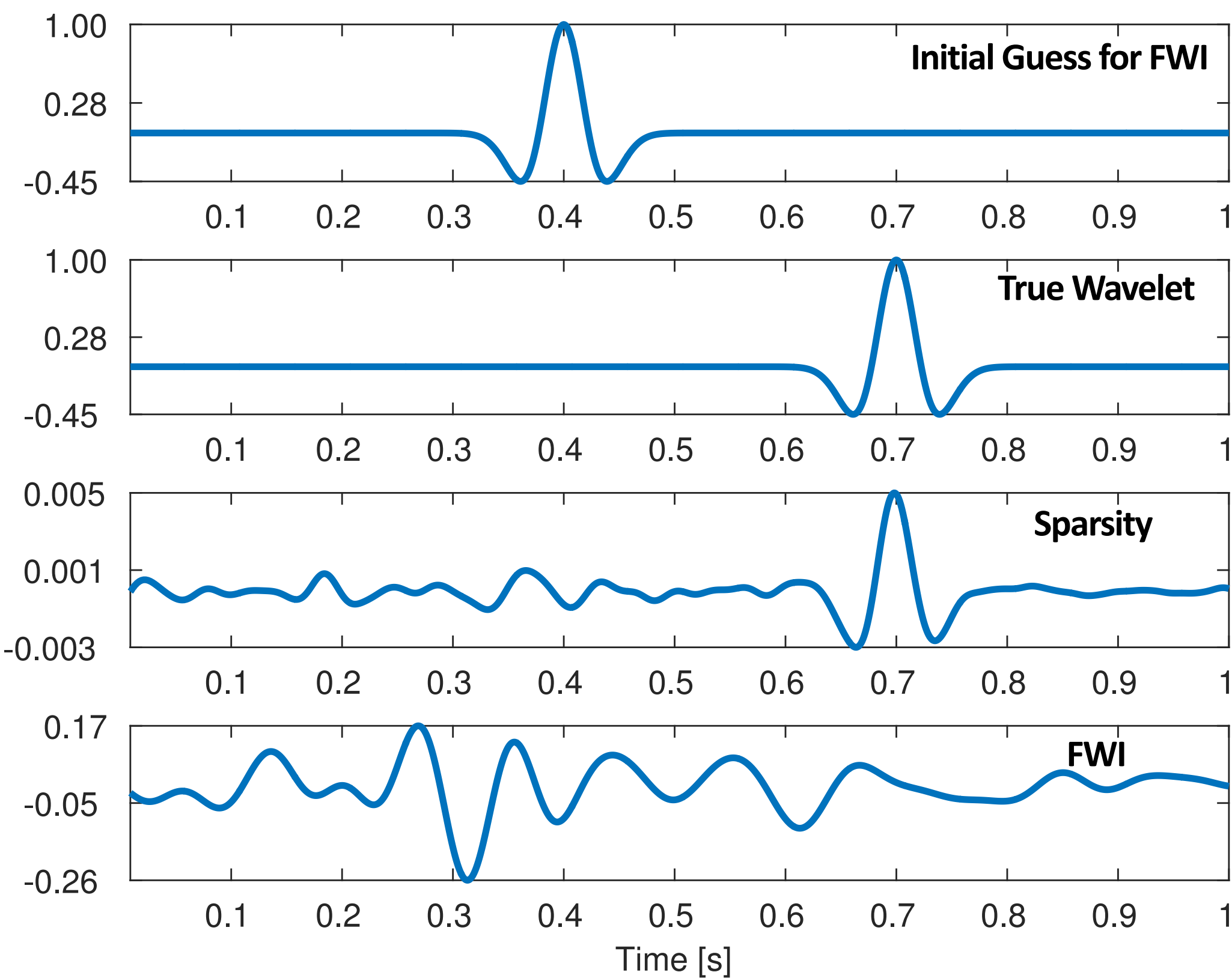
Sources within a wavelength

Location 3

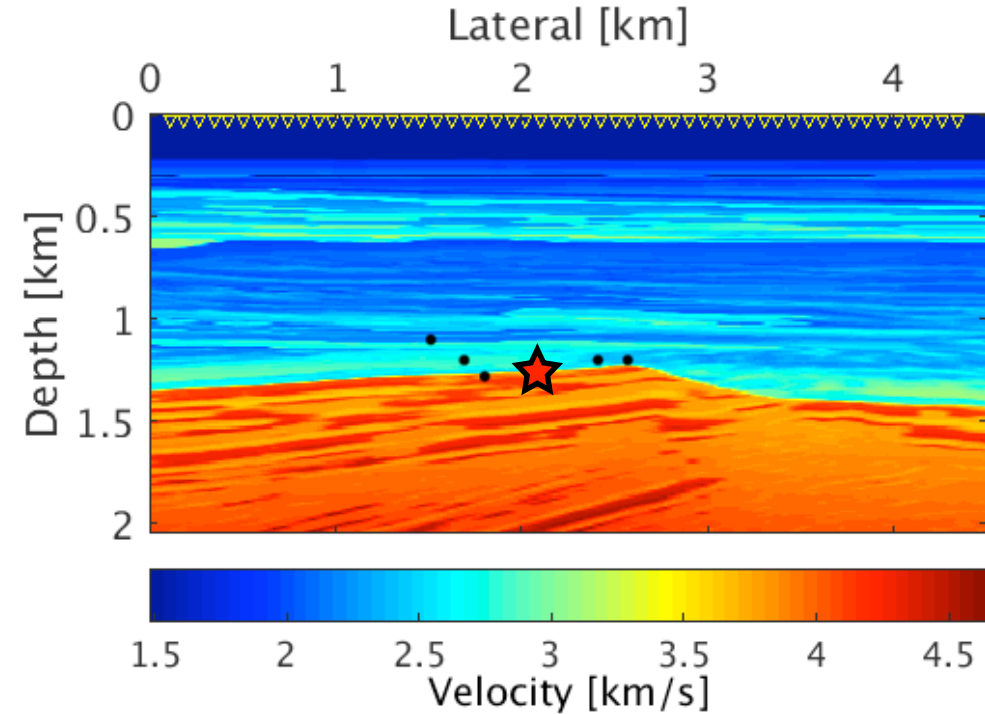


Wavelet

Spectrum

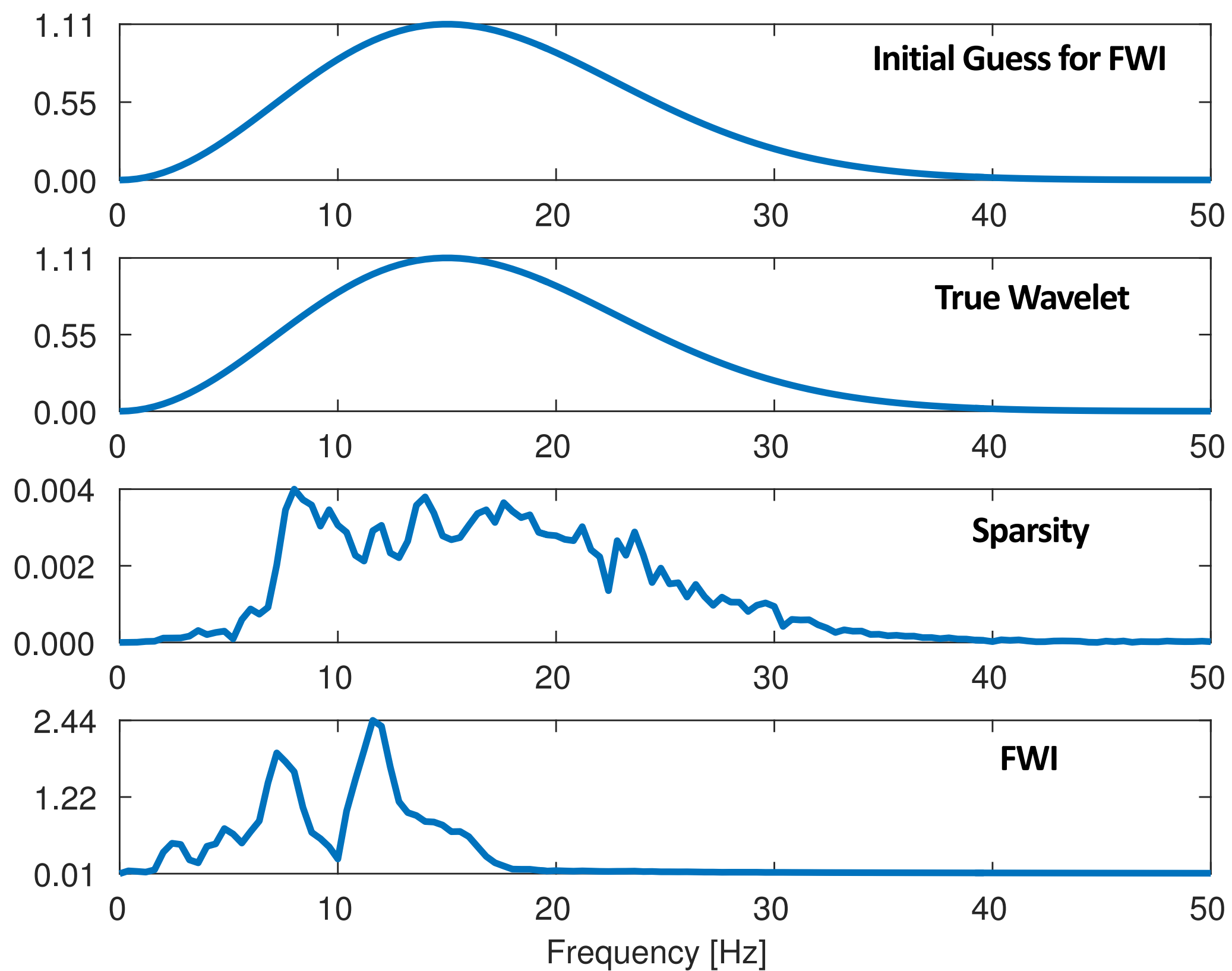
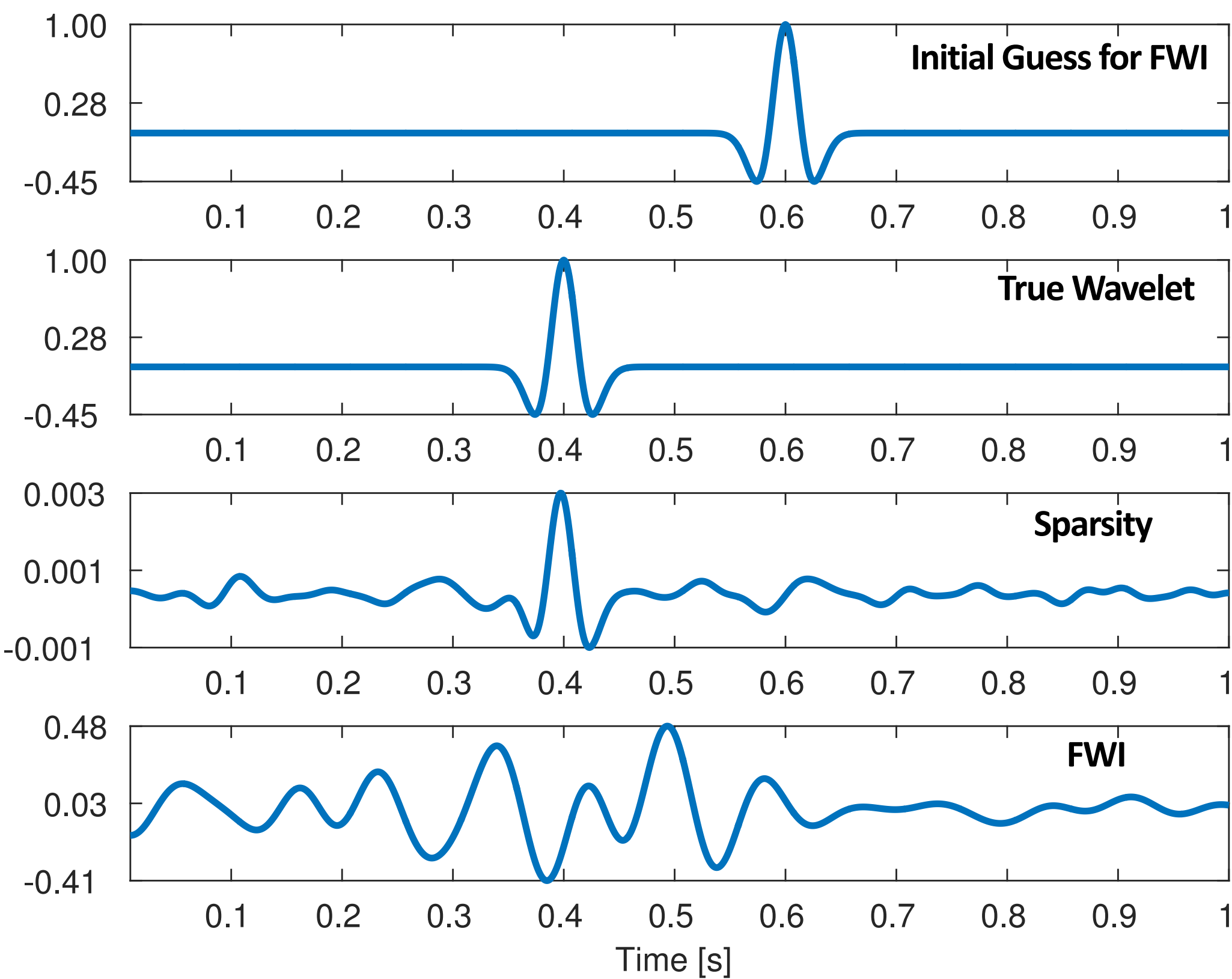


Location 4

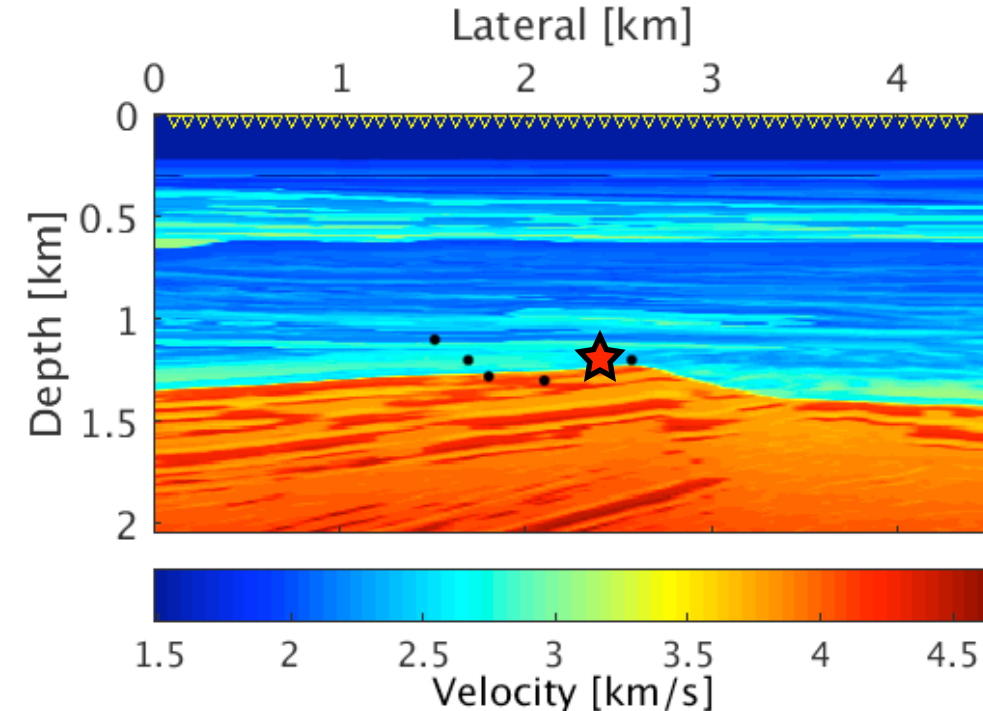


Wavelet

Spectrum

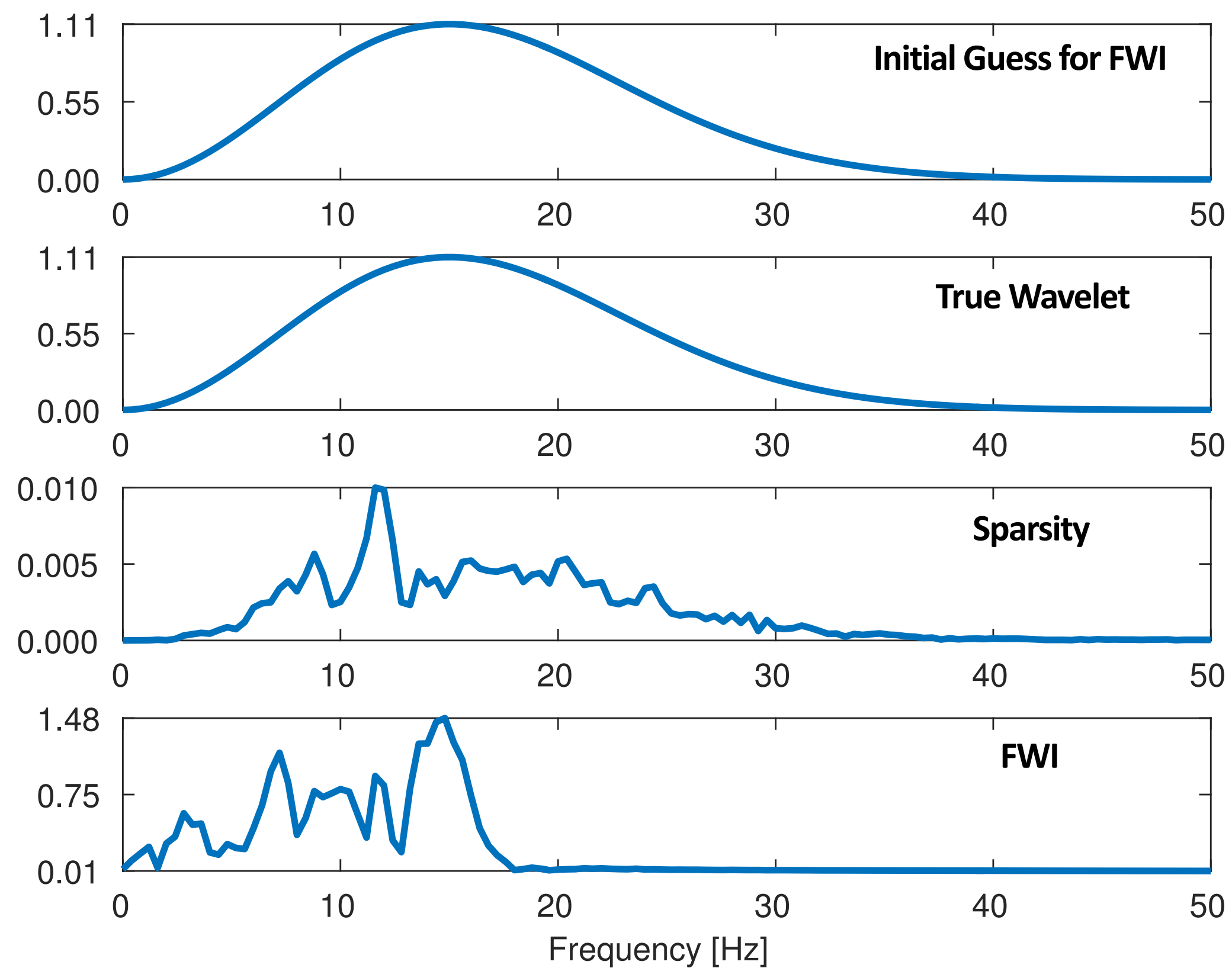
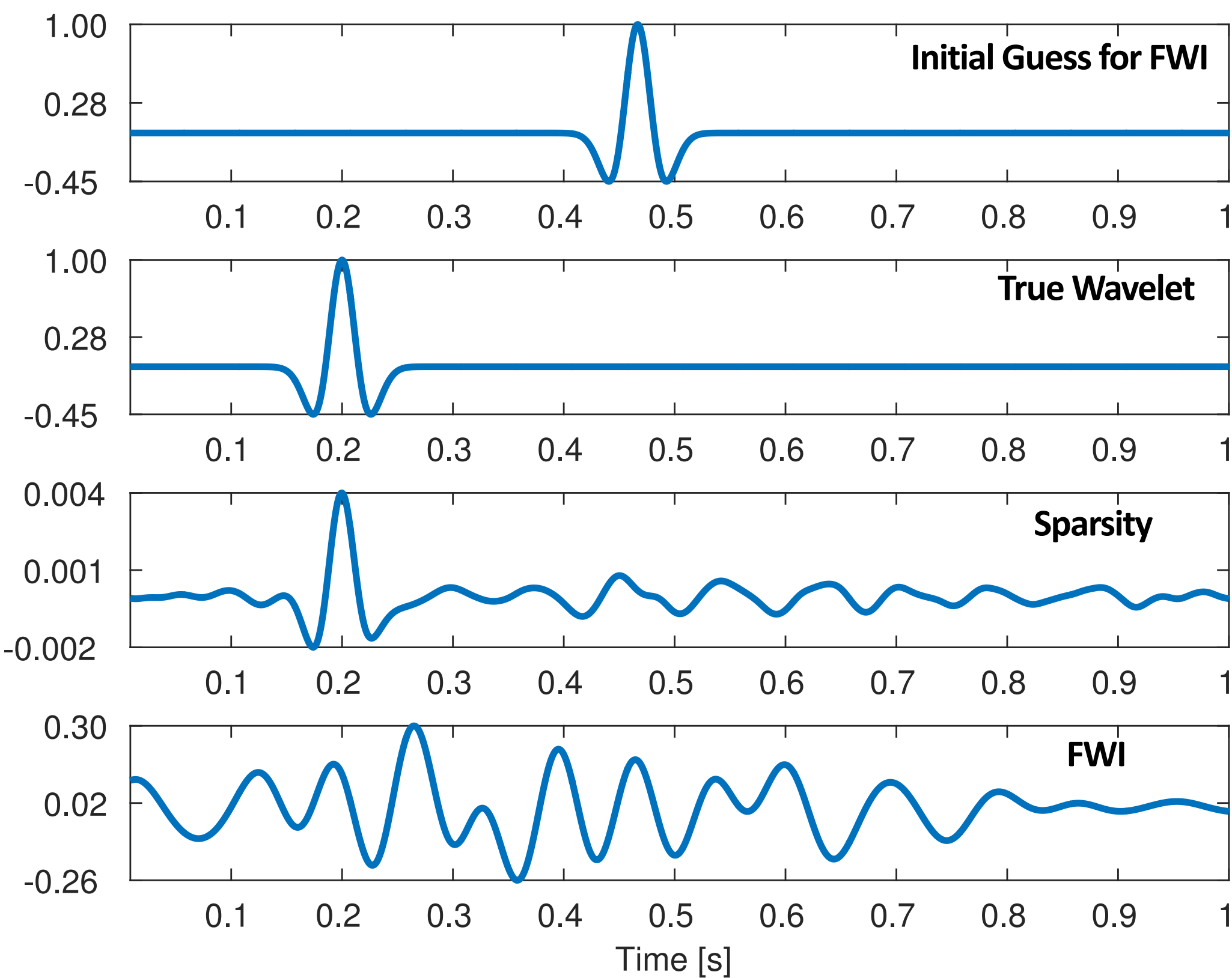


Location 5

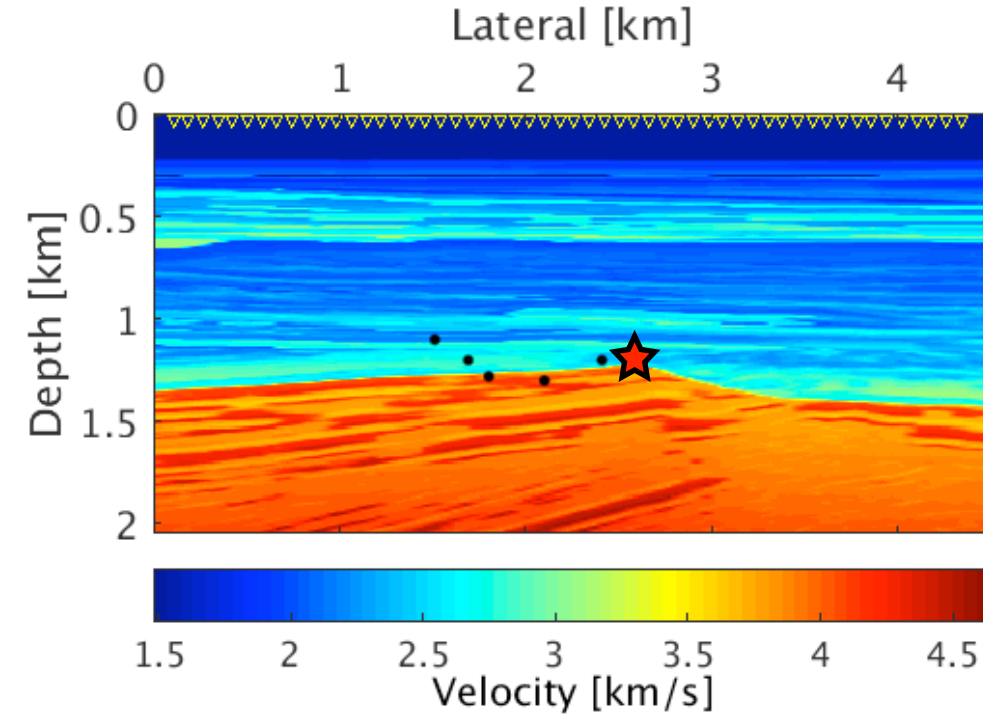


Wavelet

Spectrum

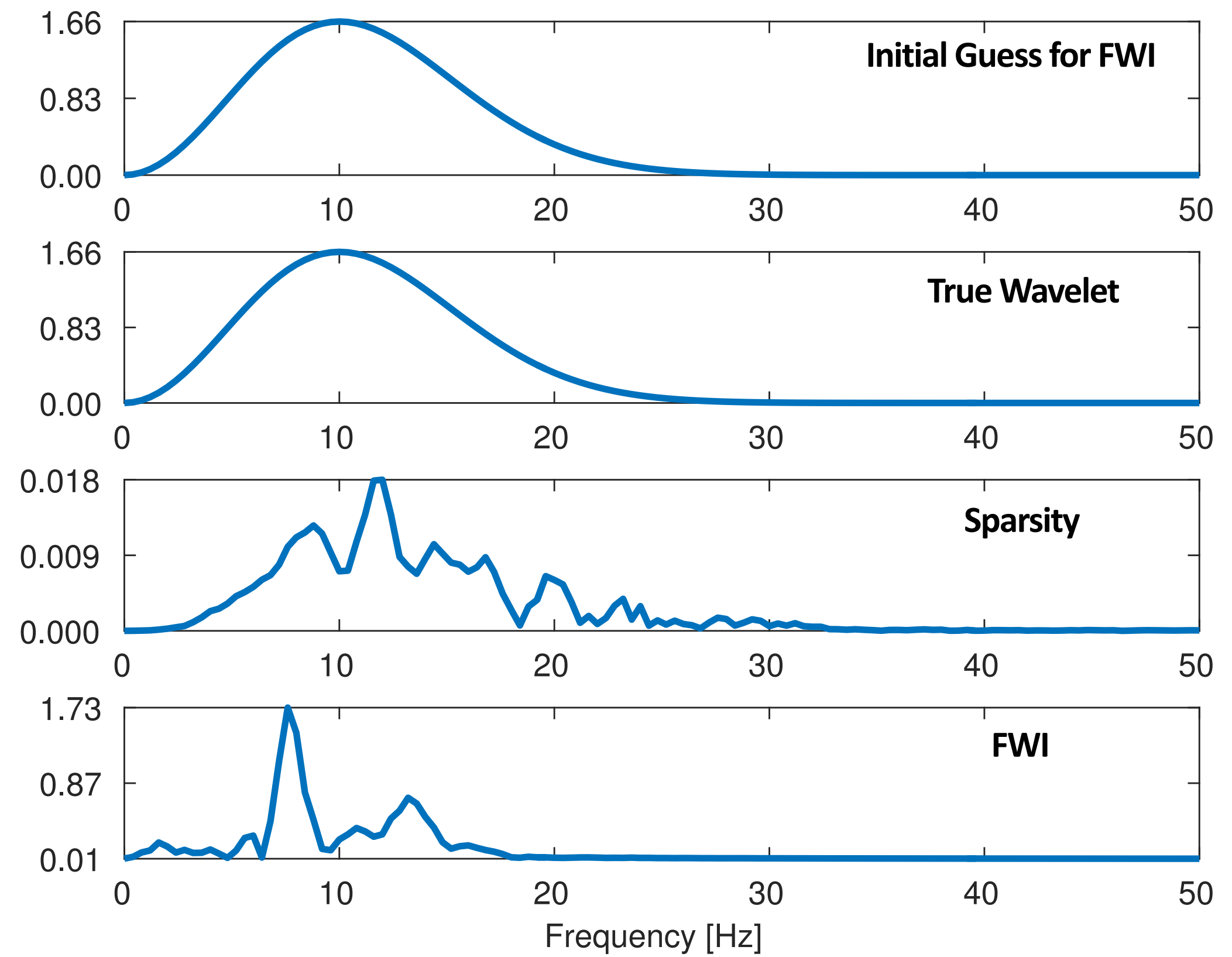
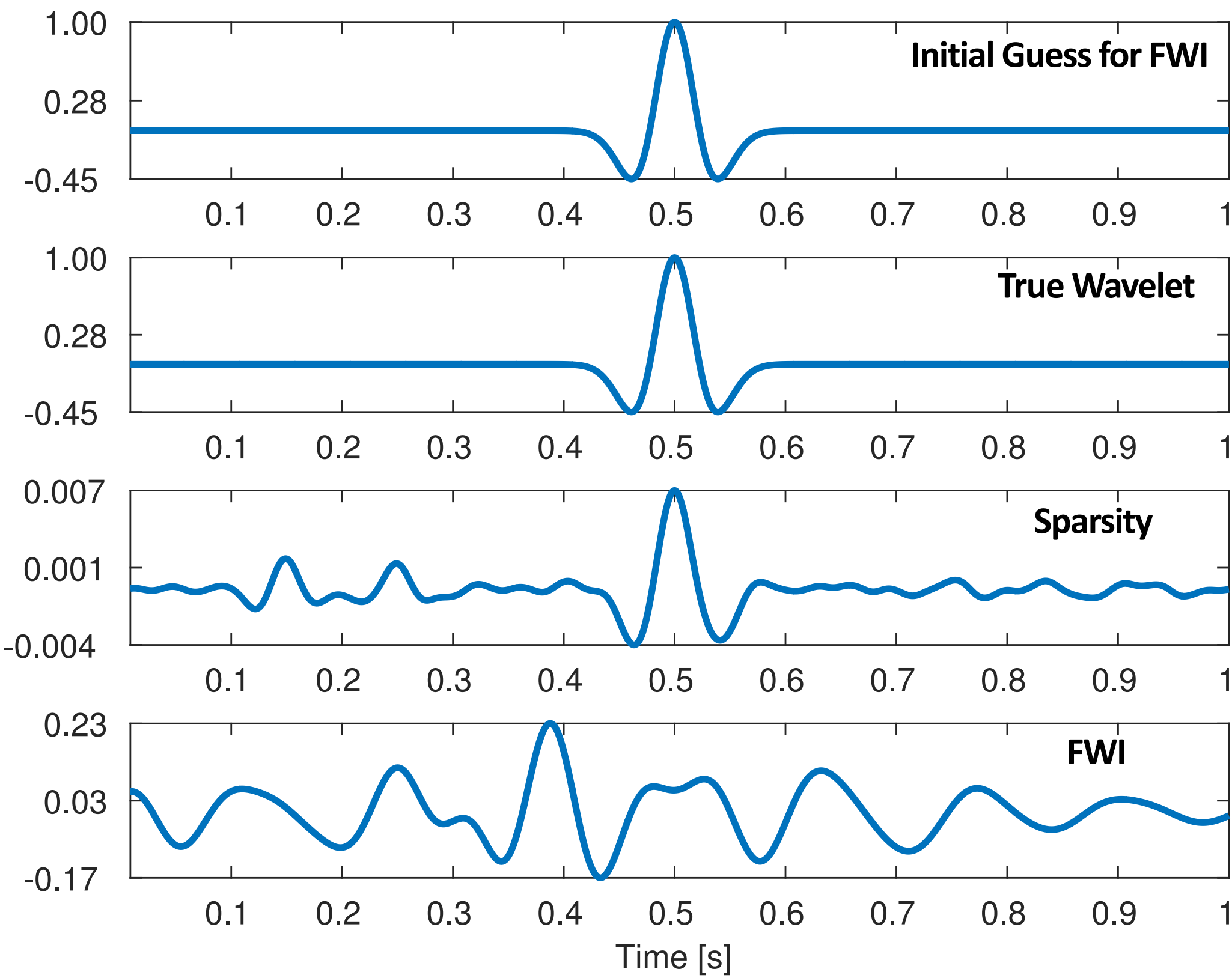


Location 6



Wavelet

Spectrum



Conclusions

A new methodology to simultaneously estimate

- ▶ source location
- ▶ source time function

Robust to noise

Conclusions

Works well with zero initial guess

Ability to work with realistic scenarios

- ▶ noisy data
- ▶ smooth background velocity model
- ▶ sources with different frequencies

Acknowledgements



The authors wish to acknowledge the SENAI CIMATEC Supercomputing Center for Industrial Innovation, with support from BG Brasil, Shell, and the Brazilian Authority for Oil, Gas and Biofuels (ANP), for the provision and operation of computational facilities and the commitment to invest in Research & Development.

Acknowledgements

This research was carried out as part of the SINBAD project with the support of the member organizations of the SINBAD Consortium.

