Comparative study of time-lapse FWI approaches

Felix Oghenekohwo & Felix J. Herrmann

SLIM
University of British Columbia

Motivation

Need for accurate migration velocity models for time-lapse seismic analysis e.g. NRMS measure

FWI in time-lapse might address some of the issues faced in 4D seismic

- acquisition geometry repeatability
- water column statics
- complex overburden changes

Main message

Review of current time-lapse FWI approaches

Present our joint time-lapse FWI method

- that leverages the shared information from the vintages
- that is relatively robust w.r.t to the starting model
- that is fairly stable in the presence of large acquisition gaps
- that can be extended to multiple surveys
- that can be easily implemented

SLIM

Full-waveform inversion

Problem

$$\underset{\mathbf{m},\alpha}{\text{minimize}}\ \frac{1}{2}\|\mathbf{d}-\alpha\boldsymbol{\mathcal{F}}[\mathbf{m}]\|_2^2$$

$$\begin{aligned}\mathbf{d}&:\quad \text{observed data}\\ \boldsymbol{\mathcal{F}}&:\quad \text{forward modelling kernel}\\ \alpha&:\quad \text{source wavelet}\\ \mathbf{m}&:\quad \text{model parameters}\end{aligned}$$

Assume known source wavelet

Full-waveform inversion

Problem

$$\underset{\mathbf{m}}{\text{minimize}} \; \frac{1}{2}\|\mathbf{d} - \boldsymbol{\mathcal{F}}[\mathbf{m}]\|_2^2$$

$$\begin{aligned} \mathbf{d} &: \quad \text{observed data} \\ \boldsymbol{\mathcal{F}} &: \quad \text{forward modelling kernel} \\ \mathbf{m} &: \quad \text{model parameters} \end{aligned}$$

Standard FWI

$$\underset{\mathbf{m}}{\text{minimize}}\ \frac{1}{2}\|\mathbf{d} - \boldsymbol{\mathcal{F}}[\mathbf{m}]\|_2^2$$

$$\begin{aligned}\text{Initialization, iteration } k = 0 : &\qquad \mathbf{m}_k \\ \text{Compute gradient} : &\qquad \delta\mathbf{m} \\ \text{Update model- iteration @ } k+1 : &\qquad \mathbf{m}_{k+1} = \mathbf{m}_k + \delta\mathbf{m}\end{aligned}$$

Linearization + sparsity on update

$$\tilde{\mathbf{x}}^k = \arg\min_{\mathbf{x}} \frac{1}{2} \| \mathbf{d} - \underbrace{\boldsymbol{\mathcal{F}}[\mathbf{m}^k; \mathbf{Q}]}_{\mathbf{b}} - \underbrace{\nabla \boldsymbol{\mathcal{F}}[\mathbf{m}^k; \mathbf{Q}]}_{\mathbf{A}} \mathbf{C}^T \mathbf{x} \|_2^2 \quad \text{s.t.} \quad \|\mathbf{x}\|_1 < \tau$$

$$\mathbf{Q} = \text{source}$$

$$\mathbf{C} = \text{curvelet}$$

model update: $\mathbf{m}^{k+1} = \mathbf{m}^k + \mathbf{C}^T \tilde{\mathbf{x}}^k$

Linearization + sparsity on update

$$\tilde{\mathbf{x}}^k = \arg\min_{\mathbf{x}} \frac{1}{2}\|\mathbf{d} - \underbrace{\boldsymbol{\mathcal{F}}[\mathbf{m}^k;\mathbf{Q}]}_{\mathbf{b}} - \underbrace{\nabla\boldsymbol{\mathcal{F}}[\mathbf{m}^k;\mathbf{Q}]}_{\mathbf{A}}\mathbf{C}^T\mathbf{x}\|_2^2 \quad \text{s.t.} \quad \|\mathbf{x}\|_1 < \tau$$

$\mathbf{Q} = \text{source}$

$\mathbf{C} = \text{curvelet}$

Computationally very expensive!!!

with all the data

model update: $\mathbf{m}^{k+1} = \mathbf{m}^k + \mathbf{C}^T\tilde{\mathbf{x}}^k$

Xiang Li, Aleksandr Y. Aravkin, Tristan van Leeuwen, and Felix J. Herrmann,
"Fast randomized full-waveform inversion with compressive sensing",
Geophysics, vol. 77, p. A13-A17, 2012.

SLIM

Fast randomized inversion

$$\tilde{\mathbf{x}}^k = \arg\min_{\mathbf{x}} \frac{1}{2}\|\underbrace{\underline{\mathbf{d}} - \mathcal{F}[\mathbf{m}^k;\underline{\mathbf{Q}}]}_{\underline{\mathbf{b}}} - \underbrace{\nabla\mathcal{F}[\mathbf{m}^k;\underline{\mathbf{Q}}]}_{\underline{\mathbf{A}}}\mathbf{C}^T\mathbf{x}\|_2^2 \quad \text{s.t.} \quad \|\mathbf{x}\|_1 < \underline{\tau}$$

$$\underline{\mathbf{Q}} = \mathbf{W}\mathbf{Q}$$

$$\underline{\mathbf{d}} = \mathbf{W}\mathbf{d}$$

Fast computations!!!

$\mathbf{W}$: matrix that encodes simultaneous or randomly selected shots

model update: $\mathbf{m}^{k+1} = \mathbf{m}^k + \mathbf{C}^T\tilde{\mathbf{x}}^k$

Time-lapse FWI approaches

Time-lapse FWI approaches

Parallel difference

$$\begin{aligned} \text{Start with similar initial model, given observed data :} &\quad \mathbf{m}_0, \mathbf{d}_1, \mathbf{d}_2 \\ \text{Invert for baseline and monitor separately :} &\quad \mathbf{m}_1, \mathbf{m}_2 \\ \text{Estimate timelapse model :} &\quad d\mathbf{m} = \mathbf{m}_2 - \mathbf{m}_1 \end{aligned}$$

Sequential difference

$$\begin{aligned} \text{Start with baseline data and initial model :} &\quad \mathbf{m}_0, \mathbf{d}_1 \\ \text{Invert for baseline :} &\quad \mathbf{m}_1 \\ \text{Inversion of } \mathbf{d}_2 \text{ using } \mathbf{m}_1 \text{ as starting model :} &\quad \mathbf{m}_2 \\ \text{Estimate timelapse model :} &\quad d\mathbf{m} = \mathbf{m}_2 - \mathbf{m}_1 \end{aligned}$$

Watanabe et al., 2004; Denli and Huang, 2009; Zheng et al., 2011;
Asnaashari et al., 2012; Raknes et al., 2013)

Time-lapse FWI approaches

Double difference or Differential FWI

$$\text{minimize } \Delta \mathbf{d} := (\mathbf{d}_2 - \mathbf{d}_1) - (\boldsymbol{\mathcal{F}}[\mathbf{m}_2] - \boldsymbol{\mathcal{F}}[\mathbf{m}_1])$$

$$\begin{aligned}
\text{Start with baseline data and initial model :} &\quad \mathbf{m}_0, \mathbf{d}_1 \\
\text{Invert for baseline :} &\quad \mathbf{m}_1 \\
\text{Construct composite data :} &\quad \widetilde{\mathbf{d}_2} = \mathbf{d}_2 - \mathbf{d}_1 + \boldsymbol{\mathcal{F}}[\mathbf{m}_1] \\
\text{Replace } \mathbf{d}_2 \text{ with } \widetilde{\mathbf{d}_2} \text{ obtain :} &\quad \widetilde{\mathbf{m}_2} \\
\text{Estimate timelapse model :} &\quad d\mathbf{m} = \widetilde{\mathbf{m}_2} - \mathbf{m}_1
\end{aligned}$$

Watanabe et al., 2004; Denli and Huang, 2009; Zheng et al., 2011;
Asnaashari et al., 2012; Raknes et al., 2013)

Time-lapse FWI approaches

Double difference or Differential FWI

$$\text{minimize } \Delta\mathbf{d} := (\mathbf{d}_2 - \mathbf{d}_1) - (\mathcal{F}[\mathbf{m}_2] - \mathcal{F}[\mathbf{m}_1])$$

Relies on accurately repeating the acquisition

Not quite conducive when the vintage noise are highly uncorrelated

SLIM

Time-lapse joint FWI approaches

Robust joint FWI with TV regularization

$$\alpha\|\mathbf{M}_1\boldsymbol{\mathcal{F}}[\mathbf{m}_1] - \mathbf{d}_1\|_2^2 + \beta\|\mathbf{M}_2\boldsymbol{\mathcal{F}}[\mathbf{m}_2] - \mathbf{d}_2\|_2^2 + \tag{1}$$

$$\gamma\|(\mathbf{M}_2^s\boldsymbol{\mathcal{F}}[\mathbf{m}_2] - \mathbf{M}_1^s\boldsymbol{\mathcal{F}}[\mathbf{m}_1]) - (\mathbf{M}_2\mathbf{d}_2 - \mathbf{M}_1\mathbf{d}_1)\|_2^2 + \tag{2}$$

$$\alpha_1\|\mathbf{W}_1\mathbf{R}_1(\mathbf{m}_1 - \mathbf{m}_1^{prior})\|_1 + \tag{3}$$

$$\beta_1\|\mathbf{W}_2\mathbf{R}_2(\mathbf{m}_2 - \mathbf{m}_2^{prior})\|_1 + \tag{4}$$

$$\delta\|\mathbf{W}\mathbf{R}(\mathbf{m}_2 - \mathbf{m}_1 - \Delta\mathbf{m}^{prior})\|_1 + \tag{5}$$

Our parallel versus joint inversion approach

Parallel FWI

Parallel inversion (uses the **fast** randomized inversion technique based on CS)

$$\text{for} \quad i = 1, 2$$

$$\tilde{\mathbf{x}}_i^k = \arg\min_{\mathbf{x}_i} \frac{1}{2} \| \underbrace{\mathbf{d}_i^k - \boldsymbol{\mathcal{F}}(\mathbf{m}_i^k)}_{\mathbf{b}_i} - \underbrace{\nabla \boldsymbol{\mathcal{F}}(\mathbf{m}_i^k) \mathbf{C}^T}_{\mathbf{A}_i} \underbrace{\mathbf{x}_i}_{\mathbf{x}_i} \|_2^2 \quad \text{s.t.} \quad \|\mathbf{x}_i\|_1 < \tau_i^k$$

$$\mathbf{m}_i^{k+1} = \mathbf{m}_i^k + \mathbf{C}^T \tilde{\mathbf{x}}_i^k$$

Objective: Invert for baseline, monitor; difference = baseline-monitor

Dror Baron , Marco F. Duarte , Shriram Sarvotham , Michael B. Wakin , Richard G. Baraniuk. An Information-Theoretic Approach to Distributed Compressed Sensing (2005).

SLIM

Distributed compressive sensing
– *joint* recovery model (JRM)

vintages ← $\mathbf{x}_1 = \mathbf{z}_0 + \mathbf{z}_1$ → *innovations*

vintages ← $\mathbf{x}_2 = \mathbf{z}_0 + \mathbf{z}_2$ → *innovations*

$\mathbf{z}_0$ → *common* part

$$\overbrace{\begin{bmatrix} \mathbf{A}_1 & \mathbf{A}_1 & \mathbf{0} \\ \mathbf{A}_2 & \mathbf{0} & \mathbf{A}_2 \end{bmatrix}}^{\mathbf{A}} \overbrace{\begin{bmatrix} \mathbf{z}_0 \\ \mathbf{z}_1 \\ \mathbf{z}_2 \end{bmatrix}}^{\mathbf{z}} = \overbrace{\begin{bmatrix} \mathbf{b}_1 \\ \mathbf{b}_2 \end{bmatrix}}^{\mathbf{b}}$$

$\mathbf{b}_1$ → *baseline*; $\mathbf{b}_2$ → *monitor*

- Decompose vintage into common and innovations
- Timelapse vintages share a lot of common information
- DCS exploits the common or shared information
- Invert for common component and innovations

$$\tilde{\mathbf{z}} = \arg\min_{\mathbf{z}} \|\mathbf{z}\|_1 \quad \text{s.t.} \quad \mathbf{b} = \mathbf{A}\mathbf{z}$$

Joint FWI

with distributed compressed sensing

SLIM

$$\tilde{\mathbf{z}}_k = \arg\min_{\mathbf{z}_k} \frac{1}{2}\|\mathbf{b}_k - \mathbf{A}_k\mathbf{z}_k\|_2^2 \quad \text{s.t.} \quad \|\mathbf{z}_k\|_1 < \tau^k$$

$$\mathbf{b}_k = \begin{bmatrix} \mathbf{d}_1^k - \boldsymbol{\mathcal{F}}(\mathbf{m}_1^k) \\ \mathbf{d}_2^k - \boldsymbol{\mathcal{F}}(\mathbf{m}_2^k) \end{bmatrix}$$

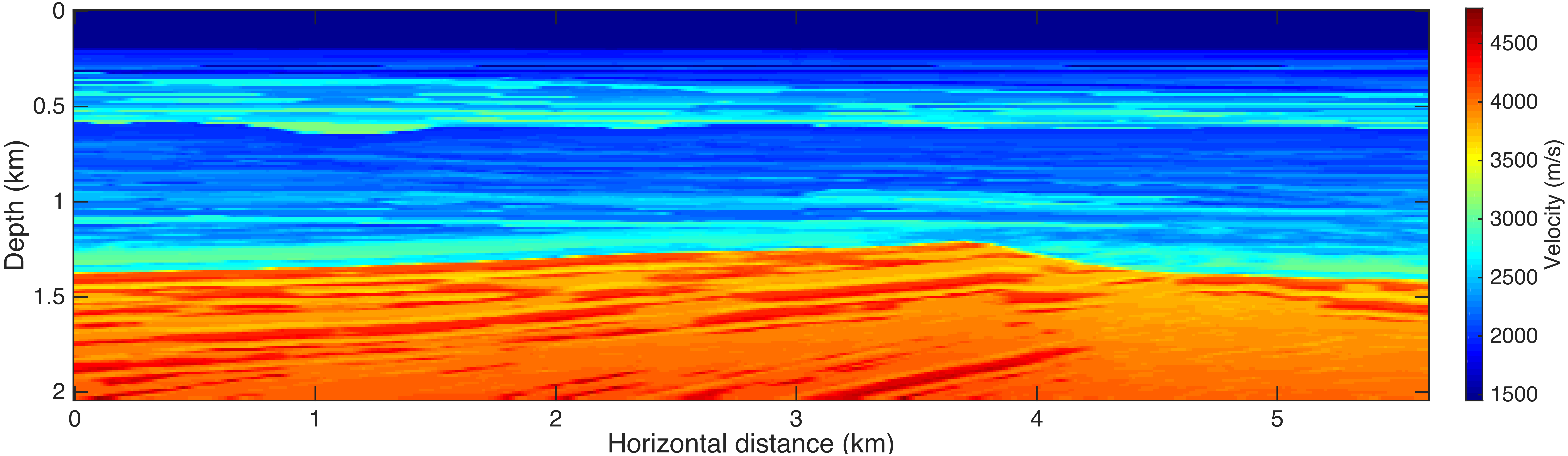
$$\mathbf{A}_k = \begin{bmatrix} \nabla\boldsymbol{\mathcal{F}}(\mathbf{m}_1^k)\mathbf{C}^T & \nabla\boldsymbol{\mathcal{F}}(\mathbf{m}_1^k)\mathbf{C}^T & \mathbf{0} \\ \nabla\boldsymbol{\mathcal{F}}(\mathbf{m}_2^k)\mathbf{C}^T & \mathbf{0} & \nabla\boldsymbol{\mathcal{F}}(\mathbf{m}_2^k)\mathbf{C}^T \end{bmatrix}$$

$$\mathbf{z}_k = \begin{bmatrix} \mathbf{z}_0^k \\ \mathbf{z}_1^k \\ \mathbf{z}_2^k \end{bmatrix}$$

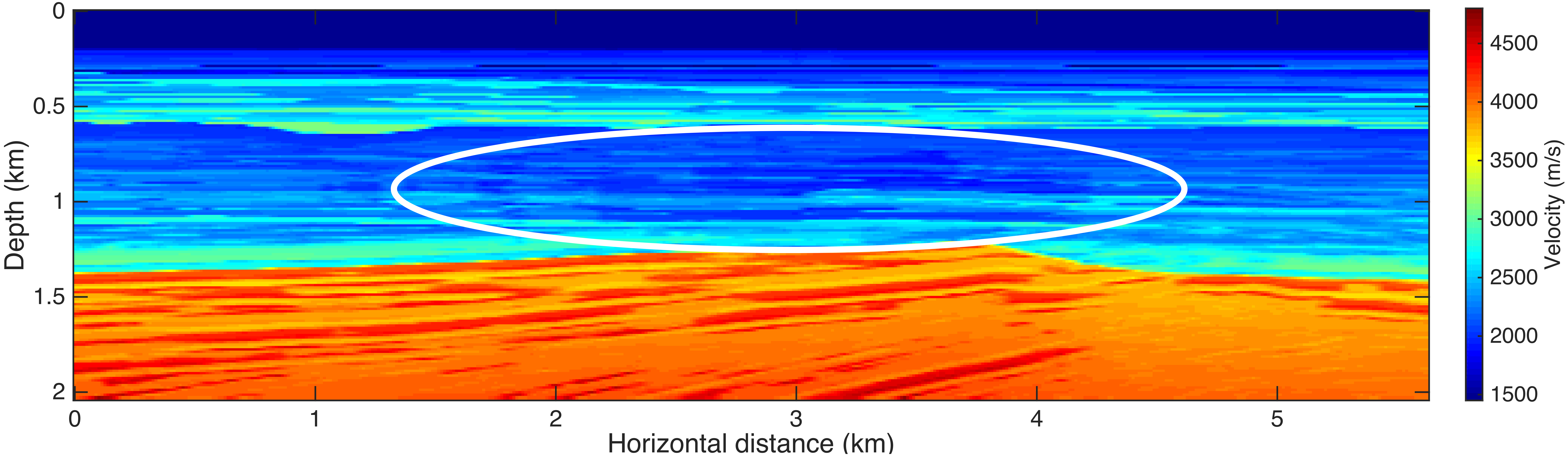
$$\mathbf{m}_i^{k+1} = \mathbf{m}_i^k + \mathbf{C}^T(\tilde{\mathbf{z}}_0^k + \tilde{\mathbf{z}}_i^k)$$

Synthetic example

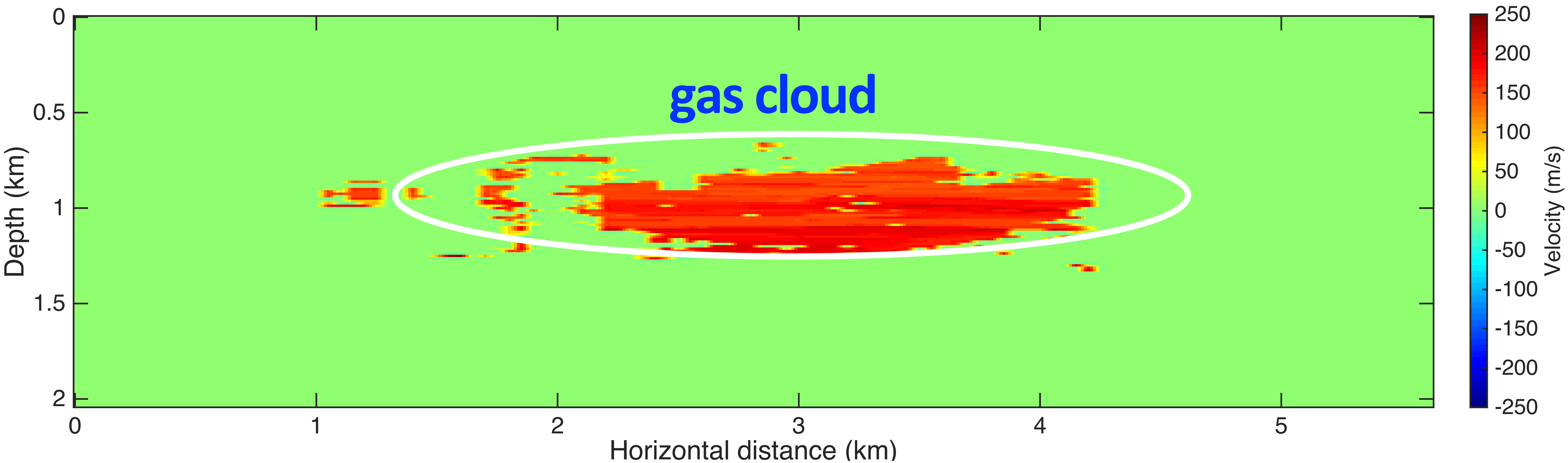
True baseline



True monitor



True time-lapse



SLIM

Parallel/Sequential/Joint inversion

Given a good starting model:

- assuming similar acquisition geometry
- assuming different acquisition geometry

Given a poor starting model

In the presence of large acquisition gap in the monitor survey

In noisy environment

Parallel/Sequential/Joint inversion

Given a good starting model:

- assuming similar acquisition geometry
- assuming different acquisition geometry

Given a poor starting model

In the presence of large acquisition gap in the monitor survey

In noisy environment

Experiment : part 1

Assuming similar geometry

"good" starting model

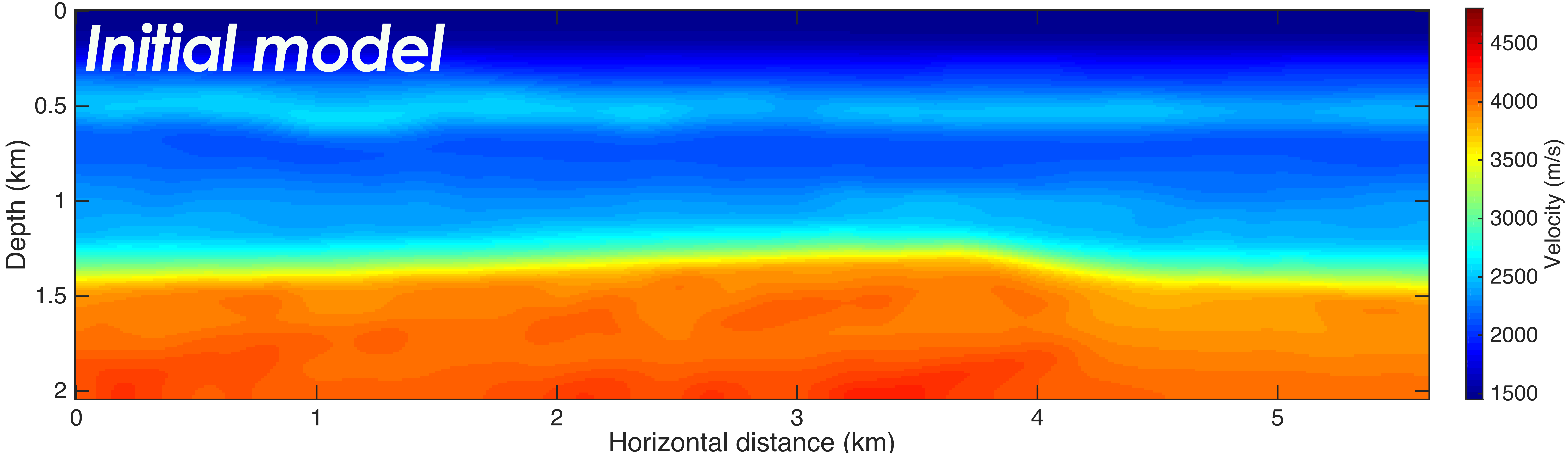
Modeling/Inversion parameters

Data simulation:

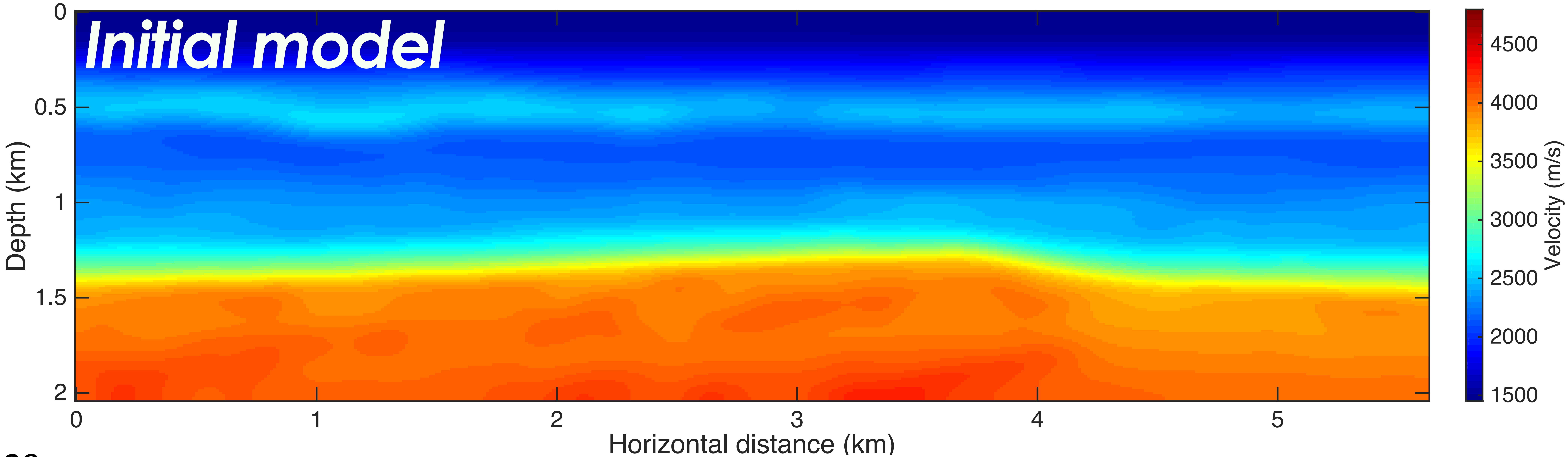
- Models ocean bottom seismic acquisition
- 23 sources @ 250m, 113 receivers @ 50m spacing
- Ricker source wavelet @ 12Hz peak frequency
- 80 frequencies between 3 and 22.5Hz

Inversion:

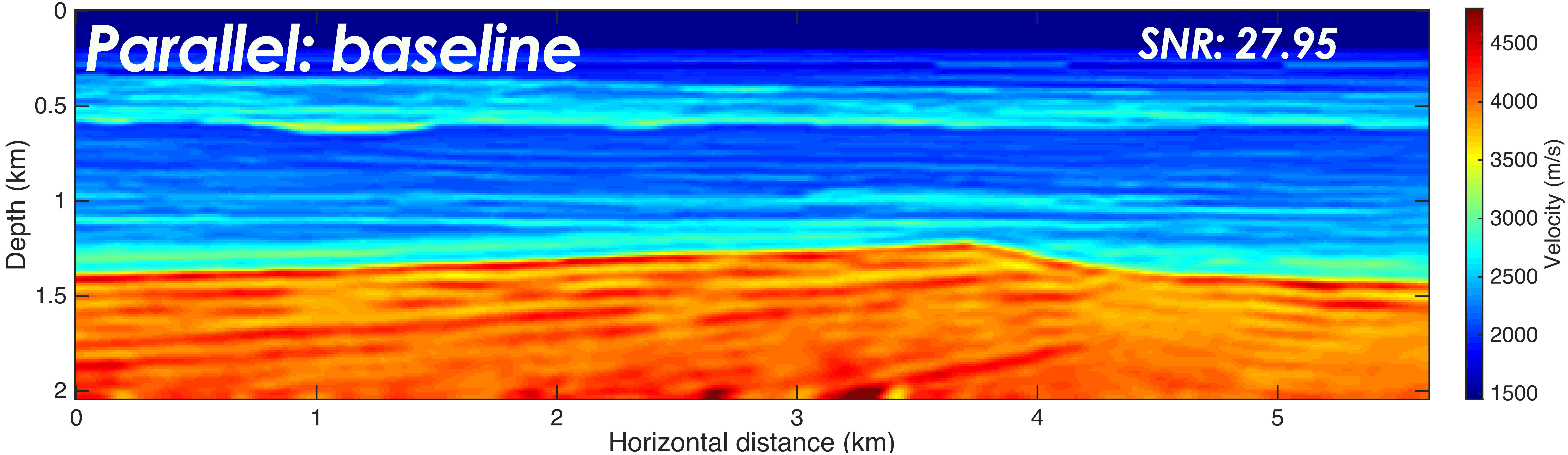
- 16 frequencies per batch, 9 batches in total with overlapping frequencies
- Maximum of 150 iterations of spgl1 per frequency batch

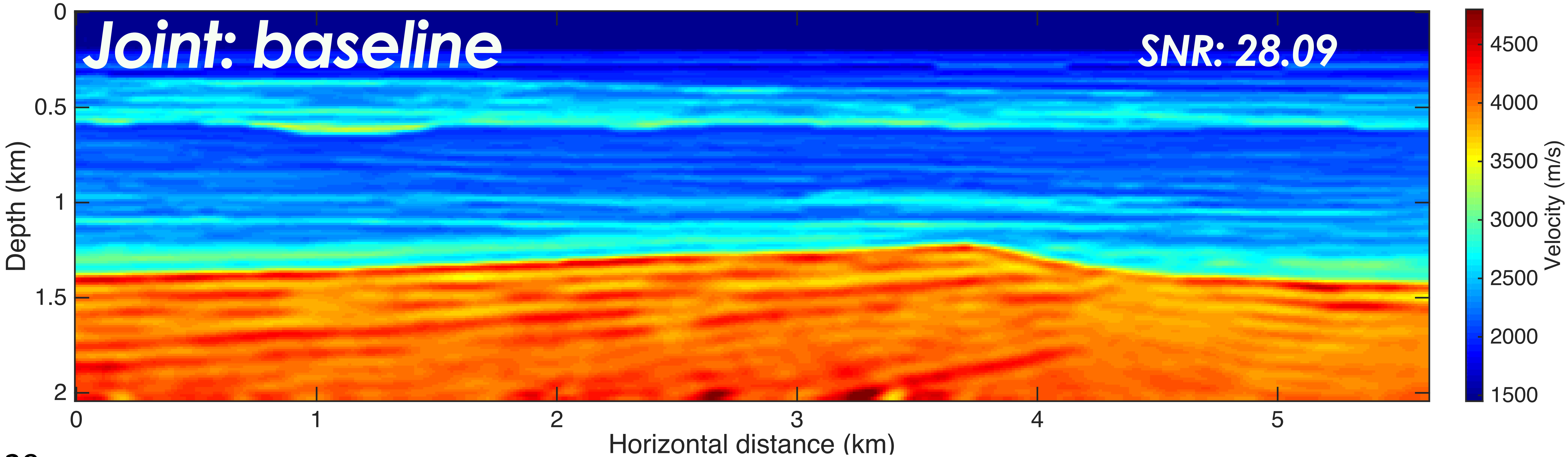


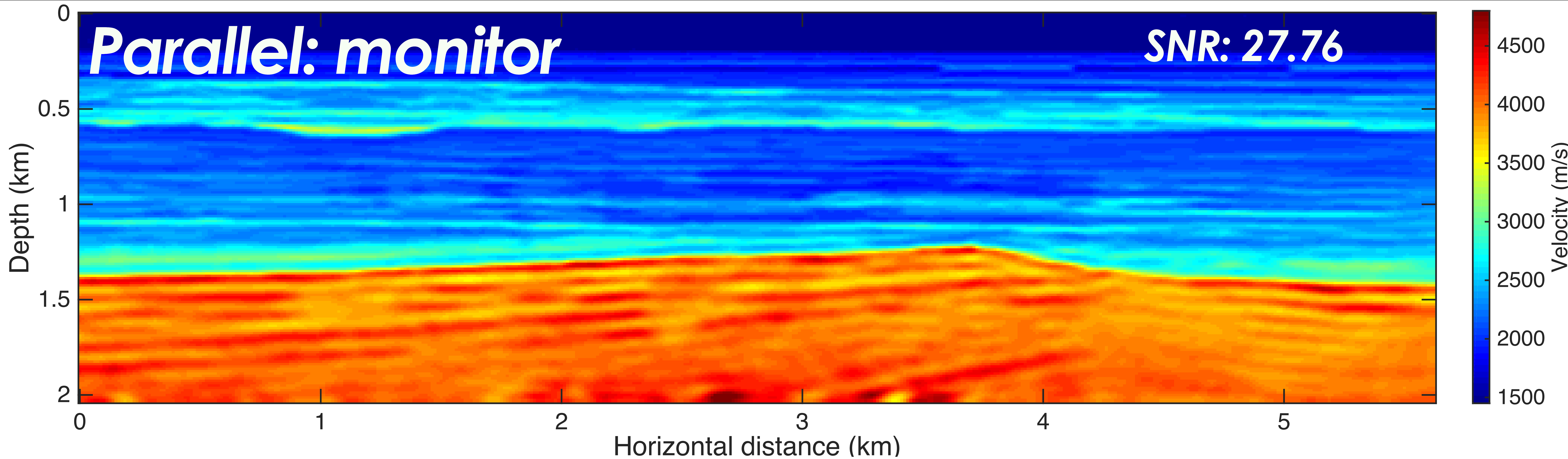
Initial model
Depth (km)
0
0.5
1
1.5
2
0
1
2
3
4
5
Horizontal distance (km)
Velocity (m/s)
4500
4000
3500
3000
2500
2000
1500

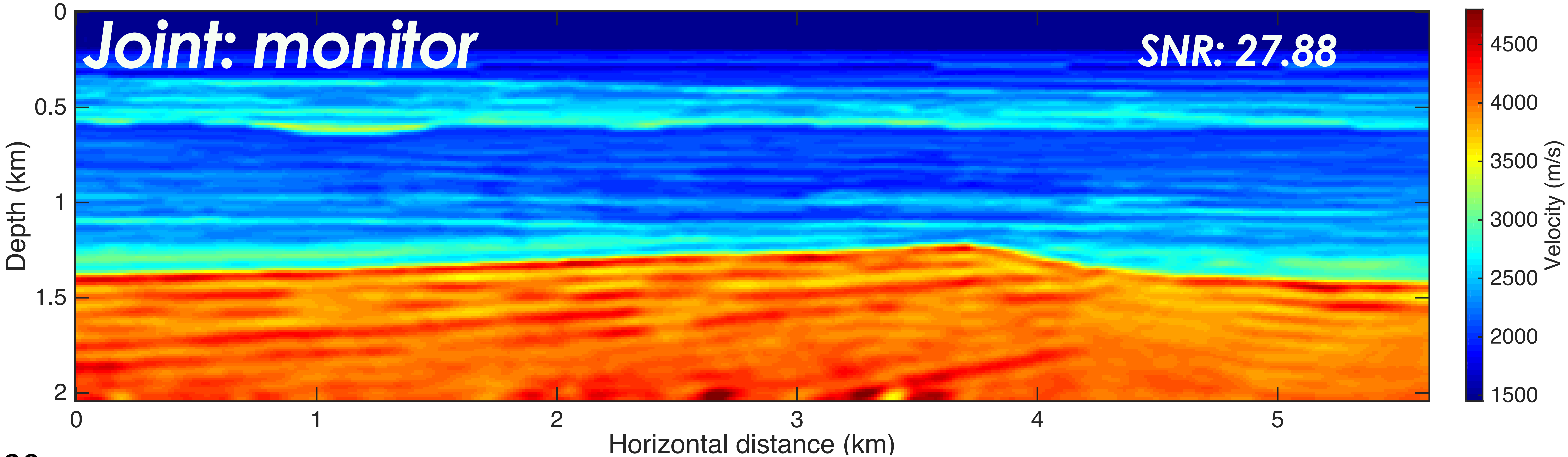


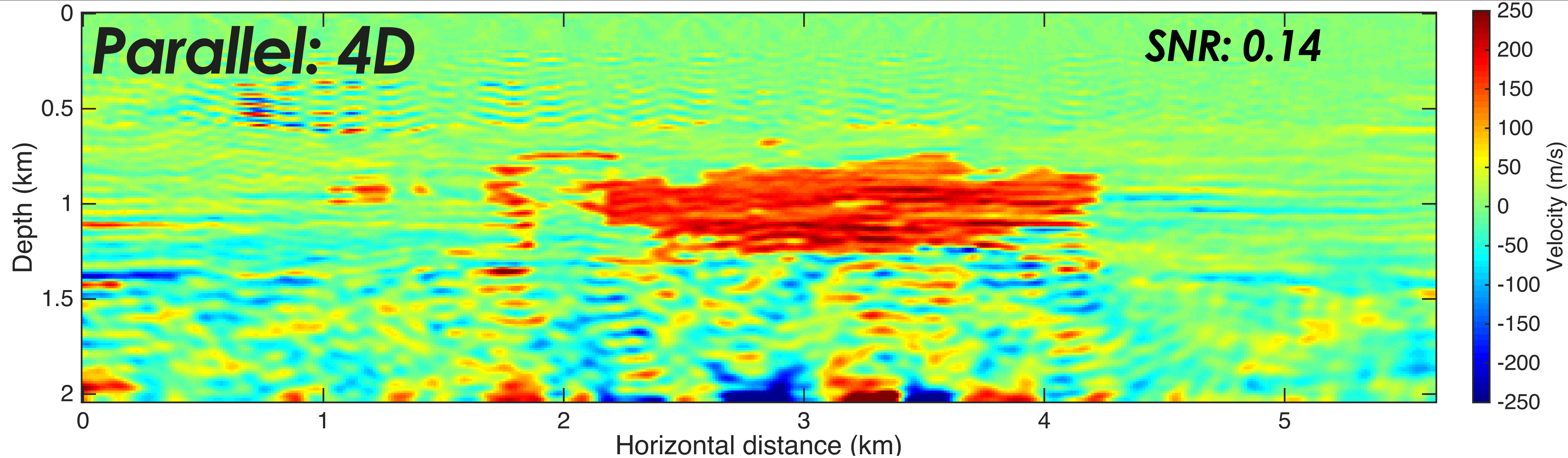
Initial model
Depth (km)
0
0.5
1
1.5
2
0
1
2
3
4
5
Horizontal distance (km)
Velocity (m/s)
4500
4000
3500
3000
2500
2000
1500

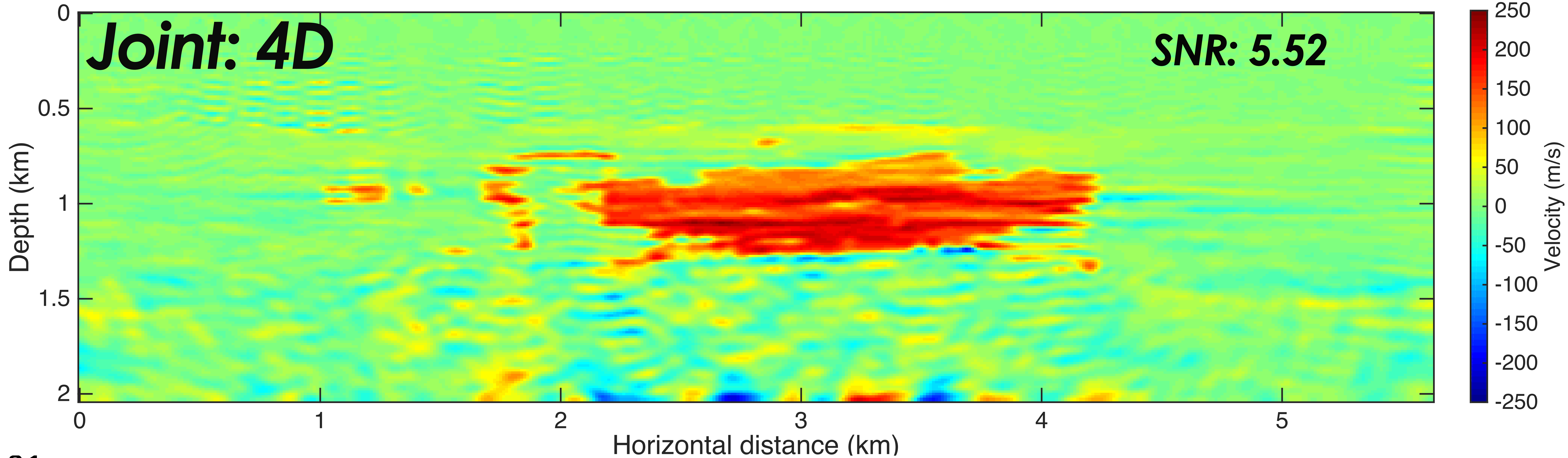

Parallel: baseline
SNR: 27.95
Depth (km)
Horizontal distance (km)
Velocity (m/s)


Joint: baseline
SNR: 28.09
Depth (km)
Horizontal distance (km)
Velocity (m/s)


Parallel: monitor
SNR: 27.76
Depth (km)
Horizontal distance (km)
Velocity (m/s)

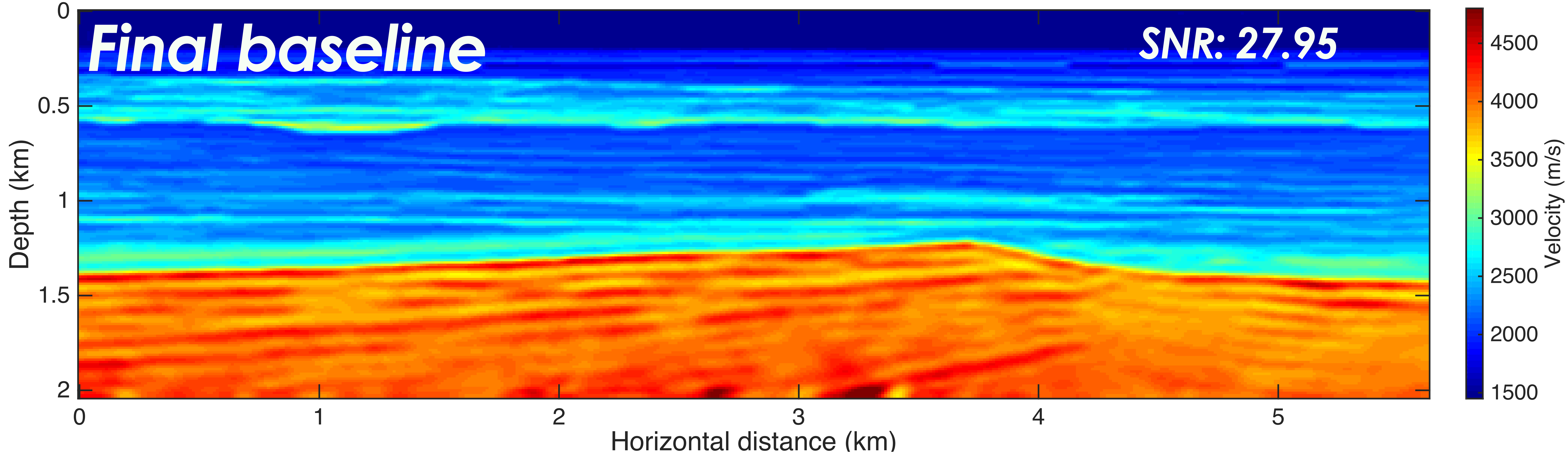

Joint: monitor
SNR: 27.88
Depth (km)
Horizontal distance (km)
Velocity (m/s)


Parallel: 4D
SNR: 0.14
Depth (km)
0
0.5
1
1.5
2
0
1
2
3
4
5
Horizontal distance (km)
Velocity (m/s)
250
200
150
100
50
0
-50
-100
-150
-200
-250

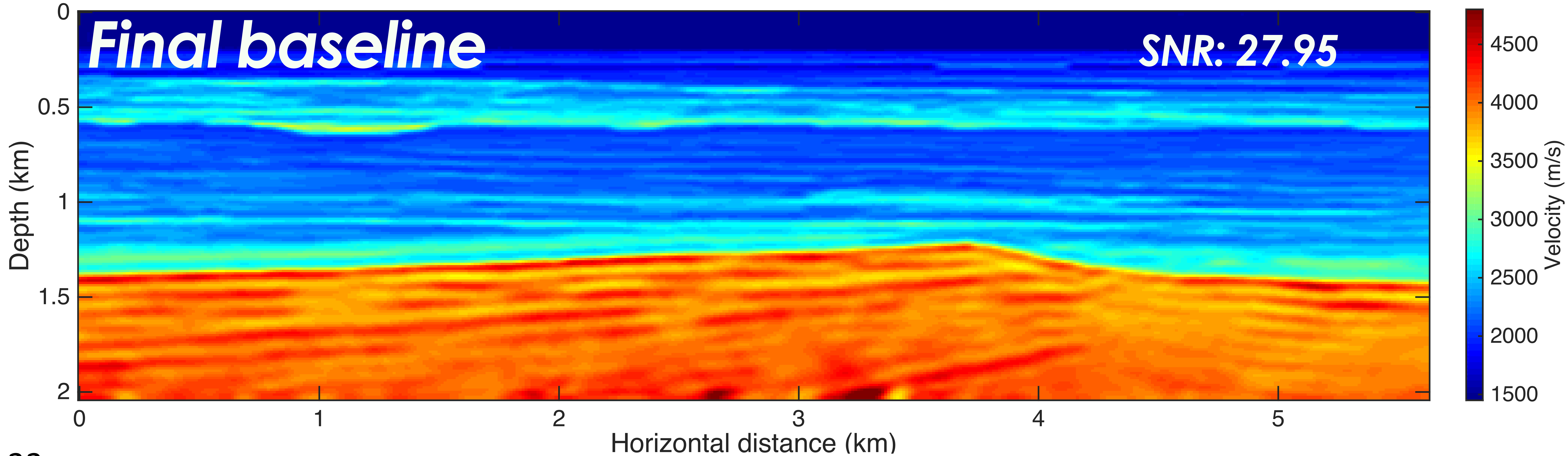

Joint: 4D
SNR: 5.52
Depth (km)
0
0.5
1
1.5
2
0
1
2
3
4
5
Horizontal distance (km)
Velocity (m/s)
250
200
150
100
50
0
-50
-100
-150
-200
-250

Sequential inversion

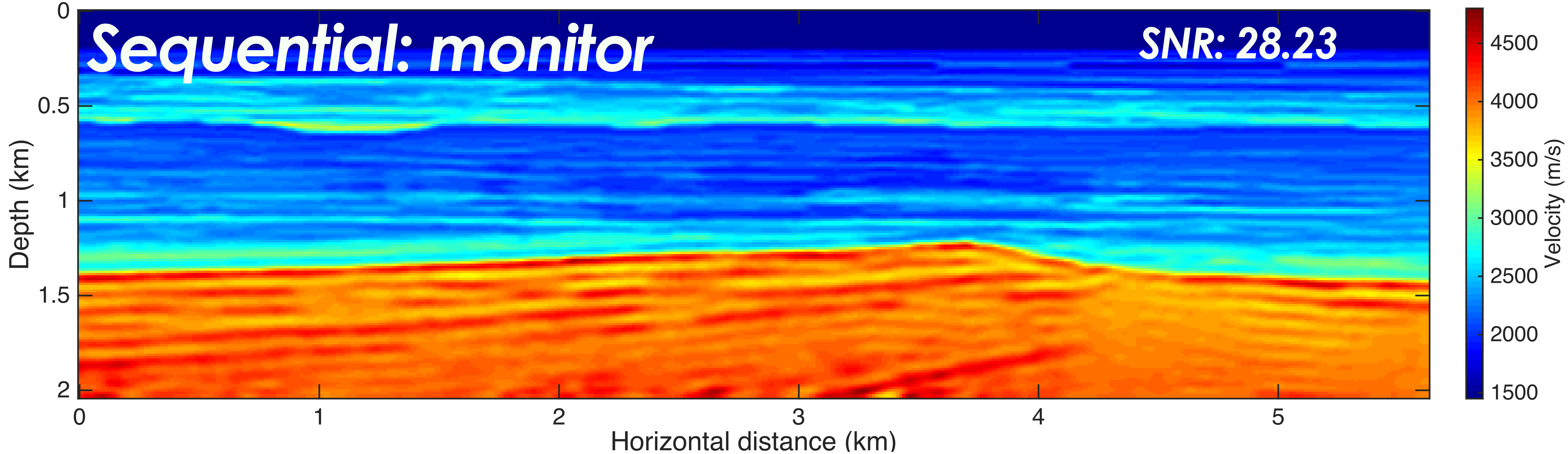
Start monitor inversion with the baseline inversion result

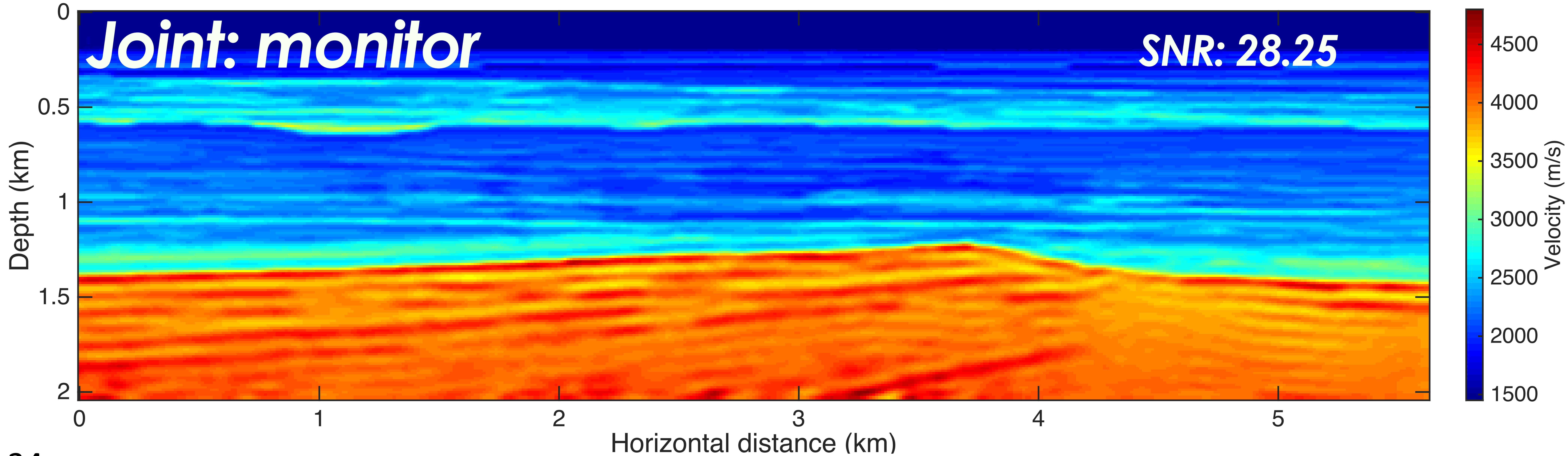


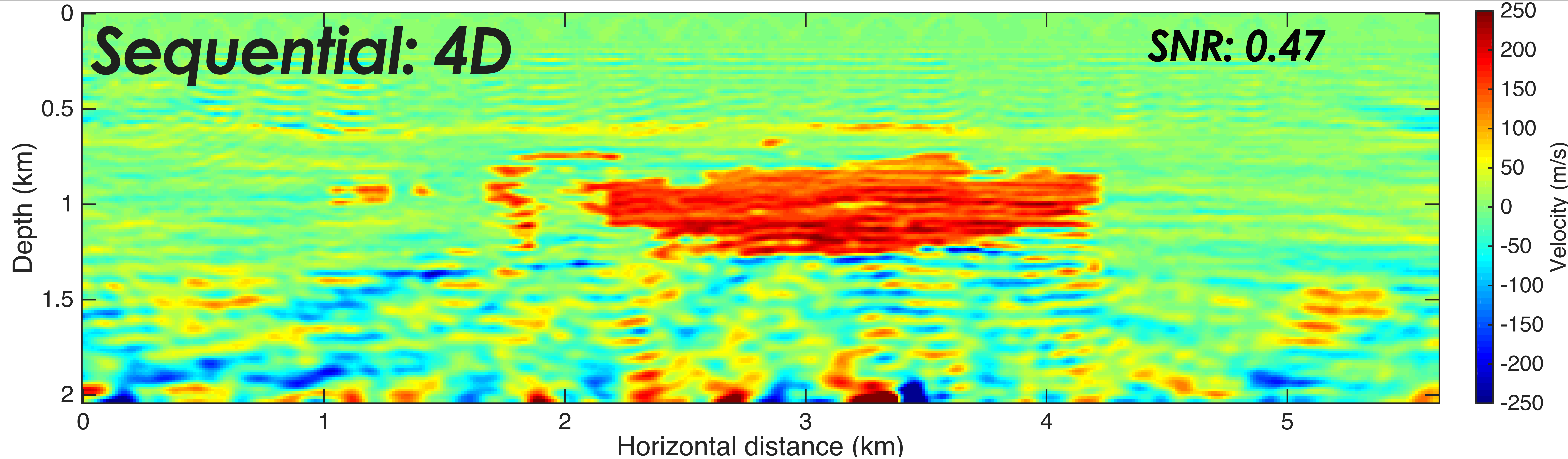
Final baseline
SNR: 27.95
Depth (km)
0
0.5
1
1.5
2
Horizontal distance (km)
0
1
2
3
4
5
Velocity (m/s)
4500
4000
3500
3000
2500
2000
1500

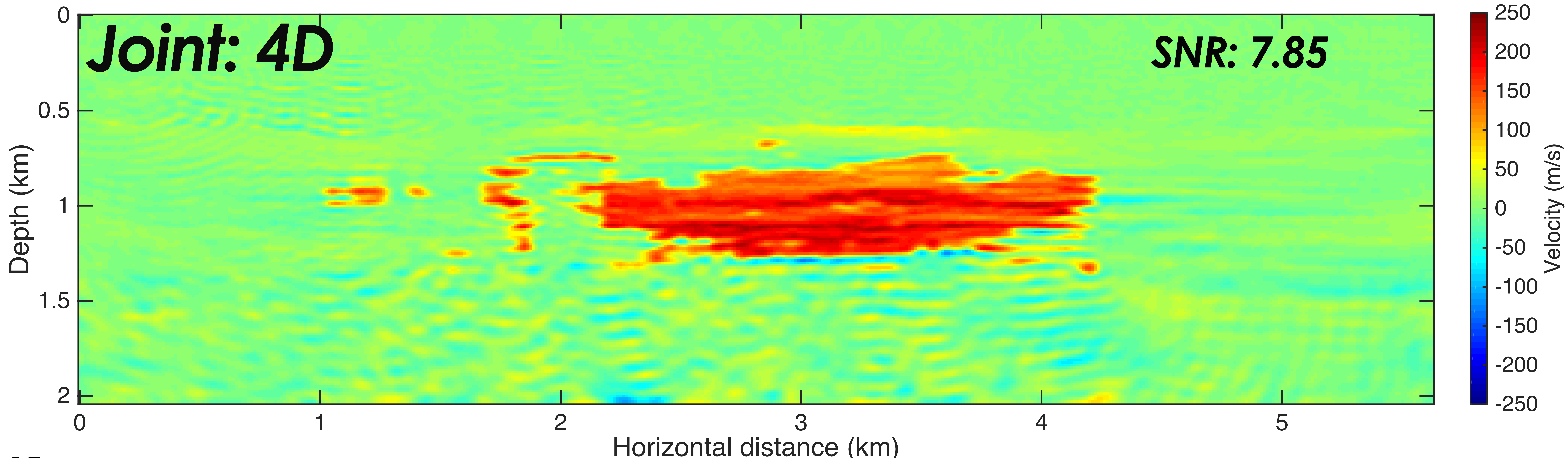


Final baseline
SNR: 27.95
Depth (km)
0
0.5
1
1.5
2
Horizontal distance (km)
0
1
2
3
4
5
Velocity (m/s)
4500
4000
3500
3000
2500
2000
1500


Sequential: monitor
SNR: 28.23
Depth (km)
Horizontal distance (km)
Velocity (m/s)

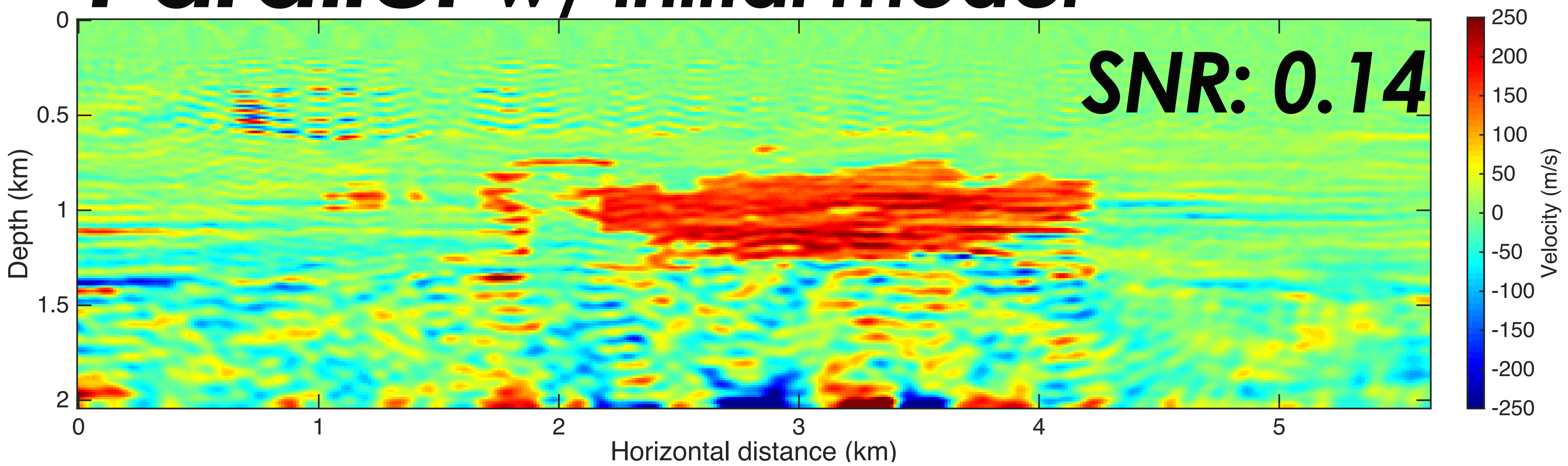

Joint: monitor
SNR: 28.25
Depth (km)
Horizontal distance (km)
Velocity (m/s)


Sequential: 4D
SNR: 0.47
Depth (km)
0
0.5
1
1.5
2
0
1
2
3
4
5
Horizontal distance (km)
Velocity (m/s)
250
200
150
100
50
0
-50
-100
-150
-200
-250

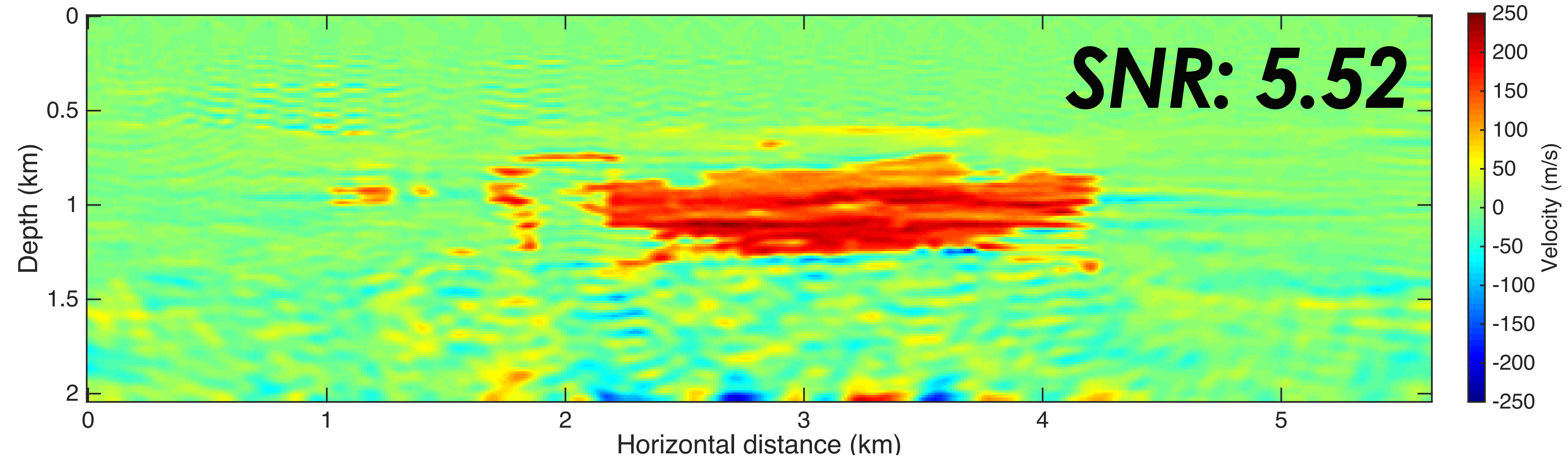

Joint: 4D
SNR: 7.85
Depth (km)
0
0.5
1
1.5
2
0
1
2
3
4
5
Horizontal distance (km)
Velocity (m/s)
250
200
150
100
50
0
-50
-100
-150
-200
-250

Time-lapse results

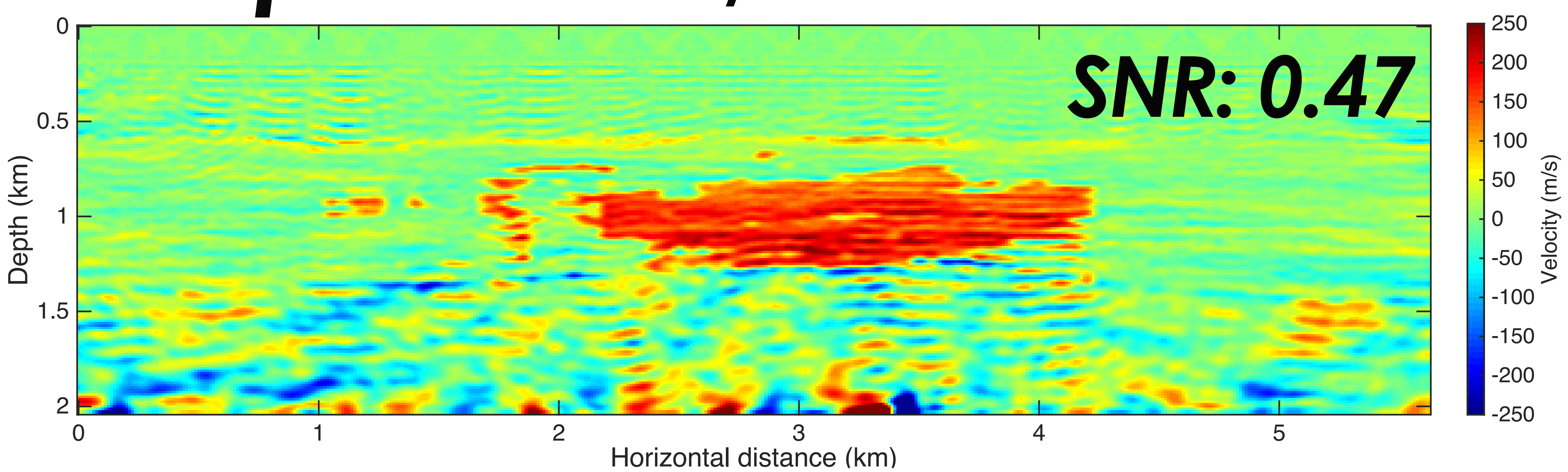
Parallel w/ initial model



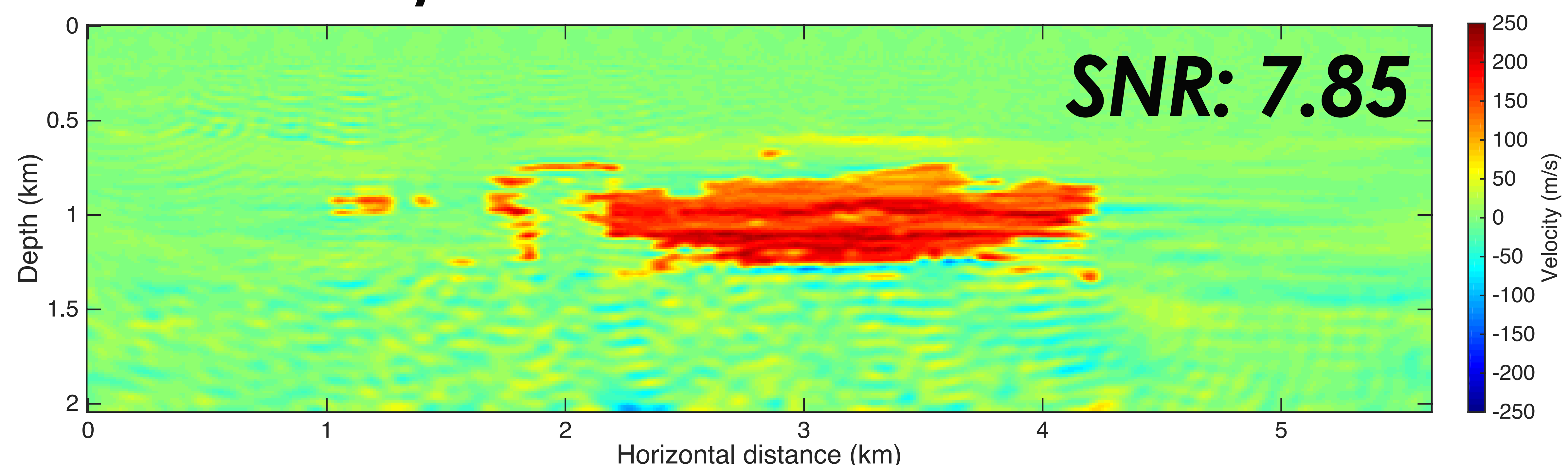
Joint w/ initial model



Sequential w/ inverted base



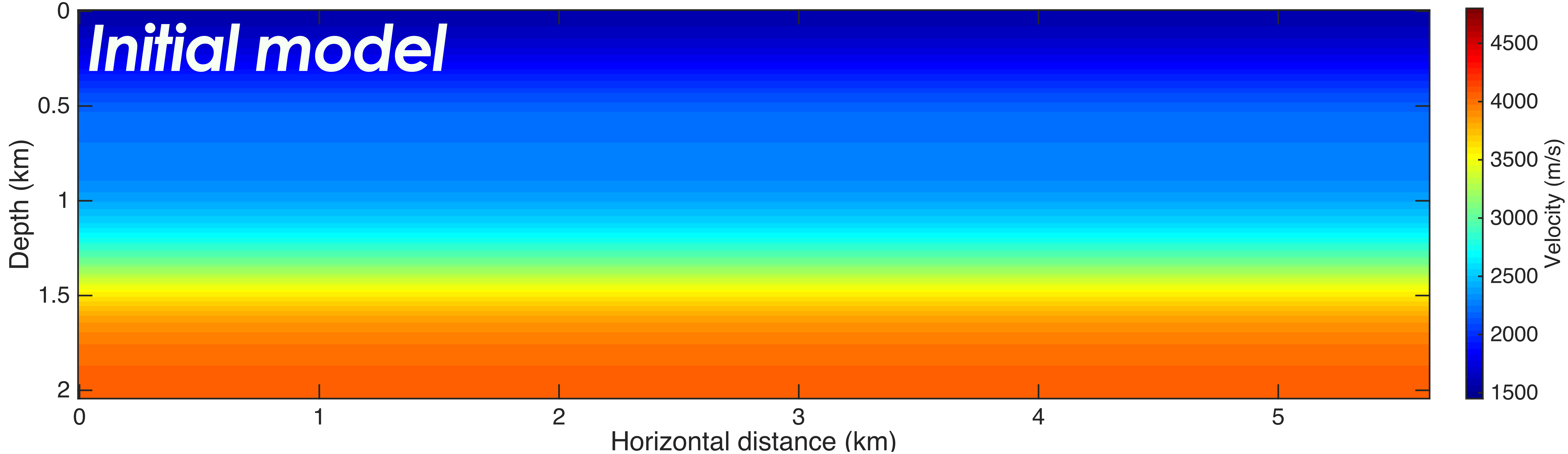
Joint w/ inverted base

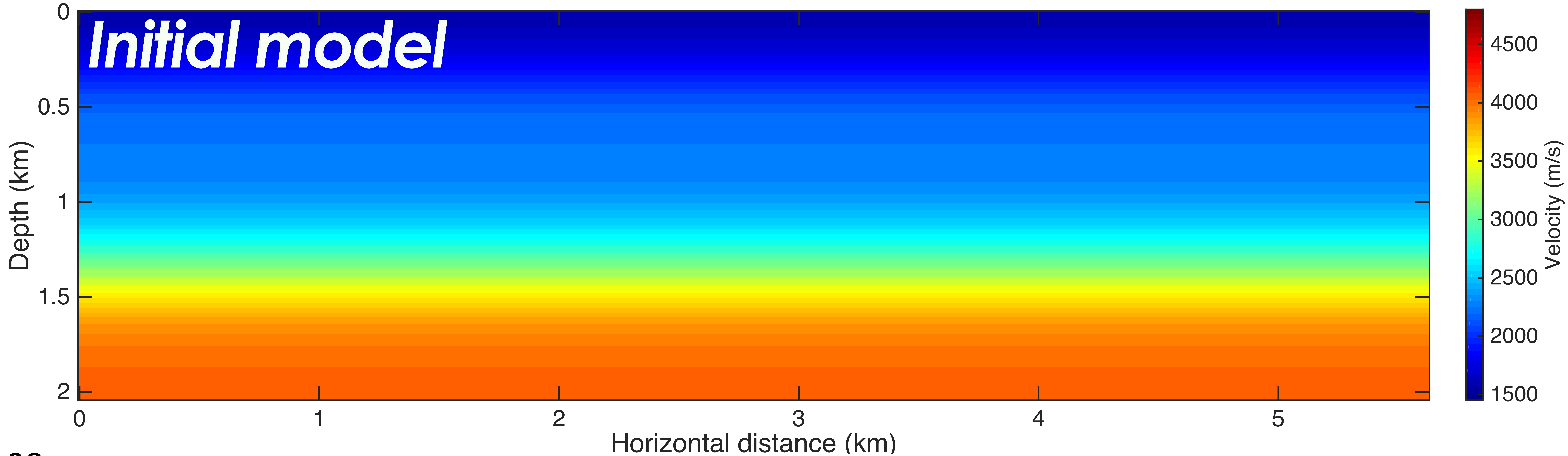


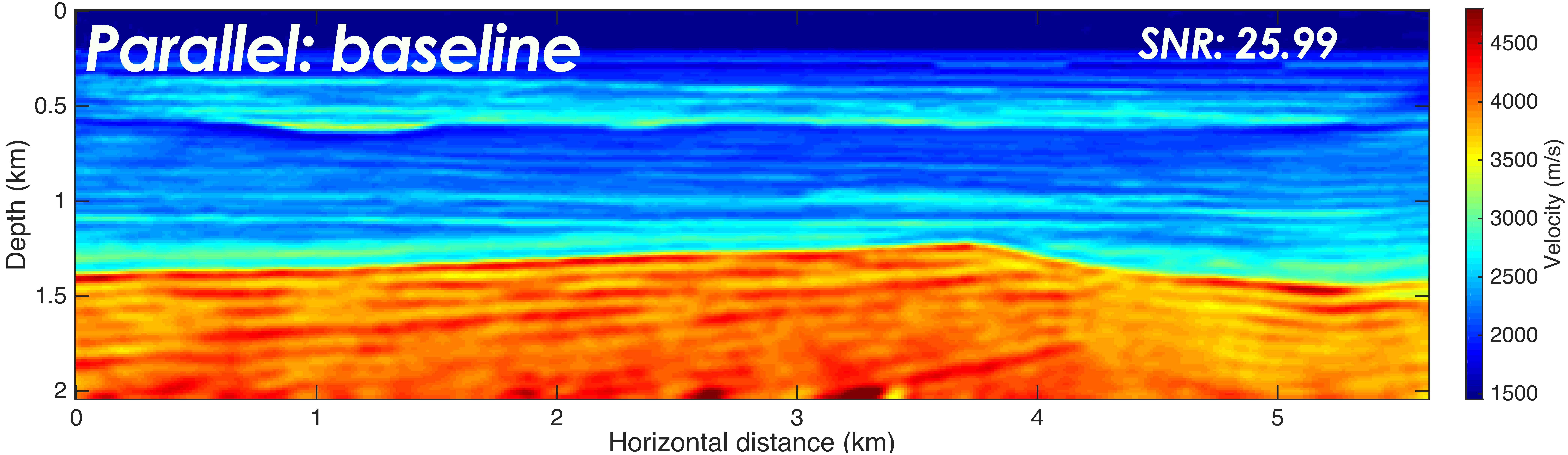
Experiment : part 2

Assuming similar geometry

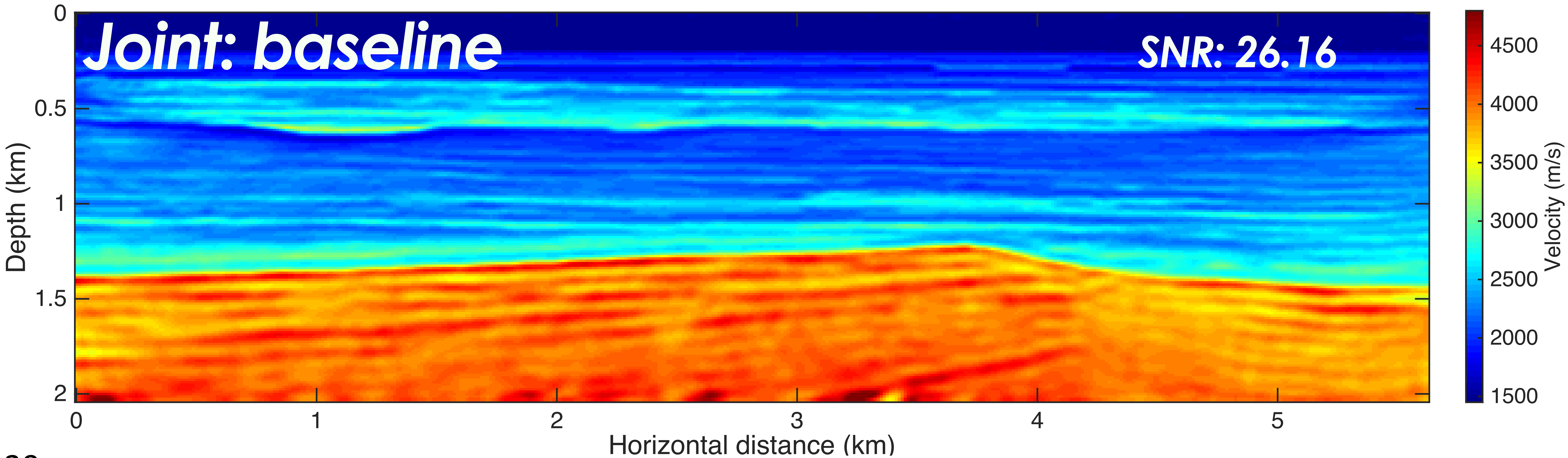
"poor" starting model


Initial model
0
0.5
1
1.5
2
Depth (km)
0
1
2
3
4
5
Horizontal distance (km)
4500
4000
3500
3000
2500
2000
1500
Velocity (m/s)

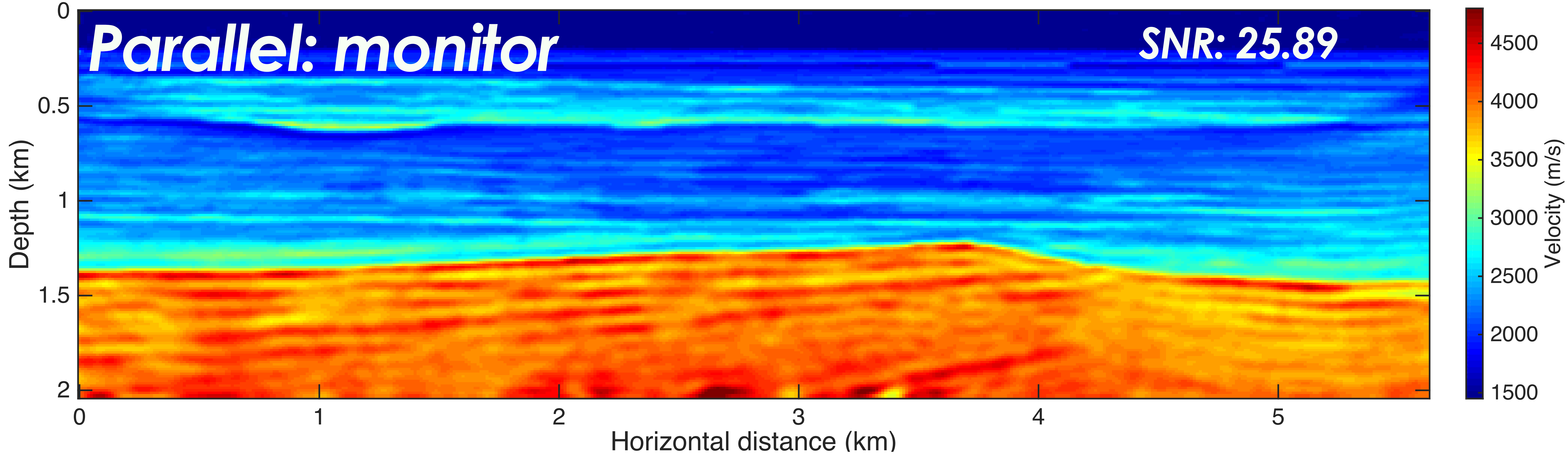

Initial model
0
0.5
1
1.5
2
Depth (km)
0
1
2
3
4
5
Horizontal distance (km)
4500
4000
3500
3000
2500
2000
1500
Velocity (m/s)

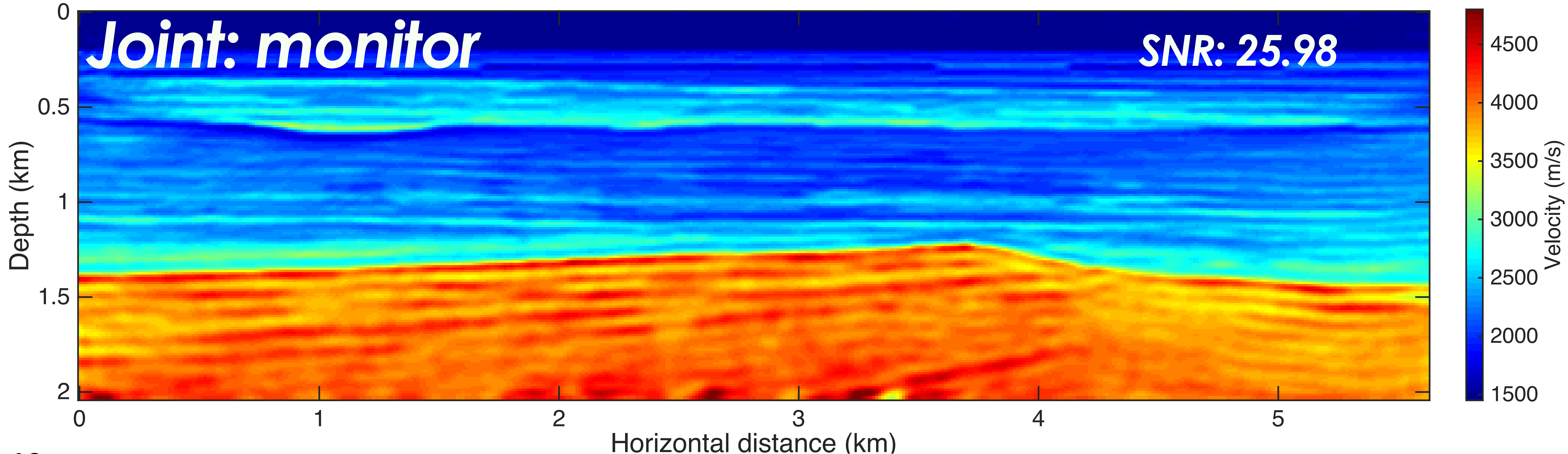


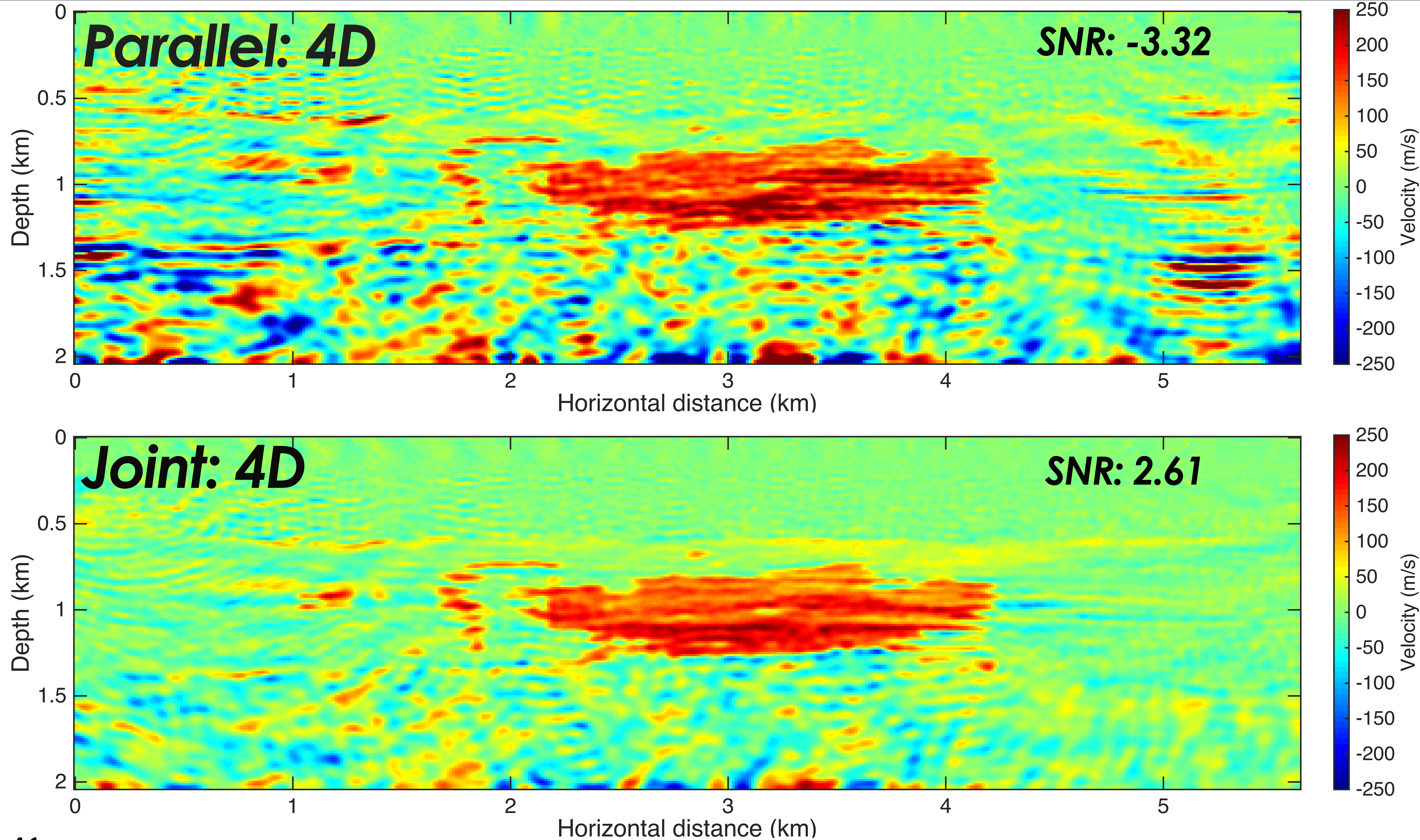
Parallel: baseline
SNR: 25.99
Depth (km)
0
0.5
1
1.5
2
0
1
2
3
4
5
Horizontal distance (km)
Velocity (m/s)
4500
4000
3500
3000
2500
2000
1500



Joint: baseline
SNR: 26.16
Depth (km)
0
0.5
1
1.5
2
0
1
2
3
4
5
Horizontal distance (km)
Velocity (m/s)
4500
4000
3500
3000
2500
2000
1500


Parallel: monitor
SNR: 25.89
Depth (km)
0
0.5
1
1.5
2
0
1
2
3
4
5
Horizontal distance (km)
Velocity (m/s)
4500
4000
3500
3000
2500
2000
1500


Joint: monitor
SNR: 25.98
Depth (km)
0
0.5
1
1.5
2
0
1
2
3
4
5
Horizontal distance (km)
Velocity (m/s)
4500
4000
3500
3000
2500
2000
1500

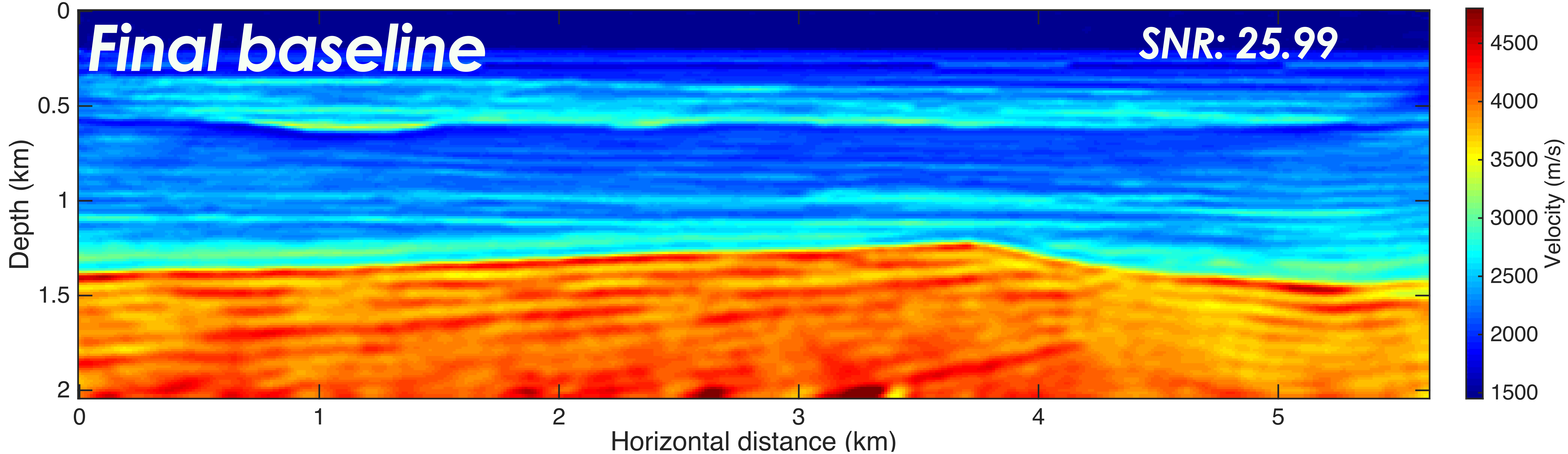


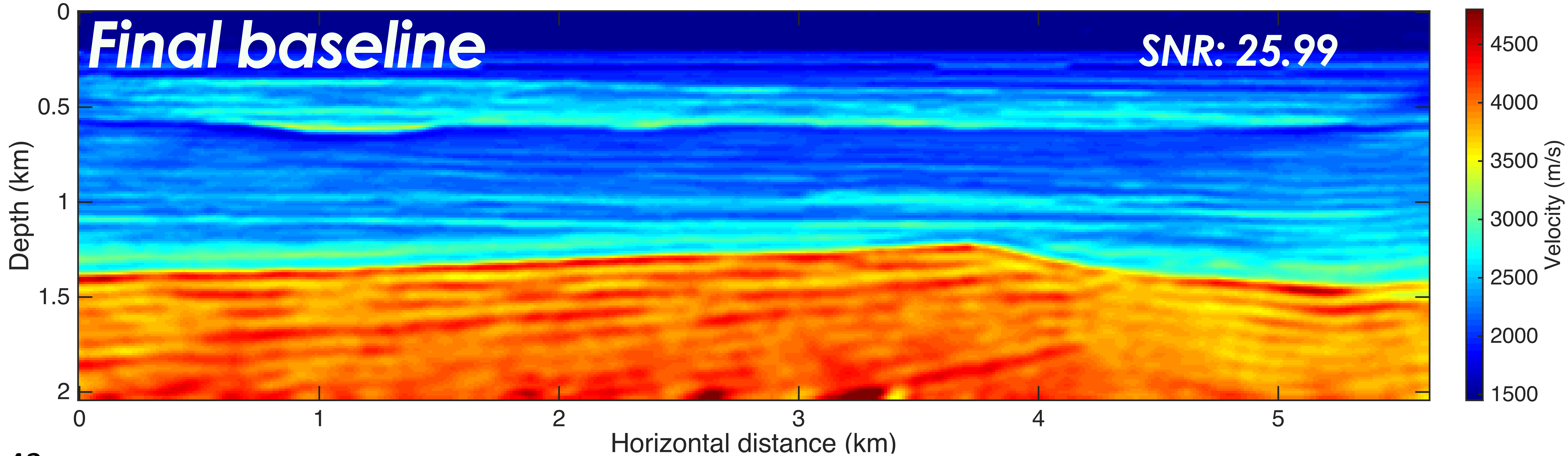
Parallel: 4D
SNR: -3.32
Depth (km)
Horizontal distance (km)
Velocity (m/s)
Joint: 4D
SNR: 2.61
Depth (km)
Horizontal distance (km)
Velocity (m/s)

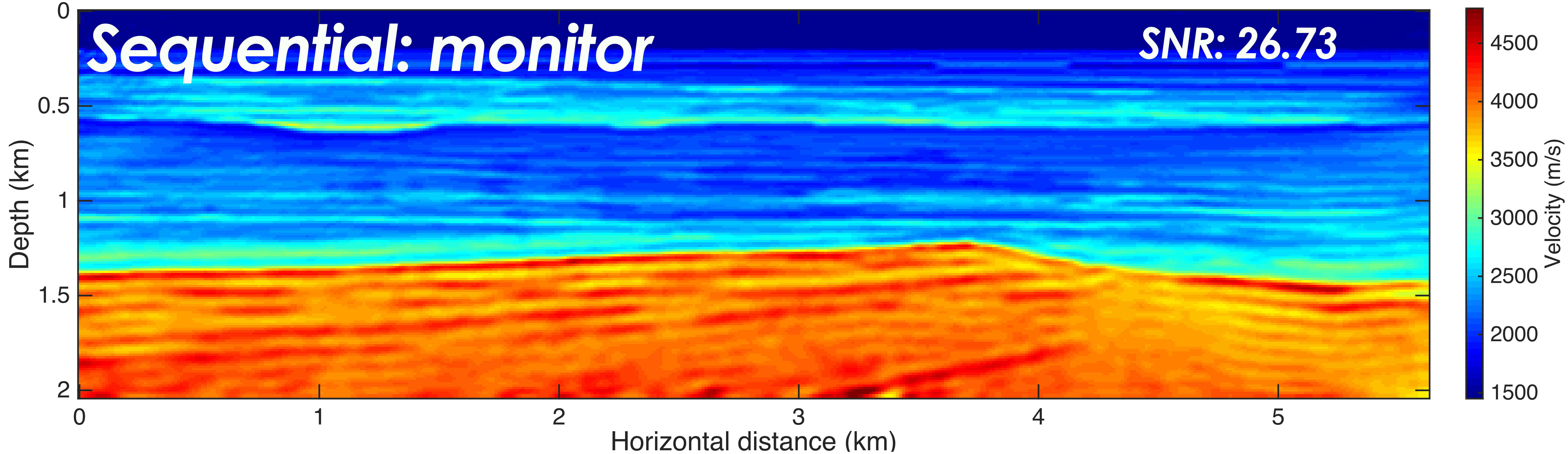
SLIM

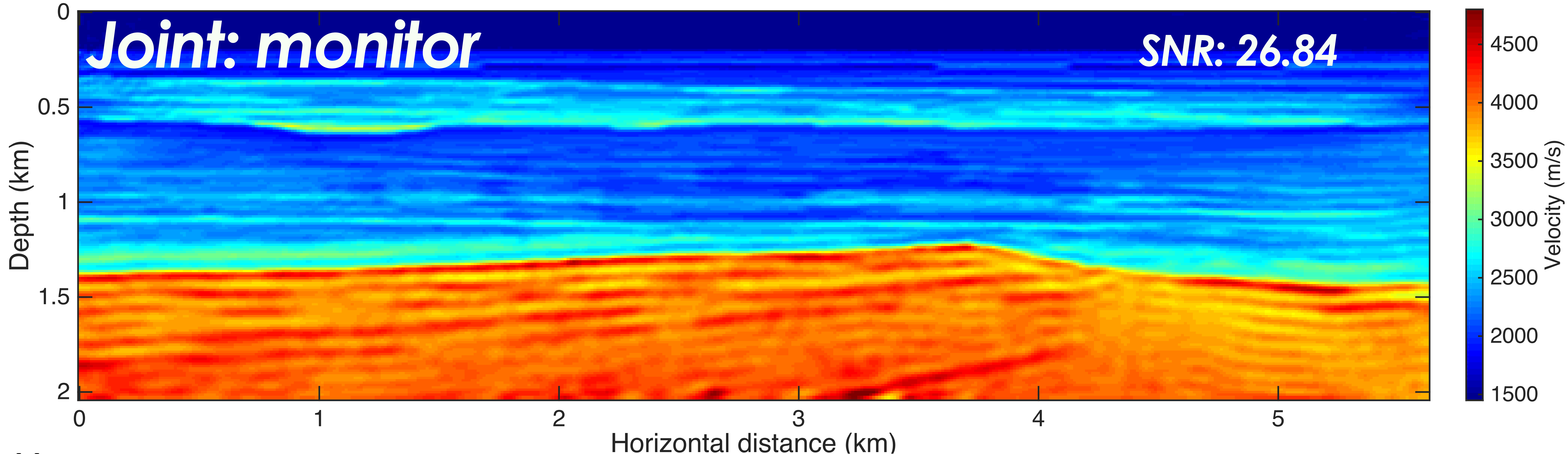
Sequential inversion

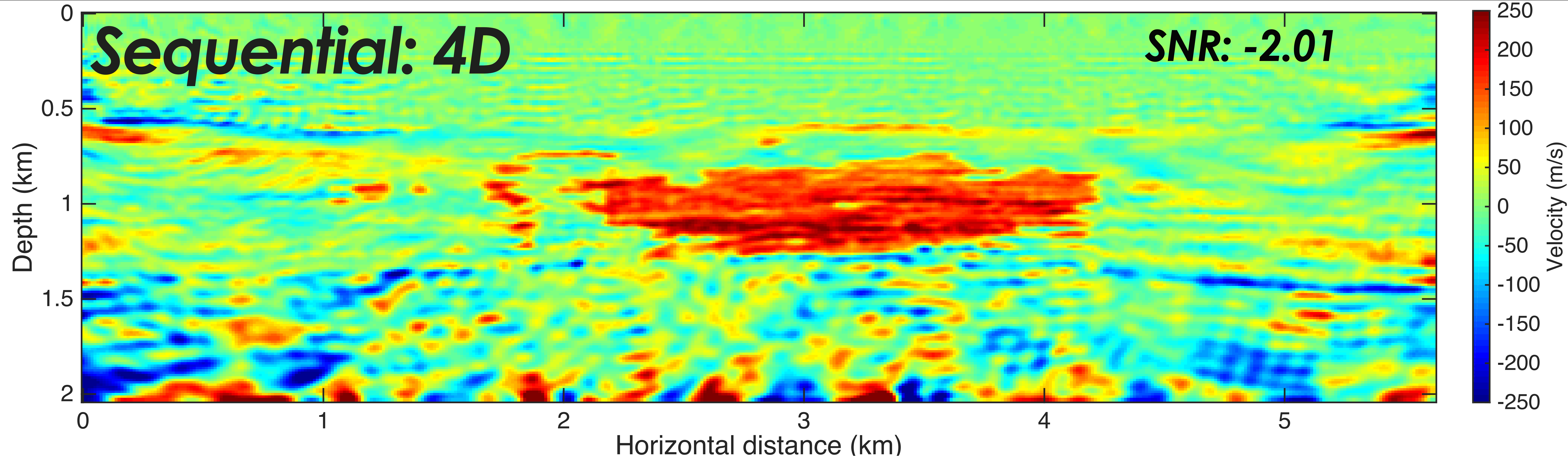
Start monitor inversion with the baseline inversion result


Final baseline
SNR: 25.99
Depth (km)
Horizontal distance (km)
Velocity (m/s)

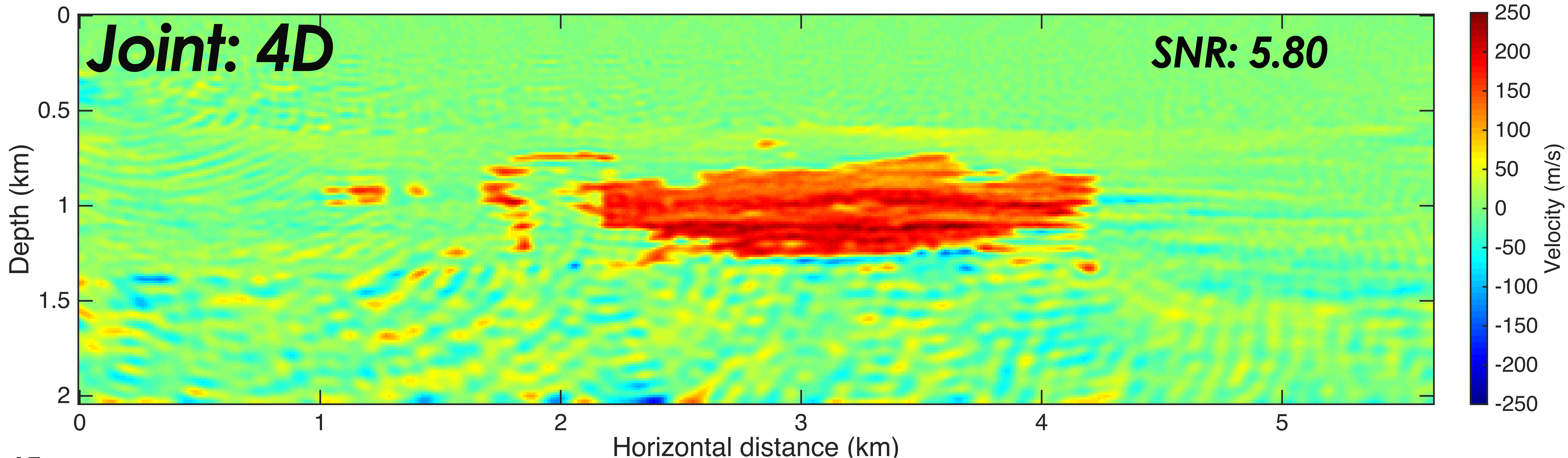

Final baseline
SNR: 25.99
Depth (km)
Horizontal distance (km)
Velocity (m/s)


Sequential: monitor
SNR: 26.73
Depth (km)
Horizontal distance (km)
Velocity (m/s)
0
0.5
1
1.5
2
0
1
2
3
4
5
1500
2000
2500
3000
3500
4000
4500


Joint: monitor
SNR: 26.84
Depth (km)
Horizontal distance (km)
Velocity (m/s)
0
0.5
1
1.5
2
0
1
2
3
4
5
1500
2000
2500
3000
3500
4000
4500



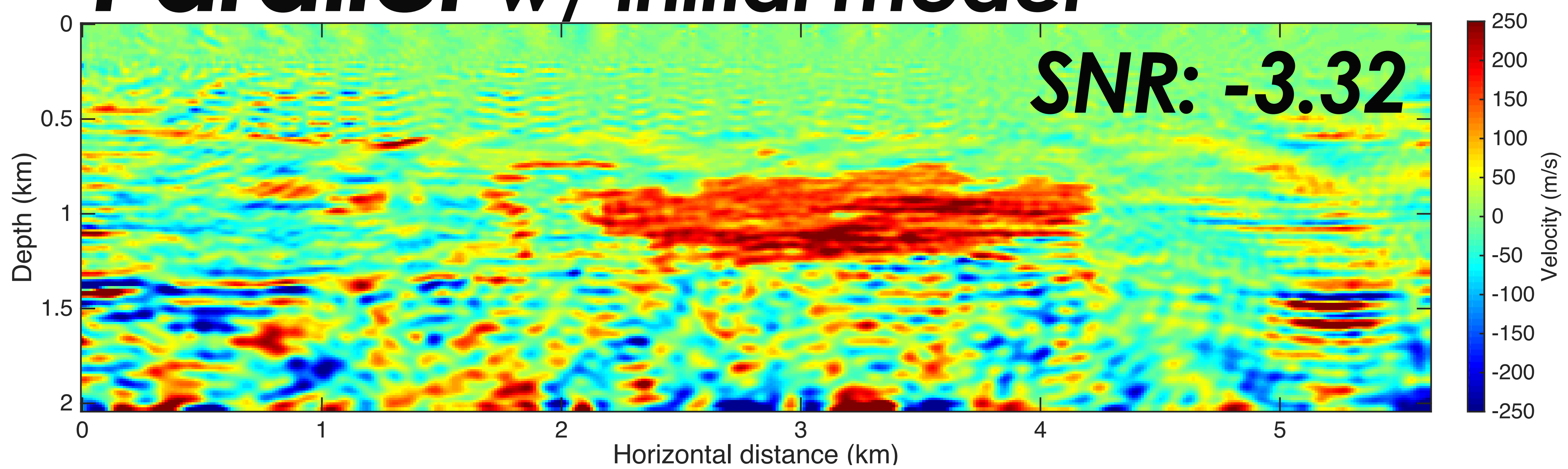
Sequential: 4D
SNR: -2.01
Depth (km)
Horizontal distance (km)
Velocity (m/s)



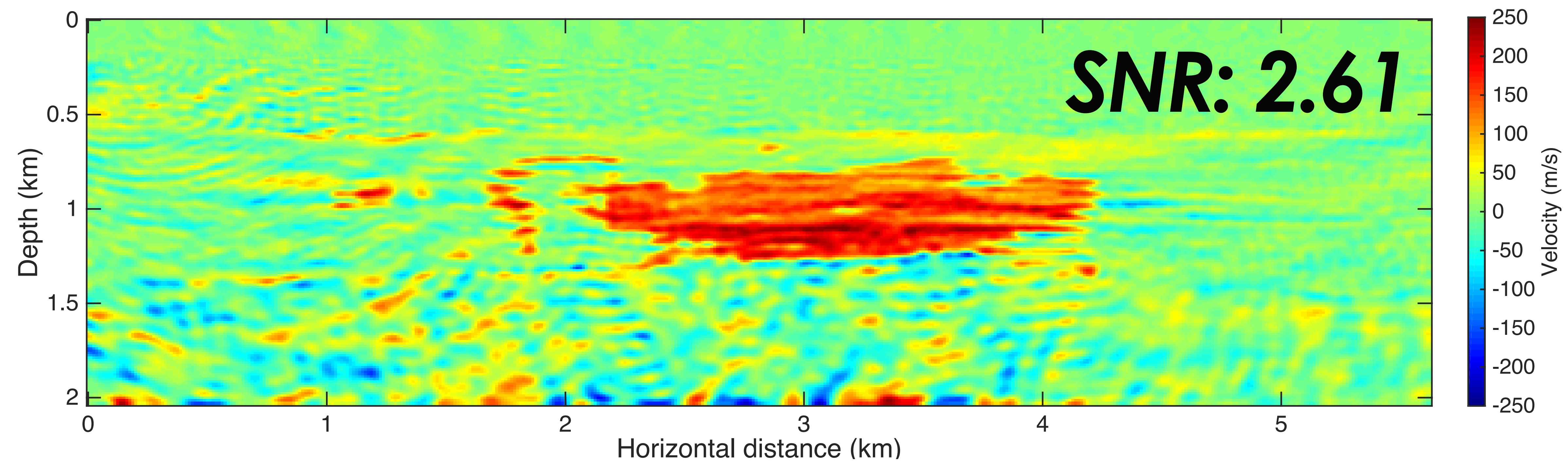
Joint: 4D
SNR: 5.80
Depth (km)
Horizontal distance (km)
Velocity (m/s)

Time-lapse results

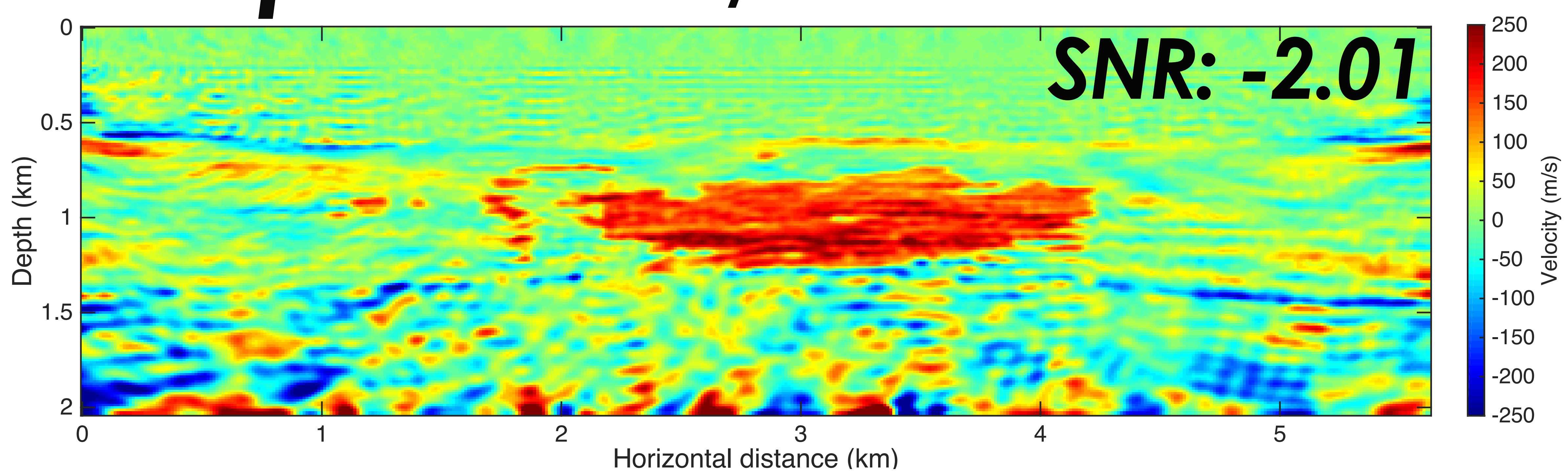
Parallel *w/ initial model*



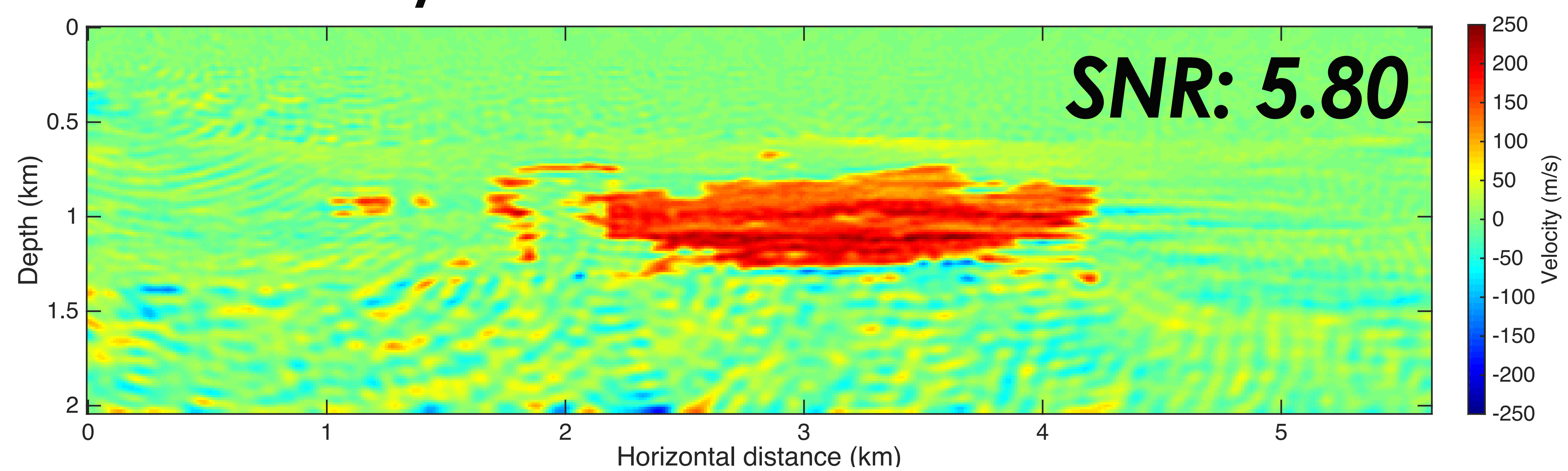
Joint *w/ initial model*



Sequential *w/ inverted base*



Joint *w/ inverted base*



Observations

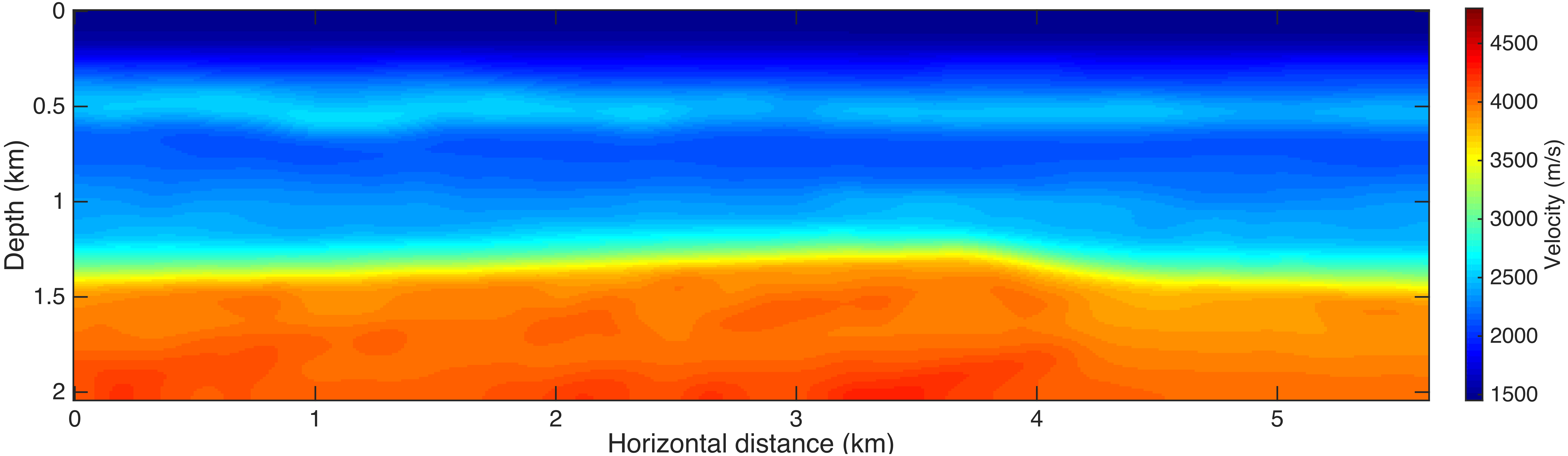
A good initial model drives the inversion results for the vintages and time-lapse model

Sequential FWI is better than parallel FWI, however joint inversion with JRM is better than both approaches

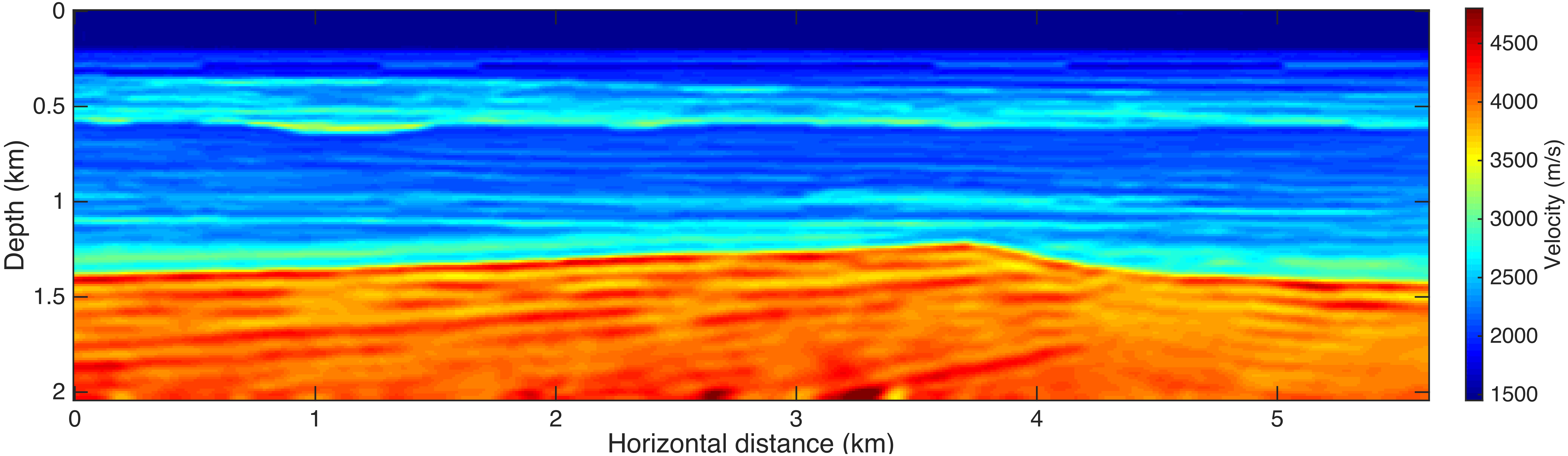
Significant attenuation of the artifacts in the time-lapse model using JRM, which exploits the shared information in time-lapse

*Assuming **accurate** baseline inversion result, and **monitor** data has a large **acquisition gap***

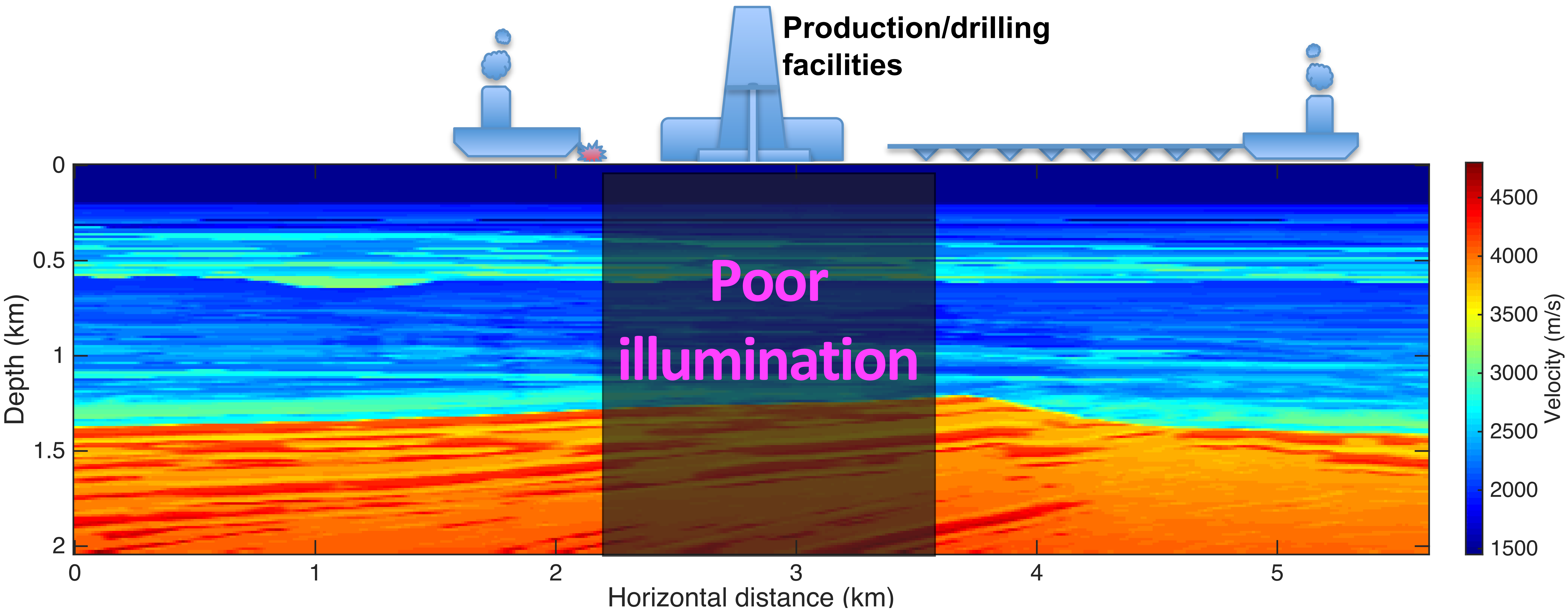
Initial model



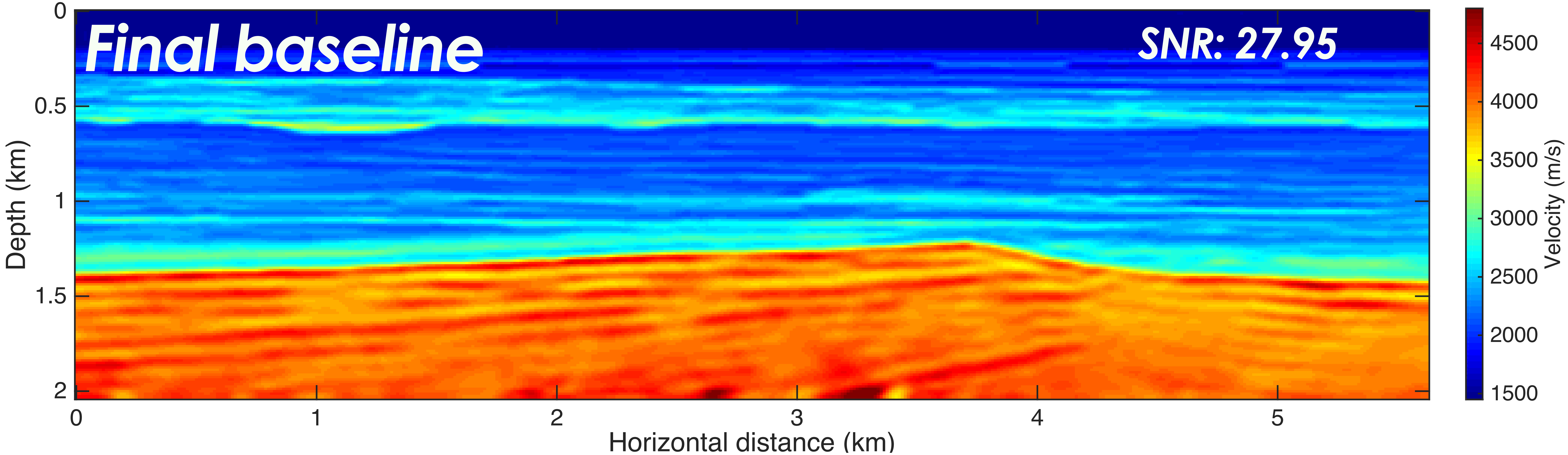
FWI baseline → monitor



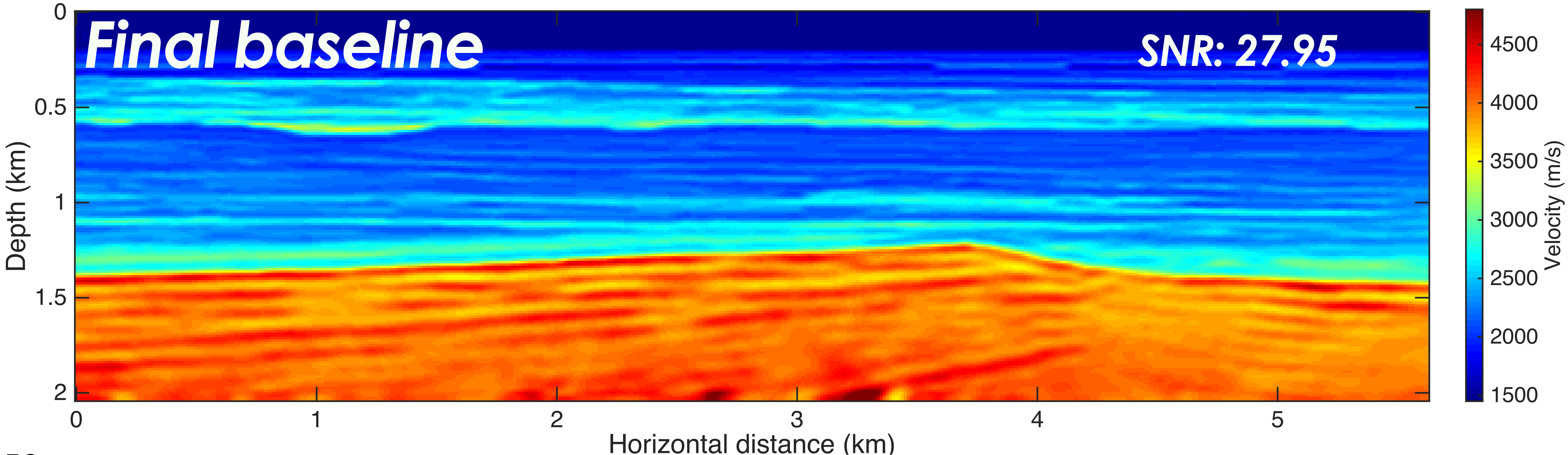
Monitor



Production/drilling
facilities
Poor
illumination
0
0.5
1
1.5
2
Depth (km)
0
1
2
3
4
5
Horizontal distance (km)
4500
4000
3500
3000
2500
2000
1500
Velocity (m/s)



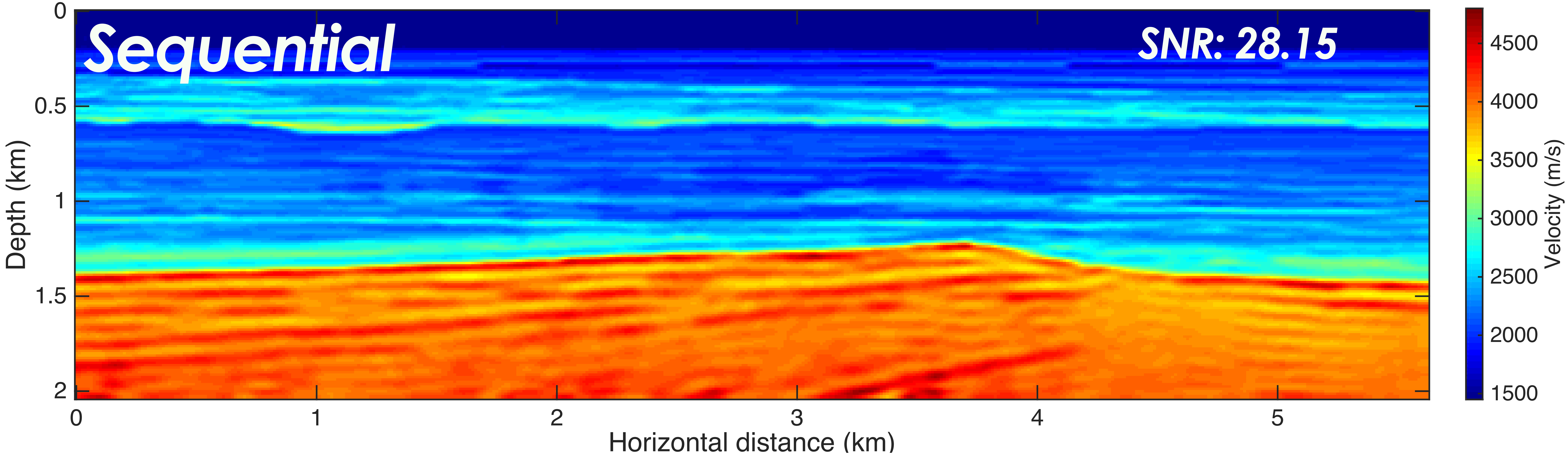
Final baseline
SNR: 27.95
Depth (km)
0
0.5
1
1.5
2
0
1
2
3
4
5
Horizontal distance (km)
Velocity (m/s)
4500
4000
3500
3000
2500
2000
1500

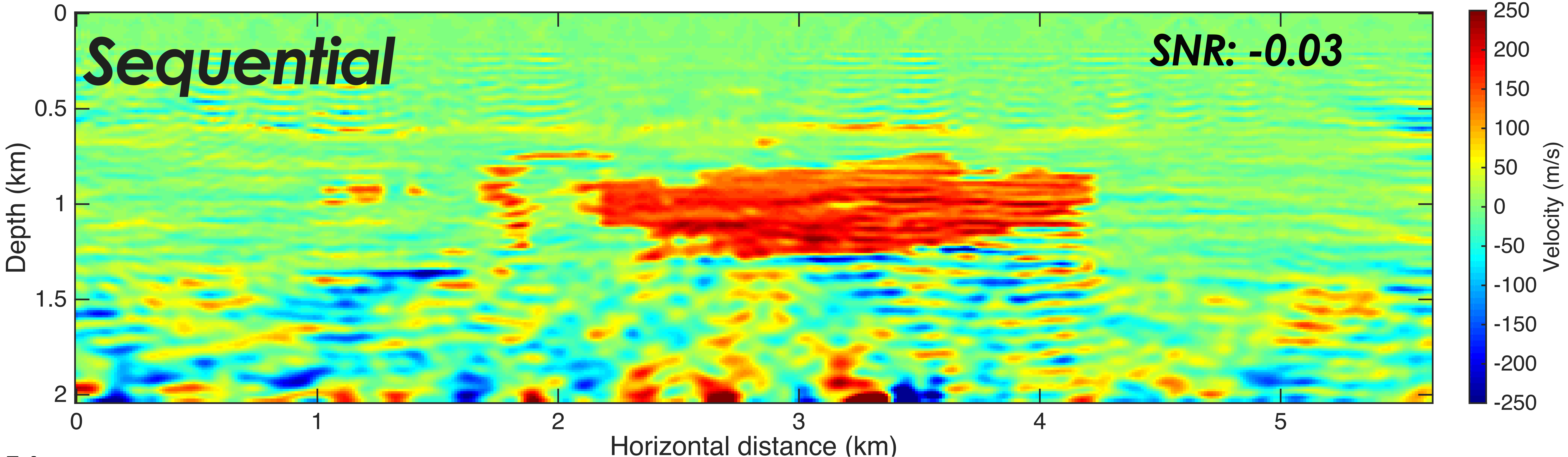


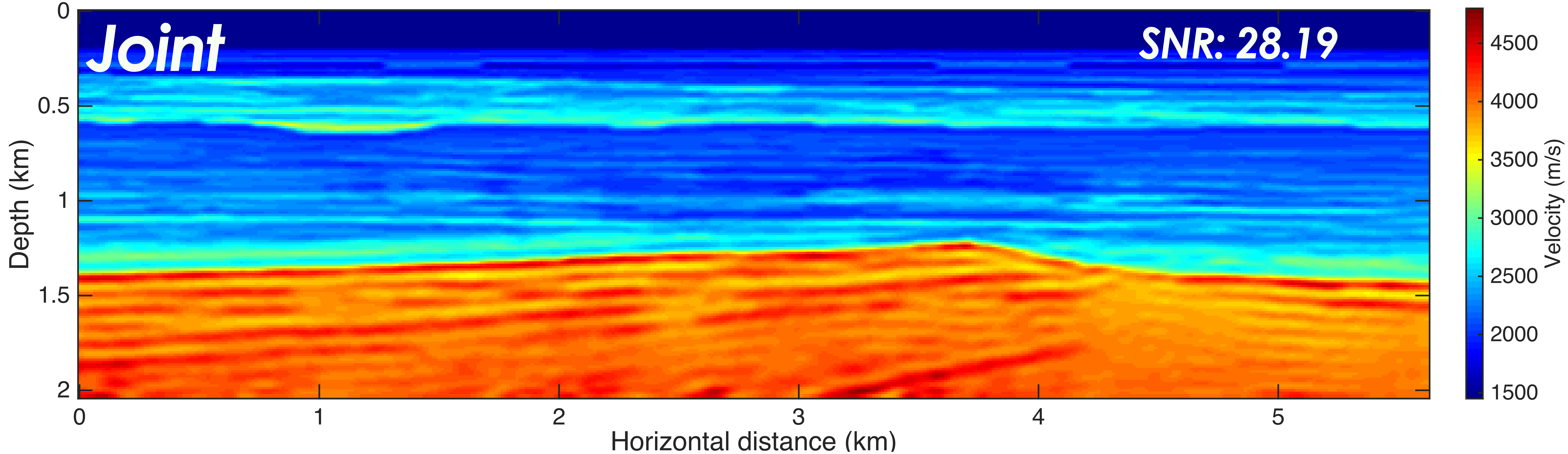
Final baseline
SNR: 27.95
Depth (km)
0
0.5
1
1.5
2
0
1
2
3
4
5
Horizontal distance (km)
Velocity (m/s)
4500
4000
3500
3000
2500
2000
1500

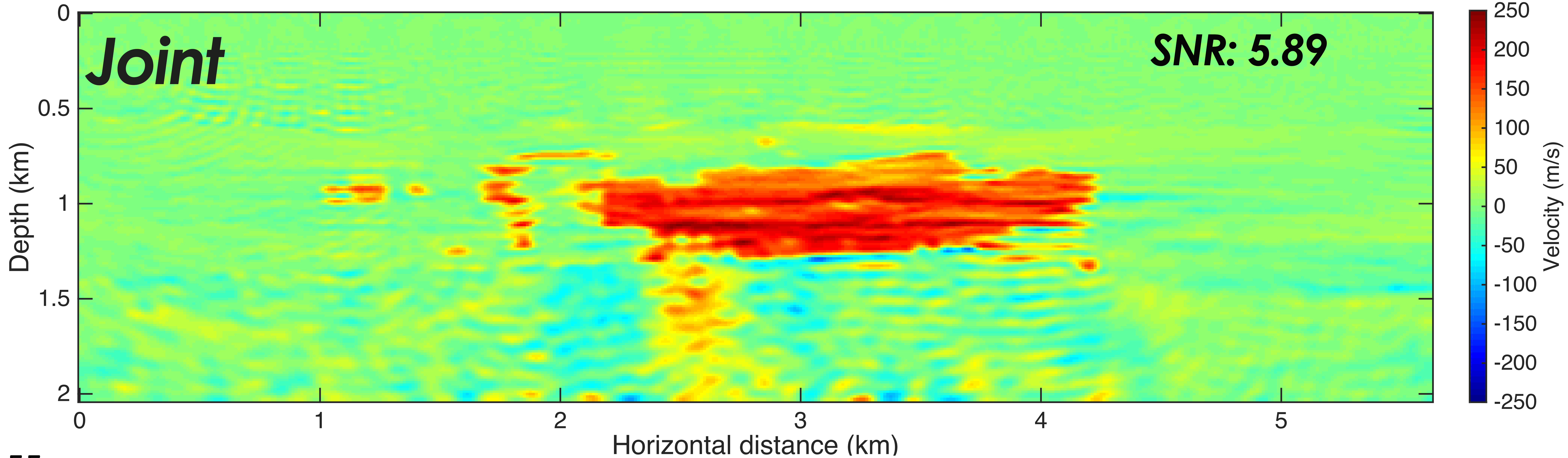
SLIM

Assuming 1000m gap in the monitor

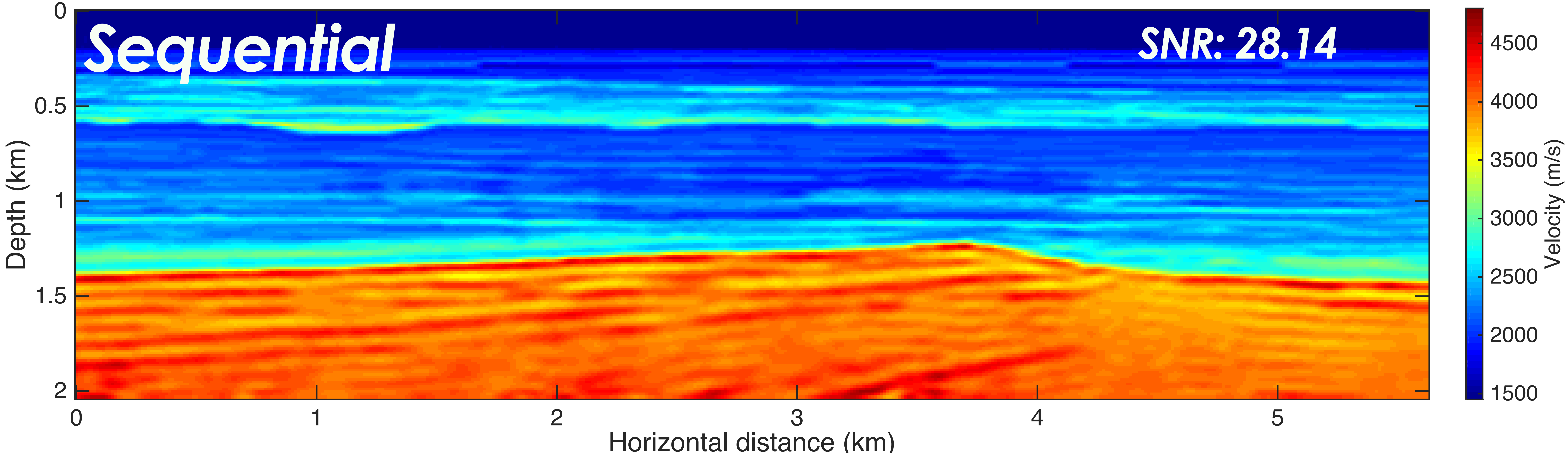

Sequential
SNR: 28.15
Depth (km)
0
0.5
1
1.5
2
0
1
2
3
4
5
Horizontal distance (km)
Velocity (m/s)
4500
4000
3500
3000
2500
2000
1500

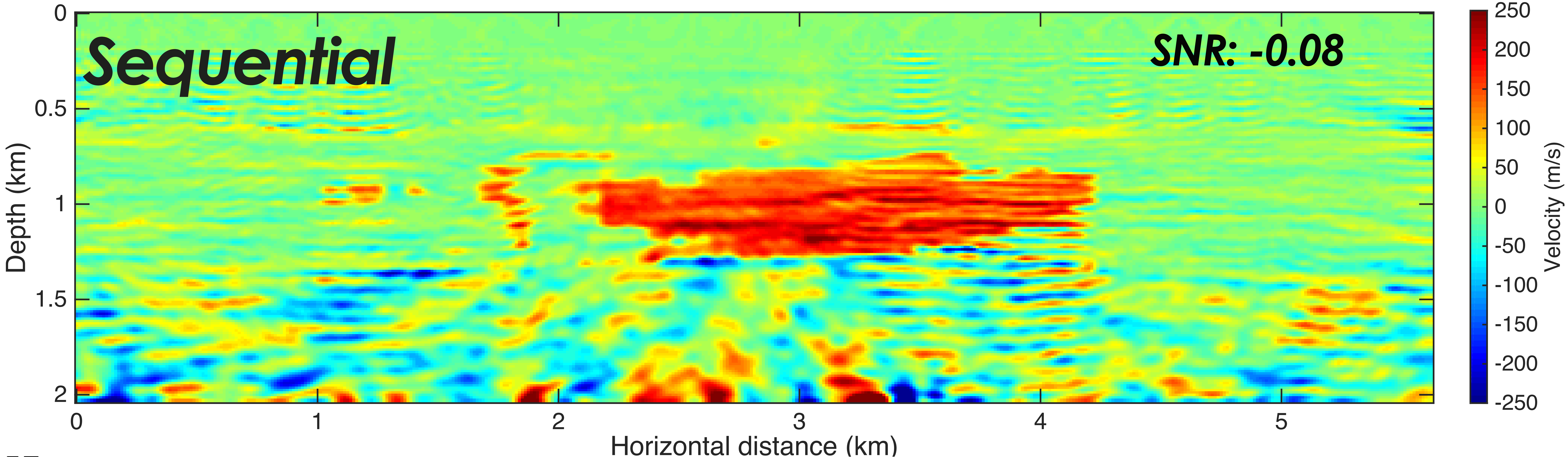

Sequential
SNR: -0.03
Depth (km)
0
0.5
1
1.5
2
0
1
2
3
4
5
Horizontal distance (km)
Velocity (m/s)
250
200
150
100
50
0
-50
-100
-150
-200
-250

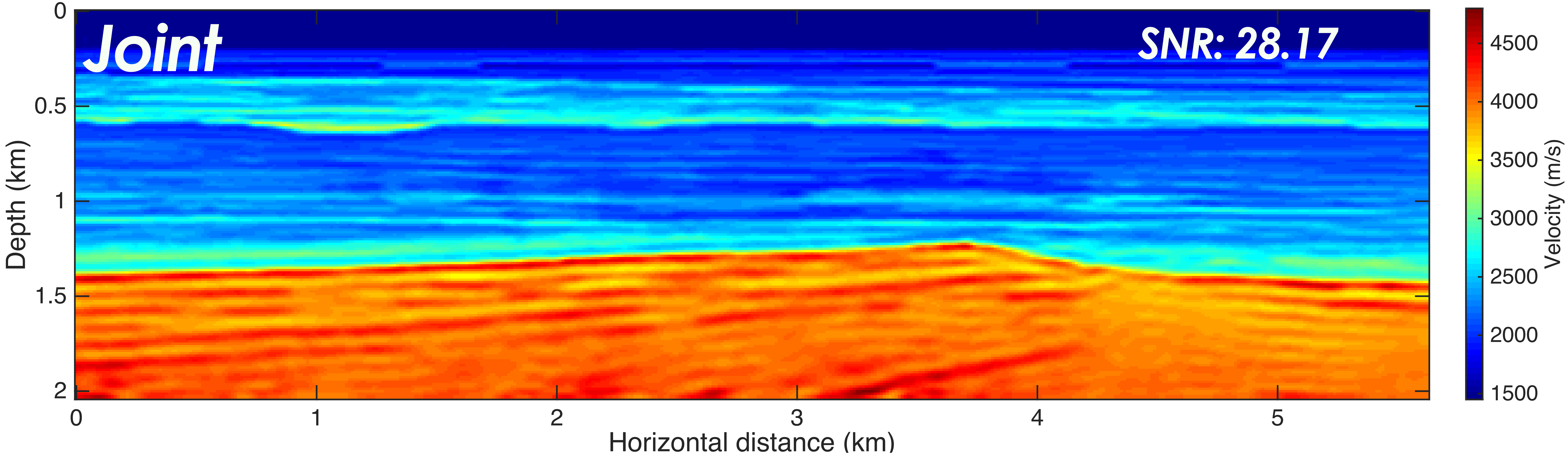

Joint
SNR: 28.19
Depth (km)
Horizontal distance (km)
Velocity (m/s)

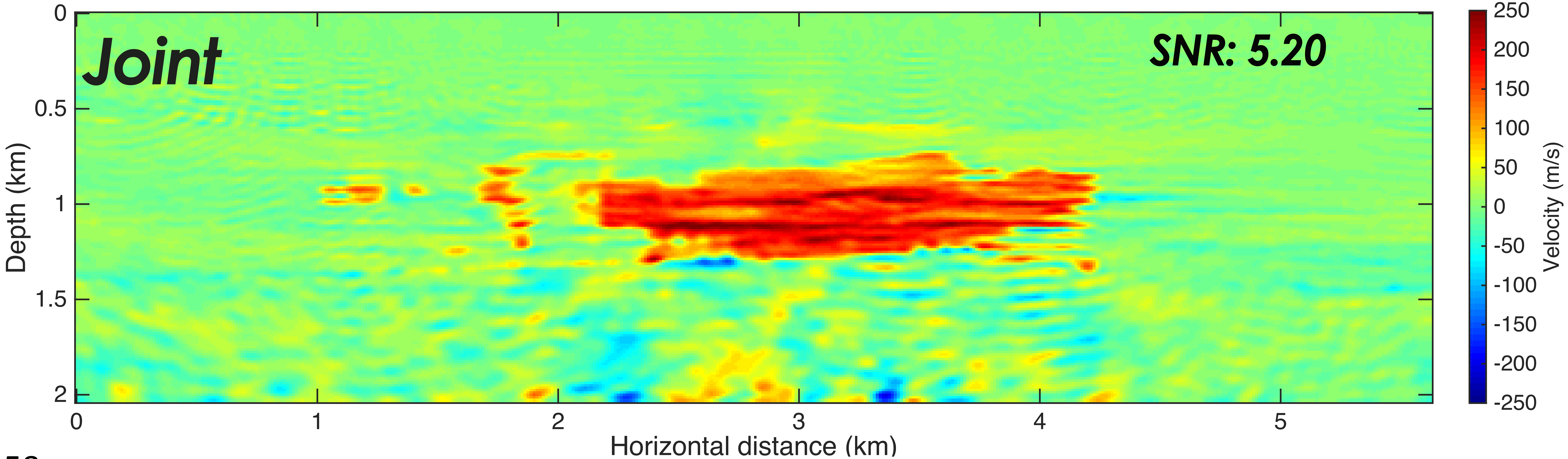

Joint
SNR: 5.89
Depth (km)
Horizontal distance (km)
Velocity (m/s)

Assuming ***1500m*** *gap in the monitor*


Sequential
SNR: 28.14
Depth (km)
0
0.5
1
1.5
2
Horizontal distance (km)
0
1
2
3
4
5
Velocity (m/s)
4500
4000
3500
3000
2500
2000
1500


Sequential
SNR: -0.08
Depth (km)
0
0.5
1
1.5
2
Horizontal distance (km)
0
1
2
3
4
5
Velocity (m/s)
250
200
150
100
50
0
-50
-100
-150
-200
-250

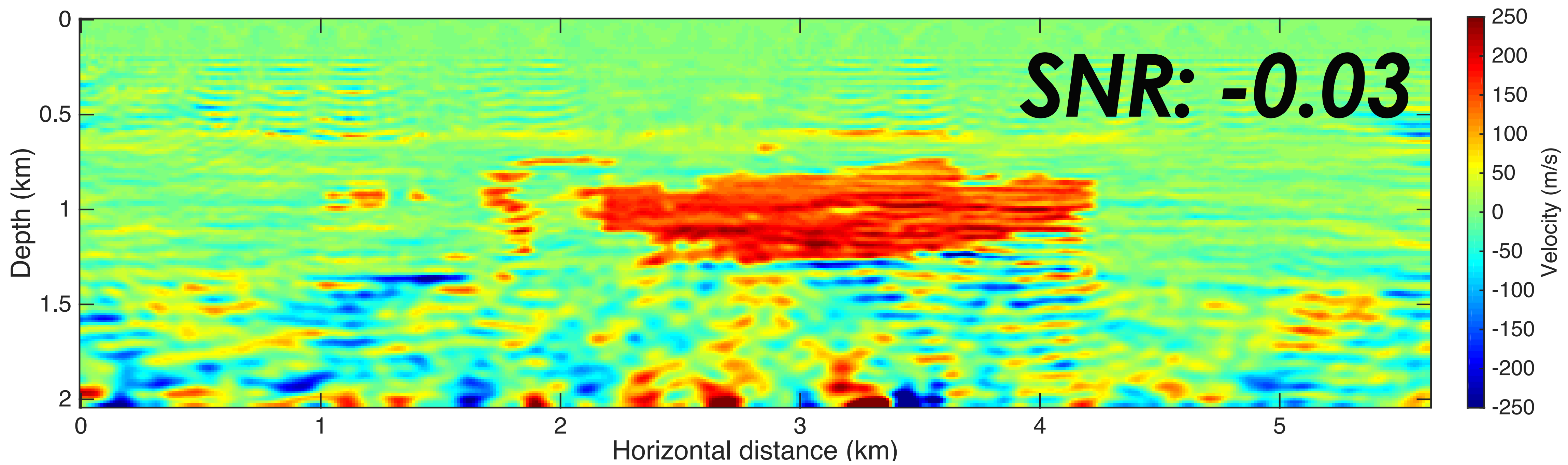

Joint
SNR: 28.17
Depth (km)
0
0.5
1
1.5
2
0
1
2
3
4
5
Horizontal distance (km)
Velocity (m/s)
4500
4000
3500
3000
2500
2000
1500


Joint
SNR: 5.20
Depth (km)
0
0.5
1
1.5
2
0
1
2
3
4
5
Horizontal distance (km)
Velocity (m/s)
250
200
150
100
50
0
-50
-100
-150
-200
-250

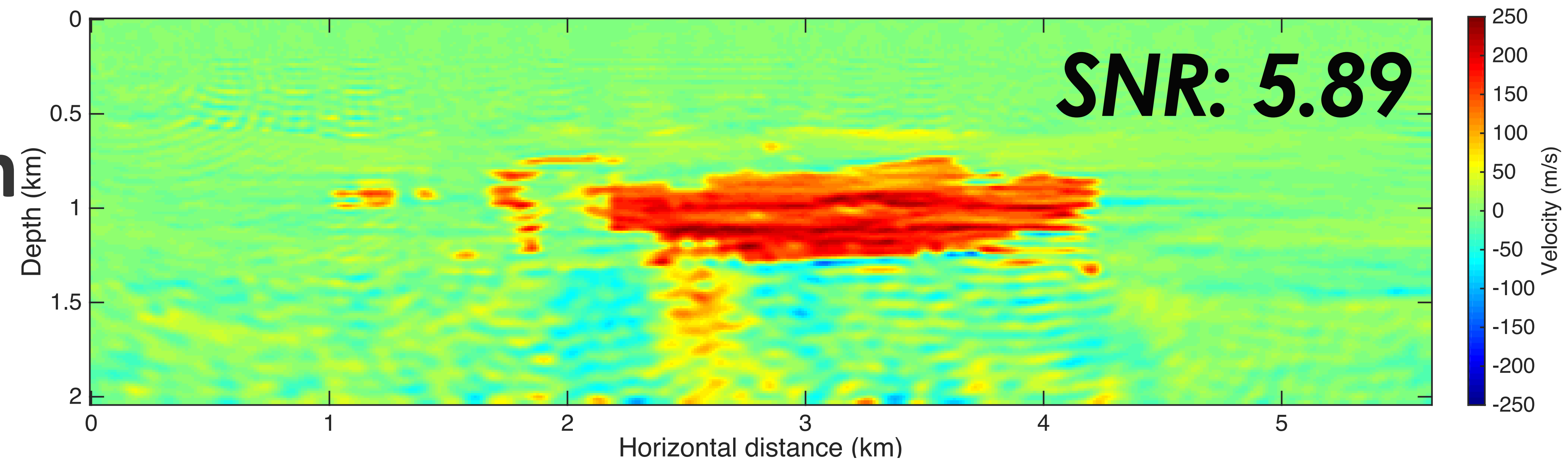
Time-lapse results

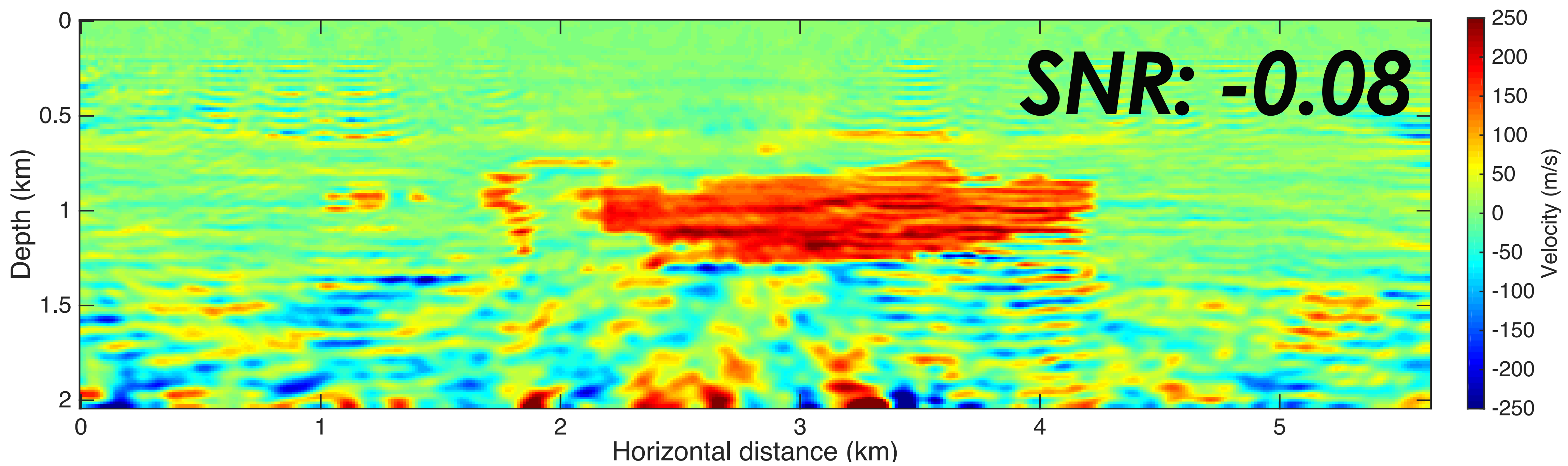
Sequential

Joint

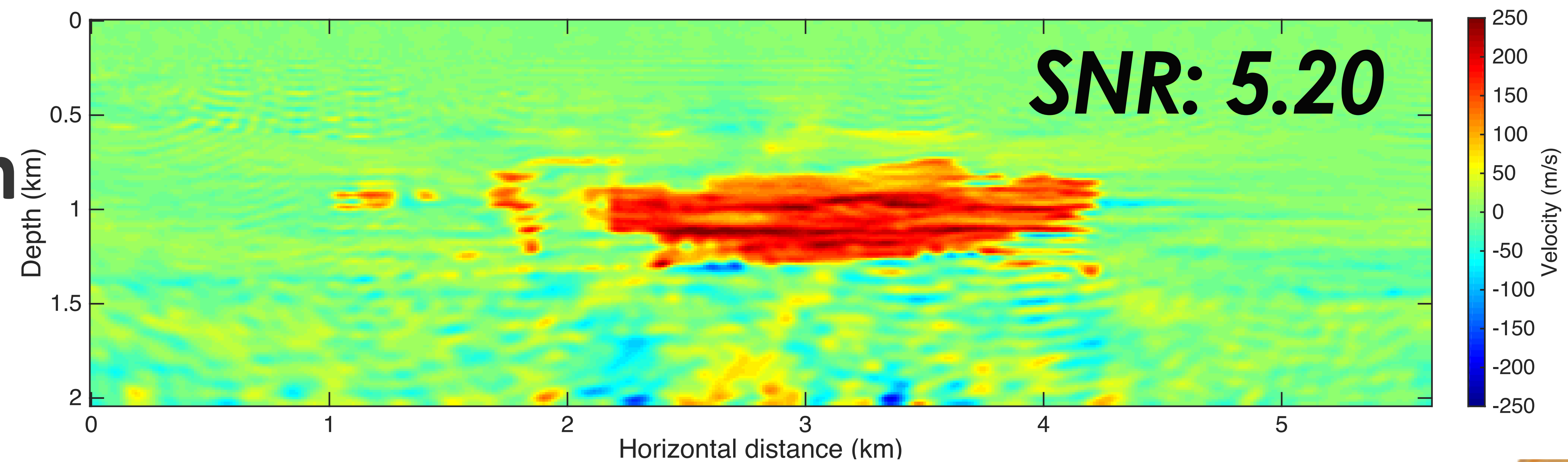


1000m gap





1500m gap



Conclusions

Parallel or/and sequential FWI on time-lapse data is more prone to errors in the time-lapse difference.

Joint inversion based on DCS gives better time-lapse models.

Larger acquisition gaps adversely affect the time-lapse difference.

Joint inversion with DCS can minimize the errors in time-lapse models caused by inaccurate initial models or/and missing data caused by large acquisition gaps.

Future work

- Extension to multiple vintages
- Explore the role of noise/other factors unaccounted for
- Implementation on a more realistic 3D-synthetic time-lapse data/ Field data

SLIM

Acknowledgements

Thank you for your attention !!!

SINBAD

NSERC CRSNG

This work was financially supported by SINBAD Consortium members BG Group, BGP, CGG, Chevron, ConocoPhillips, DownUnder GeoSolutions, Hess, Petrobras, PGS, Schlumberger, Statoil, Sub Salt Solutions and Woodside; and by the Natural Sciences and Engineering Research Council of Canada via NSERC Collaborative Research and Development Grant DNOISEII (CRDPJ 375142-08).