On simultaneous-source data separation by simultaneous inversion

Gboyega Ayeni, Ali Almomin & Dave Nichols

SEP 142: Pgs 51-75

SEP Sponsors' Meeting

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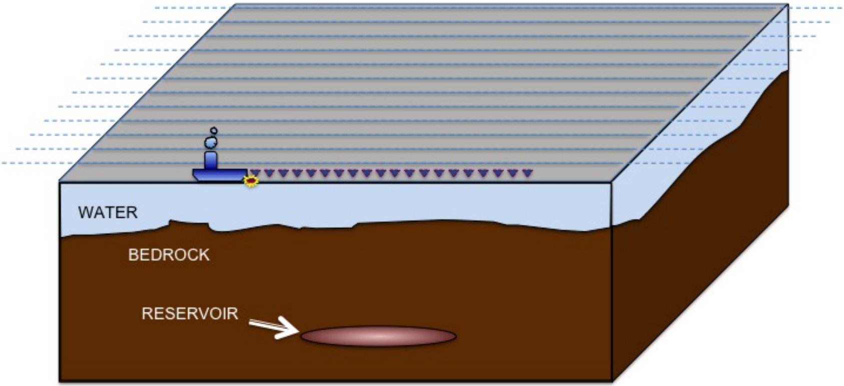
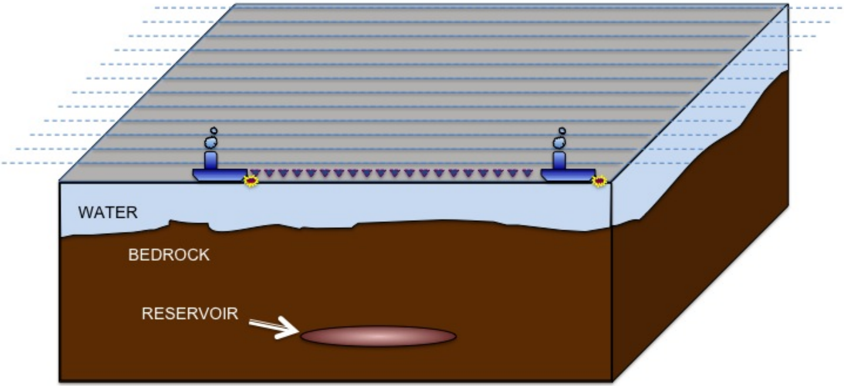
1. Introduction
   - Simultaneous sources revisited
   - Considerations
2. Methods
   - Dip-constrained Sparse Inversion (DCSI)
   - Spatio-temporal constrained Sparse Inversion (STCSI)
3. Examples
   - Example 1: Complex (salt) model
   - Example 2: Non-repeated time-lapse data
   - Example 3: Land data
   - Example 4: Marine data
4. Conclusions
   - Considerations

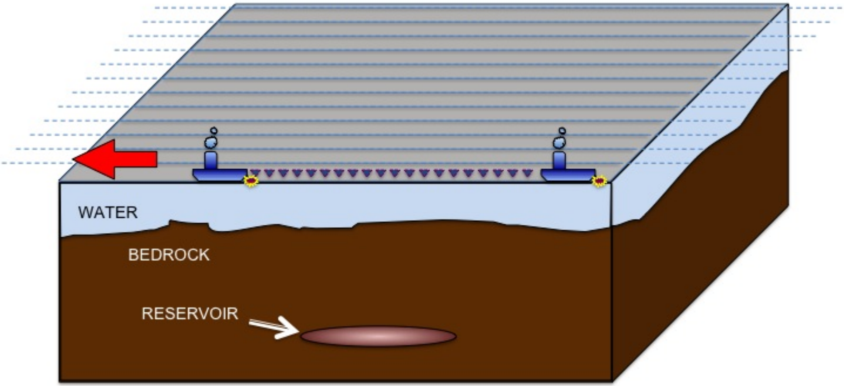
Single source



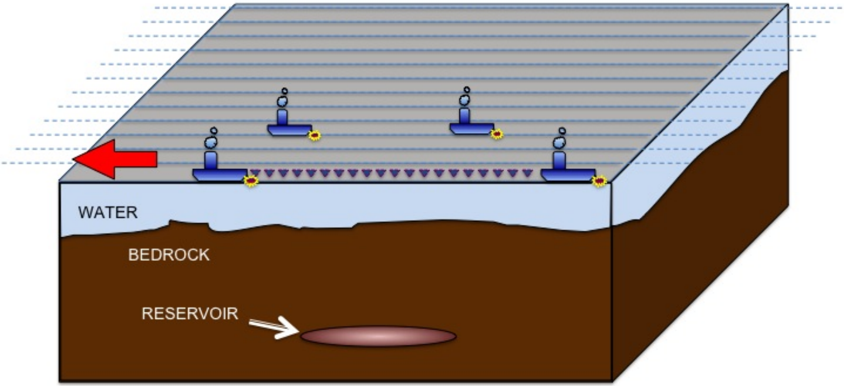
Two sources



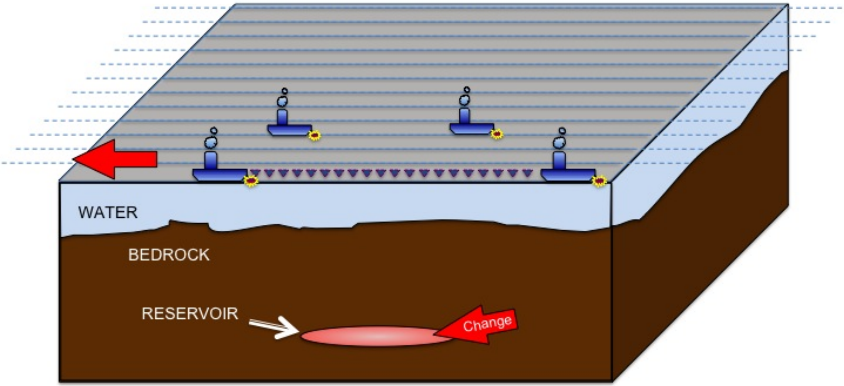
Two sources



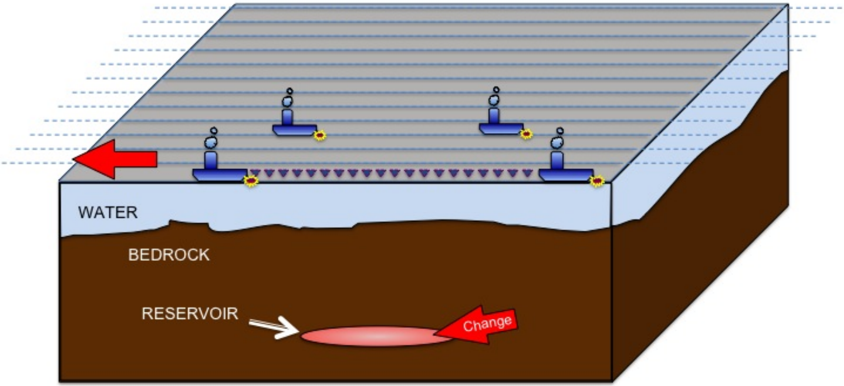
Four sources



Reservoir change



Non-repeatability



Important questions

- What is the optimal problem set-up?
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Problem set-up

$$\sum_{i=1}^{n} \mathbf{S}\mathbf{d}_i = \mathbf{d} \qquad (1)$$

n: number of sources

S: relative time-delay operator

$\mathbf{d}_i$: data due to source i

d: simultaneous-source data

Problem set-up

$$\top \mathbf{H}_i \mathbf{m} \approx \mathbf{d} \qquad (2)$$

$\top$: summation operator for sources i to n
$\mathbf{H}_i$: modeling operator for data $\mathbf{d}_i$
$\mathbf{m}$: composite model

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Problem set-up

$$\top \mathbf{H}_i \mathbf{m} \approx \mathbf{d} \tag{2}$$

$\top$: summation operator for sources i to n
$\mathbf{H}_i$: modeling *Radon* operator for data $\mathbf{d}_i$ $[t, g_x, g_y, s_x, s_y]$
$\mathbf{m}$: composite model $[\tau, v, cmp_x, cmp_y]$

Problem set-up

$$\begin{aligned} \top \mathbf{H}_i \mathbf{m} &\approx \mathbf{d} \\ \epsilon \mathbf{A} \mathbf{m} &\approx \mathbf{0} \end{aligned} \qquad (3)$$

A: Regularization

ϵ: Regularization parameter

Problem set-up

$$\begin{aligned} \mathsf{T}\mathbf{H}_i\mathbf{m} &\approx \mathbf{d} \\ \epsilon\mathbf{B}_i\mathbf{H}_i\mathbf{m} &\approx \mathbf{0} \end{aligned} \tag{4}$$

$\mathbf{B}_i$: Shot-space regularization
ϵ: Regularization parameter

Problem set-up

$$\begin{bmatrix} \top \\ \epsilon \mathbf{B}_i \end{bmatrix} \mathbf{H}_i \mathbf{m} \approx \begin{bmatrix} \mathbf{d} \\ \mathbf{0} \end{bmatrix} \tag{5}$$

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Notes

- $\mathbf{B}_i$: Non-stationary directional laplacians for source i

Problem set-up

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Notes

- $\mathbf{B}_i$: Non-stationary directional laplacians for source i
- Because $\mathbf{B}_i$ is a function of the separated data ($\mathbf{d}_i$), problem is non-linear

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- To linearize,
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Problem set-up

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- Dip-estimation based on Fomel (2002)

Problem set-up

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- Directional Laplacians based on Hale (2007)

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- Dip-estimation based on Fomel (2002)
- Directional Laplacians based on Hale (2007)
- $\mathbf{B}_i$ applied by helical convolution (Claerbout & Fomel, 2008)

Problem set-up

$$\begin{aligned} \top \mathbf{B}_i^{-1} \mathbf{H}_i \mathbf{m} &\approx \mathbf{d} \\ \epsilon \mathbf{I} \mathbf{m} &\approx \mathbf{0} \end{aligned} \tag{6}$$

Notes

- Similar to Abma et al. (2010)

Problem set-up

$$\begin{aligned} \top \mathbf{B}_i^{-1} \mathbf{H}_i \mathbf{m} &\approx \mathbf{d} \\ \epsilon \mathbf{I} \mathbf{m} &\approx \mathbf{0} \end{aligned} \quad (6)$$

Notes

- Similar to Abma et al. (2010)
- $\mathbf{B}_i^{-1}$ applied by polynomial division (Claerbout & Fomel, 2008)

Problem set-up

$$\begin{bmatrix} \top \\ \epsilon \mathbf{B}_i \end{bmatrix} \mathbf{H}_i \mathbf{m} \approx \begin{bmatrix} \mathbf{d} \\ \mathbf{0} \end{bmatrix} \qquad (7)$$

Notes

- Sparsity achieved via the hybrid-norm conjugate direction solver (Claerbout, 2009; Li et al., 2010; Zhang & Claerbout, 2010)

Problem set-up

$$\begin{bmatrix} \top \\ \epsilon \mathbf{B}_i \end{bmatrix} \mathbf{H}_i \mathbf{m} \approx \begin{bmatrix} \mathbf{d} \\ \mathbf{0} \end{bmatrix} \quad (7)$$

Notes

- Once we solve for **m**, we can model data d_i from any number of sources

Joint sim. inversion of time-lapse data sets

$$\begin{bmatrix} T \\ \epsilon \mathbf{B}_i \end{bmatrix} \mathbf{H}_i \mathbf{m} \approx \begin{bmatrix} \mathbf{d} \\ \mathbf{0} \end{bmatrix}$$

One survey

Joint sim. inversion of time-lapse data sets

$$\begin{bmatrix} T_1 \\ \epsilon \mathbf{B}_{i1} \end{bmatrix} \mathbf{H}_{i1} \mathbf{m}_1 \approx \begin{bmatrix} \mathbf{d}_1 \\ \mathbf{0} \end{bmatrix}$$

$$\begin{bmatrix} T_2 \\ \epsilon \mathbf{B}_{i2} \end{bmatrix} \mathbf{H}_{i2} \mathbf{m}_2 \approx \begin{bmatrix} \mathbf{d}_2 \\ \mathbf{0} \end{bmatrix}$$

Two surveys

Joint sim. inversion of time-lapse data sets

$$\begin{bmatrix} T_1 \\ \epsilon \mathbf{B}_{i1} \end{bmatrix} \mathbf{H}_{i1}\mathbf{m}_1 \approx \begin{bmatrix} \mathbf{d}_1 \\ \mathbf{0} \end{bmatrix}$$

$$\begin{bmatrix} T_2 \\ \epsilon \mathbf{B}_{i2} \end{bmatrix} \mathbf{H}_{i2}\mathbf{m}_2 \approx \begin{bmatrix} \mathbf{d}_2 \\ \mathbf{0} \end{bmatrix}$$

$$\begin{bmatrix} \lambda \mathbf{Z}_1\mathbf{m}_1 & -\lambda \mathbf{Z}_2\mathbf{S}_{1,2}\mathbf{m}_2 \end{bmatrix} \approx \mathbf{0}$$

Two surveys
$\mathbf{S}_{1,2}$: Warping operator between surveys 1 and 2
$\mathbf{Z}$: Temporal regularization
λ: Temporal regularization parameter

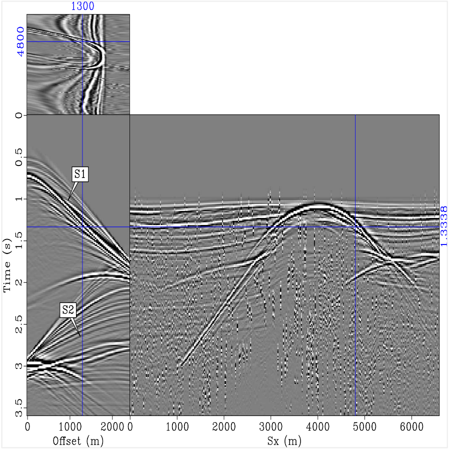
Joint sim. inversion of time-lapse data sets

$$\begin{bmatrix} T_k \\ \epsilon \mathbf{B}_{ik} \end{bmatrix} \mathbf{H}_{ik} \mathbf{m}_k \approx \begin{bmatrix} \mathbf{d}_k \\ \mathbf{0} \end{bmatrix}$$

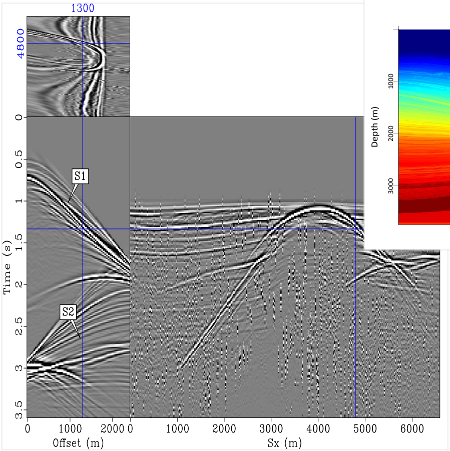
$$\begin{bmatrix} \lambda \mathbf{Z}_k \mathbf{m}_k & -\lambda \mathbf{Z}_{k+1} \mathbf{S}_{k,k+1} \mathbf{m}_{k+1} \end{bmatrix} \approx \mathbf{0}$$

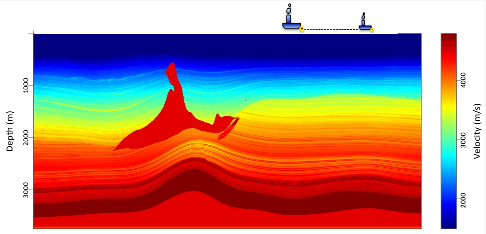
Arbitrary number of surveys
$\mathbf{S}_{k,k+1}$: Warping operator between surveys k and $k+1$
i: Shot index
k: Survey index

Simultaneous-source data



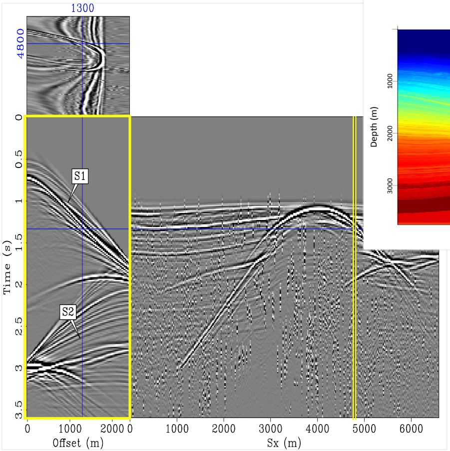
Simultaneous-source data: Two sources

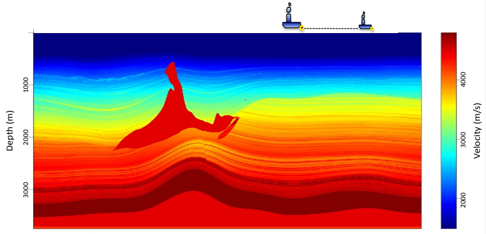




SEAM Model – Complex inline

Simultaneous-source data: Two sources





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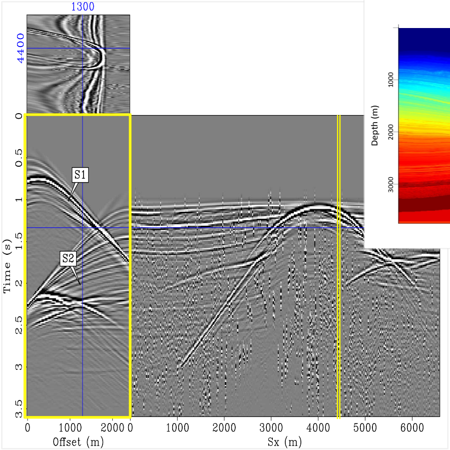

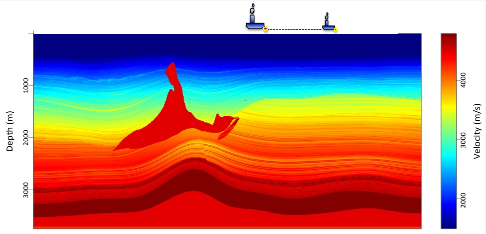

SEAM Model – Complex inline

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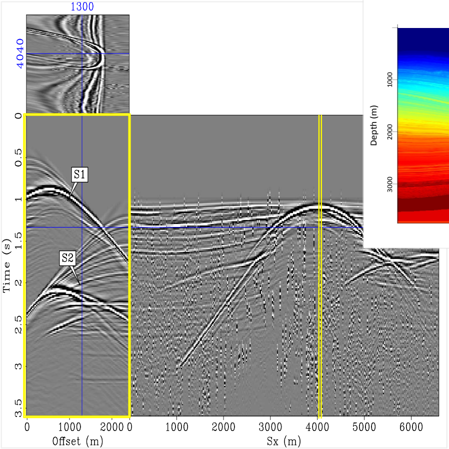

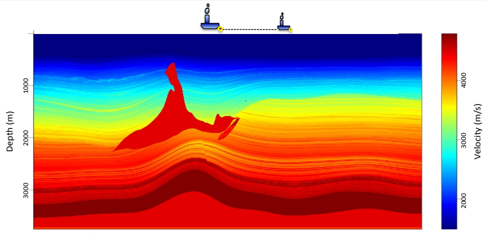

SEAM Model – Complex inline

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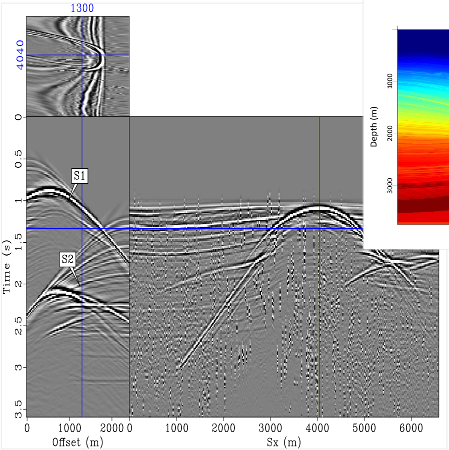
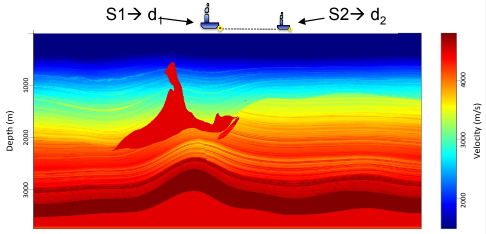
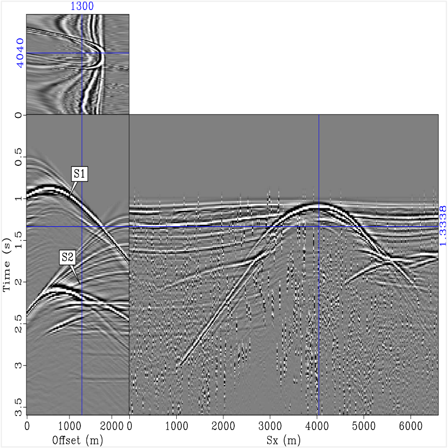
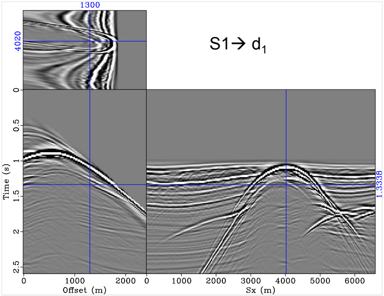


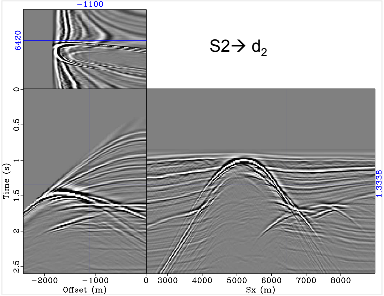


SEAM Model – Complex inline

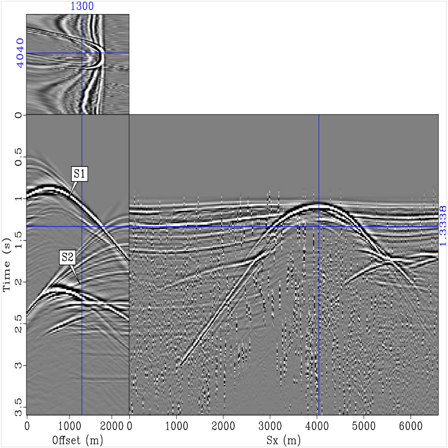
True (single-source) data

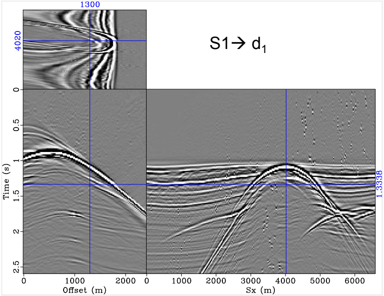


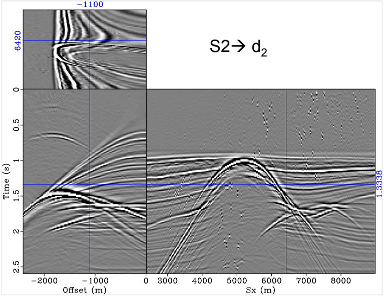




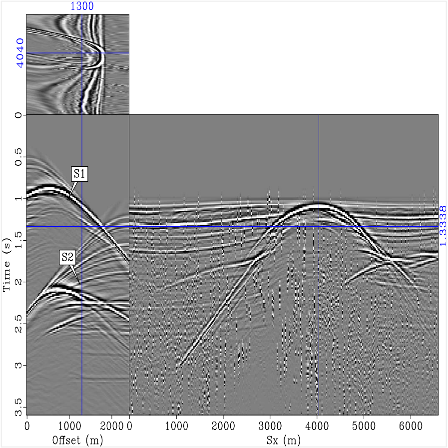
Separated data: l_2 Inversion

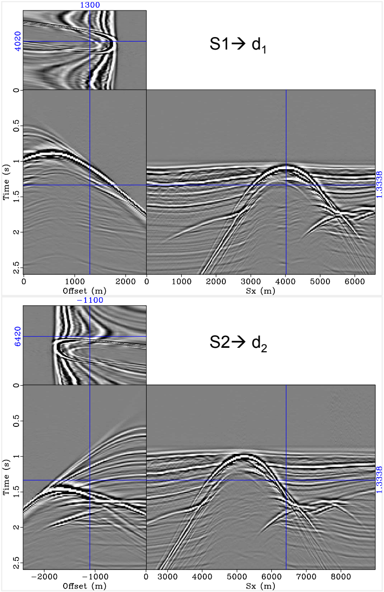






Separated data: DCSI





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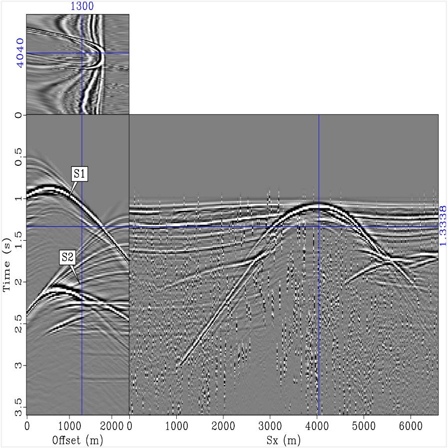
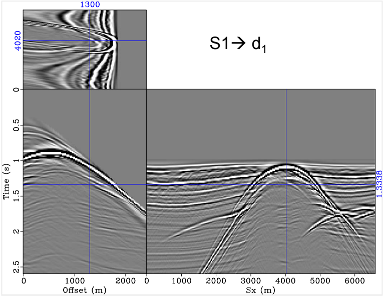
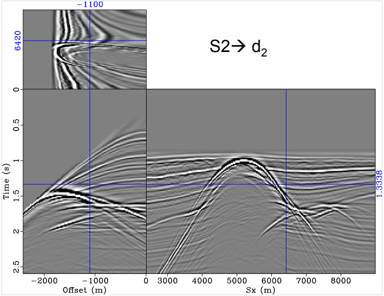
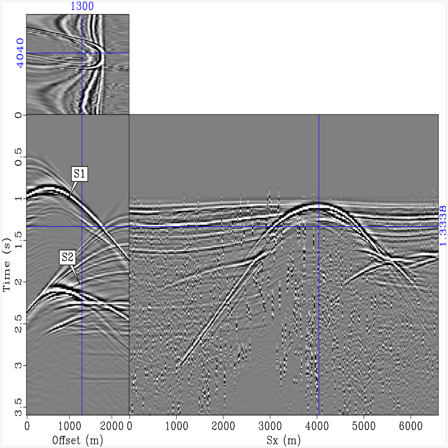
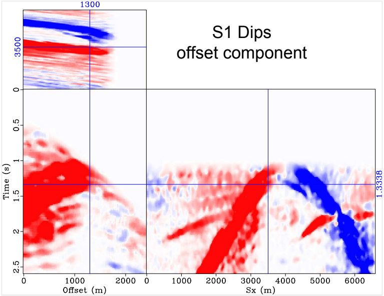


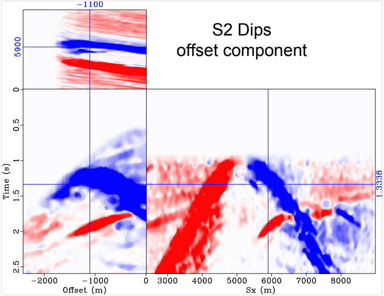




Dips: Common-offset components

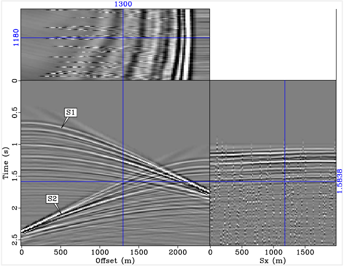




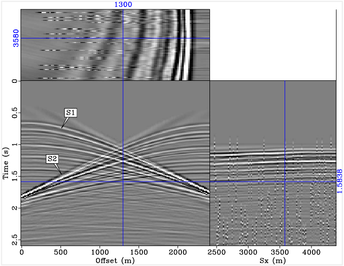


Simultaneous-source data: 2 surveys 2 sources each

Baseline

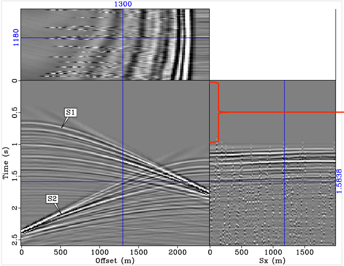


Monitor



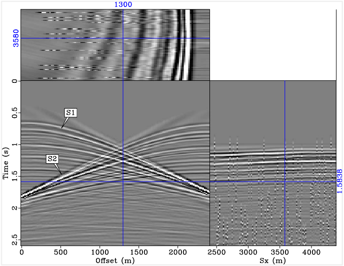
Simultaneous-source data: Timing non-repeatability

Baseline



Relative delay 1

Monitor



Simultaneous-source data: Timing non-repeatability

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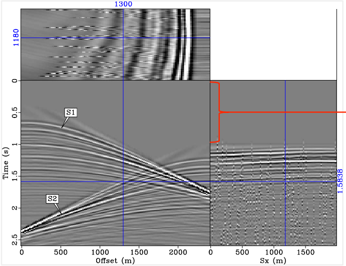
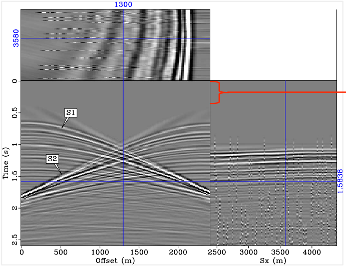


Relative delay 1

Monitor



Relative delay 2

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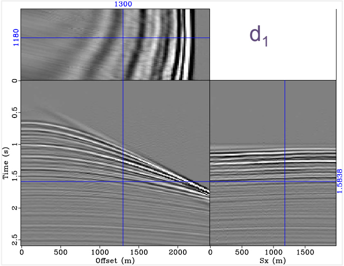
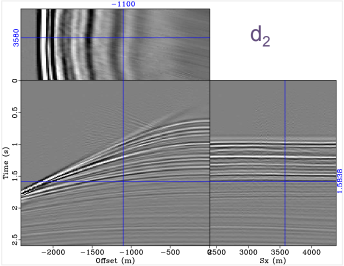
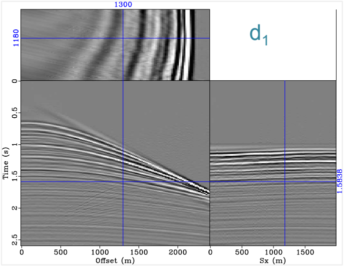
Separated data: Unconstrained sparse inversion

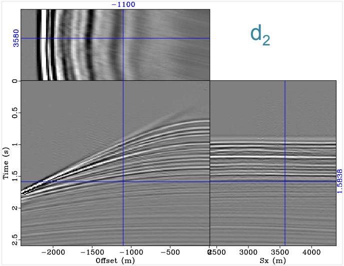
Baseline





Monitor





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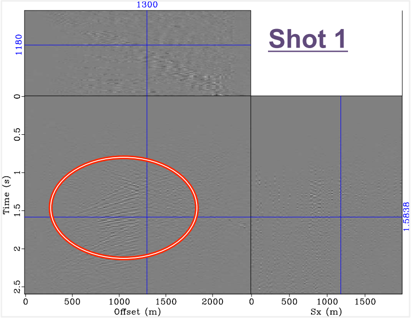
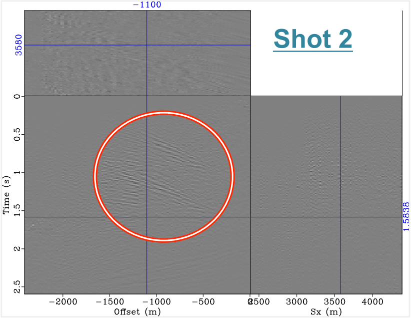
Data-difference: Unconstrained

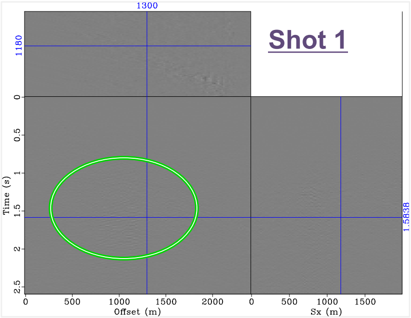


Monitor - Baseline

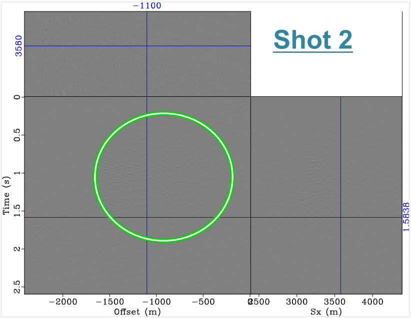


Monitor - Baseline

Data-difference: STCSI



Monitor - Baseline



Monitor - Baseline

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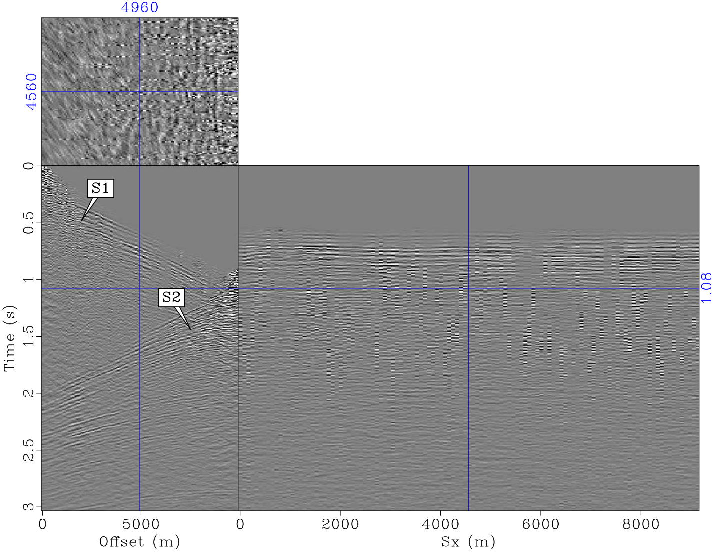
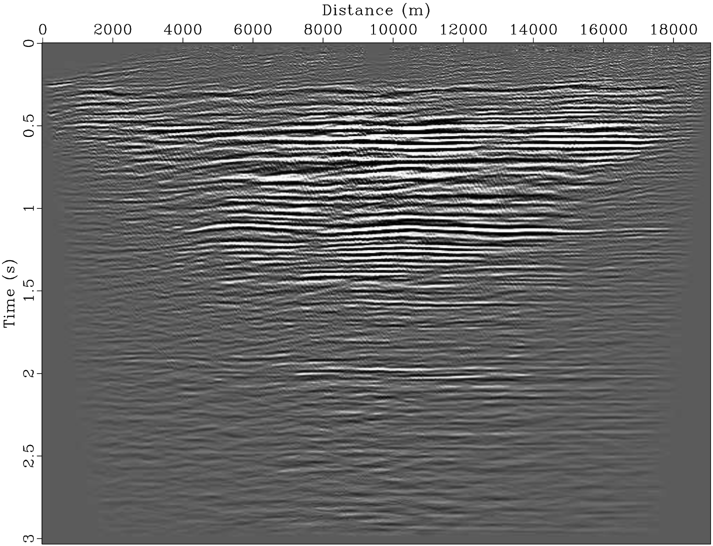
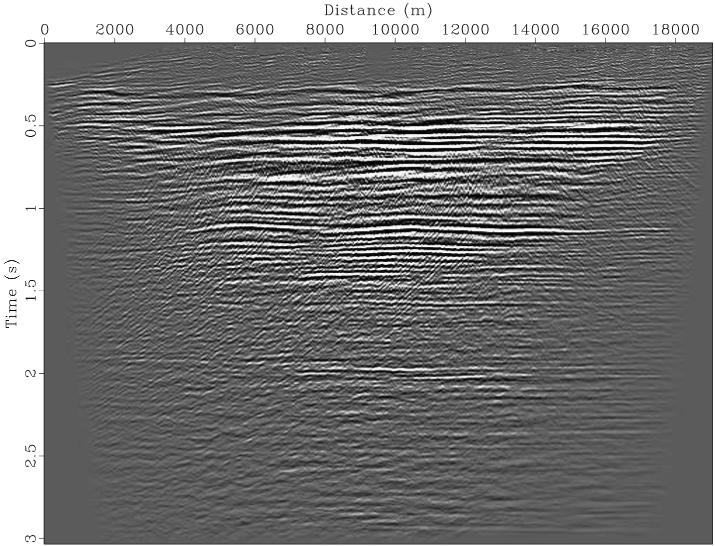
2D land data set: 2 sources



NMO Stack: True (single-source) data



NMO Stack: Simultaneous source data



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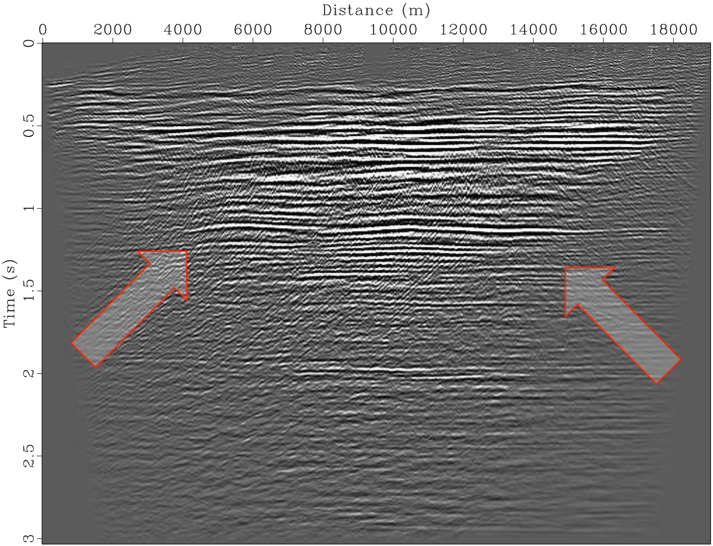
NMO Stack: Simultaneous source data



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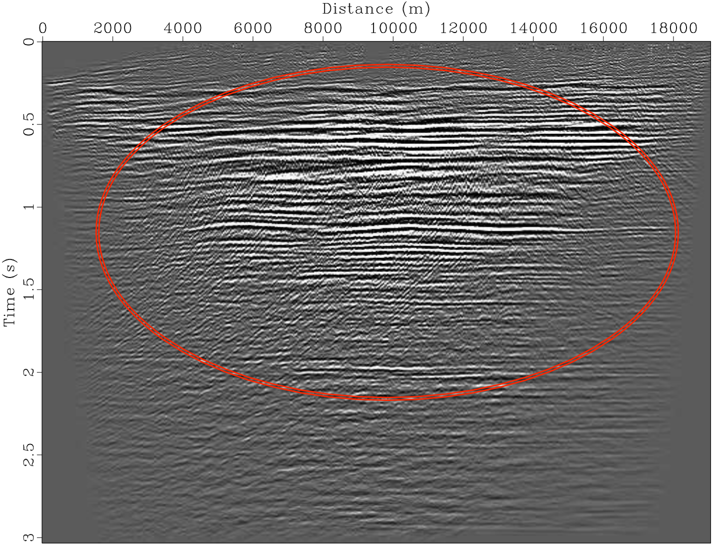
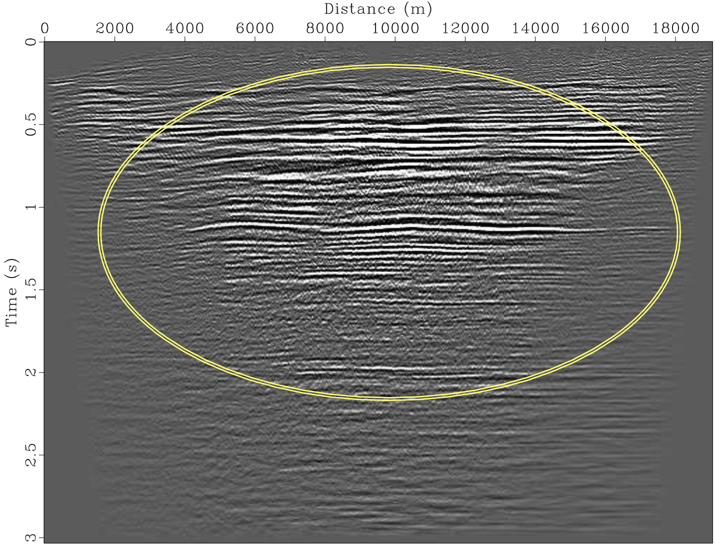
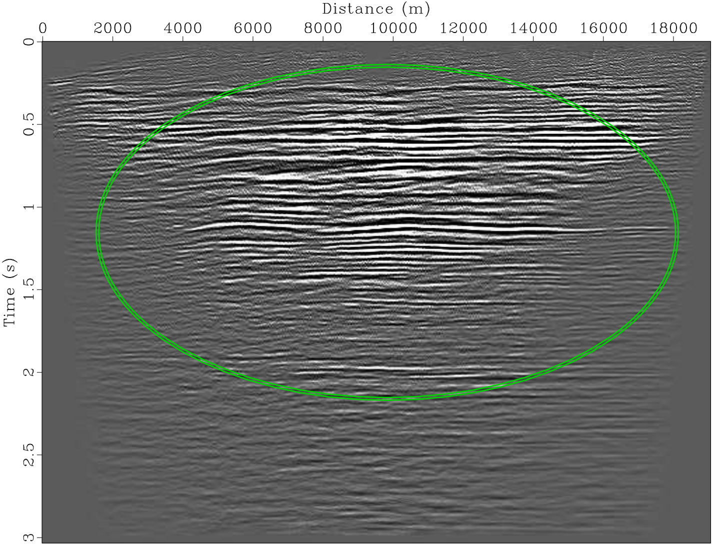
NMO Stack: Simultaneous source data



NMO Stack: Unconstrained sparse inversion



NMO Stack: Separated data by DCSI



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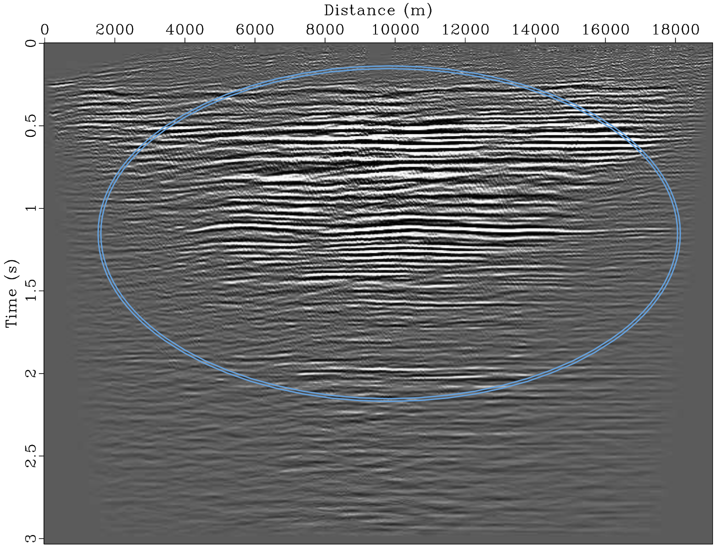
NMO Stack: True (single-source) data



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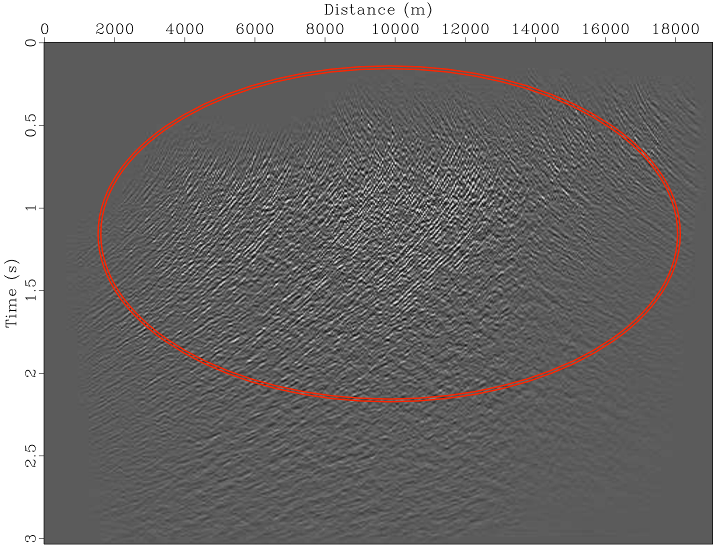
Stack Error: Simultaneous source data



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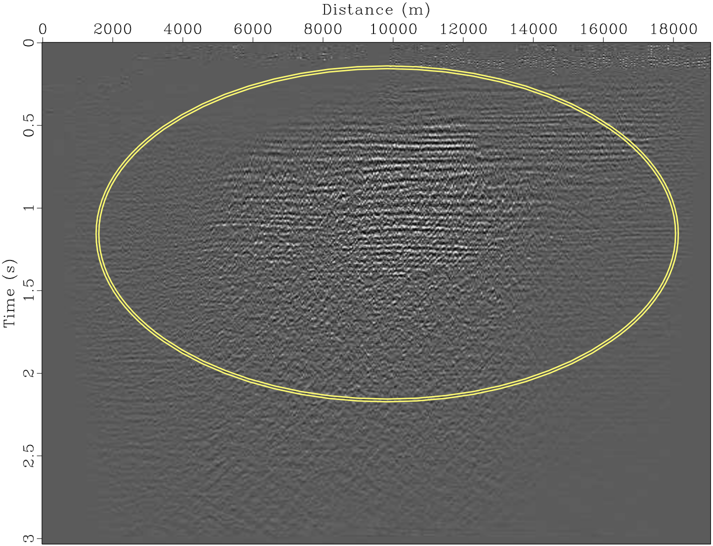
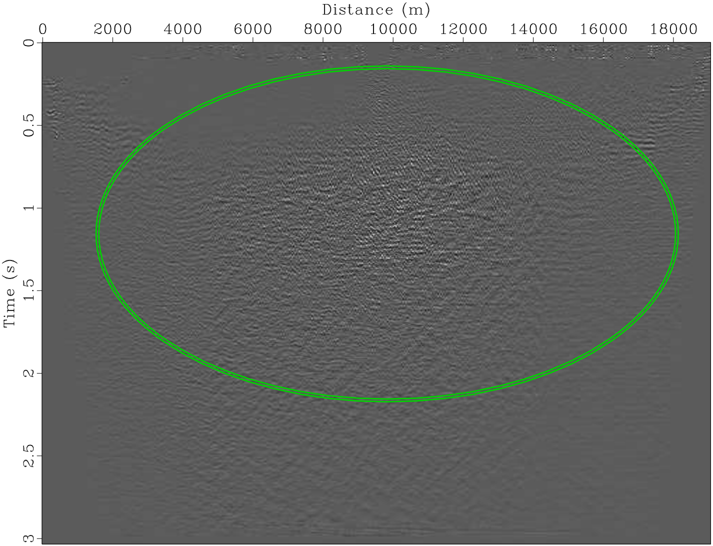
Stack Error: Unconstrained sparse inversion



Stack Error: DCSI



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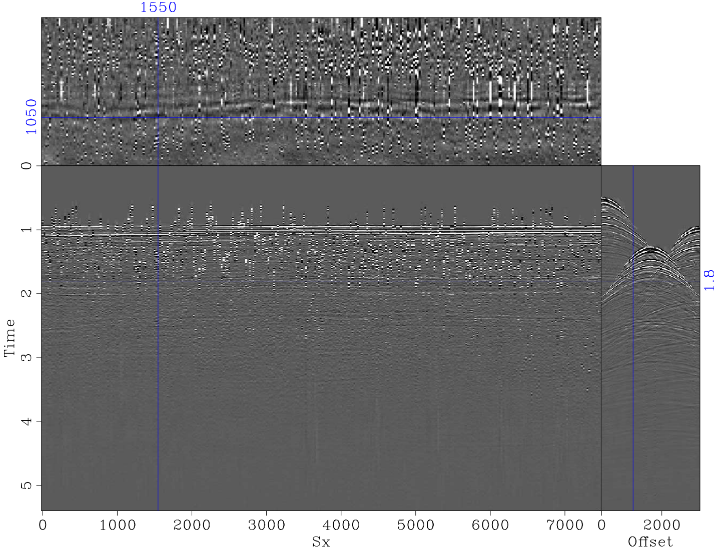
Marine data set: 3 sources



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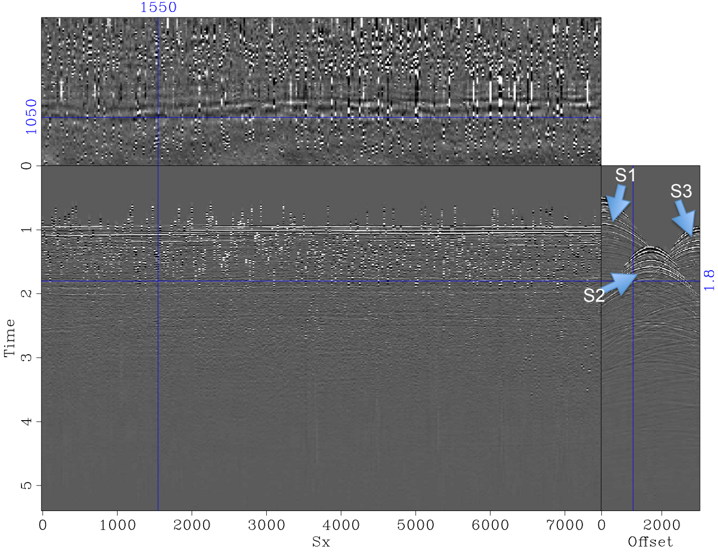
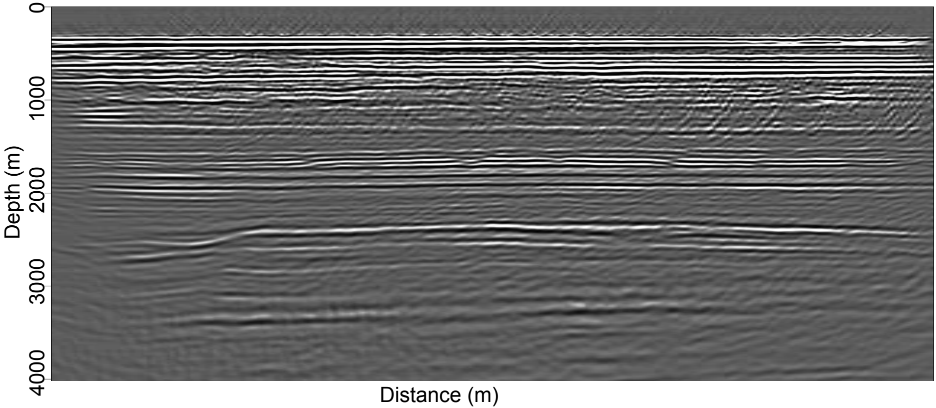


Migration Stack: Simultaneous source data



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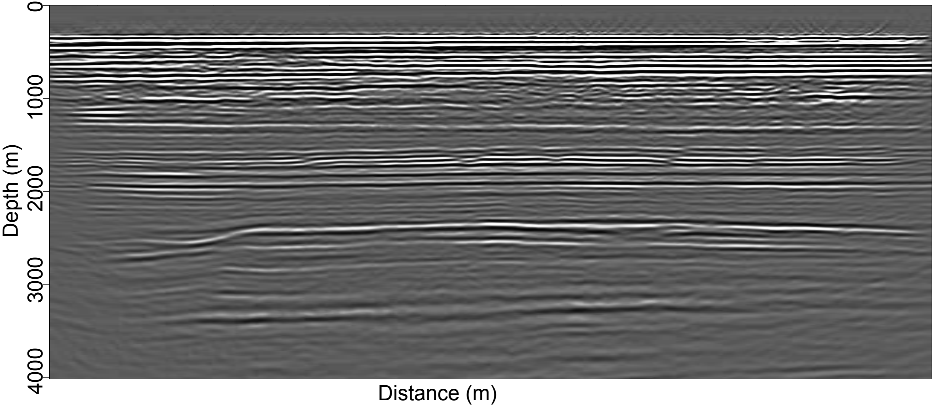
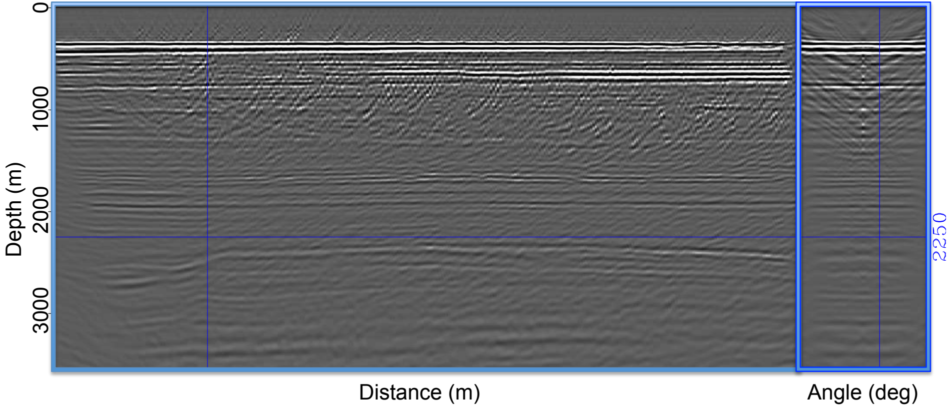
Migration Stack: Single-source data



Pre-stack image: Simultaneous source data



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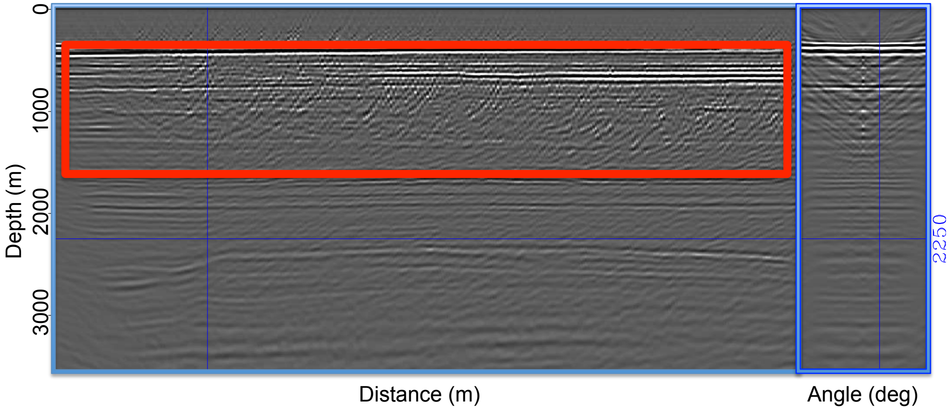
Pre-stack image: Simultaneous source data



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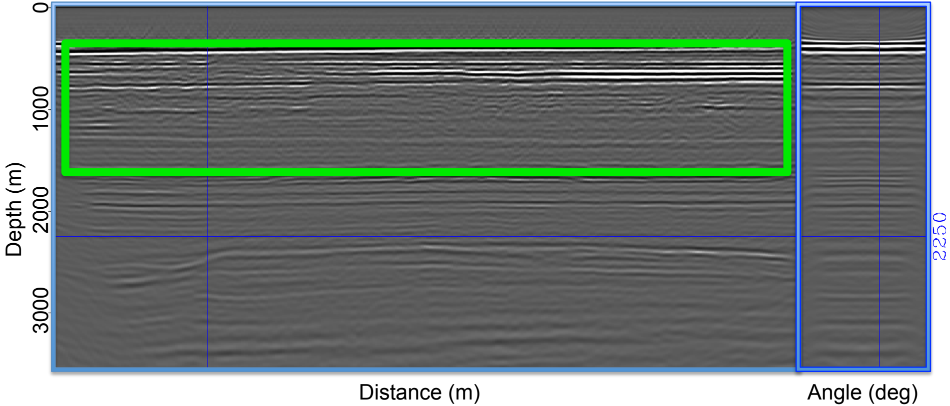

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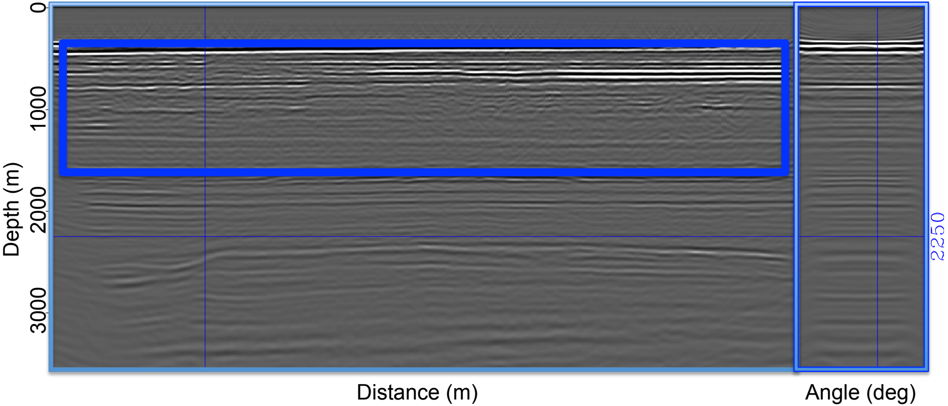

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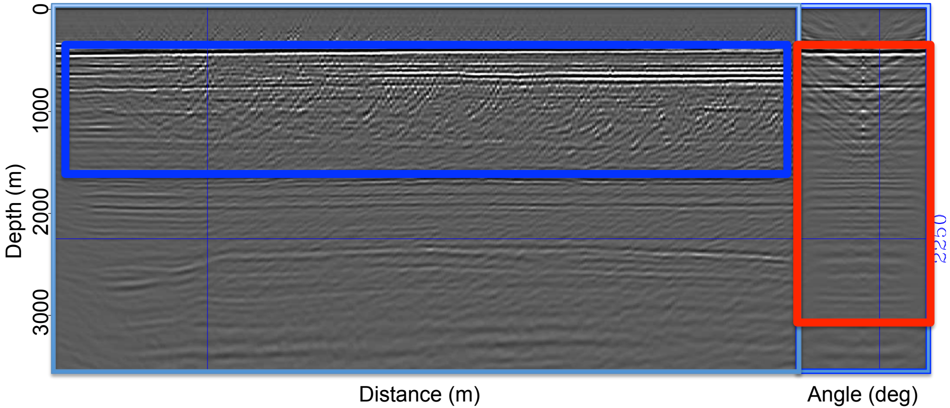
Pre-stack image: Simultaneous source data



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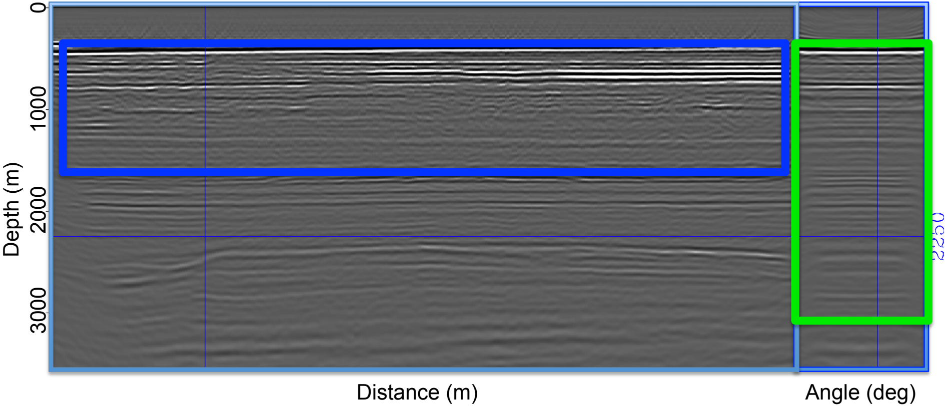

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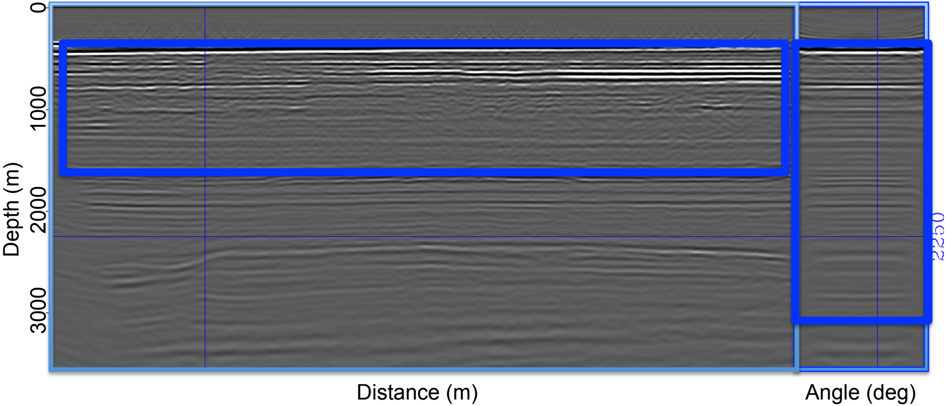

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Important questions

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- We thank Statoil and partners (ENI and Petoro) for donating the Marine data set
- We thank WesternGeco for donating the land data set.

Thanks

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