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Time-lapse data matching using neural networks with multiple reflections

Shang Huang and Daniel Trad

shang.huang1@ucalgary.ca

Time-lapse monitoring:

Monitor data | Baseline data

Residual between monitor data and baseline data: $\delta\mathbf{d}(t) = \mathbf{d}_{obsm}(t) - \mathbf{d}_{obsb}(t) = \mathbf{n}(t) + \delta\mathbf{r}(t)$

Noise | Subsurface reservoir change

Challenges:

1. The weak effect of reservoir changes on seismic amplitudes is overwhelmed by noise (near-surface complexities, different acquisitions between surveys)
2. 4D seismic captures parts of the reservoir changes due to limited subsurface illumination.

Proposed method:

Stacked LSTM on near-surface change and different acquisition settings between surveys.

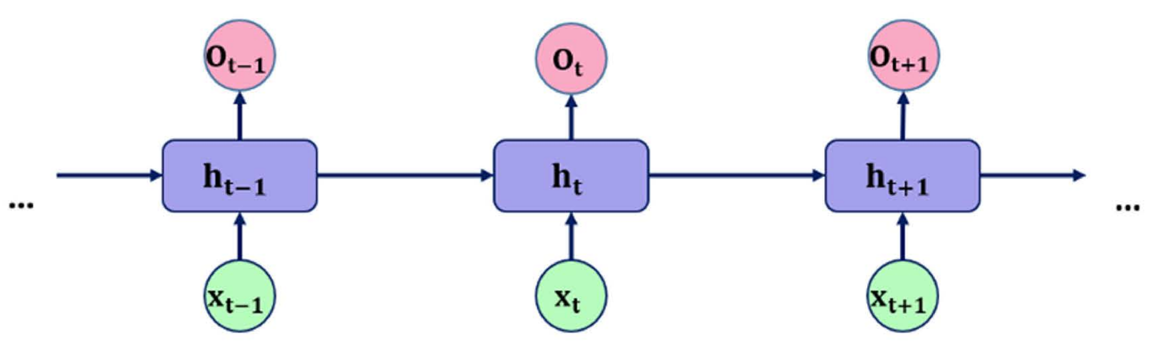


Figure 1. Stacked long short term memory (LSTM)

Two windows are constructed to predict two sets of baseline data. The first window, located at a time record of a shallow depth, matches near-surface change from baseline to estimated baseline data, given the corresponding section of the observed monitor data as labels. The other window, positioned at a time record to a greater depth, is deployed to predict another baseline data from observed baseline data. However, it is essential to note that the two sets of predicted baseline data refer precisely to the areas above the reservoir changes. The aforementioned terms individually indicate the predictions obtained from the **shallow** and **deep windows**, which are subsequently used in a double difference method. After subtraction, the near-surface noise should be reduced, and reservoir variations can be obtained.

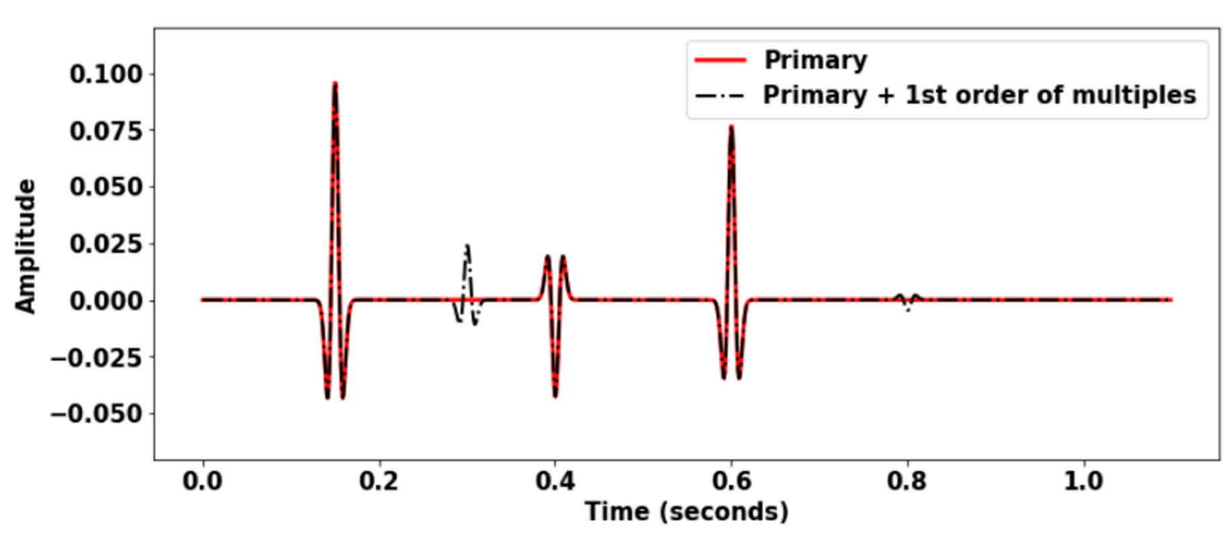


Figure 2. Example of a trace prepared for the neural network training. Primary reflections (red line) from three subsurface reflectors are observed separately at 0.15, 0.4 and 0.6 seconds. The first order of surface multiple reflections from the first and second reflectors are acquired at 0.3 and 0.8 seconds, shown in the dashed line.

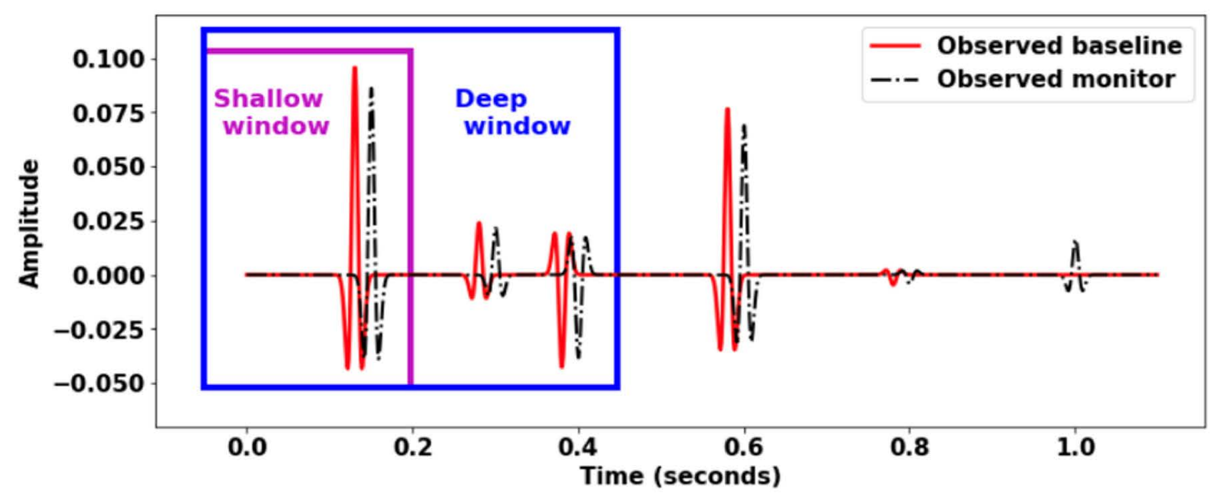


Figure 3. Example of two windowed trace inputs for the neural network training. A shallow window (purple box) contains a primary reflection, and a deep window (blue box) consists of primaries and the first order of surface multiple reflections from the first reflector

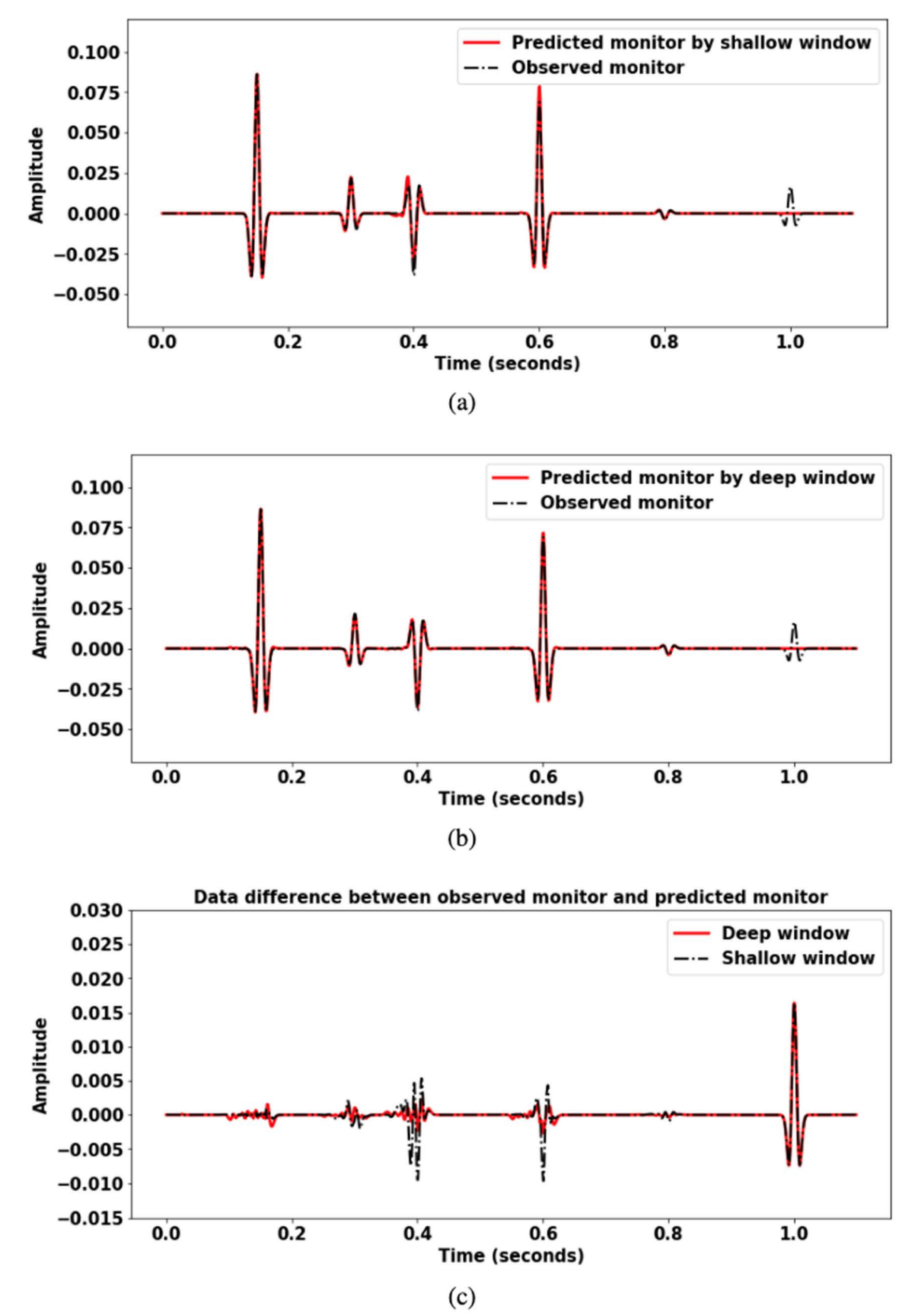
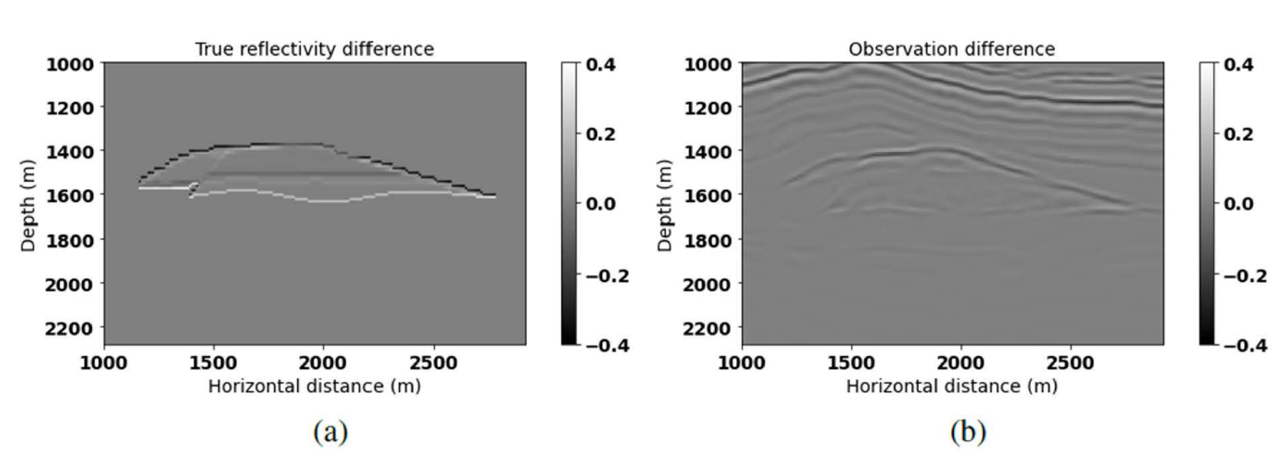
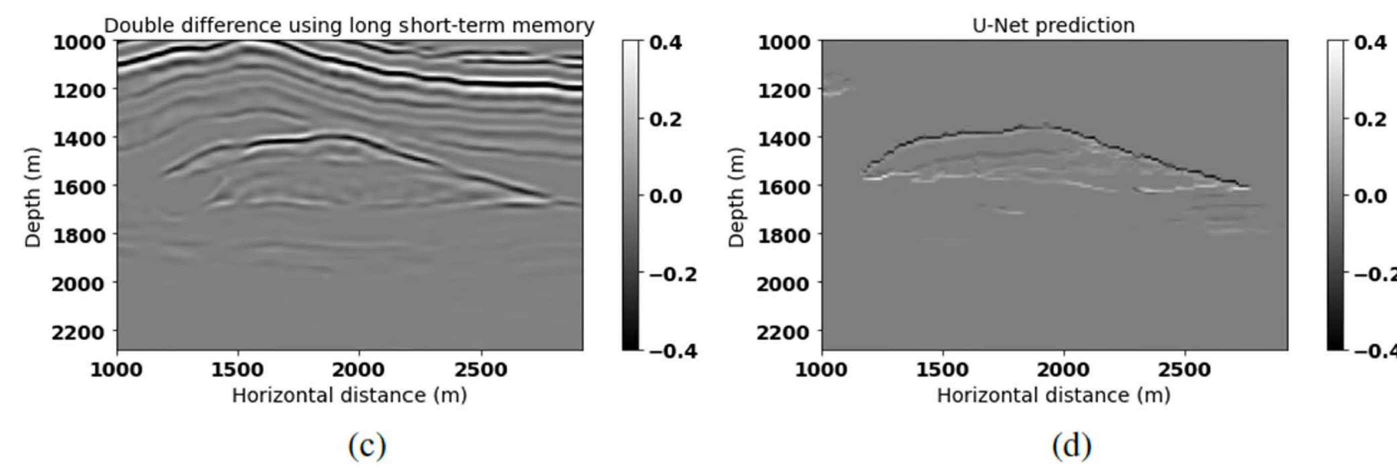


Figure 4. Prediction of the trace example. Comparisons between the predicted monitor (red line) by (a) shallow window and (b) deep window, and the observed monitor (dashed line).

Overthrust slice example:





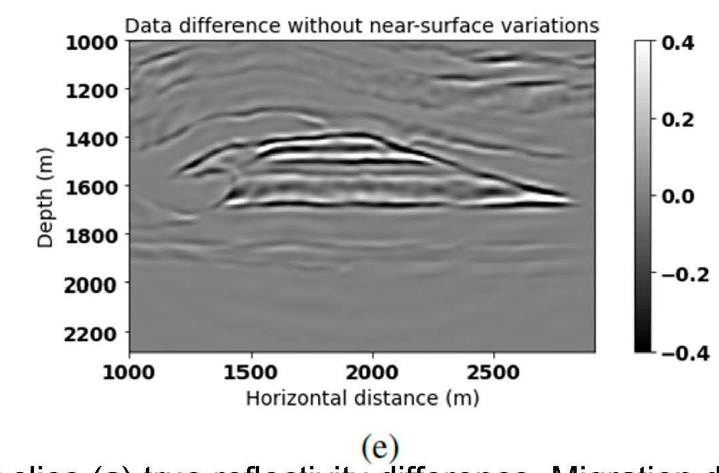


Figure 5. Overthrust slice (a) true reflectivity difference. Migration differences are generated by (b) the difference between the observed monitor and baseline, (c) the double-difference method, and (d) U-Net prediction. (e) Target migration difference without near-surface change.

DAS VSP stacked data example:

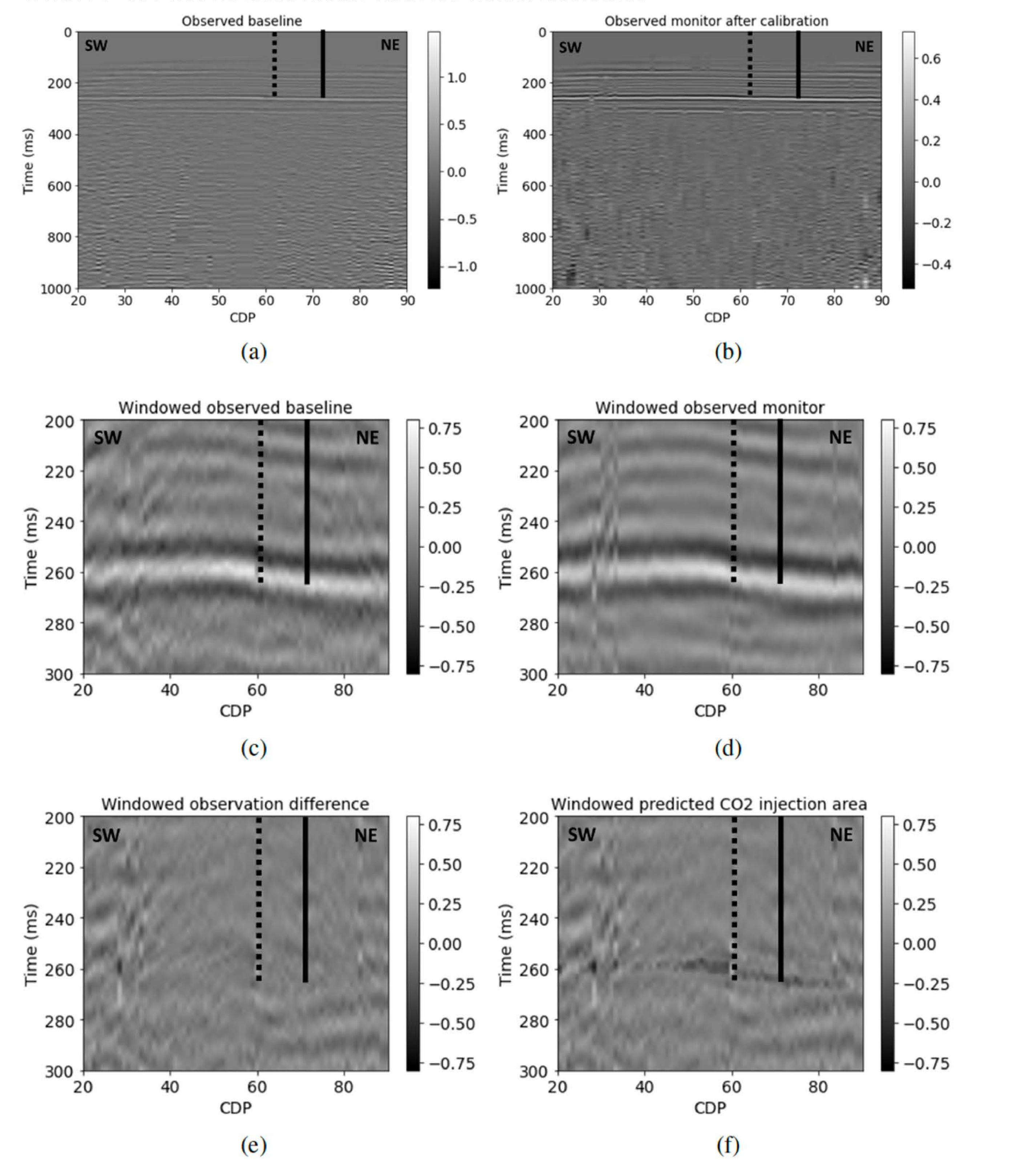


Figure 6. DAS VSP stacked data from CaMI FRS. (a) Observed baseline (b) Observed monitor after calibration. (c) Windowed observed baseline. (d) Windowed observed monitor. (e) Windowed observation difference. (f) Windowed predicted CO2 injection area.

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