Time-lapse monitoring using neural networks

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Outline

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Motivation

Challenges:

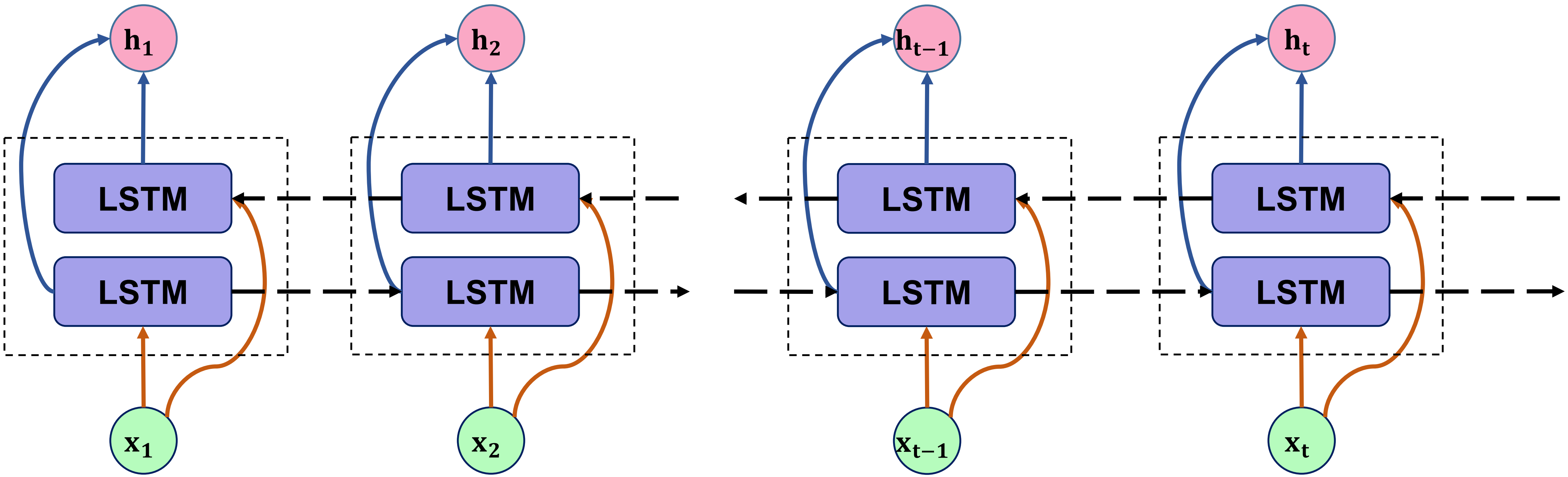
- Subtle changes in amplitude
- Poor subsurface illumination and inaccurate input image
- Only capture some reservoir changes

- Data-driven method
- Deep learning architecture
  - Stacked Bi-LSTM (eliminate differences)
  - U-Net (enhance the RTM)
- Surface multiple reflections

Theory

- Bidirectional long short-term memory (Bi-LSTM)
- Time-lapse seismic and double difference method

Bidirectional long short-term memory (Bi-LSTM)



(Graves and Schmidhuber, 2005)

- LSTM: remember values over arbitrary time; Bi-LSTM: data complexity
- Well-suited to processing and predicting based on time series data
- Relative insensitivity to gap length (long-term memory preservation)

Time-lapse seismic and double difference method

Time-lapse seismic: $$\delta\mathbf{d}(t) = \mathbf{d}_{obs_m}(t) - \mathbf{d}_{obs_b}(t) = \mathbf{n}(t) + \delta\mathbf{r}(t) \quad (1)$$

- $\delta\mathbf{d}(t)$: residual
- $\mathbf{d}_{obs_m}(t)$: monitor data
- $\mathbf{d}_{obs_b}(t)$: baseline data
- $\mathbf{n}(t)$: noise generated from data above reservoir change and non-repeatable signal
- $\delta\mathbf{r}(t)$: reservoir change

Double difference:
(Asnaashari et al., 2015)

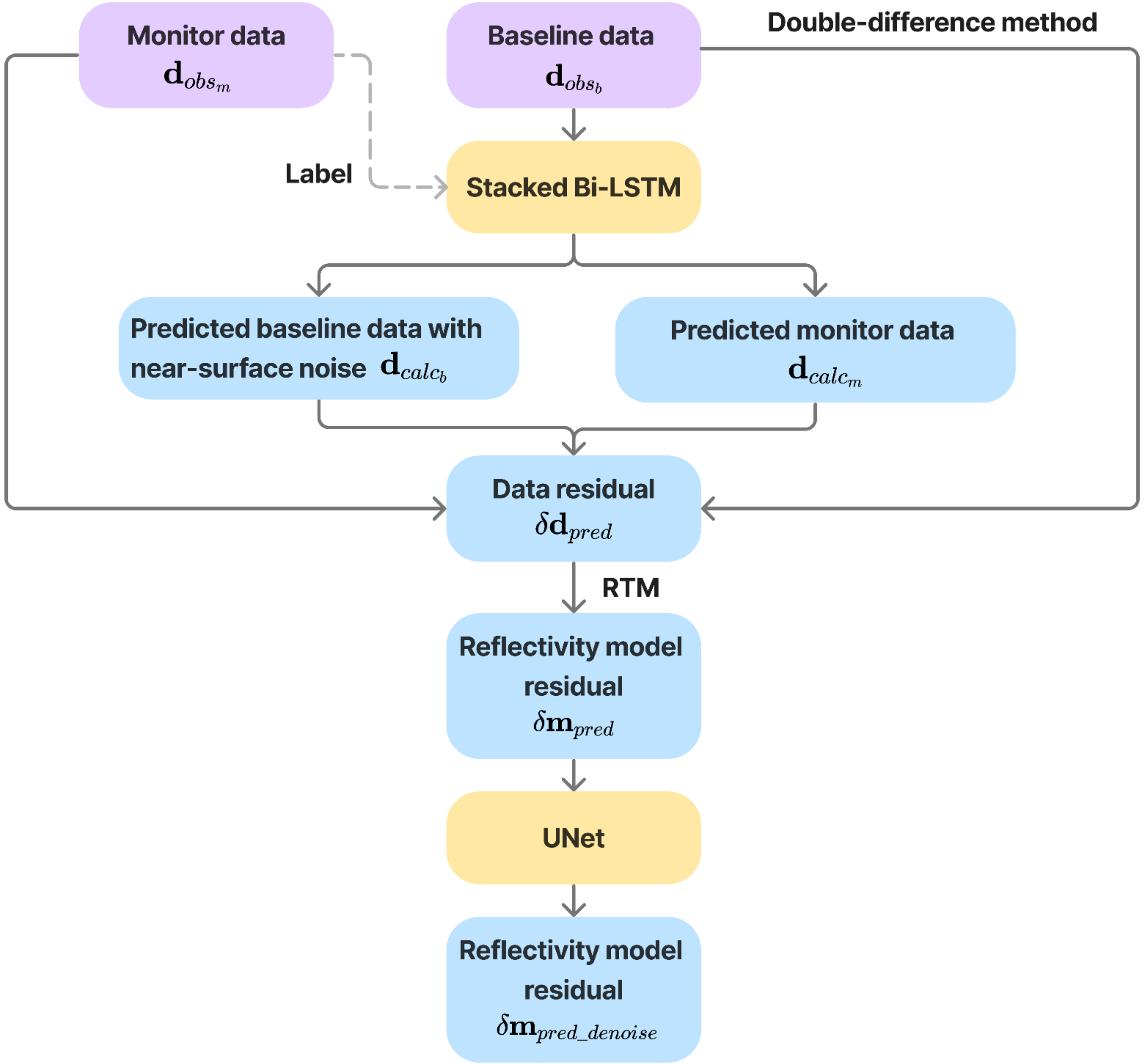
$$\delta\mathbf{d}_{time-lapse} = (\mathbf{d}_{obs_m} - \mathbf{d}_{obs_b}) - (\mathbf{d}_{calc_m} - \mathbf{d}_{calc_b}) \quad (2)$$

$$\Downarrow$$

$$\delta\mathbf{m}_{time-lapse} = \delta\mathbf{m}_{obs} - \delta\mathbf{m}_{calc} \quad (3)$$

- $\mathbf{d}_{calc_m}(t)$: predicted monitor data
- $\mathbf{d}_{calc_b}(t)$: predicted baseline data

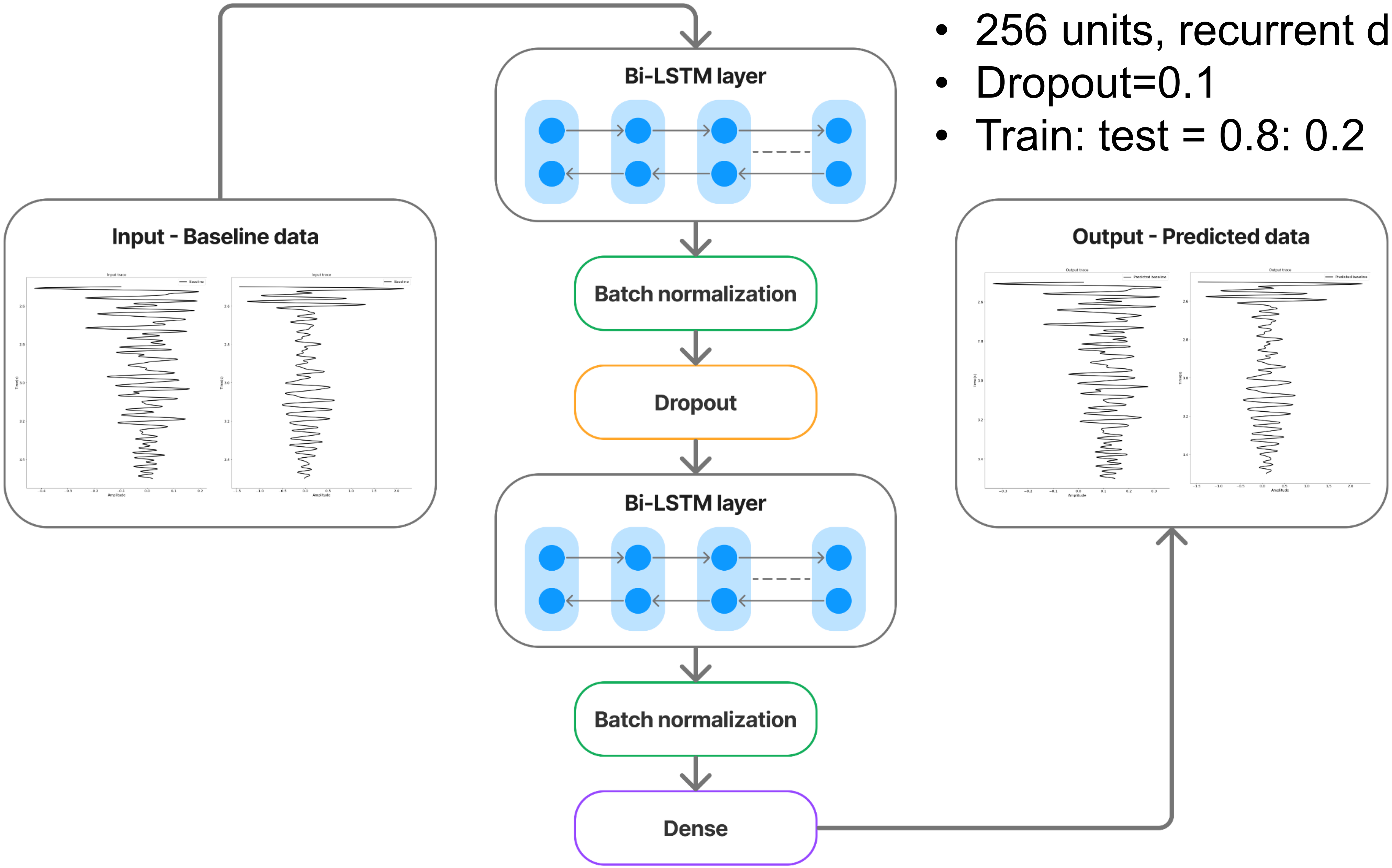
Workflow



Monitor data
$\mathbf{d}_{obs_m}$
Baseline data
$\mathbf{d}_{obs_b}$
Double-difference method
Label
Stacked Bi-LSTM
Predicted baseline data with near-surface noise $\mathbf{d}_{calc_b}$
Predicted monitor data
$\mathbf{d}_{calc_m}$
Data residual
$\delta\mathbf{d}_{pred}$
RTM
Reflectivity model residual
$\delta\mathbf{m}_{pred}$
UNet
Reflectivity model residual
$\delta\mathbf{m}_{pred\_denoise}$

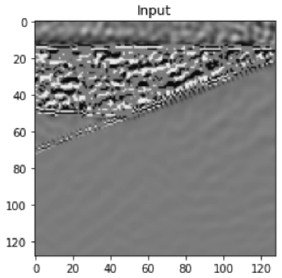
Neural network architecture – SD-Bi-LSTM

- 256 units, recurrent dropout=0.1
- Dropout=0.1
- Train: test = 0.8: 0.2



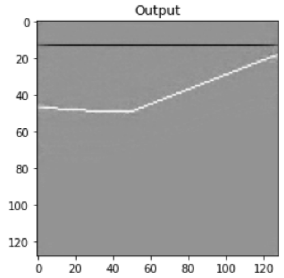
Neural network architecture – UNet

Input layer



- Input window size: 128x128
- Input data: double-difference model residual
- True label: real reflectivity difference
- Dropout=0.2

Output layer



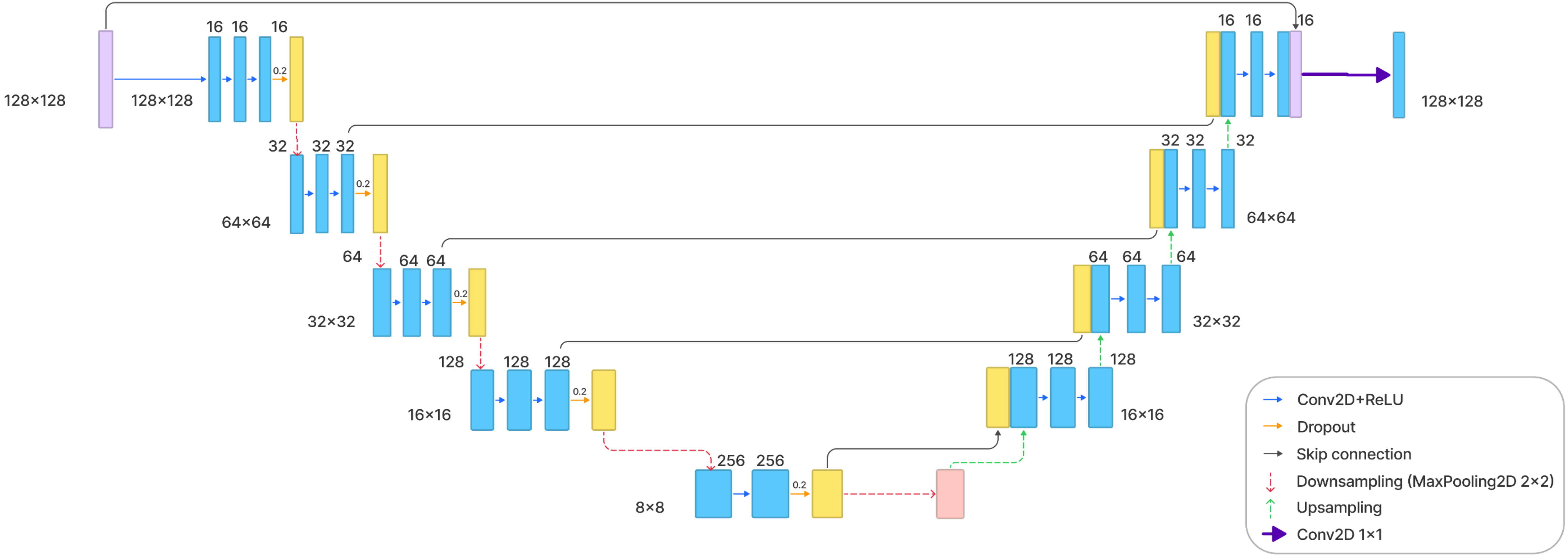


Figure adapted from Huang and Trad, 2021

Mean squared error

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\mathbf{d}_{calc}^{i} - \mathbf{d}_{obs}^{i})^2 \tag{4}$$

- n: total number of samples
- $\mathbf{d}_{calc}$: predicted monitor or baseline data
- $\mathbf{d}_{obs}$: observed monitor or baseline data

Peak signal-to-noise ratio (PSNR)

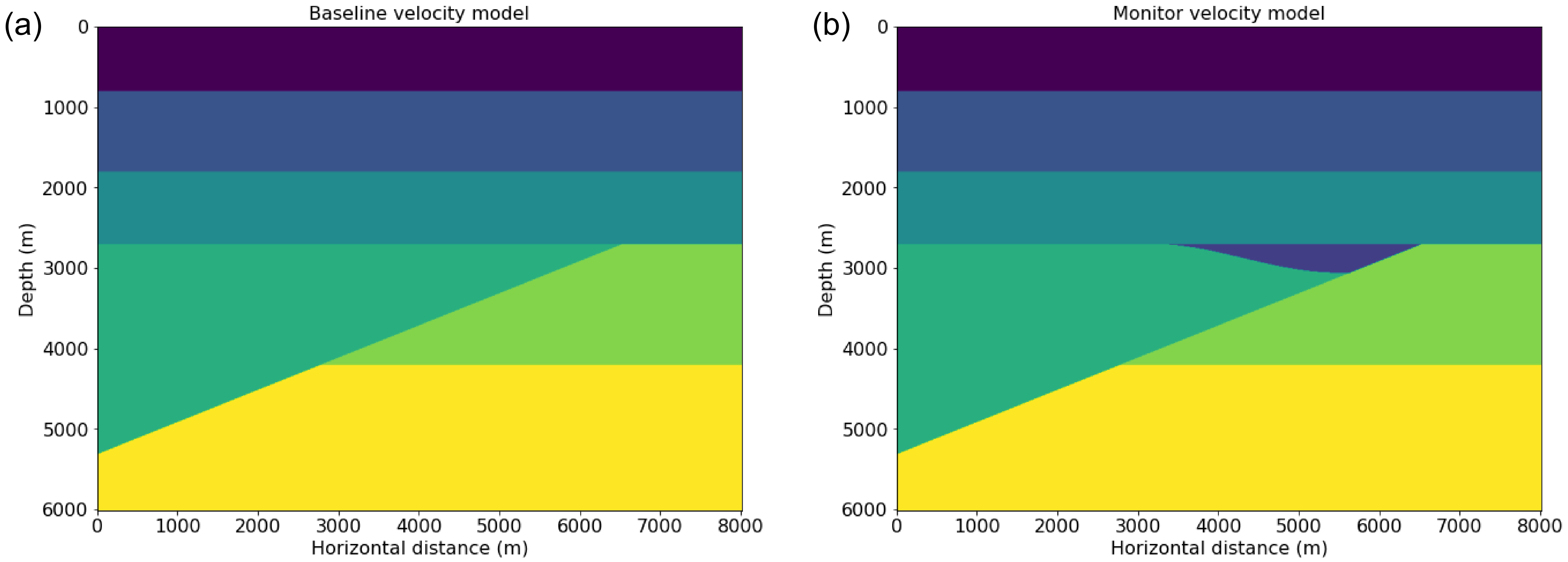
$$\mathrm{PSNR} = 20 * \log_{10}\left(\frac{\mathrm{MAX}_I}{\sqrt{\mathrm{MSE}}}\right) \tag{5}$$

- MAX_I: maximum possible pixel value of the image

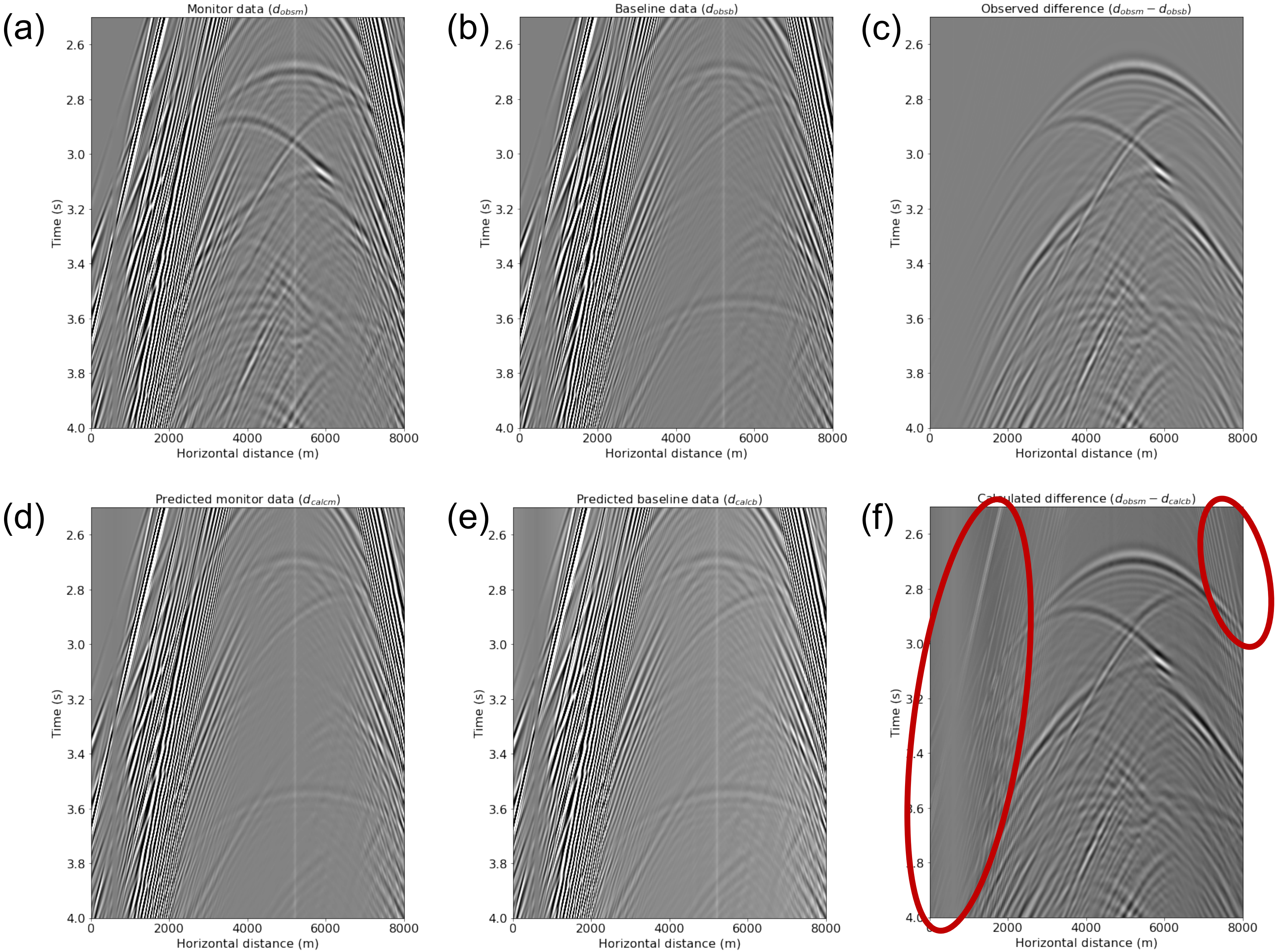
Numerical example

Assumption: monitor and baseline systems are the same for basic training purposes

- Size: 601x801, dz=dx=10 meters, dt=0.001 seconds, nt=4000
- Train and test: 16 shots, 801 receivers, ds=500 meters
- Validation: 7 shots, ds=1150 meters

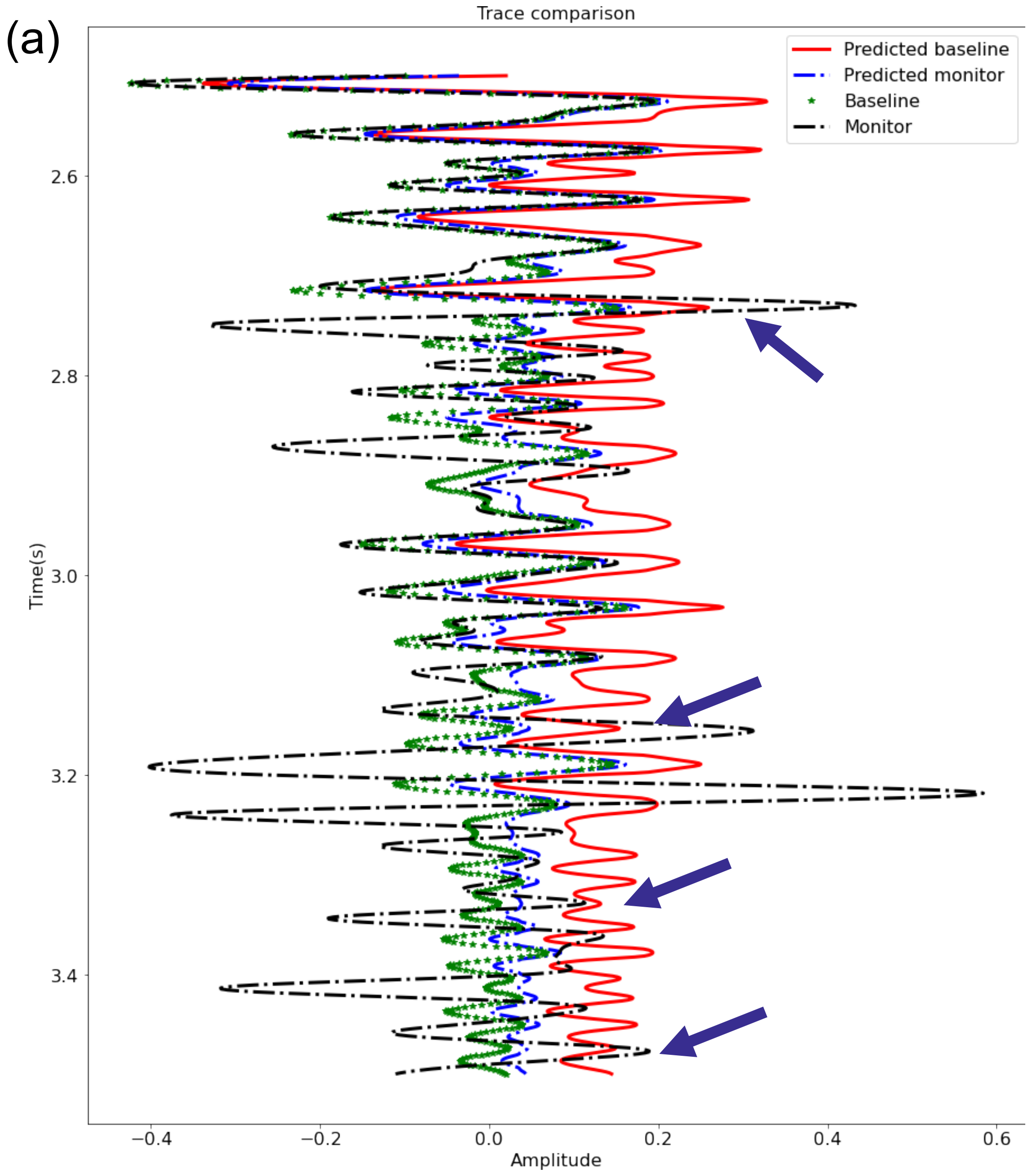


Shot record

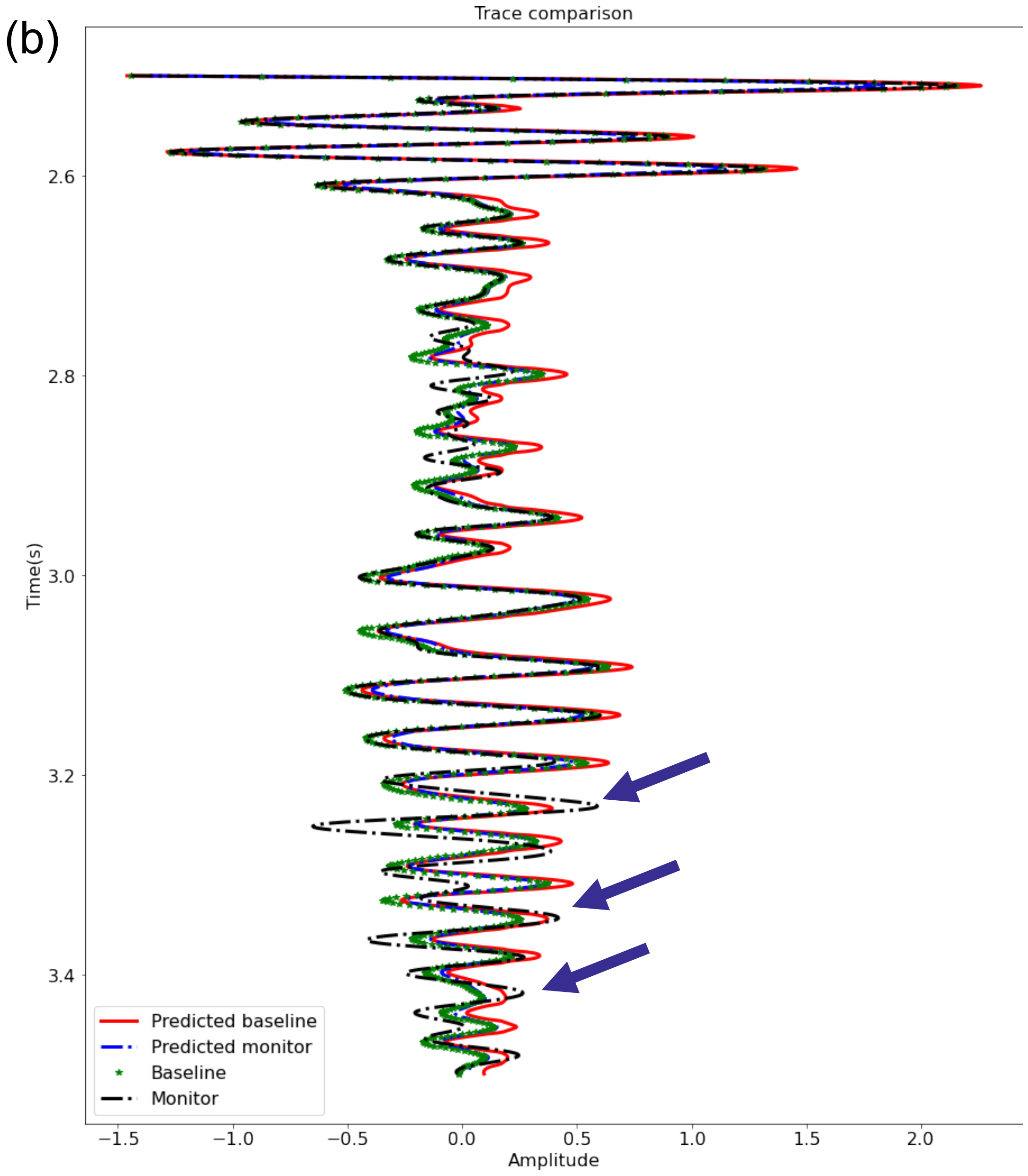


(a)
Monitor data (d_{obsm})
(b)
Baseline data (d_{obsb})
(c)
Observed difference ($d_{obsm} - d_{obsb}$)
(d)
Predicted monitor data (d_{calcm})
(e)
Predicted baseline data (d_{calcb})
(f)
Calculated difference ($d_{obsm} - d_{calcb}$)
Time (s)
Horizontal distance (m)

Trace comparison

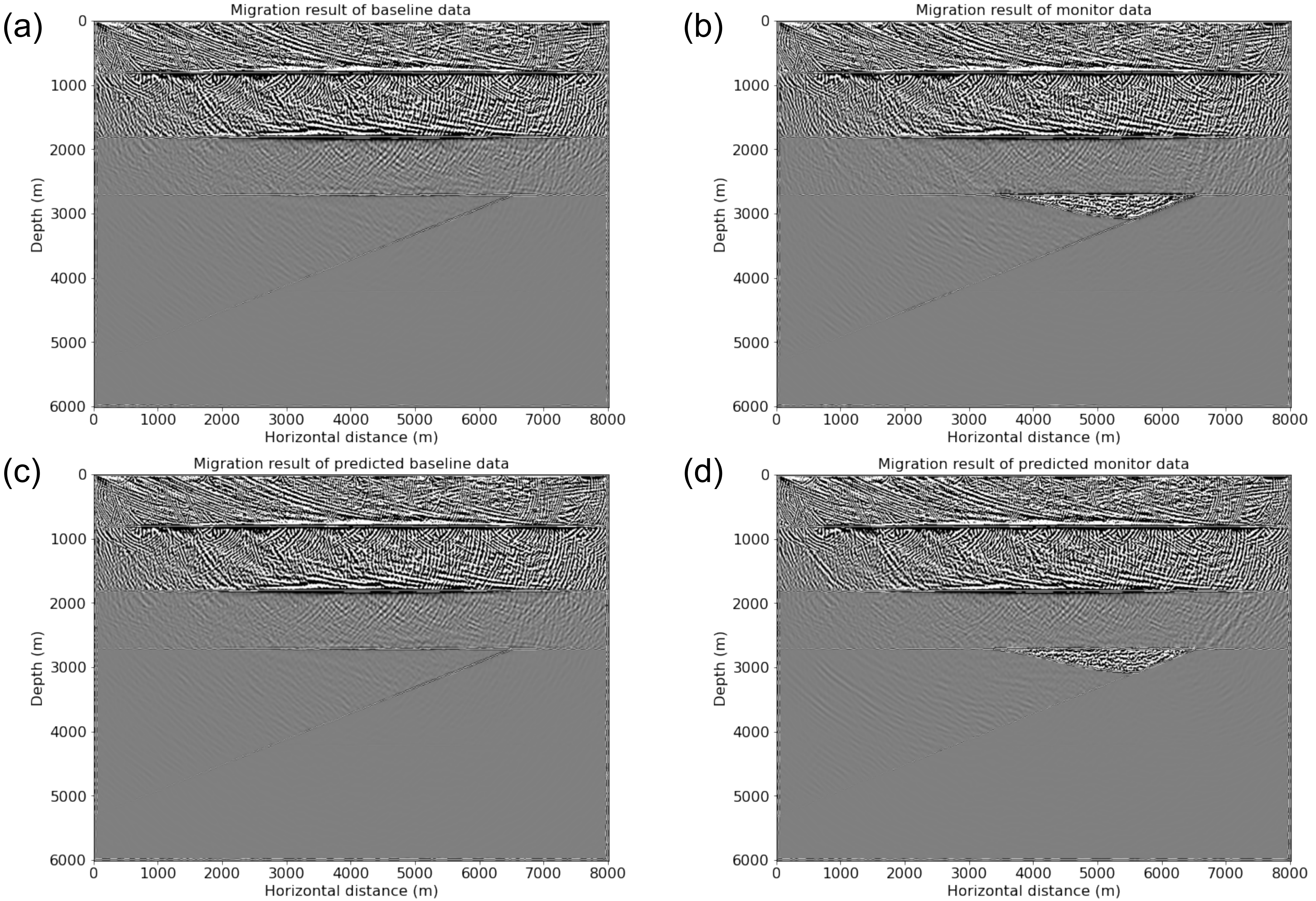


4000 meters offset



3500 meters offset

Migration comparison



Model difference comparison between double-difference and observation

PSNR = 21.12 dB

PSNR = 15.19 dB

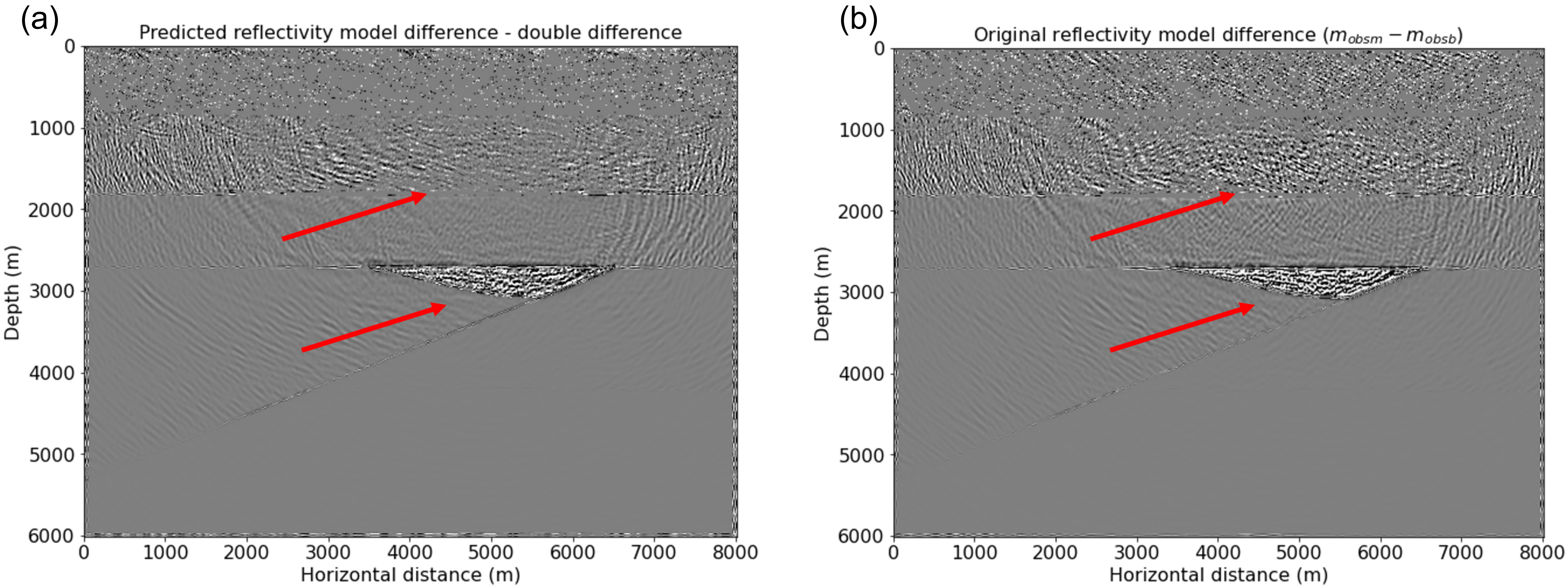


Image denoising after U-Net

(a)

PSNR
= 21.07 dB

(b)

PSNR
= 14.69 dB

(c)

PSNR
= 35.92 dB

(d)

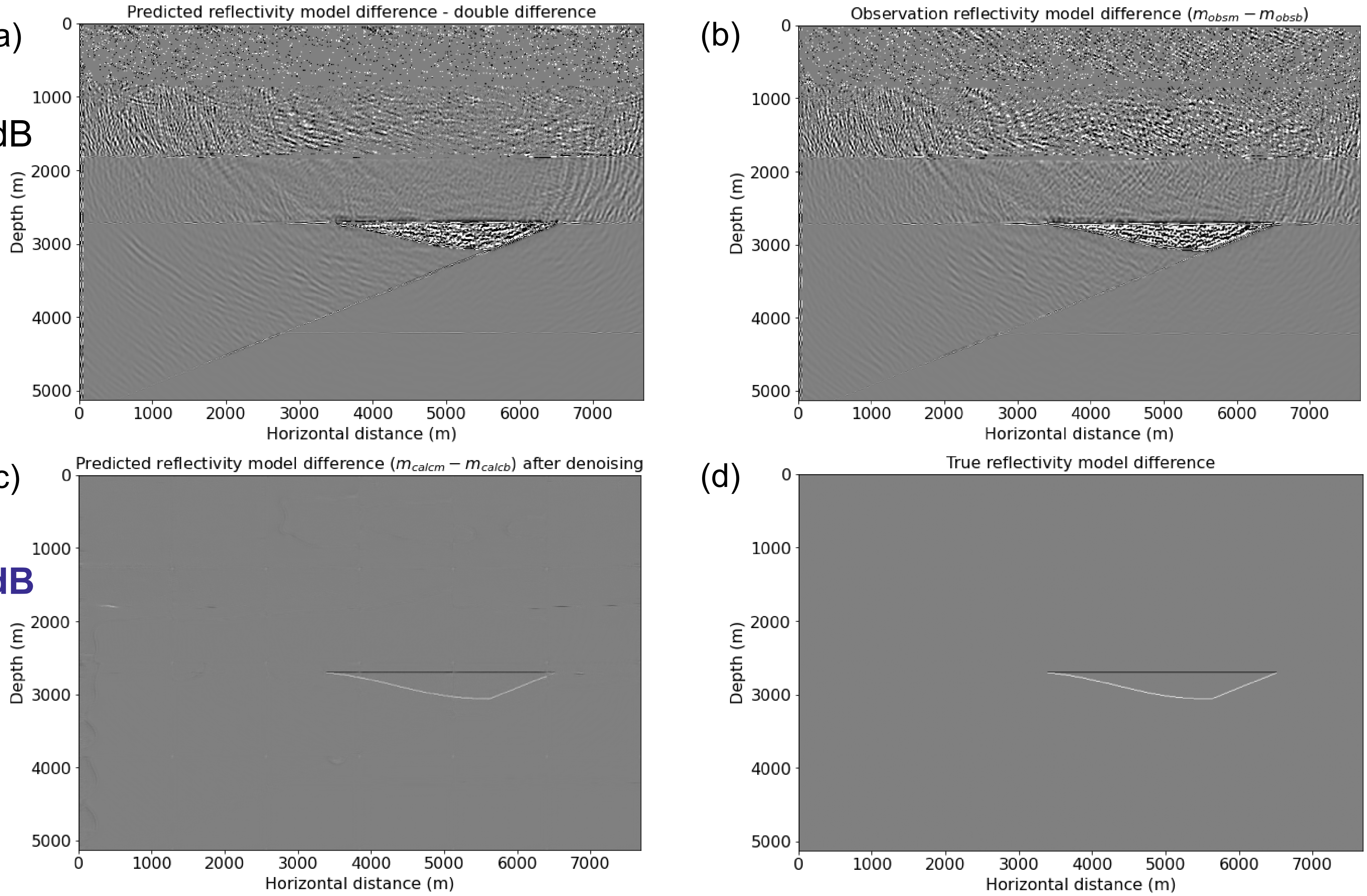
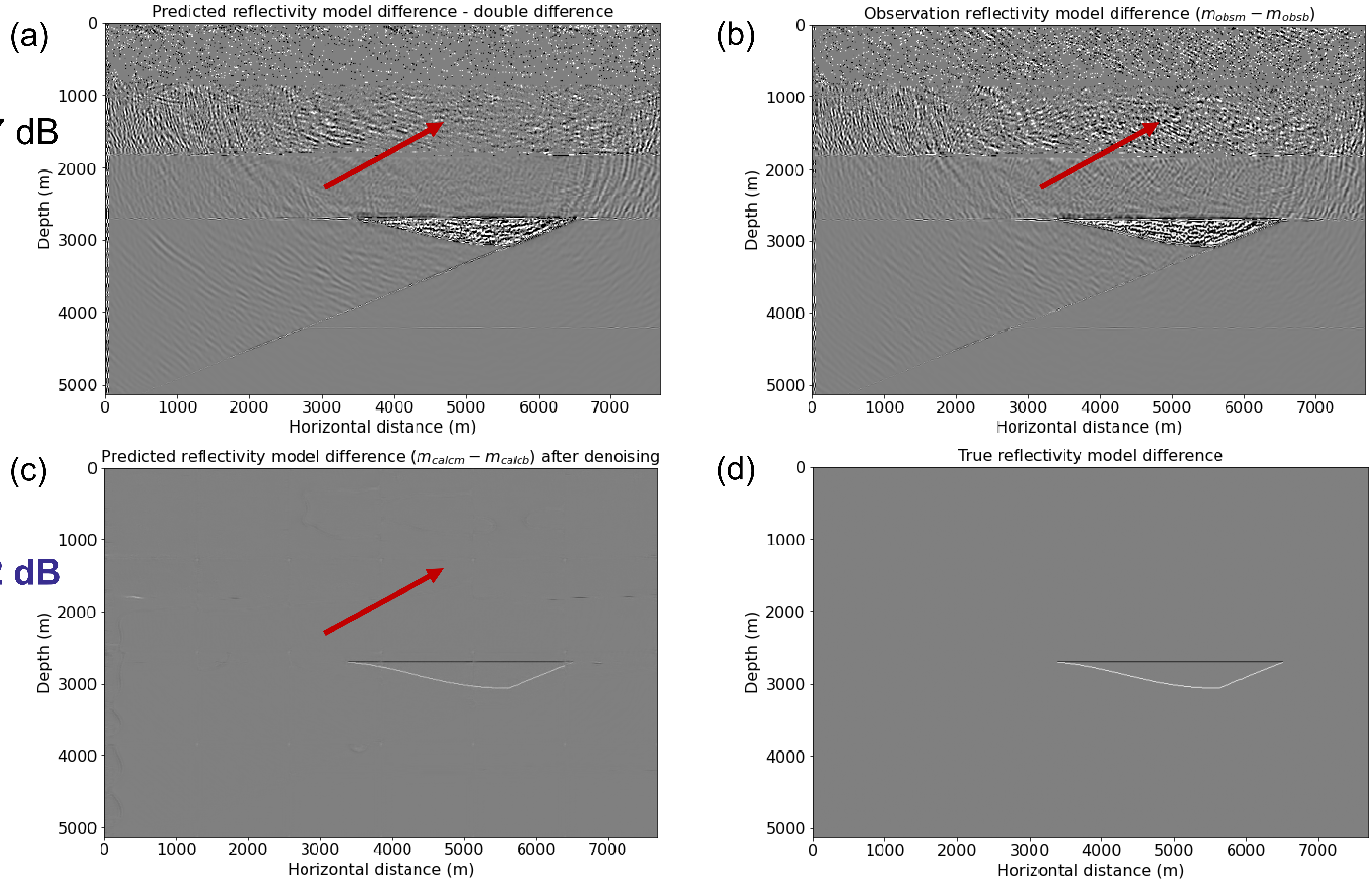


Image denoising after U-Net

PSNR = 21.07 dB

PSNR = 14.69 dB

PSNR = 35.92 dB



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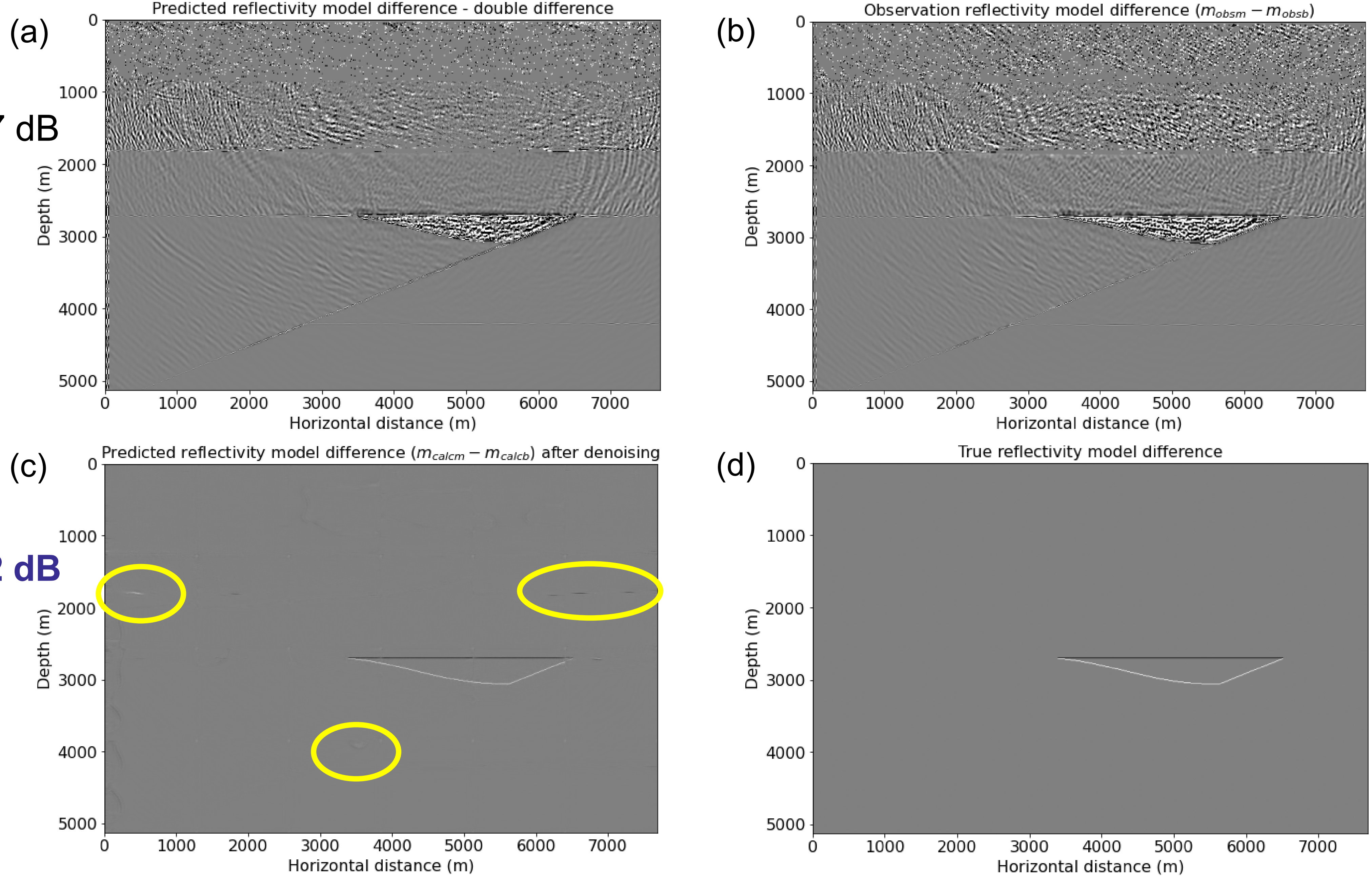
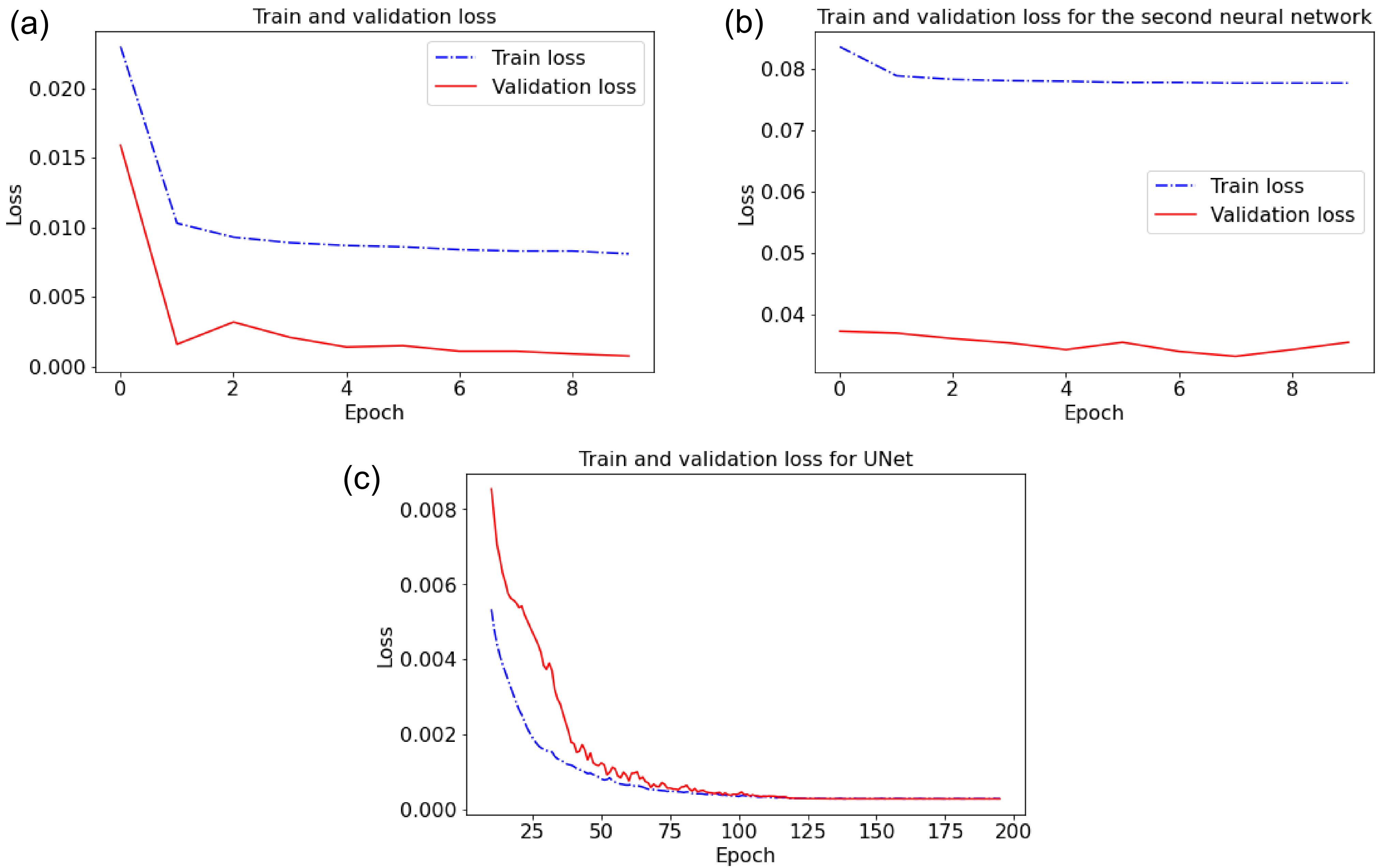


Train and validation loss



Conclusion and future work

- SD-Bi-LSTM can learn near-surface noise and shallow depth signal information of monitor data
- Double-difference method helps mitigate noise
- U-Net helps to obtain enhanced image quality with high accuracy
- In future work, try different models with unknown reservoirs to test generalization

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References

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Thank you!