Applying Deep Learning Time-Frequency Denoising Tools to DAS Recordings (SC0022733)

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Project overview

- **Title:** Developing and applying deep learning time-frequency denoising tools to DAS data to enhance passive seismic signals for seismic hazard analysis and reservoir characterization

- **Period:** Aug 2023 – Aug 2025 from DOE SBIR with a total funding of $1,614,946.19

- **Team: Zanskar:** Joel Edwards, Hao Zhang, Junzhu Shen, Postdoc
  Rice Unv.: Jonathan Ajo-Franklin, Yuanyuan Ma
  Penn State Unv.: Tieyuan Zhu, Joseph Jeorge Miller

- **Objectives:**
  1) Expanding the deep learning DAS denoising tools to surface DAS data;
  2) Monitoring induced seismicity using denoised DAS data;
  3) Building carbon storage DAS array design tool

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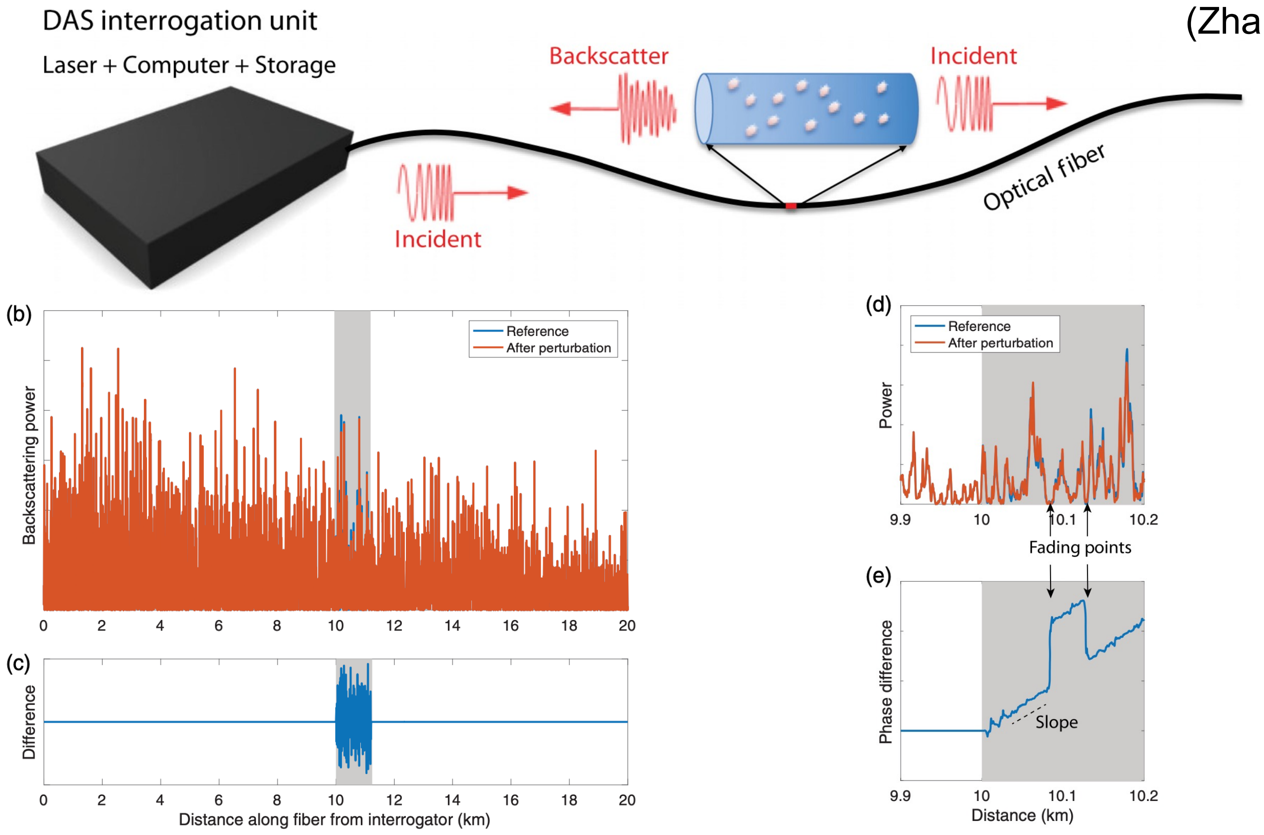
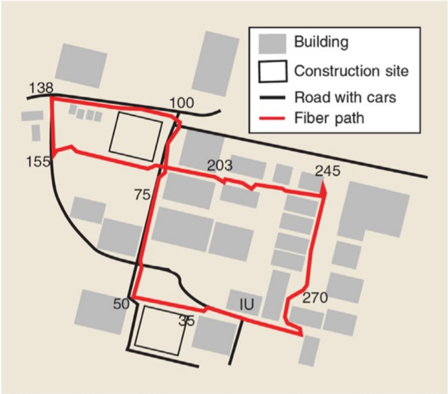
What is DAS (Distributed acoustic sensing)?

(Zhan, 2019)



Surface DAS Surveys

Stanford (2 km)

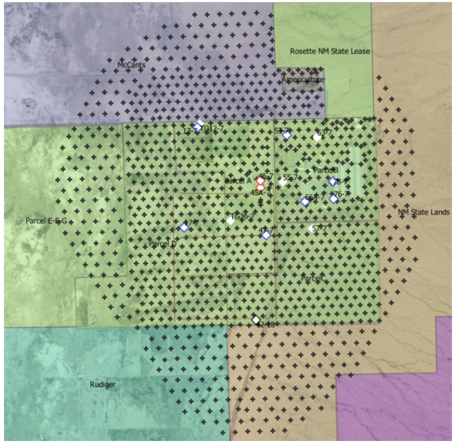


(Martin et al., 2018)

Alaska (7 km long)

(Ajo-Franklin et al., 2017)

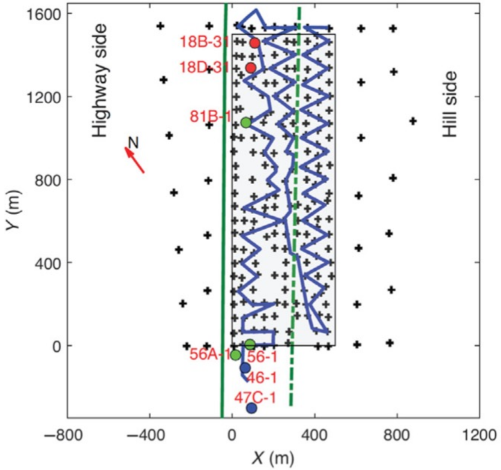
Geophone survey



LDG (1206 station)

Bradys' (1 m spacing)

Porotomo DAS array



(Wang et al., 2018)

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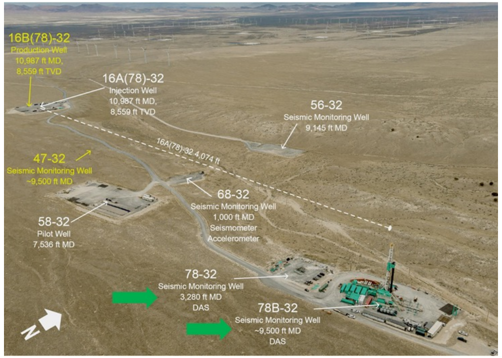
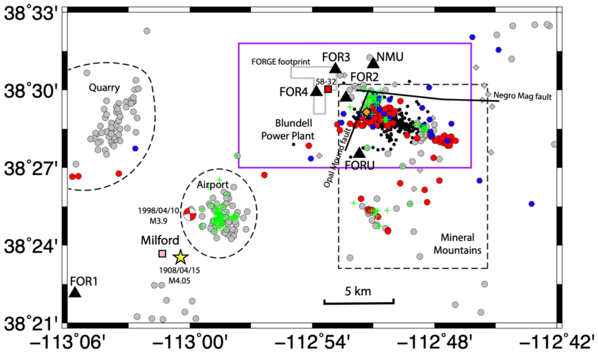
DAS geothermal applications

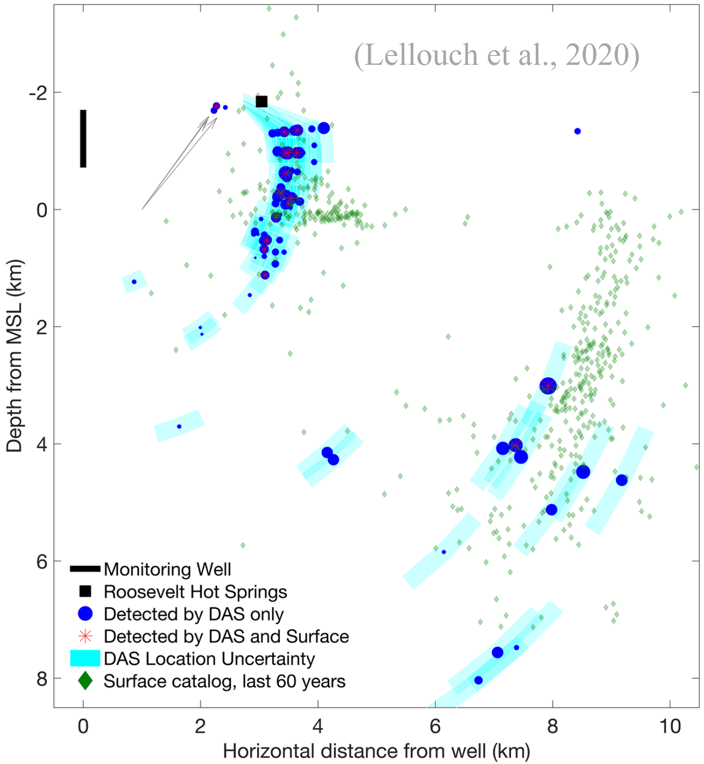
FORGE seismicity detection:

DAS detected more events with higher depth accuracy over surface array (azimuthal symmetry due to single well).





(Pankow et al., 2019)



CCS site: Otway International Test Centre, Australia

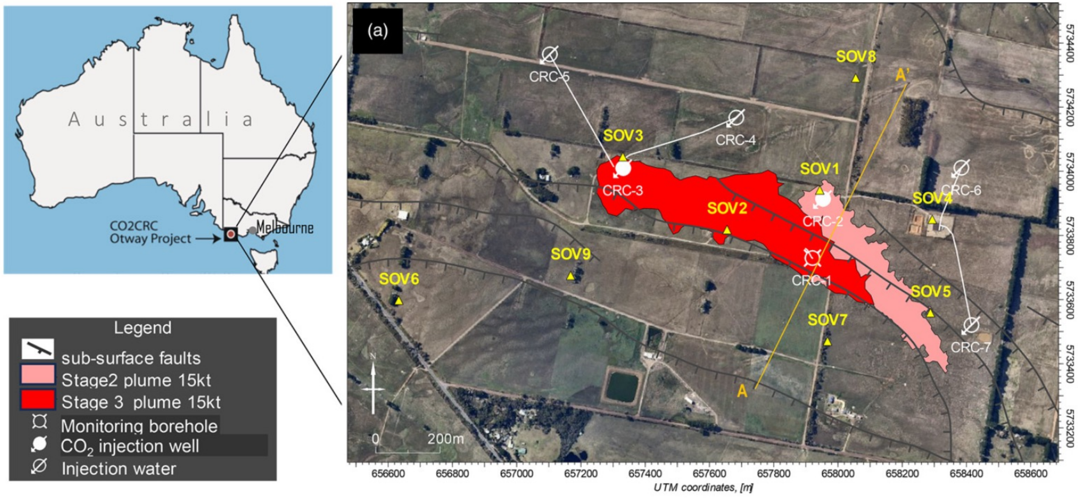
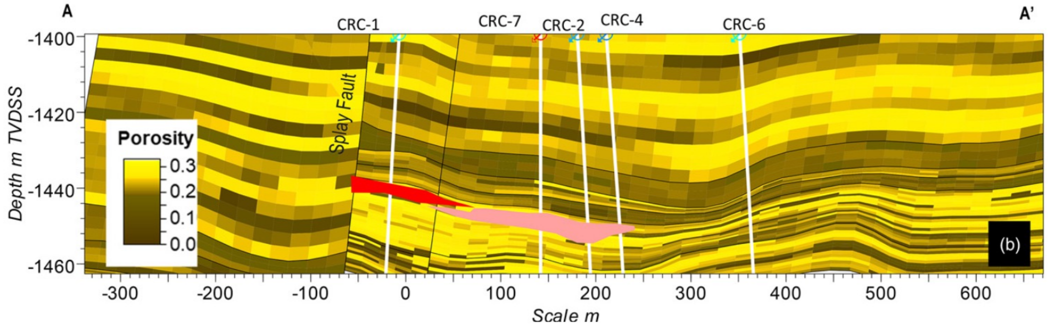
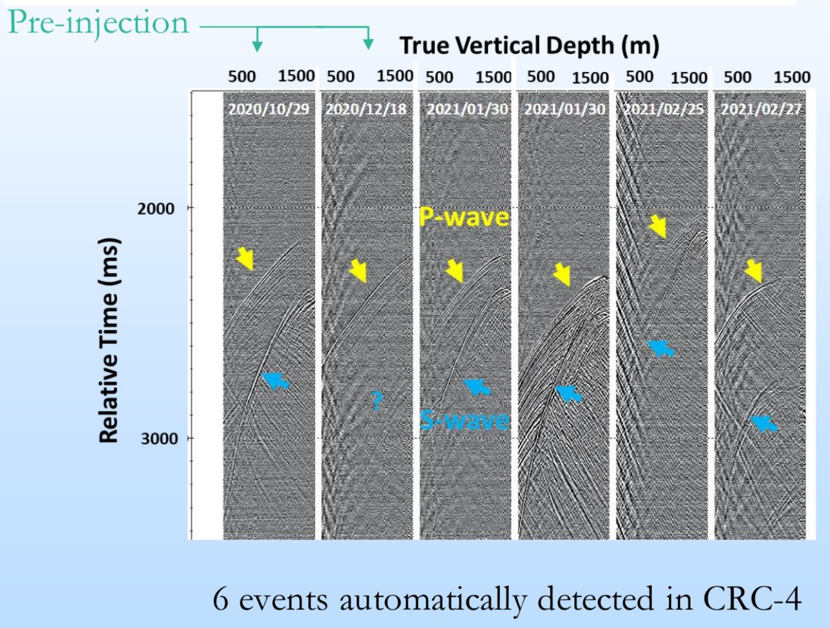


Table 1. Timeline of injections at the OITC

Name	Date	Mass CO_2 injected	Objective	Methods	Overview reference
Stage-1	2008–9	65 kt	Storage in a depleted gas field	Multiple	Jenkins *et al.* (2012)
Stage-2A	2010	-	Drilling CRC-2	-	-
Stage-2B	2011	150 t	Reservoir scale measurement of capillary trapping	Passive and reactive tracers, isotopes, fluid sampling, pressure, temperature	Paterson *et al.* (2013)
Stage-2B extension	2014	100 t	Repeat Stage-2B	Mostly as for 2B	Ennis-King *et al.* (2017)
Stage-2C	2015–18	~15 kt	Test seismic detection limit and models of plume stabilization	Buried geophone array, conventional surface seismic sources	Pevzner *et al.* (2017) Watson *et al.* (2018)
Stage-3	2016–2021	~15 kt	Test continuous source seismic, and pressure tomography	DAS/DTS fibre optics deployed on well casing, reservoir pressure, water injections, continuous acoustic sources	Jenkins *et al.* (2017), Pevzner *et al.* (2021)



(Jenkins et al. , **2024)**



(Glubokovskikh **et al., 2022)**

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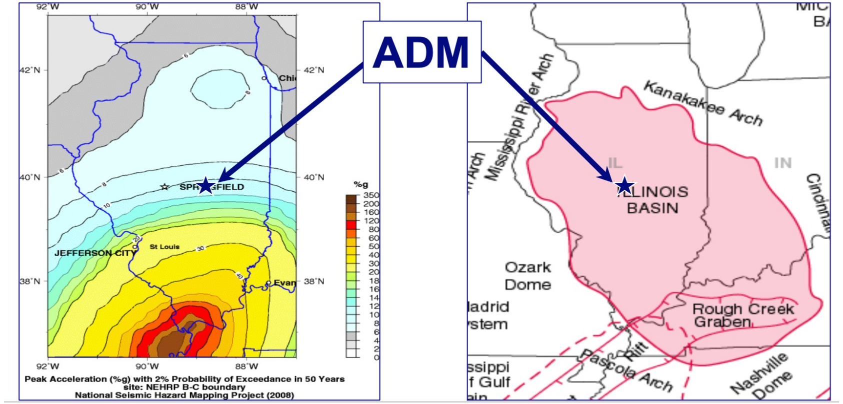
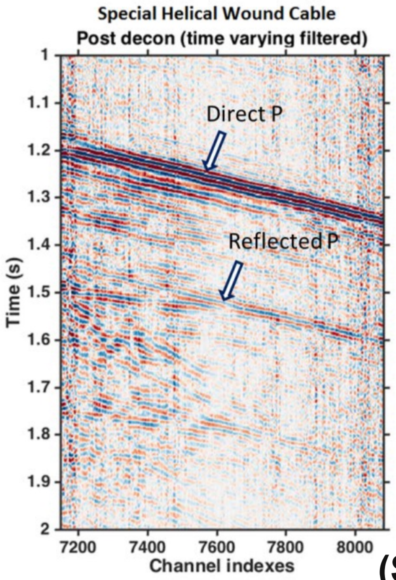
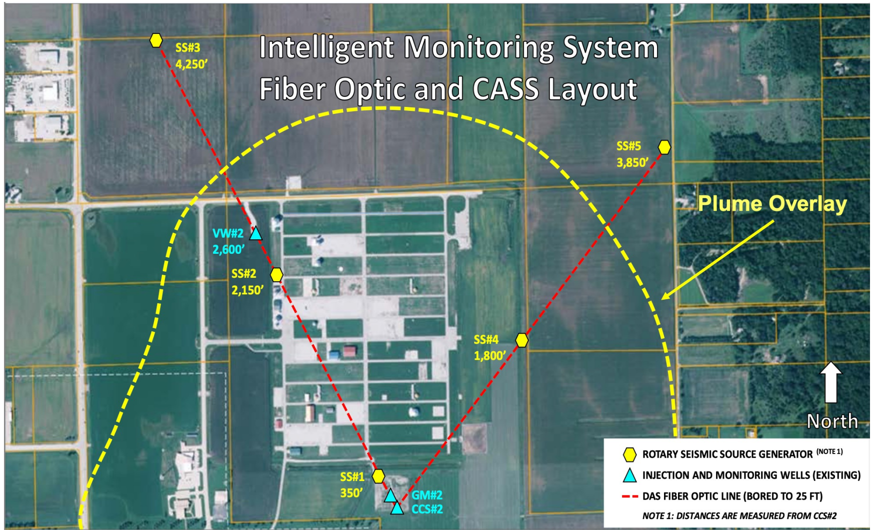
CCS site: Illinois Basin Decatur Project

- Cratonic basin
- 60,000 square mile area
- Structurally complex to the south with faulting and seismicity
- ADM Decatur facility is located near the center of this geologic formation
- Estimated CO_2 storage capacity between 27 to 109 billion metric tons







(Scott McDonald, 2017)

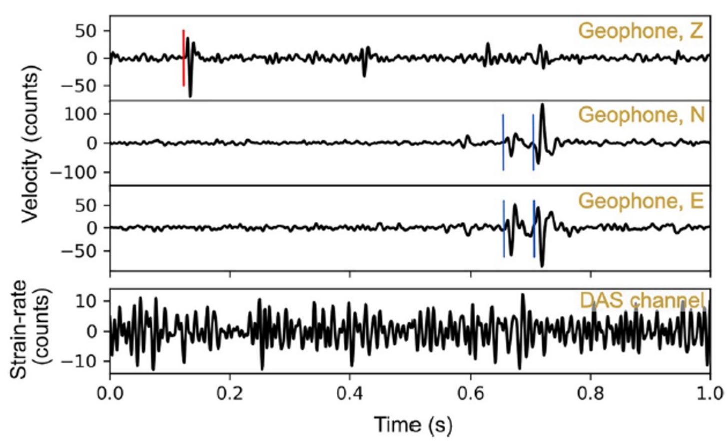
Challenges in DAS applications

- Big Data: up to terabytes per day

Name	IU	T. span (d)	Format	Sps (hz)	Vol. (Gb)	GL (m)	CL (m)	CS (m)	units
Fairbanks	iDAS	59⋆	TDSM	1,000	10,441	10	4,000	1	$\dot{\epsilon}$
FORESEE	iDAS-v2	365	HDF5	125÷	29,338	10	4,900	2	$\dot{\epsilon}$
FOSSA	iDAS-v2	7	TDSM	500	11,680	10	23,300	2	$\dot{\epsilon}$
LaFarge	iDAS	2⋆	SEG-Y	1,000	45	10	1,120	1	$\dot{\epsilon}$
Stanford-1	ODH3	940	SEG-Y	50	18,908	7.14	2,500	8.16	ϵ
Stanford-2	ODH3	14	SEG-Y	250	2,887	20	10,200	8.16	ϵ
Stanford-3	ODH4	6	SEG-Y	∼	92	∼	2,500	8.16	ϵ
Valencia	A1-R	7	HDF5	250÷	3,213	30.4	50,000	16.8	$\dot{\epsilon}$

(Spica et al., 2022)

- Low quality: low signal-to-noise ratio



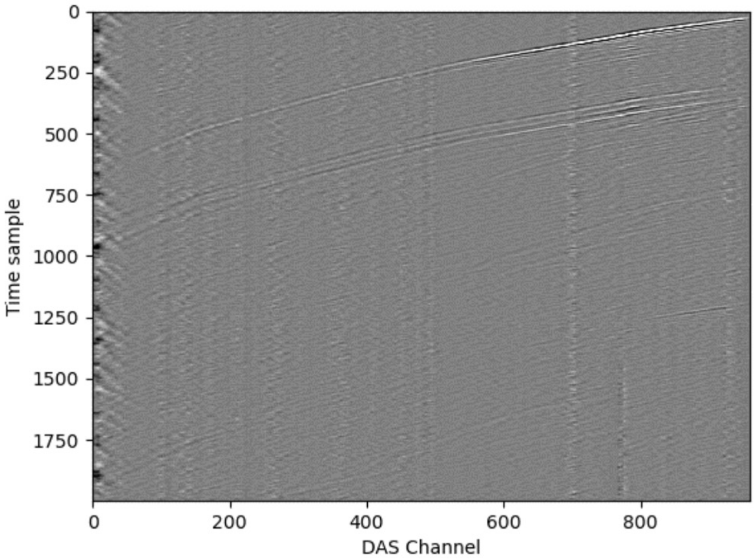
Glacier microseimic waveform

(Hudson et al., 2021)

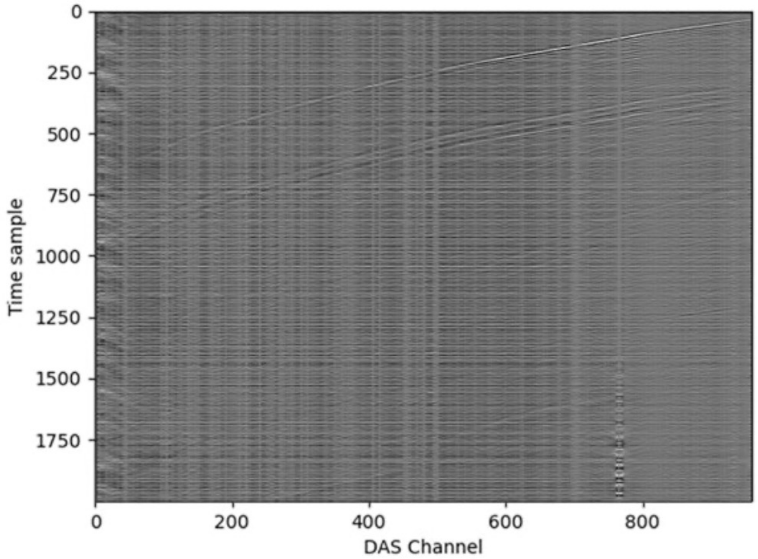
Background of Phase I of the project

Accomplishments:

- Build up a deep learning workflow for the borehole DAS data
- Better performance compared to the F-K technique

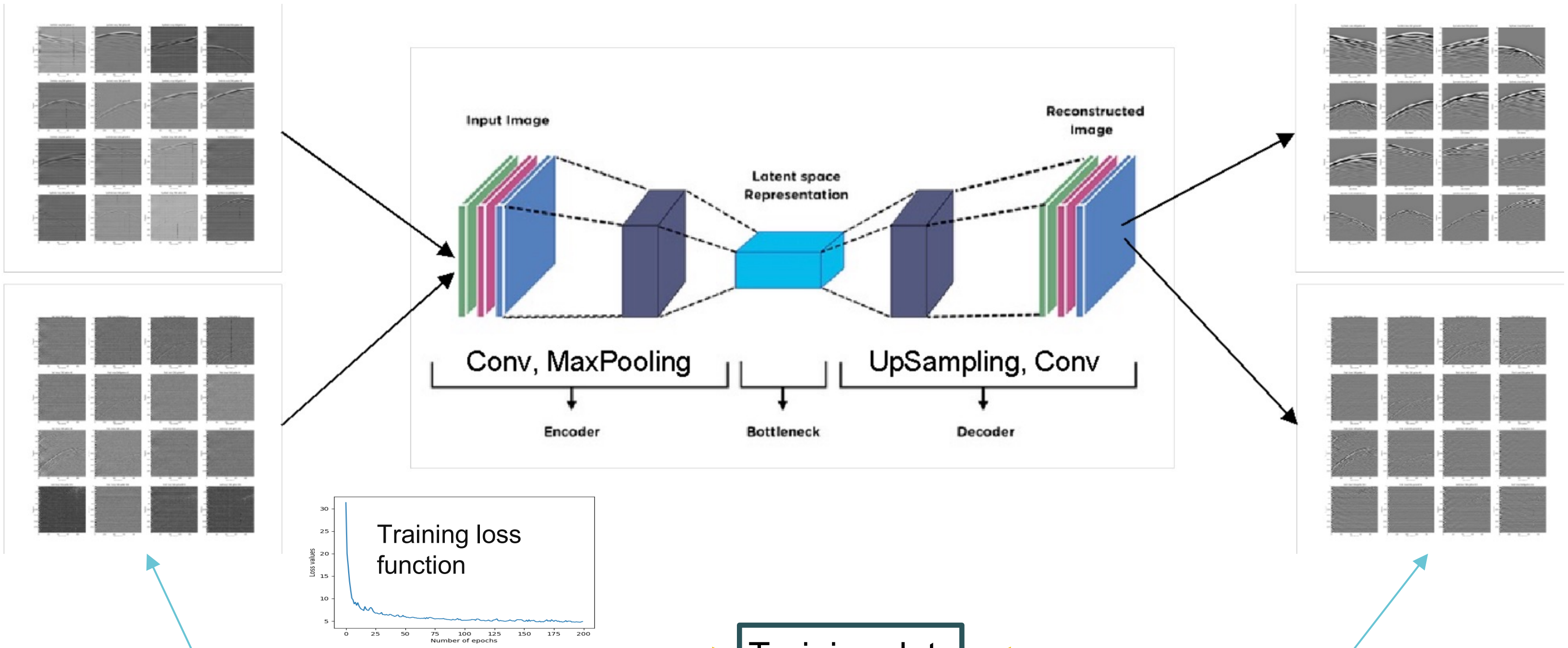


NN Predictions



F-K filtered

Autoencoder DAS denoising neural network



Training data

Raw field DAS data
Synthesized DAS data + field noise

Clean field DAS data
Synthesized DAS data

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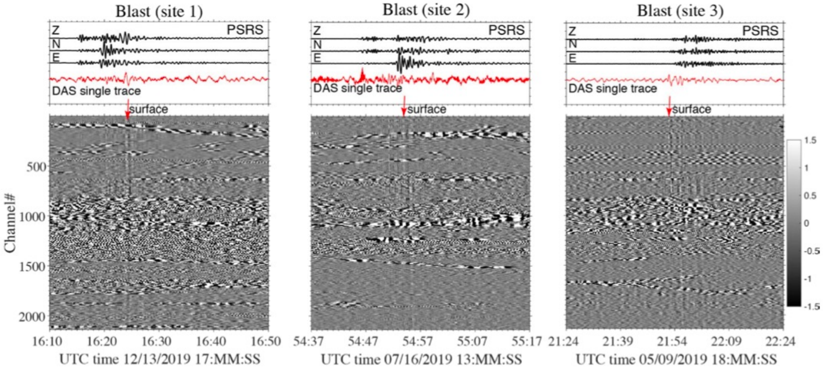
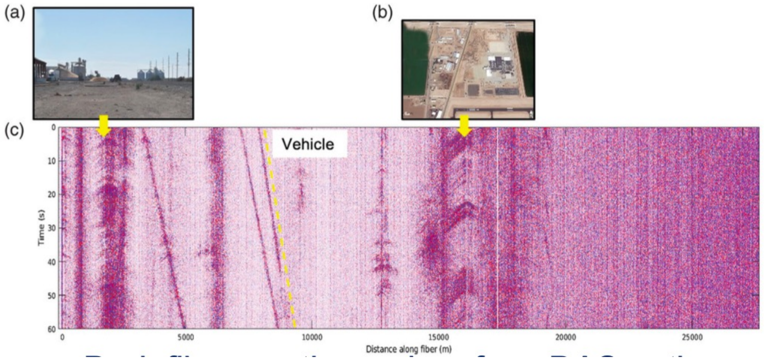
Major Problems to address for the DAS denoising process in Phase II

- Expand the training dataset to improve the prediction ability of the deep learning models for the borehole dataset.
- Compared to the borehole DAS data, the surface DAS data is much noisier. We extend the autoencoder DAS denoising neural network to surface DAS data.



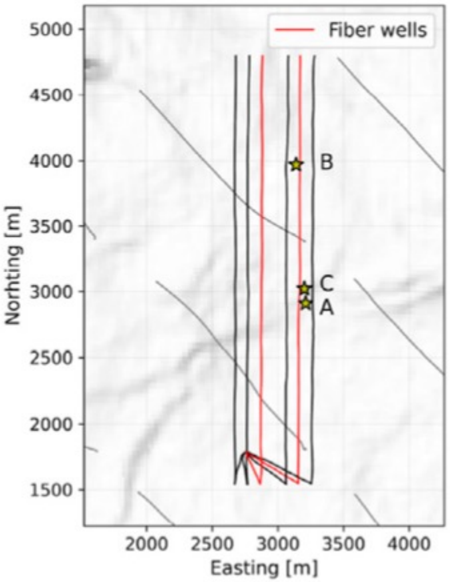
surface DAS gather (Zhu et al., 2021)



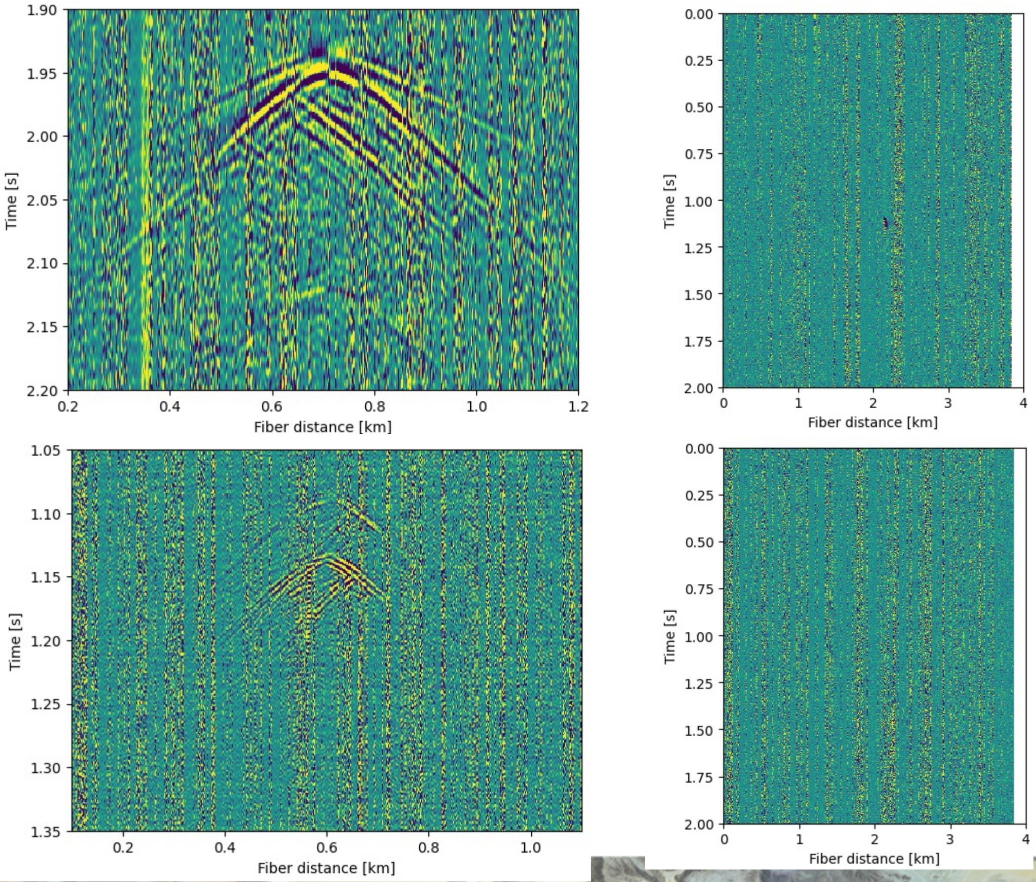
Dark fiber surface DAS gather (Ajo-Franklin et al., 2022)

Expanding the Borehole training dataset

Denver-Julesburg Basin Borehole DAS gathers



(Stanek et al., 2022)



Event A

Event B

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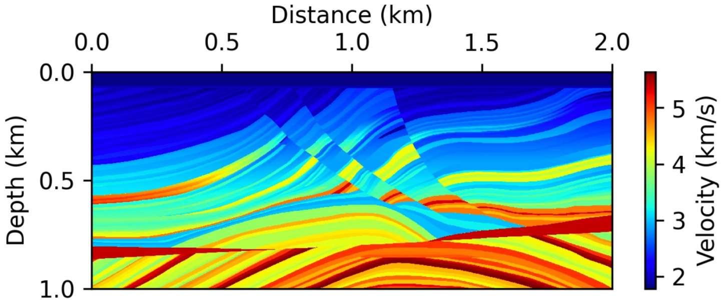
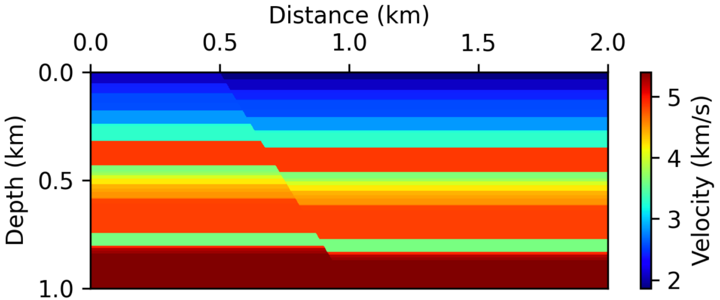
Expanding the Borehole training dataset

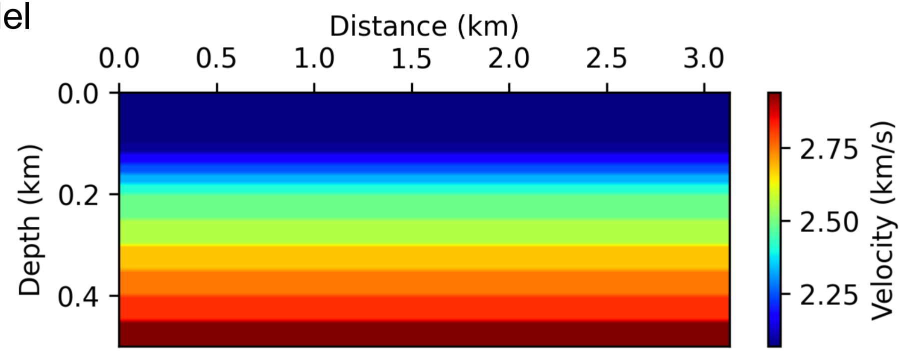
Synthesized borehole data (increase from 36 to 120)



Marmousi model



Fault model



Layered model

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Quantitatively estimate the denoising effect

Peak Signal-to-noise Ratio (PSNR)

- PSNR is a metric that can systematically identify whether a particular method produces better denoising results compared to other approaches.

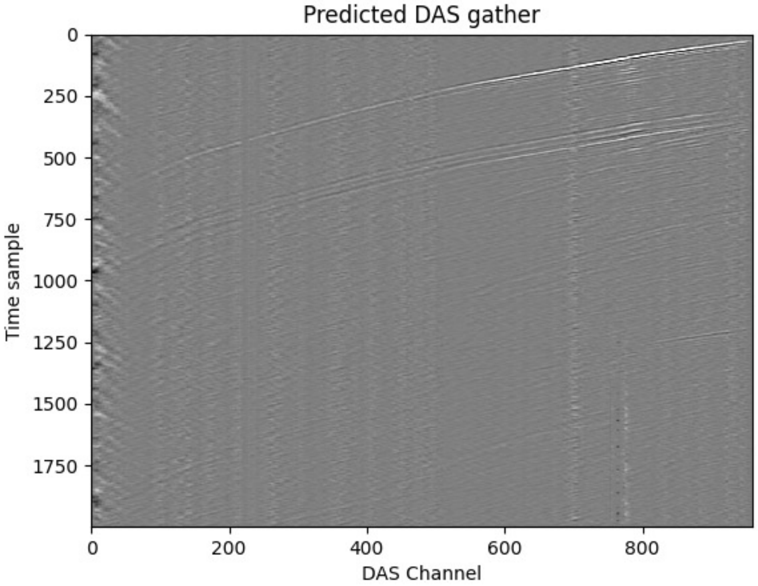
$$PSNR = 20\log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right)$$

where

$$MSE = \frac{1}{mn}\sum_{0}^{m-1}\sum_{0}^{n-1}\|f(i,j) - g(i,j)\|^2$$

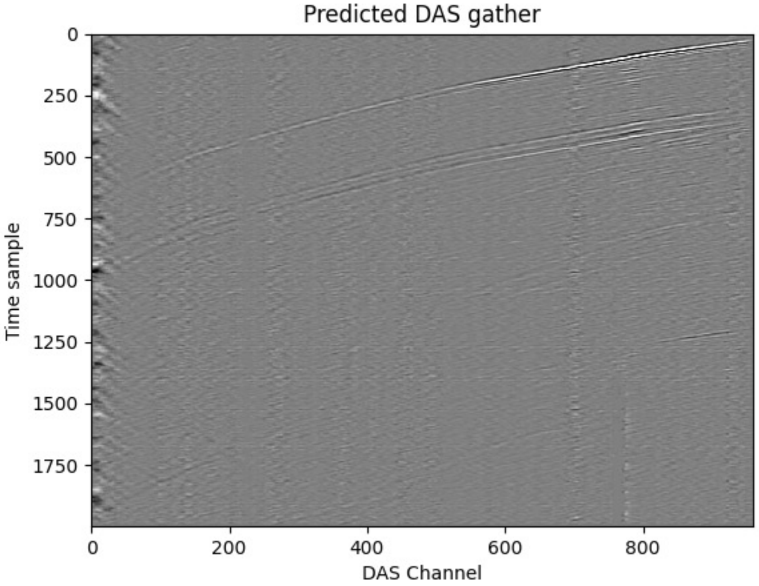
Comparison among the borehole predictions

PSNR = 5.05



Phase I

PSNR = 5.09



Phase I + Denver + Extended synthesized Borehole data

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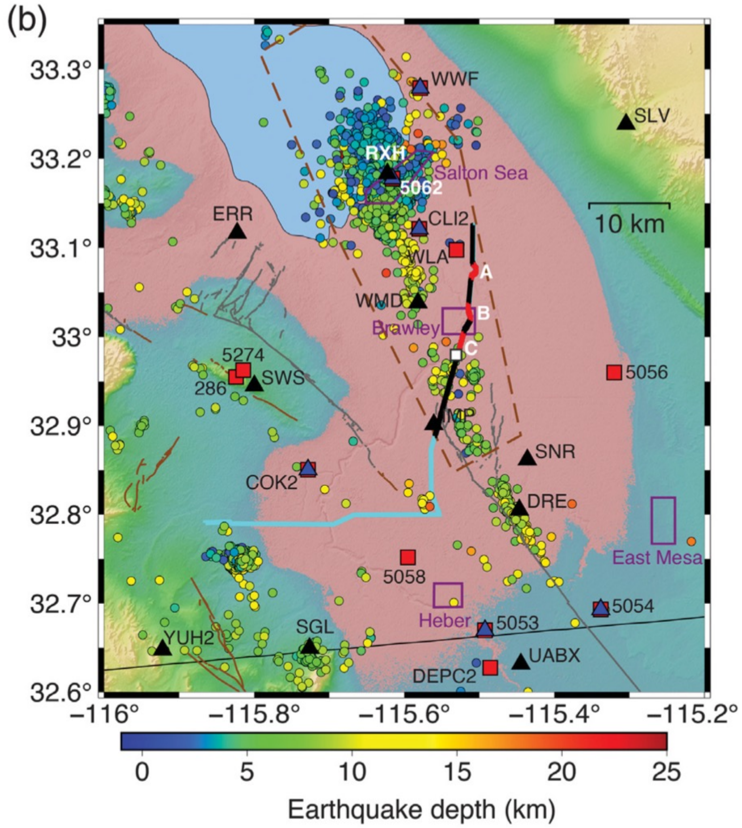
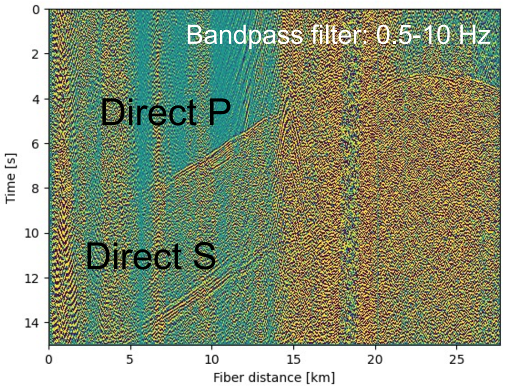
Surface training dataset

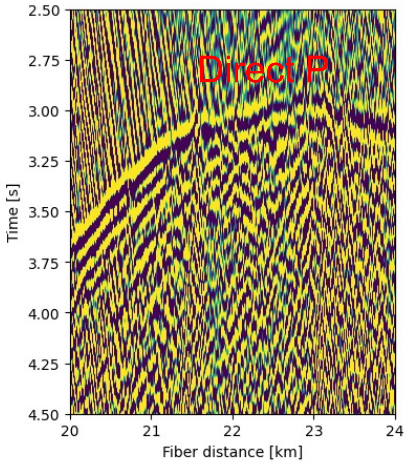
Imperial Valley Dark Fiber, CA

160 events selected



(Ajo-Franklin et al, 2018)





Clip the data to be the input of ML model

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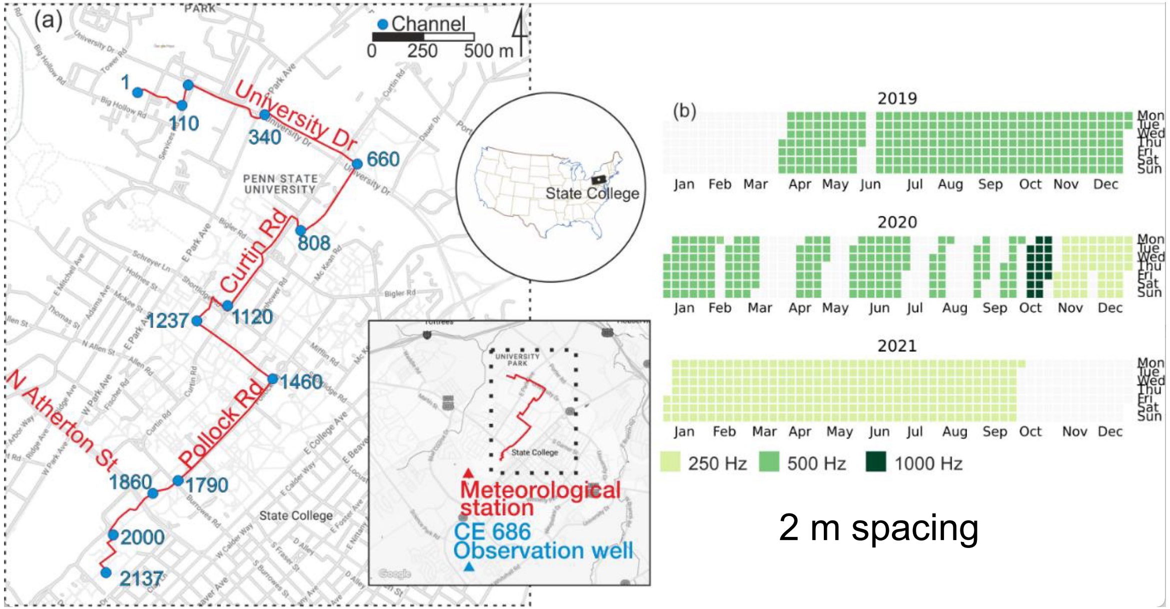
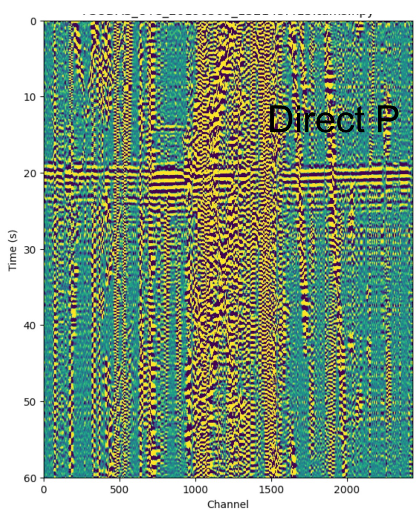
Surface training dataset

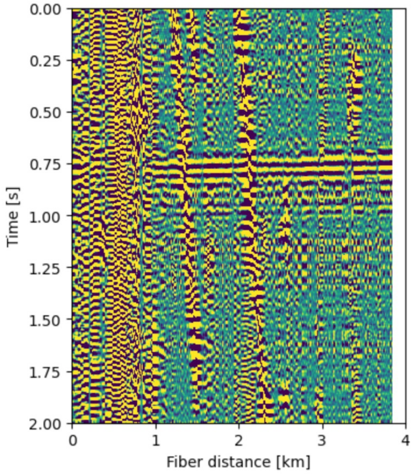
FORESEE Blasts, PA (20 events selected)



2 m spacing

(Zhu et al, 2022)





Clip the data to be the input of ML model

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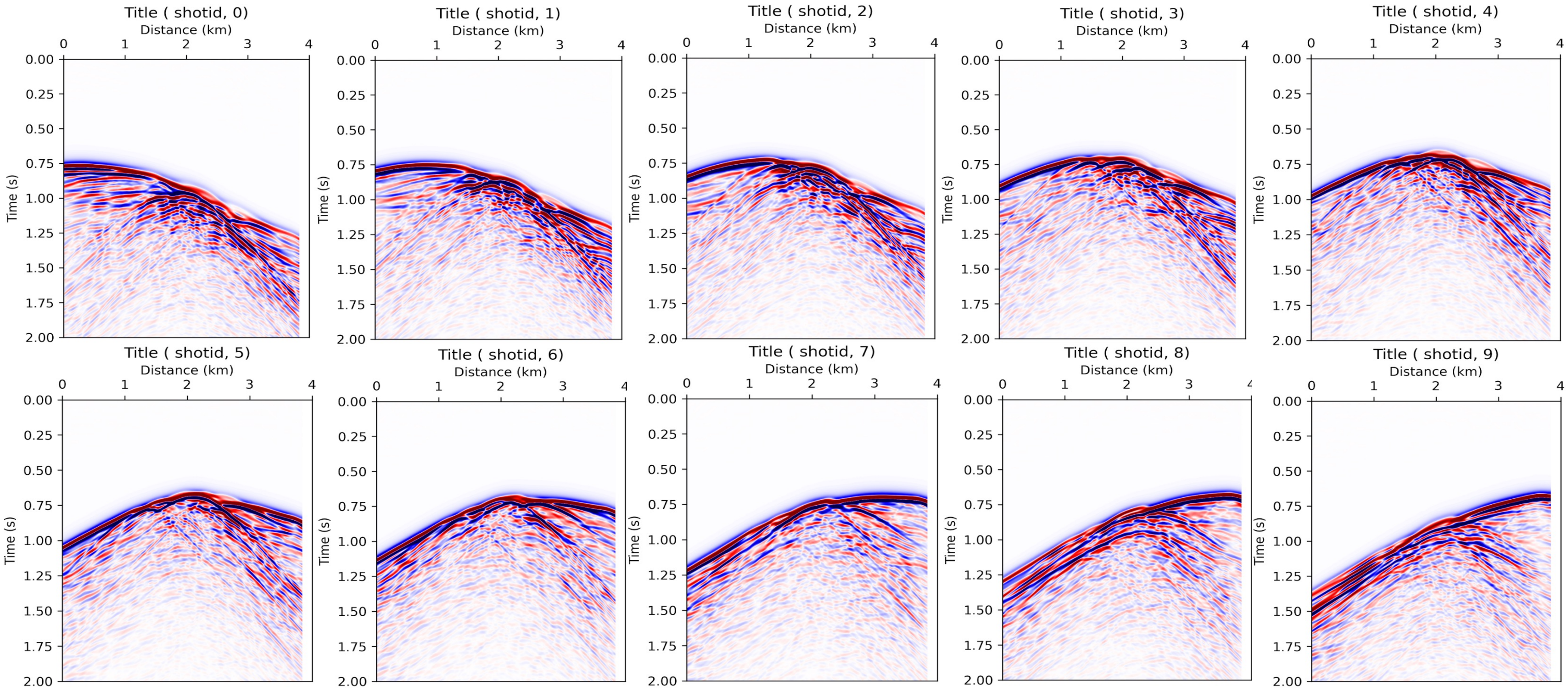
Surface training dataset

Synthesized Surface DAS gathers

(160 events synthesized)



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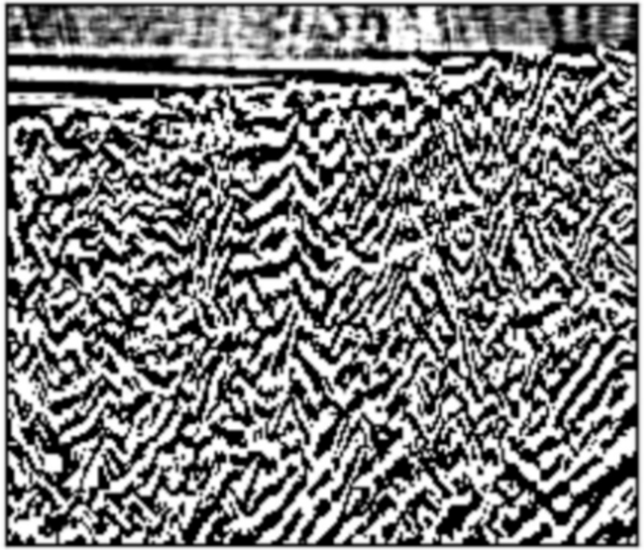
Examples: 20 Hz for shallow sources at ~1.9 km depth

Comparison of the Predictions

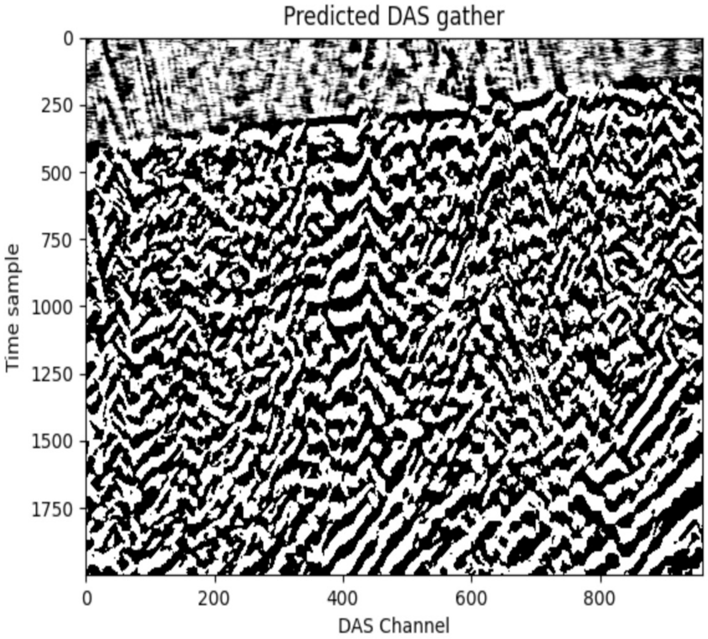
Example 1:

PSNR = 4.26



Traditional denoising workflow

PSNR = 5.25

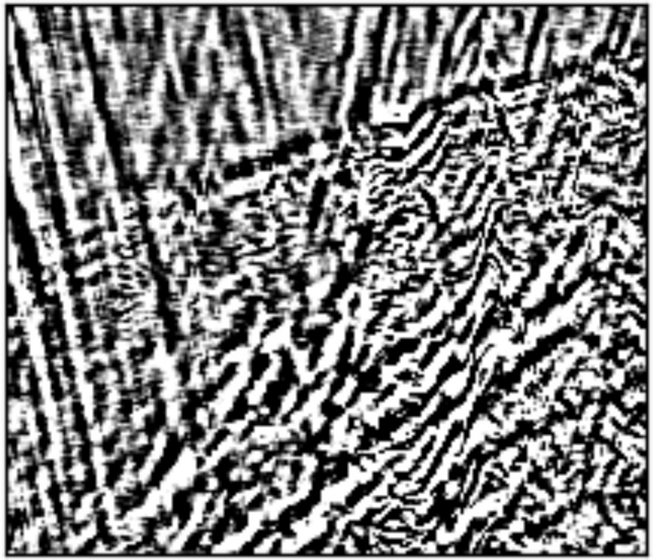


Prediction from the surface deep learning model

Comparison of the Predictions

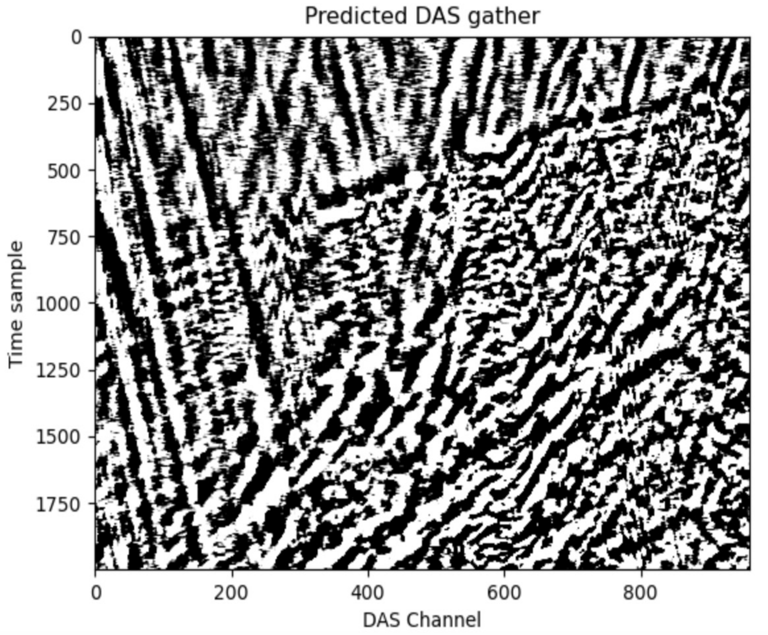
Example 2:

PSNR = 4.27



Traditional denoising workflow

PSNR = 6.47



Prediction from the surface deep learning model

Summary

- We basically accomplish the tasks related to objective 1
    - Expand the training dataset for the borehole deep learning denoising model
    - Assemble and label a training dataset for the surface DAS denoising DL model
    - Evaluation of the predictions from both borehole and surface DL models show the superior of the DL models compared to the industrial standard tool (FK filter).

Lessons learned

- The more the high-quality training dataset, the better the denoising DL model works.

- It is essential to add new data into the training dataset step by step.

Further Work

- Keep adding more field and synthesized data into the training dataset to make the DL models being a general denoising tool

- Work on tasks in Objective 2: Monitoring induced seismicity using denoised DAS data

- Work on tasks in Objective 3: Building carbon storage DAS array design tool

Detailed Tasks

Tasks for objective 1

- 1.1: Large DAS data store and management
- 1.2: Surface DAS seismic data collection
- 1.3: Seismic detection from surface DAS data
- 1.4: Surface DAS seismic events labeling
- 1.5: Synthetic surface DAS waveform generation
- 1.6: DAS denoising neural network optimization
- 1.7: Surface and borehole DAS denoising neural network training, testing, and evaluating

Tasks for objective 2

- 2.1 Small-magnitude seismicity events detection the denoised DAS datasets
- 2.2: Source imaging on the denoised DAS data to locate the detected seismicity events
- 2.3: Quantifying the magnitude of seismicity on DAS dataset
- 2.4: Case study on field DAS survey

Tasks for objective 3

- 3.1: Carbon storage generic synthetic model building
- 3.2: Developing APP for DAS geometry design
- 3.3: Forward modeling with designed DAS geometry on the model to generate synthetic DAS gathers
- 3.4: Rating the designed DAS survey geometries by evaluating imaging and inversion quality
- 3.5: Applying the developed tool for DAS array design in the selected carbon storage site

Thank you!