

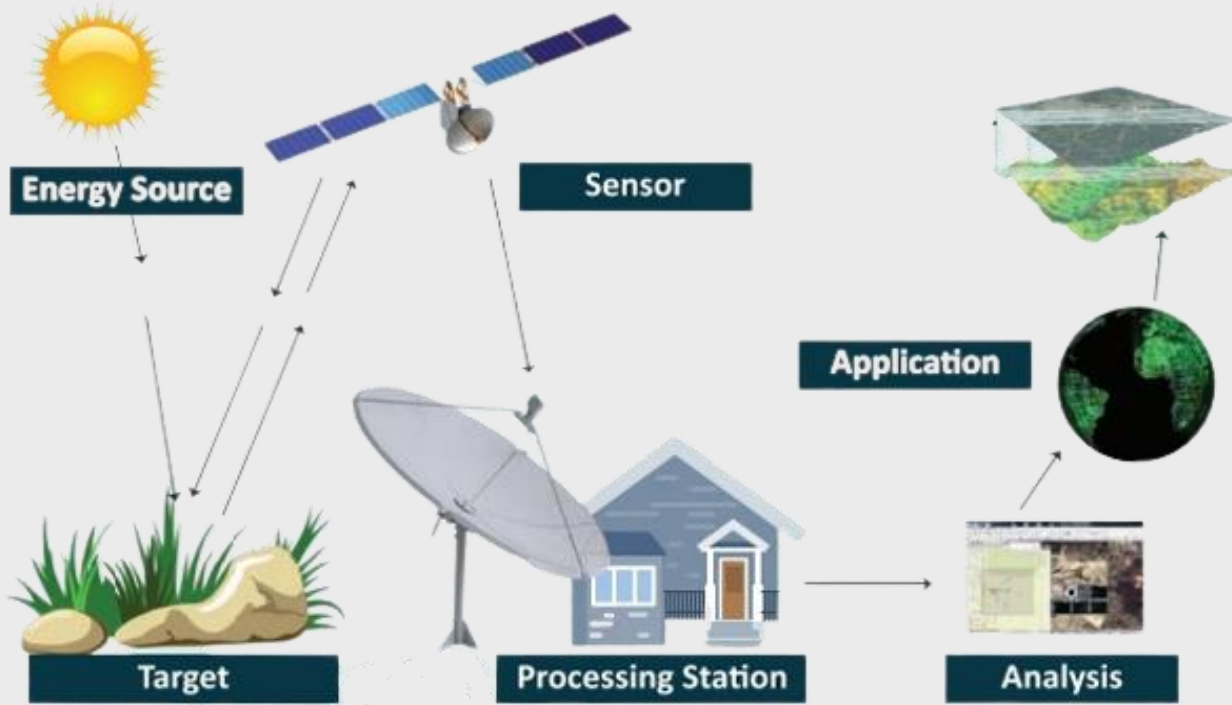
Seismic Imaging with Remote Sensing for Energy Applications

Naveed Akram, Liang Tian, Jiahua Zhao
Rocco Sedona, Gabriele Cavallaro, Eric Verschuur, Nikos Savva
Task 4.2

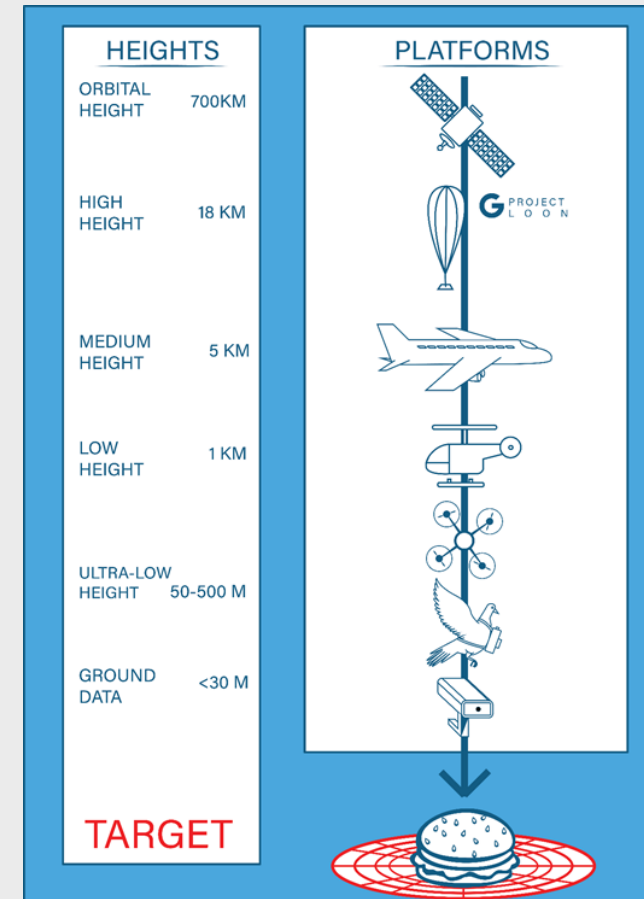
- Remote sensing principles; production of land cover maps
- Seismic imaging principles; 2D seismic imaging
- Integration of remote sensing to constrain seismic imaging: near surface
- Future works

Remote (without physical contact) Sensing (measurement of information)

- Measure radiation of different wavelengths reflected or emitted from distant objects

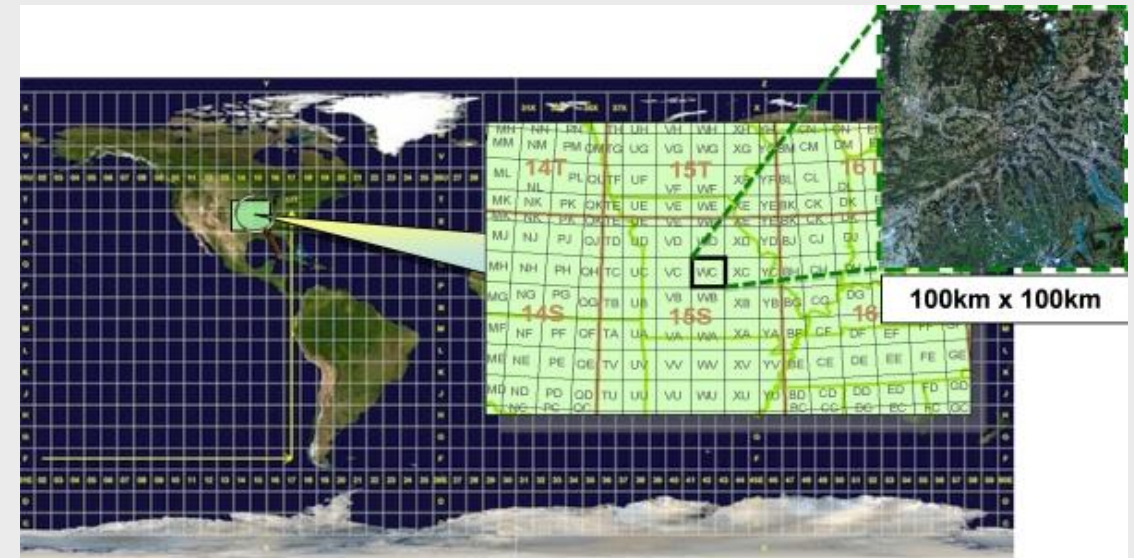


Elements of Remote Sensing, https://www.brainkart.com/article/Elements-of-Remote-Sensing_41124/

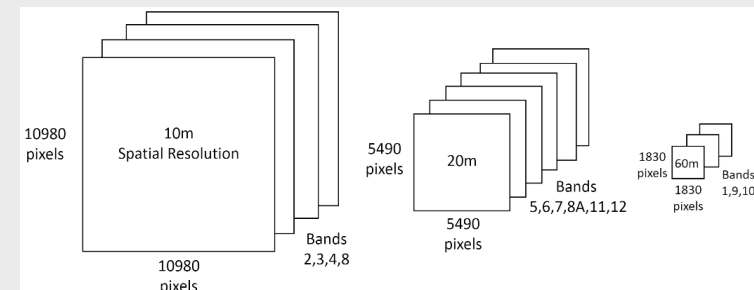


Earth Observation Mission: Copernicus Sentinel-2

- Twin polar-orbiting satellites with temporal resolution of 5 days
- Open data policy



<https://sentinels.copernicus.eu/>



Workflow in Earth Observation



DEEP CPU

JURECA GPU



DEEP supercomputer



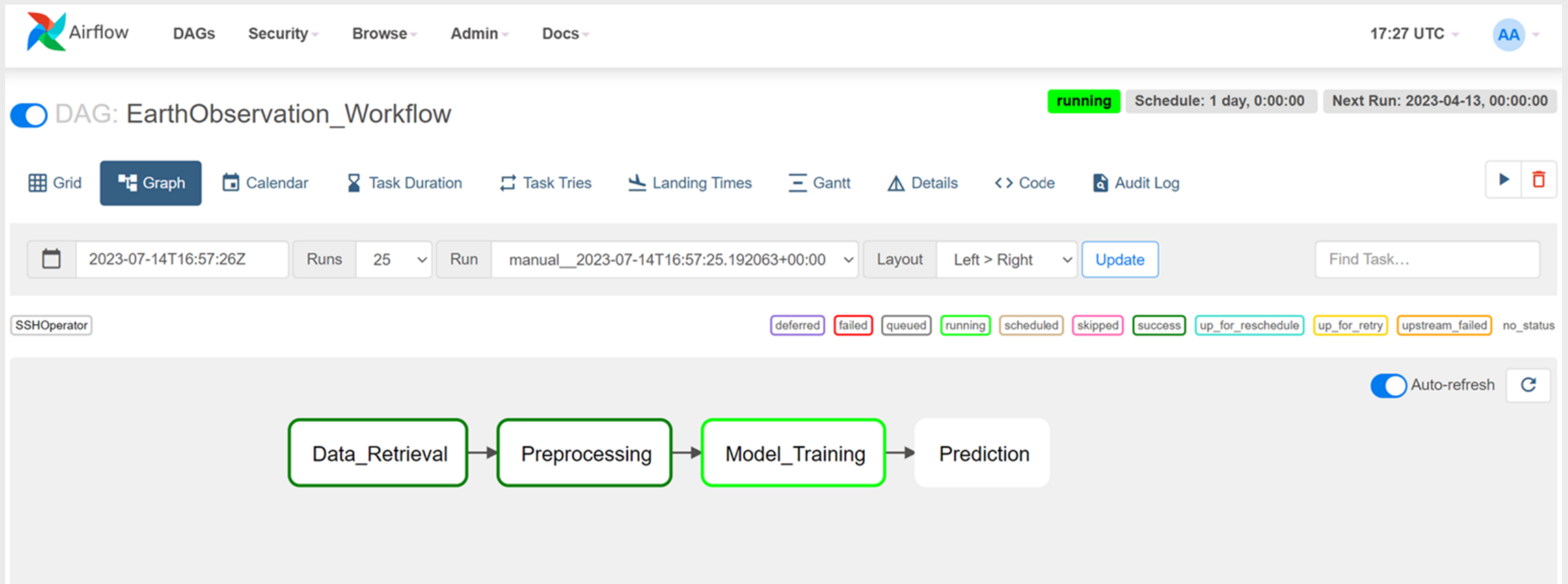
JURECA supercomputer

- Features of Apache Airflow
 - Open-source platform
 - Python based
 - Scheduling capabilities
 - Monitoring
 - Scalability



Workflow management with Apache Airflow

- Check the dependency of subtasks



The screenshot displays the Apache Airflow web interface for a DAG named "EarthObservation_Workflow". The interface shows the DAG is currently in a "running" state, with a schedule of "1 day, 0:00:00" and a next run scheduled for "2023-04-13, 00:00:00". The DAG is visualized as a linear sequence of four tasks: "Data_Retrieval", "Preprocessing", "Model_Training", and "Prediction". The first three tasks are highlighted with green borders, indicating they are currently running or have completed successfully. The interface includes navigation tabs (Grid, Graph, Calendar, Task Duration, Task Tries, Landing Times, Gantt, Details, Code, Audit Log) and a legend for task statuses (deferred, failed, queued, running, scheduled, skipped, success, up_for_reschedule, up_for_retry, upstream_failed, no_status). The "Auto-refresh" toggle is also visible.

Workflow management with Airflow

➤ Monitor the process

DAGs

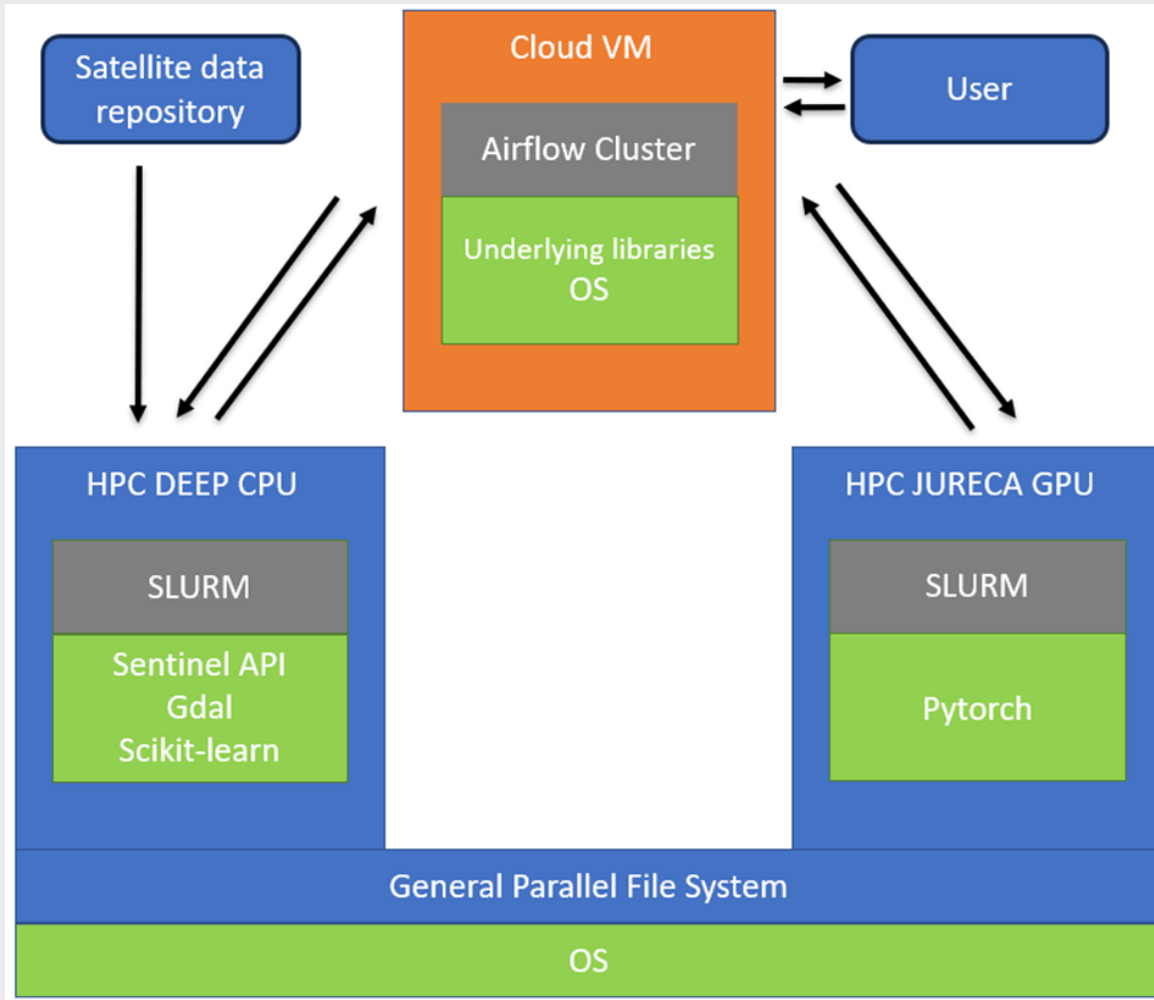
All 9 Active 7 Paused 2

Filter DAGs by tag

Search DAGs

DAG	Owner	Runs	Schedule	Last Run	Next Run	Recent Tasks	Actions	Links
<input checked="" type="checkbox"/> steps	liang	● ● ●	1 day, 0:00:00		2023-03-30, 00:00:00	● ● ●		...
<input type="checkbox"/> study_tutorial_1		● ● ●	1 day, 0:00:00			● ● ●		...
<input type="checkbox"/> test1	enxhi	● ● ●	1 day, 0:00:00		2023-03-24, 00:00:00	● ● ●		...
<input checked="" type="checkbox"/> test_date_23	enxhi	● ● ●	1 day, 0:00:00		2023-03-30, 00:00:00	● ● ●		...
<input checked="" type="checkbox"/> test_date_24	enxhi	● ● ●	1 day, 0:00:00		2023-03-30, 00:00:00	● ● ●		...
<input checked="" type="checkbox"/> test_date_25	enxhi	● ● ●	1 day, 0:00:00		2023-03-30, 00:00:00	● ● ●		...
<input checked="" type="checkbox"/> test_date_hourly	enxhi	● ● ●	1 day, 0:00:00		2023-03-30, 00:00:00	● ● ●		...
<input checked="" type="checkbox"/> test_date_none	enxhi	● ● ●	1 day, 0:00:00		2023-03-30, 00:00:00	● ● ●		...
<input checked="" type="checkbox"/> test_date_once	enxhi	● ● ●	1 day, 0:00:00		2023-03-30, 00:00:00	● ● ●		...

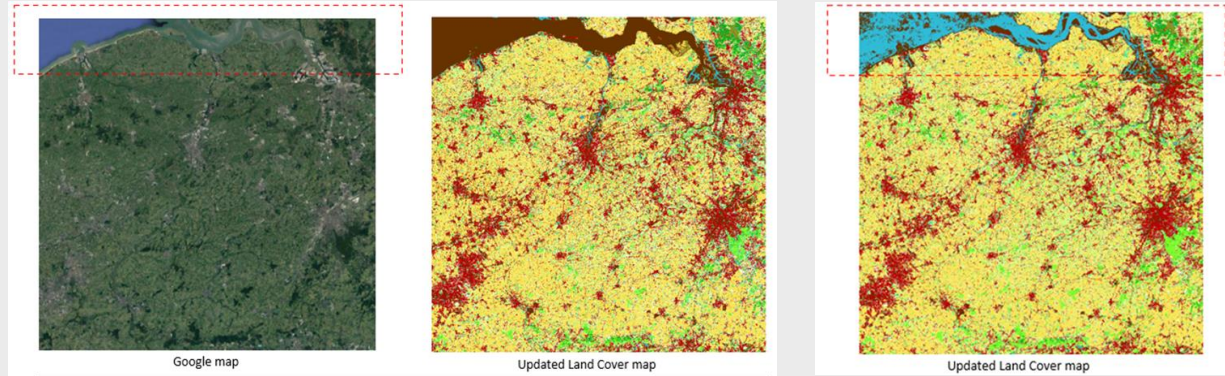
Scalable Workflow with Airflow



Airflow integrated with HPC systems



Production of Land Cover Maps



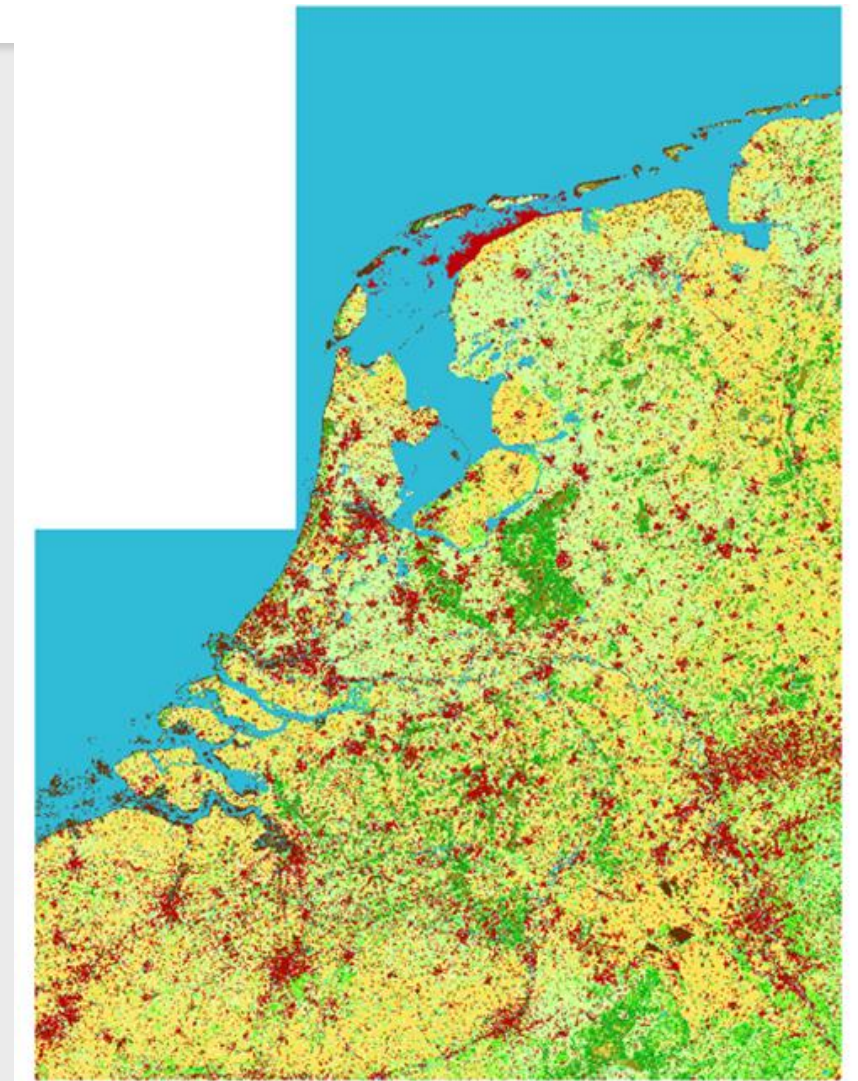
Legend			
	Artificial Land		Rice fields
	Conifers		Bareland
	Grassland		Shrubland
	Cropland		Broadleaves
	Lake		Lagoon
	Snow		

Production time
1.5 h vs. 14 h (without HPC)

➤ Validation with street-level crowdsourcing geo-tagged images



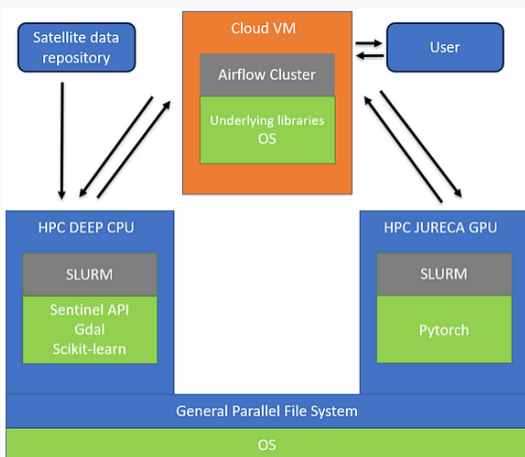
<https://land.copernicus.eu/imagery-in-situ/lucas/lucas-2018>



Earth Observation Data Workflows with Apache Airflow

This repository presents a scalable and parallelizable workflow using Apache Airflow, capable of integrating Machine Learning (ML) and Deep Learning (DL) models with Modular Supercomputing Architecture (MSA) systems [6]. To test the workflow, we considered the production of large-scale Land-Cover (LC) maps as a case study. It can generate LC maps based on Sentinel-2 data using ML and DL algorithms combined with High-Performance Computing (HPC) technology.

The workflow manager, Airflow, offers scalability, extensibility, and programmable task definition in Python. It allows us to execute different steps of the workflow in different HPC systems, leading to efficient utilization of available computing resources on the HPC machine. The workflow is demonstrated on the Dynamical Exascale Entry Platform (DEEP) and Jülich Research on Exascale Cluster Architectures (JURECA) hosted at the Jülich Supercomputing Centre (JSC), a platform that incorporates heterogeneous JSC systems.



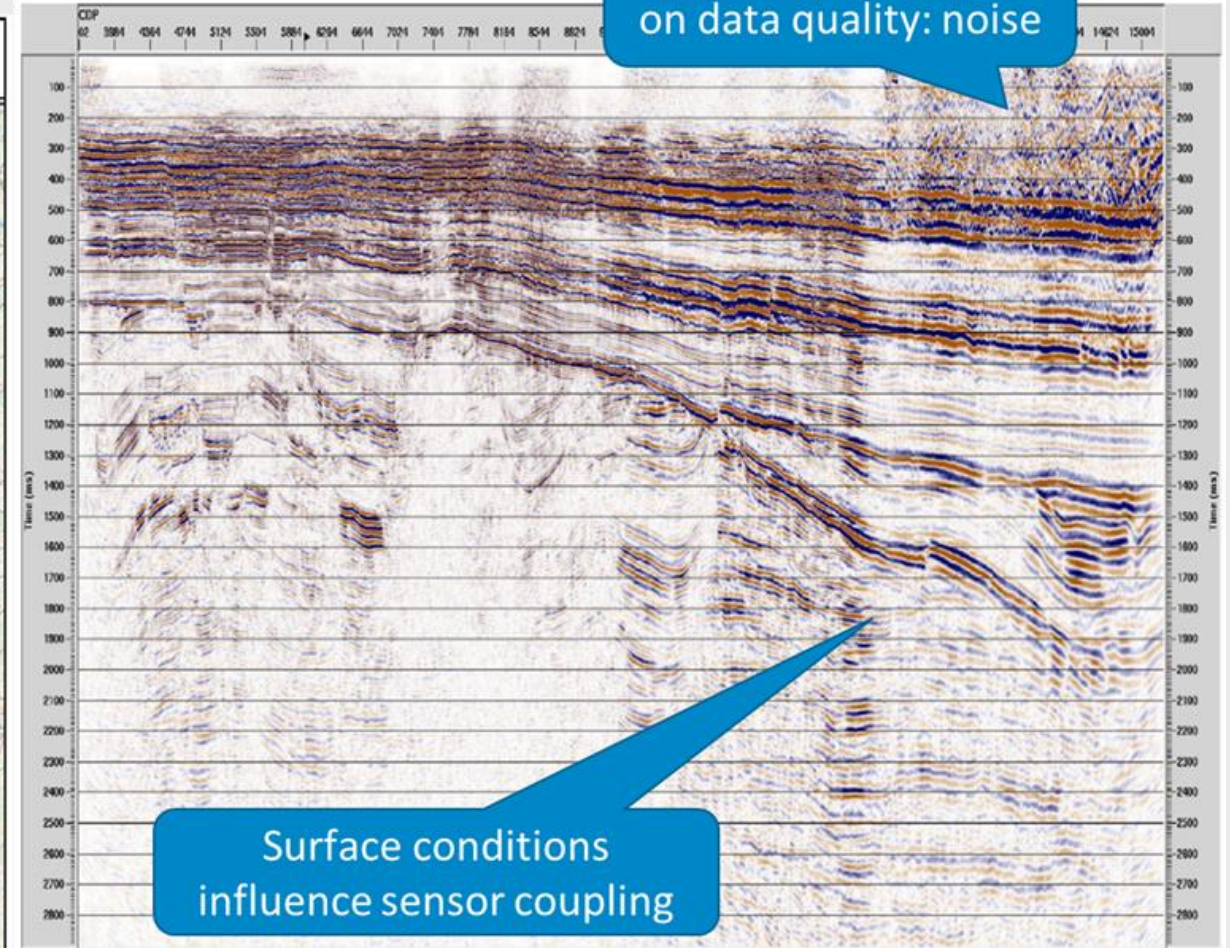
[GIT Repository](#)

File	Commit Message	Time
code	Add code of the workflow step 2 to step 5	1 minute ago
README.md	Update README.md	yesterday

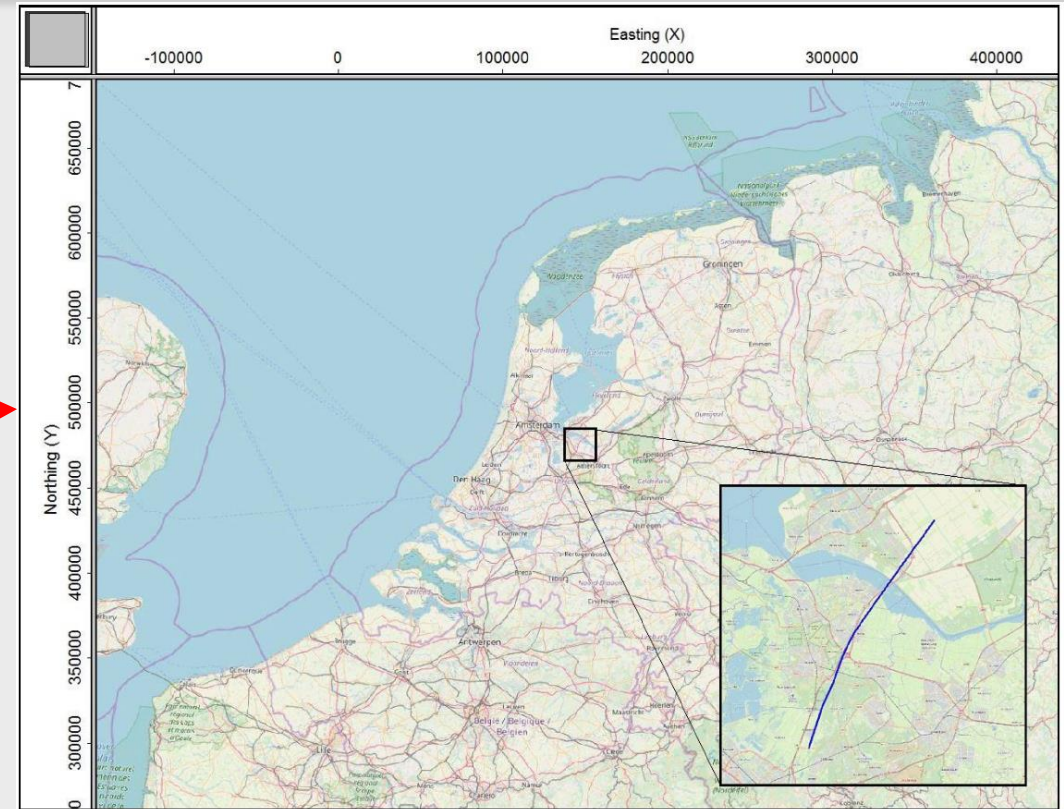
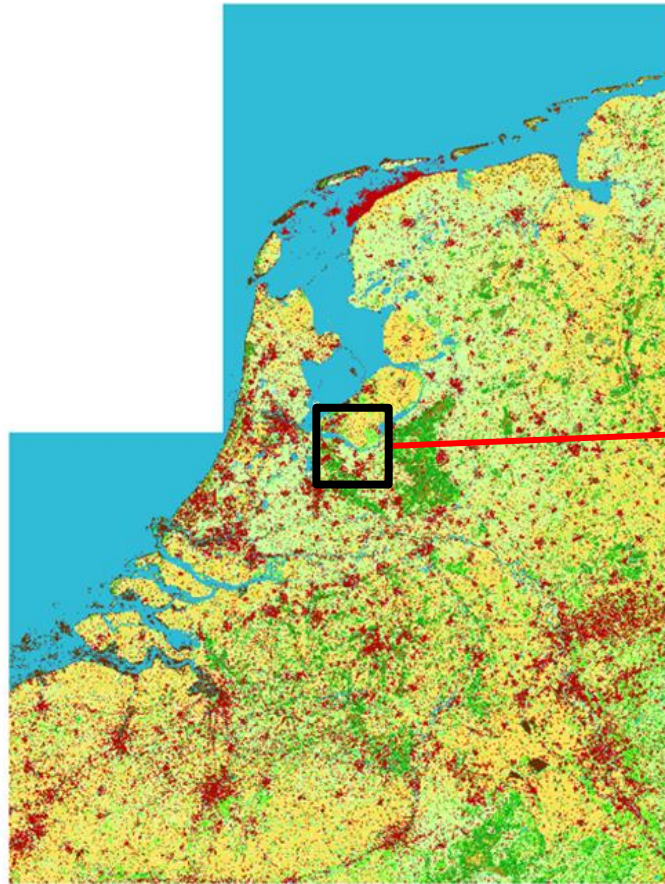
EO-Workflow-with-Airflow

This repository proposes an automated earth observation workflow that generates the Land Cover maps based on Sentinel-2 data using Machine Learning and Deep Learning algorithms combined with High Performance Computing technology. With the demonstration of Apache Airflow, tasks can be distributed across multiple HPC resources, leading to efficient utilization of available computing resources on the HPC machine.

Working on: Linking Remote Sensing with Seismic imaging



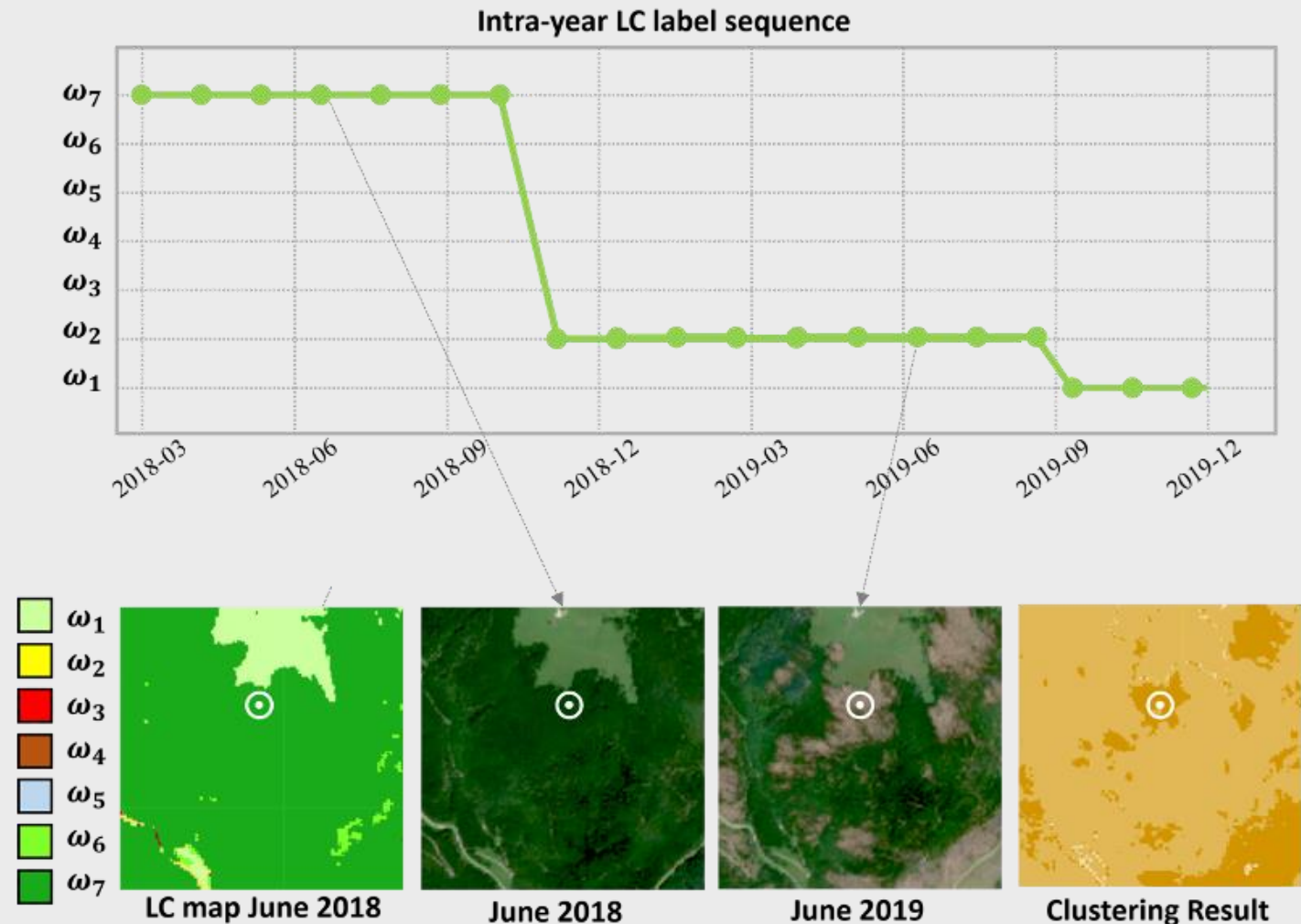
Working on: Linking Remote Sensing with Seismic imaging



- Extract LC information along the seismic record line
- Data of 2018 as a start
- Accurate validation

Multi-temporal Land Cover Maps

- Transformer with local attention mask can detect changes throughout time
- Inference: mask with sliding window
 - stride of 1 acquisition



Multi-temporal Land Cover Maps

- Rule based approach to disentangle:
 - Stable component
 - Seasonal component
 - Abrupt changes

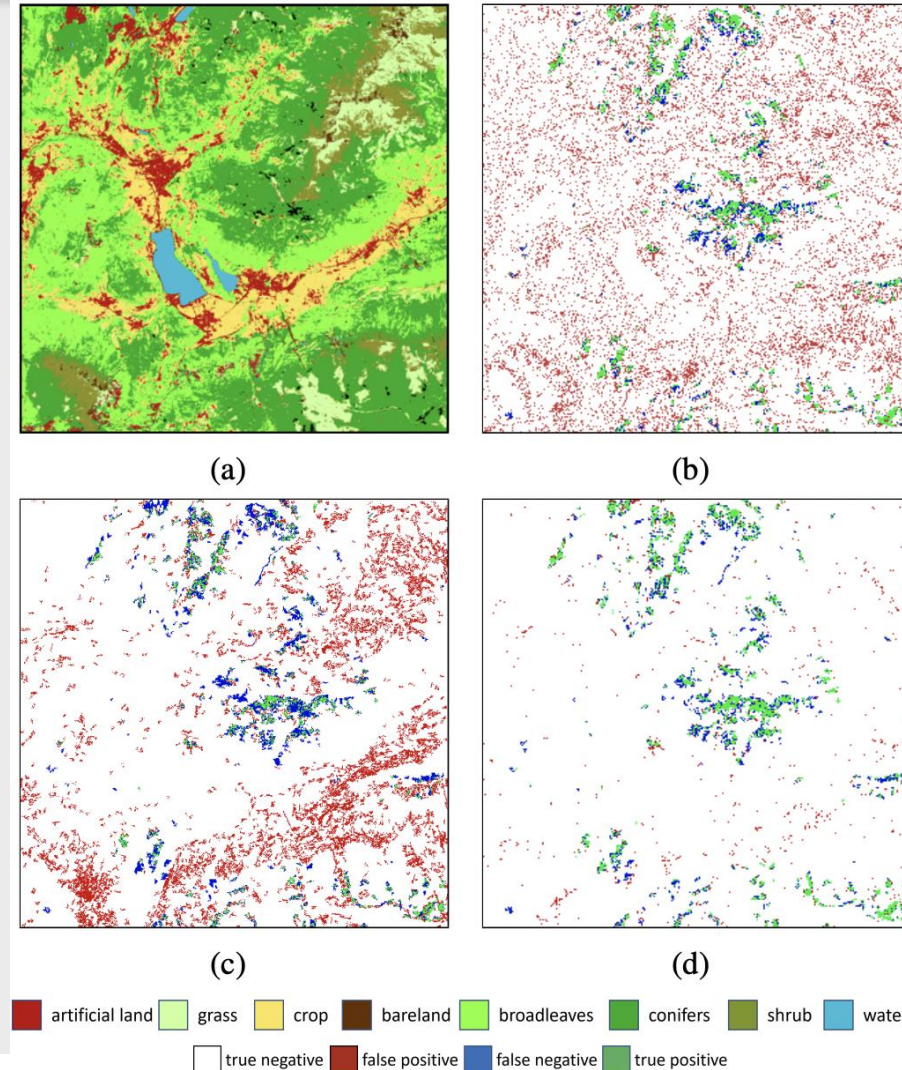
- (a) Predicted land cover map
- (b) RF: detected change
- (c) Transformer: detected change
- (d) PM: detected change

Detected abrupt change

- Estimated date of change can be extracted

	precision	recall	F1 score	IoU
RF	0.20	0.67	0.30	0.18
Transformer	0.13	0.75	0.22	0.13
PM	0.72	0.59	0.65	0.48

RF: Random forest
PM: Proposed method (ours)



Multi-temporal Land Cover Maps

- Use a solid baseline land cover map
- Add change
- Increased consistency
- Better detection of abrupt changes (validation with reference ground truth)

Multi-year agreement

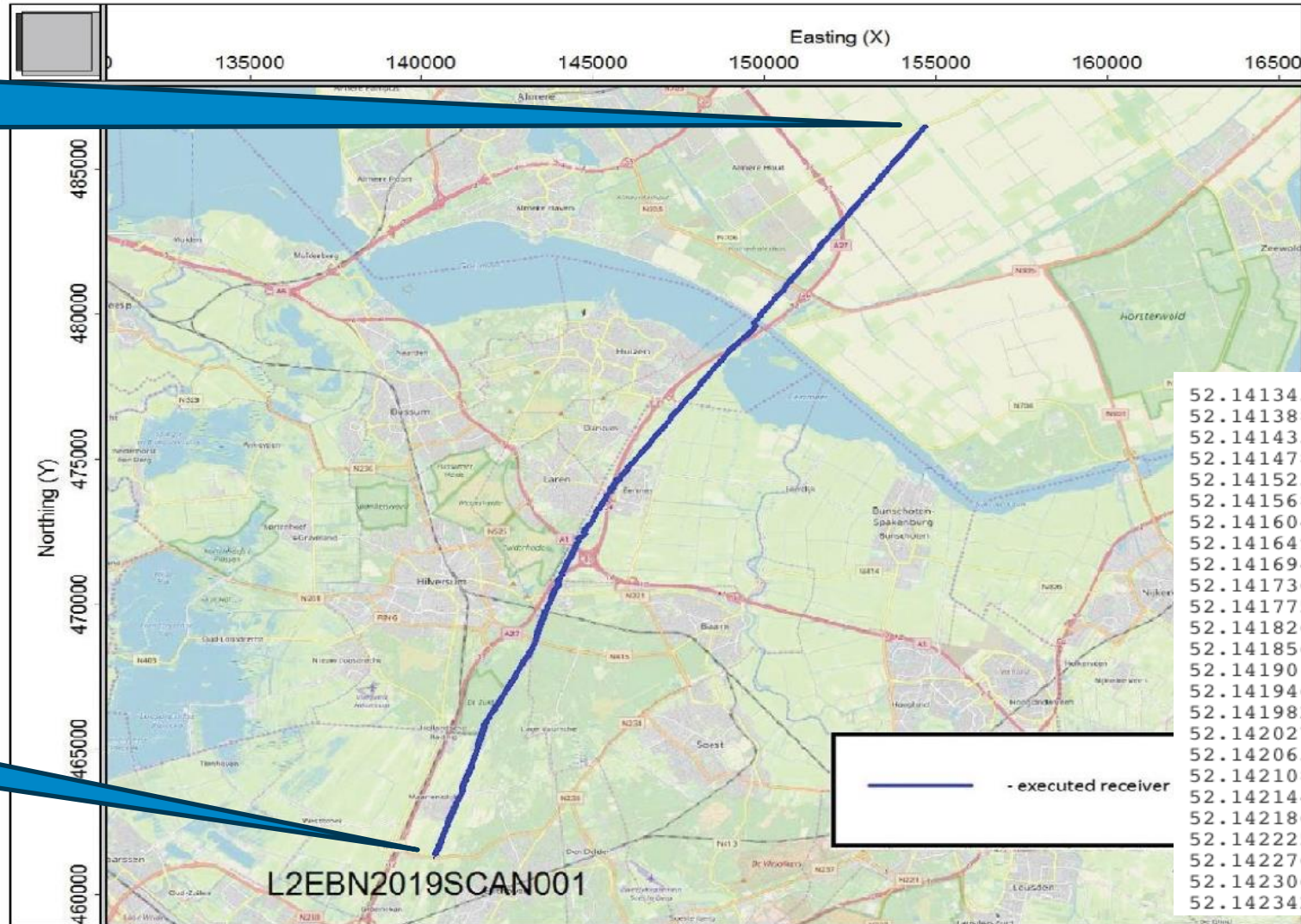
RF: Random forest
PM: Proposed method (ours)

Class	RF			Transformer			PM		
	2018-2019	2019-2020	2018-2020	2018-2019	2019-2020	2018-2020	2018-2019	2019-2020	2018-2020
Artificial land	85.4	83.1	80.3	79.3	88.0	84.4	100	100	100
Grass	87.5	79.6	79.6	84.7	52.7	62.6	100	100	100
Crop	88.0	85.1	81.2	79.3	77.8	74.2	99.9	99.9	99.9
Bareland	70.5	73.4	58.3	72.7	46.4	46.4	99.8	98.8	98.7
Broadleaves	88.1	90.5	82.8	79.6	88.1	87.3	99.9	99.8	99.7
Conifers	87.0	86.9	79.0	88.3	83.0	84.6	97.5	95.5	93.1
Shrub	74.3	81.8	66.7	45.0	62.8	64.6	99.9	99.9	99.9
Water	97.2	97.7	96.4	93.4	78.1	80.1	99.9	99.9	99.9
Overall	86.6	86.7	79.9	80.4	80.3	81.2	99.1	98.5	97.7

Linking Remote Sensing with Seismic Imaging

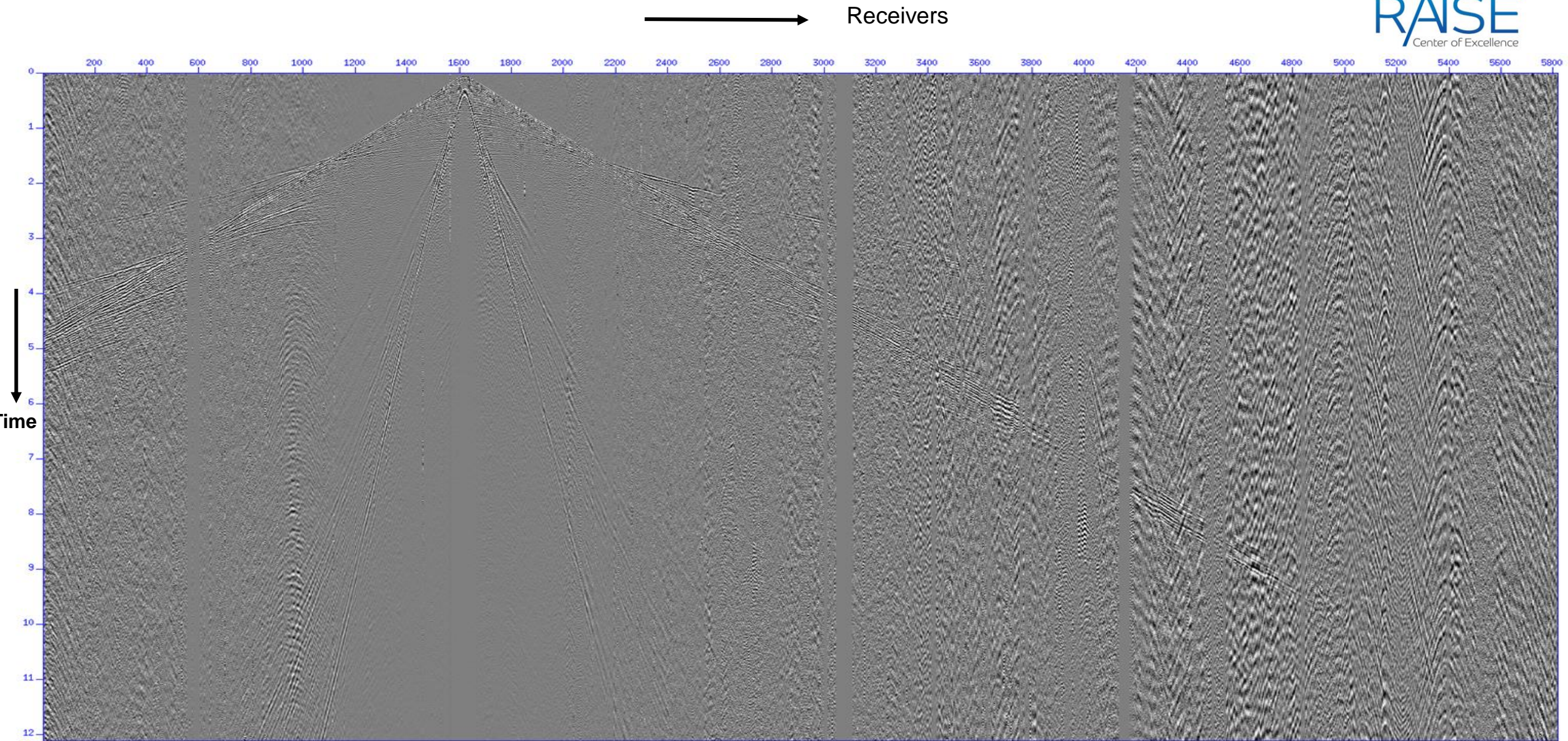
Last receiver number=7617, total 5817 receivers per shot record
Total shots= 1355

Coordinate conversion:
seismic coordinate system to global coordinate system
Line length: 29 km
R/S interval: 5/20 m



First receiver number = 1800

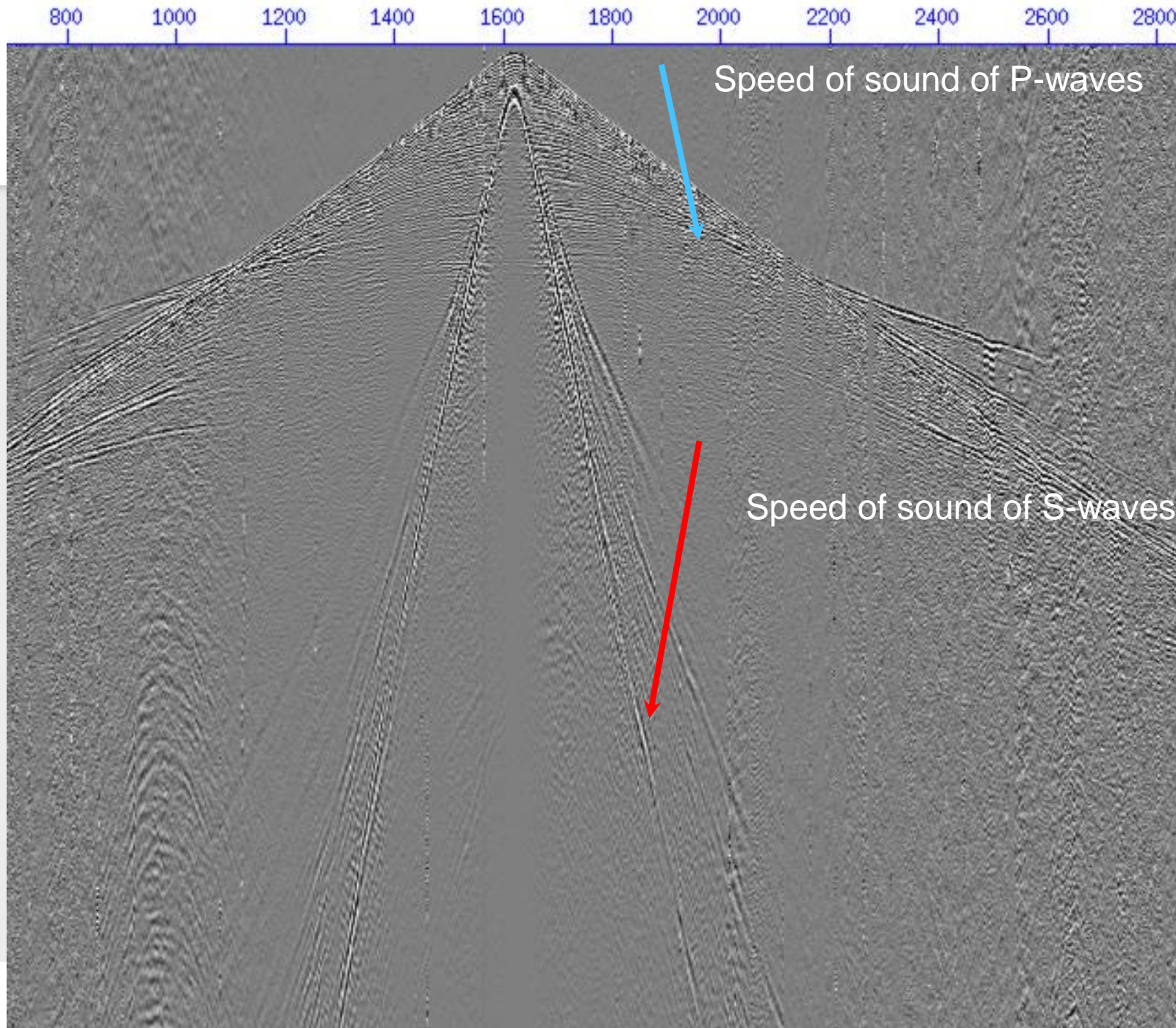
52.1413432031	5.1746851781	1.0000000000
52.1413881743	5.1746995735	1.0000000000
52.1414331454	5.1747139690	1.0000000000
52.1414781429	5.1747429742	1.0000000000
52.1415231141	5.1747573698	1.0000000000
52.1415681116	5.1747863751	1.0000000000
52.1416041201	5.1748154234	1.0000000000
52.1416490912	5.1748298191	1.0000000000
52.1416940887	5.1748588246	1.0000000000
52.1417300709	5.1748732631	1.0000000000
52.1417750420	5.1748876589	1.0000000000
52.1418200395	5.1749166645	1.0000000000
52.1418560480	5.1749457131	1.0000000000
52.1419010191	5.1749601089	1.0000000000
52.1419460166	5.1749891148	1.0000000000
52.1419820250	5.1750181635	1.0000000000
52.1420270488	5.1750617794	1.0000000000
52.1420630573	5.1750908283	1.0000000000
52.1421080810	5.1751344444	1.0000000000
52.1421440895	5.1751634933	1.0000000000
52.1421801243	5.1752071523	1.0000000000
52.1422251216	5.1752361586	1.0000000000
52.1422701453	5.1752797750	1.0000000000
52.1423061801	5.1753234342	1.0000000000
52.1423421885	5.1753524834	1.0000000000



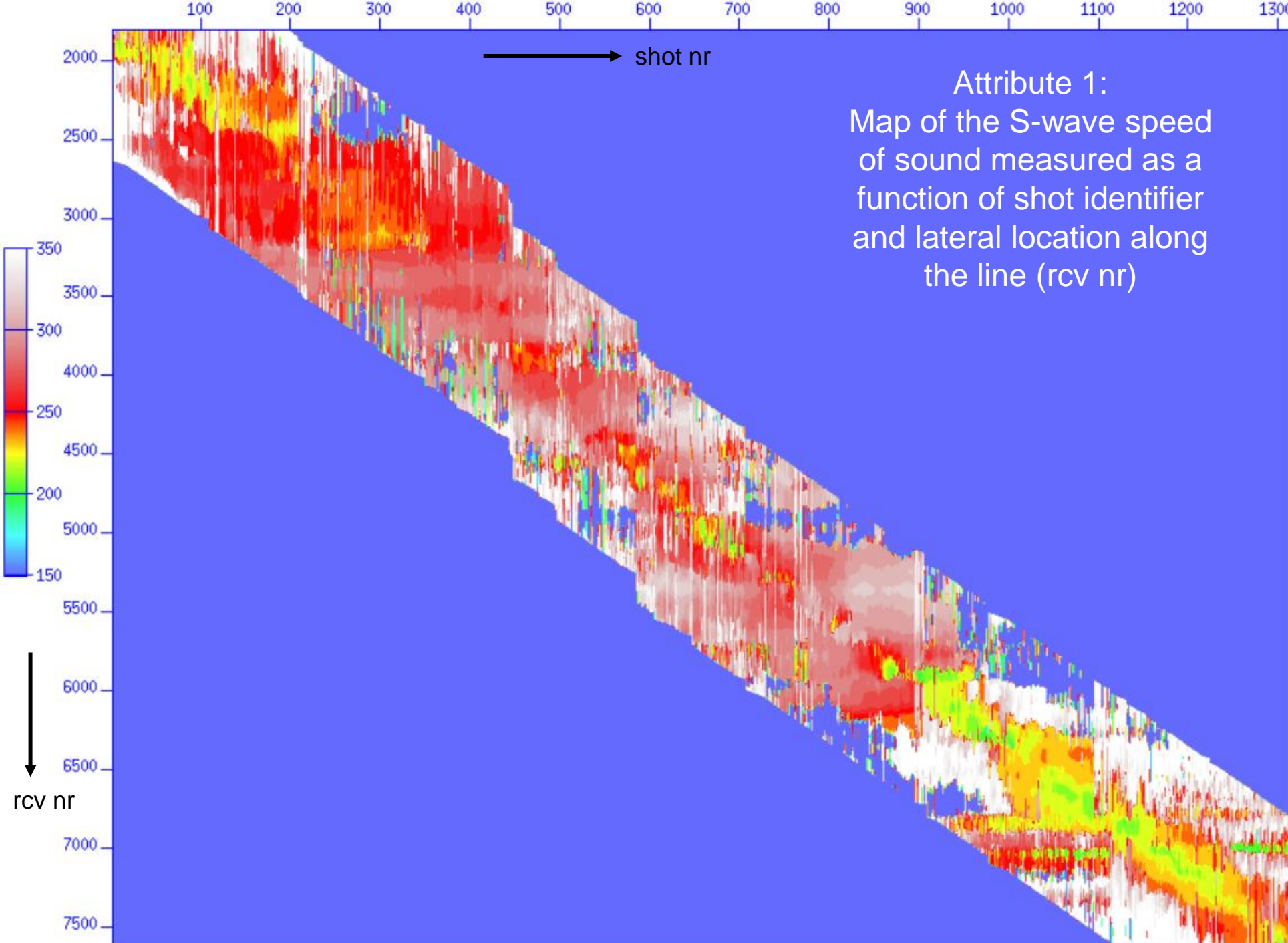
time

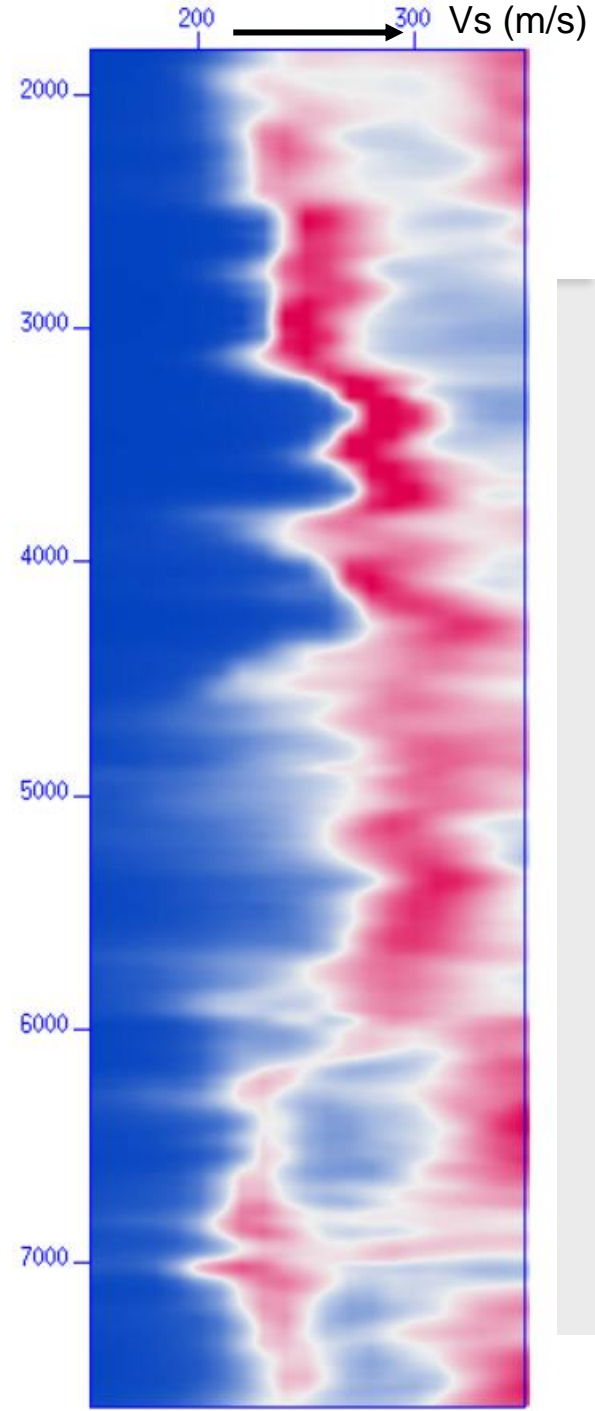
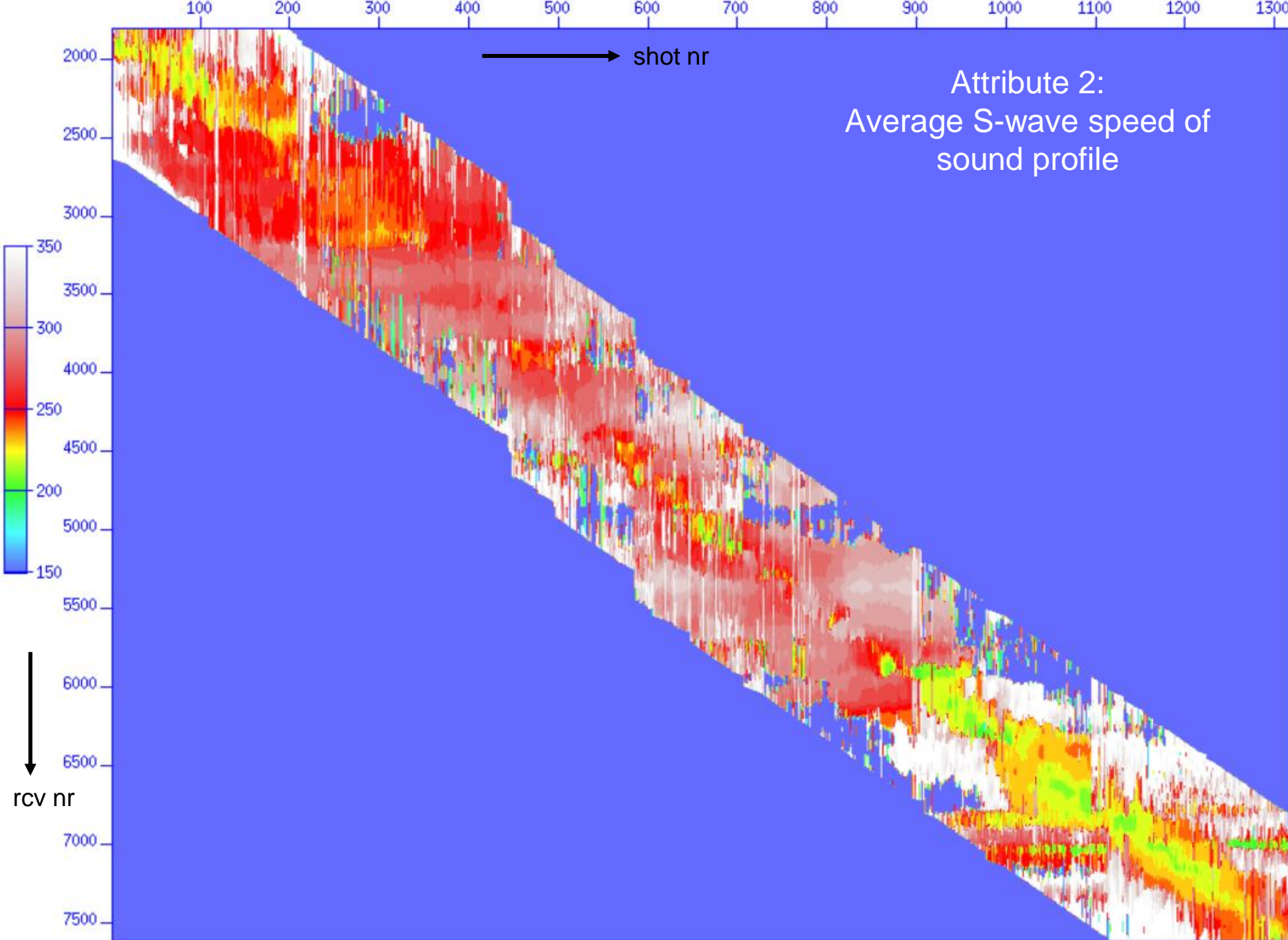
Example seismic shot

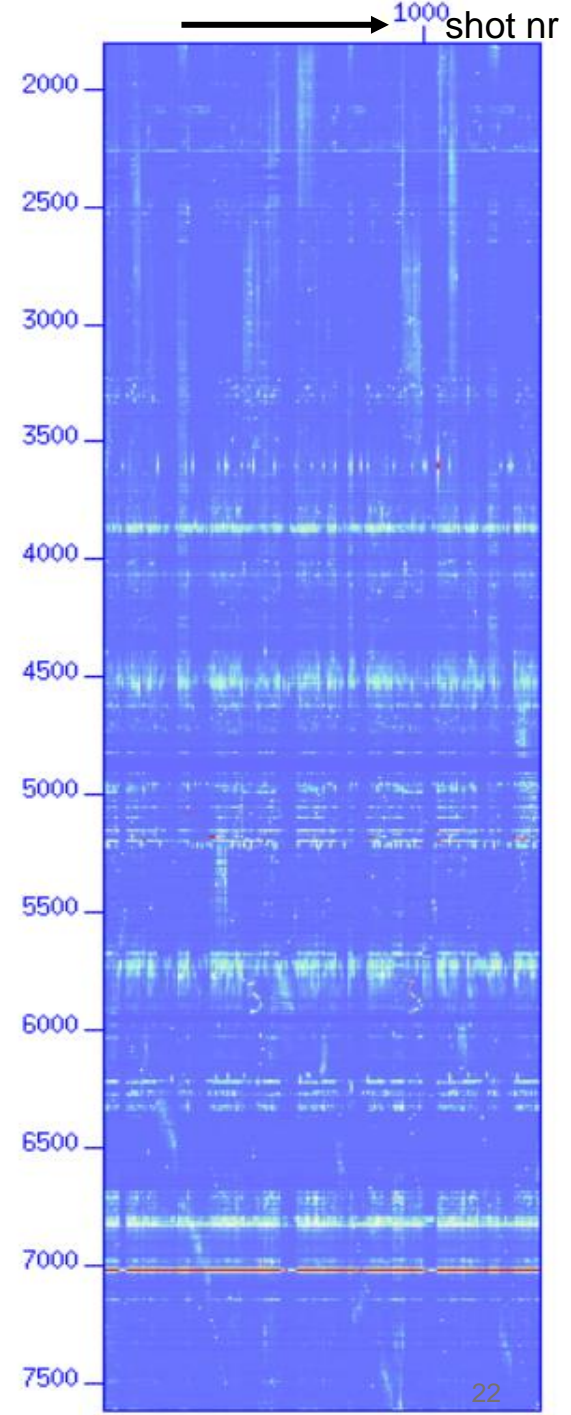
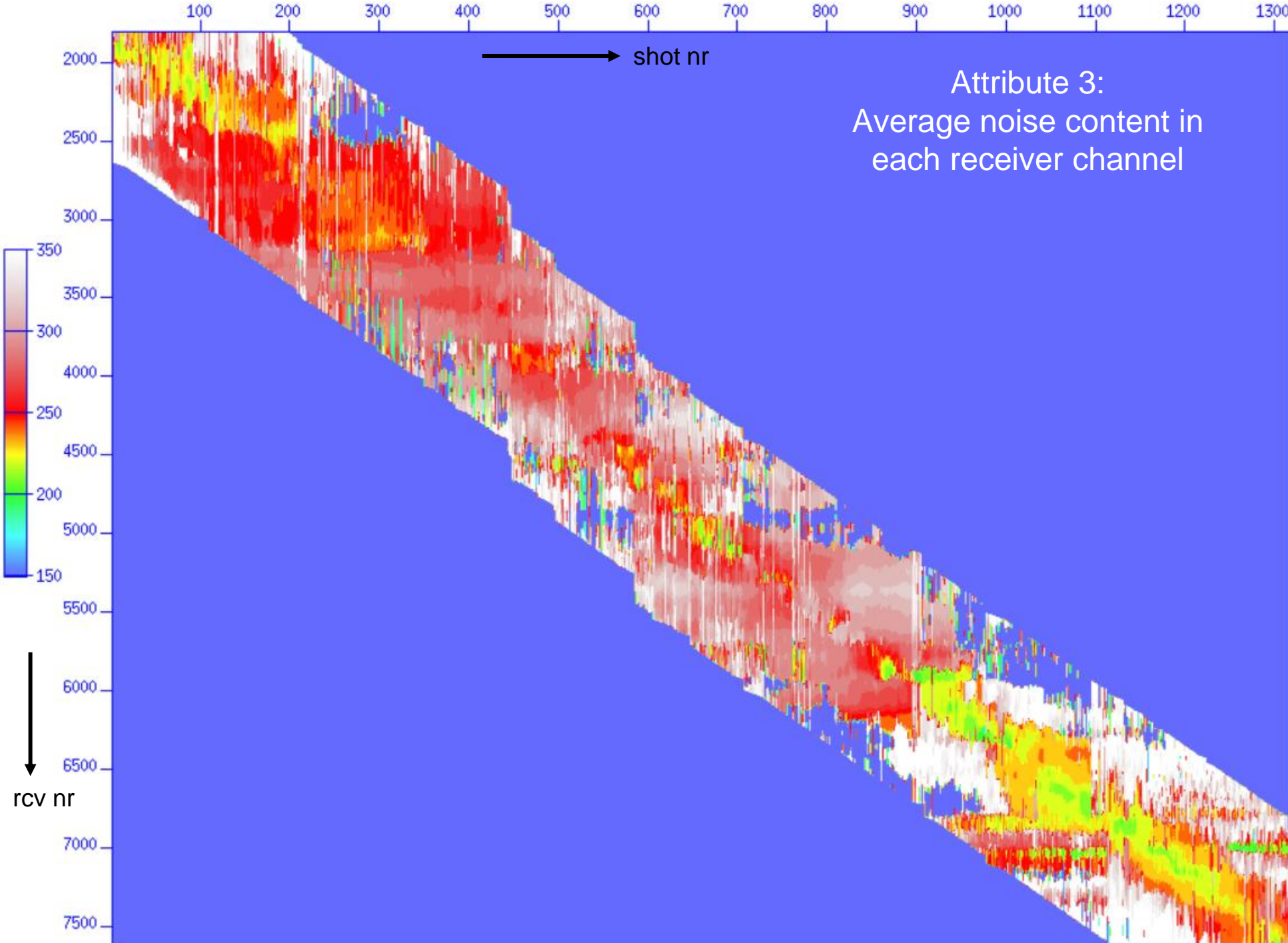


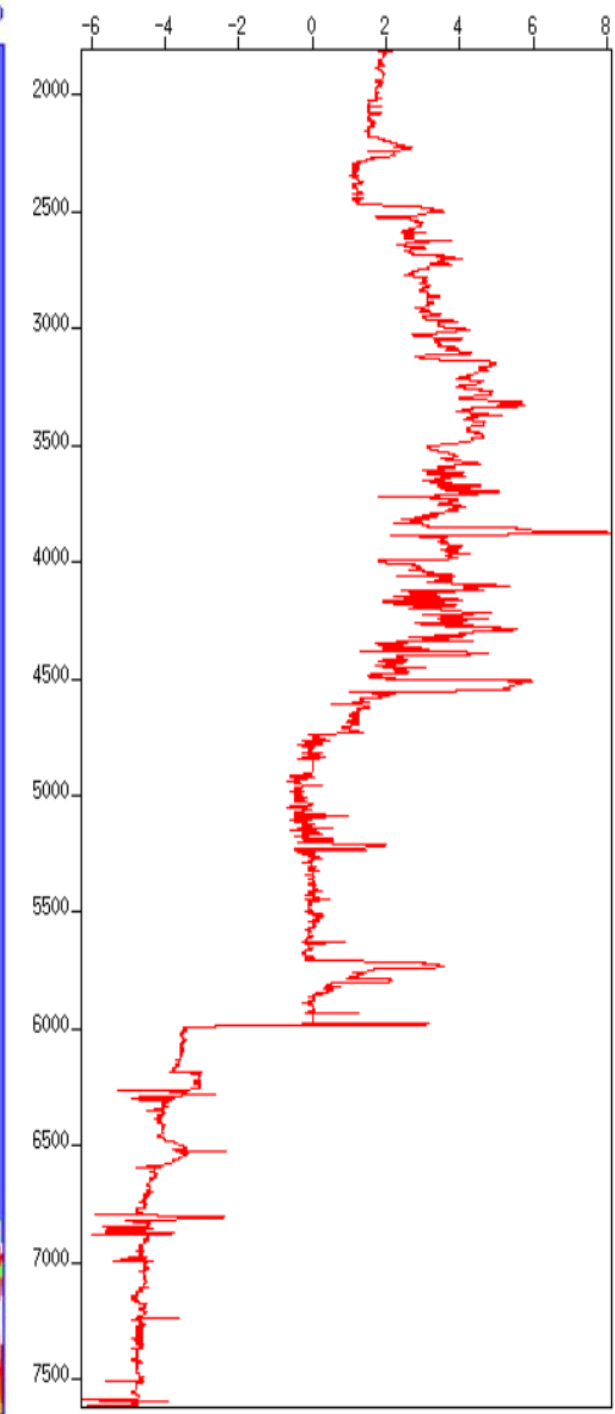
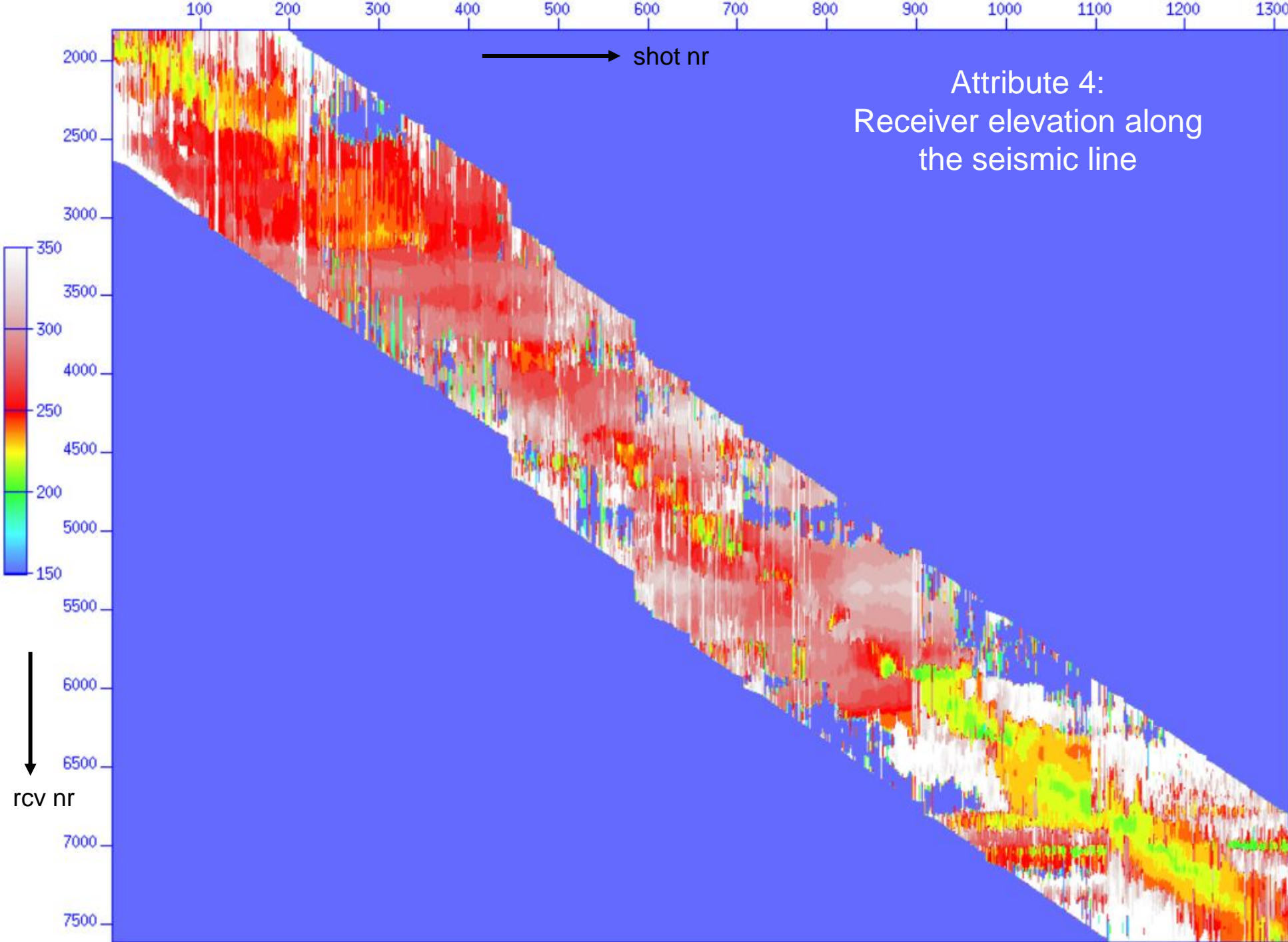


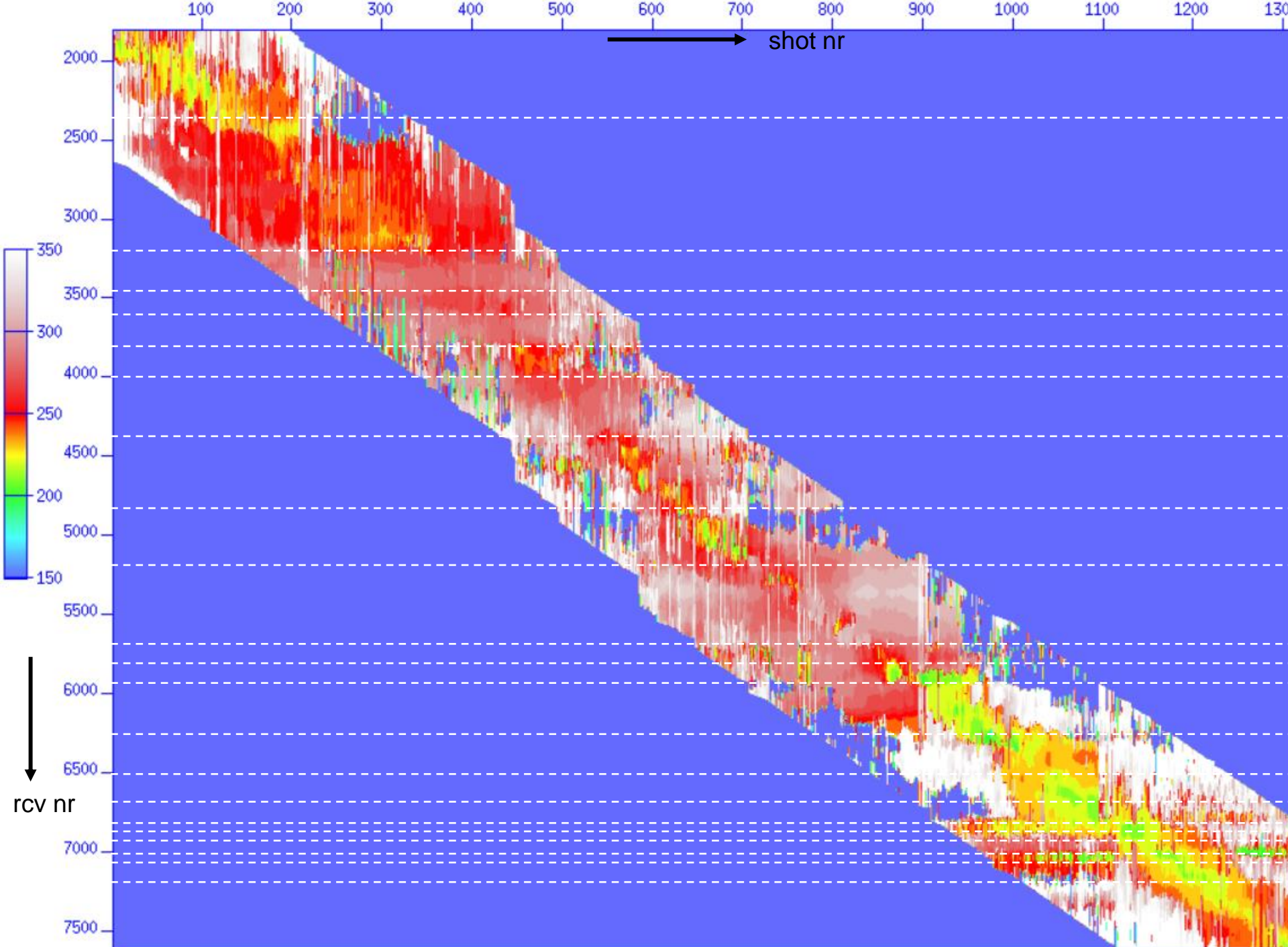
Zoom on
example
seismic shot









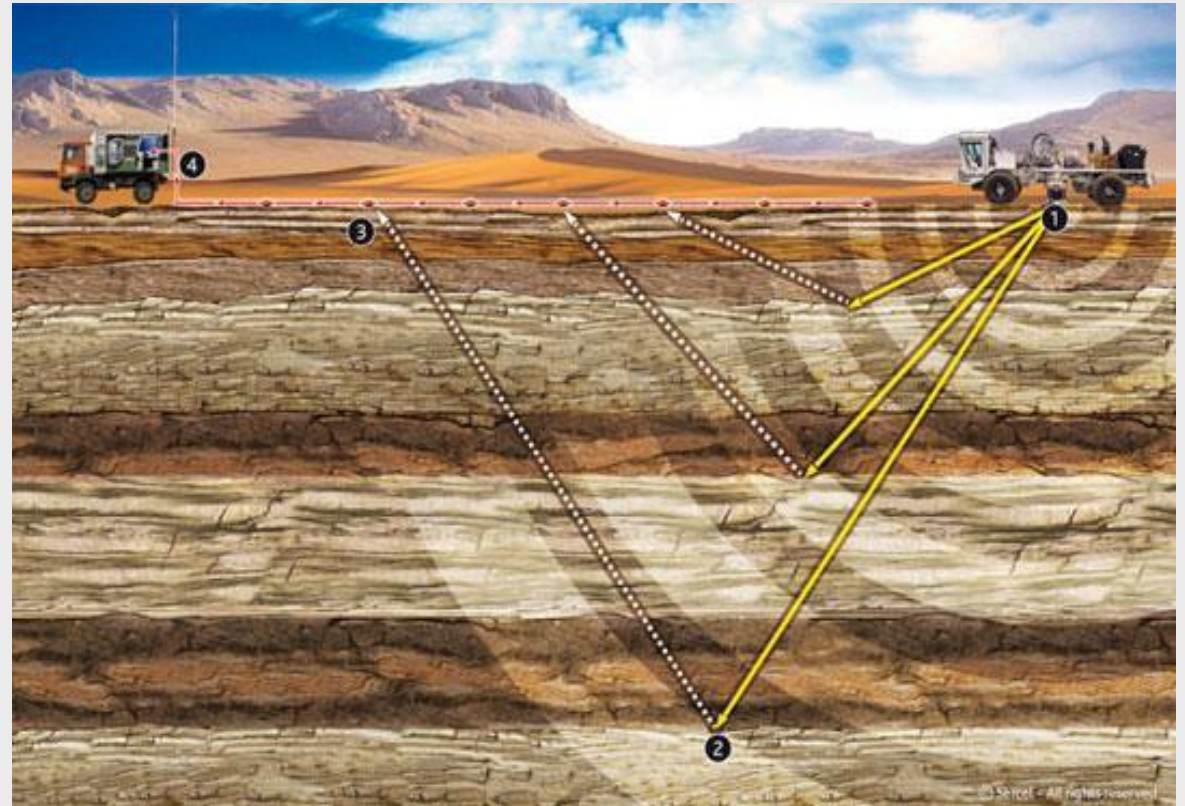


Identified
regions
using all
attributes

Seismic Imaging: Revealing Earth's Subsurface

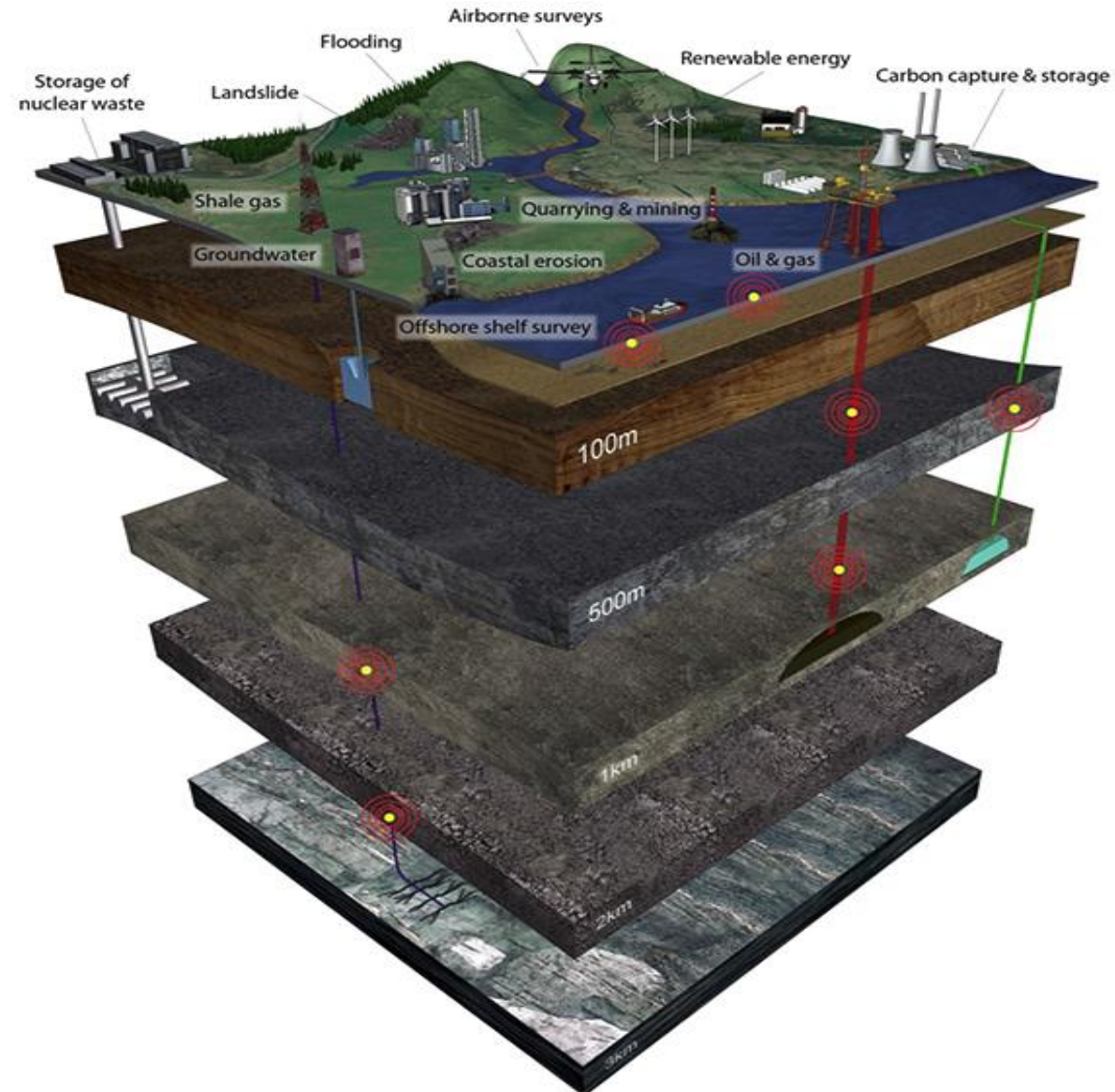
- Sub-field of Geophysics, broadly speaking Geosciences
- Seismic waves that pass through Earth's subsurface layers and recorded back on the surface by receivers called geophones.
- Recorded signals turn into subsurface images aiming to discover hidden treasures of the Earth.

Land seismic survey design



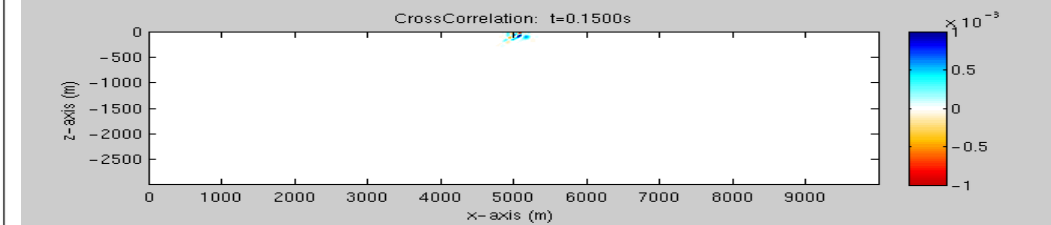
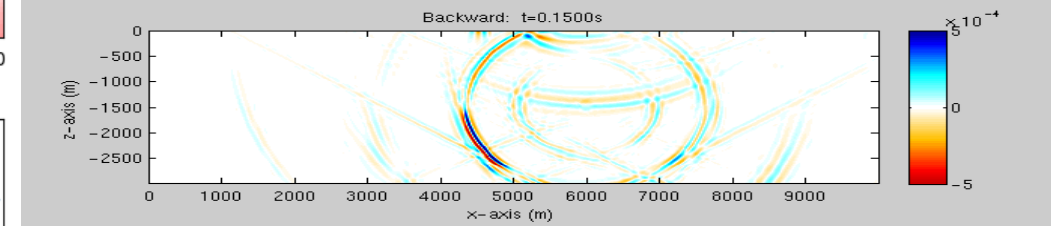
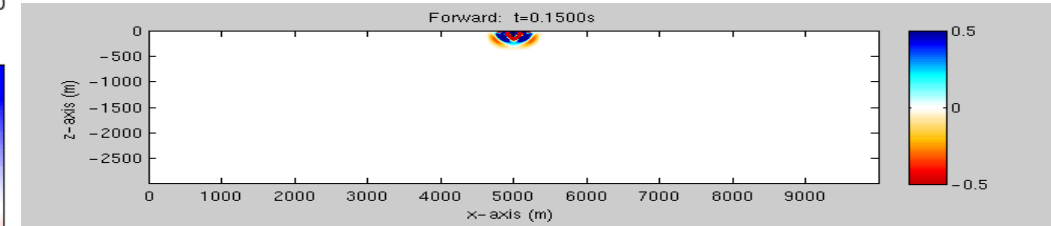
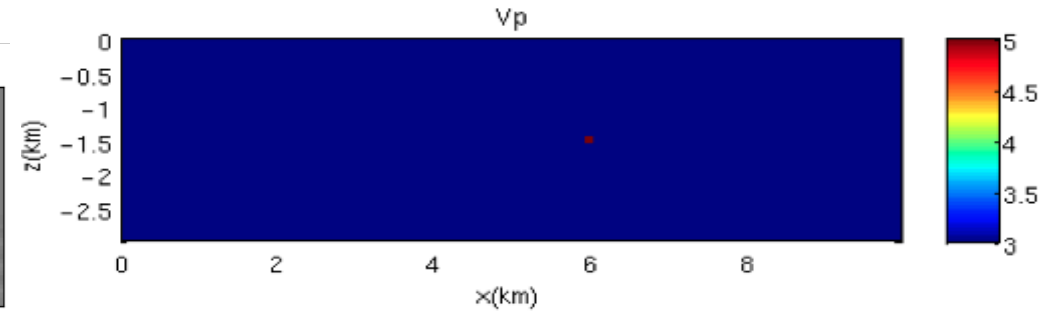
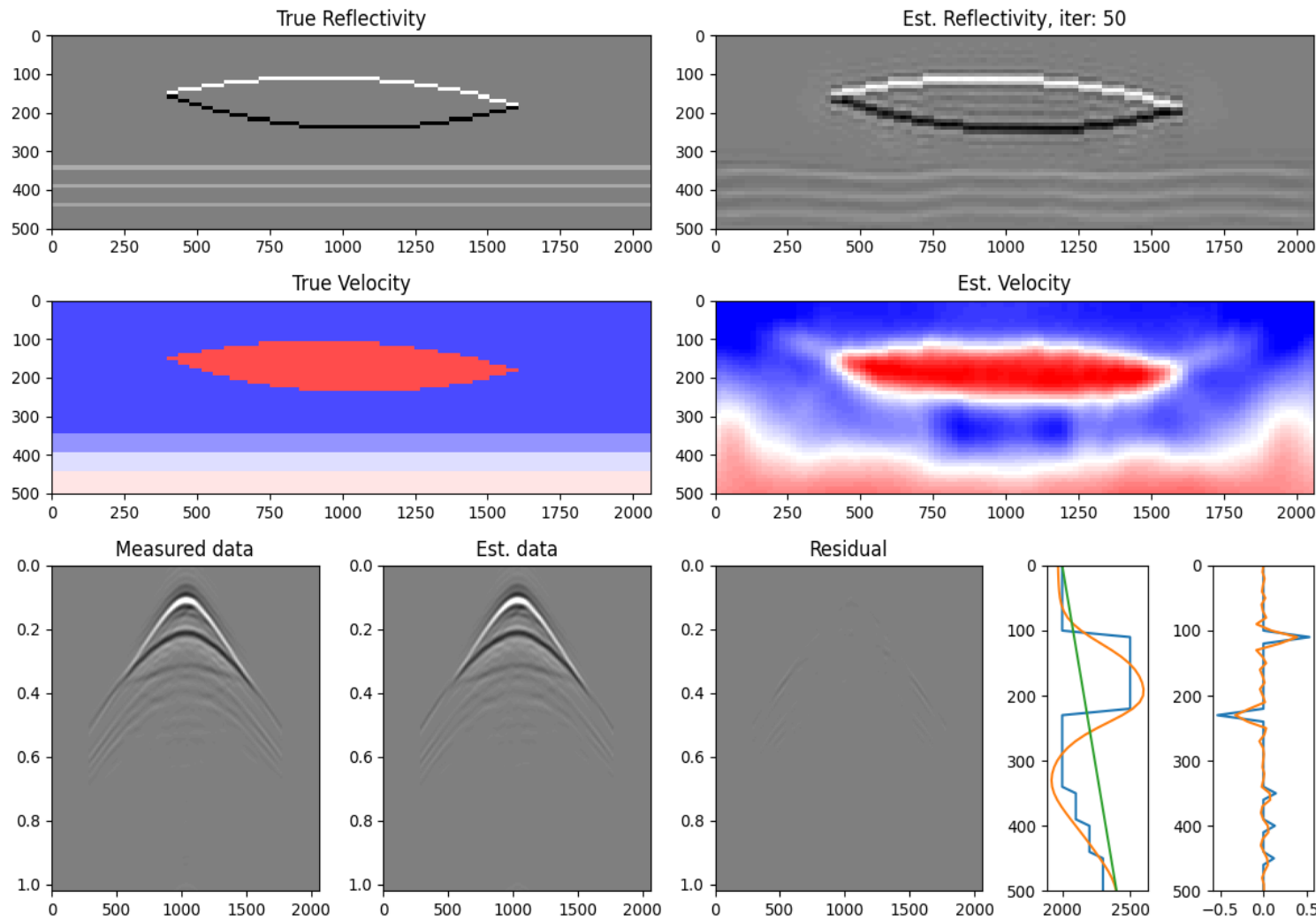
Seismic Imaging: Significant Applications

- Subsurface characterization and monitoring
- Natural hazards studies
(Earthquakes, Tsunami, volcano)
- Geo-technical industry (civil engineering)
- Green hydrogen storage (salt caverns)
- Geothermal Energy



Seismic waves modeling

Joint Migration Inversion(JMI)



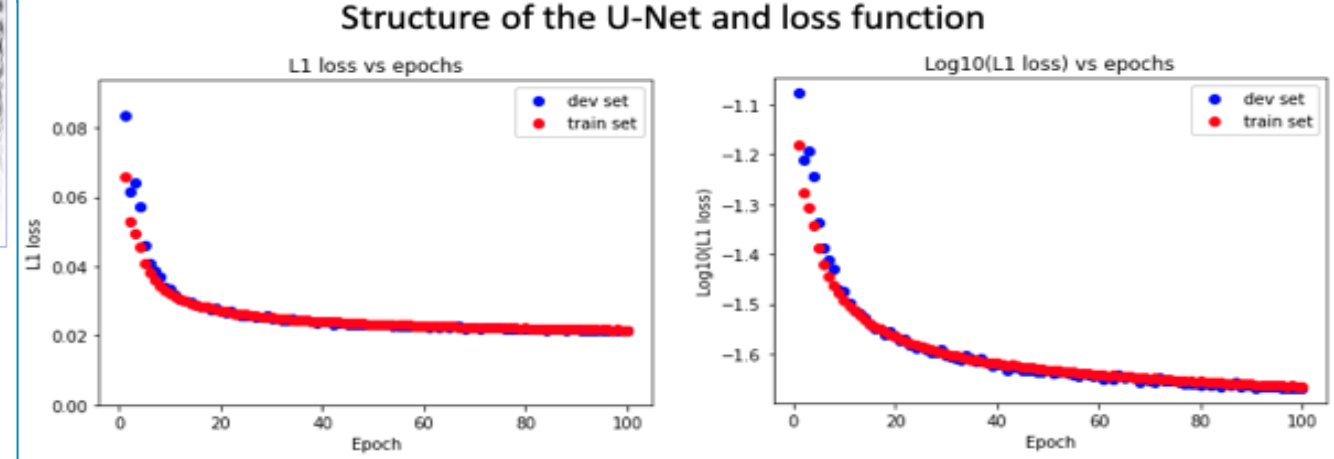
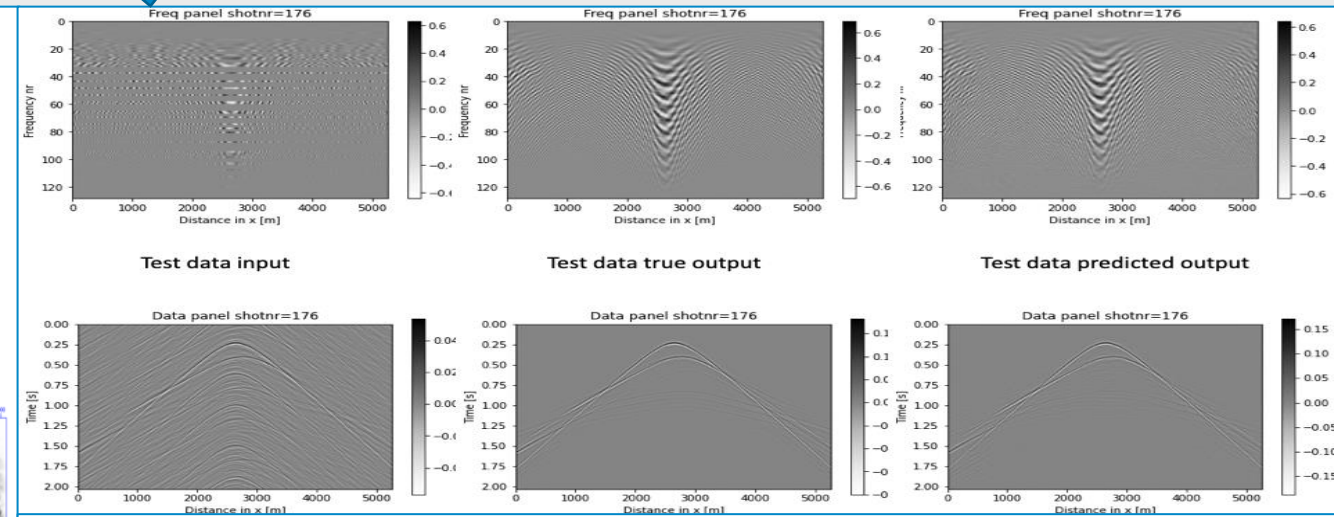
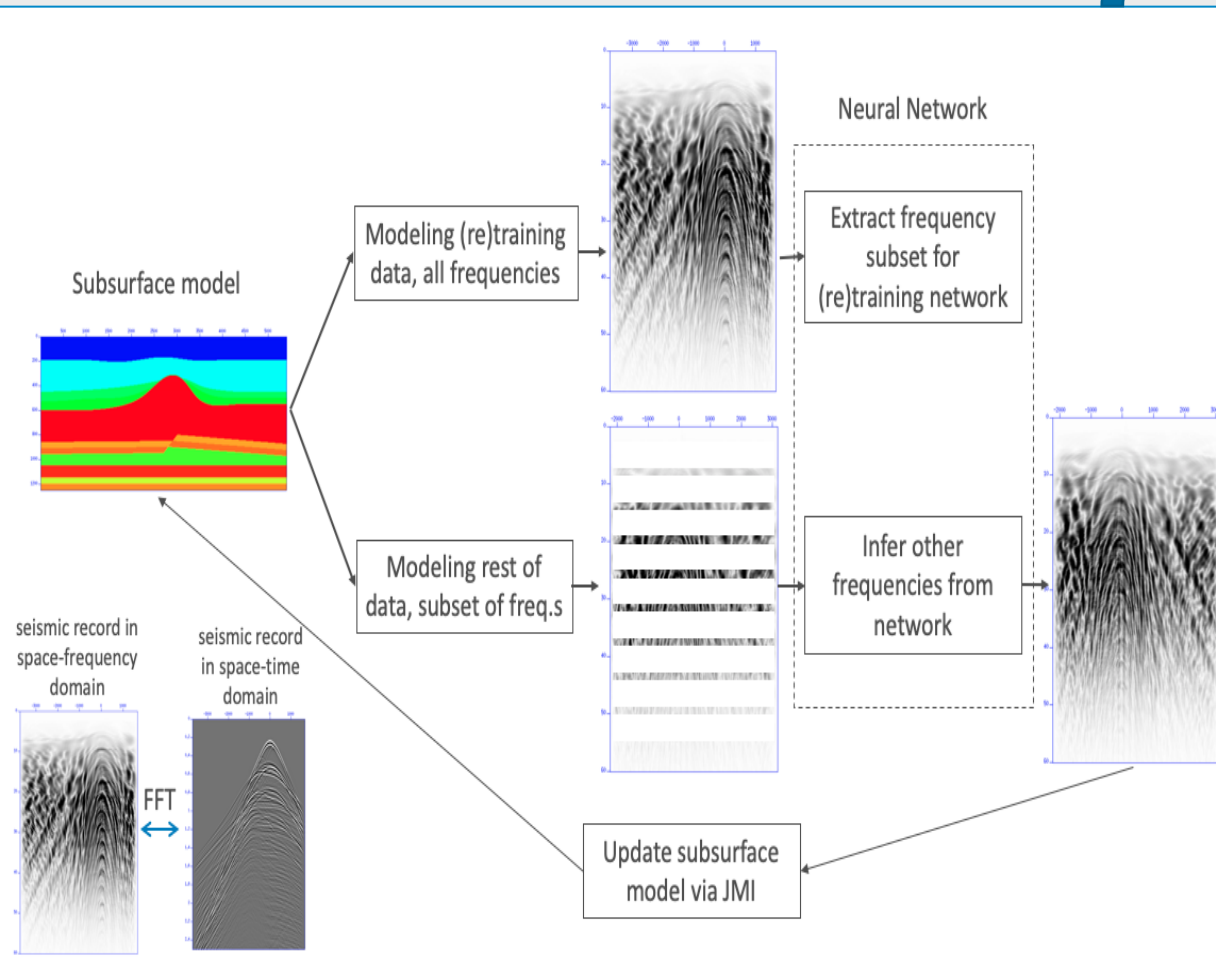
Huge seismic data volumes

- Seismic datasets are huge in size, involving 1000's of source locations, each source 'shooting' into a receiver spread of also 10,000's of sensors.
- With a basic sampling of 12.5m to 50m in both spatial directions, and covering areas spanning 25 x 25 km, the data volumes contain 10's or 100's of Tbytes, or even reaching the Pbyte.
- Explored ML methods aiming to at least partly replace computationally expensive part for wave modeling process.

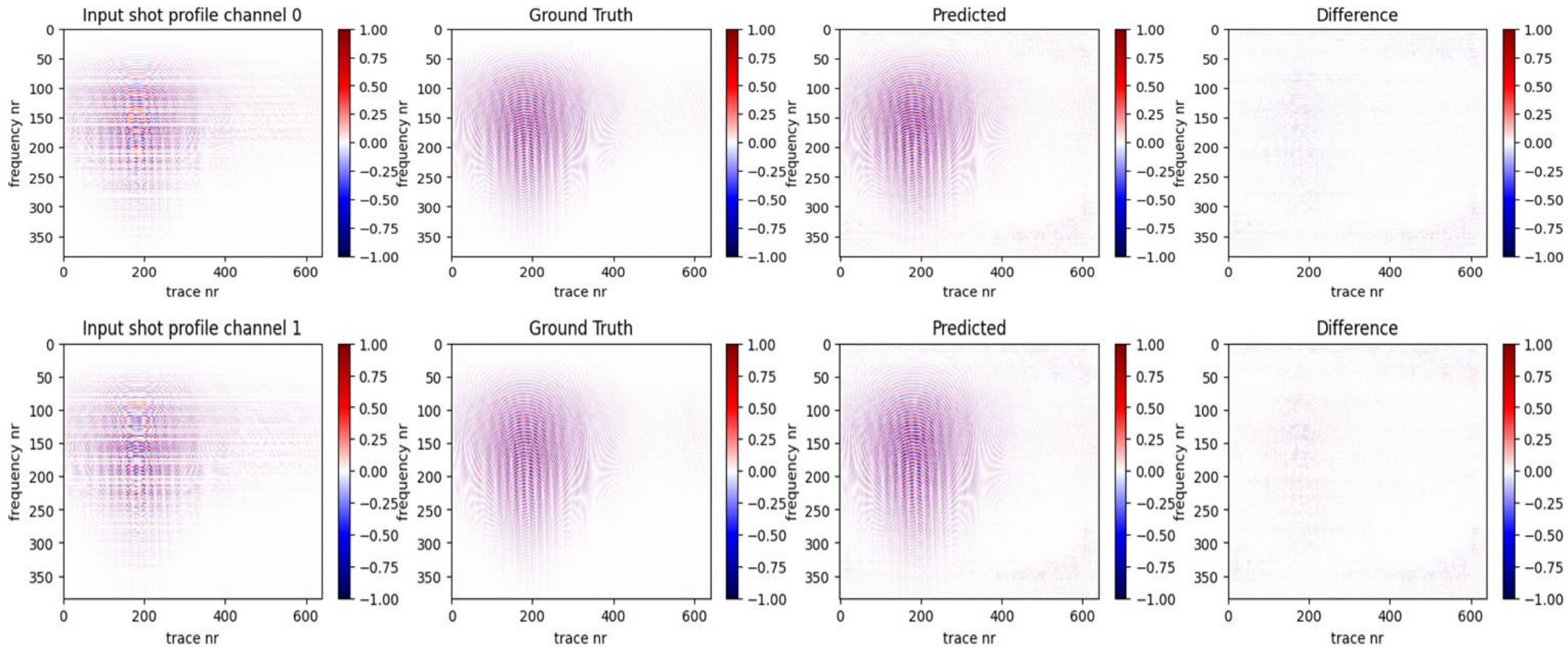
Machine Learning: Seismic Wavefield Reconstruction

Workflow

Results



Results: Pix2pix (cGAN) for SEAM industry standard model



Workflow: AI integration into regular JMI

Step1

Data generation

Make model (A)

Forward modeling (B)

Prepare training, testing pairs [full freq. 0-48 Hz]

Step2

AI-Model training [LS, 0-48 Hz]

Fine-tuning for all frequency ranges [5-10Hz], [5-20Hz], [5-30Hz], [5-40Hz].

Step3

NN Integration into JMI (C)

Outer freq. loop

Update frequencies ranges

Testing trained model

Calculate wavefield

Interpolation by NN

Residual + calculate gradient

Perturbation+step length

Update image + velocity (Single iter. output)

Inner iter. loop [5, 15, 15, 15]

Final out: reflectivity image + Velocity model

'AI' is faster than original JMI software



Iterations	JMI_AI Mod step	JMI_orig Mod step	JMI_AI Inversion	JMI_orig Inversion
1	7.54	5.38	1.99	1.65
2	3.43	5.38	1.97	1.63
3	3.54	5.13	1.96	1.63
4	3.48	5.35	2.0	1.64
5	3.46	4.68	2.02	1.62
6	3.5	5.36	2.0	1.64
7	3.49	5.14	2.01	1.62
8	3.47	5.26	2.03	1.64
9	3.52	5.17	2	1.64
10	3.48	4.71	1.98	1.63
TOTAL	38.91	51.56	19.96	16.34

Next Steps: Task 4.2

- Envisioned integration of remote sensing (RS) and seismic imaging tools. Objective: The information from the land-cover map directly defines the seismic processing parameters.
- Integrate ML trained models into regular JMI software particularly for seismic inversion calculations.
- Facilitate to update the design and workflow for seismic data acquisition and processing.

drive. enable. innovate.

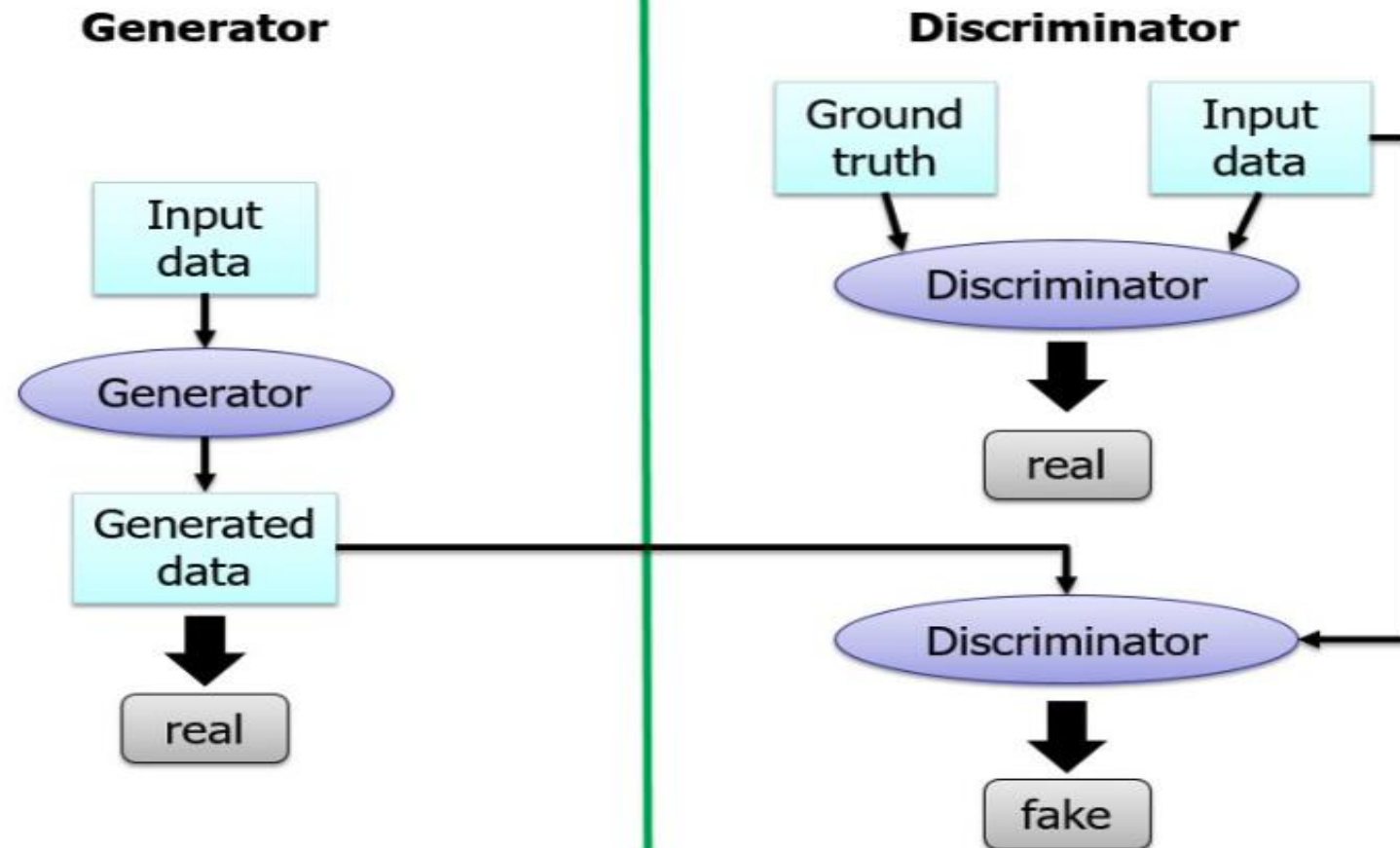


The CoE RAISE project have received funding from the European Union's Horizon 2020 – Research and Innovation Framework Programme H2020-INFRAEDI-2019-1 under grant agreement no. 951733

Follow
us:

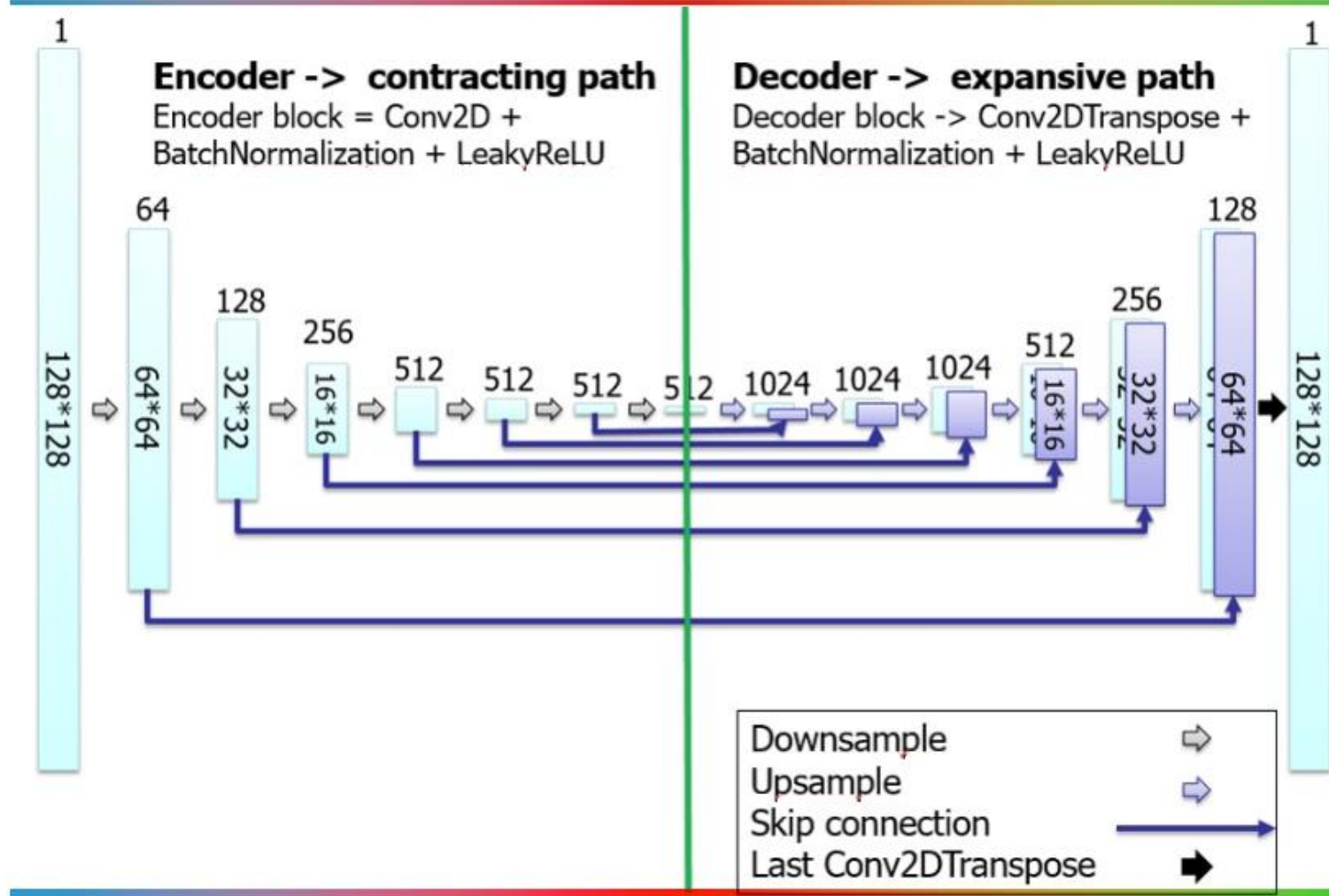


Conditional GAN (train data pair)



Generator Building:

Generator -> U-Net



Discriminator Building

Discriminator -> Encoder + patch classifier

