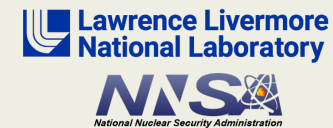


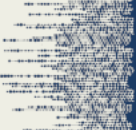
Towards Predictive Maintenance Strategy Through Waveform Anomaly Detection using Unsupervised Learning

Jiun-Ting Lin, Ana Aguiar, Qingkai Kong, Steve Myers, Amanda Price

Lawrence Livermore National Laboratory



8-12 September 2025



Introduction

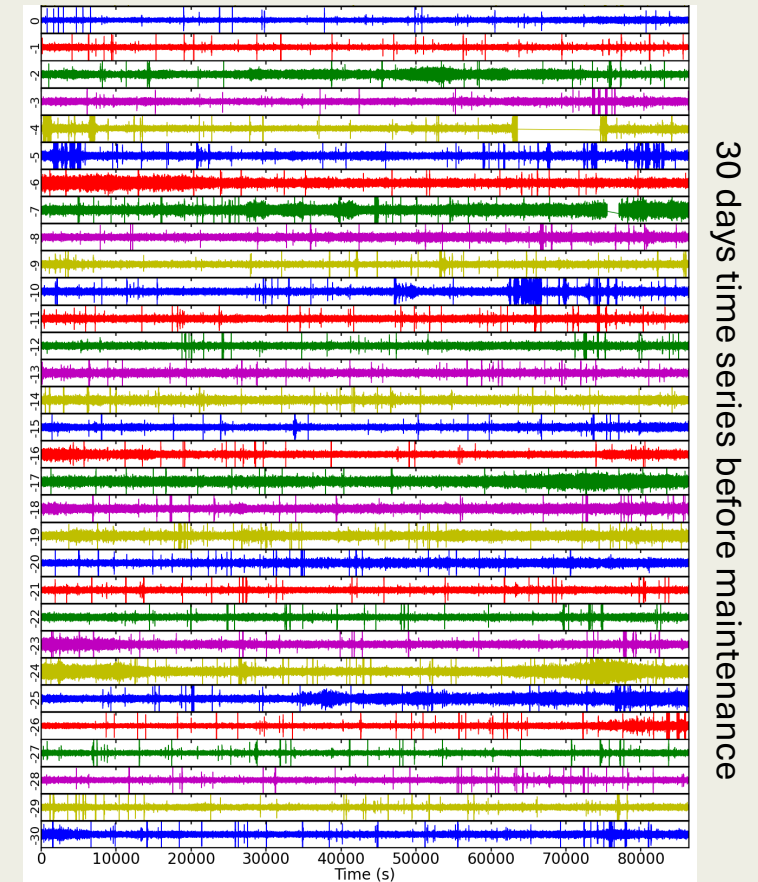
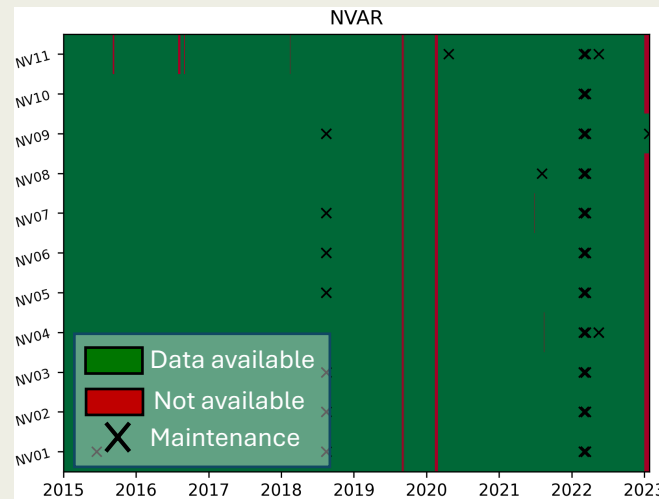
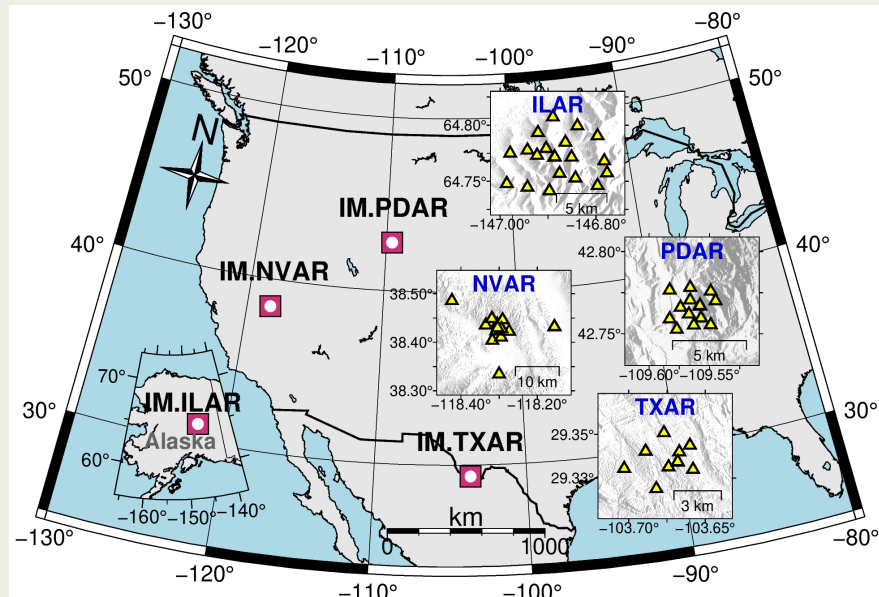
International Monitoring System (IMS):

- Consists of 300+ stations.
- Hosted by 89 countries.
- Real-time data for event monitoring.
- Station maintenance regularly for quality assurance.

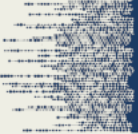


Station maintenance is costly

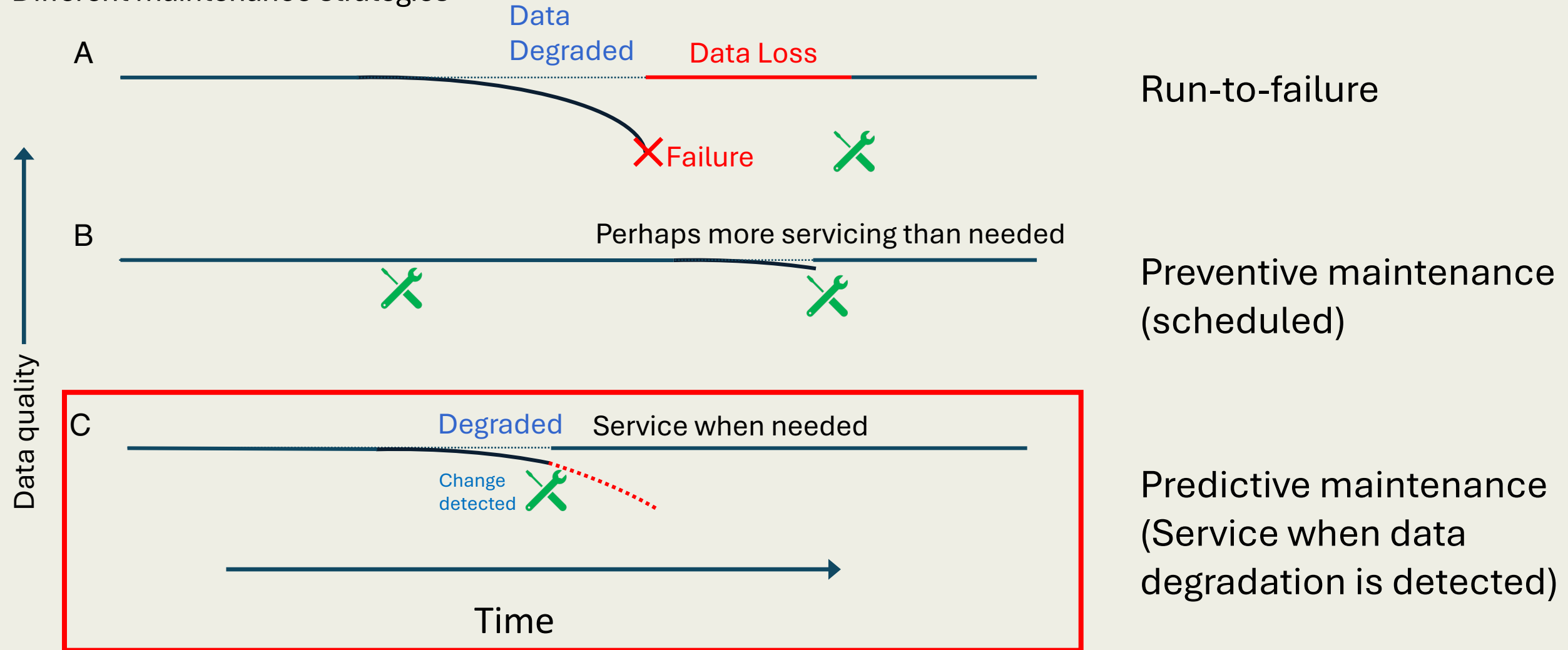
- Money, time, and human effort.
- Some of them are scheduled maintenances, **NOT** associated with actual instrument issues.
- Can we schedule maintenance more effectively?



30 days time series before maintenance

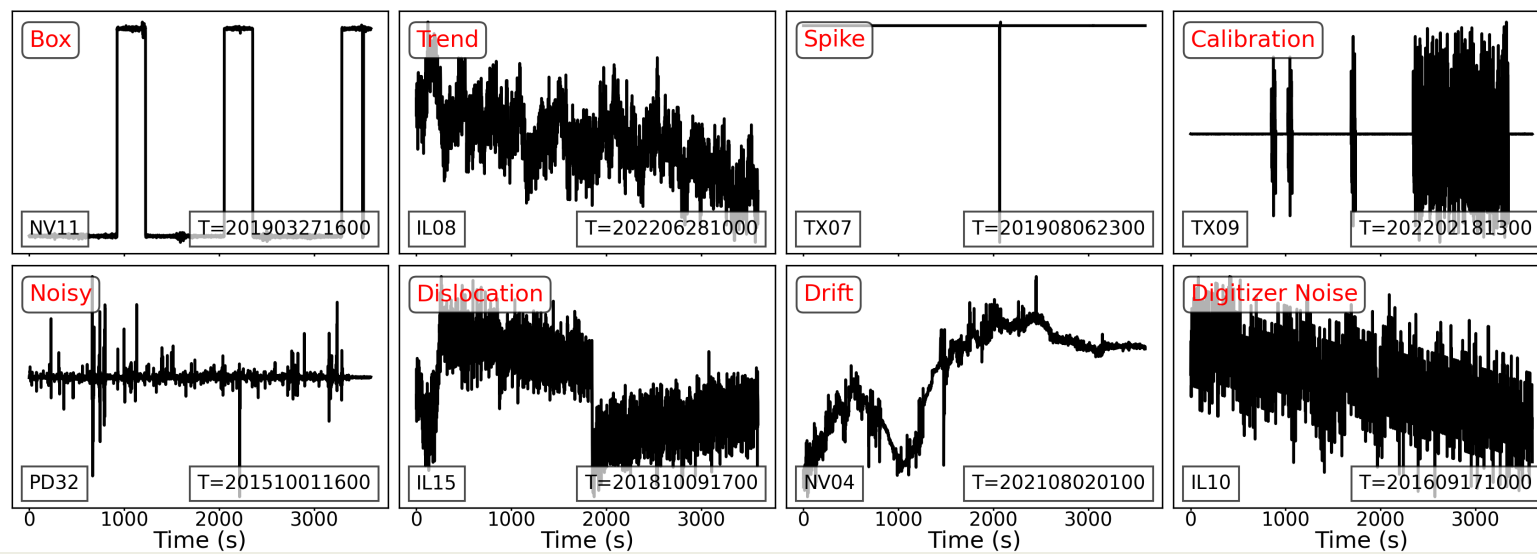


Different maintenance strategies

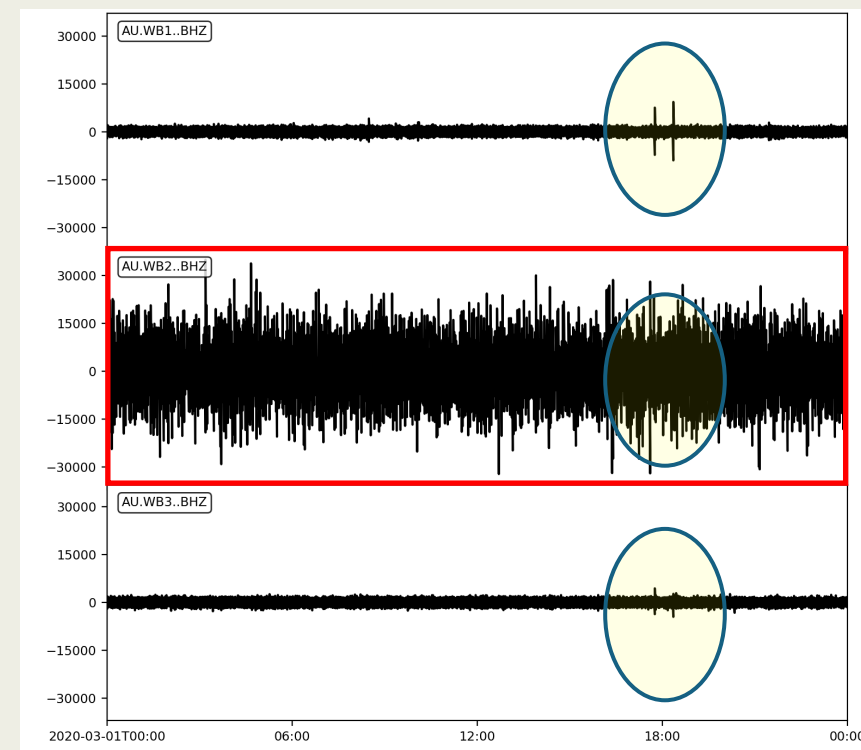


Challenges in detecting degraded signals

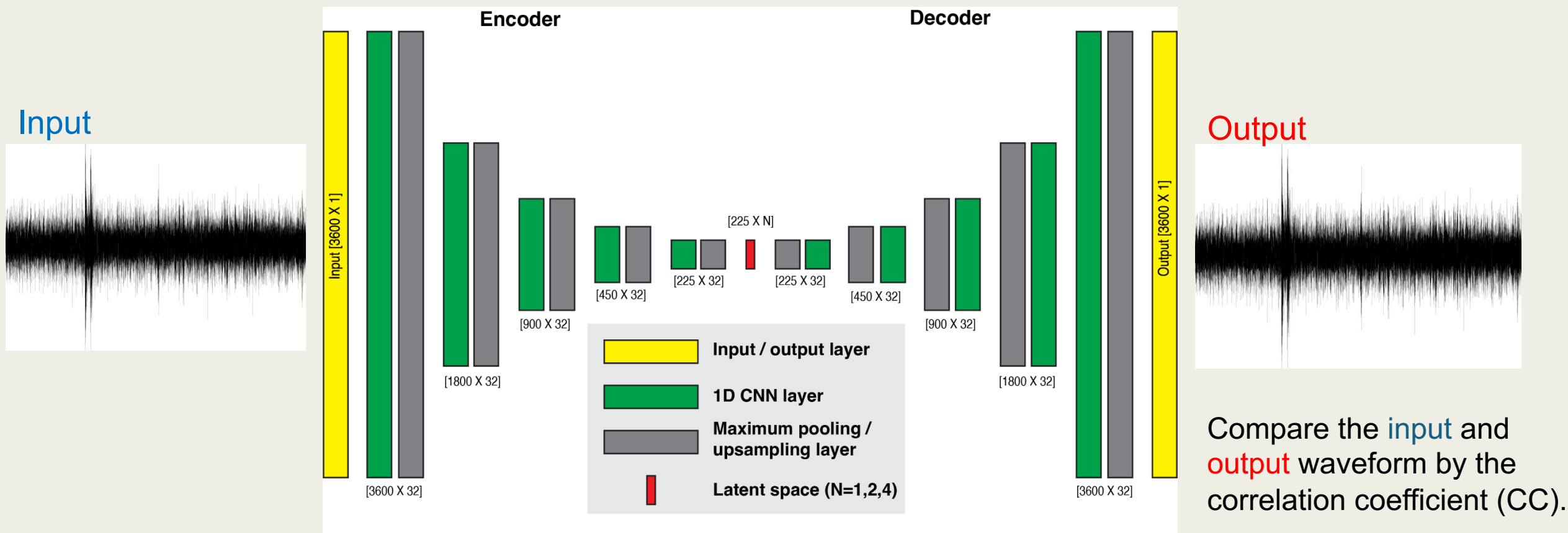
- Degraded signals or anomaly can be anything: No clear definition.
- Signals may be subtle and hidden within the data.
- No ground truth data to learn or compare.



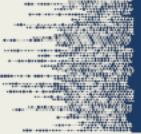
2020-03-01
AU.WB1, AU.WB2, AU.WB3 (BHZ)



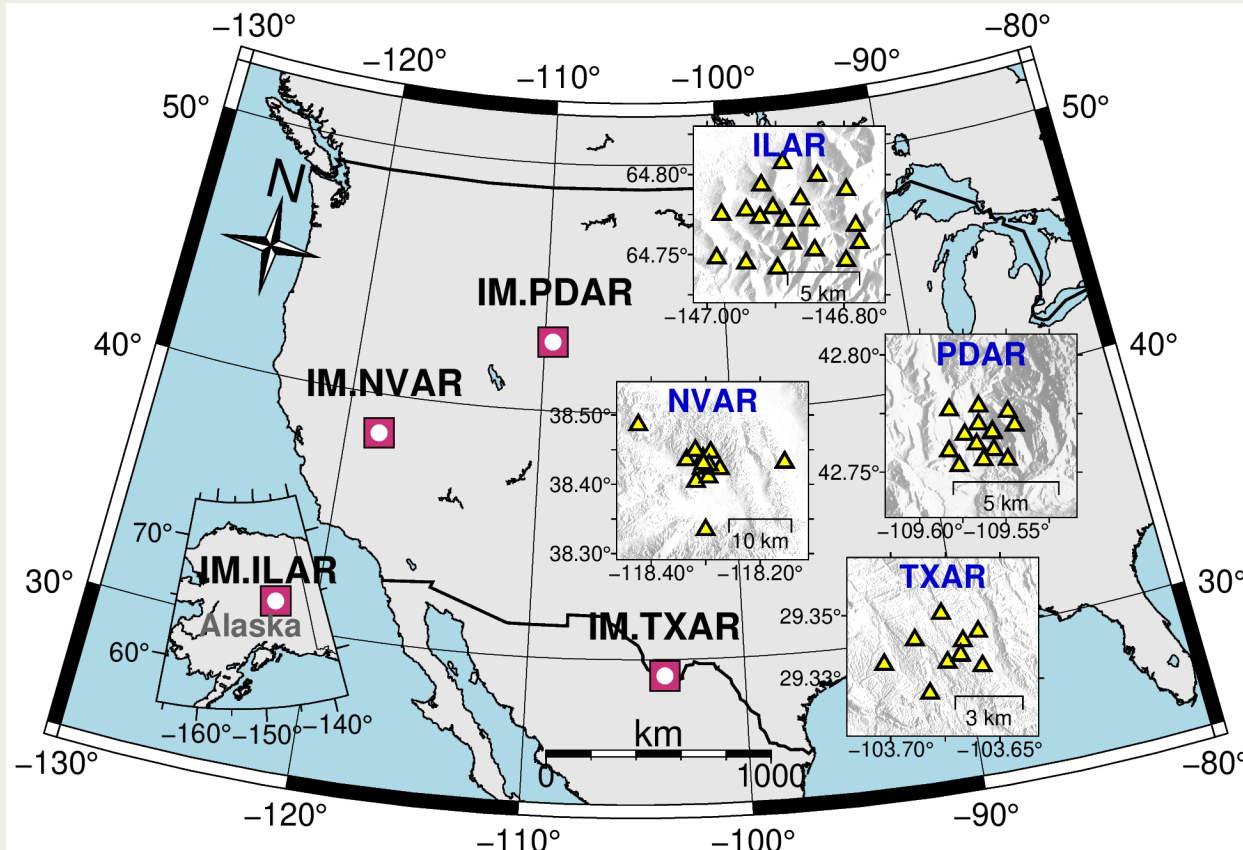
Unsupervised learning model: autoencoder



1. No assumptions on anomalous signals.
2. Exploring information in seismic data.

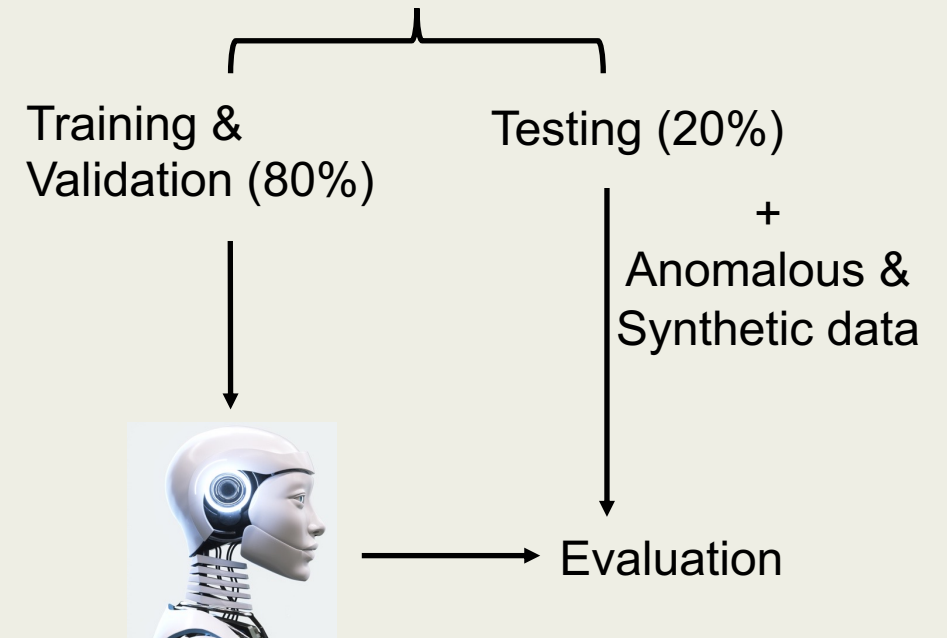


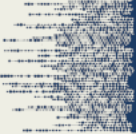
Training Data



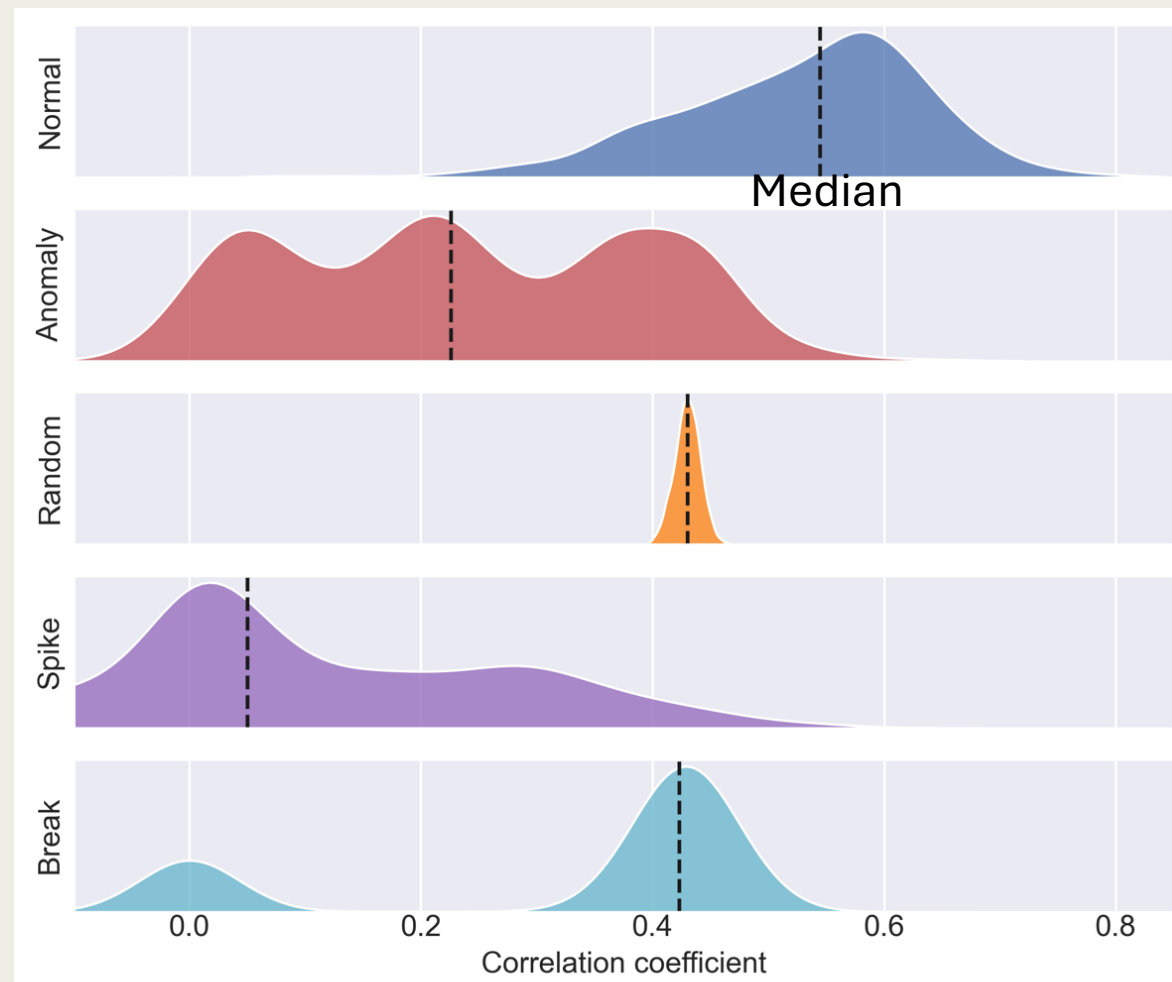
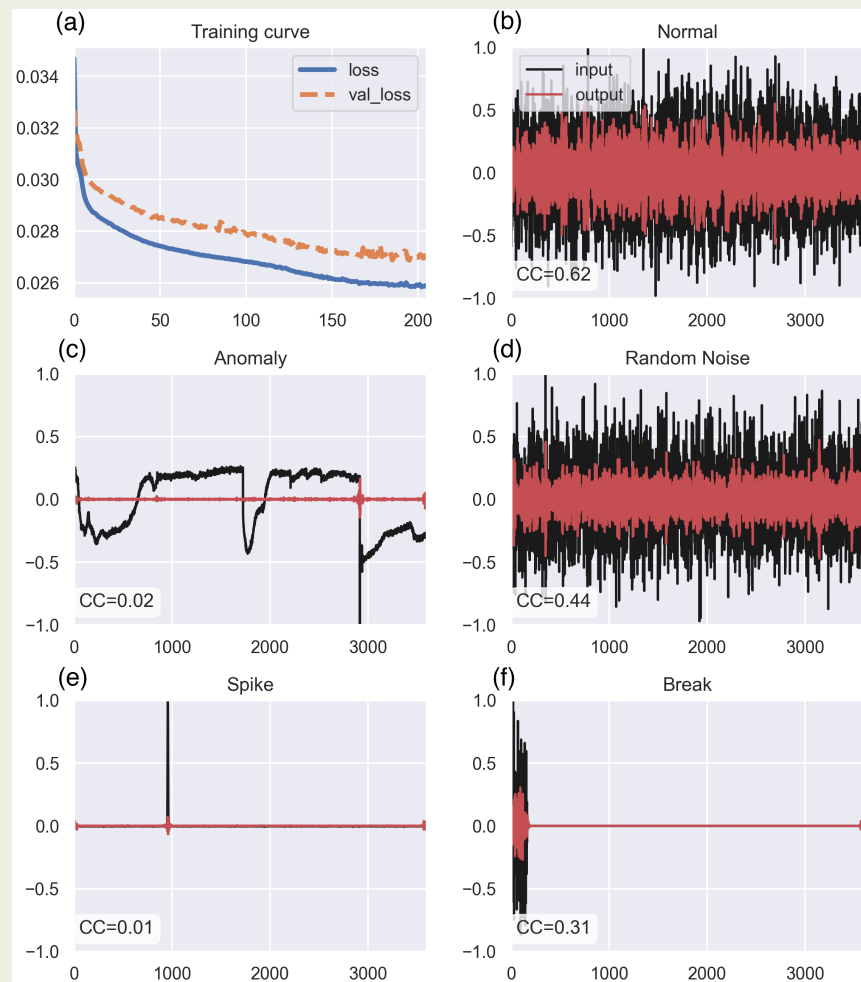
- Continuous waveform data from 2015-2023.
- Downsampled to 1 Hz, cut into hourly input segments.

Randomly select a total of 5,000 days (120,000 hours) of data.

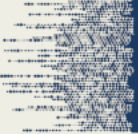




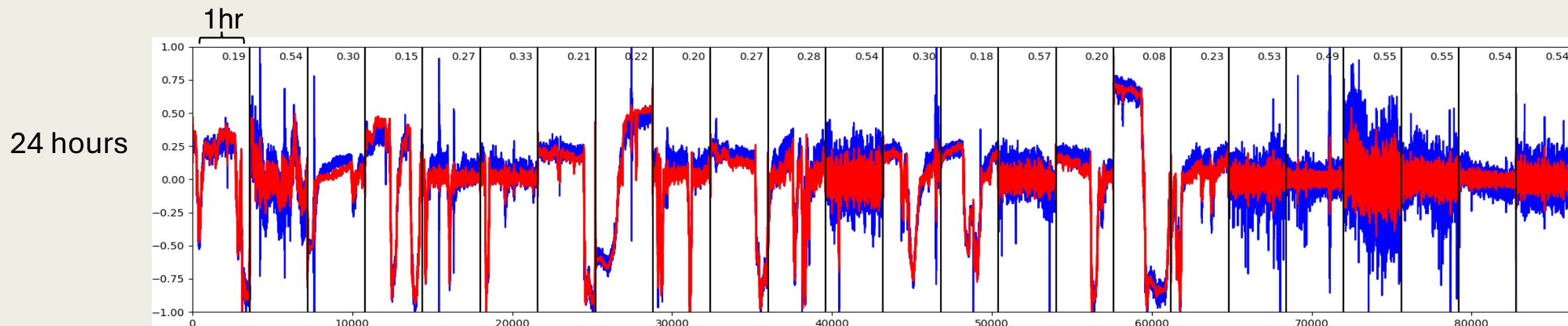
Results

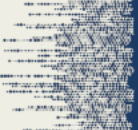


- Normal data → higher CC
- Anomalous data → lower CC

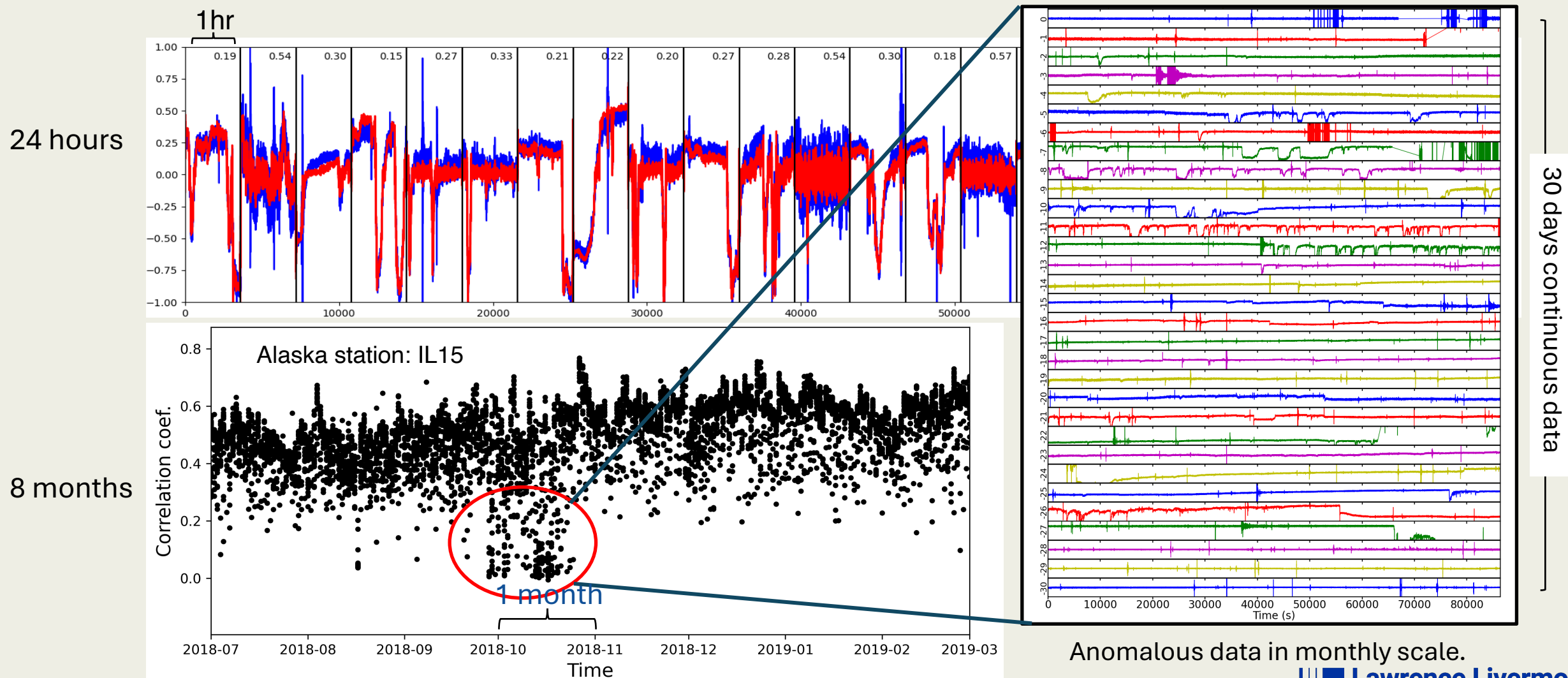


Apply to continuous data

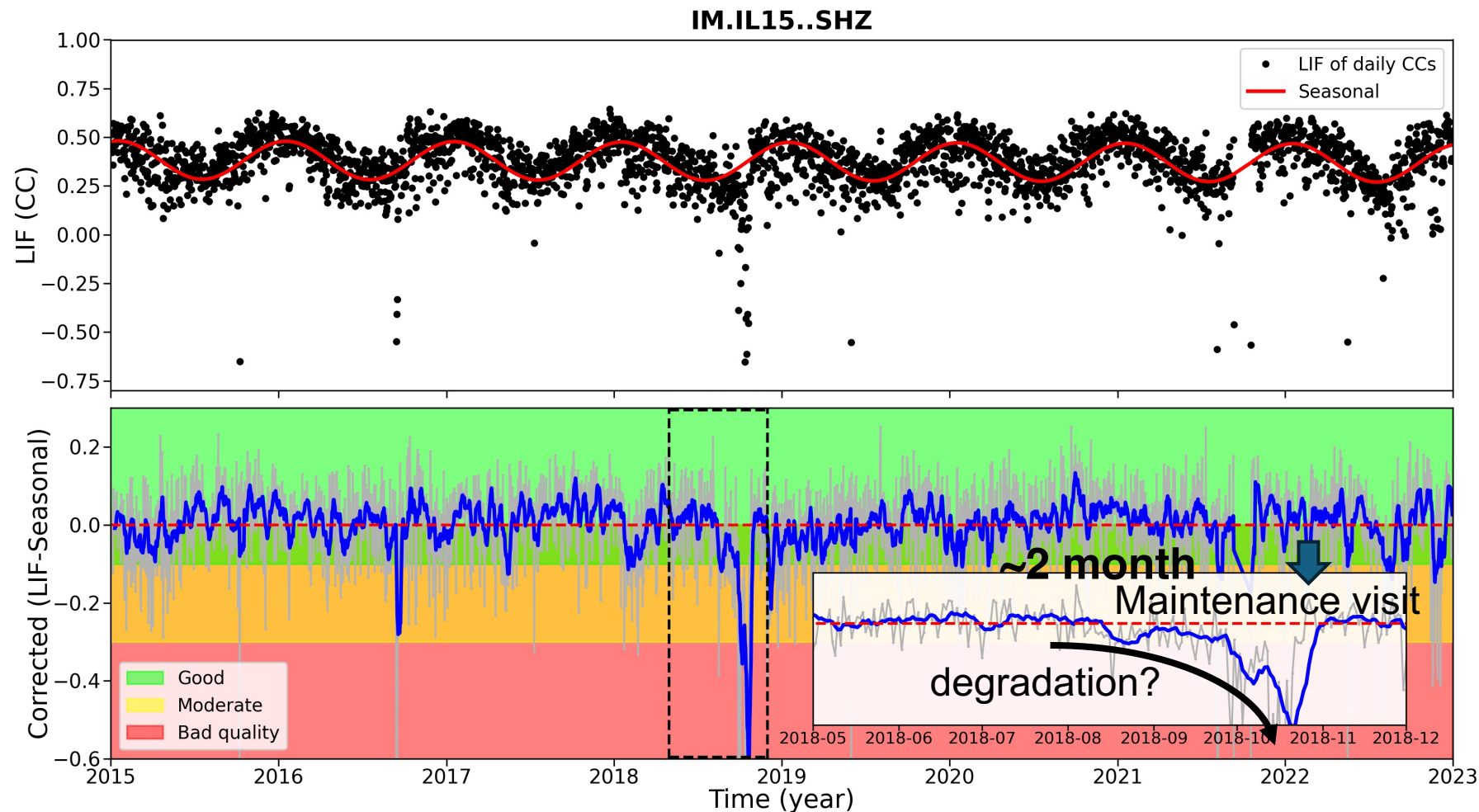
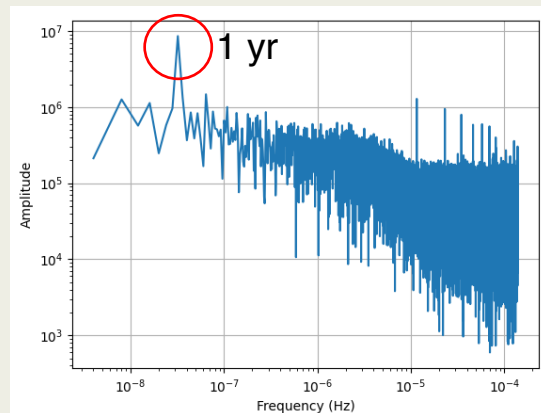




Apply to continuous data

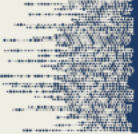


Apply to continuous data



1. Aggregate the 24 hourly CCs into one per day by the lower inner fence ($LIF = Q1 - 1.5IQR$).

2. The results are sensitive to seasonal variation that need to be corrected.



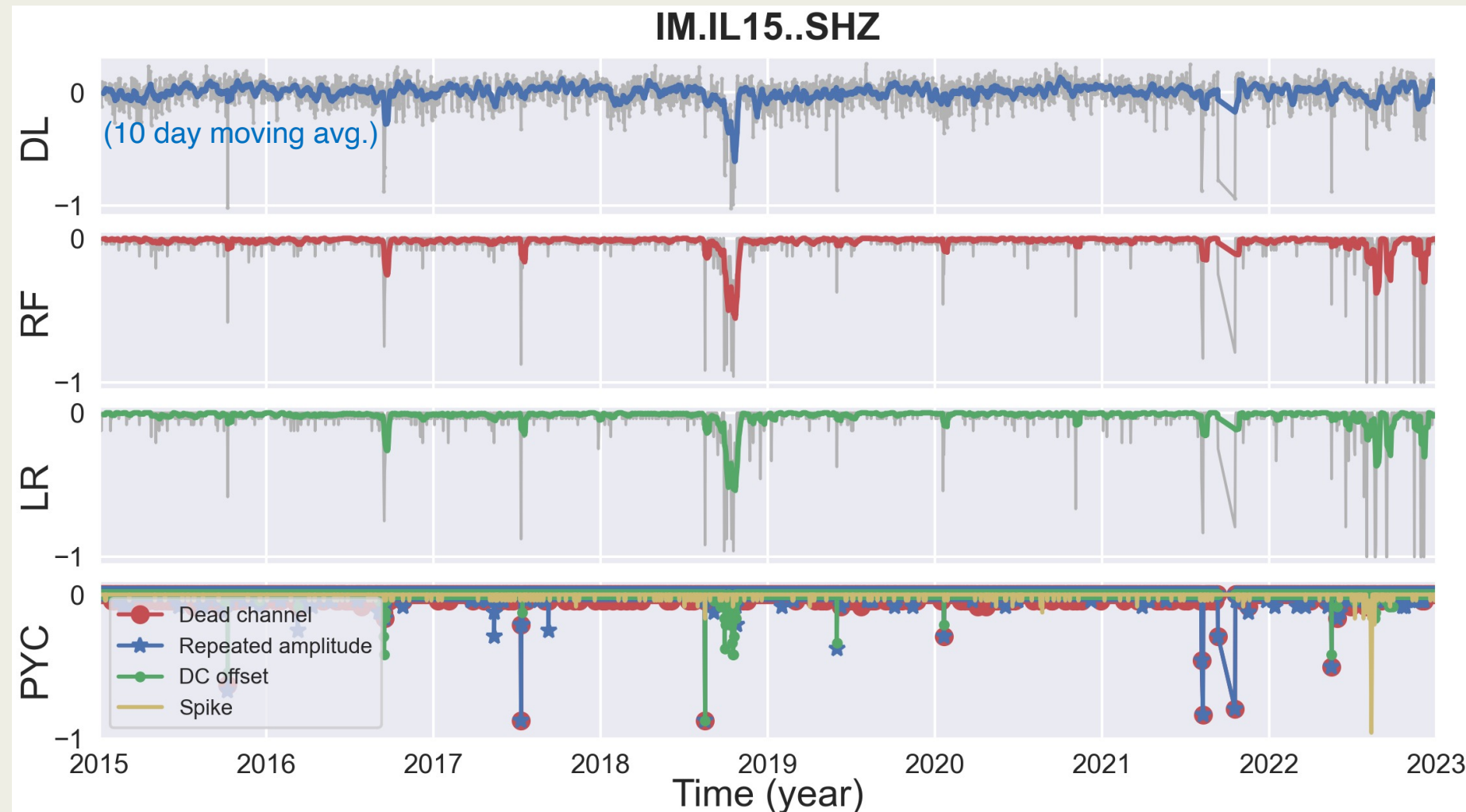
Compare to other models

DL: Deep-learning
autoencoder (unsupervised)

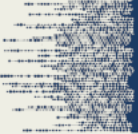
RF: Random Forest
(supervised)

LR: Logistic Regression
(supervised)

PYC: Traditional detector
(Pycheron QC tool) (Aur et al., 2021)



Performance is similar for known types of anomalies.



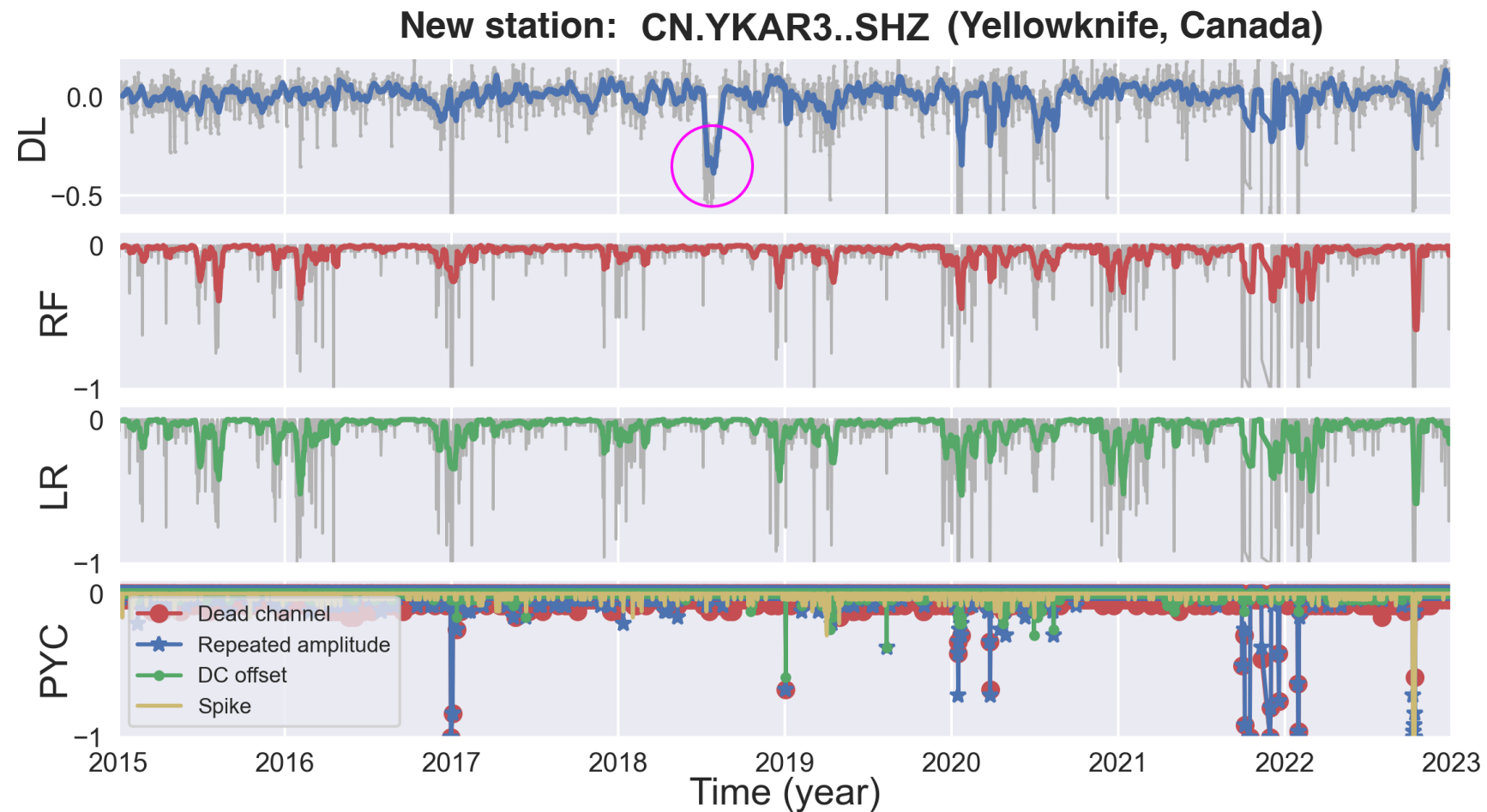
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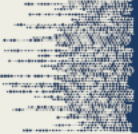
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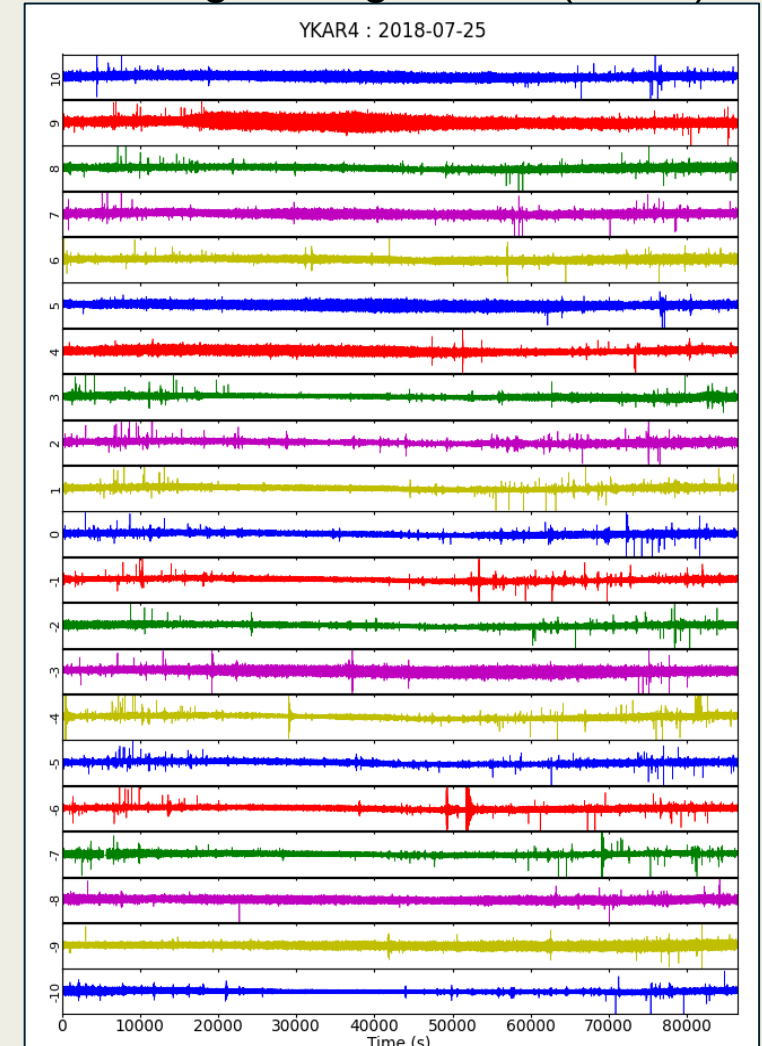
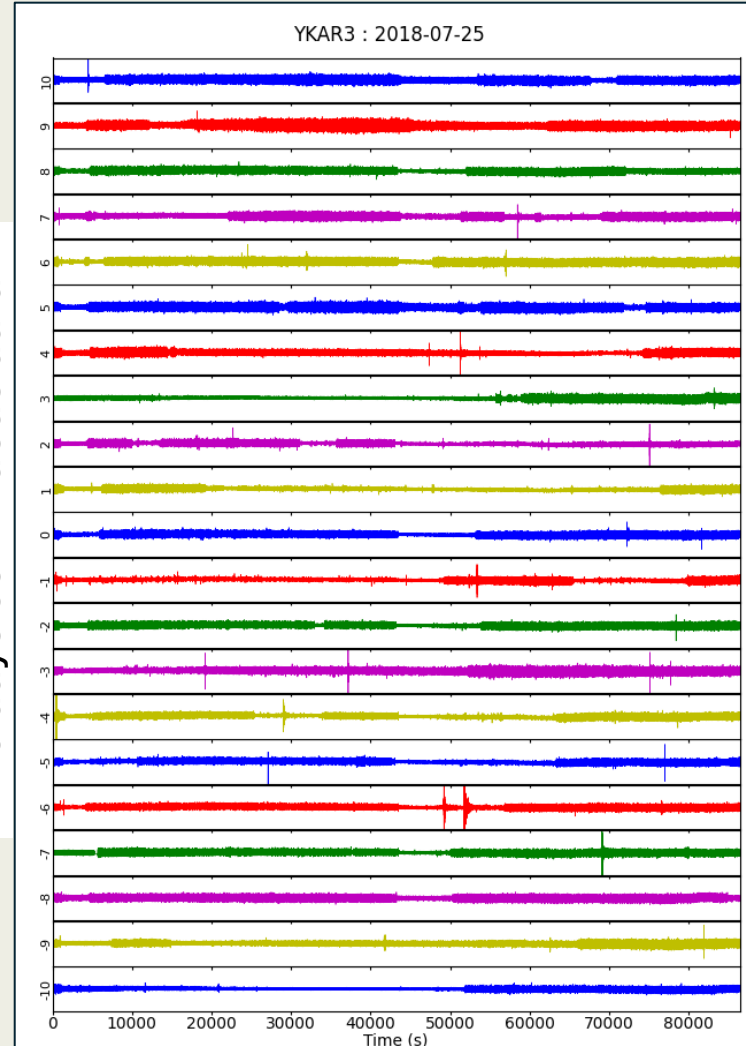
Unsupervised learning can detect unknown types of anomalies.



Compare to other models

A neighboring station (<3km)

20 days continuous data



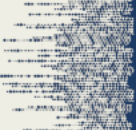
Unsupervised learning can detect unknown types of anomalies.

DL: Deep-learning
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RF: Random Forest
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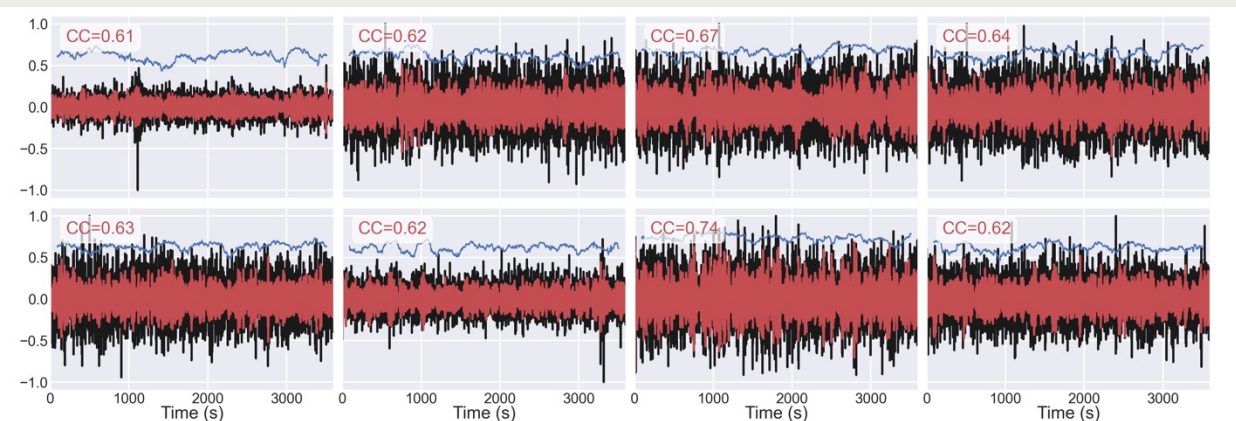
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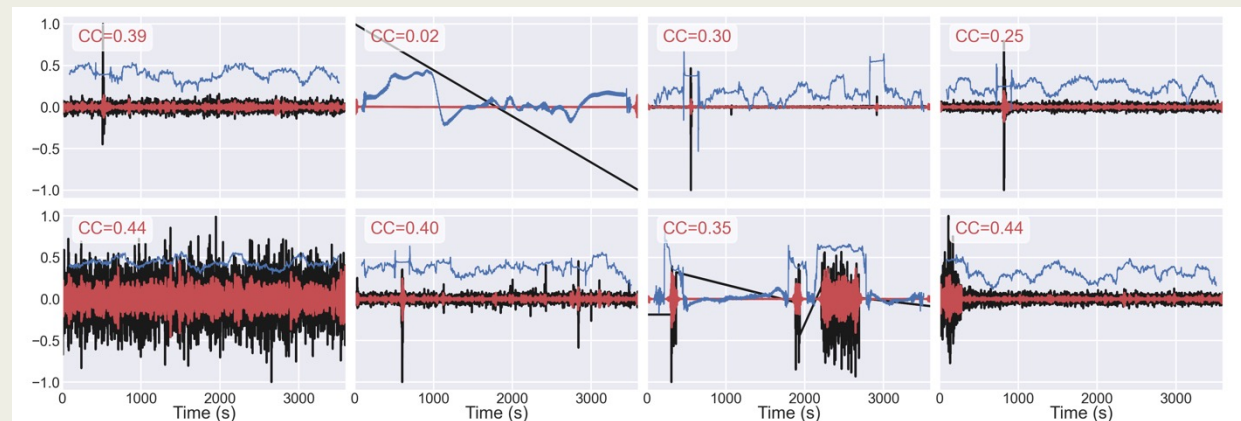


Performance evaluation

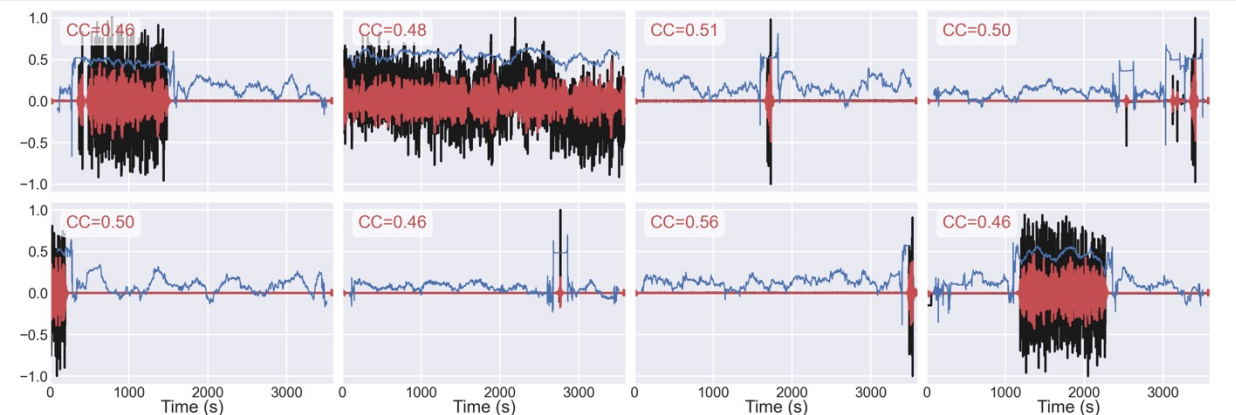
True Negative



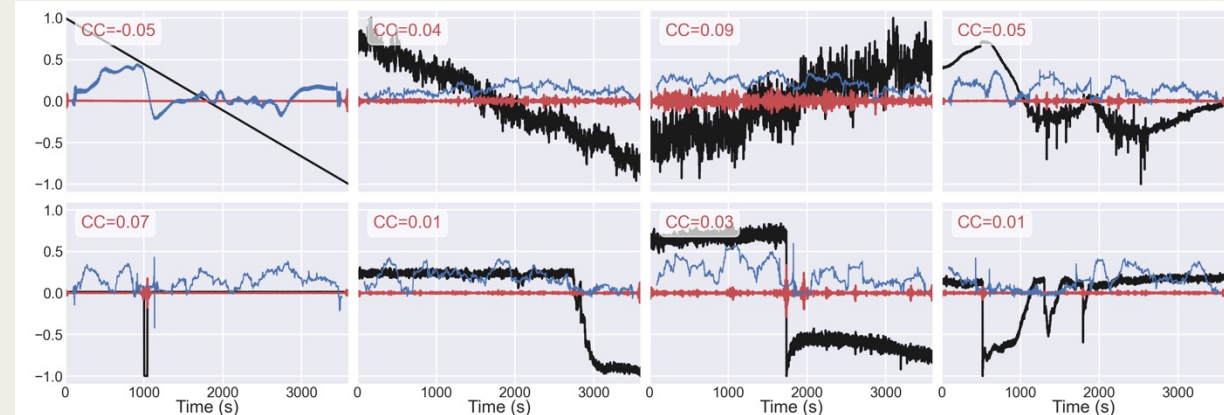
False Positive



False Negative



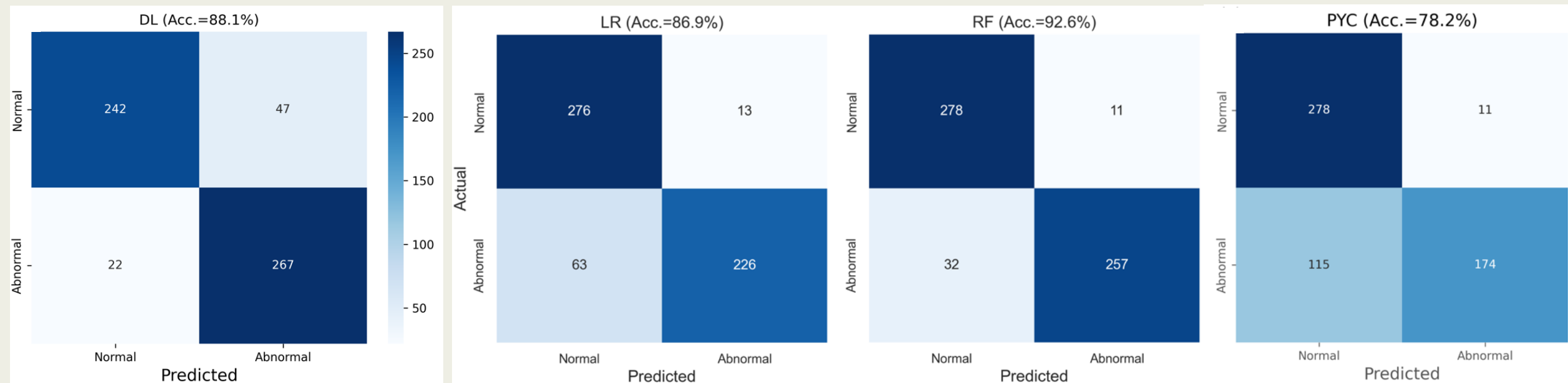
True Positive



Anomalous data: Manually selected.

Normal data: Randomly selected (may include mislabeled instances).

Performance evaluation



Our approach

- Good accuracy.
- Flexibility (Can detect unknown types of signals).

Supervised ML

- Highest accuracy.
- Less generalization capability to new types of signals.

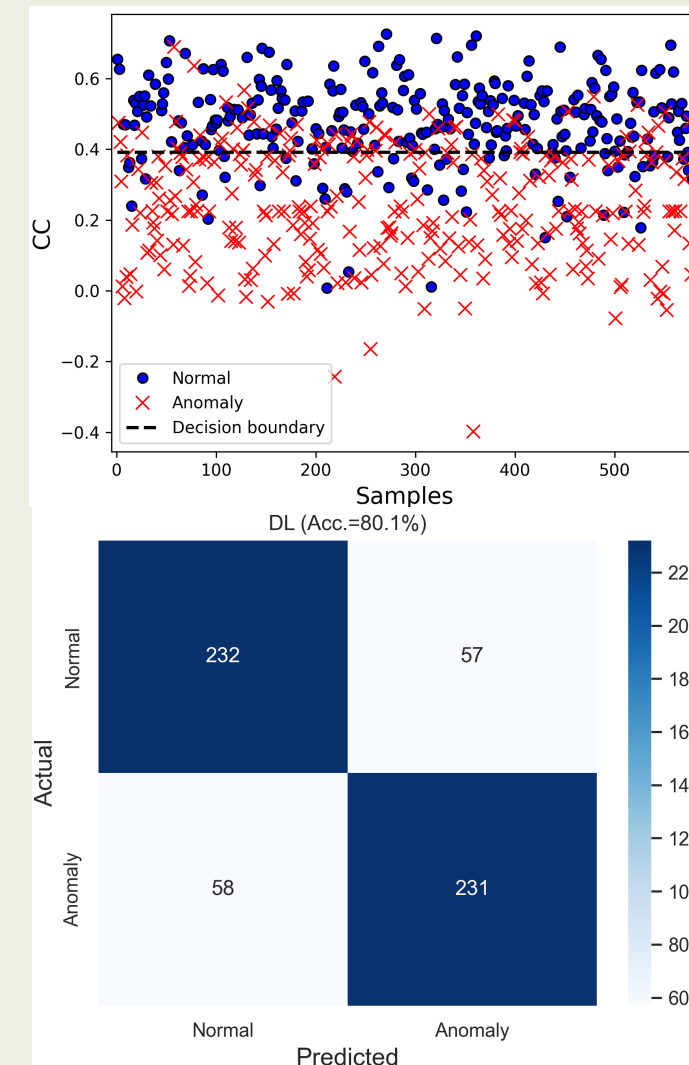
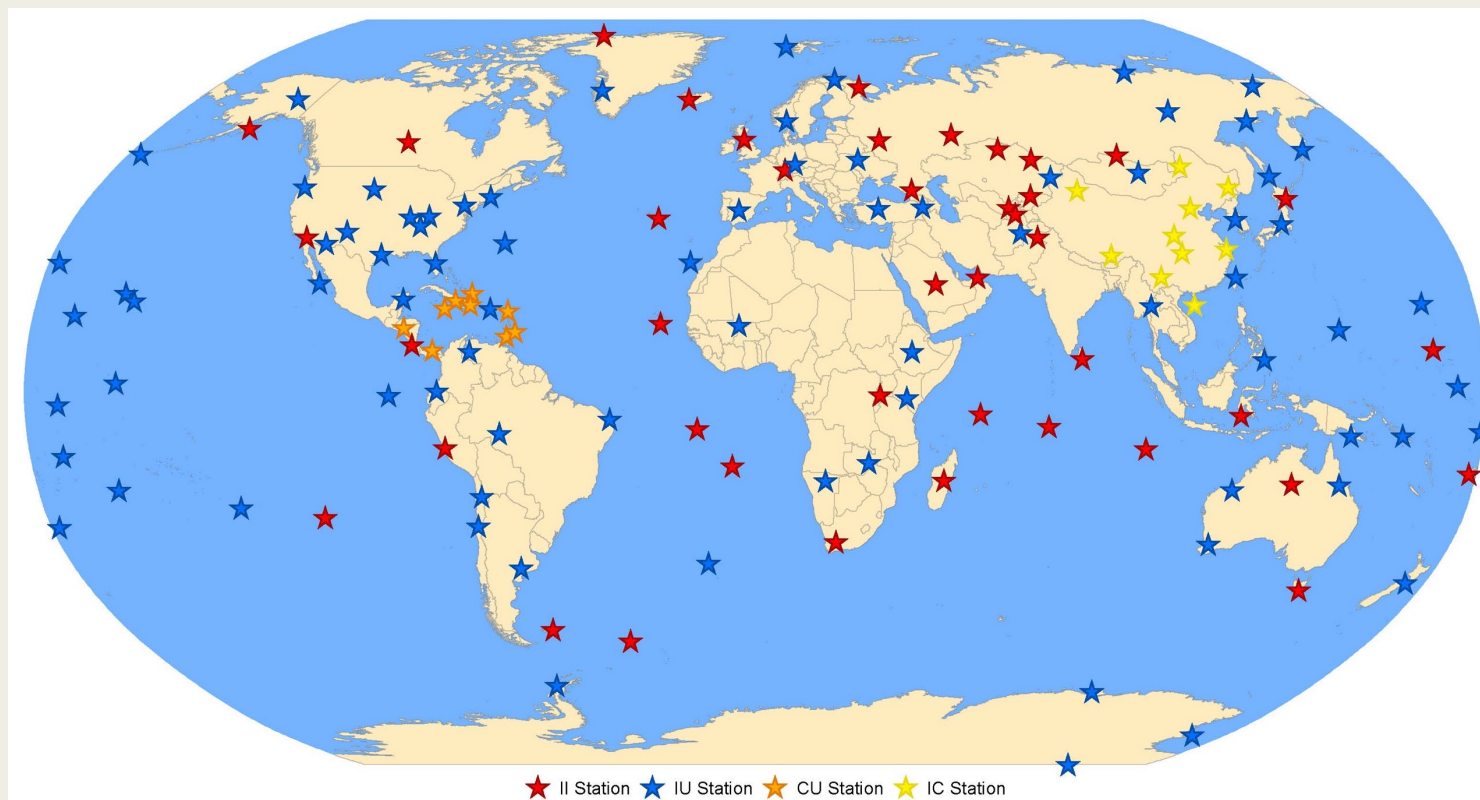
Traditional QC tool

- Detections are explicitly defined.
- Lowest accuracy for long-term anomaly detection tasks unless specifically designed for them.

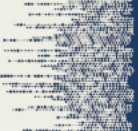
Generalization capability

A model trained with 170 GSN stations:

- Different locations and sensor types/components.

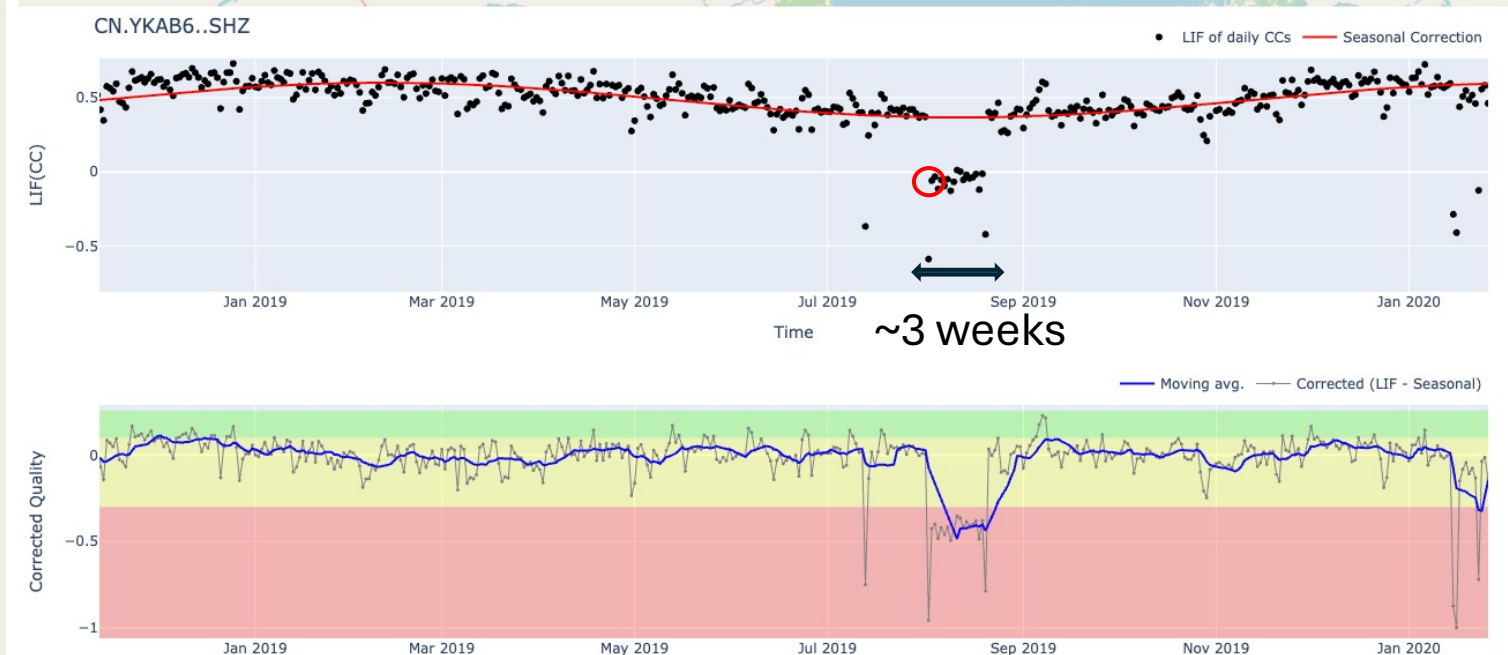
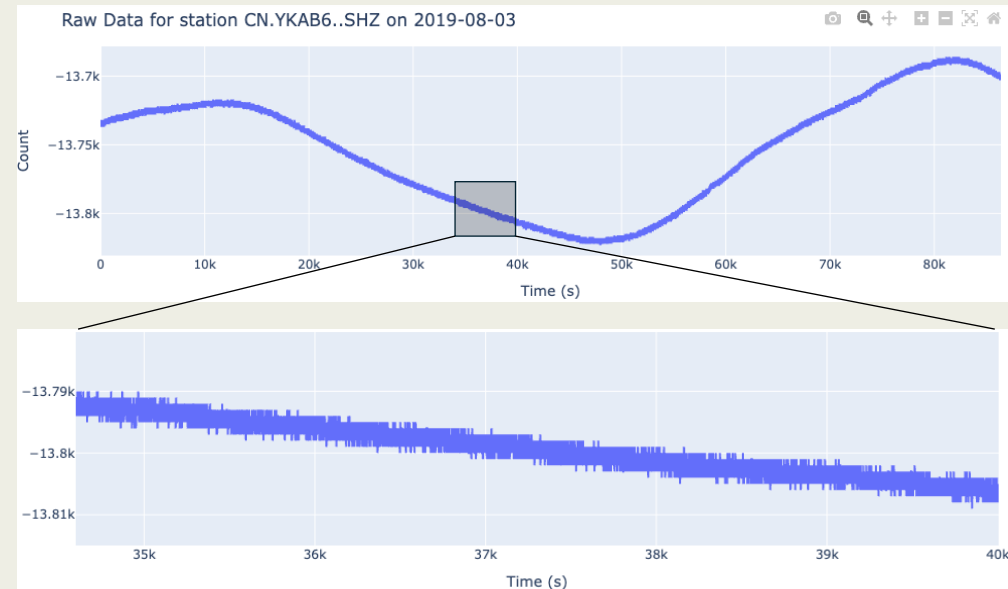


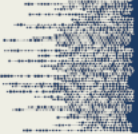
Model can transfer to new stations without significant retraining.



Application to other IMS

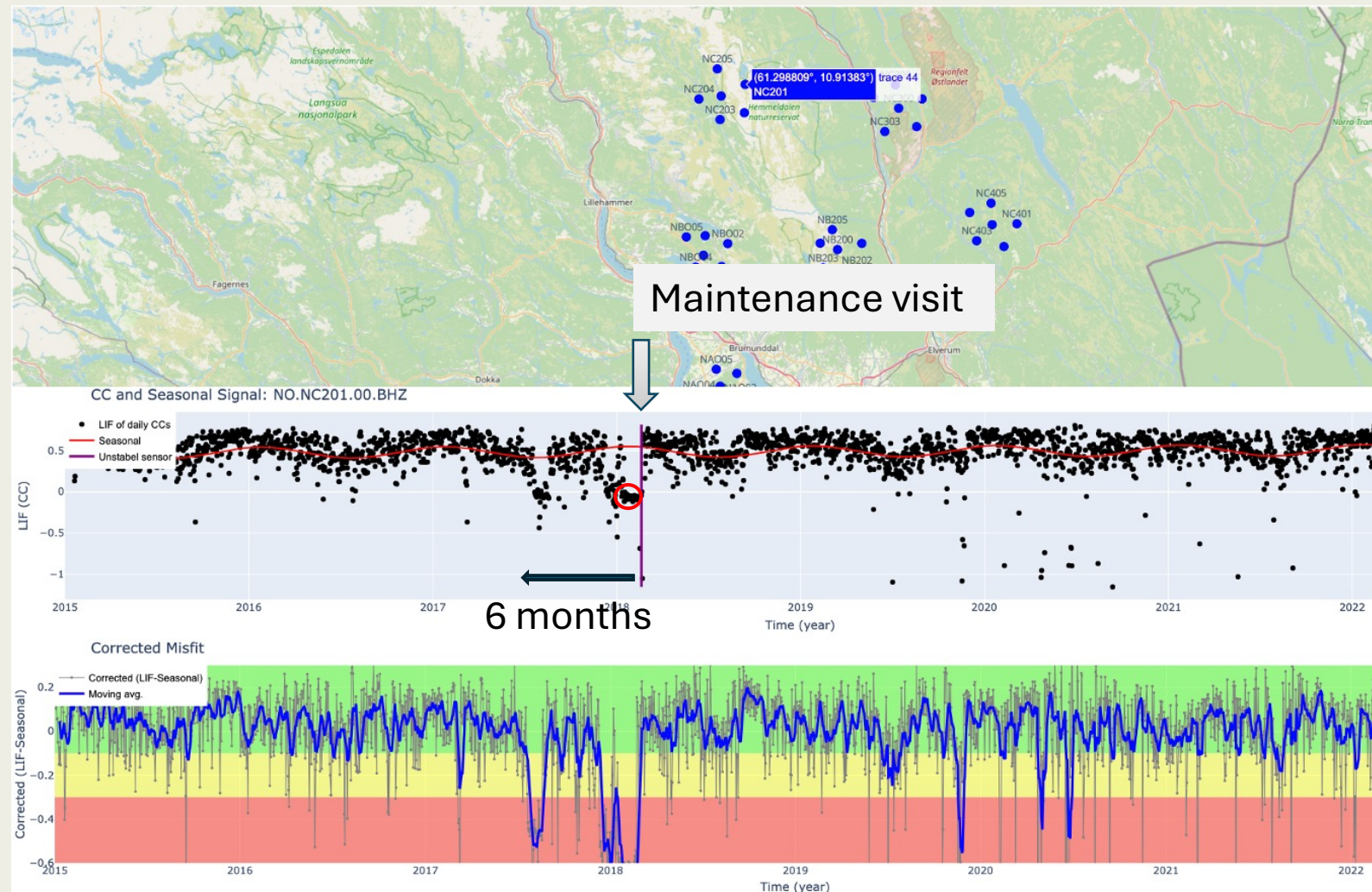
- Yellowknife Array, Canada
- Anomalies lasting three weeks were detected.

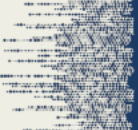




Application to other IMS

- NORSAR Array, Norway.
- Possible to detect anomalies a few months ahead of the maintenance visit.

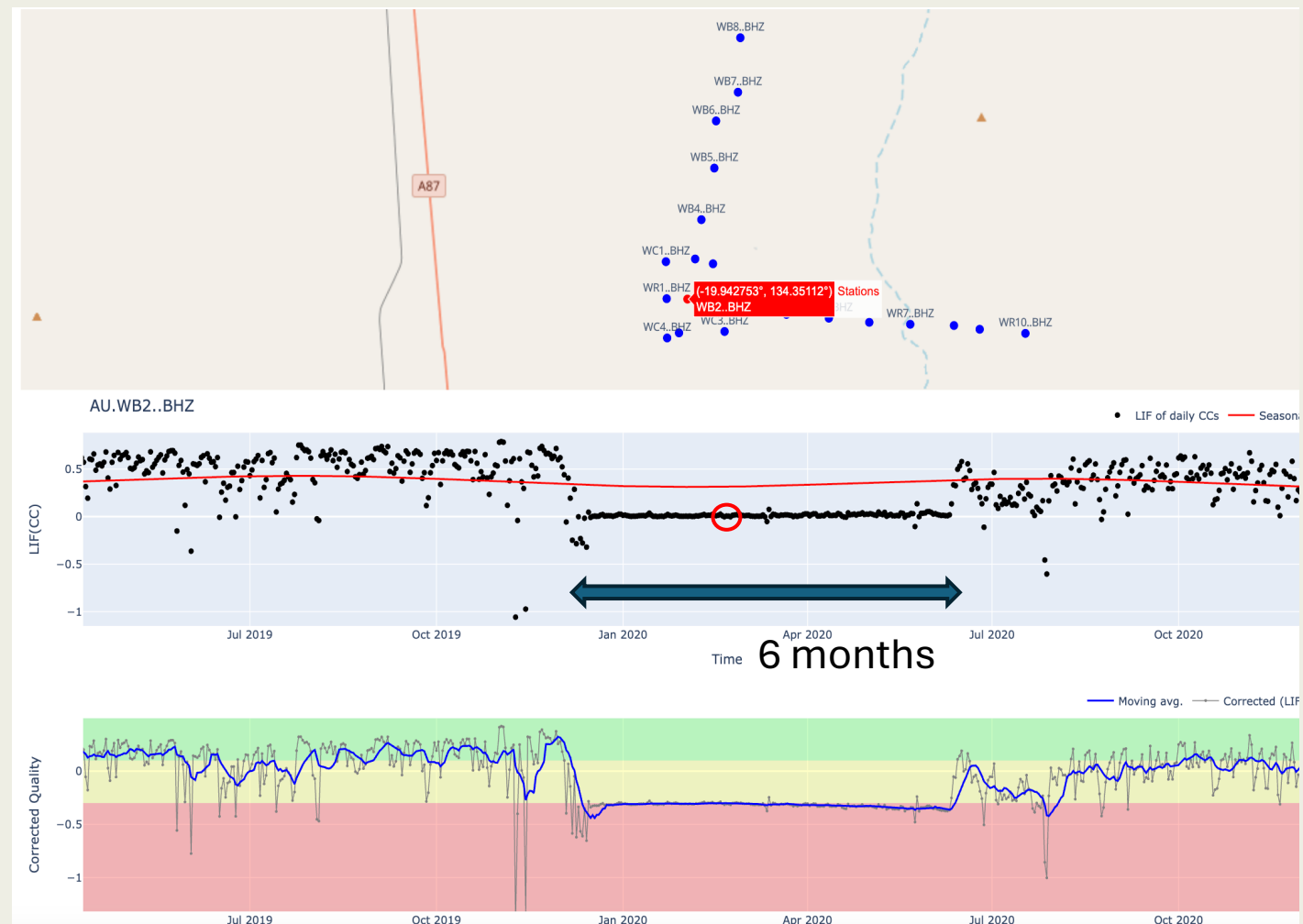
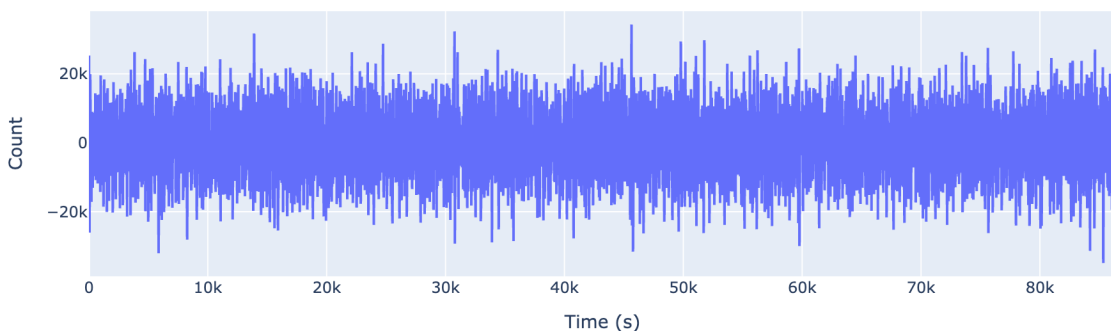


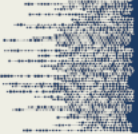


Application to other IMS

- Warramunga Array, Australia.
- The anomaly is difficult to identify from the raw data.
- Successfully detected by the model.

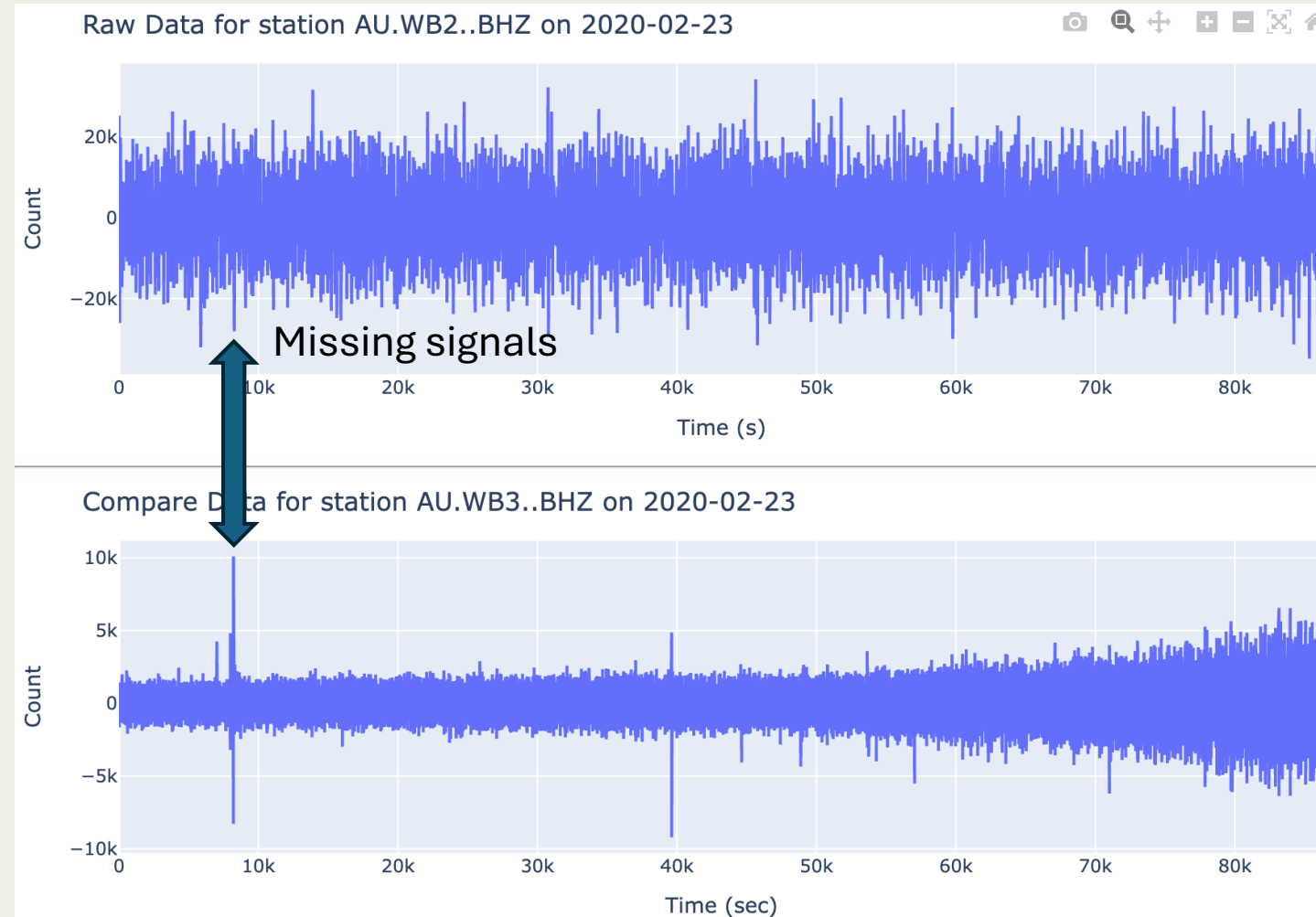
Raw Data for station AU.WB2..BHZ on 2020-02-23

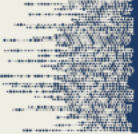




Application to other IMS

- Warramunga Array, Australia.
- The anomaly is difficult to identify from the raw data.
- Successfully detected by the model.





Conclusion

- We proposed a deep autoencoder model to detect anomalies in continuous seismic data.
- Long-term monthly anomalies can be detected by the model, allowing for the more efficient development of maintenance plans.
- The performance is similar to traditional approaches when the anomalous signals are explicit and well-defined.
- Our unsupervised approach has the capability to discover anomalous cases that were not present in the training data.
- Our approach may be expanded to other types of sensors.

RESEARCH ARTICLE | JUNE 20, 2025

Early Publication

Anomaly Detection in Seismic Data with Deep Learning: Application for Instrument Failure Detection and Forecasting ✓

Jiun-Ting Lin ; Ana C. Aguiar; Qingkai Kong; Amanda C. Price; Stephen C. Myers

Author and Article Information

Seismological Research Letters (2025) | <https://doi.org/10.1785/0220240331> | Article history



Thank you!