

Characterisation of Hydrogeological Systems using Timeseries Analysis

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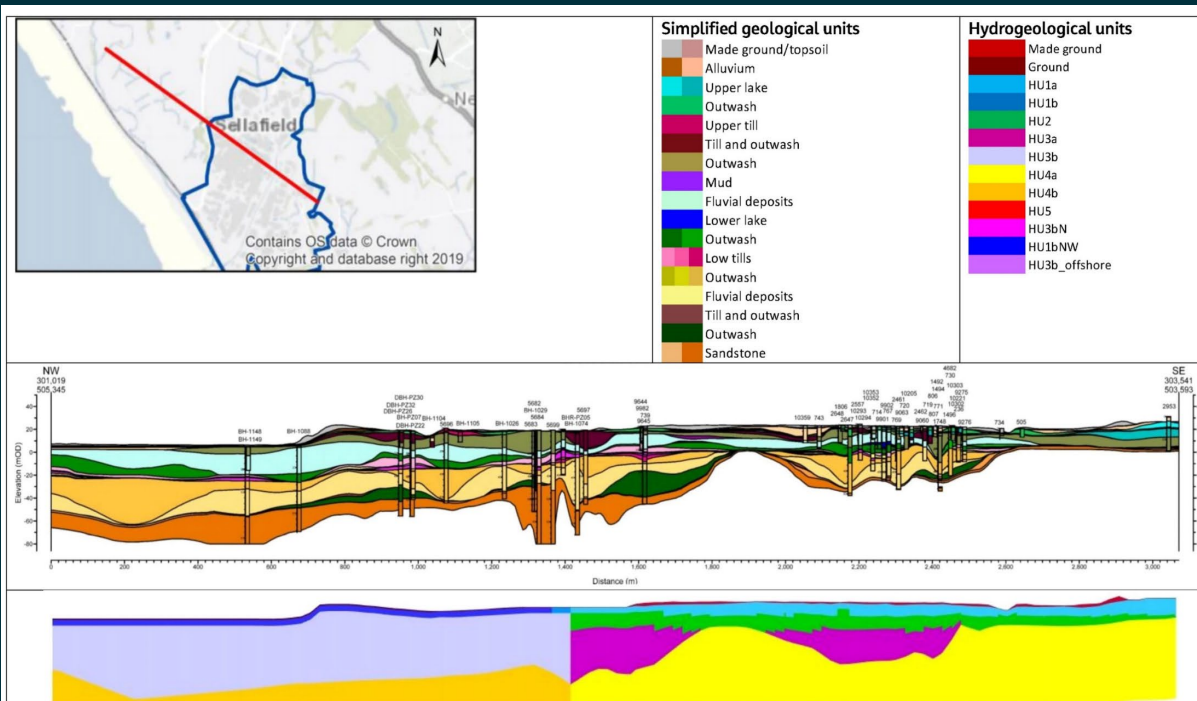
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Overview

- Characterisation efforts on nuclear sites with complex hydrogeology often face significant operational challenges
- Timeseries analysis can add value when conventional characterisation methods may be limited. We present in this talk:
 - Spectral analysis method to assess impact of earth tides.
 - Machine learning application to deliver forecasts of groundwater level in the short term.
- Case study example using data from the Sellafield site, UK.

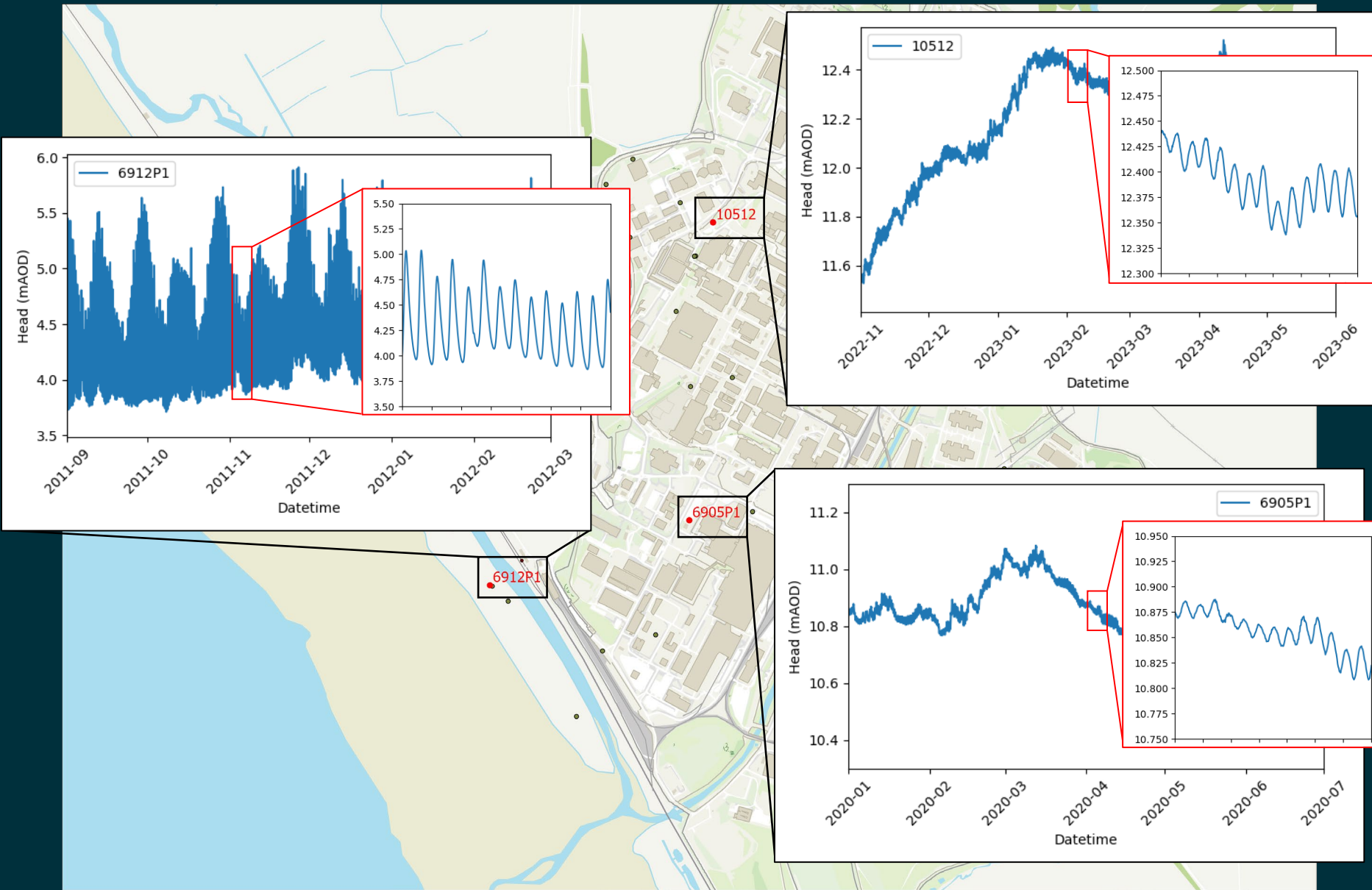
Context: Sellafield site

- Sellafield: large (for the UK!) and complex nuclear site.

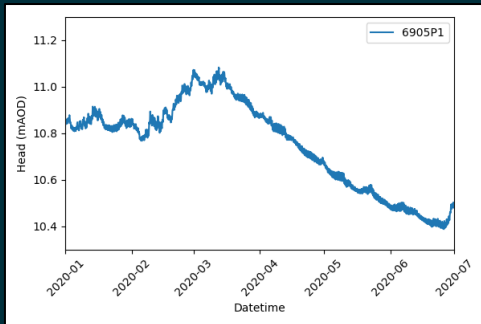


Sellafield datalogger deployments

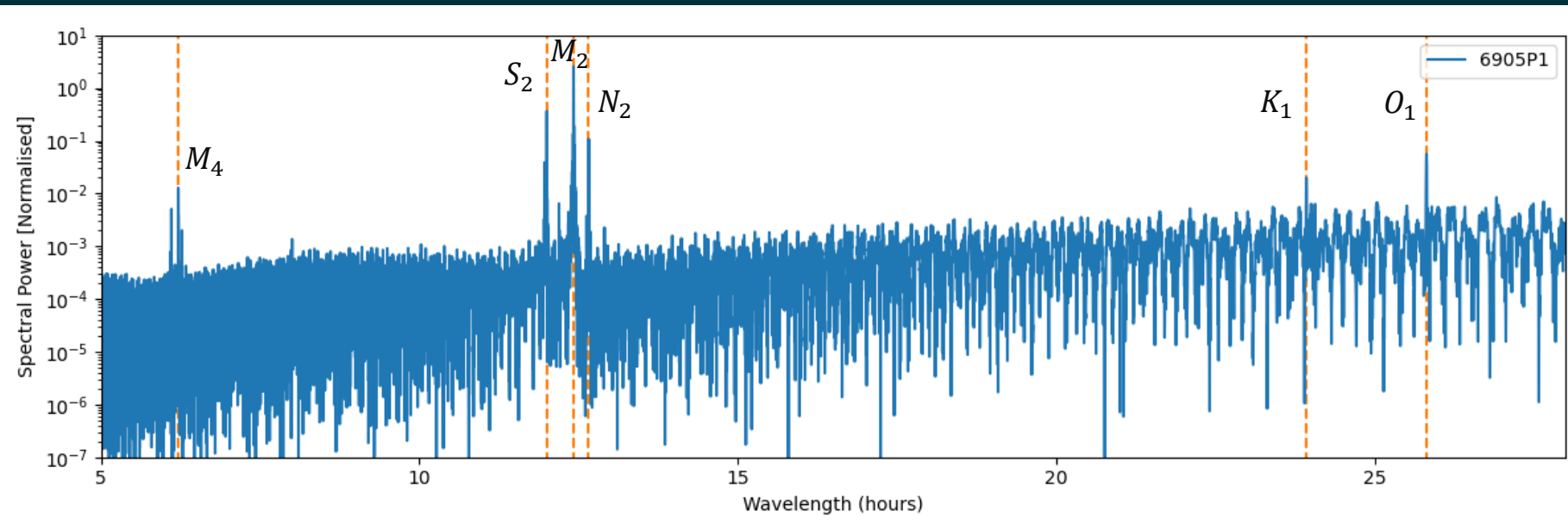




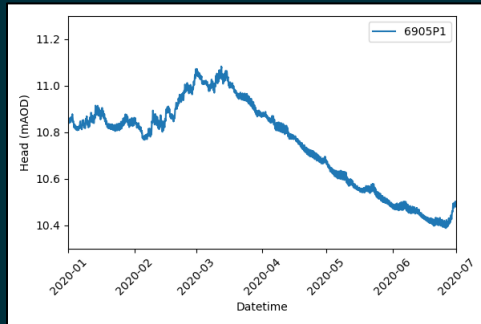
Spectral Power – Least squares periodogram



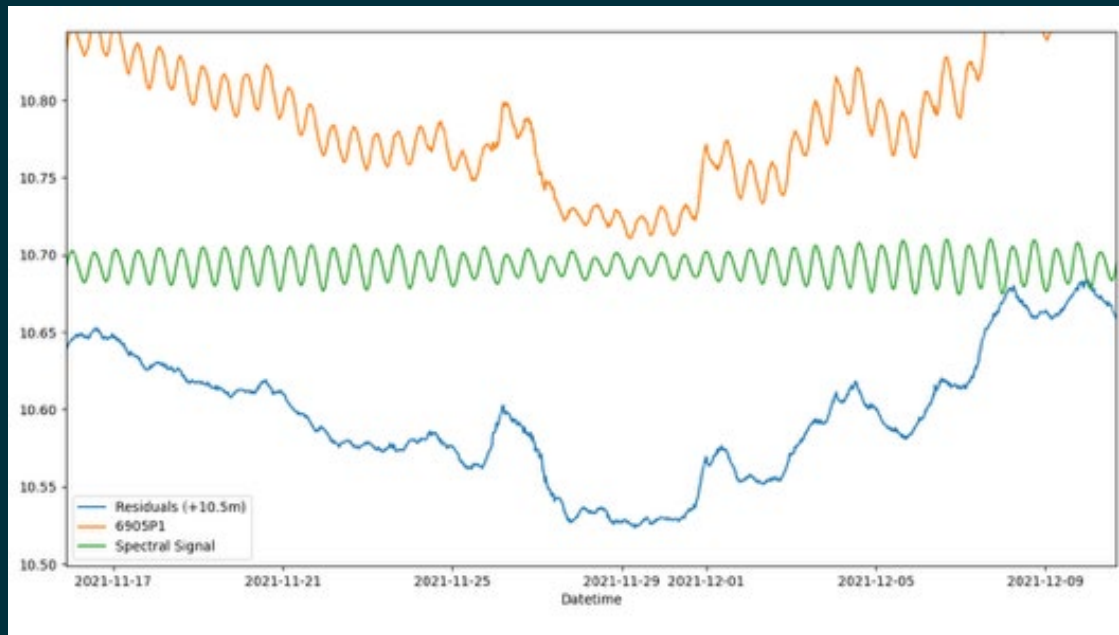
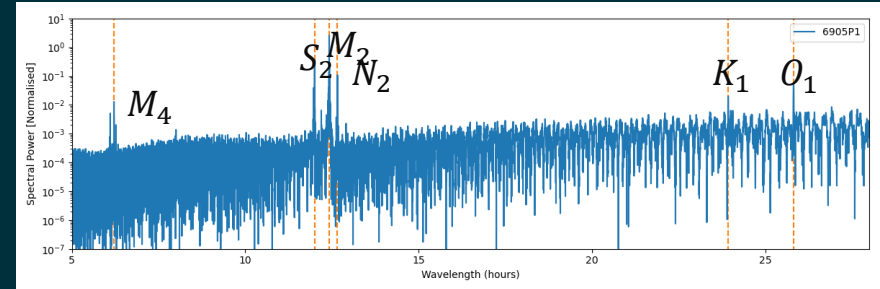
Least-squares
periodogram function



Spectral Power – timeseries decomposition

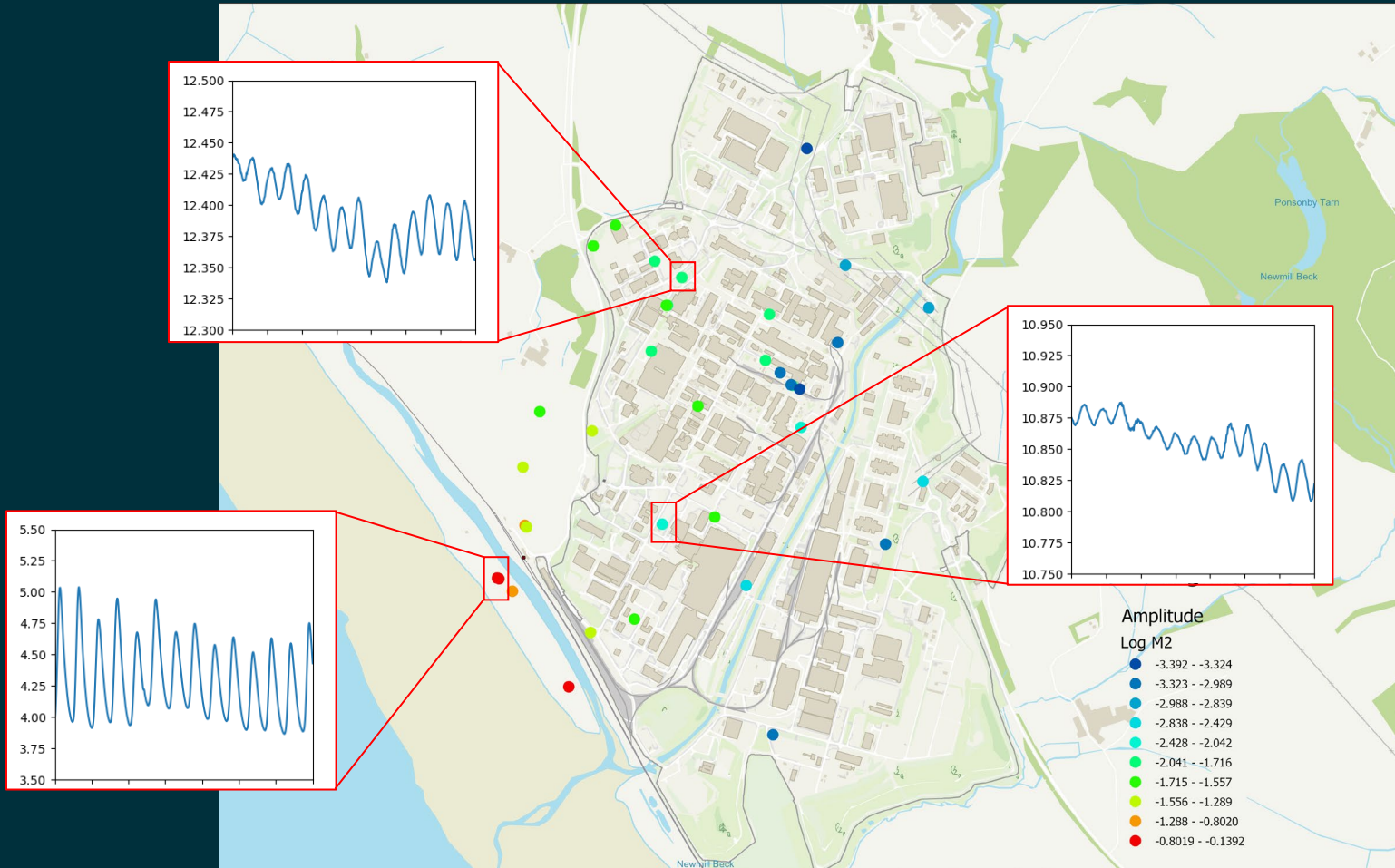


Least-squares
periodogram function

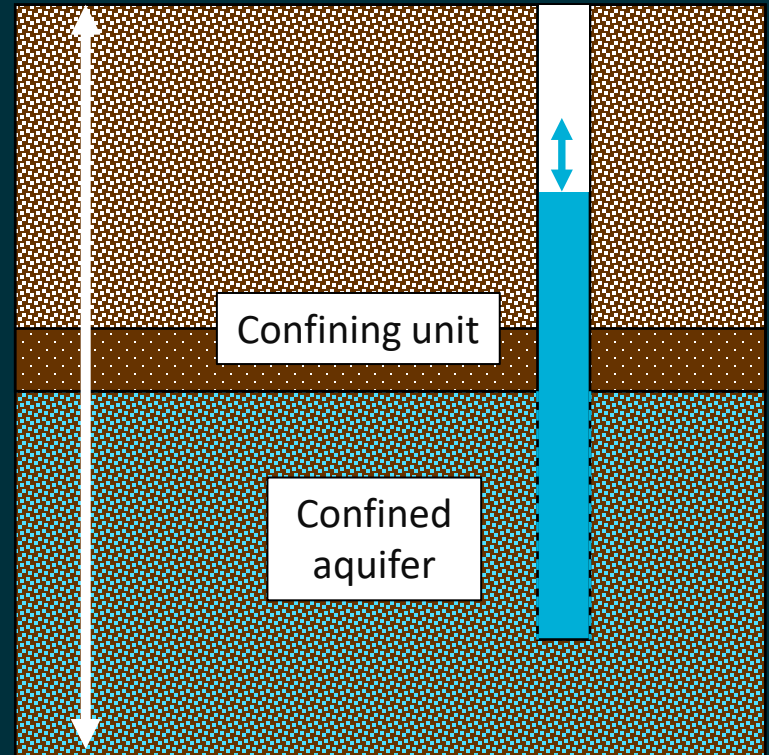
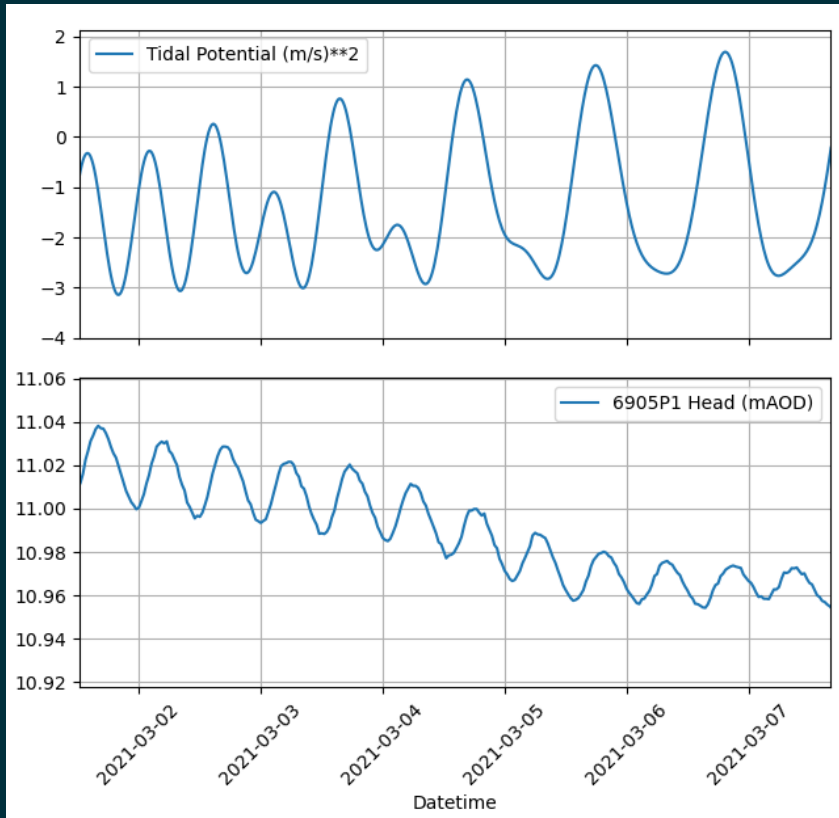


Decomposition using
spectral powers.

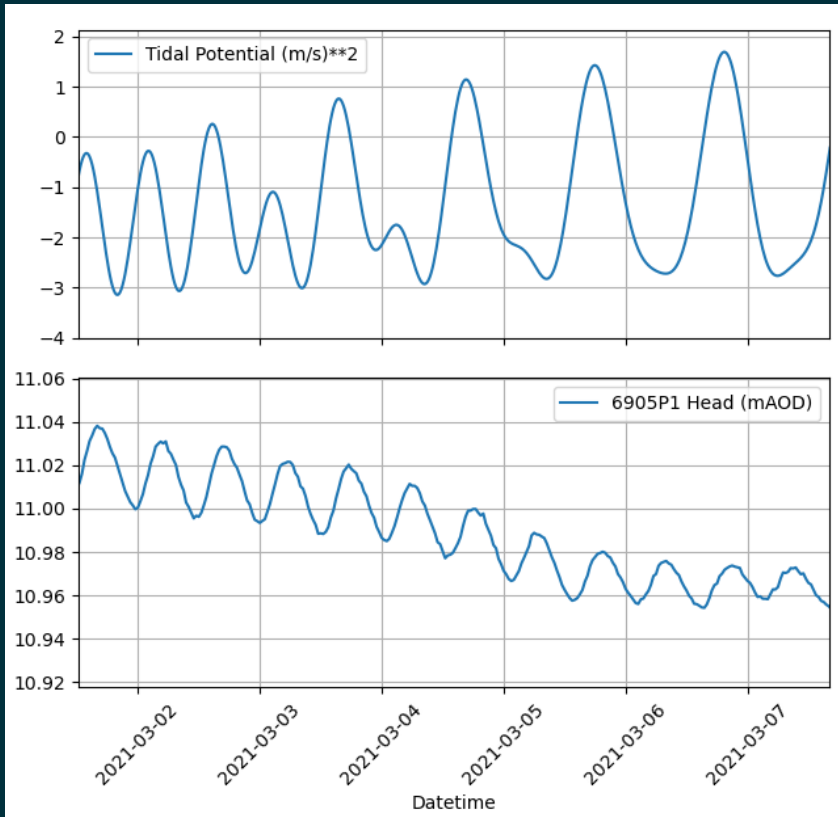
Spectral analysis: global picture



Spectral Analysis – relation to earth tides



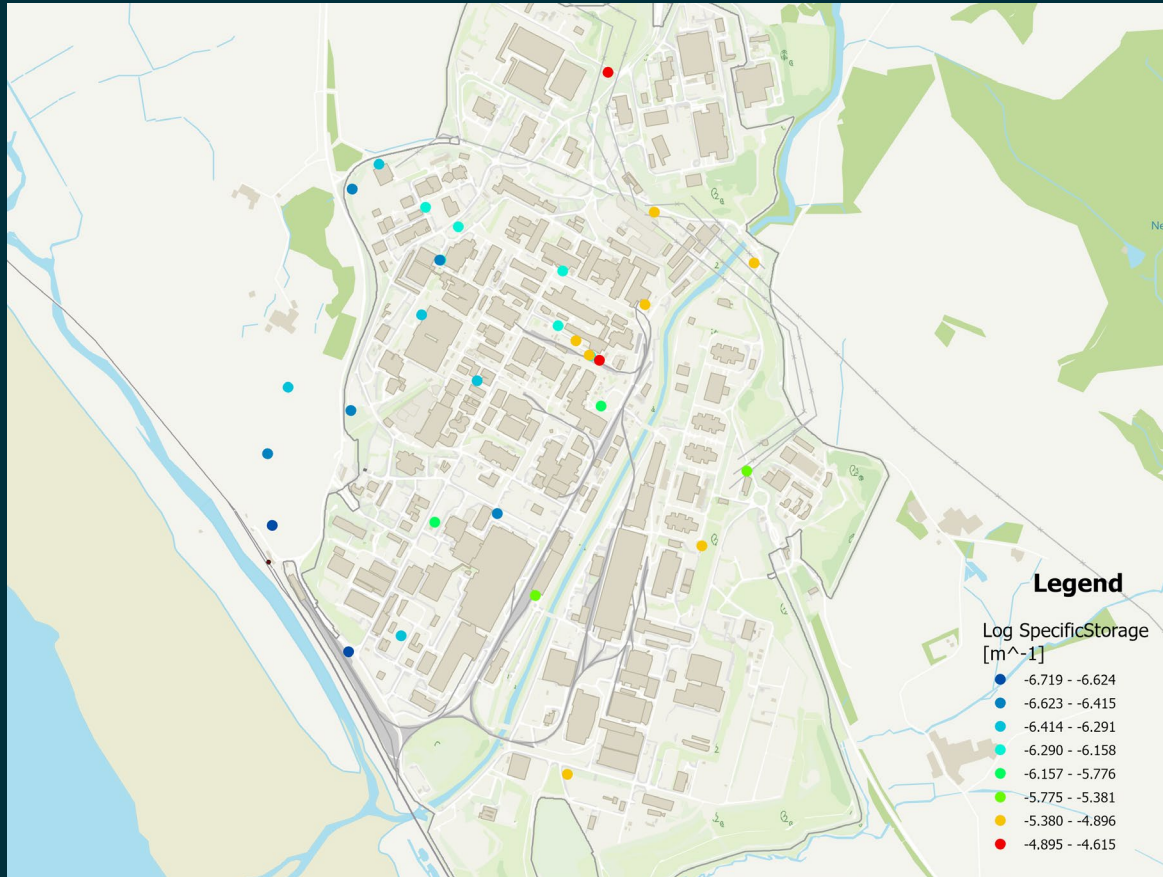
Spectral Analysis – analytic relationship with storage



$$S_s = - \left(\frac{1 - 2\nu}{1 - \nu} \right) \left(\frac{2\bar{h} - 6\bar{l}}{ag} \right) \frac{dW_2}{dh}$$

$$\frac{dW_2}{dh} \approx \frac{A_{ET}(\omega)}{A_h(\omega)}$$

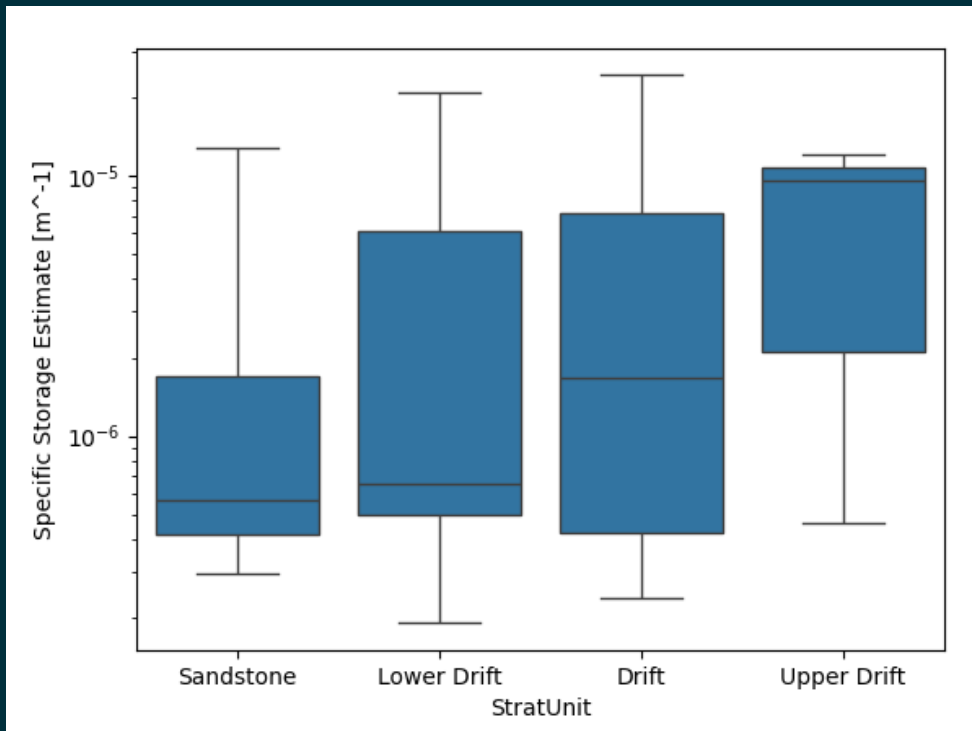
Spectral Analysis – analytic relationship with storage: global picture



$$S_s = - \left(\frac{1 - 2\nu}{1 - \nu} \right) \left(\frac{2\bar{h} - 6\bar{l}}{ag} \right) \frac{dW_2}{dh}$$

$$\frac{dW_2}{dh} \approx \frac{A_{ET}(\omega)}{A_h(\omega)}$$

Spectral Analysis – analytic relationship with storage: comparison of units.



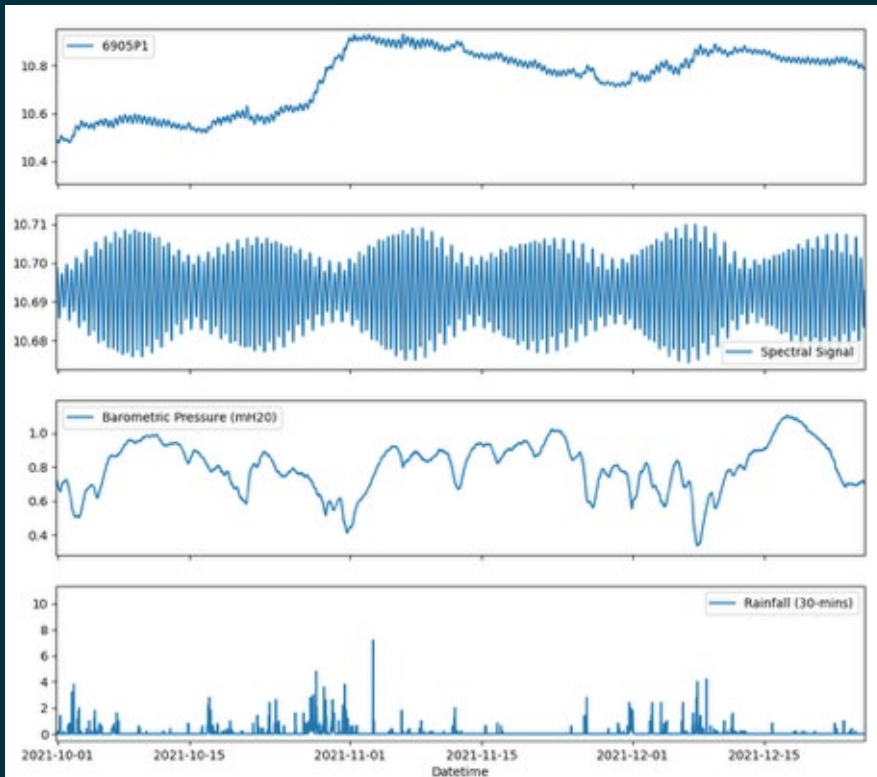
$$S_s = - \left(\frac{1 - 2\nu}{1 - \nu} \right) \left(\frac{2\bar{h} - 6\bar{l}}{ag} \right) \frac{dW_2}{dh}$$

$$\frac{dW_2}{dh} \approx \frac{A_{ET}(\omega)}{A_h(\omega)}$$

High-Frequency Forecasting: Convolutional neural networks

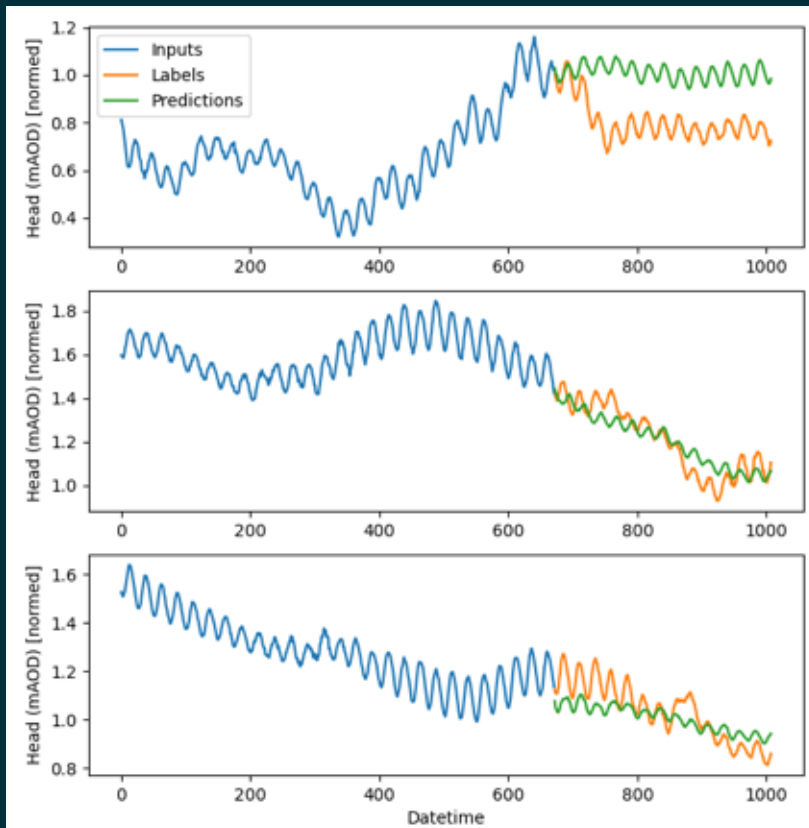
- Aim to use machine learning techniques (CNN) to provide forward predictions of groundwater levels in the short and longer term.
- Forecasts/predictions can be produced on the same frequency as datalogger sampling.
- Reduce the burden on active dataloggers.
- Enable rotation of logger locations.

CNN: Short term forecast

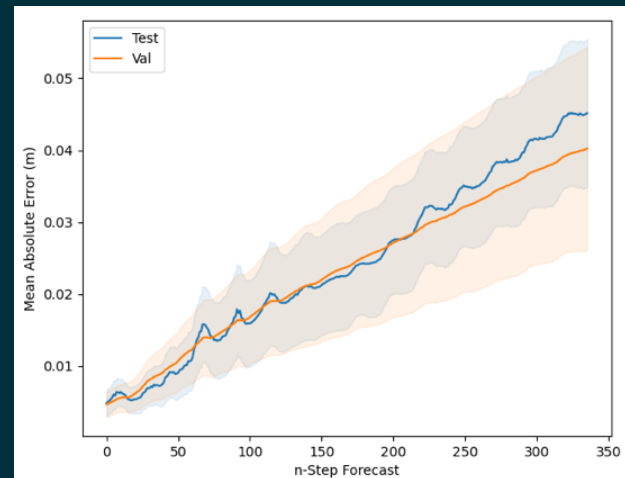


- Inputs: recent history and met parameters (rainfall, barometric pressure, earth tide signal).
- Predicted output: future week of groundwater levels at half-hourly scale.
- Simple CNN architecture is implemented in commonly used packages

CNN: Short term forecast



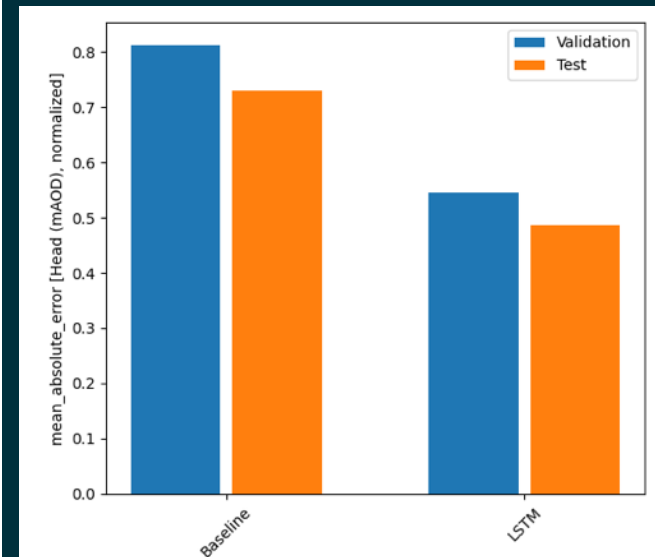
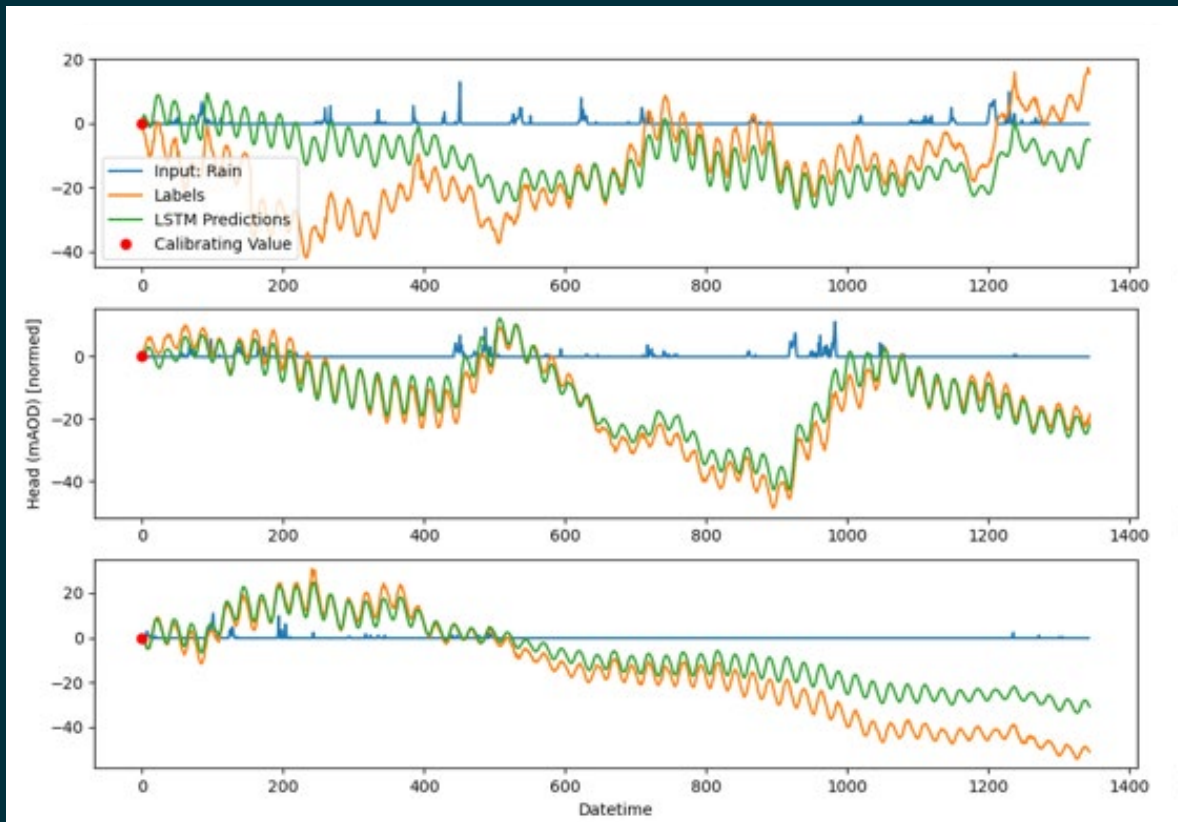
- Model deals with timeseries in discrete chunks.
- For each period of two weeks of 'history', a week of 'forecast' is generated.
- Response to rainfall and harmonic signals are learned by the model.



LSTM: live forecasting

- Model built to forecast changes in groundwater level using only environmental variables: rainfall, barometric pressure tidal signals.
- Desired ability to predict groundwater levels, based solely on live monitoring of rainfall, etc.
- LSTM model learns response to environmental data without seeing recent history of groundwater levels.

LSTM: live forecasting



Conclusions

- Spectral analysis of groundwater head timeseries can reveal insights into system properties without intrusive works.
- Machine learning techniques are readily applicable to the problem of forecasting groundwater levels (and other parameters).
- Simple architectures of models (CNNs and LSTM) enable flexibility to address multiple forecasting problems including 'live' forecasting.

Questions welcome.

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