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TAKING THE PULSE
OF OUR PLANET FROM SPACE

High Resolution Multispectral estimation of Sea Surface Temperature and Salinity in Coastal Areas

National Oceanography Centre

Cefas

THE UNIVERSITY of EDINBURGH

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CASE Partner CEFAS – Centre Environment, fisheries and aquaculture
date

Agenda

Motivation and background for project

Introduce the link between reflectance and in water properties

Ground radiometry and SST/SSS

Introduction to Machine learning models

Satellite application

Green Algal blooms over Baltic sea – July 2019 S2. Gotland Island.

Spectral image

↓

Relevant feature selection

↓

Machine learning Model

↓

Predicted values

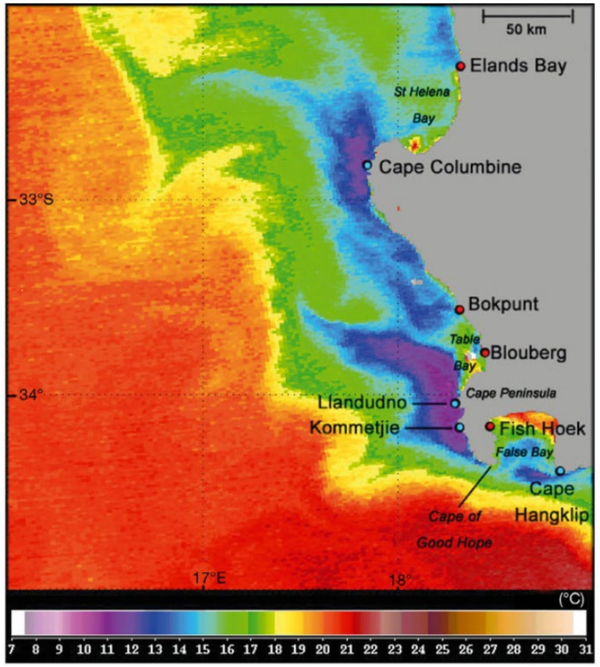
Coastal waters and sensing of Sea surface properties.

- Complex ecosystems –high biodiversity, fishing, coral reefs, mangroves.
- Rivers bring in ecological resources, upwelling, evaporation/ precipitation, advection etc.

In situ data- buoys, moorings, cruise ships. Provide sparse spatial data.

Satellite	Sensor	Spatial resolution	Revisit time
SMOS	Microwave – SSS	40 km	3 day
MODIS	Imaging Spectroradiometer	4km - SST	1-2 day
Sentinel 2	Ocean colour MSI	10 – 60m	5 days
Sentinel 3	Ocean colour OLCI	300m	<2 days

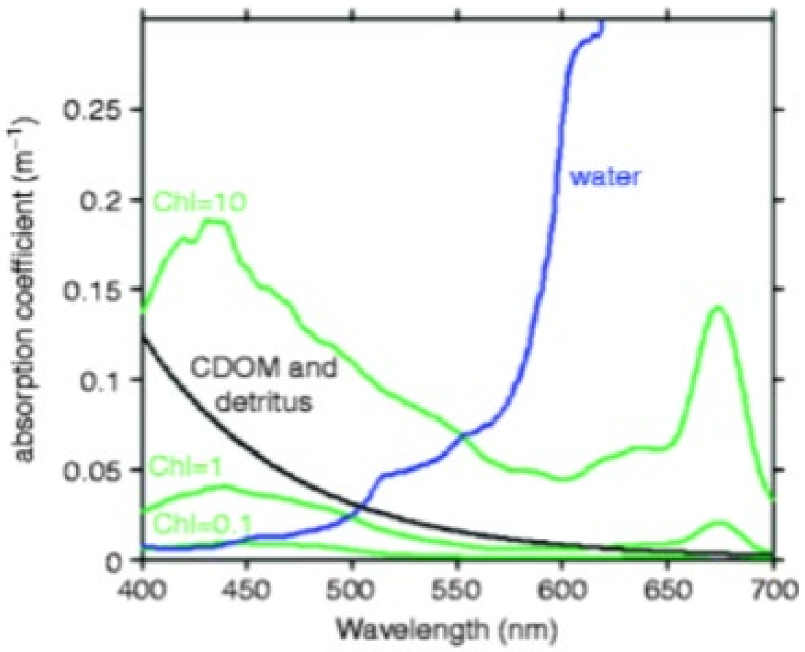
Ocean Colour/ optical remote sensing
- Assume empirical relationships, regional coefficients
- SSS Needs SST input



MODIS SST satellite image. Cape Columbine – SA.


Sentinel 2 MSI June 2019. Seville - Guadalquivir river.

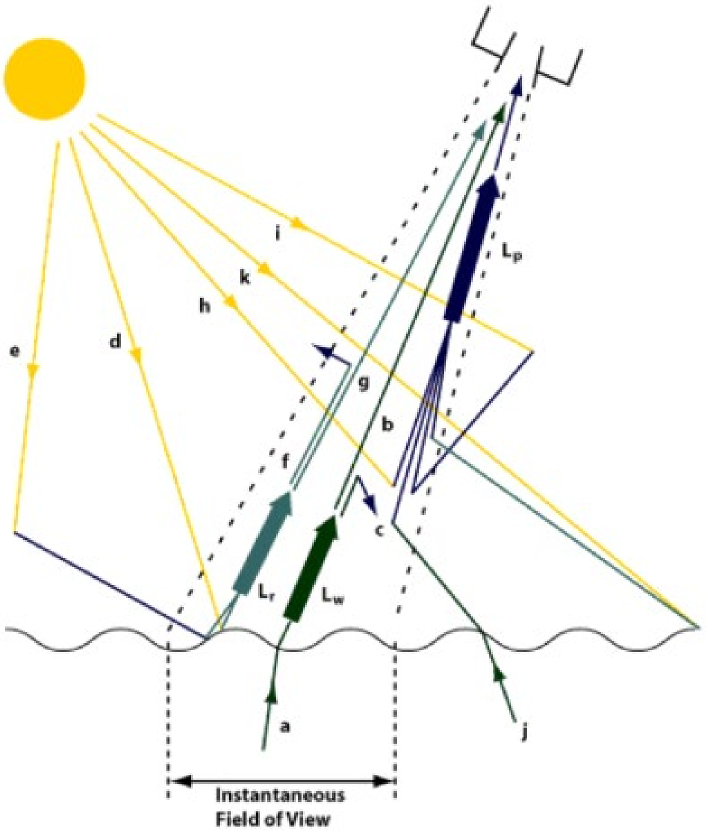
Radiometry to in-water properties



$$a(\lambda)_{Total} = a(\lambda)_w + a(\lambda)_{chl} + a(\lambda)_{CDOM}$$

$$b(\lambda)_{Total} = b(\lambda)_w + b(\lambda)_{chl} + b(\lambda)_{CDOM}$$

Coloured Dissolved Organic Matter (CDOM)
Chlorophyll (Chl)
Further water constituents: suspended particulate matter (SPM), total suspended matter (TSM) etc.



$$L_t(\lambda) = L_r(\lambda) + L_a(\lambda) + t(\lambda)L_w(\lambda)$$

L_w = Water leaving reflectance

L_r = Rayleigh scattering. L_a = Aerosol effects

t(λ) = Transmission effects from atmosphere.

Top of atmosphere (TOA) = L_t

Model implicitly finds the Apparent optical properties AOPs and the link to the IOP.

Outputs = Physical water parameters

Patagonia data – ground case study

Collected in-water Temperature and Salinity via a thermosalinograph. Also simultaneously measured ground water leaving radiance with hyperspectral radiometers. 350-900nm in 1nm spectral bands.

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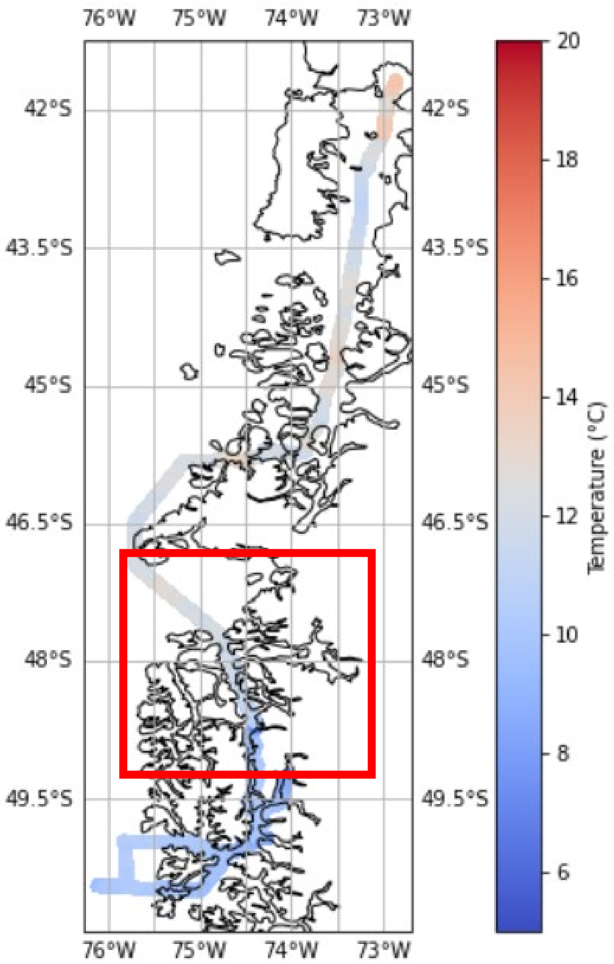
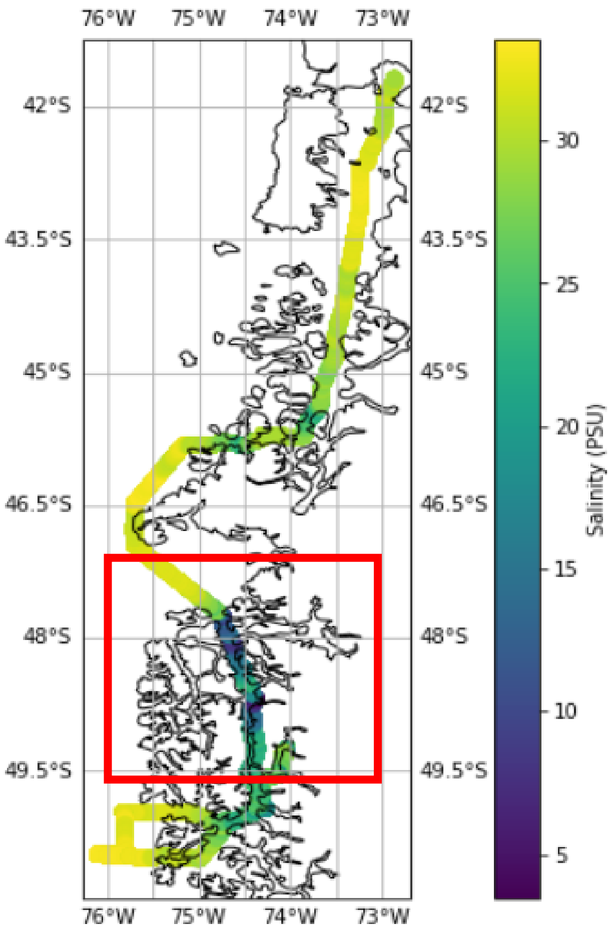
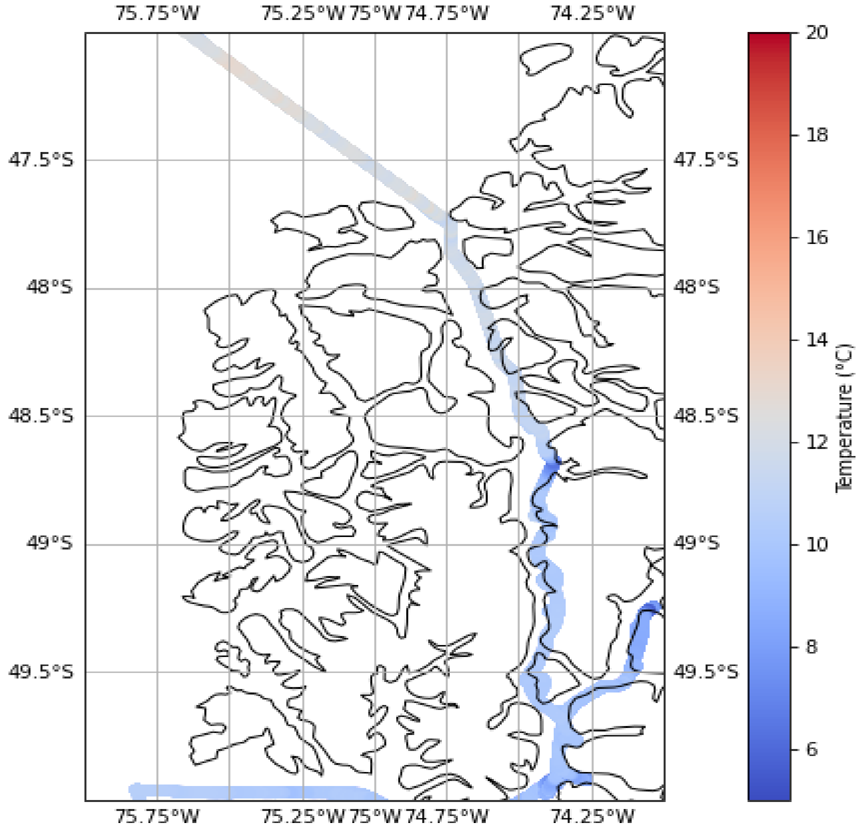
With acknowledgement to: Dr. Jose Luis Iriarte M, Universidad Austral de Chile and Dr Evangelos Spyrakos – Stirling University

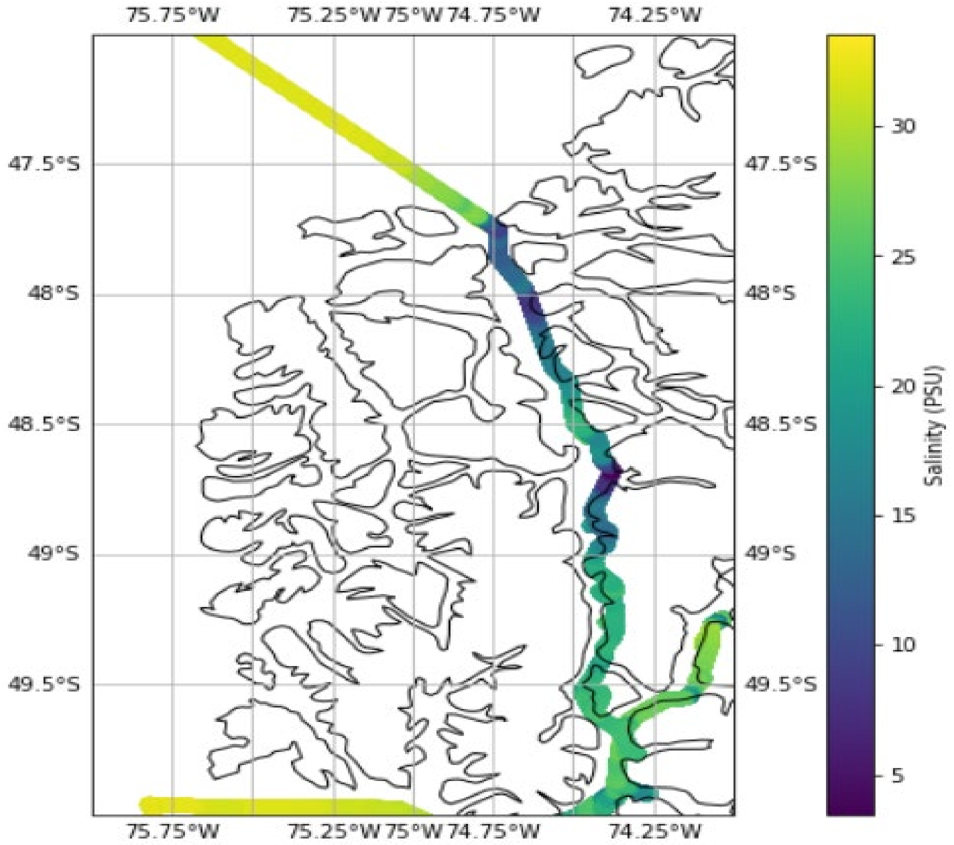




Temperature and Salinity profiles measured by the research vessel.

Glacial region

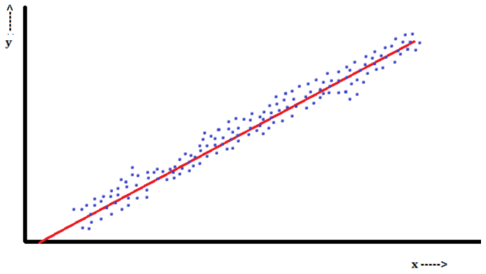


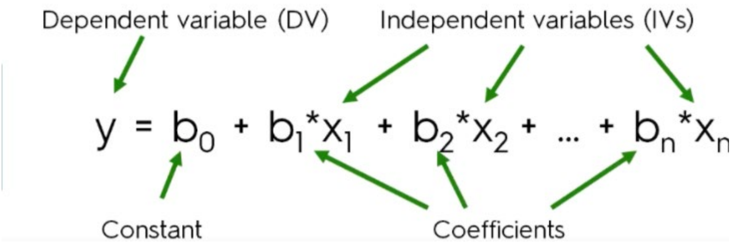


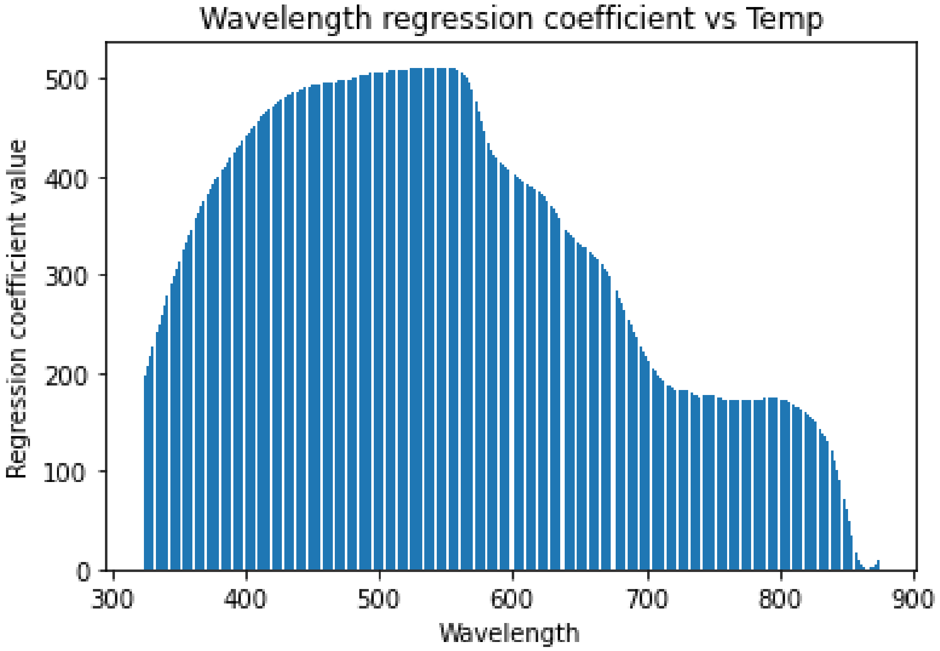
Region of interest (75W, 48S). Influx of cooler fresh glacial water is seen by lower temperature in the region 5-8°C vs 14-16°C and salinity values 15PSU below the surrounding waters.

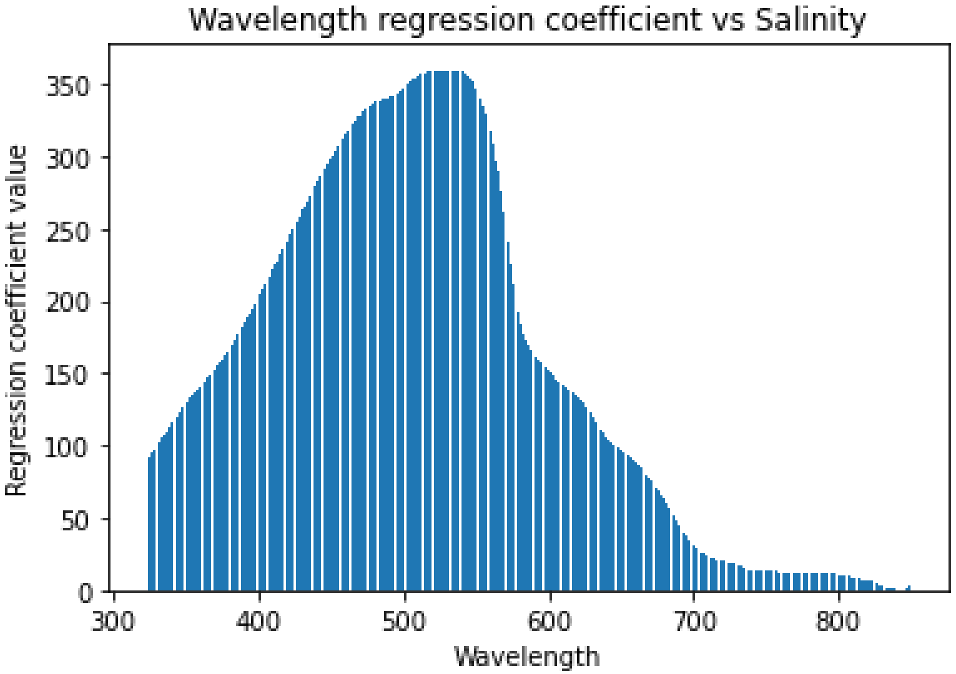
Hyperspectral regression

Regression modelling –
hyperspectral reflectance to temperature/salinity









Simple linear regression coefficients of the reflectance bands.

Regression results:

Table 1. Temperature regression results.

Regression	RMSE Train (°C)	RMSE Test (°C)	K fold (k=5) Mean RMSE (°C)
Linear Regression	8.40*10^-10	1.131	1.312
Ridge	0.469	0.667	0.492
SVM Regression	0.417	0.624	0.489
Decision Tree regression	5.76*10^-15	1.111	0.613
Polynomial regression* Power 2, (15094 inputs)	3.12*10^-11	1.652	2.740

Table 2. Salinity Regression results.

Regression	RMSE Train (PSU)	RMSE Test (PSU)	K fold (k=5) Mean RMSE (PSU)
Linear Regression	5.2*10^-9	3.708	3.845
SVM Regression	1.840	1.915	1.808
Decision Tree regression	1.957	1.900	0.899
Polynomial regression* Power 2, (15094 inputs)	7.8*10^-12	1.569	1.627

Feature Selection vs Principle component analysis vs Emulated Sentinel 2.

Principle Component analysis: PCA, reduces dimensionality by shifting the data into a new orthovector based sample space.

Feature selection – using the regression coefficient matrix to find the most relevant spectral bands.

Emulated Sentinel 2; averaging the hyperspectral bands to approximate the S2 multispectral bands.

Table 3. Temperature: - Ridge regression.

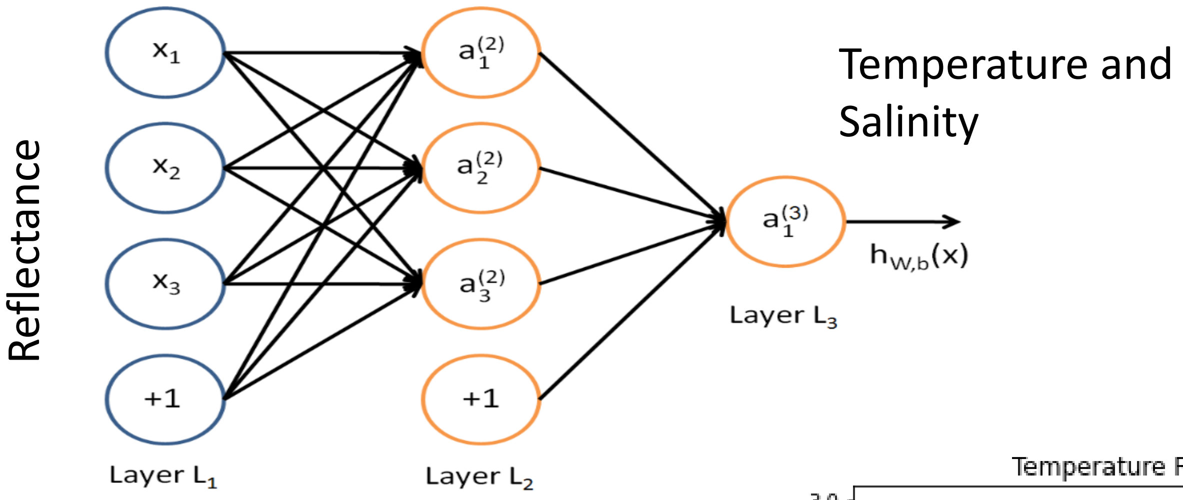
Name	Number inputs	Input band coverage	Test RMSE (°C)
PCA 99.9% variance	5	n/a	0.638
PCA 99.5%	3	n/a	0.673
Variance Thresholding (0.0001)	104	489nm-592nm	0.668
Top Regression coefficient	10	572-581nm	0.768 (tree = 0.643)
10nm averaged Regression coefficient over all frequencies.	10	409-899nm	0.624
S2 Multispectral averaged	13	443- 865nm (not possible SWIR)	0.891

Table 4. Salinity – Tested with decision tree regression.

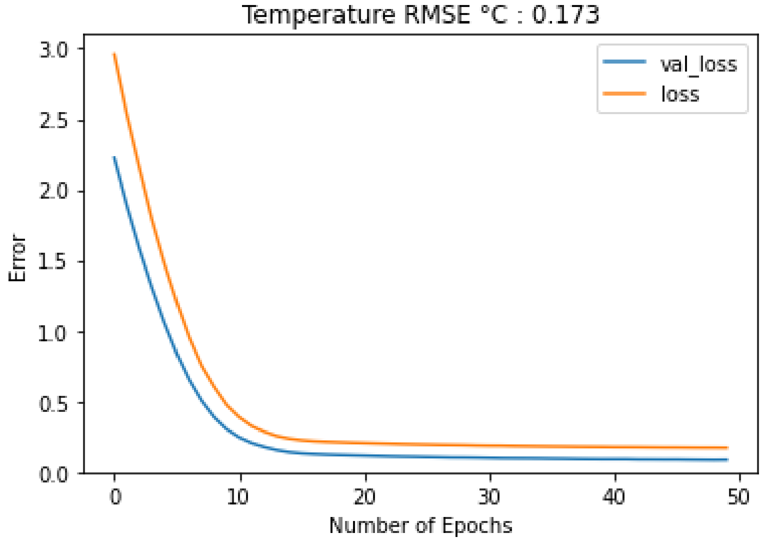
Name	Number inputs	Input band coverage	Test RMSE (PSU)
PCA 99.9% variance	5	n/a	0.830
PCA 90%	2	n/a	1.443
Variance Thresholding	104	489nm-592nm	1.127
Top 10 Regression coefficient	10	554-563nm	0.920
10 nm averaged Regression overall over all frequencies.	10	409-899nm	1.044
S2 Multispectral averaged	13	443- 865nm (not possible SWIR)	1.244

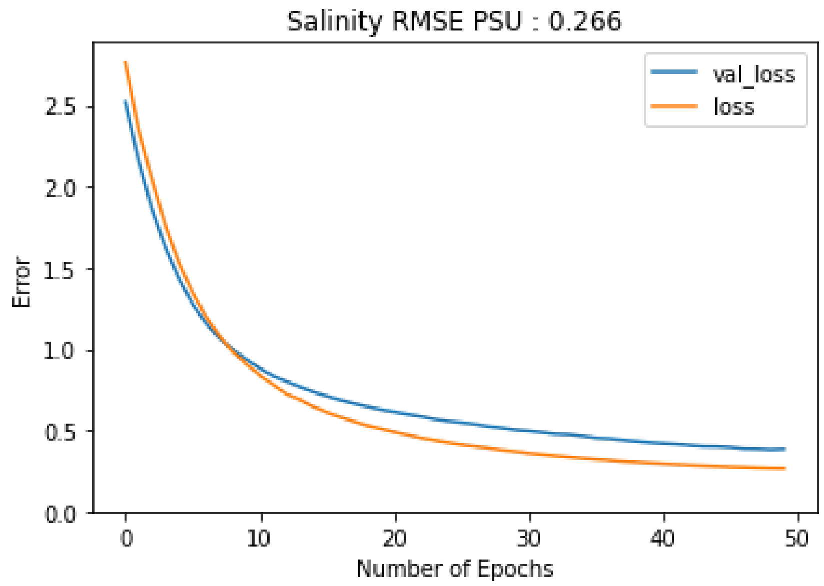
Neural Network

Simple neural network structure



Coefficient weights





Neural network loss (Root Mean Squared Error) for salinity and temperature vs number of training epochs.

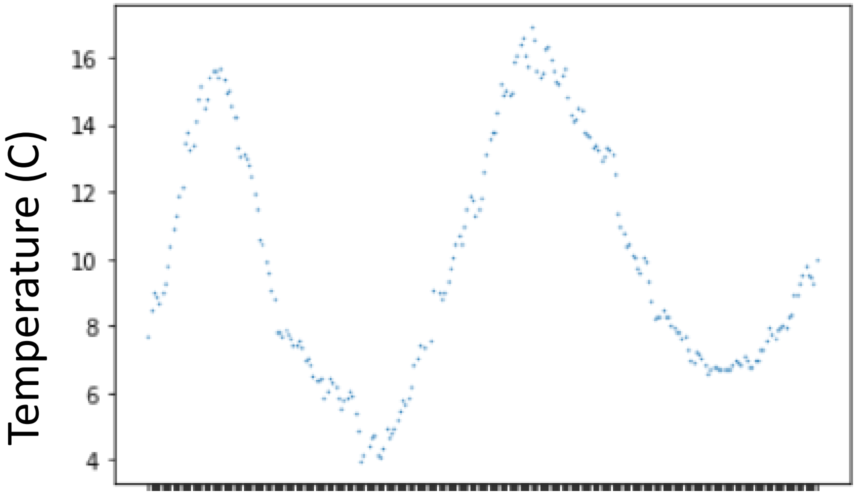
A neural network was trained on the final Sentinel 2 averaged inputs.

4 hidden layers with ReLu activation.

Both Salinity and Temperature estimated independently.

Current work: UK SmartBuoy

- 4 UK smart buoys at locations at Dowsing bay, Thames and Liverpool and West Gab.
- Matched with Sentinel 2 data, within a 3x3 pixel window and within 1 hour of pass by time.
- Test model structure with the Satellite inputs.
- Testing to see if model trained on one river performs well on similar morphology and seasonal variation in model performance.



Thames 2017-2019

Future work:
Applicability of the Patagonia and the UK smart buoy algorithms to further Case studies in the Gulf of Mexico and Copernicus Marine global buoy network.

Thank you for listening. Questions?

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