A multi-fidelity framework for ocean temperature reconstruction based on model-inferred dynamics and real time satellite and buoy measurements

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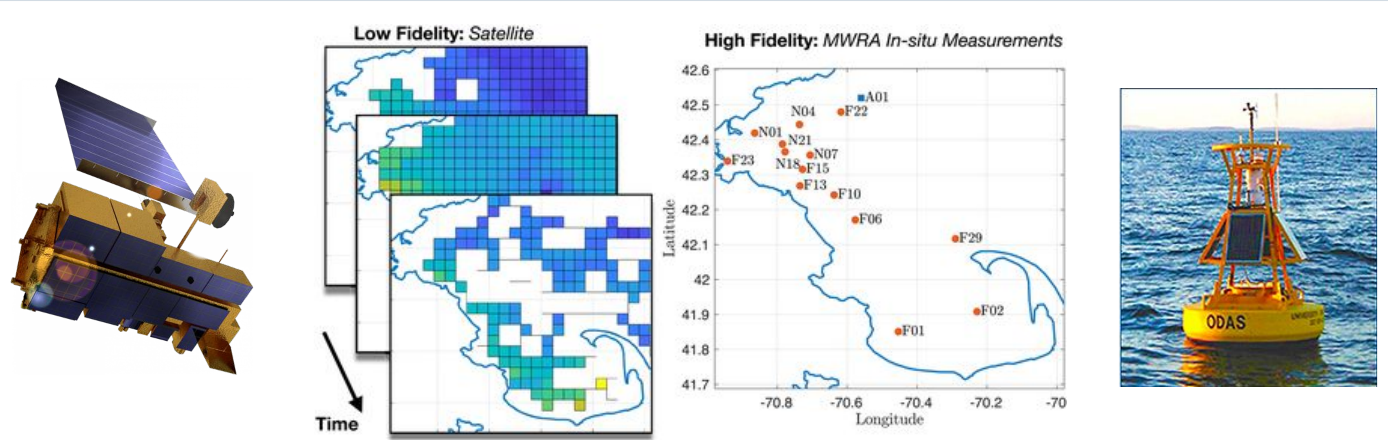
Objective

Estimate a full 3D temperature field of the ocean using a combination of numerical simulations and physical sensors.

Background

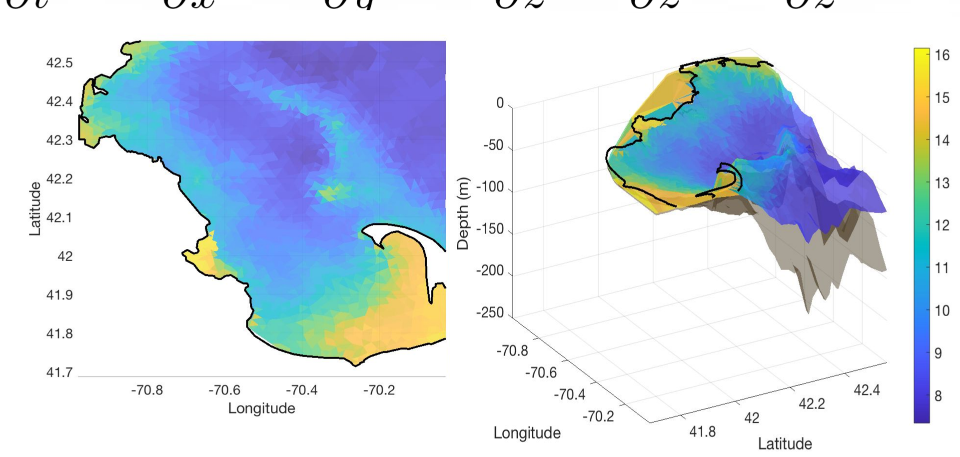


NASA Terra MODIS

MWRA NERACOOS Buoy

Babaee et al. 2020

$$\frac{\partial T}{\partial t}+u\frac{\partial T}{\partial x}+v\frac{\partial T}{\partial u}+w\frac{\partial T}{\partial z}=\frac{\partial}{\partial z}(K_h\frac{\partial T}{\partial z})+F_T$$



FVCOM Reanalysis Data

Chen et al. 2003

Techniques

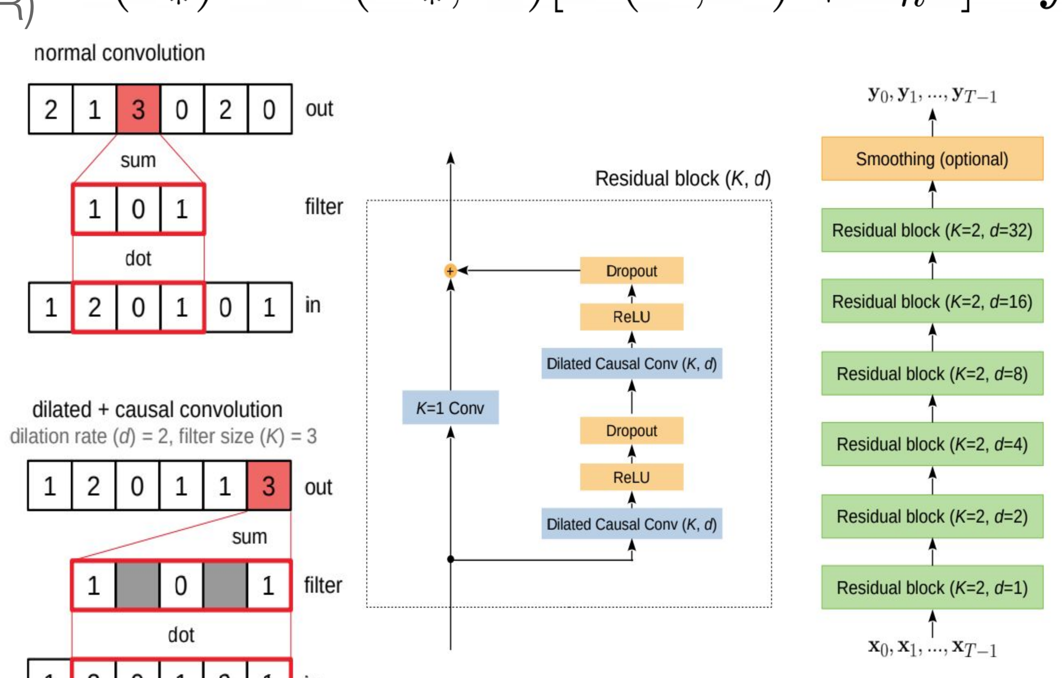
Principal Component Analysis (PCA)

$$\mathbf{T}_{proj}(\cdot,t)=\sum_{i=1}^{2}q_i(t)\boldsymbol{\phi}_i+\bar{\mathbf{T}}(t)$$

Gaussian Process Regression (GPR)

$$\bar{\mathbf{f}}(\mathbf{x}_*)=K(X_*,X)[K(X,X)+\sigma_n I]^{-1}\mathbf{y}$$

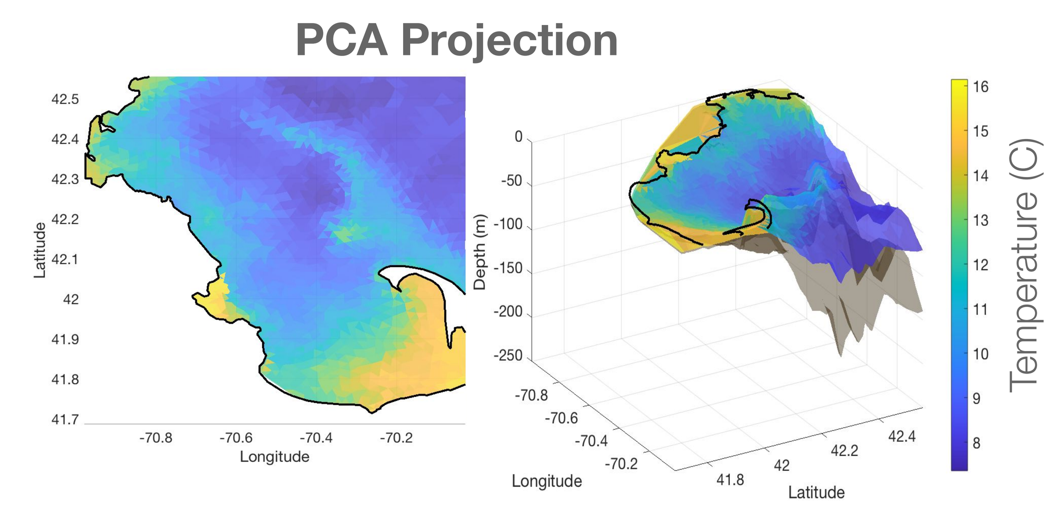
Temporal Convolutional Network (TCN)



Wan et al. 2020

Framework

Step 1: Apply PCA to Each (x,y) Point of the FVCOM Data



$$\mathbf{T}=\begin{bmatrix}T(z_1,t_1) & \dots & T(z_1,t_m)\\ T(z_2,t_1) & \dots & T(z_2,t_m)\\ & \dots & \\ T(z_n,t_1) & \dots & T(z_n,t_m)\end{bmatrix}$$

only keep the first two modes

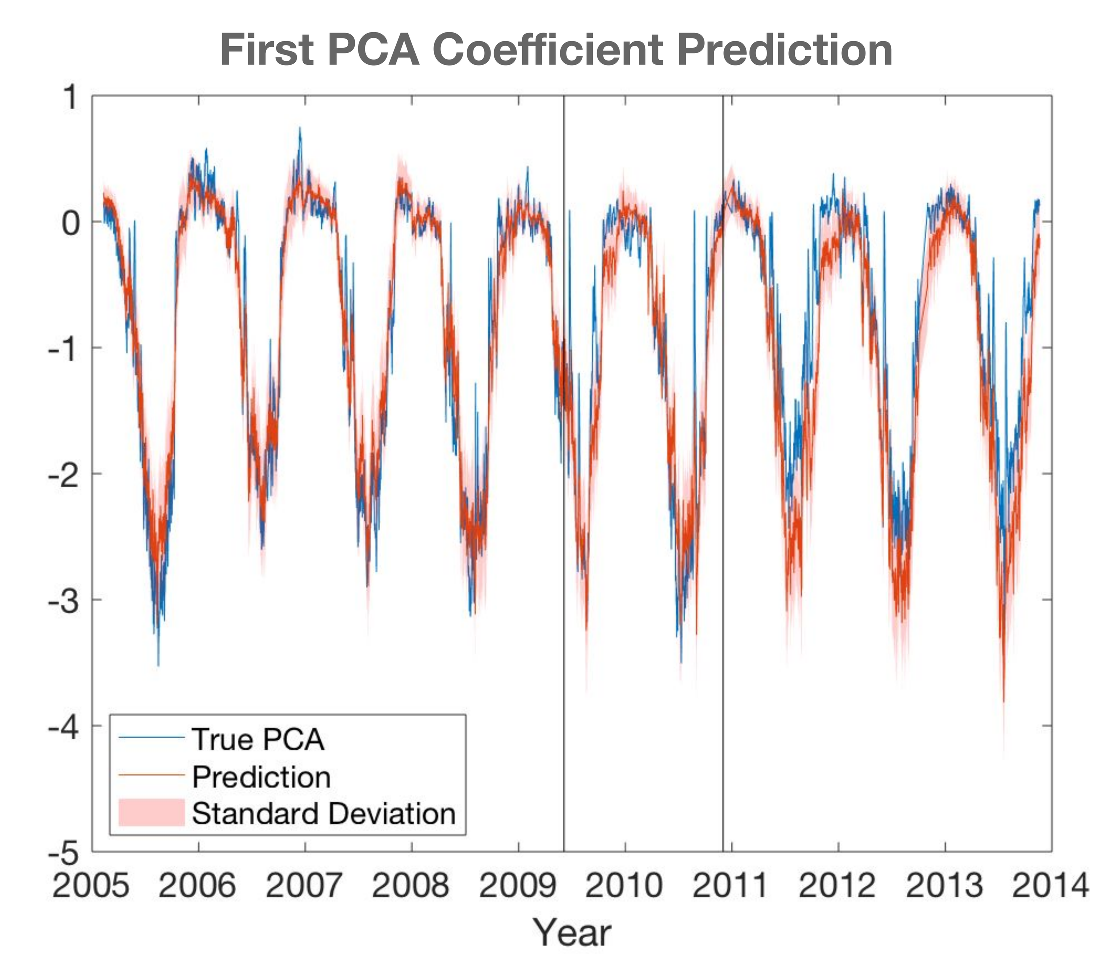
$$\mathbf{T}_{proj}(\cdot,t)=\sum_{i=1}^{2}q_i(t)\boldsymbol{\phi}_i+\bar{\mathbf{T}}(t)$$

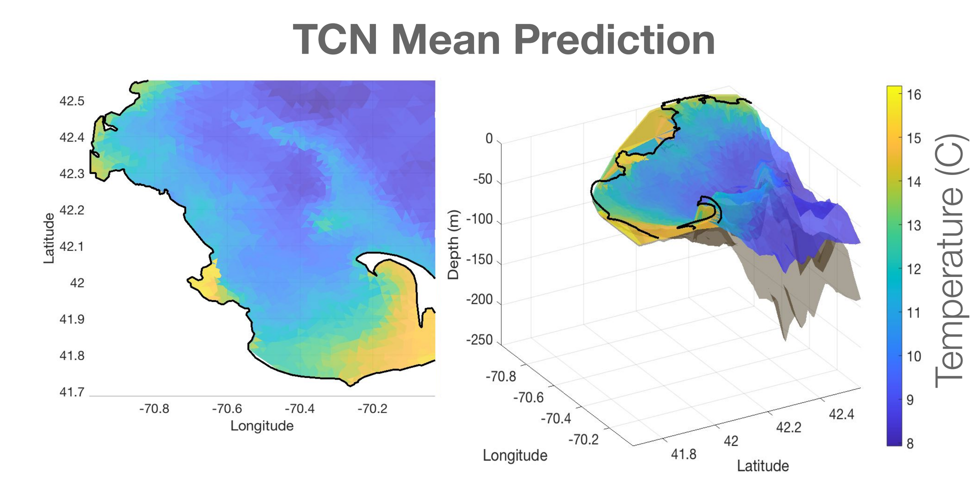
PCA coefficients

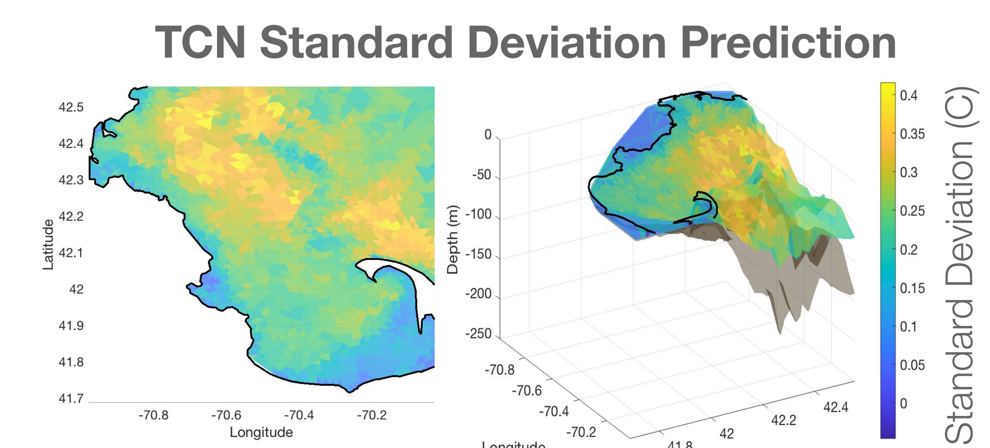
PCA modes

Holmes et al. 1996

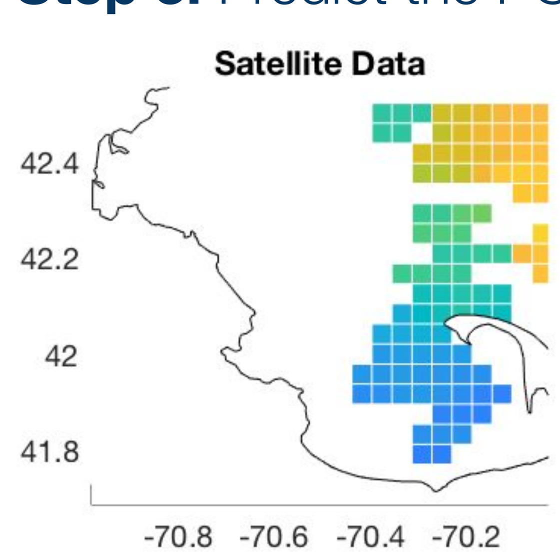
Step 2: Build a TCN to Predict the PCA Coefficients as a Function of Surface Temperature



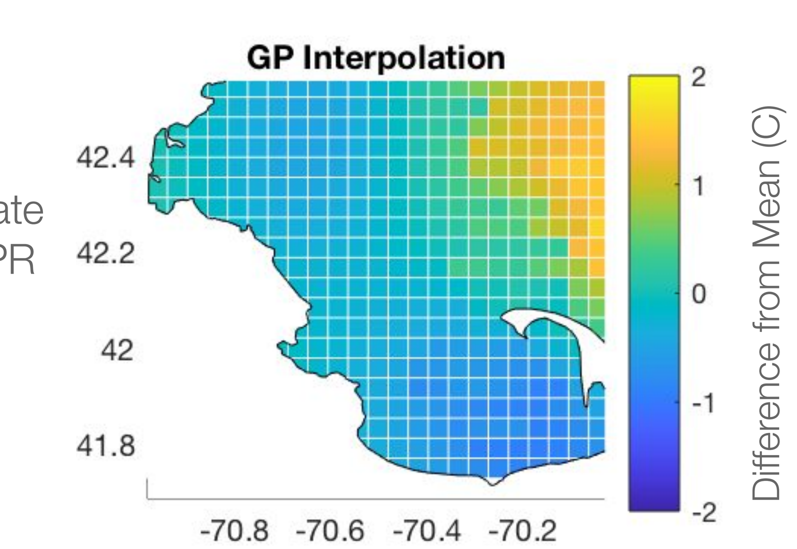




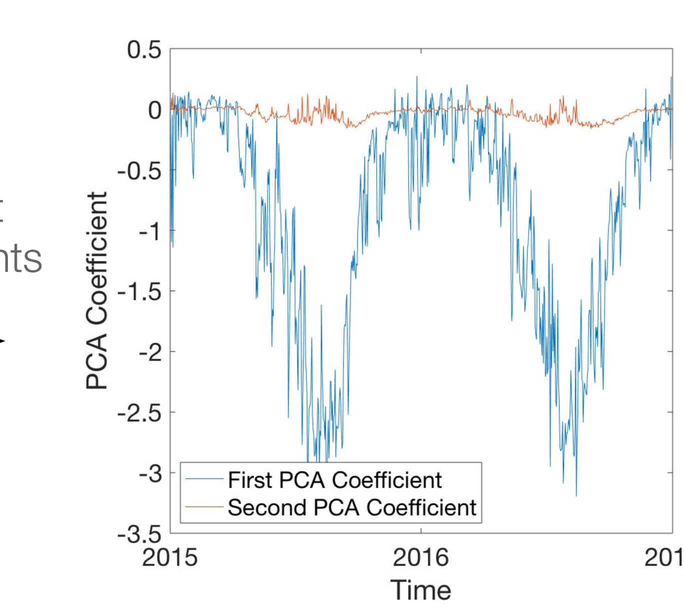
Step 3: Predict the PCA Coefficients from the Satellite Data to Reconstruct the 3D Field



interpolate with GPR



predict coefficients



Step 4: Build a Multi-Fidelity GPR Model Using the TCN Predictions and Buoy Data

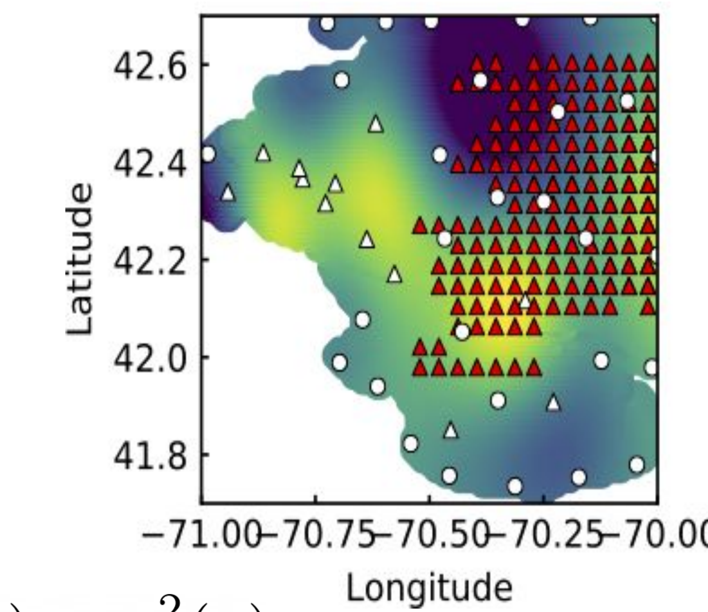
$$\left.\begin{aligned}\bar{\mathbf{f}}_1(\mathbf{x}_*)&=K(X_*,X_1)[K(X_1,X_1)+\sigma_{n1}I]^{-1}\mathbf{y}_1\\ cov(\bar{\mathbf{f}}_1)&=K(X_*,X_*)-K(X_*,X_1)[K(X_1,X_1)+\sigma_{n1}I]^{-1}K(X_1,X_*)\end{aligned}\right\}\text{ low fidelity}$$

$$\left.\begin{aligned}\bar{\mathbf{f}}_2(\mathbf{x}_*)&=\rho\bar{\mathbf{f}}_1(\mathbf{x}_*)+\mu_d+K(X_*,X_2)[K(X_2,X_2)+\sigma_{n2}I]^{-1}(\mathbf{y}-\rho\bar{\mathbf{f}}_1(\mathbf{x}_2)-\mu_d)\\ cov(\bar{\mathbf{f}}_2)&=\rho^2 cov(\bar{\mathbf{f}}_1)+K(X_*,X_*)-K(X_*,X_2)[K(X_2,X_2)+\sigma_{n2}I]^{-1}K(X_2,X_*)\end{aligned}\right\}\text{ high fidelity}$$

Rasmussen and Williams 2004

Future Work

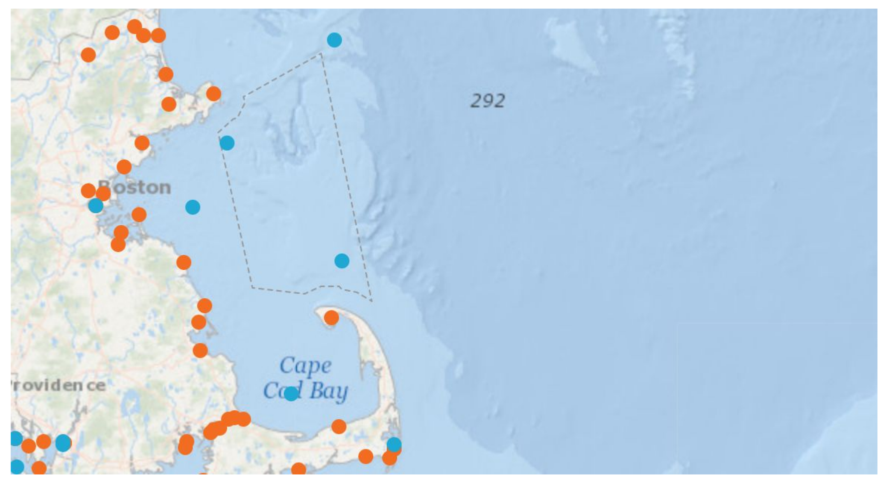
Optimal Sampling and Path Planning



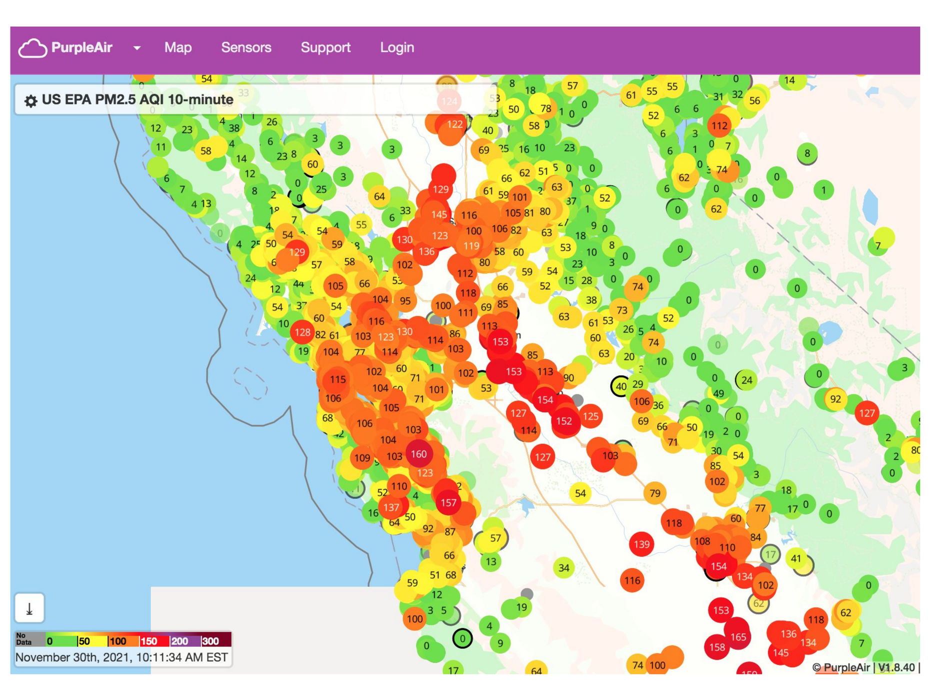
$$a_{US}(x)=\sigma^2(x)$$

Blanchard and Sapsis 2020

Incorporate Results Into SEAGLASS



Other Applications



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