Delta Flow-Salinity Modeling using Physics-Informed Neural Networks

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Dong Min Roh
UC Davis, Mathematics

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Motivation and Goal

- Motivation
  - Delta operations and control strategies frequently accessed using **flow-salinity relationships.**
  - Existing artificial neural networks (ANNs) are only data-driven and do not use flow-salinity relations.
  - Apply **Physics-informed neural network (PINN)** that incorporates flow-salinity relations.
- Goal
  - Demonstrate major improvements in salinity estimation using PINN over a conventional ANN.
    - Neural networks using outflow (input variable) and salinity (target output) data.

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What is PINN[1,2]?

- The laws of physics are described by differential equations.
- **Neural network** system for solving differential equations.
  - Inputs as independent variables of the function.
  - Differential equation **embedded** into the loss function of the neural network.
- Train the neural network to minimize the loss function.

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[1] Raissi, M.; Perdikaris, P.; Karniadakis, G. E. JCP 2019

[2] Psichogios, D. C; Ungar, L. H. AIChE 1992

Flow-Salinity Relations: Advection-Dispersion Equation

- Flow-salinity relations governed by Advection-Dispersion equation.
  - G-model [3,4].
  - Delta Simulation Model II (DSM2) [5].
- $$A\frac{\partial S}{\partial t} - Q(x,t)\frac{\partial S}{\partial x} = KA\frac{\partial^2 S}{\partial x^2}, \qquad x \in [x_a, x_b], t \in [t_a, t_b]$$
  - A is cross-sectional area
  - K is longitudinal dispersion coefficient
  - $Q(x,t)$ is volumetric flowrate
  - $S(x,t)$ is concentration of salt
  - x is longitudinal direction (increasing in upstream)
  - t is time

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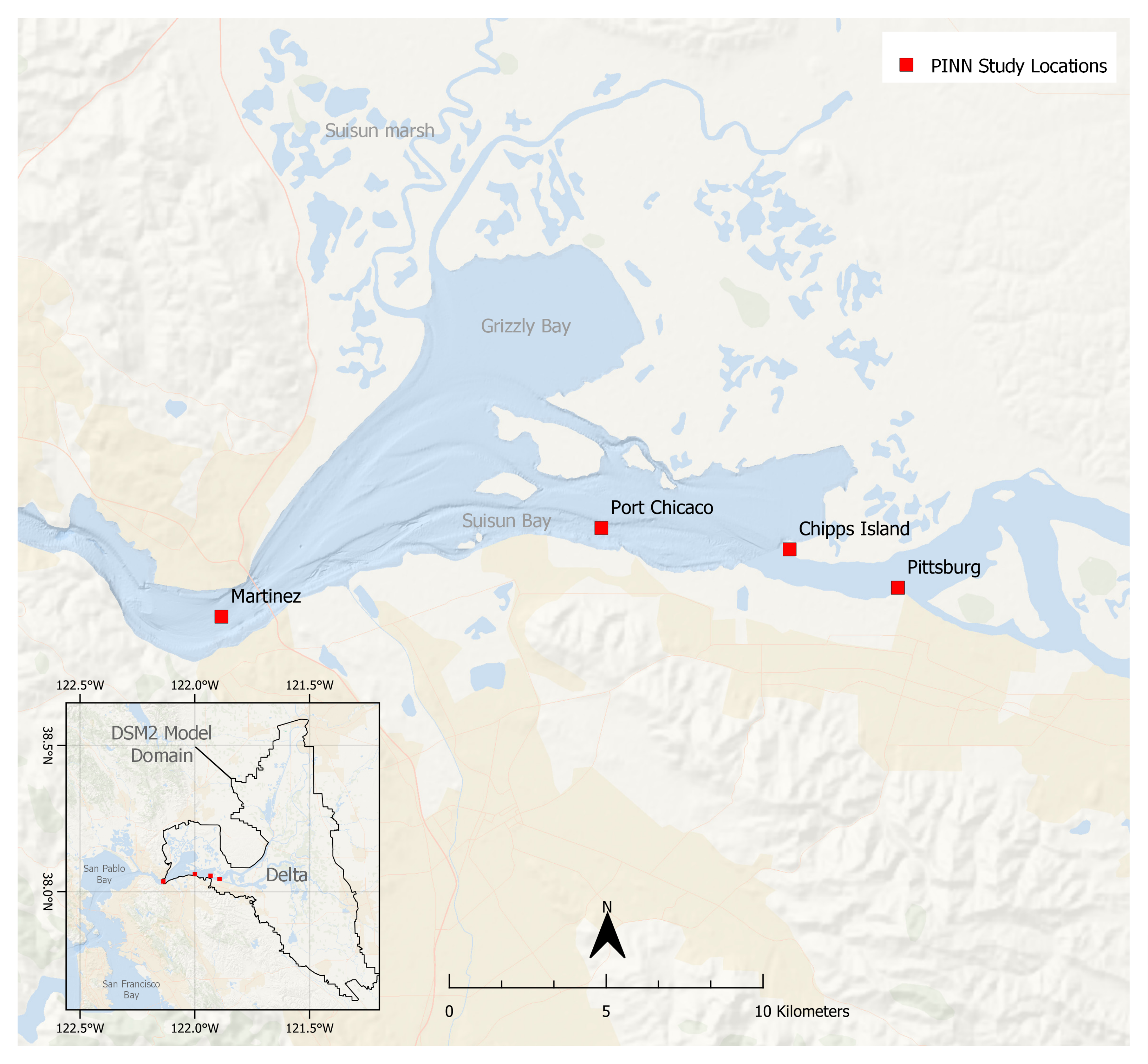
[3] Denton, Richard. ASCE 1993

[4] Denton, R.; Sullivan, G. CCWD 1993

[5] CDWR. 2019

Problem Domain



Dataset

Daily DSM2 simulated data (outflow and EC)
from **1991 to 2015** at
4 **Stations:** Martinez, Port Chicago, Chipps Island, Pittsburg

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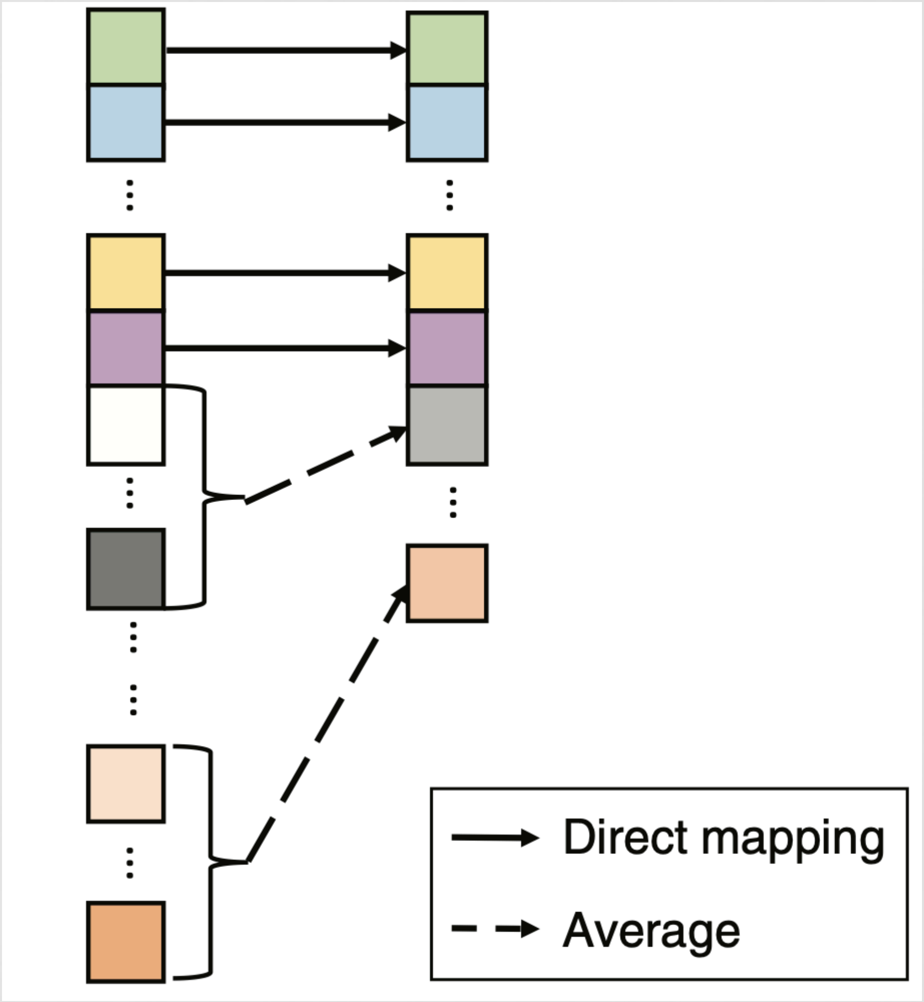
Outflow Pre-processing

- Important to use antecedent outflow information [3,4,6].
- 118 days of outflow into a 18-dimensional data vector $\overrightarrow{Q}_n = [Q_{n,1}, \ldots, Q_{n,18}]$.

$$Q_{n,i} = Q_{n-i+1}, \quad \text{for } i \in \{1,\ldots,8\}$$

$$Q_{n,i+8} = \frac{1}{11} \sum_{j=1}^{11} Q_{n-11i-j+4}, \quad \text{for } i \in \{1,\ldots,10\}$$



From [6]

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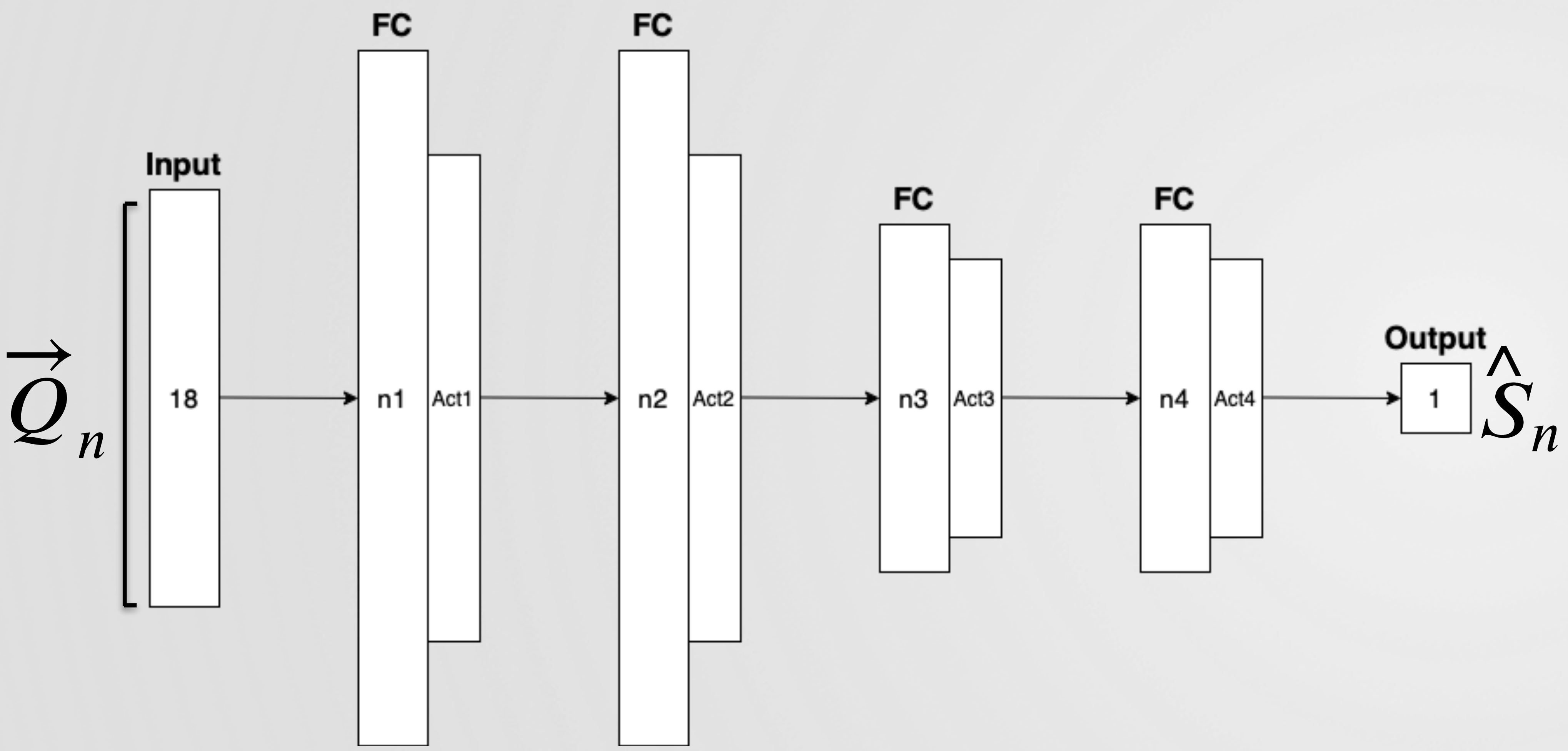
[3] Denton, Richard. ASCE 1993
[4] Denton, R.; Sullivan, G. CCWD 1993
[6] Qi S.; Bai Z.; Ding Z.; Jayasundara N.; He M.; Sandhu P.; Seneviratne S.; Kadir T. JWRPM 2021

Conventional ANN



- Feed-forward, fully-connected (MLP)
- Input: outflow data vector $\vec{Q}_n$
- Output: estimated EC $\hat{S}_n$
- Train by minimizing mean square error $\sum_n (\hat{S}_n - S_n)^2$

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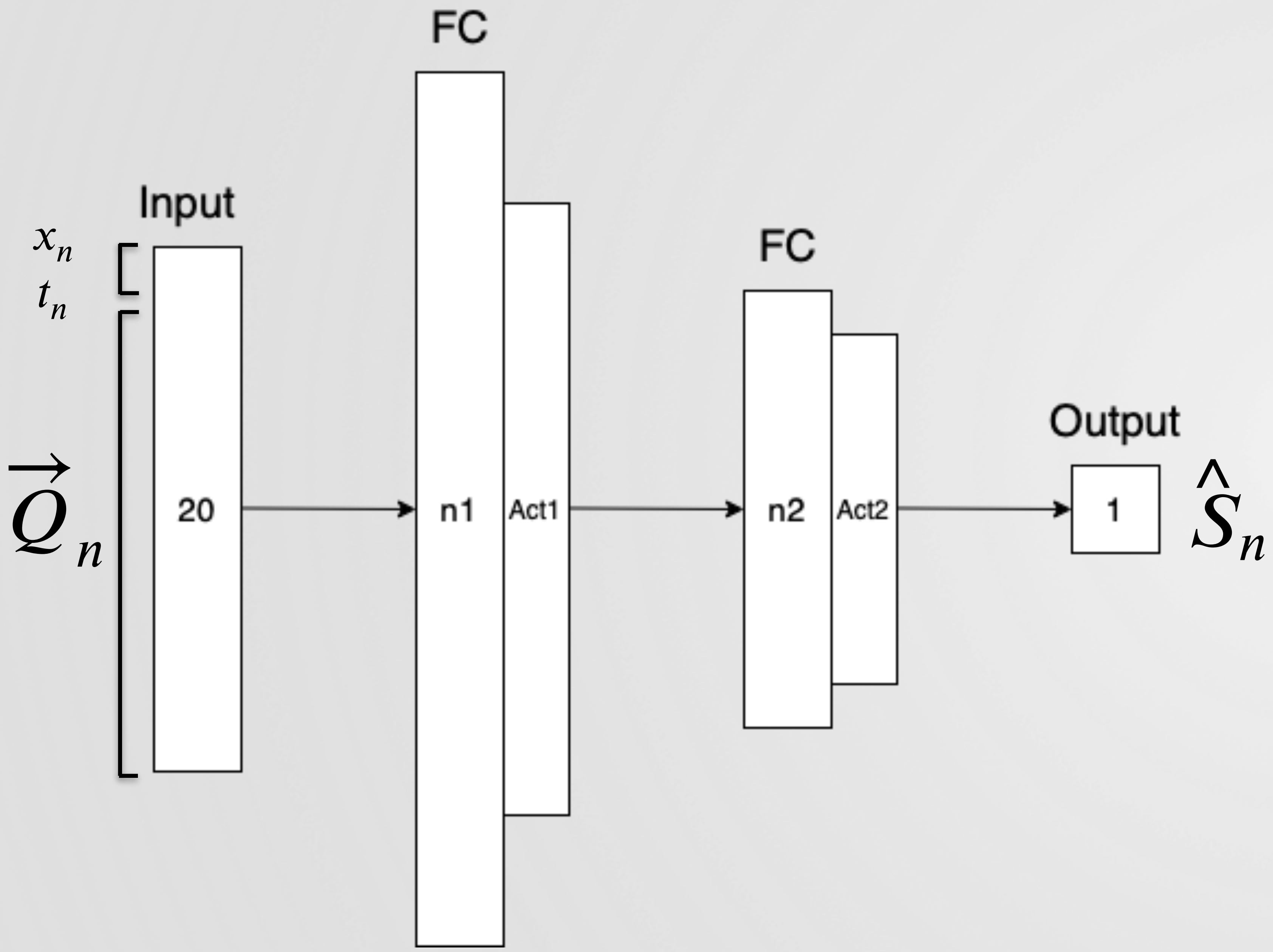
PINN



- Feed-forward, fully-connected (MLP)
- Input: outflow data vector $\vec{Q}_n$ **and** location x_n and time t_n
  - x_n ranging between Martinez and Pittsburg
  - t_n ranging between 1991 and 2015
- Output: estimated EC $\hat{S}_n$
- Train by minimizing mean squared error **and** PDE (Advection-Dispersion) loss

$$\sum_n (\hat{S}_n - S_n)^2 + \sum_n \left(A \frac{\partial \hat{S}}{\partial t}\Big|_{(x_n, t_n, \vec{Q}_n)} - Q_{n,1} \frac{\partial \hat{S}}{\partial x}\Big|_{(x_n, t_n, \vec{Q}_n)} - KA \frac{\partial^2 \hat{S}}{\partial x^2}\Big|_{(x_n, t_n, \vec{Q}_n)} \right)^2$$

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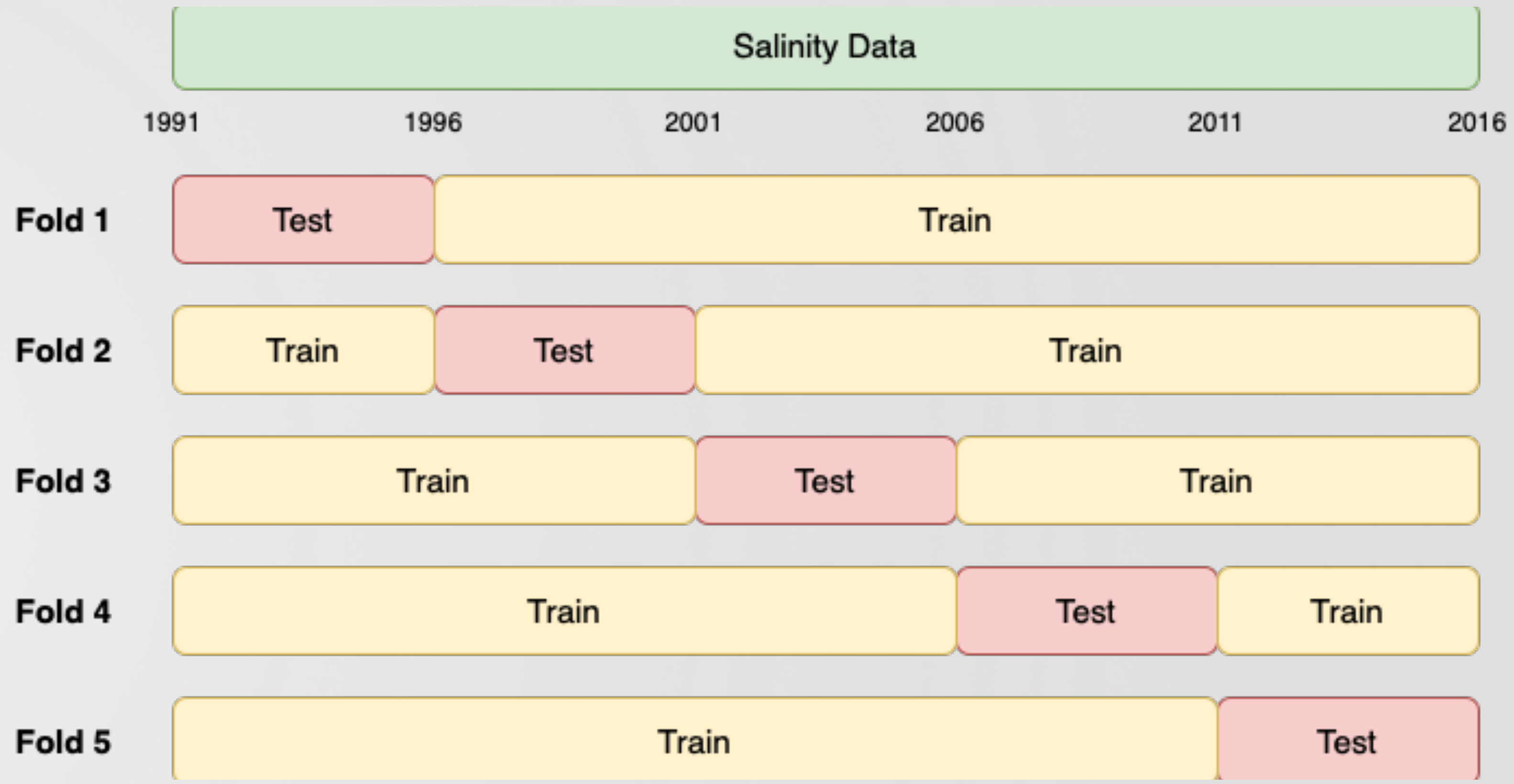
Methodologies

- K-fold cross-validation (5-fold).
- Train: 80% Martinez, Chipps Island, Pittsburg.
- Test: 20% Martinez, Chipps Island, Pittsburg.
- Also test at Port Chicago, an untrained location.
- For each fold: random hyper-parameters search, separately for ANN and PINN.
- Evaluation metrics: Bias, Nash-Sutcliffe Efficiency (NSE), r^2.
- Inspect salinity time-series.



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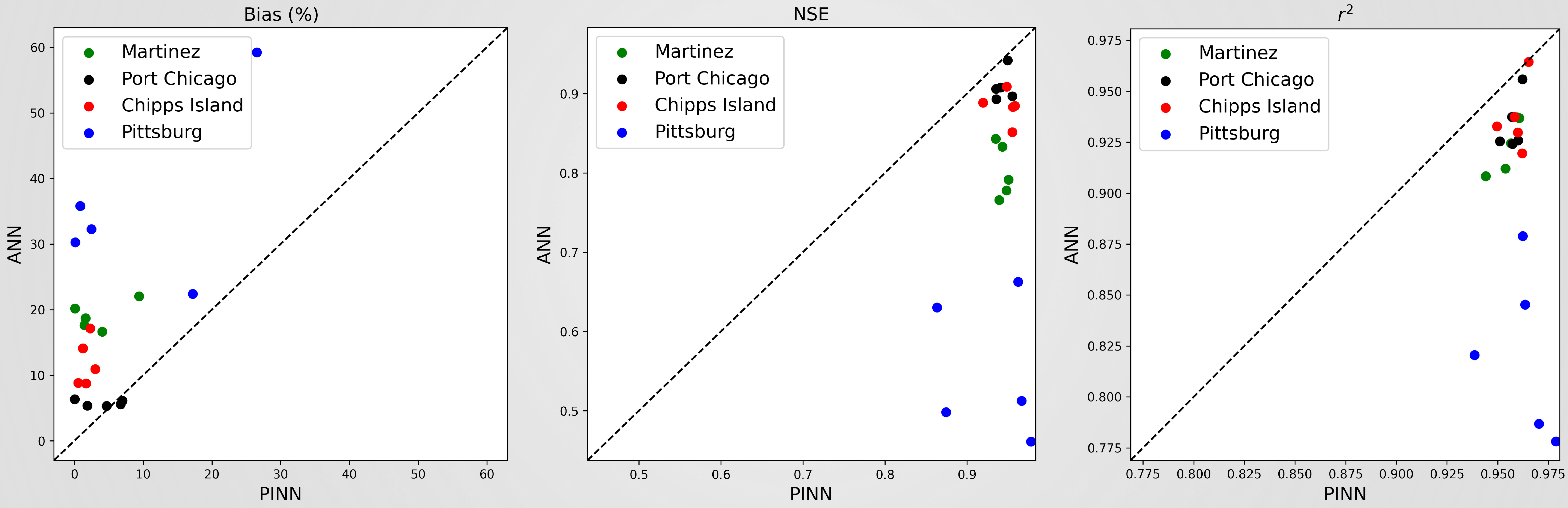
Results: Scatter Plots



Greater Performance indicator

- Smaller Bias
- Larger NSE
- Larger r^2

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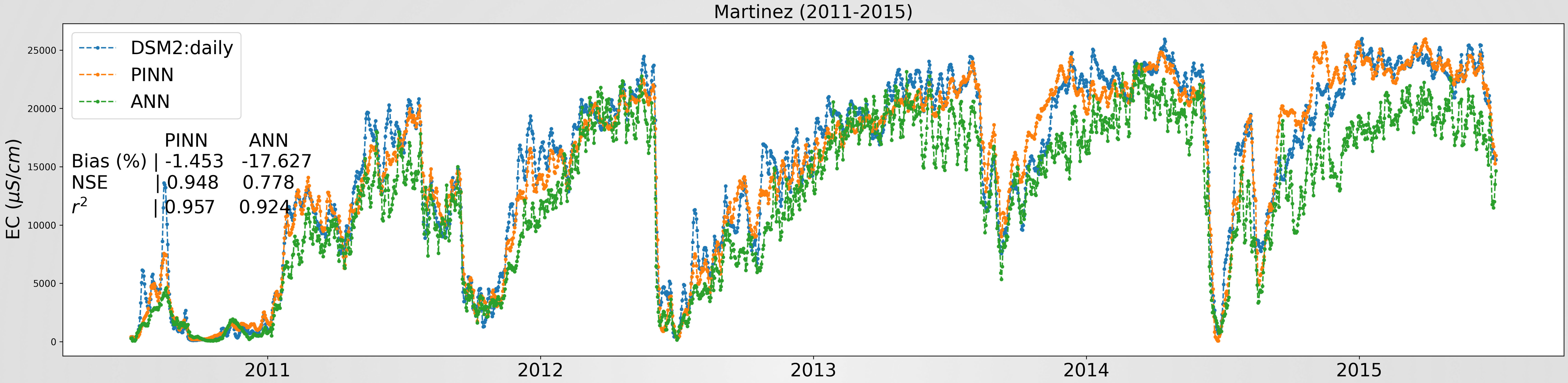
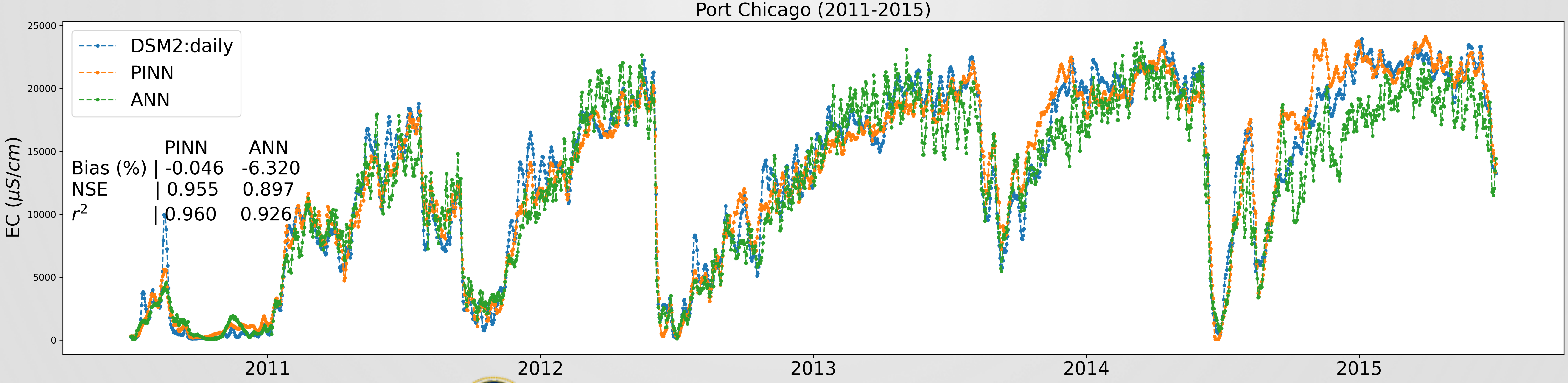
Results: Time-series Plots





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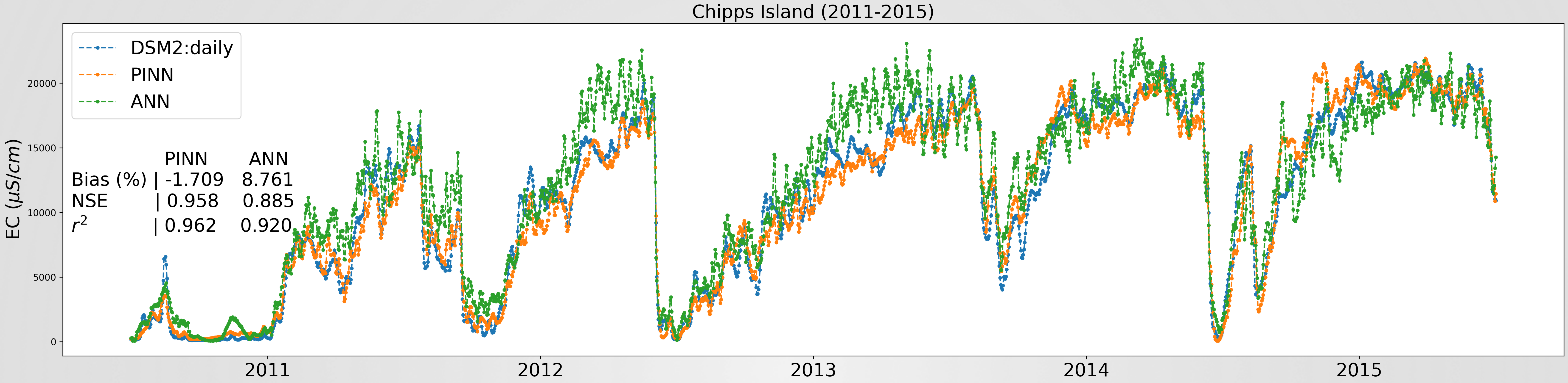
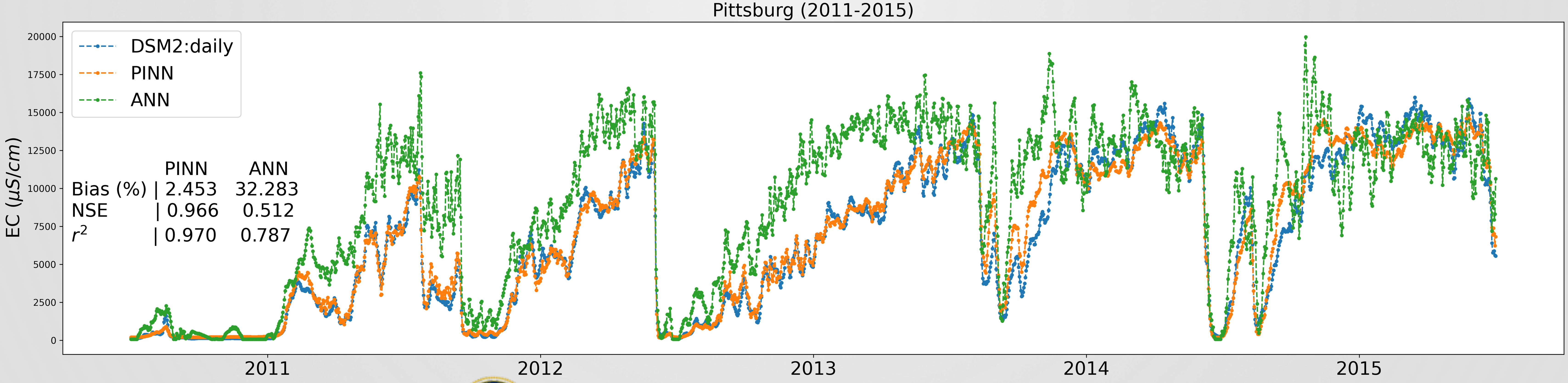
Results: Time-series Plots





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Summary and Future Work

- Summary
  - PINN model outperforms ANN model at all four locations.
  - Improvement is most significant at Pittsburg, an inner-most location.

- Future Work
  - Further evaluations on more data: other locations, observed data.
  - Varieties of PINN: Fourier Network, LSTM, DGM, etc.

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[1] Raissi, M., Perdikaris, P., and Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational physics, 378:686–707.

[2] Psichogios, D. C. and Ungar, L. H. (1992). A hybrid neural network-first principles approach to process modeling. AIChE Journal, 38(10):1499–1511.

[3] Richard A Denton. Accounting for antecedent conditions in seawater intrusion modeling—Applications for the San Francisco Bay-Delta. In Hydraulic engineering, pages 448–453. ASCE, 1993.

[4] Denton, R. and Sullivan, G. (1993). Antecedent flow-salinity relations: Application to delta planning models. Contra Costa Water District. Concord, California.

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[6] Siyu Qi, Zhaojun Bai, Zhi Ding, Nimal Jayasundara, Minxue He, Prabhjot Sandhu, Sanjaya Seneviratne, and Tariq Kadir. Enhanced artificial neural networks for salinity estimation and forecasting in the sacramento-san joaquin delta of california. Journal of Water Resources Planning and Management, 147(10):04021069, 2021.


QUESTIONS