Delta Flow-Salinity Modelling using Artificial Neural Networks: Tutorial

Workshop on Delta Flow-Salinity Modeling Using Machine Learning
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Module #3

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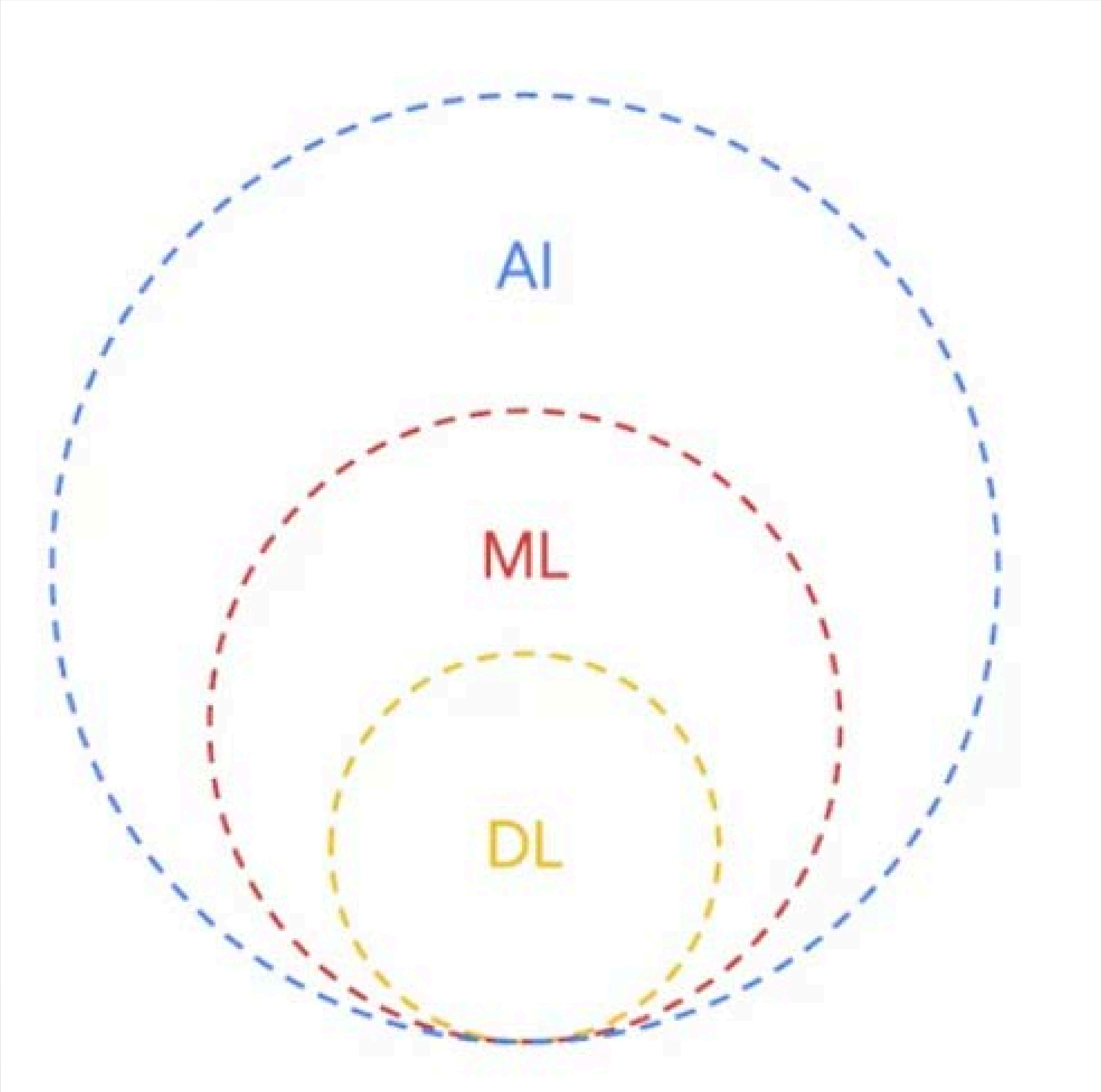
Outline

- **Overview**
  1. Datasets
  2. ANN Architectures
     1. **Baselines**:
        1. Multi-Layer Perceptron (MLP);
        2. Residual Network (ResNet);
        3. Long-Short-Term Memory (LSTM);
        4. Gated Recurrent Unit (GRU).
     2. **Proposed**: Res-LSTM; Res-GRU.
  3. Transfer Learning
- **Demo**

Overview

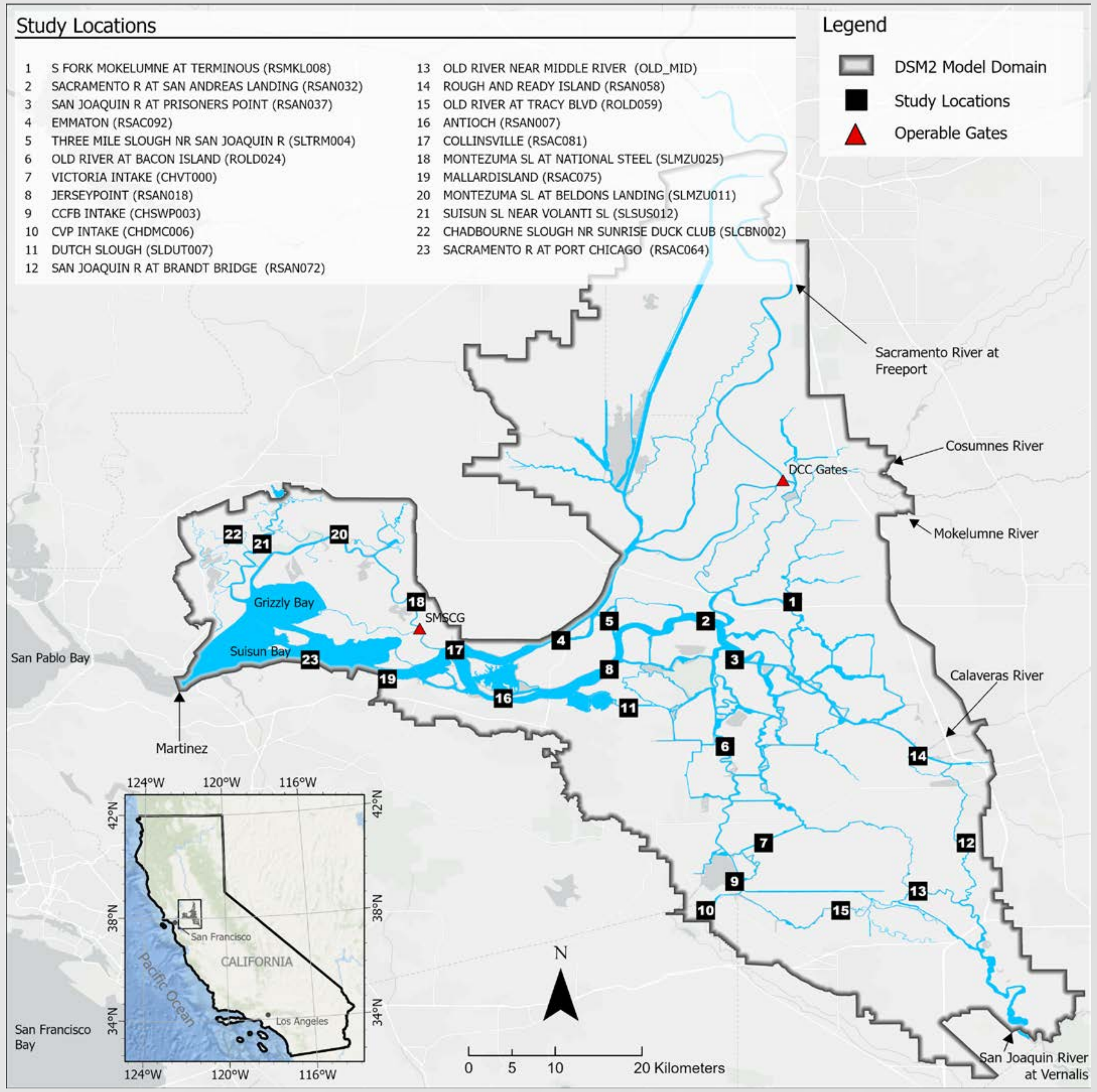
- **Artificial Intelligence (AI):** “the theory and development of computer systems able to perform tasks that normally require human intelligence.” -- *Oxford Languages*
- **Machine learning (ML):** AI that can automatically adapt with minimal human interference
- **Deep learning (DL):** ML that uses artificial neural networks to mimic the learning process of the human brain



https://www.coursera.org/articles/ai-vs-deep-learning-vs-machine-learning-beginners-guide

Overview

Index	Input Feature Name	Definition
1	Northern Flow	Sum of Sacramento, Yolo Bypass, Mokelumne River, Cosumnes River, and Calaveras River flows.
2	San Joaquin River Flow	San Joaquin River at Vernalis Flow.
3	Pumping	Sum of pumping from Banks Pumping Plant, Jones Pumping Plant, and Contra Costa Water District at Rock Slough, Old River, and Victoria Canal.
4	Delta Cross-Channel Gate Operation	Delta Cross-Channel Gate Openings.
5	Consumptive Use	Net Delta Consumptive use estimated by Delta Channel Depletion (DCD) and Suisun Marsh Channel Depletion (SMCD) models.
6	Martinez Tidal Energy	Tidal energy at Martinez, calculated as the daily maximum–the daily minimum astronomical tide at Martinez.
7	San Joaquin River EC	Electrical conductivity measured at San Joaquin River at Vernalis.
8	Sacramento River EC	Electrical conductivity measured at Sacramento River at Greens Landing.



8 Input variables

23 Electrical Conductivity (EC) Monitoring Stations

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Overview: Datasets

<table>
<tr><th>Excel File Name</th><th>Scenarios</th><th>Timespan</th><th>Usage</th></tr>
<tr><td>observed_data_daily
(Observed)</td><td>/</td><td>2000-2019</td><td>Used for training in:
1. Train_ANN_on_Observed_Data-Chronological-Test_on_Augmented_Data.ipynb
2. Transfer_Learning_from_Augmented_to_Observed_Chronological.ipynb</td></tr>
<tr><td>dsm2_ann_inputs_base
(Simulated)</td><td>/</td><td rowspan="3">1990-2019</td><td>Used for validation in:
Train_ANN_on_Augmented_Dataset.ipynb</td></tr>
<tr><td rowspan="2">dsm2_ann_inputs_$SCENARIO$
(Simulated, augmented)</td><td>rsacminus20pct, rsacplus20pct;
rsacminus15day, rsacplus15day;
rsanminus20pct, rsanplus20pct;
rsanminus15day, rsanplus15day.</td><td>Used for training in
1. Train_ANN_on_Augmented_Dataset.ipynb
2. Model pre-training for transfer learning</td></tr>
<tr><td>dcc0, dcc1;
smscg0, smscg1.</td><td>Used for test in
Train_ANN_on_Augmented_Dataset.ipynb</td></tr>
</table>

Note: all datasets are provided in daily resolution

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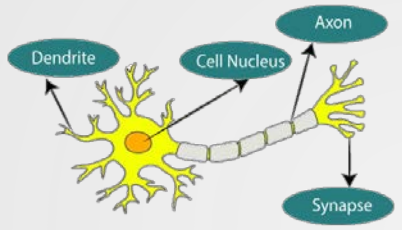
Overview: Architectures – MLP [1]

Highlights:

- Feed-forward
- Fully-connected
- Mimics neural network in human brains

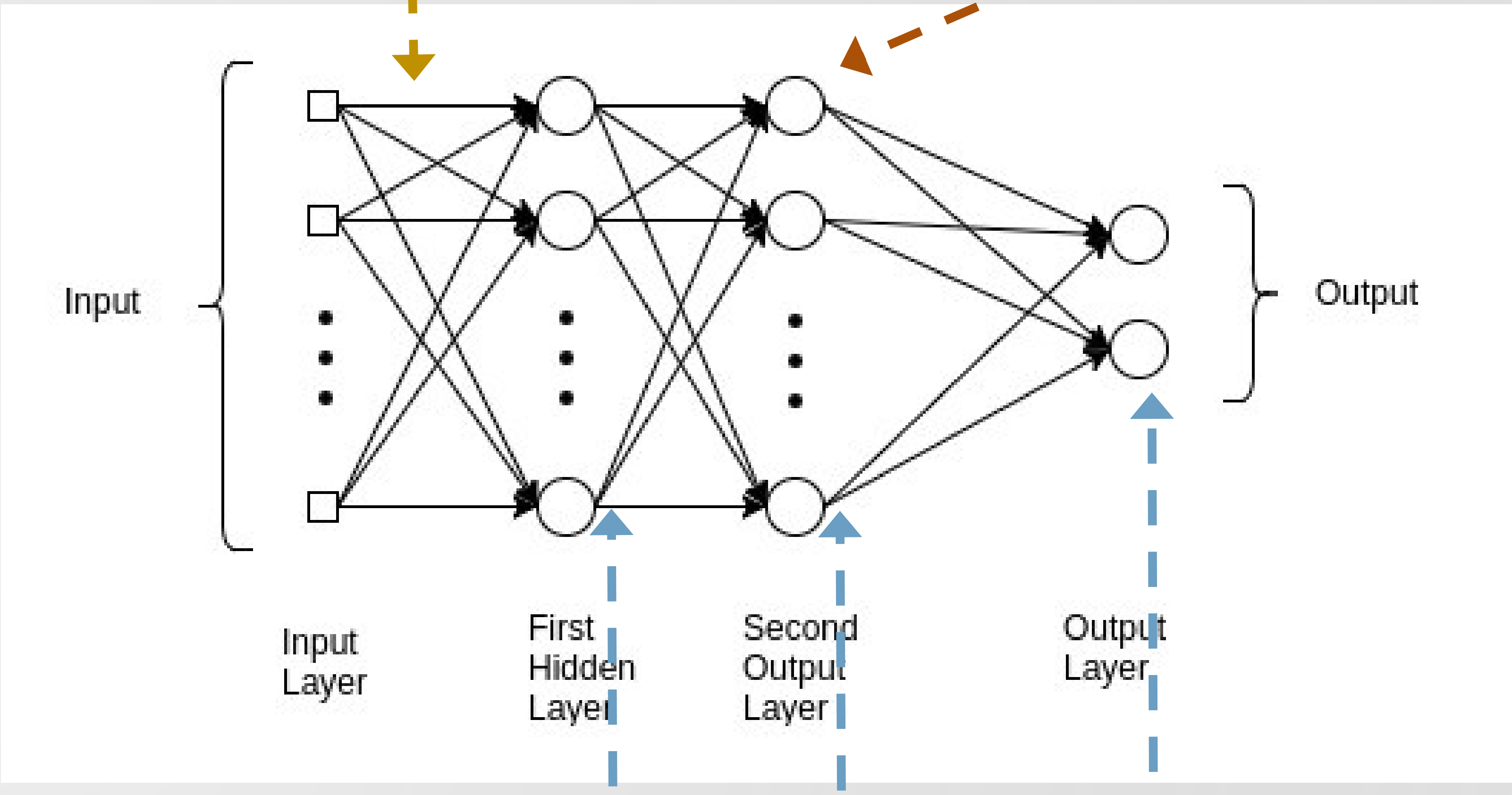


Training: provide input and output pairs (the "training set"), update weights to minimize difference between target and model outputs

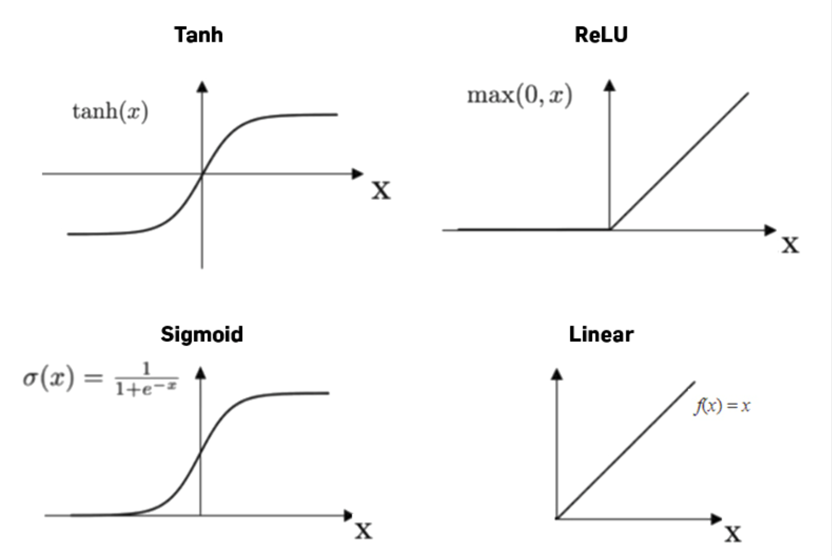
Test: use a different set (the "test set") to evaluate model performance

Multiply by "weights"

Add up products



Each layer has an **activation** function to introduce **non-linearity**



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[1] Maier, H.R.; Dandy, G.C. *Environ. Model. Softw.* 2000

Overview: Architectures – MLP [1]

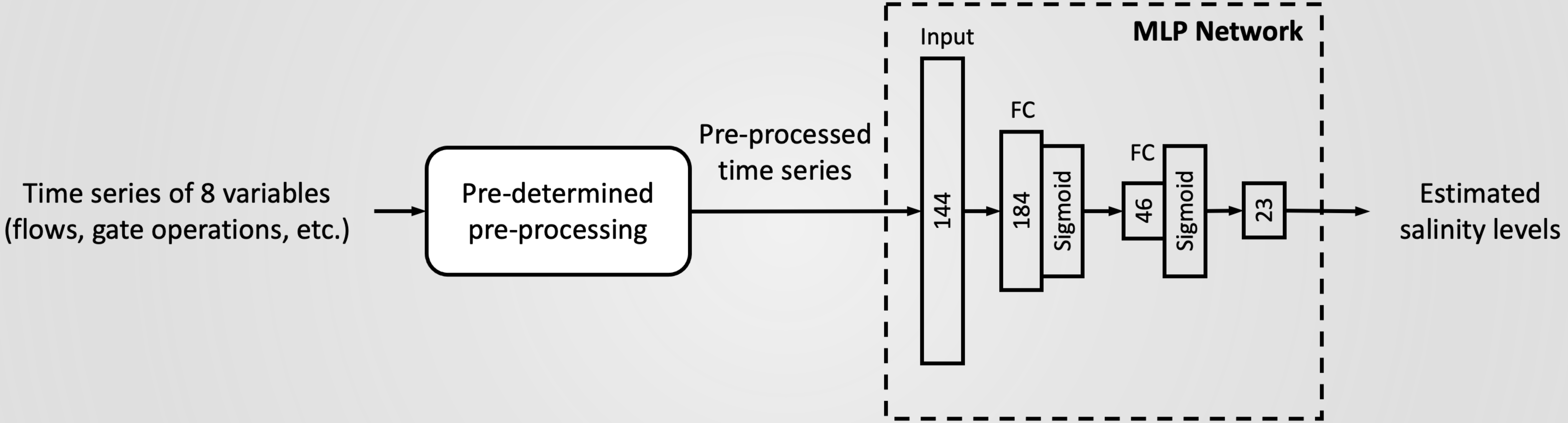

Diagram of the MLP [1] ANN in our study
Numbers in layers = numbers of neurons

[1] Maier, H.R.; Dandy, G.C. *Environ. Model. Softw.* 2000

Overview: Architectures – ResNet

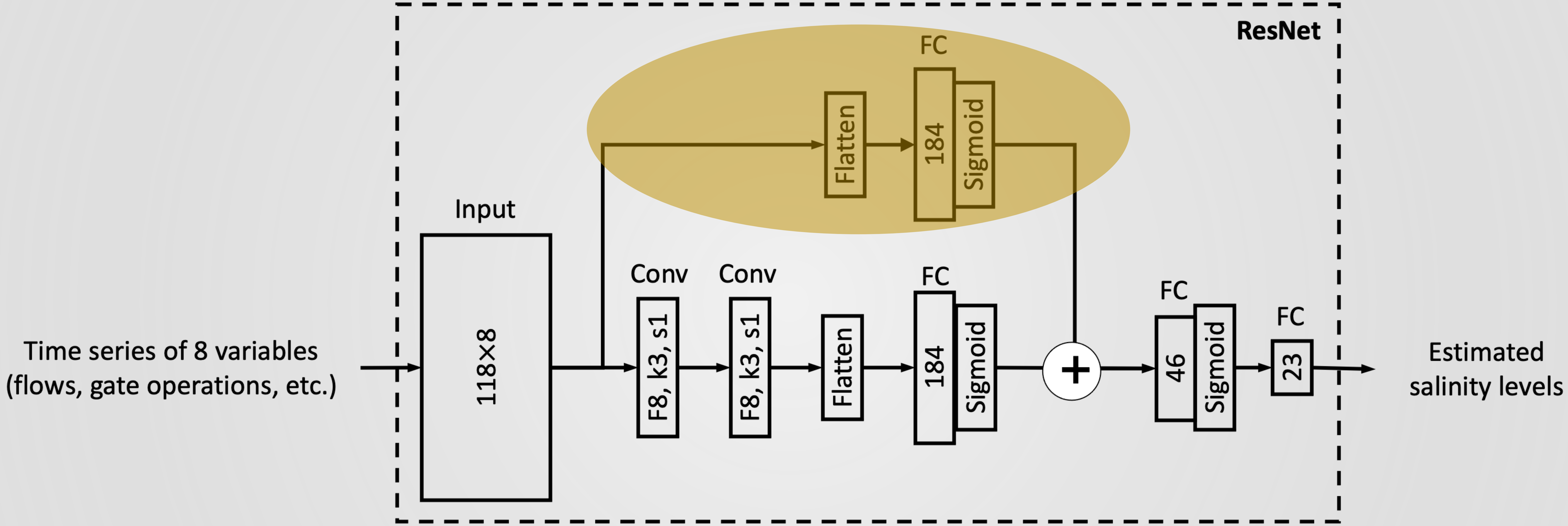

Diagram of a ResNet[2]

In the convolutional layers, "f" = number of filters, "k" = kernel size, "s" = stride.

Main concept in ResNet: a shortcut path that learns to estimate "residuals" → adopt this idea in RNNs

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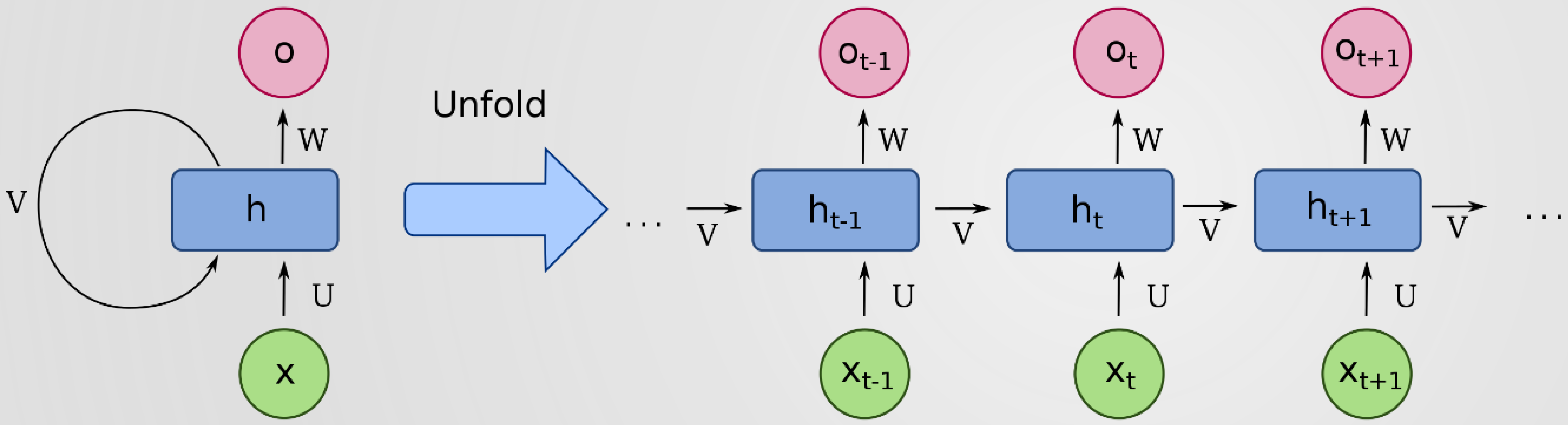
[2] He, K.; Zhang, X.; Ren, S.; Sun, J. *CVPR* 2016

Overview: Architectures – Recurrent Neural Networks (RNNs)



Highlights:

- Connection creates a cycle
- Internal **memories**
- Good at **sequential** data processing

Detailed diagram of a basic RNN. ***Left***: Compressed; ***Right***: unfolded

https://en.wikipedia.org/wiki/Recurrent_neural_network

Overview: Architectures – Long-Short-Term Memory (LSTM) [3]

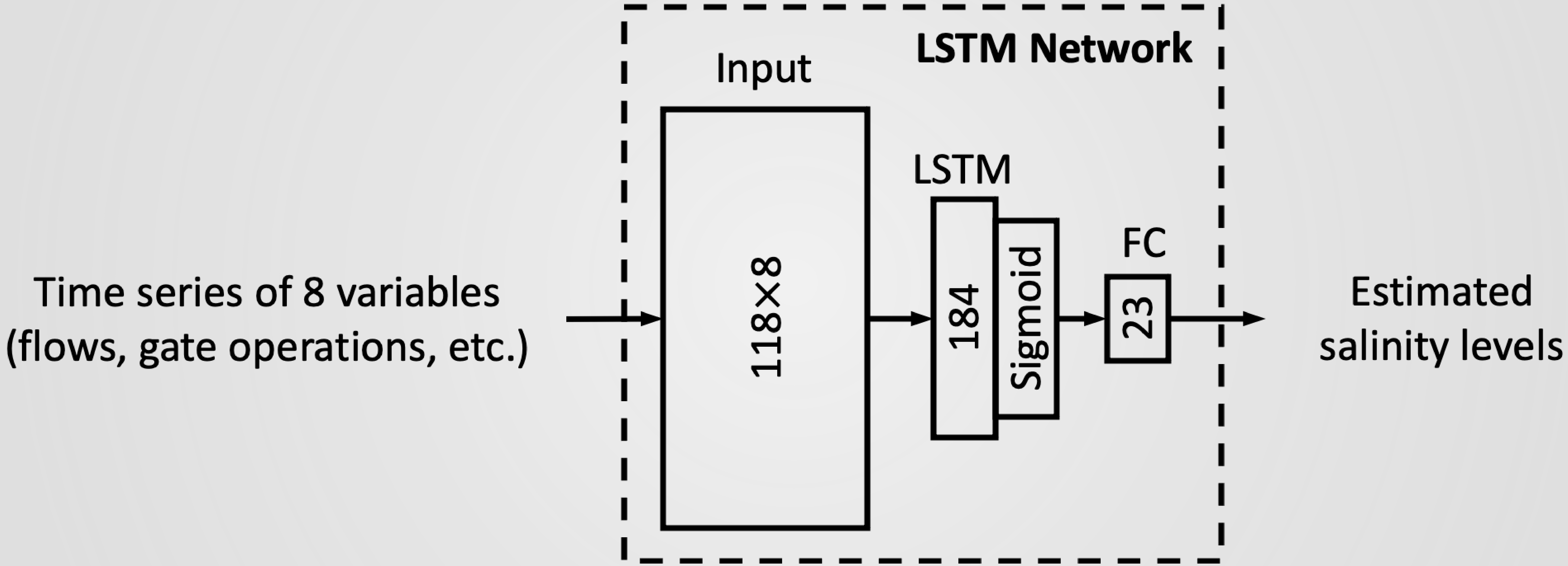


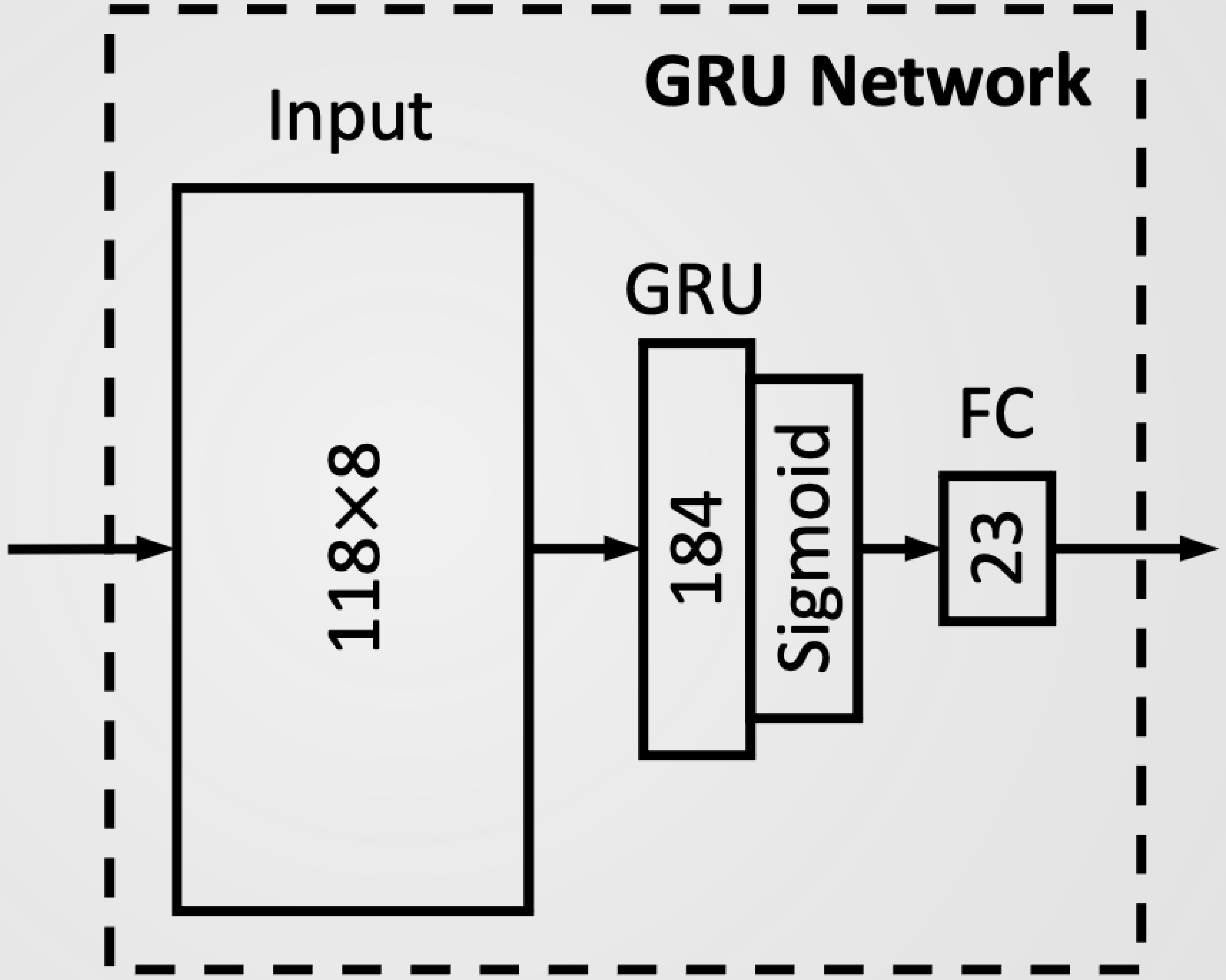
Diagram of a LSTM Network [3], a generic memory-based architecture

***Highlights**: maintains both short-term and long-term memories; good for long term sequences*

[3] Hochreiter, S.; Schmidhuber, J. *Neural Comput.* 1997

Overview: Architectures – Gated Recurrent Unit (GRU) [4]

Time series of 8 variables
(flows, gate operations, etc.)



Estimated
salinity levels

Diagram of a GRU Network [4], a generic memory-based architecture

***Highlights**: less complex hence faster than LSTM; no internal memory.*

[4] Cho, K.; Van Merriënboer, B.; Bahdanau, D.; Bengio, Y. *arXiv* 2014

Overview: Architectures – Res-LSTM

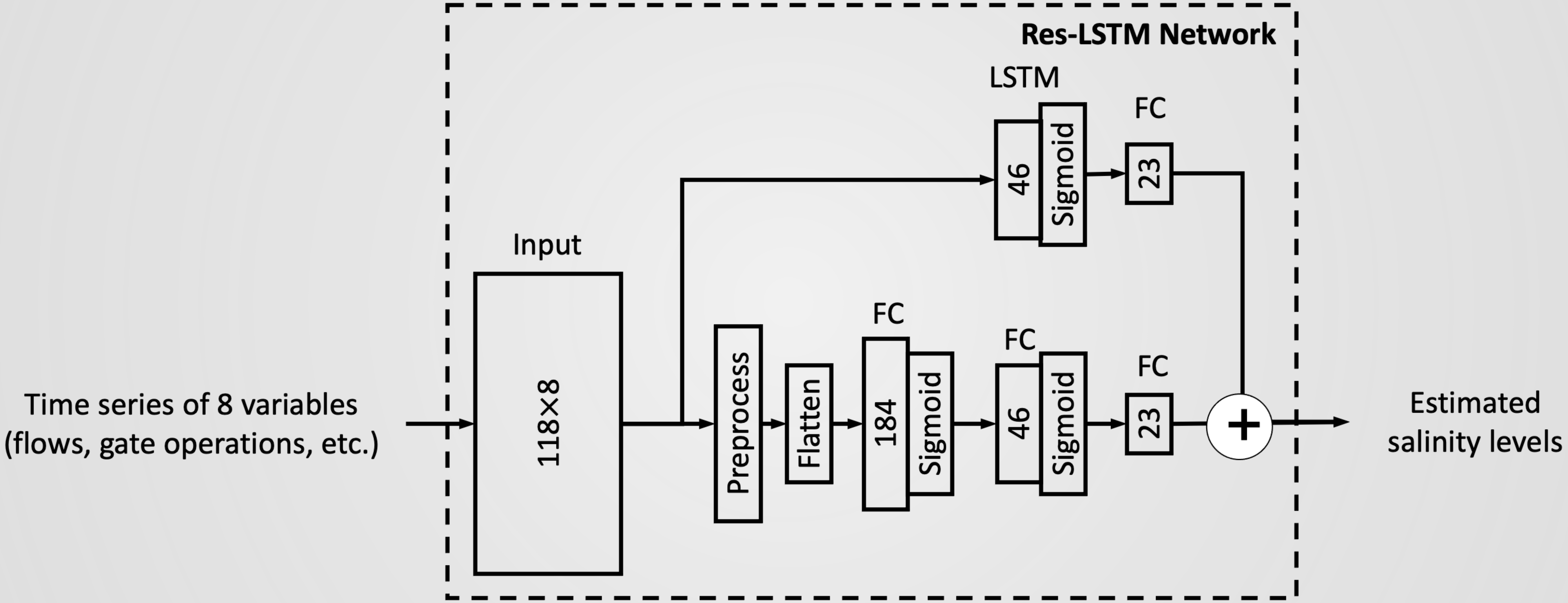


Diagram of the Proposed Res-LSTM Network, with a **simplified** LSTM layer in the shortcut connection

***Highlights**: faster than baseline LSTM; better performance than baseline MLP*

Overview: Architectures – Res-GRU

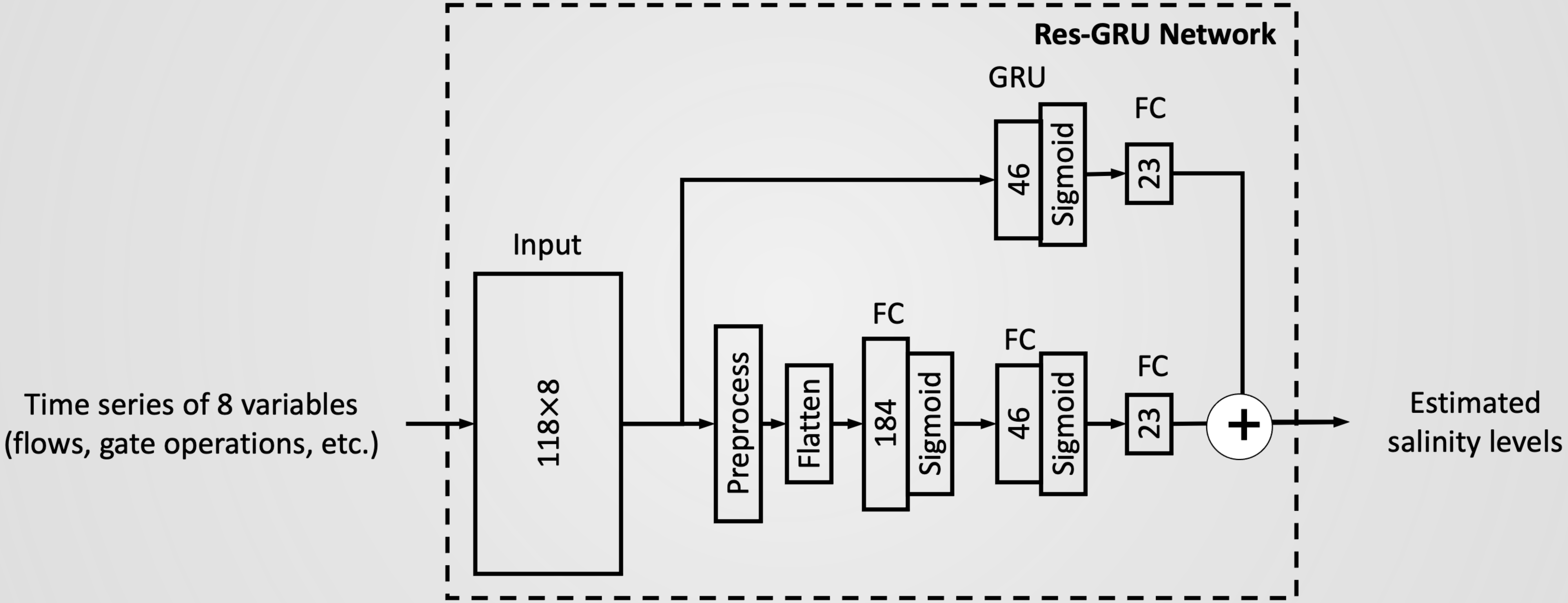


Diagram of the Proposed Res-GRU Network, with a **simplified** GRU layer in the shortcut connection

***Highlights**: faster than baseline GRU; better performance than baseline MLP*

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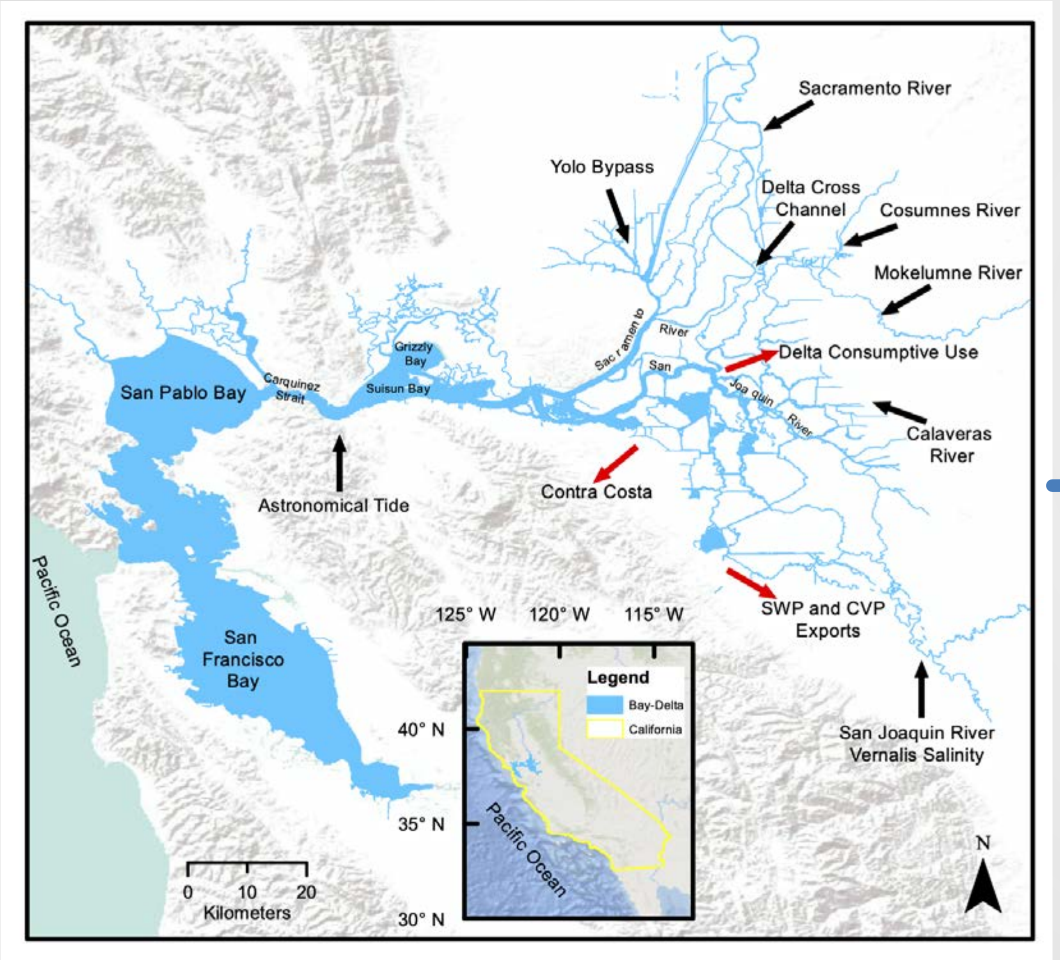
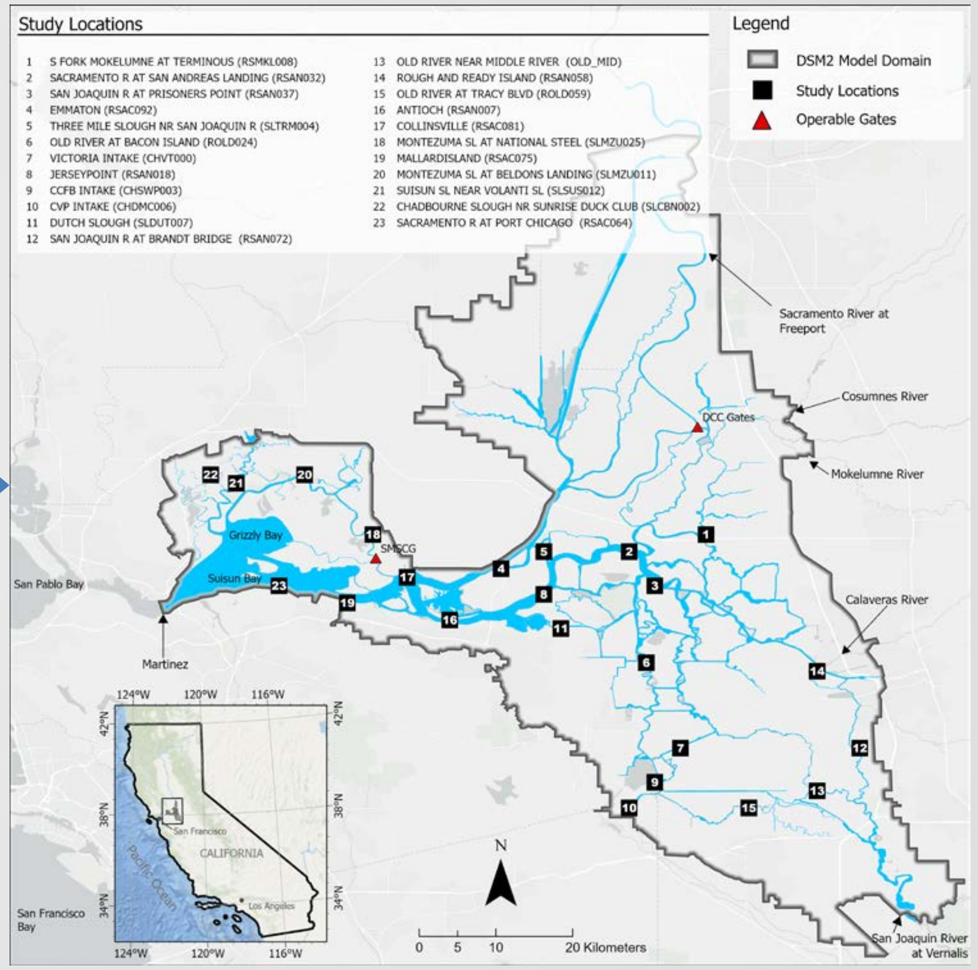
Overview: Transfer Learning[5]

Environmental Variables



ANN

Salinity Levels
(DSM2 Simulations)



Definition: Transferring the knowledge of one model to perform a new task.

Models trained on augmented simulation data (rich) ==> observed data (smaller)

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[5] Bozinovski, S.; Fulgosi, A. *Symposium Informatica*, 1976

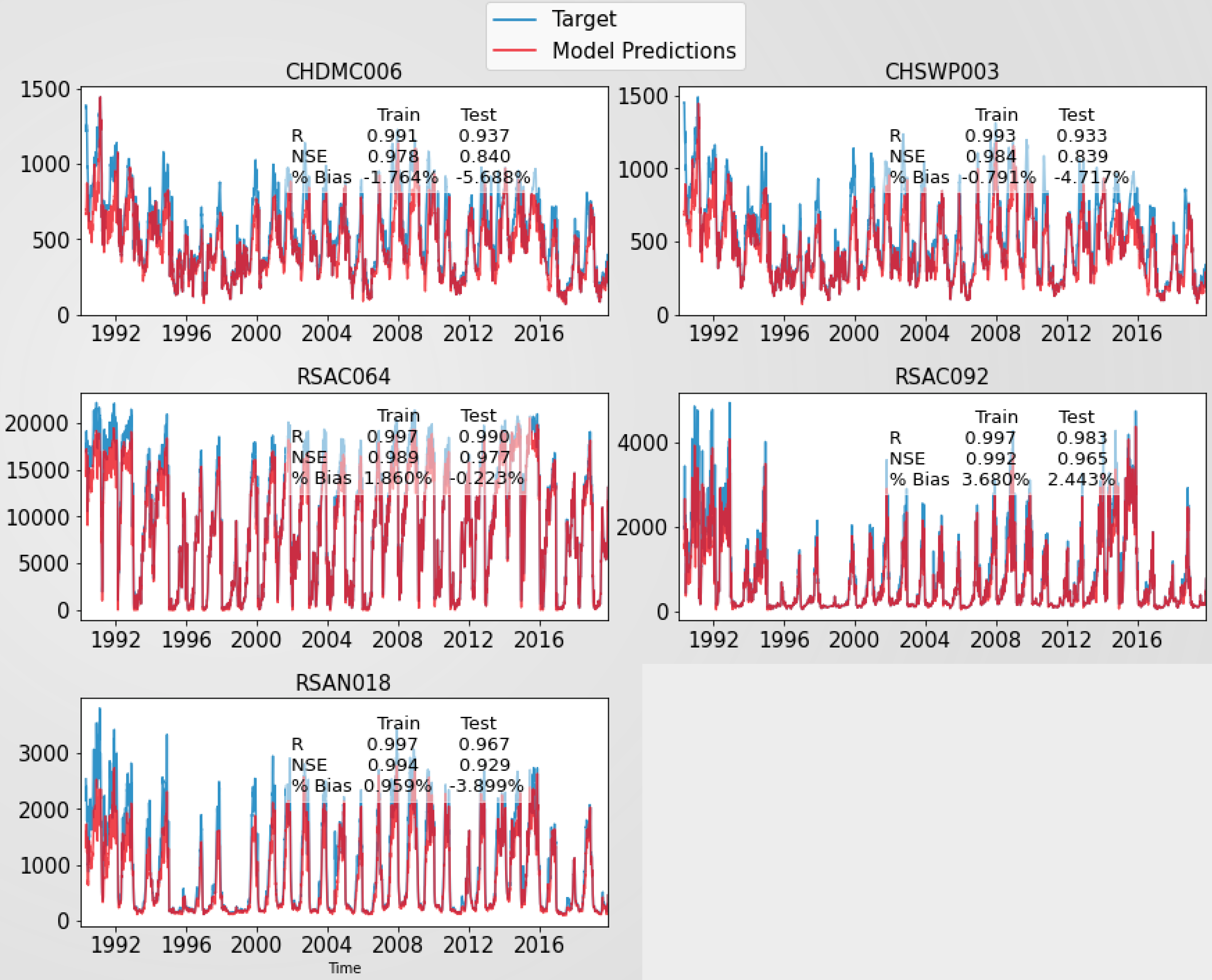
Demo: Running Python on Google Colab

Outputs of scripts:

1. **Trained models** in "models" folder
2. **Plots** in "images" folder
   1. Time Series Plots
   2. Exceedance Probability Plots
   3. Heat map
3. **Numerical results** (r2, Bias, RSR and NSE) in "results" folder

Demo: Running Python on Google Colab

- **Illustration**: Time Series Plots



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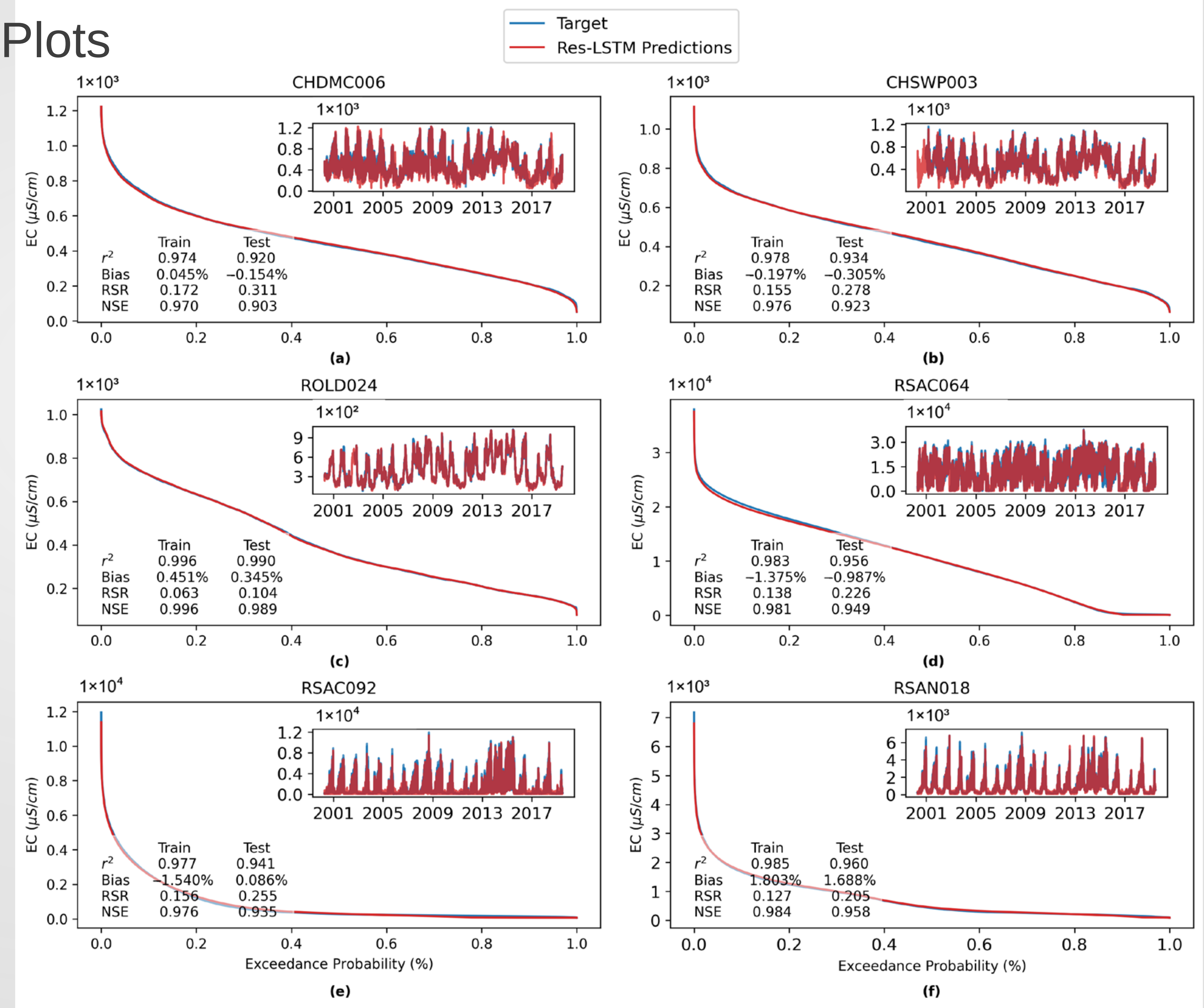
Demo: Running Python on Google Colab

- **Illustration**: Exceedance Probability Plots



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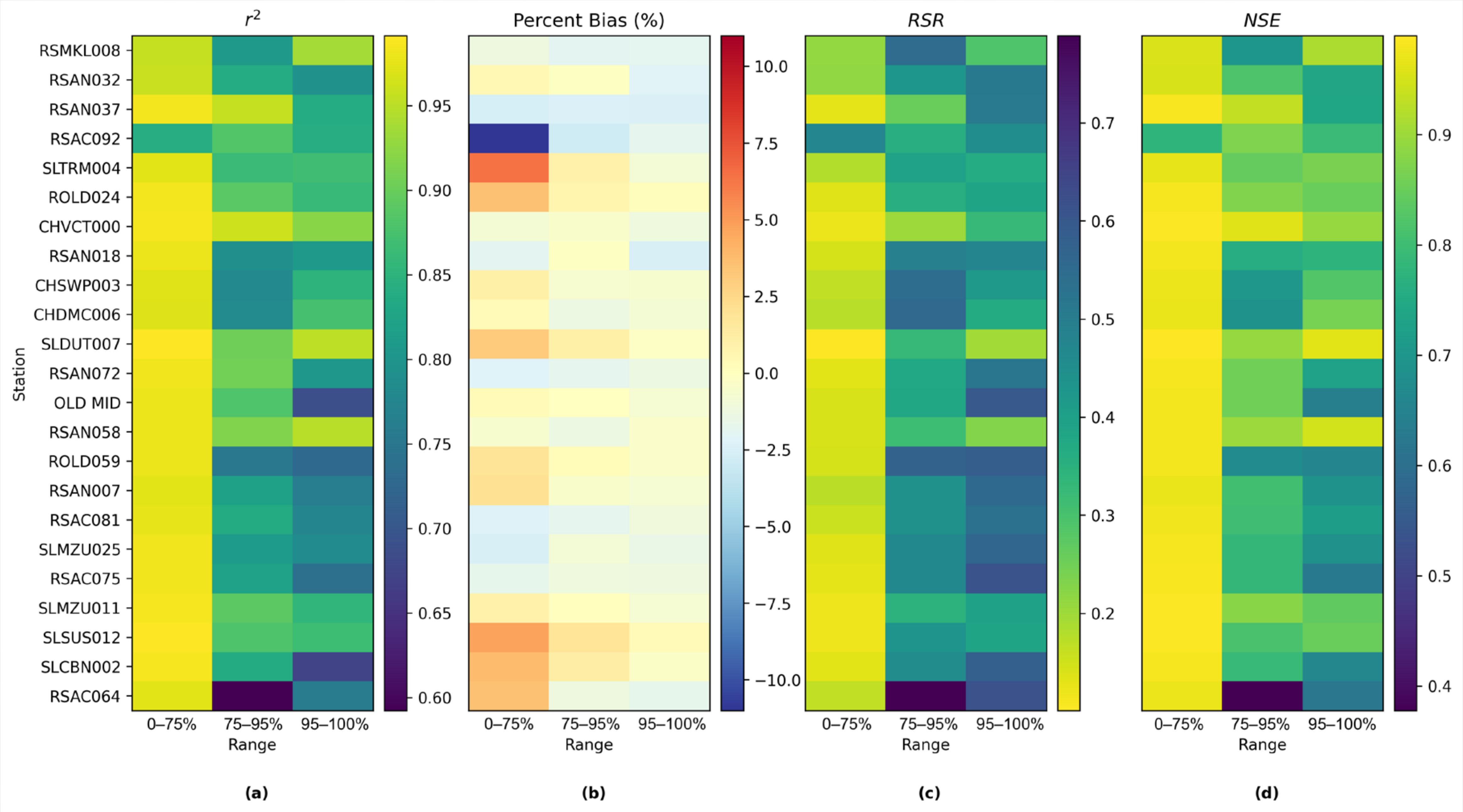
Demo: Running Python on Google Colab

- **Illustration**: Station-wise Heatmap Plots



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Demo: Running Python on Google Colab

1. Train models on **observed** data (chronological split):
   - *Colab_Train_ANN_on_Observed_Data-Chronological-Test_on_Augmented_Data.ipynb*
2. Train models on **augmented** data
   - *Colab_Train_ANN_on_Augmented_Dataset.ipynb*
3. **Transfer Learning** from augmented to observed data
   - *Colab_Transfer_Learning_from_Augmented_to_Observed_Chronological.ipynb*

References

1. Maier, Holger R., and Graeme C. Dandy. "Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications." *Environmental modelling & software* 15.1. 2000.
2. He, Kaiming, et al. "Deep residual learning for image recognition." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.
3. Hochreiter, Sepp, and Jürgen Schmidhuber. "Long short-term memory." *Neural computation* 9.8. 1997.
4. Cho, Kyunghyun, et al. "On the properties of neural machine translation: Encoder-decoder approaches." *arXiv preprint arXiv:1409.1259.* 2014.
5. Bozinovski, Stevo, and Ante Fulgosi. "The influence of pattern similarity and transfer learning upon training of a base perceptron b2." *Proceedings of Symposium Informatica*. Vol. 3. 1976.
6. https://www.coursera.org/articles/ai-vs-deep-learning-vs-machine-learning-beginners-guide
7. https://en.wikipedia.org/wiki/Recurrent_neural_network

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