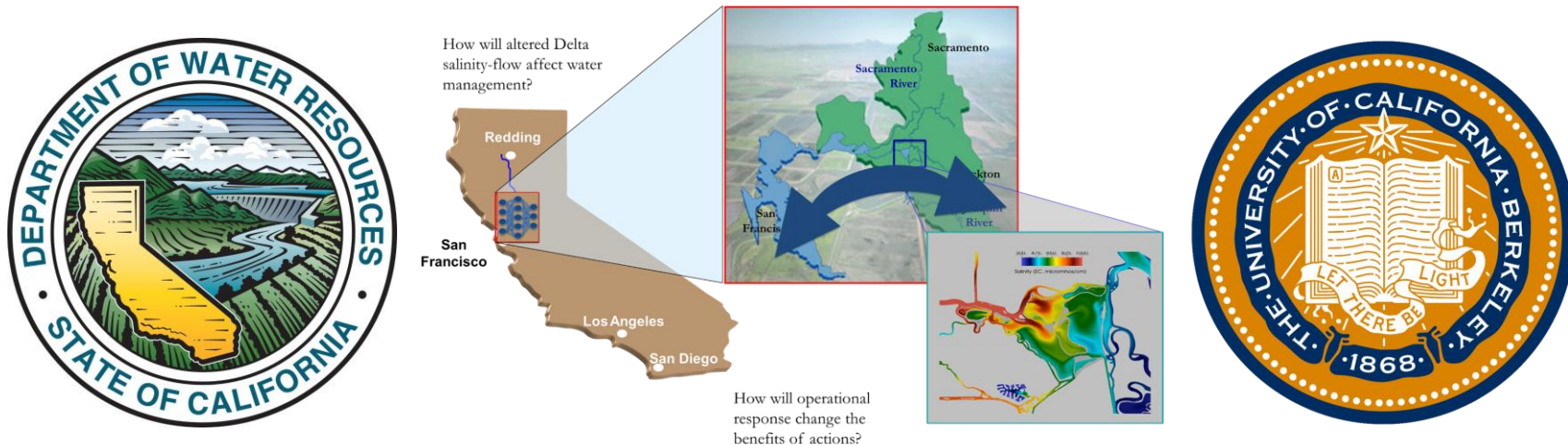


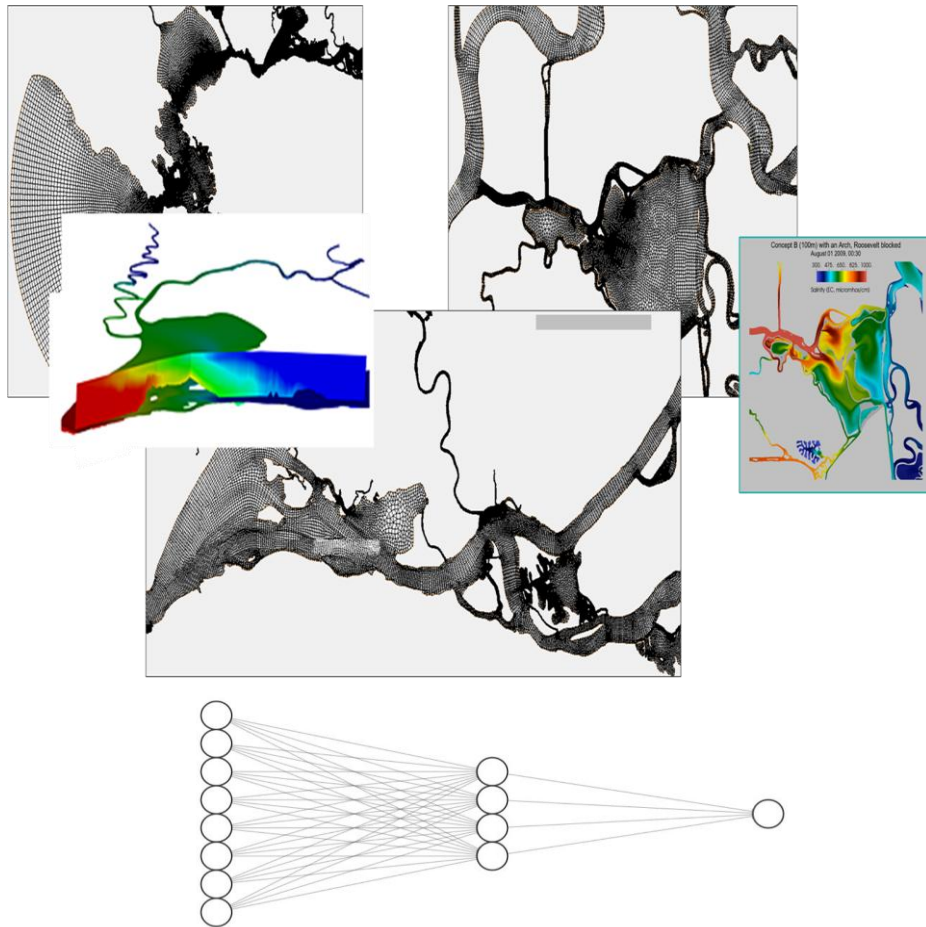
Transfer Learning for Multi-Fidelity Surrogate Modeling of Delta Salinity Under Extended Drought and Climate Scenarios



Eli Ateljevich, Lily Tomkovic, Sabi Can Ruso
CWEMF Annual Meeting | April 20-22, 2026

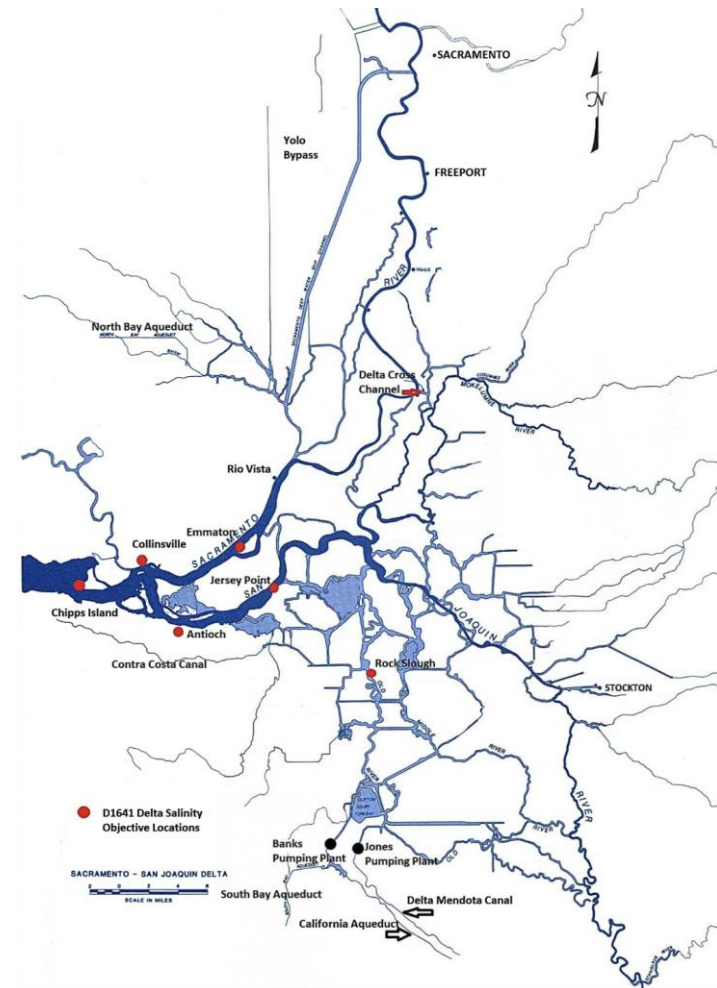
Why Surrogate ANNs for Delta Salinity?

- CalSIM plans water operations on monthly timesteps over ~**100** years of hydrology.
- Needs a **fast salinity surrogate** (currently uses DSM2).
- **Challenge:** evaluate management alternatives (Suisun Marsh, Franks Tract etc.) more robustly under a nonstationary climate future.
- **Goal:** Absolute **and** contrast accuracy.



Sacramento-San Joaquin Delta

- **Models:** DSM2, RMA, SCHISM, Surrogate ANN.
- **20 salinity monitoring stations** across Delta.
- **8 input features.**
- **Scenarios:** Base, Suisun, Cache, Franks Tract.
- **All scenarios share identical inputs**, only the hydrodynamic **outputs** differ.
- **7 simulation cases** representing different perturbed hydrologies.



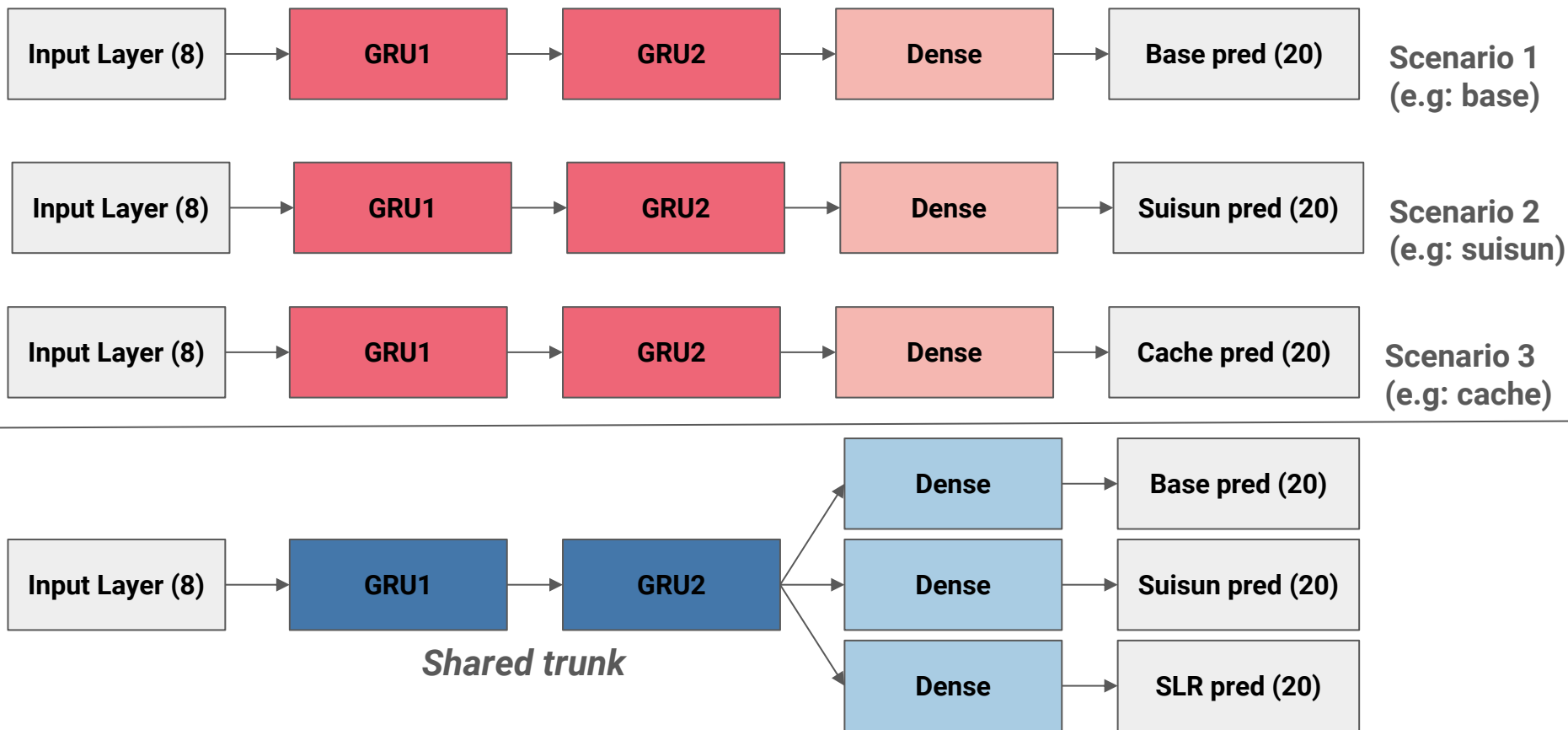
From Jayasundra, 2018

Multi-Fidelity Transfer Learning Pipeline

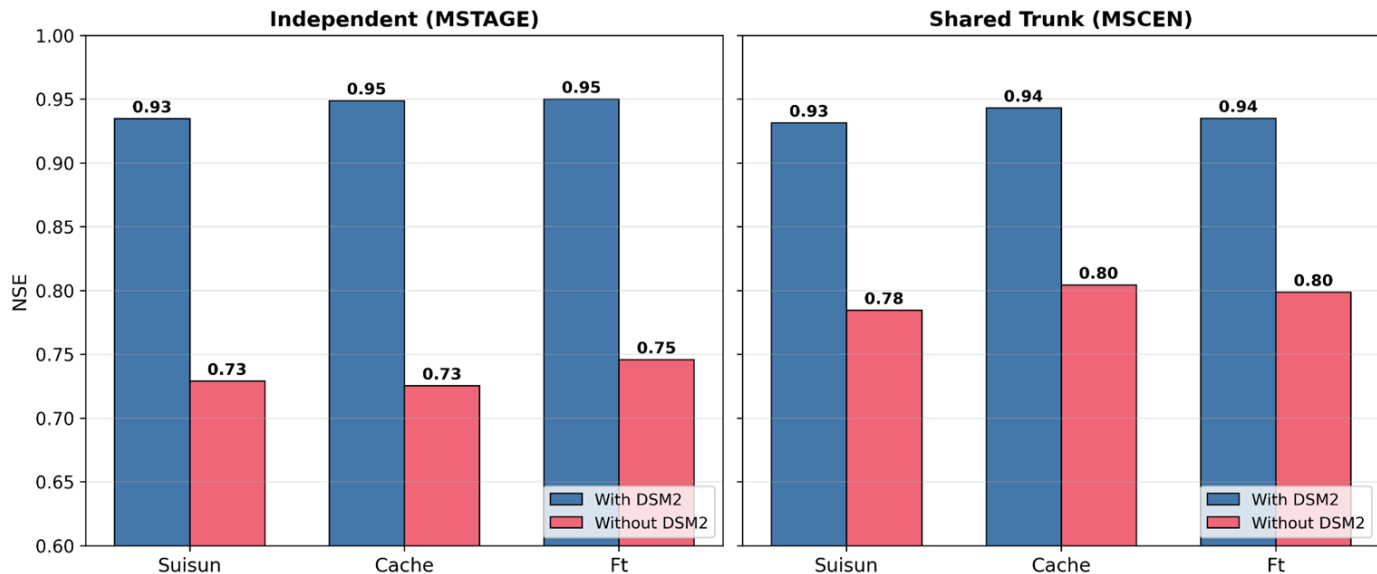


- **Lower-fidelity, abundant** data learning from DSM2.
- **High-fidelity, scarcer** data fine-tune to refine predictions using RMA/SCHISM.
- Same ANN architecture throughout, weight transfer between stages.
- We use two modeling approaches: **independent** and **shared-trunk**.

Multiple Scenarios: Independent vs Multitask

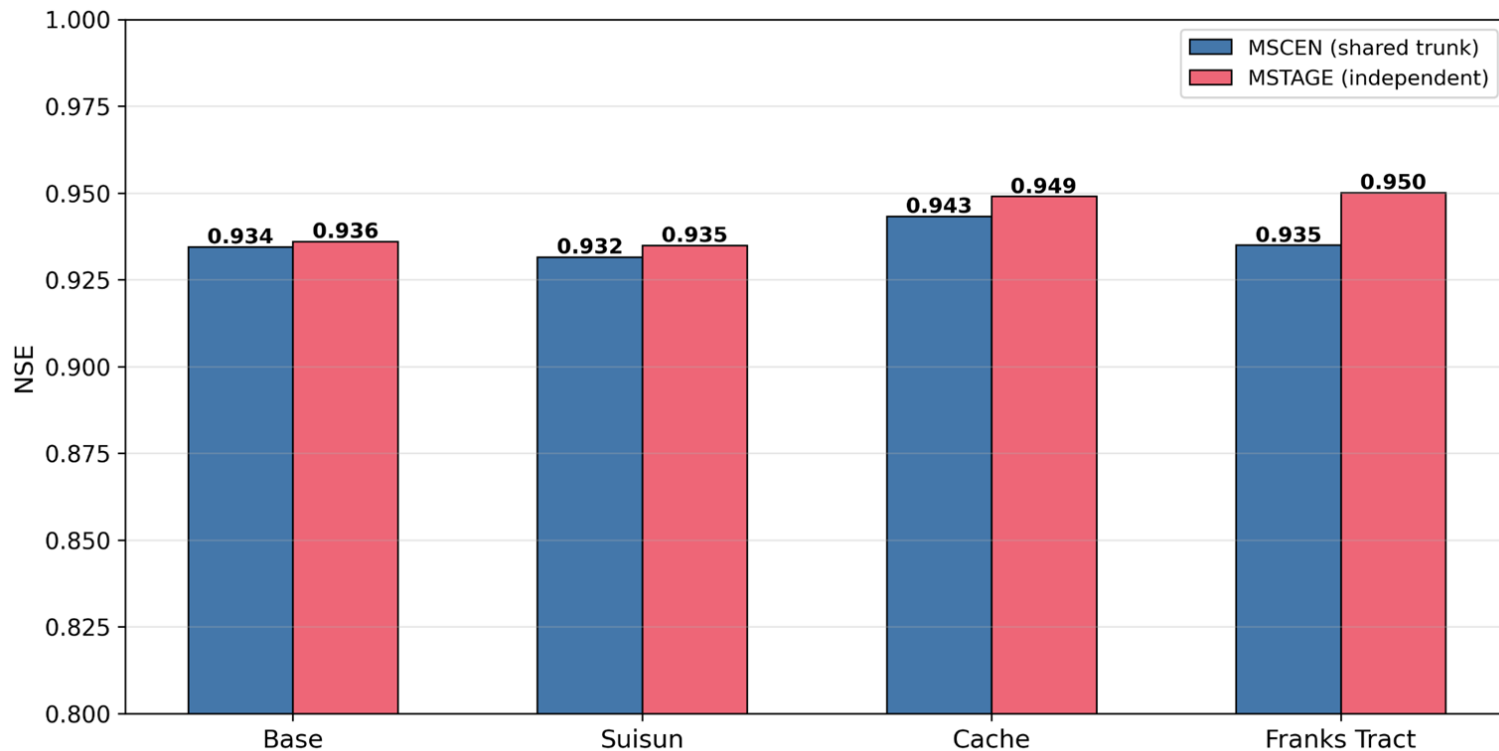


DSM2 Pretraining Improves Performance



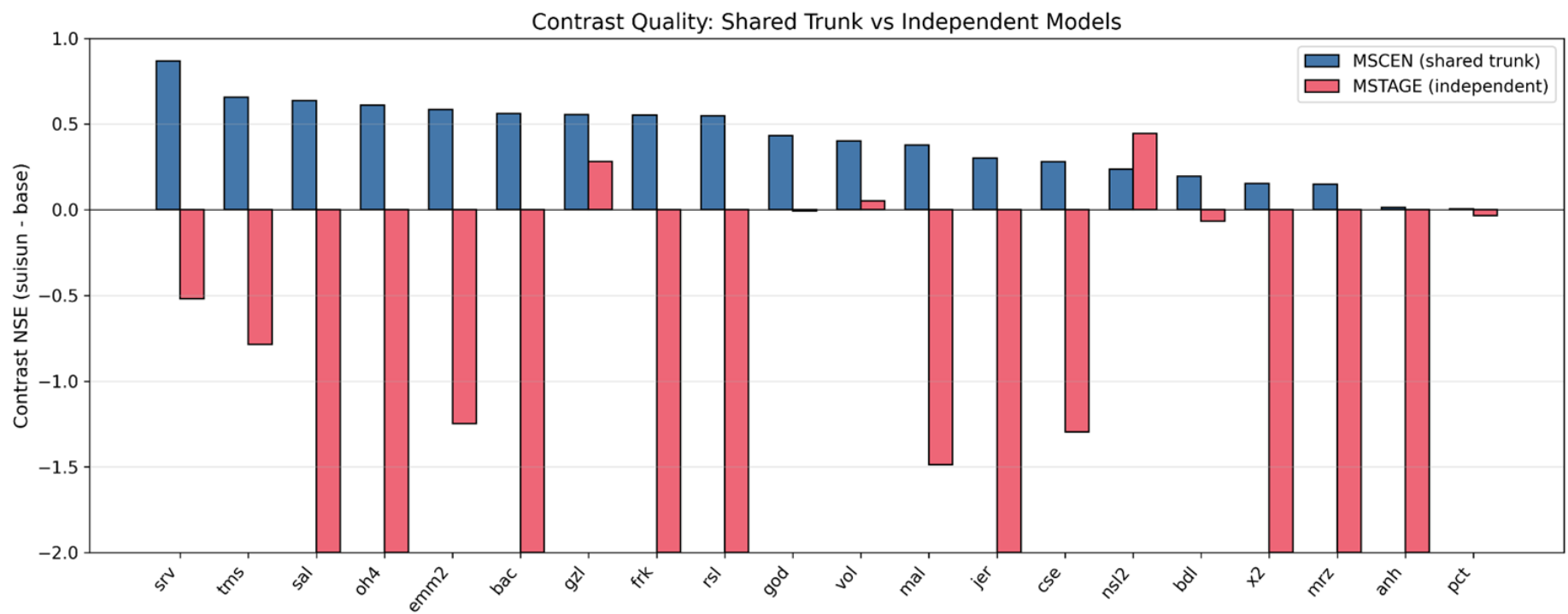
- Pretraining before RMA fine-tuning added **+0.13 to 0.22** mean NSE across stations.
- Training from scratch with 3x more epochs and different learning rate configurations did not close the gap and we plateau around 0.8 NSE.

Both Architectures Achieve Similar Absolute Accuracy



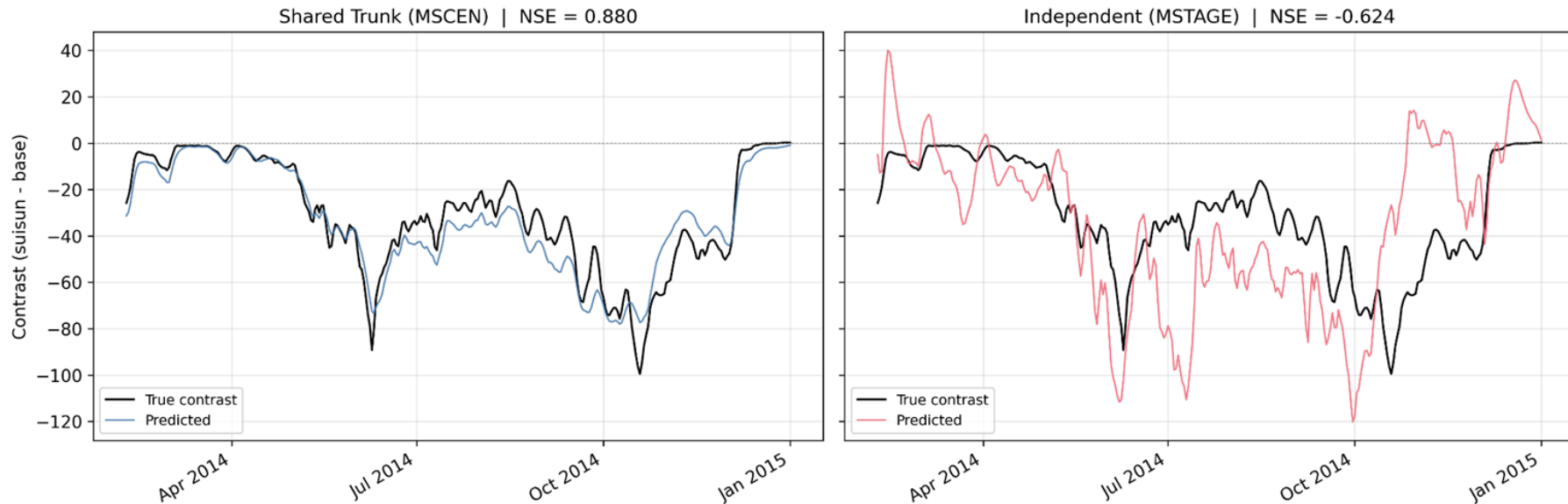
- Both architectures achieve **0.93+ NSE** (avg across all stations) across all scenarios.

Shared Trunk Improves Contrast Prediction Quality (ex: Suisun)



- **Shared trunk** achieves **above mean** (>0) contrast NSE at all stations. Individual models **negative** at 17/20.

Contrast Prediction at Station SRV (ex: Suisun)



- Shared trunk captures seasonal contrast pattern; independent model errors compound on subtraction.

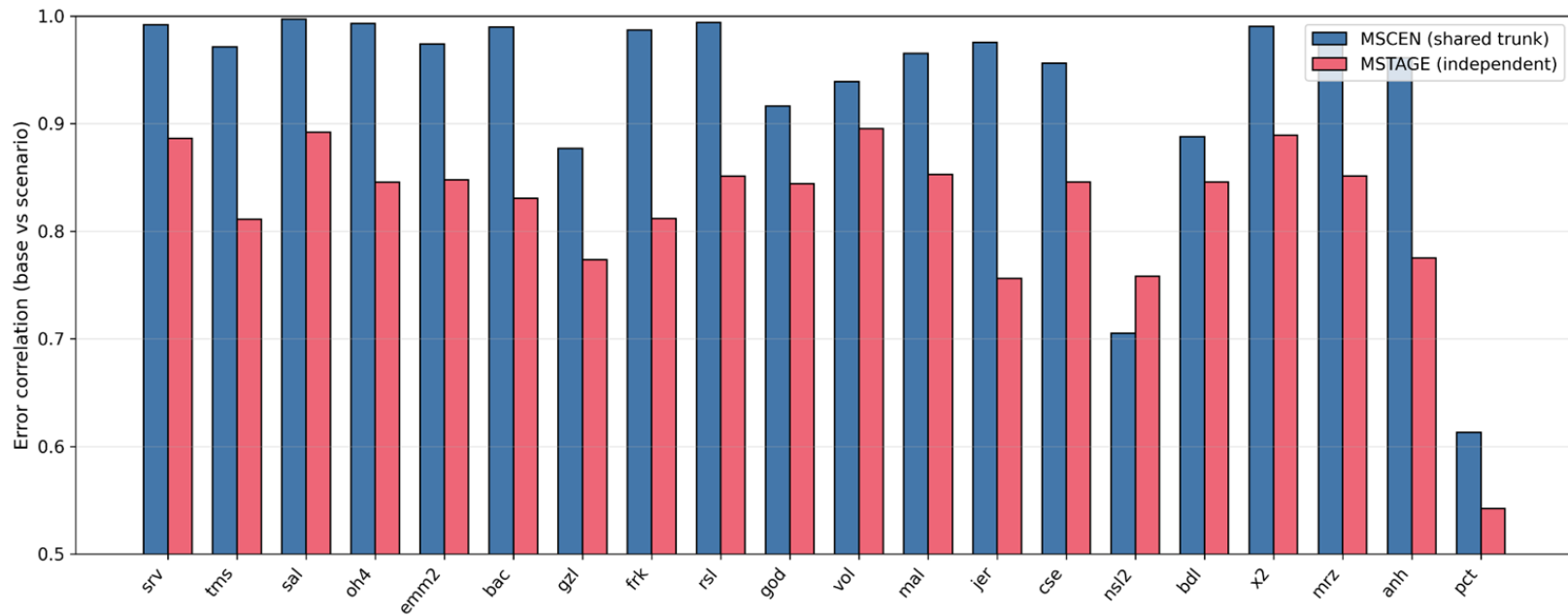
Contrast Quality Depends on Correlation of Errors

$$\hat{y}_1 = y_1 + \varepsilon_1$$

$$\hat{y}_2 = y_2 + \varepsilon_2$$

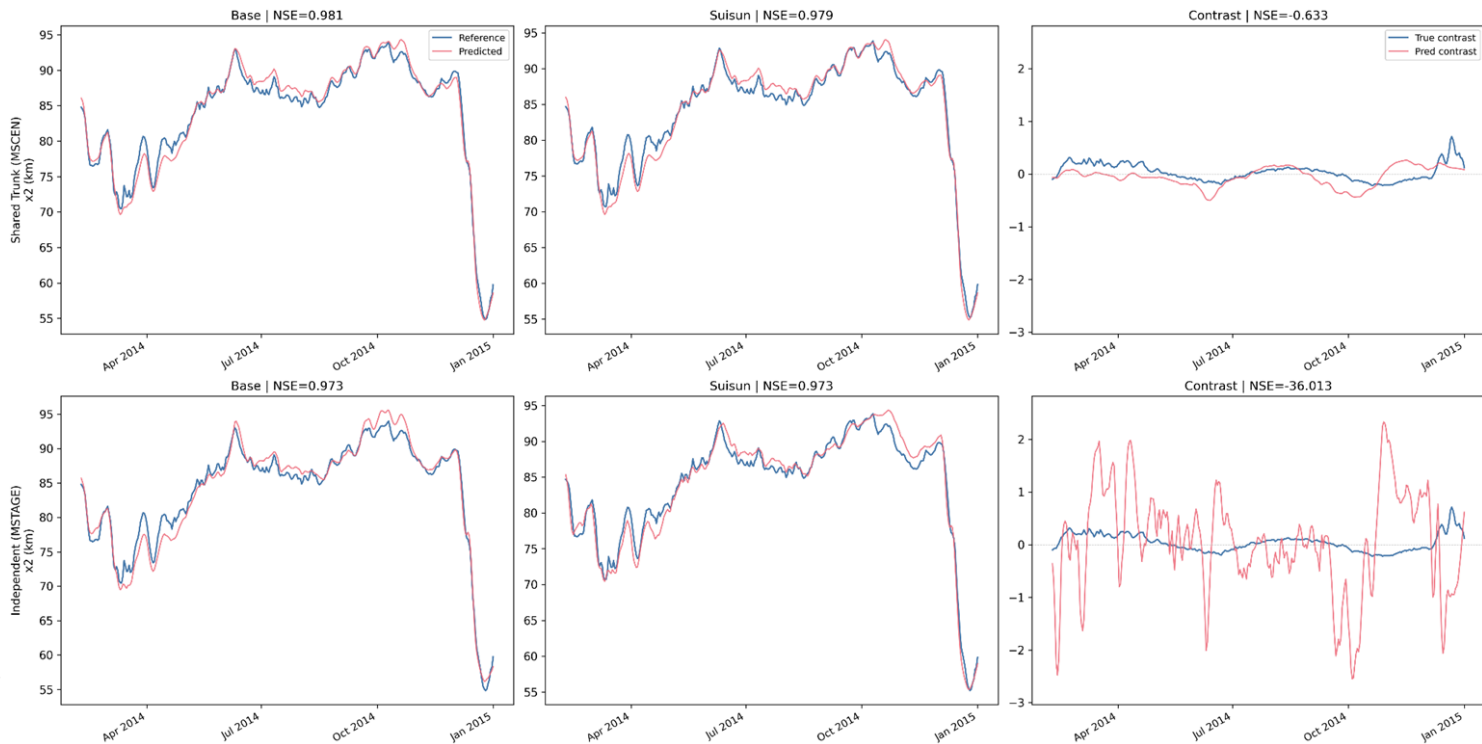
Predicted contrast **True contrast** **Difference of Errors**

$$\Delta = \hat{y}_2 - \hat{y}_1 = (y_2 - y_1) + (\varepsilon_2 - \varepsilon_1)$$

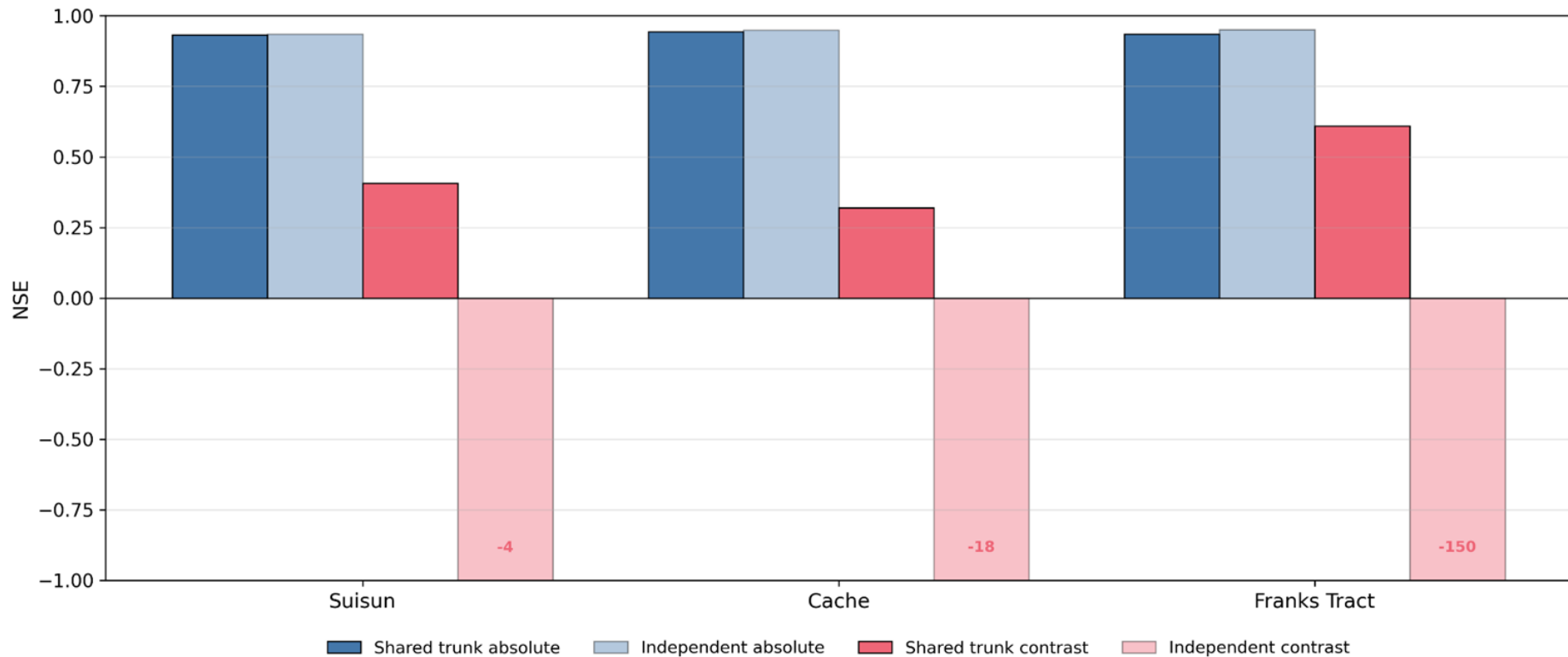


Same Absolute Accuracy, Different Contrast Quality (Ex: X2)

- **Both:** Absolute $\text{NSE} > 0.96$.
- **Contrast signal 0.3 km** while the **median absolute error** of the model is **0.9 km**.
- Shared trunk model **error correlation** = 0.99. Independent: 0.89.
- **Contrast** error diverges; correlated errors cancel, uncorrelated errors compound.

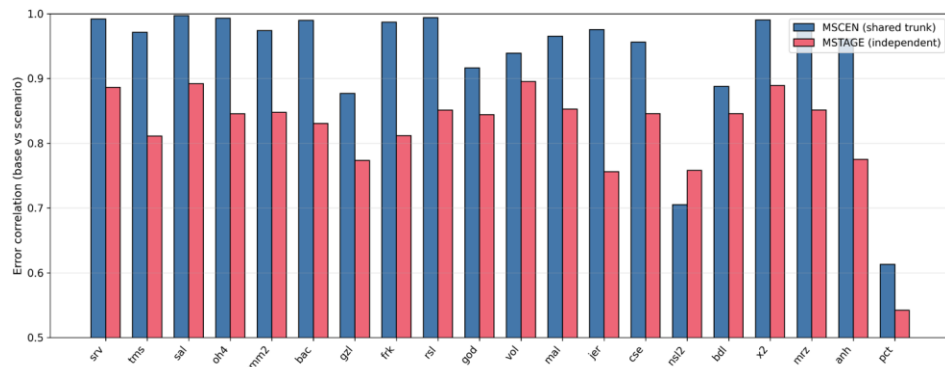
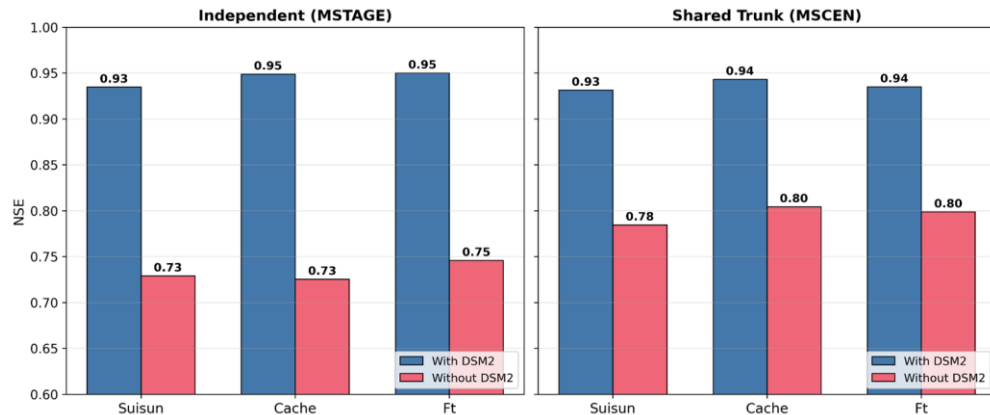


Observations Consistent Across All Scenarios



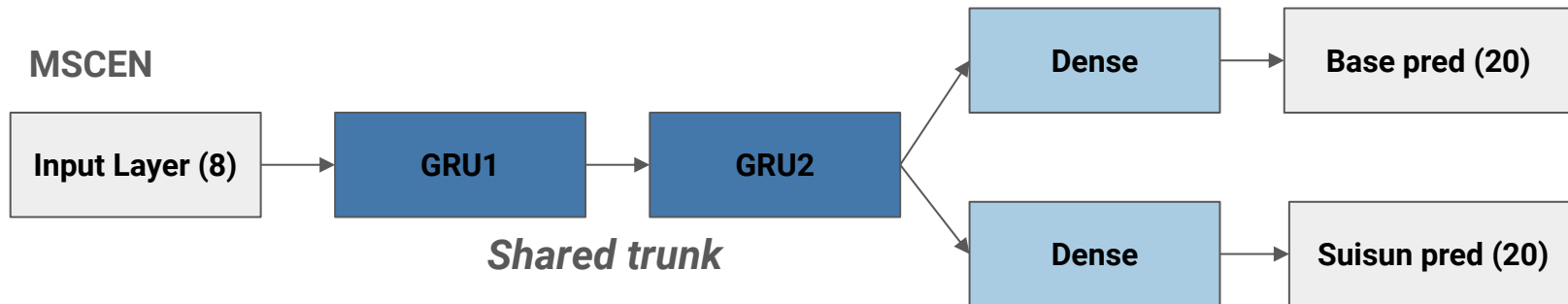
Recap of Key Findings

- DSM2 **pretraining** is **essential**.
- Both approaches achieve **similar absolute NSE** accuracy.
- Shared trunk **improves** contrast prediction.
- Contrast quality varies by station and scenario.
- Predicting contrast with operational confidence remains an **ongoing challenge**.

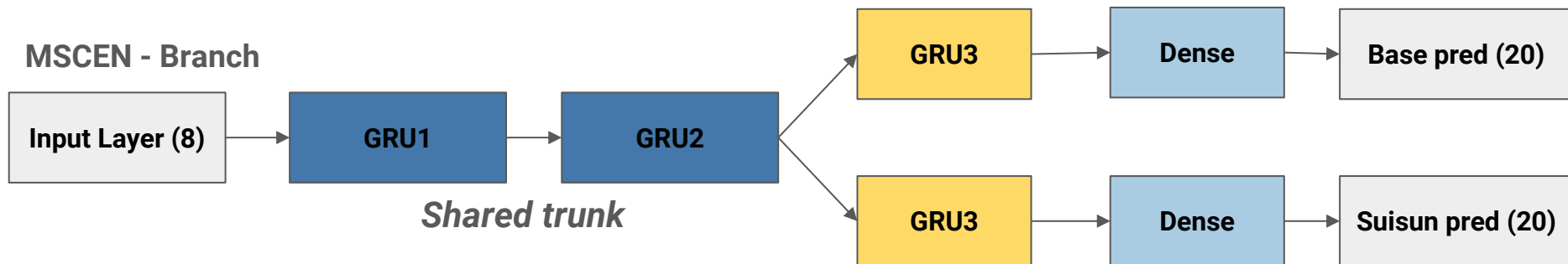


Multiscenario “Branch” Architecture

MSCEN



MSCEN - Branch



Future Work

- **Additional work on per-scenario branch architectures.** Can a GRU layer dedicated to capturing scenario-specific tidal-phase or dynamical differences improve contrast prediction?
- **Station-level analysis** - trends by location or hydrodynamic character.

Thank you - Questions?



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Supplemental slides available. For any questions reach out to
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