Sub-seasonal to Seasonal (S2S) Reference Evapotranspiration (ET_o) Forecasting in California with Deep Learning

2025 Improving Sub-seasonal to Seasonal Precipitation Forecasting Workshop
May 7-9, 2025

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Outline

1. Overarching Goal
2. Background
3. S2S ET_o Forecasting
   - **Case Study 1**:
     forecasting accuracy,
     complexity, and data efficiency
   - **Case Study 2**:
     deep global learning
4. Take-Home Messages
5. Potential Benefits

Overarching Goal

Data Science + Deep Learning (DL) → Forecast ET_o

Wealth of Measurement Data

+

Advances in Data Science and DL

→

New Knowledge about ET_o

New ET_o Models

→

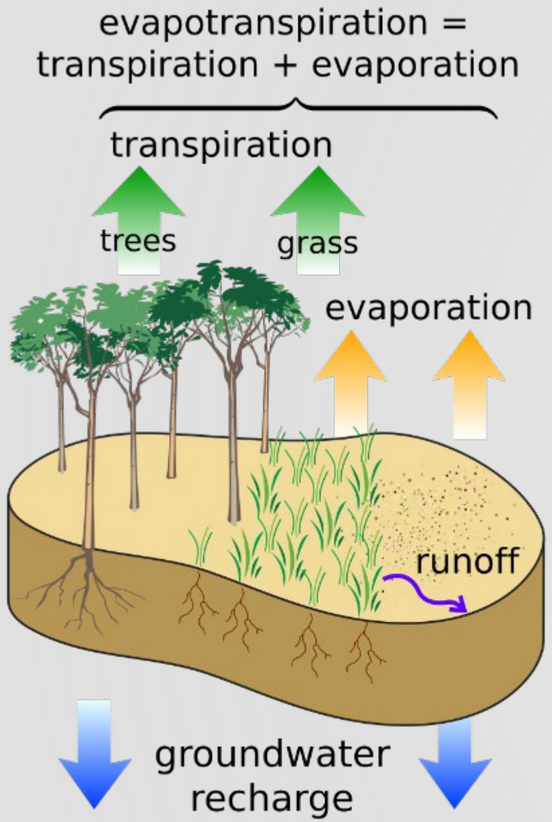
Better ET_o Forecasting

Better Inform Decision-Making

Operational/ Planning Models

Better Estimates on ET for Crops

Background: ET and ET_o



Source: https://en.wikipedia.org/wiki/Evapotranspiration

- Evapotranspiration (ET):
  - Key water cycle component
  - Affects water availability (drought, irrigation, modeling,…)
- ET_o: ET at a reference surface (well-watered)
- Estimating ET: ET = Crop Coefficient * ET_o
- Estimating ET_o: CDWR California Irrigation Management Information System (CIMIS) (https://cimis.water.ca.gov/)
  - 145 Active Weather Stations

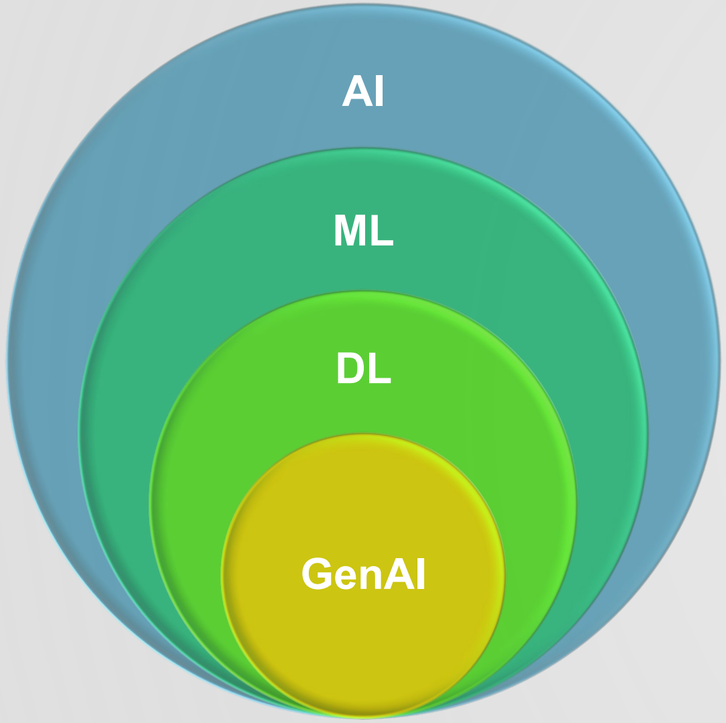
Solar Radiation
Air & Soil Temperature
Relative Humidity
Wind Speed

→ Penman-Monteith Equation* → ET_o

* Walter, I. A., et al. (2004) "ASCE's Standardized Reference Evapotranspiration Equation".

Background: Machine Learning

➢ AI Terminologies



AI: Artificial Intelligence
ML: Machine Learning
DL: Deep Learning
GenAI: Generative AI

➢ Conventional models vs. ML models

	Mechanistic Model	Statistical Model	ML Model
Approach	Physically-Based	Data + Simplified Physics	Data
Structure	Rigidly Structured	Structured	Flexible
Runtime*	Hours/Days	Sec./Min.	Sec.
Interpretability	“White Box”	"Grey Box”	“Black Box”**

* Model calibration/training time not included
** Active research area (e.g., physics-informed ML)

ML experience of the CDWR Modeling Support Office

Timeline

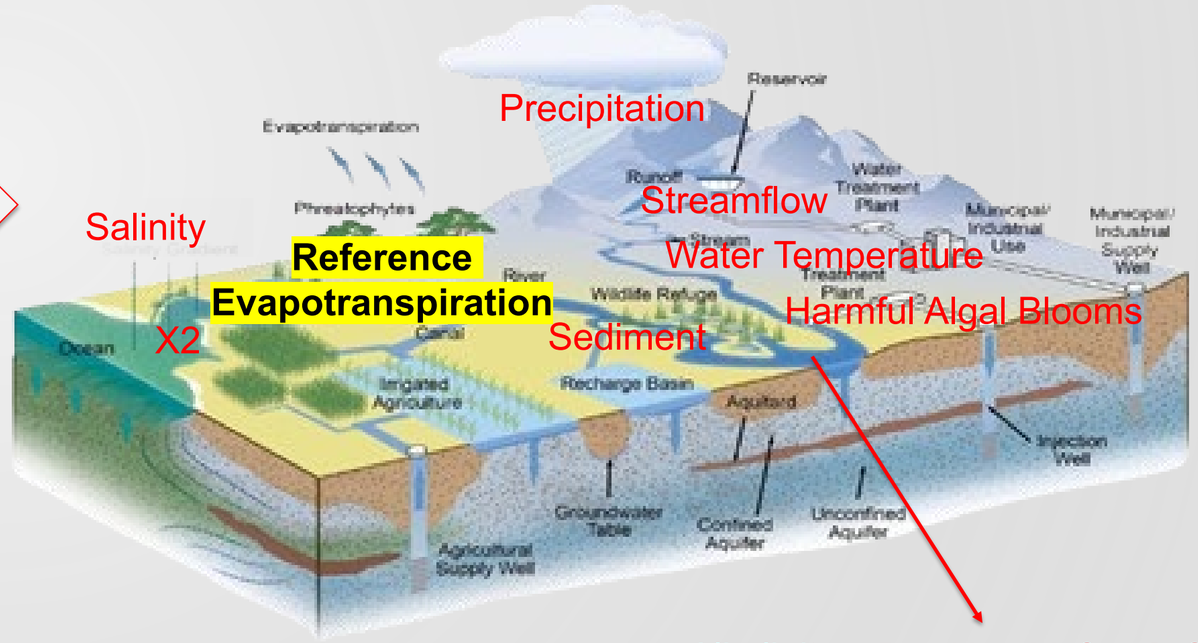
DWRSIM–MDO*	CalSim II–G Model*	CalSim II–DSM2*	CalSim 3–DSM2*	
1995	2001/2002	2007	2020	**Post-2020**

* **DWRSIM, CalSim II, CalSim 3**: 1st, 2nd, and current generation of CDWR's water resources planning model

* **MDO**: Minimum Delta Outflow **G Model**: Salinity Gradient Model **DSM2**: Delta Simulation Model II

2020 - Present

- 20+ ML Models
- 20 Variables
- 12 Articles
- 6 Dashboards
- 2 Workshops
- ML Protocols



Alkalinity Br^- K^+ Mg^{2+} Ca^{2+}
Hardness Na^+ $SO4^{2-}$ Cl^-
Dissolved Boron
Dissolved Nitrate
Total Dissolved Solids

Open Access Feature Paper Review

Protocols for Water and Environmental Modeling Using Machine Learning in California

by Minxue He *, Prabhjot Sandhu, Peyman Namadi, Erik Reyes, Kamyar Guivetchi and Francis Chung

https://doi.org/10.3390/hydrology12030059

Case Study 1: Overview

Goal: To analyze the accuracy, complexity, and data efficiency of statistical & DL for ET_o forecasting for 1-, 3-, 6-months ahead

Take-Home Messages

- Statistical models:
  - Results reasonable
  - Not necessarily run faster
- DL models
  - Larger data → better performance
  - DL model parameters ≠ computational complexity
  - Can outperform statistical models

ELSEVIER

Computers and Electronics in Agriculture

Volume 215, December 2023, 108424

Statistical and deep learning models for reference evapotranspiration time series forecasting: A comparison of accuracy, complexity, and data efficiency

Arman Ahmadi [a], Andre Daccache [a], Mojtaba Sadegh [b], Richard L. Snyder [c]

https://doi.org/10.1016/j.compag.2023.108424

Case Study 2: Goal

To develop globally-learned deep learning (DL) models to forecast monthly ET_o up to one year in the Central Valley

ELSEVIER

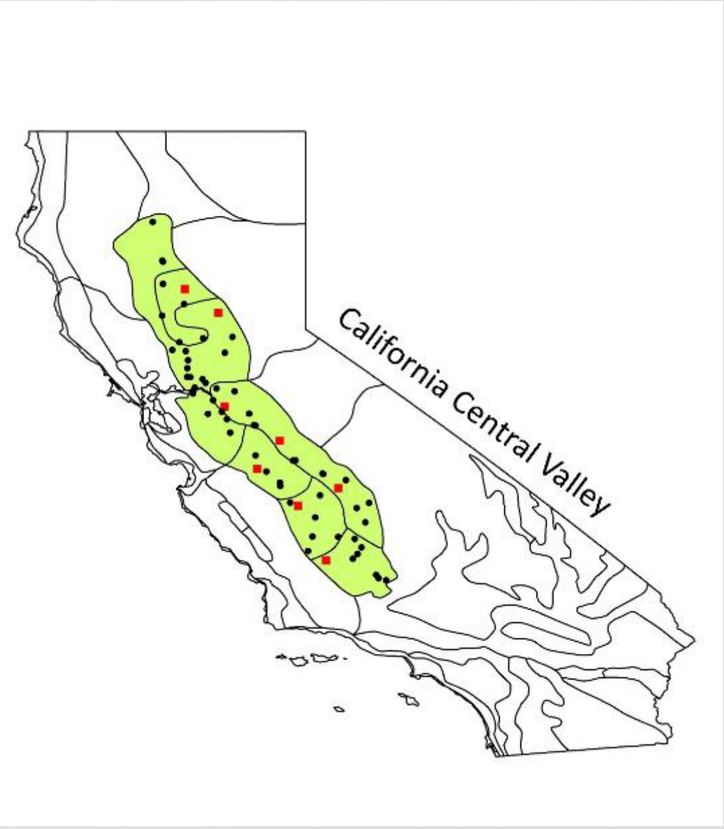
Journal of Hydrology: Regional Studies

Volume 59, June 2025, 102339

6.7 CiteScore | 4.7 Impact Factor

Enhancing the accuracy and generalizability of reference evapotranspiration forecasting in California using deep global learning

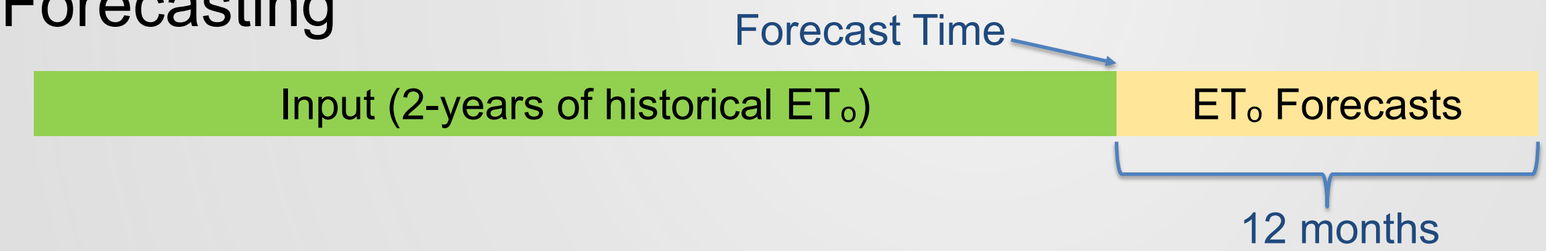
Arman Ahmadi [a], Andre Daccache [b], Minxue He [c], Peyman Namadi [c], Alireza Ghaderi Bafti [d], Prabhjot Sandhu [c], Zhaojun Bai [e], Richard L. Snyder [f], Tariq Kadir [c]



https://doi.org/10.1016/j.ejrh.2025.102339

Case Study 2: Forecasting Setup

- Univariate time series forecasting: no exogenous variables
- Forecasting lead time:12 months
- Local learning: one model per station
  - Training data: all but the last two years (July 2021-June 2023)
  - Forecasting



- Global learning: one model for all stations
  - Training data: all data from the training stations (~85% of all stations)
  - Forecasting: at test stations (remaining ~15% not used in training)

Case Study 2: Forecasting Models

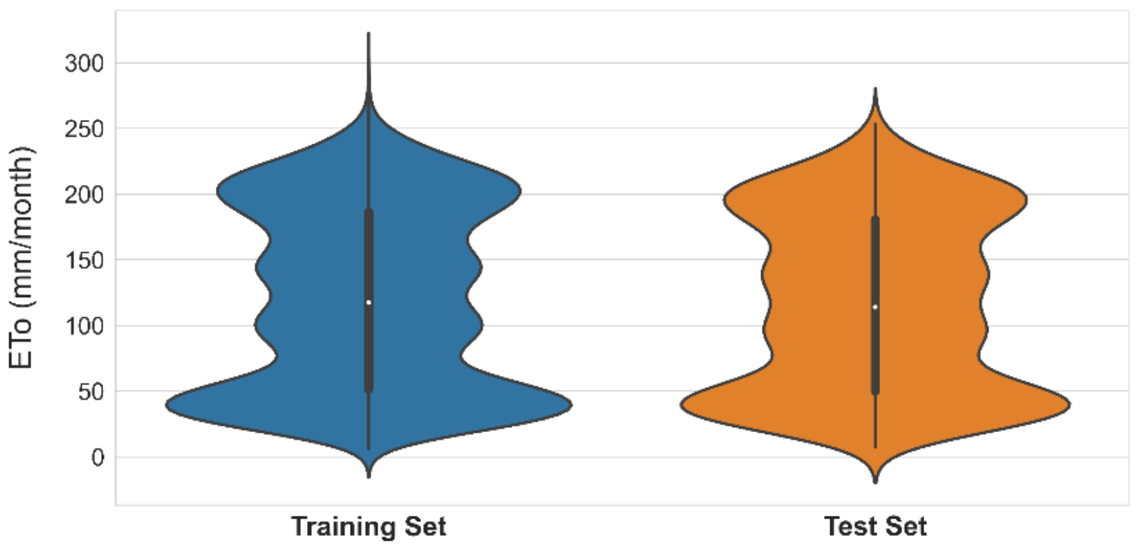
- Statistical Forecasting Models (3):
  - Seasonal Autoregressive integrated moving average (SARIMA)
  - Holt-Winters' exponential smoothing
  - Theta method
- Machine Learning Model (1): Light gradient-boosting machine (LightGBM)
- Deep Learning Models (9):
  - Neural basis expansion analysis for interpretable time series forecasting (N-BEATS)
  - Neural hierarchical interpolation for time series forecasting (N-HiTS)
  - Long short-term memory (LSTM)
  - Temporal convolutional network (TCN)
  - Transformer model
  - Temporal fusion transformer (TFT)
  - N-Linear and D-Linear
  - Time-series dense encoder (TiDE)

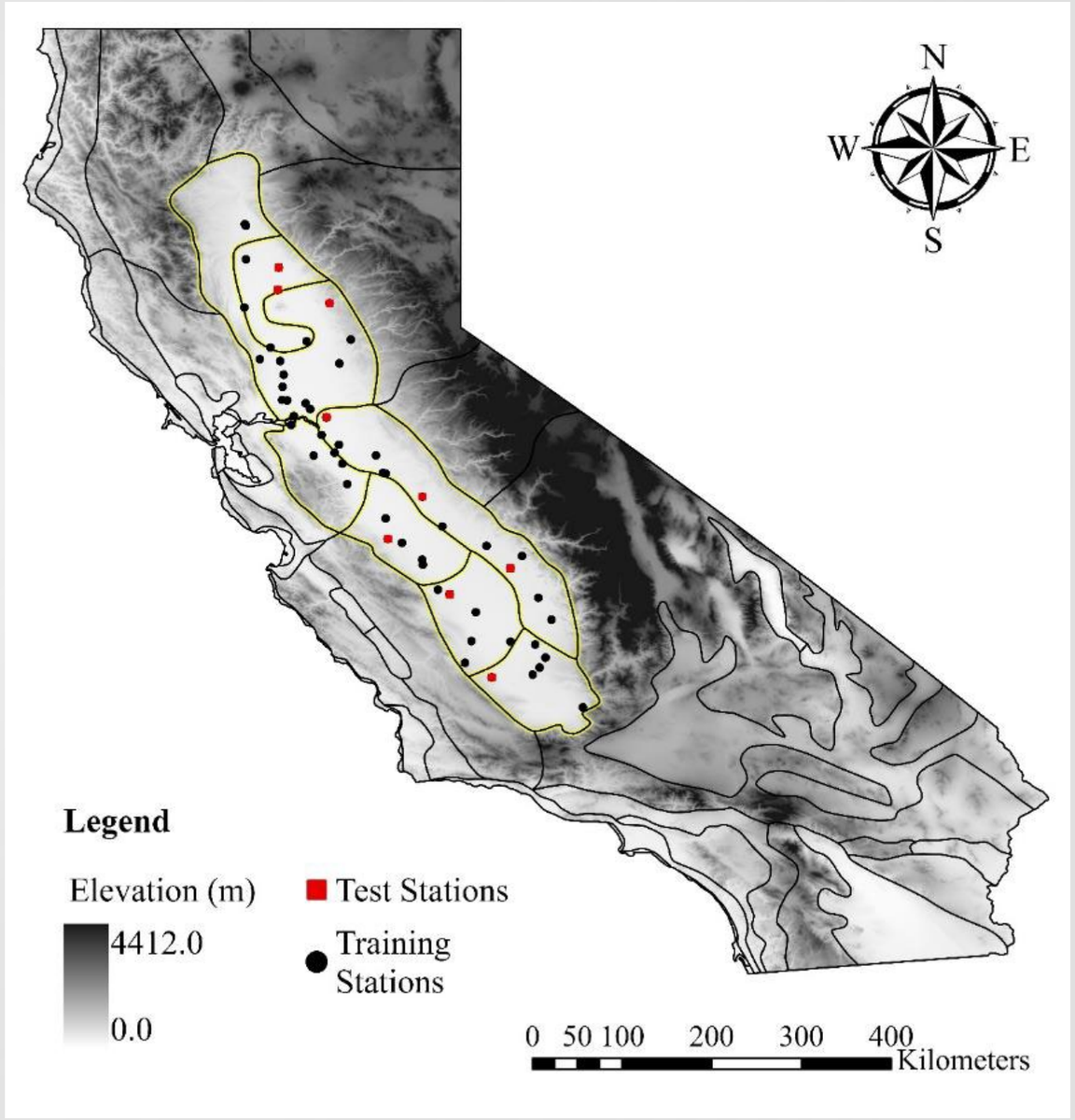
Details can be found at:

https://doi.org/10.1016/j.ejrh.2025.102339

Case Study 2: Data

- Monthly ET_o data from 55 CIMIS stations in the Central Valley
- Stations have more than six consecutive years of data
- 47 stations used as the training set
- 8 stations used as test set



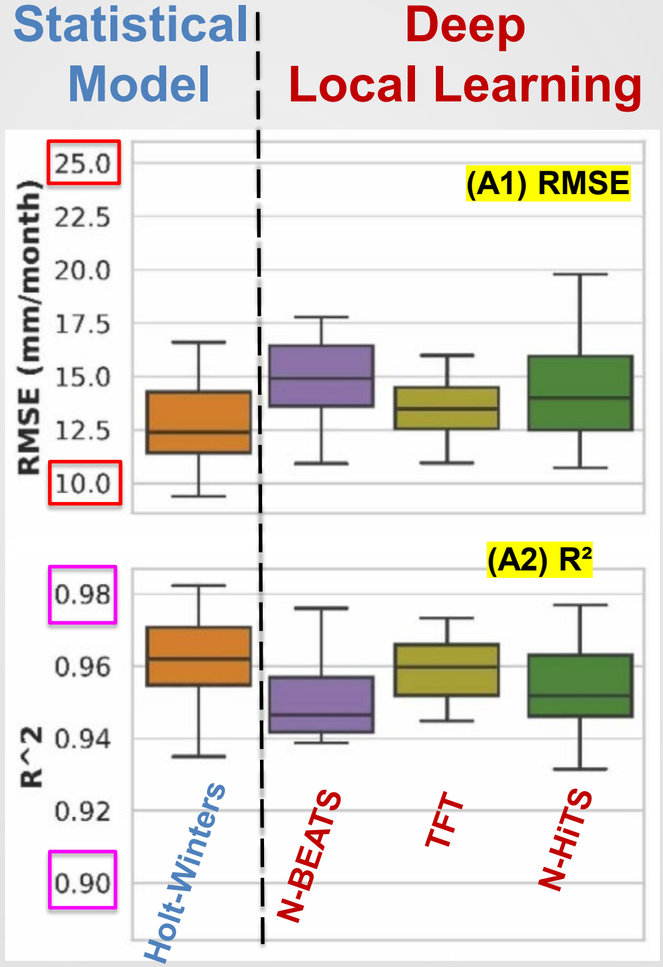


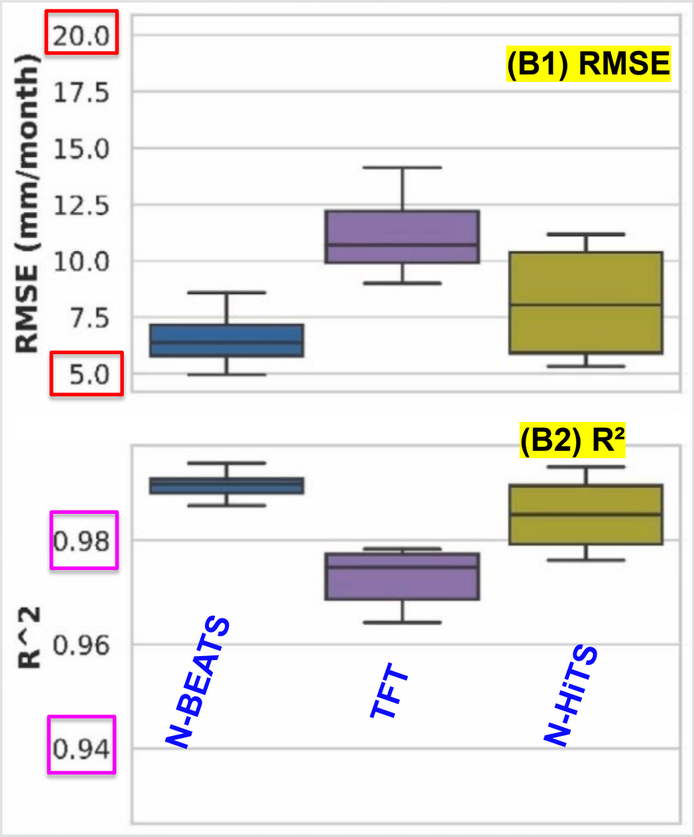
Case Study 2: Results

Box plots of Root Mean Squared Error (RMSE) and R^2

- CIMIS ET_o **vs.** forecasted ET_o
- July 2021-June 2023
- 8 test stations

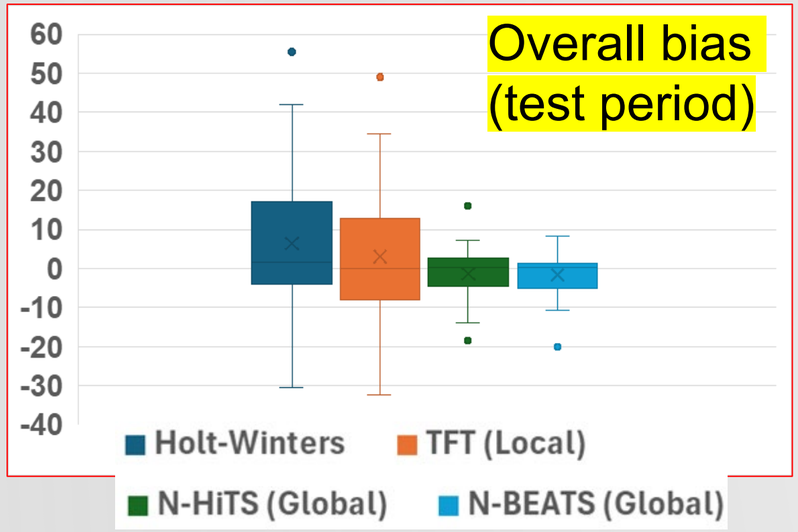
- Global learning > Statistical > Local learning
- DL Models
  Local learning: TFT best
  Overall: N-BEATS best

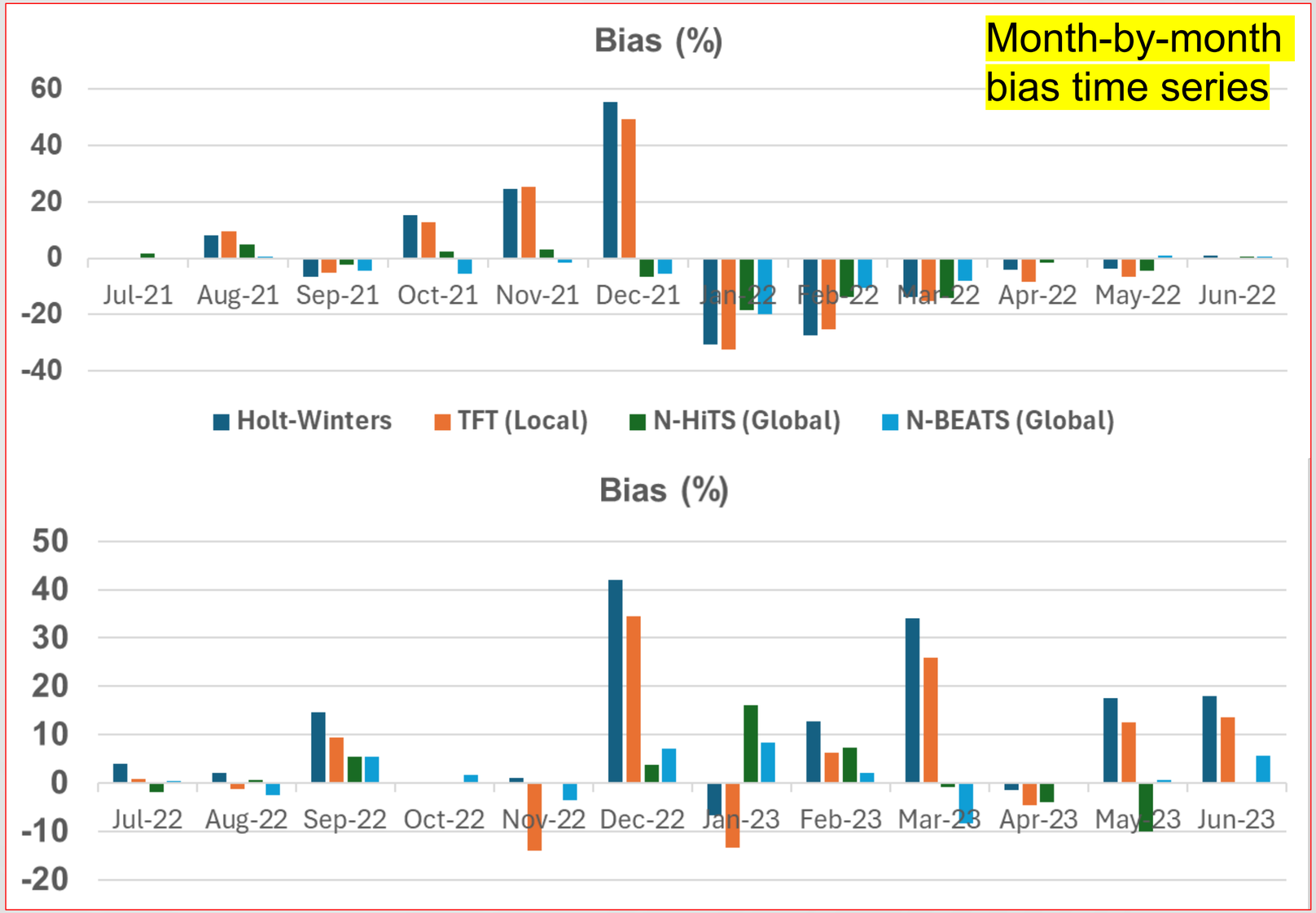




Case Study 2: Results

Percent bias of four models at Durham station





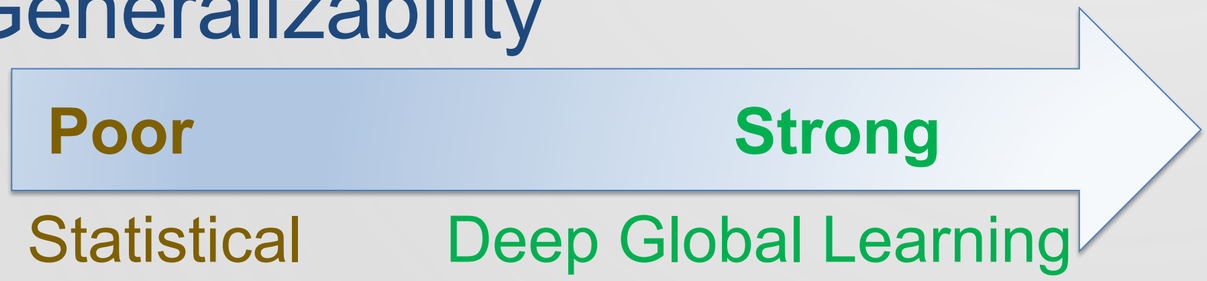
- Globally trained DL models → smaller bias
- Statistical/locally trained DL model bias: Winter > Spring > Fall > Summer

Case Study 2: Summary

Goal: To develop globally-learned deep learning (DL) models to forecast monthly ET_o up to one year in the Central Valley

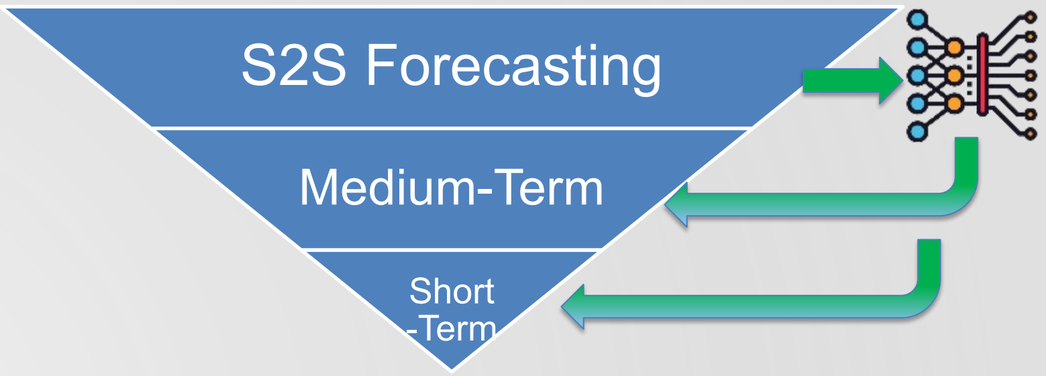
Take-Home Messages

- Statistical/local learning models:
  - Reasonable performance
  - Large bias in certain months
- Global learning
  - Higher accuracy (smaller bias)
- Generalizability



Benefits of Improved S2S ET_o Forecasting

- Short- and medium-term ET_o forecasting
  - Transferrable model architectures
  - Learned temporal and spatial patterns
  - Expected enhancements in model accuracy



- Water resources management
  - Irrigation
  - Water allocation
  - Long term planning
- Drought forecasting & management
  - Forecasting & early warning capabilities
  - Flash drought detection & response
  - Severity assessment and impact management

Image source: Hoell et al. (2019) The Causes, Predictability, and Historical Context of the 2017 U.S. Northern Great Plains Drought

Questions?

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