Reference Evapotranspiration (ET_o) Forecasting in California with Deep Global Learning

Machine Learning in Water and Environmental Modeling Workshop
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Module #3

Arman Ahmadi
UC Berkeley, Environmental Science, Policy, and Management

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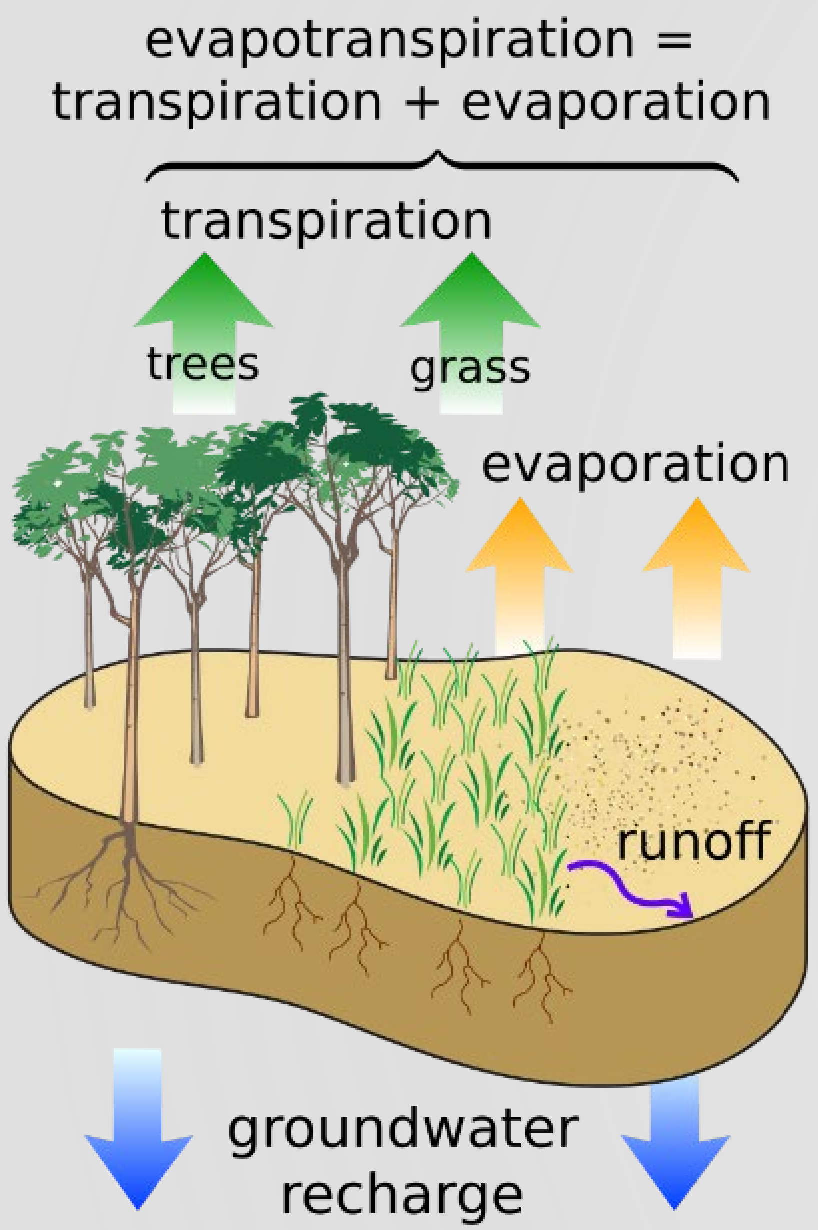
Berkeley UNIVERSITY OF CALIFORNIA

Outline

1. Overview
2. Overarching Goal
3. ET_o Forecasting
   - **Case Study 1**: forecasting accuracy, complexity, and data efficiency
   - **Case Study 2**: deep global learning
4. Key Messages

Overview: 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)
- ET = Crop Coefficient * ET_o
- DWR 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".

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Overarching Goal

To leverage the advances in data science and machine learning (ML) to forecast ET_o in California

Wealth of Measurement Data

+

Advances in Data Science and ML

→

New Knowledge about ET_o

New ET_o Models

→

Better ET_o Forecasting

→

Better Decision-Making

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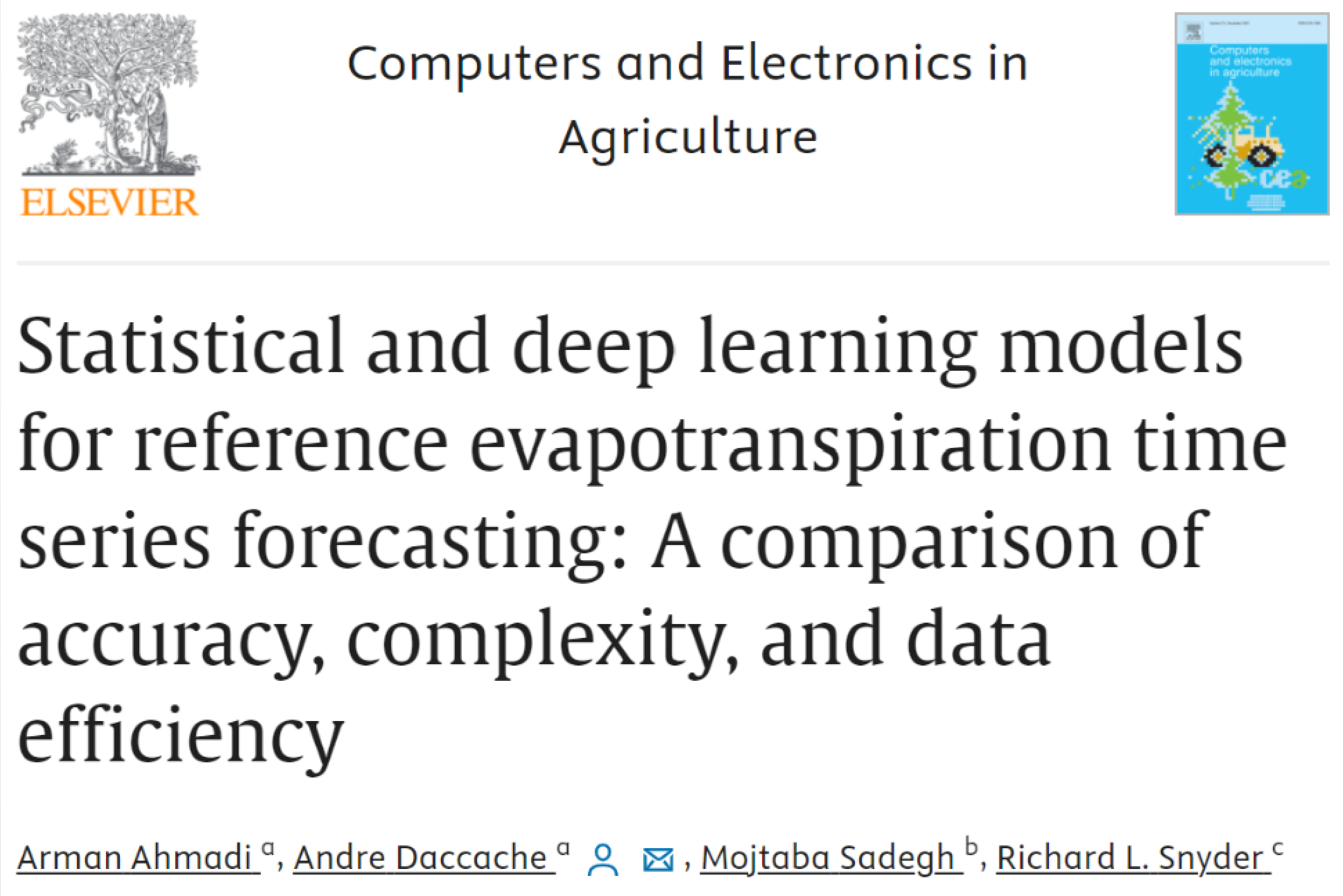
Case Study 1: Goal

To analyze the accuracy, complexity, and data efficiency of statistical and deep learning models for monthly ET_o forecasting


Computers and Electronics in Agriculture

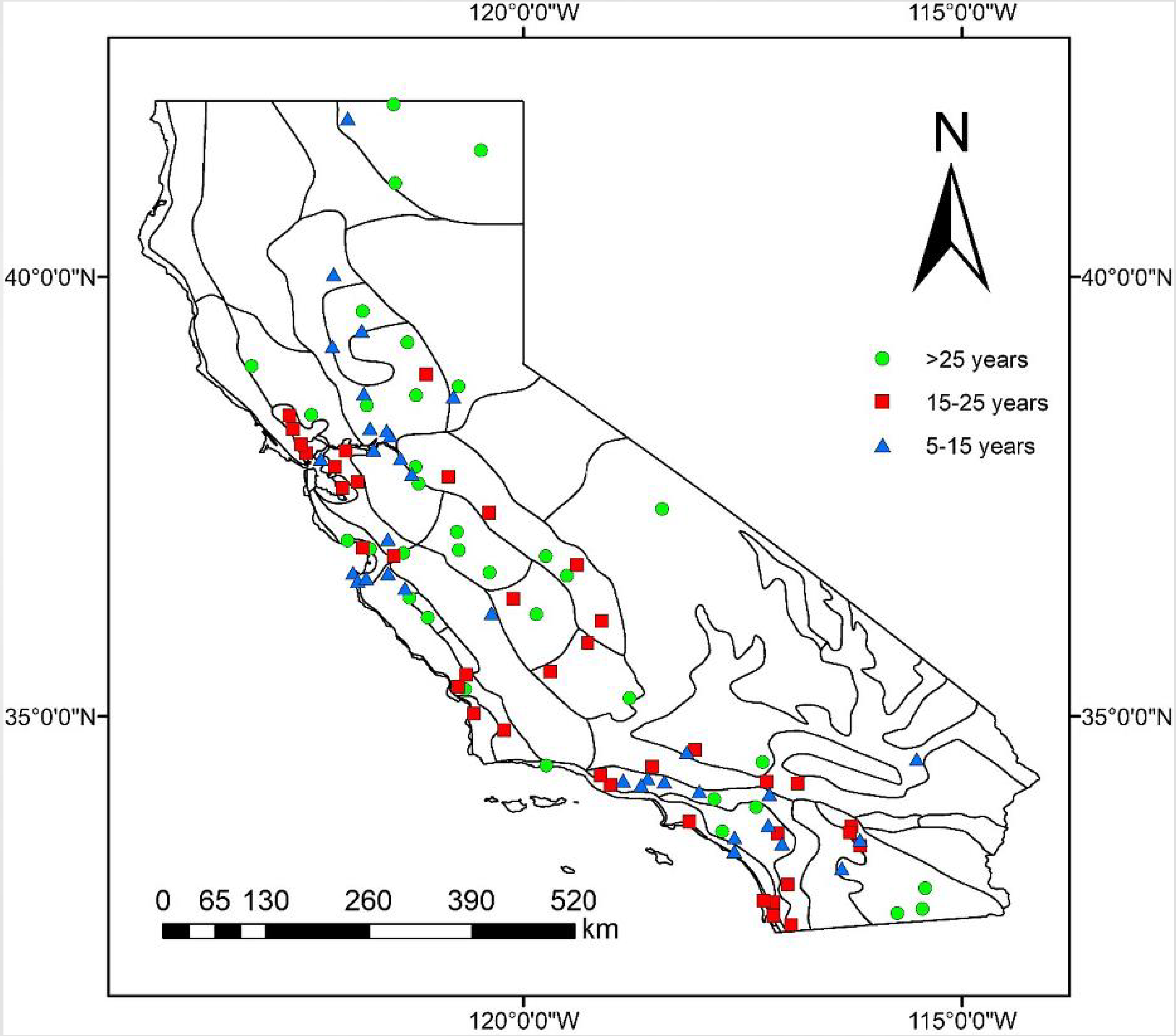
ELSEVIER

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]

Case Study 1: Data

- Monthly ET_o data from 107 active CIMIS stations
- Stations categorized based on their historical data availability:
  - Long: more than 25 years (34 stations)
  - Medium-length: 15 to 25 years (38 stations)
  - Short: 5 to 15 years (35 stations)



Case Study 1: Forecasting Setup

- Univariate time series forecasting (no exogenous variables)
- Last two years of data (July 2020 to June 2022) as the test set
- Forecasting horizons:
  - One month ahead
  - Three months ahead
  - Six months ahead
- Multi-step ahead forecasting strategies:
  - Recursive: $y_{t+1} = f(y_t, \dots, y_{t-k+1})$
  - Multi-input multi-output (MIMO): $[y_{t+H}, \dots, y_{t+1}] = F(y_t, \dots, y_{t-k+1})$

Case Study 1: Forecasting Models

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

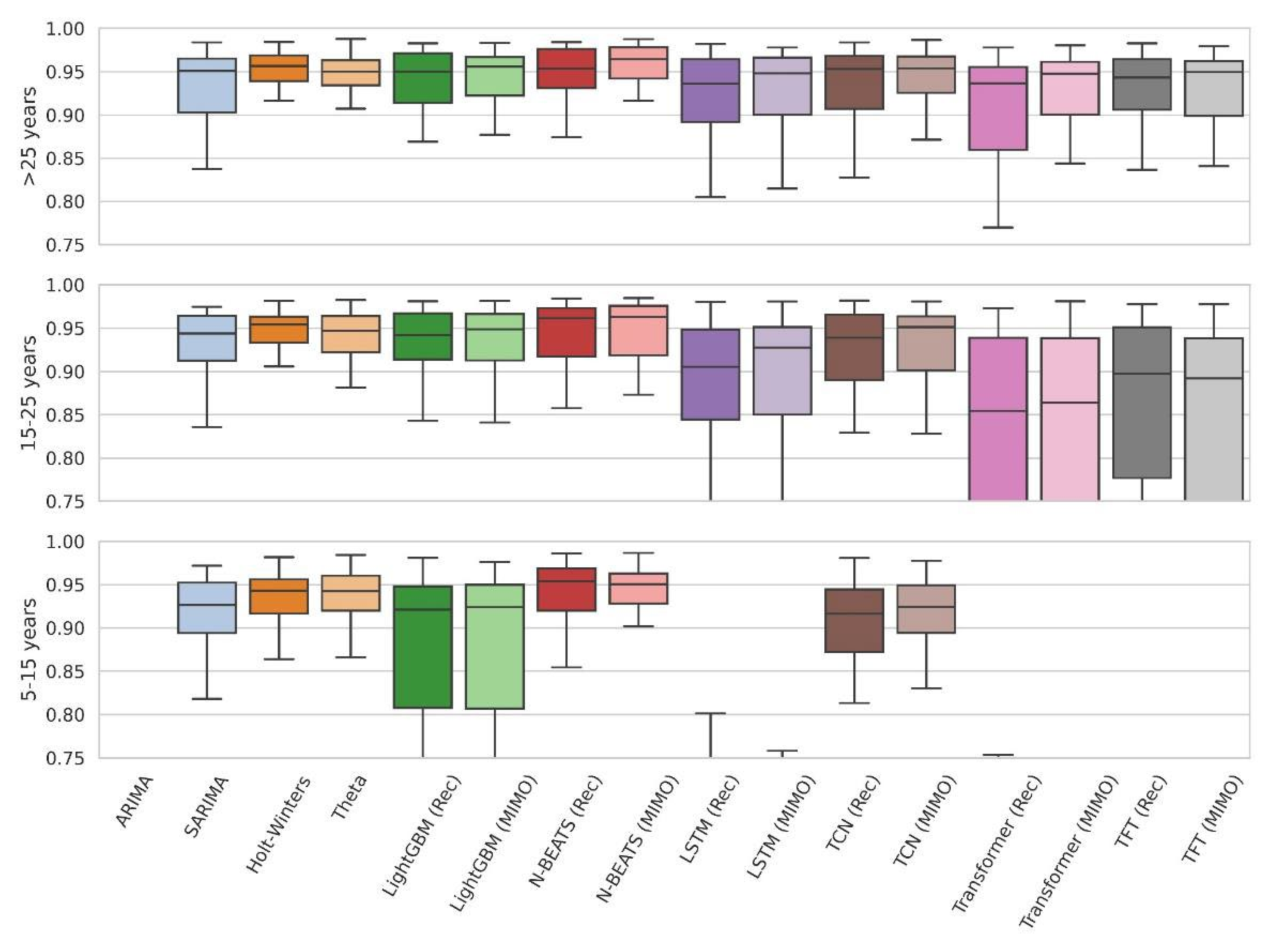
Case Study 1: Model Complexity

Model	Runtime (seconds)	Number of trainable parameters of deep learning models
ARIMA	168 (152 + 16)	-
SARIMA	266 (152 + 114)	-
Holt-Winters	4	-
Theta	1	-
LightGBM	2	-
N-BEATS	**59**	**~ 20,700**
LSTM	645	733
TCN	253	~ 4,300
Transformer	367	~ 12,100
TFT	473	~ 15,400

- Model architecture matters
- More parameters ≠ higher computational complexity

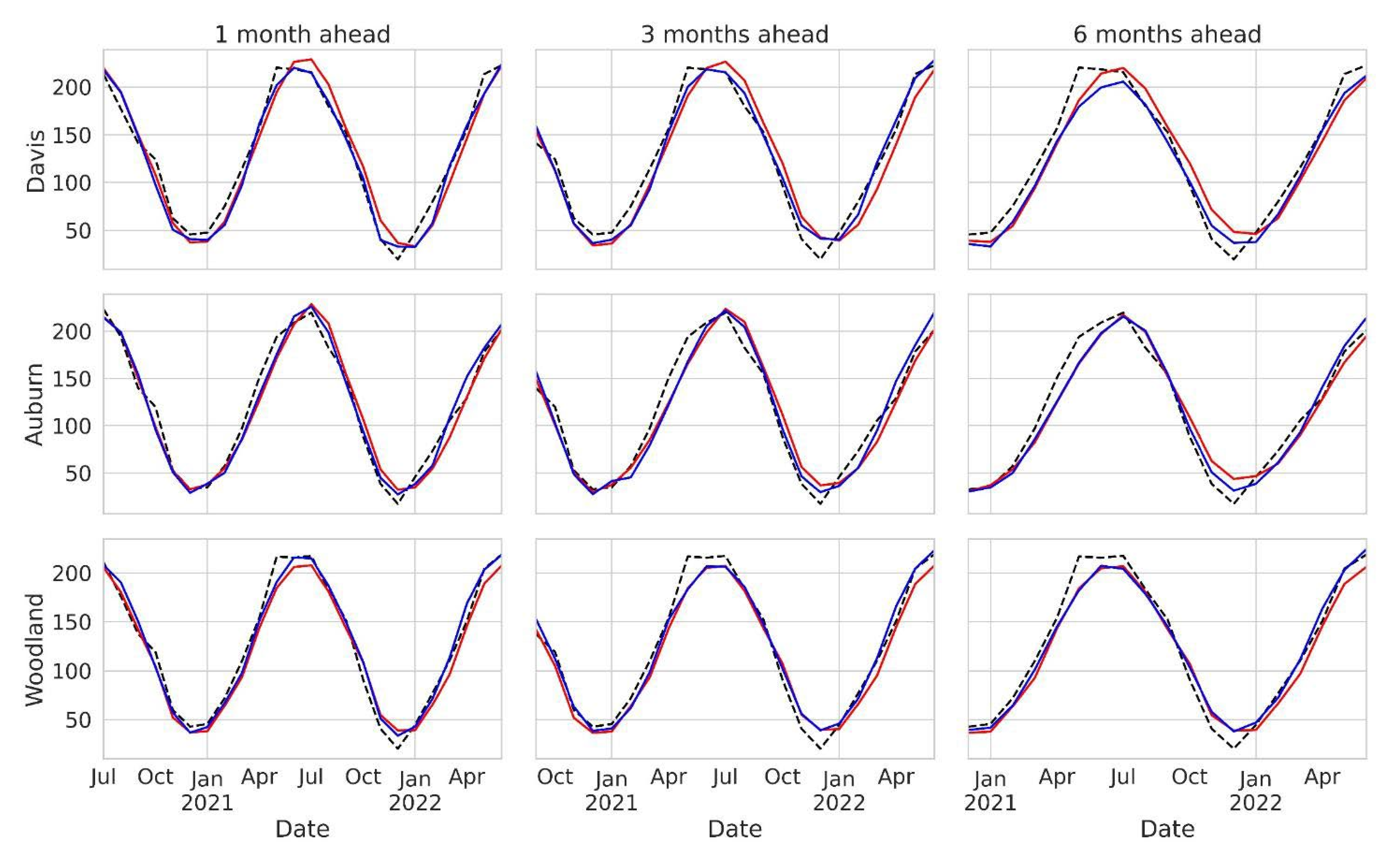
Case Study 1: Results

Forecasting Accuracy:
R^2 for 3 months ahead ET_o forecasts



- Statistical models perform well
- Data length matters for deep learning models

Case Study 1: Results



CIMIS:
Dashed line

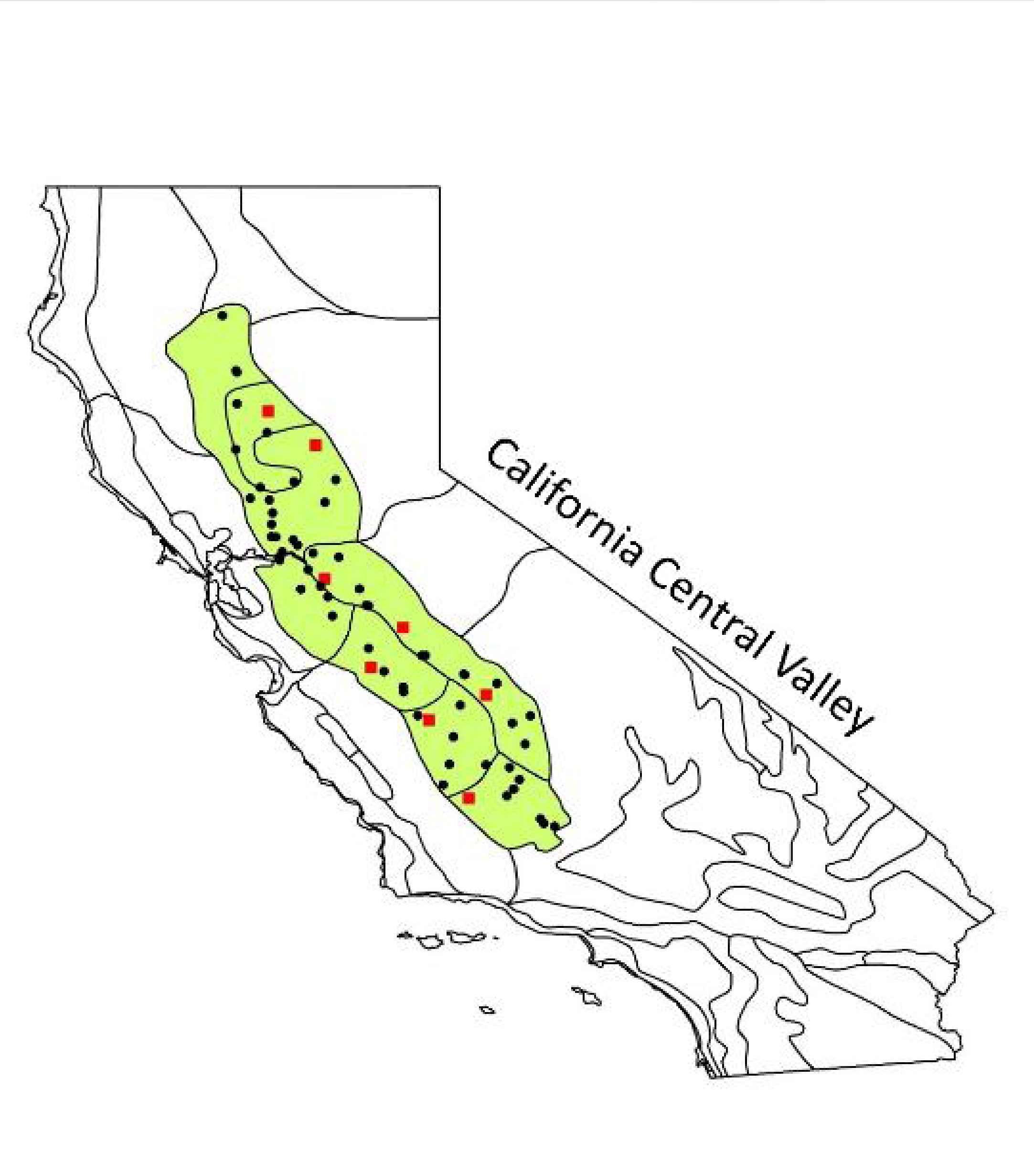
Holt-Winters:
Red

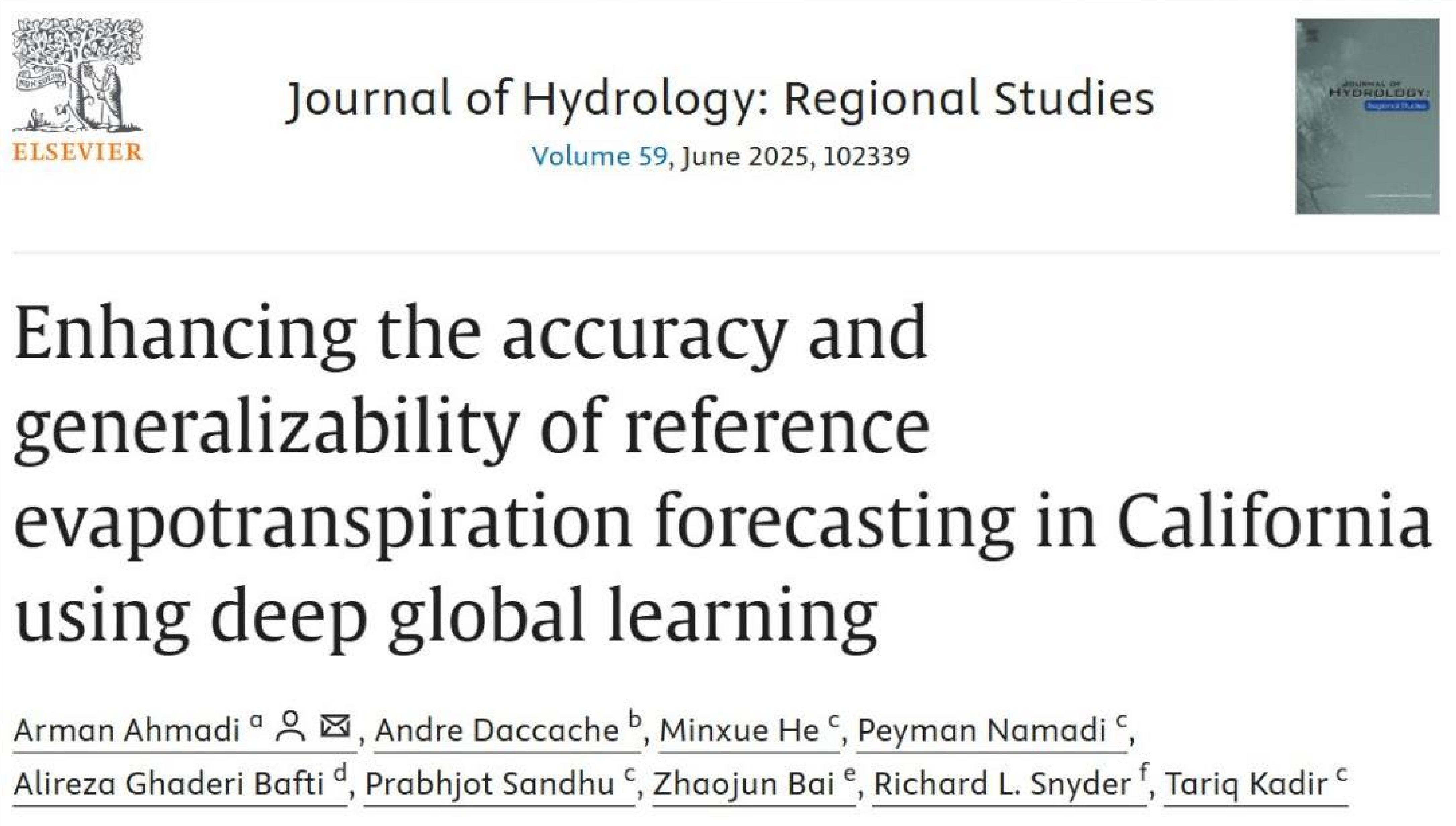
N-BEATS:
Blue

- ➢ N-BEATS ≥ Holt-Winters

Case Study 2: Goal

To Develop globally-learned deep learning (DL) models to forecast monthly ET_o in the Central Valley

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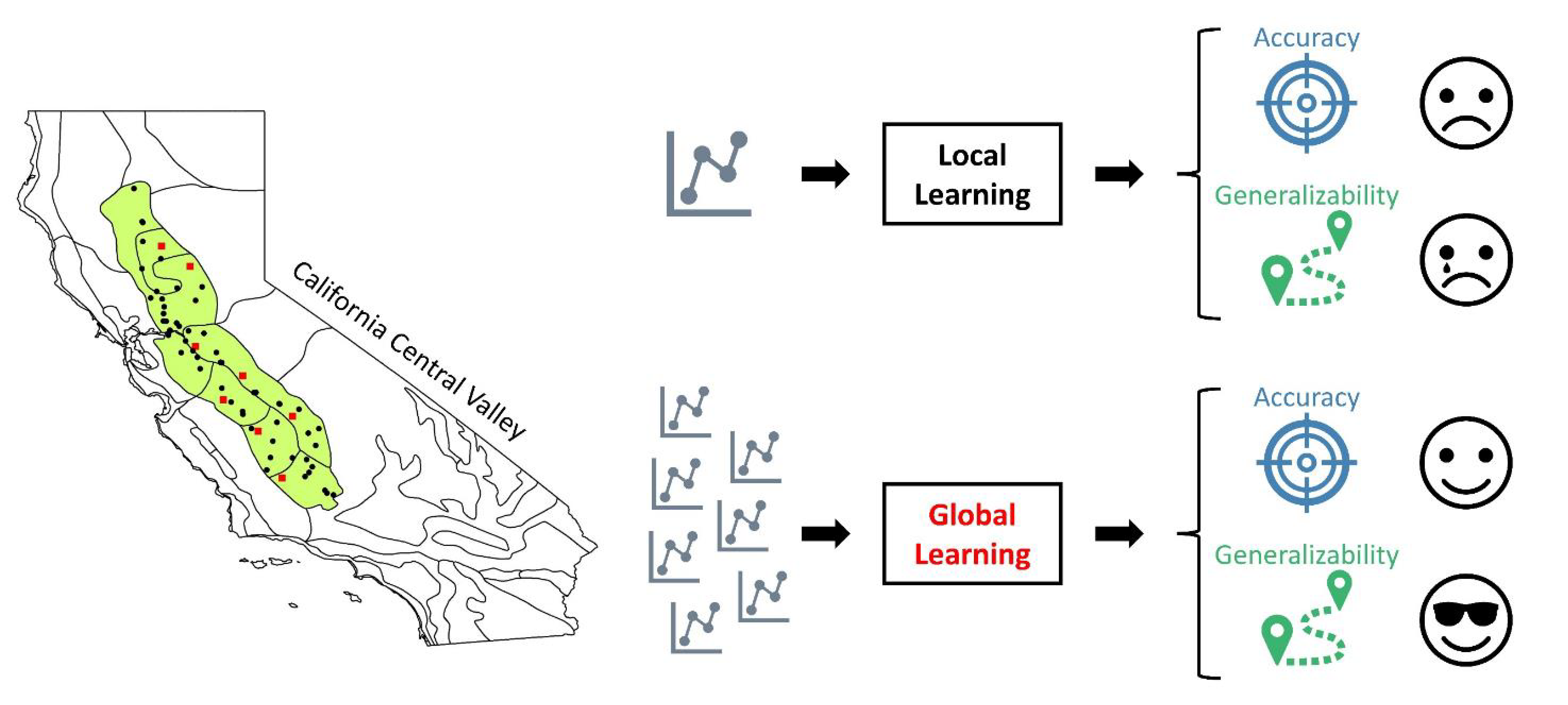
Enhancing the accuracy and generalizability of reference evapotranspiration forecasting in California using deep global learning

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]

Case Study 2: Local Learning

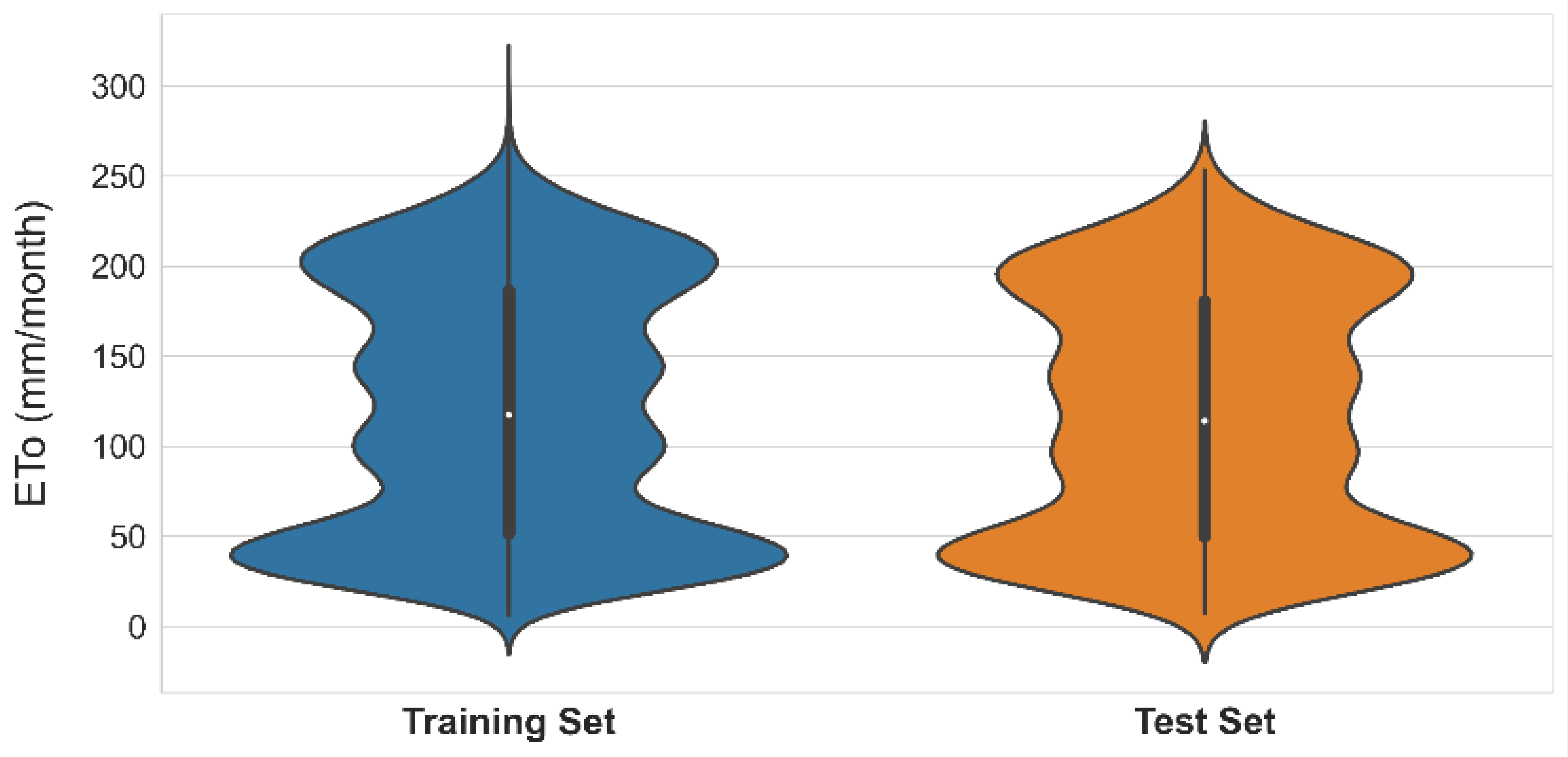
Case Study 2: Global Learning

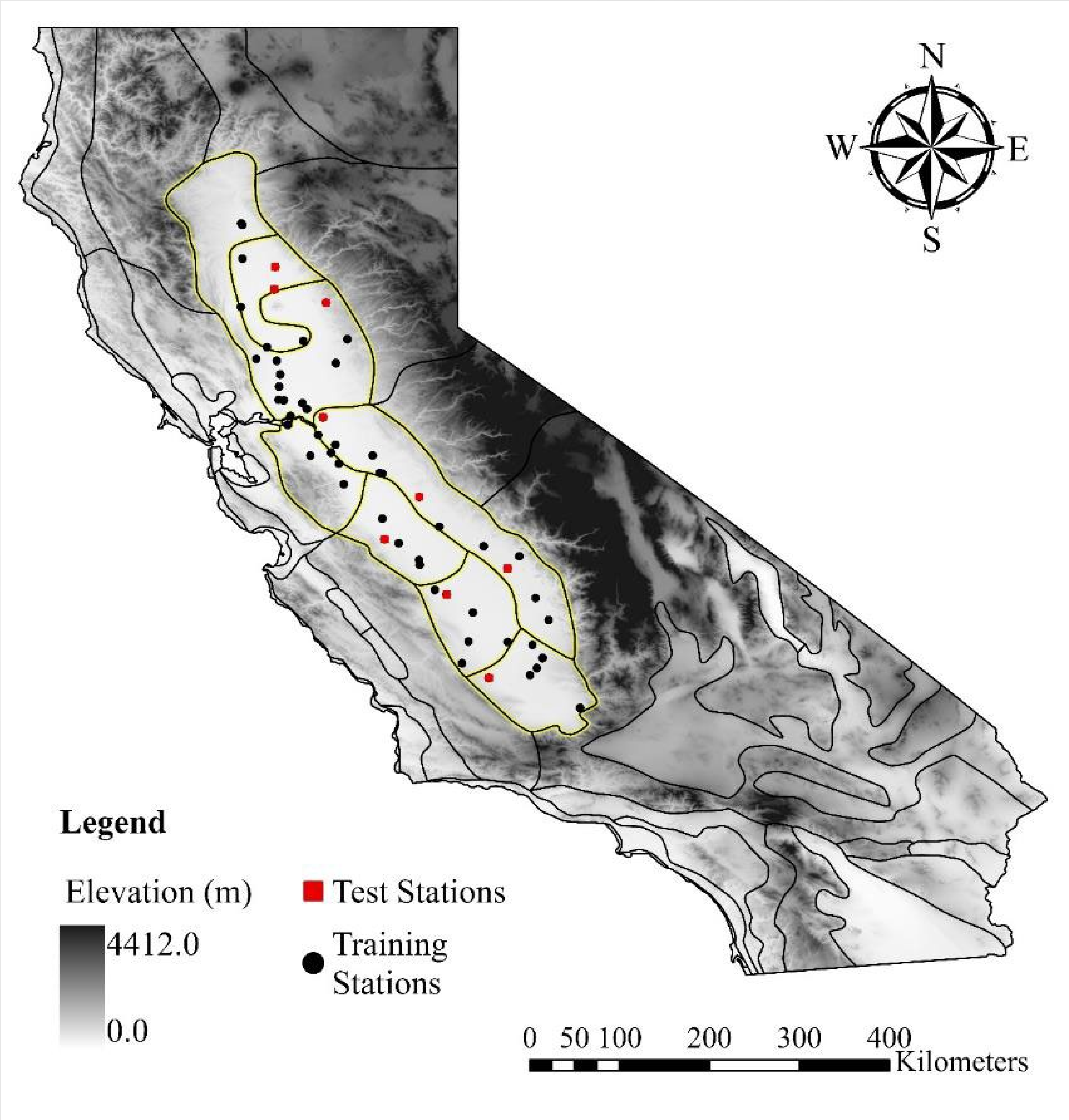
- Global Learning: training a deep forecasting model over multiple time series (stations) instead of one → model learns everything
- Testing the performance of the model over unseen locations (generalizability)



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

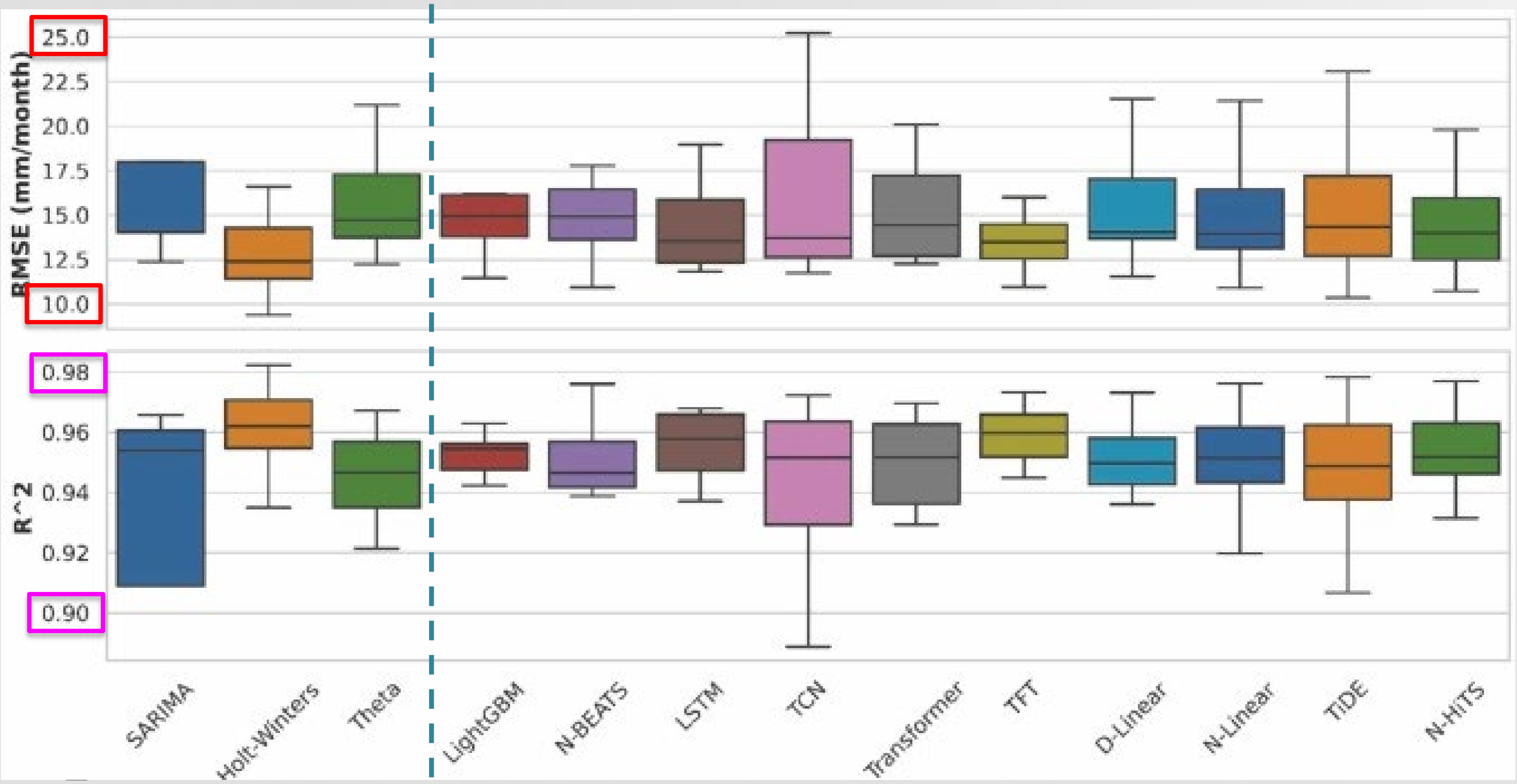
Box plots of Root Mean Squared Error (RMSE) and R^2

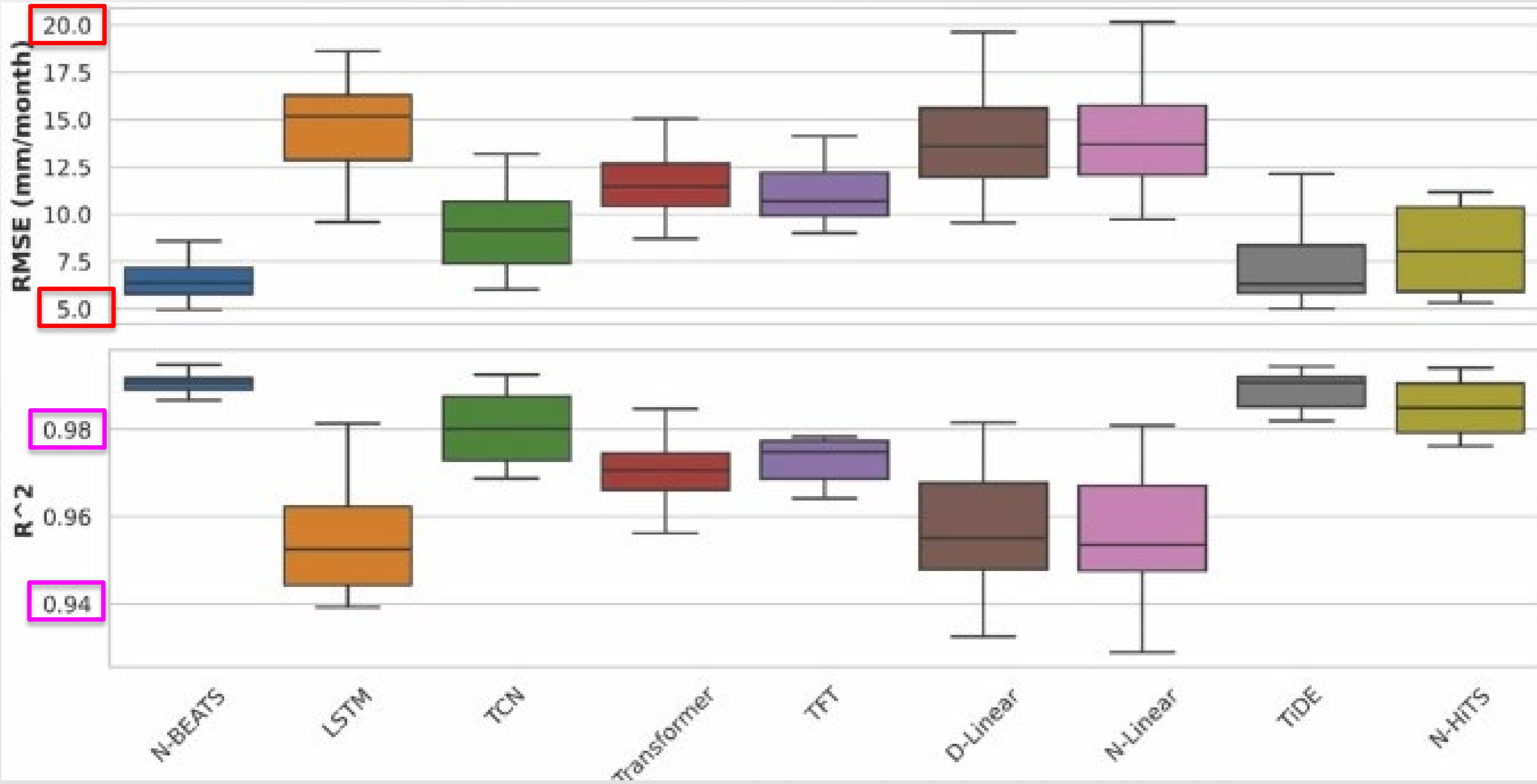
- CIMIS ET_o **vs.** forecasted ET_o
- June 2021-June 2023
- 8 test stations

Statistical models

Local learning

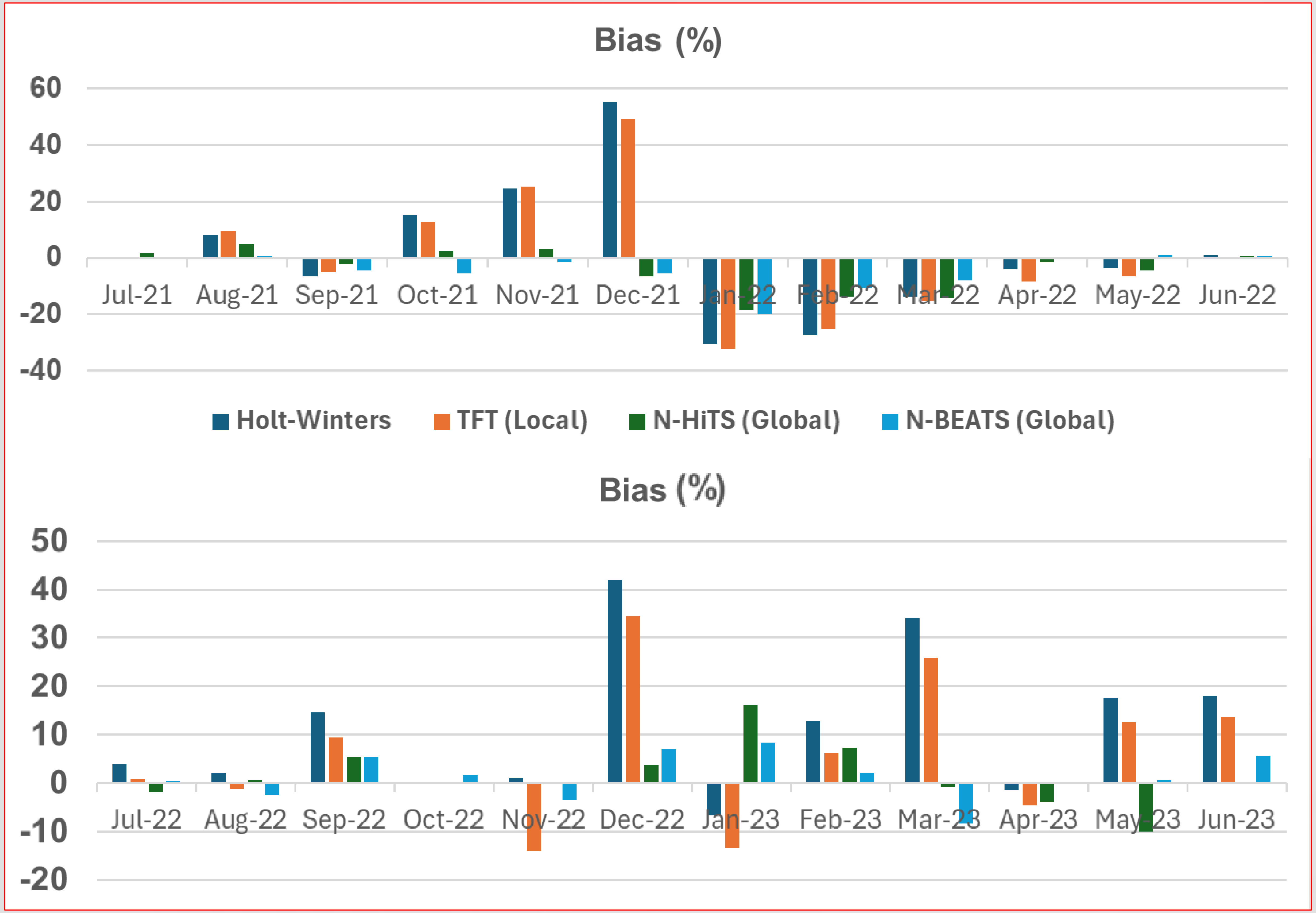
Global learning

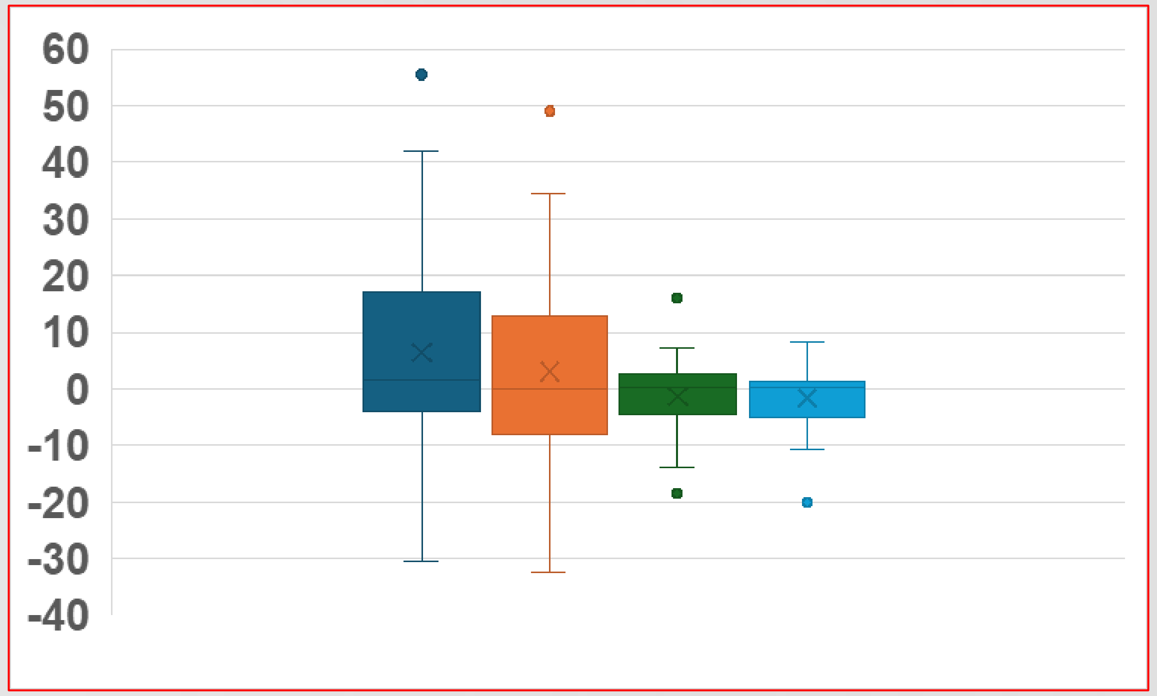




Case Study 2: Results

Percent Bias of Four Models at Durham Station





- ➢ Statistical model/ Locally trained DL → large bias
- ➢ Globally trained DL → much smaller bias

Key Messages

- Larger dataset → better performance of deep learning (DL) models
- Model complexity: DL model parameters ≠ computational complexity
- Statistical models: reasonable performance, but large bias in certain months (winter)
- Global learning → forecasting accuracy (much smaller biases)
- Generalizability

Poor → **Strong**

Statistical Models → DL Models

Questions?

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Contact: Kevin He Kevin.He@water.ca.gov