Agronomy 2024

Soil moisture forecasting for dryland fields in Australia

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Why is forecasting soil moisture important in Australia?

Soil water availability is a critical constraint to agricultural productivity.

Soil moisture forecasts provide growers with key information relating to:

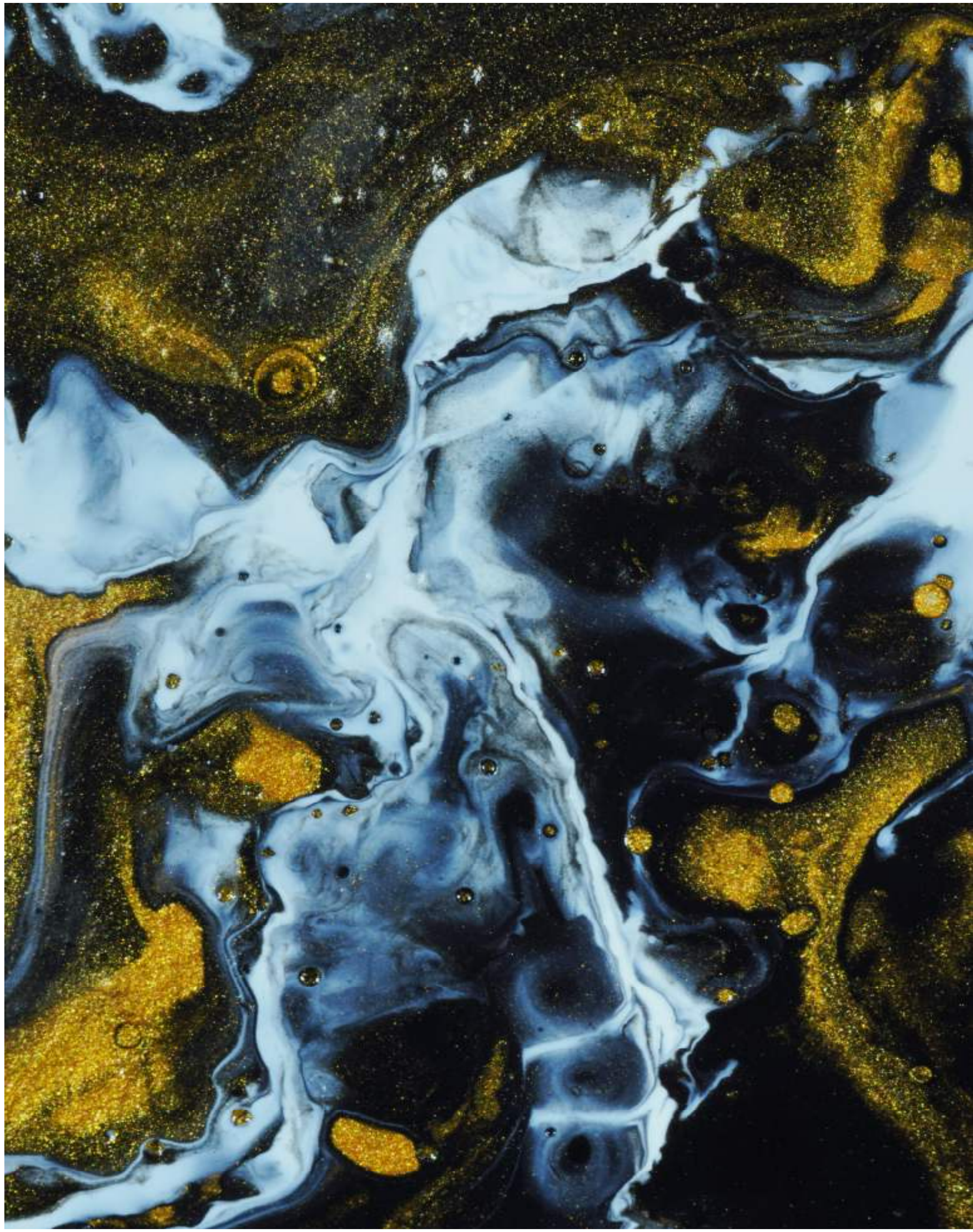
- Sowing dates
- Yield expectations
- Fertiliser use

Project aim

- Understand how accurately soil moisture can be forecasted in Australian soils.

- Determine which modelling techniques are the most accurate.

- Under which conditions soil moisture is most forecastable.



Current work

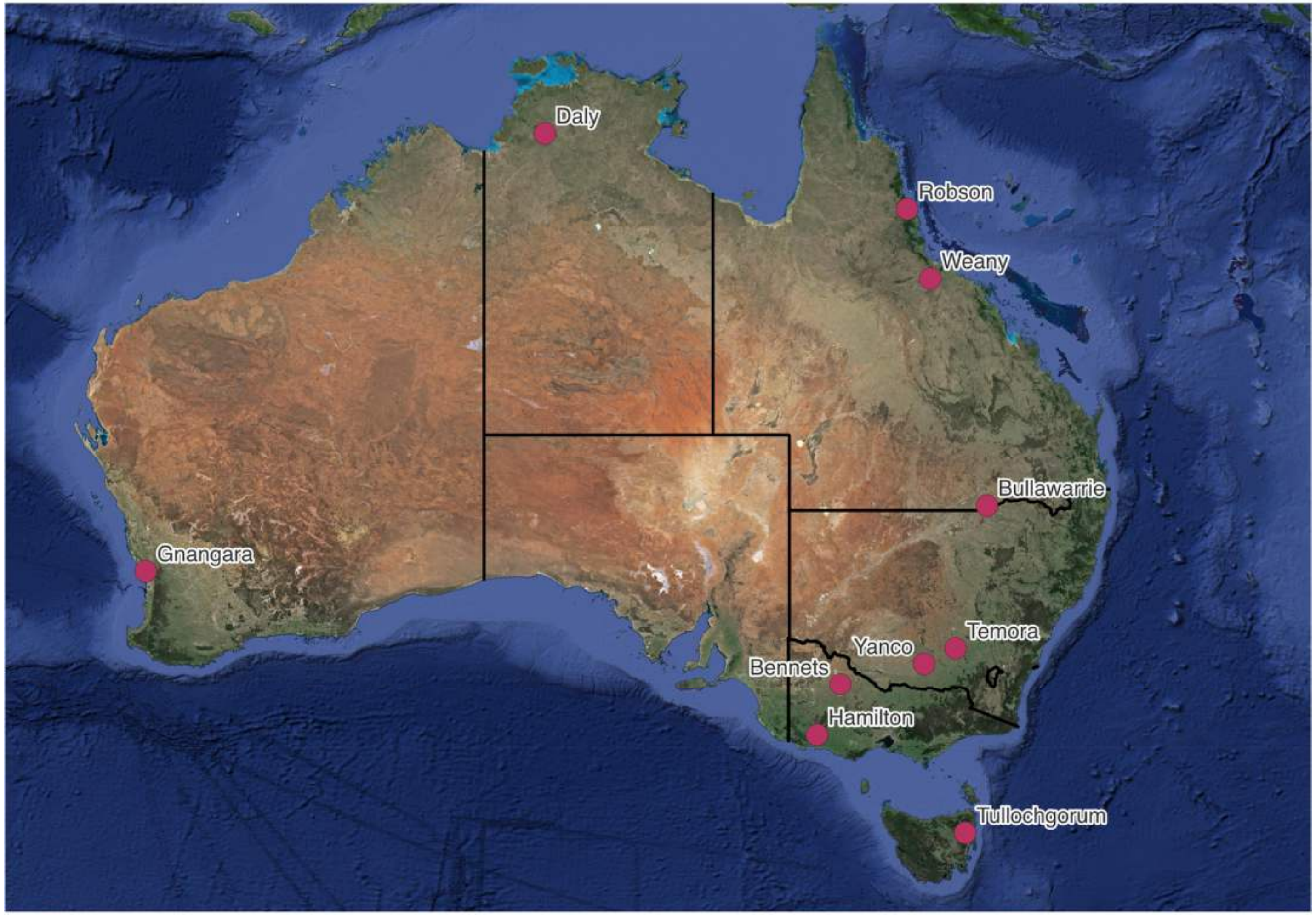
Currently the literature in forecasting soil moisture in Australia is has been conducted at:

- Limited spatial scale, across one farm or one region
- At a shallow depth
- In irrigated paddocks
- Lack of variety in modelling techniques at the same location

Our project aims to fill in these gaps by:

- Making predictions across Australia
- Testing a variety of modelling methods for each location
- Up to 30 cm depth

Domain



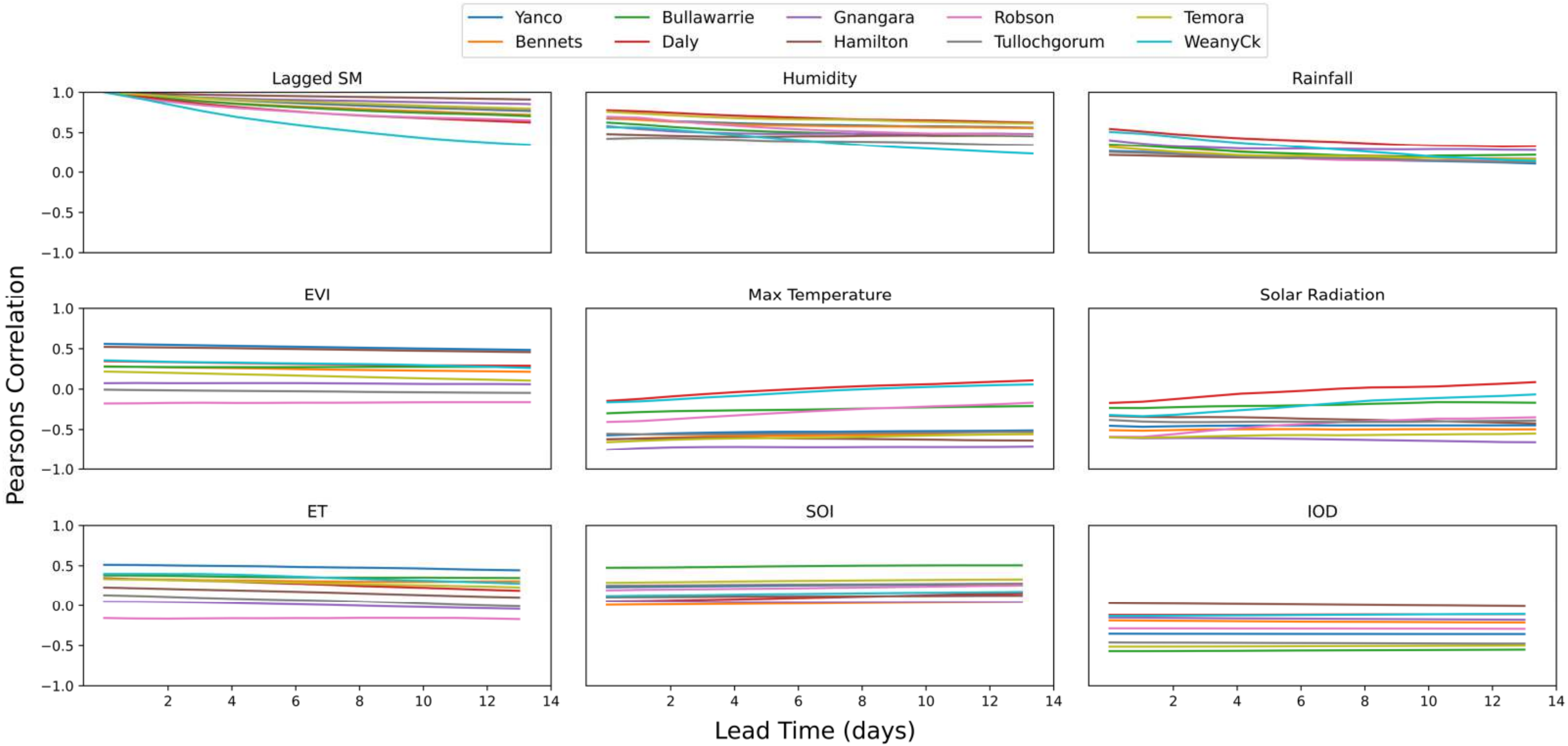
CosmOz network

- 10 selected locations
- Available from 2013 - 2023
- Hourly soil moisture (%) point data
- 30 cm depth

Features

Feature	Spatial resolution (km)	Temporal Resolution
Rainfall (mm)	5	Daily
Maximum temperature (℃)	5	Daily
Solar radiation (MJ/m^2)	5	Daily
Relative humidity at max temperature (%)	5	Daily
Evapotranspiration (mm)	0.5	8-day
Enhanced Vegetation Index (EVI)	0.25	As available
Southern Oscillation Index (SOI)	-	Daily
Indian Ocean Dipole (IOD)	-	Daily

Feature analysis



Forecasting methods

Conventional Machine Learning

Random Forest

Creates several independent decision trees and averages their output to make a prediction

XGBoost

Sequentially creates decision trees, each correction faults from the preceding trees and averages their output to make a prediction

Deep learning (Neural Networks)

Multi-Layer Perceptron (MLP)

Take each feature and predicts through a series of multiplications and additions of weights and biases, and scaling through non-linear activation functions. The predictions are optimized by altering the weights and biases to reduce the loss.

Long Short-Term Memory (LSTM)

Takes a sequence of each feature to make a prediction through a series of multiplications (weights), additions (biases), and scaling through non-linear activation functions. The predictions are optimized by altering the weights and biases to reduce the loss.

Forecasting methods

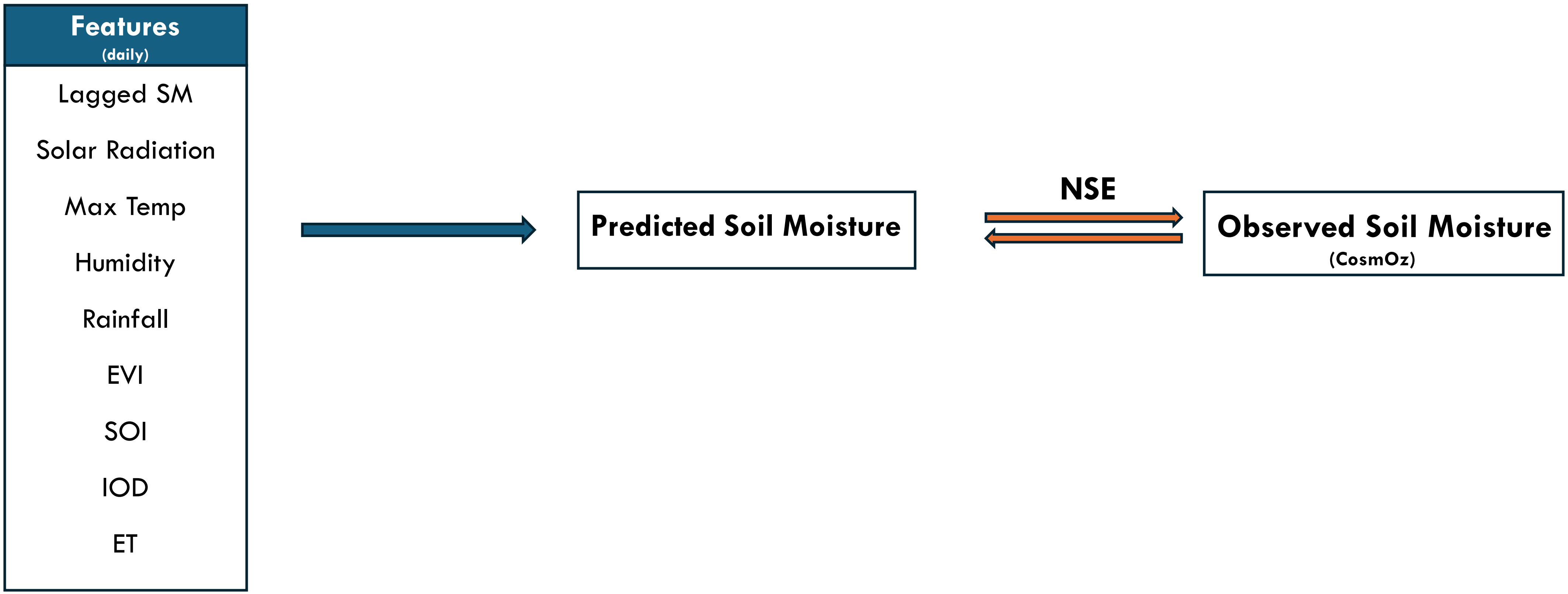
Conventional Machine Learning	**Random Forest**	**XGBoost**
Deep learning	**Multi-Layer Perceptron (MLP)**	**Long Short-Term Memory (LSTM)**

Null model: Predicts soil water to be equal to observed soil water from *n* days ago.

Where *n* is lead time (days)

Experiment Design

For each CosmOz probe site



Experiment Design

For each CosmOz probe site

Features (daily)
Lagged SM
Solar Radiation
Max Temp
Humidity
Rainfall
EVI
SOI
IOD
ET

→ **Predicted Soil Moisture** ⇄ (**NSE**) **Observed Soil Moisture** (CosmOz)

$$NSE = 1 - \frac{\sum_{i=1}^{n} (P_i - O_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2}$$

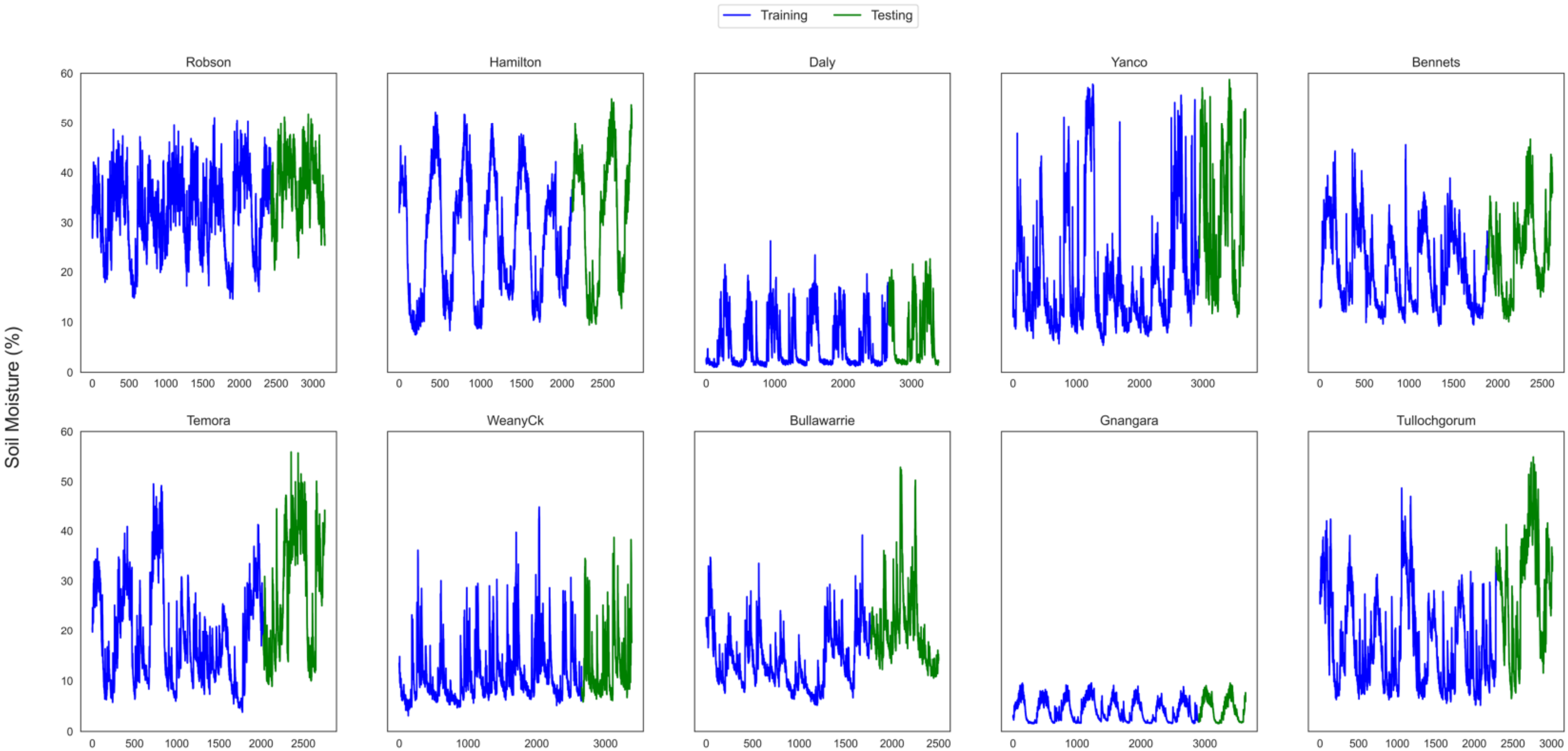
P = Predicted O = Observed

If $NSE > 0$, predictions are more accurate than the mean

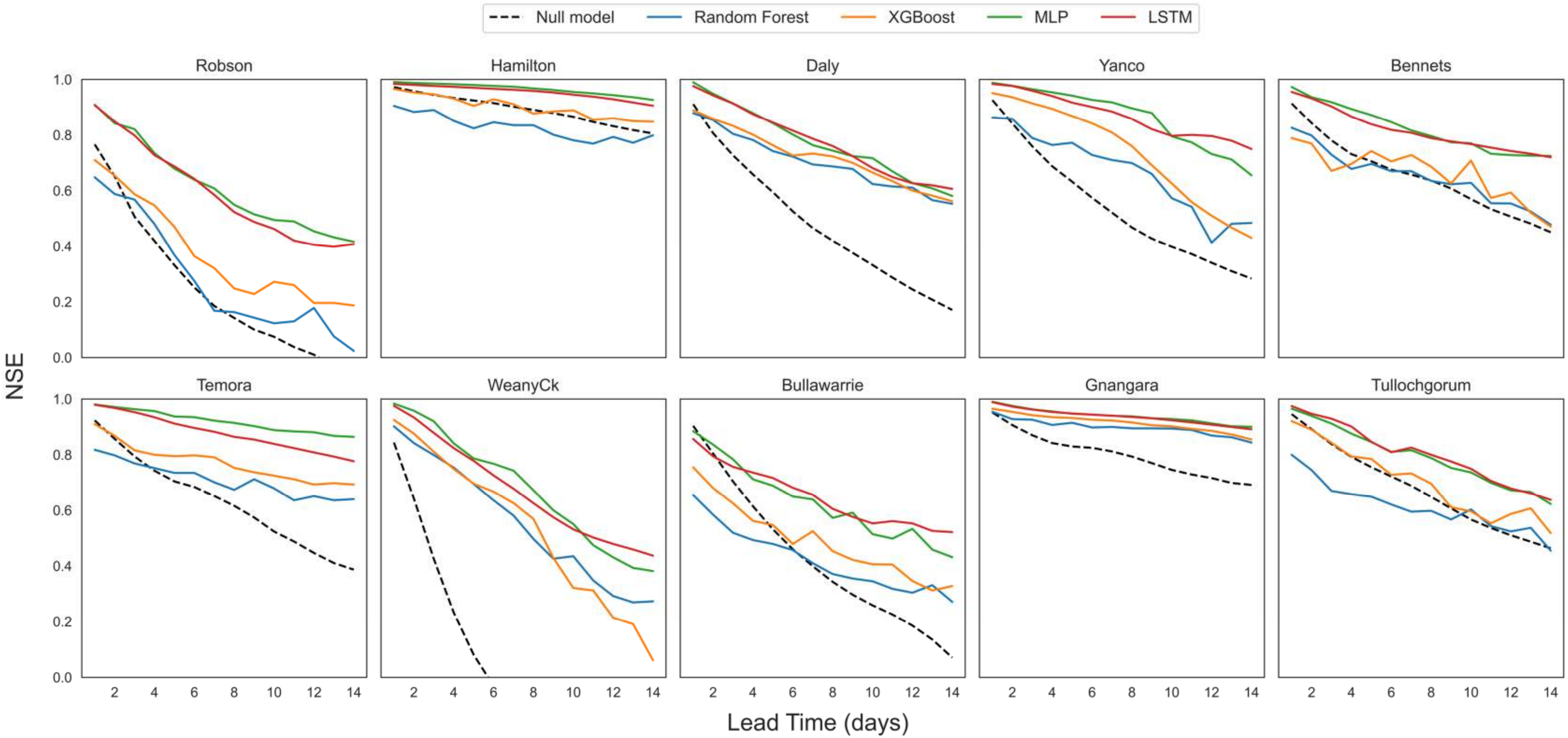
If $NSE < 0$, mean is more accurate than the prediction

$NSE > 0.7$, considered accurate

Training Testing Split



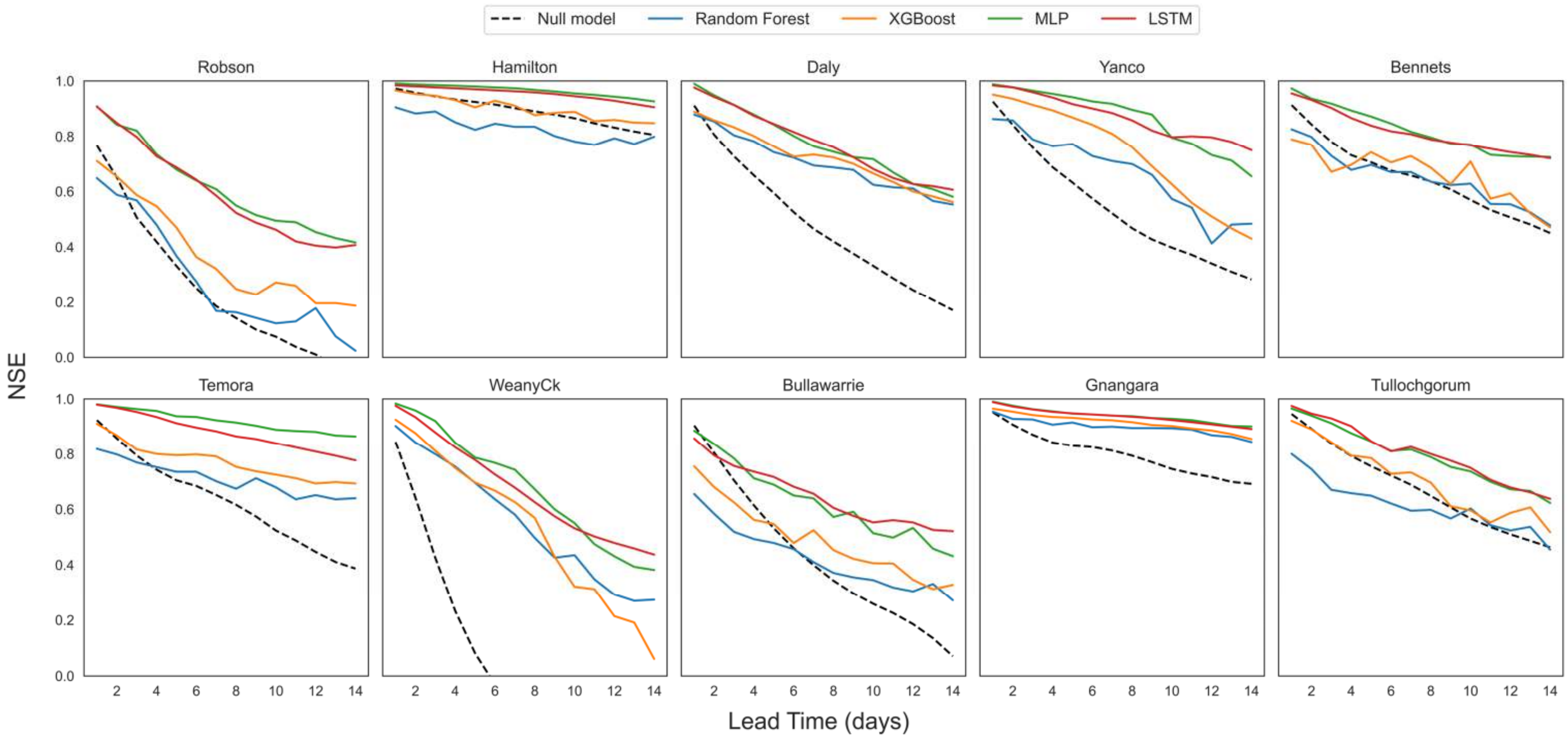
Results



Null model
Random Forest
XGBoost
MLP
LSTM
Robson
Hamilton
Daly
Yanco
Bennets
Temora
WeanyCk
Bullawarrie
Gnangara
Tullochgorum
NSE
0.0
0.2
0.4
0.6
0.8
1.0
2
4
6
8
10
12
14
Lead Time (days)

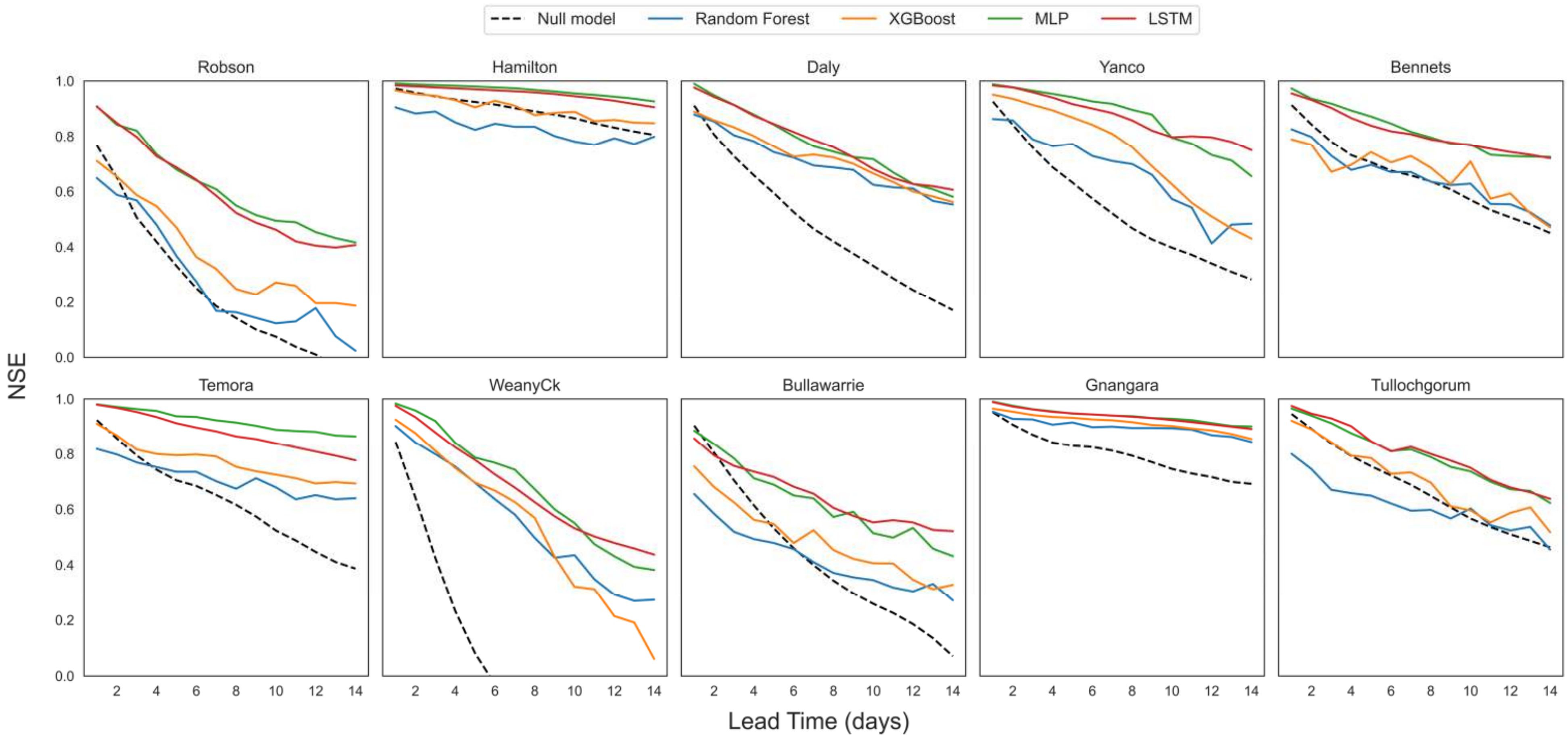
Results

Deep learning methods outperformed conventional machine learning methods at every site.



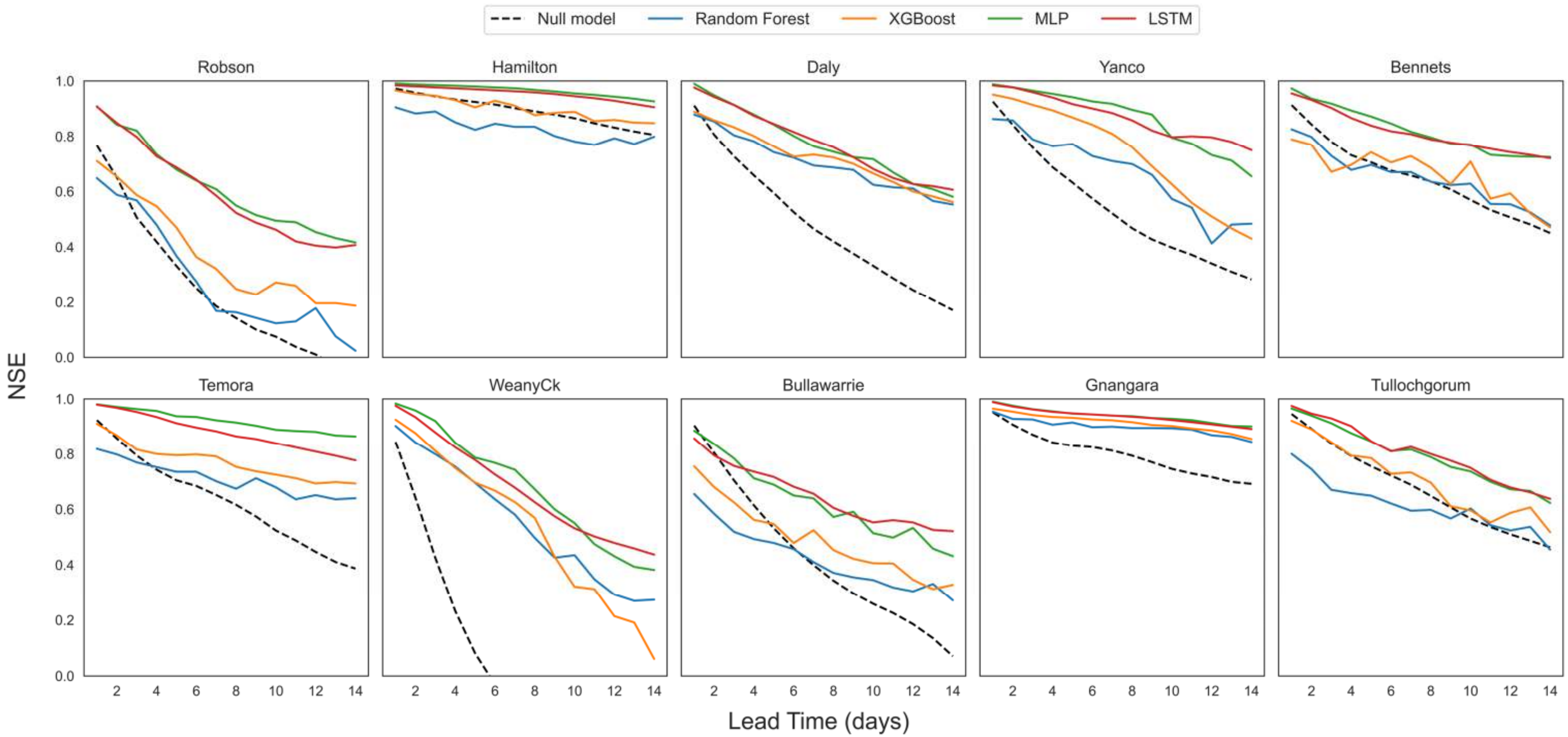
Results

At several sites, the null model outperformed Random Forest in at least the first week.



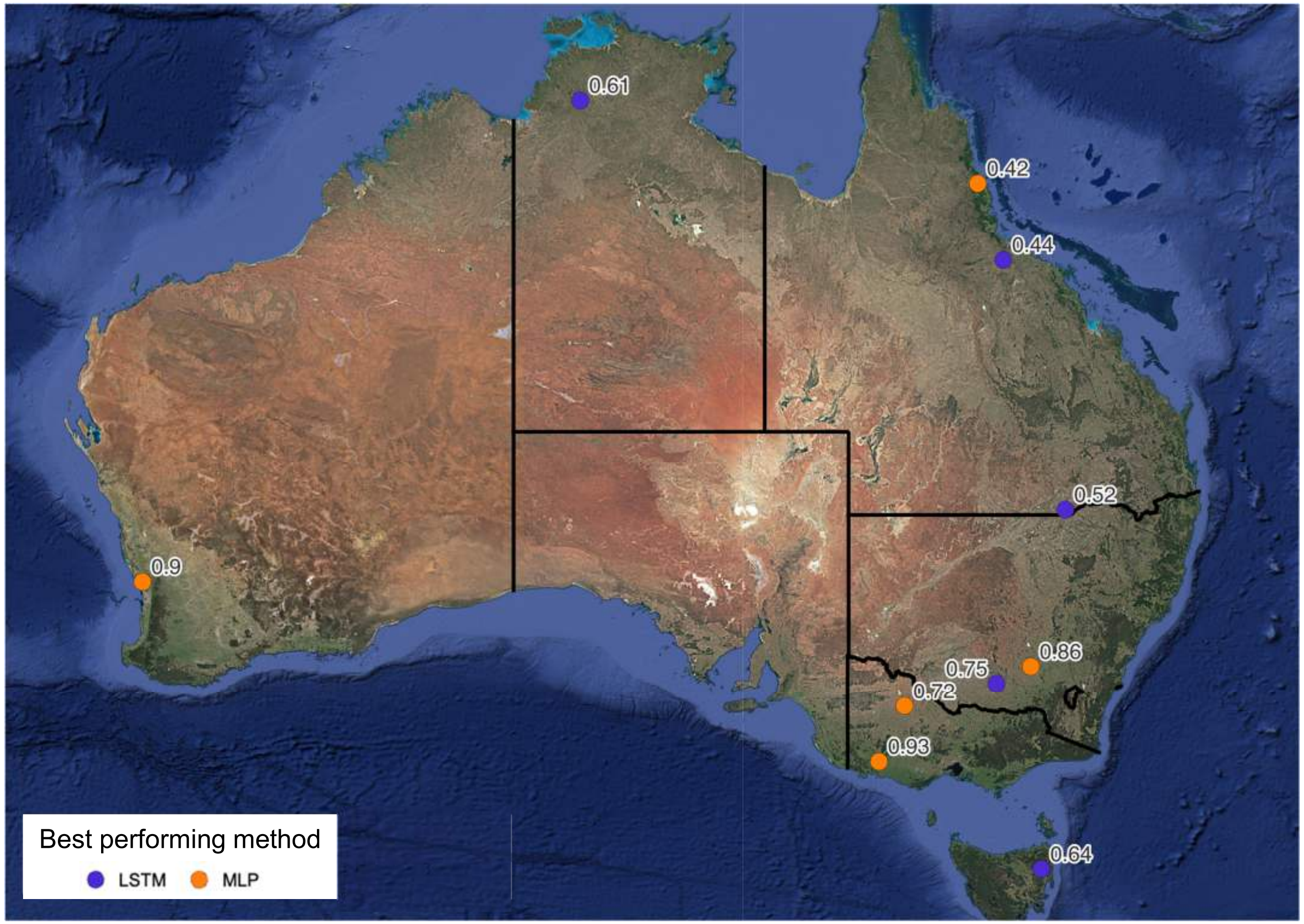
Results

LSTM and MLP perform better than each other at different sites.



Results

Map of NSE at longest lead time (14 days)



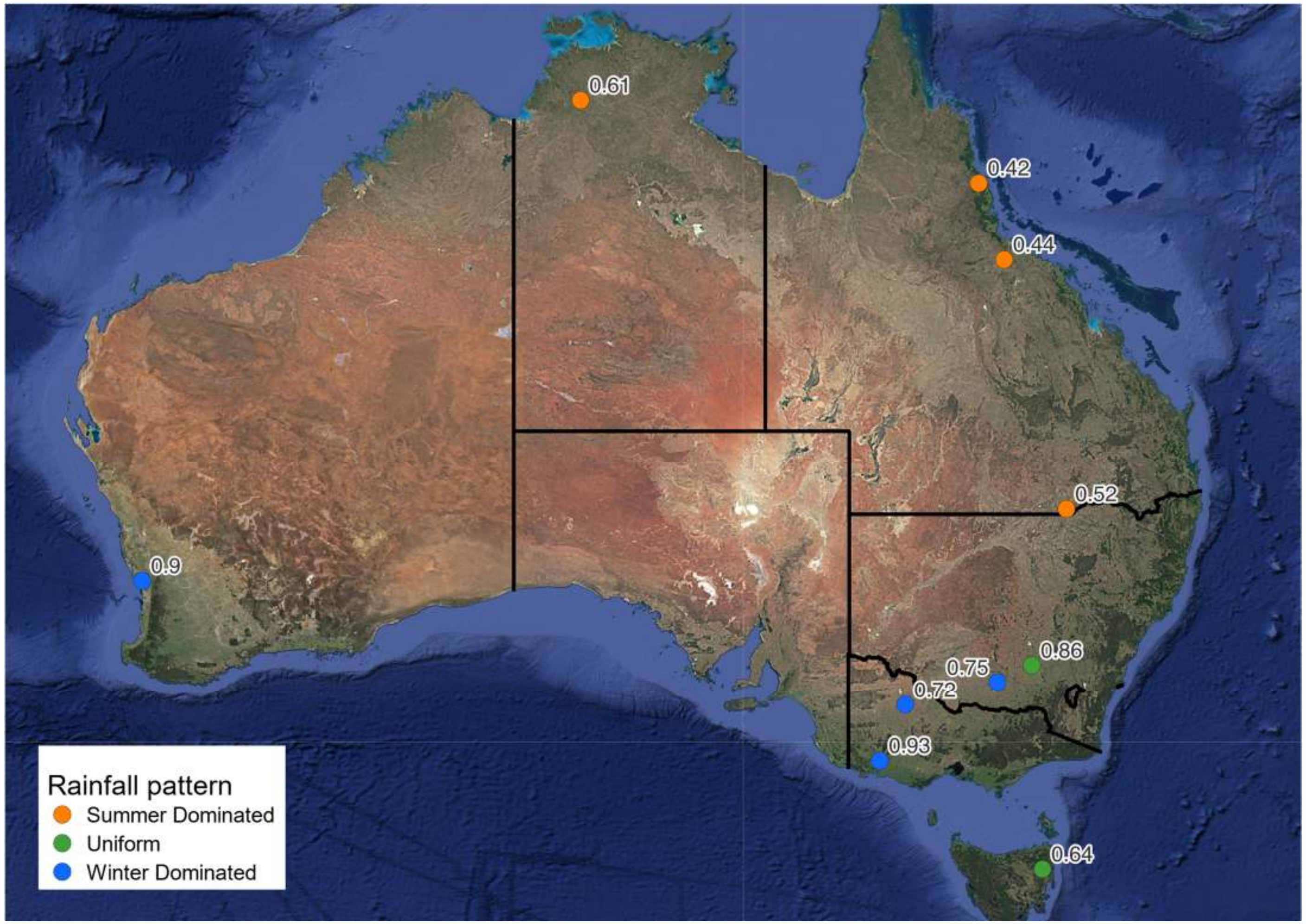
- South-East Australia is forecastable at the highest accuracy for the longest lead time.

- Queensland as a region was forecastable at the lowest overall accuracy at the longest lead time.

- No strong pattern emerges for where LSTM and MLP outperform each other

Results

Map of NSE at longest lead time (14 days)



- Winter dominated rainfall areas were forecastable at the highest accuracy for the longest lead time (14 days)
- Summer dominated rainfall areas were forecastable at the lowest accuracy for the longest lead time
- Uniformly distributed rainfall regions were forecastable with higher accuracy than summer dominant rainfall regions

Further Improvements

Attention

Make use of Attention based algorithms such as Transformers due to their popularity in literature for producing high accuracy time-series forecasts.

Attention finds the relationship between each datapoint and every other point in its sequence, accounting for a greater persistence of memory across an input sequence.

Forecasted features

Add rainfall forecasts as a feature to improve soil water forecasts

Australian Government
Bureau of Meteorology

Attention Is All You Need

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Takeaways & next steps

Deep learning

Deep learning algorithms, based on neural networks, perform better than conventional machine learning methods. Deep learning algorithms should be applied further in forecasting literature due to their high performance in modelling non-linear sequential relationships.

Rainfall patterns

Regions of winter-dominated rainfall are currently more forecastable at a higher accuracy. Further work into features that account for the variability in soil water in summer-dominated rainfall regions is needed.

Univariate forecasting

With the development of forecasting methods, developing forecasting models that take only in-situ probe data (i.e. soil water and rainfall) as features, has great potential for growers to make forecasts with minimal on-field technology.

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Thank you

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