Temporal downscaling wind climate data using Machine Learning

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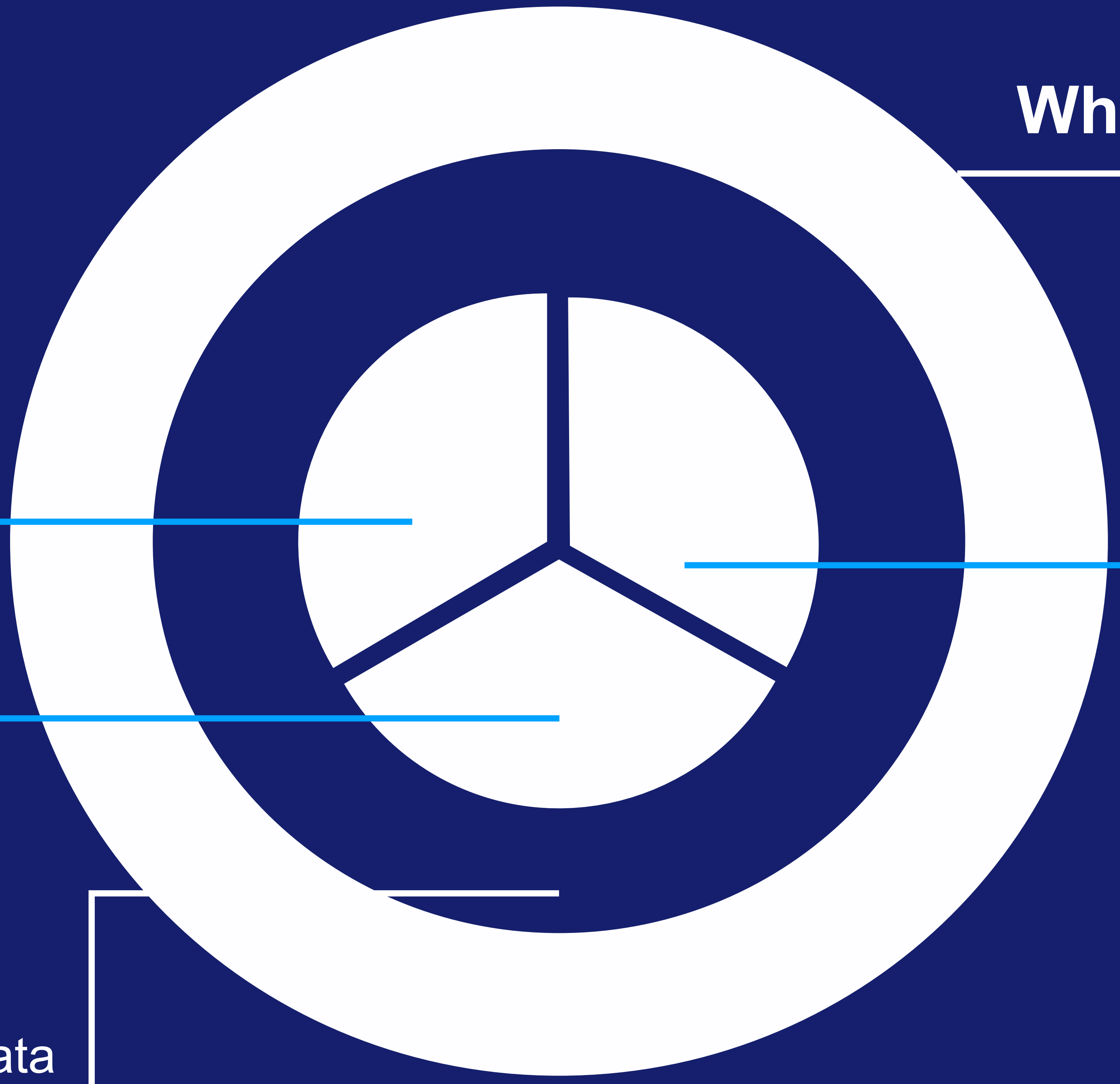
Scope

Temporal downscaling to improve climate-scale predictability of wind ramps and wind droughts



Downscaling modelling

- Literature review for model selection
- Test statistical and ML approaches
- Use different climate date sources
- Focus on surface winds

Why?

Decision support under climate uncertainty for energy security and net zero*

Validation

- Metrics selection
- Inter-model comparison against observations

Baseline analyses

- Identification of wind ramp and wind drought events
- Basis of truth
- Test feasibility for temporal downscaling

Objectives

- Compare models to downscale wind climate data onto sub-hourly temporal resolutions.
- Focus on short-duration (wind ramp) and long-duration (wind drought) events.

** Supported by: Towards Turing 2.0 under the EPSRC Grant EP/W037211/1 & The Alan Turing Institute*

- Handle TB of data
- Analyse different climate data sources
- Preserve relevant statistical properties
- Location-based analysis of historical climate surface winds (control member)

Challenges

- Spatial correlation and joint space-time
- Multivariate modelling and compound events
- Probabilistic framework
- Extension to future projections

Compromises

Methodology

1. Retrieve and process data

- **UKCP18 Local** – hourly
- **EURO-CORDEX** EUR-11 – 3-hourly
- **Observations** – 10-minute

2. Test downscaling models

Downscale climate wind timeseries to sub-hourly:

- **ARIMA** – statistical model
- **Auto-Encoders** – unsupervised ML model
- **LSTM** – supervised ML model

3. Validation

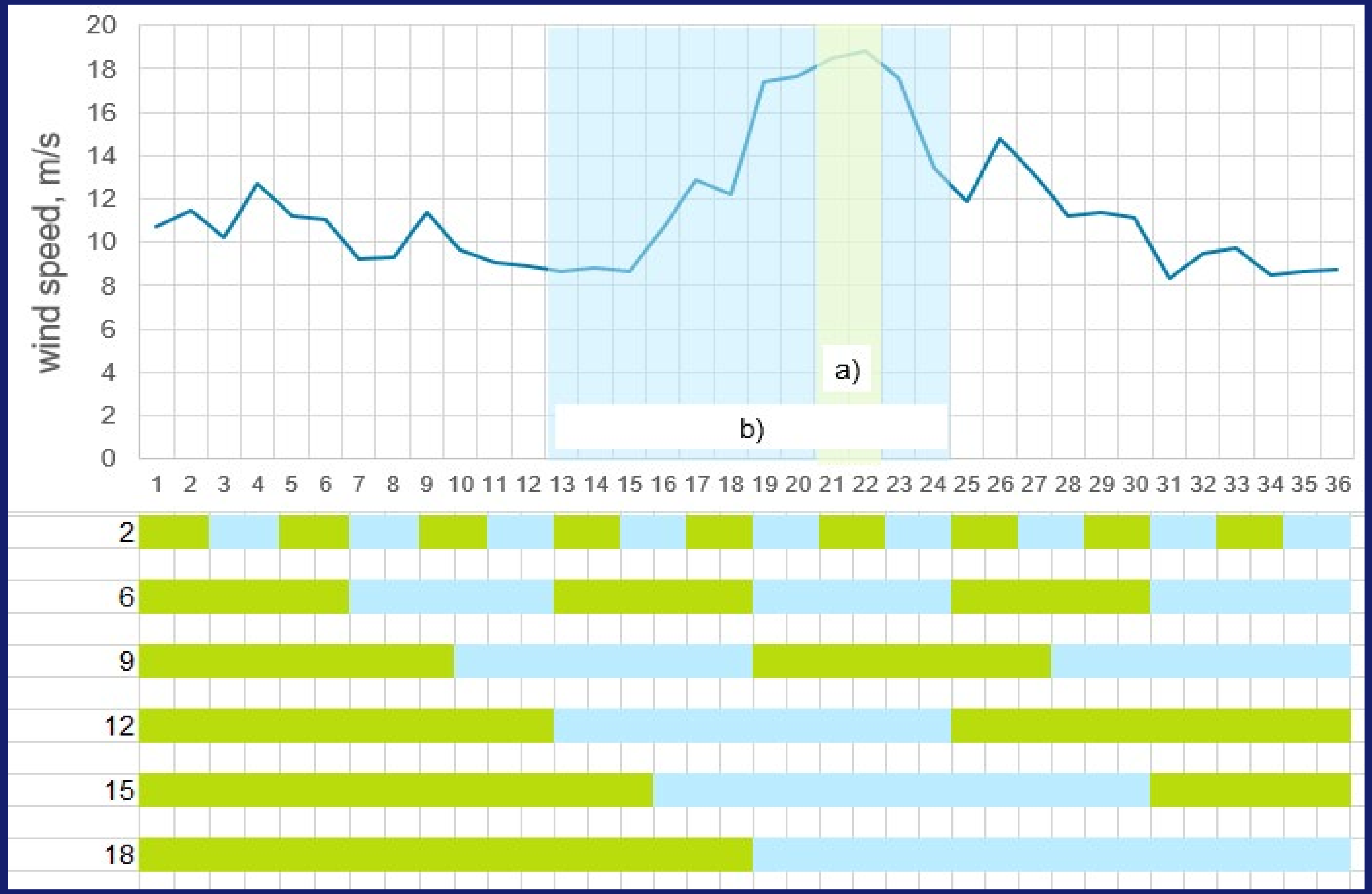
Model performance measured against observations:

- **Wind ramp** – large change in wind speed in a short period
- **Wind drought** – low wind speeds over a long period

Baseline analyses

Wind ramp events

Maximum change in capacity factor above a threshold, within a given time window.

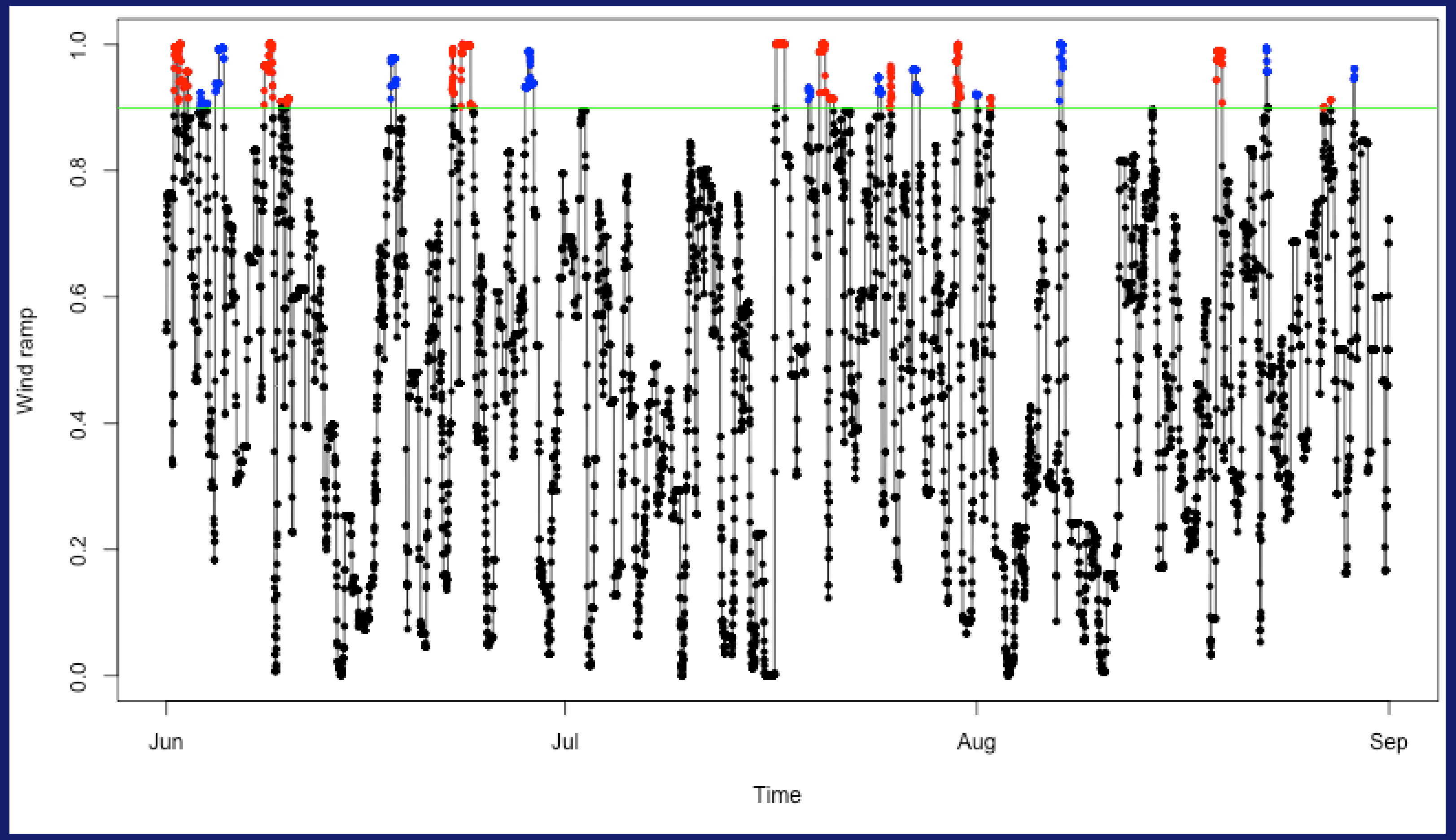


Wind drought events

Ratio of time capacity factor is below a threshold, within a given time window.

Declustering

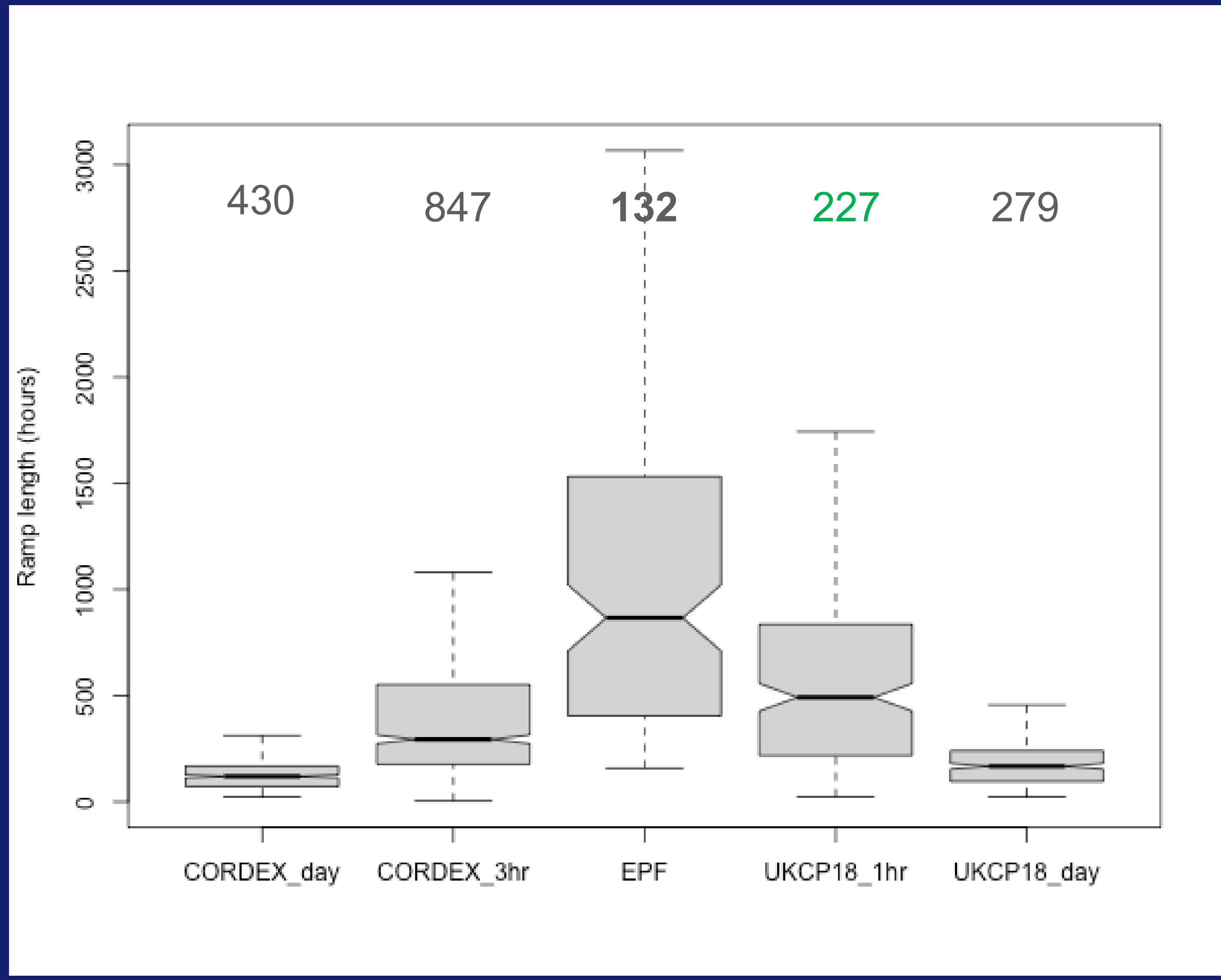
Group events exceeding threshold into independent clusters; retain only most extreme.

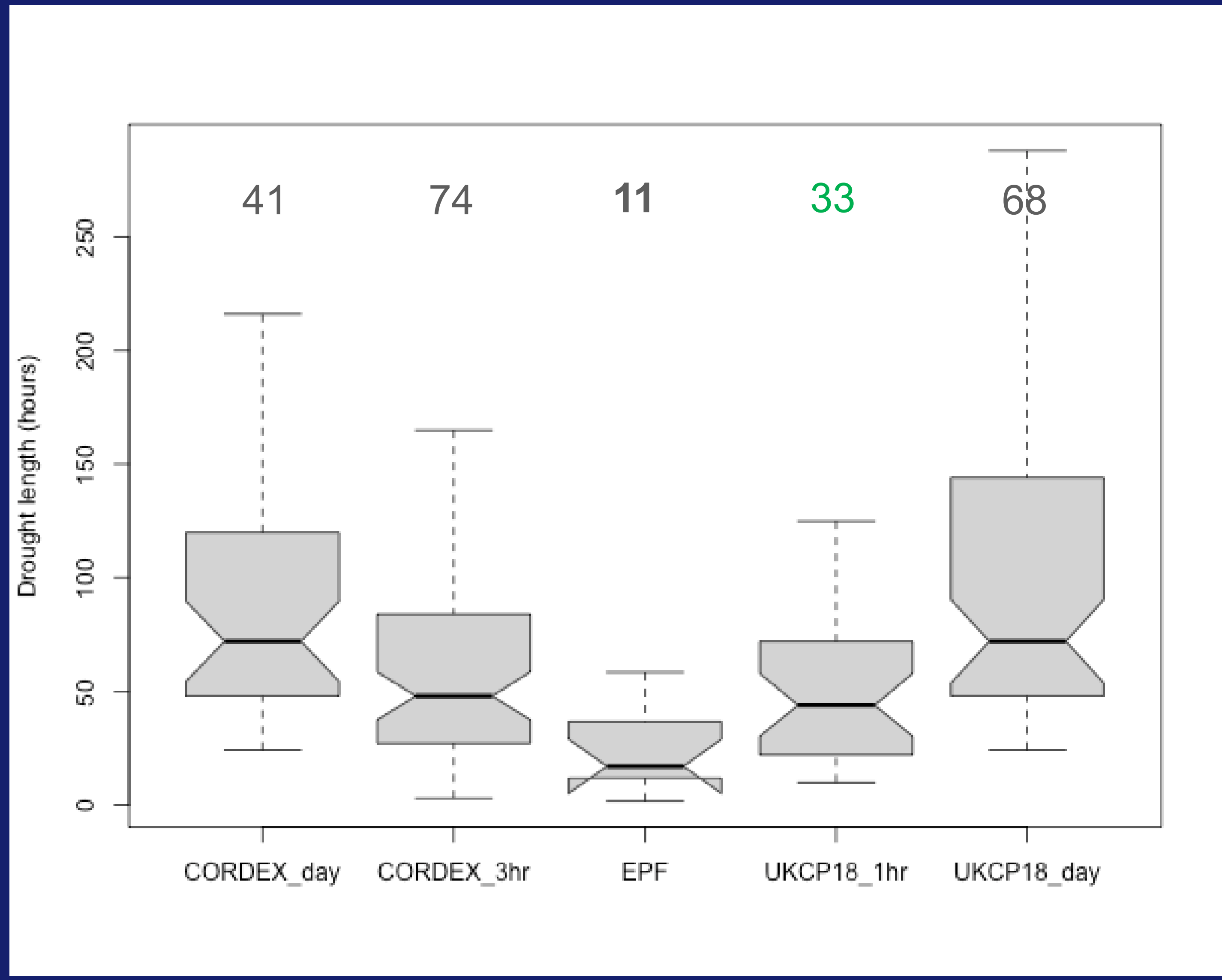


Ramp events

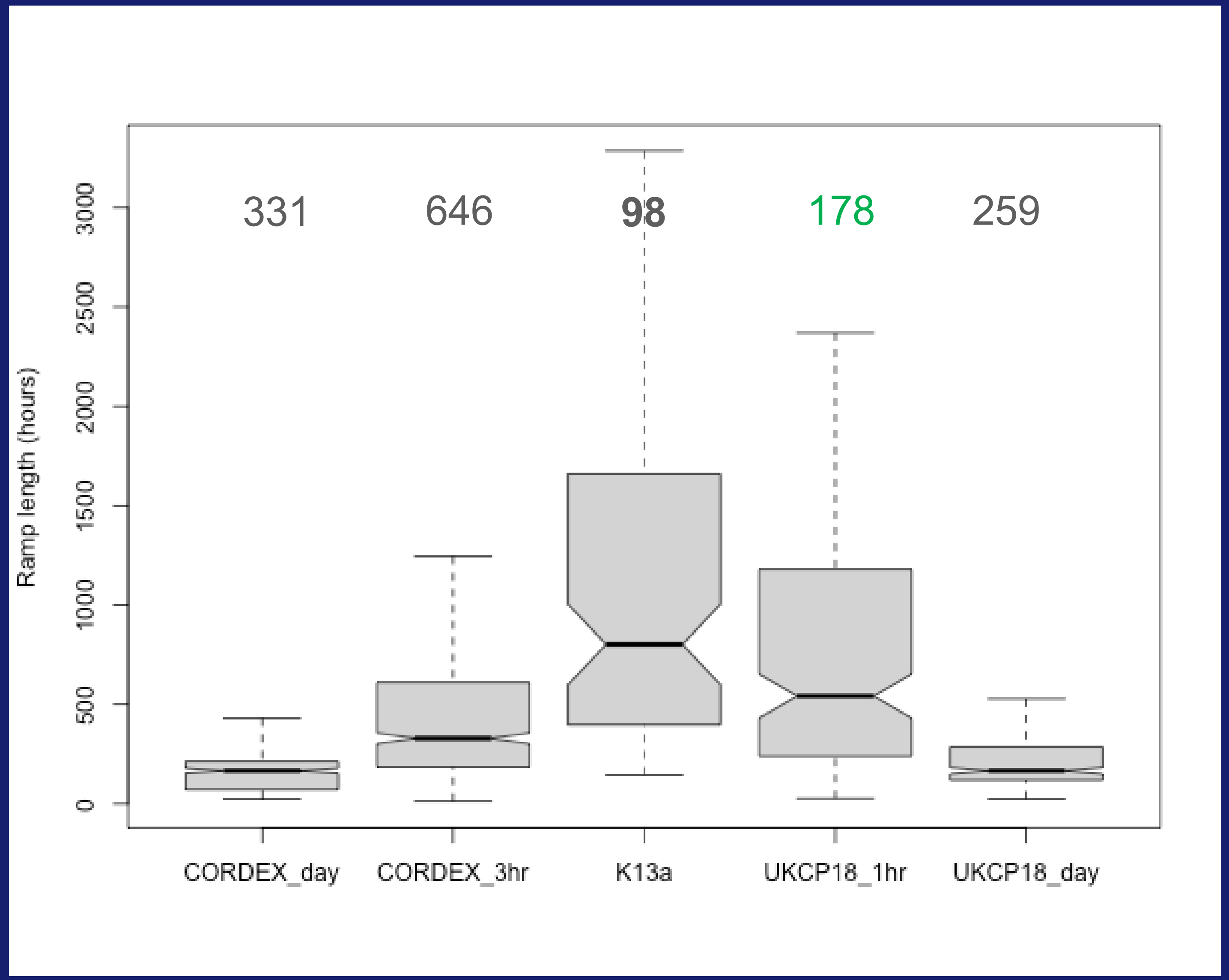
Drought events

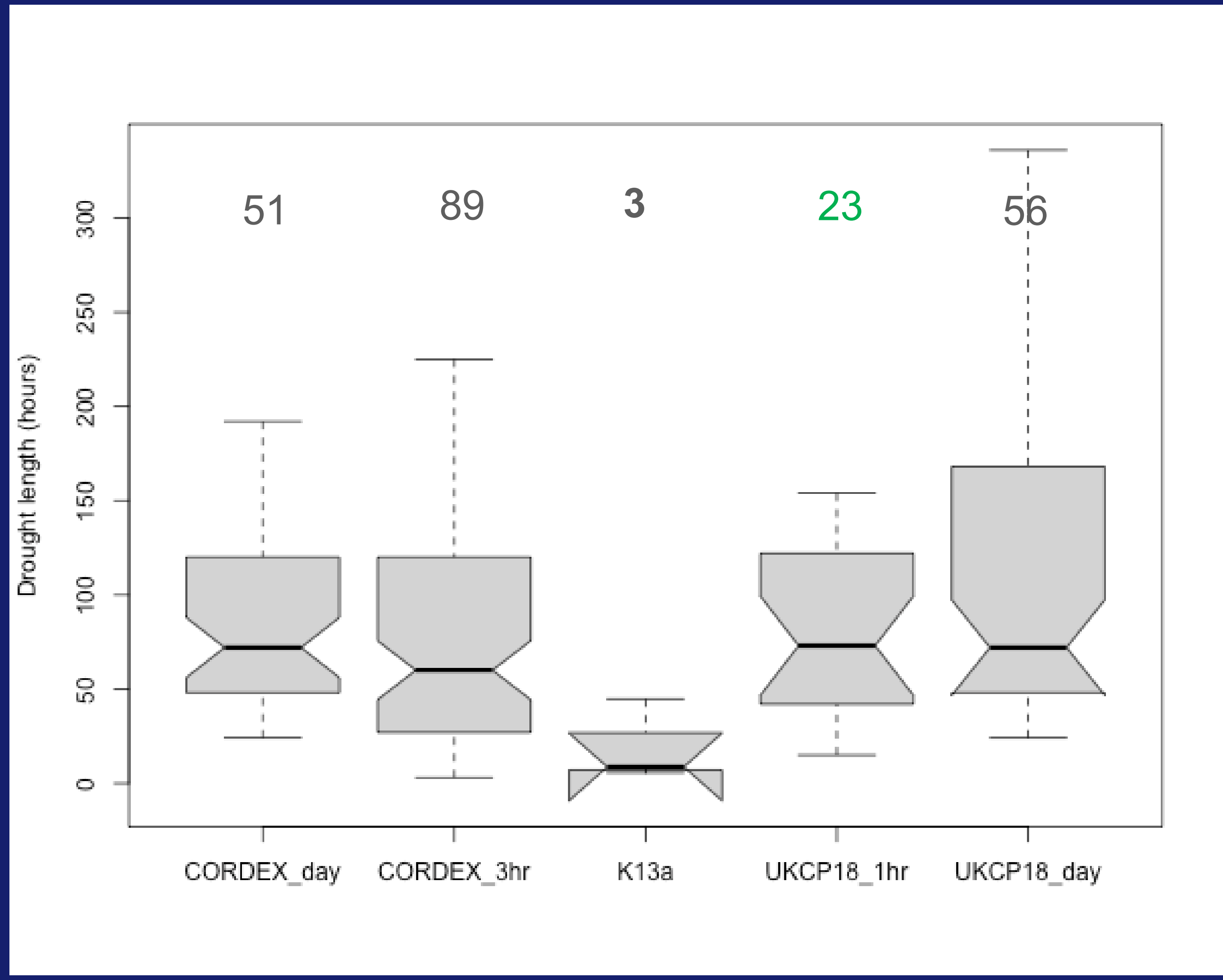
S2





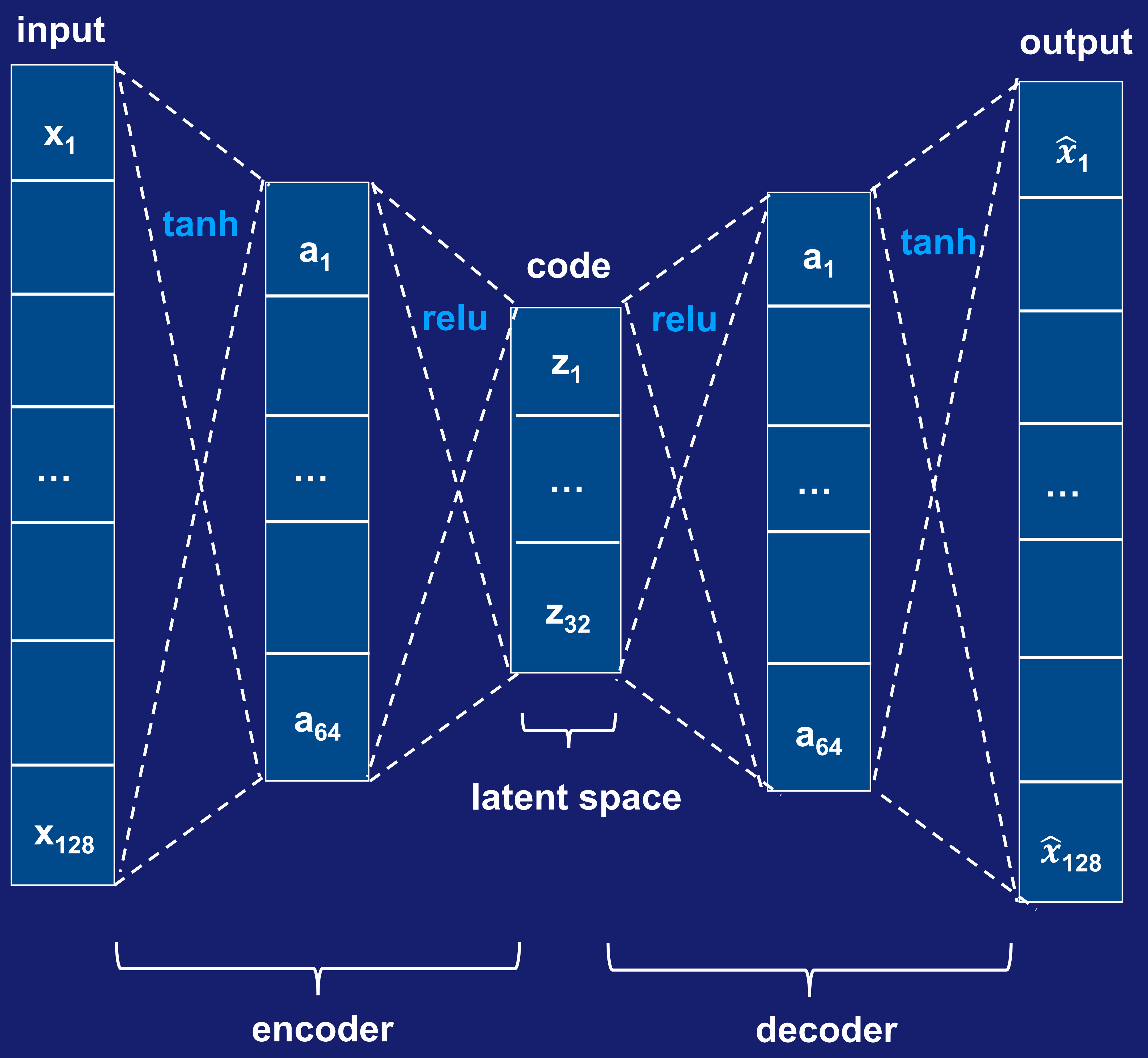
S1



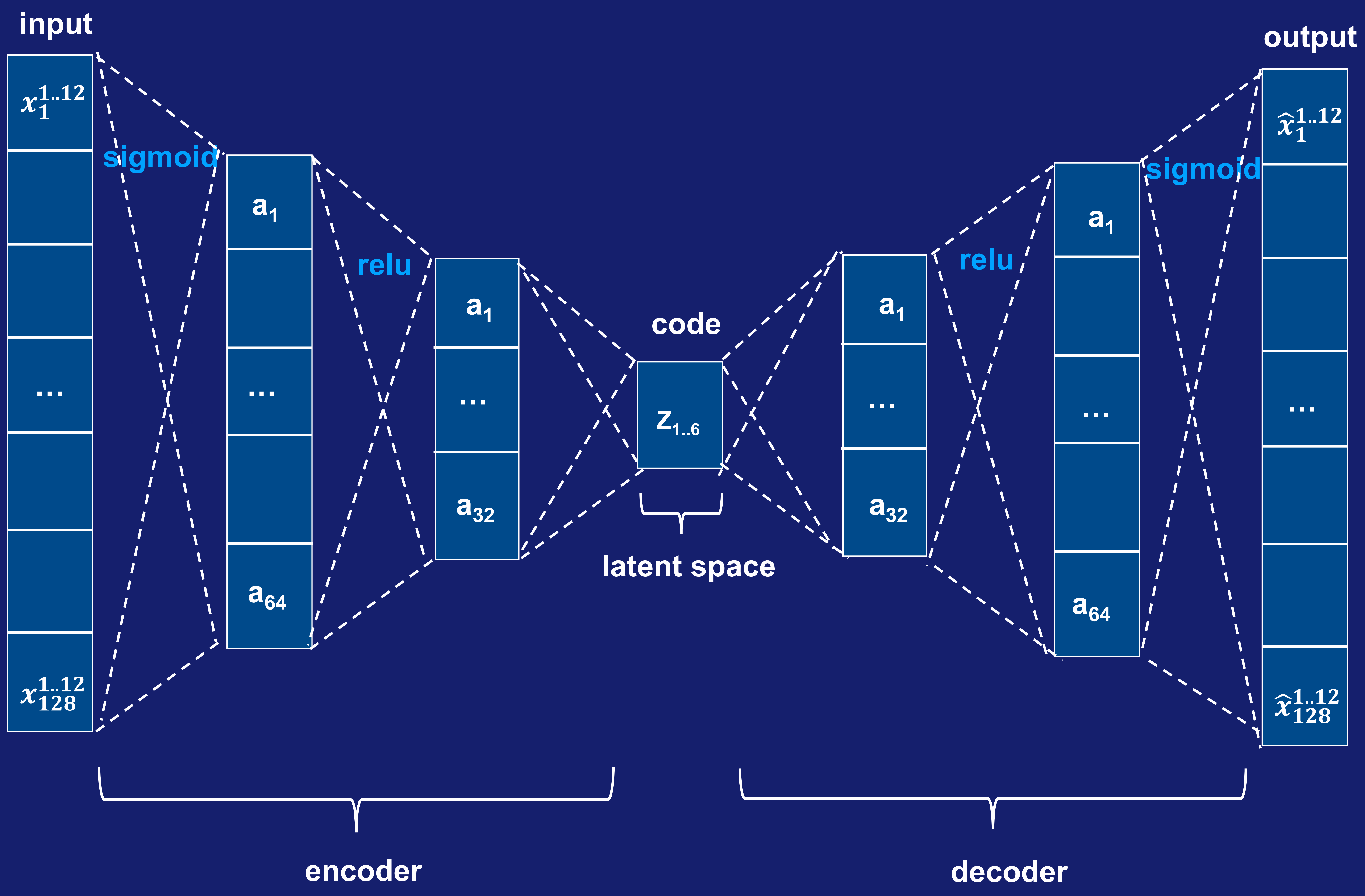


Auto-Encoders

(a)


input
output
x_1
x_{128}
tanh
a_1
a_{64}
relu
code
z_1
z_{32}
relu
a_1
a_{64}
tanh
$\hat{x}_1$
$\hat{x}_{128}$
latent space
encoder
decoder

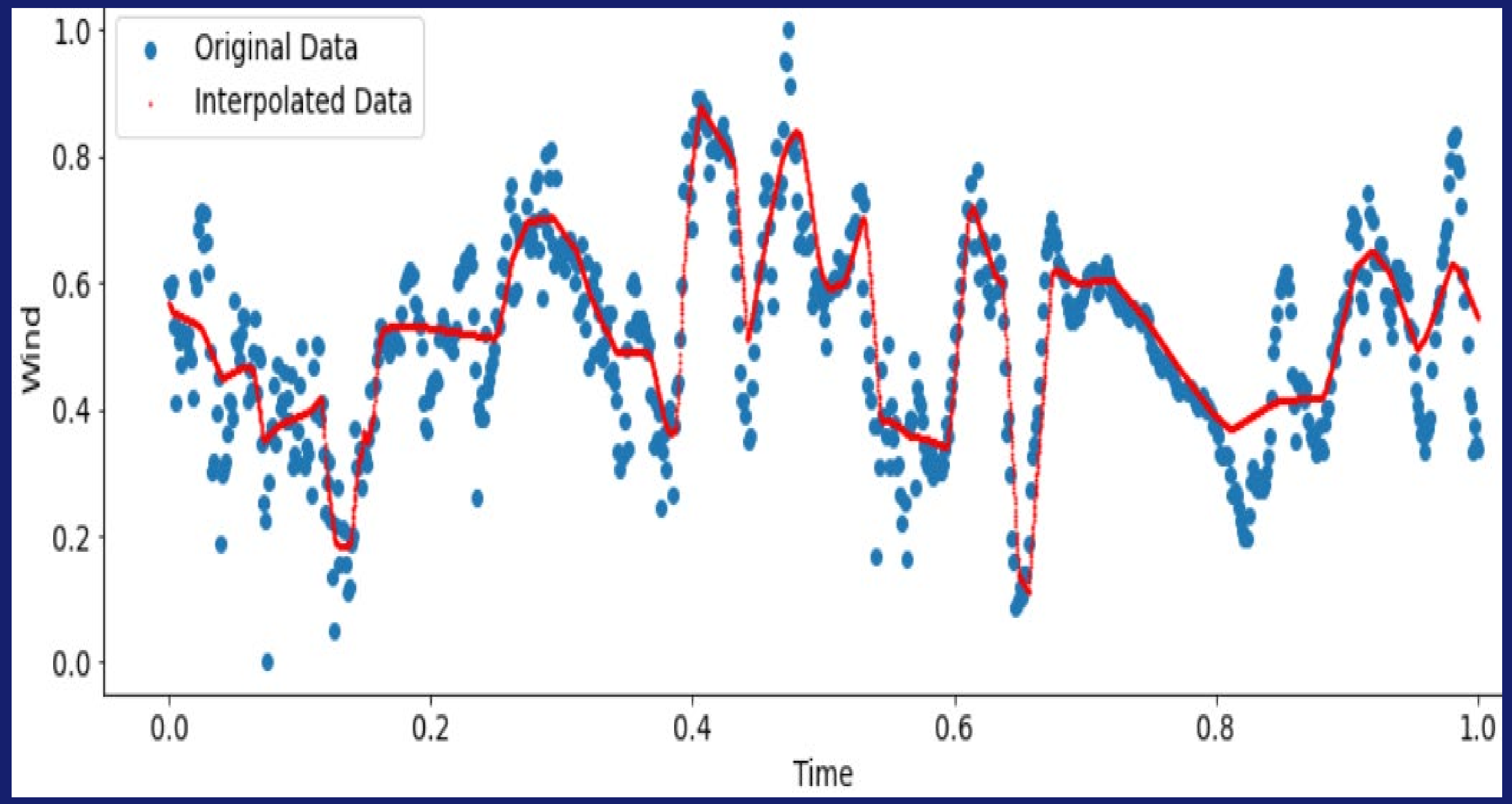
(b)



input
$x_1^{1..12}$
...
$x_{128}^{1..12}$
sigmoid
a_1
...
a_{64}
relu
a_1
...
a_{32}
code
$z_{1..6}$
latent space
a_1
...
a_{32}
relu
a_1
...
a_{64}
sigmoid
output
$\hat{x}_1^{1..12}$
...
$\hat{x}_{128}^{1..12}$
encoder
decoder

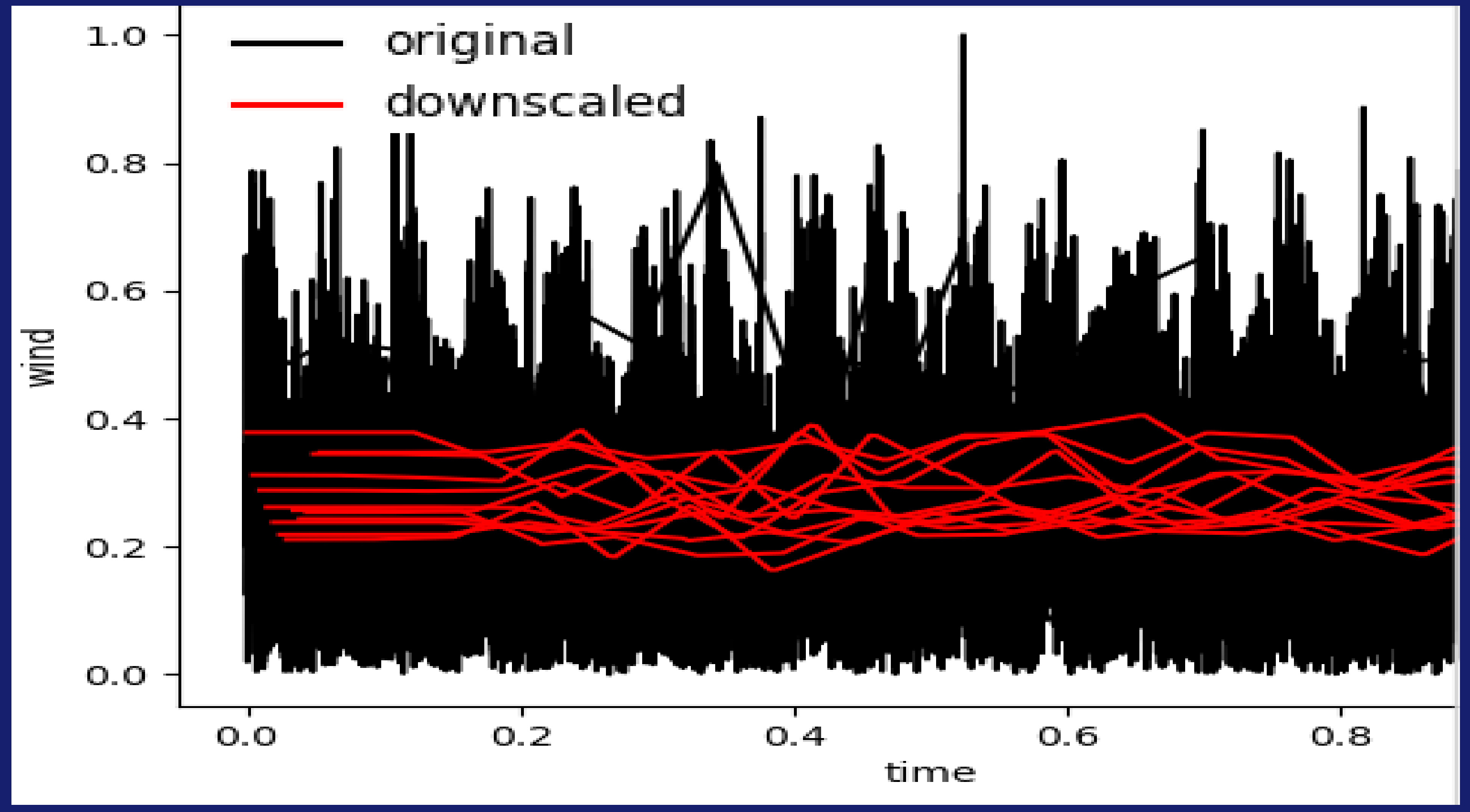
(a)

Train: 1 month; Predict: 1 week



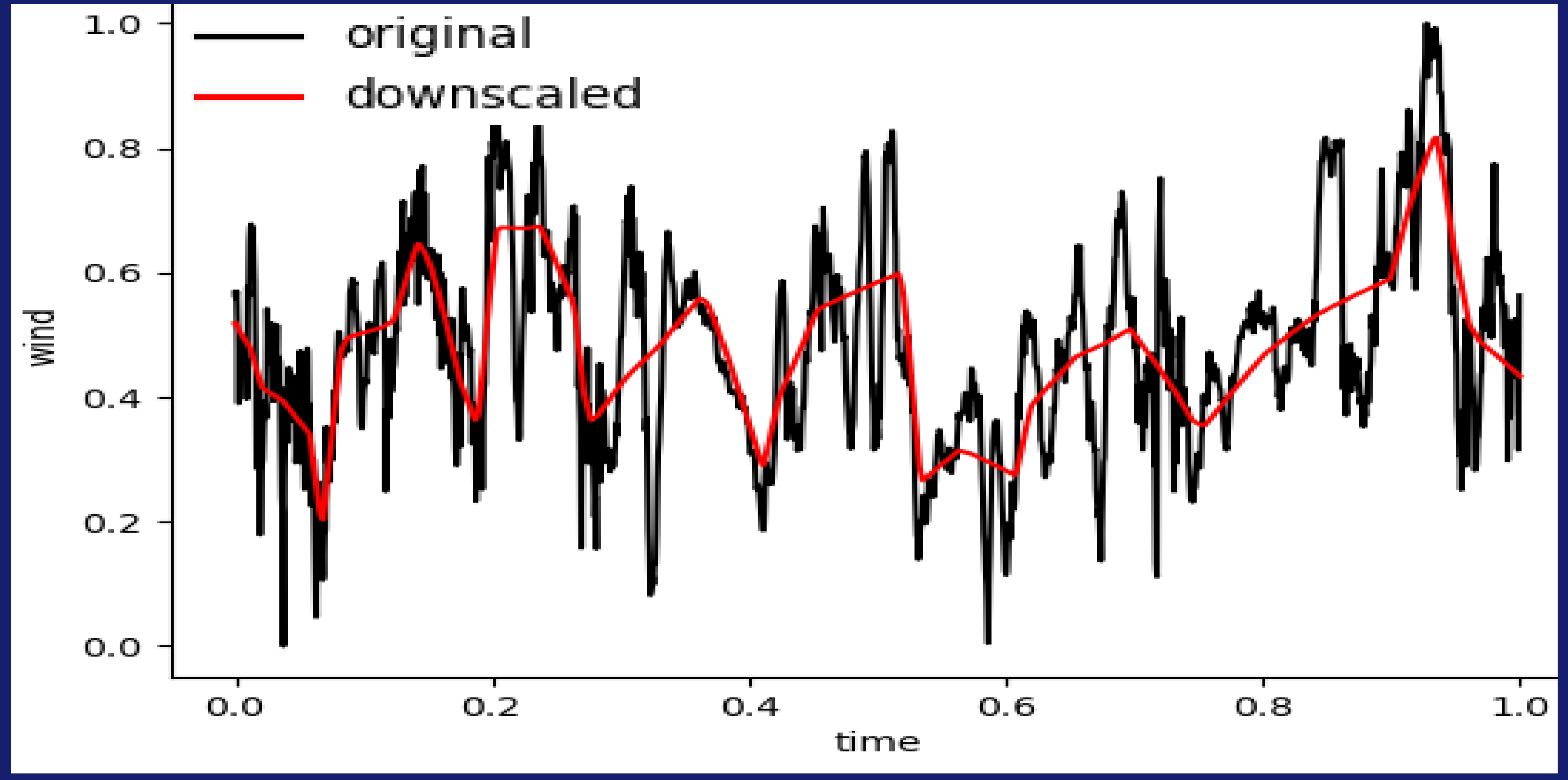
Train: 17 years; Predict: 2 years

(b)

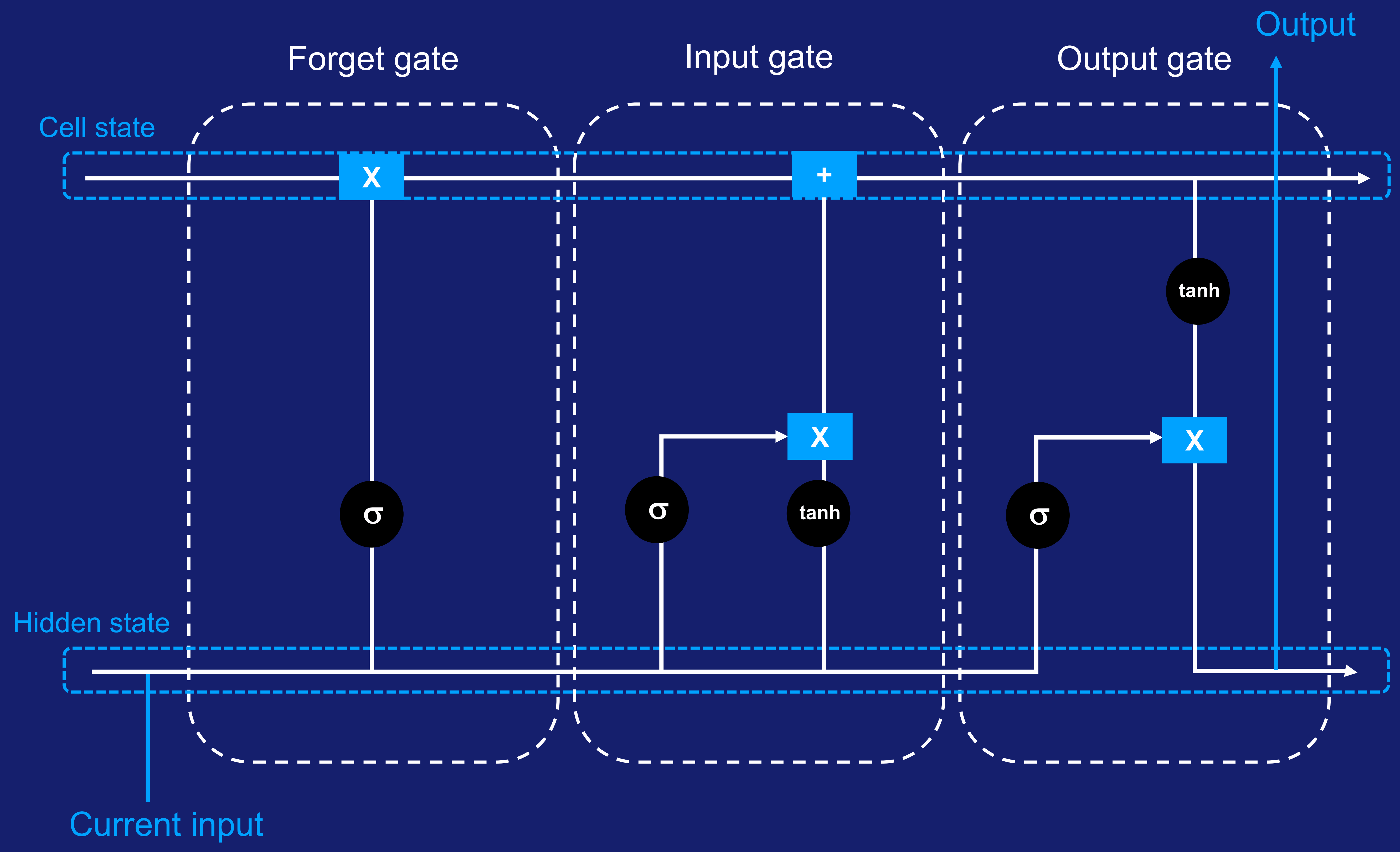


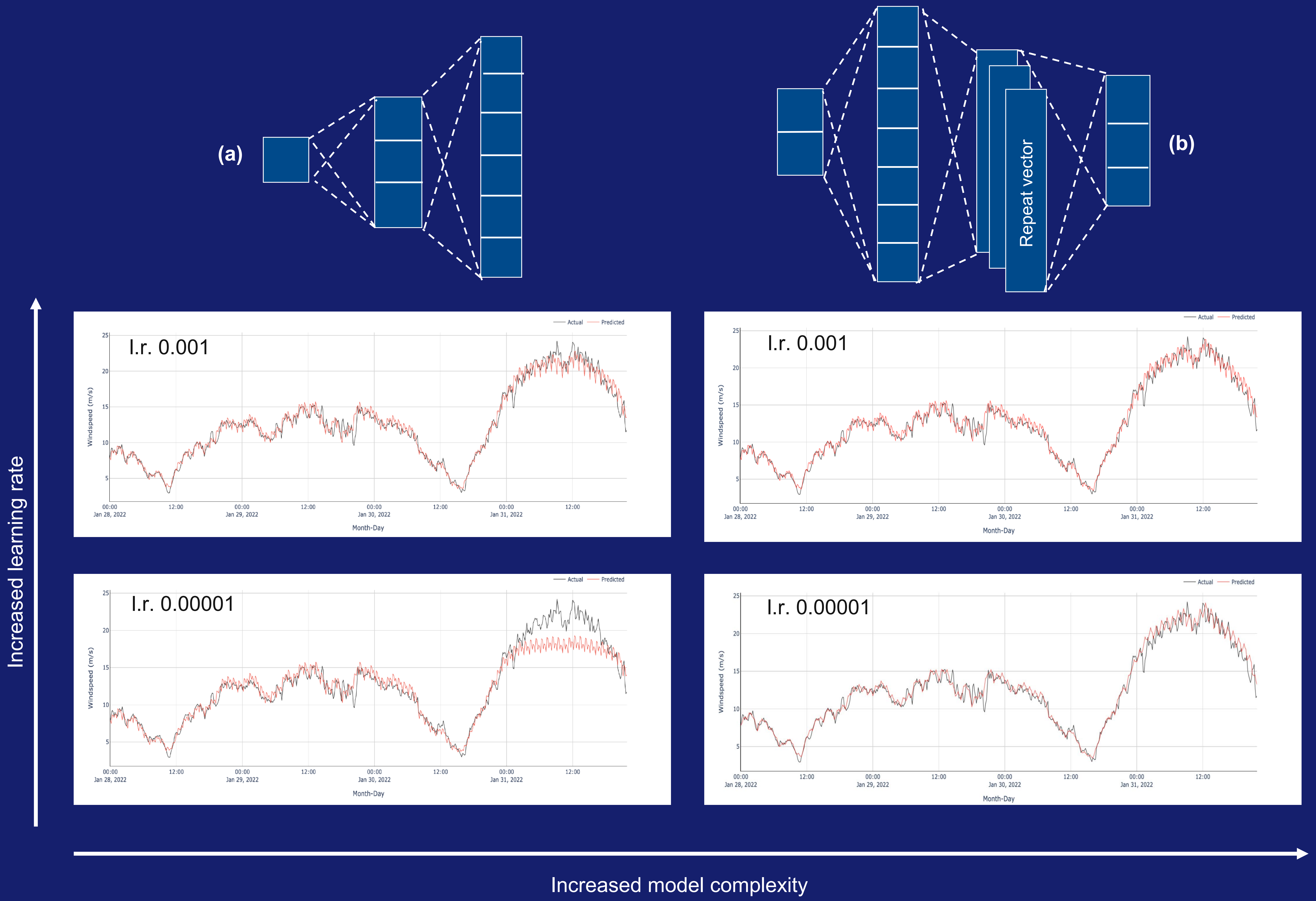
(a)

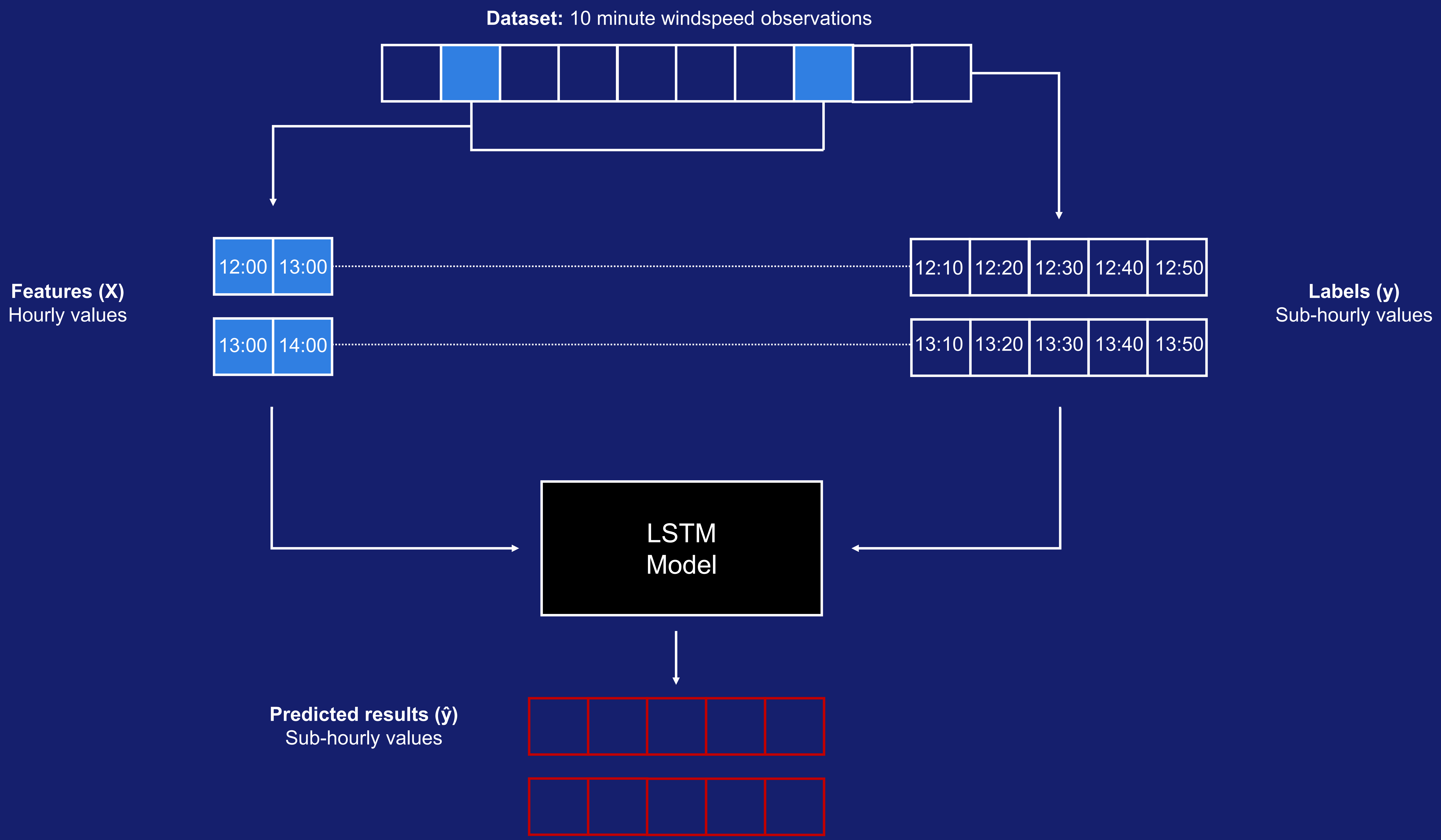
Train: 2 months; Predict 1 month

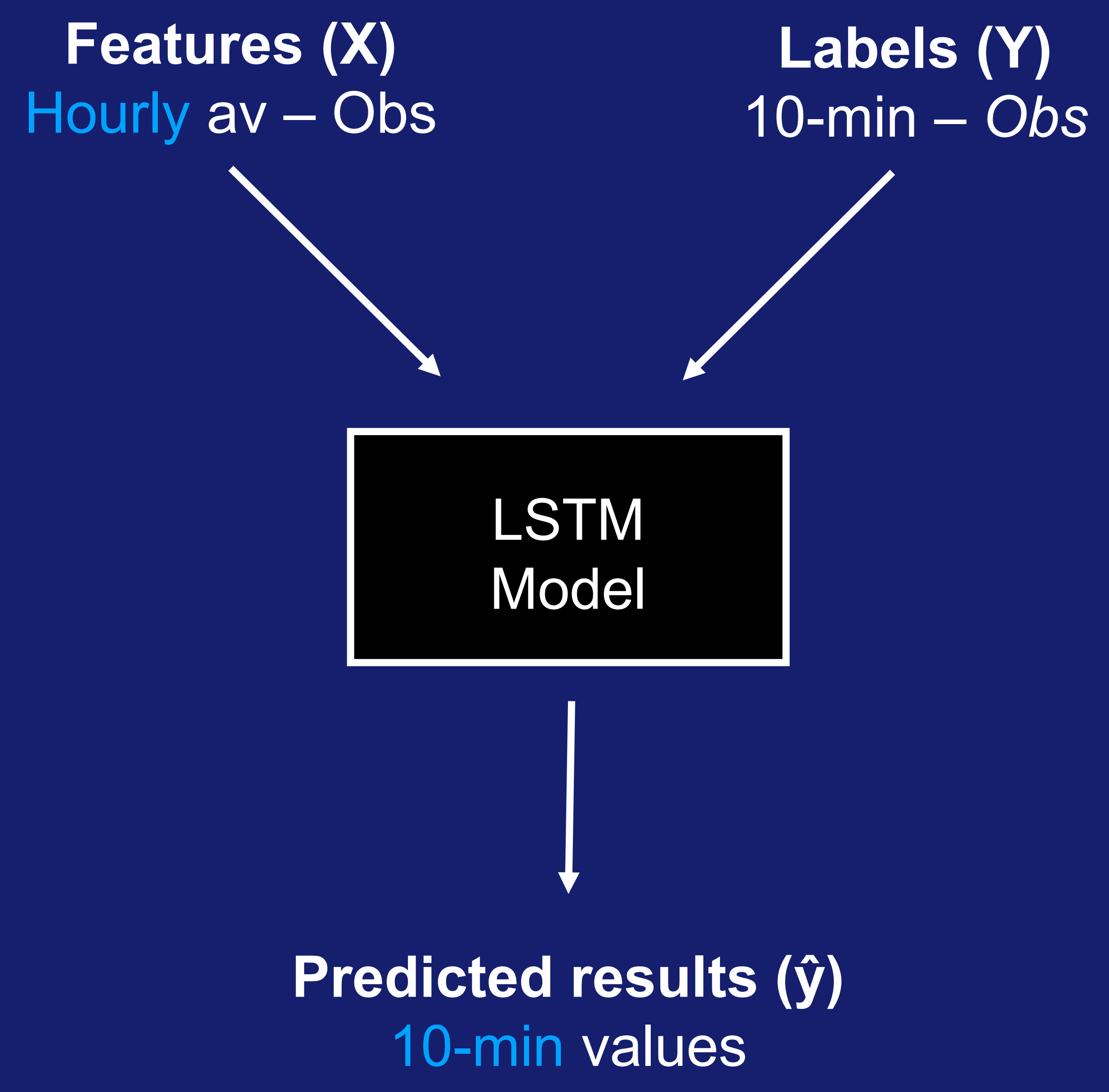


Long-Short Term Memory

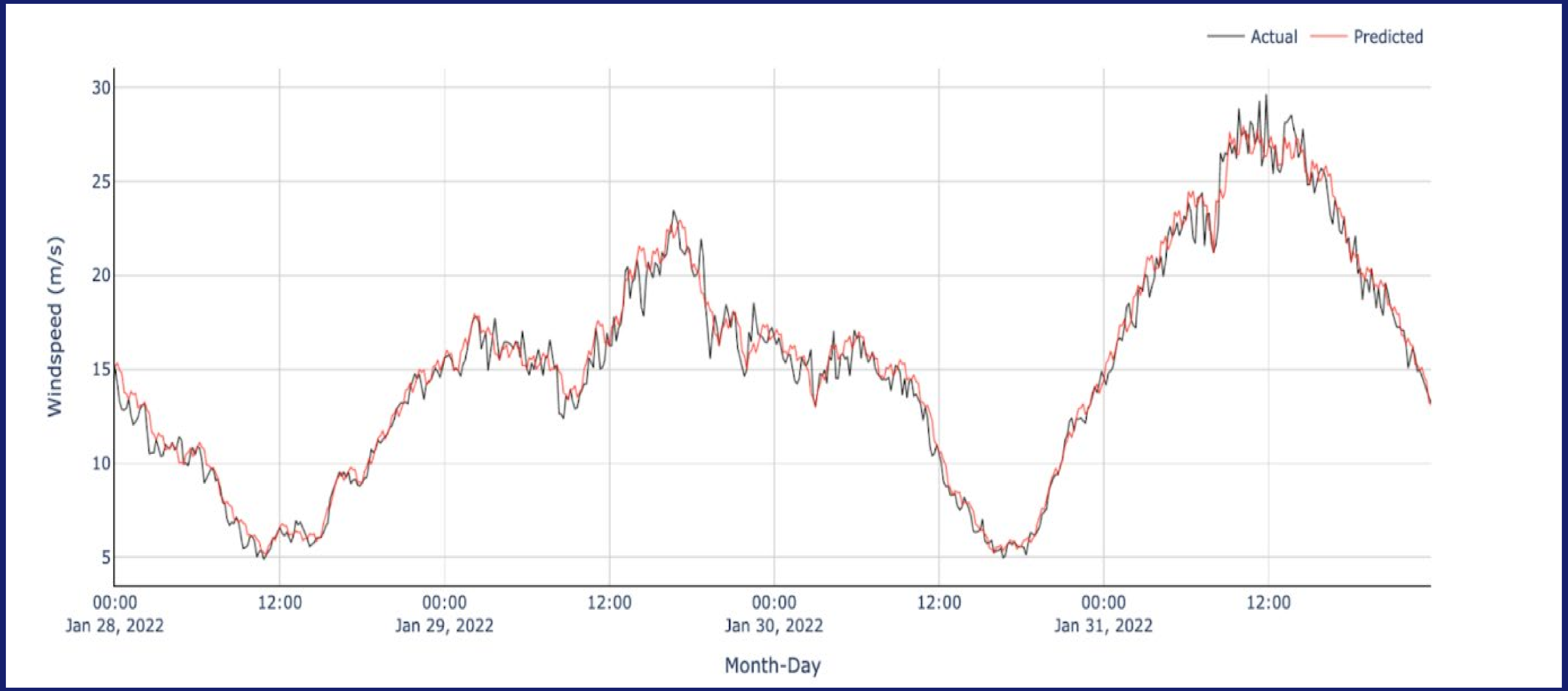

Output
Forget gate
Input gate
Output gate
Cell state
X
+
tanh
X
σ
σ
tanh
σ
X
Hidden state
Current input


(a)
(b)
Repeat vector
Increased learning rate
Increased model complexity
l.r. 0.001
l.r. 0.00001
l.r. 0.001
l.r. 0.00001
Actual
Predicted
Windspeed (m/s)
Month-Day
00:00 Jan 28, 2022
12:00
00:00 Jan 29, 2022
12:00
00:00 Jan 30, 2022
12:00
00:00 Jan 31, 2022
12:00


Dataset: 10 minute windspeed observations
Features (X)
Hourly values
12:00
13:00
13:00
14:00
12:10
12:20
12:30
12:40
12:50
13:10
13:20
13:30
13:40
13:50
Labels (y)
Sub-hourly values
LSTM Model
Predicted results (ŷ)
Sub-hourly values



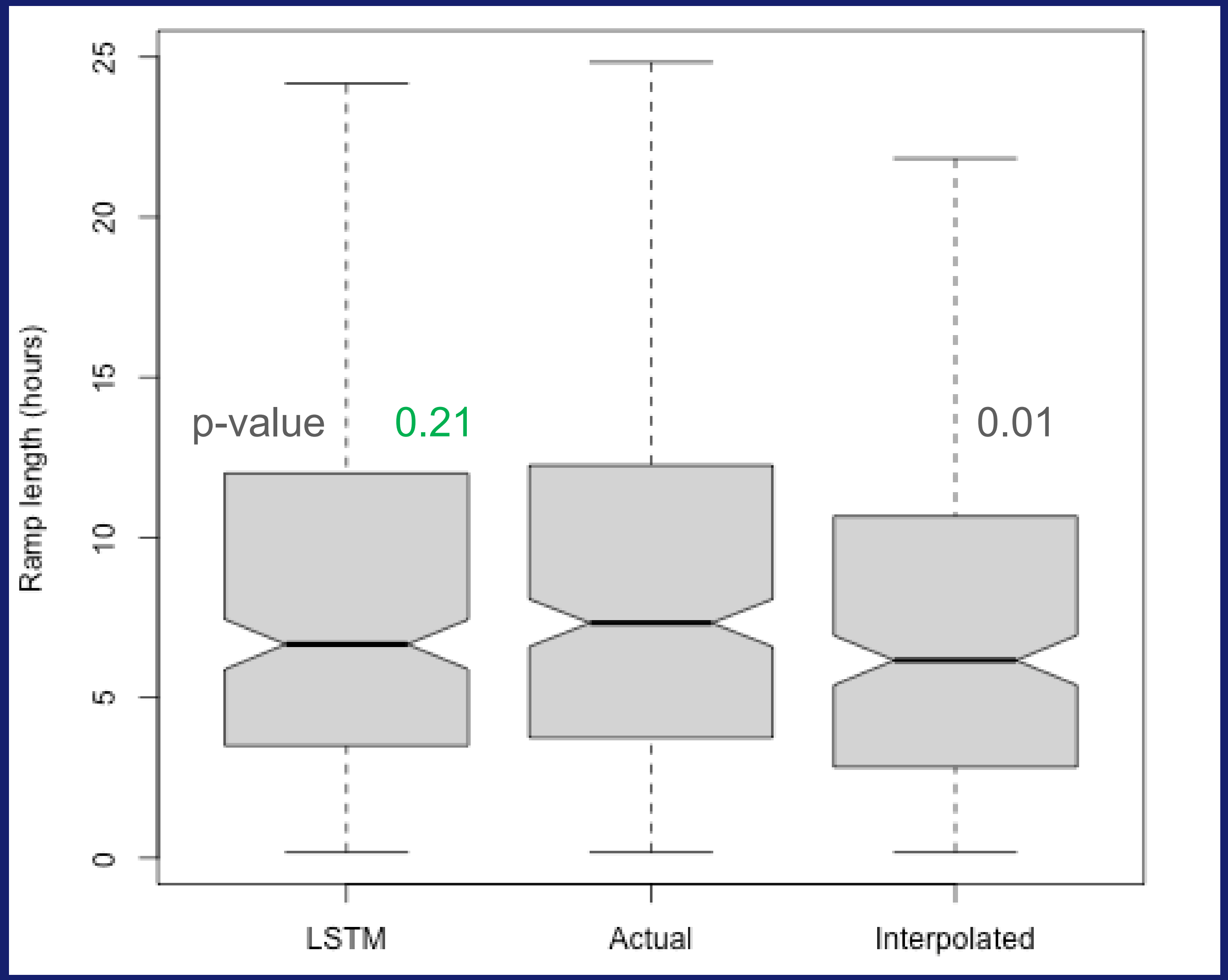
Features (X)
Hourly av – Obs
Labels (Y)
10-min – Obs
LSTM Model
Predicted results (ŷ)
10-min values

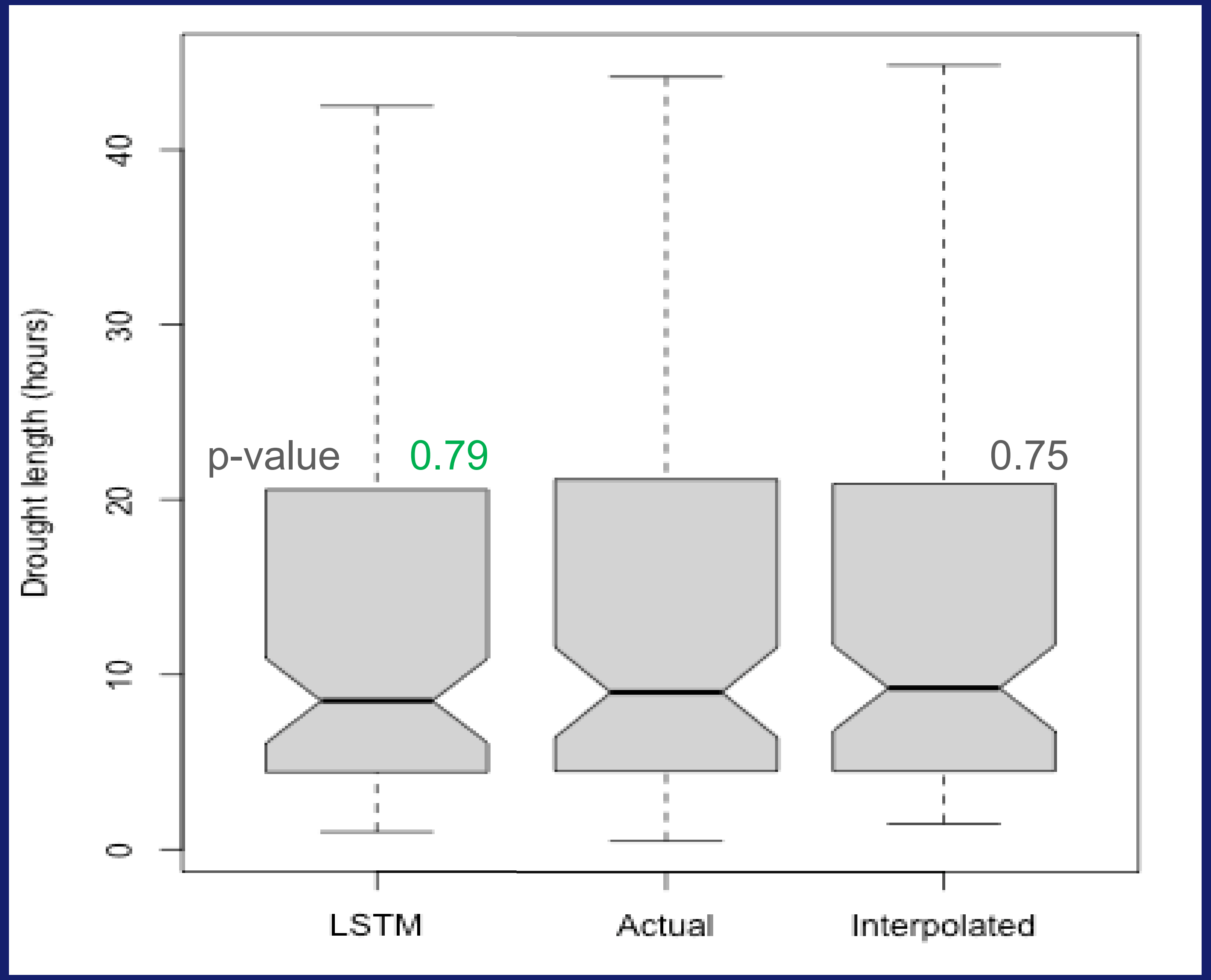


Actual
Predicted
Windspeed (m/s)
30
25
20
15
10
5
00:00 Jan 28, 2022
12:00
00:00 Jan 29, 2022
12:00
00:00 Jan 30, 2022
12:00
00:00 Jan 31, 2022
12:00
Month-Day

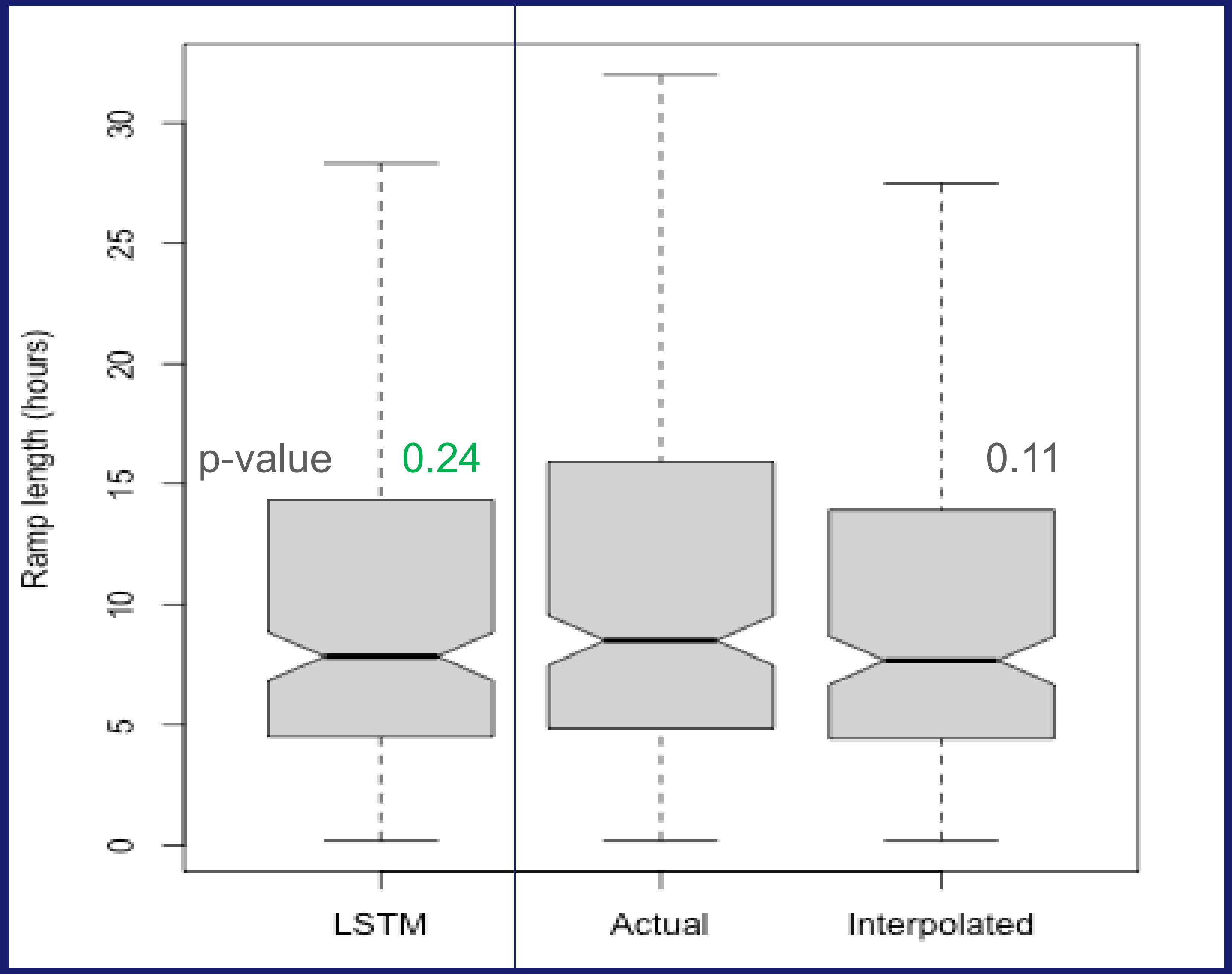
Ramp events **Drought events**

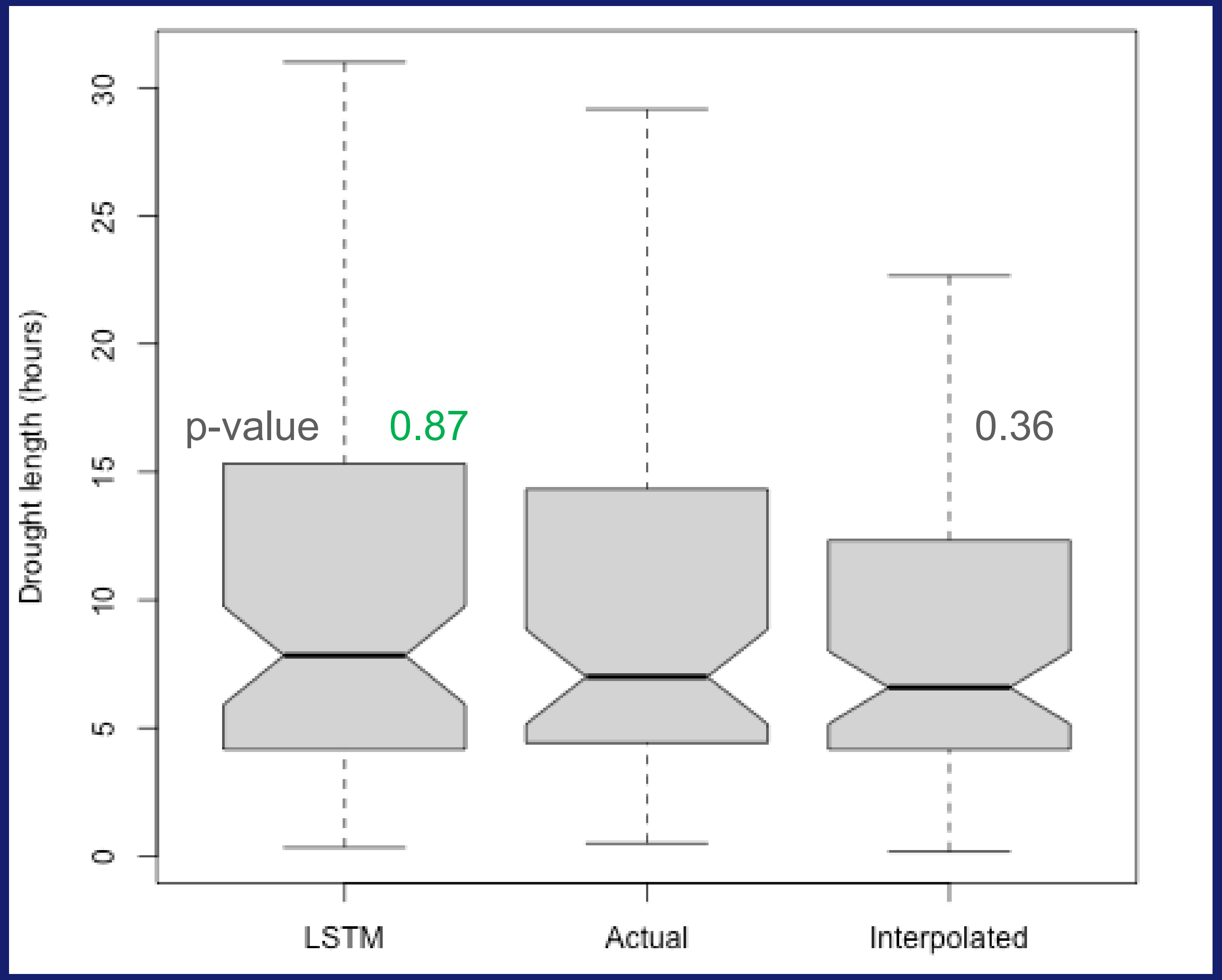
S2





S1



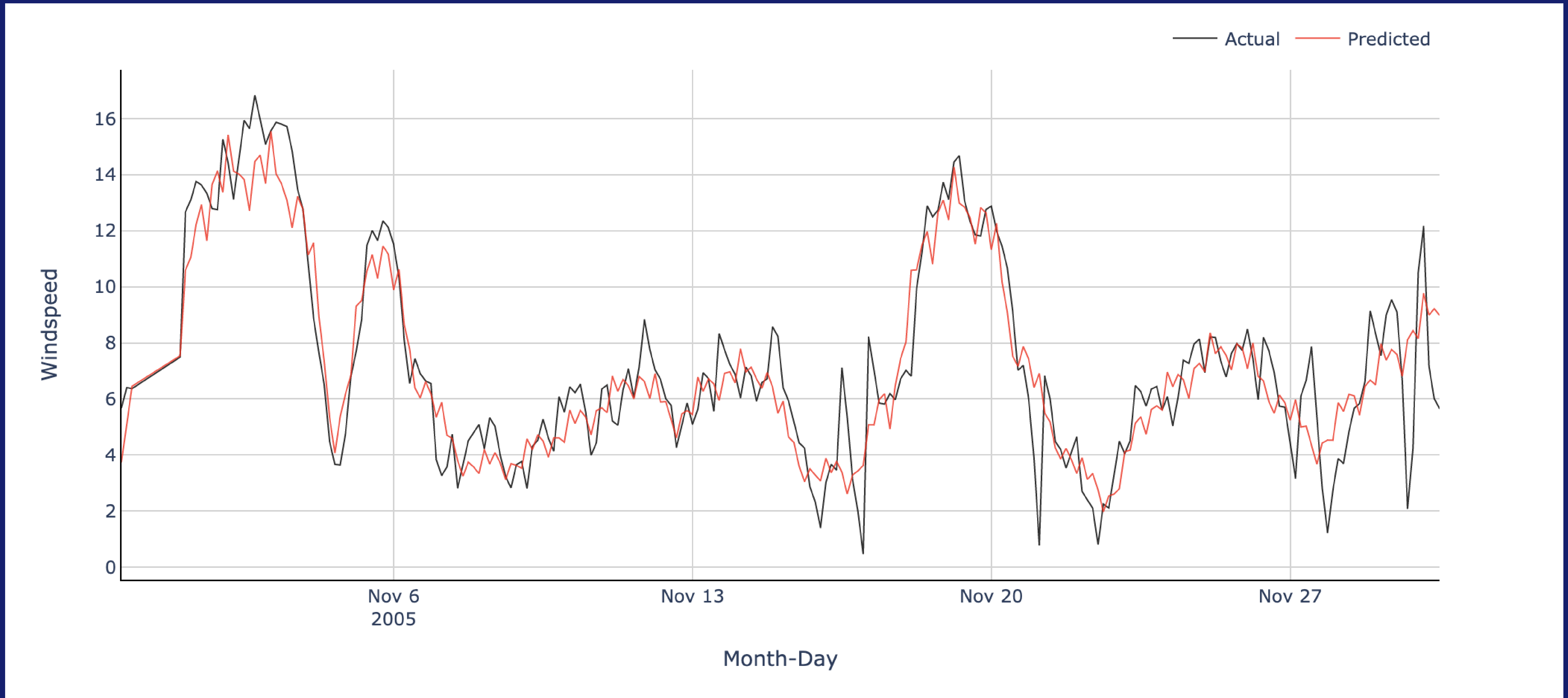


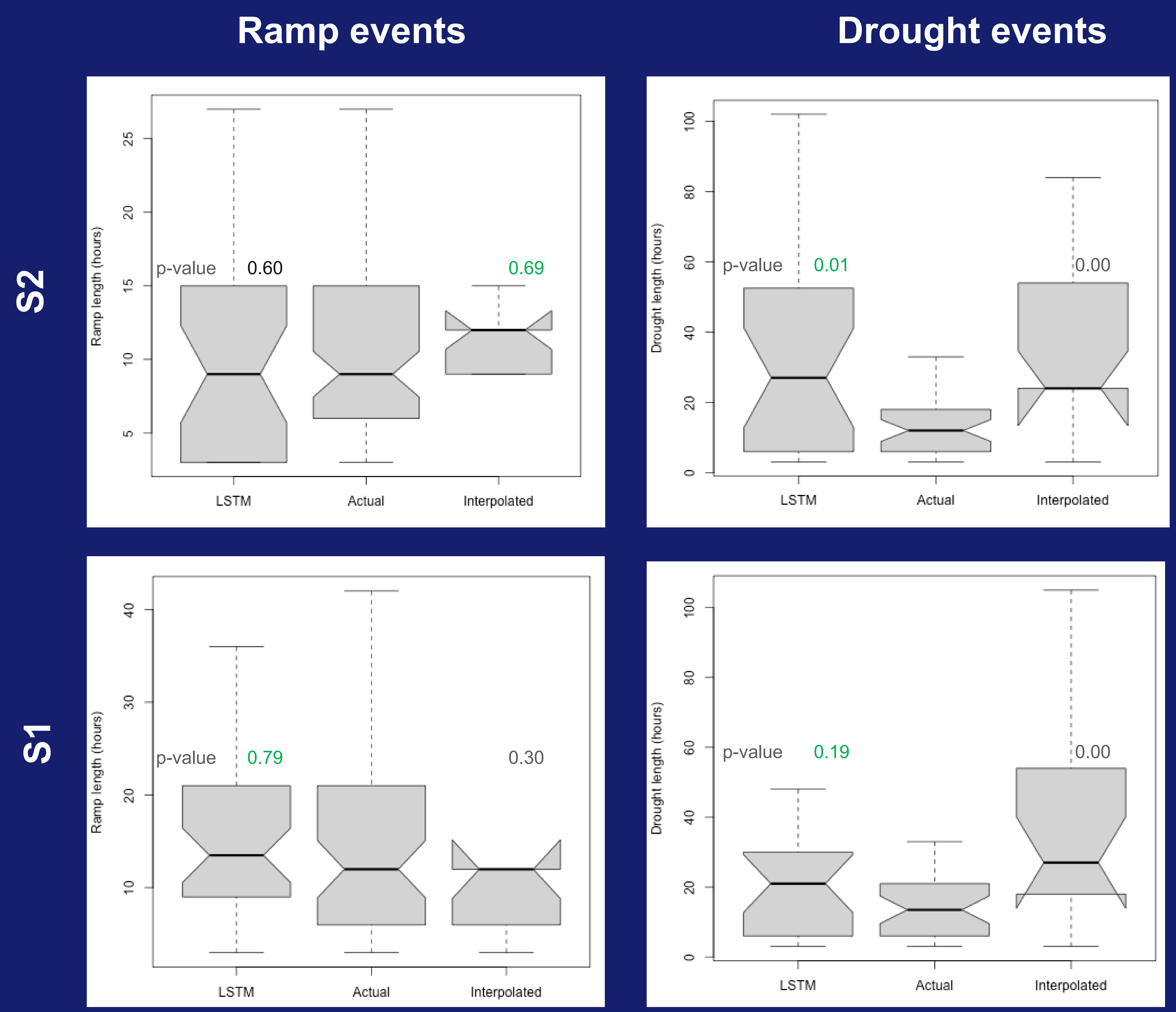
Features (X)
Daily av – *EUR11*

Labels (Y)
3 hourly – *EUR11*

LSTM Model

Predicted results (ŷ)
3-hourly values





Ramp events
Drought events
S2
S1
Ramp length (hours)
p-value 0.60 0.69
LSTM
Actual
Interpolated
Drought length (hours)
p-value 0.01 0.00
p-value 0.79 0.30
p-value 0.19 0.00

Summary

Help improve information used to support decisions for security of future electricity supply under climate change uncertainty

- Machine Learning models tested for temporal downscaling wind climate data to sub-hourly timescales
- Preserve relevant statistical properties such as long-term variability and extremes
- Selected different climate models and offshore locations
- Model performance measured against wind ramp and wind drought metrics

UKCP18 Local captures both ramps and droughts better than EUR-11

Auto-Encoders can reproduce 10-min timeseries over period of few months, but not in longer term nor extremes

LSTM can improve climate-scale predictability of wind ramps and wind droughts, outperforming linear interpolation

Over to you…