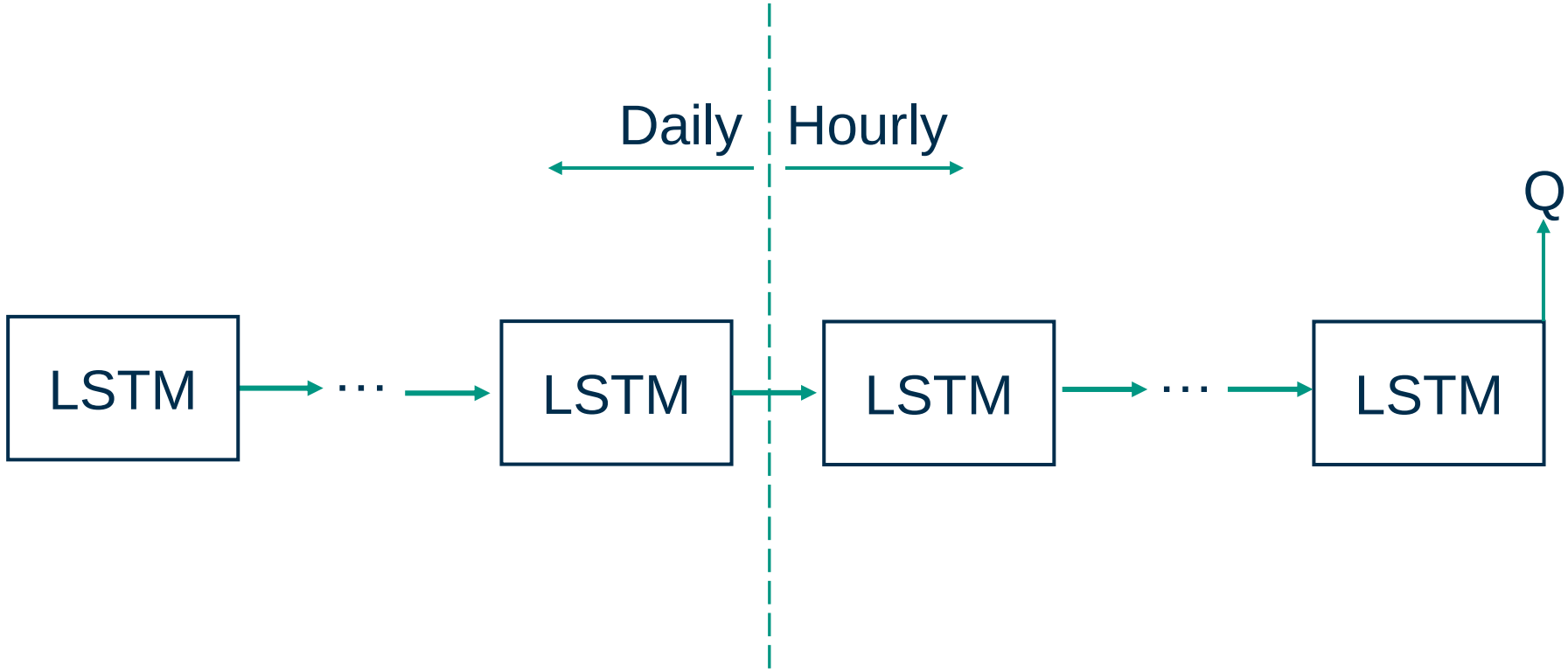
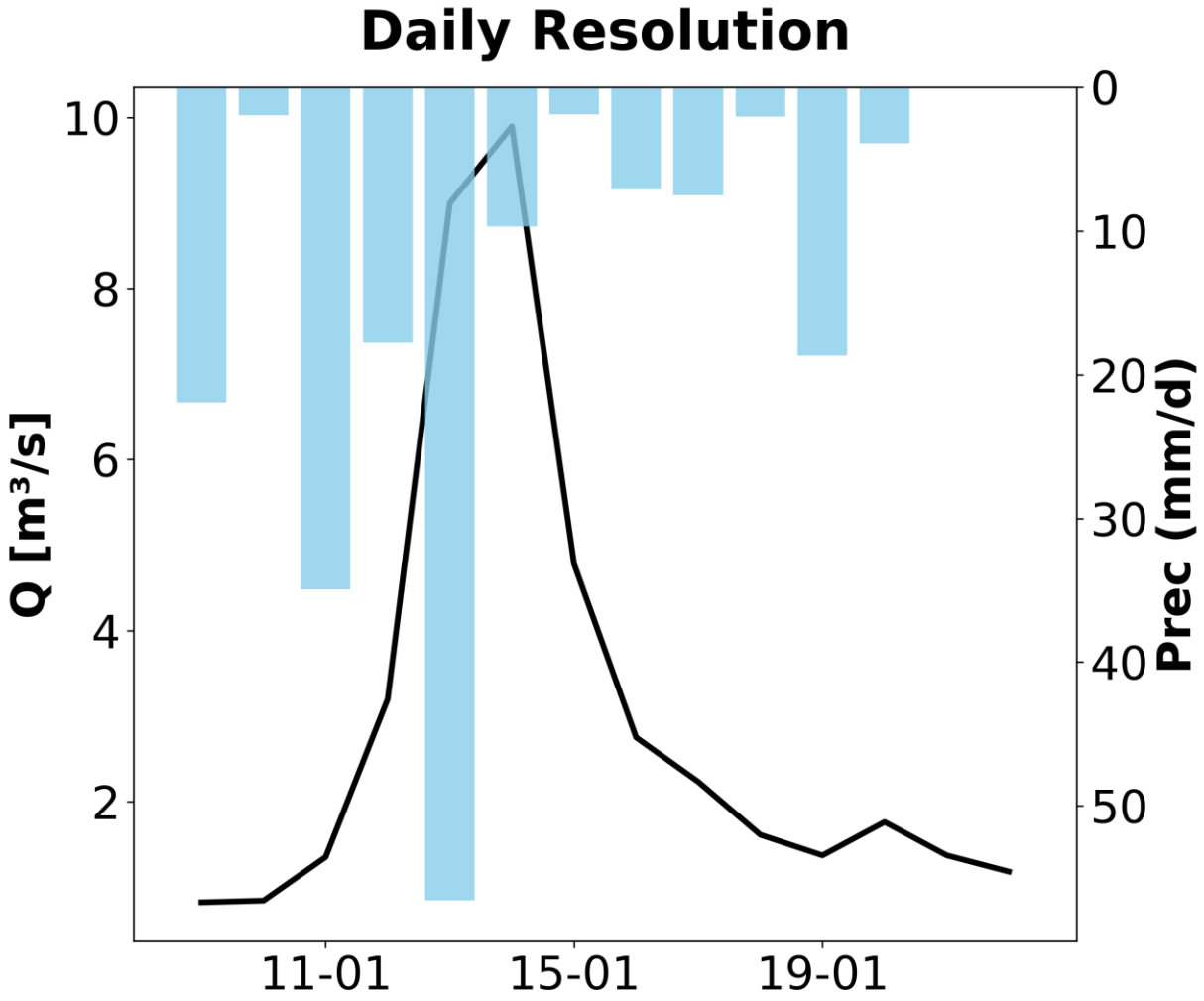
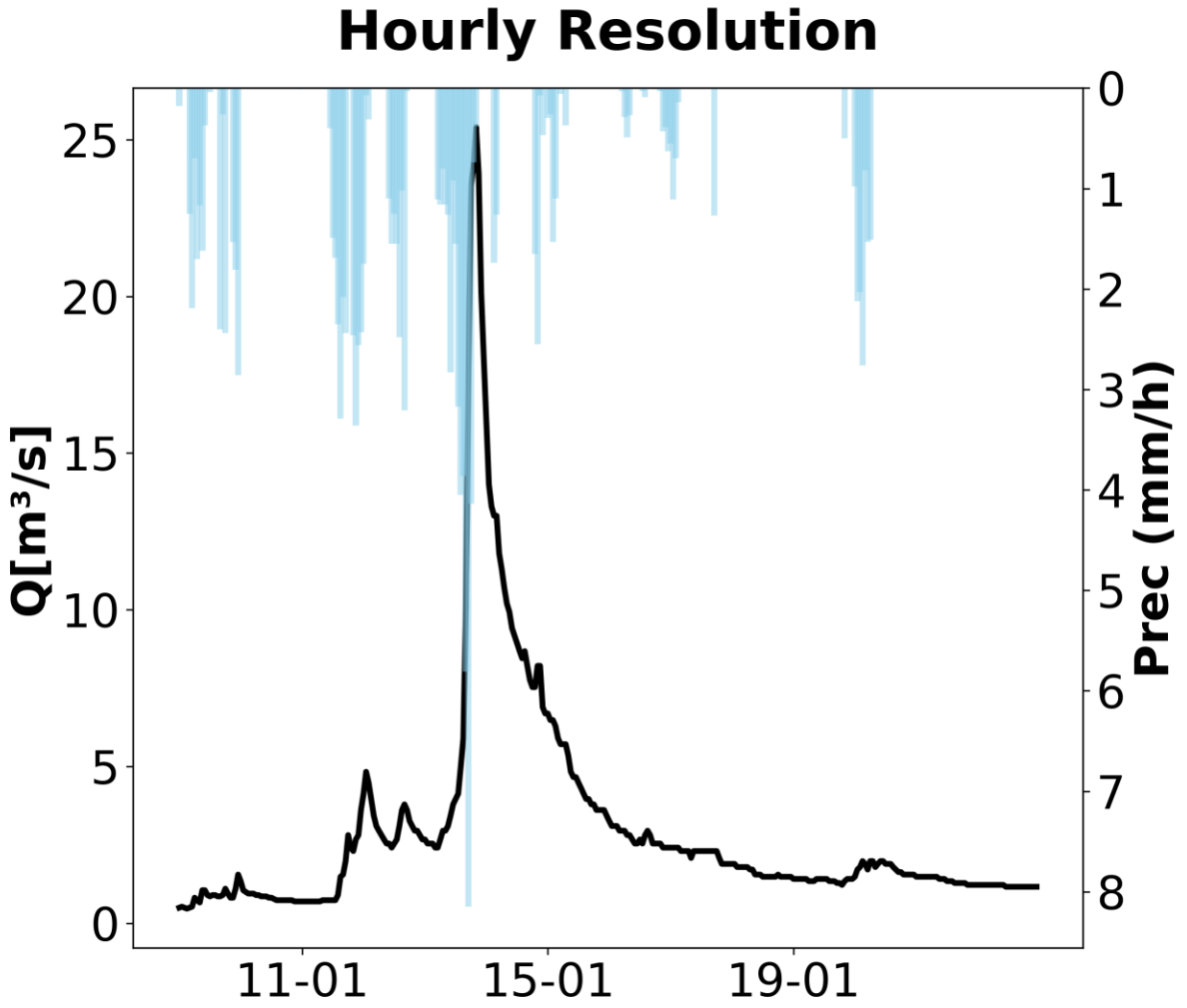


Multi-frequency LSTM: a machine learning architecture for operational flood forecasting

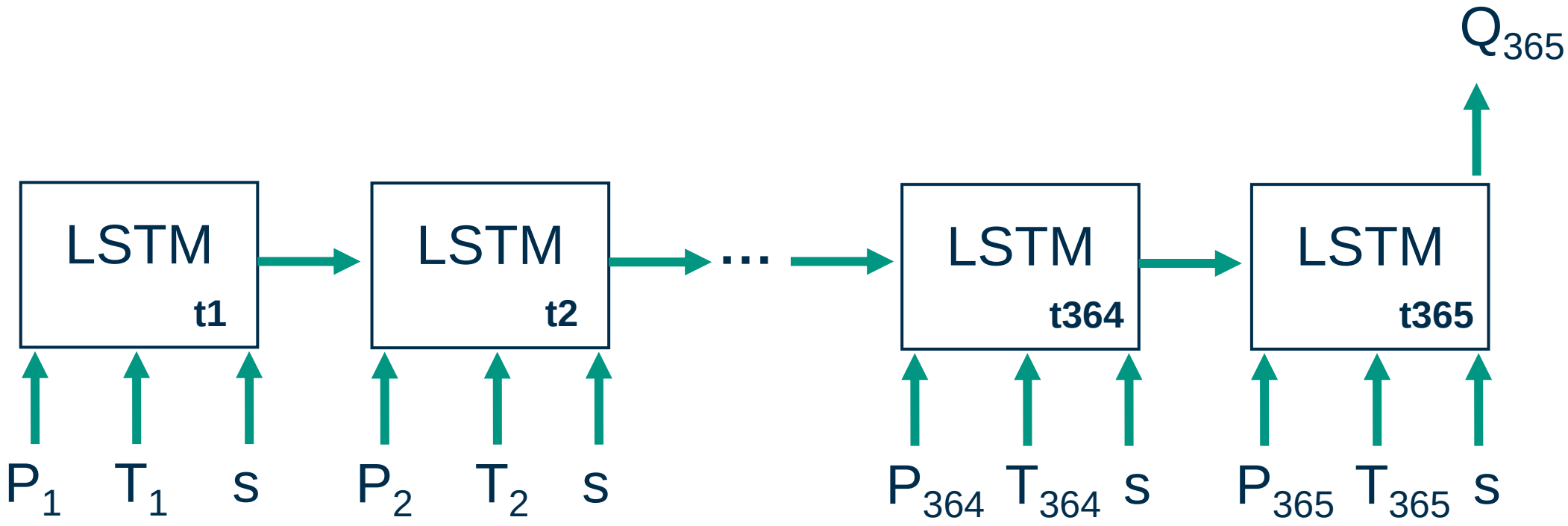
Eduardo Acuña, Uwe Ehret, Dirk Aigner, Dominik Elfgang and Ute Badde

Rainfall-runoff modeling

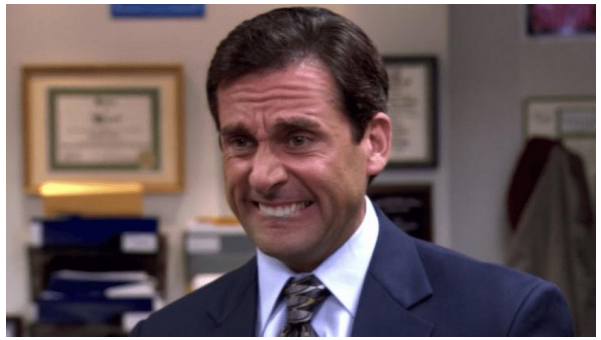


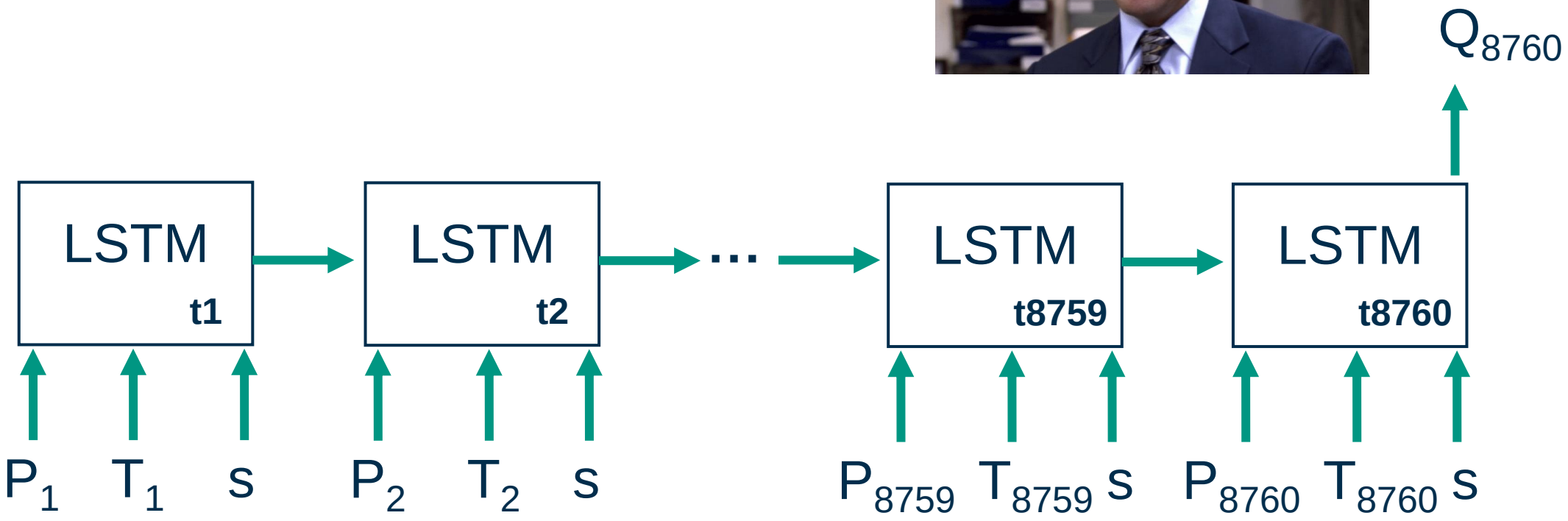


Daily resolution



Hourly resolution

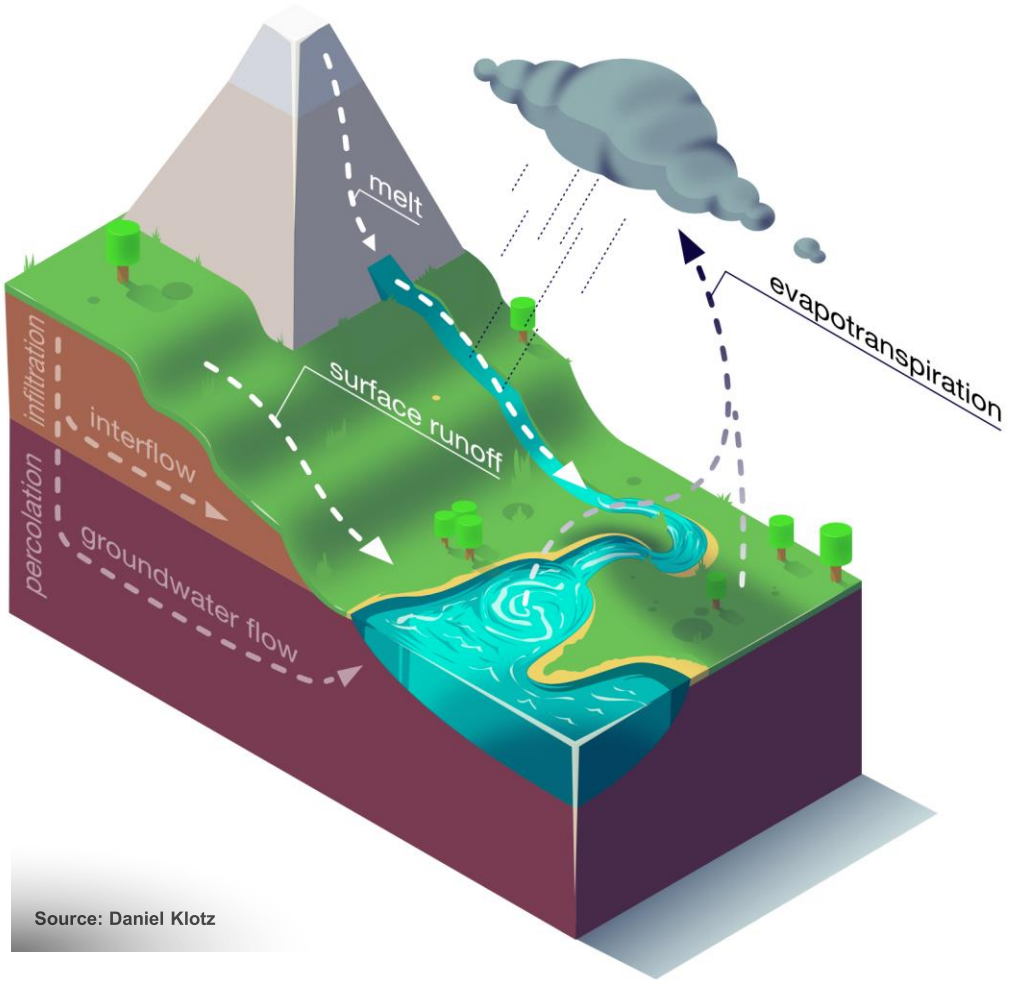




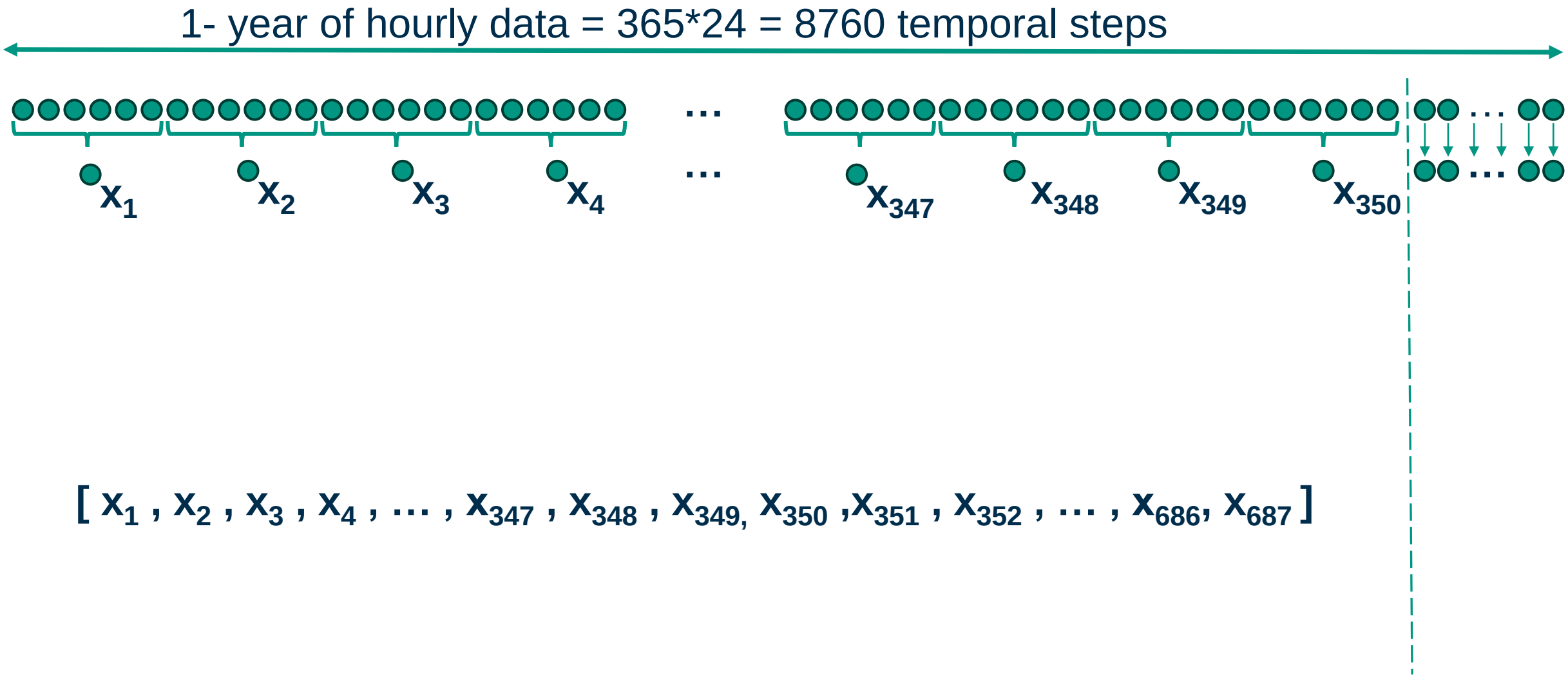
What do we know?

- The effect of the input's temporal distribution diminishes the further we look back in time.

- LSTM cells have no inherent limitation in processing data at different temporal frequencies.

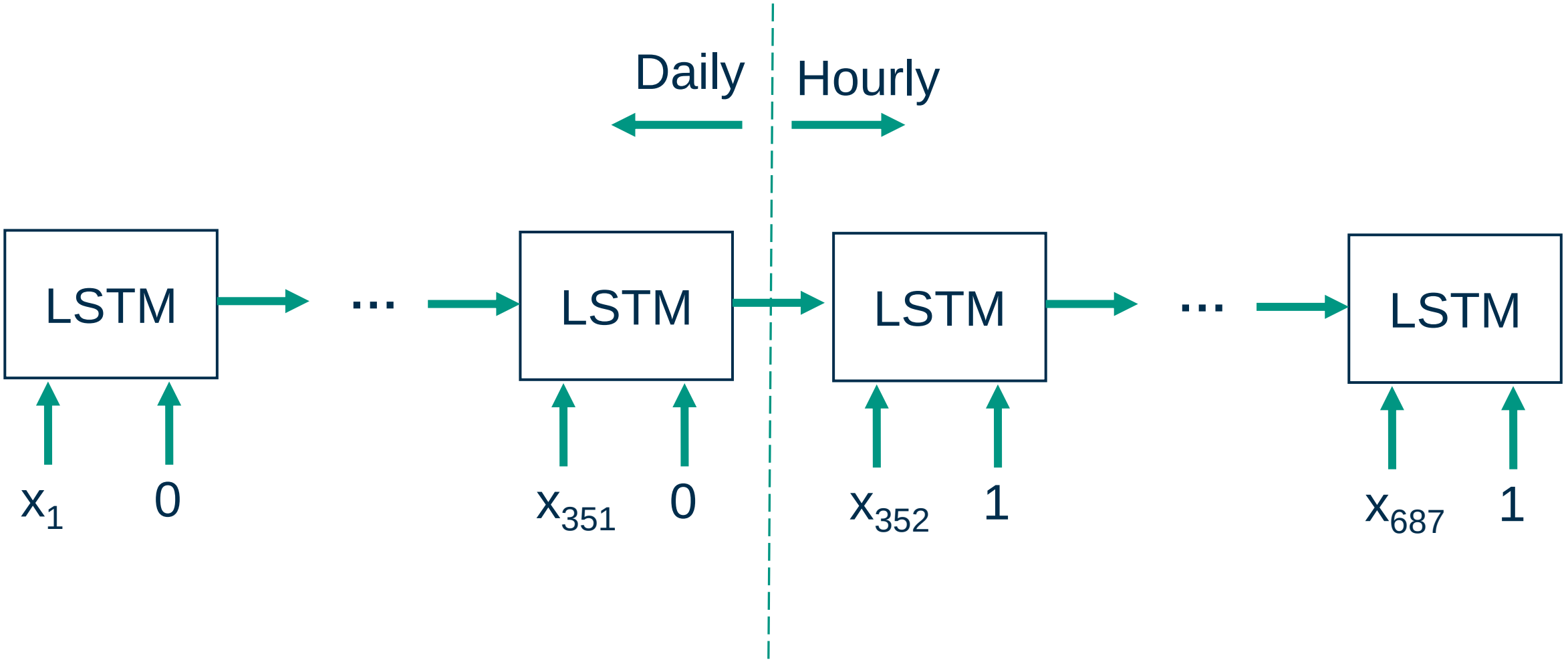


MF-LSTM: Multi-frequency LSTM



$$[\, x_1 , x_2 , x_3 , x_4 , \dots , x_{347} , x_{348} , x_{349}, x_{350} , x_{351} , x_{352} , \dots , x_{686}, x_{687} \,]$$

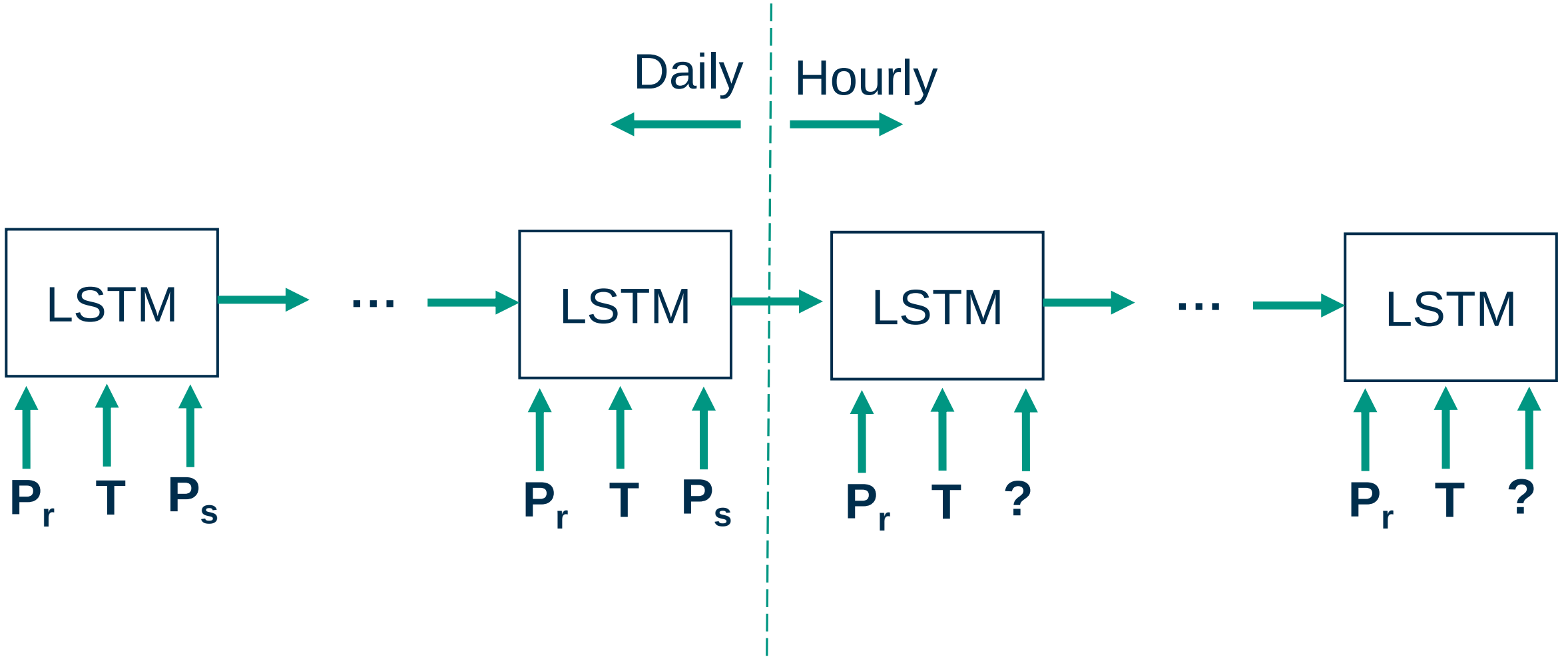
MF-LSTM: Multi-frequency LSTM



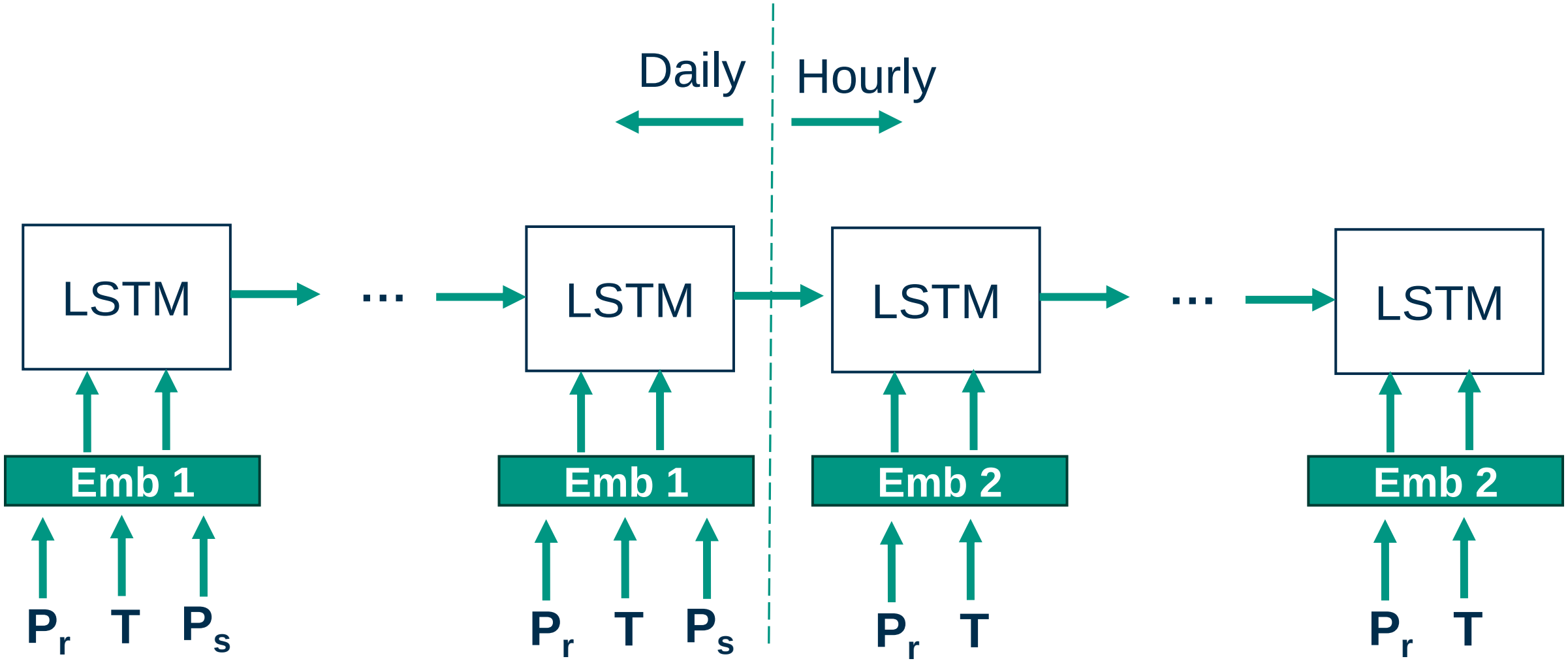
Flexibility in operational model

Daily resolution	Hourly resolution
Precipitation (radar)	Precipitation (radar)
Precipitation (satellite)	Temperature
Temperature	

Flexibility in operational model



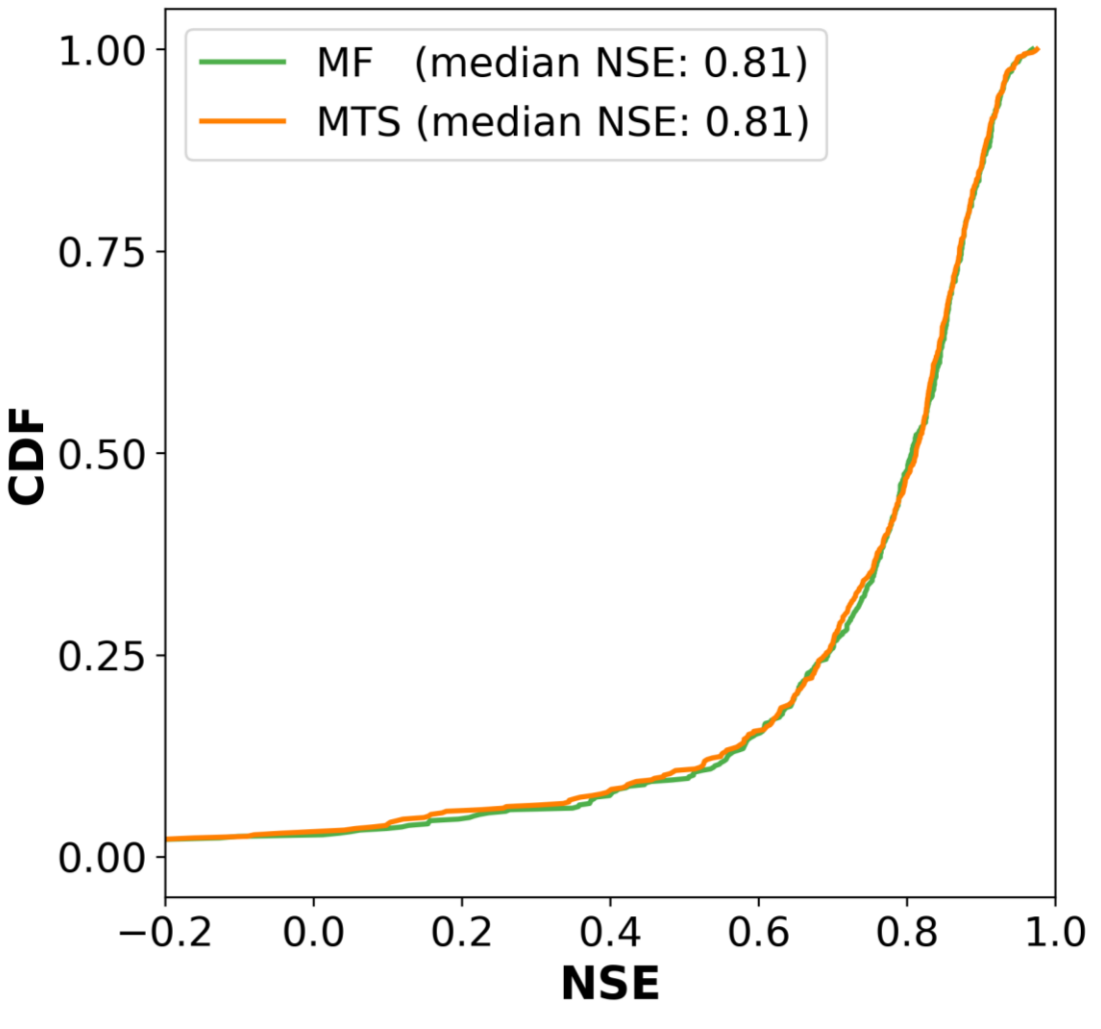
Flexibility in operational model



Experiments

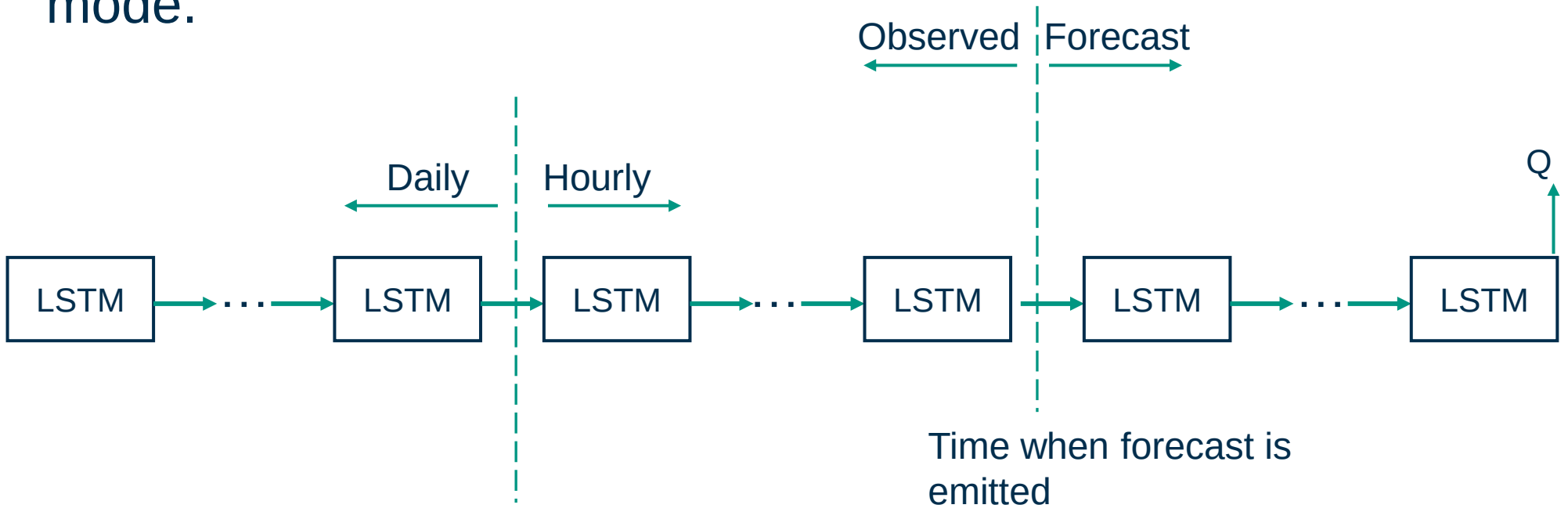
- Experiments on 516 catchments in CAMELS-US.
  - 10 variables on daily resolution
  - 21 variables on hourly resolution.

- Comparable performance with current state-of-the-art, while having a simpler architecture.



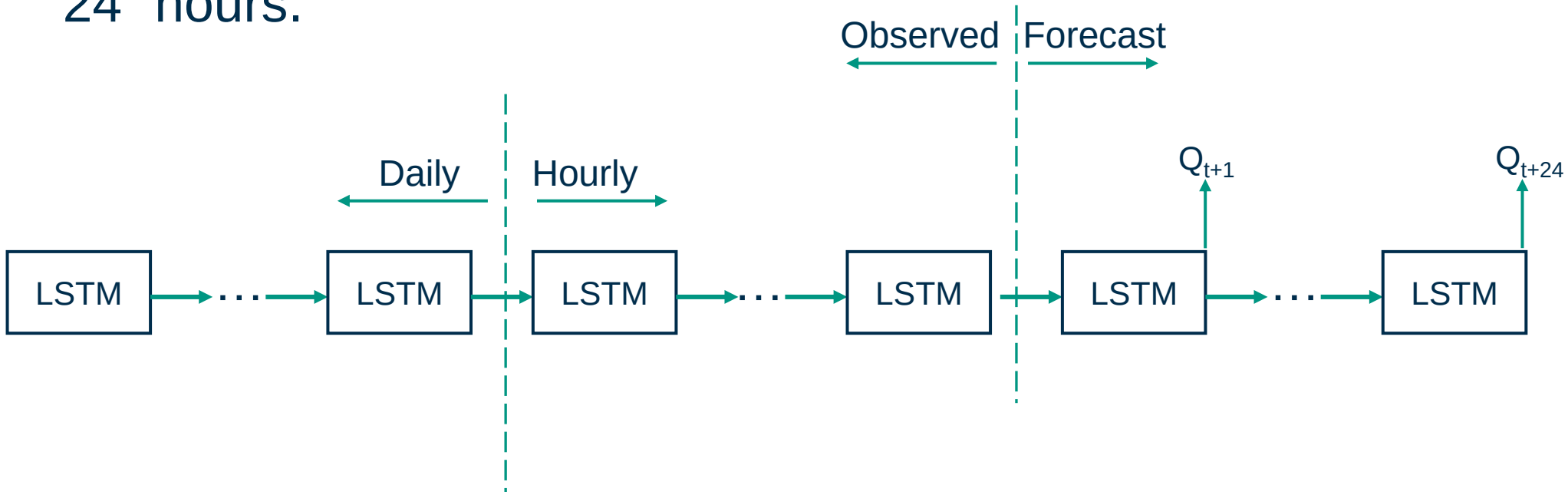
Forecast mode

- We can use a similar logic to switch between observed and forecast mode.



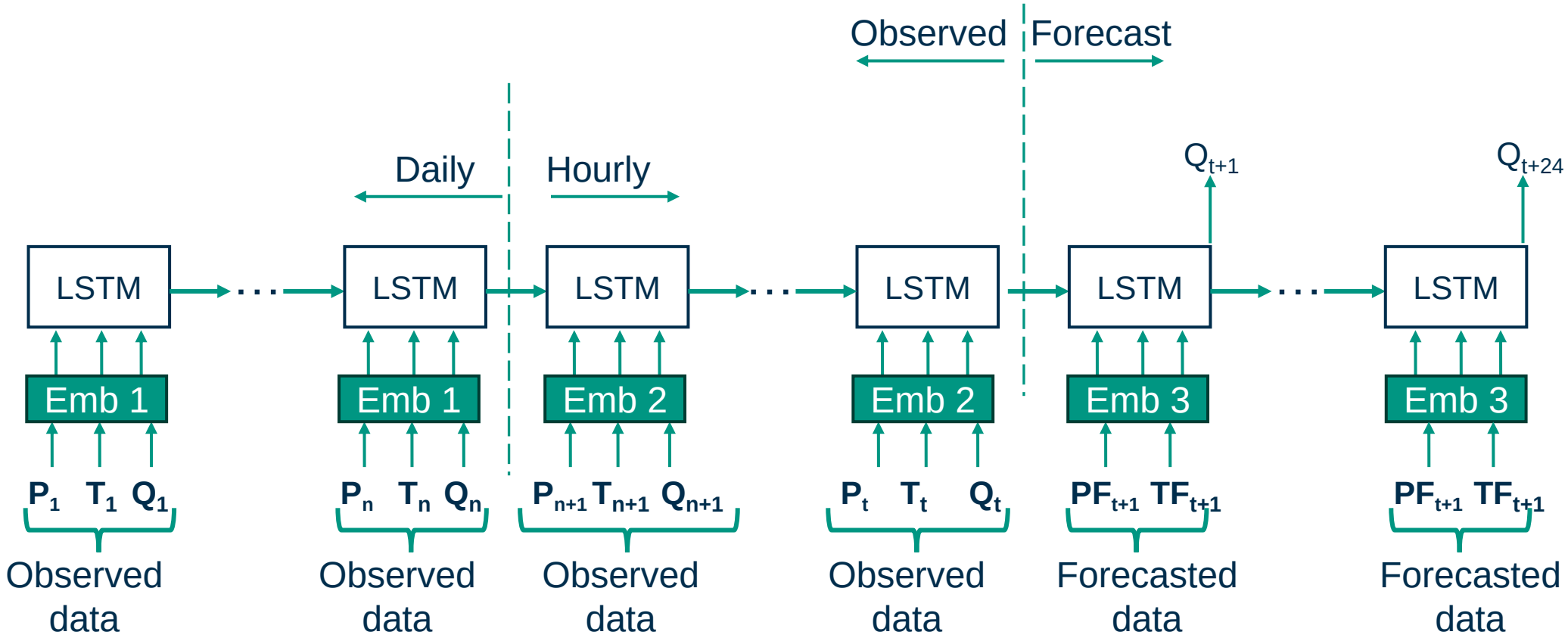
Forecast mode

- We can operate it in a seq-seq mode to retrieve the forecast for the next “24” hours.



Forecast mode

- We need to handle different type and number of inputs.



Conclusions

- The MF-LSTM architecture allows us to handle multiple temporal frequencies with different input dimensions using a single LSTM cell.

- The MF-LSTM architecture maintains state-of-the-art performance, while presenting a simpler and more parsimonious architecture.

Thank you!

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Technical note: An approach for handling multiple temporal frequencies with different input dimensions using a single LSTM cell

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