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LARGE-SCALE EVALUATION OF TEMPORAL TRENDS IN ANN BEHAVIOUR FOR DAILY FLOW FORECASTS IN CANADIAN CATCHMENTS

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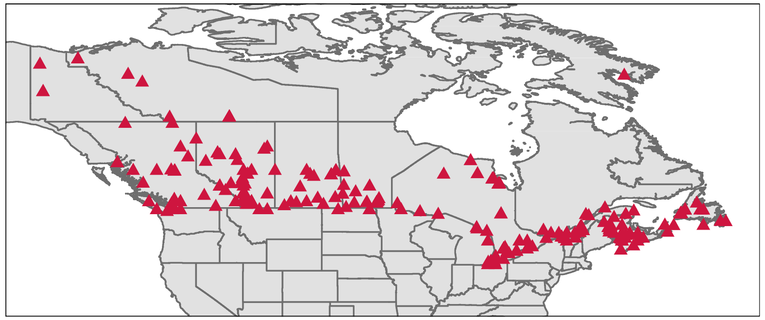
Hydrological systems are non-stationary

- Many hydrological systems are non-stationary, which is commonly attributed to factors such as **climate change** and **urbanisation** (Wang et al., 2016; Tyralis et al., 2019; Crochemore et al., 2016; Yaseen et al., 2015)
- Machine learning models typically assume stationarity

Research objectives

1. Present a large-scale study of **ML-based flow forecasting for watersheds across Canada**
   - Local models trained to each watershed
2. Evaluate **temporal trends** in forecast performance
   - Train models using 3 training data schemes
3. Evaluate spatiotemporal trends in **feature importance**
   - Calculate feature importance using a rolling temporal window across the available training data
4. Study the **spatial relationship** between model performance and watershed characteristics
   - Use feature importance to predict model performance based on static attributes

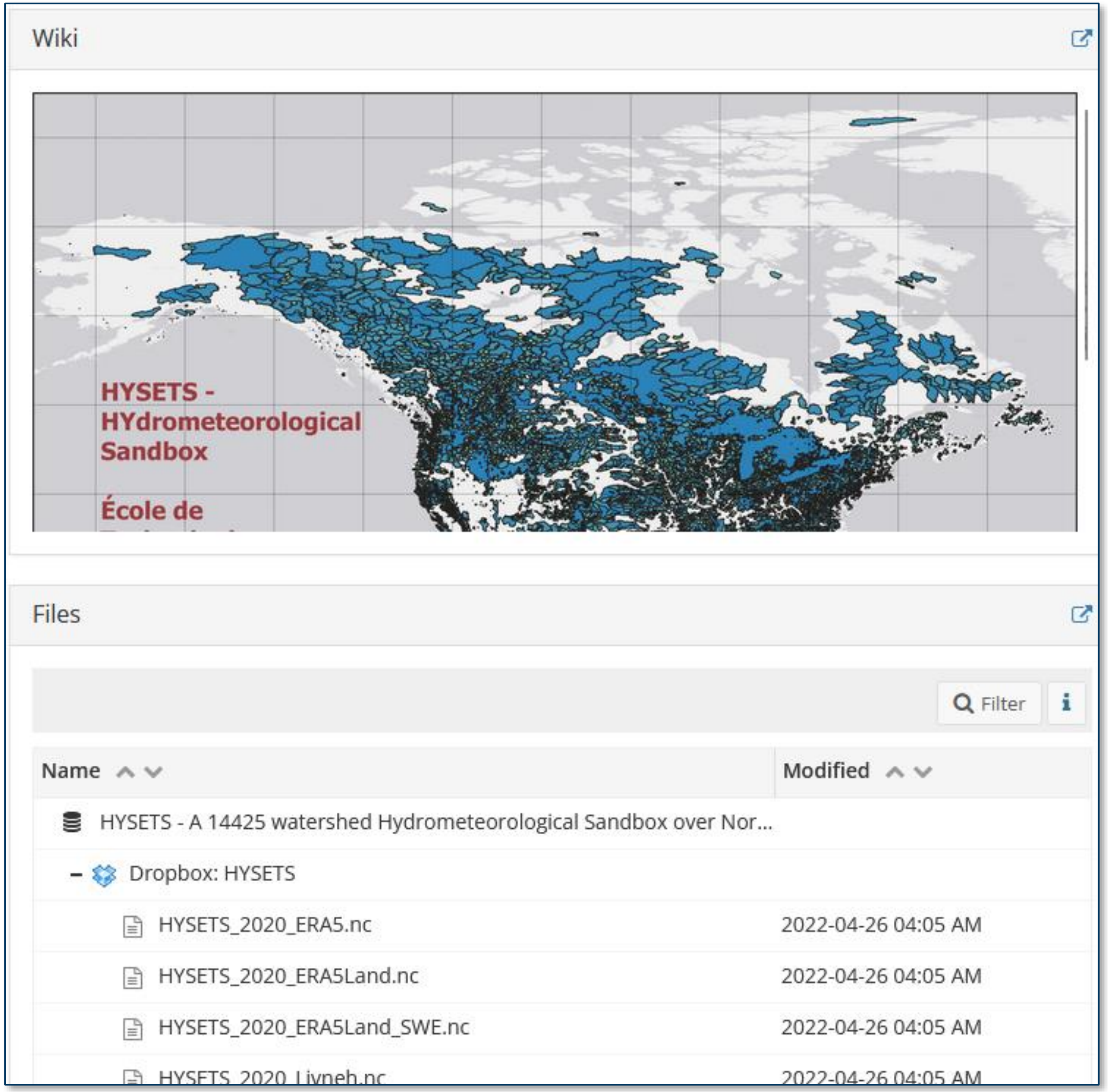
Historic floods in Canada



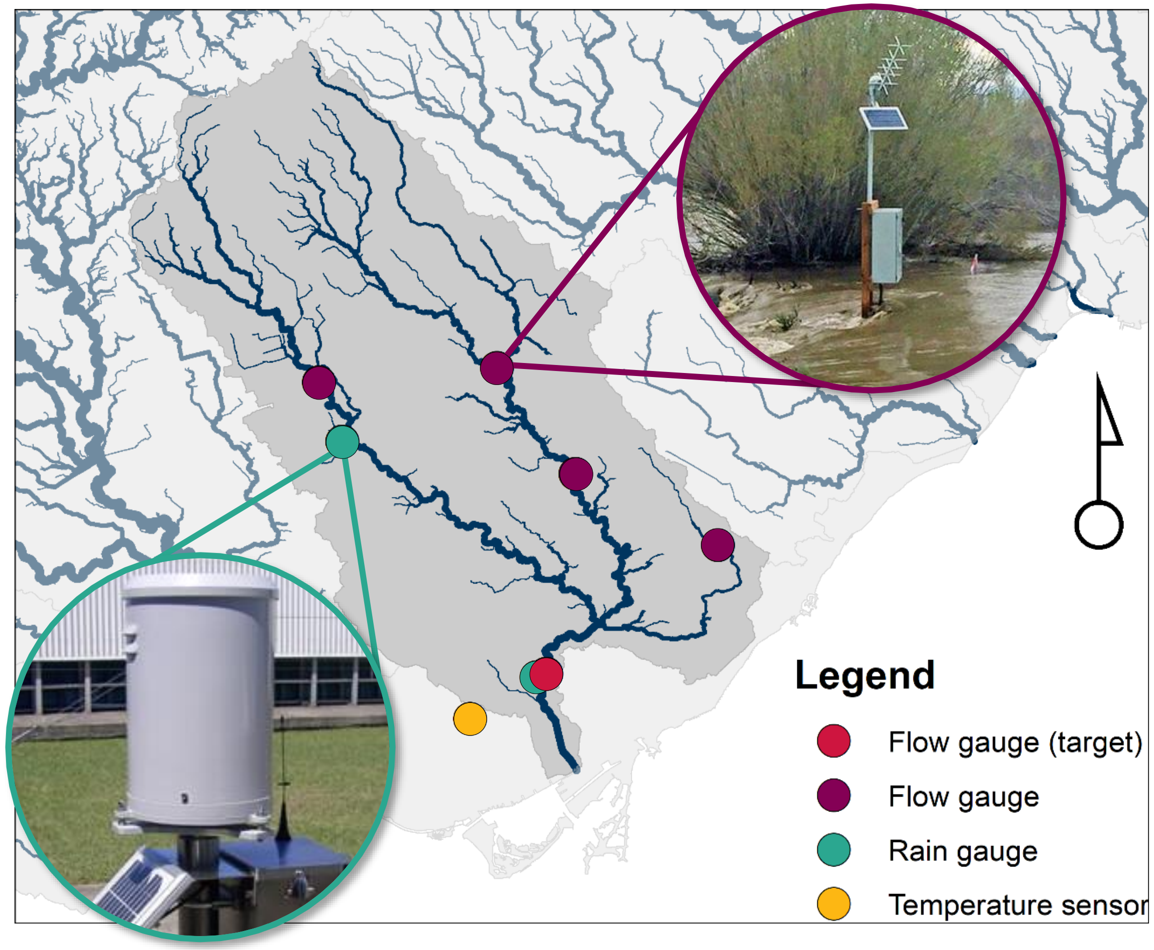
Recent flooding in NWT

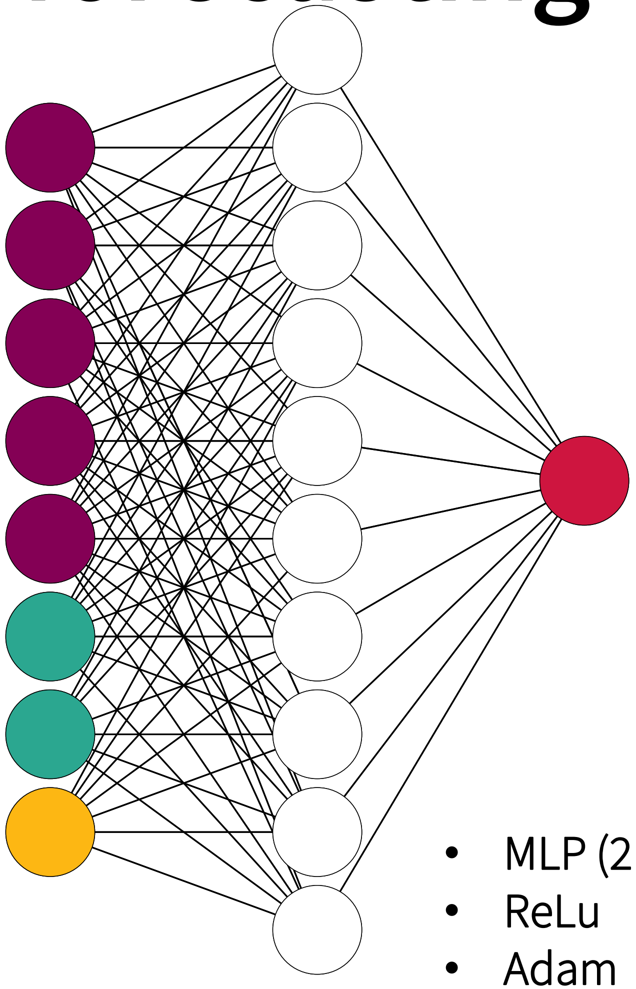
HYSETS

- Hydrometeorological dataset for North America assembled by Arsenault et al. (2020)
    - Contains **flow**, **temperature**, and **precipitation** daily timeseries'
    - Also contains catchment attributes, SWE, among others



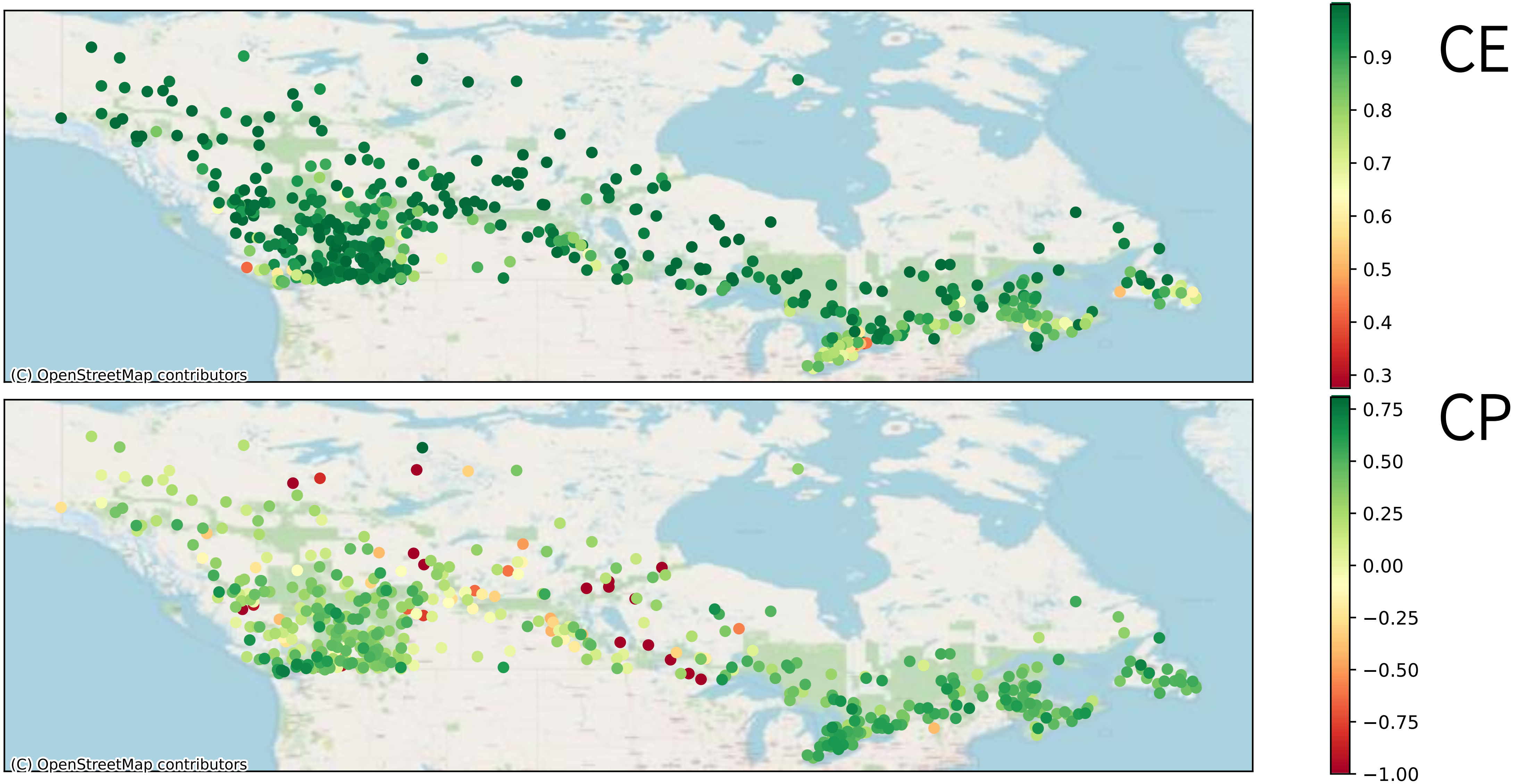
Machine learning-based flow forecasting





- MLP (21-16-1)
- ReLu
- Adam
- Dropout (0.2)
- Stop-training (0.25)

Baseline model performance



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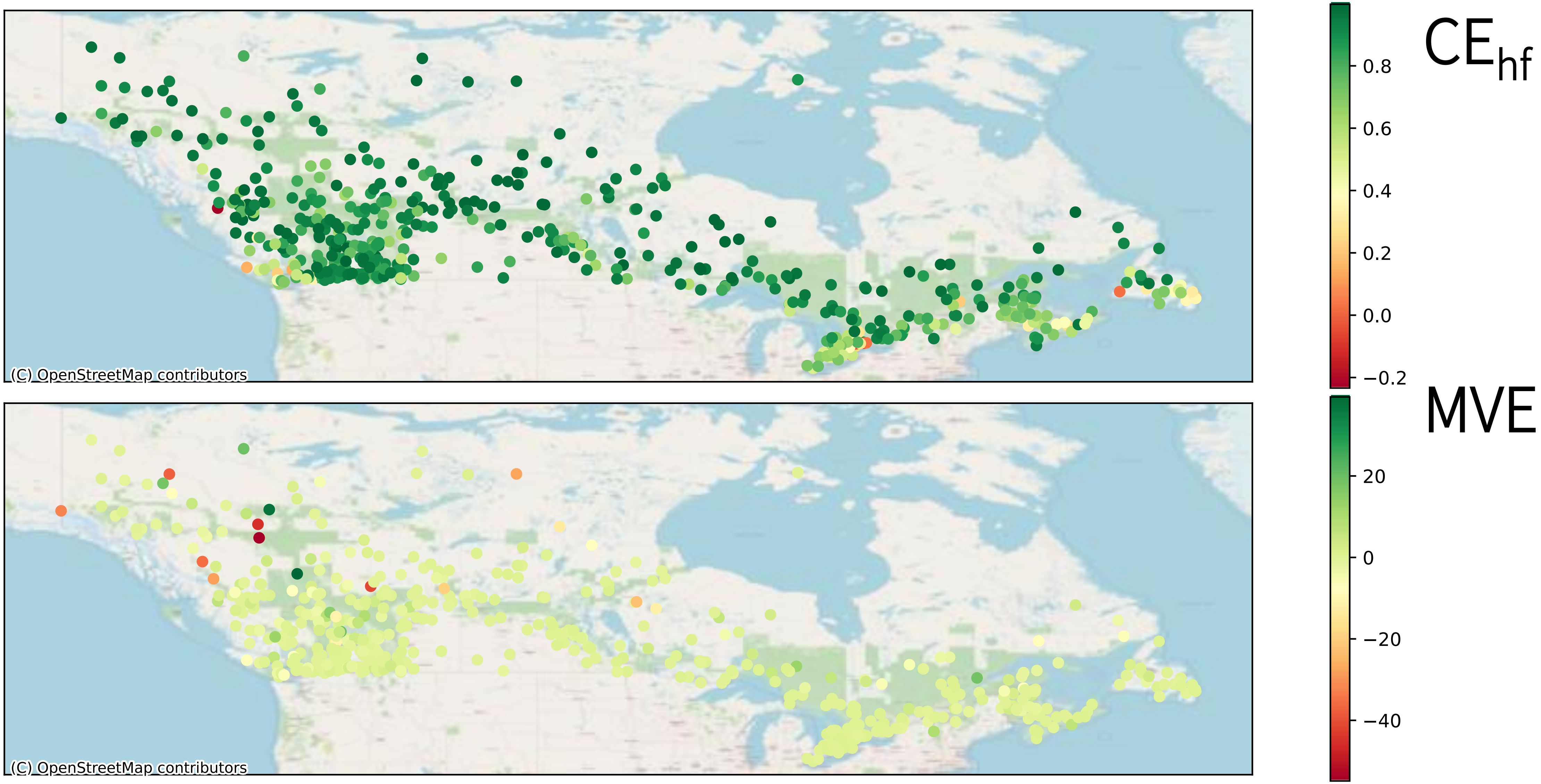
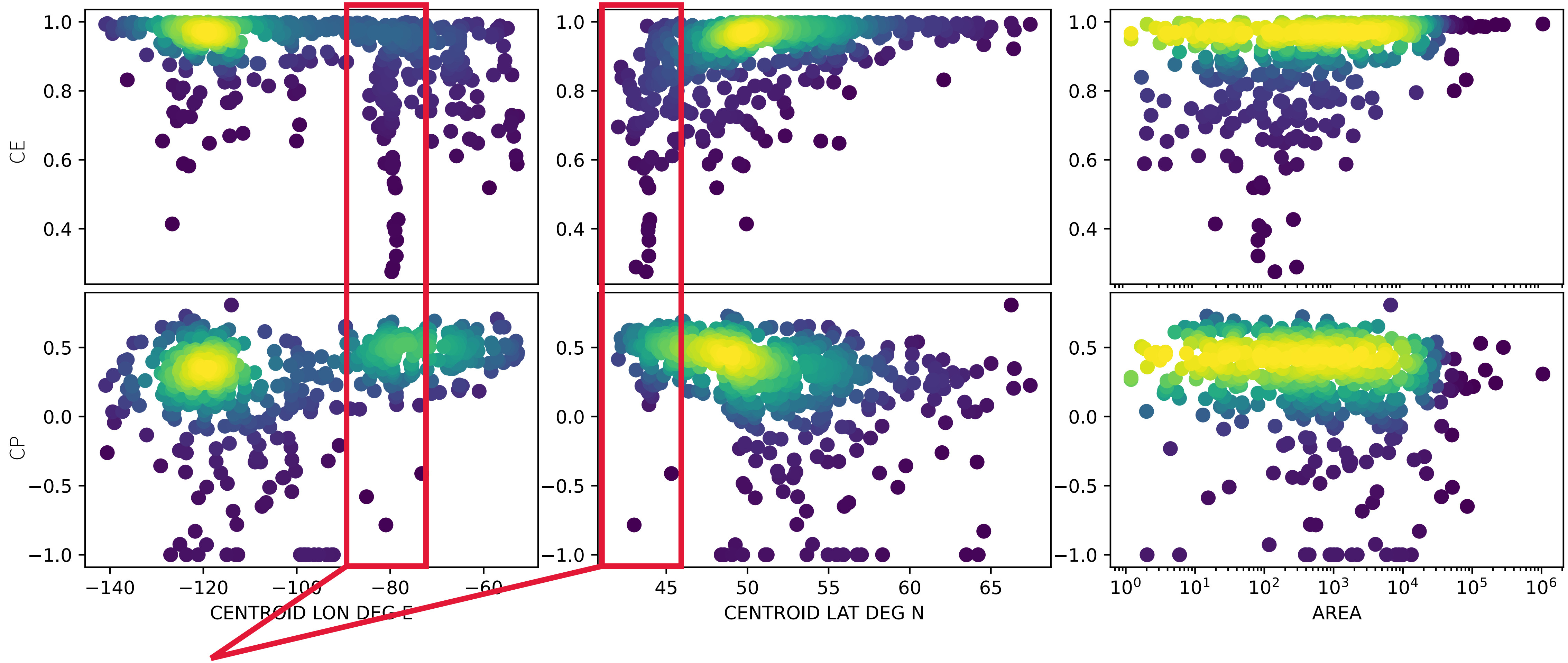


Performance versus catchment position and size

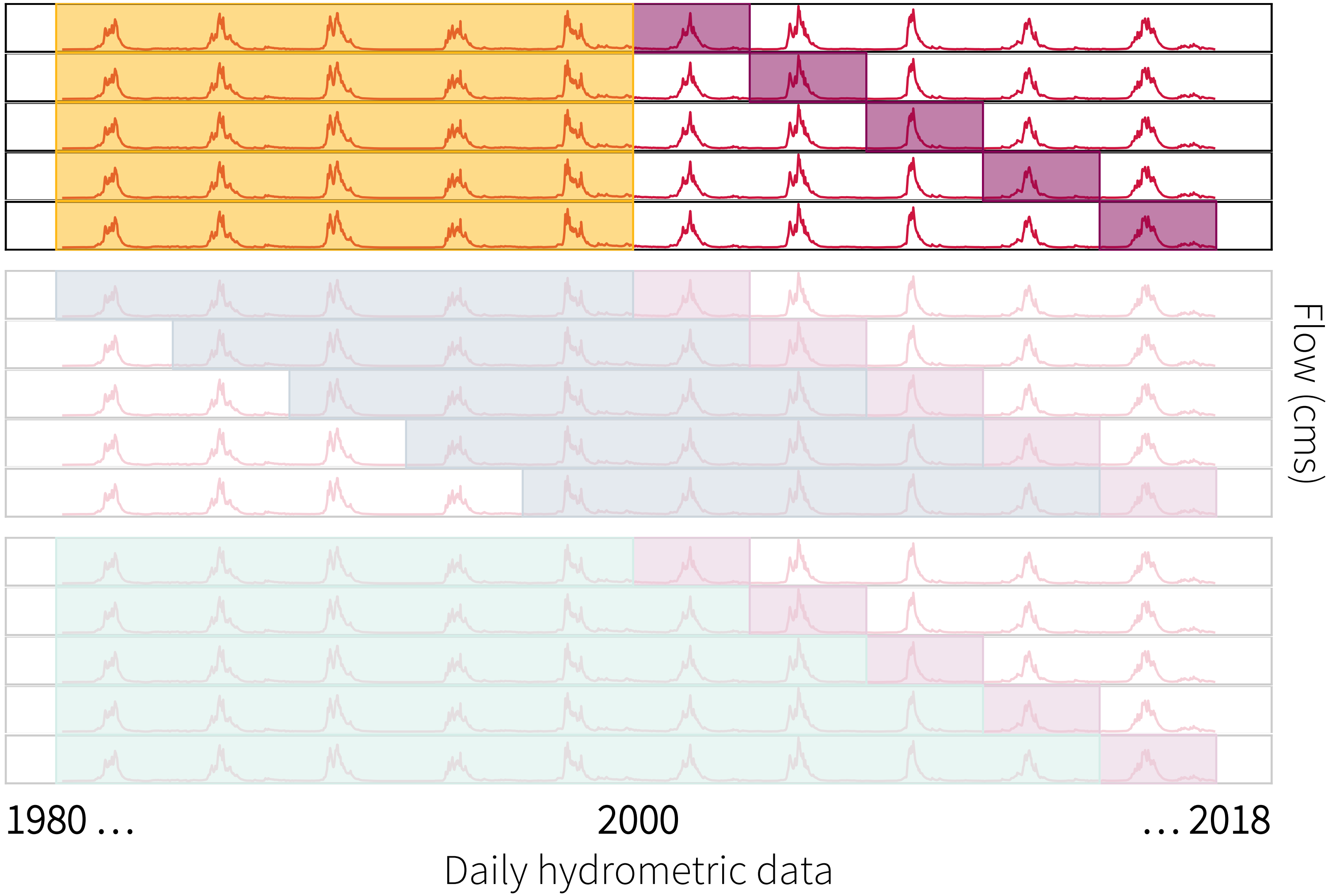


Catchments in Southern Ontario have poor CE, but fair CP

In order to understand how the performance of these models changes over time, so we set up the following experiment…

Quantifying change in model performance

- ‘Fixed training data’
  - Data from 1980-2000
- ‘Recent training data’
  - Most recent 20 years
- ‘All training data’
  - 1980 to validation year



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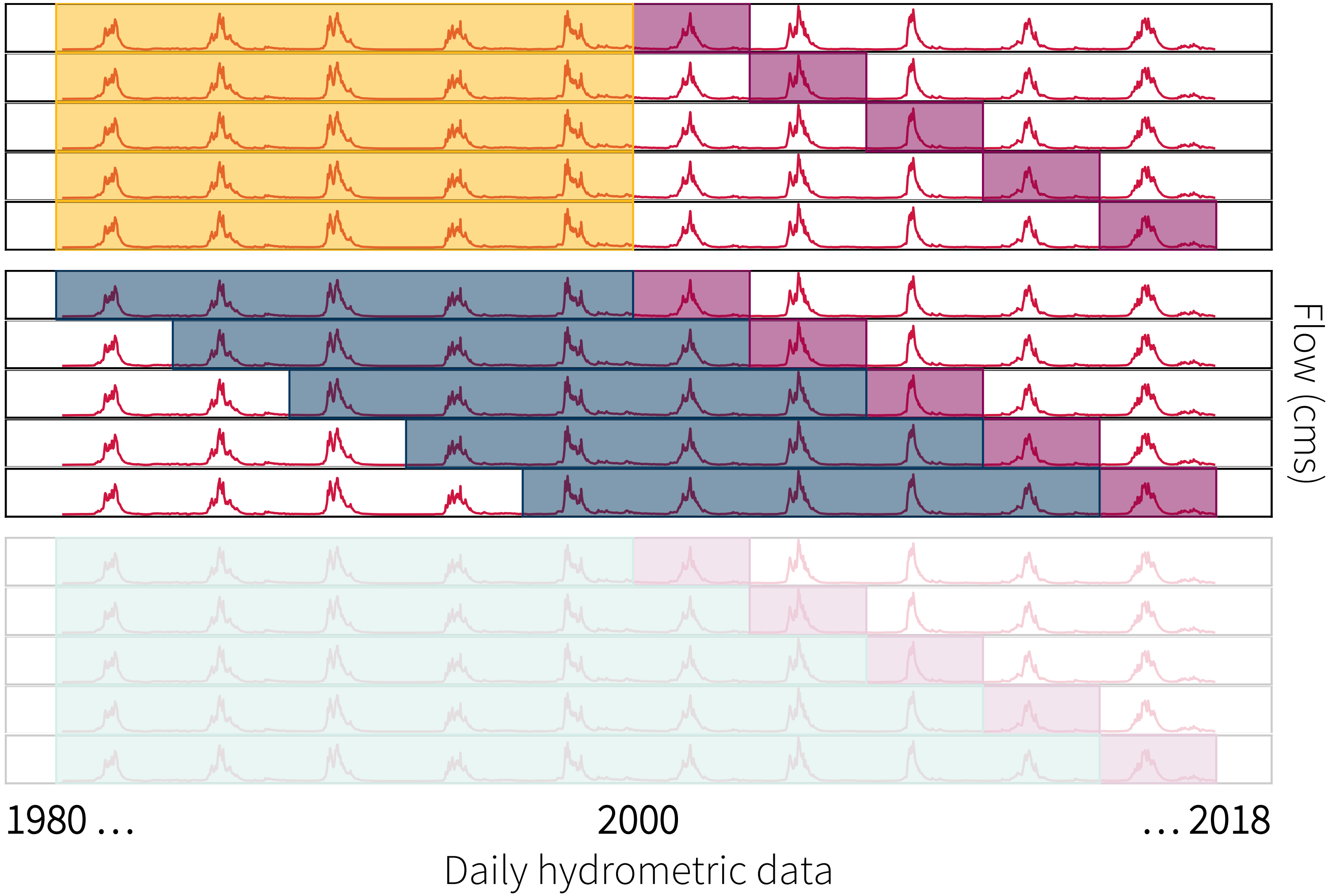

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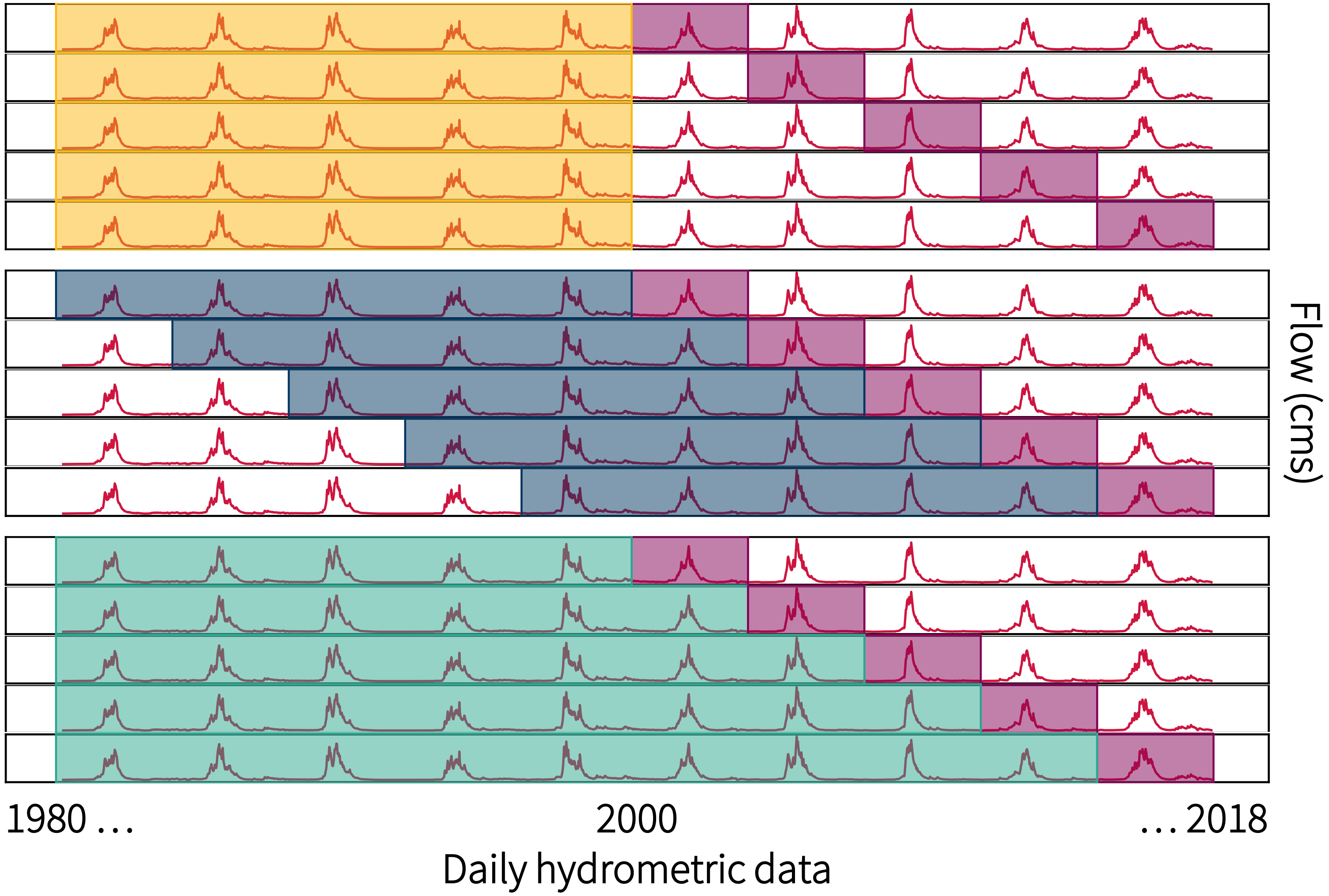
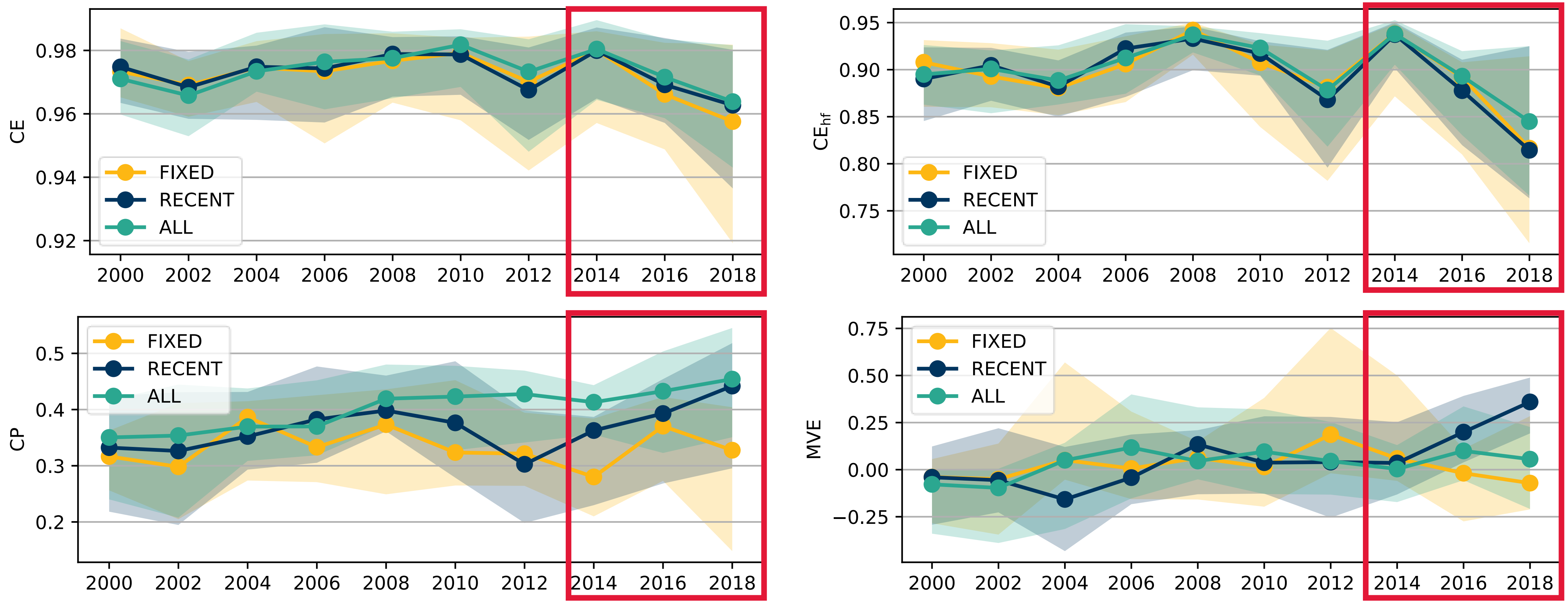


Temporal trends in model performance

CE – Coefficient of Efficiency
CE_{hf} – Coefficient of Efficiency for High Flows (Q>Q80)
CP – Coefficient of Persistence
MVE – Mean Volume Error



In addition to model performance, we want to understand whether feature importance is changing over time

Feature importance

2000

1. **Q_{t-1}**
2. P_{t-3}
3. Q_{t-2}
4. T_{t-4}

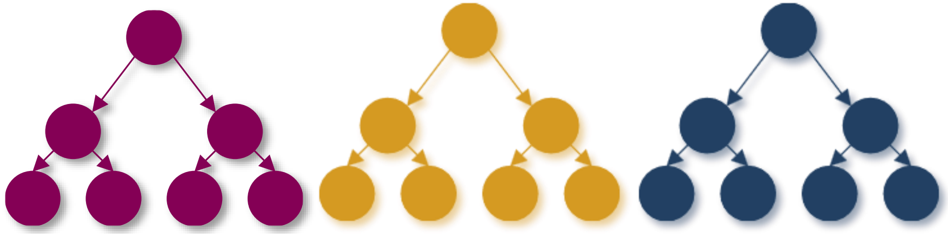
2001

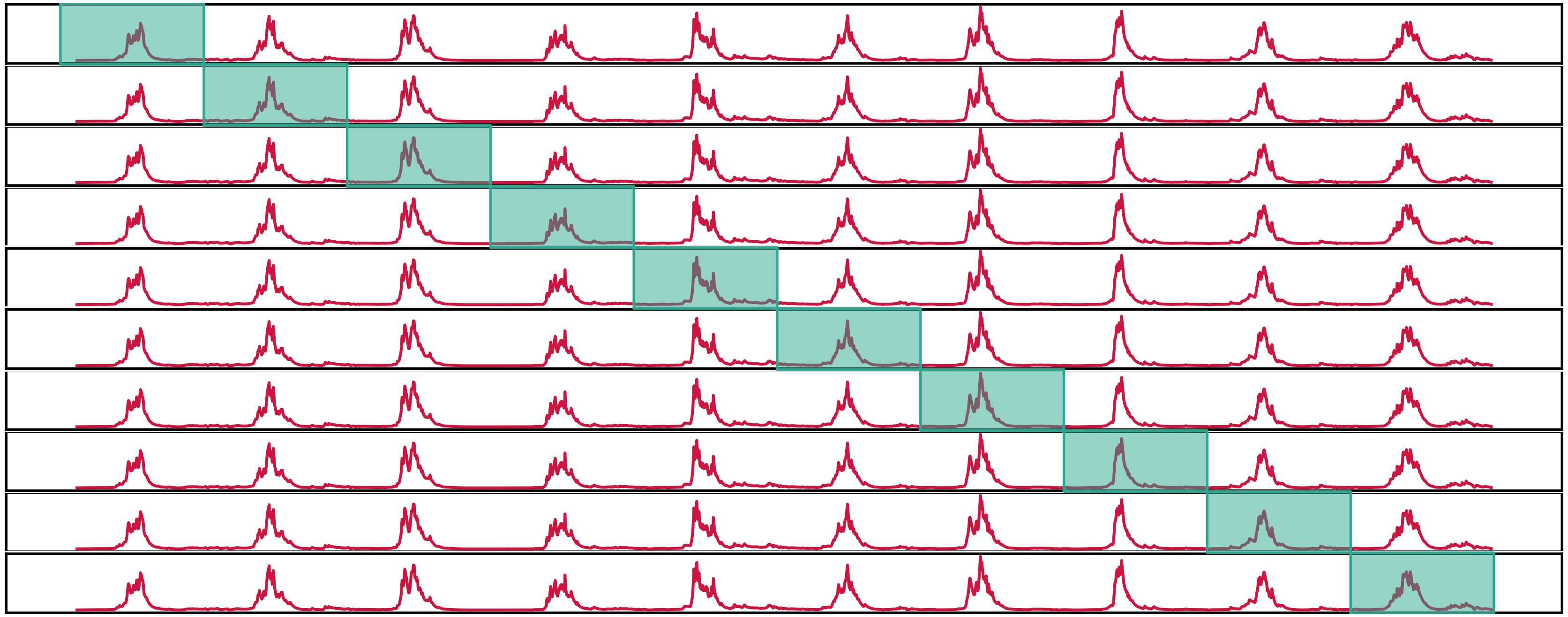
1. P_{t-3}
2. **Q_{t-1}**
3. Q_{t-2}
4. T_{t-4}

2002

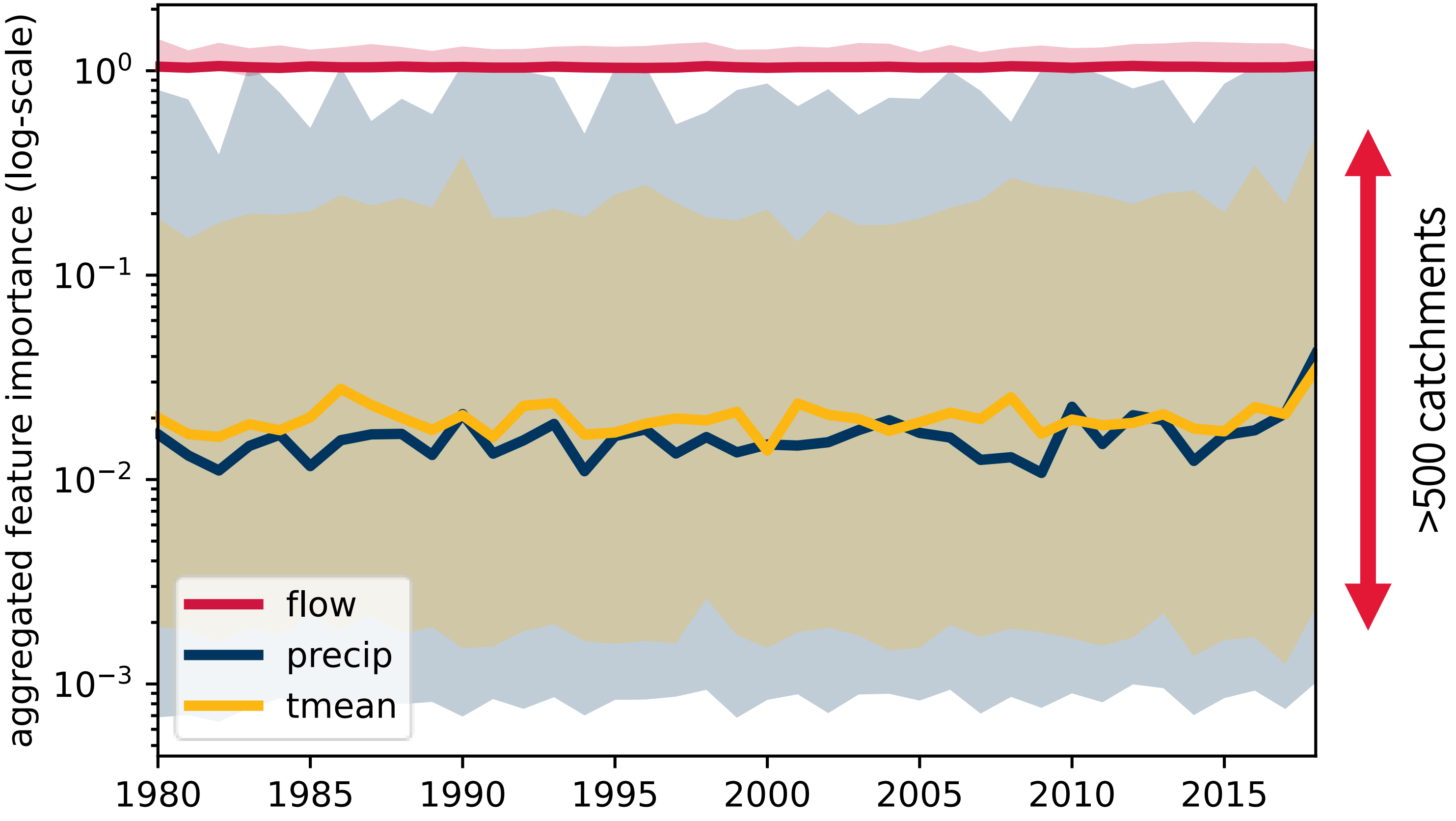
1. **Q_{t-1}**
2. P_{t-3}
3. Q_{t-2}
4. T_{t-4}

Random Forest-based feature importance





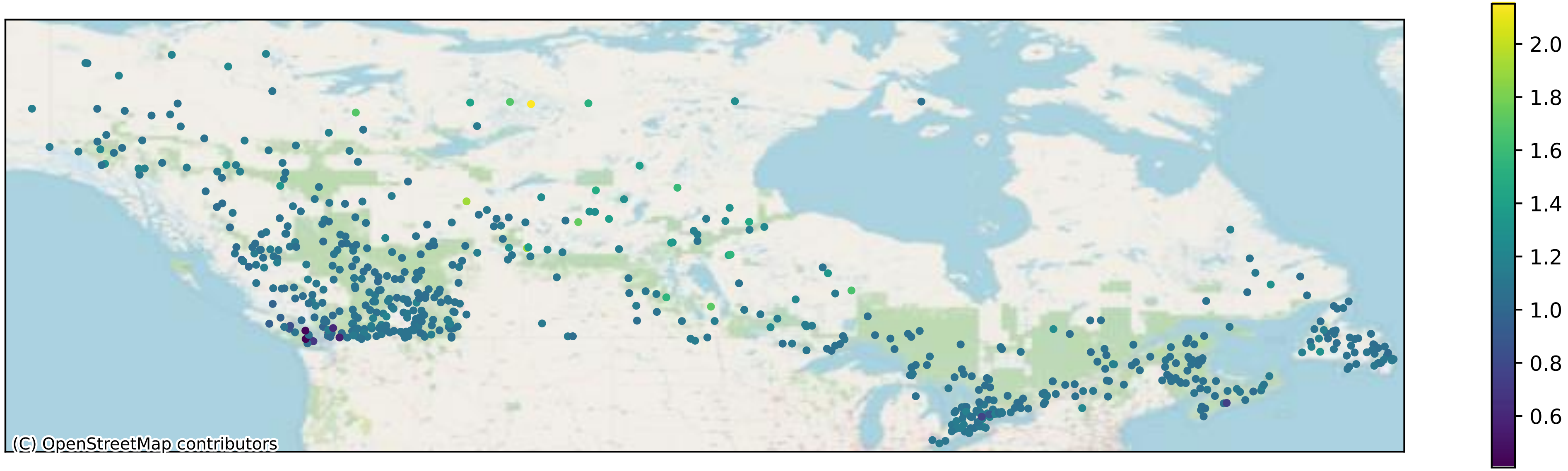
Temporal trends in feature importance



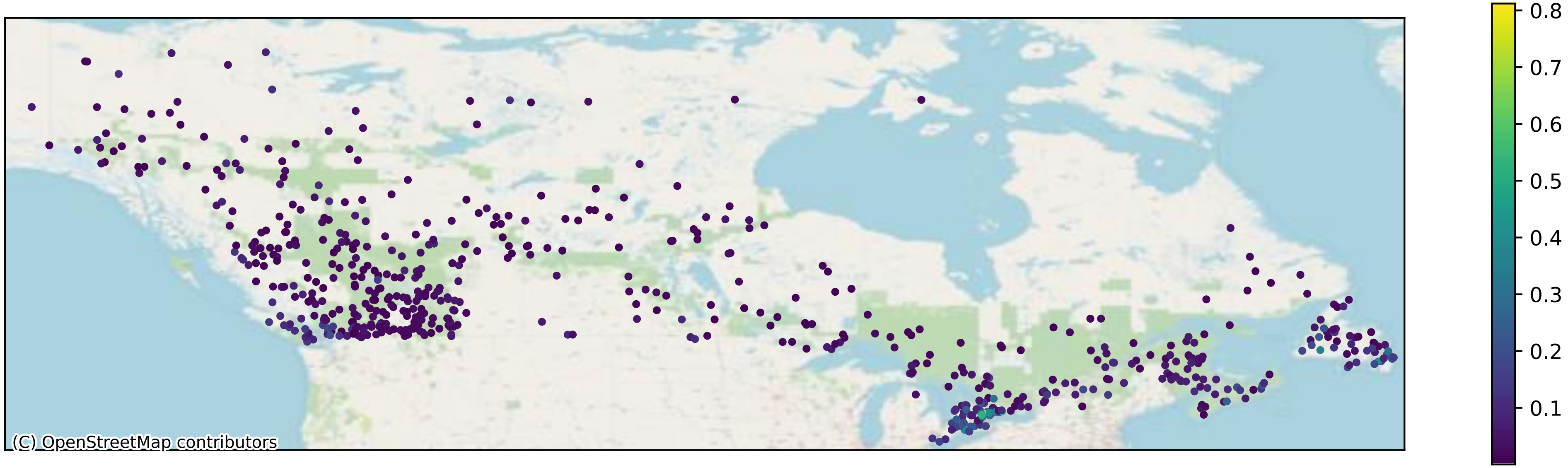
If we aggregate feature importance for the entire period, we can also search for spatial patterns…

Spatial trends in feature importance

Flow

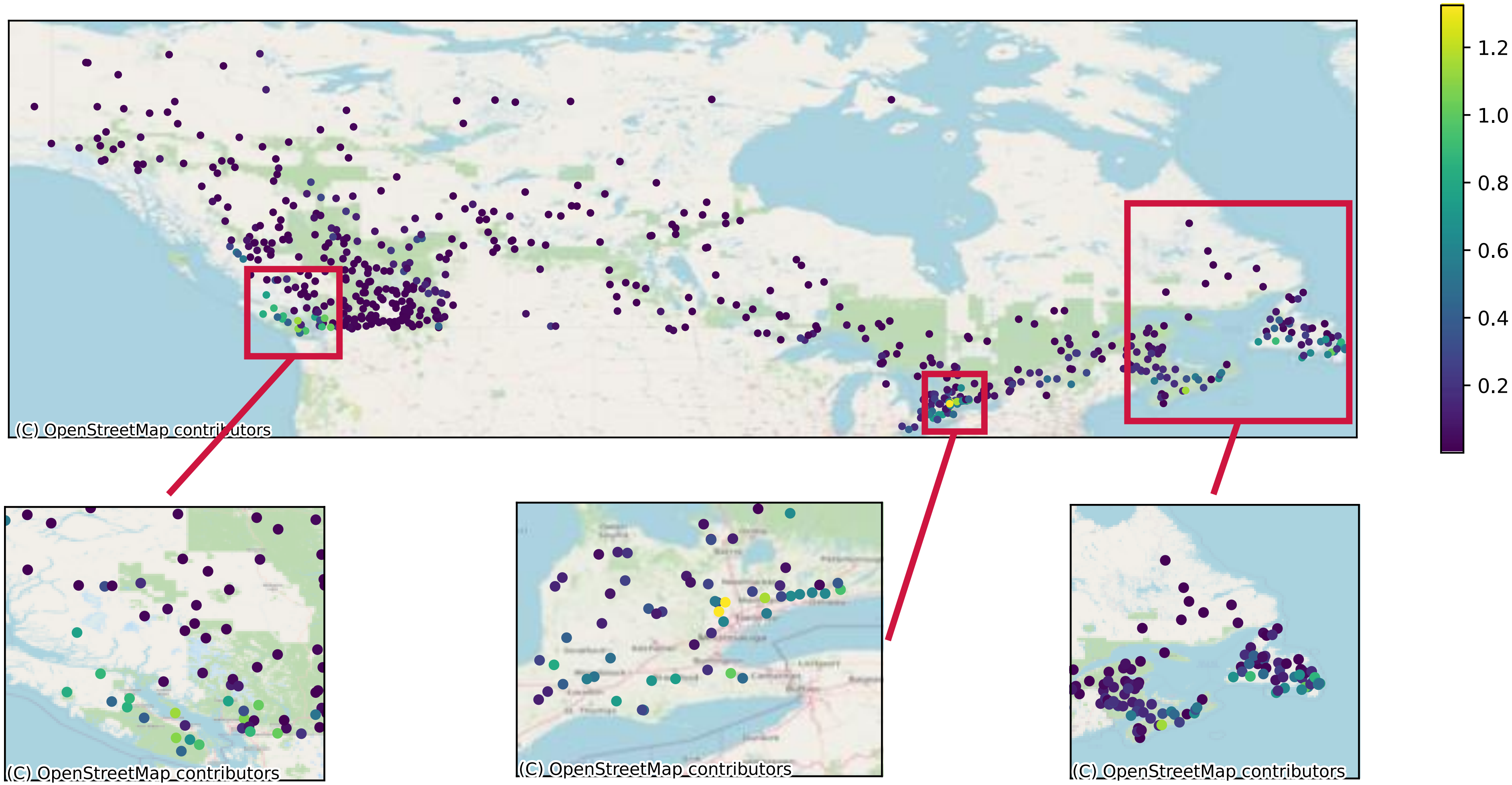


Temp.

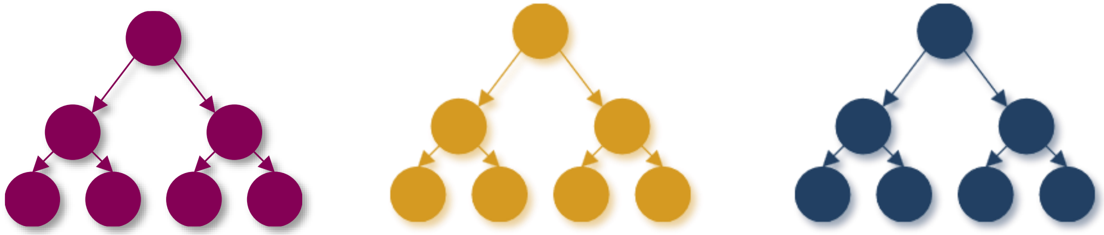


Spatial trends in feature importance

Precip.

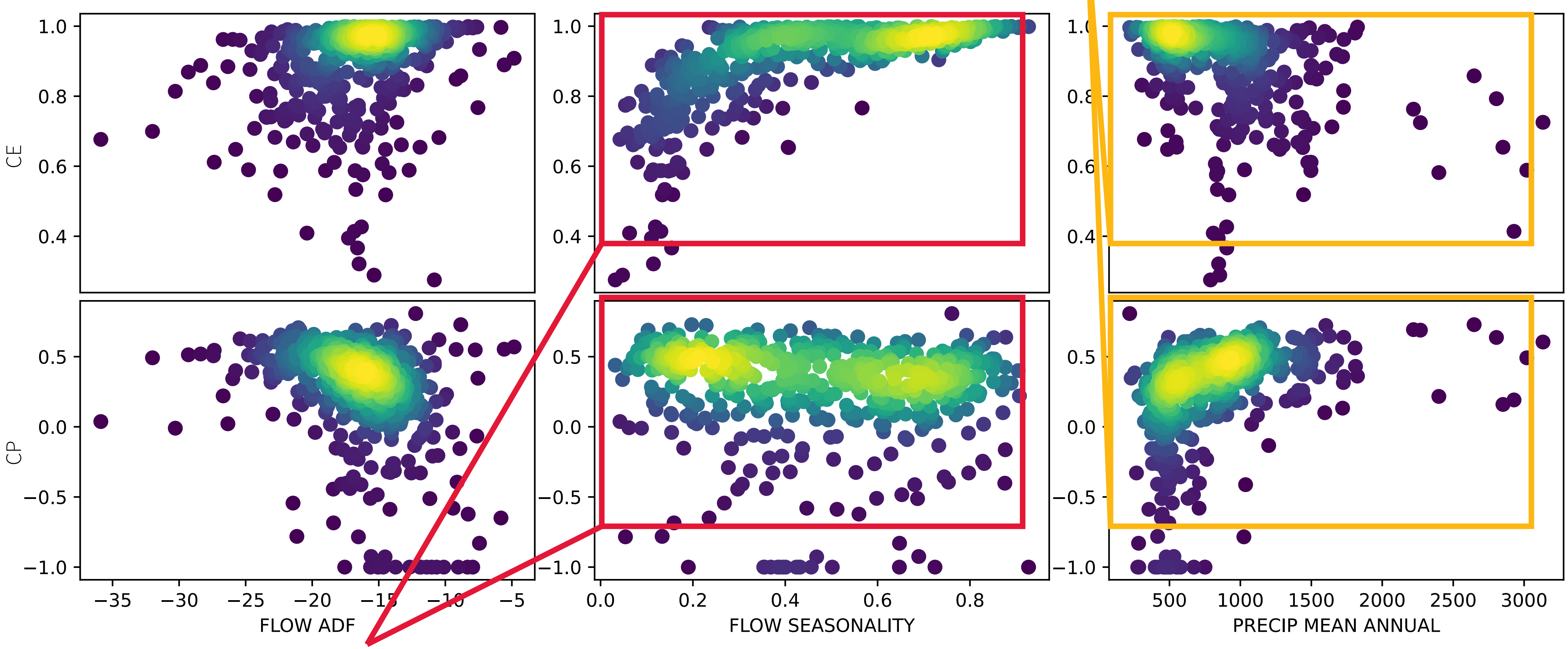


Next, we use a random forest to identify patterns between static watershed characteristics and model performance



Performance versus static catchment attributes

However, CP improves with increasing precipitation



CE improves with seasonality, but CP does not

Conclusions and future work

- Preliminary results confirm that updating model parameter values is important for maintaining performance year to year
- Feature importance does not change much year to year, but exhibits strong spatial patterns
- Relationships between CE and flow seasonality, CP and precipitation
- Future work will look at hydrological and regional connectivity between catchments, additional feature selection algorithms, and additional forcing data

Thank you

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Questions?

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