Short-term Cascade Inflow Forecasting using Causal Multivariate Variational Mode Decomposition (CVD)

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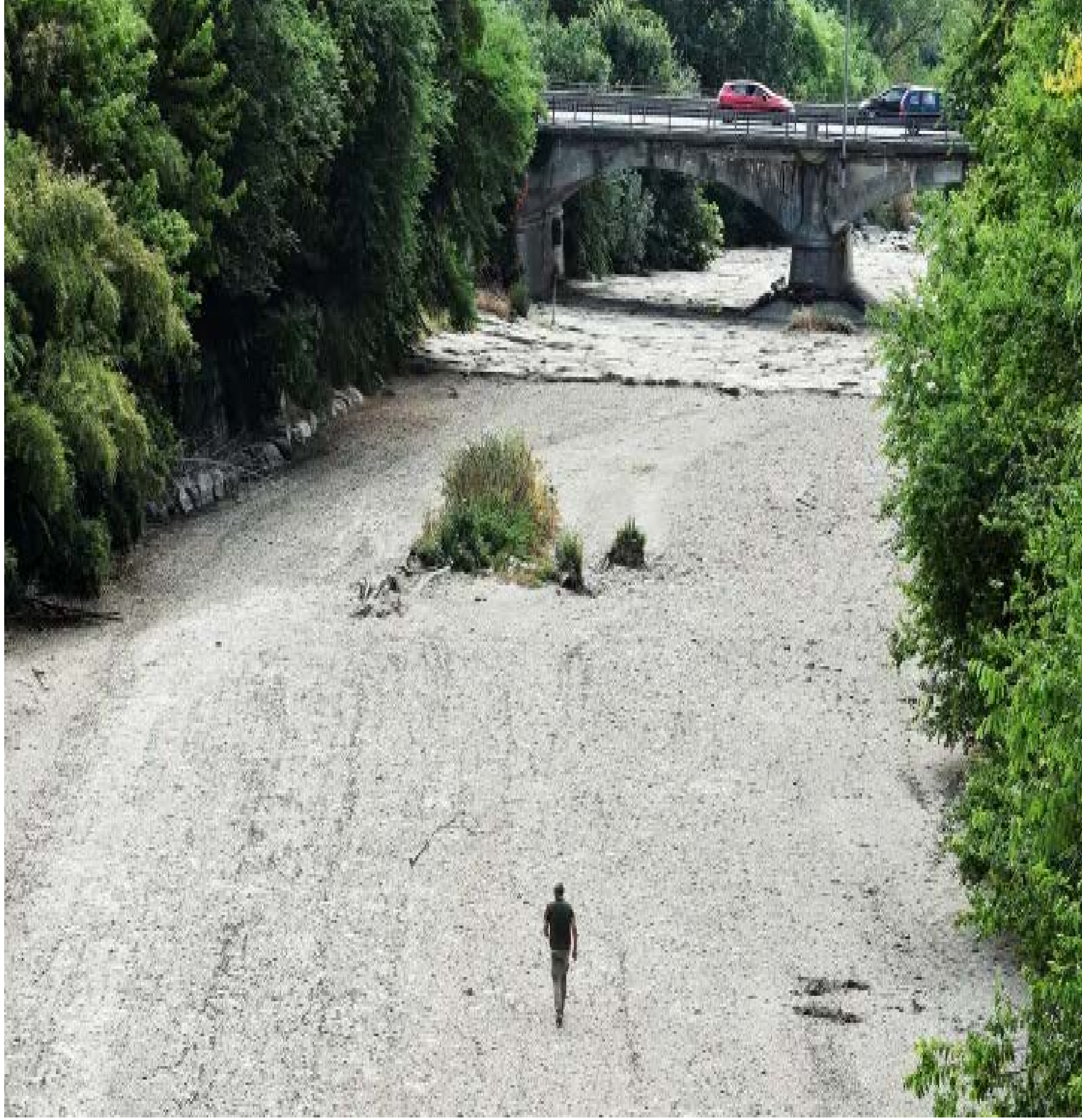
Motivation

Reliable and accurate inflow forecasting is essential to:

- Meet the energy balance
- Hydropower scheduling
- Comply with environmental constraints
- Enhance flood management
- Optimal water allocation for drinking or agriculture
- Facing climate crises



Po river, which experiences its worst drought for 70 years.

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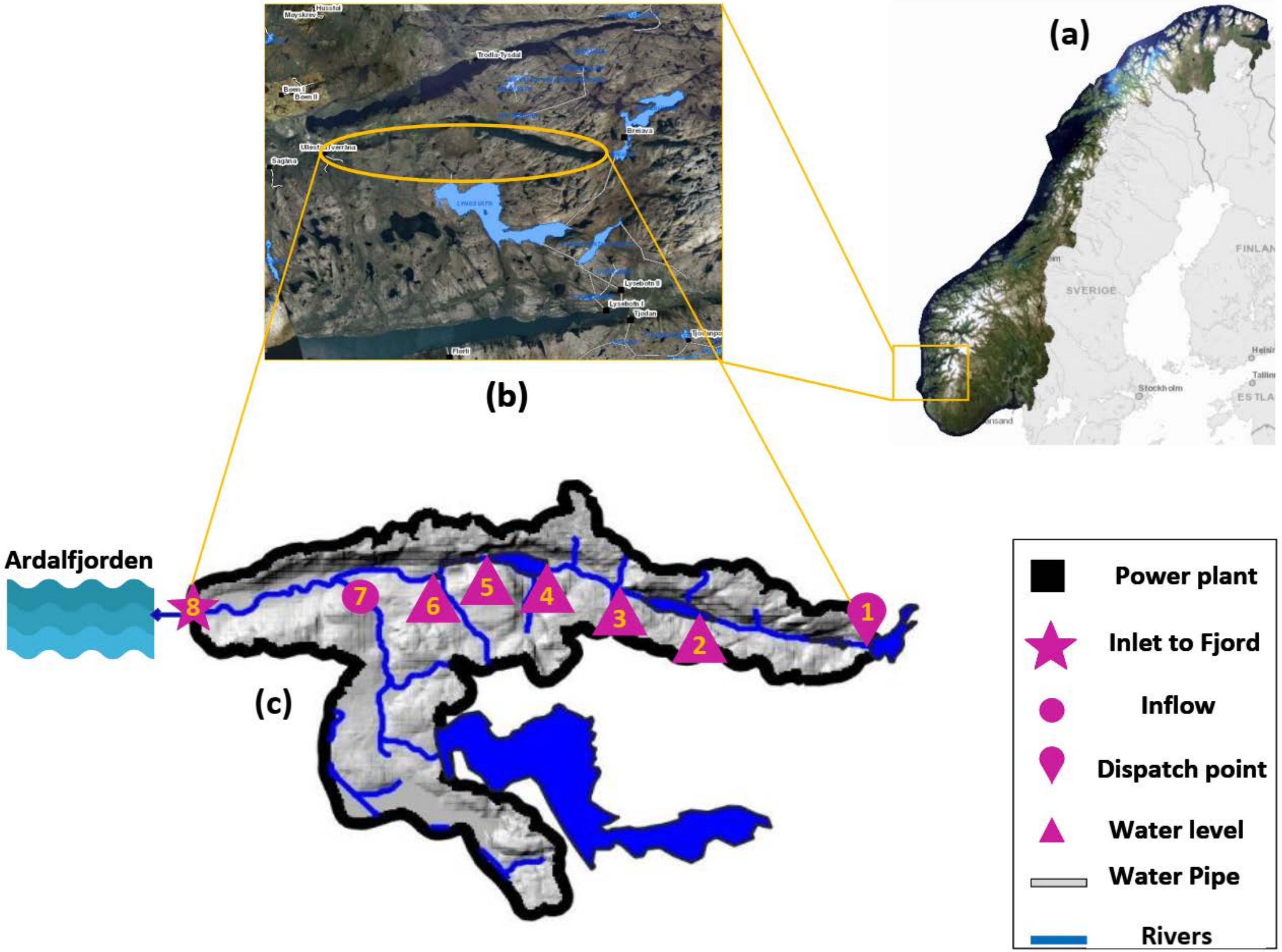
Use Case

- Location:

  Storåna river in Hjemland, Rogaland

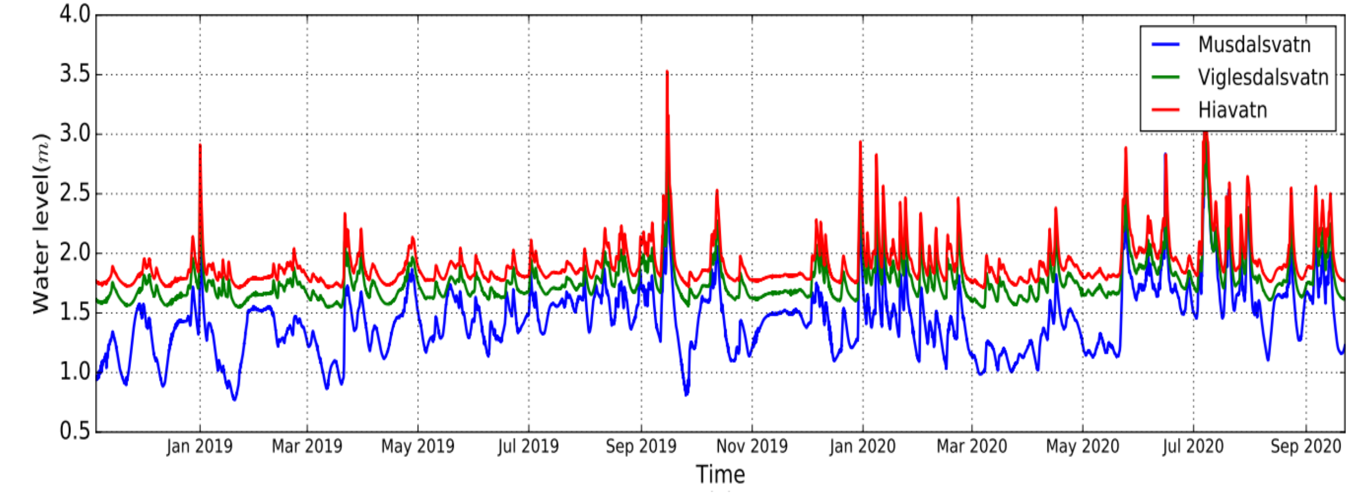
- Related Hydropower stations:

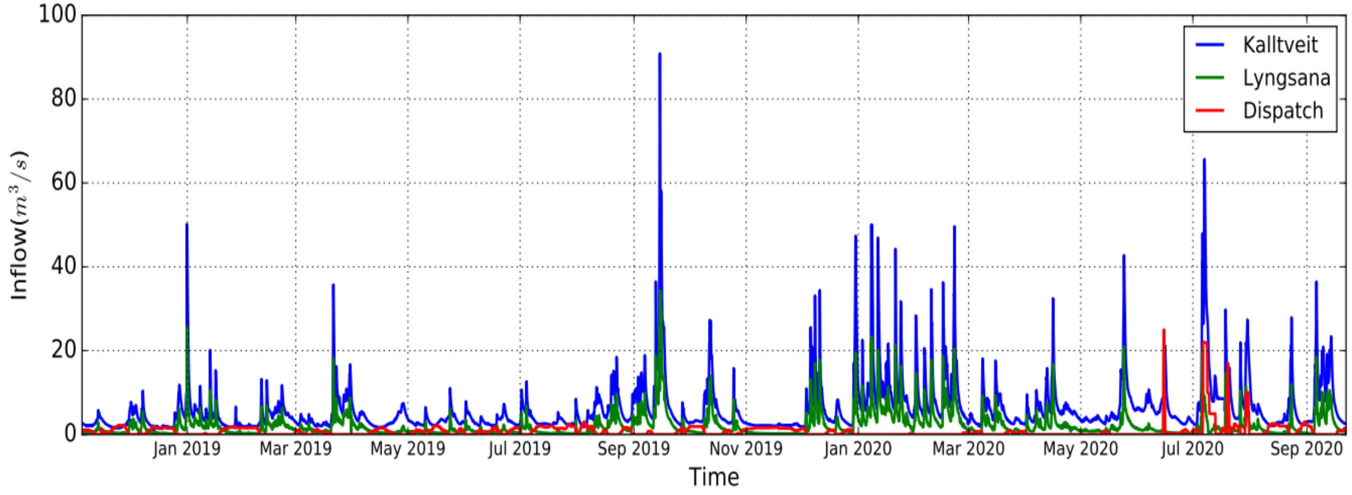
  Lyseboten I and Lyseboten II



Use Case

- Collected data:
  - Hourly historical inflow
  - Hourly meteorological data
  - Hourly hydrological data
  - Hourly simulated hydrological data provided by HBV





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Inflow Fortecsating Challenges

- Inflow forecasting is a highly stochastic problem.
- Inflow is related to complex topographical, hydrological, and metrological aspects.
- Most of models are heuristical and are highly depends on historical data. However, the climate change brings more surprises.

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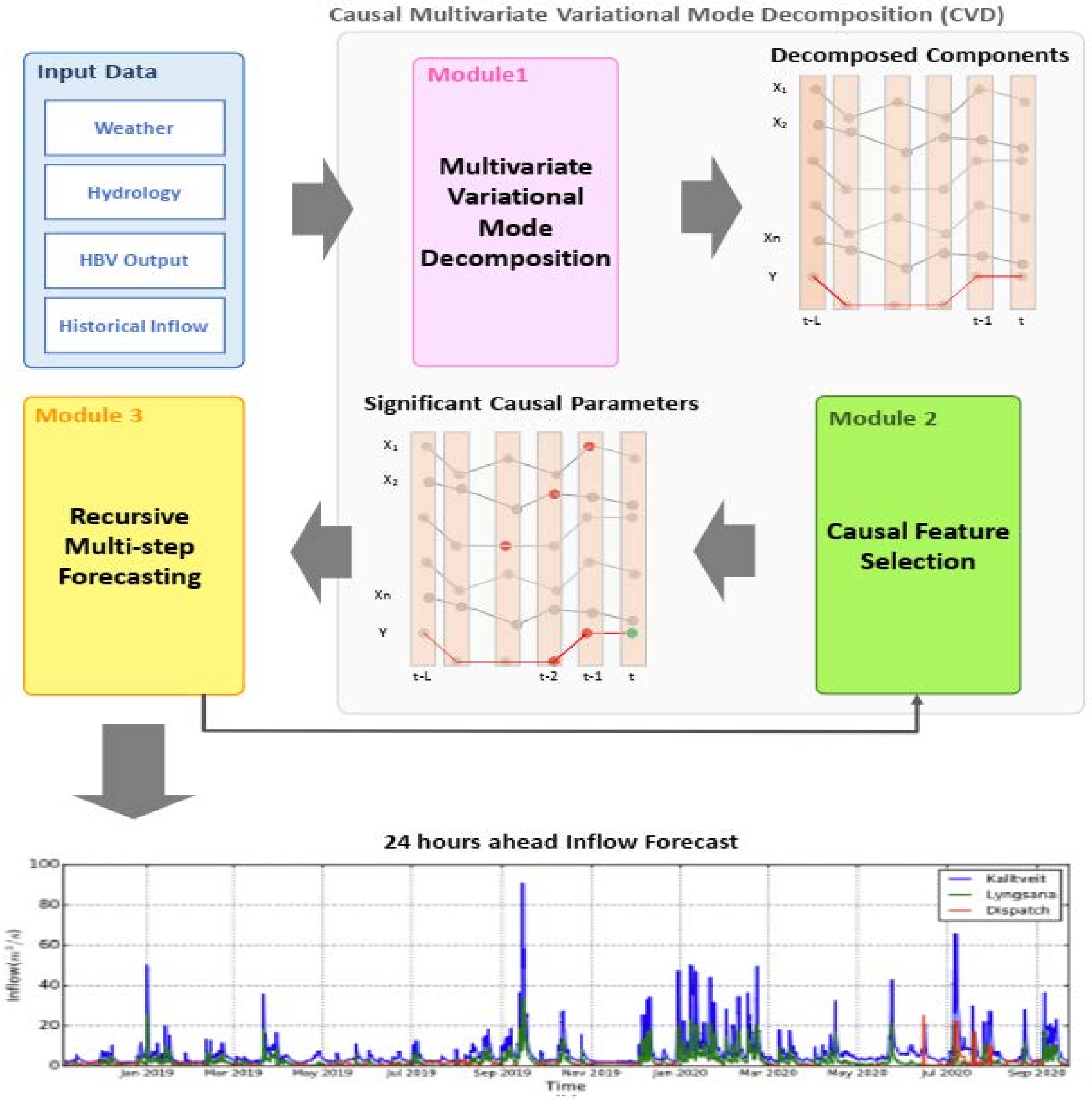
Methodology

- Module 1: Multivariate Variational Model Decomposition
  - It is a self-adaptive technique designed for nonlinear and non-stationary data
  - Eliminate less useful data or noise
- Module 2: Causal Feature Selection
  - Improve information richness by removing irrelevant and redundant variables.
  - Reveal cause and effect relationships that govern complex systems

Methodology

Causal Multivariate Variational Mode Decomposition (CVD)



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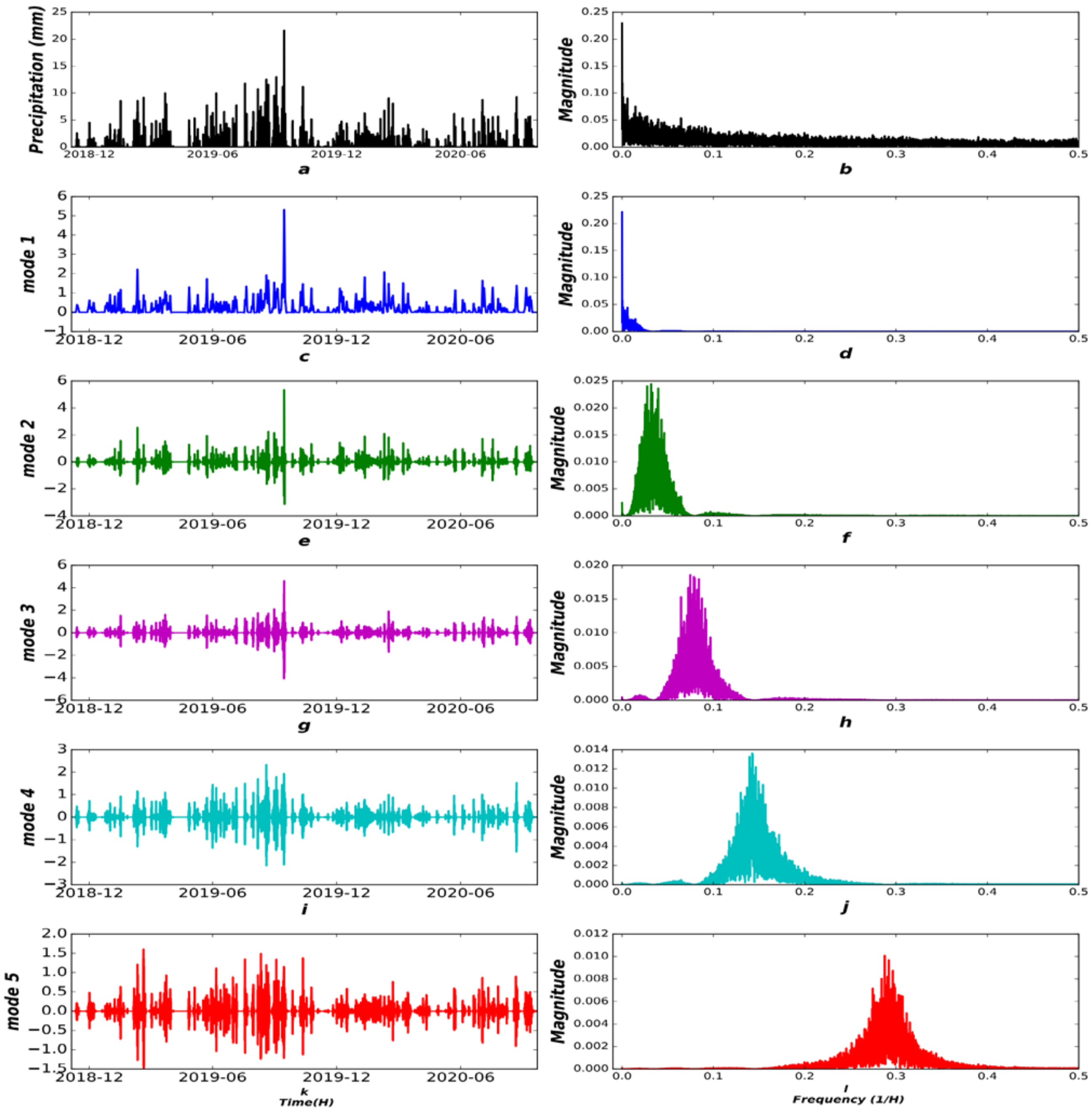
Results

Module 1 Output: Multivariate Variational mode decomposition

Here we only show the precipitation time-series for location 8:

- Each original time-series decomposed to 5 major subseries named mode
- Each mode contains a specific frequency band of the original time-series



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Results

Module 2 Output: Causal Feature Selection

33 parameters x 5 modes x 24 hr = 3984 values

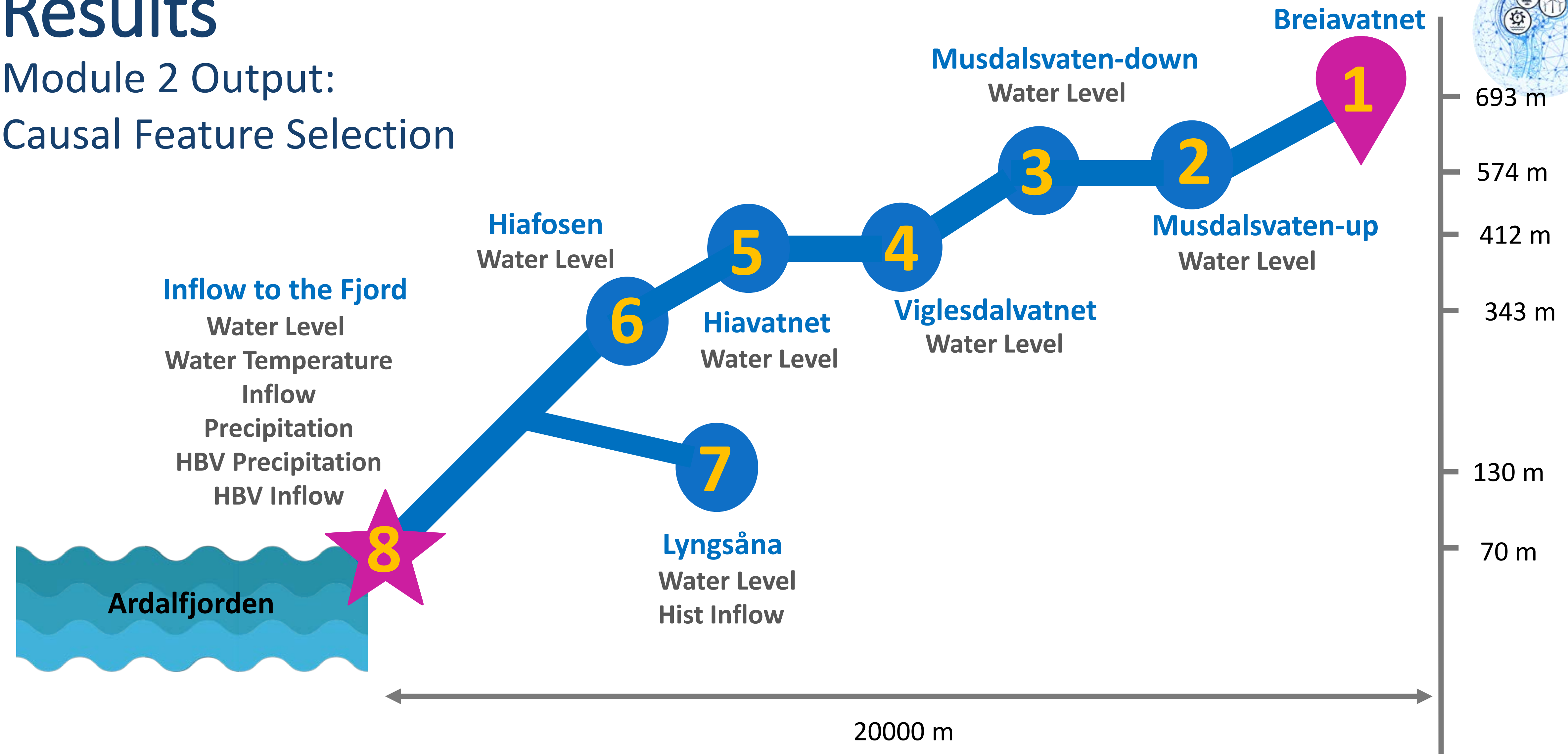
3984 values >>> 33 causal values

SIGNIFICANT SELECTED MODES BY CAUSAL FEATURE SELECTION ALGORITHM

Variable	Location	Mode	Lag
Precipitation	Location 8 Actual (Kalltviet)	3	4
	Location 8 HBV	3	2
		5	4
Inflow	Location 7 (Lyngsåna)	3	1
		4	4
		5	3
	Location 8 HBV	1	5
		4	1
Difference Inflow	Location 8-Location 1 actual	1	1
		2	1
		3	5
		4	5
		5	1
Water temperature	Location 8 actual	1	1
Water level	Location 3 Actual (Musdalsvatn down stream)	2	5
	Location 7 Actual	1	5
		3	1
		4	1
		5	1
	Location 6 Actual (Hiafossen)	3	5
		4	3
		5	2
	Location 5 actual (Hiavatn)	1	1
		2	1
		3	5
		4	1
	Location2 Actual (Musdalsvatn)	3	3
	Location 4 Actual (Viglesdalsvatn)	2	1
		5	5

Results

Module 2 Output:
Causal Feature Selection



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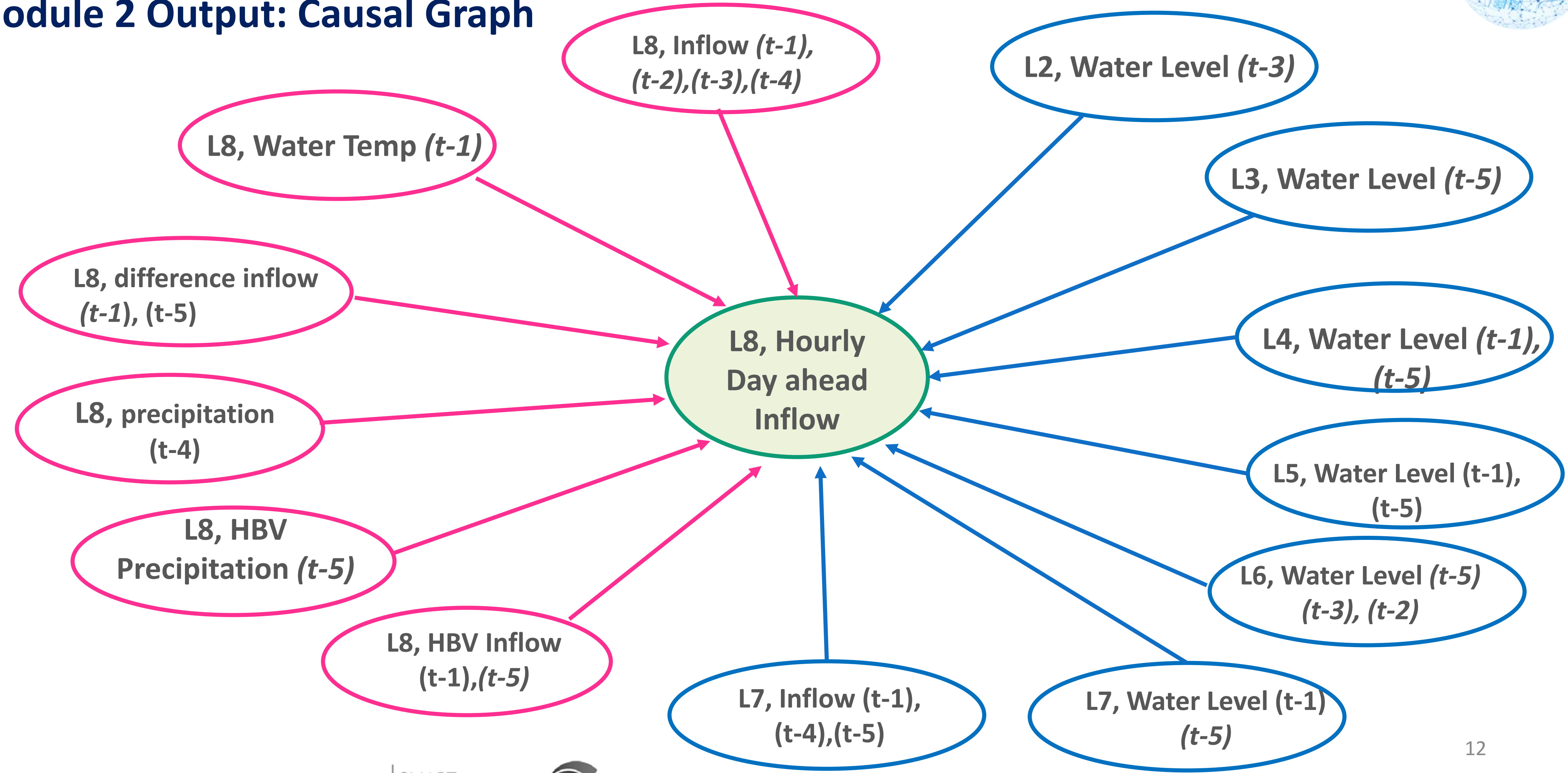
Results

Module 2 Output: Causal Graph



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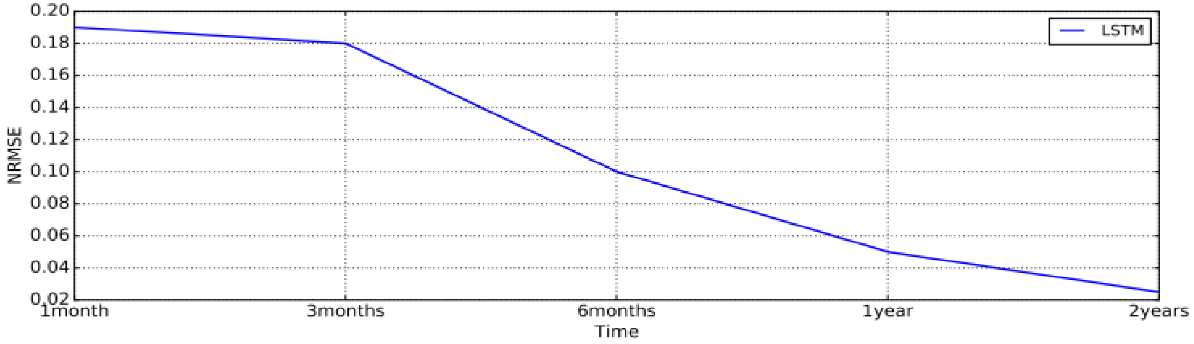
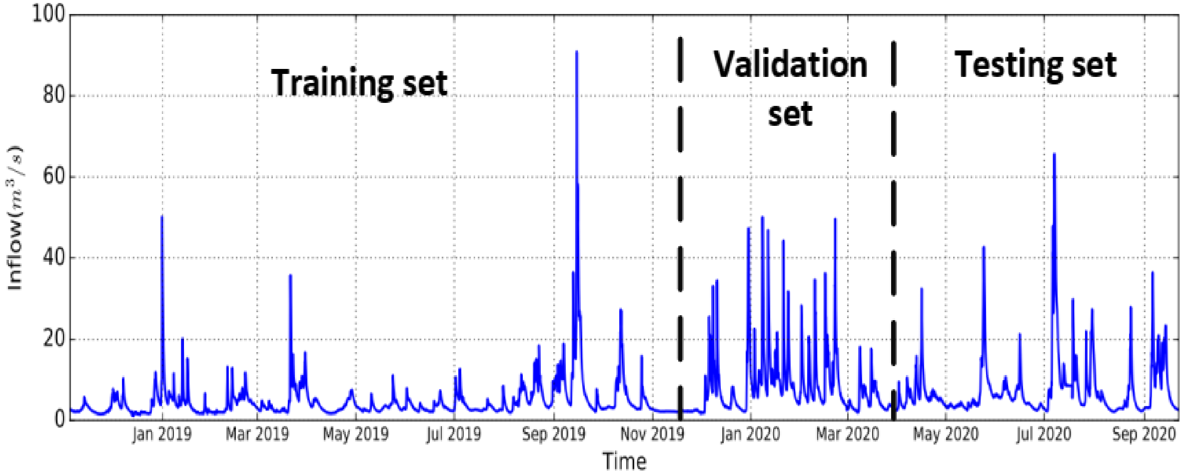
Results

Module 3 Outputs: Forecasting Results





Model	Data	NRMSE
CVD-LSTM	weather+ hydrological data+HBV	0.45
CVD-LR	weather+ hydrological data+HBV	0.44
CVD-RF	weather+ hydrological data+HBV	0.34
CVD-MLP	weather+ hydrological data+HBV	**0.32**

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Results

Hourly day ahead results average over 1 month period.

Data	Model	NRMSE	Computation time(s)
weather	CVD-MLP	0.5	60
weather+ hydrological data	CVD-MLP	0.45	62
weather+ hydrological data+HBV	CVD-MLP	**0.32**	**61**

36% improvement

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Results

Hourly day ahead results average over 1 month period.

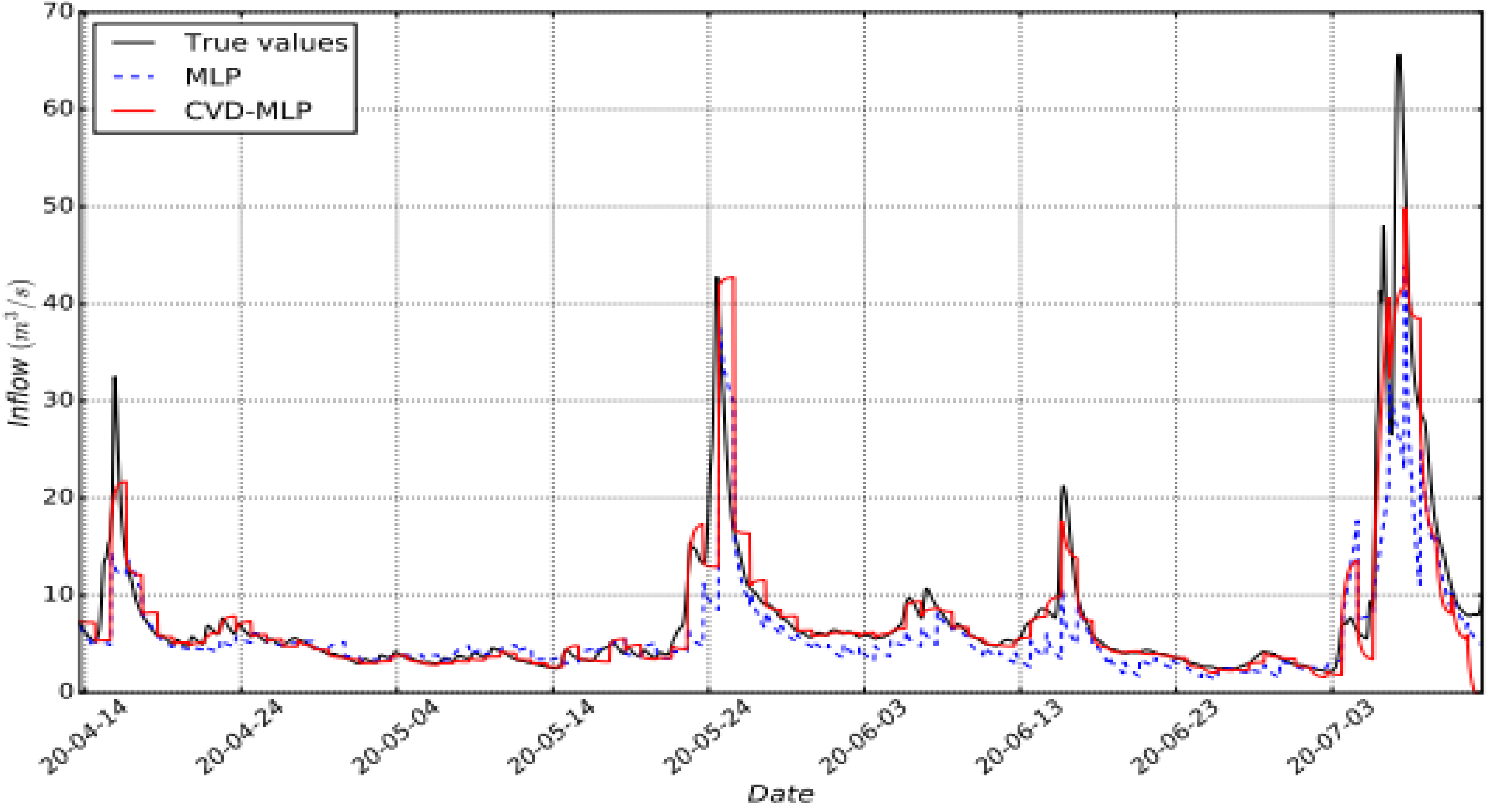
Data	Model	NRMSE	Computation time(s)
weather	MLP	0.8	60
weather+ hydrological data	MLP	0.6	90
weather+ hydrological data+HBV	MLP	0.6	120
weather+ hydrological data+HBV	CVD-MLP	**0.32**	**61**

60% improvement

46.6% improvement

Results

Forecast results for 3 months in spring and summer



Conclution

- The developed preprocessing framework CVD has:
  - Better accuracy for inflow forecasting
  - Less computation time
  - Reduce curse of dimensionality using causal inference
- **Future works**
  - Help in discharge decision making: release how much water and when?
  - Performing hydropower scheduling problem using the more accurate inflow forecast model and scenario reduction techniques.

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Publications

- Yousefi, Mojtaba, et al. "Day-ahead inflow forecasting using causal empirical decomposition." Journal of Hydrology, 128265, 2022.

- Jinghao Wang, et al. " Self-organizing maps for scenario reduction in long-term hydropower scheduling " , IEEE IECON, 2022.

- Cheng, Xiaomei, et al. "Inflow Forecasting Based On Principal Component Analysis and Long Short Term Memory." *IEEE DASC,* 2021.

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