Uncertainty in modeling pollutant build-up and wash-off processes at the urban catchment scale

Zhaokai Dong, Ph.D, Civil and Environmental Engineering, Western University
Pradeep Goel, Ph.D., Ontario Ministry of the Environment, Conservation and Parks
Clare Robinson, Ph.D, Civil and Environmental Engineering, Western University

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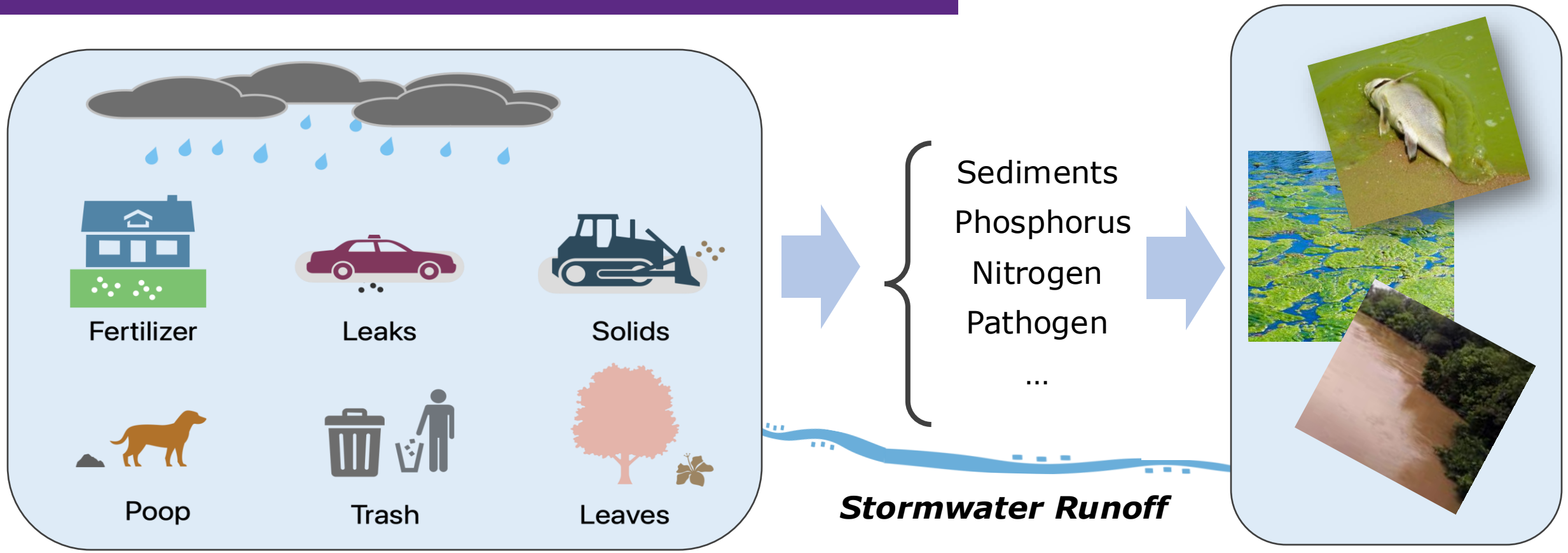
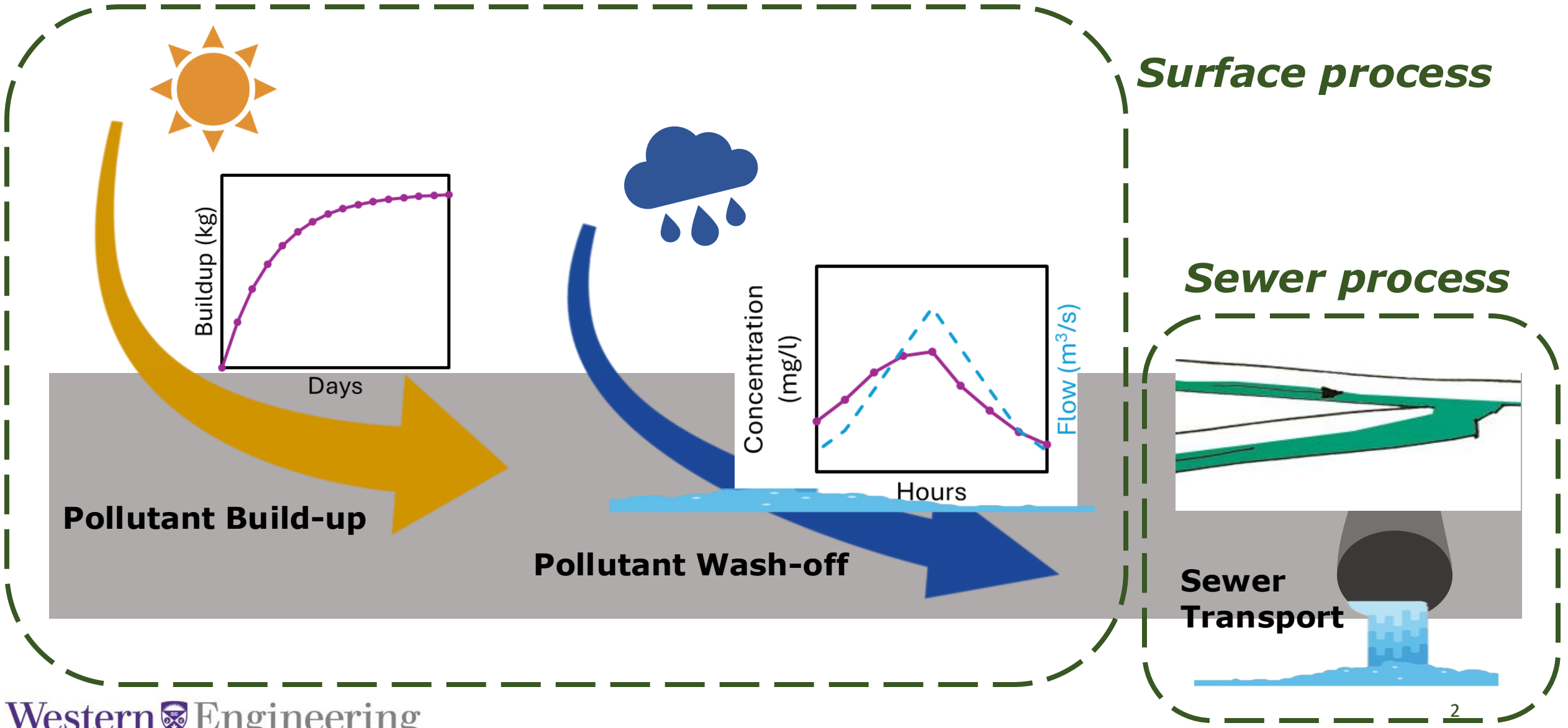
Urban non-point pollutant sources

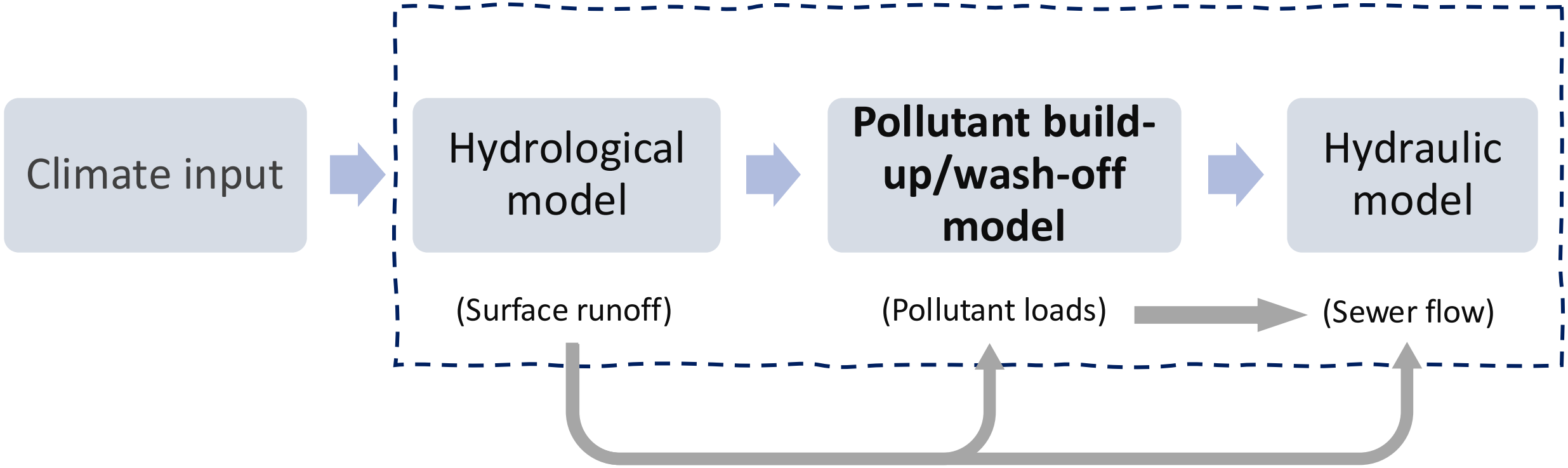


Stormwater pollutant loads need to be quantified and better understood to inform **land and stormwater management strategies**.

Stormwater pollutant fate and transport



Stormwater quality model



Build-up/wash-off model – Empirical equations

Exponential build-up

$$B = C_1(1 - e^{C_2 t})$$

- C_1 – build-up max
- C_2 – build-up rate
- Depends on t, antecedent dry days

Exponential wash-off

$$W = C_3 q^{C_4} B$$

- C_3 – wash-off coefficient
- C_4 – wash-off exponent
- Depends on *q* (runoff flow rate) and available *B* (mass of build up) during event

- Four parameters for calibration

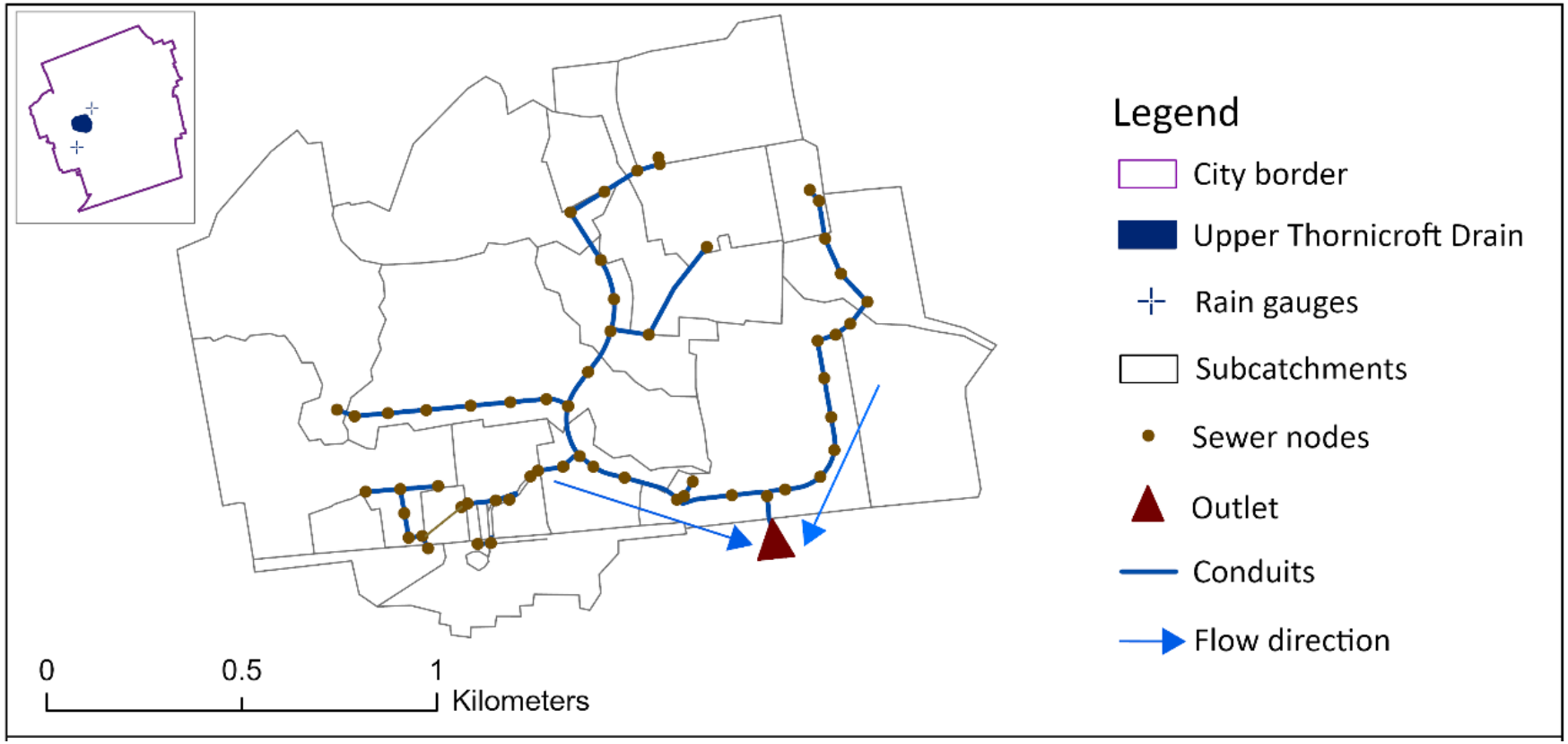
Catchment-scale modeling

Build-up/wash-off model is typically calibrated for individual **land-use** types using catchment **outlet** data.

Can the catchment-scale calibration approach capture **seasonal** load **variations** across different urban land uses?

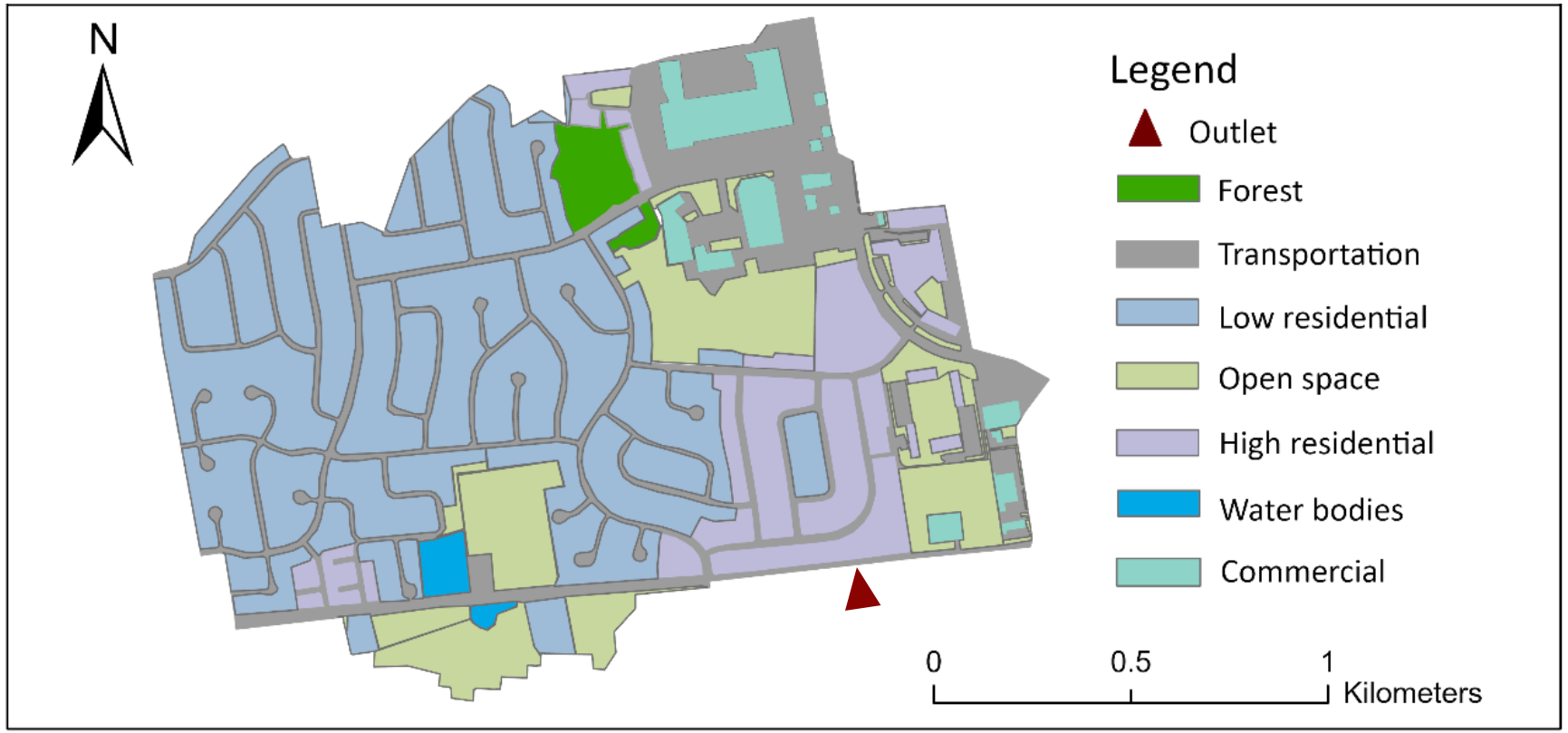
Study area – *Upper Thornicroft Drain Watershed*

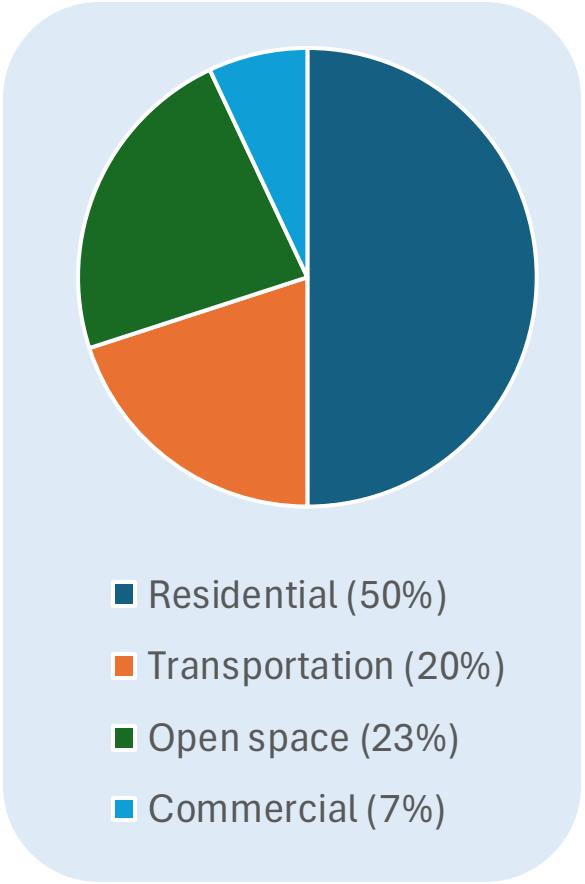
- 240-ha urban waterhsed in London, ON, Canada.
- SWMM hydrological and hydraulic model.



Build-up/wash-off model

- Event-based sampling of total suspended solids (TSS), total phosphorus (TP), and soluble reactive phosphorus (SRP) at outlet.
- Calibrating build-up/wash-off parameters for six land-use types using outlet data.





Simulations and uncertainty analyses

- Simulating TSS, TP, and SRP loads for nine events from 2022-2023.
- Generalized Likelihood Uncertainty Estimation (GLUE) approach used to evaluate model uncertainty, with each event running 100,000 Monte Carlo simulations.

Number of events

	Summer	Fall
Calibration	4	3
Validation	1	1
Total	5	4

Objectives

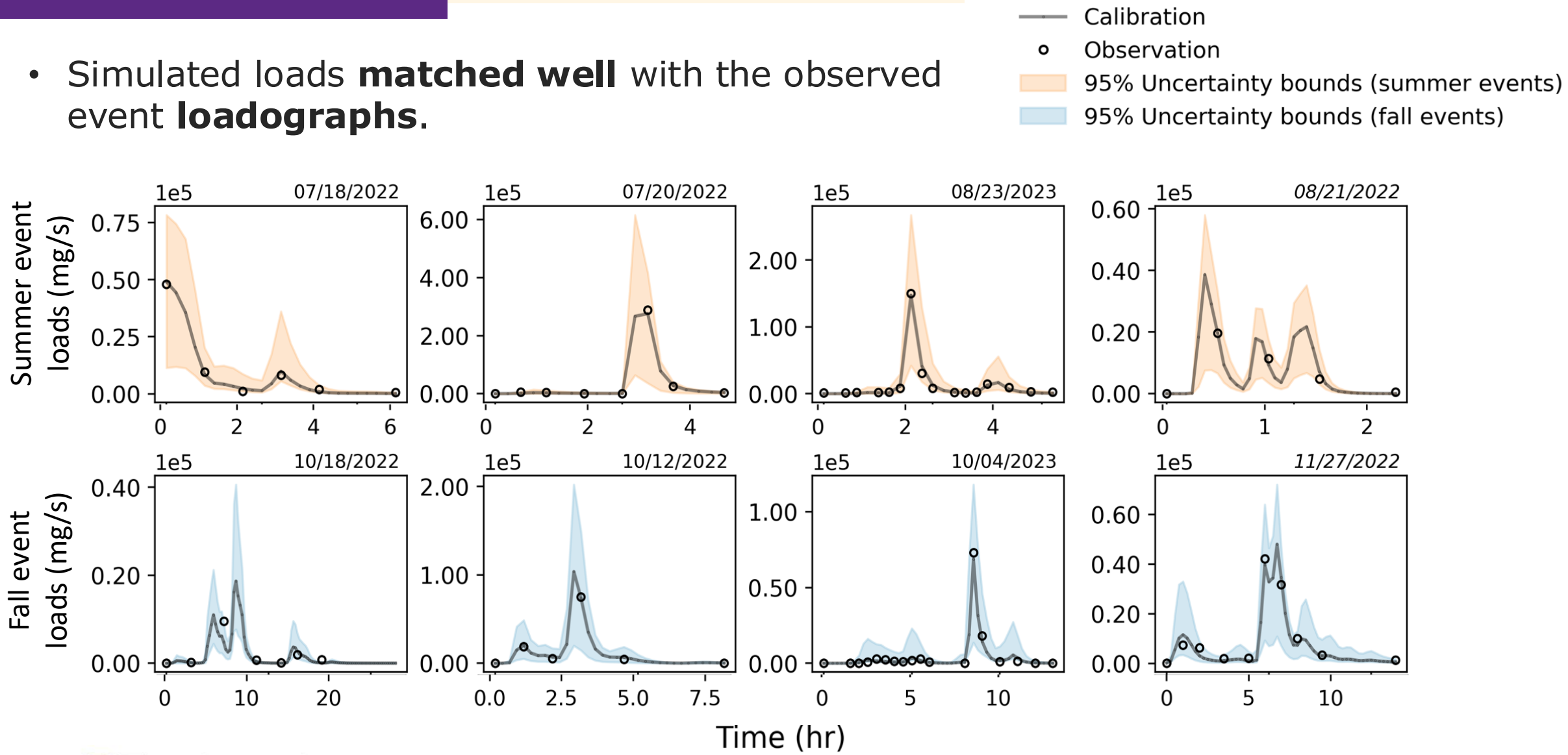
1. Evaluate the uncertainty in load predictions when the build-up/ wash-off model is calibrated using outlet data

2. Investigate the seasonality in parameter values across different land uses

3. Assess the influence of including more monitoring data on model uncertainty

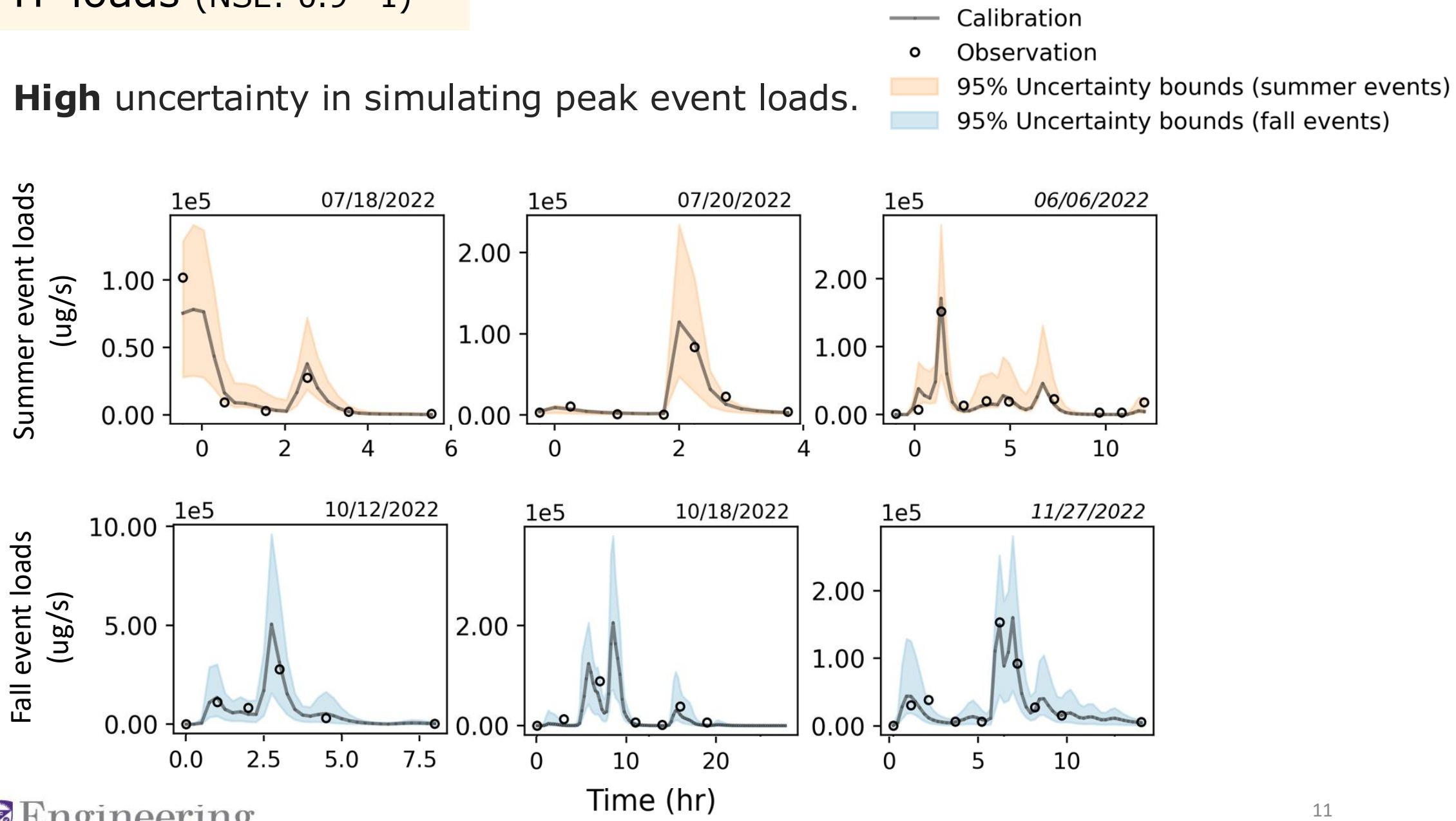
Load predictions – TSS loads (NSE: 0.9—1)

- Simulated loads **matched well** with the observed event **loadographs**.



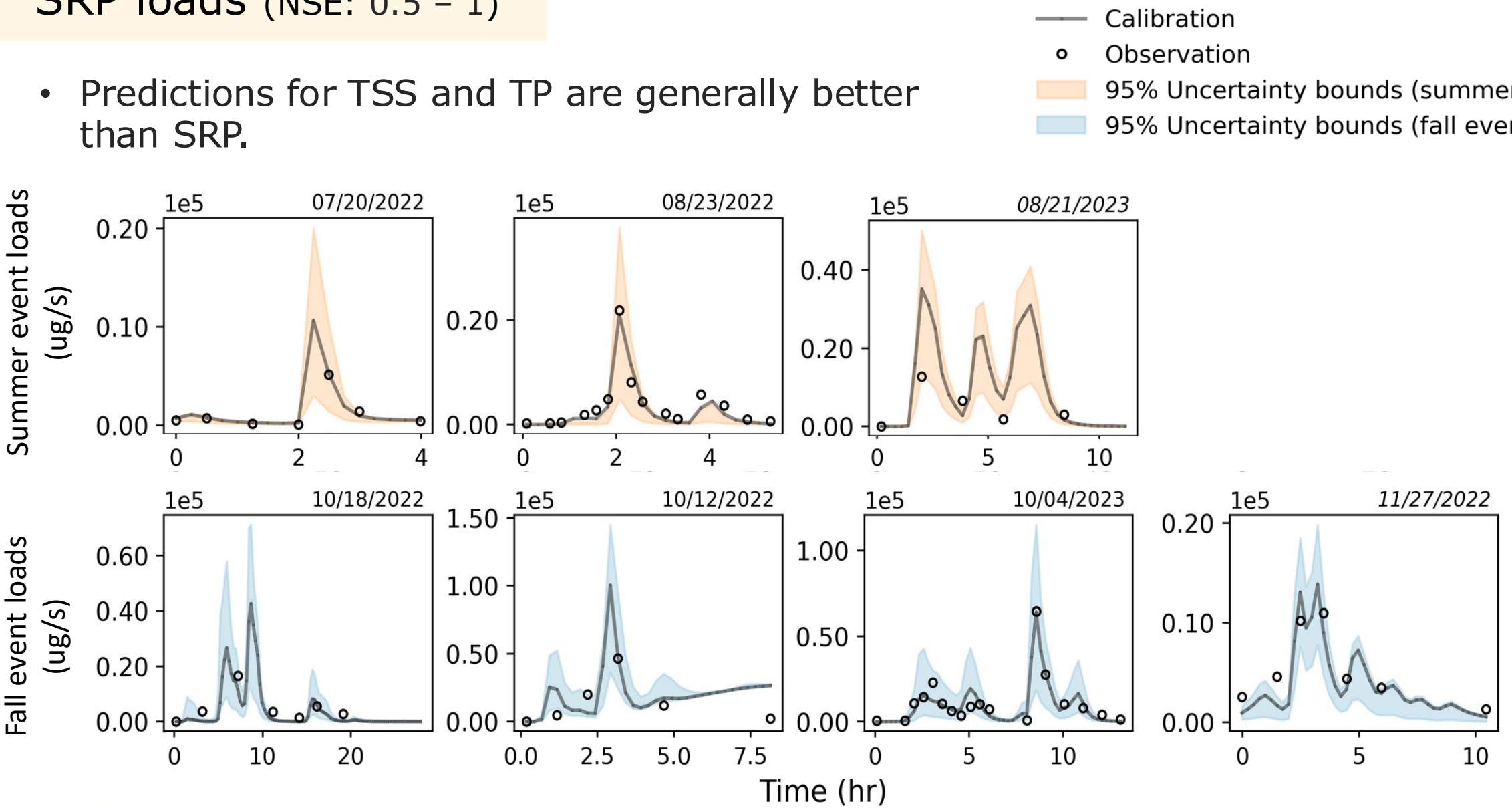
TP loads (NSE: 0.9—1)

- **High** uncertainty in simulating peak event loads.



SRP loads (NSE: 0.5 – 1)

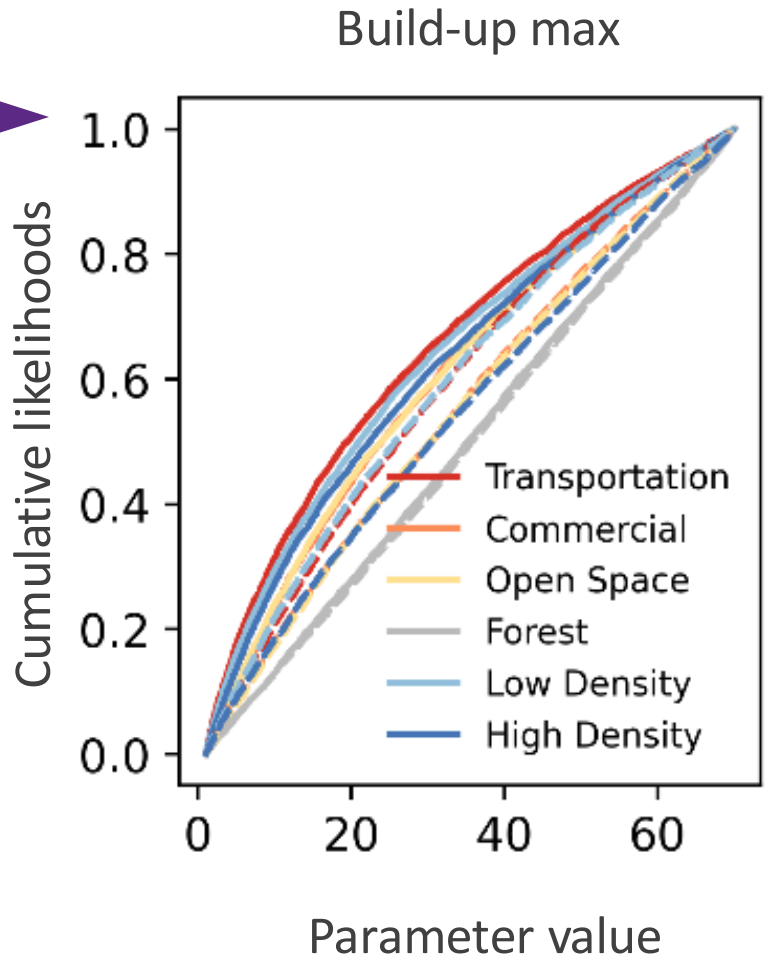
- Predictions for TSS and TP are generally better than SRP.

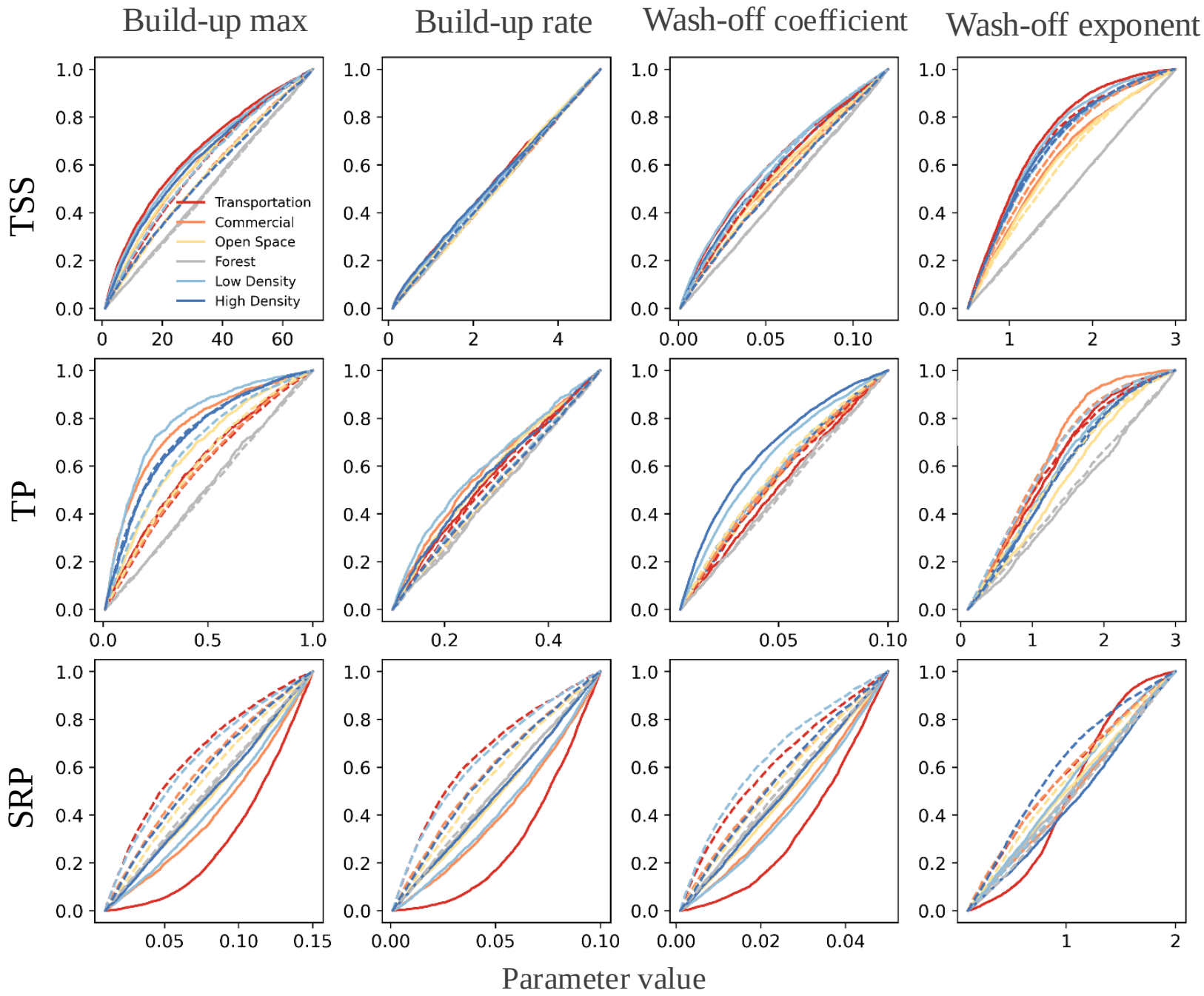


Parameter uncertainty

Cumulative likelihoods:
Solid line – summer
Dashed line – fall

- Less uncertainty in parameter values as shape of cumulative likelihoods **deviates** from a 1:1 line.

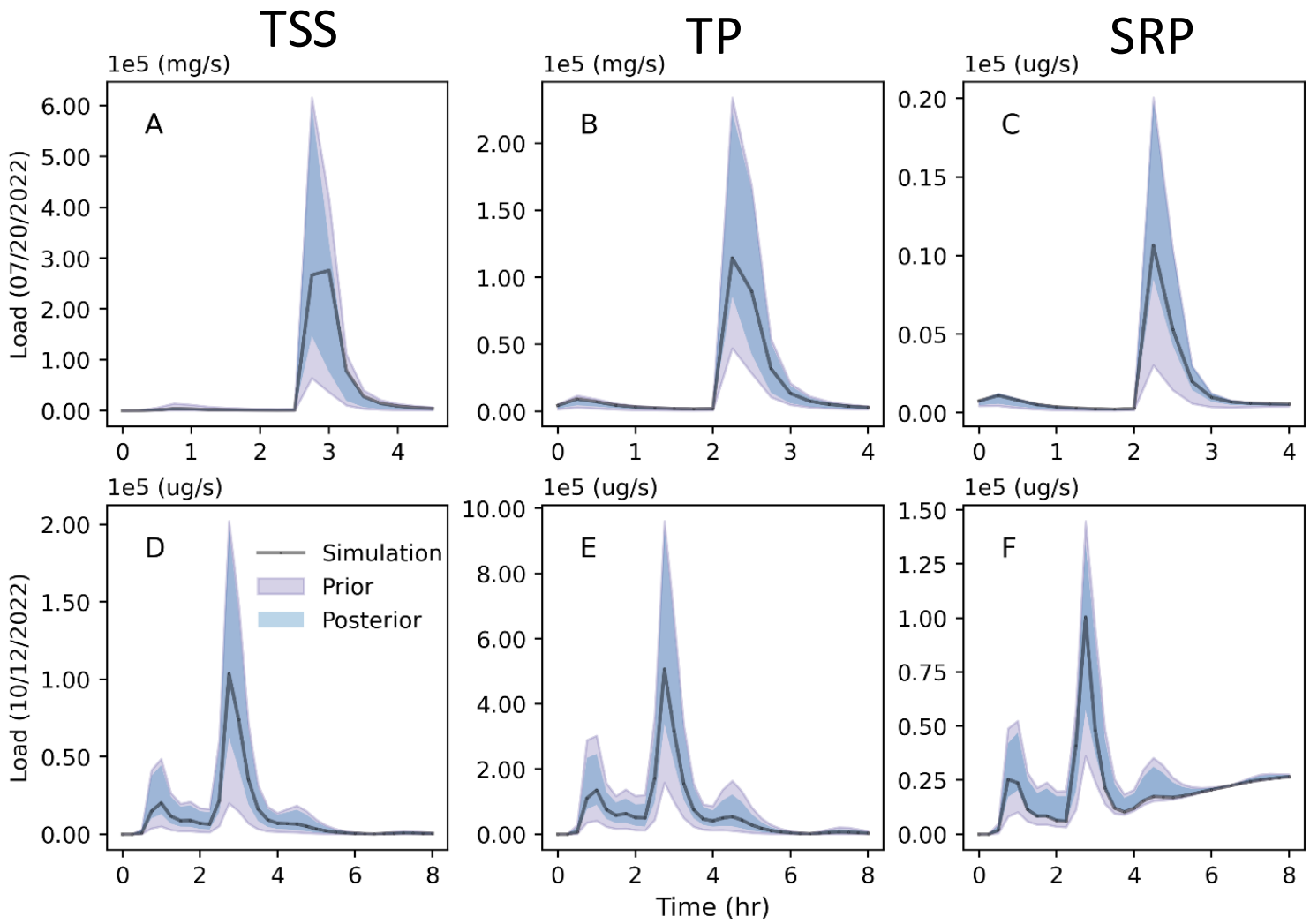




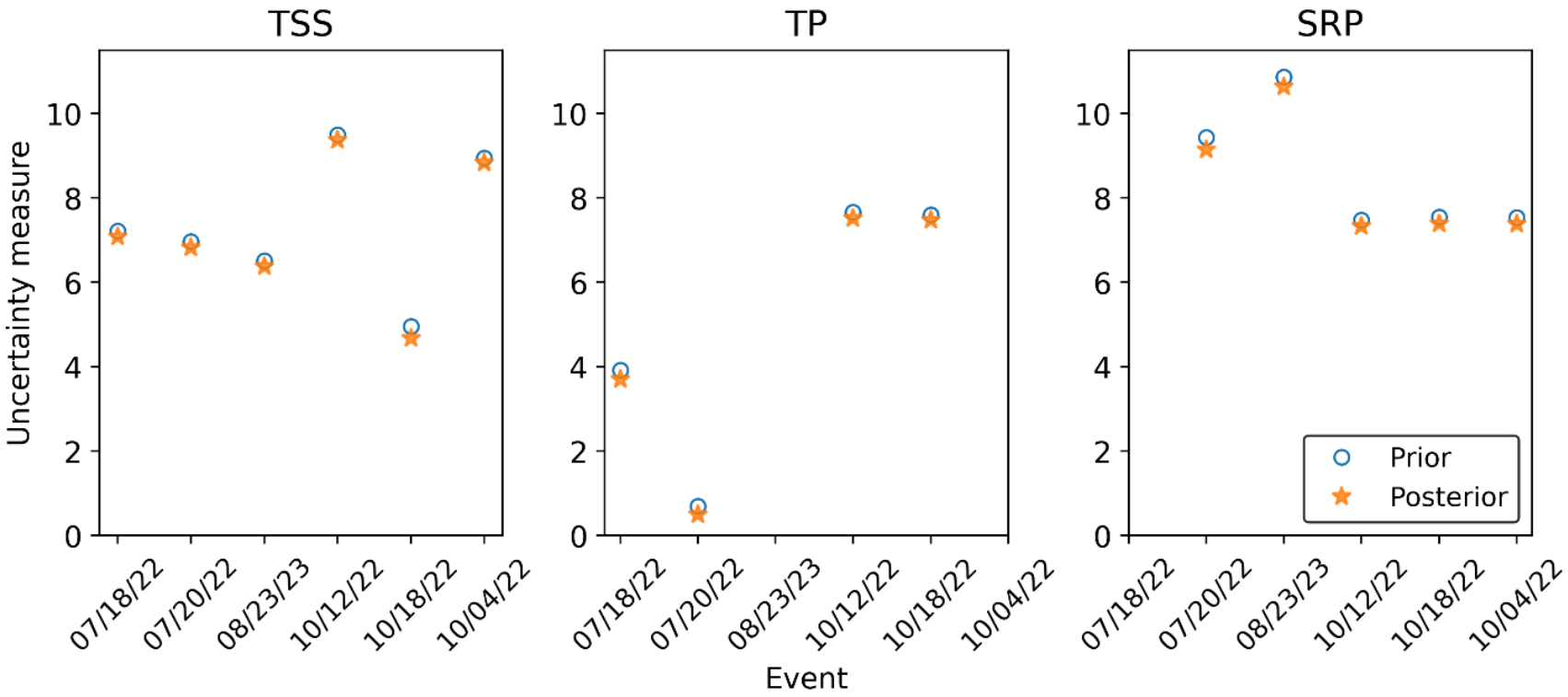
- Land uses with **high impervious cover** have less uncertainty in possible parameter values.
- **Seasonality** in parameter values is evident, particularly for SRP.
- Simulating SRP is more challenging.

Impact of data availability – Validation event as new data

- Using Bayesian Inference to update likelihoods :
  $L_y(Y|\theta) \propto L_y(\theta|Y) \cdot L_o(\theta)$
- 95% uncertainty bands became **narrower** when using posterior likelihood compared to prior likelihood.



Entropy – measure of uncertainty



- Overall uncertainty is not substantially reduced by including additional monitoring data.
- Data availability is NOT a primary factor contributing to model uncertainty.

Conclusion

- Model can **reproduce** event pollutant loads but with **uncertainty** in predictions.
- Model is more challenging for simulating loadgraphs for dissolved pollutants (SRP) compared to **particulate** (TSS) and **mixed** (TP) pollutants.
- **Lower** uncertainty in parameter calibration for land uses with higher impervious cover.
- **Seasonality** in calibrated parameter values is evident, especially for SRP.
- Catchment-scale calibration approach, **not** data availability, primarily contributes to model uncertainty.

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Thank you!

Rainfall events

Event index	Event date	Total depth (mm)	Duration (hr)	Flow NSE	TSS	TP	SRP	Simulations
S1	06/06/2022	29.0	16.29	0.81		X		Validation
S2	07/18/2022	18.8	1.58	0.91	X	X		Calibration
S3	07/20/2022	10.0	6.82	0.97	X	X	X	Calibration
S4	08/21/2022	12.4	12.1	0.89	X		X	Validation
S5	08/23/2023	13.1	9.66	0.90	X		X	Calibration
F1	10/12/2022	7.3	14.31	0.98	X	X	X	Calibration
F2	10/18/2022	18.5	4.01	0.88	X	X	X	Calibration
F3	11/27/2022	9.0	10	0.87	X	X	X	Validation
F4	10/06/2023	12.3	10.27	0.93	X		X	Calibration

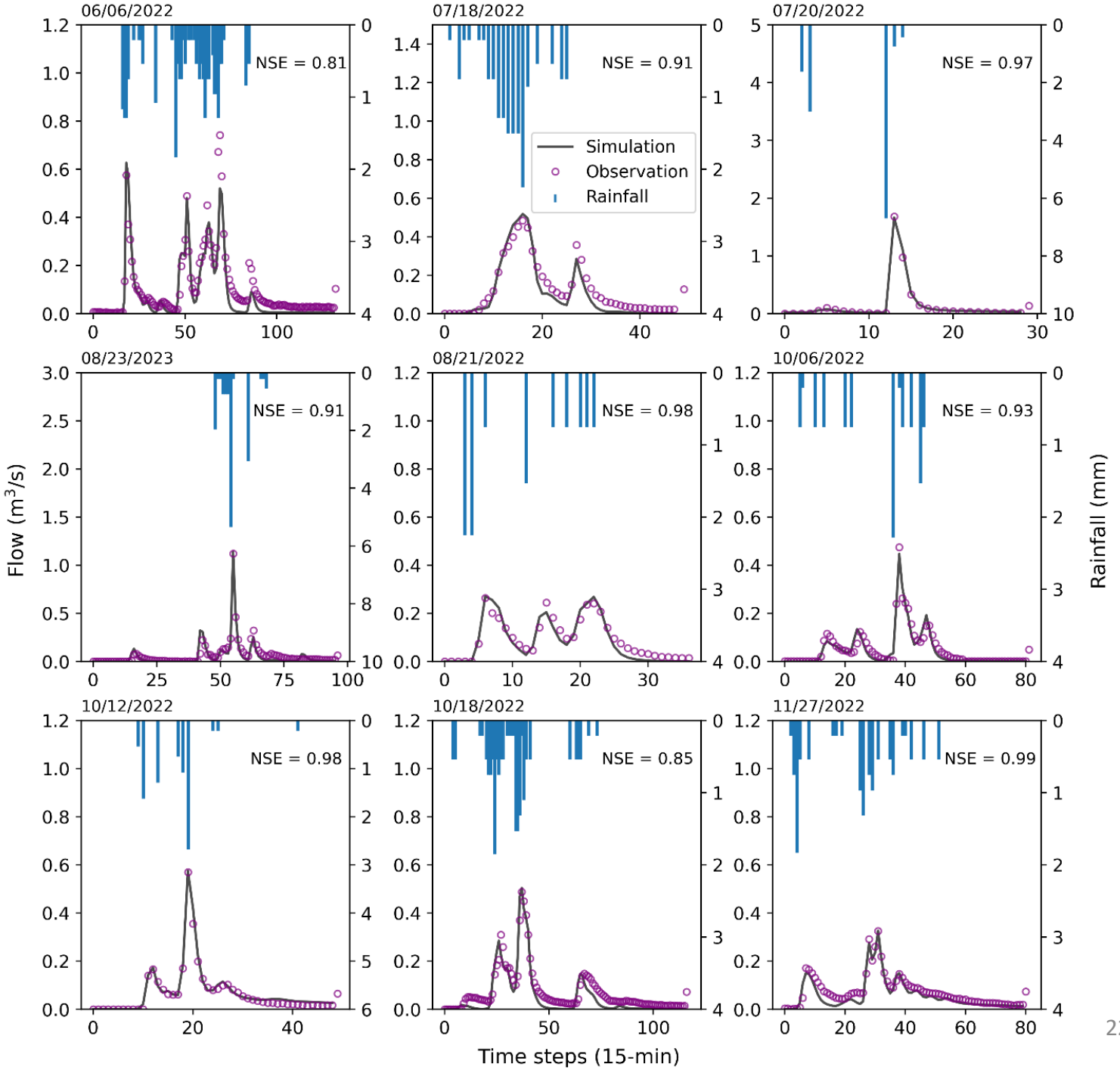
S – summer; F – fall; X – available data

Initial distribution

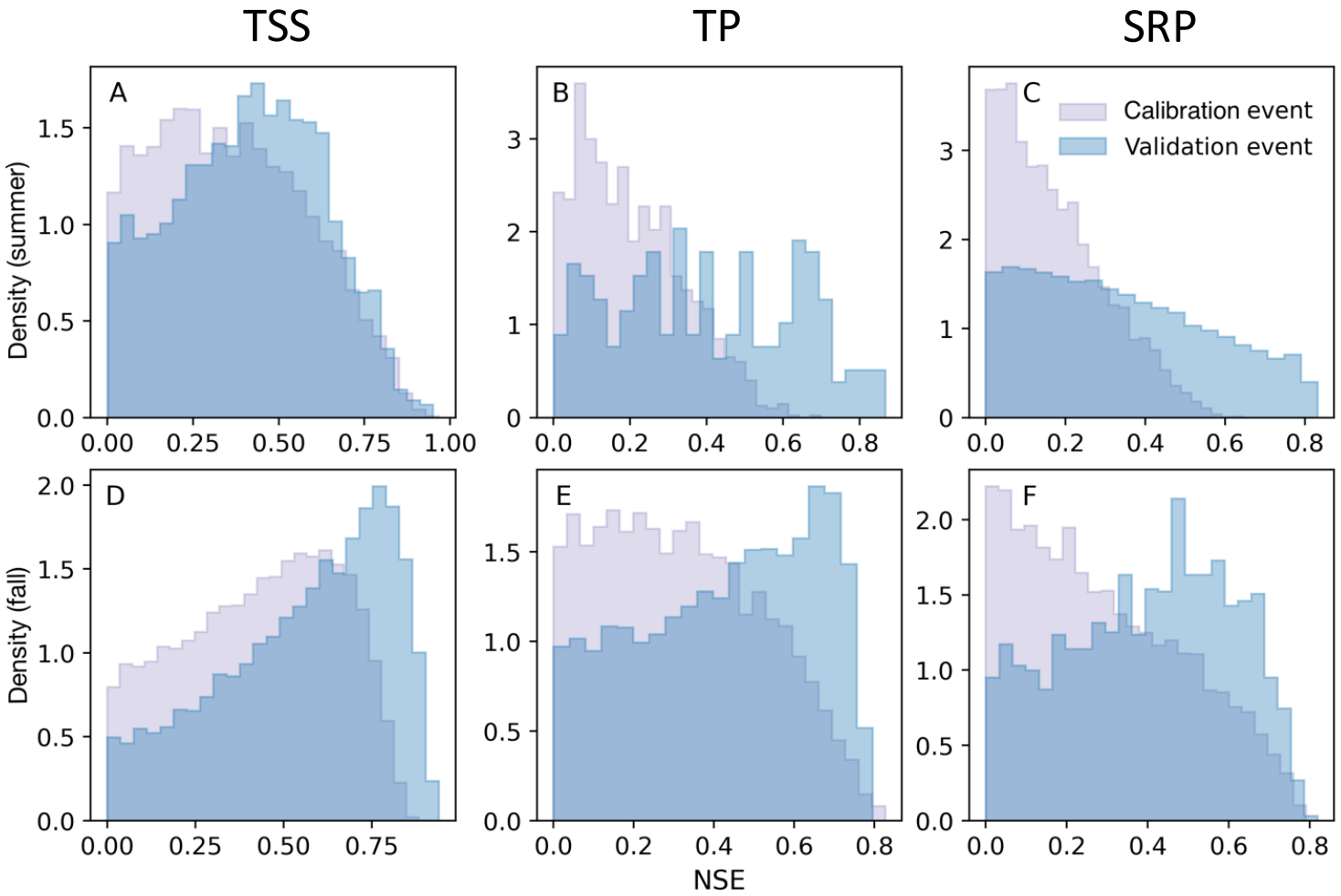
	B_{max}	B_{rate}	C_{coef}	C_{exp}	PDF
TSS	1–100	0.01–5	0.001–0.15	0.5–3	Uniform
TP	0.01–1	0.01–0.5	0.005–0.1	0.1–3	Uniform
SRP	0.01–0.15	0.0001–0.01	0.001–0.05	0.1–2	Uniform

Flow simulation

NSE: 0.81-0.97



Model validation



- Simulations for validation events yielded **higher** NSE values than those for calibration events.
- Calibrated parameter values can be used for simulating **new** events.