EGU2020-845

HS3.1

GA-BASED CALIBRATION AND ANN-BASED REAL-TIME BIAS CORRECTION FOR SWMM

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Introduction: background

- Flood damage is increasing due to rapid urbanization and climate change effects.
- Flow forecasting models are among the best ways to mitigate flood damage.
- Traditionally, physically-based rainfall runoff models have been used for forecasting.
- Such models can be challenging to calibrate, as they may contain thousands of uncertain parameters.
- This project studies predictions made by SWMM, a popular semi-distributed rainfall-runoff model developed by the U.S. Environmental Protection Agency.

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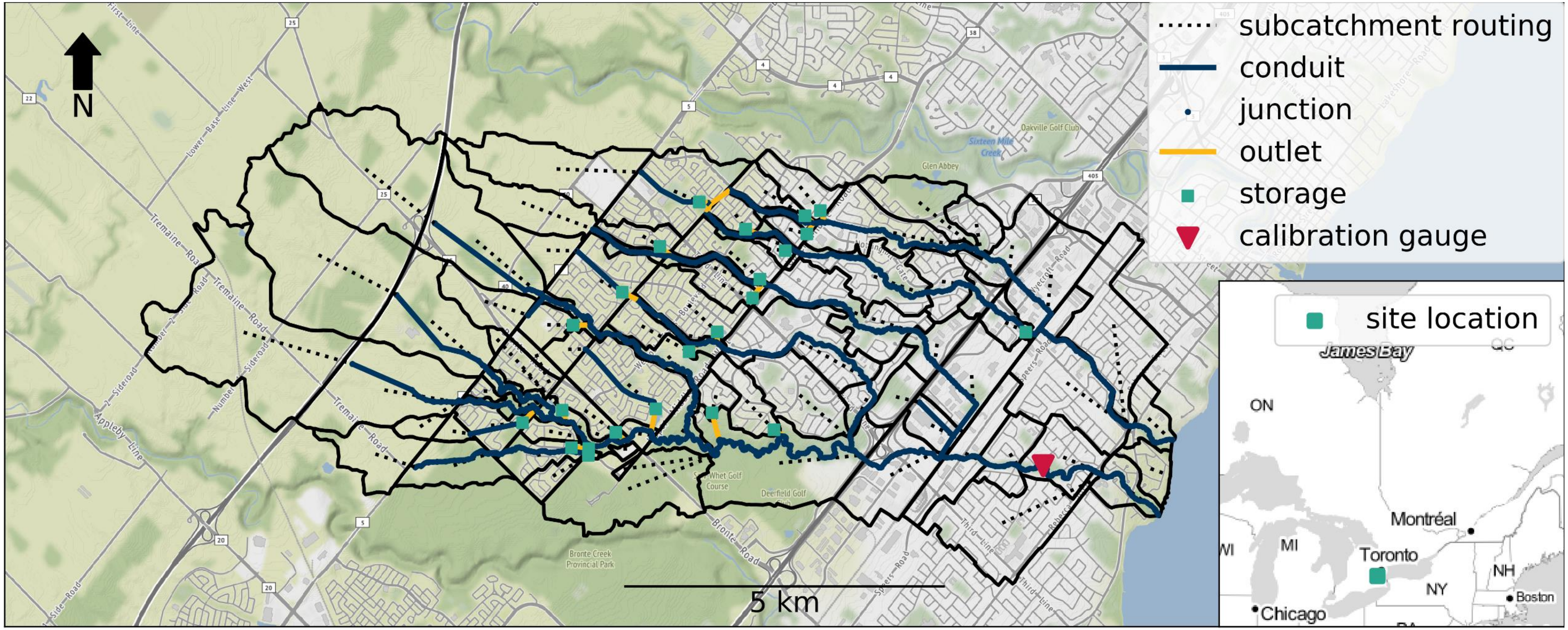

Figure 1: SWMM model of the Fourteen Mile Creek watershed.

Introduction: background

- Data-driven models, which rely on machine learning techniques for characterizing rainfall runoff systems, have been subject to extensive research throughout the past three decades; though, their operational use remains scarce.
- Despite widespread use of both model paradigms, there are relatively few studies in which they are explicitly compared.
- The Fourteen Mile Creek watershed, illustrated in Figure 1, is the focus of this study. The watershed is 70 ha in size, covers natural forest and urban areas, and was identified by the town of Oakville as the highest priority for flood mitigation measures [1].
- One year of data (2019) is available at a 5-minute temporal resolution, including radar derived areal rainfall estimates and flow levels at one gauge, illustrated above.

Introduction: objectives

- Calibrate SWMM and ANN flow forecasting models.
- Develop a hybrid approach that combines the benefits of both SWMM and ANN models, which include: strong performance, real-time adaptability, and a basis in physical hydrology.
- Assess the generalizability of each of the three model types through cross-validation on rainfall events that were not used for calibration.

Stormwater management model (SWMM)

- The model is relatively large, featuring more than 70 catchments, 800 irregular conduit cross-sections, 20 stormwater ponds, and radar-derived rainfall input.
- The model was obtained in an uncalibrated state. Calibration is performed using a Genetic Algorithm (GA), maximizing NSE as the objective (cf. [2]).
- Calibration of models of this size are computationally intensive as there are over 1000 model parameters to optimize, which is why the model is calibrated on an event basis over a continuous simulation.

Methods: stormwater management model (SWMM)

- A summary of the relative uncertainties associated with select SWMM parameters, determined based on expert judgement, is shown in Table 1. The GA searches for optimum values from a uniformly distributed initial population.

Table 1: Summary of SWMM GA calibration parameters.

Attribute	Description	Uncertainty
Width	Characteristic width	200%
PercentSlope	Average slope	25%
PercentImperv	Percent impervious land cover	20%
N_Imperv	Impervious area roughness	10%
N_Perv	Pervious area roughness	50%
S_Imperv	Impervious depression storage	20%
S_perv	Pervious depression storage	50%
Suction	Suction head at the wetting front	50%
Ksat	Saturated hydraulic conductivity	50%
IMD	Initial moisture deficit	25%
Roughness	Channel roughness	25%

Methods: artificial neural network (ANN) model

- ANNs, which can take advantage of real-time flow observations for short-term predictions and adaptive learning, are developed in this research.
- This study uses simple multi-layer perception ANNs, which are the most frequently used ANN architecture for water resources applications [3], to correct SWMM predictions with a lead time of 4-hours.
- Lagged rainfall and flow timeseries are used as the input variables for this model [3, 4].
- In order to improve model generalization and prevent overfitting, a small hidden layer consisting of only 3 hidden neurons is used. ANN generalization is also improved by using an ensemble of ANNs, which use randomly sampled data used for training and as a validation stopping criterion.

Methods: hybrid model (SWMM-ANN)

- Hybrid models are emerging as a popular method for combing the advantages of physically-based and data-driven models (cf. [5, 6]).
- The hybrid model uses lagged rainfall and flow timeseries as inputs, and also uses the SWMM flow predictions as a model input parameter, as shown in Figure 2.

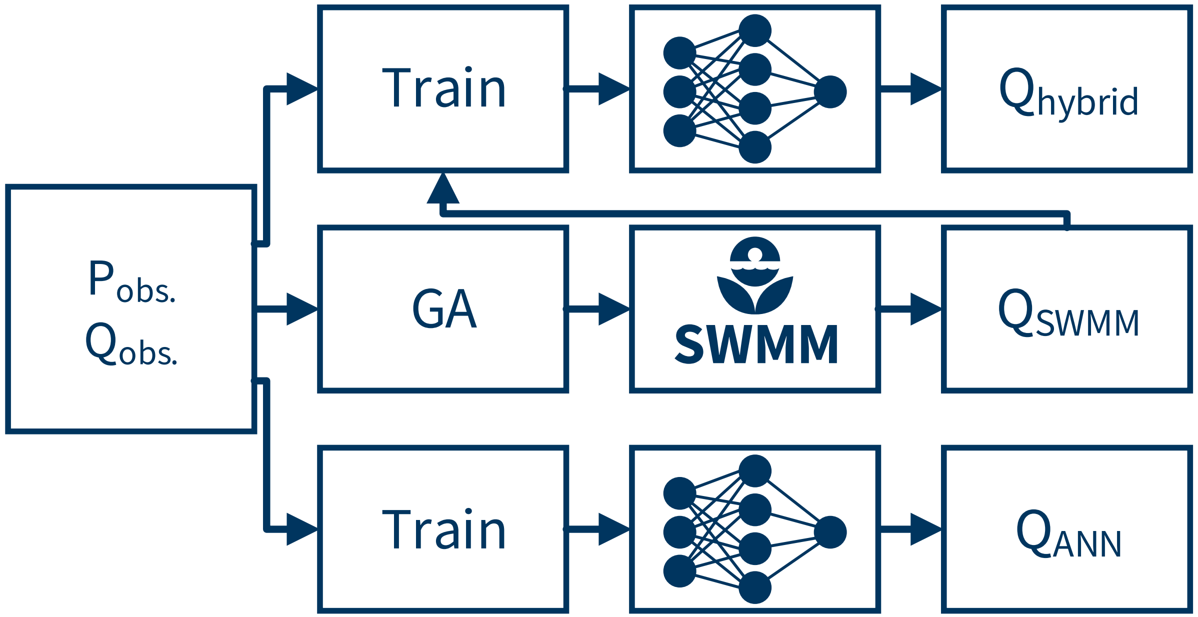

Figure 2: Configuration of SWMM, ANN, and hybrid models.

Methods: model evaluation

- All three model types are calibrated on each rainfall event shown in Table 2, and their performance is evaluated on each of the 5 remaining events (referred to as validation events).
- The model performance is assessed using two common criteria, the Nash-Sutcliffe Efficiency (NSE) and Persistency Index (PI), which both quantify model performance with a value from $-\infty$ to 1, having an optimum value of 1 [4].

Table 2: Summary of 2019 rainfall events.

start date	duration [hours]	total rainfall [mm]	peak intensity [mm/hr]
25-May-2019	32.8	24.7	20.0
05-Jun-2019	26.7	22.3	21.6
15-Jul-2019	54.1	24.2	16.1
01-Oct-2019	72.8	30.1	36.5
26-Oct-2019	28.7	32.2	10.9
30-Oct-2019	51.8	30.0	5.1

Results: SWMM GA optimization

- The GA is used to optimize the NSE of a SWMM model to 6 different rainfall events, summarized in Table 2 and illustrated in Figure 4.
- Figure 3 shows the increase in NSE produced by the GA, from an initial range of approximately −0.75 to 0.50, to a calibrated range of 0.25 to 0.80.

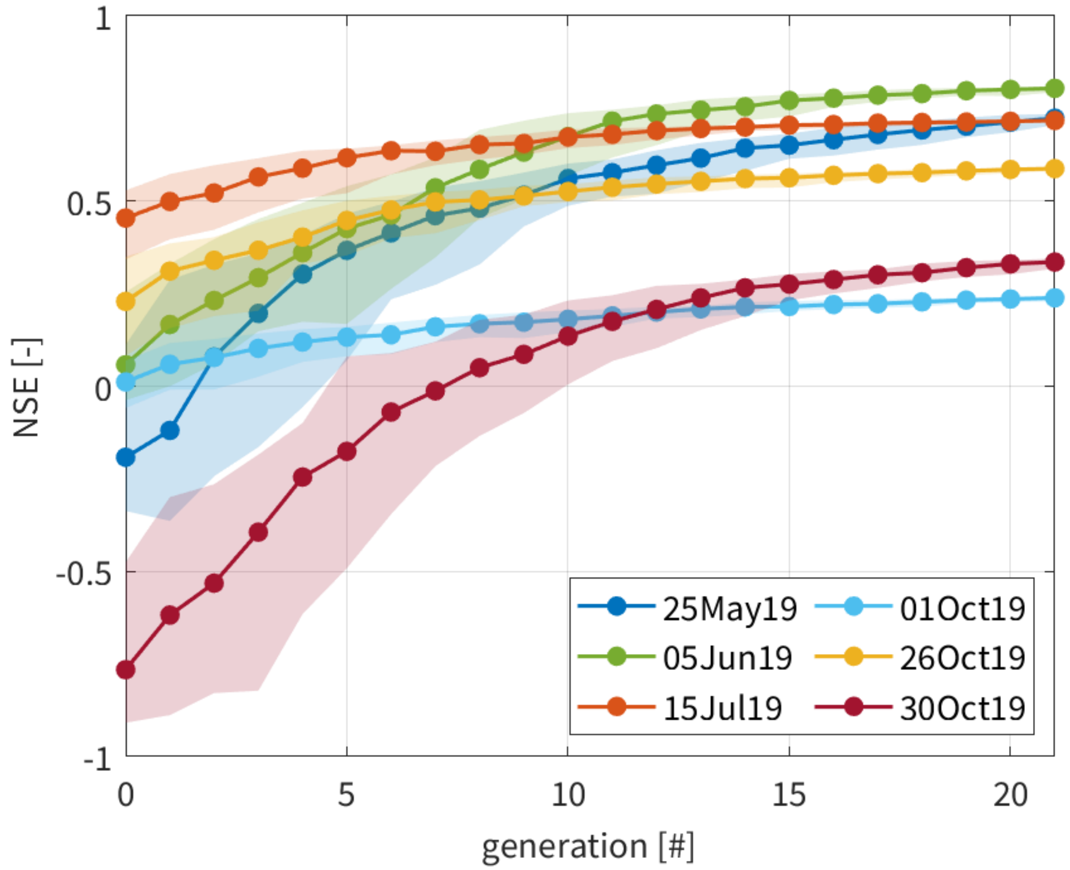

Figure 3: Objective function versus GA generations for calibration of SWMM models on six different rainfall events.

Results: Comparison of SWMM, ANN, and hybrid model performance

- While the SWMM models achieve satisfactory performance on the calibration events, as shown in Figure 5 below, the models do not perform well when evaluated on other rainfall events.
- The pure ANN model achieves much stronger performance on the calibration events, but exhibits similarly poor generalization to the SWMM model on validation events.
- The hybrid models achieve excellent performance on the calibration events and very good generalization. In particular, the models calibrated on the 05Jun19 events achieves positive NSE and PI values across all validation events.

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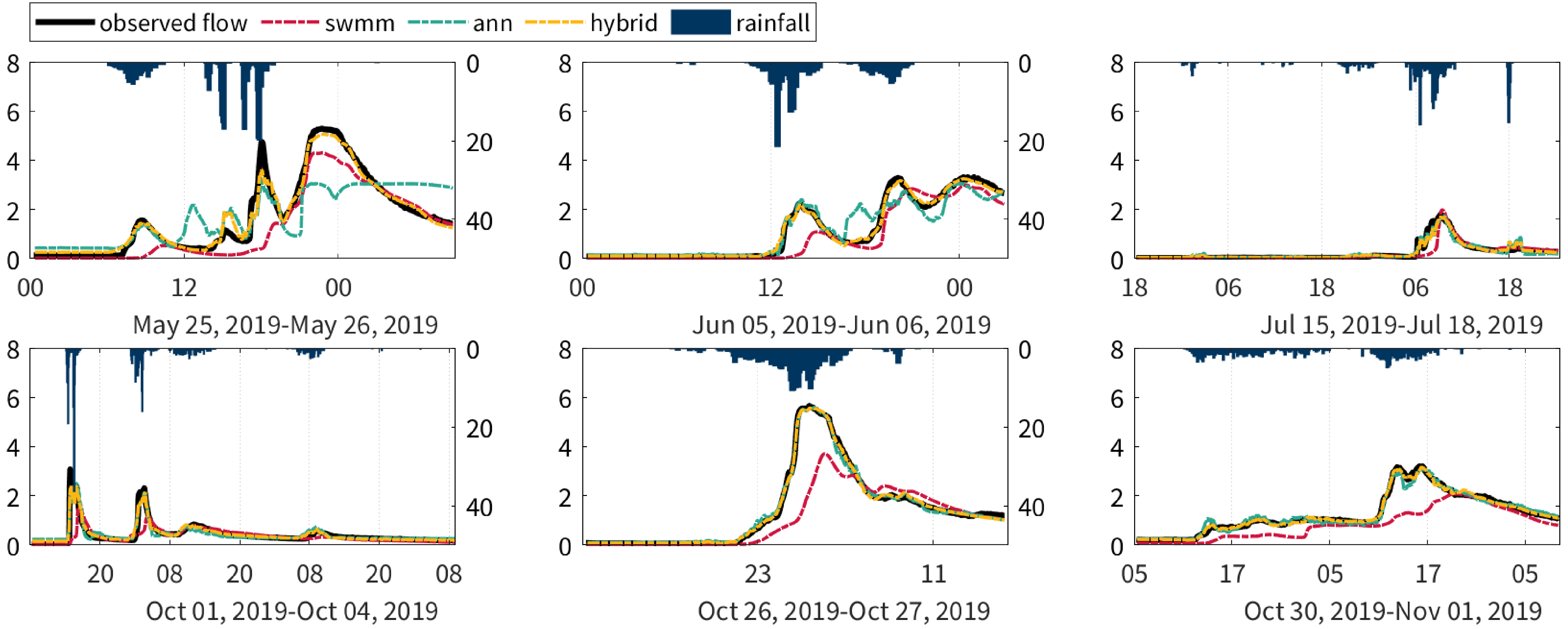

Figure 4: Event-based calibration performance for SWMM, ANN, and hybrid models.

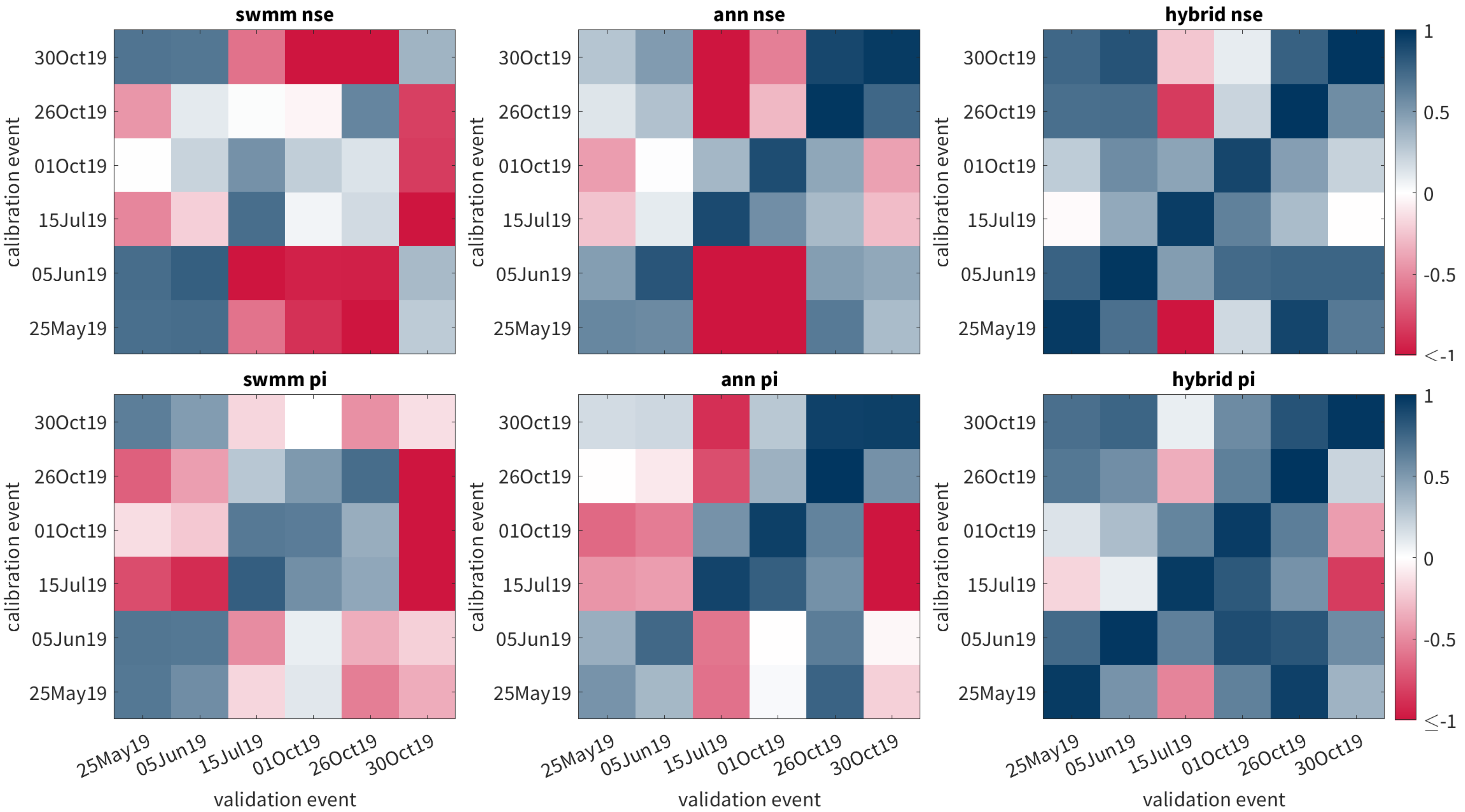

Figure 5: NSE (top row) and PI (bottom row) of the three models and six events considered. The events along the Y-axis are used for calibration while the X-axis are used for validation. The diagonal shows the calibration performance of each event whereas the remaining cells show the validation performance.

Conclusions and Future Work

- This study demonstrated that GA can be used for optimization of a large scale semi-distributed rainfall-runoff model in SWMM.
- ANN-based and hybrid (SWMM-ANN) models were developed to improve real-time predictions.
- The pure SWMM and ANN models exhibit poor cross-validation performance, whereas the hybrid model performed reasonably well.
- Ongoing research is evaluating the impacts of multi-event and continuous calibrations on model generalization and improving the hybrid model performance for lead-times larger than 4-hours.

References

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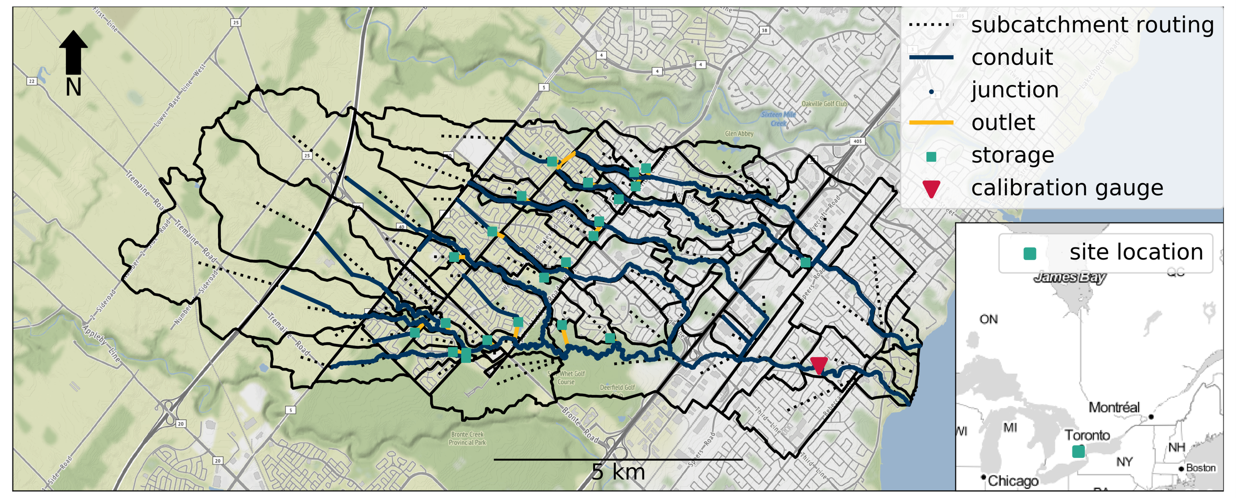

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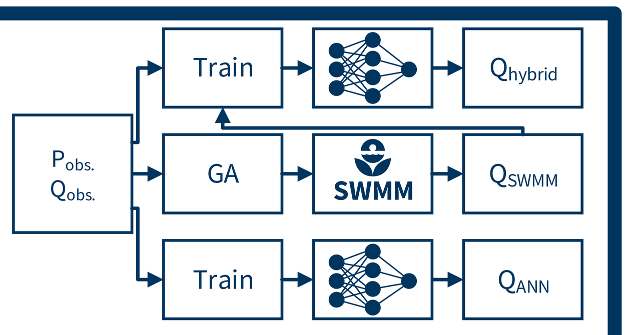

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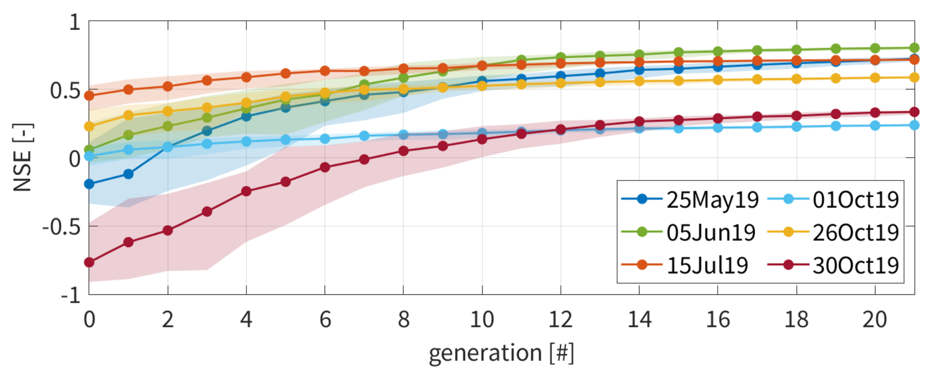

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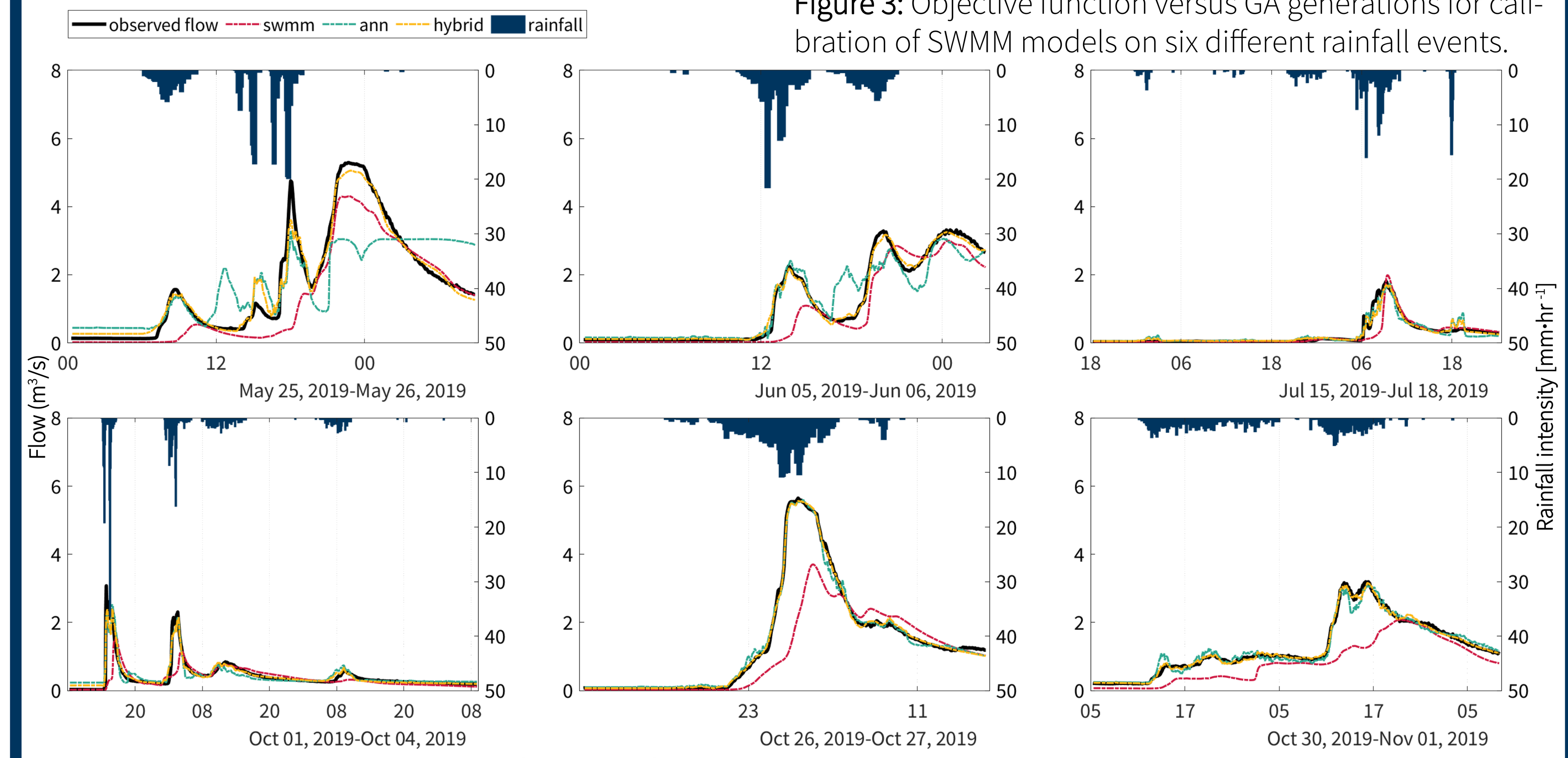

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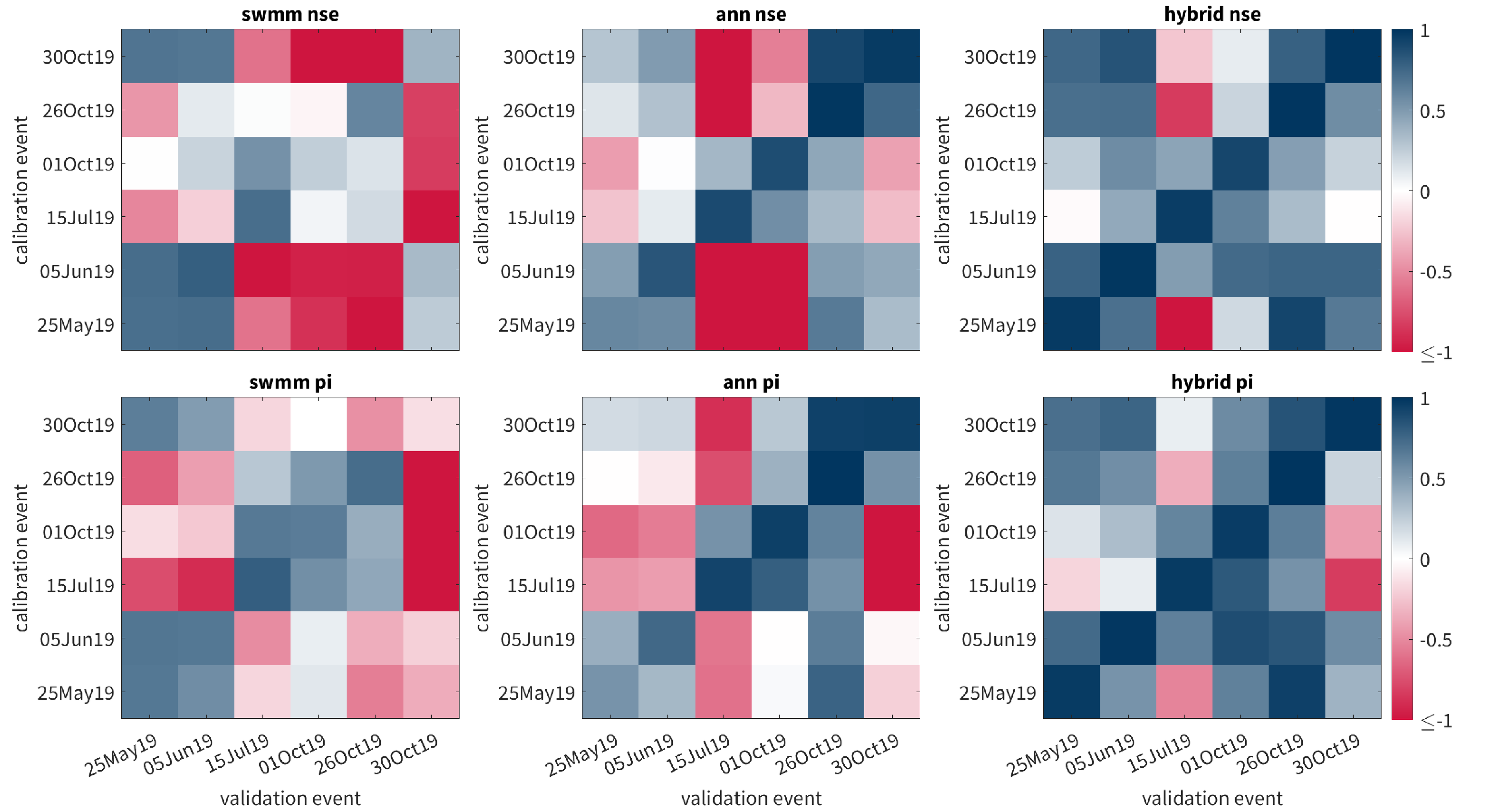

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