# Multi-Objective Optimization of Don River PCSWMM/SWMM5 Model

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## Introduction

The availability of spatially distributed hydrologic data makes distributed hydrologic models superior tools for understanding spatially spread hydrologic processes and the effects of natural and human activities on watersheds [1]. In operational flood forecasting systems, distributed/semi-distributed models are increasingly preferred [2]. In this study a multi-objective genetic algorithm (NSGAII) is adapted for optimizing the peak flow sensitive parameters of Don River watershed PCSWMM/SWMM5 model exploiting observed rainfall data from several storm events and several stream gauges simultaneously to improve peak flow estimation.

## Objectives

- Considering the spatial variability of discharge and rainfall data across the Don River watershed in a systematic automatic model optimization approach
- Assessing the single site versus multi-site model optimization
- Evaluate the effects of different performance measure criteria as objective functions in model optimization.

## Case Study and Data

Don River watershed covers municipalities of Toronto, York, Markham , Richmond Hill, and Vaughan. The area of the watershed is 358 km2 and length of major tributaries are 9–43 Km with monthly mean streamflow of 4 m3/s. Don river watershed land use is 96% urban with 8% forest , 6% meadow , 1% successional and 0% wetland [3].

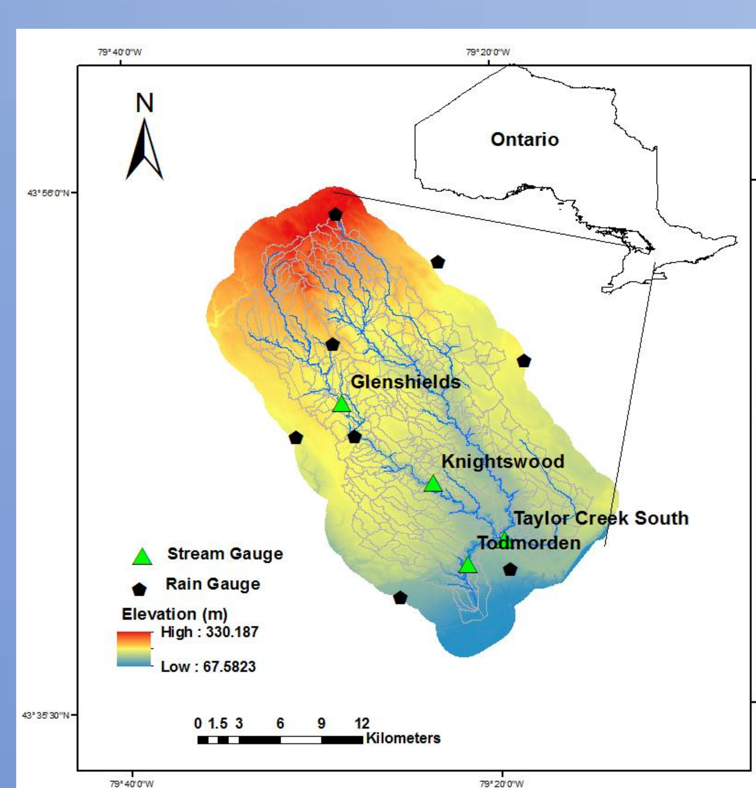


**Fig. 1 Don River watershed**

**Table 1 Observed precipitation and discharge data of storm events**

| Location Name | Observed discharge data availability |
|---|---|
| Glenshield | 6 events of 2008-2015 |
| Knightswood | 2 events of 2008-2010 and 2 events of 2014-2015 |
| Taylor Creek South | 2 events of 2013 and 2 events of 2014-2015 |
| Todmorden | 6 events of 2008-2015 |

**Table 2 Calibration and validation events**

| Event | | Total rainfall (mm) | Duration (hr) |
|---|---|---|---|
| Calibration Events | | | |
| E1 | 23-Jun-08 | 22.24 | 22 |
| E2 | 25-Jul-10 | 36.61 | 27 |
| E3 | 28-May-13 | 47.87 | 33 |
| E4 | 8-Jul-13 | 46.76 | 24 |
| Validation Events | | | |
| E5 | 4-Aug-14 | 27.1 | 22 |
| E6 | 8-Jun-15 | 37.5 | 37.5 |

## Methodology

Automatic Genetic Algorithm single objective SWMM5 model optimization with four different objective functions (average performance for calibration storm events at watershed outlet)

KGE | VE | NSE | Peak Flow Error

Multi-objective GA optimization using best identified metric at four stream gauges

Evaluate the performance of single and multi-objective optimization

Compare the performance

### Performance measure criteria

**Nash Sutcliffe efficiency (NSE)**

$$NSE = 1 - \left[\frac{\sum_{i=1}^{N}(Q_{obs} - Q_{sim})^2}{\sum_{i=1}^{N}(Q_{obs} - \overline{Q_{obs}})^2}\right]$$

**Absolute value of Volume Error (VE)**

$$VE = \frac{\left|\sum_{i=1}^{N} Q_{sim} - \sum_{i=1}^{N} Q_{obs}\right|}{\sum_{i=1}^{N} Q_{obs}}$$

**Absolute value of Volume Error (VE)**

$$\text{PeakFlowE} = \frac{|MaxQobs - MaxQsim|}{MaxQobs}$$

**Kling–Gupta Efficiency (KGE)**

$$KGE = 1 - \sqrt{(r-1)^2 + (a-1)^2 + (b-1)^2}$$

r=$corr(Q_{sim}, Q_{obs})$
a=std($Q_{sim}$)/std($Q_{obs}$)
b= mean($Q_{sim}$)/mean($Q_{obs}$);

Where $\boldsymbol{Q_{sim}}$ and $\boldsymbol{Q_{obs}}$ are simulated and observed streamflow, r, a and b are correlation coefficient, proportion of standard deviation and mean of simulated and observed flow respectively.

### Multi-objective Optimization

NSGA11 [4] is an improved version of NSGA , a non-dominated multi-objective genetic algorithm. It initials the population based on parameters range and sorts it based on non-domination. The evolved population through subsequent generations will be selected as Pareto front.

## Results

Table 3 presents the performance of four single-objective model optimization scenarios. In each scenario, one performance measure criterion of most downstream gauge (Todmorden) is optimized. The different performance measure criteria used as objective functions revealed very close performance. Although, the difference between the performances is not significant, the first-best performing criterion , KGE is used as an objective function in the multi-objective optimization framework for the four stream gauges.

**Table 3 Mean model performance of single objective optimized model for four scenarios (each scenario uses one of the performance measure criteria of watershed outlet)**

| | | Perf. 1 | Perf. 2 | Perf.3 | Perf.4 | Perf. 1 | Perf. 2 | Perf.3 | Perf.4 |
|---|---|---|---|---|---|---|---|---|---|
| | | Todmorden | | | | Glenshield | | | |
| Calibration (3 events) | NSE | 0.90 | 0.91 | 0.89 | 0.90 | 0.24 | 0.25 | 0.23 | 0.25 |
| | VE | 0.12 | 0.09 | 0.16 | 0.15 | 0.28 | 0.21 | 0.30 | 0.27 |
| | KGE | 0.87 | 0.84 | 0.82 | 0.85 | 0.42 | 0.40 | 0.34 | 0.37 |
| | PeakE (%) | 29.95 | 33.3 | 30.91 | 32.83 | 11.40 | 10.0 | 12.86 | 14.91 |
| Validation (3 events) | NSE | 0.37 | 0.40 | 0.38 | 0.41 | 0.12 | 0.09 | 0.11 | 0.08 |
| | VE | 0.36 | 0.32 | 0.34 | 0.33 | 0.15 | 0.19 | 0.21 | 0.16 |
| | KGE | 0.44 | 0.54 | 0.55 | 0.51 | 0.48 | 0.51 | 0.49 | 0.50 |
| | PeakE (%) | 12.6 | 8.7 | 10.6 | 9.3 | 29.5 | 26.8 | 27.7 | 30.5 |
| | | Knightswood | | | | Taylor Creek | | | |
| Calibration (3events) | NSE | 0.15 | 0.20 | 0.13 | 0.18 | -0.73 | -0.70 | -0.60 | -0.46 |
| | VE | 0.35 | 0.46 | 0.51 | 0.49 | 0.76 | 0.67 | 0.71 | 0.69 |
| | KGE | 0.44 | 0.49 | 0.39 | 0.40 | -0.14 | -0.11 | -0.10 | 0.01 |
| | PeakE (%) | 68.75 | 65.75 | 66.75 | 67.75 | 20.07 | 19.07 | 22.07 | 18.07 |
| Validation (2 events) | NSE | -0.98 | -0.48 | -0.48 | -0.68 | 0.51 | 0.59 | 0.49 | 0.54 |
| | VE | 1.39 | 1.32 | 1.12 | 1.52 | 1.08 | 1.02 | 1.14 | 1.21 |
| | KGE | 0.02 | 0.01 | -0.01 | -0.01 | 0.39 | 0.43 | 0.41 | 0.45 |
| | PeakE (%) | 27.5 | 28.8 | 29.9 | 31.8 | 135.2 | 125.6 | 121.4 | 115.2 |

Perf. 1 (Performance measure) : VE Perf. 2 : KGE Perf. 3: NSE Perf. 4: Peak Flow Error

**Table 4 Model parameters with total uncertainty range for 475 sub-watersheds along with single-objective (SO) and multi-objective (MO) optimized parameters' range**

| Parameter | Unit | Initial Range | SO-optimized | MO-optimized |
|---|---|---|---|---|
| Watershed Width | m | 3.65 - 3739.5 | 6.11-2723.19 | 7.37-1734.03 |
| Percent of Imperviousness | % | 0.91-152.5 | 0.92-126.32 | 1.42-133.29 |
| Manning of pervious area | _ | 0.09 - 0.8 | 0.10-.70 | 0.093-0.69 |
| Pervious area depression storage | mm | 2.5 - 22.9 | 2.65-20.54 | 2.5-20.19 |
| Hydraulic conductivity | mm/hr | 0.18-15 | 0.29-13.10 | 0.25-14.38 |

In the second experiment, the KGE values for the four stream gauges are used as objective functions in a multi-objective optimization framework. The Pareto front solution of multi-objective optimization is displayed in Fig. 2.

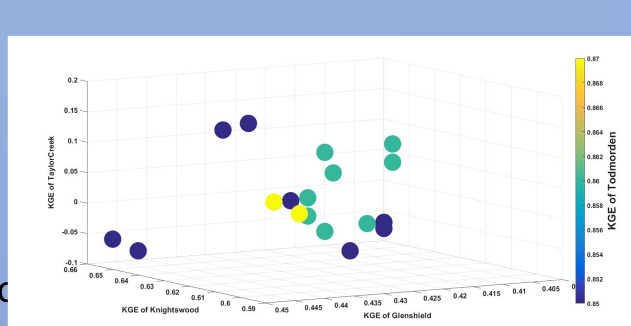

**Fig.2 Plot of Pareto front for multi-objective optimization**

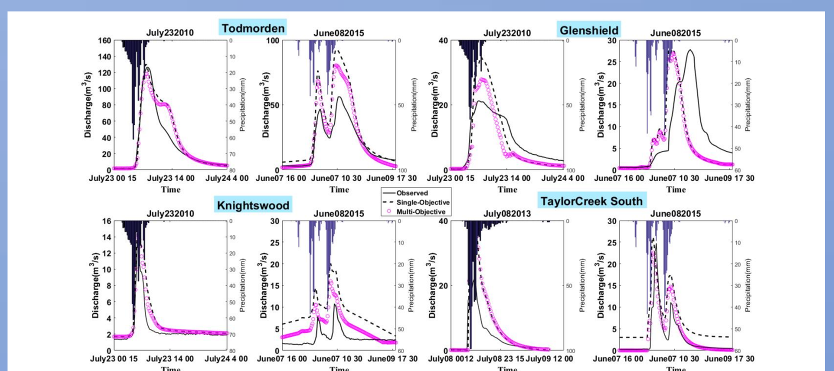

**Fig. 3 The hydrographs of one calibration event and one validation event for single and multi-objective optimized models at each stream gauge**

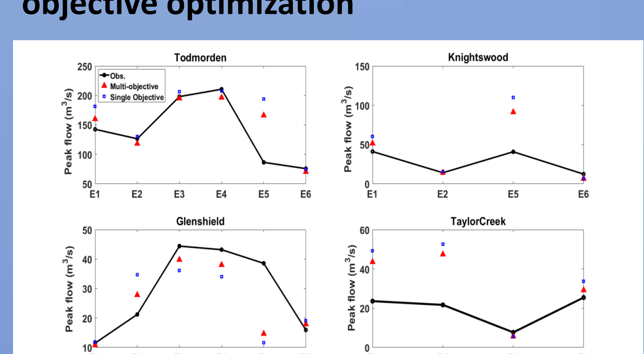

**Fig.4 Simulated and observed peak flow of calibration and validation events**

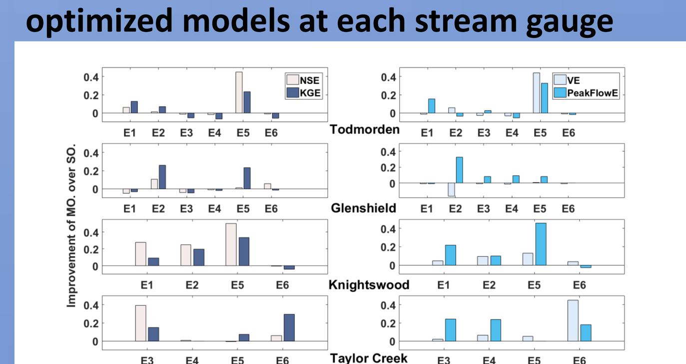

**Figure 5 Improvements of multi-objective (MO.) over single-objective (SO.) optimized model performance metrics.**

## Discussion

The results of this study reveal the superior performance of multi-objective automatic parameters optimization for validation events at watershed outlet and both calibration and validation events at other stream gauges. The common calibration of the PCSWMM/SWMM5 model for operational storm water management and real-time flood forecasting is a heuristic expert-knowledge-based approach that fits the model output to observed discharge data of one stream gauge at a time and a few storm events. This approach is appropriate for initial parameterization of the model and can achieve an acceptable model performance for calibration events and for the stream gauge to which the model is calibrated; however, these results may not be generalized to validation or verification events. This study presented a model optimization framework for EPA SWMM5 model that can exploit the rainfall data of several storm events and stream gauges simultaneously and could improve the model optimization for all stream gauges.

## Conclusion

The results of this study indicated that the Pareto-optimal solution obtained from multi-objective optimization framework improved the validation events of all stream gauges compared to single-objective optimized model. It was found that the investigated multi-objective optimization framework improved the peak flow error of the storm events by 23.9 %, NSE value by 0.26, VE value by 0.82, and KGE value by 0.30 on average. Furthermore, the results of this study point out that using different performance measure criteria such as KGE, VE , NSE and peak flow error as an objective function in model optimization can slightly change the optimization results. Moreover, the multi-objective optimization framework reduces the uncertainty range of optimized parameters.

## References

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[3] Don River watershed, report card 2013, TRCA.
[4] Deb, Kalyanmoy, Amrit Pratap, Sameer Agarwal, and T. Meyarivan. 2002. "A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II." *IEEE Transactions on Evolutionary Computation* 6(2): 182–97

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