Robust optimal design of urban drainage systems

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SINGAPORE UNIVERSITY OF TECHNOLOGY AND DESIGN
VEOLIA

Veolia

- PhD funded by Veolia

- Veolia issues
  - Design of efficient urban drainage systems
  - Considering SUDS hydraulic performance
  - Applicable to large urban scales
  - Good balance between overflow risk and investment costs

- PhD deliverable: User-friendly computer tool

VEOLIA

Veolia is the global leader in optimized resource management, providing innovative waste, water and energy management solutions

168,800 employees worldwide
300 researchers & scientists

SUDS: Sustainable Urban Drainage System (aka LID Low Impact Development in the US)

THE STRAITS TIMES, 21 November 2009, Page 1

Deluge a 'freak' event

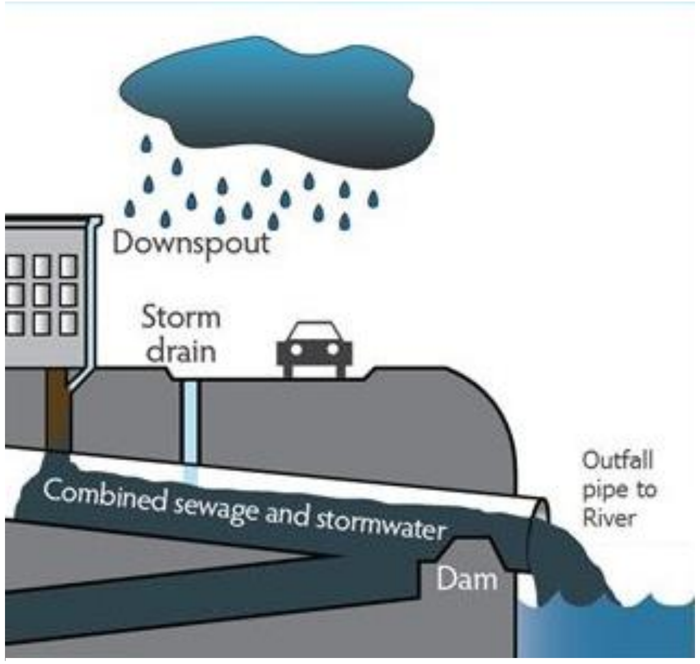
THURSDAY'S deluge which submerged parts of Bukit Timah was a "freak" event that comes once in 50 years, Minister for the Environment and Water Resources Yaacob Ibrahim said yesterday.

Source: STOMP
Bukit Timah, 19 Nov 2009

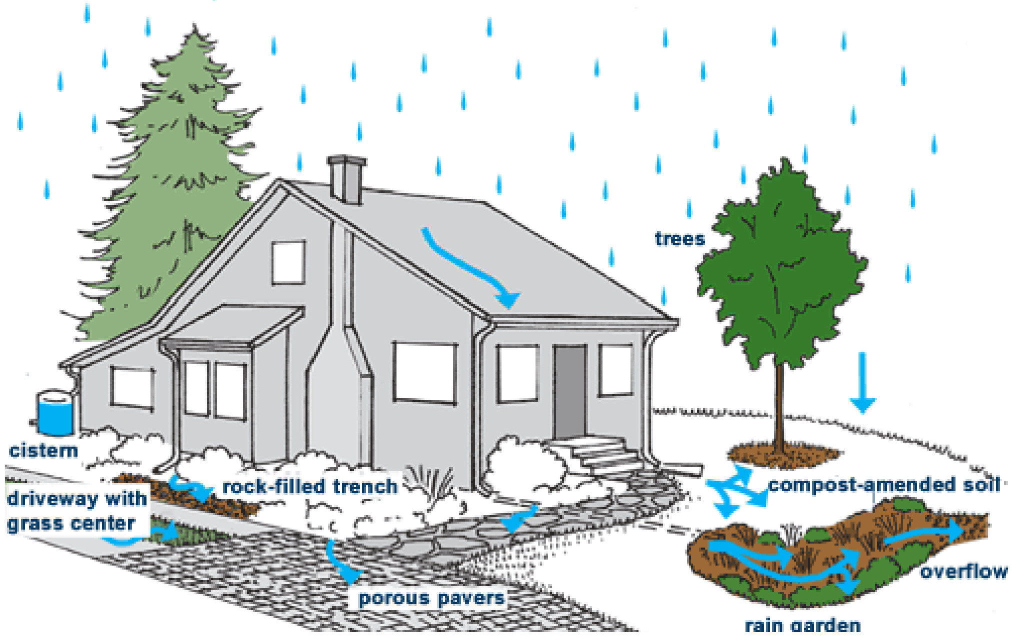
7 months later

Source: Twitter
Orchard, 16 June 2010

Introduction



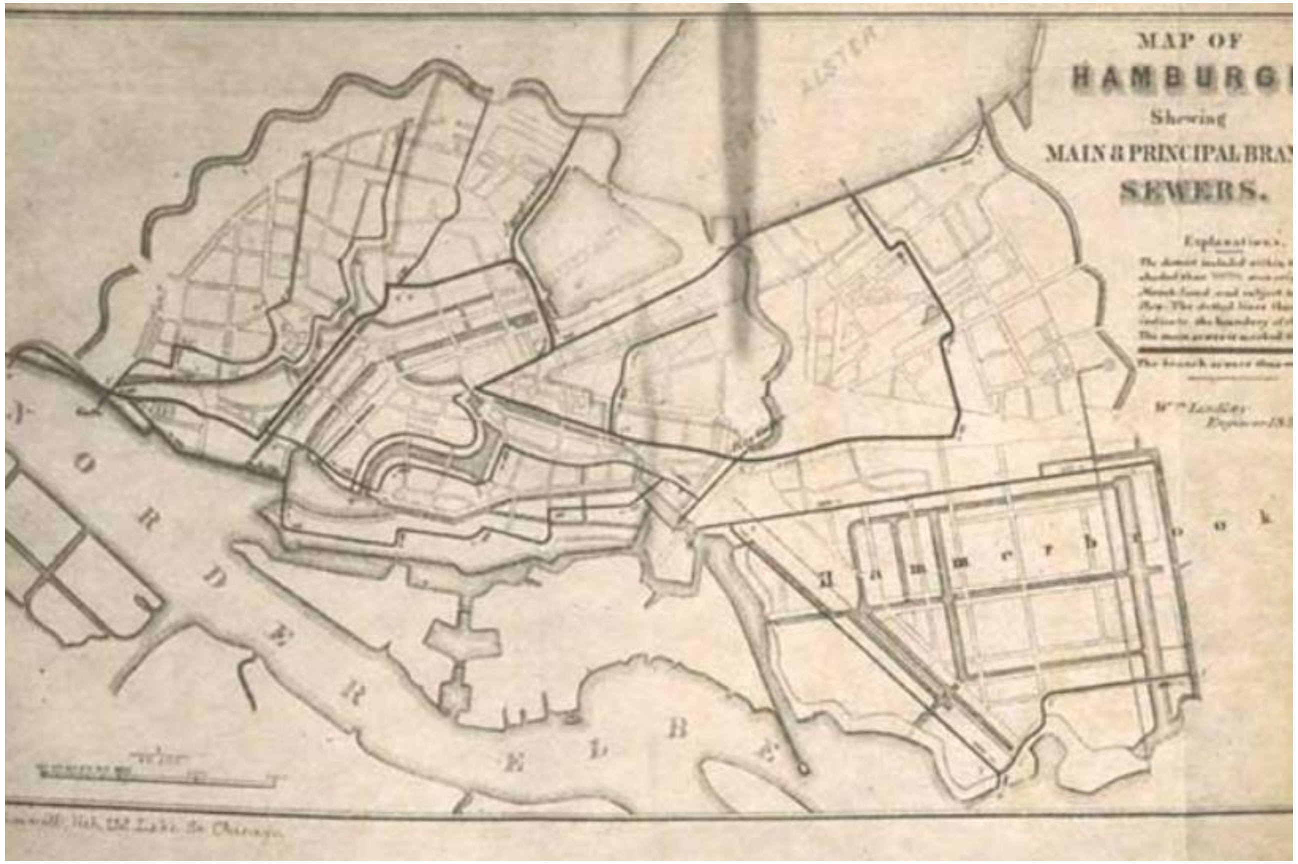
From US Environmental Protection Agency



From Seattle Public Utilities
Illustration of Low Impact Development (LID)

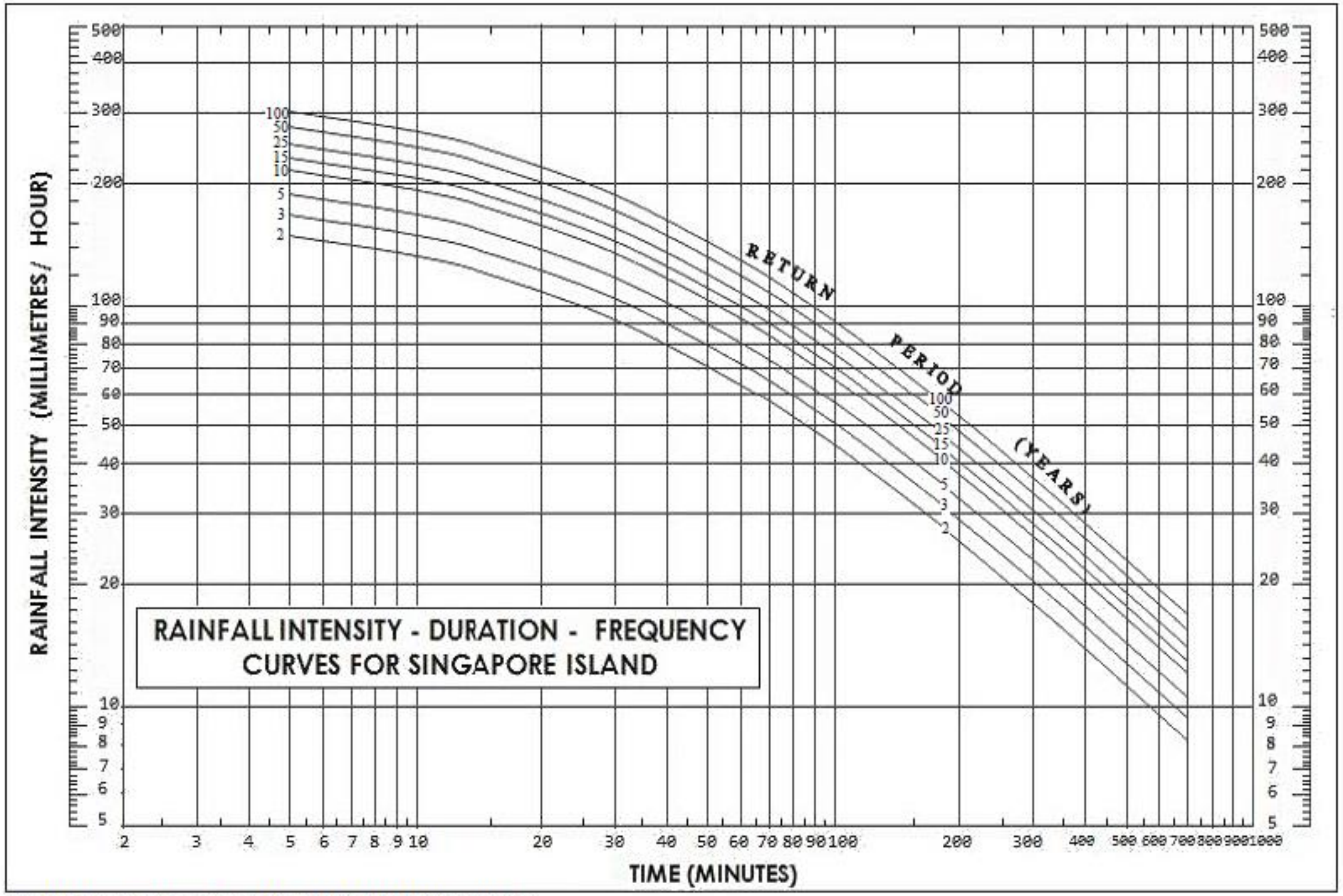
Introduction

- First comprehensively designed drainage system was installed in Hamburg in 1843
- Success was emulated in America and other European countries
- Designs based on empirical equations or look-up tables



Outline of the main sewage system, Hamburg, Germany, 1857
Source: We Are Water Foundation

Introduction



The IDF Curve has been revised to include till 2009 rainfall data.

- IDF curves (intensity-duration-frequency) first derived in 1930s
- Marked the beginnings of 'design storms'

From PUB

Introduction

- Early optimization techniques in 1960s: LP, NLP, DP
  - Oversimplification and inaccurate hydrological and hydraulic evaluations
  - Curse of dimensionality
- Hydrological and hydraulic computation models developed in 1970s
- Current commonly used optimization technique: Metaheuristics
  - Allow for precise hydraulic evaluations using simulation
  - Computationally expensive

Mays, L.W., & Wenzel Jr, H. G. (1976). Optimal design of multilevel branching sewer systems. *Water Resources Research*, *12*(5), 913-917.
Rossman, L.A. (2015). *Storm water management model user's manual, version 5.1*. Cincinnati: National Risk Management Research Laboratory, Office of Research and Development, US Environmental Protection Agency.
Wang, Q., Zhou, Q., Lei, X., & Savić, D.A. (2018). Comparison of Multiobjective Optimization Methods Applied to Urban Drainage Adaptation Problems. *Journal of Water Resources Planning and Management*, *144*(11), 04018070.

Challenges

- Drainage solutions may only work well against design storms

- Optimization-based design is computationally expensive
  - Large decision space
  - Challenging simulation runtime

Challenges

- Drainage solutions may only work well against design storms

Not robust

- Optimization-based design is computationally expensive
  - Large decision space
  - Challenging simulation runtime

Poor scalability:
may prevent application to large watersheds

Objectives

To develop a tool for the robust optimal design of urban drainage systems

Features:

- Able to provide optimal configuration (location, type, size, operations) of LID and sewer systems (pipes, pumps, valves, storage tanks)
- Able to handle multiple objectives
- Can be applied to various test cases readily for urban rehabilitation plan or master planning of new systems
- Scalable (large catchment area, reasonable computation time)
- User-friendly

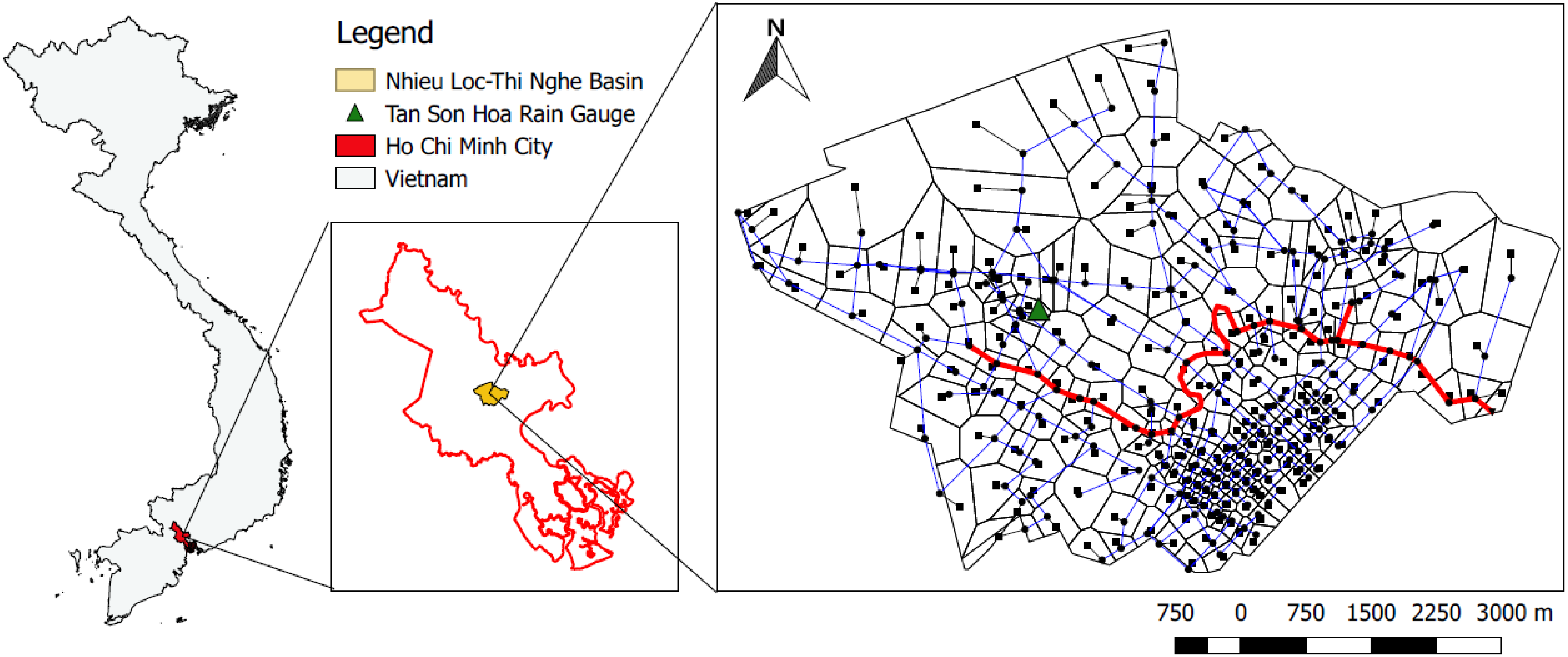
Research questions

- Do design storms yield robust urban drainage systems?
- How can we design (robust) optimal urban drainage systems at large urban scales within reasonable computation time?

DO DESIGN STORMS YIELD ROBUST DRAINAGE SYSTEMS? HOW RAINFALL DURATION, INTENSITY, AND PROFILE CAN AFFECT DRAINAGE PERFORMANCE

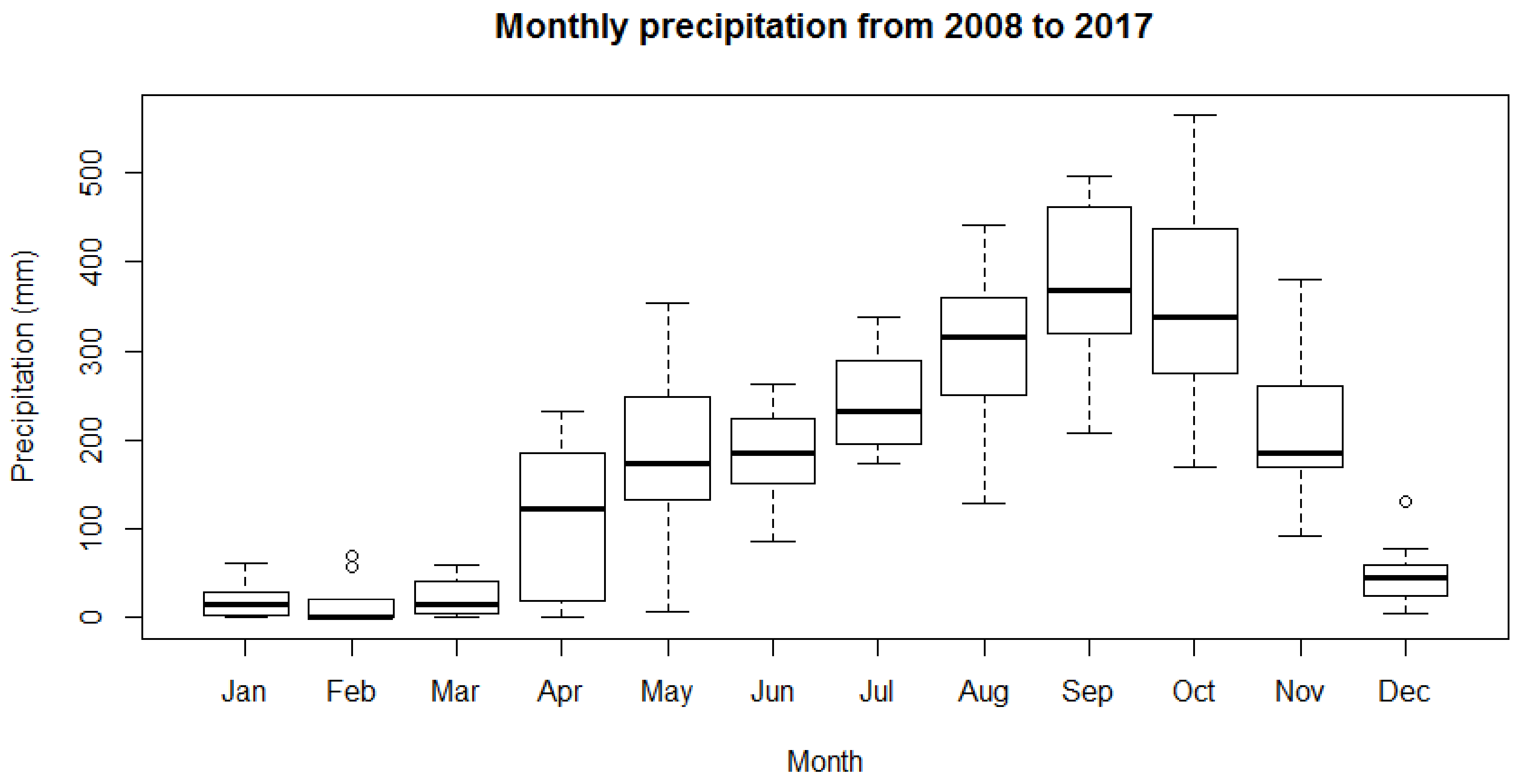
CASE STUDY

Nhieu Loc-Thi Nghe (NL-TN) Basin

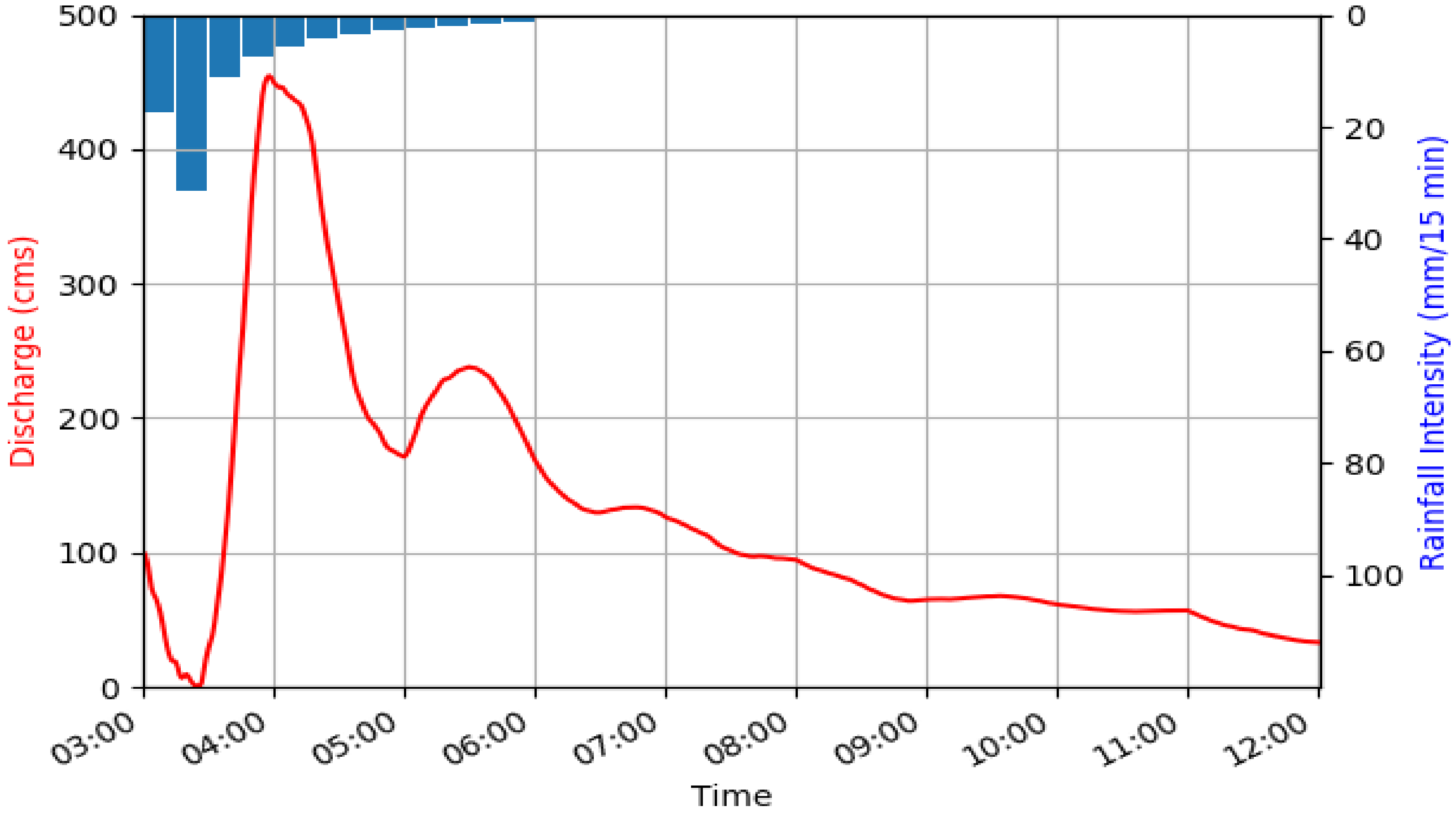


Loc, H. H., Babel, M. S., Weesakul, S., Irvine, K. N., & Duyen, P. M. (2015). Exploratory Assessment of SUDS Feasibility in Nhieu Loc-Thi Nghe Basin, Ho Chi Minh City, Vietnam. *International Journal of Environment and Climate Change*, 91-103.

Precipitation for NL-TN Basin

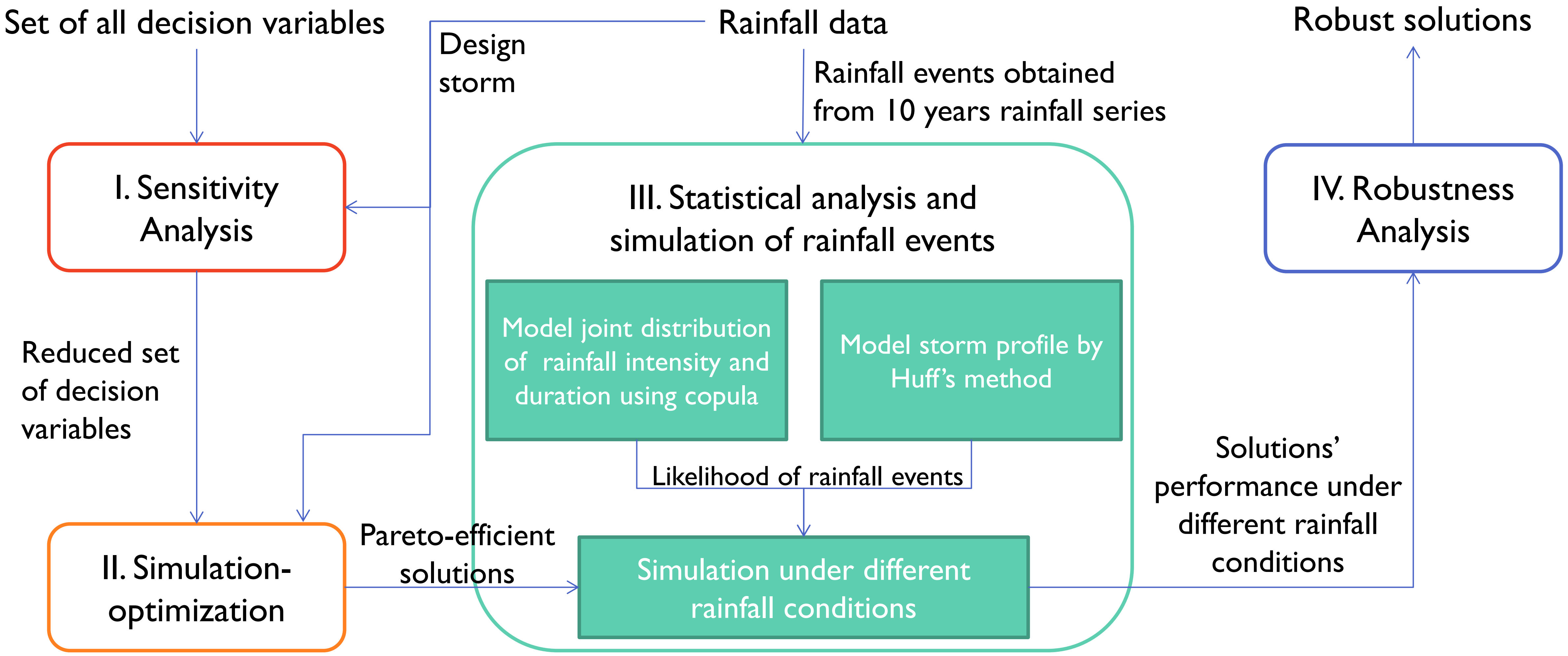


Precipitation for NL-TN Basin

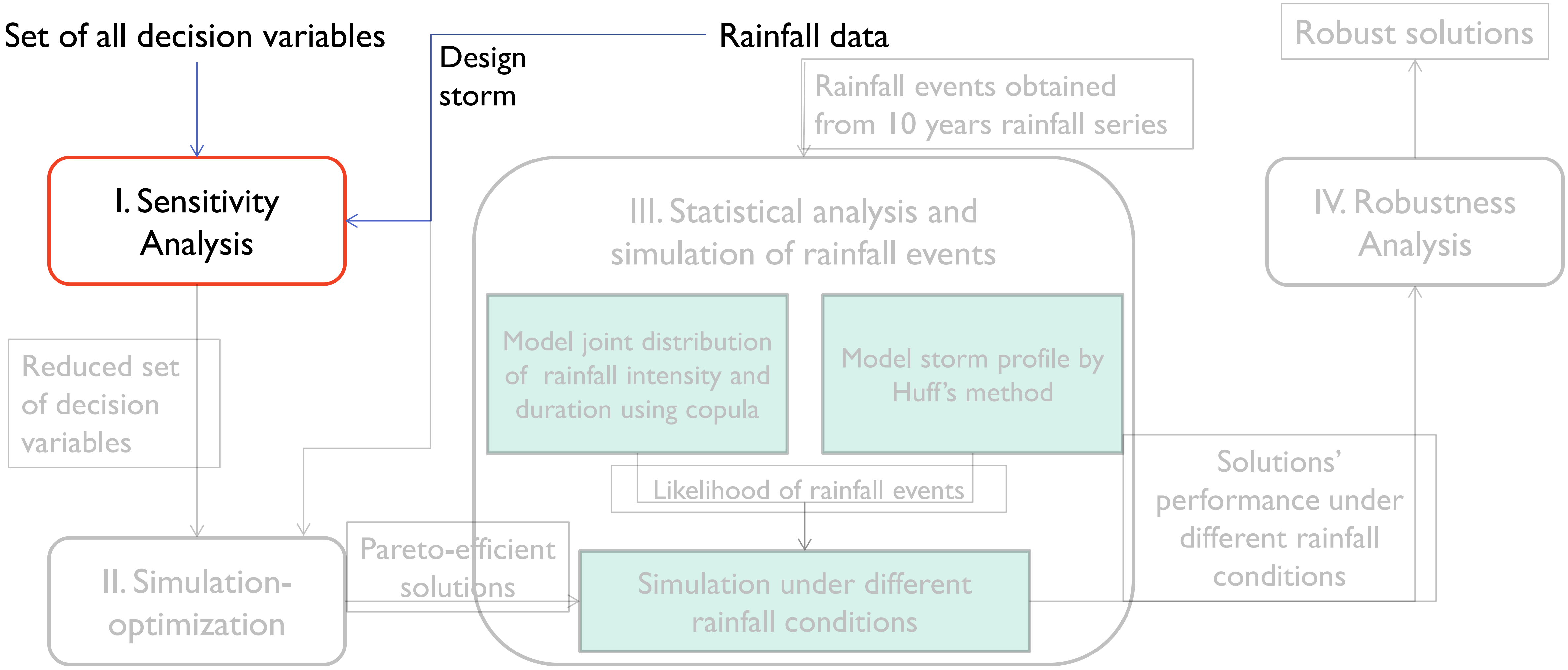


METHODS

Computational framework



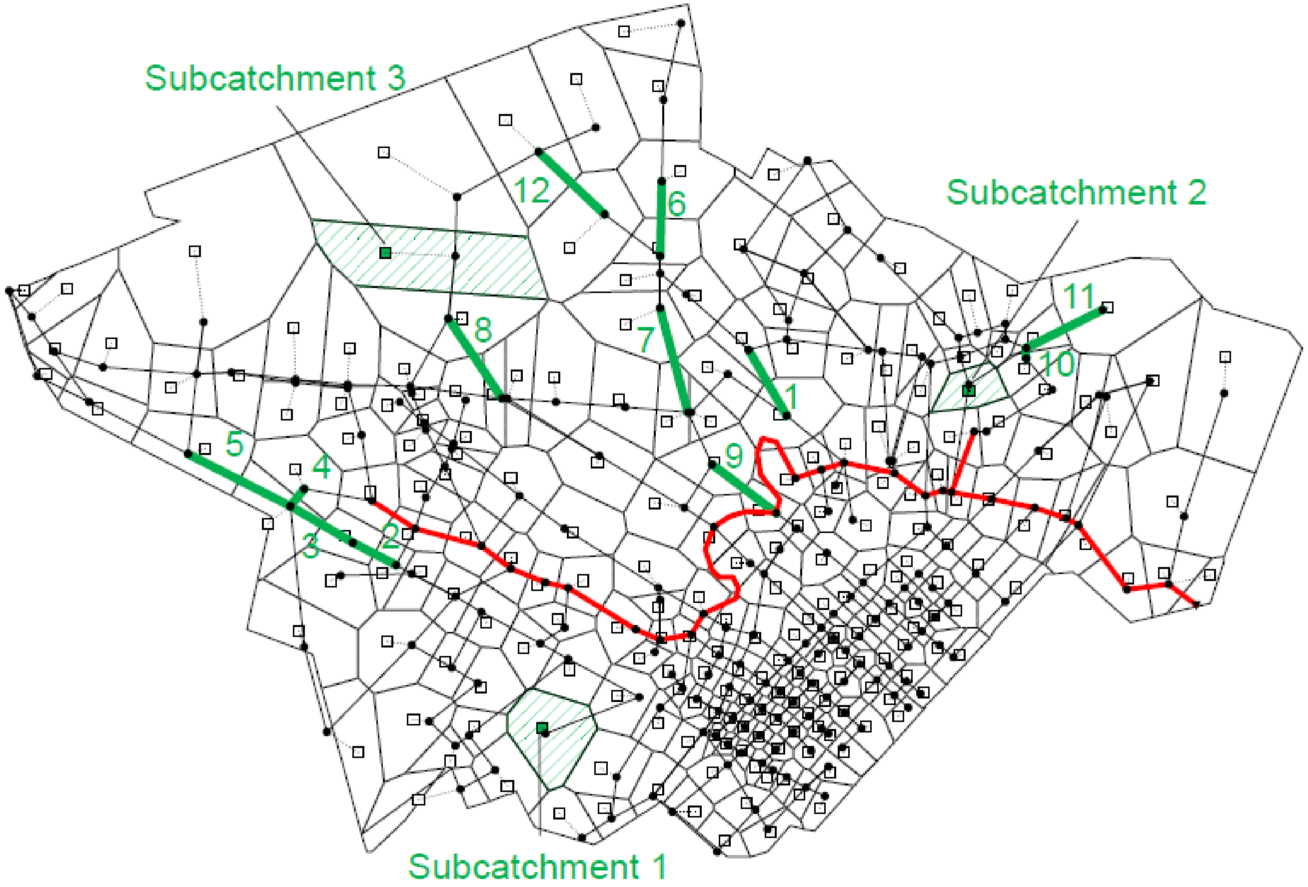
Computational framework



Sensitivity Analysis

- Input: diameter of 308 pipes and area of 12 LIDs
- Output: overflow reduction

- EET and eFAST to reduce decision space from 320 variables to 12 pipe variables and 8 LID variables



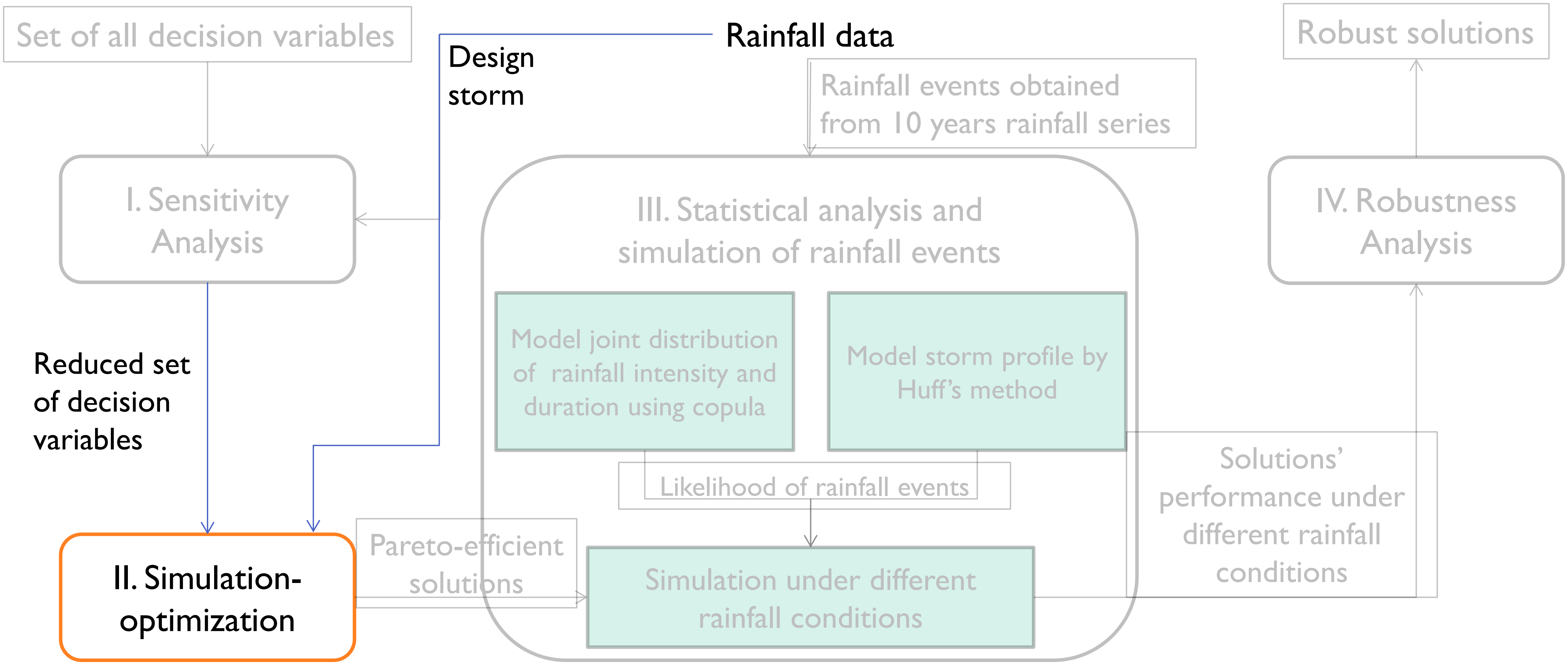
EET: Elementary effect test
eFAST: extended Fourier amplitude sensitivity test

Pianosi, F., Beven, K., Freer, J., Hall, J. W., Rougier, J., Stephenson, D. B., & Wagener, T. (2016). Sensitivity analysis of environmental models: A systematic review with practical workflow. *Environmental Modelling & Software*, 79, 214-232.
Saltelli, A., Tarantola, S., & Chan, K. S. (1999). A quantitative model-independent method for global sensitivity analysis of model output. *Technometrics*, *41*(1), 39-56.

Selected decision variables

Decision variable, x_j	Pipe no.	Shape	Length, l_j (m)	Size, d_j (m)	Maximum size (m)
x_1	1	Rectangular closed	546	2.5 x 2.5	4
x_2	2	Circular	360	1.5	2.5
x_3	3	Circular	510	1.2	2.2
x_4	4	Circular	180	1	2
x_5	5	Rectangular closed	840	1.5 x 2.8	4
x_6	6	Rectangular closed	600	1.2 x 2	4
x_7	7	Rectangular closed	727	2 x 4	4
x_8	8	Rectangular closed	540	0.8 x 5	4
x_9	9	Rectangular closed	551	1.2 x 5	4
x_{10}	10	Rectangular open	200	3.2 x 10	4.2
x_{11}	11	Rectangular open	610	2.7 x 10	4
x_{12}	12	Rectangular closed	900	1.8 x 4	4
	LID	Sub-catchment properties			Maximum no. of units
		Sub-catchment no.	Area (ha)	Impervious %	
x_{13}	Green roofs	1	31.45	70	1102
x_{14}	Pervious pavements				900
x_{15}	RWH system				1102
x_{16}	RWH system	2	12.55	70	406
x_{17}	Green roofs	3	102	70	2726
x_{18}	Pervious pavements				1400
x_{19}	Urban green spaces				4000
x_{20}	RWH system				2726

Computational framework



Optimization problem -- formulation

$$\mathbf{x}^* = \arg\min_{\mathbf{x}} \mathbf{J}(\mathbf{x})$$

$$\mathbf{x} = \left(\overbrace{x_1, \dots, x_{M_p}}^{\text{Diameter of pipes}}, \overbrace{x_{M_p+1}, \dots, x_{M_p+M_L}}^{\text{Numbers of LID units}} \right)$$

Decision variables

Total # of pipes

Total # of LIDs

$$\mathbf{J}(\mathbf{x}) = \begin{bmatrix} -J^{Overflow}(\mathbf{x}) \\ -J^{Node}(\mathbf{x}) \\ J^{Cost}(\mathbf{x}) \end{bmatrix}$$

Reduction in total overflow volume

Reduction in # of flooded nodes

Optimization problem -- formulation

Total time instances

Total # of nodes

Overflow volume at i-th node at time t (SWMM)

$$J^{Overflow} = 1 - \frac{\sum_{t=1}^{T}\sum_{i=1}^{N} f_{i,t}(\mathbf{x})}{F_{baseline}}$$

Total overflow volume for existing drainage system

$$J^{Node} = 1 - \frac{\sum_{i=1}^{N} \mathbb{1}_{\{\sum_{t=1}^{T} f_{i,t}(\mathbf{x}) > 0\}}}{N_{baseline}}$$

Total # of flooded nodes for existing drainage system

Original diameter of pipe j

Area of LID k

$$J^{Cost} = \sum_{j=1}^{M_p} \alpha \times x_j \times l_j \times \mathbb{1}_{\{x_j > d_j\}} + \sum_{k=1}^{M_L} \beta_k \times a_k \times x_{M_p+k}$$

Unit cost of LID k

Length of pipe j

Unit cost of pipe

Optimization problem -- algorithm

Initialize population
↓
Evaluate individual fitness
↓
Rank population
↓
Select parents
↓
Crossover and mutation
↓
Evaluate offspring fitness
↓
Rank population (parents + offspring)
↓
Select individuals
↓
No — Stopping criteria met? — Yes → Output

NSGAII + SWMM

Set-up

Population size: 200

# of generations: 250

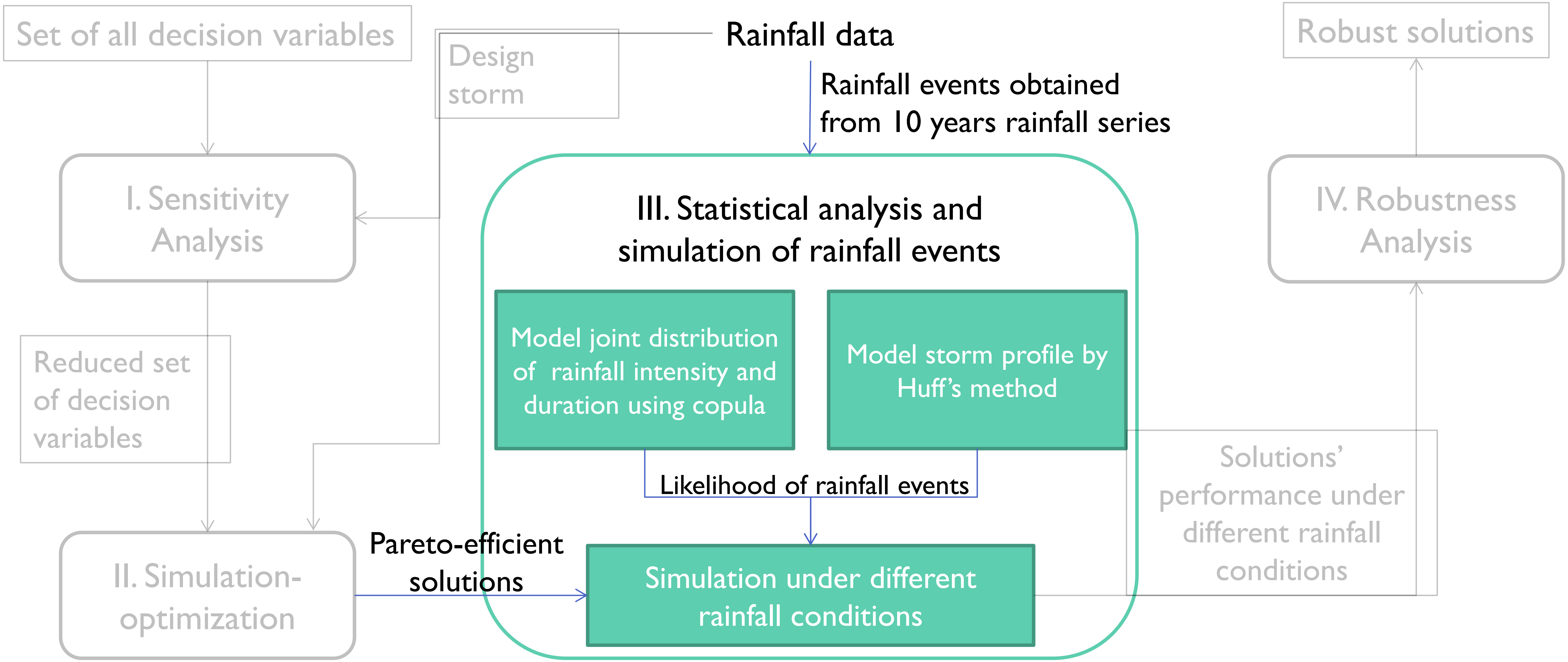
# of function evaluations: 50,000

# of random seeds: 10

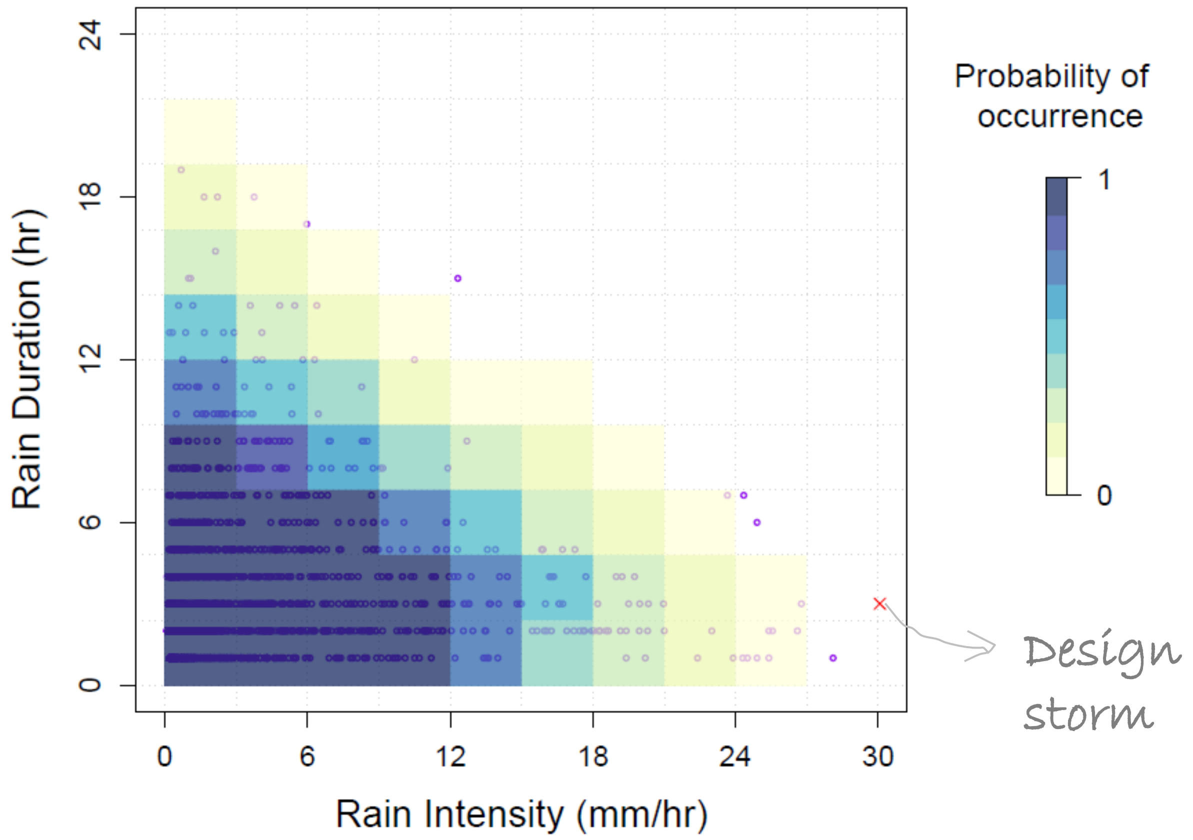
Time taken per random seed: 72 hours

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. A. M. T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE transactions on evolutionary computation*, *6*(2), 182-197.

Computational framework



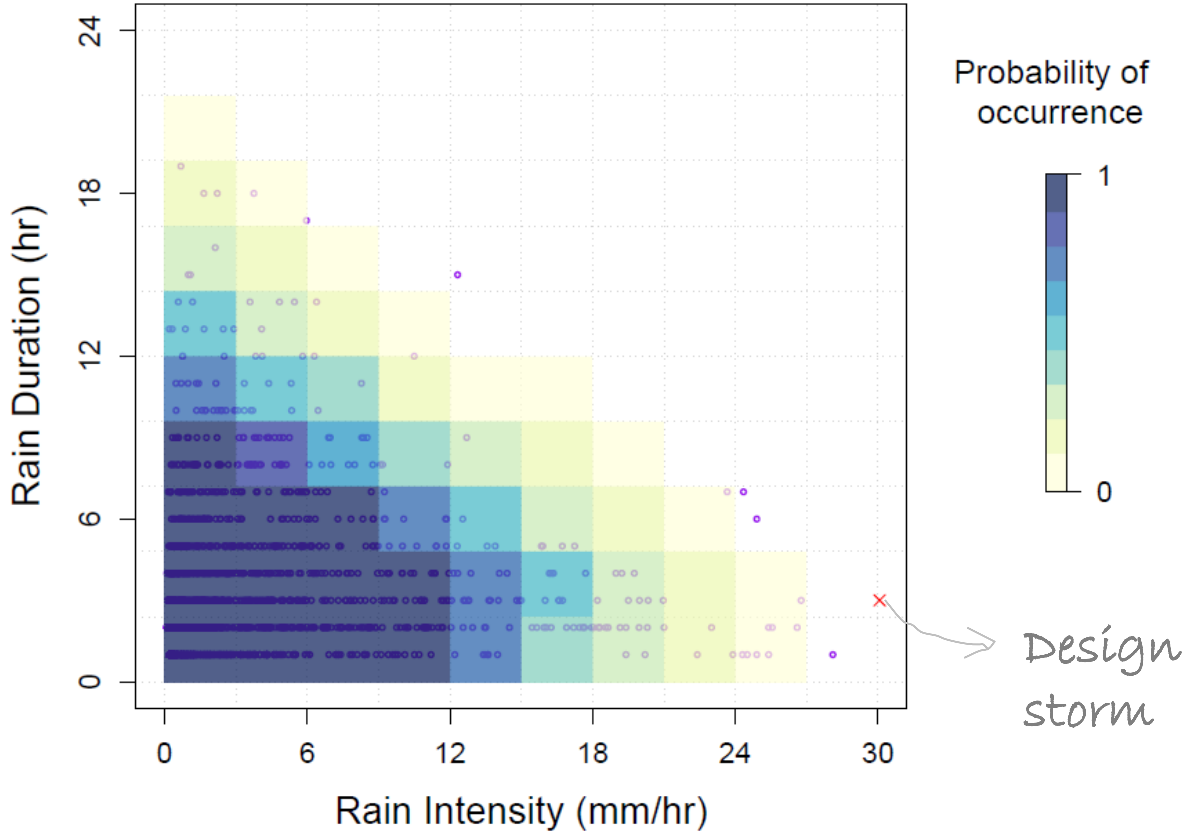
Analysis and generation of rainfall events

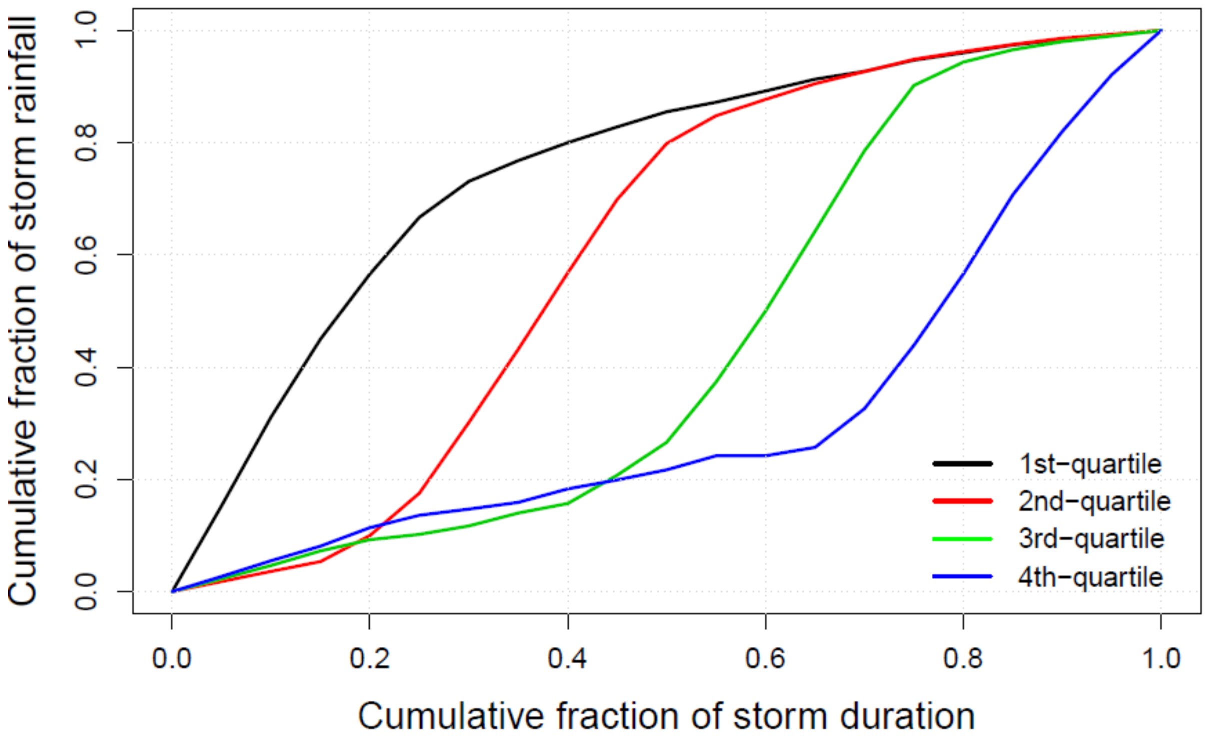


- Duration fitted to lognormal distribution
- Intensity fitted to gamma distribution
- Joint probability distribution modeled by a Frank copula
- 49 events selected with varying duration and intensity

Genest, C., & Favre, A. C. (2007). Everything you always wanted to know about copula modeling but were afraid to ask. *Journal of hydrologic engineering*, *12*(4), 347-368.

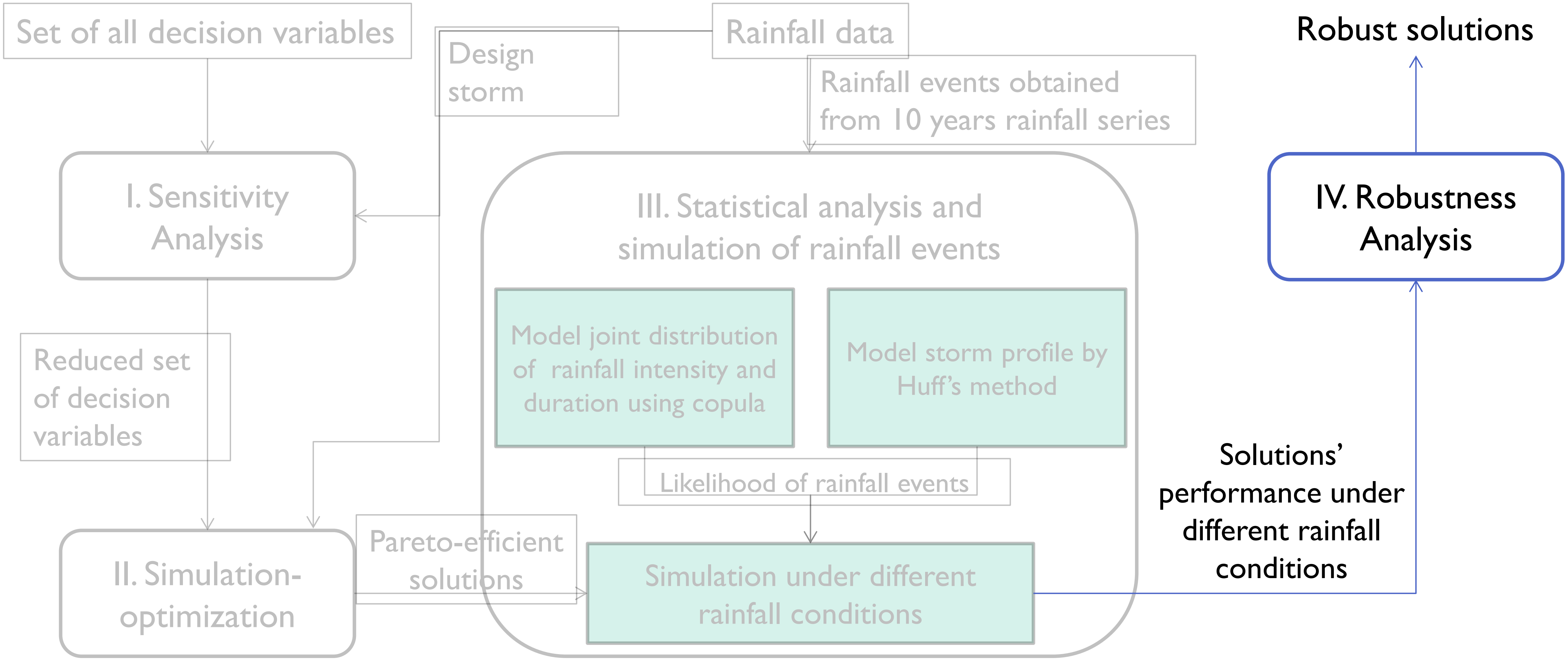
Analysis and generation of rainfall events





Huff, F.A. (1990). Time distributions of heavy rainstorms in Illinois. *Circular no. 173*.

Computational framework



Robustness metric

Performance of solution s in event q

Success of solution s in event q $$S_{s,q} = \begin{cases} 1 & \mathbf{P_{s,q}} \geq \mathbf{T_s} \\ 0 & otherwise \end{cases}$$

Solution-specific performance threshold $$\mathbf{T_s} = \begin{bmatrix} J^{Overflow}(\mathbf{x_s}) \\ J^{Node}(\mathbf{x_s}) \end{bmatrix}$$

# of rainfall events that have overflow in existing drainage system

Robustness of solution s $$R_s = \sum_{q=1}^{N_E} S_{s,q} \times w_q$$

Probability of event q

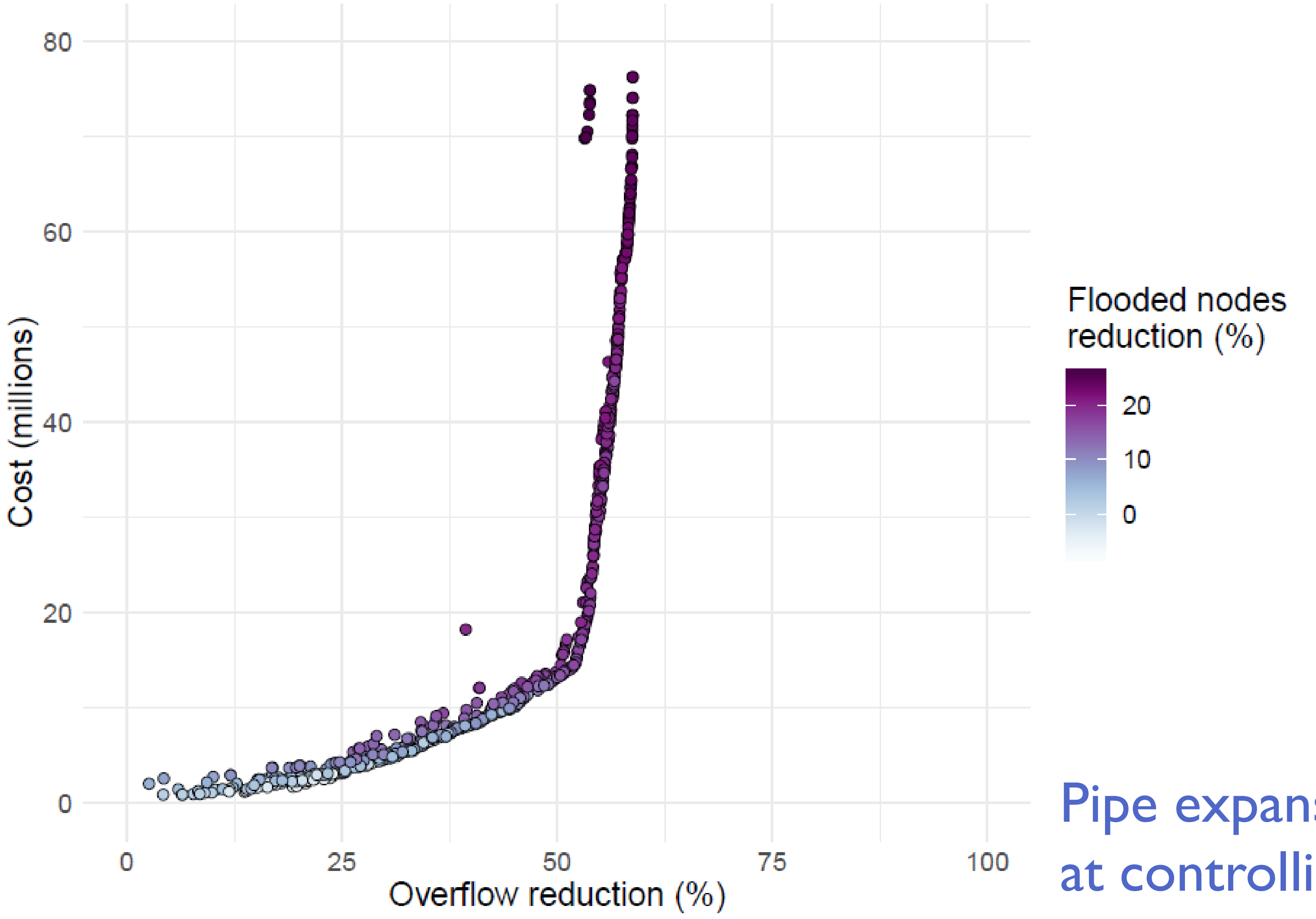
Weight of event q $$w_q = \frac{Pr_q \times F_q}{\sum_{l=1}^{N_E} Pr_l \times F_l}$$

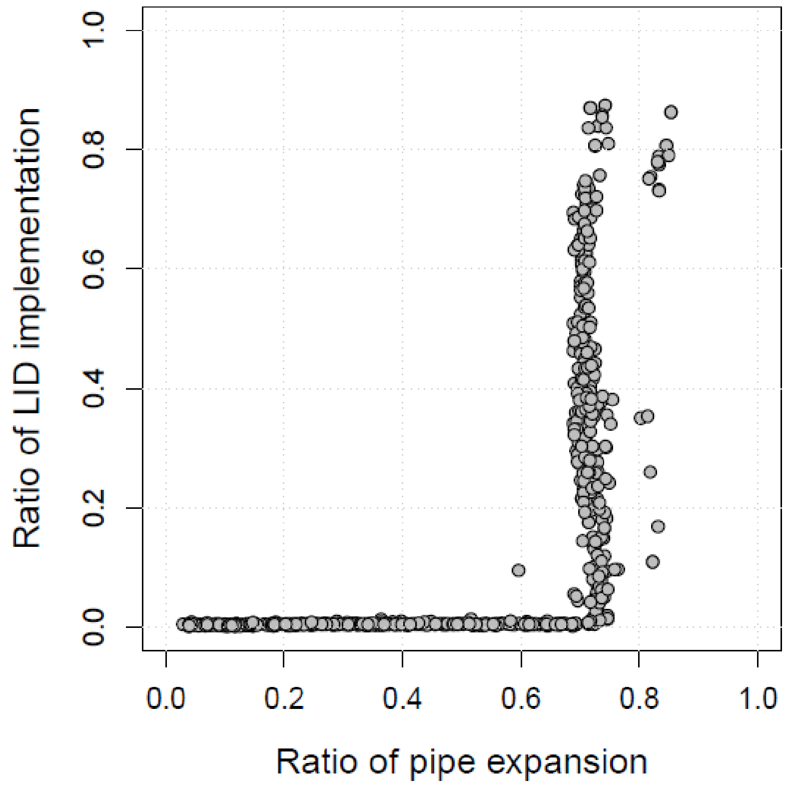
Overflow volume in existing drainage system in event q

Herman, J. D., Reed, P. M., Zeff, H. B., & Characklis, G. W. (2015). How should robustness be defined for water systems planning under change?. *Journal of Water Resources Planning and Management*, *141*(10), 04015012.

RESULTS

Performance of Pareto-efficient solutions

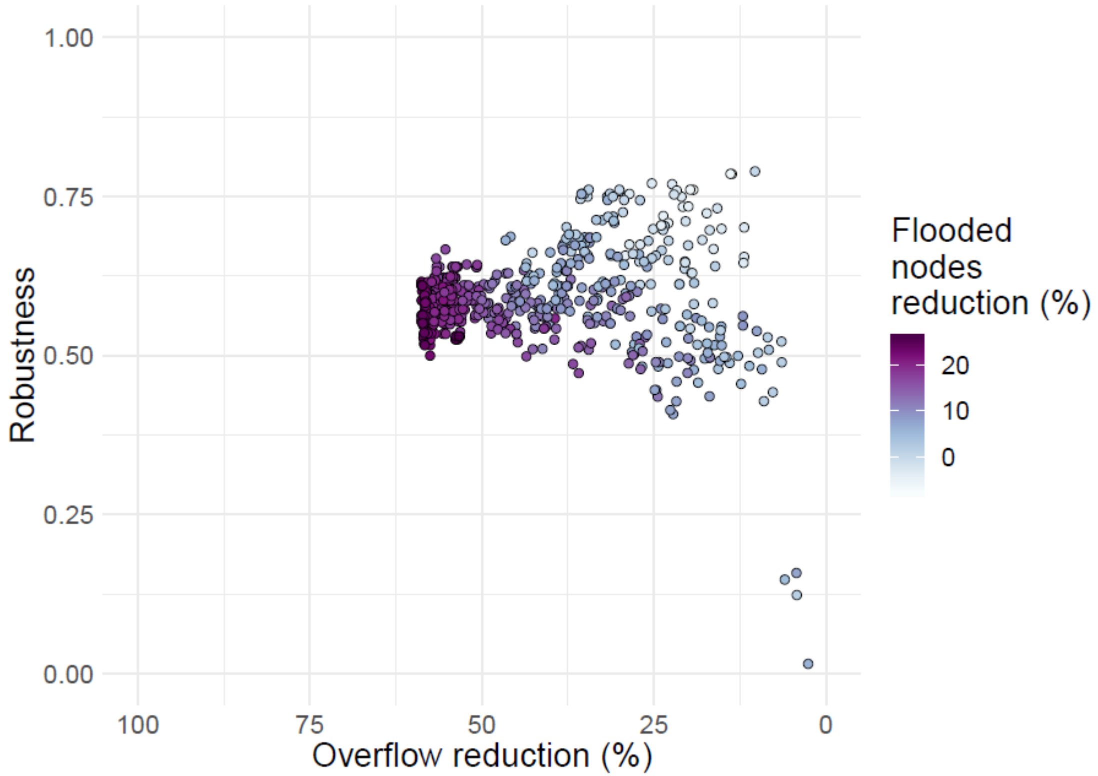




Pipe expansions are more effective than LIDs at controlling pluvial flood in the NL-TN basin

Robustness of solutions

None of the Pareto-efficient solutions are perfectly robust!

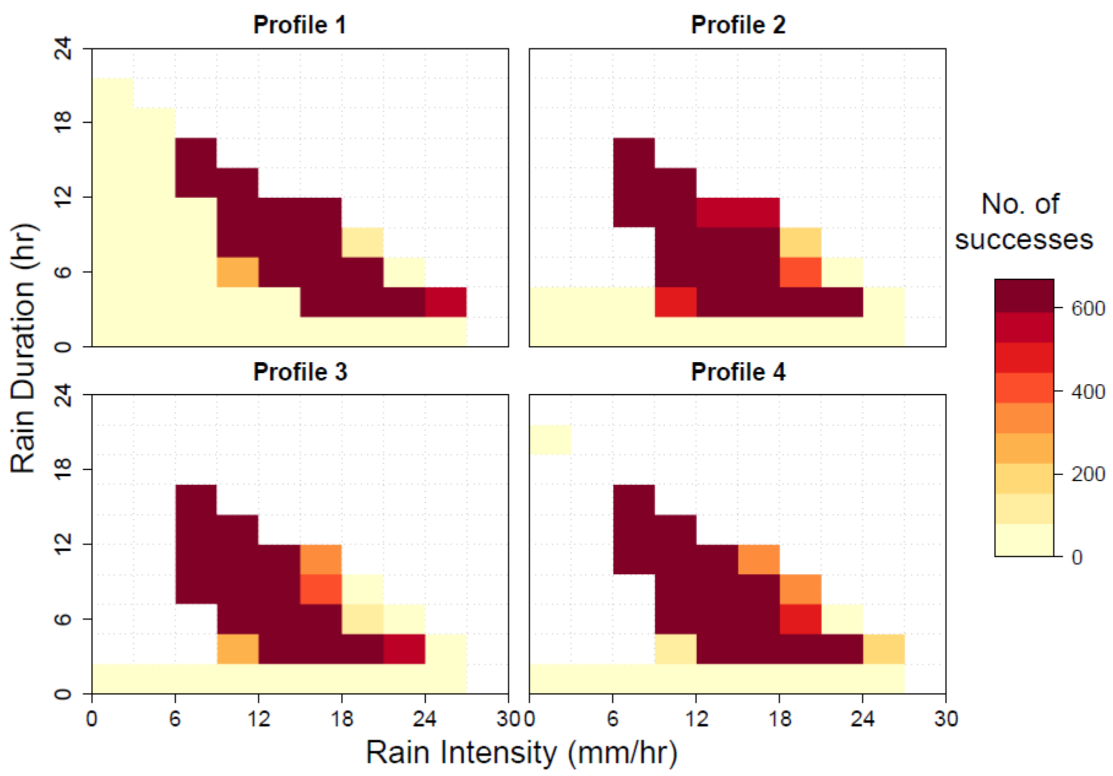


Performance of each solution

All solutions underperformed in some rainfall events

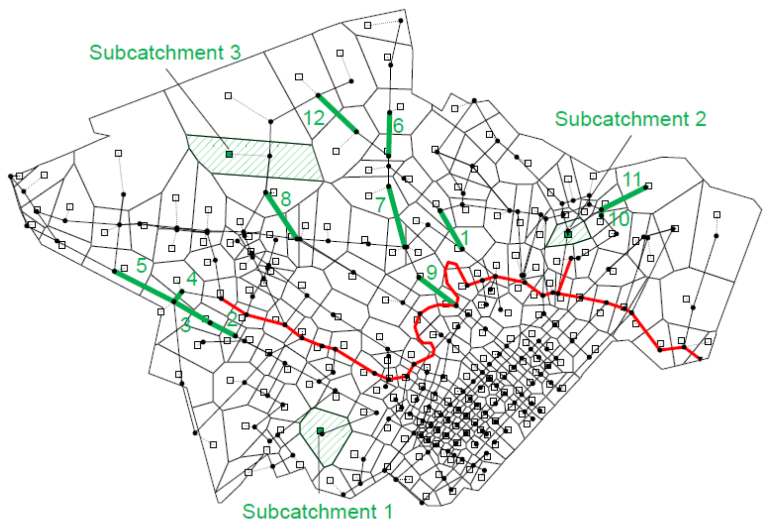
Robustness is primarily determined by pipe expansions

No. of successes for each rainfall event

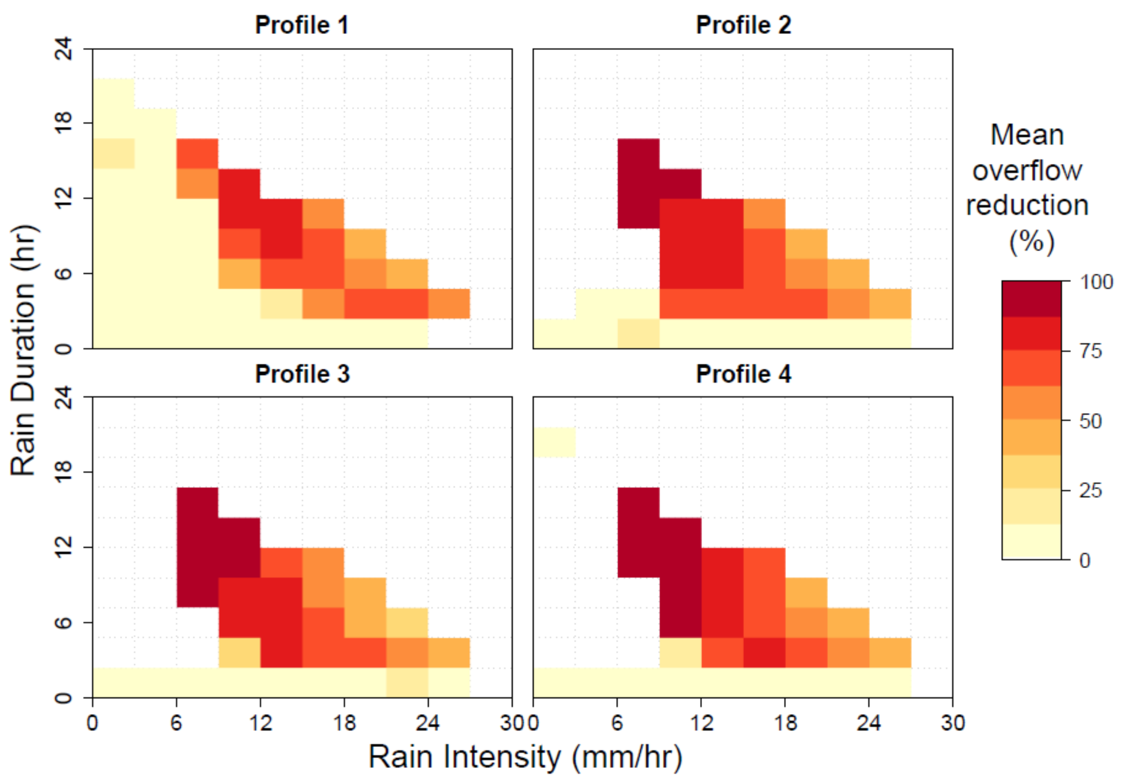


Many solutions underperformed in intense events

All solutions underperformed in small events



Mean performance of solutions for all rainfall events



Mean overflow reduction for design storm is 43%

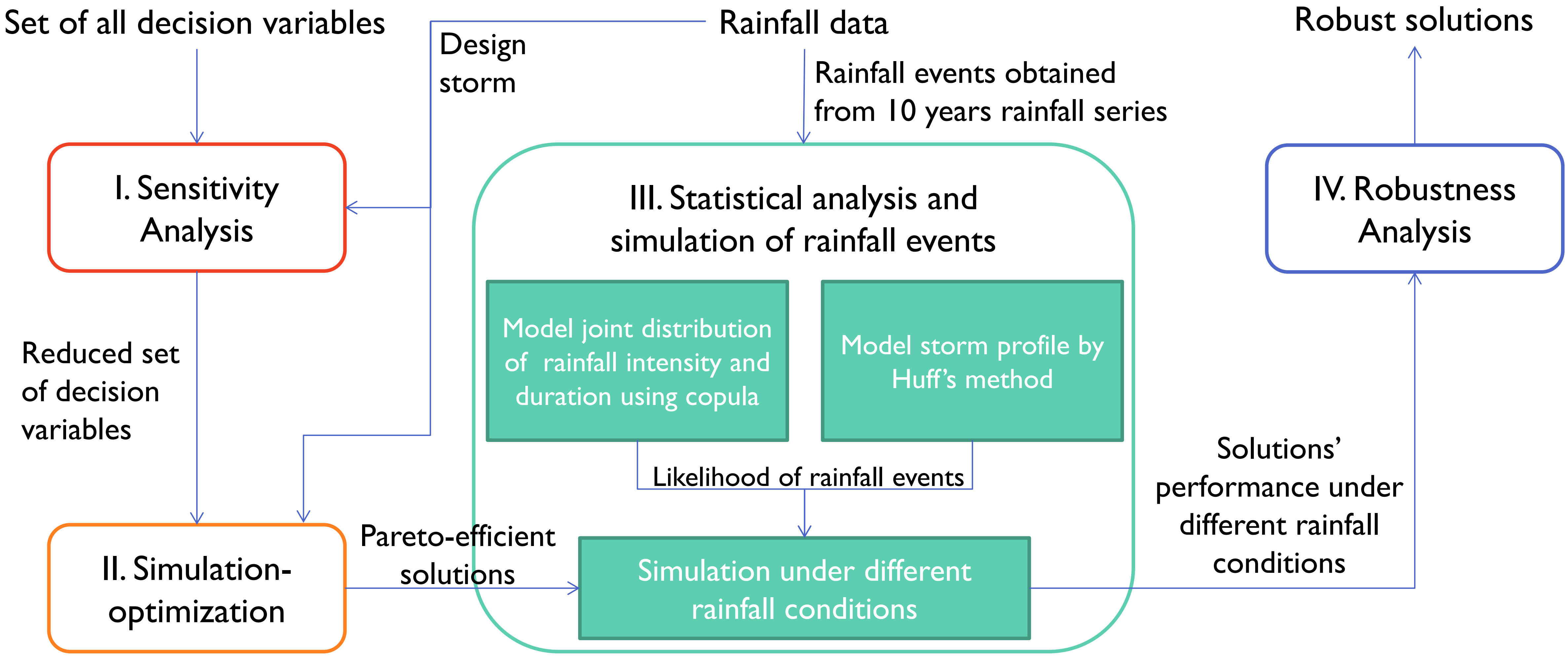
Overflow reduction is more sensitive to rainfall depth and intensity

Conclusions

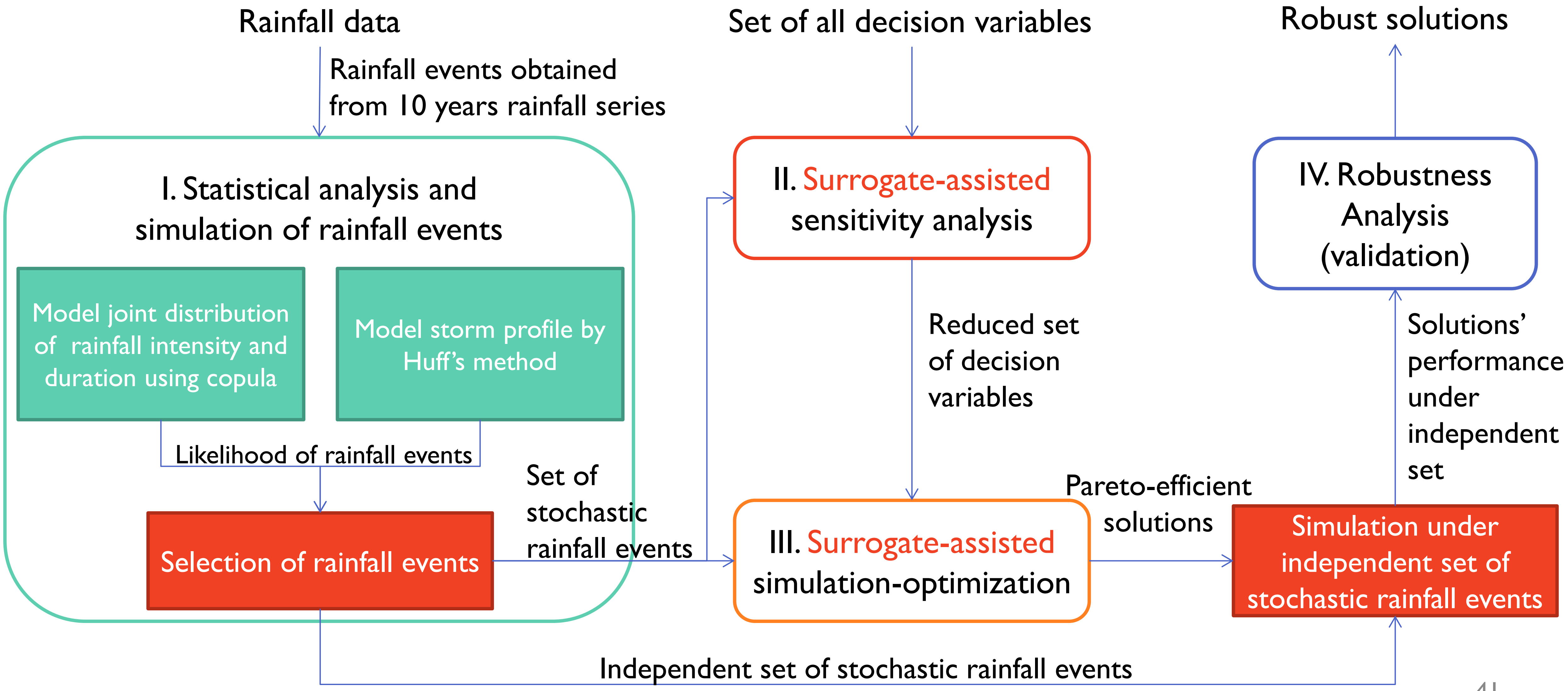
- None of drainage solutions are completely robust
- Pipe expansions in NL-TN Basin are more effective than LIDs to reduce flood and increase robustness
- Solutions are not robust for 2 types of rainfall events:
  - Less intense but longer rainfall events which have greater depth than the design storm
  - Small, yet frequent, rainfall events
- Stochastic rainfall events need to be included within the design process

HOW TO DESIGN ROBUST OPTIMAL URBAN DRAINAGE SYSTEMS

Computational framework

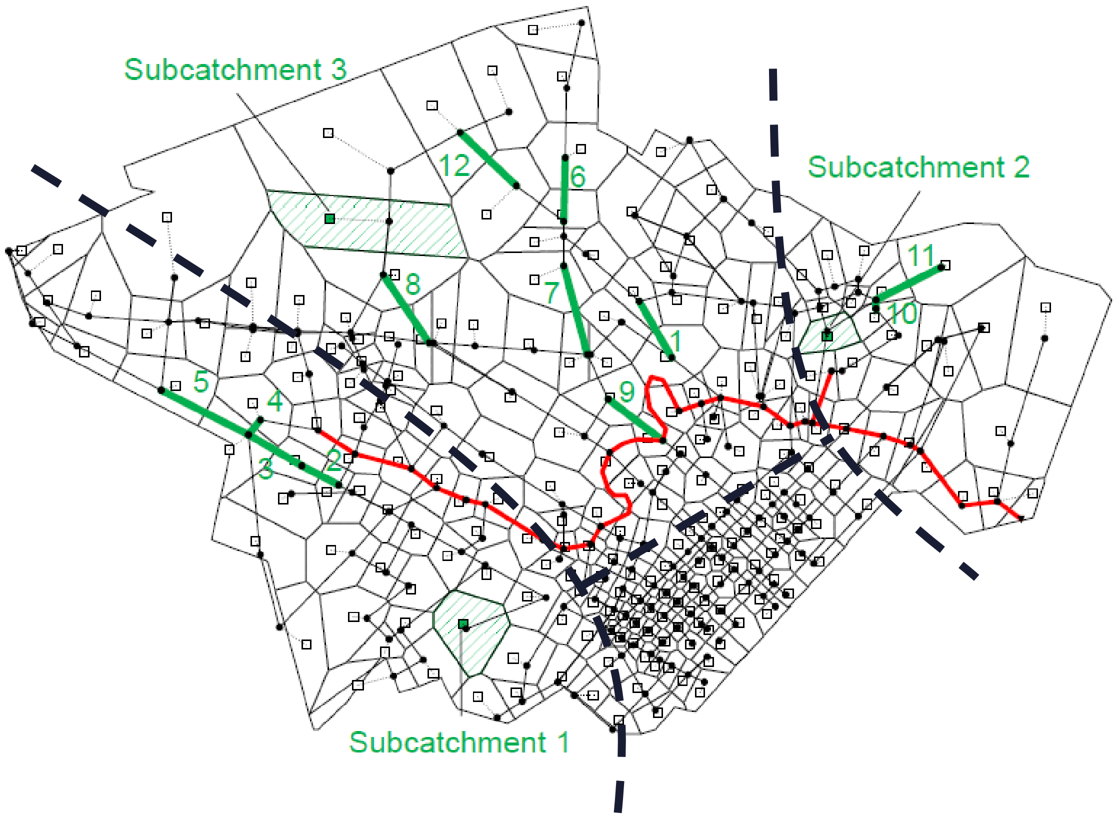


Surrogate-assisted computational framework



Ideas

- Iterative update of surrogate models
- Multi-fidelity models
  - Using both low-fidelity (surrogate) and high-fidelity (simulation) models to improve accuracy of model estimates
- Decomposition of network

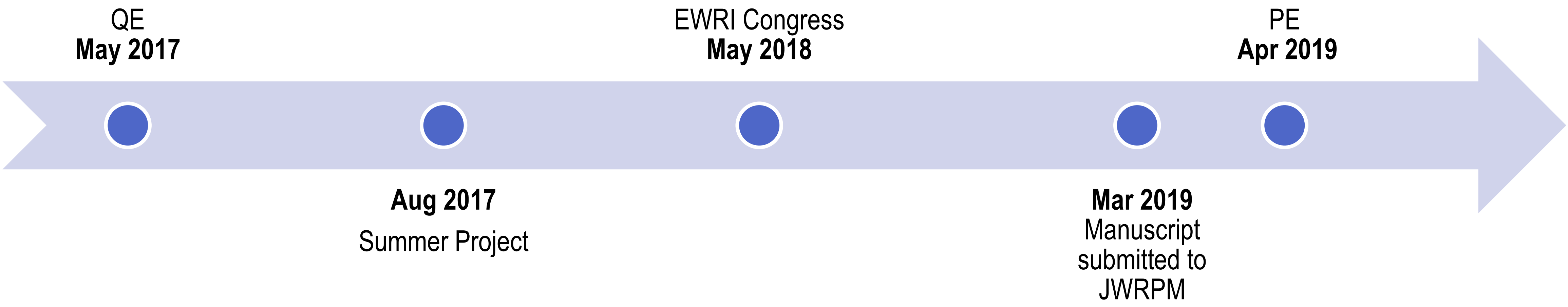


Akhtar, T., & Shoemaker, C. A. (2019). Efficient Multi-Objective Optimization through Population-based Parallel Surrogate Search. *arXiv preprint arXiv:1903.02167*.
Peherstorfer, B., Willcox, K., & Gunzburger, M. (2016). Optimal model management for multifidelity Monte Carlo estimation. *SIAM Journal on Scientific Computing*, *38*(5), A3163-A3194.
Pecci, F., Abraham, E., & Stoianov, I. (2019). Model Reduction and Outer Approximation for Optimizing the Placement of Control Valves in Complex Water Networks. *Journal of Water Resources Planning and Management*, *145*(5), 04019014.

MILESTONES & TIMELINE

Timeline

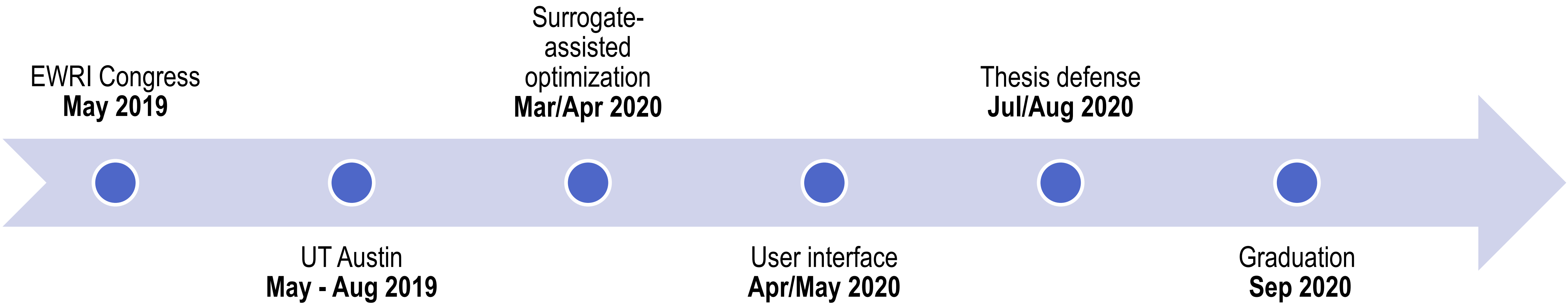
- What I have done



EWRI: Environmental & Water Resources Institute
JWRPM: Journal of Water Resources Planning and Management

Timeline

- What I plan to do



Acknowledgements

This research is supported by VE City Modelling Centre through the Singapore Economic Development Board's Industrial Postgraduate Programme. We would also like to acknowledge Veolia Recherche et Innovation (VERI) for their support.

REFERENCES

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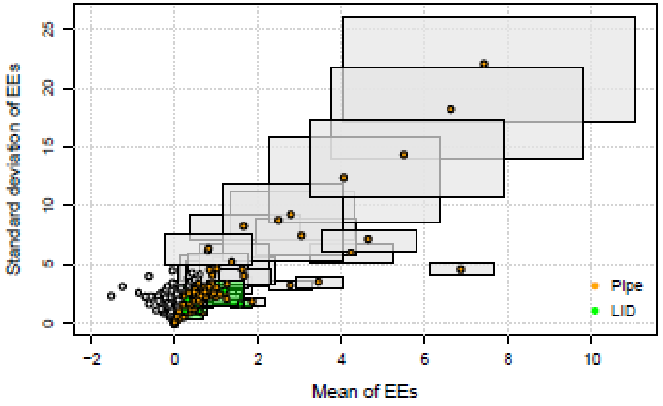
APPENDIX

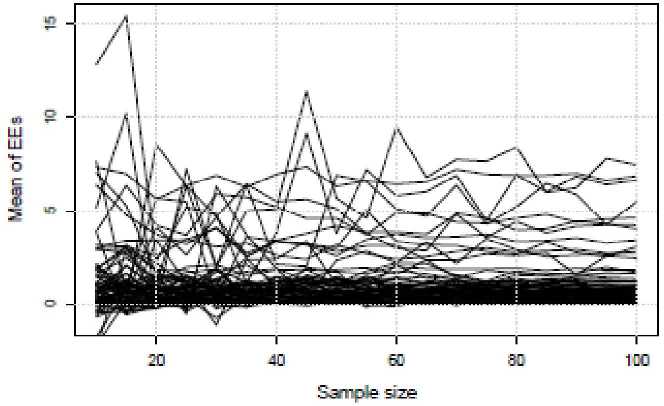
Sensitivity analysis (round 1)

- Elementary effect test (EET)
  - Input factors: 308 pipes + 12 LIDs
  - Outputs: Total overflow reduction, peak flow reduction
  - 78 pipes and 8 LIDs selected
    - Positive 95% lower one-sided bound for mean of EEs for either output

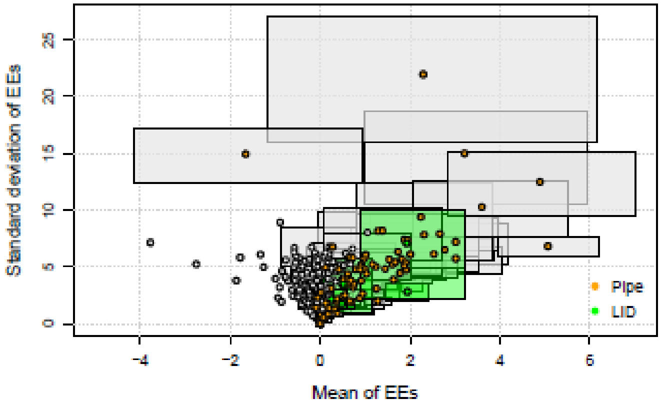
I st EET results



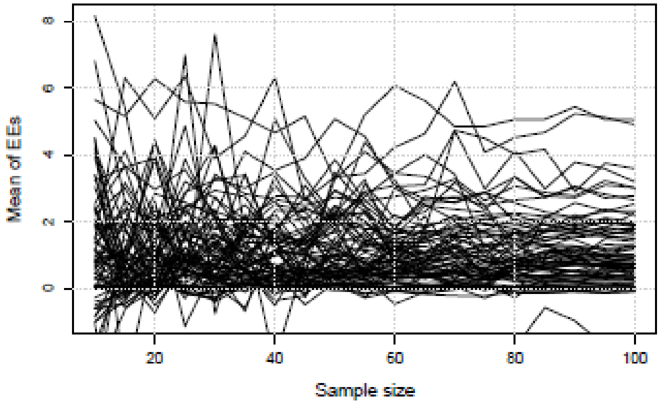
(a) EET plot when output is total overflow reduction



(b) Convergence plot when output is total overflow reduction



(c) EET plot when output is peak overflow reduction



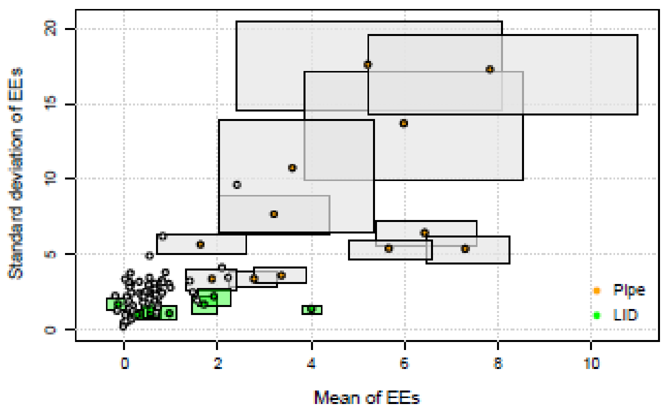
(d) Convergence plot when output is peak overflow reduction

Sensitivity analysis (round 2)

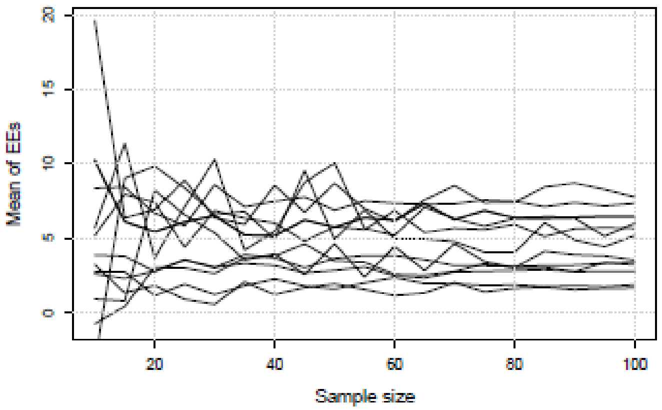
- EET & eFAST
  - Input factors: 78 pipes + 8 LIDs
  - Outputs: Total overflow reduction, peak flow reduction
  - 12 pipes and 8 LIDs selected
    - Ranked according to mean of EEs (for EET) and total order index (for eFAST) for each output
    - Selected if ranked in the top 20 in both eFAST and EET for the same output

eFAST: extended Fourier amplitude sensitivity test

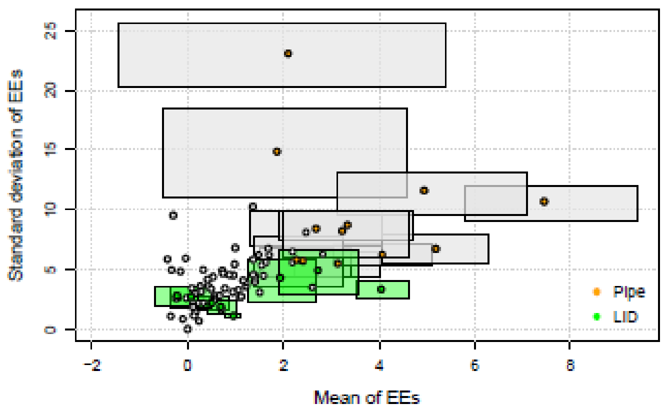
2nd EET results



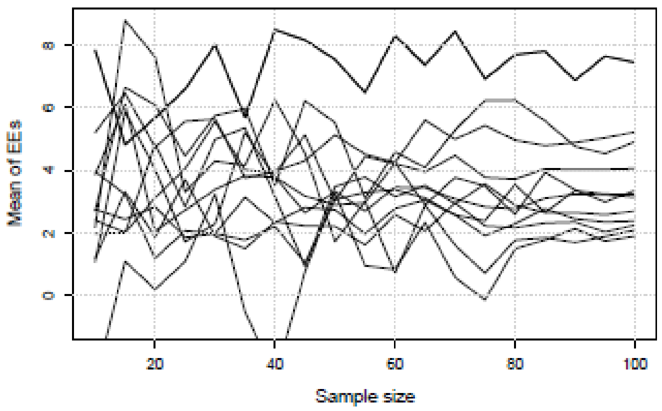
(a) EET plot when output is total overflow reduction.



(b) Convergence plot when output is total overflow reduction.

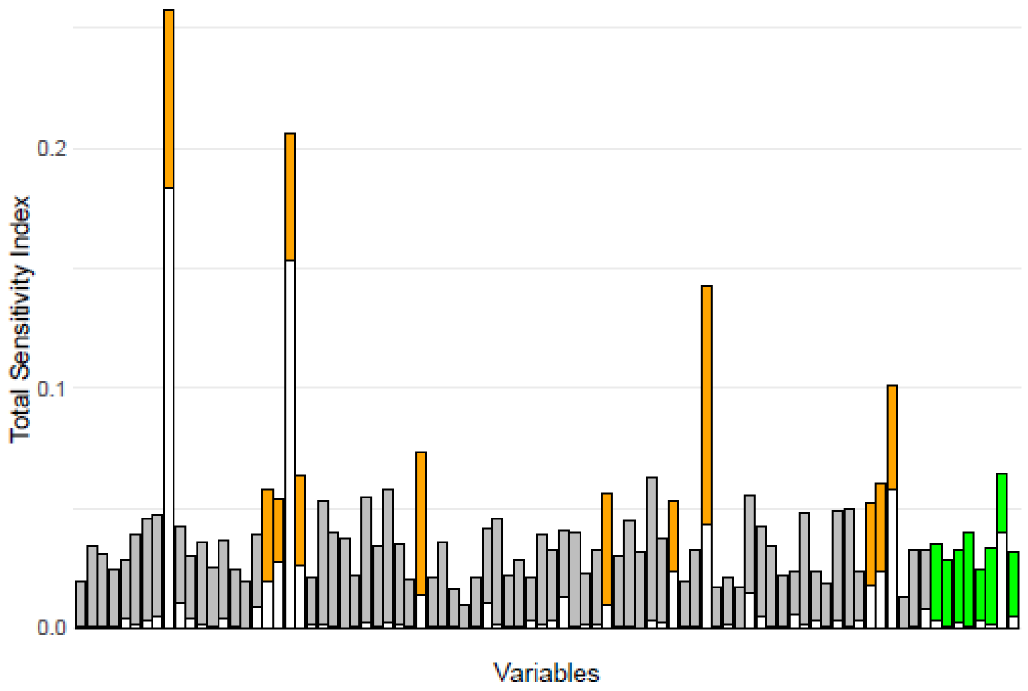


(c) EET plot when output is peak overflow reduction.

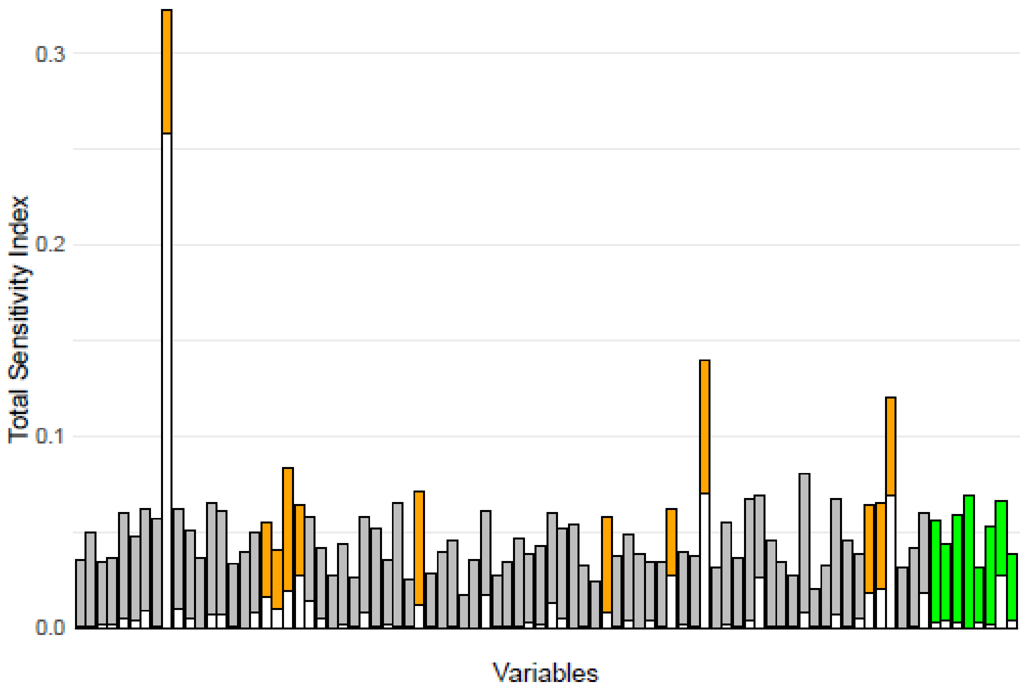


(d) Convergence plot when output is peak overflow reduction.

eFAST results



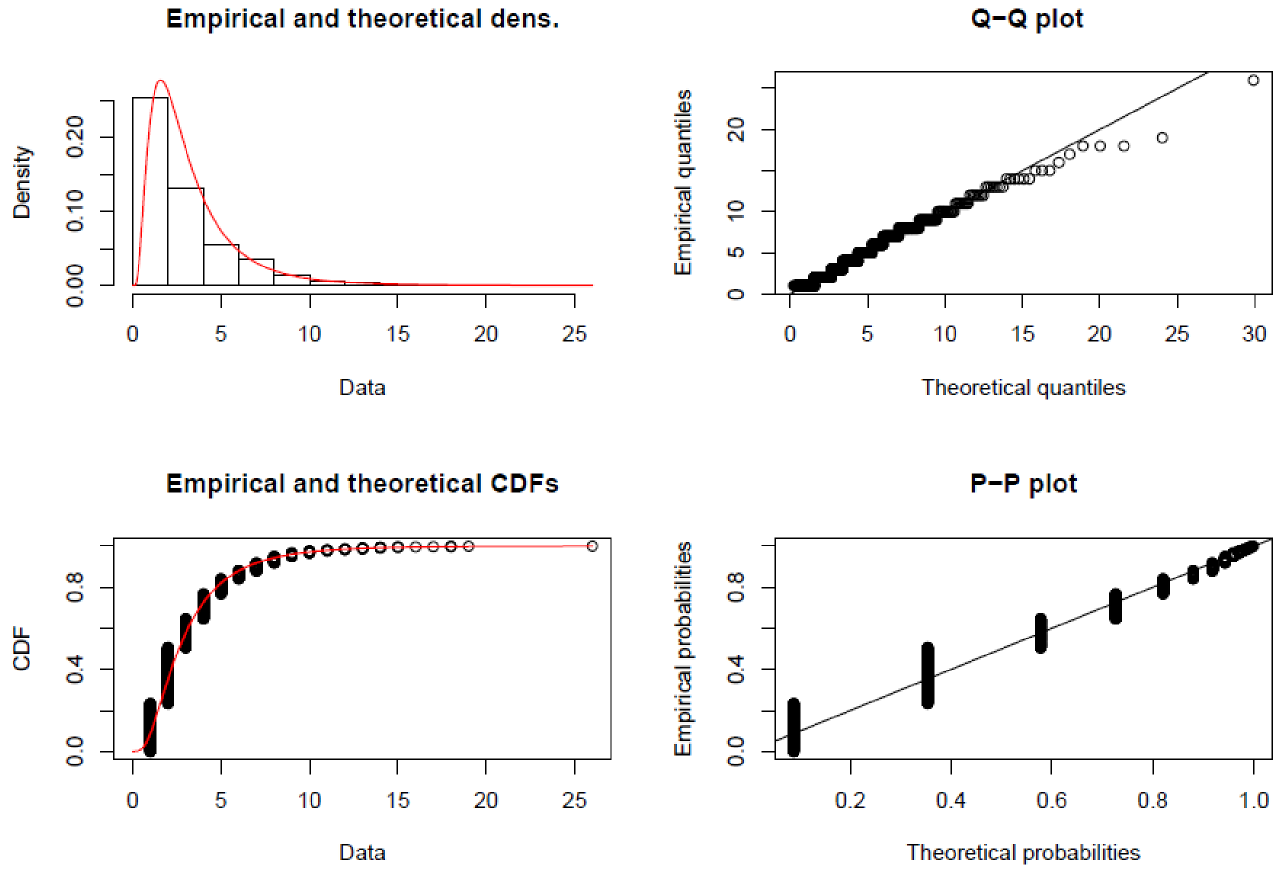
(a) Sensitivity of total overflow



(b) Sensitivity of peak overflow

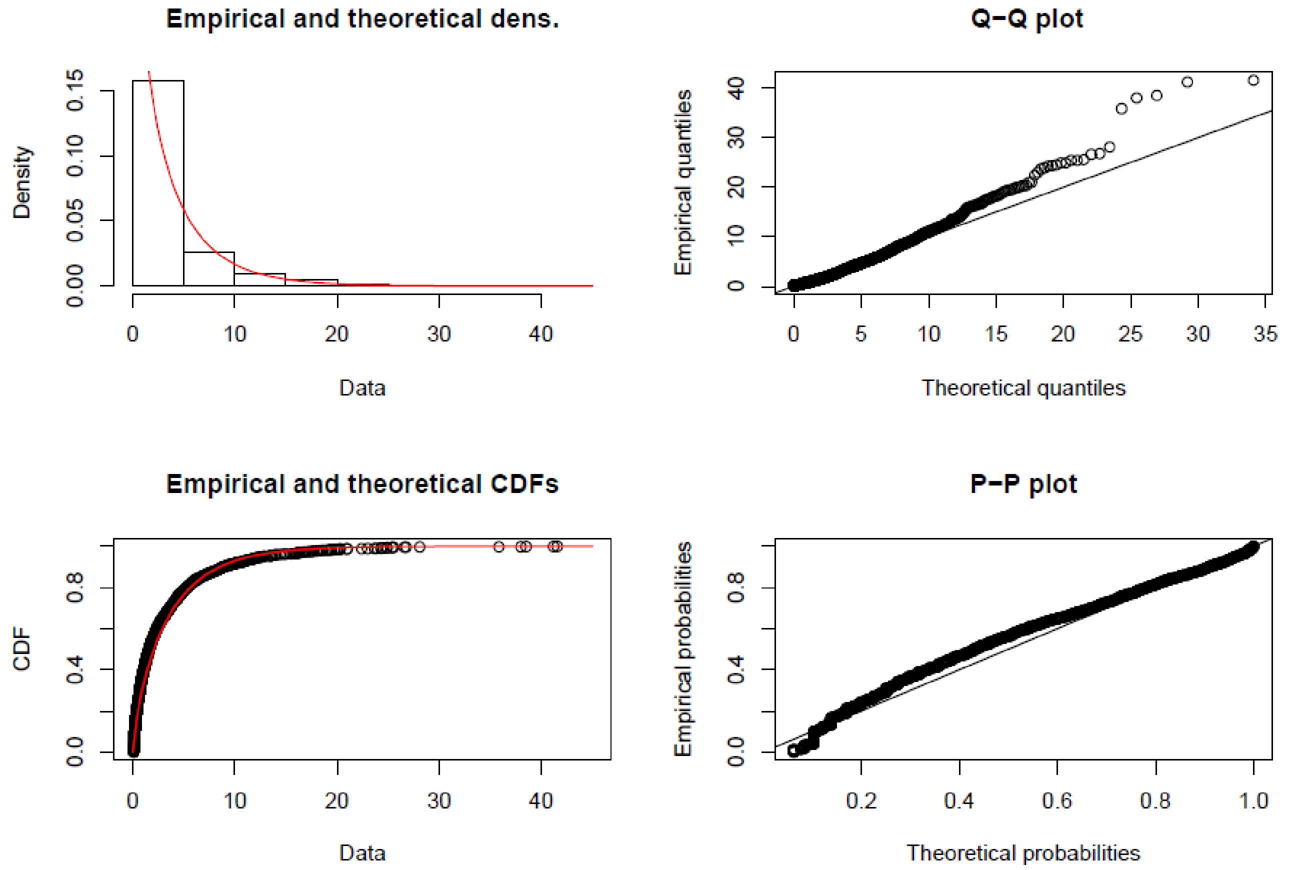
Rainfall modelling

Rainfall duration (in hours) is fitted to a lognormal distribution (mean = 0.961, standard deviation = 0.709)



Rainfall modelling

Rainfall intensity (in mm/hour) is fitted to a gamma distribution (shape = 0.746, rate = 0.217).



Copula

Consider the random vector $(X_1, \dots, X_p)$ with continuous marginals $F_1(x_1), \dots, F_p(x_p)$.

By applying probability integral transform, we obtain the random vector

$$(U_1, \dots, U_p) = (F_1(X_1), \dots, F_p(X_p))$$

which has standard uniform marginals.

The copula of $(X_1, \dots, X_p)$ is then the joint cumulative distribution function of $(U_1, \dots, U_p)$, namely:

$$C(u_1, \dots, u_p) = Pr(U_1 \leq u_1, \dots, U_p \leq u_p)$$

Copula

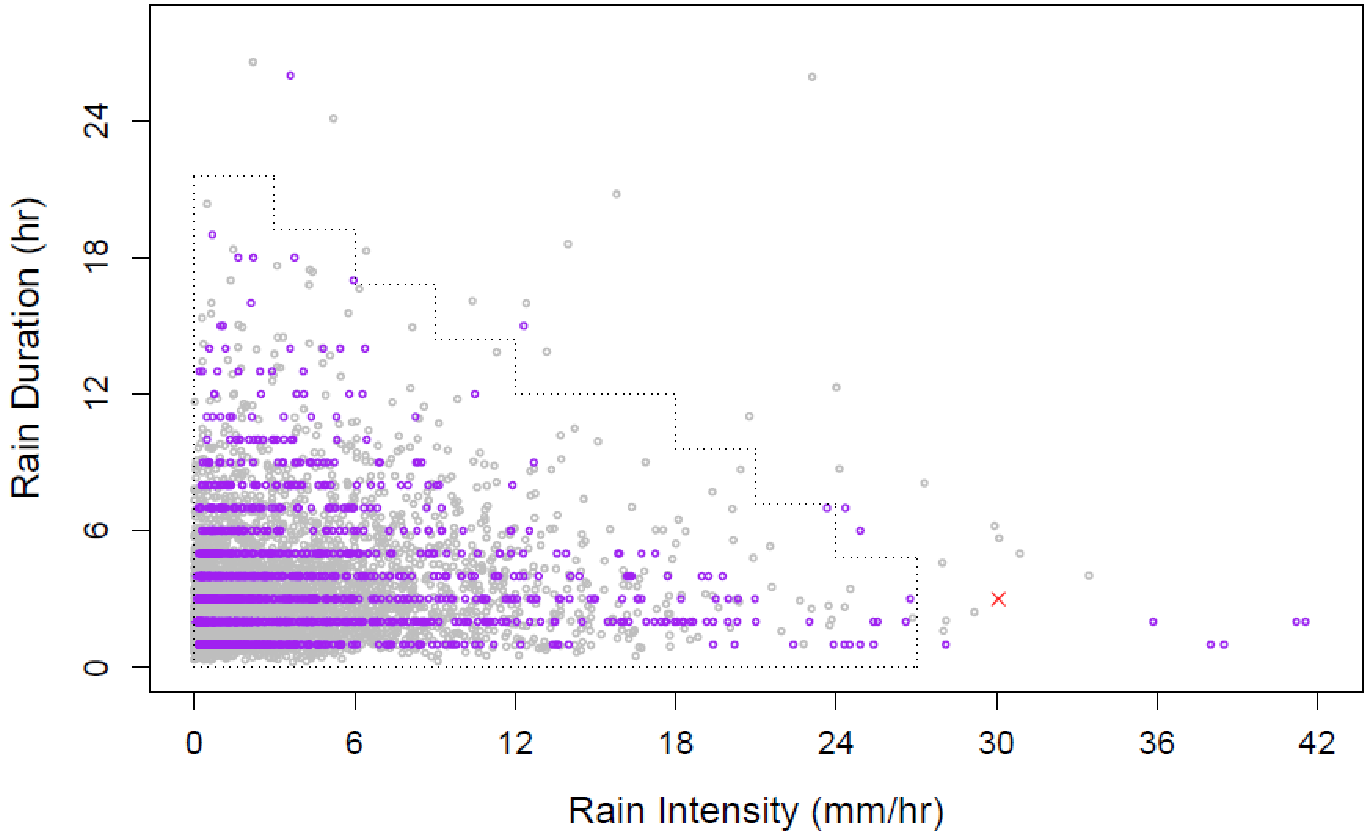
Six copulas considered: Gaussian, t, Clayton, Gumbel, Frank, and Joe

TABLE 1. Bivariate Archimedean Copulas

Family	Bivariate Copula $C(u_1, u_2)$	Parameter α
Clayton	$(u_1^{-\alpha} + u_2^{-\alpha} - 1)^{-1/\alpha}$	$\alpha > 0$
Gumbel	$\exp\{-[(-\ln u_1)^{\alpha} + (-\ln u_2)^{\alpha}]^{1/\alpha}\}$	$\alpha \geq 1$
Frank	$-\frac{1}{\alpha} \ln(1 + \frac{(e^{-\alpha u_1}-1)(e^{-\alpha u_2}-1)}{e^{-\alpha}-1})$	$\alpha \neq 0$
Joe	$1 - [(1 - u_1)^{\alpha} + (1 - u_2)^{\alpha} - (1 - u_1)^{\alpha}(1 - u_2)^{\alpha}]^{1/\alpha}$	$\alpha \geq 1$

Random samples

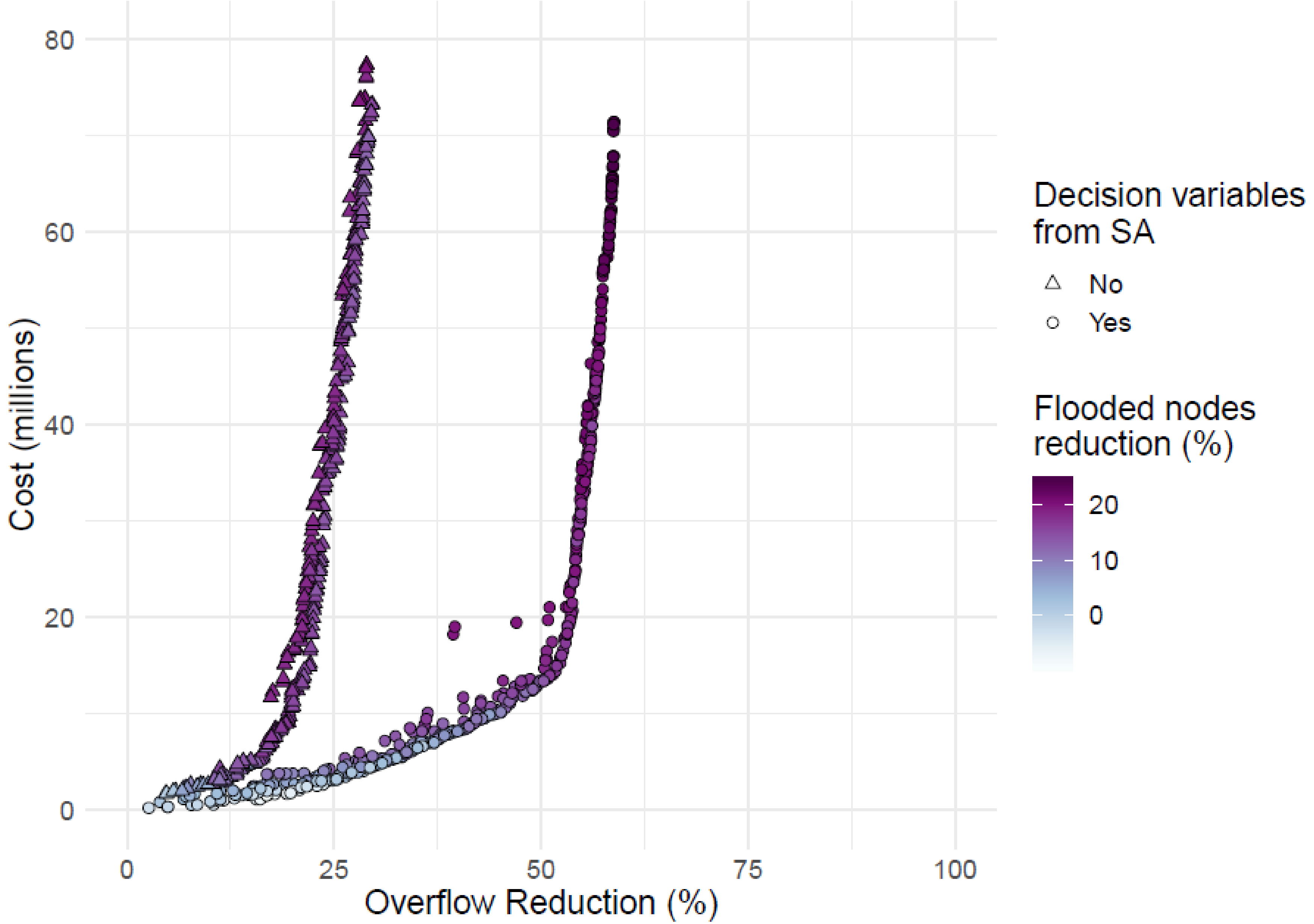
4,000 rainfall events randomly generated using the Frank copula (α = 1.4) and the univariate distributions for intensity and duration (grey dots)



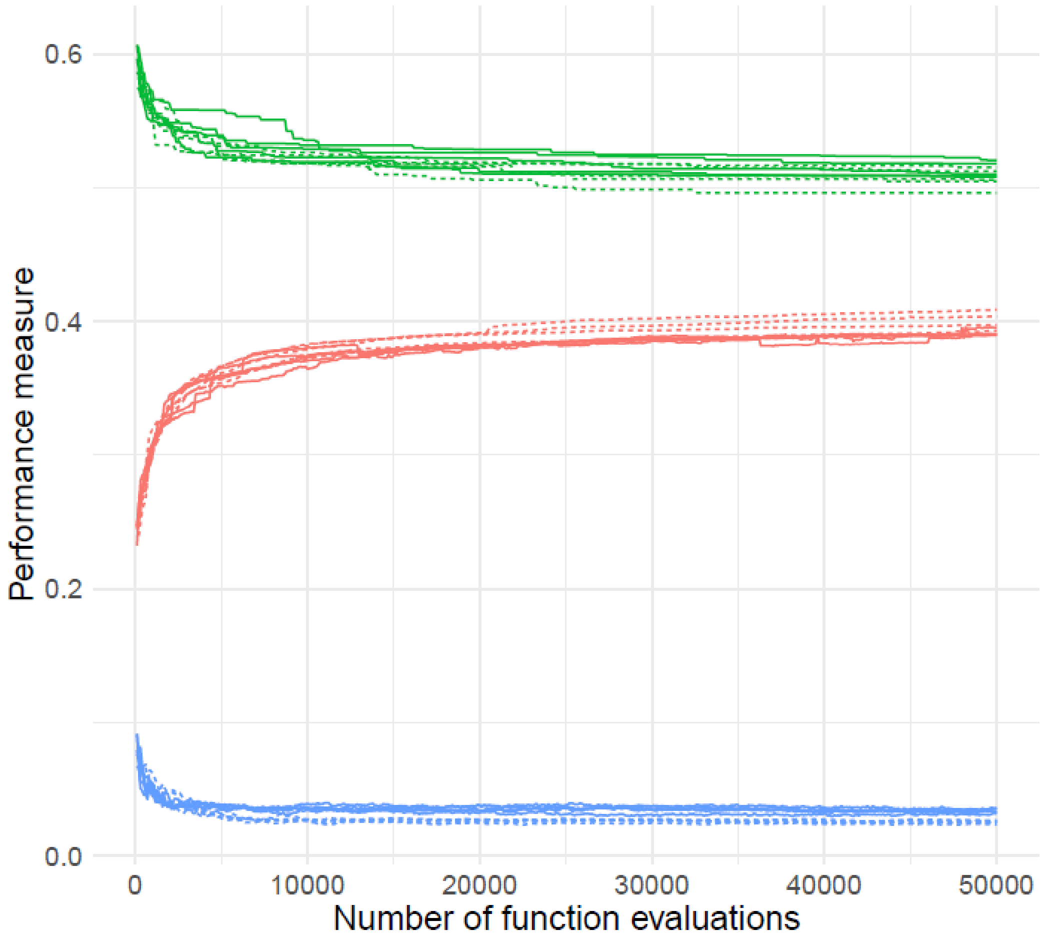
Preliminary simulation-optimization

- 10 initial random seeds:
  - 5 with population size 100 and 500 generations
  - 5 with population size 200 and 250 generations
- Decision variables:
  - 16 pipe variables that reach full capacity for >3 hours since beginning of design storm
  - 12 LID variables

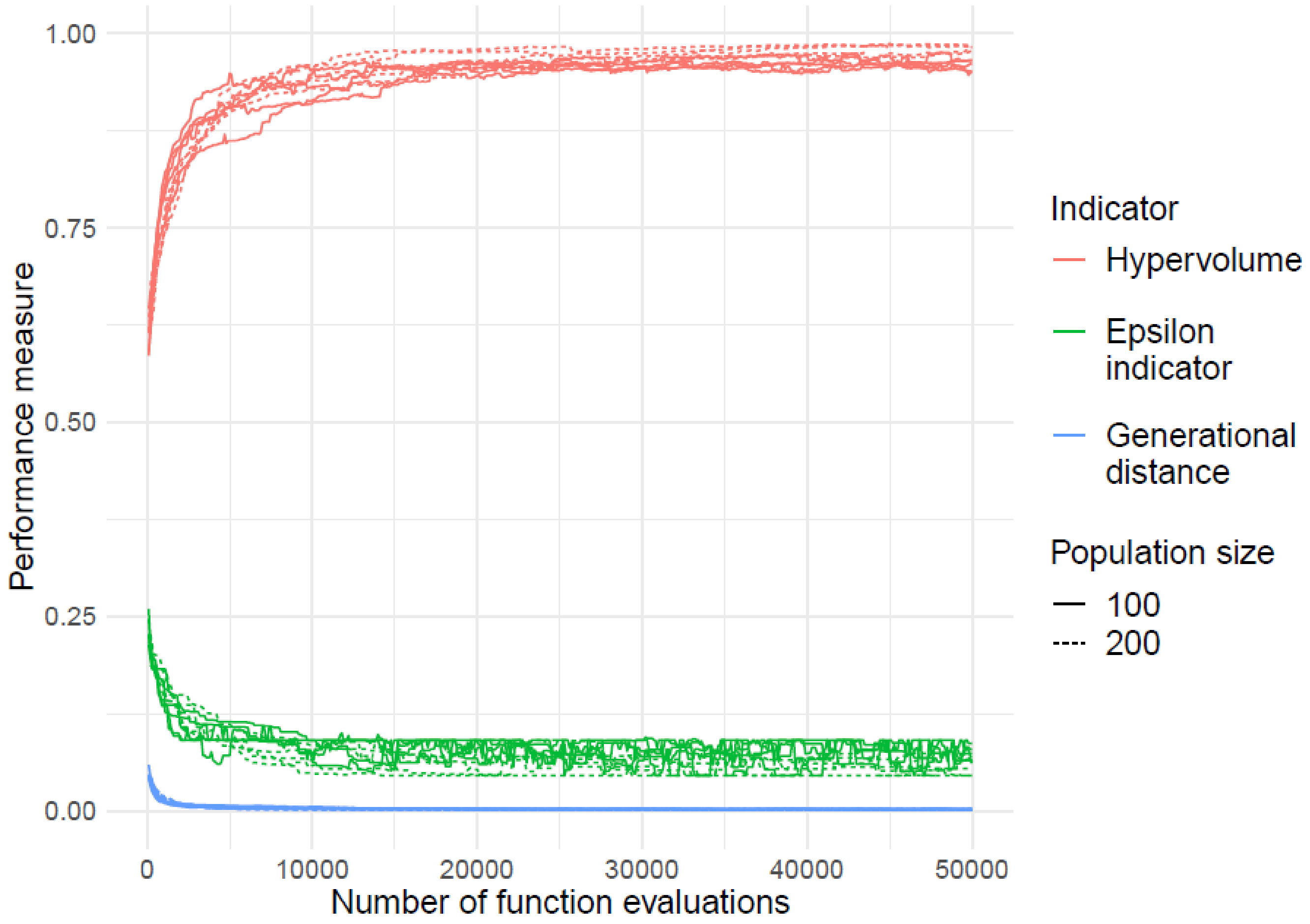
Preliminary simulation-optimization



Runtime dynamics



Preliminary simulation-optimization



Simulation-optimization using decision variables selected using sensitivity analysis

Robustness analysis for flooded nodes reduction