Parametric Uncertainty Quantification in Urban Flooding Models

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Abstract

Multiphysics urban flood models are commonly used for urban infrastructure development planning and evaluating risk due to climate change and sea level rise. However, these integrated flood models rely on several parameters that are hard to measure directly, and the resulting uncertainty in model prediction needs to be quantified, often without observable data. As a part of the Urban Flooding Open Knowledge Network (UFOKN) project, in this study we quantify parametric uncertainty in urban flood models. UFOKN incorporates flood model predictions in combination with machine learning, data and computer science, epidemiology, socioeconomics, and transportation and electrical engineering to minimize economic and human losses from future urban flooding in the United States. As a case study, we choose the Interconnected Channel and Pond Routing (ICPR) numerical model to simulate flooding in the city of Minneapolis in response to the design storms (e.g., 100-year rainfall). Through a sensitivity study, we reduce the number of uncertain model parameters to the Manning's roughness coefficient and vertical hydraulic conductivity of soil, and construct the distributions of these parameters using open databases. We employ the multilevel Monte Carlo (MLMC) method that combines a small number of high-resolution ICPR simulations with a larger number of low-resolution simulations to reduce the computational cost of computing the key statistics of the quantities of interest describing the urban flooding. Our results show that the uncertainty in the flood predictions (as described by the coefficient of variation of the flood water depth) is distributed highly non-uniformly in the urban area with the coefficient of variation exceeding 0.5 limited to a relatively few computational elements in the ICPR model. Our results demonstrate that urban flood models such as ICPR can provide reliable flood predictions and can be used for a targeted data acquisition to further reduce the parametric uncertainty.

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Outline

- **Introduction**
- **Case Study**

  UF-OKN Project
  City of Minneapolis
  ICPR Model

- **Results**

  Surface Roughness
  Hydraulic Conductivity
  Model Resolution

- **Conclusions**

Introduction

- Urbanization and population growth: developed areas replacing natural environment
- Climate change: more intense and frequent rainfall events, rise of sea level

Excessive runoff in populated urban areas leads to urban flooding that impacts almost everything in cities.
A series of failures propagating through urban infrastructure.

Flooding in Texas caused by Hurricane Harvey in 2017 (Source: Wikipedia)

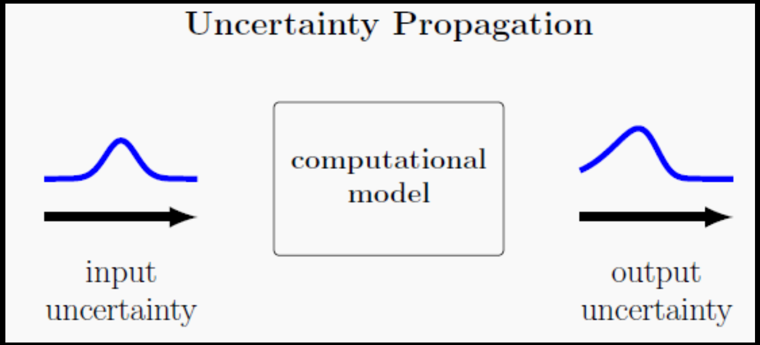
Flooded power grid

Flooded road

Introduction

Flood models can provide predictions of different hypothetical scenarios, but they also deal with different types of uncertainty.

- Complex real-world problems
- Imperfect models
- Imprecise input data
- Lack of knowledge
- Model simplifications



Output values are subject to uncertainty.

- **Structural uncertainty**: doubt on if the model structurally correct
- **Parametric uncertainty**: correct values of parameters are not certain

different parameter values → different simulated behavior → different predictions

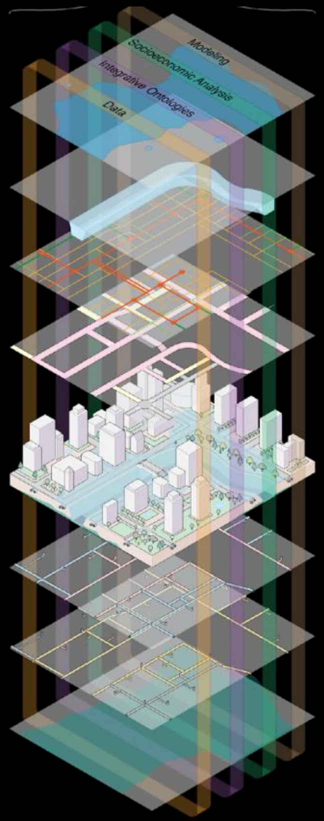
UQ goals: quantitative characterization and reduction of uncertainties

UF-OKN Project

Urban Flooding Open Knowledge Network

- Cities are highly complex systems and include multiple layers of infrastructures including transportation network, power grid, and water systems.
- Considering cascading failures through interconnected urban infrastructure
- Customizing the search result of "flood near me" for different users

How flooding impacts cities?
How certain are flood predictions?
What locations are more important?
How to reduce uncertainty in key areas?

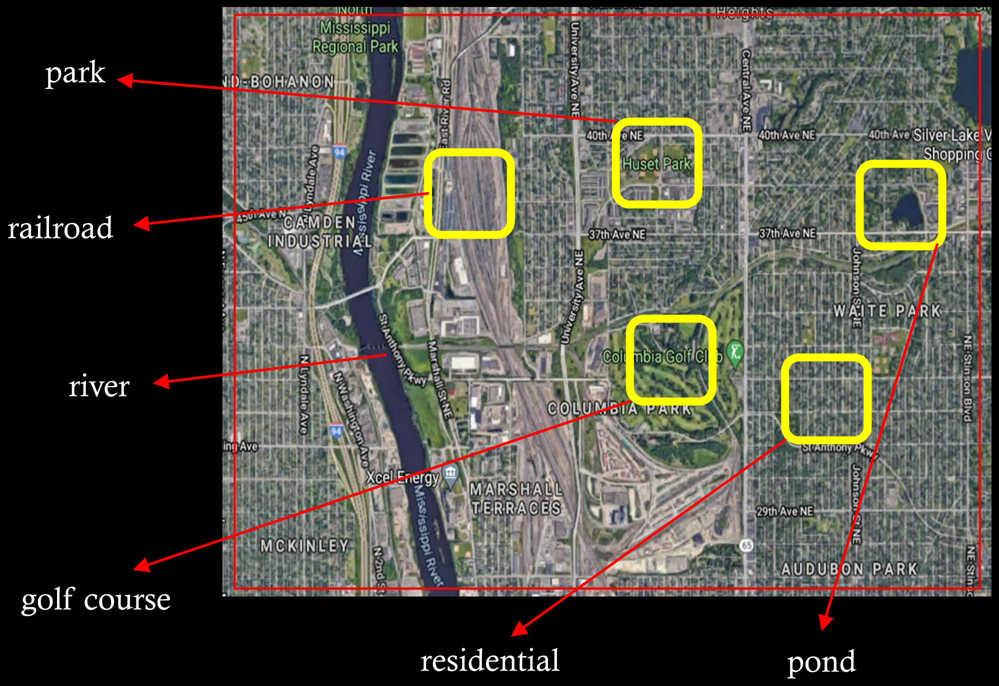


UF-OKN aims to link real-world urban infrastructure to <u>dynamic flood predictions</u>.

Case Study
City of Minneapolis

Approach:

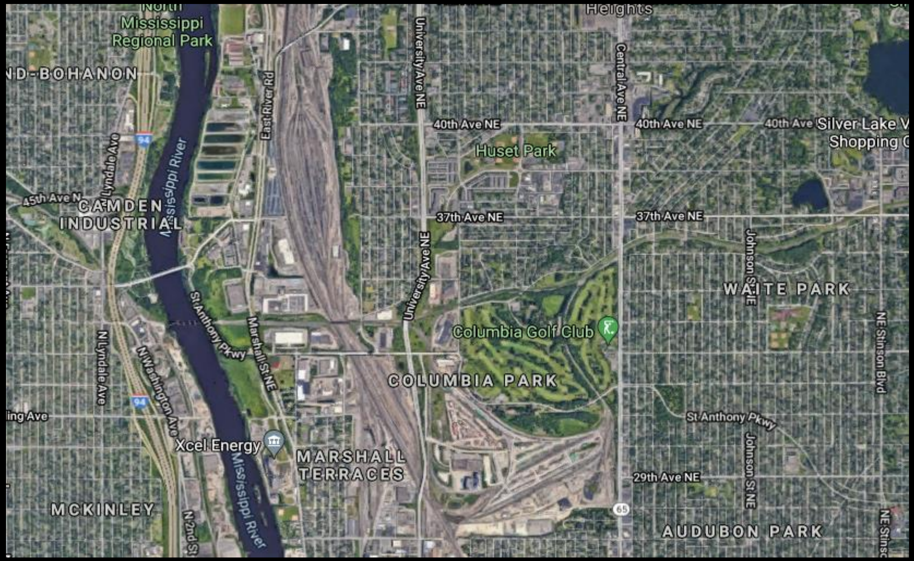
- Reduce number of uncertain parameters and produce their distributions
- Study statistics of quantities of interest over many realizations of flood simulations
- Track variation of ensemble mean and standard deviation for convergence

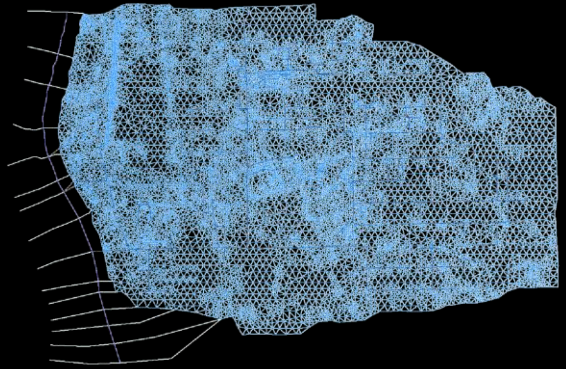


(All images from Google Maps)

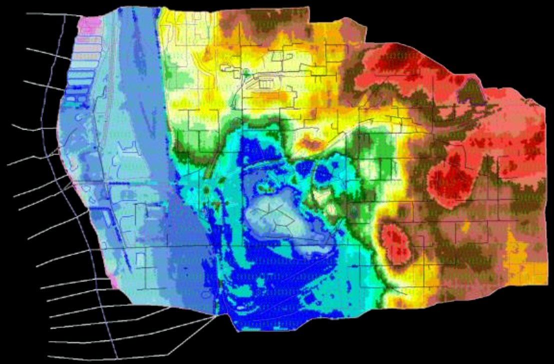
Case Study

City of Minneapolis





Computational mesh



Surface elevation

Land use map

- Input: land use, soil zones, surface elevation (data from NRCS)
- Output: statistics of quantities of interest such as flood depth and flowrate in pipes
- 100-year rainfall event for a 24-hour period and 72-hour simulation (data from NOAA)

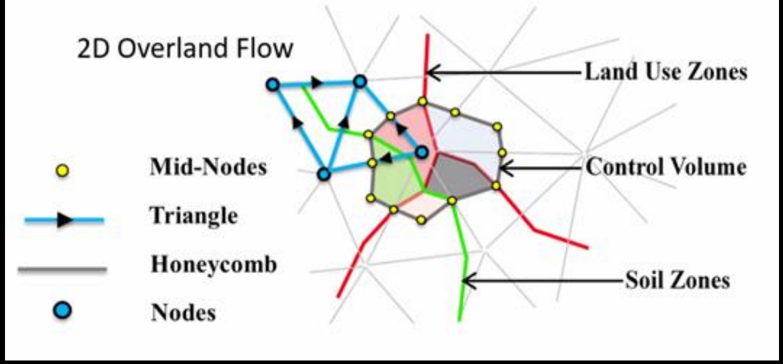
Uncertain parameters: Manning's roughness coefficients & vertical hydraulic conductivity

ICPR Model

Interconnected Channel and Pond Routing

Source: 2018, Streamline Technologies, Inc.

- Hydrologic & hydraulic urban flood model
- Predicting surface water inundation due to rainfall
- Interconnected and interdependent hydraulic systems
- Physically-based distributed model
- Based on link-node modeling concept
- Supercomputing capability



2D overland flow model (finite volume approach)
2D groundwater flow (finite element approach)
Different layers of unstructured mesh: triangle, honeycomb, diamond

$$dz = \left(\frac{Q_{in} - Q_{out}}{A_{surface}}\right) dt$$

$$\frac{\partial Q}{\partial t} + \frac{\partial (Q^2/A)}{\partial x} + gA\frac{\partial Z}{\partial x} + gAS_f = 0$$

$$q = K_v I$$

$$I = (H + Z_f + h_c)/Z_f$$

$$\frac{K(\theta)}{K_s} = \left(\frac{\theta - \theta_r}{\phi - \theta_r}\right)^n$$

Surface Roughness

Four types of land use:

1. Water zone
2. Developed zone
3. Forest zone
4. Agriculture zone

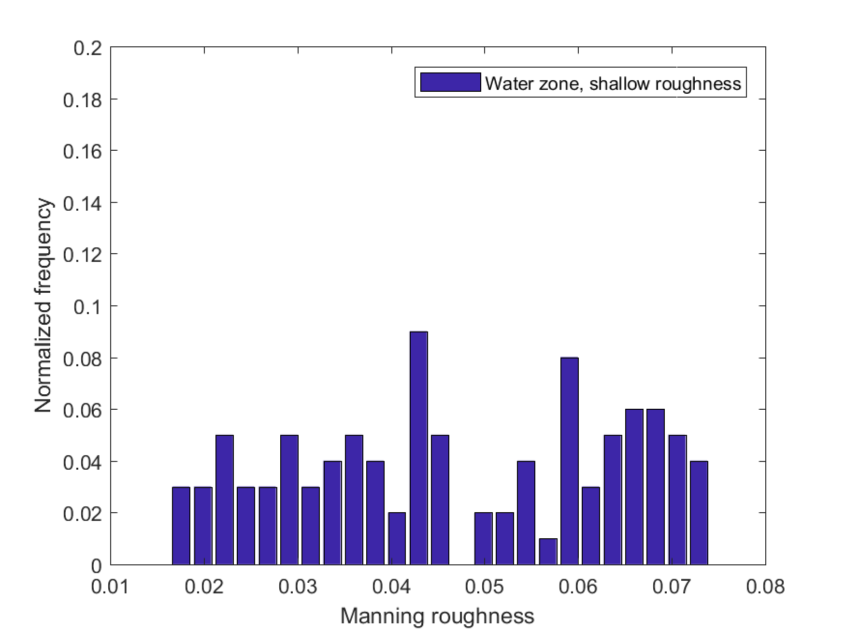
$$n = n_{sh}\, exp(k \times d)$$

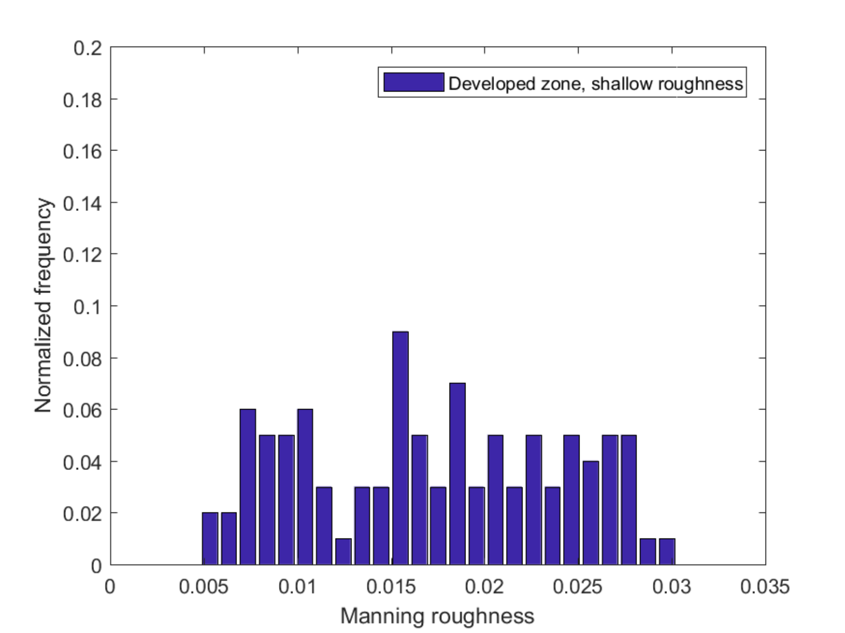
$$k = ln(\frac{n_d}{n_{sh}})/d_{max}$$

n_{sh} : shallow Manning's roughness coefficient
n_d : deep Manning's roughness coefficient

Manning's roughness coefficients

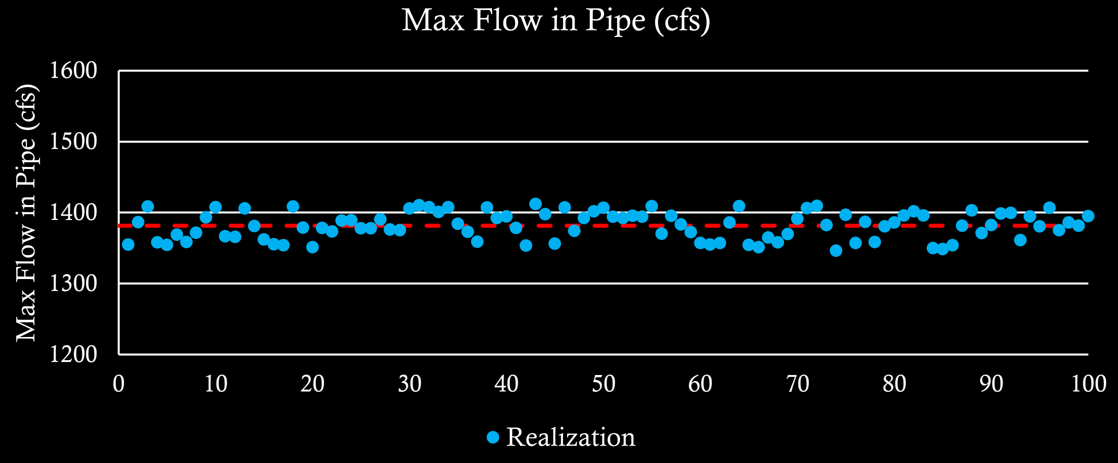
	shallow	*deep*
Water	0.045	0.035
Developed	0.015	0.011
Forest	0.198	0.184
Agriculture	0.2	0.1





Experimental Manning's coefficient of different types of land from various studies:
Chow (1959), French (1985), Barnes (1967), and Arcement, et al (1989)

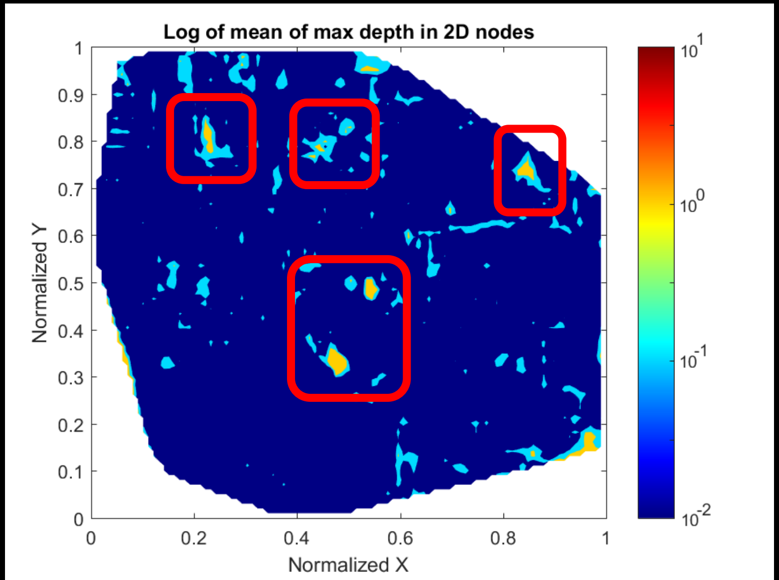
Variation of extreme values over 100 realizations of simulations:

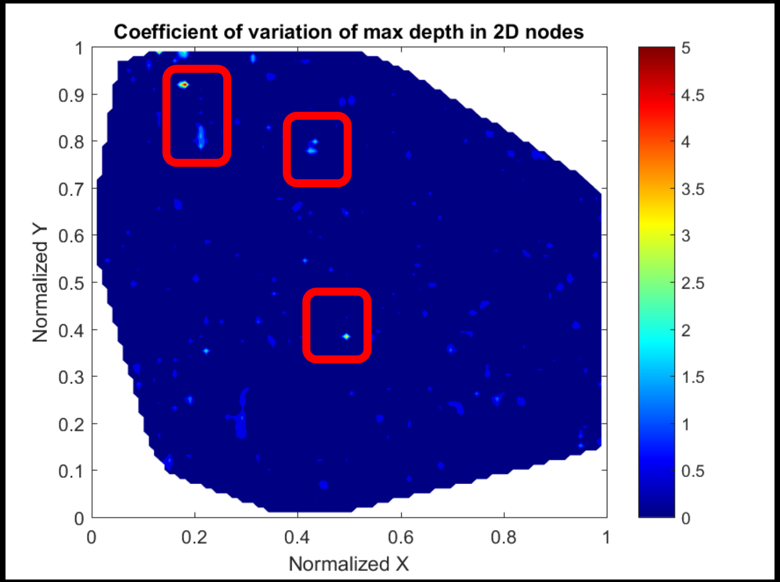


Spatial distribution

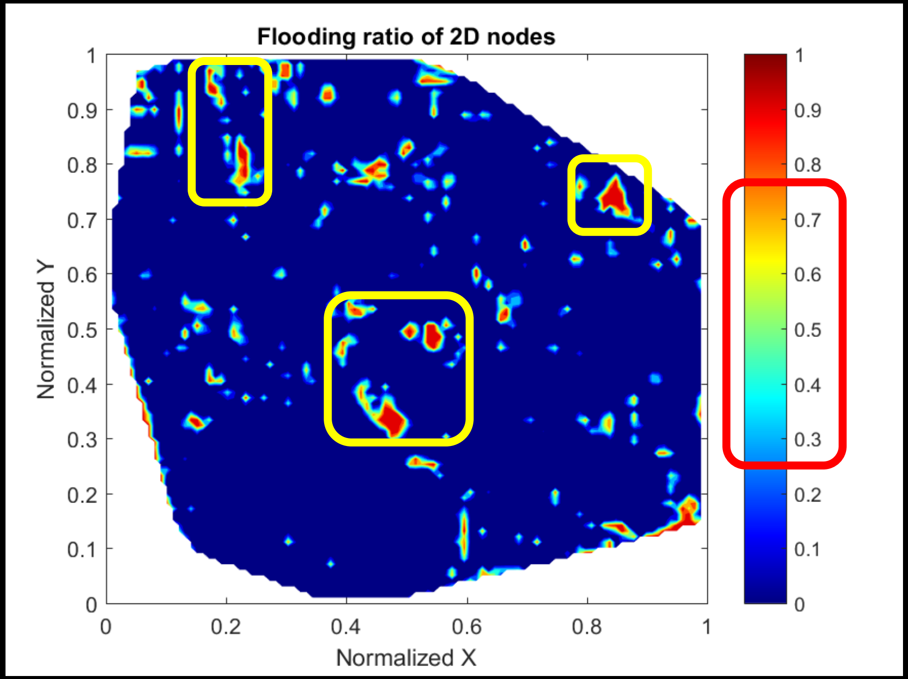
- Coefficient of variation to measure degree of uncertainty
- Variation of statistics over realizations
- Heatmap of quantities of interest
- Mean, standard deviations, and coefficient of variation

$$\mathrm{CV} = \frac{std.deviation}{mean}$$

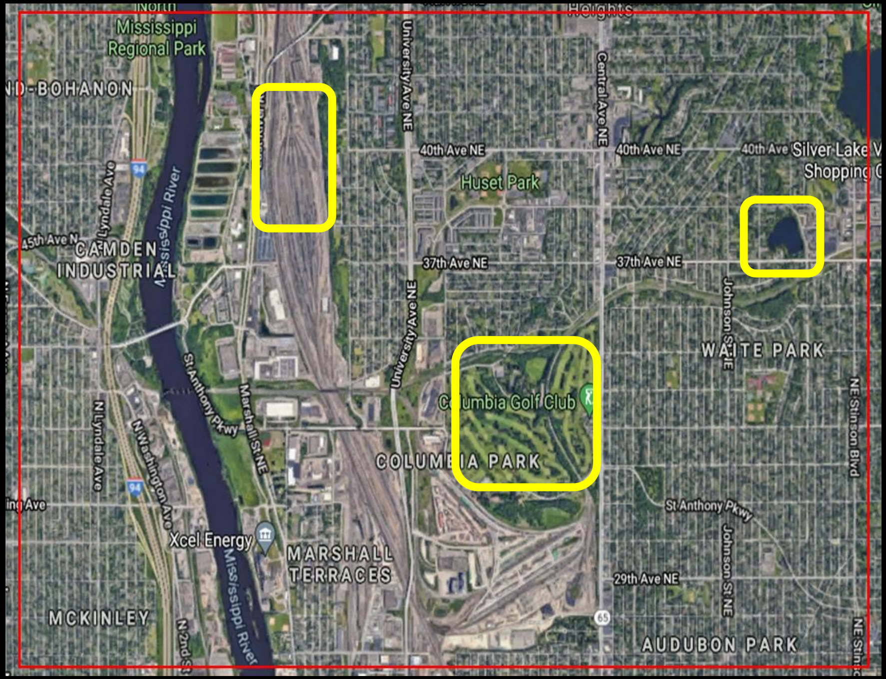




Probability of flood depth exceeding certain threshold (0.5 feet)



Distribution of flooding from 100 realizations



satellite view

Total number of nodes	10022	%
Always flooded	635	6.34
Sometimes flooded	140	1.40
More uncertain	**59**	**0.59**

$$R = \frac{no.\,of\ flooded\ realizations}{total\ no.\,of\ realizations}$$

$R < 0.25$	mostly not flooded
$0.25 < R < 0.75$	more uncertain
$R > 0.75$	mostly flooded

Hydraulic Conductivity

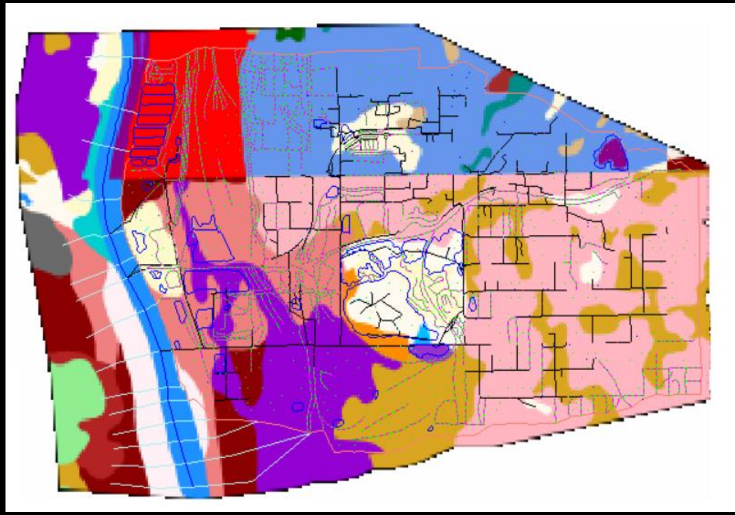
- 29 different soil zones (data from NRCS)
- Three-layer soil column in vadose zone
- Availability of data on vertical hydraulic conductivity
- Using truncated log-normal distribution for vertical hydraulic conductivity (Kv)
- Controlling the mean, min, max of distributions

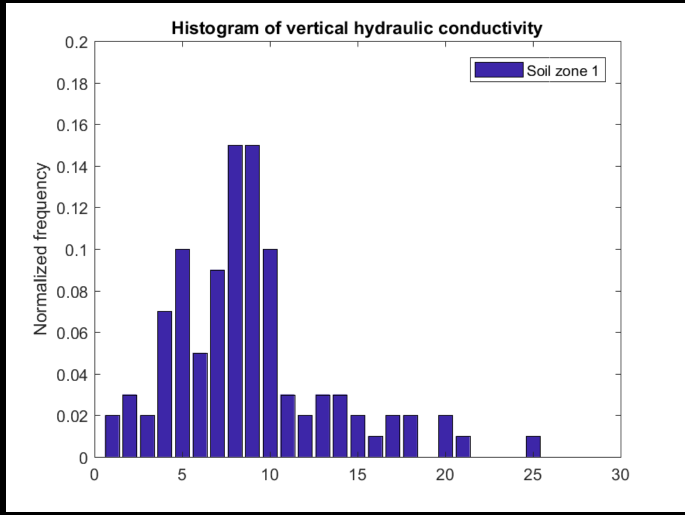
Kv_o = the original database value
$Kv_{min} = 0.5Kv_o, Kv_{max} = 2Kv_o$
follows truncated log-normal distribution

Example:

Soil label 1146302 / Zone 1

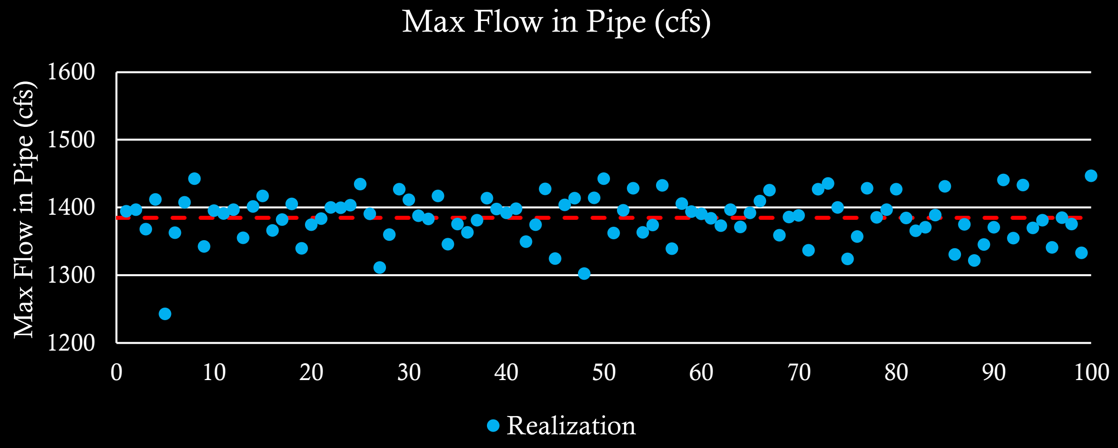
$Kv_o = 0.8505$ f/s
$Kv_{min} = 0.4253$ f/s
$Kv_{max} = 1.7010$ f/s

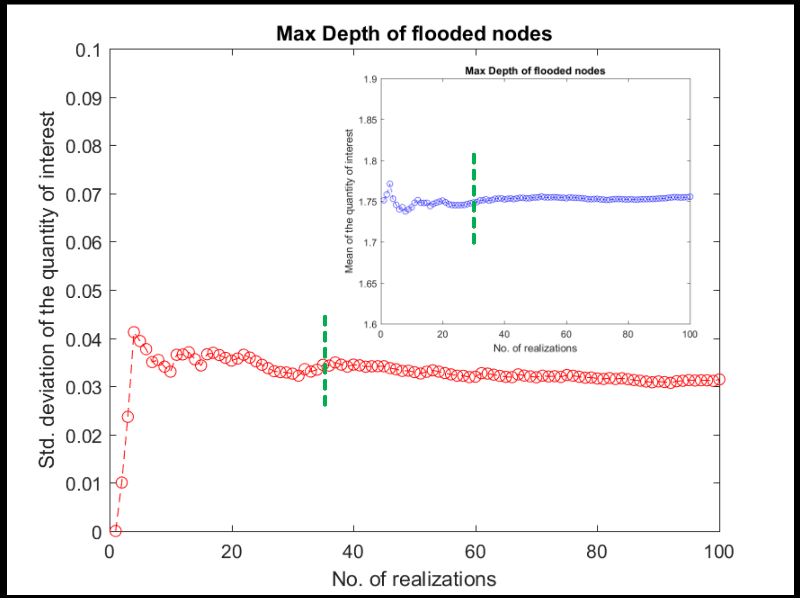


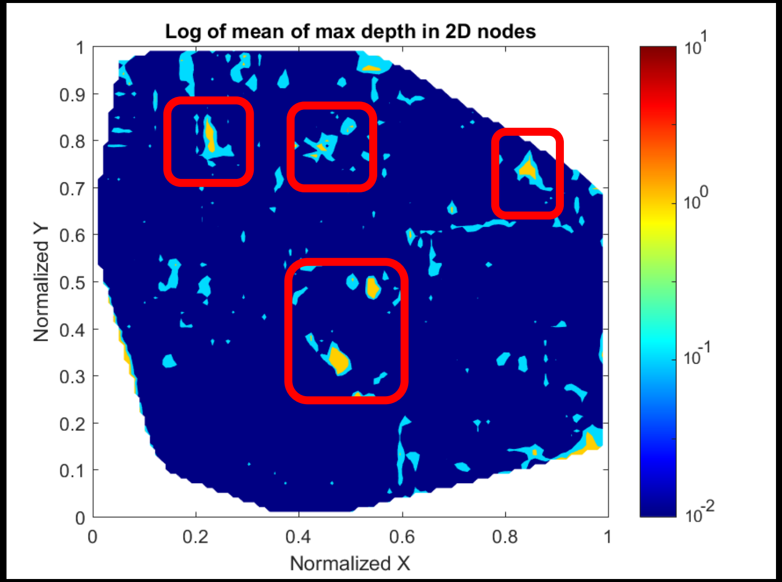


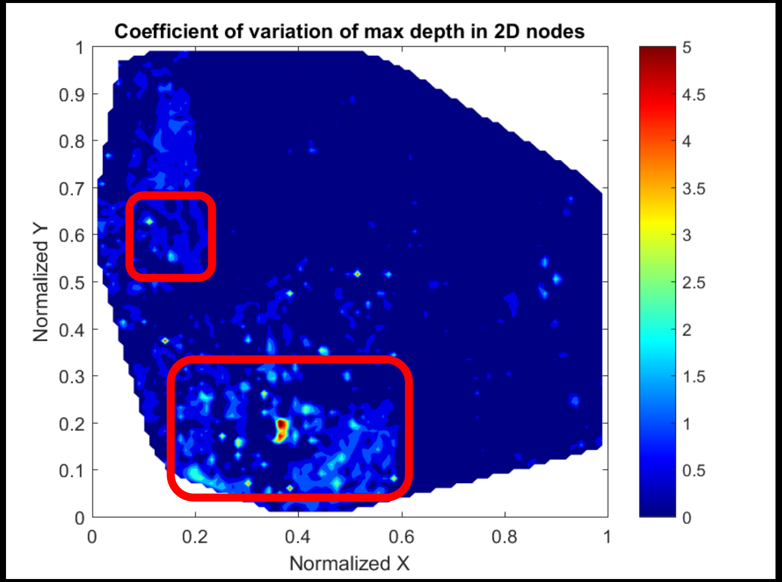
Label 1146302 / Zone 1	
Layer	Kv Saturated
1	0.8505
2	0.425
3	0.2125

Variation of extreme values over 100 realizations of simulations:





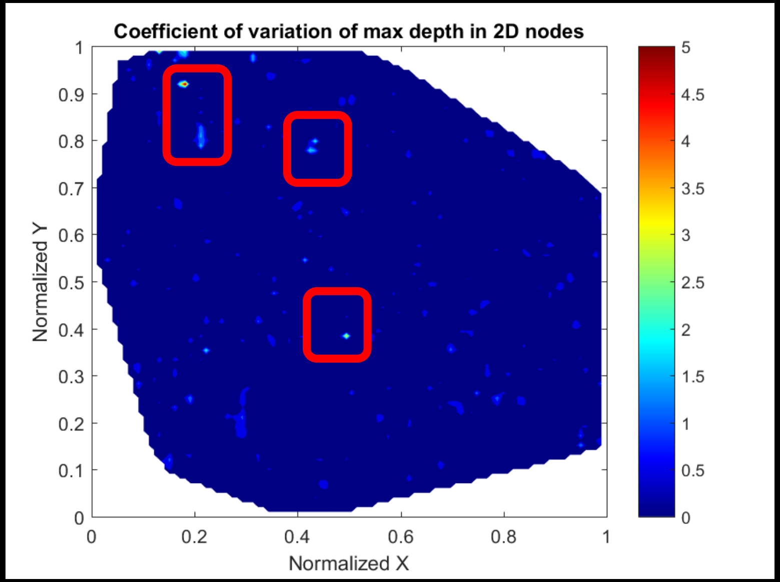


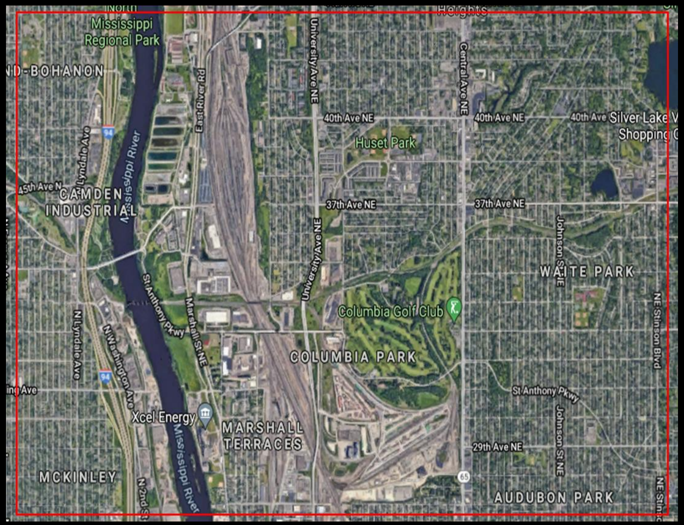


Comparison of parametric uncertainties

Surface roughness study

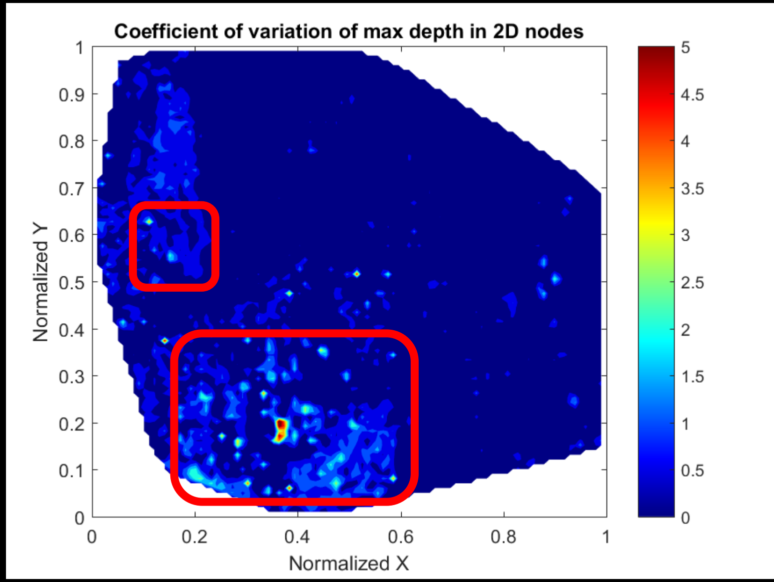
Total number of nodes	10022	%
Always flooded	635	6.34
Sometimes flooded	140	1.40
More uncertain	**59**	**0.59**





Hydraulic conductivity study

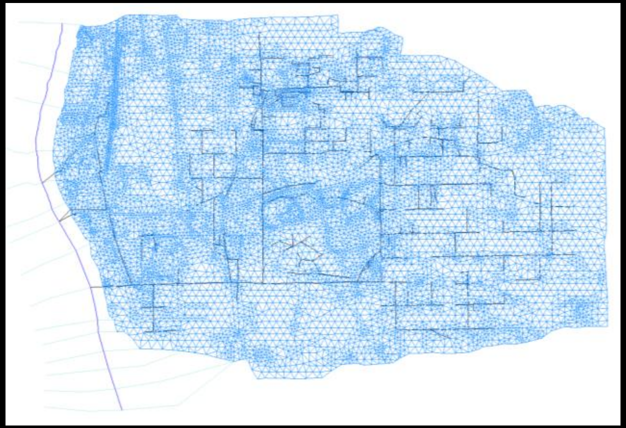
Total number of nodes	10022	%
Always flooded	537	5.36
Sometimes flooded	329	3.28
More uncertain	**111**	**1.11**



Uncertain locations are entirely different even though the mean of input parameters were similar.

Model Resolution

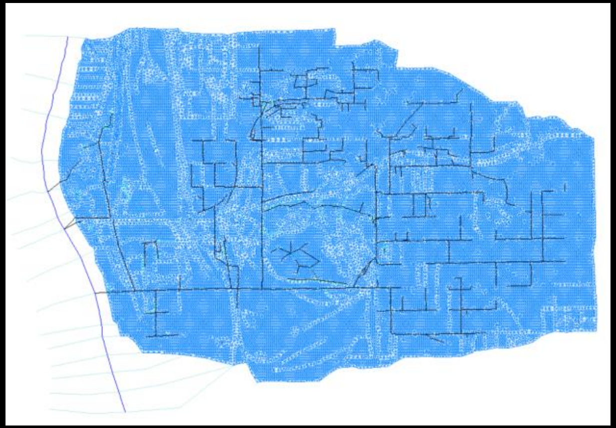
Low-resolution model (10,022 nodes)



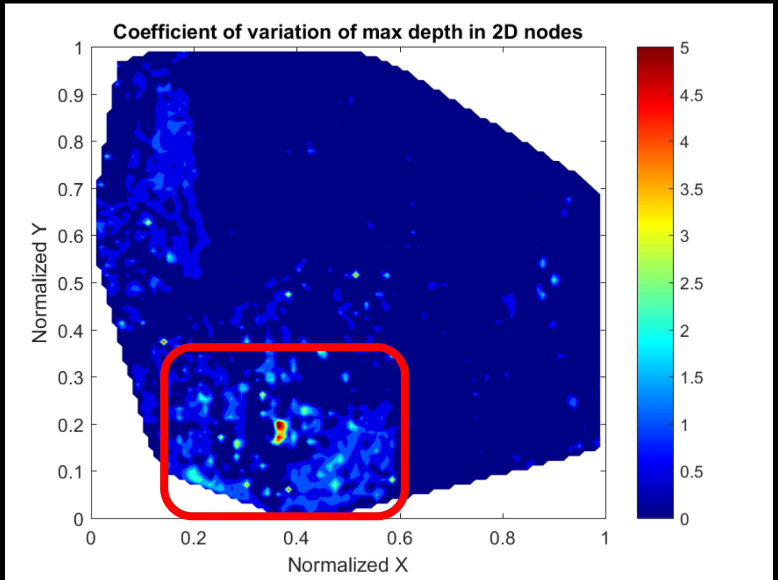
Increasing:
- Number of nodes
- Simulation time
- Data storage

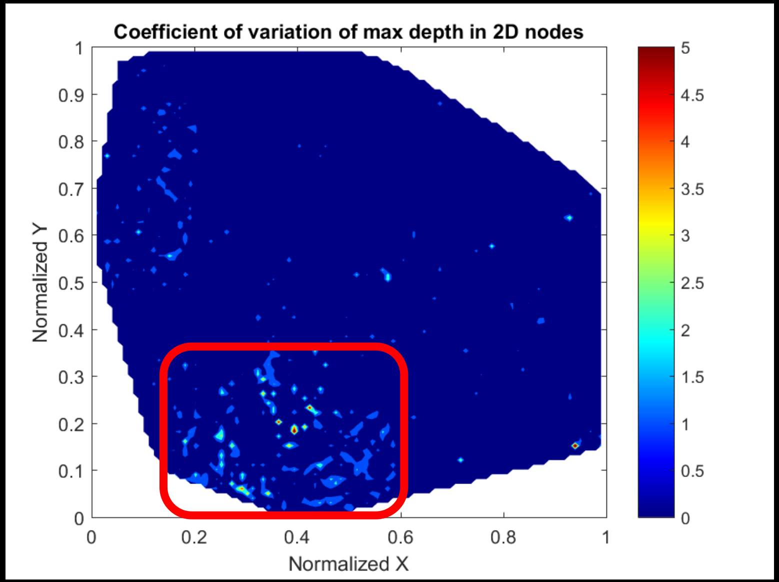
Reducing:
- Uncertainty

High-resolution model (44,412 nodes)



Level of parametric uncertainty is reduced by using higher resolution of mesh.





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Model Resolution

Multilevel Monte Carlo approach

$\bar{Y}(x) = Y_H(x) - Y_L(x)$ difference between resolutions

- Combining results from low-resolution and high-resolution mesh simulations
- Estimating mean and standard deviation

$$E\{Y_H(x)\} \approx \mu_{MLMC} = \underbrace{\frac{1}{N_L}\sum_{n=1}^{N_L} Y_L^n(x)}_{\text{from low-resolution}} + \underbrace{\frac{1}{N_H}\sum_{n=1}^{N_H} \bar{Y}^n(x)}_{\text{from high-resolution}}$$

Hydraulic conductivity study

Estimation of mean

$N_L = 100$, $N_H = 100$	Max Flow in Pipe (cfs)
Mean of Lo-Res	1381.4
Mean of Hi-Res	1411.5
Est. mean of Hi-Res ($N_H = 20$)	1413.2

Estimation of standard deviation

$N_L = 100$, $N_H = 100$	Max Flow in Pipe (cfs)
Std dev of Lo-Res	35.03
Std dev of Hi-Res	27.24
Est. std dev of Hi-Res ($N_H = 20$)	32.17

Conclusions

- Urban flood models such as ICPR can provide reliable flood predictions and can be used for a targeted data acquisition to further reduce the parametric uncertainty.

- Parametric uncertainty of both input parameters is highly localized.

- Parametric uncertainty of surface roughness and hydraulic conductivity occurs in quite different locations while the distribution of ensemble mean of flood depth remains similar.

- Increasing the mesh resolution of the model reduces uncertainty of flood depth in both parametric uncertainty studies while input parameters are not changing.

- Using multilevel Monte Carlo approach with few high-resolution simulations enabled us to obtain the same level of accuracy and degree of uncertainty, as in high-resolution model, with less computational costs.

UF-OKN

Thank you!

Acknowledgement

- NSF
- UFOKN Team
- NOAA National Water Center
- USACE
- USEPA
- USGS
- FEMA
- State and local partners

Urban Flooding Open Knowledge Network

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