USC Center for Artificial Intelligence in Society

Leveraging AI for Disaster-Resilient Infrastructure Mitigation Planning

Bistra Dilkina

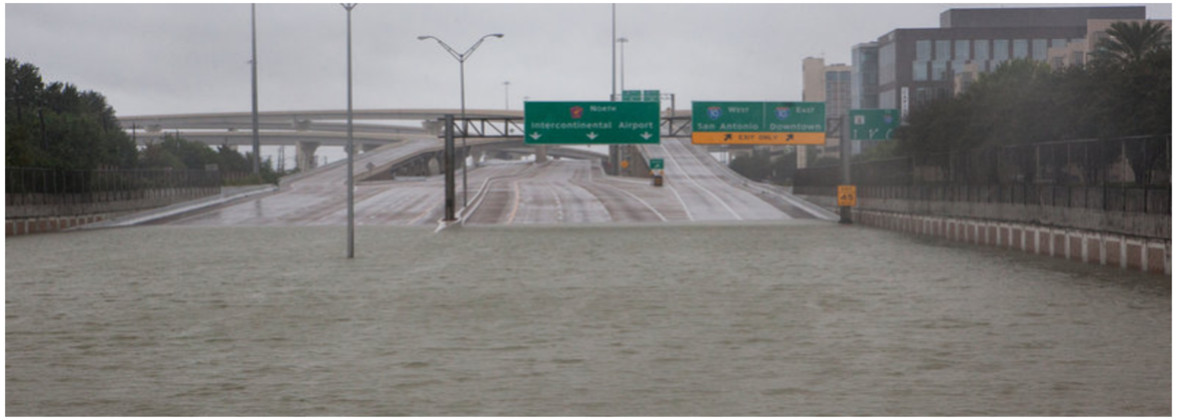
Associate Professor of Computer Science, USC
Co-Director, USC Center of AI in Society

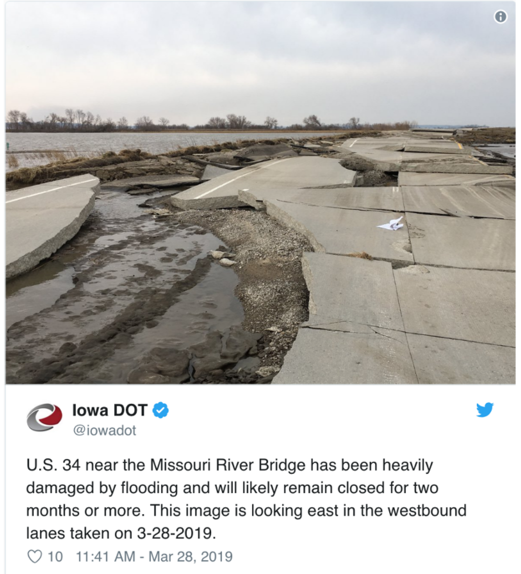
March 24, 2021
CIRI Webinar Series

USC Center for Artificial Intelligence in Society

Critical Infrastructure Systems are Vulnerable to Natural Disasters

Flooding submerges **roads** and accelerates degradation





According to NOAA, flooding events cost on average **$4.3 billion per event**

floods are responsible worldwide in 2017 for **52% of deaths** and **44% of economic damages** from natural disasters *(CRED)*

Impacts:
Mobility
- **Longer emergency response time**
- **Increased evacuation time**
- **Reduced transportation of goods, raw materials**

Impacts:
Economic
- **Cost of repairs**
- **Loss in productivity**

Critical Infrastructure Systems are Vulnerable to Natural Disasters

USC Center for Artificial Intelligence in Society

Wellington is losing drinking water but it could take months to find and stop the leaks

Pipes in New Zealand's capital are leaking a million litres (220,000 gallons) of water a day as a result of the powerful November 2016 earthquake.

M 7.8 earthquake
on San Andreas Fault, CA could cause
$24 billion in business interruption losses due to water supply interruption alone
(>13% of the total estimated costs)

Earthquakes damage underground **water pipe networks**

Impacts:

Service Disruption

- **Reduced effectiveness of disaster response (fire department, hospitals, disaster recovery centers)**
- **Loss of public access to water**

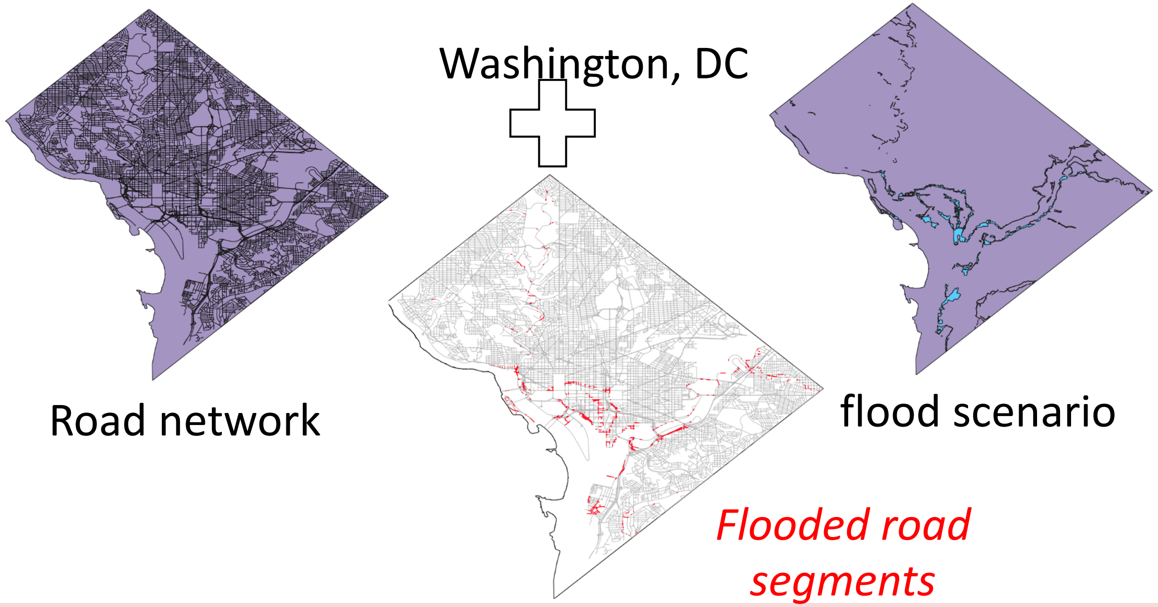
Economic

- **Cost of repairs**
- **Loss in productivity**

USC Center for Artificial Intelligence in Society

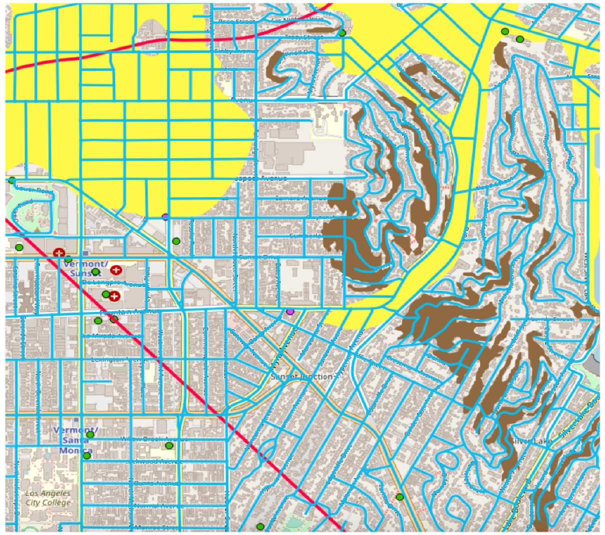
Mitigation planning: targeted infrastructure network fortification to maximize resilience

Given a road network and flood risks, how to upgrade roads to **maximize resilience to floods or other disasters?**



Challenges: limited budget, many subnetworks possible, several metrics, predict mobility needs

Given water pipe network and earthquake risks, select parts of the network to replace with **seismic resilient pipes**



Critical customers (hospitals, fire/police stations, emergency evacuation centers, power, sanitation, etc) **must be directly connected to the resilient network.**

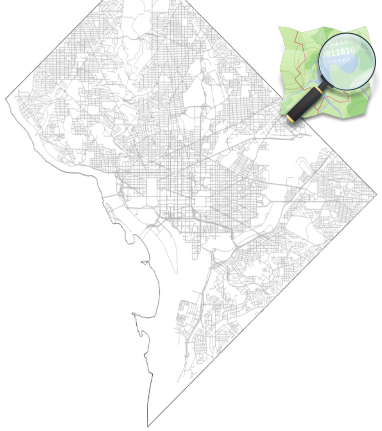
All households **must be within 1mi** of the resilient network (reachable by fire hose).

Challenges: limited budget, many sub-networks possible, complex constraints

Data-driven framework for flood resilience road mitigation planning

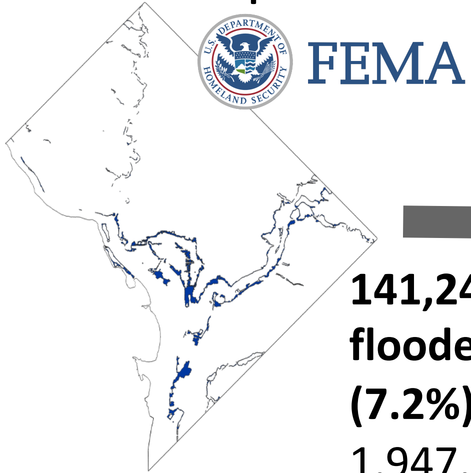
USC Center for Artificial Intelligence in Society

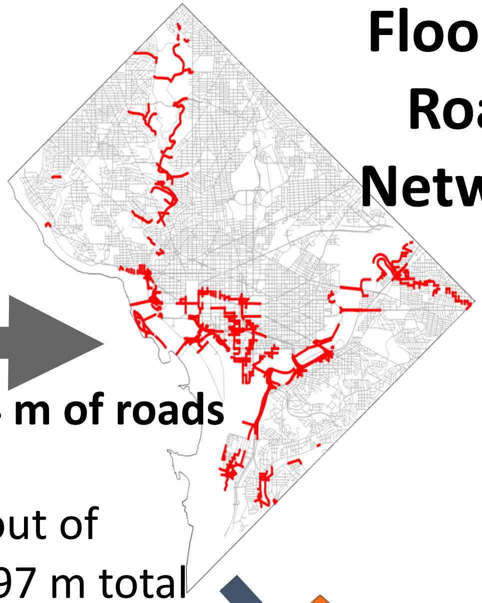
Road Network[1]



+

Flood Map[2]

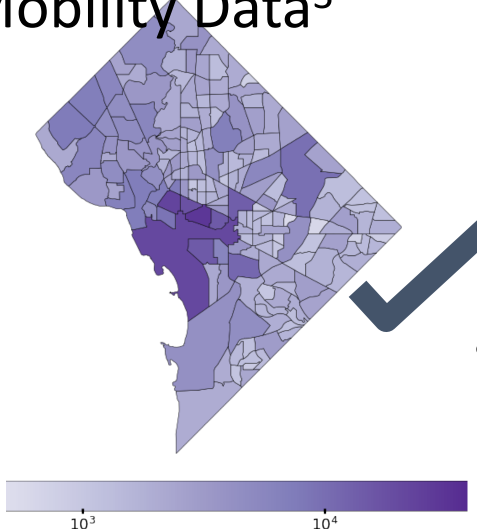




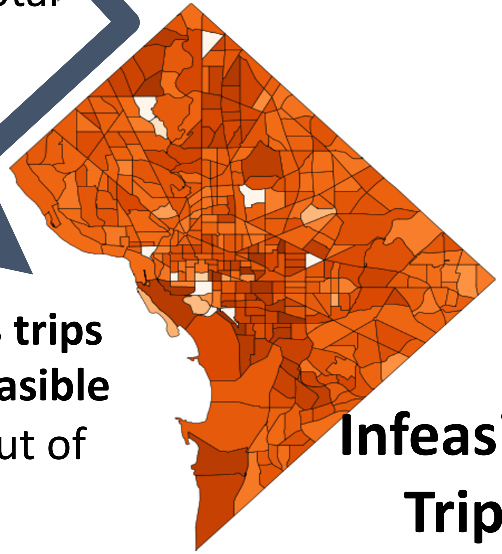
Flooded Road Network

141,244 m of roads flooded (7.2%) out of 1,947,597 m total

Mobility Data[3]

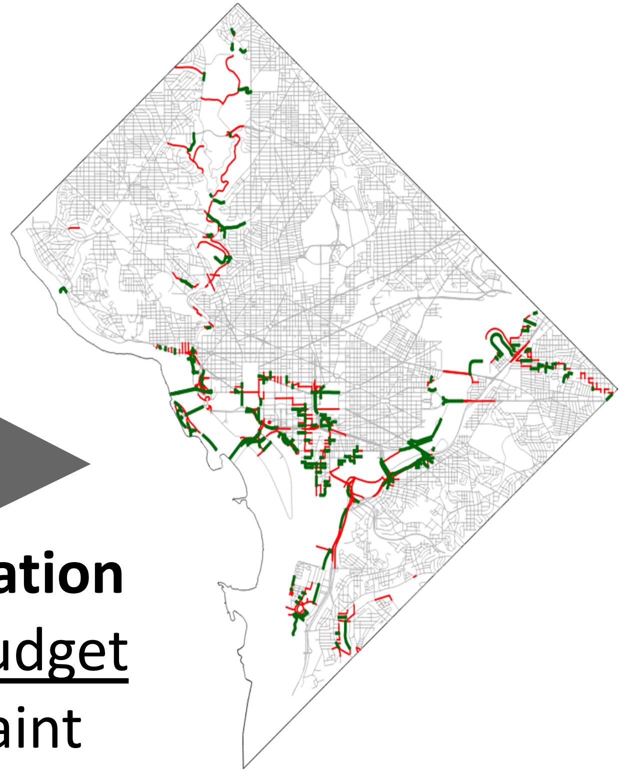


187,388 trips are infeasible (32%) out of 582,671



Infeasible Trips

Optimization under <u>budget</u> constraint



Fortified Road Network

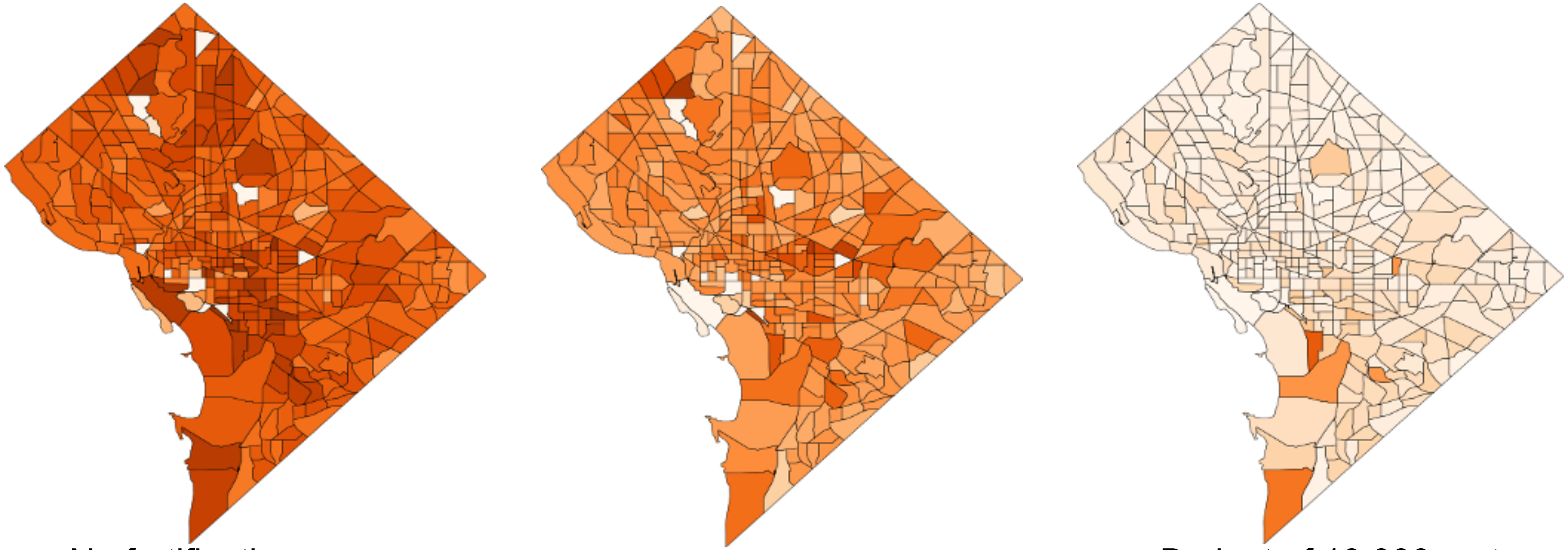
1. OSMnx
2. FEMA
3. National Capital Region Transportation Planning Board

Washington, DC - city

USC Center for Artificial Intelligence in Society

Small targeted investments can have huge impacts

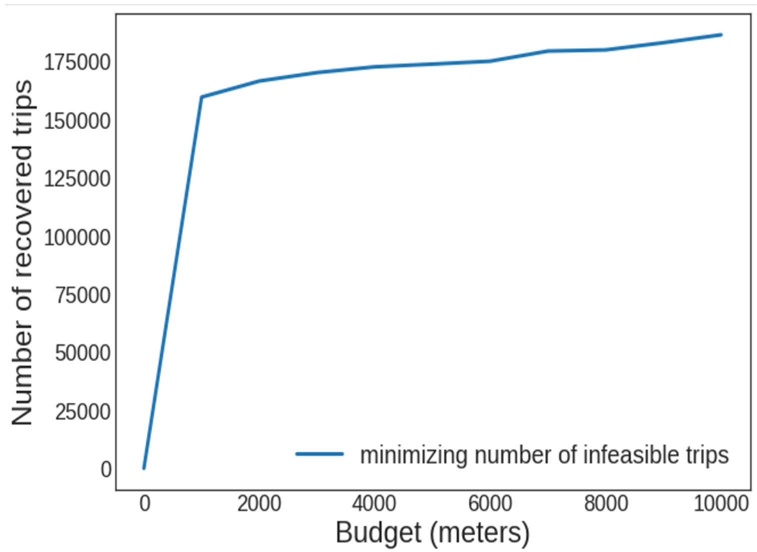
Number of Infeasible Outgoing Trips per Zone Under Varying Budgets



No fortification:
187388 infeasible trips

Budget of 500 meters:
Recovered 82.9% of infeasible trips

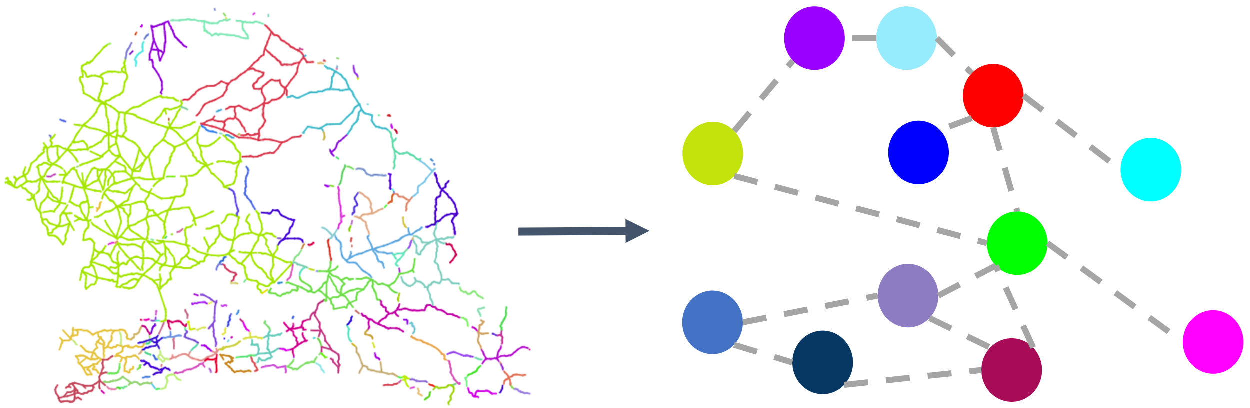
Budget of 10,000 meters:
Recovered 99.6% of infeasible trips



Washington, DC - city

Road Flood Mitigation Planning for Mobility

- **Given:** a road network annotated with flood exposure and mitigation costs, as well as pairwise mobility needs
- **Find:** which flooded roads should we upgrade to maximize how many trips can still be completed on the road network given the remaining flood exposure?



Graph (road network contraction):

- Vertex: connected unflooded component
- Edge: flooded road segment

Edge cost: cost of upgrading road segment

Budget: total cost of upgrades allowed

Profit function: aggregated travel demand between unflooded components

Budget-Prize Collecting Steiner Forest

- **Given:** graph $G=(V, E)$, edge costs $c_e \geq 0$, budget B, and profit function $p_{v1, v2} \geq 0$
- **Find:** a set of edges forming a forest F (no cycles) such that the cost of edges in F is less than B, and the profit of pairs of vertices connected in F is maximized

Johnson, David S., Maria Minkoff, and Steven Phillips. "The prize collecting steiner tree problem: theory and practice." *SODA*. Vol. 1. No. 0.6. 2000.

Budget-Prize Collecting Steiner Forest (Budget-PCSF)

USC Center for Artificial Intelligence in Society

- **NP-Hard**
  - PCSF: APX-Hard (3-approx)
  - Quota-PCSF: $O(2\,|V|^{2/3}\log|V|)$-approximation

- **Past Budget-PCSF Solution Methods**
  - MILP models: poor computational scalability
  - Greedy heuristic: arbitrarily bad solutions and slow

- **Our approach:** prove optimization problem is restricted supermodular, and develop novel scalable algorithms

Theorem: Budget-PCSF exhibits Restricted Supermodularity

- the marginal benefit of adding an element (edge) to a superset T is larger than that of adding the element to a subset S (compounding effects),
- when considering restricted subsets satisfying specific constraints (budget constraint and no-cycles/graph-matroid constraint)

Novel function characterization: previous work focused on restricted **sub**modularity (diminishing returns) and only a single type of constraint

Solution Approach: Semigradient Ascent (Iyer et al. [2013], Bai et al. [2018])

Step 0: Choose initial solution S

we show how to compute modular lower bounds for the ***restricted*** supermodular Budget-PCSF objective

Step 1: Use current solution S to compute coefficients for **modular** function that is a **lower bound** for the original objective function value

set S = S'

Step 2: Find a new solution S' that maximizes this modular lower bound (MLB), satisfyi *budget and graph matroid constraint*

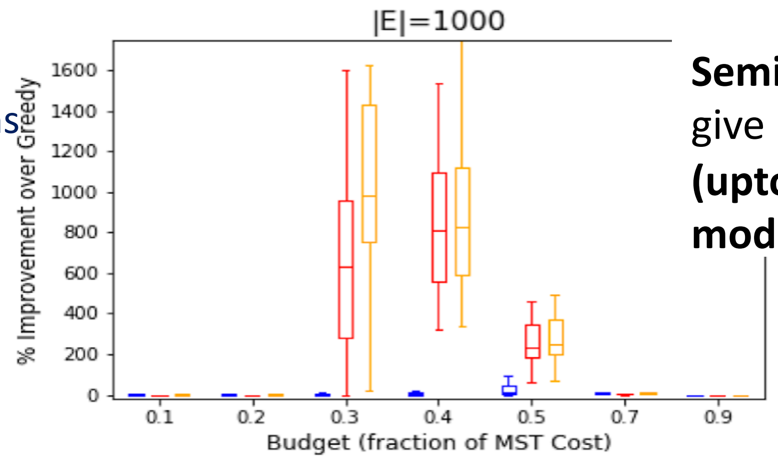
we propose 2 algorithms for maximizing our bounds subject to ***both*** these constraints

Solving Budget-constrained Prize-Collecting Steiner Forest

USC Center for Artificial Intelligence in Society

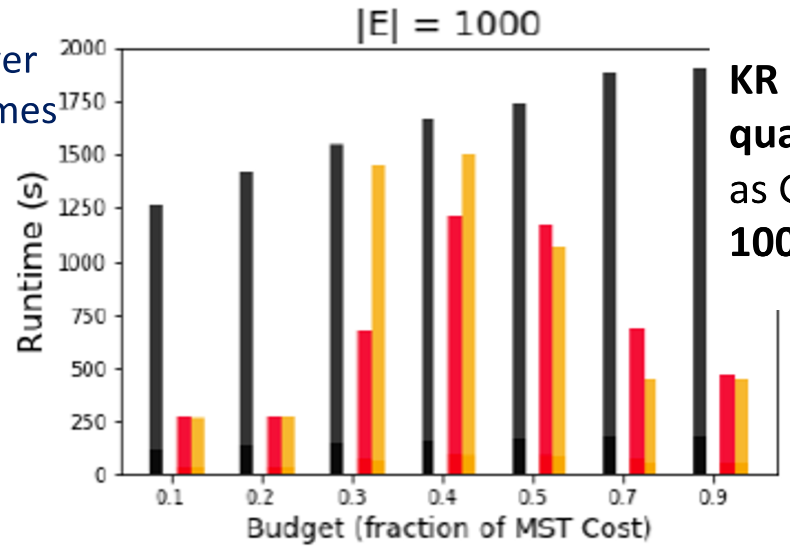
1. **Greedy** [COMPASS 2018]: add one edge at a time resulting in best mobility gain
2. Maximizing restricted supermodular function s.t. budget + matroid constraints
   - **Semigrad-GreedyMLB**: Iterate to convergence using greedyMLB (adding edge with best MLB to cost ratio)
   - **Semigrad-KR**: Iterate to convergence using a Knapsack-Repair to maximize modular lower bounds
   - **KR**: One iteration of Semigrad-KR

better solutions



Semigrad algorithms give **better solutions (upto 1000%)** and are **moderately faster**

slower runtimes



KR gives **same quality of solutions** as Greedy with **1000x speedup**

"Budget-Constrained Demand-Weighted Network Design for Resilient Infrastructure". Gupta, A. and Dilkina, B. IEEE International Conference on Tools with Artificial Intelligence (ICTAI), 2019.

What if we don't have mobility data?

USC Center for Artificial Intelligence in Society

Common real-world workflow: **Predict then Optimize**

1) Predict daily travel flows between pairs of **census tracts** in urban areas based on geographical, census and job data.

Can we build mobility models that generalize to new cities?

2) Optimize road **flood mitigation planning** using predicted travel flows / mobility needs

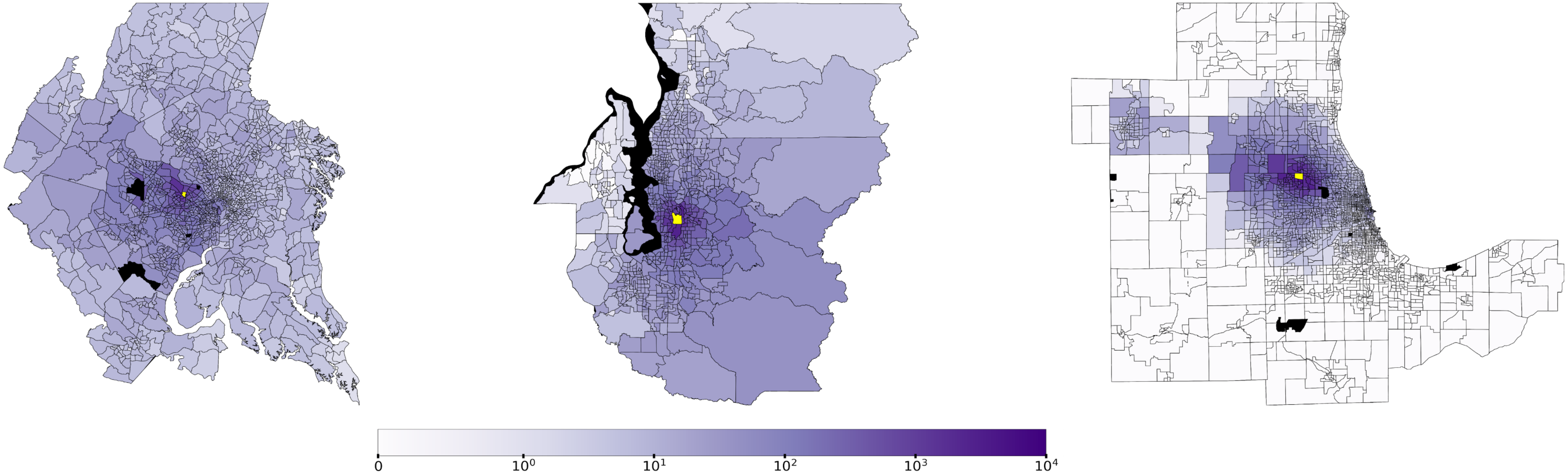
How do the errors in mobility flow prediction impact downstream optimization for road flood mitigation planning?

Mobility Flow Data for three metro areas

USC Center for Artificial Intelligence in Society

	Washington D.C.	Seattle	Chicago
# Census Tracts	1,547	772	2,432
# Inter-Tract Pairs	**2,391,662**	**595,212**	**5,912,192**
Total Daily Trips	13,251,320	7,438,891	17,217,448
Population	7,152,353	3,994,119	10,500,691
Area (sq mi)	7,096	6,599	11,039

Outgoing trips from a census tract (in yellow)

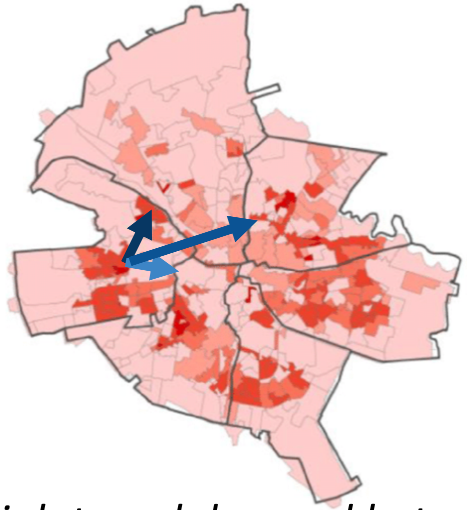


3-fold cross-validation across Washington DC, Seattle and Chicago

Can we predict CensusTract-to-CensusTract travel flows?

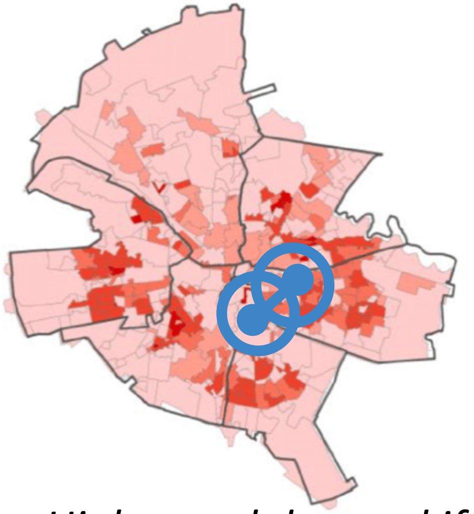
USC Center for Artificial Intelligence in Society

Gravity Model



High travel demand between densely populated, nearby areas

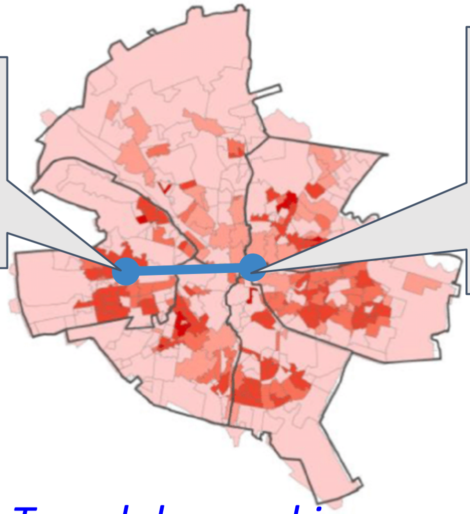
Intervening Opportunities Model



High travel demand if there are few nearby alternatives

ML: Extended Gravity Model. Random Forest Model

High population density,
mixed land use,
low number of jobs



Low population density,
developed/urban land,
high number of jobs

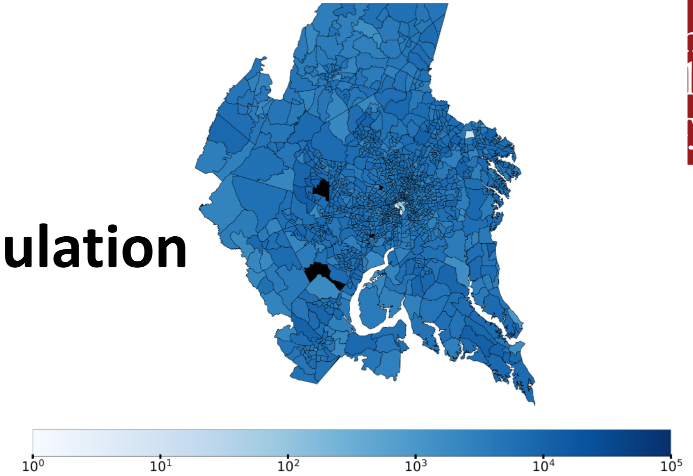
Travel demand is a complex function of origin and destination zone attributes

Category	Method	CPC	CPC_d	NRMSE	r^2
Traditional models	Gravity, exponential decay, euclidean distance	0.583±0.032	0.860±0.063	6.099±2.854	0.338±0.118
	Gravity, exponential decay, travel distance	0.590±0.039	0.865±0.061	6.197±2.881	0.316±0.116
	Gravity, power decay, euclidean distance	0.552±0.070	0.790±0.081	6.993±3.711	0.155±0.257
	Gravity, power decay, travel distance	0.552±0.078	0.781±0.077	7.427±4.039	0.051±0.318
	Schneider's model	0.533±0.021	0.841±0.032	6.036±2.553	0.344±0.057
	Radiation model	0.297±0.046	0.430±0.036	17.660±7.619	-4.612±0.545
	Extended radiation model	0.553±0.064	0.799±0.081	6.692±3.239	0.211±0.160
Learning based models	Random Forest	0.654±0.068	**0.907±0.084**	**5.287±2.529**	**0.506±0.095**
	Extended gravity, exponential decay	**0.658±0.067**	0.879±0.134	5.597±3.260	0.462±0.221
	Extended gravity, power decay	0.629±0.060	0.826±0.160	6.216±3.606	0.340±0.269

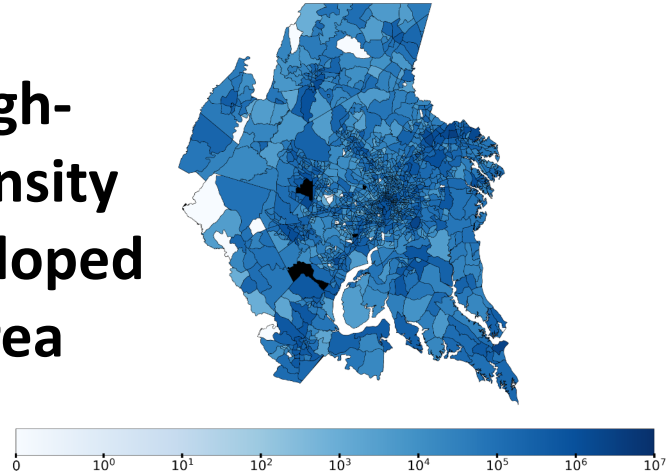
Features

Feature category	Origin/destination feature
Population	• Population • Population density
Geographical	• Area • Low-, medium-, and high-intensity development areas • Forest area
Work	• Employed population • Unemployed population • Average commute time • Number of jobs • Per capita income

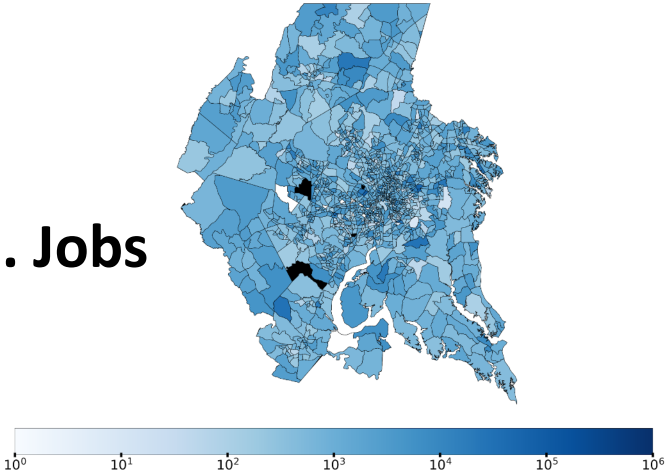
Population



High-Intensity Developed Area



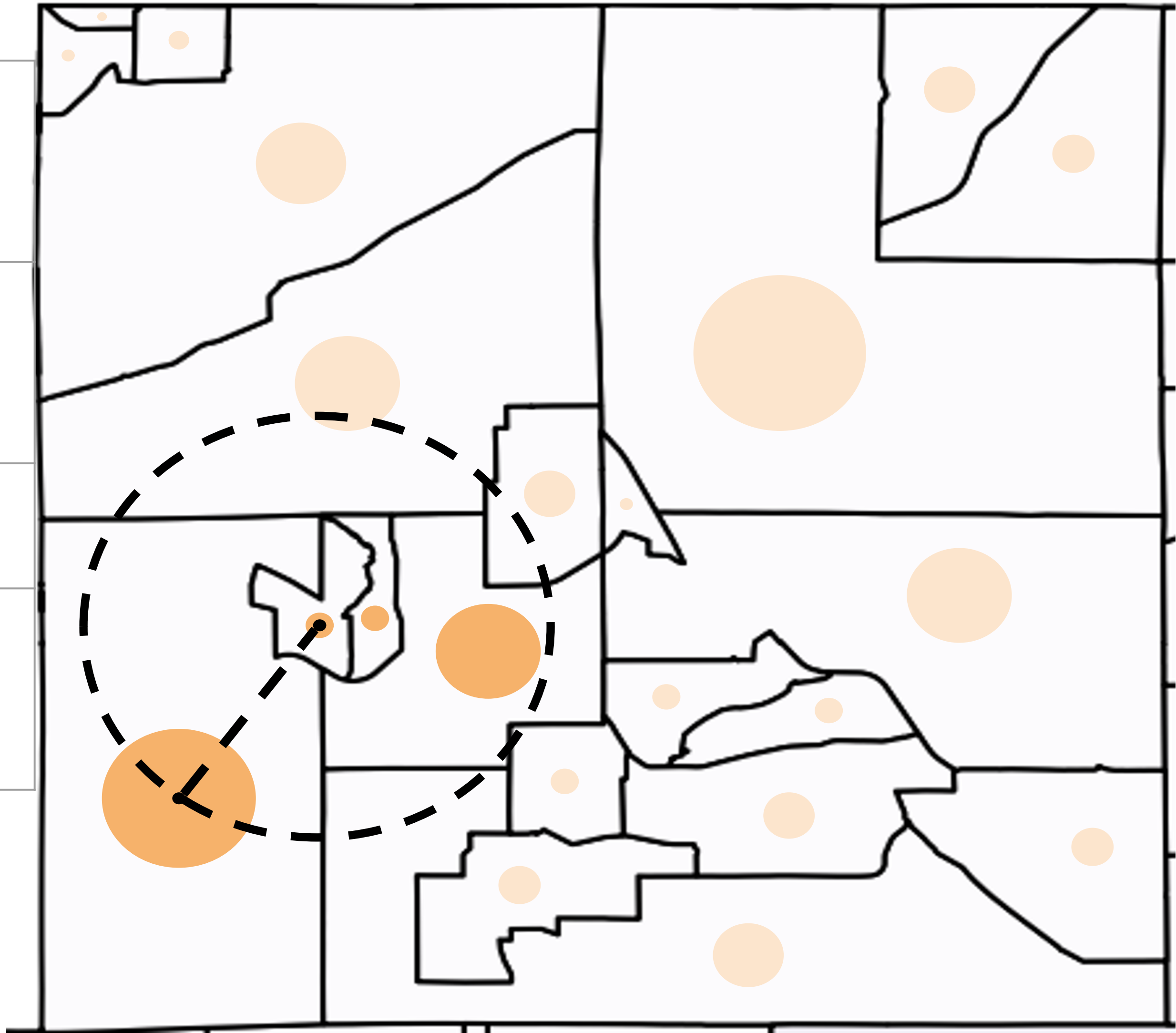
Num. Jobs



Features

Feature category	Origin-destination pair feature
Geographical	• Distance (Euclidean or road distance)
Population	• Intervening population
Work	• Intervening jobs • Intervening income

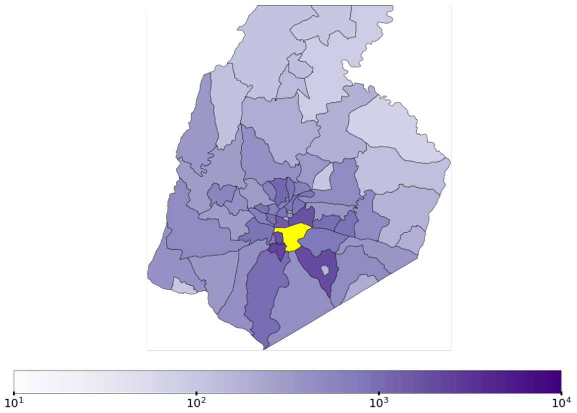
Intervening Features

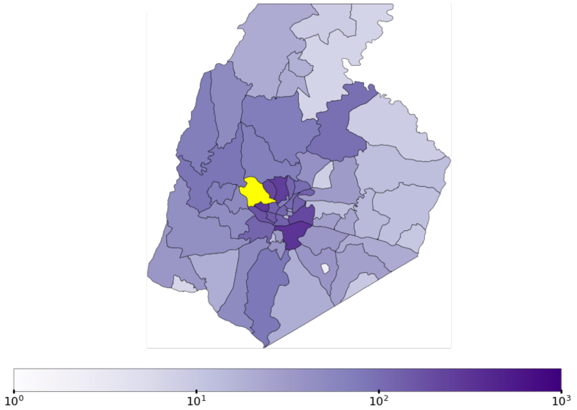


How do prediction errors affect downstream optimization?

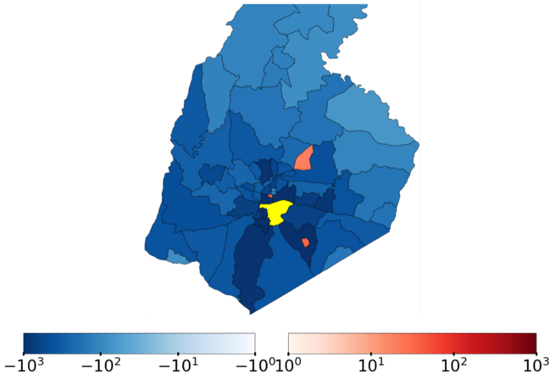
USC Center for Artificial Intelligence in Society

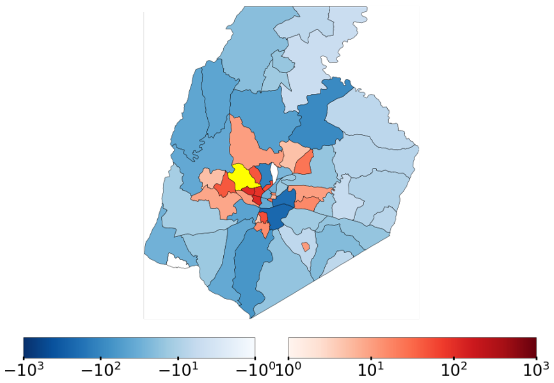
Washington DC Metro: Frederick County, MD





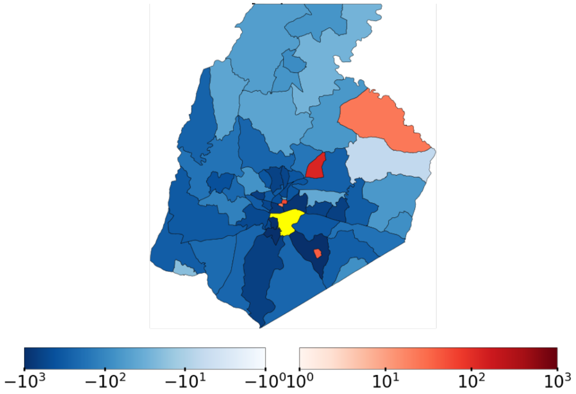
Gravity Exponential
Errors in Predicted Outbound Flow

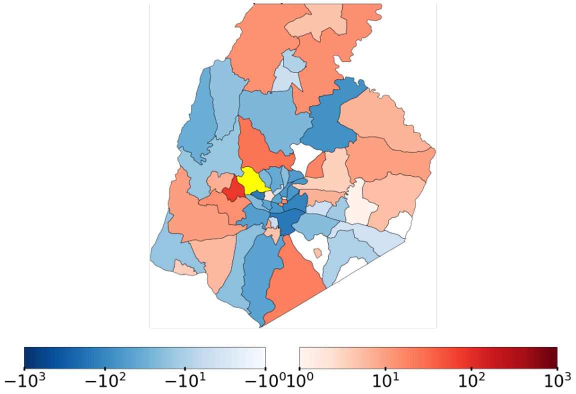




Underestimate --- overestimate

Random Forest
Errors in Predicted Outbound Flow

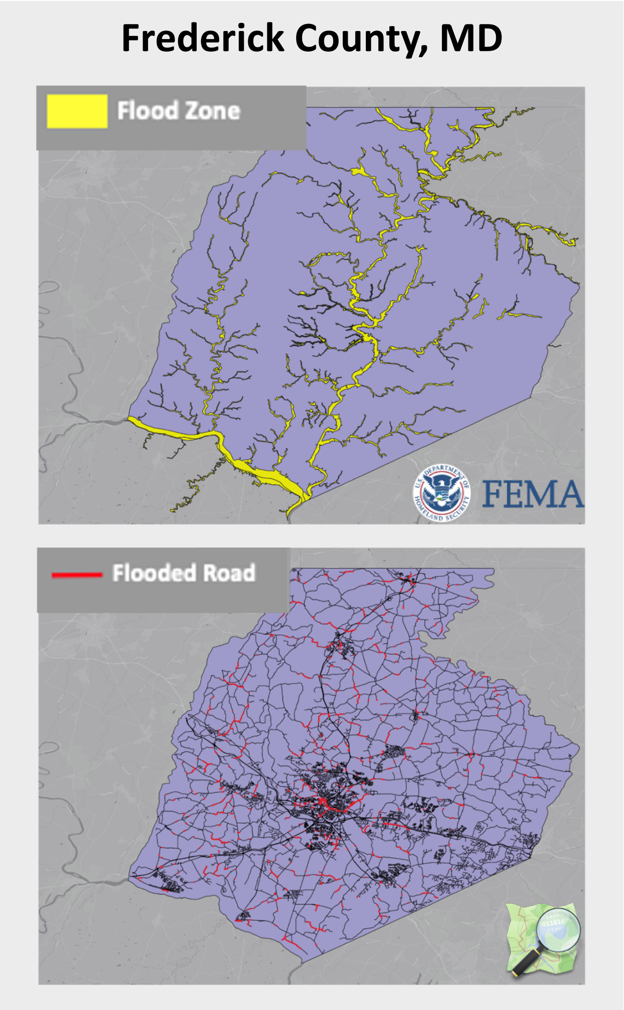


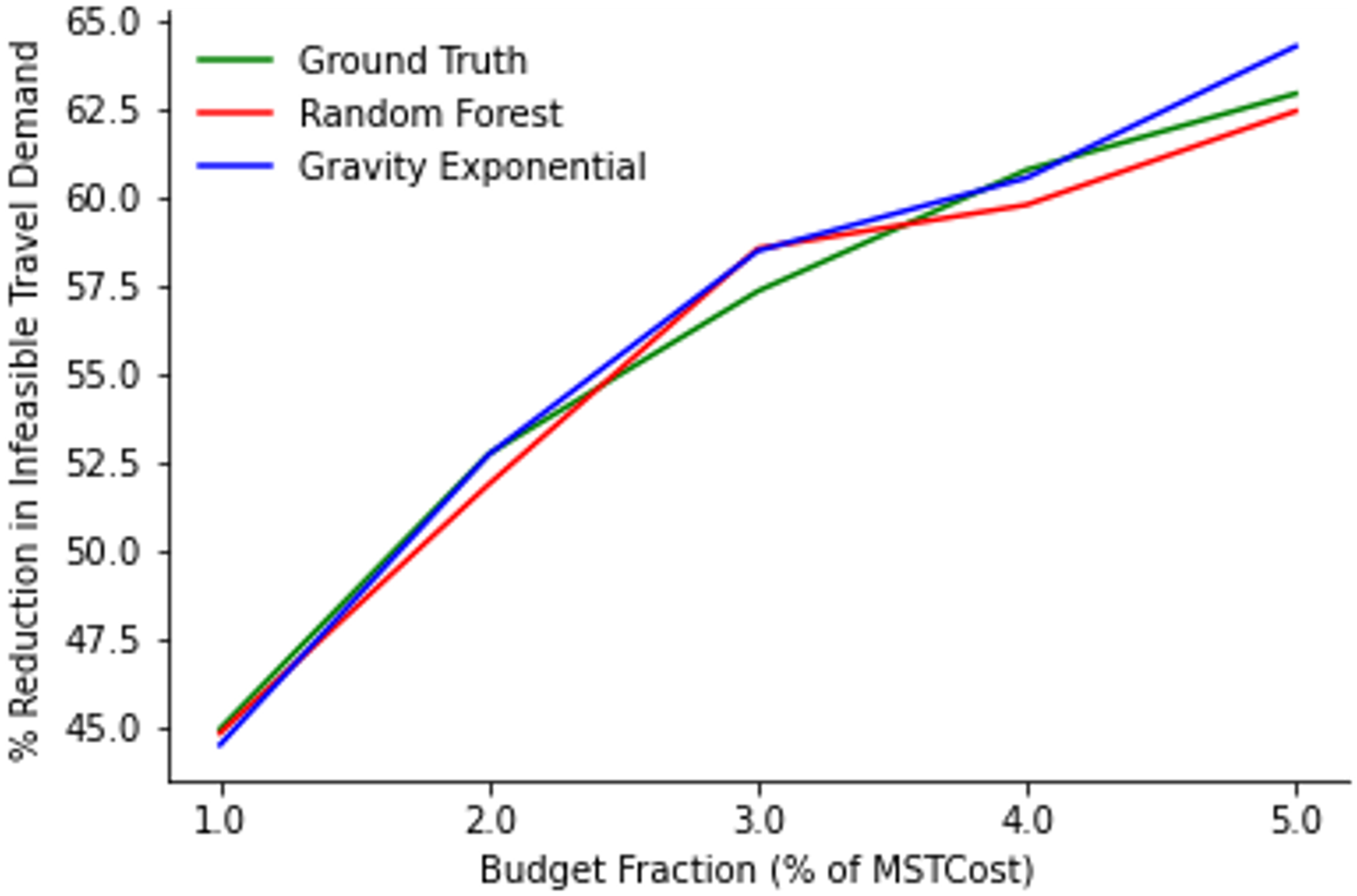


Underestimate --- overestimate

How do prediction errors affect downstream optimization?

USC Center for Artificial Intelligence in Society





ML mobility almost as effective as true data for planning

FEMA flood scenarios
109 km flooded roads
compressed graph: |V|=312, |E|=461

"Learning-Based Travel Prediction in Urban Road Network Resilience Optimization". Qiu, G., Gupta, A., Robinson, C., Feng, S. and Dilkina, B. AAAI Workshop on Urban Computing, 2021.

2017 UN Challenge on Data for Climate Action: infrastructure planning for mobility during floods

USC Center for Artificial Intelligence in Society

1 NO POVERTY
8 DECENT WORK AND ECONOMIC GROWTH
9 INDUSTRY, INNOVATION AND INFRASTRUCTURE
13 CLIMATE ACTION

United Nations

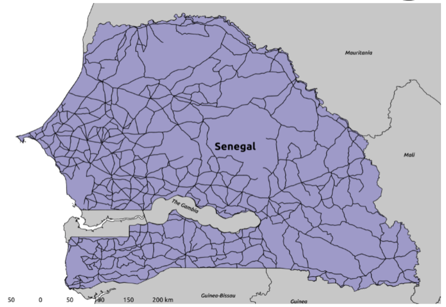
GLOBAL PULSE

DATA FOR CLIMATE ACTION

JOIN THE CHALLENGE TO
HARNESS DATA
FOR CLIMATE ACTION

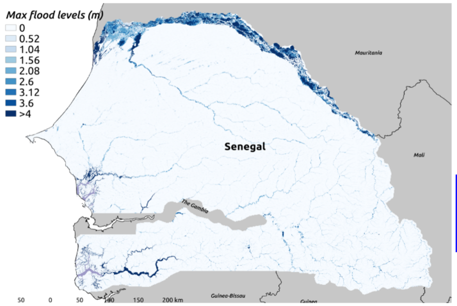
UN Challenge
Thematic Winner
for Climate Adaptation

Senegal



Road network

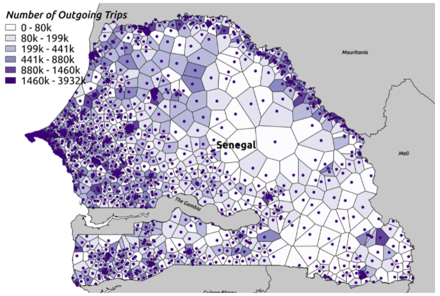
Open Street Maps



Estimated flood maps

Fathom.Global

FATHOM



Mobility Needs (from CRD)

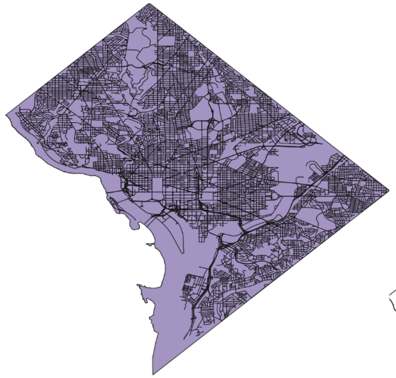
Orange S.A.

orange™

USC Center for Artificial Intelligence in Society

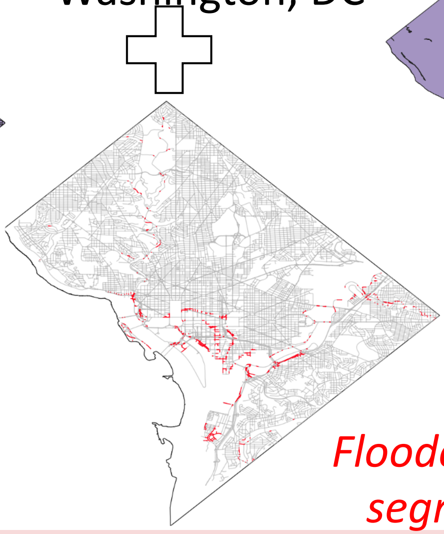
Mitigation planning: targeted infrastructure network fortification to maximize resilience

Given a road network and flood risks, how to upgrade roads to **maximize resilience to floods or other disasters?**

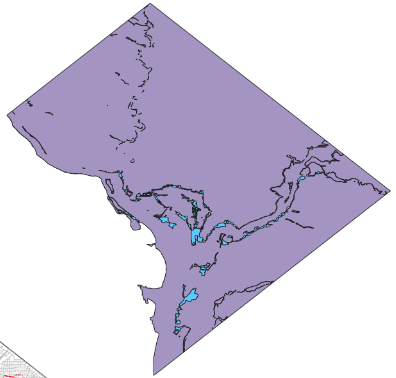


Road network

Washington, DC

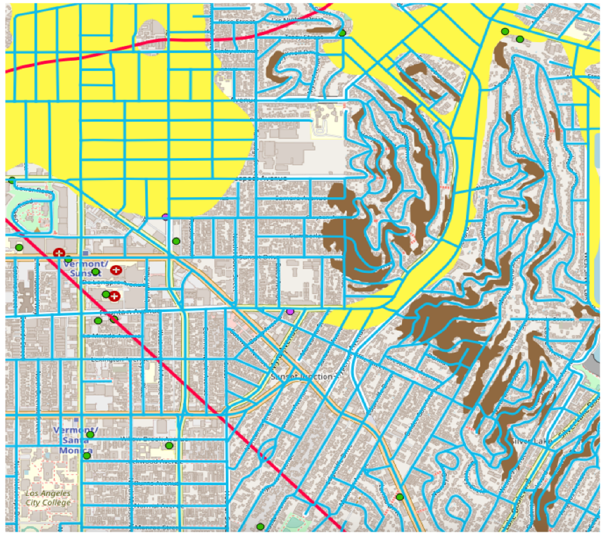


Flooded road segments



flood scenario

Given water pipe network and earthquake risks, select parts of the network to replace with **seismic resilient pipes**



<u>Critical customers</u> (hospitals, fire/police stations, emergency evacuation centers, power, sanitation, etc) **must be directly connected to the resilient network.**

<u>All households</u> **must be within 1mi** of the resilient network (reachable by fire hose).

Challenges: limited budget, <u>many subnetworks possible</u>, several resilience metrics, <u>predict mobility needs</u>

Challenges: limited budget, many sub-networks possible, complex constraints

USC Center for Artificial Intelligence in Society

City of Los Angeles Resilience Goals

A water main break following a 6.0 earthquake in Napa, California.
https://www.cbsnews.com/pictures/strong-earthquake-knocks-napa-valley/17/

https://www.lamayor.org/sites/g/files/wph446/f/page/file/Resilient%20Los%20Angeles.pdf

Action 61: Advance seismic safety, prioritizing the most vulnerable buildings, infrastructure, and systems

"Expand Seismic Resilient Pipe Network
The City will expand development of the seismic resilient pipe network. … Resilient pipeline planning, design, and construction **requires the development of new informational tools and mapping of geohazards** …."

[Craig Davis, 2017] *"The proper layout of seismically robust pipe will allow the network to cost-effectively suffer damage while meeting performance criteria supporting community resilience goals."*

LA DWP

USC Center for Artificial Intelligence in Society

Challenge: Master Plan for Water Pipe Network Upgrades

Given a water network and seismic risk maps, we know which pipes are likely to break.

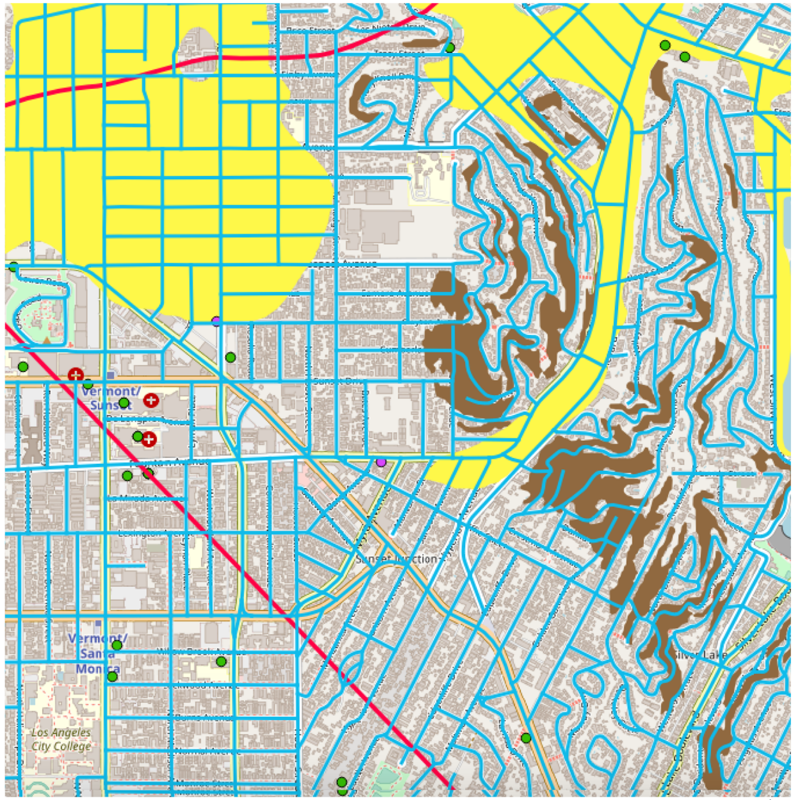
Critical customers must be **directly connected** to the resilient network (hospitals, fire/police stations, emergency evacuation centers, power, sanitation, etc).

All households must be "**covered**", e.g. **within 1mi** of the resilient network (reachable by fire hose).

Challenges: many sub-networks possible, complex constraints

Select parts of the network to replace with **seismic resilient pipes**

2 mi



2 mi

water pipes

health facilities

other critical customers

fault lines

liquefaction zones

landslide zones

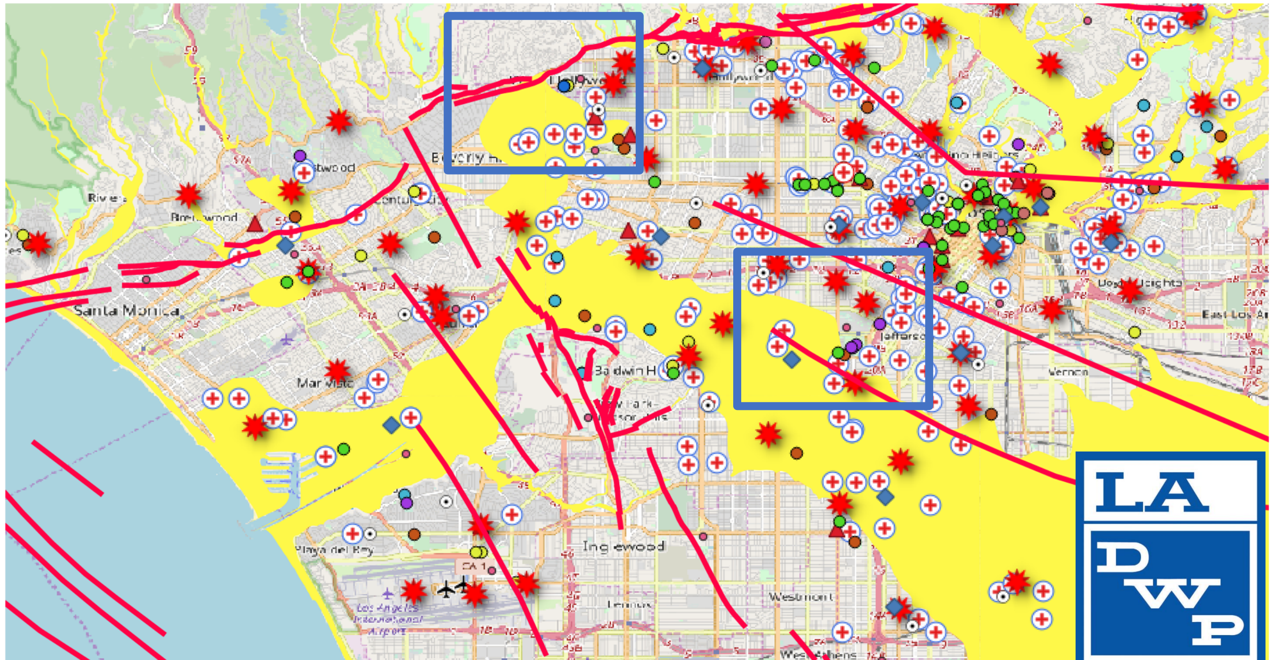
LA DWP

USC Center for Artificial Intelligence in Society

Data

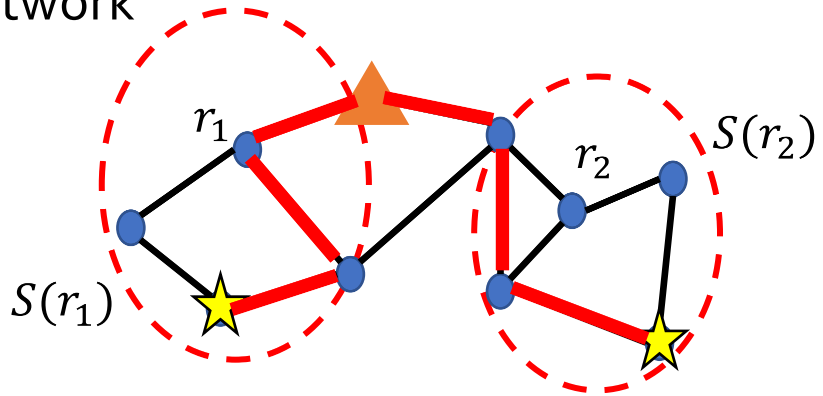
- **Infrastructure data: Pipe network** (pipes and joints) and **water sources (**trunk lines, pumps, etc.) of service zones
- Locations of **critical customers** (hospitals, evac. centers, police & fire stations, etc.)
- **Hazard data: Fault zones and liquefaction** areas to determine pipes and customers threatened by earthquakes

	#Edges	#Nodes
2mi x 2mi	853.9	563.3
4mi x 4mi	3,264.8	2,132.6



Model

- E: The set of pipes
- V: Intersections of pipes including pump stations, valves and hydrants etc.
- $G = (V, E)$: An undirected graph representation of the water network
- $c(e)$: The cost of replacing pipe e with seismic-resilient pipes
- $T \subseteq V$: The set of water sources
- $C \subseteq V$: The set of critical customers
- R: The set of residential areas



and $S(r) \subseteq E, r \in R$: The set of pipes that are close enough to serve r

Find:

- A set of edges $E' \subseteq E$ with **minimum sum of costs**, such that
  - each customer is connected to a source node ← Node constraints
  - at least one edge from each $S(r)$ is connected to a source node ← Coverage constraints

Steiner Network Problem with Coverage Constraints (SNP-CC)

NP-hard and cannot be approximated to a factor of o($\ln |R|$) in poly time.

A Flow-Based MILP formulation

$$\min_{x,y,z} \sum_{(i,j)\in E} c(i,j)(x_{i,j} + x_{j,i})$$

$$x_e \in \{0,1\} \qquad \forall e \in \hat{E} \qquad (1)$$

x_e: whether edge e is selected (binary)

y_e: the number of units of flow on edge e

$$x_{i,j} + x_{j,i} \le 1 \qquad \forall (i,j) \in E \qquad (2)$$

$$z + \sum_{t\in T} y_{0,t} = |\hat{E}| + |V| \qquad (3)$$

Inject flow to the sources

$$0 \le y_e \le (|\hat{E}| + |V|)x_e \qquad \forall e \in \hat{E} \qquad (4)$$

Edge e consumes 1 unit of flow if chosen

$$\sum_{e\in\delta^-(v)} y_e = 1_{[v\in C]} + \sum_{e\in\delta^+(v)} (y_e + x_e) \qquad \forall v \in V \qquad (5)$$

Flow conservation; Each critical customer absorbs 1 unit of flow

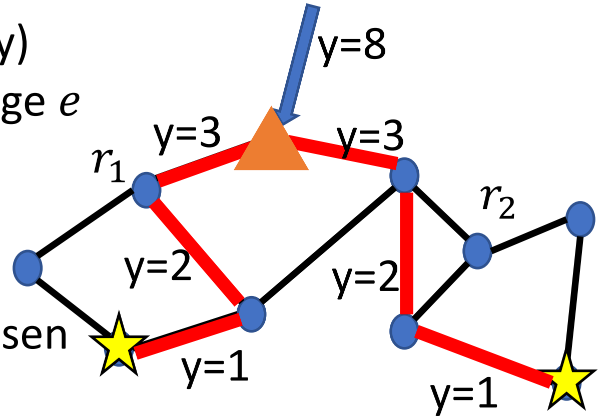
$$\sum_{t\in T} y_{0,t} = |C| + \sum_{e\in\hat{E}} x_e \qquad (6)$$

Flow conservation at sources and sinks; ensure all critical customers are connected

$$\sum_{(i,j)\in S(r)} x_{i,j} + x_{j,i} \ge 1 \qquad \forall r \in R \qquad (7)$$

Imposing **coverage** constraints

Inject flow to the source

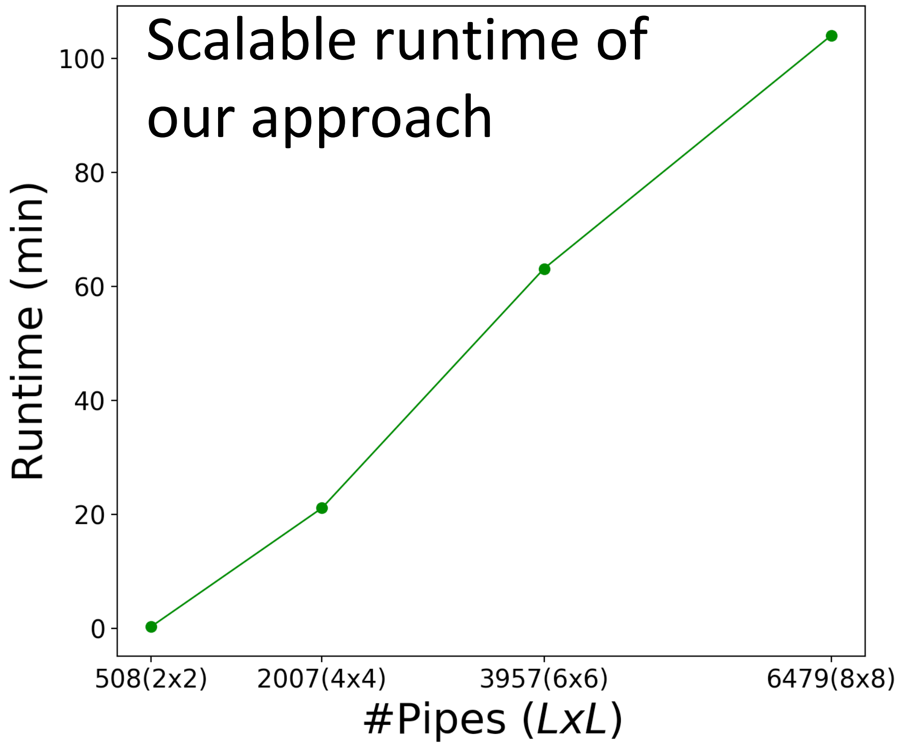


Chosen edges and customers consume 1 unit of flow (maintain **connectivity** to water sources)

- $O(|V| + |E|)$ variables with $O(|V| + |E| + |R|)$ constraints

Optimized Mitigation Planning

- **Developed an optimization algorithm that finds the minimum cost plan for upgrading water pipes that satisfy both the critical customer connectivity and fire hose coverage constraints**
- **3 locations on the map of Los Angeles**
  - For each location, we use a square of $L \times L$ miles ($L = 2,4,6,8$ miles)
  - *The baseline solutions from iterative decisions cost* ***6% to 23% more*** *than our solutions*
- **Entire Service Zone in LA**
  - It includes 34,462 pipes and 300 critical customers,
  - out of which 8,434 threatened pipes and 93 threatened customers.
  - Our approach finds the optimal solution with cost 23.47 miles in 18 minutes
- **Currently applying across Los Angeles wit LA DWP**



"Enhancing Seismic Resilience of Water Pipe Networks". Huang, T. and Dilkina, B. ACM SIGCAS Conference on Computing and Sustainable Societies (COMPASS), 2020.

USC Center for Artificial Intelligence in Society

Data + AI Algorithms helps answer questions like:

- **Which are the components** of the infrastructure system that are most at risk?
- **Who is affected and how much** -- how are the consequences of infrastructure disruptions distributed, who and where are the most vulnerable and at-risk populations?
- **Where can we plan** (near) optimally infrastructure *upgrades* to maximize resilience, given limited resources?
- **What are the trade offs** between optimizing for different metrics (cost-benefit analysis)?

- Funded by: CIRI | CRITICAL INFRASTRUCTURE RESILIENCE INSTITUTE

A DEPARTMENT OF HOMELAND SECURITY CENTER OF EXCELLENCE

References

1. **“Infrastructure resilience for climate adaptation”**. Gupta, A., Robinson, C. and Dilkina, B. ACM SIGCAS Conference on Computing and Sustainable Societies (COMPASS), 2018.

2. **“Budget-Constrained Demand-Weighted Network Design for Resilient Infrastructure”**. Gupta, A. and Dilkina, B. IEEE International Conference on Tools with Artificial Intelligence (ICTAI), 2019.

3. **“Learning-Based Travel Prediction in Urban Road Network Resilience Optimization”**. Qiu, G., Gupta, A., Robinson, C., Feng, S. and Dilkina, B. AAAI Workshop on Urban Computing, 2021.

4. **“Enhancing Seismic Resilience of Water Pipe Networks”**. Huang, T. and Dilkina, B. ACM SIGCAS Conference on Computing and Sustainable Societies (COMPASS), 2020.