SAFE-NET: A Computing Platform for Public Safety Applications

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Background

Emergency management is a complex real-time operation that involves several interdependent processes, including:

a) Emergency situation awareness

b) Scheme design for response and rescue

c) Equipment and personnel deployment

d) Start-to-finish mission support

Research Objectives

This research aims at accelerating public safety innovation through the development of **SAFE-NET**.

SAFE-NET is a novel computational platform to support efficient and safe dynamic mobilization of resources and personnel for emergency response.

Presented Problems

Problem 1:

Area-wide Workload Balancing for Robust Response Time

Problem 2:

Spatial Risk Modeling of Traffic Accidents for Emergency Vehicle Routing

Problem 3:

Crowd Sourcing Flood Hazards

Part 1:

Area-wide Stochastic Workload Balancing for Robust Response Time

Dr. Khaled Abdelghany
In Collaboration with:
Parya Roustaee and Aline Karak
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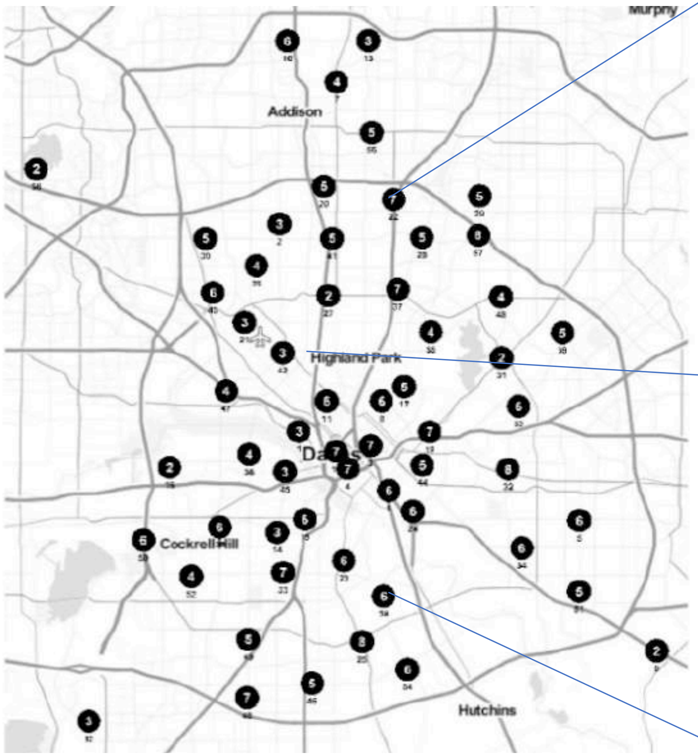
Problem Overview

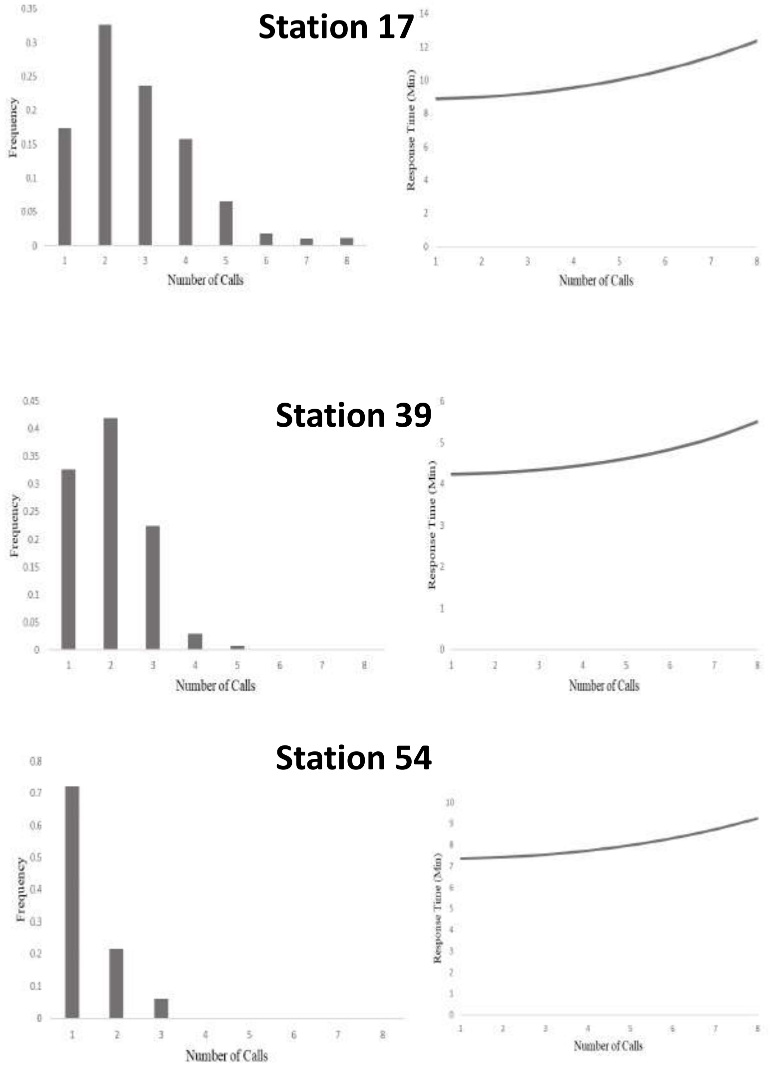
Given:
(1) Workload distribution for all stations in the service area
(2) Response time performance function for each station

Objective:
Maximize service robustness
Minimize
Expected Response Time + Response Time Variation

Decision Variables:
The workload cutoff for each station



Service Area

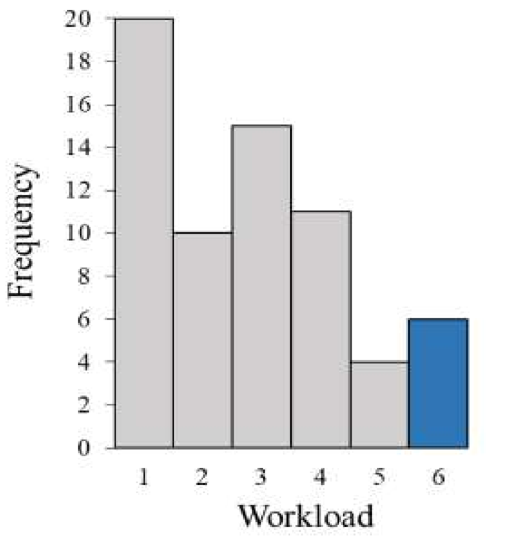


Workload Distribution

Response Time

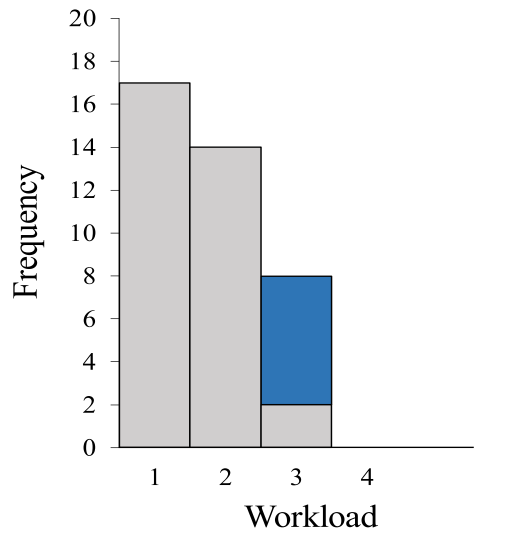
Two Stations Example – Workload Cutoff

Original Workload Distribution for Station A



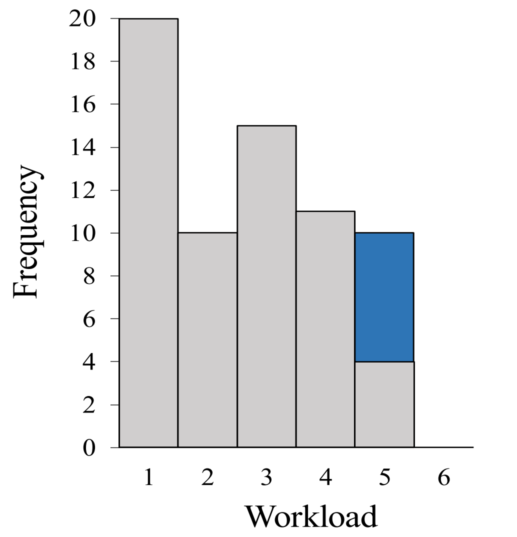
Cutoff=6

Original Workload Distribution for Station B



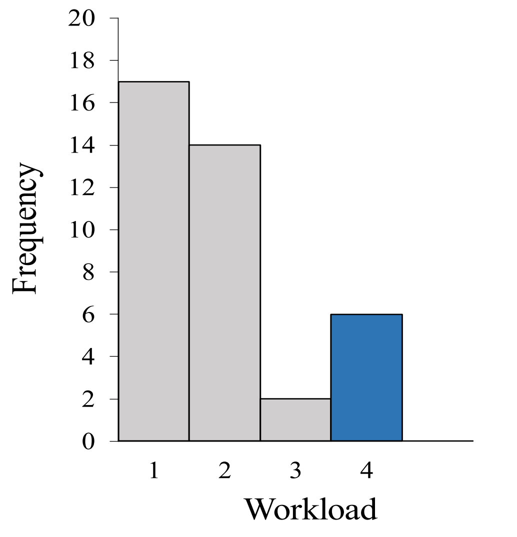
Cutoff=3

Modified Workload Distribution for Station A



Cutoff=5

Modified Workload Distribution for Station B



Cutoff=4

Workload Distribution
Before Workload Balancing

Workload Distribution
After Workload Balancing

Station A reduces its workload cutoff while Station B extends its workload cutoff

Problem Formulation

Objective Function

Minimize $Z = \sum_i (\dot{t}_i + \ \omega \cdot \ddot{t}_i)$ (1)

$\dot{t}_{ik} = \ \sum_t t \cdot g_i \ (t|k)$ $\qquad \forall \ k \in K_i, \forall \ i \in S$ (2)

$\dot{t}_i = \ \sum_{k=1:\acute{k}_i} p_i(k) \cdot \dot{t}_{ik}$ $\qquad \forall \ i \in S$ (3)

$\ddot{t}_i = \ \sum_{k=1:\acute{k}_i} p_i(k) \cdot (\ \dot{t}_{ik} - \ \dot{t}_i)^2$ $\qquad \forall \ i \in S$ (4)

Conservation of workload frequencies across all stations

$N \ = \sum_i n_i$ (5)

$N_l \ = \sum_s \sum_{k=1:\acute{k}_i} n_{ilk}$ $\qquad \forall \ l \in L$ (6)

$n_{ik} \ = \sum_l n_{ilk}$ $\qquad \forall \ k \in K_i, \forall \ i \in S$ (7)

$n_i \ = \sum_{k=1:\acute{k}_i} n_{ik}$ $\qquad \forall \ i \in S$ (8)

Problem Formulation (Cont.)

Probability distribution for each station

$p_i(k) = \frac{n_{ik}}{n_i}$ $\forall\, i \in S$ (9)

$\sum_{k=1:\acute{k}_i} p_i(k) = 1$ $\forall\, i \in S$ (10)

$p_i(k) \geq 0$ $\forall\, k \in K_i, \forall\, i \in S$ (11)

Workload shifting constraints

$\Delta n_i = \sum_j \Delta n_{ij} \,.\, \delta_{ij}$ $\forall\, i \in S$ (12)

$n_i = \tilde{n}_i + \Delta n_i$ $\forall\, s \in S$ (13)

Station capacity constraint

$\acute{k}_i \leq \mathrm{C}_i$ $\forall\, i \in S$ (14)

Nonnegativity constraints

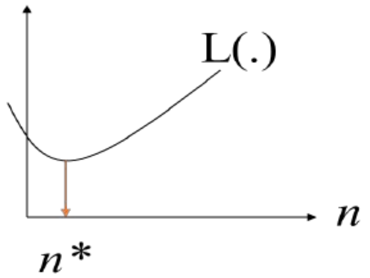
n_{ilk}, n_{ik} and n_i are positive integers $\forall\, k \in K_i,\ \forall\, i \in S$ (15)

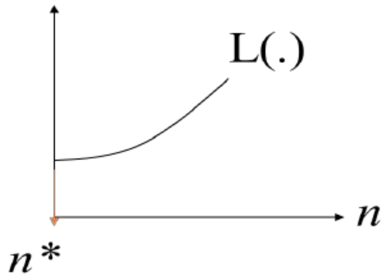
The Equilibrium Conditions

Lagrangian representation of the objective function

$$L = Z + \mu \cdot (N - \textstyle\sum_i n_i) \tag{16}$$

L is convex. Thus, the **optimality conditions** can be derived by differentiating $L(.)$ with respect to n_i for each station i $\in S$





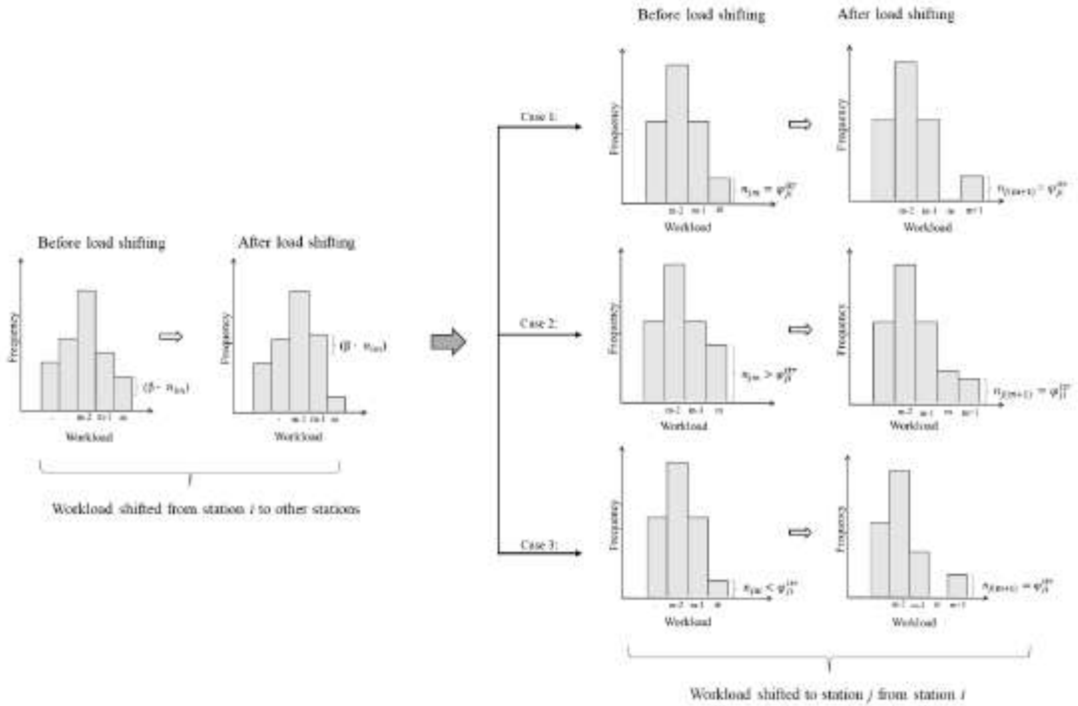
Define $\pi_i = \frac{\Delta Z(.)}{\Delta n_i}$, the term $\frac{\Delta L(.)}{\Delta n_i}$ can then be written as $(\pi_i - \mu)$

$$n_i^* . (\pi_i^* - \mu) = 0 \qquad \forall\, i \in S \tag{19}$$

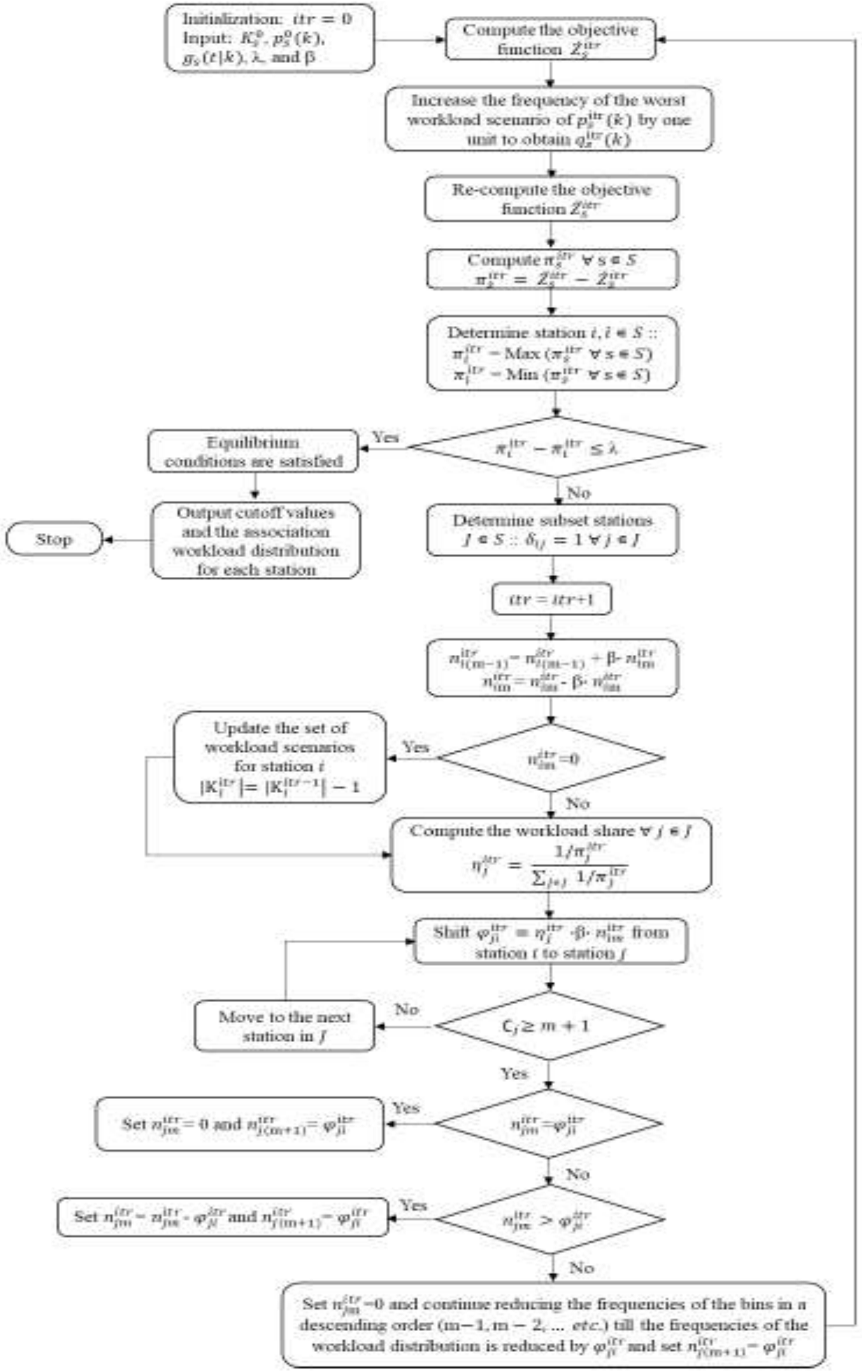
$$\pi_i^* - \mu \ \geq 0 \qquad \forall\, i \in S \tag{20}$$

At equilibrium, all stations are having the same marginal cost of uncertainty

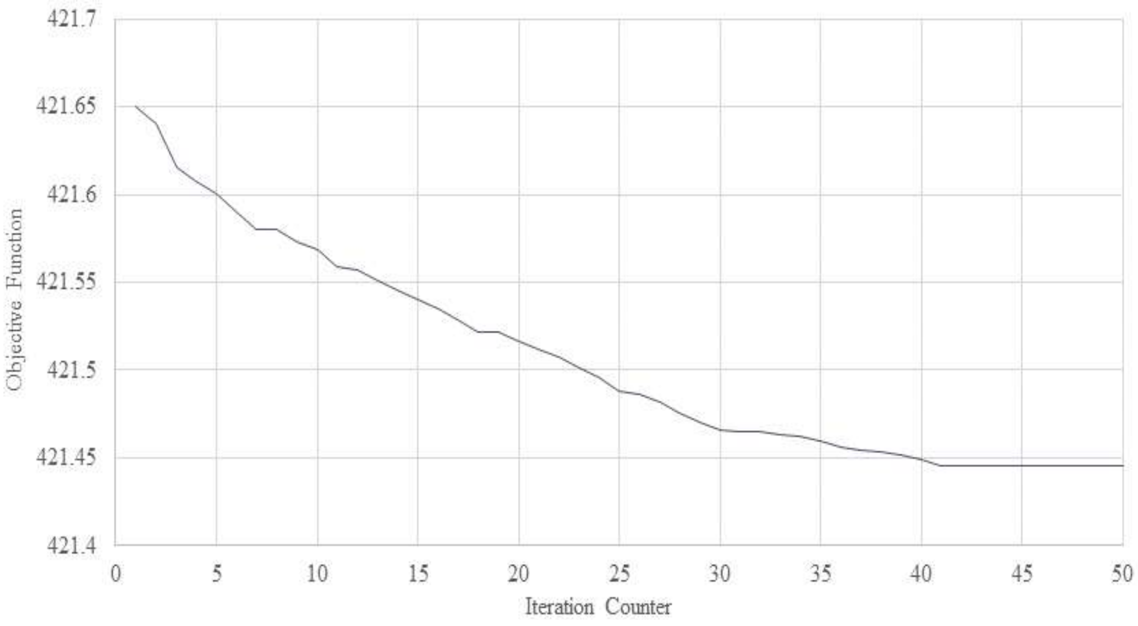
Solution Algorithm



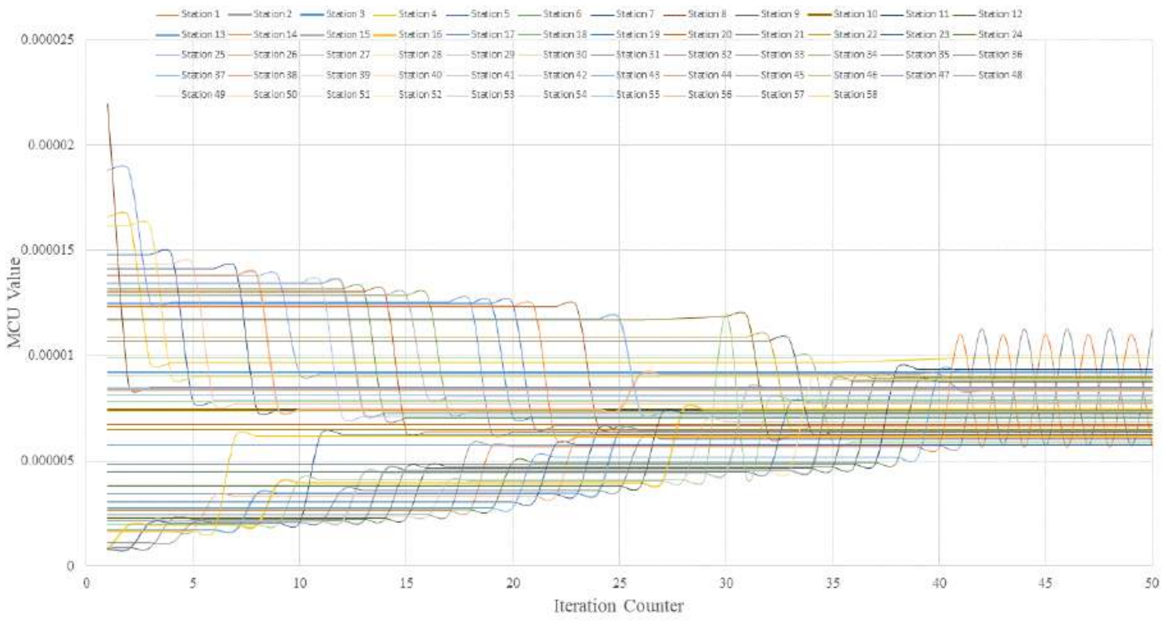
Shifting workload from stations with high MCU to stations with low MCU until the state of equilibrium is reached



Case Study: City of Dallas



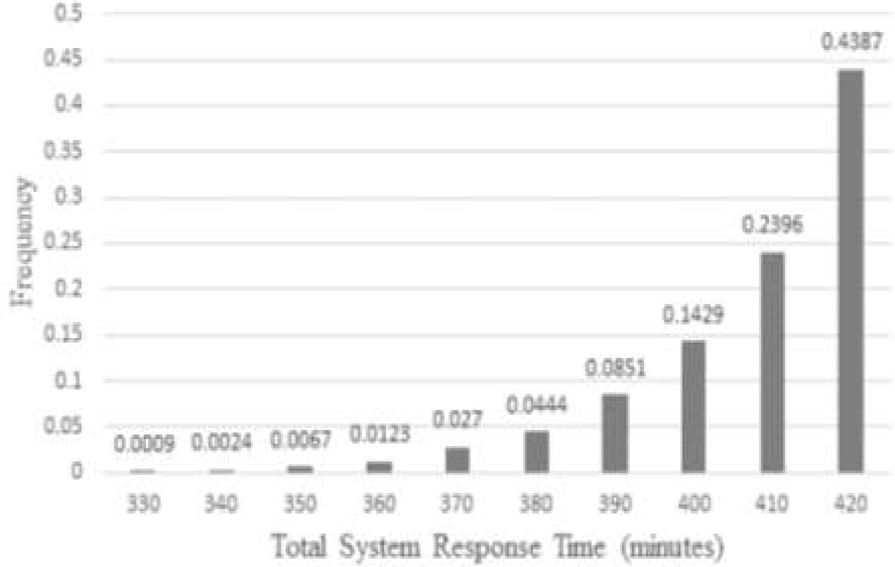
Objective Function

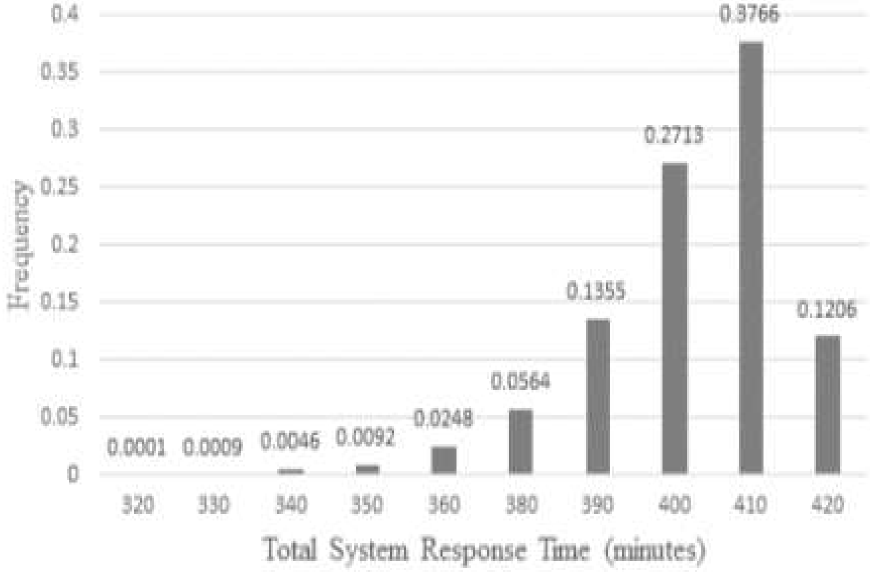


MCU values for the Stations

The Algorithm’s Convergence Pattern

Case Study: City of Dallas (Cont.)





Before	After
Mean = 405.51 (Min); Variance = 219.45 Response Time = 3.55 (Min/Call)	Mean = 398.91 (Min); Variance = 177.91 Response Time = 3.49 (Min/Call)

Before Workload Balancing | **After Workload Balancing**

Simulated Response Time Distribution Before and After Workload Balancing

Conclusion

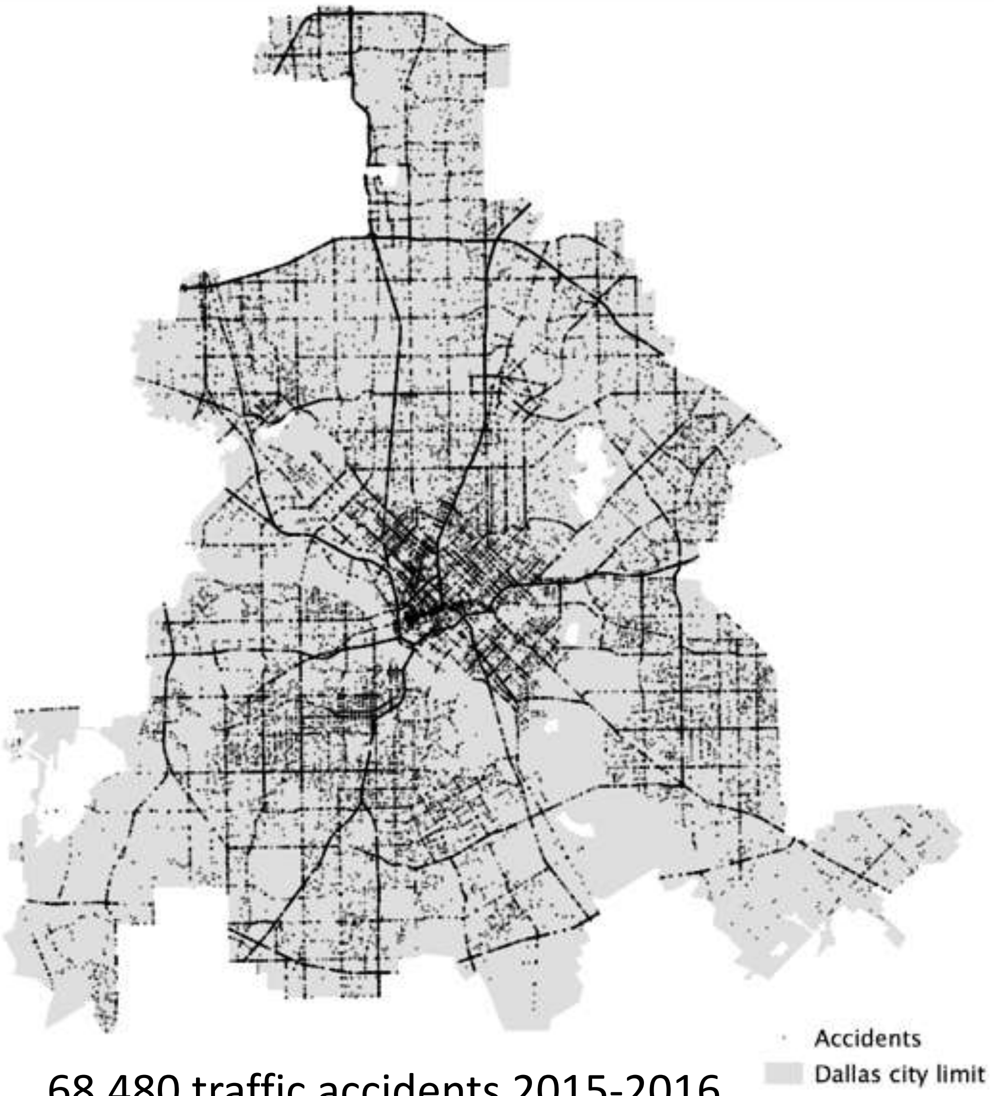
- An equilibrium-based modeling framework for robust ER workload balancing is introduced.
- The modeling framework is formulated as a NLP that determines the optimal workload cutoff for each station.
- The solution to the NLP is equivalent to an equilibrium state in which no station can improve its MCU value by unilaterally shifting a portion of its workload to any other station.
- Based on the obtained results DFRD is adopting a near-optimal workload balancing strategy.
- The framework can be applied to determine the optimal workload balancing strategy considering changes in the operation conditions of the service area.

Part 2:

Spatial demand modeling of emergency vehicle routing

Dr. May Yuan
The University of Texas at Dallas

According to the National Highway Traffic Safety Administration (NHTSA), there were approximately 31,600 accidents involving fire trucks from 2000 to 2009 in the nation, and 70% of these fire truck accidents occurred while in emergency use. In the period from 1992 to 2011, there were an estimated 4,500 accidents per year involving ambulances. About 60% of ambulance accidents occurred during emergency response operations. Therefore, it is important to consider spatial risk during dispatch.

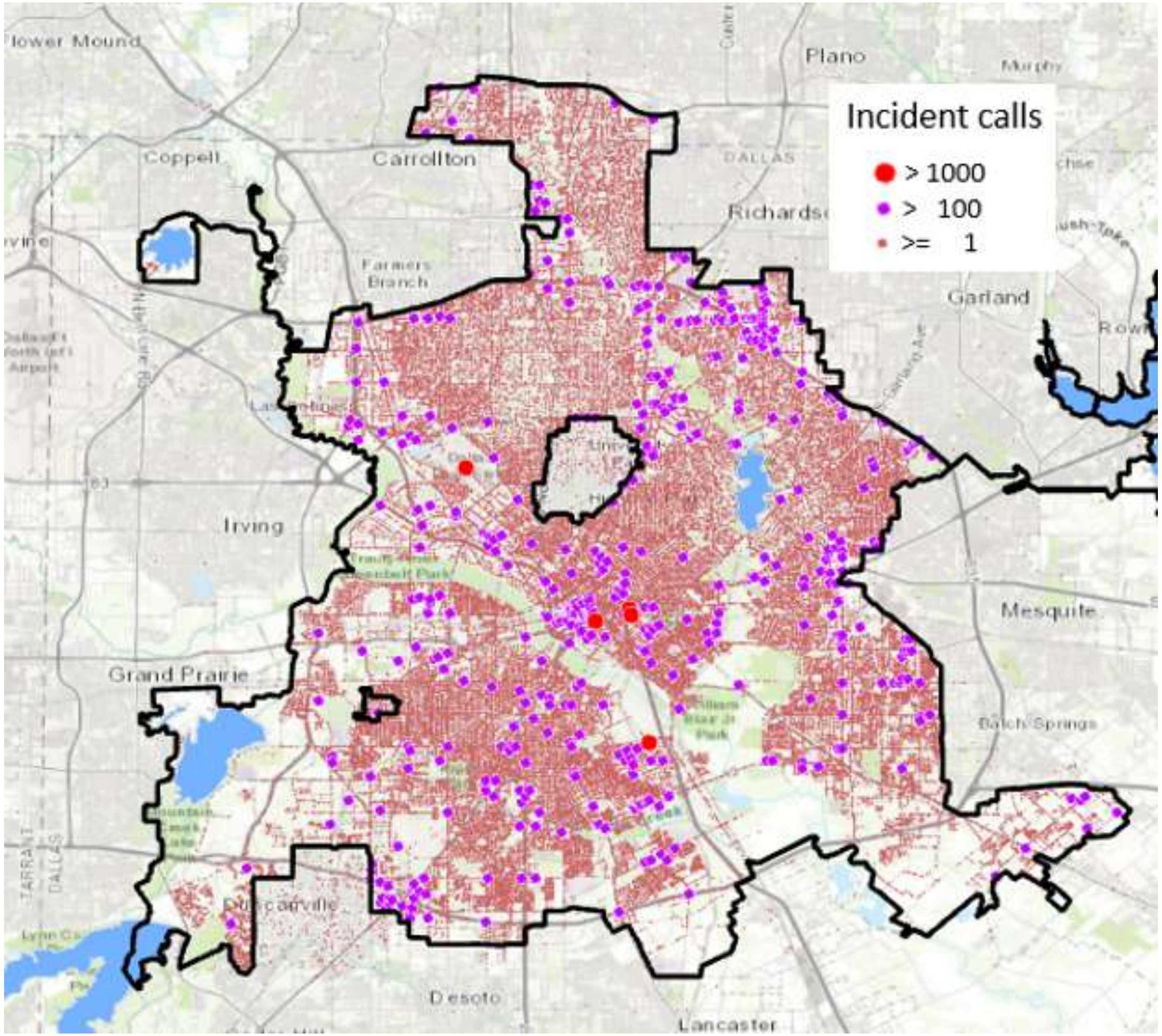


68,480 traffic accidents 2015-2016

Our presentation in 2018 summarized findings of which streets and when are of higher risk to traffic accidents than other streets in Dallas

This year, we focus on incident calls and routing:

1. Where were the emergency calls from?
2. What were routes taken?
3. Where could the routes be more efficient?

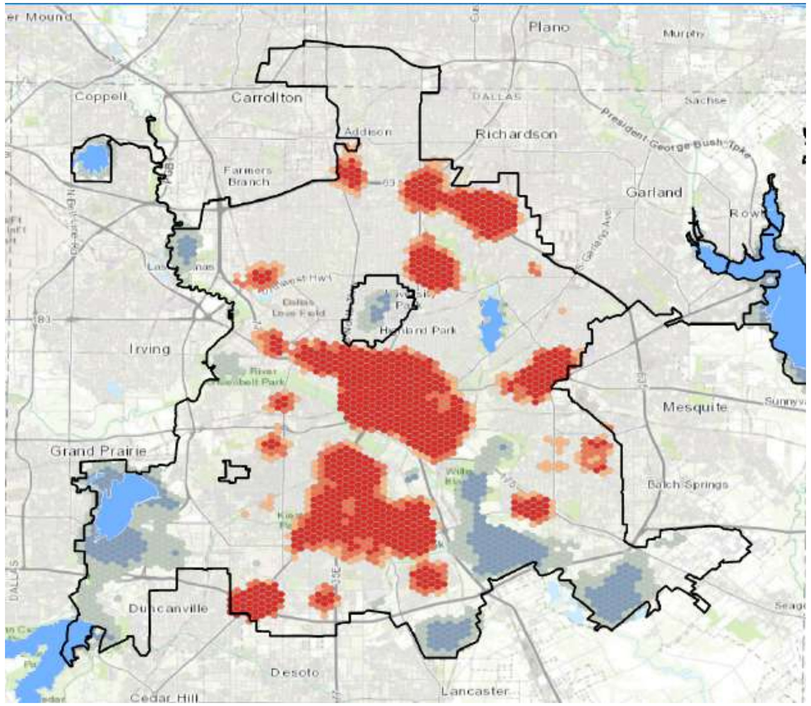


Incident calls:

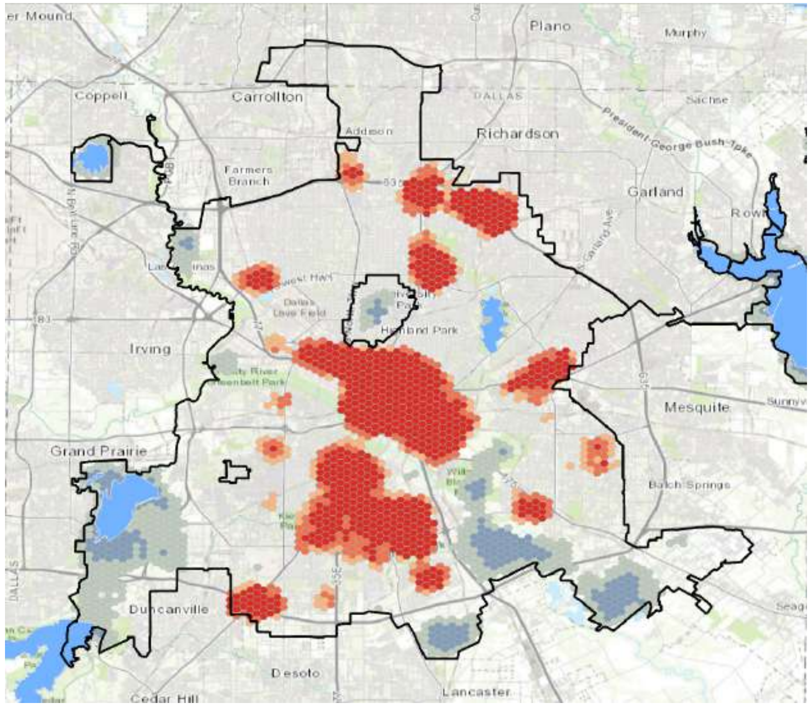
- 20 Oct 2015- 30 Nov 2017
- 535,825 calls from 114,485 locations
- 527 locations: more than 100 calls
- 6 locations: more than 1000 calls

Hot spot analysis of incident calls: Getis-Ord G* statistics with 0.33 mile (0.53km) squared bins

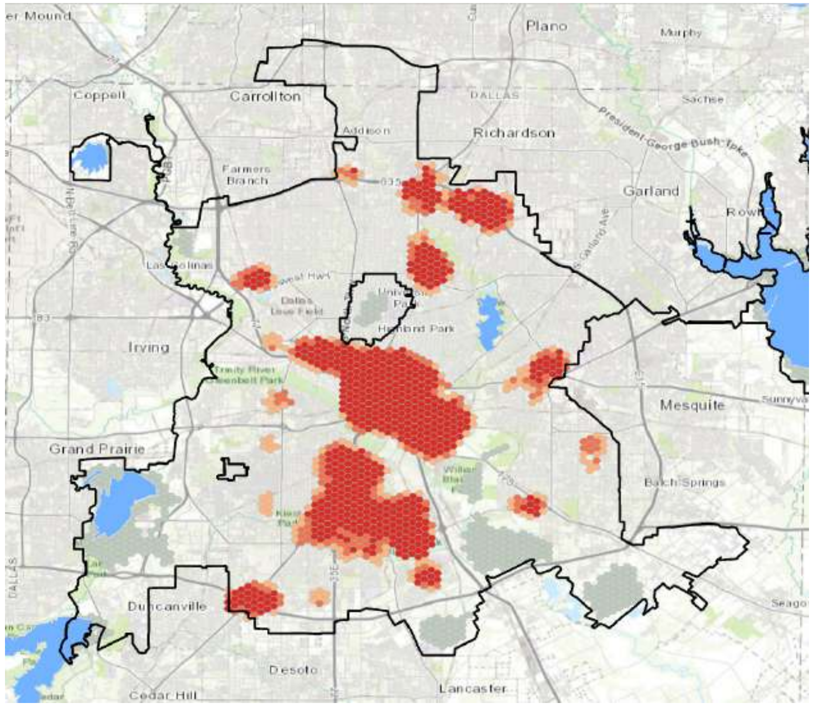
2015



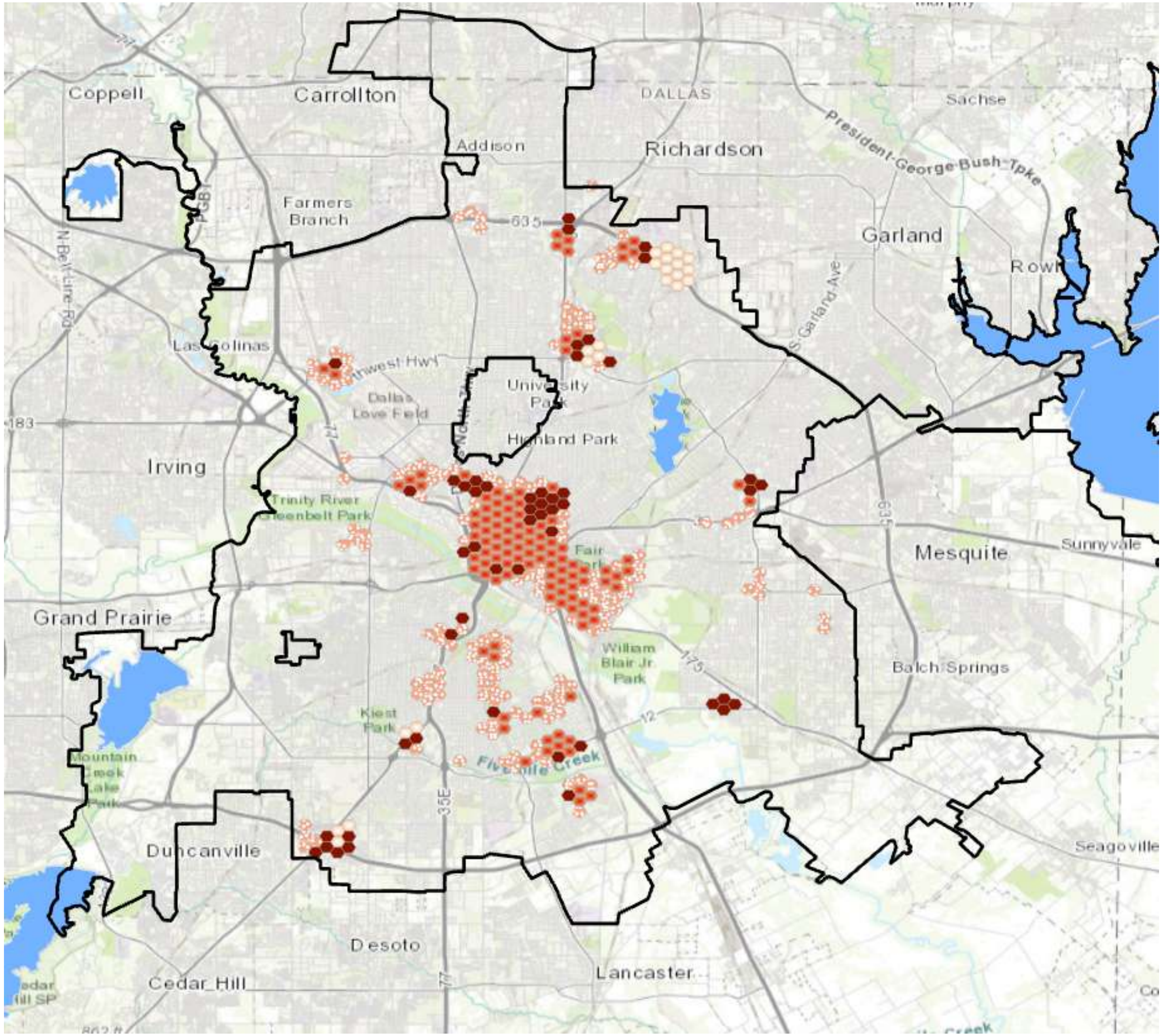
2016



2017



Cold Spot - 99% Confidence
Cold Spot - 95% Confidence
Cold Spot - 90% Confidence
Hot Spot - 90% Confidence
Hot Spot - 95% Confidence
Hot Spot - 99% Confidence

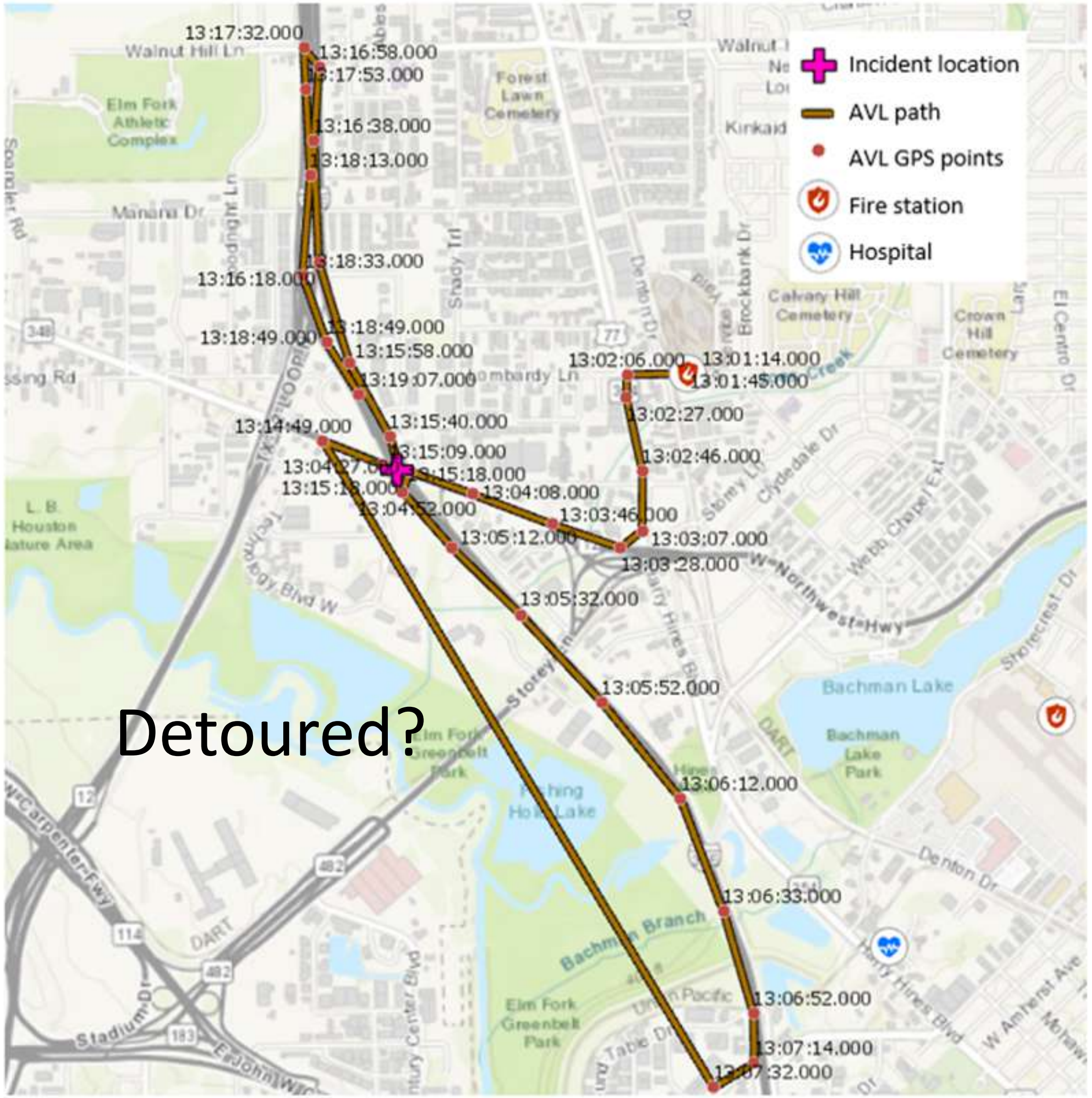


Incident Calls

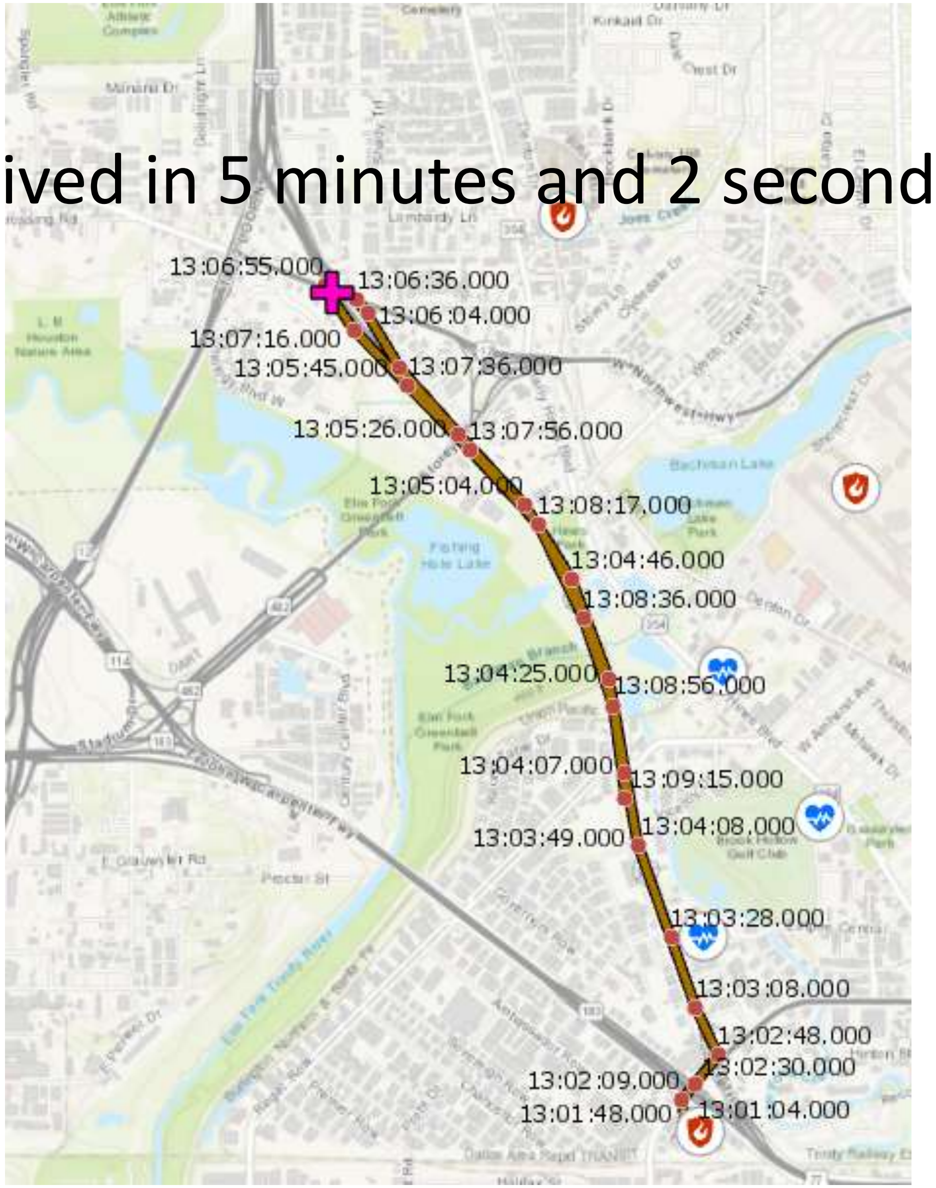
- Intensifying Hot Spot
- Persistent Hot Spot
- Diminishing Hot Spot
- Sporadic Hot Spot

While persistent hotspots were limited and localized, the sizable area of an intensifying hotspot in downtown and surrounding area would lead to an increasing demand for emergency service and hence routing needs.

An example: routes to an incident

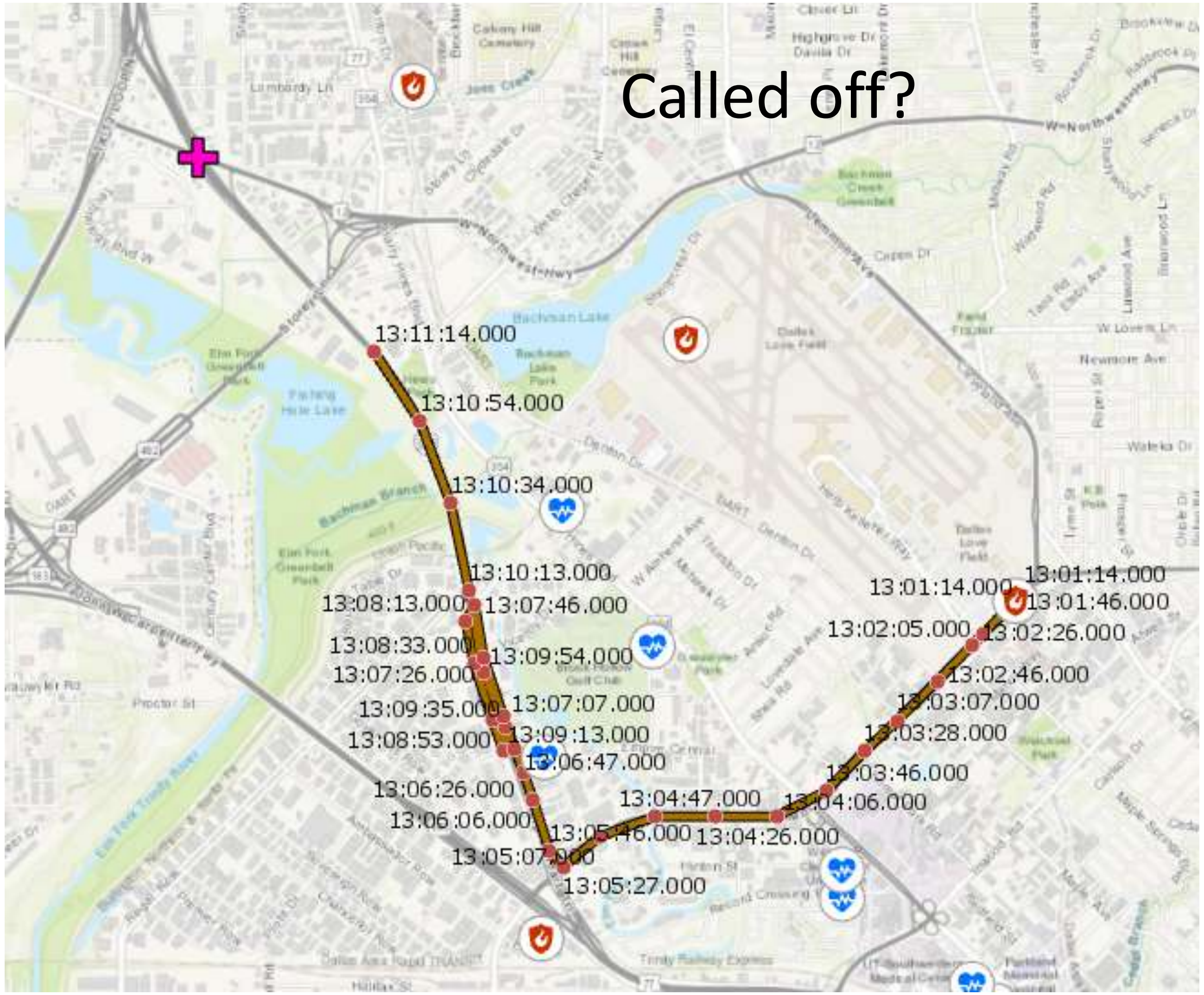


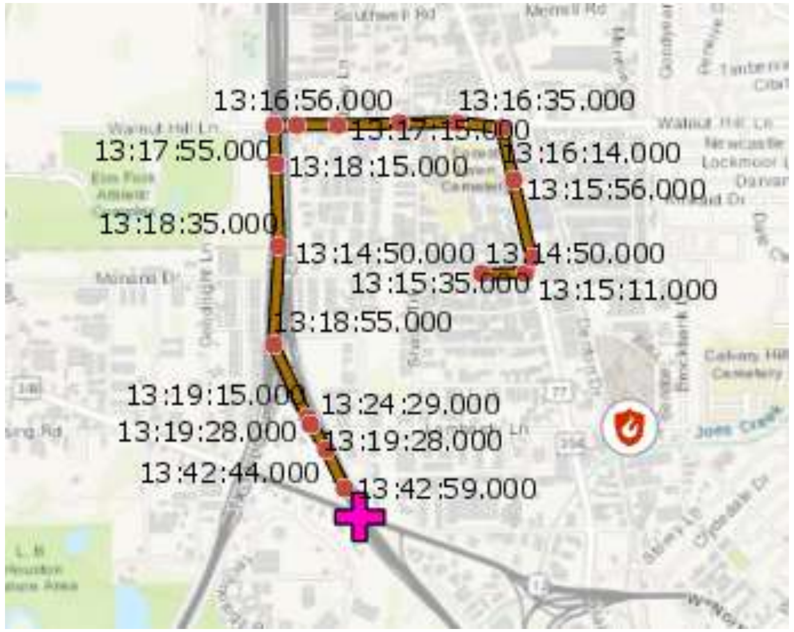
Detoured?



Arrived in 5 minutes and 2 seconds

An example: routes to an incident (Cont'd)





Block?

Data Analytics of all incident calls from 20 Oct 2015 to 30 Nov 2017

1. An AVL run arrived at the incident location if the end-point of the AVL run was within 60 m (~197 ft) of the corresponding incident;
2. If an incident didn’t have any vehicle arriving within 60m, the incident was called off before or during emergency dispatches;
3. An incident was called off if there was no AVL run recorded with the incident;
4. The response time to an incident is the earliest time that a GPS point on any AVL at its minimum distance (< 60 m) to the incident.

Summary statistics of emergency vehicle dispatches to incidents in the AVL data provided by Dallas Fire Department

Period	Total Incident calls (a)	beyond 60m	called off, no dispatch (b)	Arrived within 60m (c)	Arrived within 60m in 8 min (d)	Rate of responses in 8 minutes (c/d)
20 Oct to 31 December 2015	47,561	7,323	238	40,000	12,127	30.32%
1 January to 31 December 2016	254,419	40,438	1,372	212,609	62,536	29.41%
1 January to 30 November 2017	233,845	37,465	3,121	193,259	59,080	30.57%

Longitudinally, responses were rather consistent over the three years

	2015	2016	2017
% incidents with one vehicle arrived within 60 m of the incident	69.59%	68.32%	68.97%
% incidents with two vehicles arrived within 60 m of the incident	27.04%	28.69%	27.95%
% called-off incidents	3.37%	2.99%	3.08%

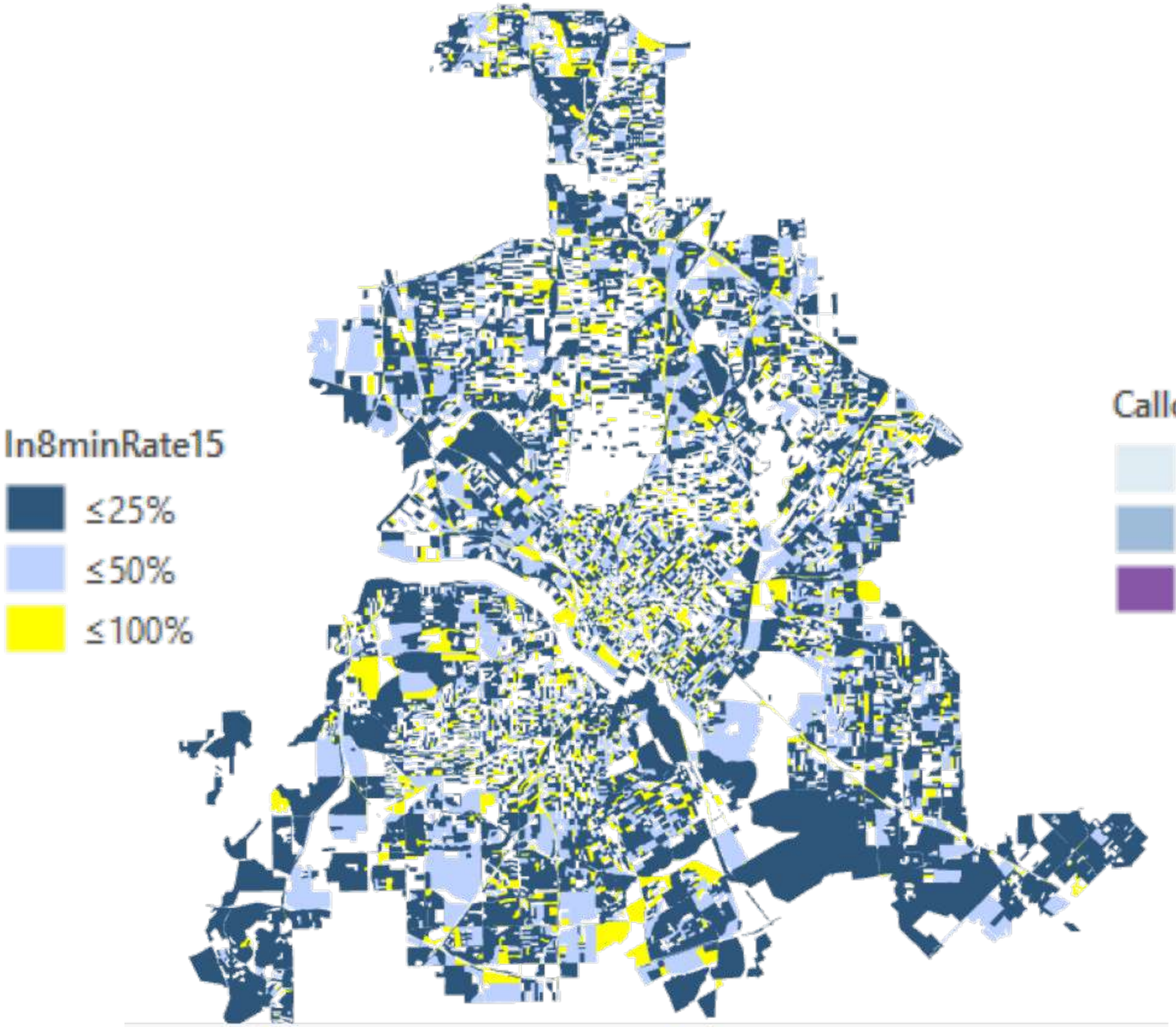
How about geographically (hence, social-economical disparity)?
Are places with higher or lower rates?

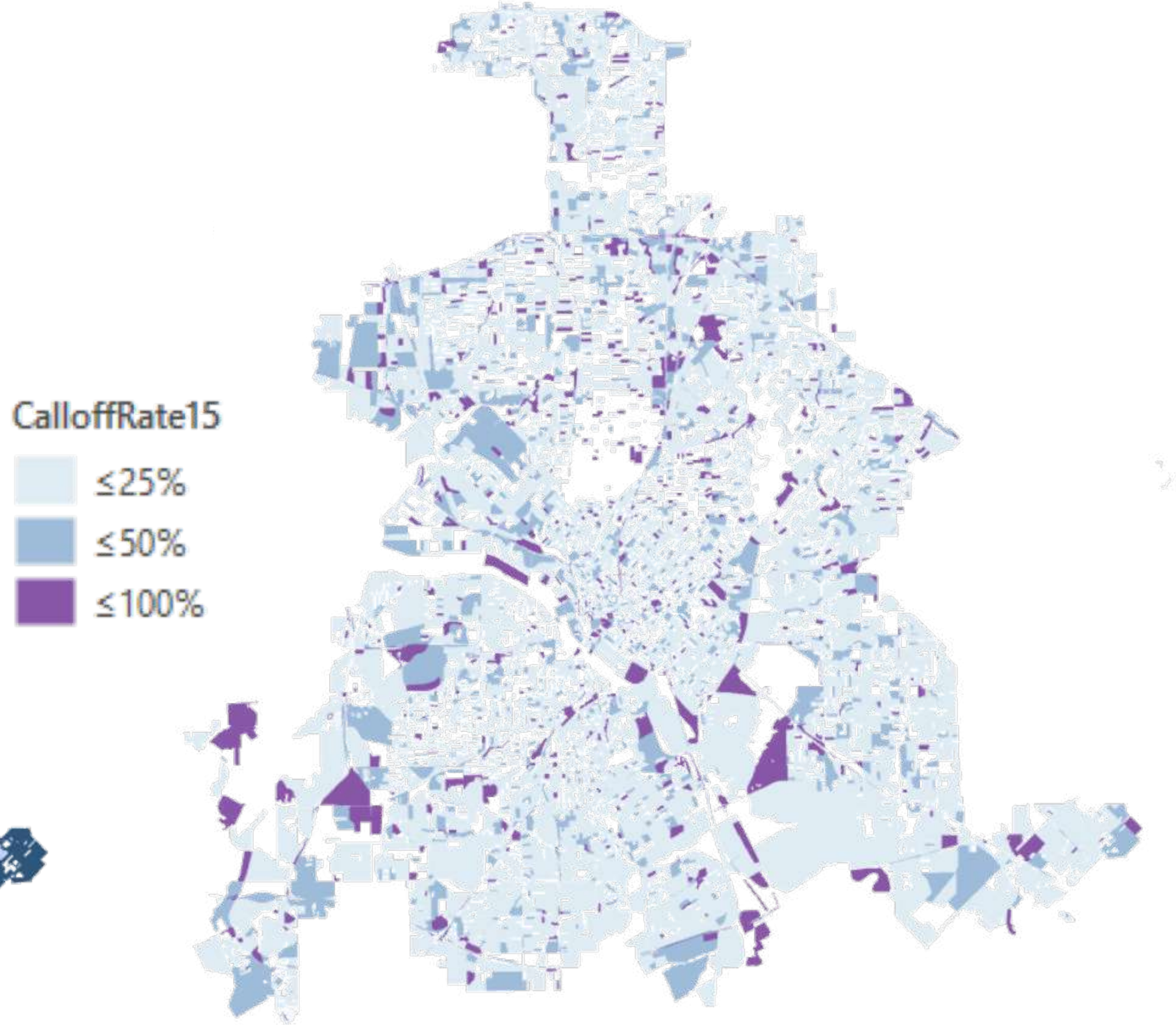
Calculate the InTime rate and CallOff rate in each census block

A = the number of incidents with arrivals in 8 minutes
B = the number of incidents with arrivals later than 8 minutes
C = the number of incidents with no arrivals within 60 m

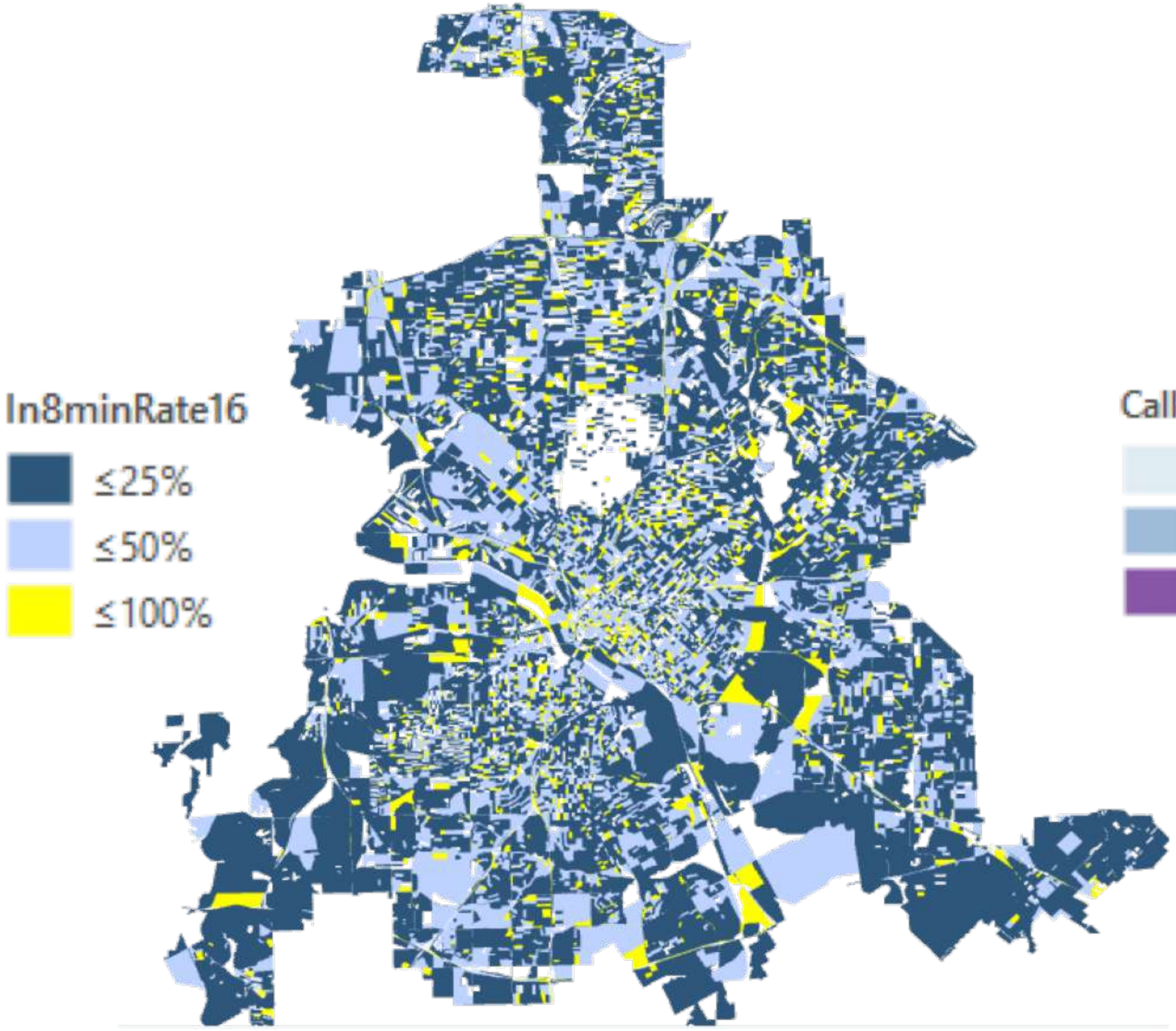
InTime Rate (or In8min Rate) = A/(A+B)
CallOff Rate = C / (A+B+C)

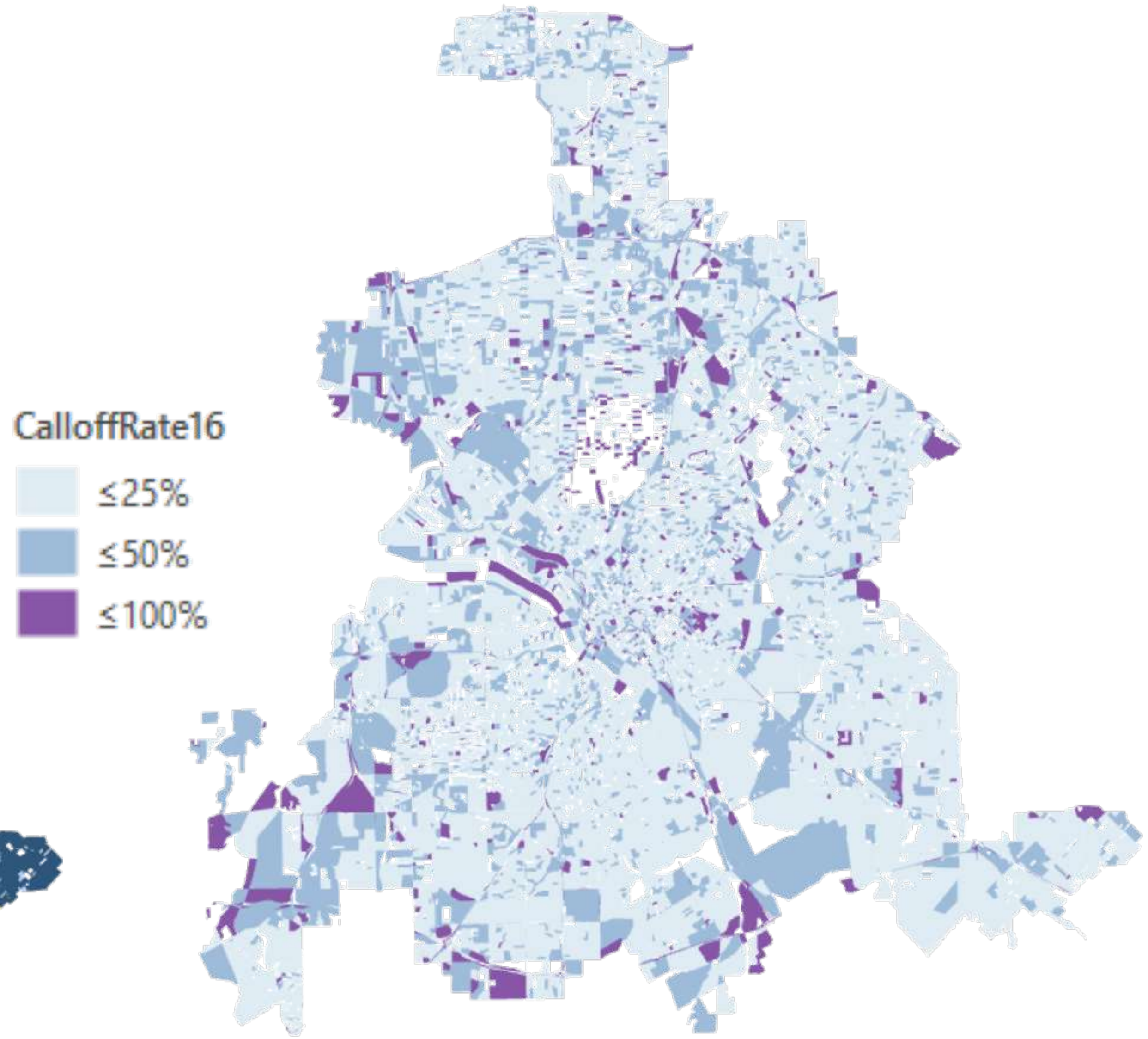
2015 Census Blocks



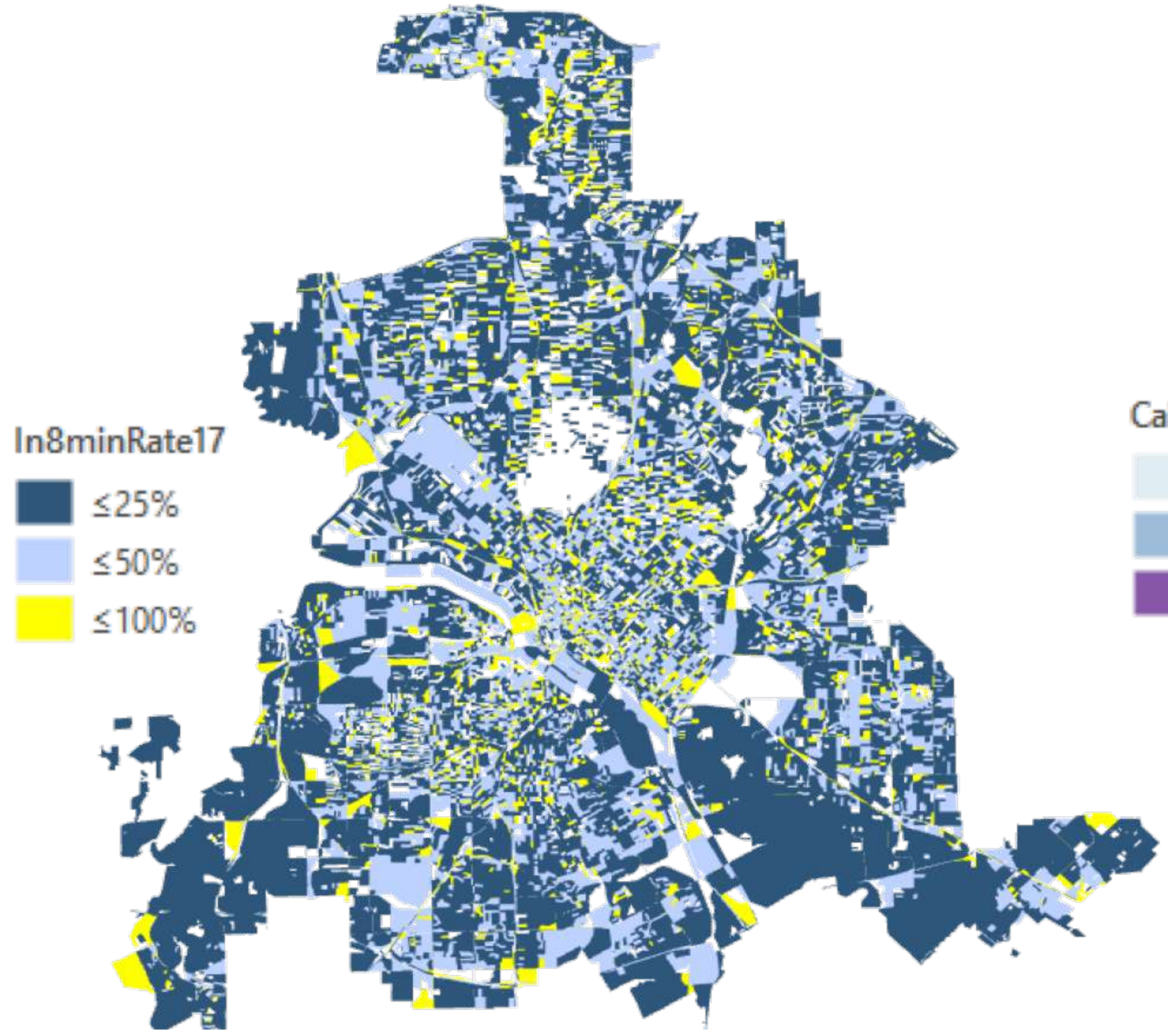


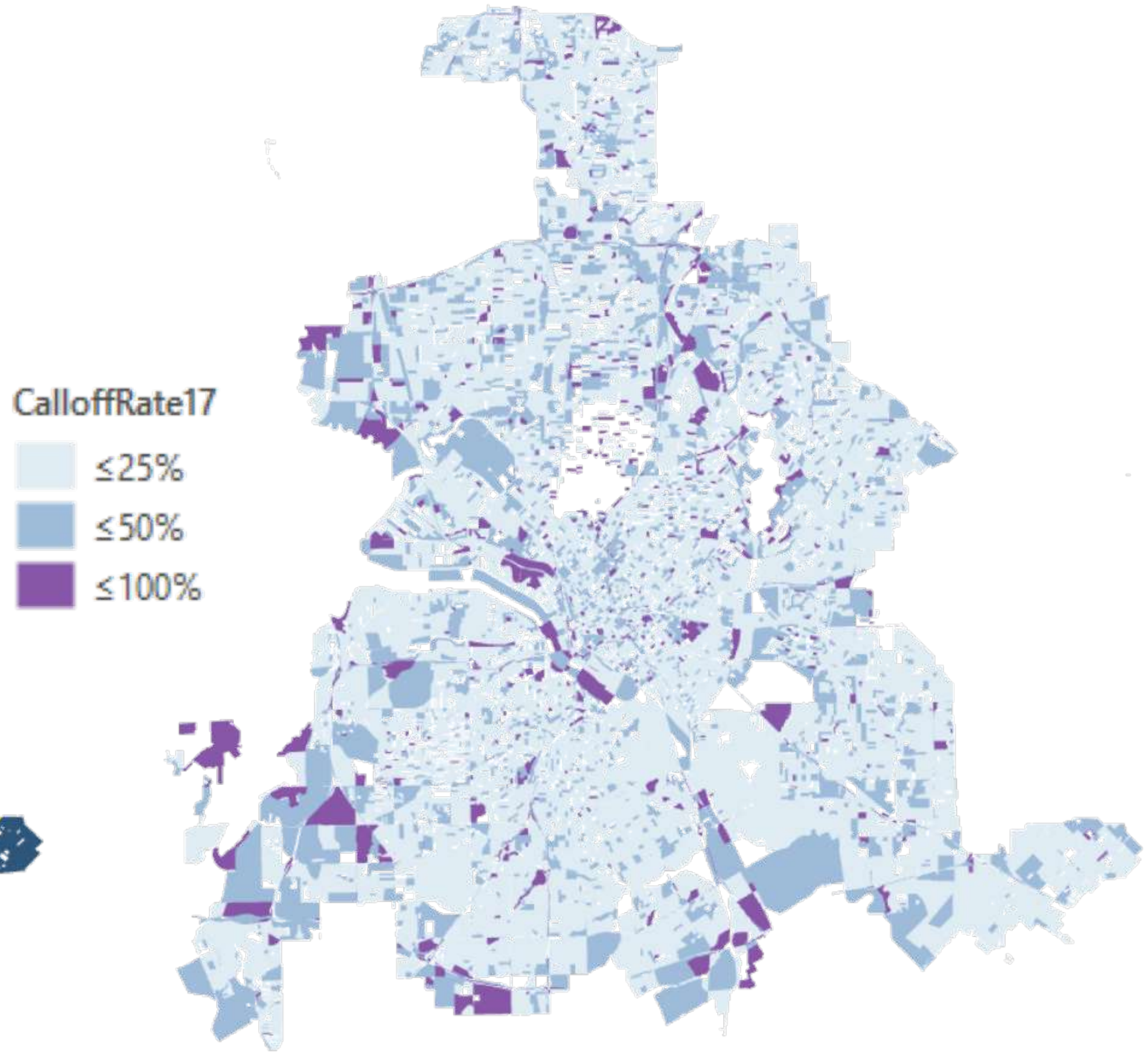
2016 Census Blocks



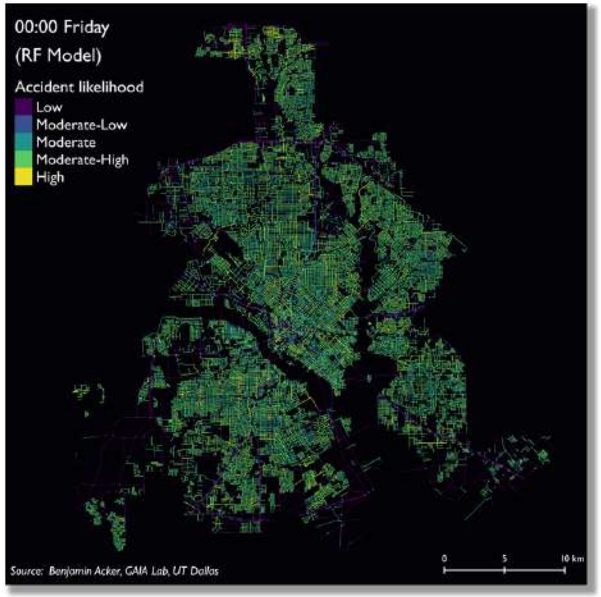


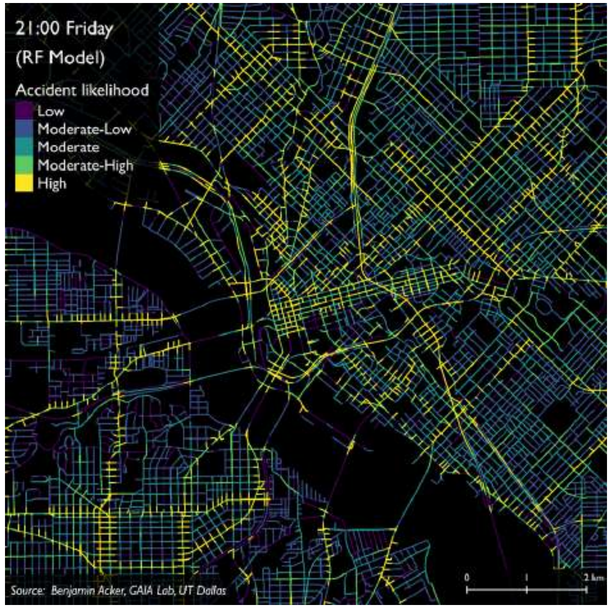
2017 Census Blocks





Spatial risk of traffic accidents





The spatial patterns of InTime rates echo the interwoven patterns of traffic accident risk.

Next step: register incident calls to street segments and conduct spatial data analytics of traffic risk impacts on emergency vehicle routing

2015

In8minRate17

≤25%

≤50%

≤100%

2016

2017

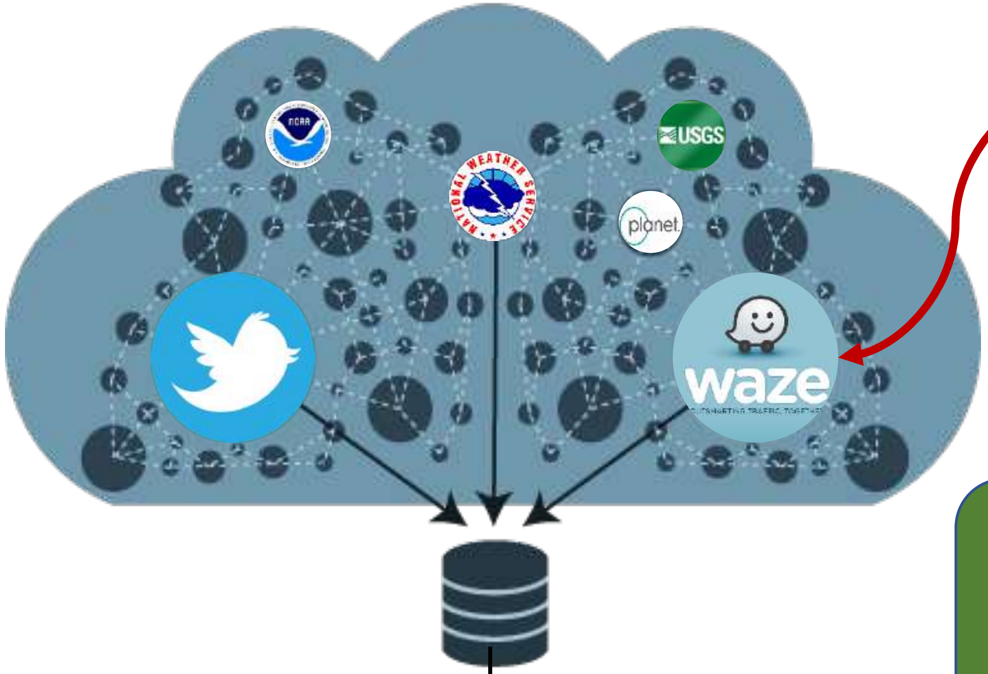
Part 3:

Crowd Sourcing Flood Hazards

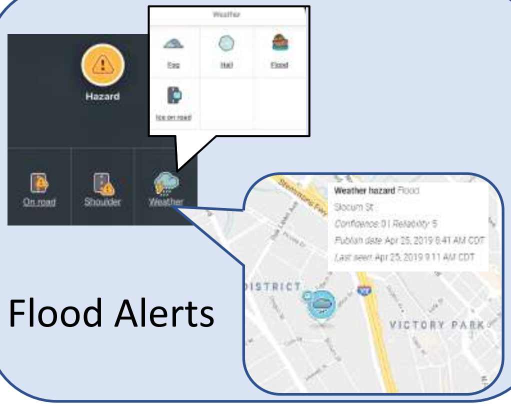
Arefeh Safaei Moghadam
Barbara Minsker, Ph.D., P.E.
Southern Methodist University

Crowdsourcing Flood Hazards

Urban Flooding:
- Fluvial (River Flooding)
- Pluvial (Surface Flooding)



Real-time information on flood conditions



Flood Alerts

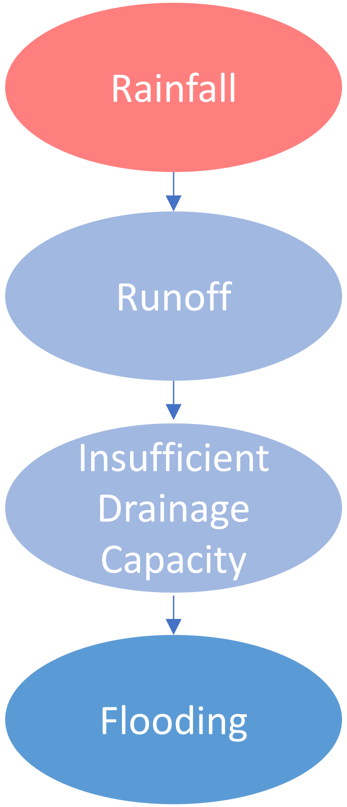
✓ Identification of road segments with high flood risk

Citizen observations
Official data sources

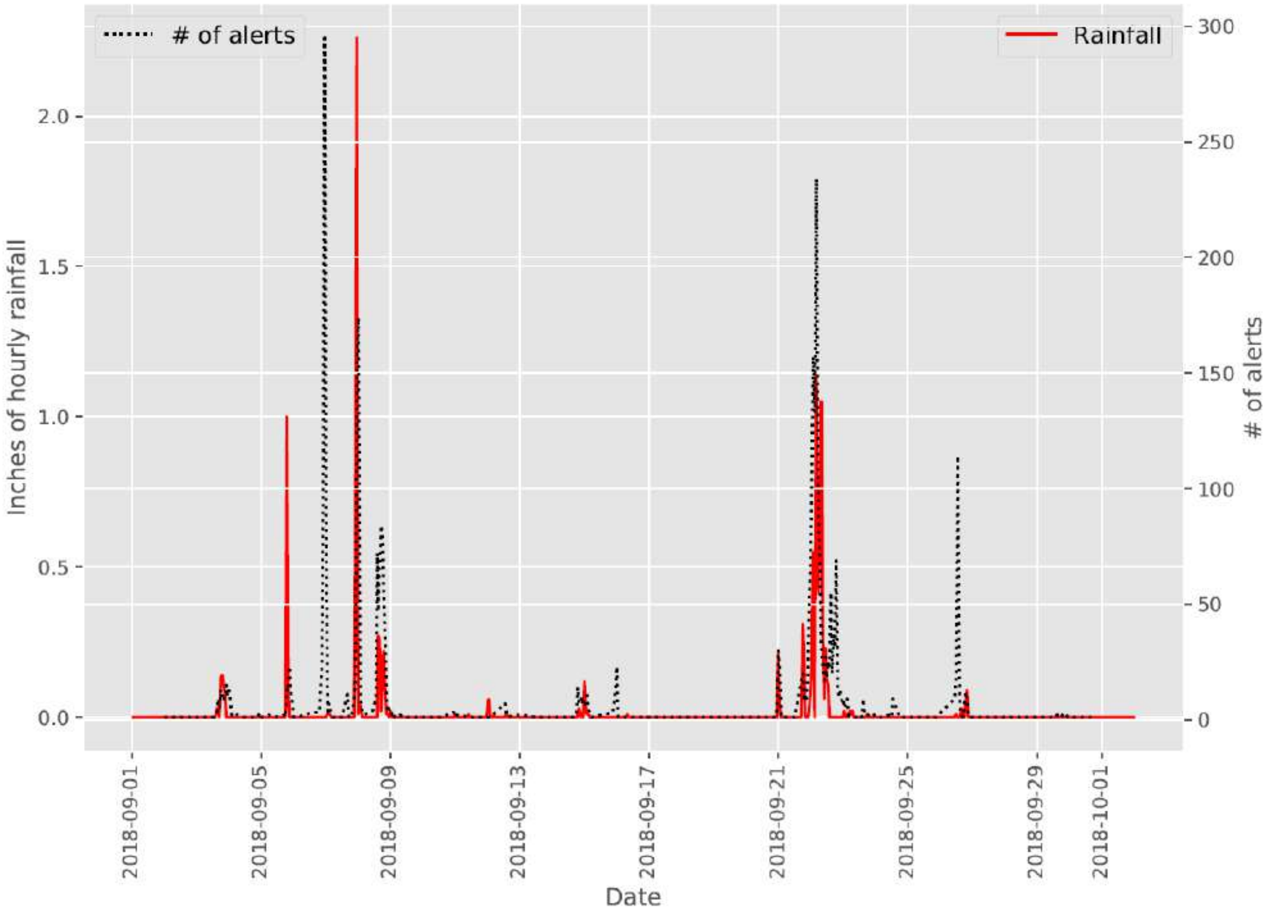
Sensor networks
Citizen observation
Aerial Imagery

Waze Flood Alerts Versus Rainfall

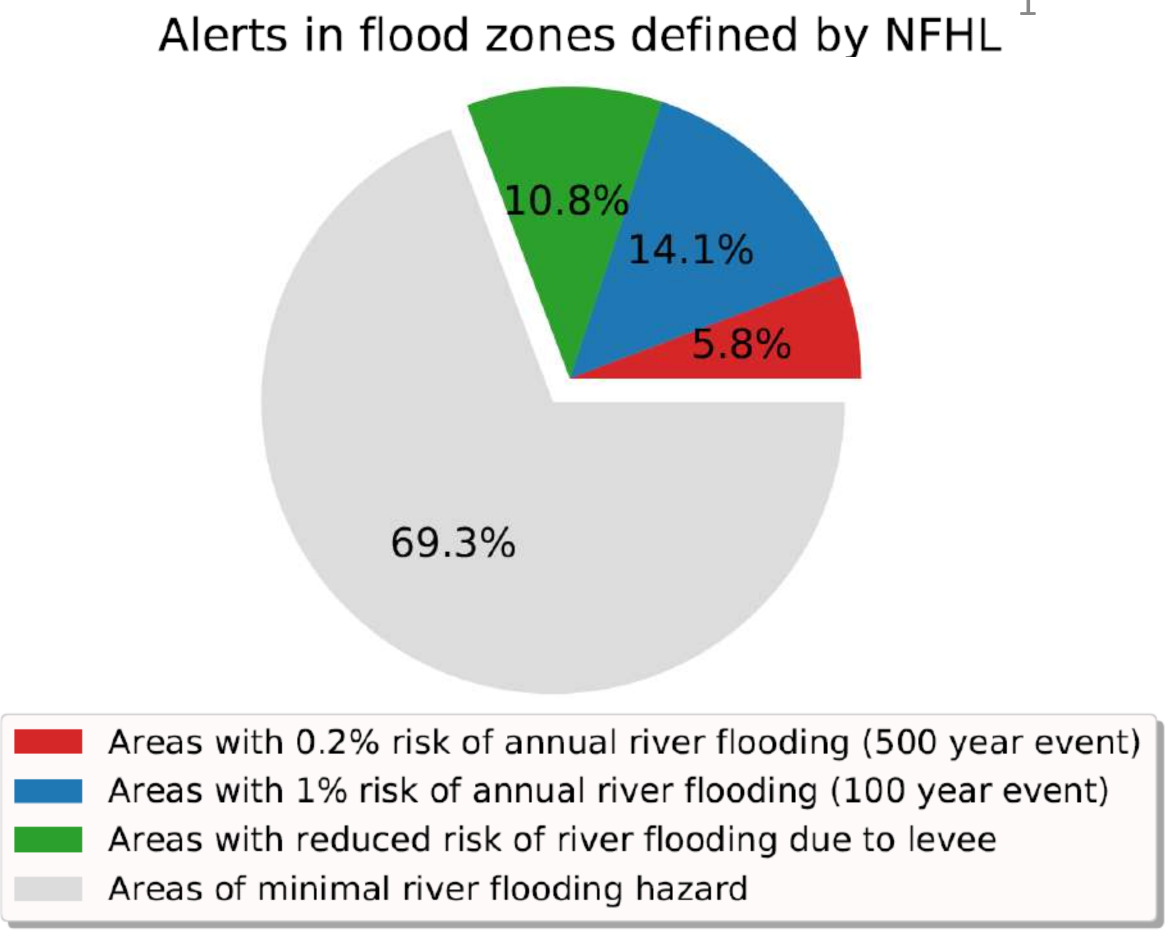
What is the correlation between rainfall intensity and flood alerts?

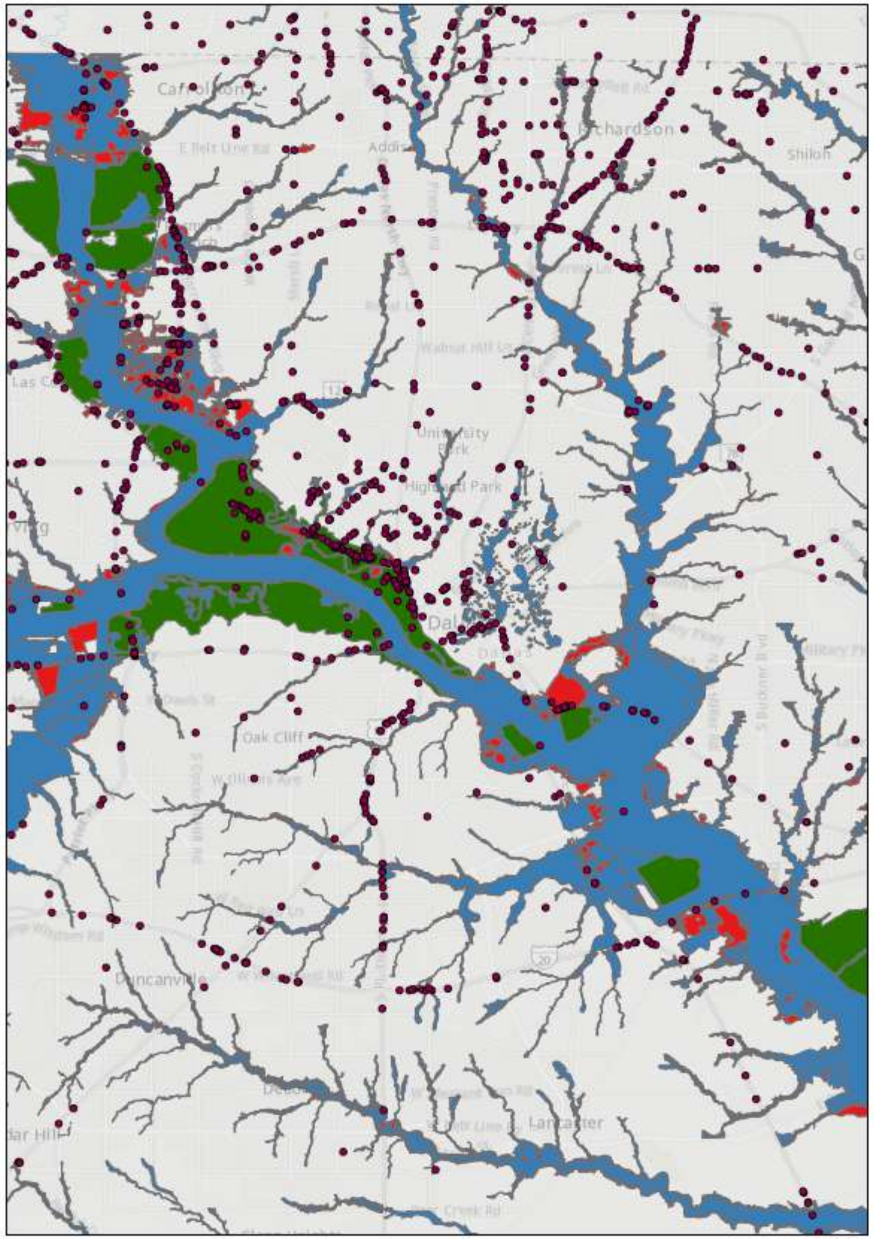


- In September 2018 two major floods occurred in Dallas
- Precipitation of 2.5 and 1 inches per hour on September 8th and 22nd respectively.
- Number of flood alerts posted to Waze is consistent with the rainfall intensity



Waze Flood Alerts Versus River Flooding

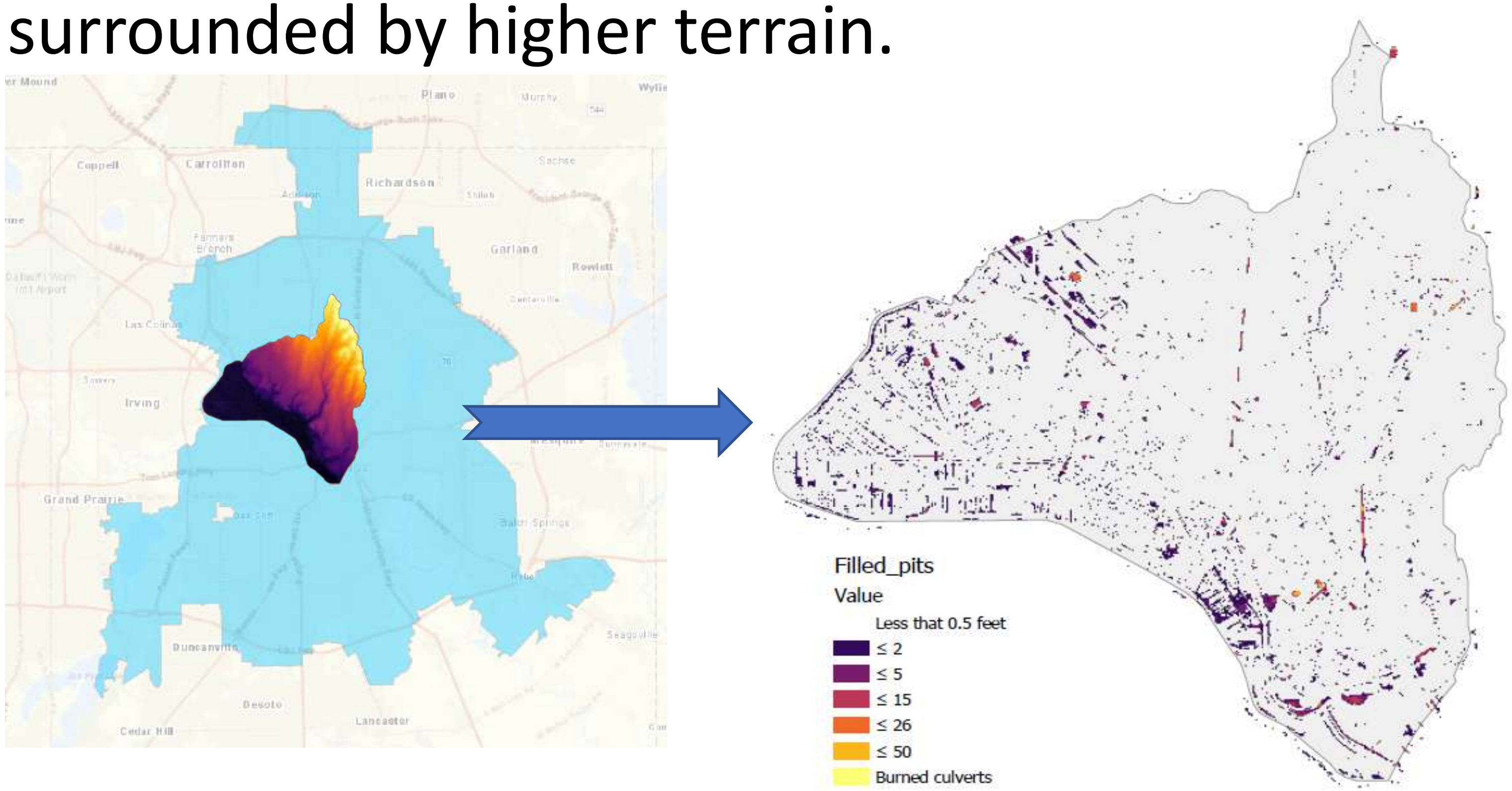


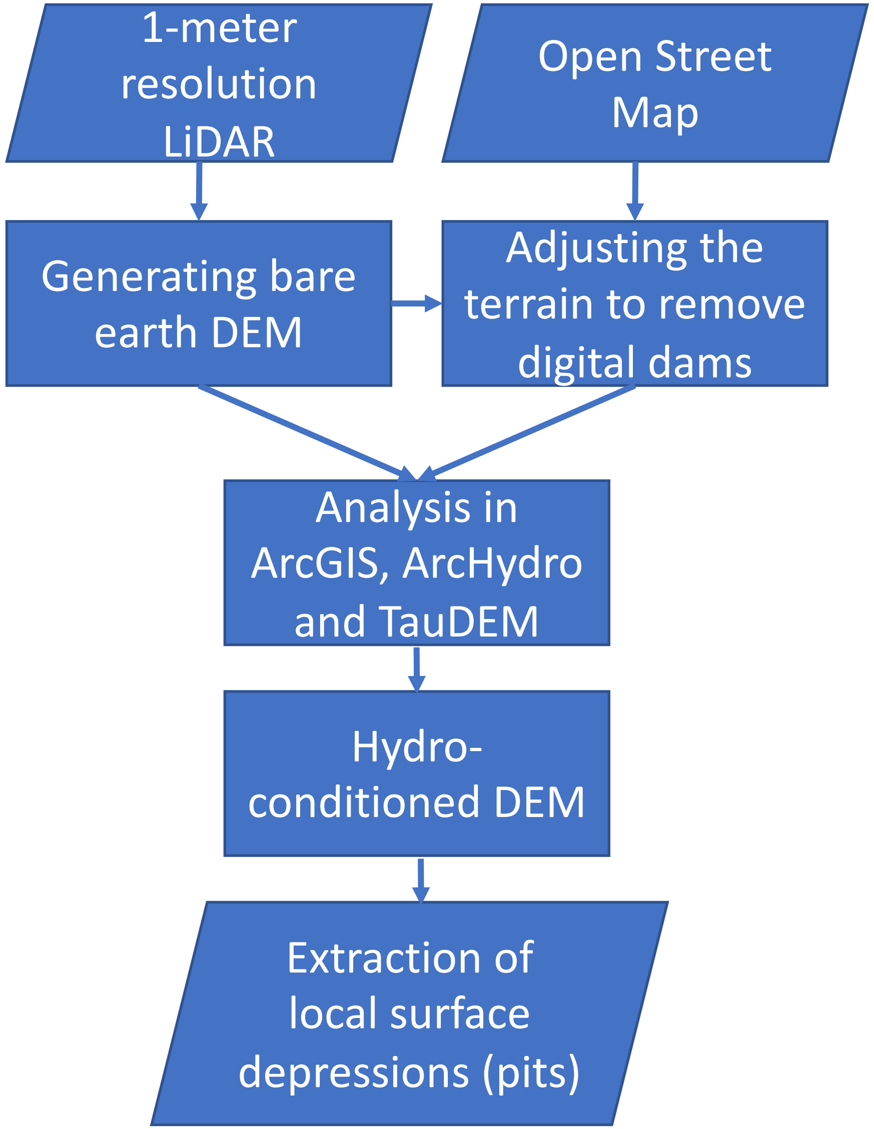


1 - National Flood Hazard Layer

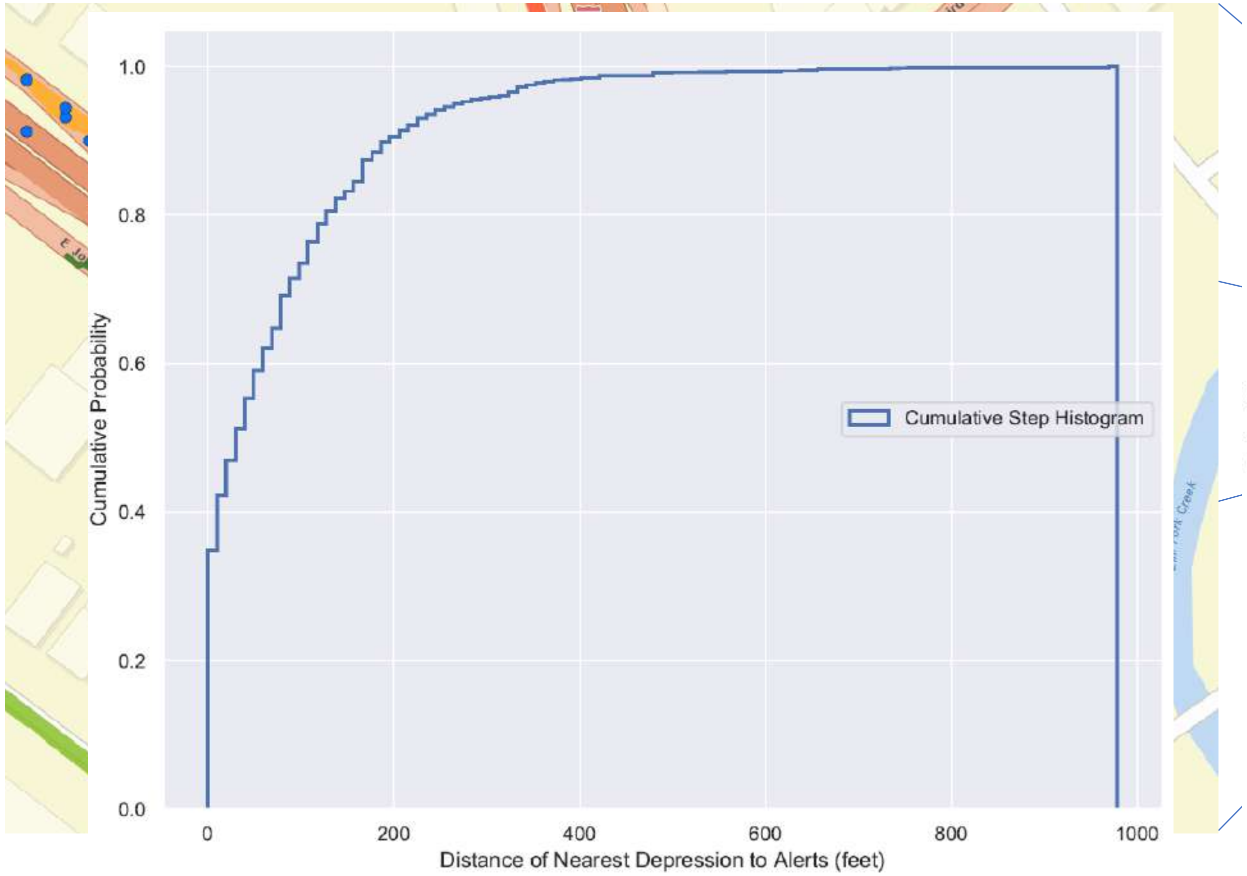
Identifying Low-Lying Areas (Pits) Susceptible to Surface Flooding

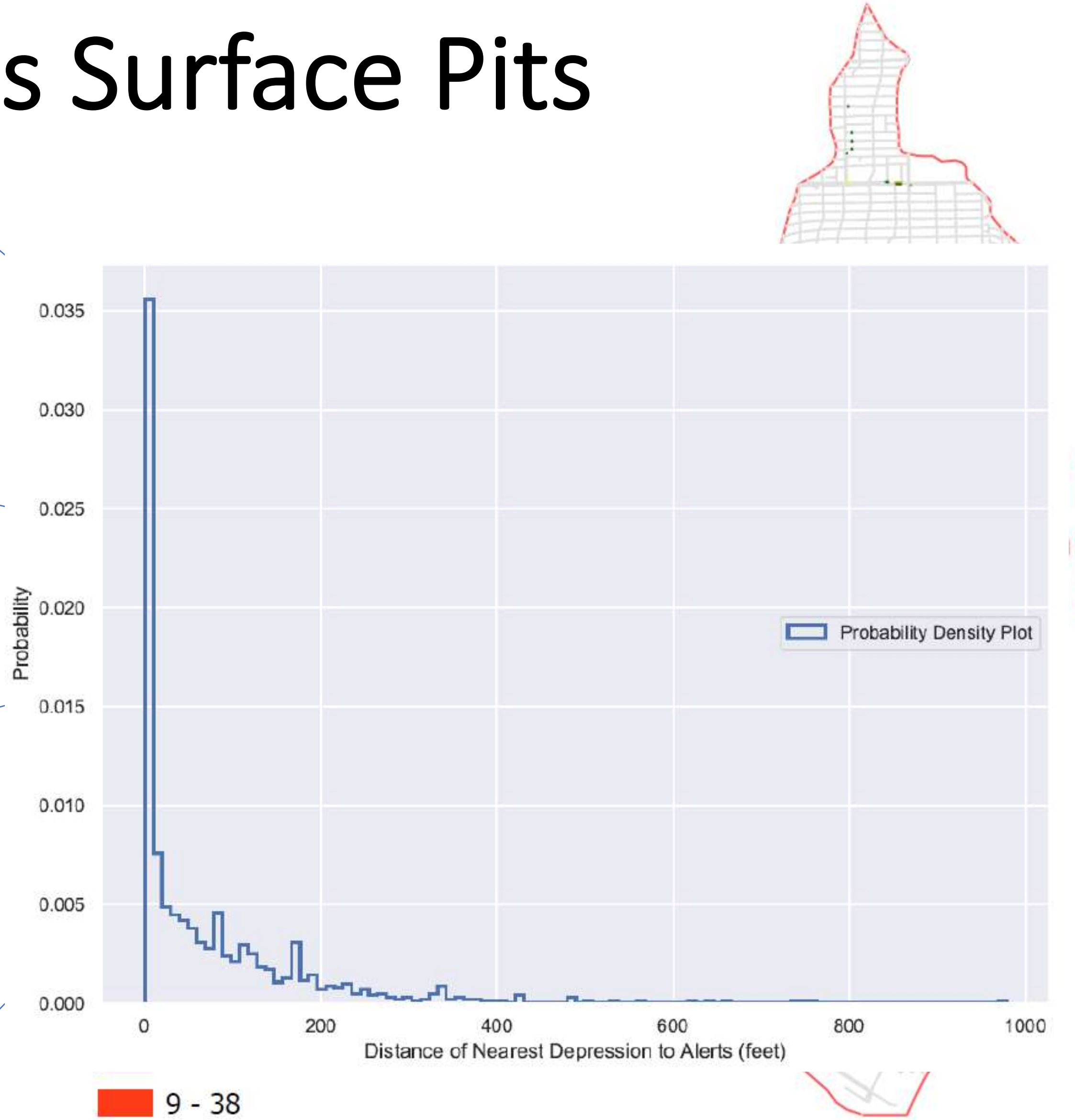
Pits: Low elevation grid cells in an area surrounded by higher terrain.





Waze Flood Alerts Versus Surface Pits





Future Steps

- Investigating criteria that affect number of flood alerts

  Road characteristics:

  ❖Traffic load

  ❖Length of road inside the pit

  ❖Number of lanes inside and outside the pit

  Pit characteristics:

  ❖Size, depth, and slope of depression

  ❖Contributing Area

  ❖Land Cover

- Investigating utility of satellite imagery to detect local surface flooding, verify Waze reports

Questions?

#PSCR2019

Get your hands on the tech!

Demos Open