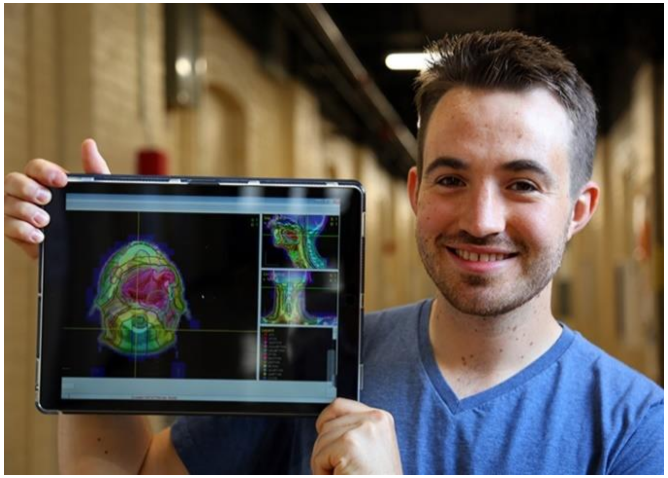
Optimization for AED placement and emergency response

Timothy C. Y. Chan K.H. Benjamin Leung
University of Toronto

International Seminar on Geospatial Analytics
and Operations Research in Emergencies
Singapore General Hospital
February 18, 2019

What We Do – Centre for Healthcare Engineering

- Data-driven research to improve system efficiency and enhance patient care



- Research Areas:
  - Policy and Strategy
  - Healthcare Operations
  - Medical Technologies
  - Information Engineering
  - Human Factors

What We Do – Applied Optimization Laboratory

- Quantitative methods for decision making
  - Optimization
  - Machine Learning
  - Simulation
- Applications
  - Healthcare
  - Energy
  - Sports

Acknowledgments

- Toronto
  - Laurie Morrison
  - Steve Brooks
  - Sheldon Cheskes
  - Michael Feldman
  - Damon Scales
- Copenhagen
  - Fredrik Folke
  - Lena Karlsson
  - Christian Torp-Pedersen
- Students
  - Christopher Sun
  - Justin Boutilier
  - Benjamin Leung
  - Clara Stoesser
  - Minha Lee
  - Derya Demirtas
  - Auyon Siddiq
  - Heyse Li
  - Alyf Janmohamed

Today's topics

- Understand where (and when) OHCA **risk** is…
  - Data analytics
  - Simulation
  - Stochastic modeling

- …and then **optimize** AED placements accordingly
  - Integer optimization (robust, stochastic)
  - Queuing
  - Routing

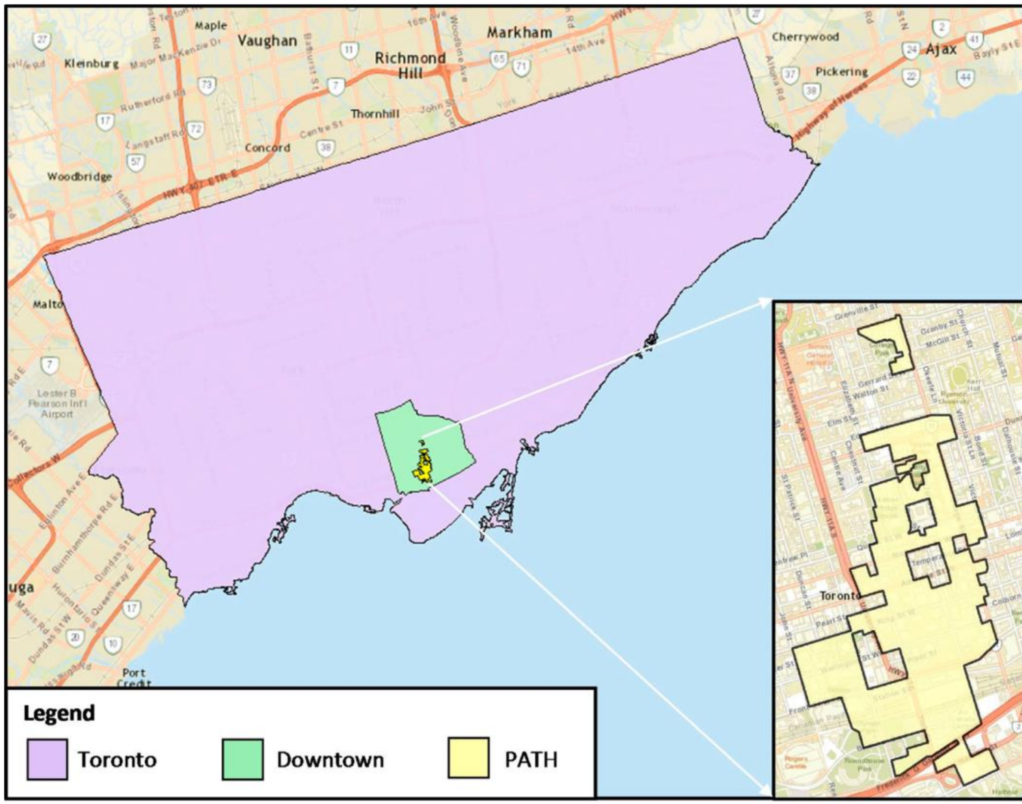
Risk

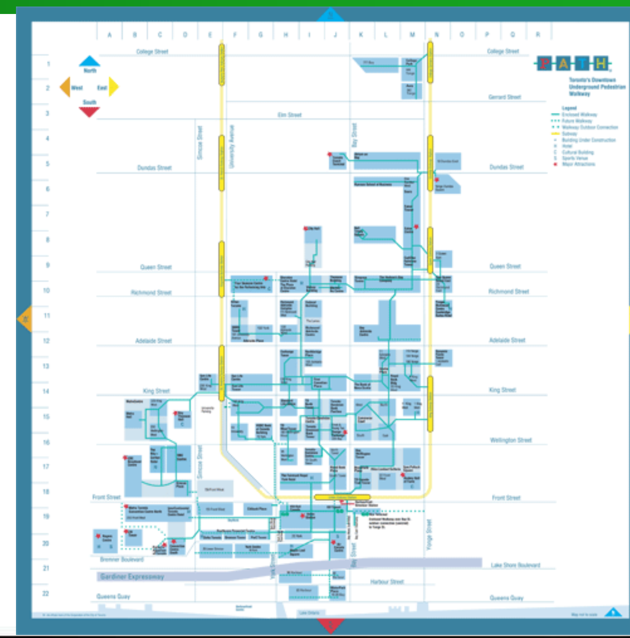
- Spatial risk by location type (*Ann Emerg Med* 2013)
- Spatial risk in enclosed pedestrian walkways (*Resuscitation* 2017)
- Spatiotemporal risk by location type (*Circulation* 2017)

Risk

- Spatial risk by location type (*Ann Emerg Med* 2013)
- Spatial risk in enclosed pedestrian walkways (*Resuscitation* 2017)
- Spatiotemporal risk by location type (*Circulation* 2017)

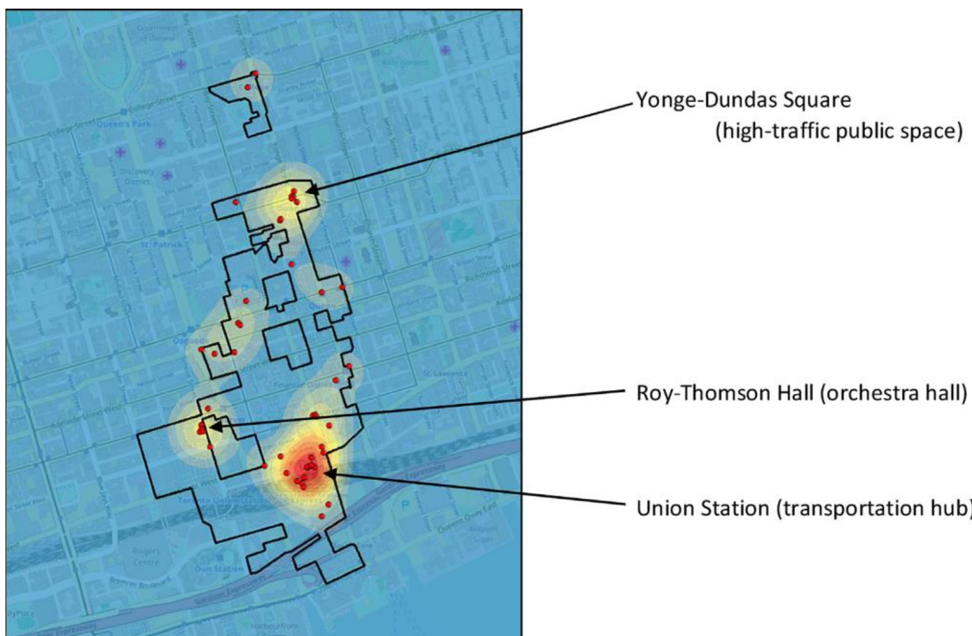
Toronto’s PATH System





Results: Spatial Risk and OHCA Characteristics

Characteristic	PATH-accessible (n = 49)	Downtown (n = 371)	p-values[†]	Toronto (n = 1752)	p-values[‡]
Age, mean ± SD, yrs	60.4 ± 18.0	55.2 ± 16.9	0.047	61.5 ± 17.4	0.662
Male proportion, %	89.8	83.6	0.259	80.6	0.106
Bystander Witness, n (%)	41 (83.7)	214 (58.5)	0.001	1091 (62.6)	0.003
Bystander CPR, n (%)	36 (73.5)	196 (53.0)	0.007	991 (56.6)	0.019
Bystander AED use, n (%)	20 (42.6)	51 (14.1)	<0.001	189 (11.0)	<0.001
911 Call-to-arrival, mean ± SD, min	5.34 ± 1.44	5.45 ± 2.15	0.736	6.30 ± 2.30	0.004
911 Call-to-first rhythm analysis, mean ± SD, min	9.43 ± 3.71	10.65 ± 10.88	0.486	10.61 ± 4.29	0.089
911 Call-to-first shock[*], mean ± SD, min	10.76 ± 4.82	12.61 ± 6.59	0.178	12.93 ± 6.72	0.109
Shockable, n (%)	35 (72.9)	147 (40.3)	<0.001	786 (45.5)	<0.001
Survival, n (%)	16 (33.3)	66 (18.2)	0.014	319 (18.5)	0.009
Survival among shockable, n (%)	14 (41.2)	52 (36.1)	0.582	264 (34.2)	0.402
Survival among non-shockable, n (%)	1 (7.7)	11 (5.2)	0.693	43 (4.6)	0.603
Bys. CPR among bystander-witnessed, n (%)	32 (78.0)	138 (64.5)	0.091	683 (62.7)	0.045
Bys. AED use among bystander-witnessed, n (%)	19 (47.5)	36 (17.4)	<0.001	134 (12.6)	<0.001



Risk

- Spatial risk by location type (*Ann Emerg Med* 2013)
- Spatial risk in enclosed pedestrian walkways (*Resuscitation* 2017)
- Spatiotemporal risk by location type (*Circulation* 2017)

Coffee, Tea or an AED?

- How many cardiac arrests occurred <u>within 100 m</u> of certain businesses and public points of interest <u>when those locations were actually open</u>?

Toronto Private Schools

Toronto Pools

Results: Top 10 List

Rank	Location Type‡	Location Category	Actual Coverage	Assumed 24/7 Coverage (Rank)	No. of Facilities (Rank)	Coverage Efficiency (Rank)	Coverage Loss, % (Rank)
1	Tim Hortons	Coffee shop	200	234 (1)	312 (2)	0.64 (18)	14.5 (16)
2	RBC ATM	Bank ATM	172	193 (2)	264 (4)	0.65 (16)	10.9 (12)
3	Subway	Restaurant chain	162	190 (3)	281 (3)	0.58 (21)	14.7 (17)
4	Scotiabank ATM	Bank ATM	136	148 (5)	181 (9)	0.75 (7)	8.1 (9)
5	CIBC ATM	Bank ATM	134	152 (4)	187 (8)	0.72 (8)	11.8 (13)
6	Green P Parking	Parking lot	127	135 (7)	229 (5)	0.55 (23)	5.9 (7)
7	TD ATM	Bank ATM	121	146 (6)	178 (10)	0.68 (14)	17.1 (19)
8	Starbucks	Coffee shop	104	125 (8)	166 (11)	0.63 (19)	16.8 (18)
9	BMO ATM	Bank ATM	101	104 (10)	142 (13)	0.71 (9)	2.9 (6)
10	Pizza Pizza	Restaurant chain	69	90 (12)	100 (19)	0.69 (12)	23.3 (23)

Optimization

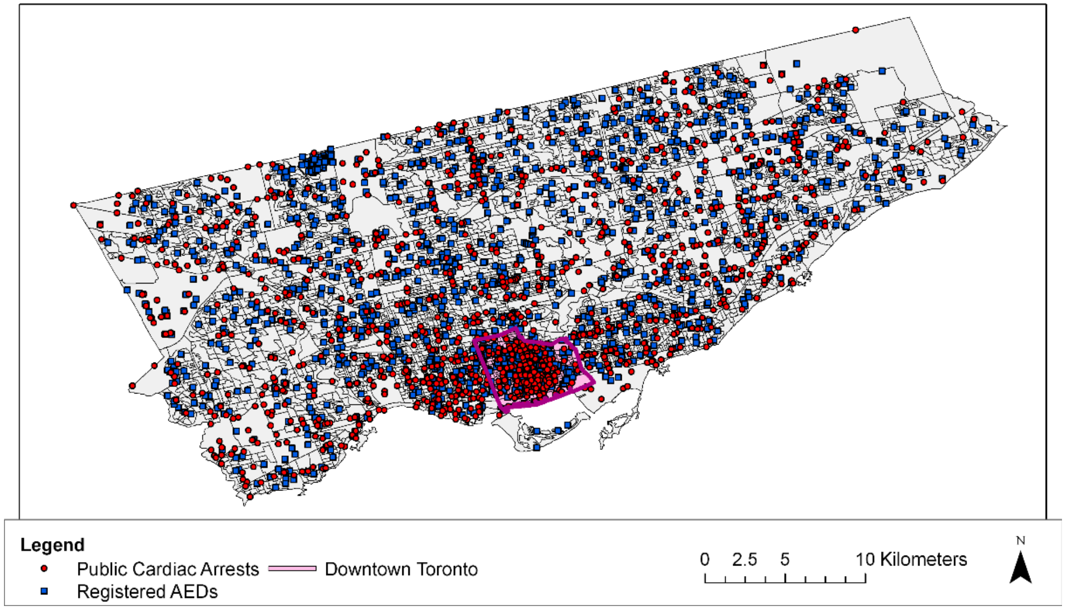
- First optimization model (*Circulation* 2013)
- Effect of varying coverage radius (*Resuscitation* 2013)
- Optimization with coverage decay (*Manag Sci* 2016)
- Spatiotemporal optimization (*JACC* 2016)
- Optimization with uncertain OHCA locations (*Oper Res* 2017)
- AED optimization in high-rises (*Prehosp Emerg Care* 2017)
- Drone-delivered AEDs (*Circulation* 2017)
- Generalizability of spatiotemporal optimization (*Resuscitation* 2018)

Optimization

- First optimization model (*Circulation* 2013)
- Effect of varying coverage radius (*Resuscitation* 2013)
- Optimization with coverage decay (*Manag Sci* 2016)
- Spatiotemporal optimization (*JACC* 2016)
- Optimization with uncertain OHCA locations (*Oper Res* 2017)
- AED optimization in high-rises (*Prehosp Emerg Care* 2017)
- Drone-delivered AEDs (*Circulation* 2017)
- Generalizability of spatiotemporal optimization (*Resuscitation* 2018)

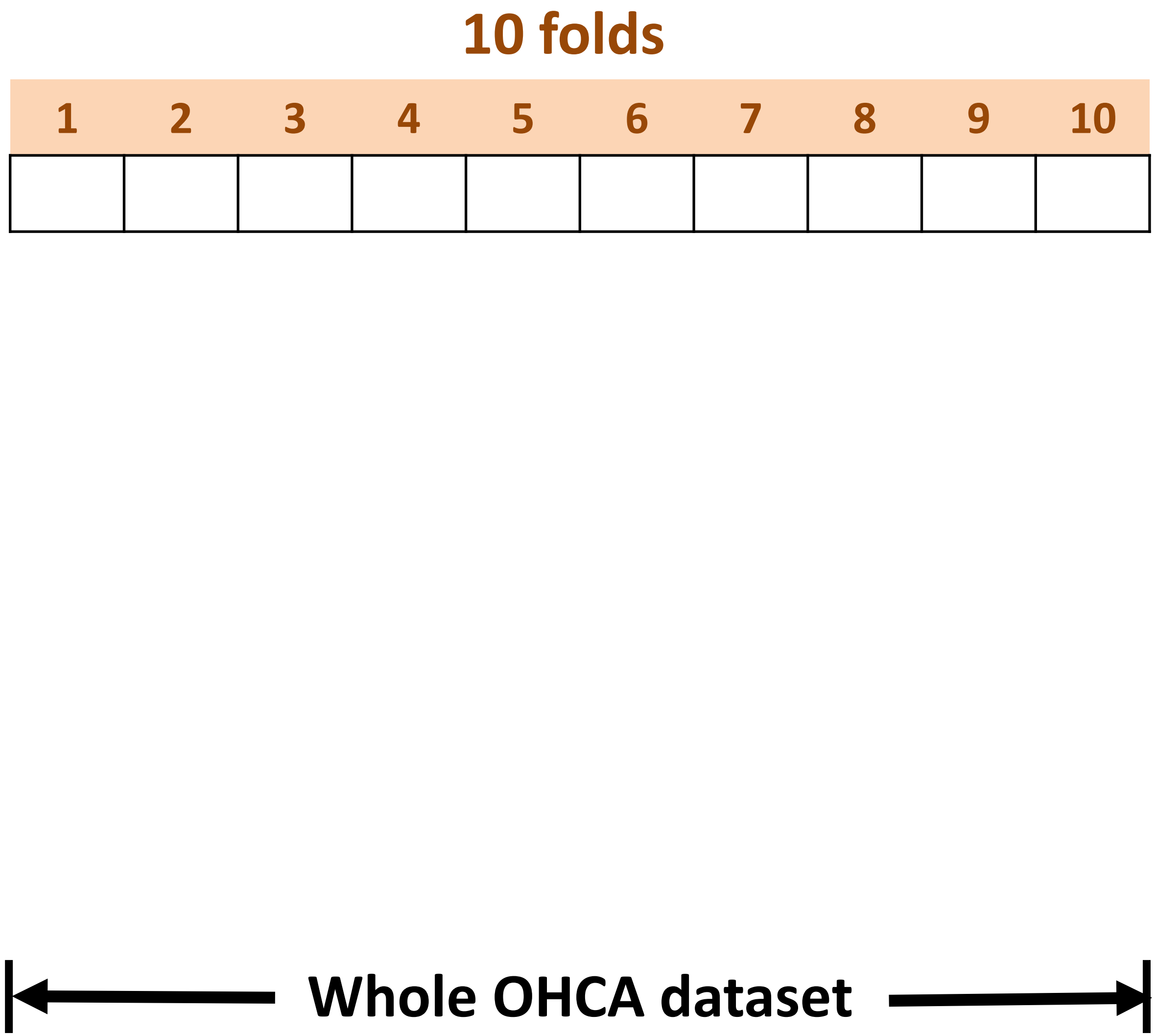
A First Optimization Model

- Data
  - Five years of OHCAs
  - Locations of existing, registered AEDs
  - Large database of public buildings

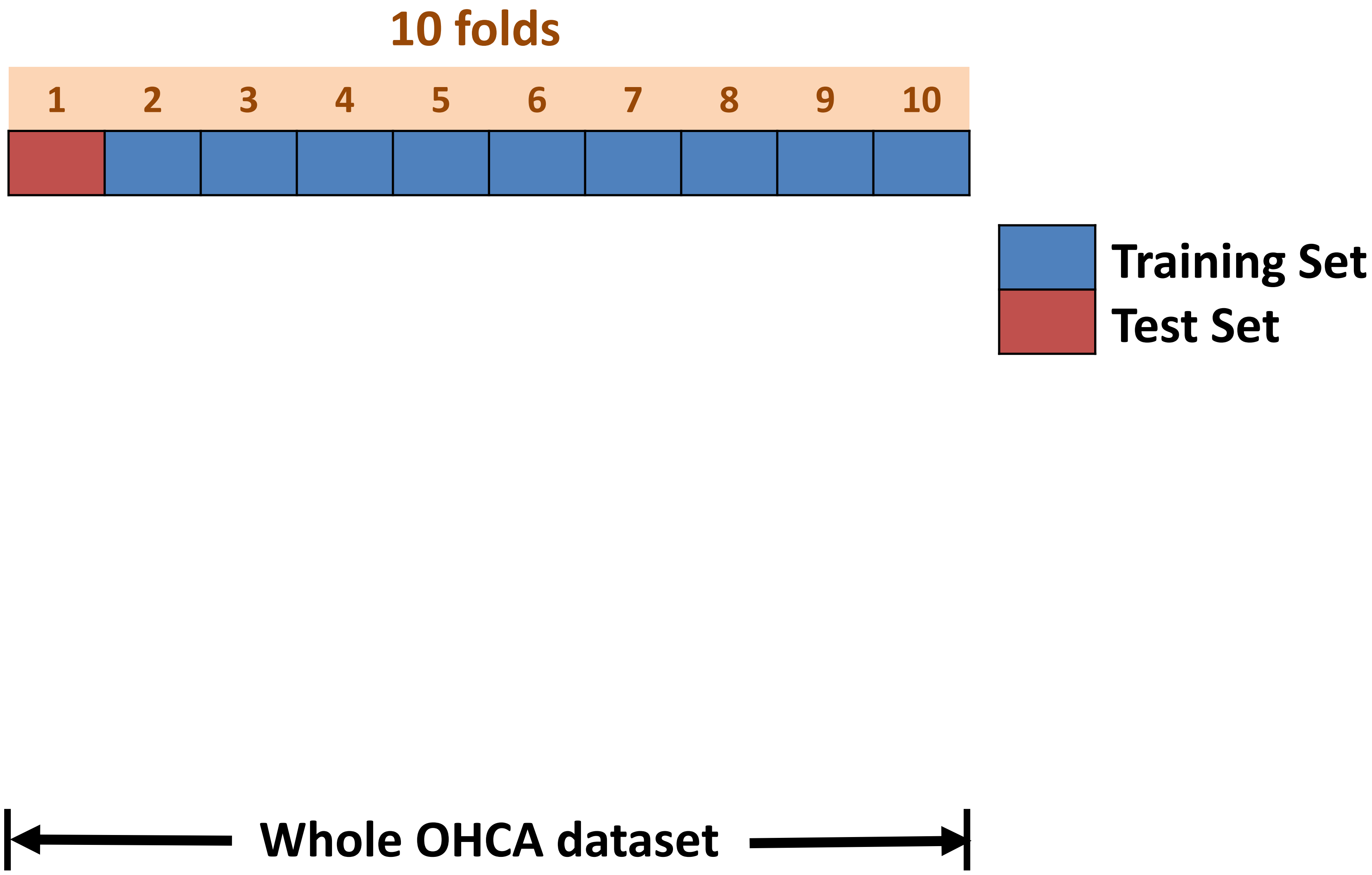


- Optimization model to place AEDs to maximize cardiac arrest coverage
- Compared with population-guided approach to AED placement based on estimated daytime population spread across buildings in a census tract

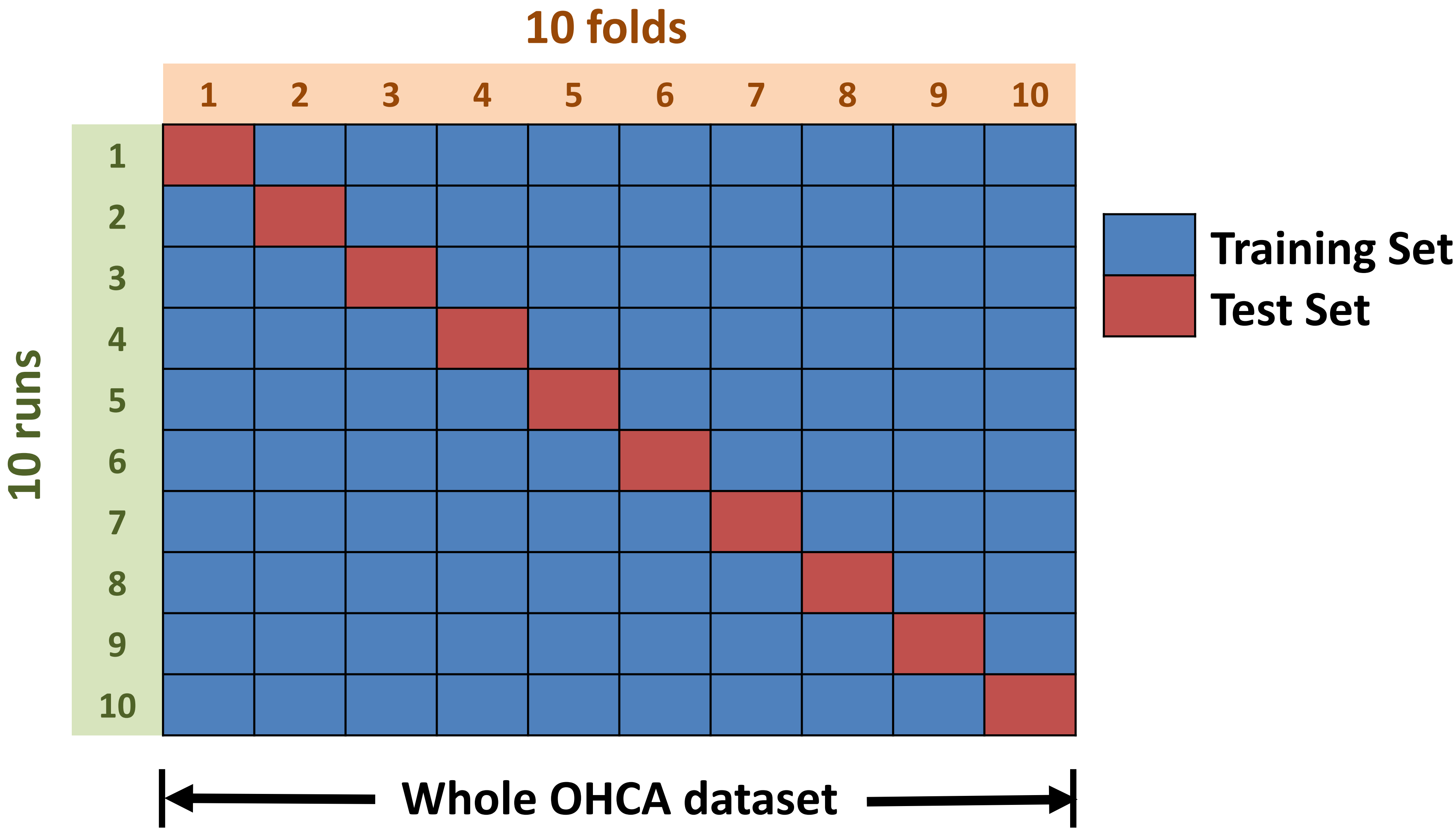
10-Fold Cross Validation



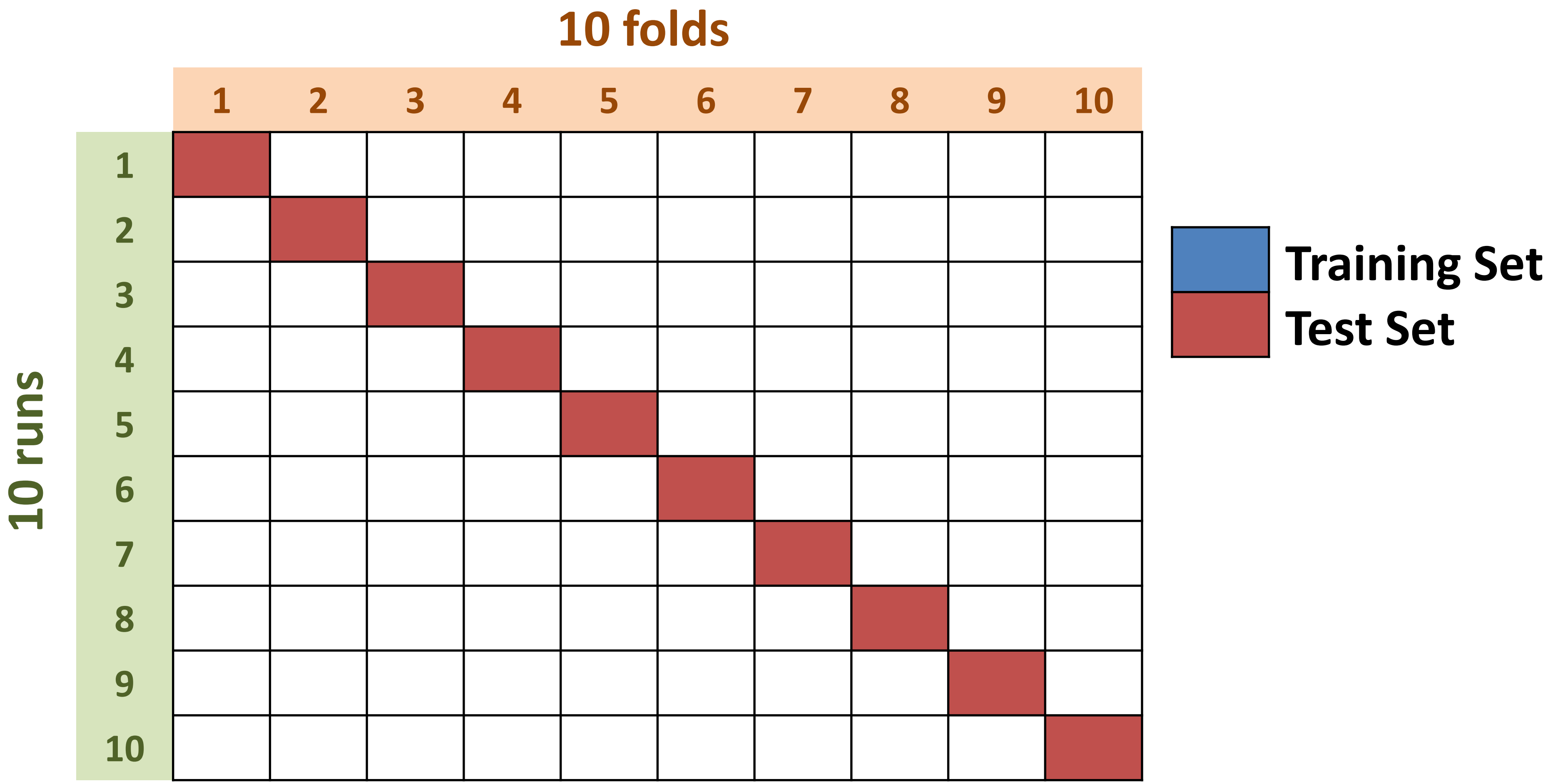
10-Fold Cross Validation



10-Fold Cross Validation



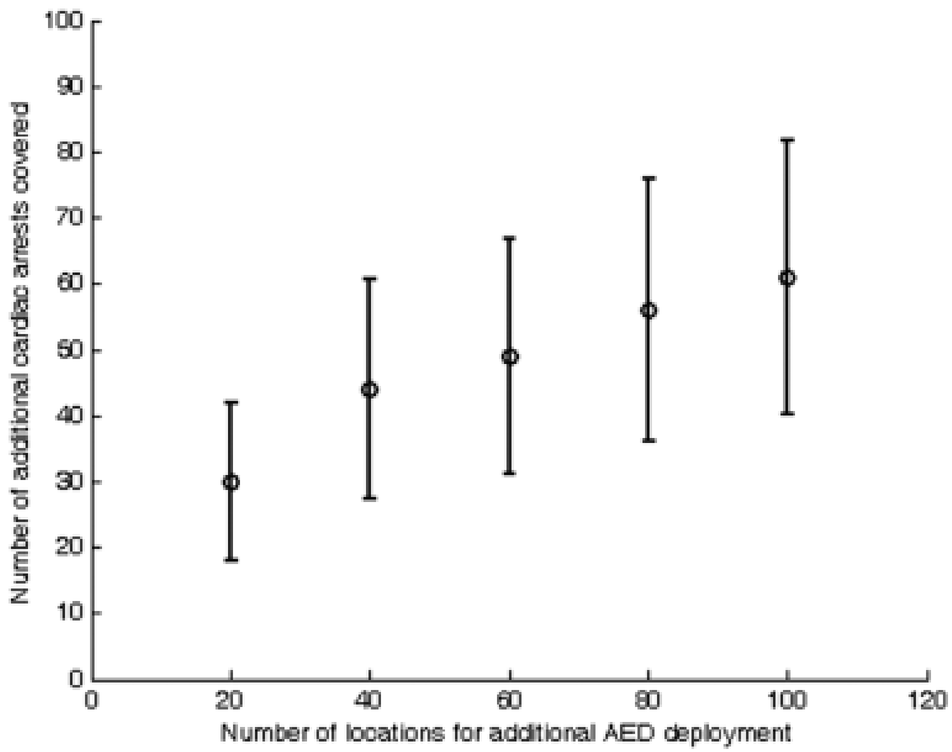
10-Fold Cross Validation



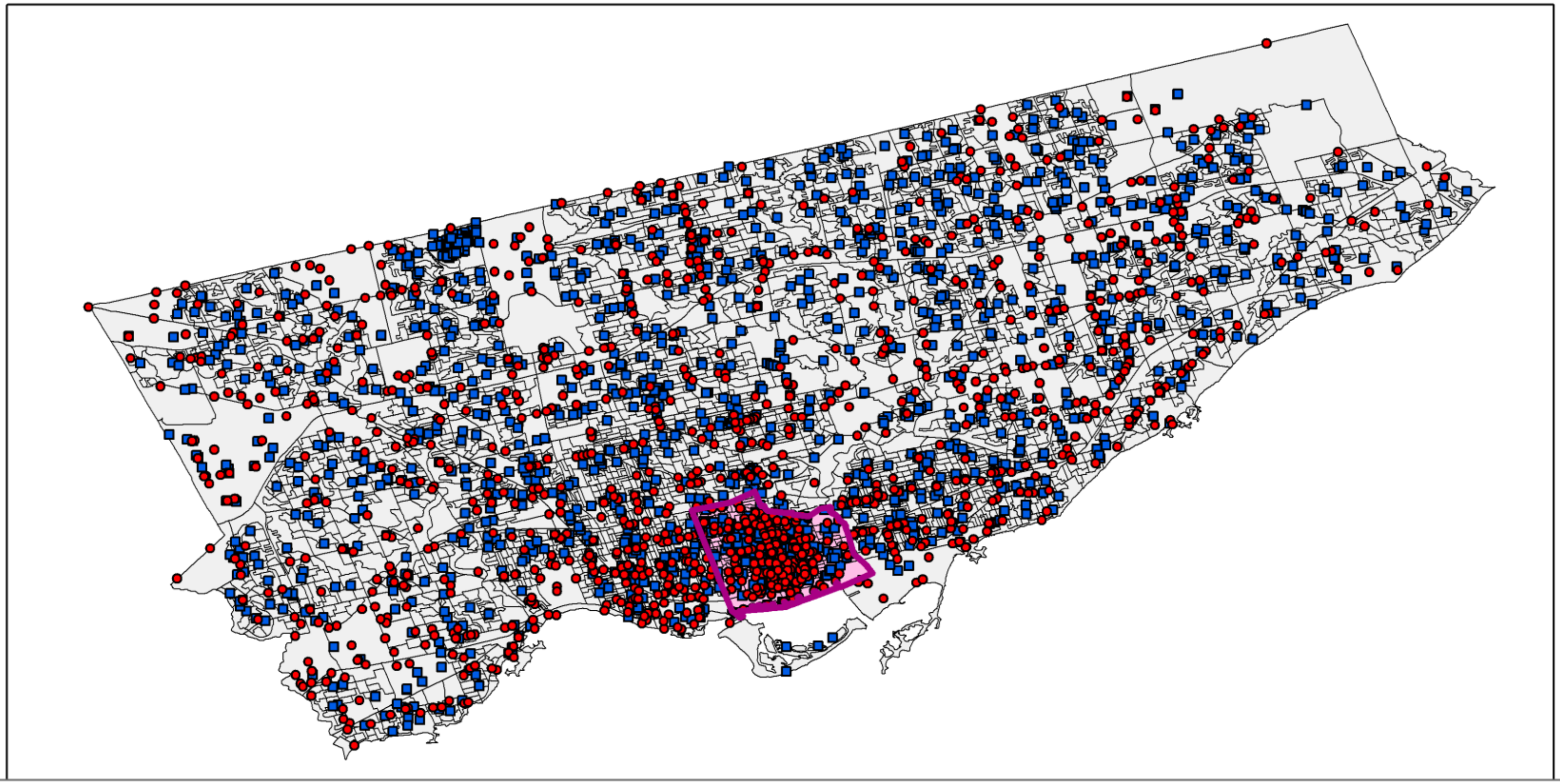
Performance (coverage) based of the OHCAs in the test sets, summed over the 10 folds

Results

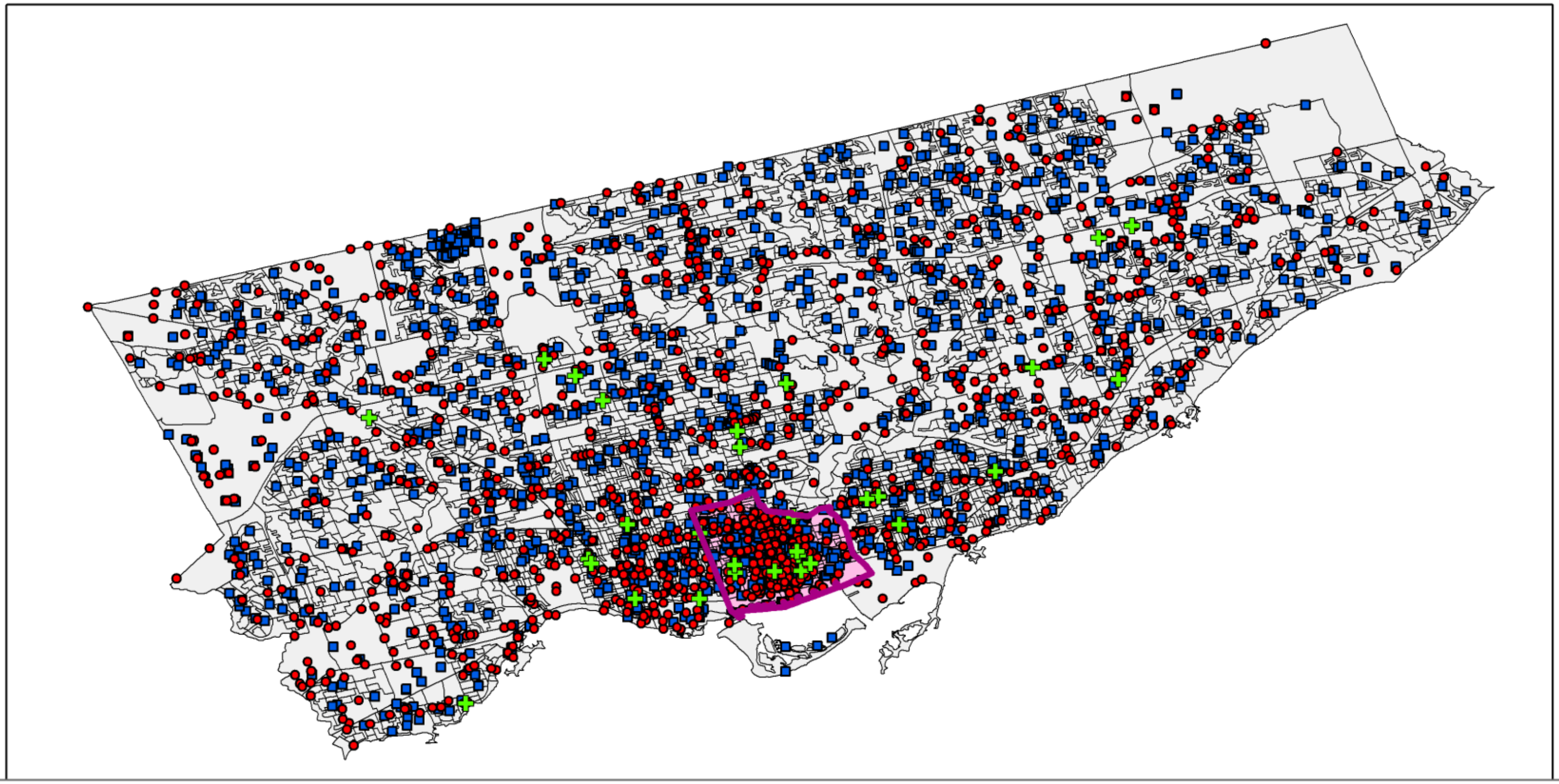
- Optimization approach consistently outperforms population-guided approach



Registered AEDs in Toronto



Where Do You Place the Next 30 AEDs?



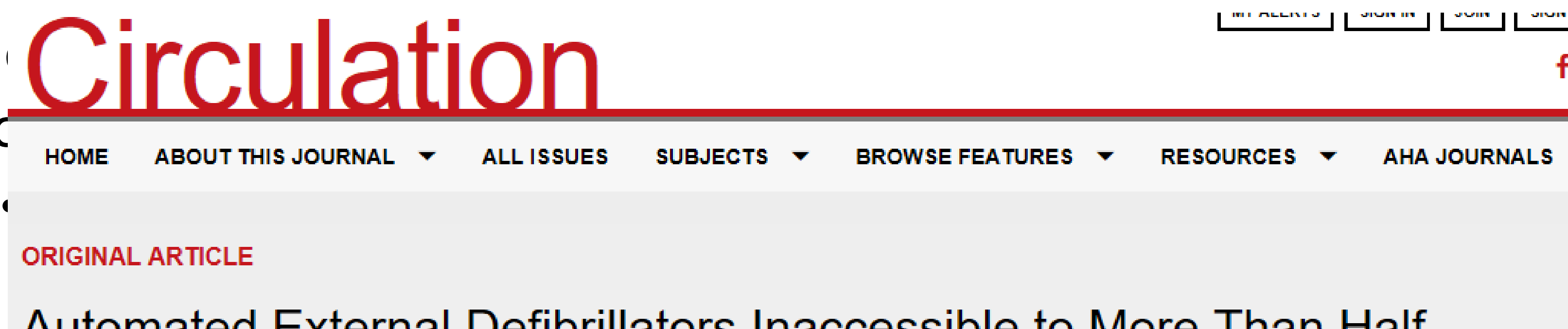
Optimization

- First optimization model (*Circulation* 2013)
- Effect of varying coverage radius (*Resuscitation* 2013)
- Optimization with coverage decay (*Manag Sci* 2016)
- Spatiotemporal optimization (*JACC* 2016)
- Optimization with uncertain OHCA locations (*Oper Res* 2017)
- AED optimization in high-rises (*Prehosp Emerg Care* 2017)
- Drone-delivered AEDs (*Circulation* 2017)
- Generalizability of spatiotemporal optimization (*Resuscitation* 2018)

Spatiotemporal Optimization Model

- Most studies focus on spatial factors; limited study of temporal factors
  - American Heart Association guidelines: place AEDs "in public locations where there is a relatively high likelihood of witnessed cardiac arrest"

- Two related questions:
  - How much is AED availability overestimated when we do not consider building hours of operation?
  - H
    co



Methods

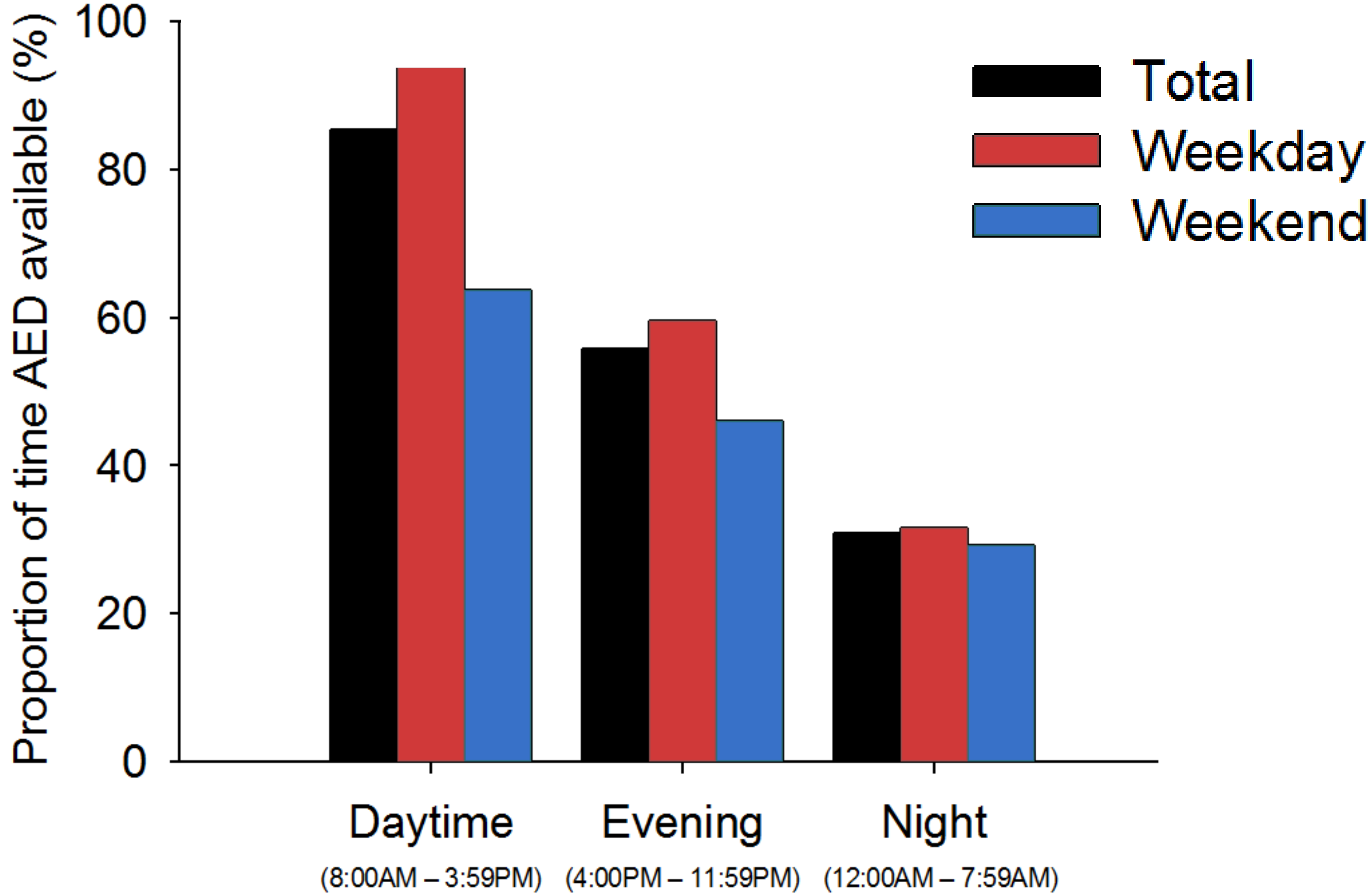
- Data
  - Eight years of historical cardiac arrest data
  - Location and hours of operation for registered AEDs

- Analysis
  - *Assumed 24/7 coverage*: number of cardiac arrests that occur within 100 m of AED
  - *Actual coverage*: number of cardiac arrests that occur within 100 m of AED <u>and</u> when the AED is available
  - Coverage loss = $\dfrac{\text{(assumed 24/7 – actual)}}{\text{assumed 24/7}}$

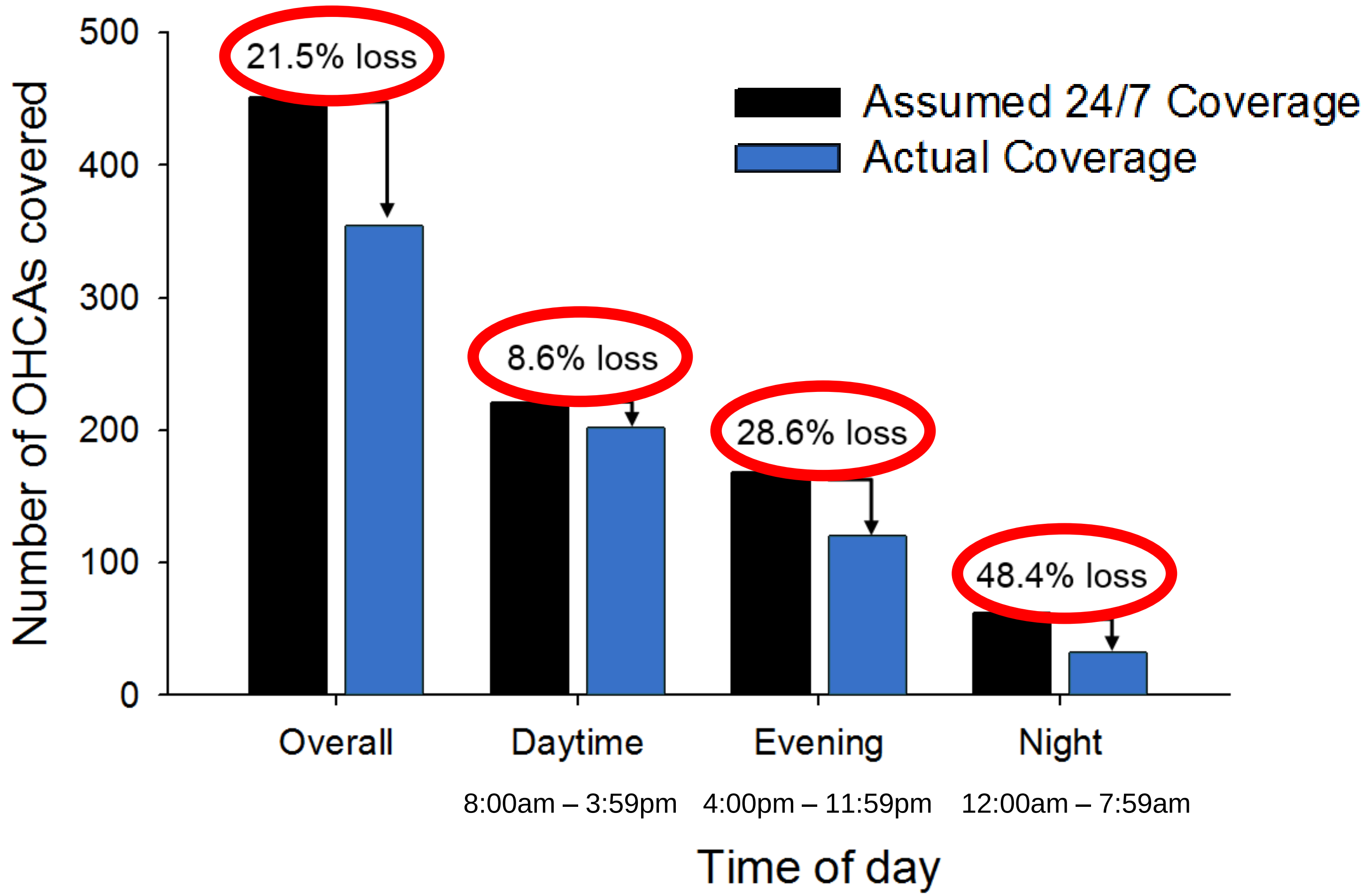
Results: Characteristics of Cardiac Arrests

Characteristic*	Total (n=2440)	Cardiac Arrests Daytime (n=1252)	Evening (n=840)	Night (n=348)
Average age ±SD	59.0±17.5	60.3±17.9	58.9±16.8	54.6±16.9
Male	58.9±16.7	60.1±17.2	58.7±16.1	55.1±15.7
Female	59.4±20.6	61.1±21.0	60.3±19.5	52.6±20.7
Male sex, n (%)	1979 (81.1)	1021 (81.5)	686 (81.7)	272 (78.2)
Witnessed by bystander, n (%)	1142 (46.8)	590 (47.1)	446 (53.1)	106 (30.5)
Received bystander CPR, n (%)	1019 (41.8)	533 (42.6)	371 (44.2)	115 (33.0)
Bystander applied AED, n (%)	191 (7.8)	96 (7.7)	75 (8.9)	20 (5.8)
Ambulance response interval, median (IQR), minutes	5.88 (2.68)	5.75 (2.60)	5.82 (2.62)	6.45 (2.58)
Initial cardiac rhythm, n (%)				
Shockable	868 (35.6)	465 (37.1)	327 (38.9)	76 (21.8)
Not Shockable	1504 (61.6)	747 (59.7)	494 (58.8)	263 (75.6)
Survival to discharge, n (%)	361 (14.8)	196 (15.7)	129 (15.4)	36 (10.3)

Results: AED Availability in Toronto



Results: Coverage Loss by Time of Day



Results: Coverage Loss by Location Type

Location Type	Number of locations with an AED, n (%)	OHCAs covered		Coverage loss (%)
		Assumed 24/7 coverage, n	*Actual coverage,* n	
School	190 (25.8)	68	41	39.7
Recreation/sports facility	165 (22.4)	89	56	37.1
Transportation facility	93 (12.6)	144	144	0.0
Industrial facility	62 (8.4)	28	17	39.3
Office	54 (7.3)	56	36	35.7

Discussion: Toronto vs. Copenhagen

	Toronto	Copenhagen (Hansen et al*)
Overall coverage loss	21.5%	33.5%
Percent of AEDs available 24/7	26.5%	9.1%
Daytime coverage loss	5.7%	4.1%
Evening, night, and weekends coverage loss	31.6%	53.4%
Location Type Coverage Loss		
Schools	39.7%	40.8%
Transportation Facilities/Train Stations	0.0%	0.0%
Offices	35.7%	49.0%
Recreation/Sports Facilities	37.1%	12.5%

*Hansen, C. M., Wissenberg, M., Weeke, P., Ruwald, M. H., Lamberts, M., Lippert, F. K., … Folke, F. (2013). Automated external defibrillators inaccessible to more than half of nearby cardiac arrests in public locations during evening, nighttime, and weekends. *Circulation*, *128*(20), 2224–31. doi:10.1161/CIRCULATIONAHA.113.003066

Spatiotemporal Optimization Model

- What is the improvement potential if we deploy “prospective” AEDs with knowledge of building hours?

- Compare an optimization model that combines both spatial and temporal information with one that uses spatial information only

Methods

- Data
  - Eight years of historical cardiac arrest data
  - Location and hours of operation for registered AEDs
  - Location and hours of operation for candidate AED sites

- Model
  - Spatial (basic) model: Place AEDs in *N* locations to maximize *assumed 24/7 coverage* of cardiac arrests
  - Spatiotemporal model: Place AEDs in *N* locations to maximize *actual coverage* of cardiac arrests
  - 10-fold cross validation (90/10 training/testing)

Model Comparison

Model Inputs

Candidate AED locations
- Address / Location
- Hours of operations

Historical OHCAs
- Address / Location
- Time of arrest

Spatiotemporal Model

Model Outputs
- Selected candidate AED locations
- Covered OHCAs

Model Inputs

Candidate AED locations
- Address / Location

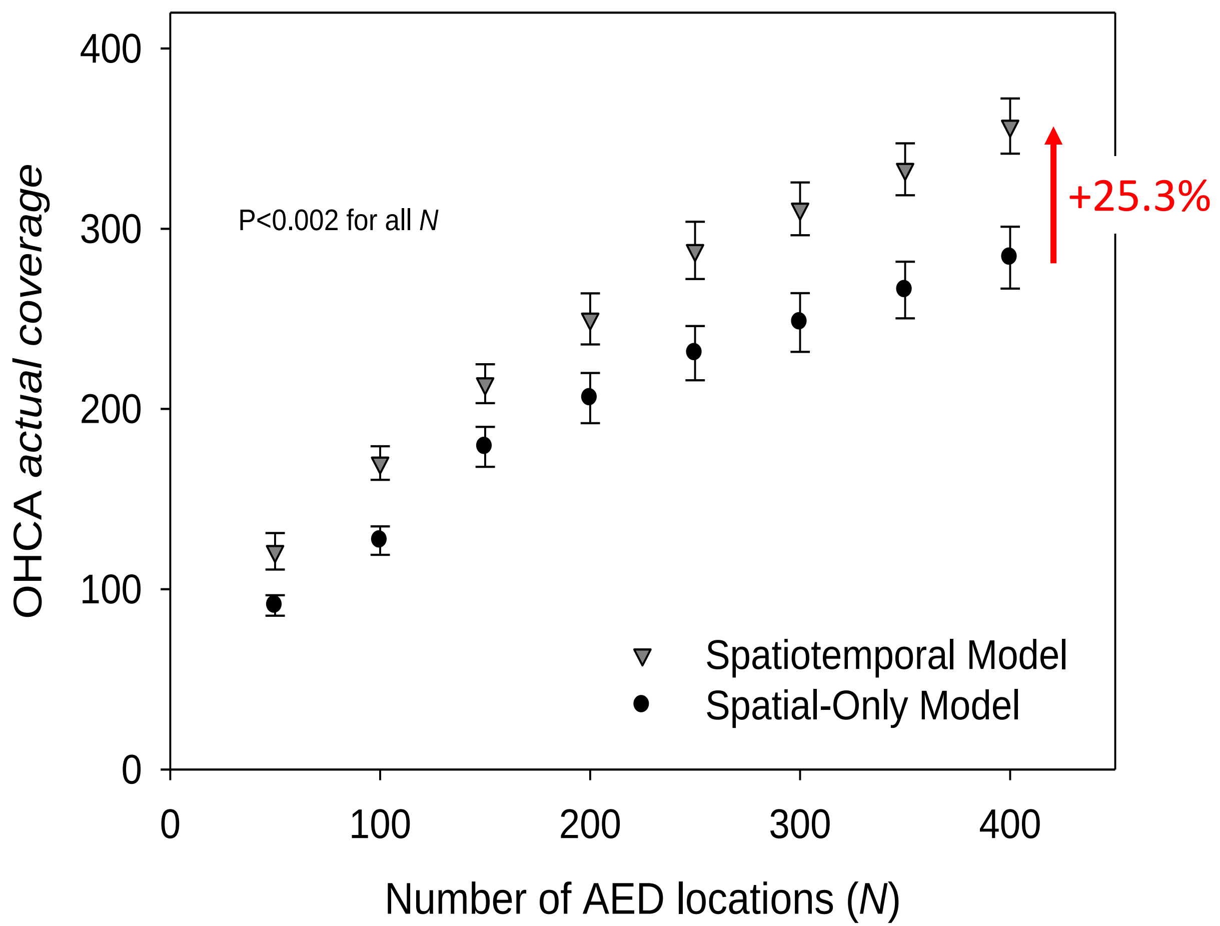
Historical OHCAs
- Address / Location

Spatial-only Model

Model Outputs
- Selected candidate AED locations
- Covered OHCAs

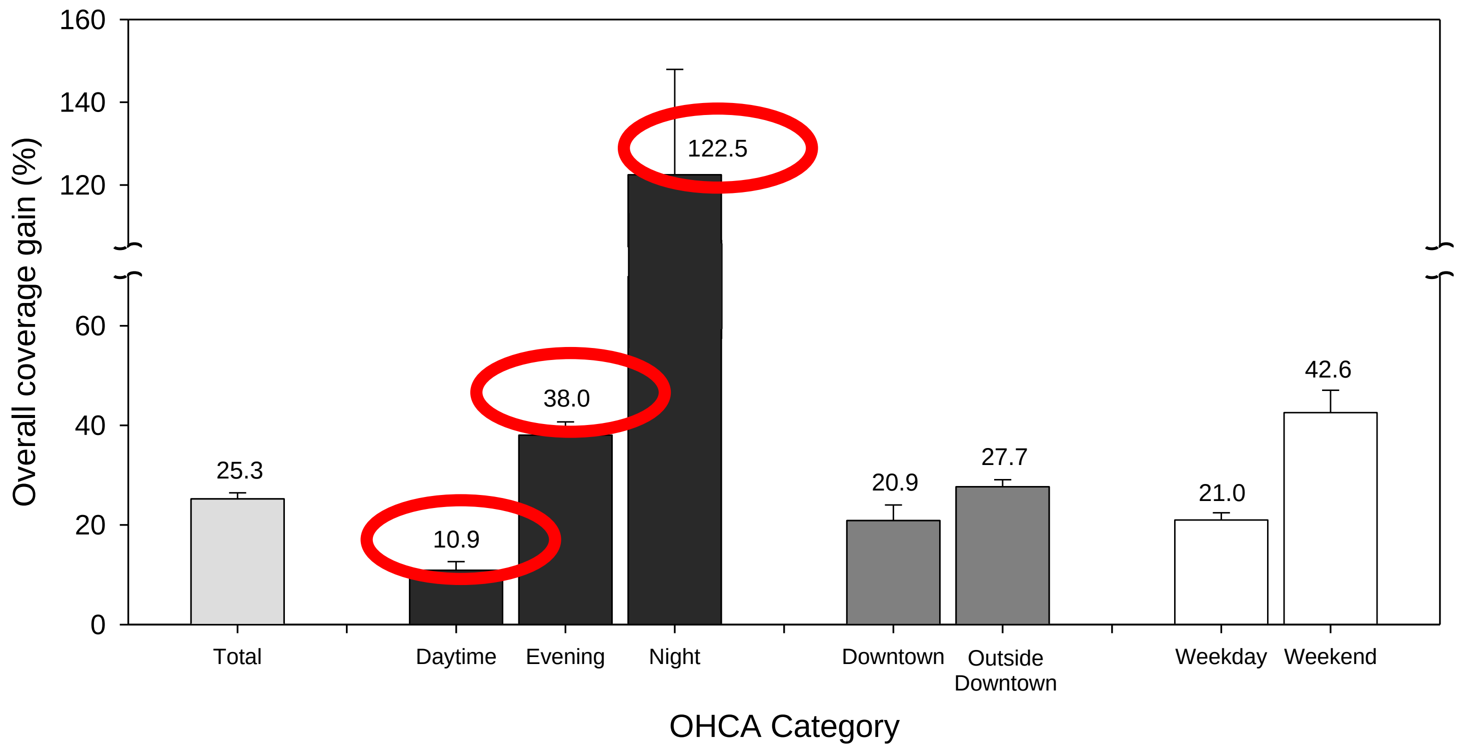
Compare in terms of *actual coverage*

Results: Spatiotemporal Optimization



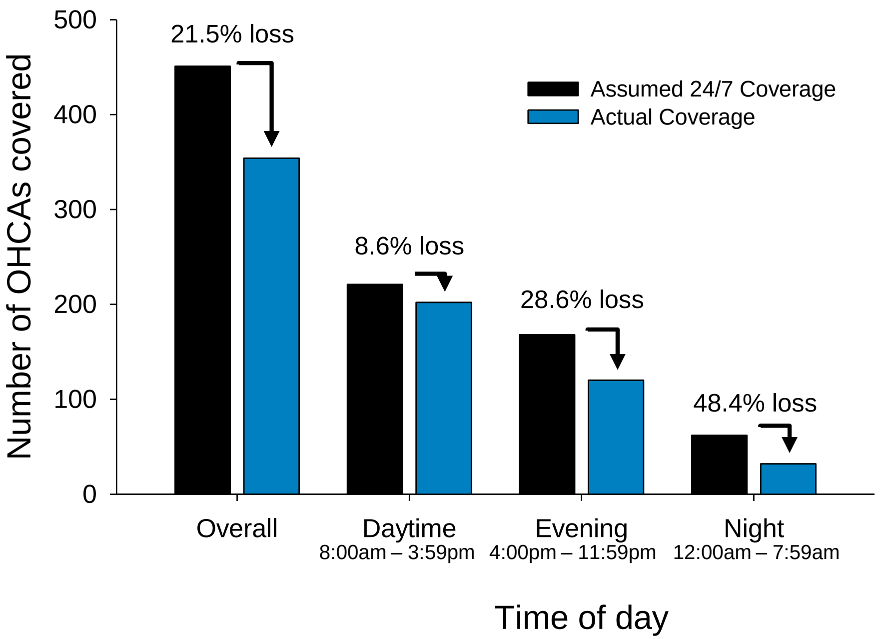
Results: Coverage Gain Due to Spatiotemporal Opt.

- Relative coverage gain = $\frac{\text{(spatiotemporal – spatial)}}{\text{spatial}}$
- Overall coverage gain: weighted average over *N*

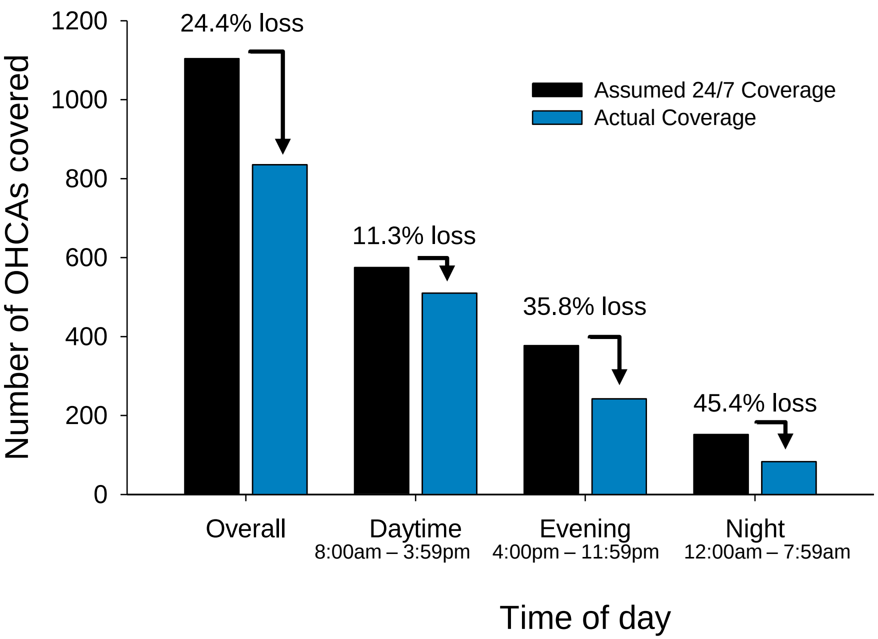


Generalizing the Spatiotemporal Approach

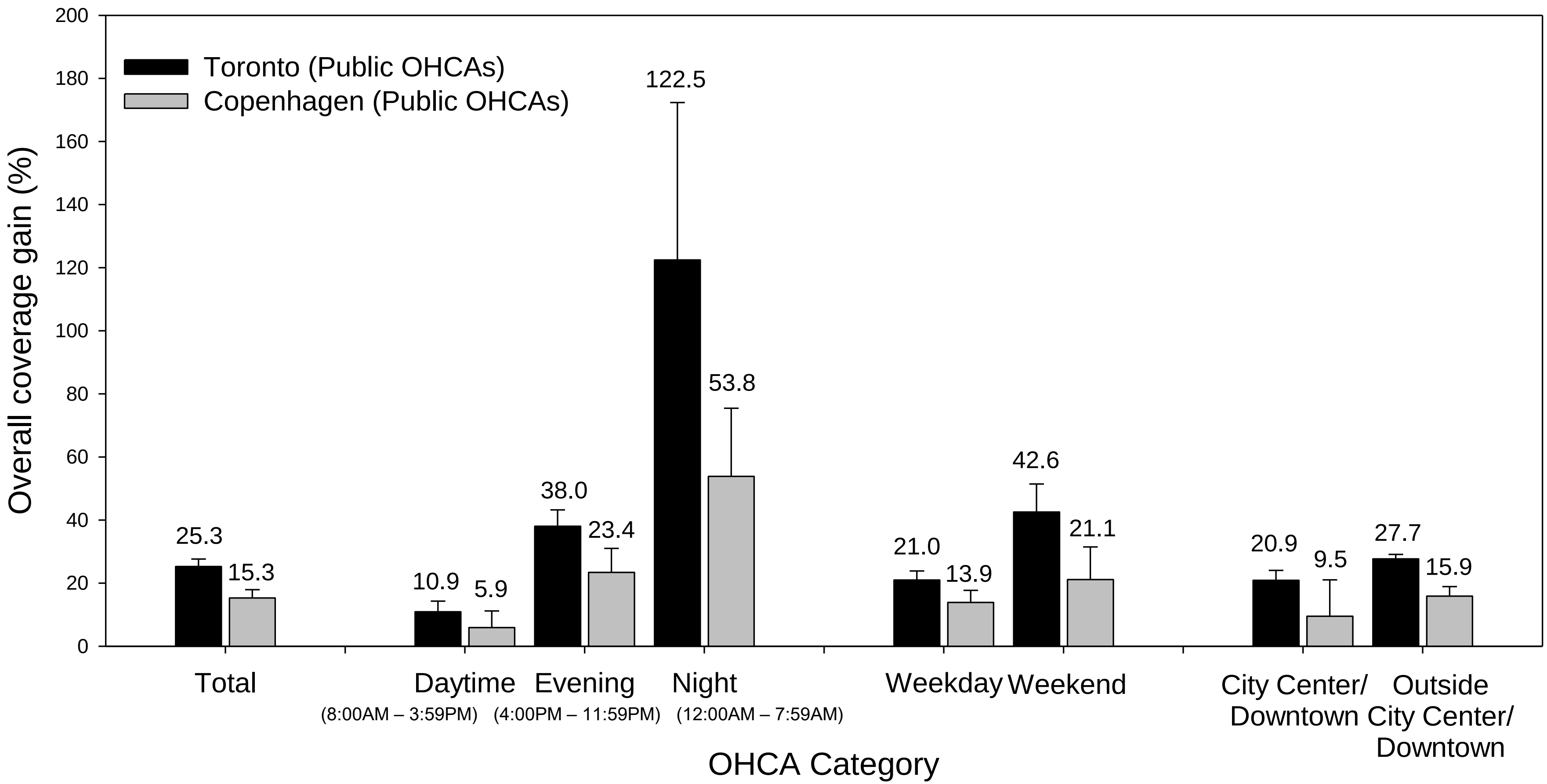
Toronto, Canada



Copenhagen, Denmark



Generalizing the Spatiotemporal Approach



Optimization

- First optimization model (*Circulation* 2013)
- Effect of varying coverage radius (*Resuscitation* 2013)
- Optimization with coverage decay (*Manag Sci* 2016)
- Spatiotemporal optimization (*JACC* 2016)
- Optimization with uncertain OHCA locations (*Oper Res* 2017)
- AED optimization in high-rises (*Prehosp Emerg Care* 2017)
- Drone-delivered AEDs (*Circulation* 2017)
- Generalizability of spatiotemporal optimization (*Resuscitation* 2018)

Vertical AED Placement

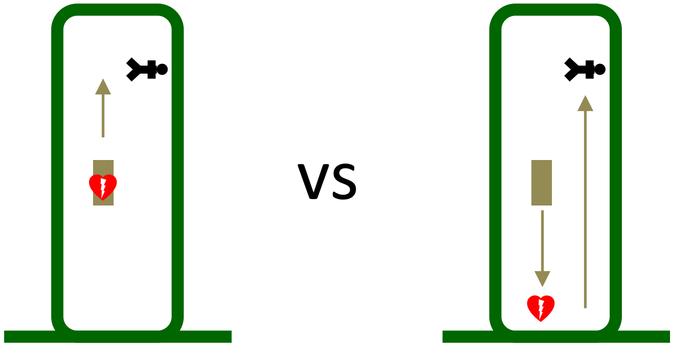
- Almost all studies have focused on “2D” problem
- Response delays and lower survival in high-rises
- No guidelines on vertical AED placement

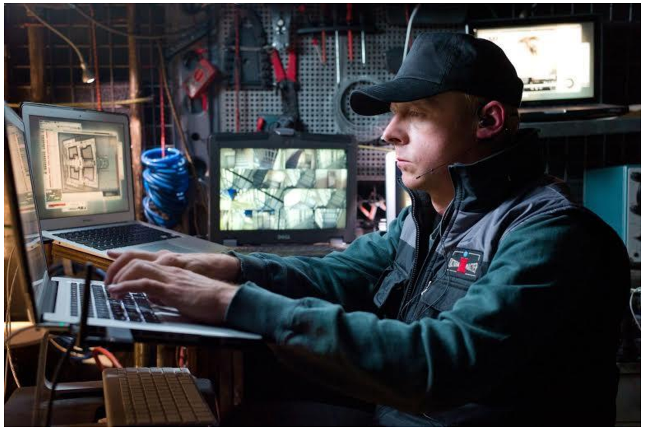
CMAJ RESEARCH

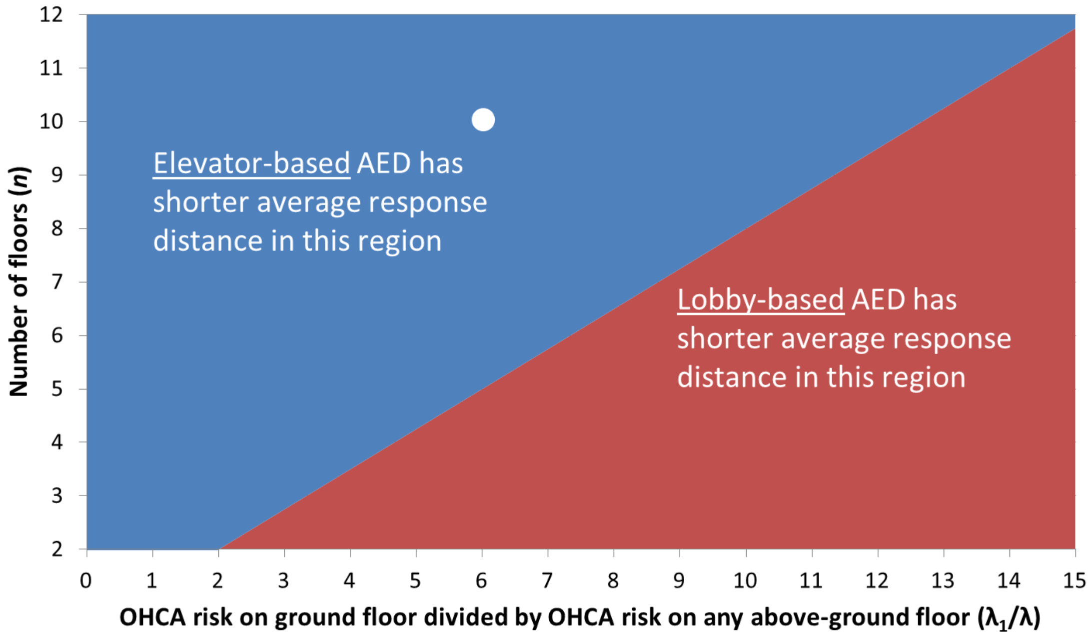
Out-of-hospital cardiac arrest in high-rise buildings: delays to patient care and effect on survival

Ian R. Drennan ACP, Ryan P. Strum PCP BSc, Adam Byers BSc, Jason E. Buick PCP MSc, Steve Lin MDCM MSc, Sheldon Cheskes MD, Samantha Hu, Laurie J. Morrison MD MSc; for the Rescu Investigators

Elevator vs. Lobby?





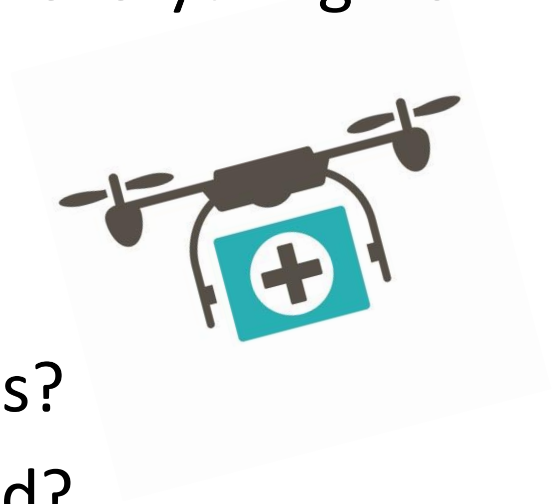


Optimization

- First optimization model (*Circulation* 2013)
- Effect of varying coverage radius (*Resuscitation* 2013)
- Optimization with coverage decay (*Manag Sci* 2016)
- Spatiotemporal optimization (*JACC* 2016)
- Optimization with uncertain OHCA locations (*Oper Res* 2017)
- AED optimization in high-rises (*Prehosp Emerg Care* 2017)
- Drone-delivered AEDs (*Circulation* 2017)
- Generalizability of spatiotemporal optimization (*Resuscitation* 2018)

Drone-Delivered AEDs

- Most OHCAs occur in private locations
- Drones are being tested to deliver everything from pizza to medicine
- Specialized AED-drones exist



- Where would you put drone bases?
- How many drones would you need?
- How do drones compare to existing EMS response?

Defibrillator Drone

Objective

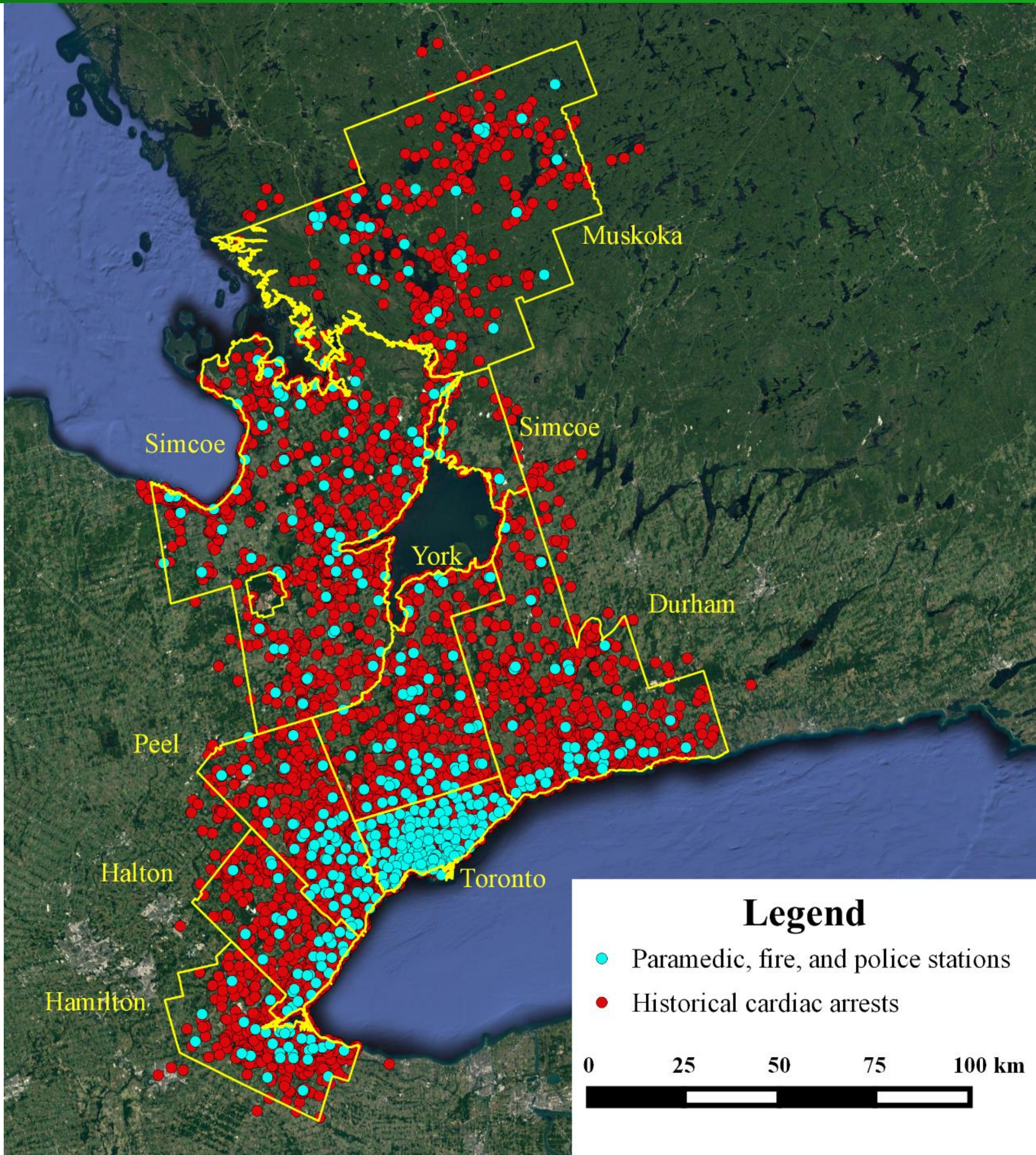
The goal of this study is to develop a mathematical approach that determines:

1. the number and location of drone bases, and
2. the number of the drones required at each base,

to meet any AED arrival time goal in any geographical area.

Data

- 8 regions
  - 7.5 million people
  - 10,000 sq. miles
- 53,702 OHCAs from 2006 to 2014
  - 86% private location
  - 7.8% survival
- 538 paramedic, fire, and police stations



Mathematical Model

- Two-stage mathematical model:

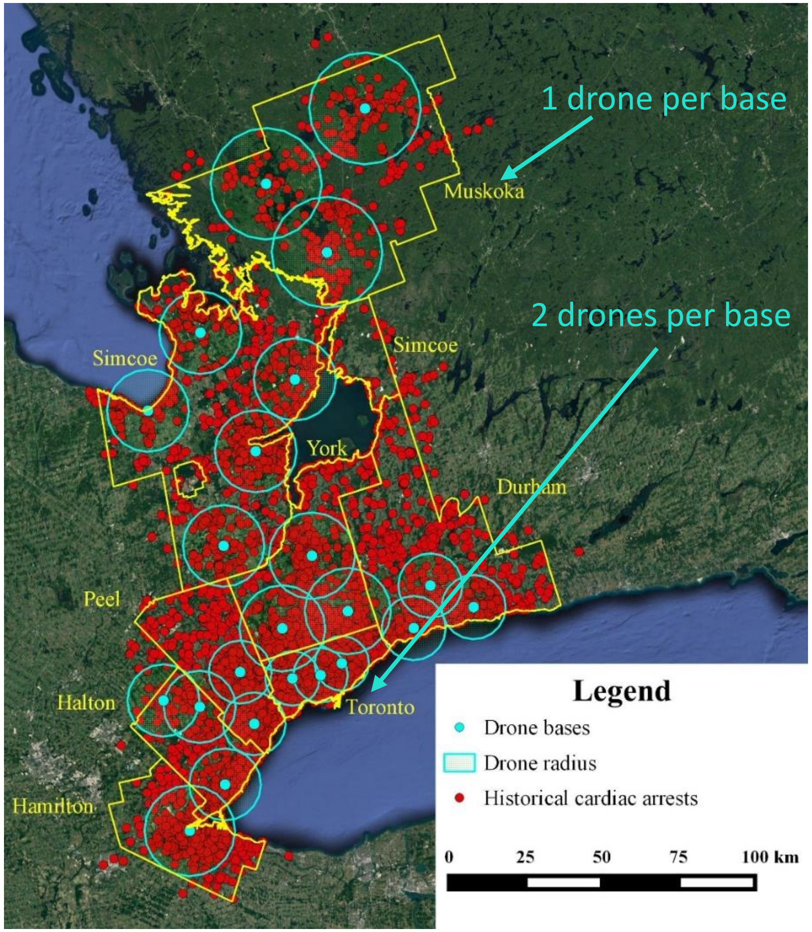
1. Optimization model to determine base locations to cover *f%* of historical OHCAs in under *t* minutes
2. Queuing model to determine number of drones at each base so there is 99% chance drone is free when a OHCA occurs inside that base's catchment area

Analysis

- Determine the number and location of drones to improve the historical median 911 response by 1, 2, and 3 minutes
- Compare region-specific drone networks with coordinated drone-network integrating all eight regions

Results: An Example Drone Network

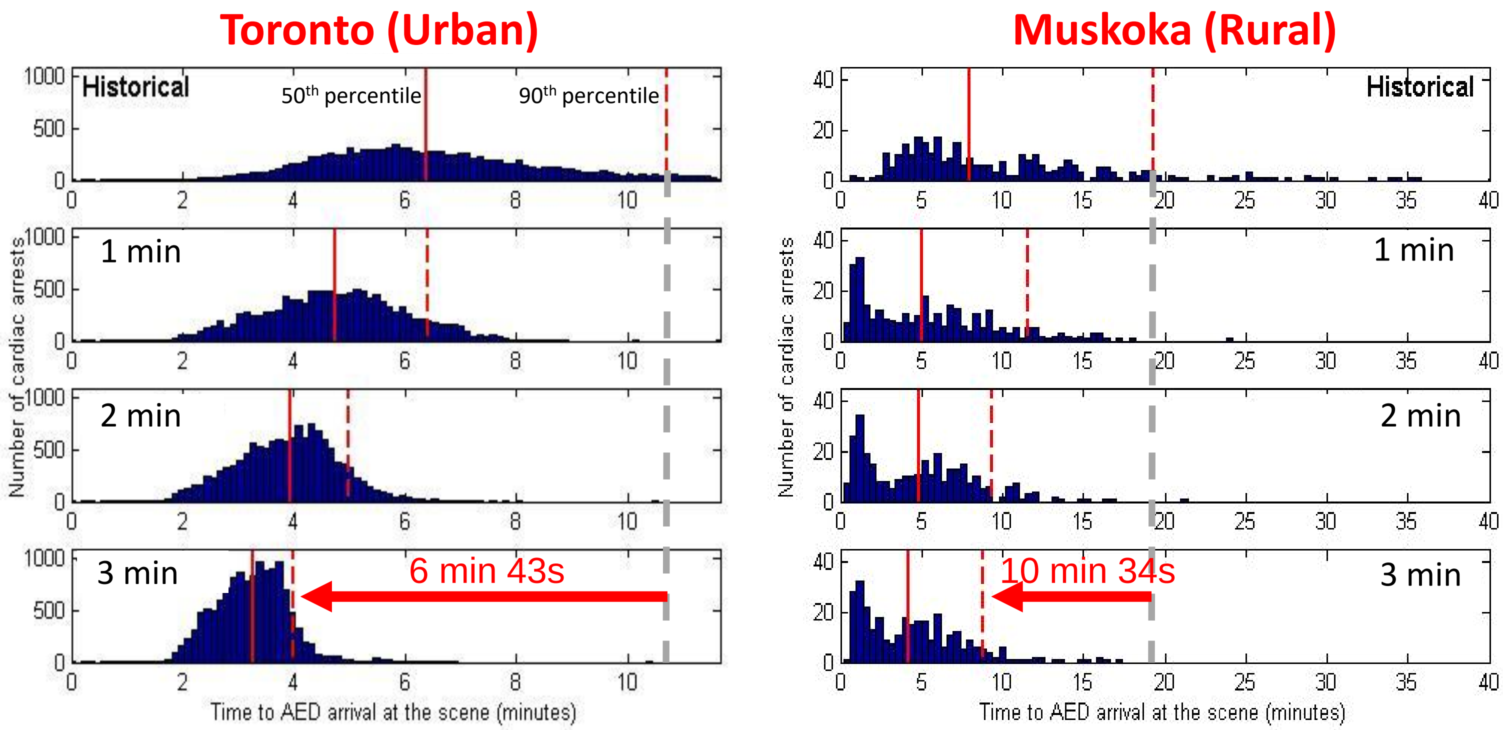
- 23 bases, 37 drones:
  - Reduce median response time by 1 minute
  - Reduce 90th percentile response time by over 6 min in some regions
  - Drone arrives ahead of EMS 2/3 of the time



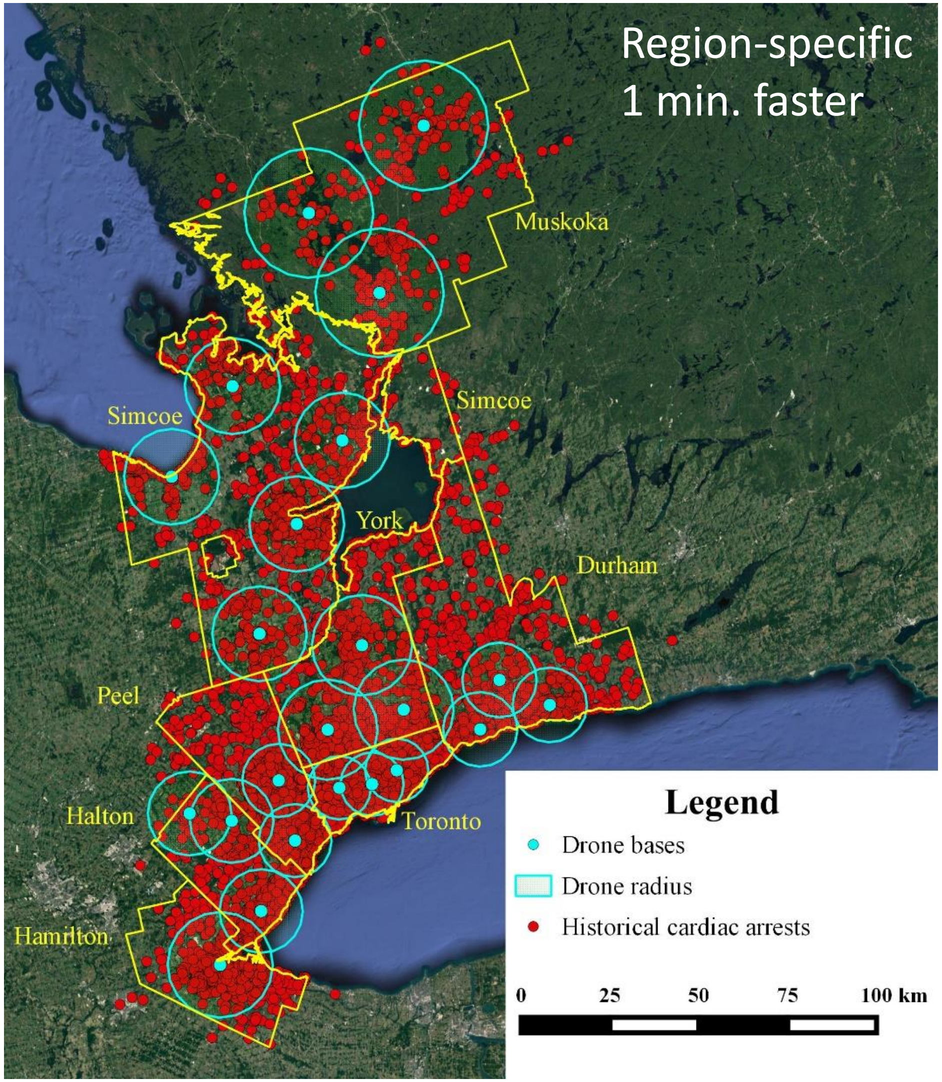
Drone Network Performance

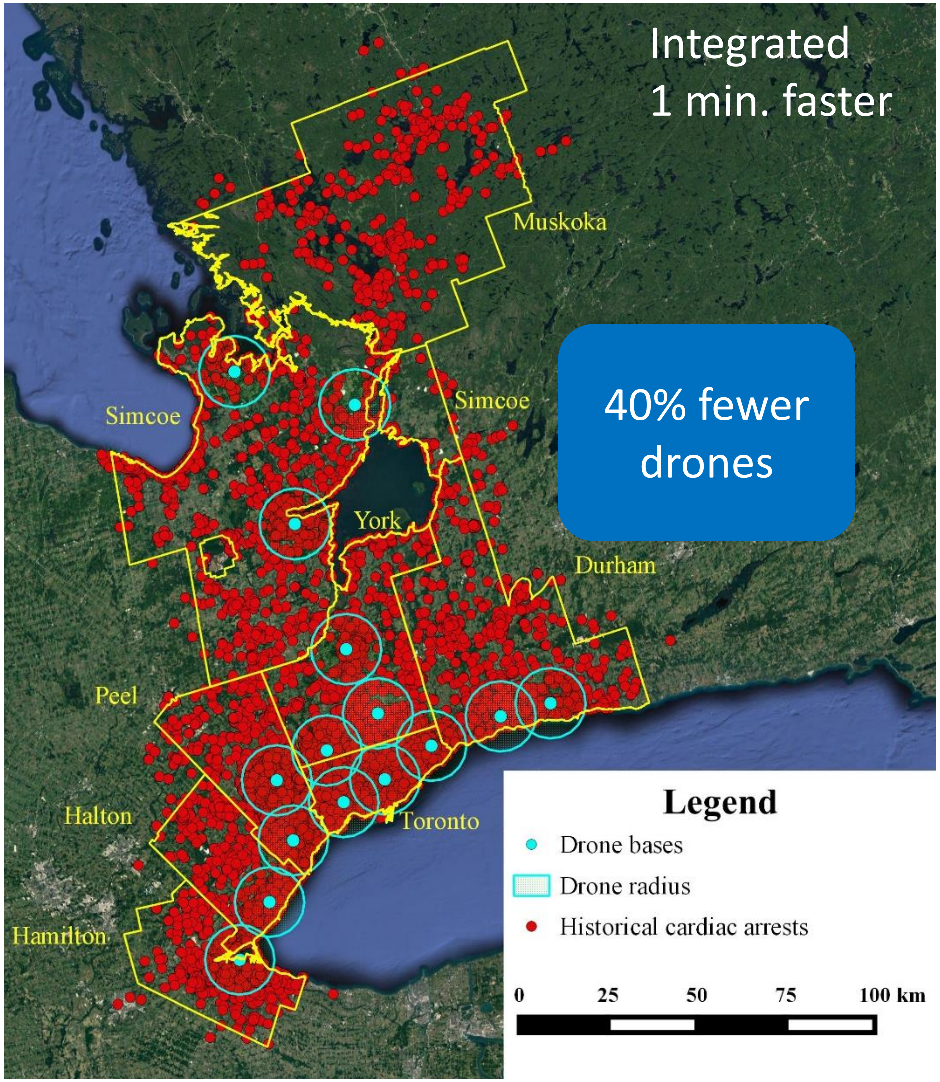
	Goal	Region								
		Toronto	Durham	Simcoe	Muskoka	Peel	Hamilton	Halton	York	All
Number of bases (number of total drones)	1 min. faster	3 (6)	3 (6)	5 (6)	3 (3)	2 (4)	1 (2)	3 (4)	3 (6)	23 (37)
	2 min. faster	6 (12)	5 (7)	11 (12)	5 (5)	4 (8)	1 (2)	3 (4)	5 (7)	40 (57)
	3 min. faster	13 (26)	14 (16)	20 (20)	6 (6)	10 (11)	5 (7)	5 (5)	8 (9)	81 (100)
Proportion of cases where drone AED arrives prior to 911 (%)	1 min. faster	69.0	64.2	65.0	76.3	71.7	54.1	64.4	63.9	67.9
	2 min. faster	87.6	82.1	78.6	79.7	84.7	75.3	73.9	79.5	84.6
	3 min. faster	96.1	94.6	89.6	84.2	94.6	92.2	92.7	89.2	94.6

Impact on Response Time Distribution



Results: Equity vs. Efficiency





40% fewer drones

Summary of Past/Current Work

- Data-driven mathematical models for AED placement or delivery
  - Models that improve accessibility or consider bystander response
  - Utilizing drones to deliver AEDs, other medicines
  - Application to new contexts (LMICs, indoor networks)

Going Forward

- Continue to be interested in innovative applications of optimization in emergency response
  - New problem contexts
    - Integrating static and moving AEDs
    - Simulated clinical trials
    - High-rise response
    - Traffic accidents
    - Centralized decision-making systems
  - New technologies
    - Optimal notification radius for mobile app-based responders
    - Analysis of wearables data
    - OHCA recognition via security systems

Thank You!