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Optimizing a Drone Network to Deliver Automated External Defibrillators

Running Title: *Boutilier et al.; Optimizing Drone-Delivered AEDs*

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Abstract

Background—Public access defibrillation programs can improve survival after out-of-hospital cardiac arrest (OHCA), but automated external defibrillators (AEDs) are rarely available for bystander use at the scene. Drones are an emerging technology that can deliver an AED to the scene of an OHCA for bystander use. We hypothesize that a drone network designed with the aid of a mathematical model combining both optimization and queuing can reduce the time to AED arrival.

Methods—We applied our model to 53,702 OHCAs that occurred in the eight regions of the Toronto Regional RescuNET between January 1st 2006 and December 31st 2014. Our primary analysis quantified the drone network size required to deliver an AED one, two, or three minutes faster than historical median 911 response times for each region independently. A secondary analysis quantified the reduction in drone resources required if RescuNET was treated as one large coordinated region.

Results—The region-specific analysis determined that 81 bases and 100 drones would be required to deliver an AED ahead of median 911 response times by three minutes. In the most urban region, the 90th percentile of the AED arrival time was reduced by 6 minutes and 43 seconds relative to historical 911 response times in the region. In the most rural region, the 90th percentile was reduced by 10 minutes and 34 seconds. A single coordinated drone network across all regions required 39.5% fewer bases and 30.0% fewer drones to achieve similar AED delivery times.

Conclusions—An optimized drone network designed with the aid of a novel mathematical model can substantially reduce the AED delivery time to an OHCA event.

Key-Words: emergency medical services; cardiac arrest; automated external defibrillator; Drones, Optimization

Clinical Perspective

What is new?

- We demonstrate, using data from over 50,000 historical OHCAs covering over 26,000 square kilometers in Ontario, Canada, that a theoretical drone network designed with the aid of a mathematical model has the potential to significantly reduce the AED delivery time for bystander use.
- We found that a drone network designed to reduce the median AED arrival time by 3 minutes relative to the historical 911 response, also reduced the 90th percentile of the AED arrival time by between 6 minutes and 43 seconds (most urban region) and 10 minutes and 34 seconds (most rural region).

What are the clinical implications?

- Drone-delivered AEDs have the potential to be a transformative innovation in the provision of emergency care to cardiac arrest patients, especially those who arrest in a private or rural setting.
- Drones require careful integration with 911 response and future clinical research is needed to understand the challenges associated with implementation and to determine the cost-effectiveness of such a system.

Introduction

Public access defibrillation programs have demonstrated that significant improvements in survival from out-of-hospital cardiac arrest (OHCA) are possible, with the majority of the survival advantage accruing to patients who arrest in public settings.[1-3] However, the majority of OHCAs occur in private settings[4, 5] with correspondingly slower emergency response times,[5-7] especially in rural settings. While deployment of automated external defibrillators (AEDs) may be cost-effective in certain public venues,[8, 9] especially if locations are optimized,[10] static AEDs deployed broadly for use in private OHCA emergencies are unlikely to be cost-effective.[7, 11, 12] There is a fundamental coverage limit of cardiac arrest risk that cannot be overcome using static AEDs alone.[13] Moreover, in part due to access and availability issues,[14] static AEDs have low utilization historically.[15] Improving AED access and reducing the time to defibrillation are important for improving survival from OHCA. Thus, a new approach is necessary to make a significant impact in OHCA survival, especially for rural and private locations.

Recently, several companies and researchers have developed prototype drone technology that can be used to deliver AEDs to the scene of a cardiac arrest.[16, 17] Google has successfully obtained a patent for drone delivery of medical supplies including AEDs.[18] AED delivery is only one of the many proposed applications for drones, formally known as unmanned aerial vehicles. Companies have proposed to use drones to deliver everything from pizza[19] to official documents[20] to medicine.[21, 22] Although there are technical challenges to overcome, drone-delivered AEDs are a potential transformative innovation in the provision of emergency care to cardiac arrest patients, especially to those who arrest in a private or rural setting.

The goal of this study is to determine if a drone network designed with the aid of a mathematical model combining both optimization and queuing can reduce the time to AED arrival. Our mathematical model determines, for a given geographical area, the number and location of drone bases, along with the number of the drones required at each base, to meet any specified AED arrival time goal. We applied our model to a large area composed of rural and urban regions surrounding Toronto, Canada and quantified the size of the drone network required to achieve AED arrival times that improve upon historical 911 response times. We determine the reduction in time to AED arrival, relative to 911 first responders, by using drone networks determined by our model to deliver an AED for bystander use.

Methods

Study setting

The Toronto Regional RescuNET comprises eight regions in Southern Ontario, Canada: Toronto, Durham, Simcoe, Muskoka, Peel, Hamilton, Halton, and York, with a total population of 7.12 million in a total area of 26,364 km^2. Each region is served by a single paramedic service, though neighboring services may respond to emergencies if they are closer. There is a tiered response to emergency calls, where fire fighter first responders are dispatched to all suspected OHCAs along with paramedics.

Data Sources

Cardiac arrest episodes

All non-traumatic, private and public, treated and untreated OHCA episodes throughout RescuNET from January 1st 2006 to December 31st 2014 were included in the study. Data was obtained from the Rescu Epistry cardiac arrest database,[23, 24] which has research ethics board approval from all destination hospitals and from the institution providing oversight to the paramedic and fire services. Universal Transverse Mercator (UTM) coordinates were determined for each episode after applying various geocoding techniques (Supplemental Figure 1). Cardiac arrests that could not be accurately geocoded due to lack of sufficient location information were excluded.

Candidate base locations

All fire, paramedic, and police stations within RescuNET were considered as candidate drone base locations. Addresses for each station were obtained from the regional provider and converted to UTM coordinates.

Drone specifications

Drone parameters used in our model were based on specifications reflecting current technological capabilities. Vertical acceleration/deceleration was set to 9.81 m/s^2 while horizontal acceleration/deceleration was set to 19.6m/s^2.[25, 26] Horizontal acceleration/deceleration is done simultaneously with vertical deceleration (Supplemental Figure 2). Maximum forward velocity was set at 27.8 m/s.[16] Flying height was assumed to be 60 m, which is below the maximum height allowed in Canada.[27, 28] Accounting for maximum speed and height, 10 seconds is required for takeoff and landing. The maximum distance a drone can reach – it's "radius" – is determined using the average regional dispatch time and the maximum flying time used in the optimization model (see Supplemental Methods).

Model

For each region, the OHCA data was split into two disjoint sets of equal size: a training set and a testing set. The training set was used as the input into our models while the testing set was used to evaluate the performance of the theoretical drone networks.

Our modeling approach consisted of two stages. The first stage used an integer optimization model (Supplemental Methods) to determine the minimum number and location of drone bases, chosen from the set of candidate base locations, required to improve the historical median response time by one, two, or three minutes. The coverage radius for each potential base was determined using the average regional dispatch time and the maximum flying time used in the optimization model (see Supplemental Methods). Each base defined a catchment area through its coverage radius and we treated each catchment area independently in the second stage.

Once the base locations were determined by the optimization model, the second stage used a queuing model (Supplemental Methods) to determine the number of drones to be stationed at each base so there is a 99% chance a drone is free when an OHCA occurs inside that base's catchment area. The calculation is specific to each base, requiring two inputs: an average rate of OHCA occurrences in each catchment area and an average time interval between successive mission departures for the same drone ("drone busy time"). We calculated a separate rate of OHCA occurrences for daytime (8:00AM–7:59PM) and night time (8:00PM–7:59AM),[29] and we used the daytime rate in the queuing model. The time interval required between successive departures by the same drone – drone busy time – comprises the outbound travel time, on-scene time, inbound travel time, and "reset" time. Supplemental Table 1 displays each of these computed time intervals. Figure 1 summarizes the relevant time intervals in the operationalization of the drone response.

Analyses

Primary analysis: Delivery of drone AEDs prior to 911 responder arrival

We determined the historical median and 90th percentile 911 response times (i.e., dispatch plus drive time) from the training OHCA data for each region. For each region independently, we use our two-stage (optimization and queuing) approach to find the region-specific drone network that improves the median regional 911 response time by at least one minute; we repeated this process for two and three minutes. For each combination of drone response time improvement goal (one, two and three minutes faster than the median 911 response time) and region, we quantified the number of bases and drones required. Using the out-of-sample testing set OHCAs, we determined the response time distribution of the optimized drone network. We also determined the response time distribution of the combined drone and 911 network, by taking the minimum of the drone response time and historical 911 response time for each cardiac arrest. Finally, we calculated the proportion of testing set OHCAs in which the drone response time was shorter than the 911 response time.

Secondary analysis: The value of centrally coordinated drone response across regions

We repeated the primary analysis treating RescuNET as one large, integrated region. We computed the same metrics as in the primary analysis. To quantify the value of coordination, we computed the difference in the number of bases and total drones required by the "region-specific" versus the "integrated" network.

Statistical analysis

We use a right tailed Sign Test to determine if the observed median response time reductions were statistically significant at the 0.05 significance level. To do this, we tested the null hypothesis that the difference between the historical 911 response time distribution and the estimated response time distribution of a combined 911 and drone network had a zero median.

Sensitivity analysis

Variability in the drone busy time will influence the number of drone resources suggested by the mathematical model. To determine the impact of possible changes in drone busy time, we conducted a sensitivity analysis by varying the overall busy time by ±15 and ±30 minutes.

Results

After geocoding and eliminating OHCAs with missing data, 53,702 OHCAs remained (96% of OHCAs occurring during the study time frame) for our analysis. The training and testing sets both contained 26,851 OHCAs. Supplemental Table 2 provides information on historical 911 response times and annual OHCA incidence.

Table 1 provides a summary of the eight RescuNET regions. Figure 2 displays all geocoded cardiac arrests and the paramedic, fire, and police stations. A summary of the geocoding results is given in the Supplemental Material.

Table 2 shows the number of bases and drones in each region for both the region-specific and integrated drone networks for each response time improvement goal, along with corresponding response time metrics. For example, to deliver an AED via drone one minute prior to 911 arrival on average, the region-specific network required 23 bases and 37 drones, whereas the integrated network required 15 bases and 28 drones. For the two- and three-minute goals, a reduction in drone bases (15.0% and 39.5% reduction, respectively) and number of drones (10.5% and 30.0%, respectively) was also observed in the integrated network.

Figure 3 compares the region-specific and integrated drone networks for the one-minute improvement goal. In the region-specific network, there is broad geographical coverage across all regions. However, the integrated network chooses to concentrate most of the bases in the region surrounding the high cardiac arrest density areas (e.g., Toronto) in order to minimize the number of bases required. For example, in Figure 3, there are no drone bases located in Muskoka. Supplemental Figures 3 and 4 illustrate the drone network configurations for the two- and three-minute improvement goals.

Figure 4 compares the historical 911 response time distribution to the estimated response time distribution of a combined 911 and drone network in both Toronto and Muskoka, the regions with the highest and lowest population density, respectively. In both regions, we see a marked shift of the response time distribution to the left (i.e., toward shorter response times) as the response time improvement goal increases. For the three-minute goal in Toronto, the 90th percentile of the combined 911 and drone response represents a 63.1% reduction of the 90th percentile of the historical 911 distribution. In Muskoka, the corresponding reduction was 54.0%. Across all regions, adding drones results in a similar improvement (Supplemental Figures 5 to 10).

Our statistical analysis found that for region-specific drone networks the reduction in median response time was statistically significant across all regions and all response time improvement goals. For the integrated drone networks, the reduction in median response time was statistically significant for all regions except Muskoka (1, 2, and 3 minute goal) and Halton (1 minute goal)

Table 3 summarizes our sensitivity analysis, which reveals that the drone busy time is critical in determining the drone network size. In particular, when the drone busy time is decreased by 30 minutes, almost all bases require only a single drone, except for the busiest bases in Toronto, which still require several. However, when the drone busy time is increased by 30 minutes, then many regions, especially the denser ones, have bases requiring multiple drones, sometimes double the number from before.

Discussion

Main Findings

This study investigated the theoretical benefit of drone-delivered AEDs using a mathematical model to optimize drone base locations and fleet size. The primary analysis determined the size and structure of the network needed to achieve AED delivery time improvement goals of one, two, and three minutes relative to historical median 911 response times in the Toronto Regional RescuNET. We found that drones not only improve the median time to defibrillator arrival on scene, but reduce the entire response time distribution. Our statistical analysis found that all observed reductions in median response time greater than 13 seconds were statistically significant.

The secondary analysis demonstrated that the performance of an integrated drone network can achieve the same overall performance as eight independent regional networks but with substantially fewer resources. However, the trade-off for this efficiency gain was a loss in geographical coverage in more rural areas. For example, in certain regions and for certain response time improvement goals, there was near elimination of drone coverage, which illustrates the potential inequality that can arise between regions if we simply optimize for all of RescuNet as one integrated region. Such an efficiency-equity trade-off arises because the majority of OHCAs are concentrated in a few regions and our models optimize with respect to median response time; optimizing for the 90^{th} percentile instead of the median would result in more bases in rural areas.

Potential benefits

Drone-delivered AEDs have the potential to improve survival for patients with OHCA because the probability of ventricular fibrillation and survival decays with time.[30] Our analysis has demonstrated that, in theory, a drone network can be optimized to allow delivery of AEDs ahead of 911 response. Currently, less than 3% of all cardiac arrests have a public access defibrillator used.[15] If drone networks are designed with the goal to deliver AEDs to every cardiac arrest in the region and achieve earlier defibrillation of patients with OHCA, then they are very likely to have a meaningful impact on cardiac arrest survival.

There are numerous benefits to using drones to augment the current 911 system and static public access defibrillators. First, drones offer the potential to actively mobilize defibrillators along with the traditional 911 response. In contrast, the current approach to public access defibrillation is passive. Static defibrillators are deployed in the community with the hope that one is nearby when needed. Most communities do not have systems to mobilize public access defibrillators to the scene of an emergency in a targeted way. Second, drone technology offers many potential tactical advantages. For example, rapid AED delivery may be possible due to straight line travel and traffic avoidance. Drone-delivered AEDs could in principle be available 24/7, unlike most static AEDs.[14] Drones may be able to deliver AEDs at height via a balcony or roof for cardiac arrests that occur in high rise buildings, which are known to suffer a survival disadvantage.[31] The drone's camera, which is used for navigation, could also be leveraged by the 911 dispatcher to visually assess the patient and support bystander CPR and AED application. Third, drones may be able to quickly reach private location cardiac arrests, which comprise the vast majority of all cardiac arrests and are typically associated with worse outcomes.[4] Currently, static public access defibrillators are almost never used for private location cardiac arrests.

Previous literature

Prior work on drone delivery of AEDs is limited to a single preliminary study that found drone-delivered AEDs have the potential to reduce response times in Salt Lake county, Utah.[32]

However, the study was limited by the fact that they did not use actual cardiac arrest data to inform the drone network design, and omitted several technical and realistic details about drone operation such as dispatch time, busy time, and drone acceleration/deceleration. Moreover, the model used did not consider the need to have multiple drones per base, tacitly assuming that no OHCAs occur when a drone is busy. Our sensitivity analysis showed that the drone busy time is an important operational parameter that heavily influences the number of drones per base.

Limitations

Our modeling approach includes both the determination of drone base locations and the number of drones per base. The latter depends on the estimated incidence of cardiac arrests in each base's catchment area; bases located in high call volume areas will be busier and require more drones. Our parameter choices are meant to induce a more conservative solution, so our drone network size is generally an overestimate. We applied daytime OHCA occurrence rates to determine the number of drones required at each base, which will overestimate the numbers of drones needed because OHCAs occur less frequently at night.[29] We used current drone specifications rather than projecting future advances in speed and acceleration, which are progressing rapidly. One factor that may contribute to an underestimation of required drone resources is that we used 911 responder-assessed OHCA for our analysis; we did not have access to all 911 calls that were identified to be potential cardiac arrests at the time of dispatch but were unconfirmed on arrival of the 911 response team, for which a drone would have also been dispatched. In contrast, we used both treated and untreated arrests to test the effectiveness of the drone networks, which may contribute to an overestimation in the required drone resources because in practice, a small fraction of cases may be ruled out for drone deployment. Lastly, response time data was missing for 7.8% of the cases and access time was missing for 49% of cases (see Supplemental Table 3). Access time is hand recorded or estimated by 911 responders and as such, is often left blank or difficult to validate. However, given that we only use this data to determine the median access time, the impact of the missing data is likely small.

Implementation factors

Our sensitivity analysis focused on the drone busy time (Figure 1). The two components of the overall busy time that are the largest and most uncertain are the reset time and on-scene time. The reset time is associated with uncertainty because it depends on how the drone system is operationalized, along with technological impacts such as battery and AED swap-out/recharge, and drone maintenance. The possibilities range from automated status checks and battery swaps to manual inspection by base staff.[33-35] Scene time is also uncertain, since the drone could be sent home as soon as the AED is dropped off, or only after the 911 responders arrive, or only when the 911 responders depart the scene, depending on how drone operations would be integrated with standard 911 response procedures.

Vertical delays for OHCAs in high-rise buildings are an important factor for determining AED availability.[36] As shown in Table 1, “Access time” adds an additional three-minute delay to patient contact after the 911 responders have arrived at the scene (i.e., wheels stop). To account for this delay, our tacit modelling assumption is that the drone will suffer a similar delay to patient contact as the 911 responders. For instance, for the AED to be applied in most cases there must be two bystanders on scene; one to call 911 and stay with the patient doing CPR, and another to retrieve and apply the AED. In this scenario, we assume the bystander can provide building access and therefore, the time delay to patient contact should be essentially the same between the 911 responder and the bystander. Given the assumption that access time is equal for drones and 911 responders, comparing response time is analogous to comparing patient arrival time. However, for cases where the drone is able to land directly on the balcony, access delays can be mitigated and as a result, our assumption of equal access delay may be conservative. In either case, it is important to note that for both drones and 911 responders, there may be additional access delays that increase the time to AED application

Many regulatory and technical challenges must be addressed before drone-delivered AED systems can be realized. Drones would require permission to fly beyond operator line-of-sight, which is currently permitted in some countries (e.g., Canada) but not others (e.g., United States). It is expected that over time, as drone applications become more widespread and the technology is advanced, such restrictions will be loosened. Inclement weather may adversely impact drone operation. Drone navigation will need to avoid no fly zones (e.g., airports) and negotiate around high-rise buildings. A vigorous public awareness campaign will need to accompany any implementation to ease apprehension and discourage mischievous behavior towards the drones. Most importantly, drones will need to be integrated with the 911 response and such integration will be critical in determining the network scope. Our secondary analysis, which highlights the efficiency-equity trade-off, is a first step towards exploring this issue.

Conclusions

In summary, strategically locating and using drones has the potential to substantially reduce the time to defibrillator arrival at the scene of a cardiac arrest. Drone-delivered AEDs represent a logical progression for both drone applications and technology-enabled emergency response. An integrated drone network can achieve the same overall performance as eight independent regional networks but with substantially fewer resources. Cost-effectiveness of an eventual drone network should be evaluated and weighed against the potential benefits outlined in this paper.

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Disclosures

None.

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Table 1. Summary statistics for the eight regions comprising RescuNET.

Characteristics		Region								
		Toronto	Durham	Simcoe	Muskoka	Peel	Hamilton*	Halton*	York*	All
Population (2011)		2,615,060	608,124	446,063	100,209	1,296,814	519,949	501,669	1,032,524	7,120,412
Population density (per square km, 2011)		4149.5	241.0	91.8	7.6	1040.0	465.4	520.4	585.9	270.1
Average annual number of cardiac arrests		2977	570	440	73	848	618	355	666	746
Female sex (%)		38.3	36.2	34.4	29.3	37.7	36.1	36.6	38.9	37.4
Average age (yr.)		68.4	65.1	64.9	66.5	65.6	66.0	67.2	68.9	67.2
Dispatch time (mm:ss)	Median	1:34	0:39	1:00	0:20	0:45	1:00	0:51	0:32	1:00
	90th percentile	2:57	1:09	1:48	1:00	1:30	2:00	1:41	1:44	2:29
Response time (mm:ss)	Median	6:12	5:33	7:00	8:00	5:41	6:00	6:00	6:44	6:00
	90th percentile	10:39	9:07	14:00	19:35	8:22	11:00	10:00	10:38	10:35
Access time† (mm:ss)	Median	3:18	3:02	2:45	2:51	2:47	3:00	3:02	2:33	3:02
	90th percentile	7:24	6:28	6:00	7:33	6:28	6:36	6:20	5:34	6:55
Public location (%)		9.6	8.2	10.8	16.1	11.7	7.5	11.1	8.9	9.8
Treated (%)		54.5	56.9	59.2	54.0	64.1	57.9	57.0	66.5	57.5
Initial shockable cardiac rhythm* (%)		19.3	25.2	24.4	27.8	22.7	19.3	24.2	20.8	21.2
Survival to hospital discharge* (%)		6.9	10.2	7.7	8.5	8.5	6.0	11.0	8.9	7.8
Number of paramedic, fire, and police stations		158	44	76	32	68	51	41	68	538

†Access time is defined as the time interval from arrival of the 911 responder (i.e., wheels stop) to patient contact.
*Hamilton, Halton, and York reported data for only 8, 7, and 5 years, respectively. Initial shockable cardiac rhythm and survival to discharge include treated OHCAs only. The number of missing data points for each characteristic and region can be found in Supplemental Table 3.

Table 2. Region-specific and integrated drone network characteristics for the three response time improvement goals evaluated using the testing set OHCAs.

		Drone response time improvement goal	Region: Toronto	Durham	Simcoe	Muskoka	Peel	Hamilton	Halton	York	All
Region-specific	Number of bases (number of total drones)	1 min.	3 (6)	3 (6)	5 (6)	3 (3)	2 (4)	1 (2)	3 (4)	3 (6)	23 (37)
		2 min.	6 (12)	5 (7)	11 (12)	5 (5)	4 (8)	1 (2)	3 (4)	5 (7)	40 (57)
		3 min.	13 (26)	14 (16)	20 (20)	6 (6)	10 (11)	5 (7)	5 (5)	8 (9)	81 (100)
	Improvement in median time to AED on scene (mm:ss)	1 min.	1:07	1:00	1:01	1:06	1:11	1:00	1:05	1:05	0:59
		2 min.	2:09	2:10	2:10	2:01	2:01	2:08	2:03	2:04	1:58
		3 min.	3:05	3:00	3:04	3:08	3:02	3:03	3:00	3:09	2:56
	Improvement in 90th percentile time to AED on scene (mm:ss)	1 min.	3:36	0:00	1:30	6:14	1:37	0:05	0:53	0:00	2:45
		2 min.	5:28	3:09	5:43	9:06	2:43	1:57	0:00	3:15	4:47
		3 min.	6:43	4:37	7:47	10:34	4:21	3:24	4:30	4:50	6:05
	Proportion of cases where drone AED arrives prior to 911 (%)	1 min.	69.0	64.2	65.0	76.3	71.7	54.1	64.4	63.9	67.9
		2 min.	87.6	82.1	78.6	79.7	84.7	75.3	73.9	79.5	84.6
		3 min.	96.1	94.6	89.6	84.2	94.6	92.2	92.7	89.2	94.6
Integrated	Number of bases (Total drones)	1 min.	3 (7)	2 (4)	3 (4)	0 (0)	2 (4)	1 (2)	1 (2)	3 (5)	15 (28)
		2 min.	6 (12)	4 (6)	7 (7)	1 (1)	4 (7)	2 (4)	4 (6)	6 (8)	34 (51)
		3 min.	13 (26)	5 (7)	7 (7)	0 (0)	8 (10)	4 (7)	5 (5)	7 (8)	49 (70)
	Improvement in median time to AED on scene (mm:ss)	1 min.	1:41	0:32	1:21	0:00	0:57	1:34	0:13	1:08	1:10
		2 min.	2:37	1:47	3:34	0:00	1:32	2:11	2:11	2:12	2:12
		3 min.	3:35	2:48	3:43	0:00	2:34	3:09	2:57	3:25	3:09
	Improvement in 90th percentile time to AED on scene (mm:ss)	1 min.	4:39	0:00	0:00	0:00	1:30	1:49	0:00	0:00	3:28
		2 min.	5:36	2:28	3:31	0:00	2:43	3:54	3:37	4:09	4:59
		3 min.	7:05	0:00	0:14	0:00	4:04	5:09	4:45	1:18	6:24
	Proportion of cases where drone AED arrives prior to 911 (%)	1 min.	79.5	53.1	59.1	0.0	68.4	68.9	48.1	61.3	70.2
		2 min.	90.6	78.7	86.8	32.9	79.4	79.1	85.5	82.1	85.6
		3 min.	97.9	85.3	79.8	0.0	92.4	93.5	92.7	81.3	92.3

Table 3. Summary of the sensitivity analysis.

	Change in busy time	**Drone response time improvement goal**	**Region**								
			Toronto	Durham	Simcoe	Muskoka	Peel	Hamilton	Halton	York	All
Region-specific	-30 minutes	1 min.	6	3	5	3	2	2	3	3	27
		2 min.	10	5	11	5	4	2	3	5	45
		3 min.	14	14	20	6	10	5	5	8	82
	-15 minutes	1 min.	6	5	5	3	4	2	4	5	34
		2 min.	12	6	11	5	7	2	3	6	52
		3 min.	20	15	20	6	10	6	5	8	90
	0 minutes	1 min.	6	6	6	3	4	2	4	6	37
		2 min.	12	7	12	5	8	2	4	7	57
		3 min.	26	16	20	6	11	7	5	9	100
	+15 minutes	1 min.	7	6	6	3	4	2	4	6	38
		2 min.	12	7	13	5	8	2	5	8	60
		3 min.	26	16	21	6	13	8	6	12	108
	+30 minutes	1 min.	9	6	6	3	4	2	4	6	40
		2 min.	13	7	13	5	8	2	5	8	61
		3 min.	26	17	22	6	18	8	8	12	117
Integrated	-30 minutes	1 min.	6	2	3	0	4	2	1	4	22
		2 min.	11	4	7	1	4	2	4	6	39
		3 min.	16	5	7	0	8	4	5	7	52
	-15 minutes	1 min.	6	4	3	0	4	2	2	5	26
		2 min.	12	5	7	1	7	4	4	7	47
		3 min.	26	6	7	0	9	5	5	7	65
	0 minutes	1 min.	7	4	4	0	4	2	2	5	28
		2 min.	12	6	7	1	7	4	6	8	51
		3 min.	26	7	7	0	10	7	5	8	70
	+15 minutes	1 min.	8	4	4	0	4	2	2	6	30
		2 min.	13	6	8	1	7	4	6	9	54
		3 min.	26	8	8	0	14	7	6	9	78
	+30 minutes	1 min.	8	4	4	0	4	2	2	6	30
		2 min.	13	6	8	1	7	4	6	9	54
		3 min.	26	9	8	0	16	7	8	11	85

The numbers represent the total number of drones required for each improvement goal and reset time pair. The number of drone bases is unaffected by the busy time and is omitted for clarity (See Table 2 for results on drone bases). Note that the “0 minutes” case corresponds to the results in Table 2.

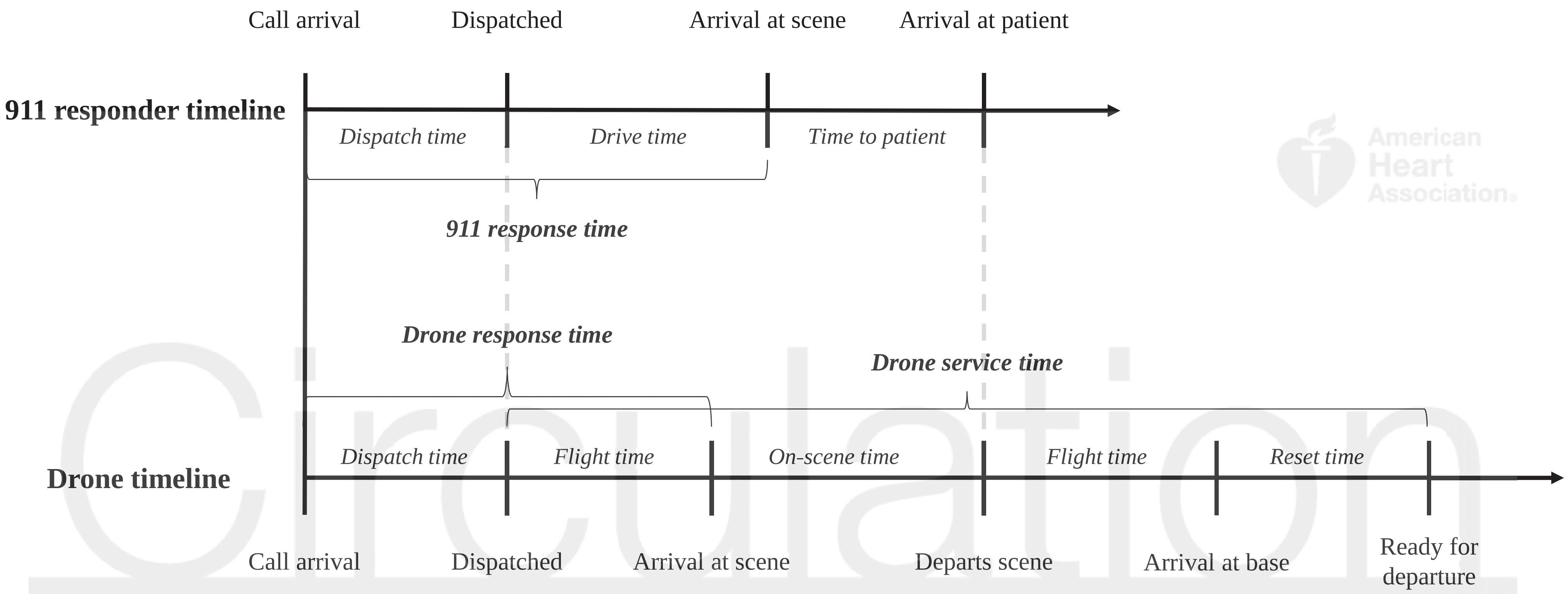
Figure Legends

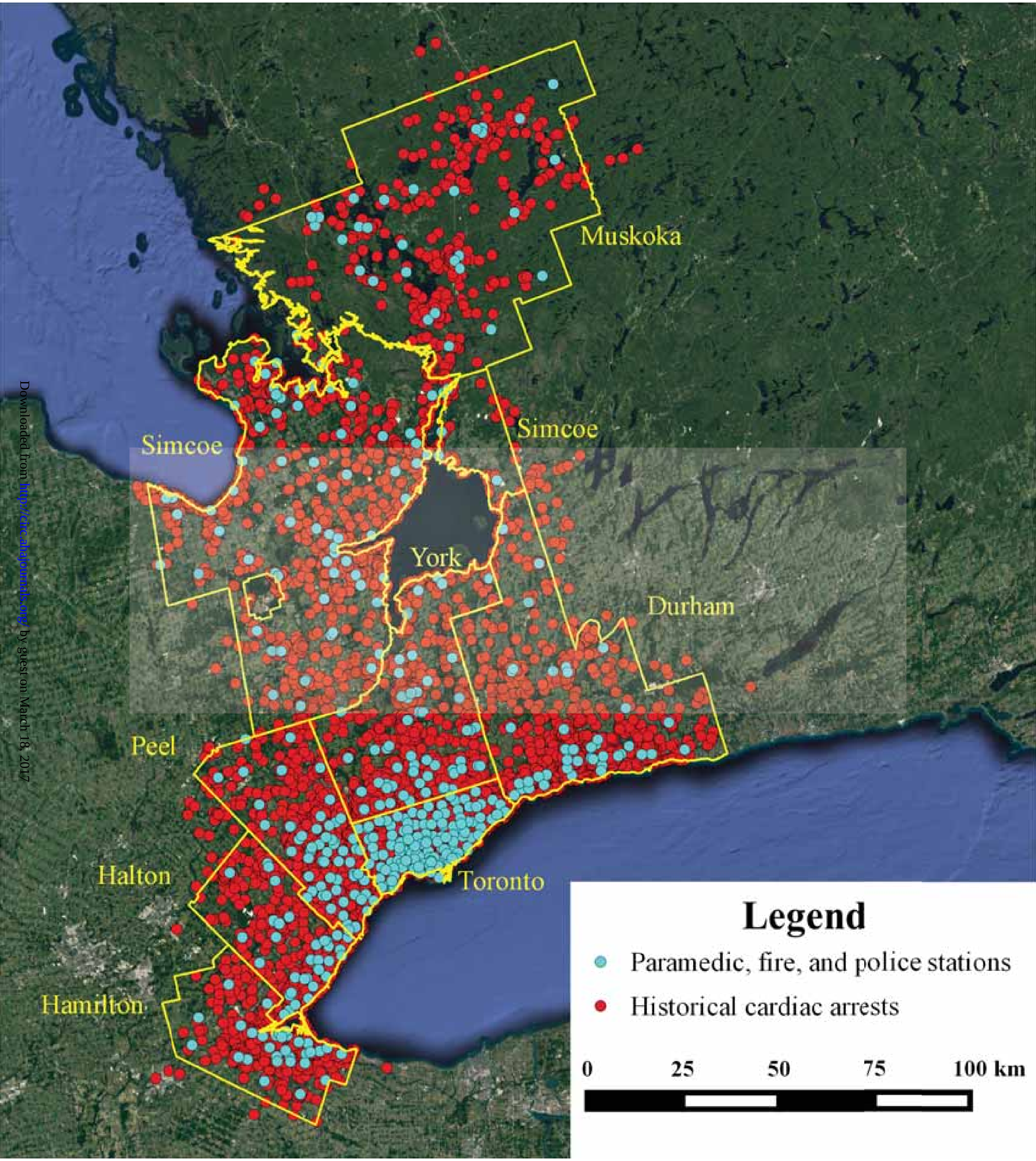
Figure 1. 911 first responder and drone timelines. The on-scene time will be zero if 911 responders arrive prior to the drone. The drone may or may not arrive at the patient during the on-scene time interval, and this time point is not shown because it is not used in any calculations.

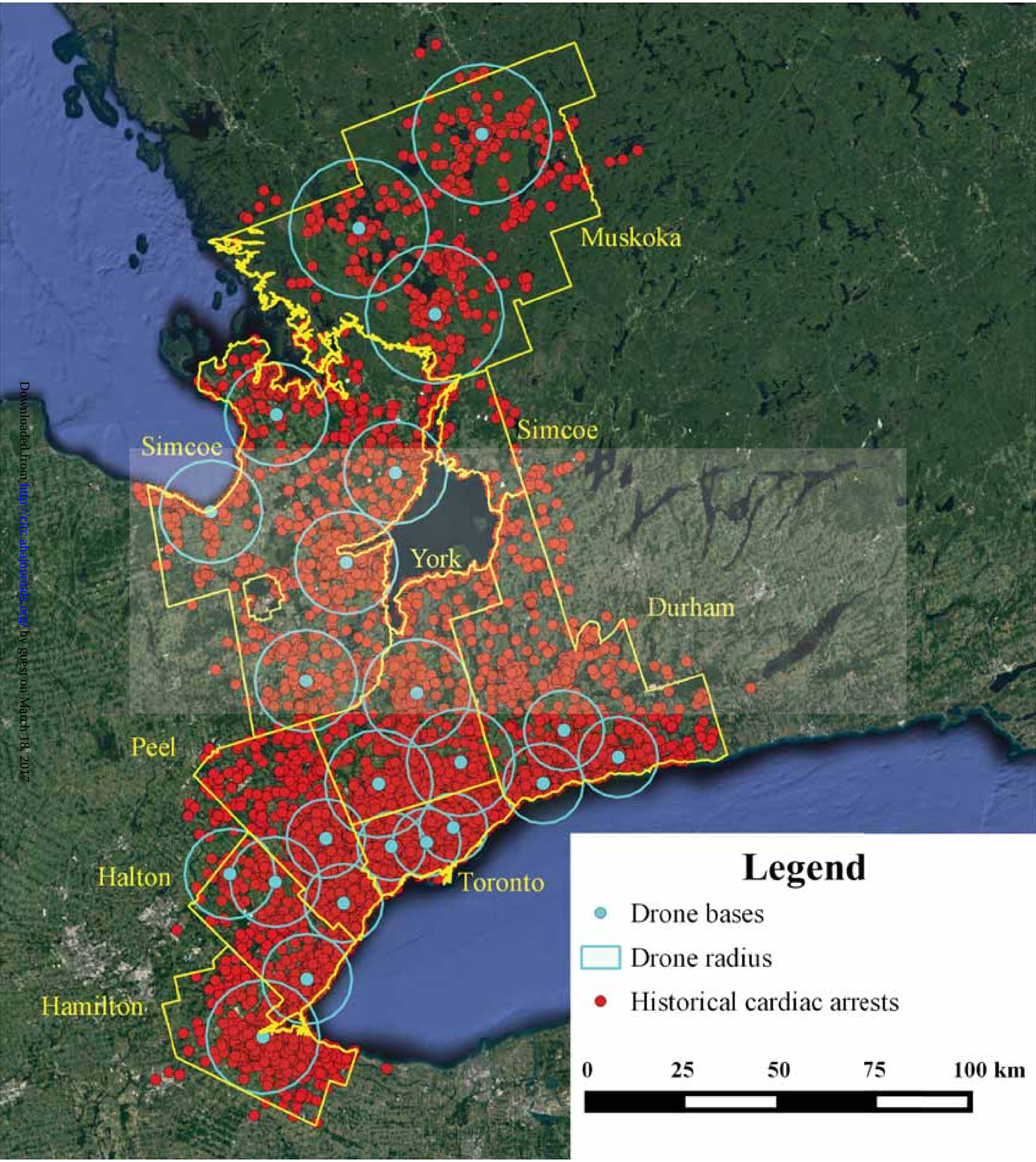
Figure 2. Historical OHCAs and paramedic, fire, and police station locations.

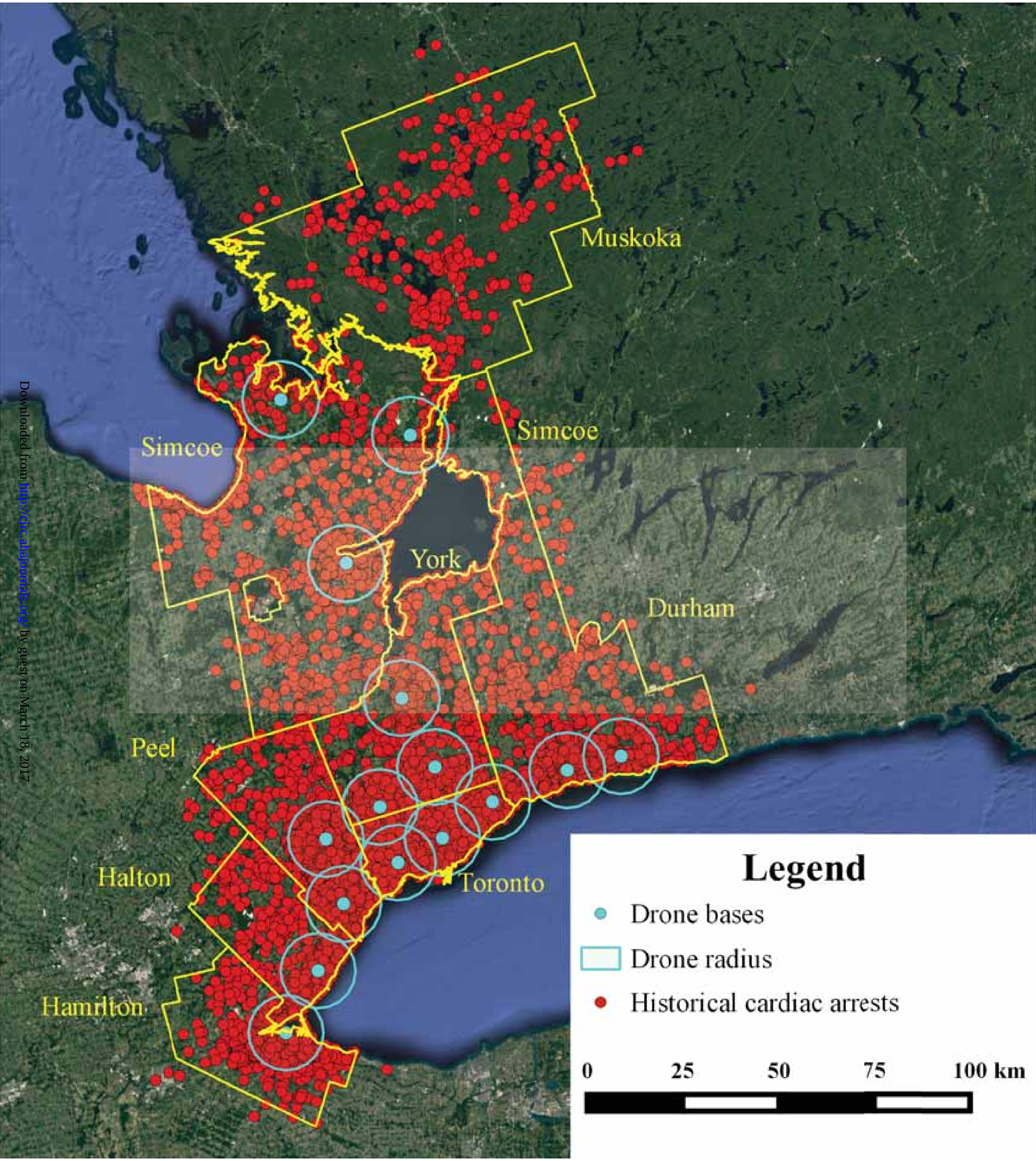
Figure 3. Geographic layout of the (a) region-specific and (b) integrated drone networks for the one-minute improvement goal. Radius of circle represents the maximum distance or available flying time of the drone in order to improve the median 911 response time by one minute in each region, taking into account region-specific dispatch and response times.

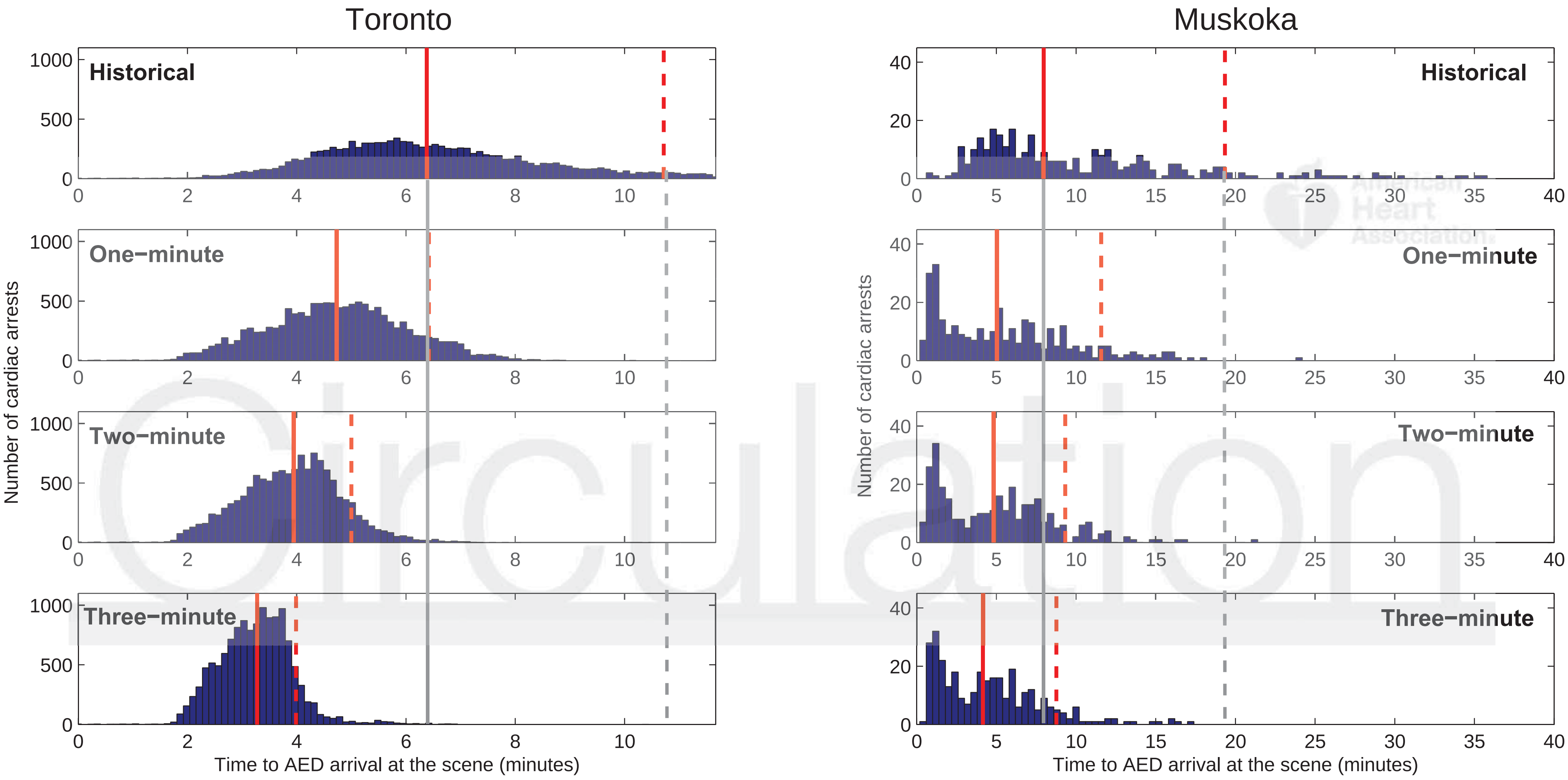
Figure 4. The first row, labelled “Historical”, shows the distribution of historical 911 response times in Toronto (the most urban region in the Toronto RescuNET) and Muskoka (the most rural region in the Toronto RescuNET). The second row, labelled “One-minute”, shows the estimated response time distribution corresponding to the drone network configuration designed to improve the historical median response time by one minute. The third and fourth rows show the response time distributions corresponding to the drone network configurations designed to improve the historical median response by two and three minutes, respectively. The solid line is the median of the distribution and the dashed line is the 90th percentile. The historical distribution is extended in grey across all three distributions as a reference.


Call arrival
Dispatched
Arrival at scene
Arrival at patient
911 responder timeline
Dispatch time
Drive time
Time to patient
911 response time
Drone response time
Drone service time
Dispatch time
Flight time
On-scene time
Flight time
Reset time
Drone timeline
Call arrival
Dispatched
Arrival at scene
Departs scene
Arrival at base
Ready for departure


Muskoka
Simcoe
Simcoe
York
Durham
Peel
Halton
Toronto
Hamilton
Legend
Paramedic, fire, and police stations
Historical cardiac arrests
0
25
50
75
100 km


Muskoka
Simcoe
Simcoe
York
Durham
Peel
Halton
Toronto
Hamilton
Legend
Drone bases
Drone radius
Historical cardiac arrests
0
25
50
75
100 km


Muskoka
Simcoe
Simcoe
York
Durham
Peel
Halton
Toronto
Hamilton
Legend
Drone bases
Drone radius
Historical cardiac arrests
0
25
50
75
100 km


Toronto
Muskoka
Historical
One−minute
Two−minute
Three−minute
Number of cardiac arrests
Time to AED arrival at the scene (minutes)

Circulation

Optimizing a Drone Network to Deliver Automated External Defibrillators

Justin J. Boutilier, Steven C. Brooks, Alyf Janmohamed, Adam Byers, Jason E. Buick, Cathy Zhan,
Angela P. Schoellig, Sheldon Cheskes, Laurie J. Morrison and Timothy C. Y. Chan
on behalf of the Rescu Epistry Investigators

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SUPPLEMENTAL MATERIAL

Optimizing a drone network to deliver automated external defibrillators

Table of Contents

Supplemental Methods

Geocoding Procedure

The location of each OHCA episode was provided as either an address or a latitude/longitude pair. For all entries without latitude/longitude information, geocoding was used to convert the recorded addresses into latitude and longitude coordinates. We used Geocoder.ca, Google Maps API, and manual methods for our conversions. To verify the geocoding accuracy, all OHCAs were geographically plotted by region and manually inspected. Figure S1 summarizes our geocoding procedure. All ambulance, fire, and police stations were provided as addresses and manually converted to a latitude/longitude pair. Finally, all latitudes and longitudes were analytically converted to Universal Transverse Mercator (UTM) coordinates for input to the optimization model. Figure 2 in the main text shows the locations of all geocoded OHCAs, ambulance stations, fire stations, and police stations.

Optimization Model

The mathematical model we use to determine the number and location of drone bases is outlined below.

Overview

To begin our optimization process, the user selects a threshold value for improvement over the historical median 911 response time. In particular, we consider three different threshold values for improvement (one, two, and three minutes). We then use an iterative process to determine values for f and t that yield a drone network configuration that exceeds the chosen threshold. In each iteration, we solve the model outlined below with fixed f and t (and therefore fixed R and a_{ij}).

Model parameters

- f is a parameter that indicates the percentage of covered cardiac arrests.
- t is a parameter that indicates the maximum drone flying time.
- The coverage radius is given by $R = (t\text{-}d\text{-}10)*27.8$, for $t\text{-}d > 10$ seconds, where d represents the average dispatch time. Recall that accounting for maximum speed and height, 10 seconds are required for takeoff and landing.
- a_{ij} is a binary data parameter that indicates whether OHCA j can be covered by location i. To determine a_{ij}, we first compute the distance (in meters) between each OHCA and each ambulance, fire, and police station. If the distance is less than or equal to R, then $a_{ij} = 1$, else $a_{ij} = 0$.
- I is the number of ambulance, fire, and police stations (i.e., candidate drone bases).
- J is the number of OHCAs in the training set.

Decision variables

- z_{ij} is a binary variable indicating whether OHCA j is covered by a drone base at location i.
- y_i is a binary variable indicating whether a drone base is stationed at location i.

$$
\begin{aligned}
\text{Minimize}\quad & \textstyle\sum_{i=1}^{I} y_i \\
\text{Subject to}\quad & \textstyle\sum_{i=1}^{I} z_{ij} \leq 1, \forall\, j = 1, \dots, J, \\
& \textstyle\sum_{i=1}^{I} \sum_{j=1}^{J} z_{ij} \geq \left(\frac{f}{100}\right) \times J\,, \\
& z_{ij} \leq a_{ij} y_i, \forall j = 1, \dots, J, i = 1, \dots, I, \\
& z_{ij} \epsilon \{0,1\}, \forall\, j = 1, \dots, J, i = 1, \dots, I, \\
& y_i \epsilon \{0,1\}, \forall\, i = 1, \dots, I.
\end{aligned}
$$

The objective function minimizes the total number of drone bases. The first constraint ensures that each OHCA is assigned to at most one drone base to avoid double-counting, while the second constraint ensures that f% of all OHCAs are reached within a maximum time of t minutes. The third constraint ensures that OHCA j can be covered by a drone base i only if a base is opened at location i and that base is able to cover OHCA j (i.e., $a_{ij} = 1$). The fourth and fifth constraints force the decision variables to be binary. The input cardiac arrest data for this model is the training set of OHCAs.

Queuing Model

The mathematical model we use to determine the number of drones stationed at each base is outlined below.

Each selected drone base (i.e., each i such that $y_i = 1$) has a catchment area defined by its radius at the macro level, but more precisely by the cardiac arrests the base is assigned to cover (i.e., those j such that $z_{ij} = 1$).

For each catchment area we assume that a Poisson process with an OHCA arrival rate of λ_i governs the occurrences of OHCAs. To determine λ_i, we first find the number of daytime (8:00AM to 7:59PM) training set OHCAs occurring in catchment area i. Next, we determine the duration, in months, over which these OHCAs occurred. Finally, we multiply the number of daytime training set OHCAs by two and divide by the duration over which they occurred. Table S1 shows the average OHCA arrival rate for each region.

For each region, we assume that the "busy" time is an exponentially distributed random variable with rate parameter μ. The busy time comprises the outbound travel time, on-scene time, inbound travel time, and "reset" time. We compute the mean busy time $1/\mu$ for each region and for each problem instance (i.e, each (t, f) pair).

Given the optimal drone base locations, as determined by the optimization model with user inputs t and f, we first determine the outbound and inbound travel time, which we assume to be equal. For each OHCA in the training set, we determine the straight line distance to the closest drone base and we use the assumed drone flying speed of 27.8m/s (plus 10 seconds for acceleration/deceleration and cruising altitude assumptions) to compute the travel time.

The on-scene time, referring to the interval from drone landing to paramedic arrival at patient side, was computed using historical data. To determine the on-scene time, we first compute the drone response time, defined as the time interval from call arrival to drone landing. Next, we determine the historical 911 time-to-patient side, defined as the time interval from call arrival to arrival at patient side. We then compute the difference to determine the on-scene time. If the difference is negative (i.e., 911 arrives before the drone), the on-scene time is assumed to be zero because the drone would turn around mid-flight. Table S1 shows the average scene time for each region, along with the average flight time, on-scene time, and assumed 30 minute reset time.

To model system congestion, we consider each drone base as a multi-server queue with m servers. Given Poisson arrivals and exponentially distributed busy times, we can represent the queuing system as a continuous-time Markov Chain (CTMC). Let S={0,1,2…} denote the state space, where the state number refers to the number of calls in the system. Let $\rho = \frac{\lambda}{m\mu} < 1$ and let π^k denote the steady-state amount of time spent in state k, which we determined from solving the well-known, steady-state equations (Kleinrock 1975):

$$\pi_0 = \left[\sum_{k=0}^{m-1} \frac{(mp)^k}{k!} + \frac{(mp)^m}{m!} * \frac{1}{1-p}\right]^{-1}$$

$$\pi_k = \begin{cases} \dfrac{m^k p^k \pi_0}{i!}, k = 1,2, \dots, m-1 \\ \dfrac{m^m p^k \pi_0}{m!}, k = m, m+1, \dots \end{cases}$$

To determine the number of drones (i.e., *m*), we use an iterative process that increases *m* until the probability that at least one drone is available when an OHCA occurs is greater than 0.99. More specifically, we increase *m* until $\pi_0 + \sum_{k=1}^{m-1} \pi_k \geq 0.99$. We repeat this process for each catchment area.

Experimental Setup

For each region, the OHCA data was split into two disjoint sets: a training set and a testing set. The training set was used as the input into our optimization model to determine the number and location of bases. The training set was also used as input to the queuing model to determine the arrival rate and busy times, which result in the required number of drones per base. The disjoint testing set was used to evaluate the performance of the resulting drone networks. In particular, we use the testing set OHCAs to compute the improvement in time to AED metrics, drone response time distributions, and the proportion of cases where the drone AED arrived prior to 911 responders.

Supplemental Tables

Supplemental Table 1. Summary of drone busy time and its components.

		Drone response time improvement goal	Region								
			Toronto	Durham	Simcoe	Muskoka	Peel	Hamilton	Halton	York	All
Region-specific	Flight time (minutes)	1 min.	7.37	11.17	11.19	12.12	7.61	9.99	8.93	10.36	9.84
		2 min.	5.06	7.59	8.05	10.92	5.96	7.28	7.79	7.85	7.56
		3 min.	3.45	4.63	5.86	8.87	3.99	4.02	4.87	5.91	5.20
	On-scene time (minutes)	1 min.	5.27	4.52	5.27	7.70	5.12	4.71	5.02	5.07	5.33
		2 min.	6.35	5.76	6.56	8.15	5.89	5.90	5.59	5.90	6.26
		3 min.	7.15	6.85	7.60	9.03	6.85	7.48	6.93	6.85	7.34
	Reset time (minutes)	1 min.	30	30	30	30	30	30	30	30	30
		2 min.	30	30	30	30	30	30	30	30	30
		3 min.	30	30	30	30	30	30	30	30	30
	Drone busy time (minutes)	1 min.	42.64	45.68	46.46	49.81	42.72	44.71	43.95	45.43	45.18
		2 min.	41.42	43.34	44.60	49.07	41.86	43.18	43.38	43.75	43.83
		3 min.	40.60	41.48	43.46	47.91	40.84	41.50	41.79	42.77	42.54
Integrated	Flight time (minutes)	1 min.	7.24	11.14	16.33	63.74	7.53	8.19	11.95	9.88	17.00
		2 min.	5.38	7.17	7.21	32.75	6.01	5.81	5.86	6.71	9.61
		3 min.	3.54	7.34	9.15	67.77	4.39	4.11	4.49	5.79	13.32
	On-scene time (minutes)	1 min.	5.85	4.11	4.62	0.39	4.91	5.46	3.93	4.82	4.26
		2 min.	6.76	5.45	7.05	2.62	5.58	6.59	6.29	5.99	5.79
		3 min.	7.67	5.80	6.53	0.32	6.42	7.44	6.97	6.56	5.96
	Reset time (minutes)	1 min.	30	30	30	30	30	30	30	30	30
		2 min.	30	30	30	30	30	30	30	30	30
		3 min.	30	30	30	30	30	30	30	30	30
	Drone busy time (minutes)	1 min.	43.09	45.25	50.95	94.13	42.44	43.65	45.87	44.71	51.26
		2 min.	42.14	42.62	44.25	65.37	41.59	42.40	42.15	42.70	45.40
		3 min.	41.21	43.13	45.68	98.09	40.81	41.54	41.46	42.34	49.28

The “All" column represents all of RescuNet (i.e., all eight regions combined). The flight time comprises both the outbound and inbound times. The drone busy time is the summation of flight time, on-scene time, and reset time.

Supplemental Table 2. The annual number of OHCAs and annual median time intervals for various 911 response time metrics.

	Year	Region								
		Toronto	Durham	Simcoe	Muskoka	Peel	Hamilton	Halton	York	All
Number of OHCAs	2006	2237	500	334	66	124	474	-	-	3735
	2007	2769	516	395	74	704	501	-	-	4959
	2008	2975	561	325	65	847	502	234	-	5509
	2009	2997	536	366	88	920	551	337	-	5795
	2010	3030	569	460	59	936	606	339	608	6607
	2011	2924	588	493	79	970	381	366	600	6401
	2012	3121	591	539	84	989	464	408	640	6836
	2013	3375	624	525	71	1029	226	391	705	6946
	2014	3365	647	526	73	1114	-	412	777	6914
	All	26793	5132	3963	659	7633	3705	2487	3330	53702
Dispatch time (i.e., the interval from call arrival at 911 to asset mobilization)	2006	1:26	0:45	0:58	0:17	1:00	1:00	-	-	1:04
	2007	1:35	0:32	0:45	0:24	1:00	1:00	-	-	1:11
	2008	1:37	0:31	1:00	0:22	1:00	1:00	1:00	-	1:07
	2009	1:39	0:34	1:00	0:24	0:49	1:00	1:00	-	1:05
	2010	1:37	0:35	1:00	0:22	0:47	1:00	1:00	0	1:00
	2011	1:36	1:00	1:00	0:20	0:47	1:00	1:00	1:00	1:00
	2012	1:30	1:00	1:00	0:19	0:42	1:00	0:42	0:33	1:00
	2013	1:31	1:00	1:00	0:12	0:43	1:00	0:39	0:31	1:00
	2014	1:34	1:00	1:00	0:19	0:21	-	0:37	0:31	1:00
	All	1:34	0:39	1:00	0:20	0:45	1:00	0:51	0:32	1:00
Response time (i.e., the interval from call arrival at 911 to arrival at the scene)	2006	5:44	5:18	7:33	9:48	5:50	6:00	-	-	5:55
	2007	5:59	5:11	7:18	7:29	5:46	6:00	-	-	6:00
	2008	6:03	5:30	7:00	7:29	6:00	6:00	6:00	-	6:00
	2009	6:05	5:33	7:00	8:37	5:46	6:00	6:00	-	6:00
	2010	6:27	5:29	7:00	8:09	5:44	5:30	6:00	7:00	6:02
	2011	6:28	6:00	8:00	7:51	5:34	6:00	6:09	7:00	6:04
	2012	6:21	5:34	7:00	9:57	5:41	6:00	6:00	6:35	6:04
	2013	6:17	5:50	7:00	7:23	5:44	6:00	5:49	6:32	6:04
	2014	6:24	6:00	7:00	7:00	5:16	-	6:21	6:35	6:08
	All	6:12	5:33	7:00	8:00	5:41	6:00	6:00	6:44	6:00
Patient time (i.e., the interval from call arrival at 911 to arrival at the patient	2006	10:01	8:40	10:29	14:49	10:09	8:52	-	-	9:49
	2007	9:57	9:07	10:33	10:01	9:22	9:00	-	-	9:44
	2008	9:40	9:13	11:00	9:56	9:24	10:00	10:31	-	9:49
	2009	9:40	8:38	9:40	13:05	8:52	11:00	10:29	-	9:39
	2010	9:53	8:50	10:12	11:59	8:57	9:00	10:11	10:21	9:40
	2011	9:28	9:13	10:47	14:12	8:37	10:00	10:05	9:59	9:28
	2012	9:13	9:06	10:21	13:42	8:30	10:00	9:12	9:35	9:12
	2013	9:03	9:00	10:46	11:20	8:29	10:00	8:53	9:15	9:02
	2014	9:02	8:15	10:20	10:53	8:08	-	8:56	9:09	8:54
	All	9:31	8:59	10:30	11:51	8:48	10:00	9:40	9:35	9:25

Note that for certain time frames and regions response time data was only available in minutes (e.g., Hamilton dispatch time).

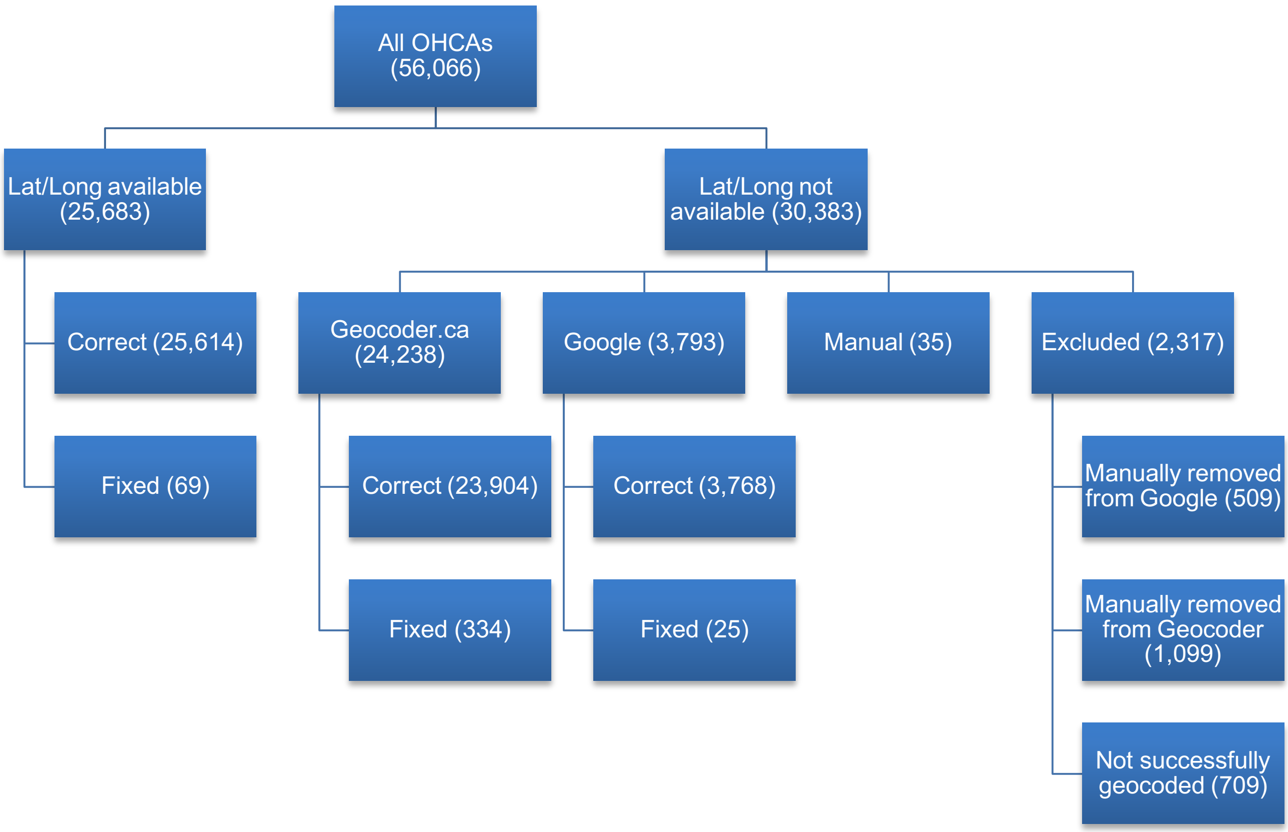
Supplemental Table 3. The number of missing data points for each characteristic and region.

Characteristics (n=53702)		Region								
		Toronto	Durham	Simcoe	Muskoka	Peel	Hamilton*	Halton*	York*	All
Female sex		78	7	6	0	26	15	0	14	146 (0.3%)
Average age		6	5	0	0	4	1	0	0	16 (0.03%)
Dispatch time	Median	191	57	418	5	20	885	67	275	1918 (3.6%)
	90th percentile	191	57	418	5	20	885	67	275	1918 (3.6%)
Response time	Median	393	123	1086	16	78	1165	274	1069	4204 (7.8%)
	90th percentile	393	123	1086	16	78	1165	274	1069	4204 (7.8%)
Access time	Median	13404	2194	2211	284	2747	2223	1295	1968	26326 (49.0%)
	90th percentile	13404	2194	2211	284	2747	2223	1295	1968	26326 (49.0%)
Public location		449	65	55	7	95	1	47	86	805 (1.5%)
Treated		0	0	0	0	0	0	0	0	0 (0%)
Shockable initial heart rhythm		478	69	74	32	98	239	48	83	1121 (2.1%)
Survival to discharge		16	10	34	0	10	37	7	0	114 (0.2%)

*In addition, Hamilton is missing one and a half years of data (2013-2014), Halton is missing 2 full years of data (2006-2007), and York is missing 4 full years of data (2006-2009). This table corresponds to Table 1 in the main body text.

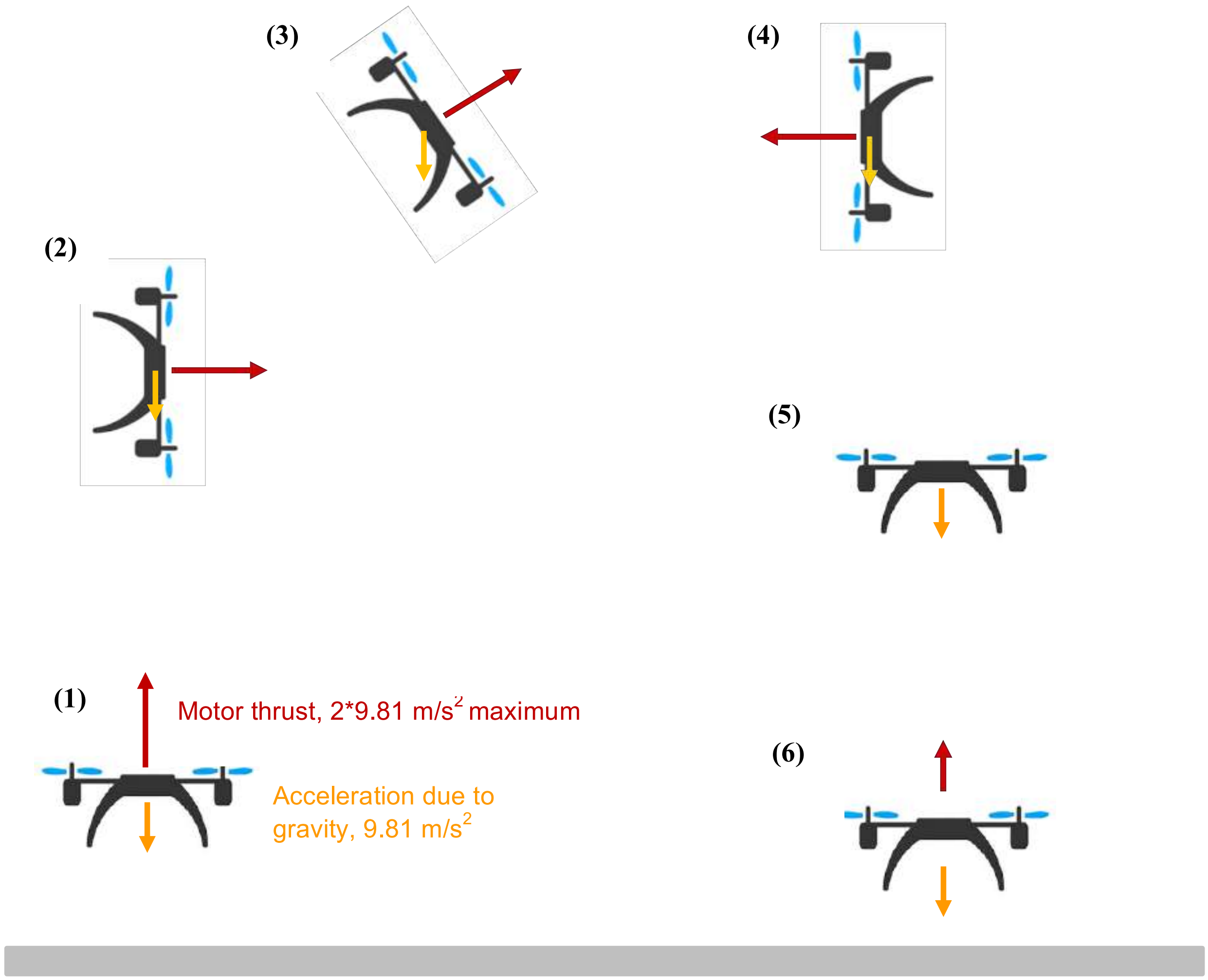
Supplemental Figures

Supplemental Figure 1. Summary of geocoding procedure.

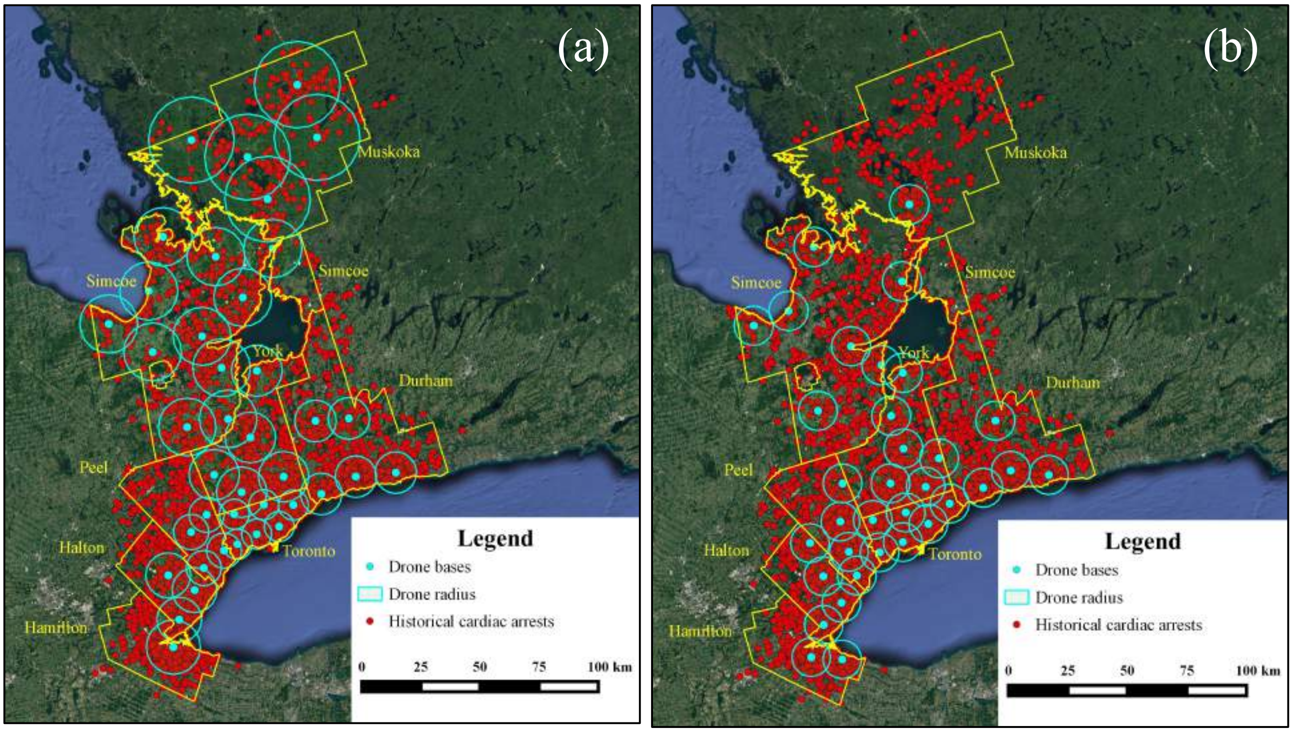


Fixed refers to OHCA locations that were manually checked, found to be incorrect, and changed to the correct location. *Manual* refers to OHCA locations that could not be successfully geocoded by Geocoder.ca or Google API, but whose locations were found manually. OHCA locations were manually removed after geocoding (from Geocoder or Google) if the locations could not be successfully verified or fixed (e.g., geocoded location was in another city or province). OHCA locations were excluded if the locations could not be successfully geocoded (e.g., incomplete or ambiguous address).

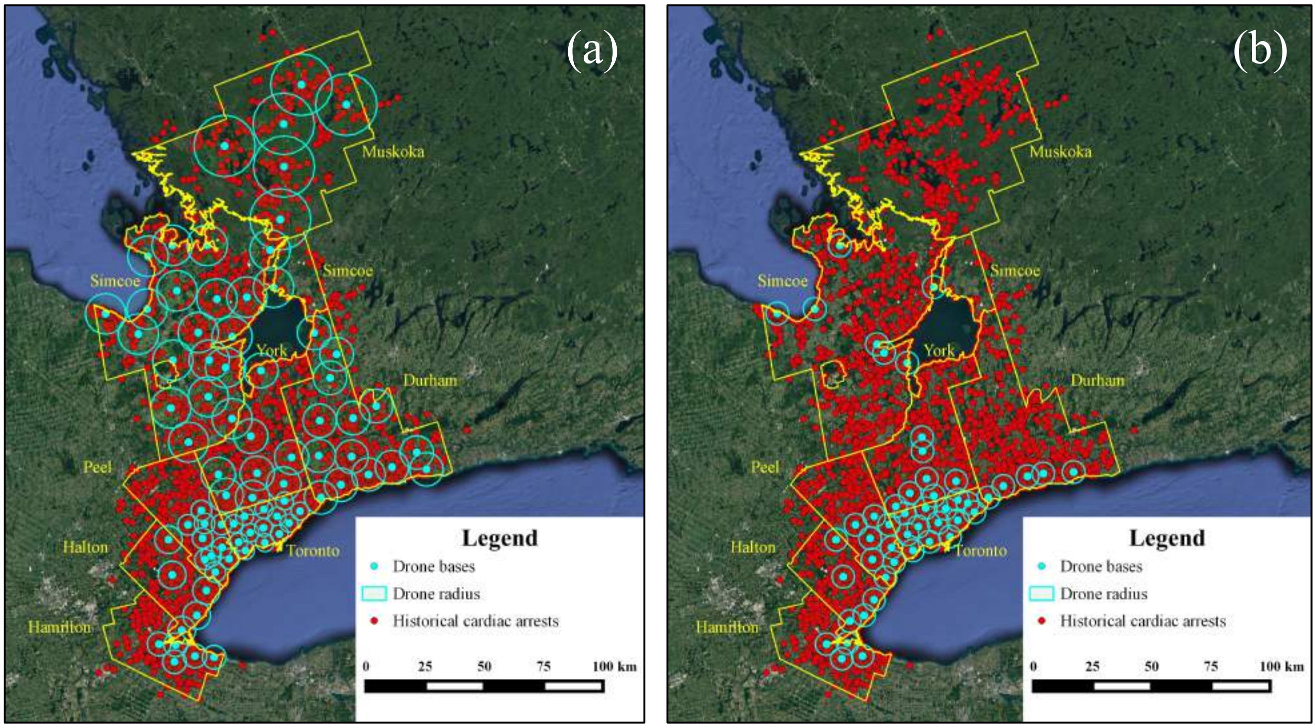
Supplemental Figure 2. A schematic of the drone takeoff and landing phases focusing on acceleration/decelleration. (1) Maximum vertical acceleration. (2) Maximum vertical deceleration and simultaneous maximum horizontal acceleration. (3) Horizontal motion at maximum speed. (4) Maximum horizontal deceleration and simultaneous maximum vertical deceleration. (5) Maximum vertical deceleration. (6) Force balance to safely land.



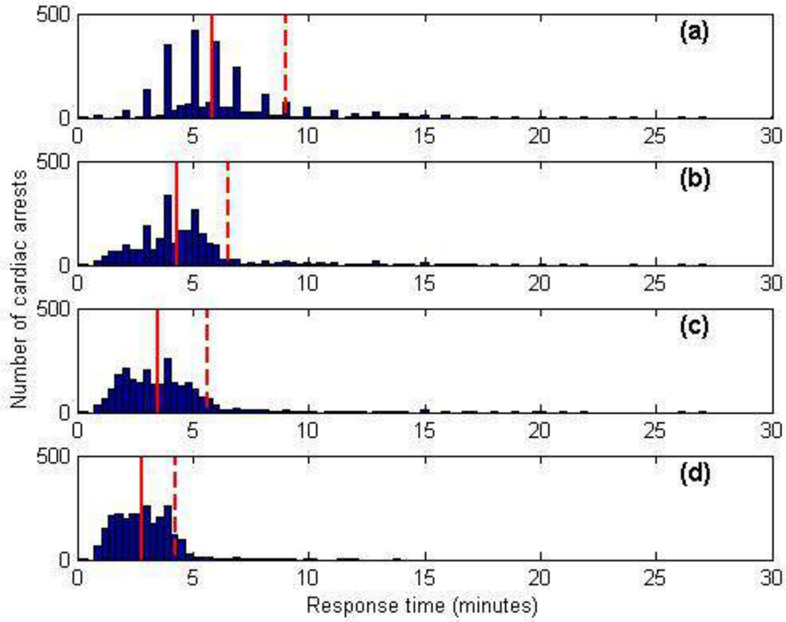
Supplemental Figure 3. Geographic layout of the (a) region-specific and (b) integrated drone networks for the *two-minute response time improvement goal*.



Supplemental Figure 4. Geographic layout of the (a) region-specific and (b) integrated drone networks for the *three-minute response time improvement goal.*

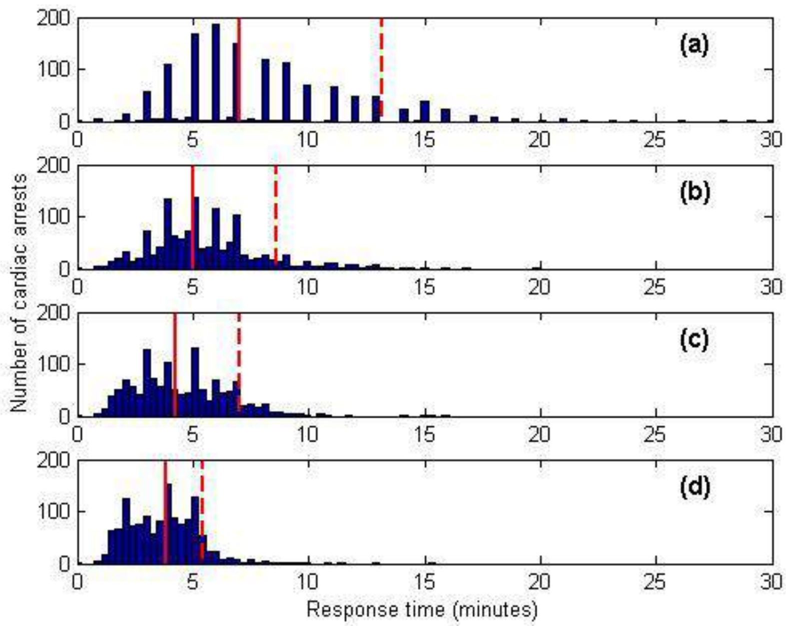


Supplemental Figure 5. Comparison of the historical 911 response time (a) with estimated distribution of response time by combining historical 911 response times with calculated drone response times under the (b) one-minute, (c) two-minute, and (d) three-minute response time improvement goals for Durham.



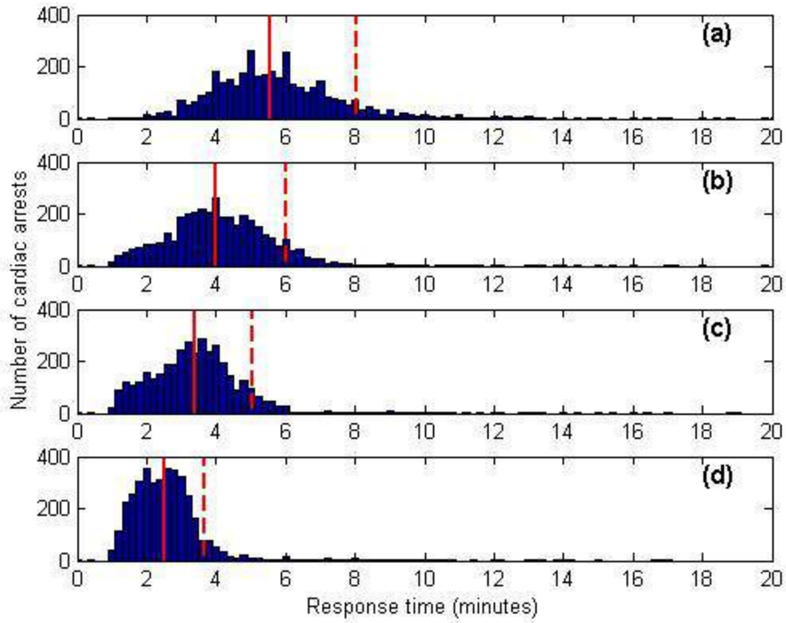
Historical 911 response times in Durham were rounded to the nearest minute up until 2013.

Supplemental Figure 6. Comparison of the historical 911 response time (a) with estimated distribution of response time by combining historical 911 response times with calculated drone response times under the (b) one-minute, (c) two-minute, and (d) three-minute response time improvement goals for Simcoe.

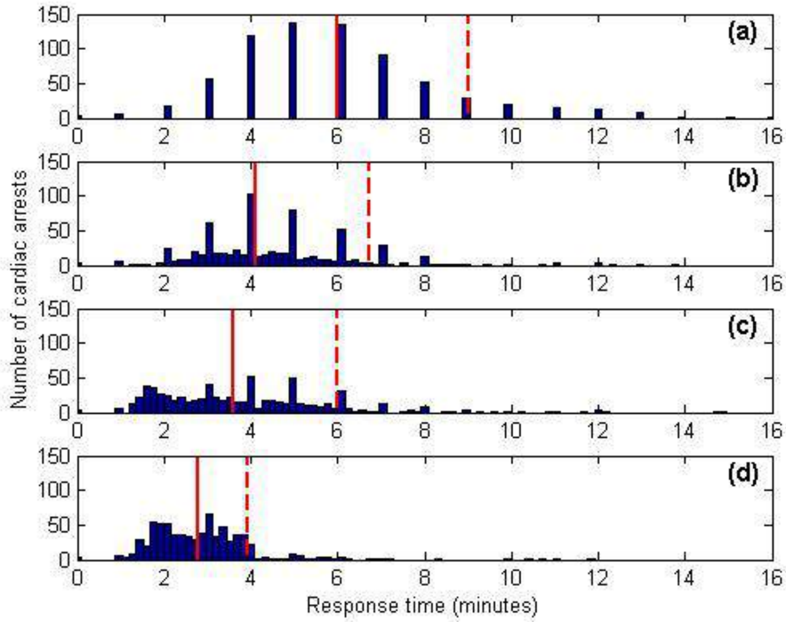


Historical 911 response times in Simcoe were rounded to the nearest minute up until 2013.

Supplemental Figure 7. Comparison of the historical 911 response time (a) with estimated distribution of response time by combining historical 911 response times with calculated drone response times under the (b) one-minute, (c) two-minute, and (d) three-minute response time improvement goals for Peel.

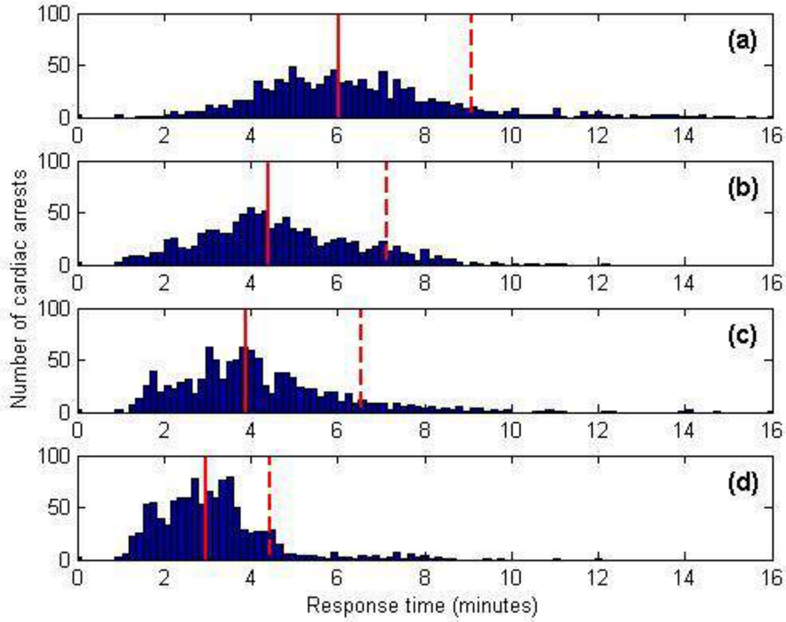


Supplemental Figure 8. Comparison of the historical 911 response time (a) with estimated distribution of response time by combining historical 911 response times with calculated drone response times under the (b) one-minute, (c) two-minute, and (d) three-minute response time improvement goals for Hamilton.



All historical 911 response times in Hamilton were provided to us rounded to the nearest minute.

Supplemental Figure 9. Comparison of the historical 911 response time (a) with estimated distribution of response time by combining historical 911 response times with calculated drone response times under the (b) one-minute, (c) two-minute, and (d) three-minute response time improvement goals for Halton.



Supplemental Figure 10. Comparison of the historical 911 response time (a) with estimated distribution of response time by combining historical 911 response times with calculated drone response times under the (b) one-minute, (c) two-minute, and (d) three-minute response time improvement goals for York.