Minimizing Travel Distance: A Modeling Framework for Homeless Shelter Accessibility in Toronto

1.0 Introduction

Being homeless in Toronto often means more than just lacking a place to sleep; it means constantly moving. As the city expands, the number of people experiencing homelessness on a single night in 2024 is roughly 15,401 people, with shelter spaces being unevenly distributed across the city and most shelters operating at 98–99% occupancy [1][2]. With the current system, there is little flexibility to place people near where they actually are. Even when someone travels to the closest shelter, they often have no certainty that a bed will be available, leading many to move from shelter to shelter just to find a safe place to stay. Consequently, this creates spatial mismatches on where people are and where beds actually exist. Thus, our team aims to approach the problem from both the perspective of people experiencing homelessness and those responsible for their placement, by addressing the question: "How can shelter spaces be allocated to minimize the distance individuals must travel, while accounting for capacity limits, accessibility needs, and geographic imbalances across Toronto?"

2.0 Data

All sources of data used in this study originate from the City of Toronto Open Data Portal and Statistics Canada. From this, two key timeframes of shelter occupancy and capacity data were extracted, the first dataset spanning 2017-2020, and the second spanning 2021-2025. These datasets provide records of nightly occupancy, daily beds and rooms, and overall utilization rates across Toronto's shelter network. Additionally, the monthly shelter system flow dataset was also sourced from the City of Toronto Open Data Portal. Due to data cleanliness, the data that will be used is restricted to sector men and women with location Toronto.

Table 1. Summary of Data Sources and Key Variables

Dataset	Period	Size	Key Variables	Description
Shelter Occupancy and Capacity	2017-2020	156,977 rows	shelter_name, program_name, address, capacity, occupancy, occupancy_rate, date_time, sector	Daily shelter occupancy and capacity counts are used to measure utilization and calculate empirical arrival/departure rates.
Shelter Occupancy and Capacity	2021-2025	240,050 rows		
Monthly Shelter System Flows	2018-2025	608 rows	actively_homeless, returned_from_housing,	The monthly shelter occupancy is used to calculate the flow of individuals entering and exiting the shelter system
FSA Profiles	2021	2604 rows, 159 columns	median after-tax income, number in low-income measure after tax (LIM-AT), low-income measure after tax (LIM-AT) prevalence (%),	Socioeconomic data per neighbourhood. Used to calculate a poverty index to estimate the distribution of homeless people across the city.

2.1 Data Preparation and Cleaning

All raw datasets were imported and cleaned to ensure completeness, consistency, and spatial validity. Records with missing or invalid addresses, duplicate facility entries, or incomplete occupancy values were removed. To maintain analytical coherence, the dataset was restricted to shelters located within the City of Toronto and limited to the men's and women's sectors due to their consistent reporting. After cleaning, the integrated dataset contained 388,718 standardized records with reliable geographic identifiers, forming the basis for the geocoding, hotspot identification, and modeling phases that followed.

2.2 Exploratory Data Analysis

2.2.1 Hotspot Identification

To identify the origins of homeless demand, the study used census-based socioeconomic data from the 2021 Census Dataset to estimate FSA-level vulnerability, drawing on prior research that demonstrates a strong and consistent association between poverty indicators and homelessness prevalence in urban environments [**5**]. Three key indicators were selected because they represent fundamental socioeconomic pressures that increase the likelihood of housing precarity: median after-tax household income, number of individuals under the Low-Income Measure After Tax (LIM-AT), and the prevalence of low income under the LIM-AT [**5**]. Together, these indicators capture income adequacy, affordability strain, labour-market attachment, and household structure; dimensions that consistently are associated with elevated homelessness risk [**11**].

The census dataset was first cleaned, and then selected poverty-related variables were extracted, renamed, and normalized to a common 0–1 scale. A composite poverty index was computed using an average, and the largest 16 were chosen. These top 16 poverty scores were designated as hotspots, ensuring that only the most socioeconomically disadvantaged areas were included. The geographic centroids of these high-vulnerability FSA were then used as the hotspots in the distance calculations and allocation models.

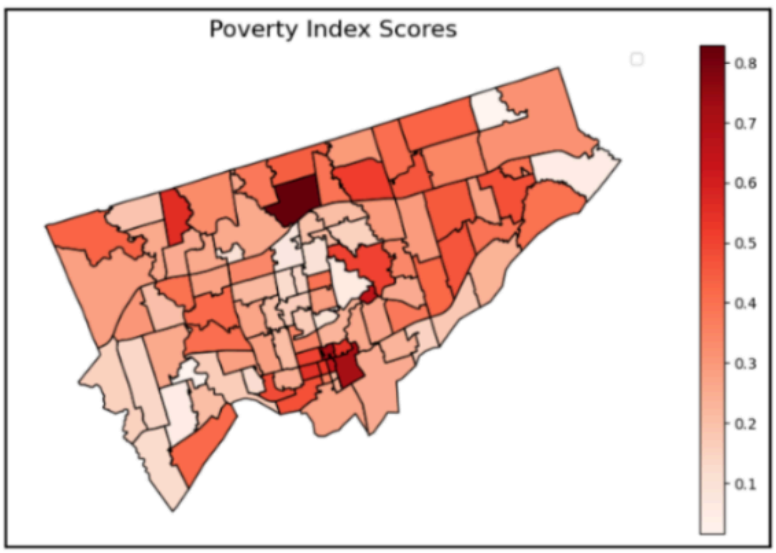

Figure 1. Poverty Index Scores Heatmap

2.2.2 Distance Matrix Computations

To measure travel distances between hotspots and shelters, we constructed a full origin–destination distance matrix. Shelter locations with valid coordinates and the geographic centroids of each hotspot were projected from EPSG:4326 to EPSG:3857 to express distances in meters. Pairwise Euclidean distances were then calculated between all hotspot–shelter pairs and stored in a distance matrix. These values, converted to kilometers, were used as the travel-cost inputs for the optimization model.

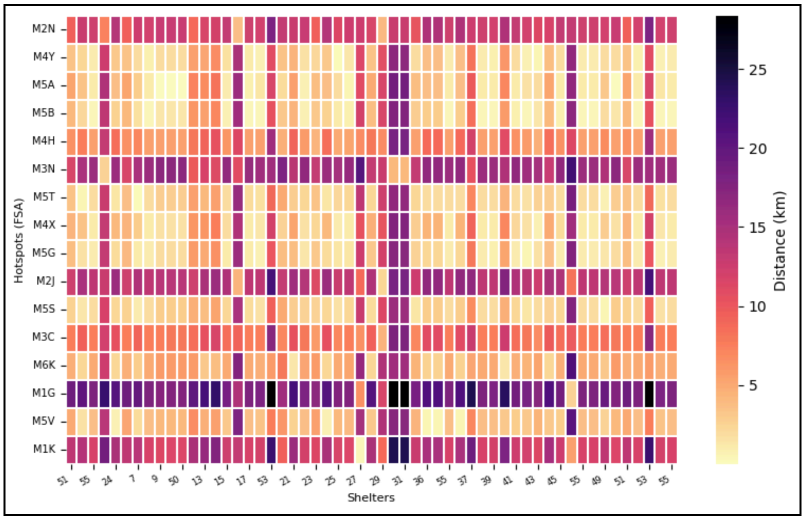

Figure 2. Distance Matrix for Shelters against Hotspots

3.0 Methodology

3.1 Simulations

The simulations were designed to approximate how individuals may actually search for shelters within Toronto's system using limited information and simple decision rules. Two simulation models (Figure 3) were implemented with two different behavioural heuristics: a random choice heuristic simulation model that represents uninformed movement through the system, and a greedy heuristic model that represents individuals attempting the closest shelters first. These simulations provide realistic benchmarks to compare against the optimized allocation results.

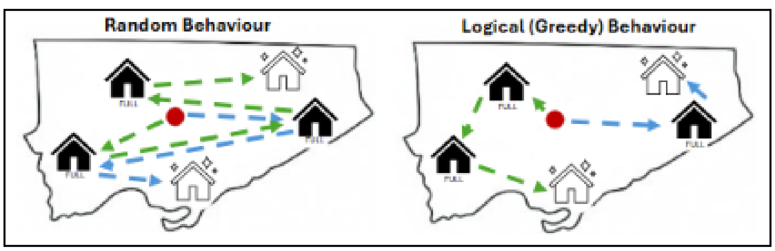

Figure 3. Simulation Policy Visualization

3.1.1 Random Allocation Simulation

The random allocation model attempts to represent situations where individuals have little information about which shelters have available space. In practice, many people rely on word-of-mouth, fragmented information, or immediate necessity when seeking shelter. This can result in unpredictable patterns of movement where individuals visit shelters in a trial-and-error fashion. The random simulation is meant to capture this behavior and illustrate how inefficient the system becomes when people are forced to search without guidance, while also serving as an effective lower bound on future performance.

Individuals are generated at each hotspot based on monthly demand estimated using the system shelter flow data and the relative low-income ratio of that area. For each month, the algorithm begins at a random hotspot and proceeds sequentially till all hotspots are processed. All individuals originating from a hotspot are drained in full before moving to the next hotspot using the two behavioural heuristics. Each person is assigned to a randomly selected eligible shelter, and the assignment continues as long as the chosen shelter has remaining capacity. When a shelter becomes full, another random eligible shelter is selected. If all eligible shelters reach capacity, the individual is recorded as unsheltered. This process is repeated for every hotspot and every month, and travel distances are logged using the hotspot shelter distance matrix.

3.1.2 Greedy Allocation Simulation

The greedy simulation represents a more informed behavioural model in which individuals attempt to enter the closest shelter first. As in the random model, monthly demand and shelter capacities are initialized. For each hotspot, eligible shelters are sorted by distance. Individuals attempt to enter the nearest shelter and, if it is full, proceed to the next closest option, continuing until a placement is found or all shelters reach capacity; if no placement is possible, the individual remains unsheltered for that month, and travel distance is recorded based on the final assignment.

3.2 Mathematical Optimization Model

The allocation of individuals to shelters was formulated as a two-stage mathematical optimization model (Figure 4) designed to prioritize service maximization while minimizing travel distance. The central aim of the model is to assign individuals from each hotspot and gender group to eligible shelters in a way that respects shelter capacity and gender constraints, reduces the number of people left unsheltered, and minimizes total travel distance across the system.

$x_{s,h,g}$: the number of individuals assigned to shelter **s**, coming from hotspot ***h***, of gender group ***g***. This variable represents every feasible assignment between an origin, demographic group, and destination.

$z_{h,g}$: the number of individuals from hotspot ***h*** of gender ***g***, who remain unsheltered. This variable captures the proportion of demand that cannot be accommodated anywhere in the system.

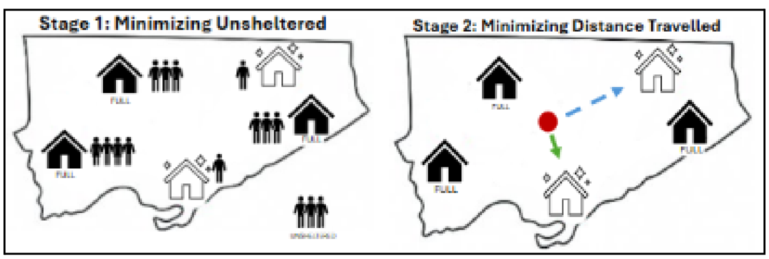

Figure 4. Two-Stage Optimization Procedure

3.2.1 Stage 1: Minimizing Unsheltered Individuals

Stage 1 determines the maximum number of individuals who can feasibly be accommodated in Toronto's shelter system under existing capacity and gender-eligibility constraints. Using the decision variables defined earlier, the model seeks to minimize the total number of people who remain unsheltered. This ensures that service maximization is treated as the highest-priority objective before any consideration of travel distance. By prioritizing service maximization, the model avoids the mathematical pitfall of minimizing travel distance by leaving the population unserved.

$$\min \quad Z^* = \sum_{h\in H}\sum_{g\in G} z_{h,g} \qquad \text{Objective Function}$$

$$\text{subject to: } \sum_{s\in S} x_{s,h,g} + z_{h,g} = d_{h,g} \quad \forall h \in H, \forall g \in G, \qquad \text{(1) Demand Balance}$$

$$\sum_{h\in H}\sum_{g\in G} x_{s,h,g} \le c_s, \forall s \in S, \qquad \text{(2) Shelter Capacity}$$

$$x_{s,h,g} \le e_{s,g} d_{h,g}, \ \forall s \in S, \forall h \in H, g \in G, \qquad \text{(3) Eligibility}$$

Constraint (1) acts as a demand balance rule, ensuring that every individual at each hotspot and gender group is accounted for, either through assignment to a shelter or by being captured in the unsheltered variable ($z_{h,g}$). Constraint (2) enforces physical capacity, ensuring that the total number of people assigned to a specific shelter does not exceed its bed limit **(c_s).** Constraint (3) applies eligibility logic, strictly forcing assignments to zero if a shelter is not permitted to host a specific gender. Solving this model yields the minimum possible number of unsheltered individuals, denoted Z^* . This value serves as a fixed parameter in Stage 2, allowing the model to shift its objective to minimizing travel distance without sacrificing the maximum service coverage achieved in Stage 1.

3.2.2 Stage 2: Minimizing Total Travel Distance

Stage 2 refines the allocation by minimizing the total travel distance between hotspots and shelters while strictly preserving the maximum shelter coverage determined in Stage 1. Having computed the minimum number of unsheltered individuals (Z^*), this stage fixes the total unsheltered population at that value, ensuring that improvements in travel efficiency do not come at the expense of sheltering fewer people. Using the same assignment variables $x_{s,h,g}$ and unsheltered variables $z_{h,g}$, Stage 2 reallocates individuals across shelters to achieve the most spatially efficient distribution that remains feasible under capacity and eligibility constraints.

$$\min \sum_{s\in S}\sum_{h\in G}\sum_{g\in G} dist_{s,h} x_{s,h,g} \qquad \text{Objective Function}$$

subject to: Constraints (1), (2), (3) from Stage 1

$$\sum_{h\in H}\sum_{g\in G} z_{h,g} = Z^* \qquad \text{(4) Fixed Unsheltered Count}$$

The objective function minimizes the total travel distance required to place individuals into shelters, weighting each assignment $x_{s,h,g}$ by the corresponding distance parameter $dist_{s,h}$. Constraints (1)–(3) are carried forward from Stage 1, ensuring that all assignments remain feasible with respect to demand balance, shelter capacity, and gender eligibility. Constraint (4) enforces that the total number of unsheltered individuals remains exactly equal to the optimal minimum Z^* found in Stage 1. With system-wide coverage preserved through this fixed unsheltered count, Stage 2 focuses exclusively on improving the spatial efficiency of assignments, producing the minimum-distance feasible allocation across Toronto's shelter network.

4.0 Results

4.1 Simulation results

Both simulation models produced unsheltered totals identical to the optimization outputs, with monthly values ranging from 5,353 to 5,614 individuals. Since shelter capacities were fully utilized in all runs, the main differences appeared in the average travel distances experienced by men and women under each behavioural assumption.

Under the random allocation model, travel distances were consistently high across all months. Overall average distances ranged from 7.220 km in Month 3 to 9.650 km in Month 8, illustrating the inefficiency of uninformed movement through the shelter system. Men's average monthly travel distances varied between 6.303 km (Month 2) and 11.062 km (Month 1), while women's averages ranged from 6.617 km (Month 1) to 11.827 km (Month 2). Notable gender differences appeared in Month 2, where women traveled 11.827 km compared to 6.303 km for men. Despite these fluctuations in travel efficiency, unsheltered counts for both groups remained relatively stable across the year, indicating that random assignment affects distance burden rather than overall shelter coverage. The greedy allocation model produced substantially shorter distances, with overall monthly averages ranging from 5.488 km in Month

9 to 6.874 km in Month 2. Men's average monthly travel distances ranged from 4.979 km (Month 10) to 5.875 km (Month 6), while women's averages ranged from 6.499 km (Month 10) to 6.839 km (Month 2). Despite these modest month-to-month fluctuations in travel efficiency, total unsheltered counts remained relatively stable between 4,380 and 5,614, indicating that proximity-based allocation improves efficiency but does not significantly alter overall system feasibility.

4.2 Optimization results

4.2.1 Decision variables: Unsheltered Populations ($Z_{h,g}$)

The $Z_{h,g}$ variable provides a granular map of service failure, identifying specific hotspots where the optimization consistently failed to address local demand. Several hotspots, including M4H, M4X, and M3C, had 100 percent of their demand unmet every month. Others, such as M2N, M2J, M5G, and M1K, consistently recorded very high unmet proportions between 82 and 96 percent across all months. Mid-range hotspots such as M4Y, M3N, M5T, and M1G typically exhibited unmet demand between 60 and 80 percent, while a smaller subset, including M5A, M5S, and M6K, ranged between 25 and 50 percent. Only two hotspots, M5B and M5V, regularly fell below 10 percent in several months. A crucial finding is the gender-asymmetric behavior of hotspots such as M5A. While this hotspot achieved near-perfectly addressed demand for men (leaving as few as 5 in some months), it simultaneously failed to serve a vast majority of its female population, consistently leaving as many as 147 women unsheltered.

4.2.2 Decision variables: Assignment Flows ($x_{s,h,g}$) and Distance

The assignment variables expose assignment patterns required to minimize the travel burden of the homeless population. Downtown hotspots such as M5A, M5B, M5T, and M4Y generated the largest assignment flows, with many individuals being placed in nearby shelters at distances typically below 1 km. In contrast, more peripheral hotspots such as M2N, M3N, M2J, and M1G were often assigned to shelters several kilometers away, reflecting the limited availability of nearby capacity. Across all months, the model consistently assigned individuals to the closest feasible shelters first, resulting in dense clusters of short-distance assignments and a smaller number of long-distance allocations where local capacity was exhausted. Further, the assignment organization reveals instances of hotspots having to use multiple shelters instead of a reduced, singular local sink. Demand from M5B, for example, routing to nine distinct shelters (2, 7, 34, 37, 46, 51) indicates a lack of a consolidated local capacity that forces the algorithm to spray assignments across the city in an attempt to clear the queue.

4.2.3 Objective Function:

The optimization model reveals a system operating at the absolute limit of its physical capacity. Across all twelve monthly runs of the model, Stage 1 indicated a state of total saturation, with the number of sheltered individuals remaining fixed at 1757 for men and 758 for women, per month. Since the infrastructure is fully utilized throughout the year, the seasonality of demand is absorbed entirely by the unsheltered (z) variable. From 4251 homeless individuals in autumn (month 10) to a peak of 5571 individuals in winter (month 2). In Stage 2, the system-wide average travel distance remained similar between 1.355km to 1.397 km. However, if you look at the gender specific travel distance, a persistent inequity is revealed where men traveled an average of 1.21km to 1.24 km, while for women, the average distance remained between 1.71 km to 1.76 km, a persistent accessibility penalty of over 40%.

5.0 Discussion

5.1 Uneven Demand and Geographic Service Failures

The spatial distribution of unmet demand reveals a fundamental structural imbalance in how Toronto's shelter infrastructure is positioned relative to where homelessness actually occurs. The optimization results show a pattern consistent with a city organized around a centralized service hub surrounded by peripheral service deserts. Downtown areas benefit from dense, walkable access to beds, enabling most local demand to be absorbed without requiring long-distance movement.

In contrast, suburban and outer-zone hotspots experience systemic service exclusion. These areas generate significant demand but lack nearby facilities capable of absorbing it, creating a structural barrier to access rather than a behavioral or logistical one. Individuals originating from these zones effectively face a geographical penalty: unless they relocate toward the core, they remain structurally sidelined by the system. The optimization model exposes this rigid spatial mismatch, illustrating that without redistributing shelter capacity across the city, certain neighborhoods will continue to produce chronic, unavoidable service failures.

5.2 Stage 1 Optimization vs Simulation Capacity Ceiling

When comparing Stage 1 optimization to the Random and Greedy simulations, the central insight is that algorithmic strategy is irrelevant under conditions of absolute capacity saturation. Regardless of how intelligently or unintelligently individuals are routed, the system converges to the same limit because the supply of beds is fixed and insufficient for city-wide demand. This demonstrates a state of perfect supply inelasticity, where additional demand produces no increase in service uptake, only increased displacement.

This finding reframes the nature of the homelessness bottleneck: the city does not suffer from routing inefficiency but from a hard infrastructure ceiling. As a result, no amount of improved software, better queueing logic, or smarter individual decisions can substantially change outcomes. The only viable path to reducing total unsheltered counts involves physical expansion or redistribution of capacity, not behavioral or algorithmic interventions. The Stage 1 results, therefore, represent a diagnosis of infrastructure scarcity rather than behavioral inadequacy.

5.3 Stage 2 Optimization vs Simulation Accessibility Improvements

While capacity constraints dominate Stage 1, Stage 2 highlights the role that system-level coordination can play in improving equity and accessibility within these constraints. Unlike the greedy simulation, which models individuals acting independently in their own short-term best interest, the optimization model evaluates the city as an interconnected system. By moderating local competition for nearby beds, the optimization controls cascading effects that would otherwise push individuals into long-distance travel.

5.5 Recommendations
A system-wide review of the optimization outputs points to a clear set of infrastructure priorities for the City. The most urgent gap is in North York's M2N region, which consistently functions as the city's largest service desert and generates the highest volume of unserved individuals each month. Establishing a high-capacity, mixed-gender facility of roughly 650 beds in this zone would directly absorb the persistent local deficit and prevent hundreds of people from being displaced toward the downtown core. A second critical intervention concerns the severe gender asymmetry in M5A, where women face a concentrated shortage despite sufficient male capacity. Introducing a women-only shelter or converting existing male-designated space in this neighbourhood would substantially reduce the systemic travel penalty experienced by women. Downtown Yonge (M5B) presents a different issue: extremely fragmented assignment flows caused by the absence of a dominant intake hub. A consolidated, high-capacity "super-shelter" in M5B would anchor local demand, minimize dispersal across distant facilities, and streamline overall routing. Finally, the strong seasonality of unmet demand indicates a need for flexible winter surge infrastructure. Temporary overflow sites in peripheral hotspots such as M1K and M3C would absorb winter peaks at their source and prevent seasonal migration toward the already saturated downtown system. Together, these targeted investments including decentralizing capacity in M2N, gender-aligning facilities in M5A, consolidating intake in M5B, and creating seasonal surge sites outline a coherent, data-driven strategy to reduce unmet demand, improve accessibility, and stabilize system performance across the year.

6.0 Future Directions

6.1 **Limitations of the Model**
The model estimates travel using straight-line distances between hotspots and shelters, which helps keep the analysis efficient but does not reflect how people actually move through the city. Real travel is shaped by the street network, available transit, construction barriers, and weather conditions. The simulations also simplify how people search for shelters by assuming either random allocation or the closest available choice, even though real decisions are influenced by safety, familiarity, referrals, access to transit, and previous experiences in the system.

6.2 **Model Improvement**
Future work can address the limitations of the model by using network-based travel distances or travel times instead of straight-line measures. Incorporating data from tools such as OpenStreetMap or Google Directions would allow the model to reflect actual walking routes, transit paths, and other real-world constraints. The behavioural assumptions in the simulations could also be expanded to better reflect how people actually navigate the system, including preferences for familiar shelters or areas they consider safer.

7.0 Conclusions
This project shows that Toronto's shelter system operates at its physical limit, leaving thousands of people unsheltered each month, regardless of how individuals search for beds or how efficiently placements are coordinated. Optimized allocation lowers travel distance compared to random or greedy behaviour, but it cannot overcome the shortage of beds or the uneven distribution of shelters across the city. High-demand downtown areas and underserved peripheral regions continue to experience significant service gaps, and women consistently face longer travel distances even under the best-case allocation. These results indicate that improving coordination alone is not enough. Meaningful progress requires new and strategically located capacity, supported by more realistic modelling of travel patterns and behaviour, to reduce unsheltered counts and improve accessibility across the system.

8.0 References

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Appendices

Appendix A. Optimization Results Table

YEARLY SUMMARY

Month	TOTAL		MEN			WOMEN		
	Unshelt	AvgKM	Shelt	Unshelt	AvgKM	Shelt	Unshelt	AvgKM
1	5535	1.369	1757	3716	1.214	758	1819	1.728
2	5571	1.368	1757	3729	1.214	758	1842	1.726
3	5065	1.379	1757	3388	1.222	758	1677	1.741
4	5079	1.378	1757	3371	1.223	758	1708	1.739
5	4680	1.387	1757	3066	1.232	758	1614	1.747
6	4526	1.391	1757	2939	1.235	758	1587	1.750
7	4455	1.392	1757	2852	1.238	758	1603	1.749
8	4430	1.393	1757	2836	1.238	758	1594	1.750
9	4260	1.397	1757	2732	1.242	758	1528	1.756
10	4251	1.397	1757	2705	1.242	758	1546	1.754
11	4540	1.390	1757	2934	1.235	758	1606	1.749
12	5514	1.370	1757	3690	1.215	758	1824	1.728

Appendix B. Random Simulation Results Table

YEARLY SUMMARY

Month	TOTAL		MEN			WOMEN		
	Unshelt	AvgKM	Shelt	Unshelt	AvgKM	Shelt	Unshelt	AvgKM
1	5535	9.722	1757	3716	11.062	758	1819	6.617
2	5571	7.968	1757	3729	6.303	758	1842	11.827
3	5065	7.220	1757	3388	6.957	758	1677	7.830
4	5079	7.545	1757	3371	7.264	758	1708	8.197
5	4680	9.331	1757	3066	9.922	758	1614	7.960
6	4526	7.645	1757	2939	6.689	758	1587	9.861
7	4455	7.633	1757	2852	7.406	758	1603	8.159
8	4430	9.650	1757	2836	10.512	758	1594	7.653
9	4260	9.105	1757	2732	8.915	758	1528	9.544
10	4251	9.316	1757	2705	9.080	758	1546	9.864
11	4540	8.341	1757	2934	7.603	758	1606	10.050
12	5514	8.288	1757	3690	8.633	758	1824	7.488

Appendix C. Greedy Simulation Result

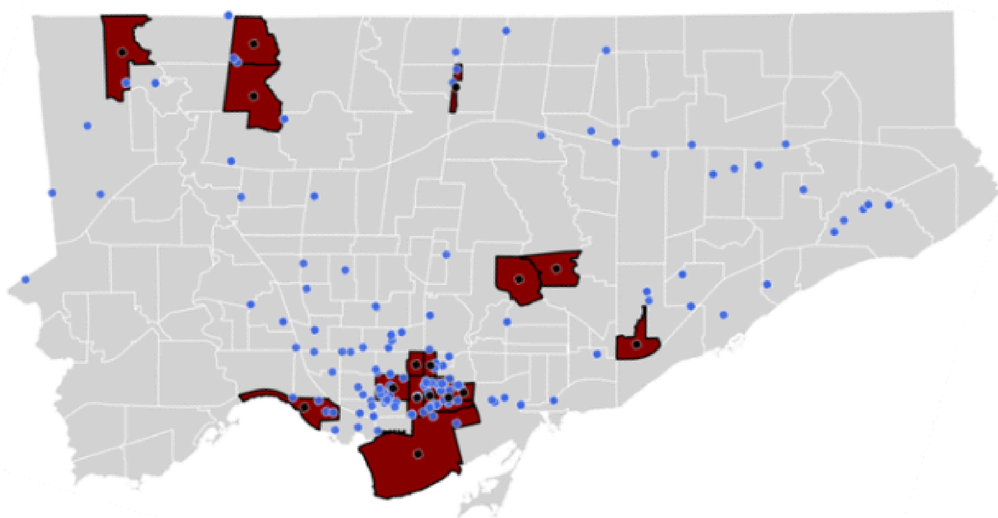
YEARLY SUMMARY

Month	TOTAL		MEN			WOMEN		
	Unshelt	AvgKM	Shelt	Unshelt	AvgKM	Shelt	Unshelt	AvgKM
1	5535	6.063	1757	3716	5.736	758	1819	6.819
2	5571	6.074	1757	3729	5.744	758	1842	6.839
3	5065	5.672	1757	3388	5.251	758	1677	6.649
4	5079	5.664	1757	3371	5.218	758	1708	6.699
5	4680	5.496	1757	3066	5.042	758	1614	6.546
6	4526	5.512	1757	2939	5.075	758	1587	6.524
7	4455	5.537	1757	2852	5.105	758	1603	6.539
8	4430	5.538	1757	2836	5.110	758	1594	6.531
9	4260	5.488	1757	2732	5.054	758	1528	6.494
10	4251	5.437	1757	2705	4.979	758	1546	6.499
11	4540	5.513	1757	2934	5.071	758	1606	6.538
12	5514	6.052	1757	3690	5.721	758	1824	6.819

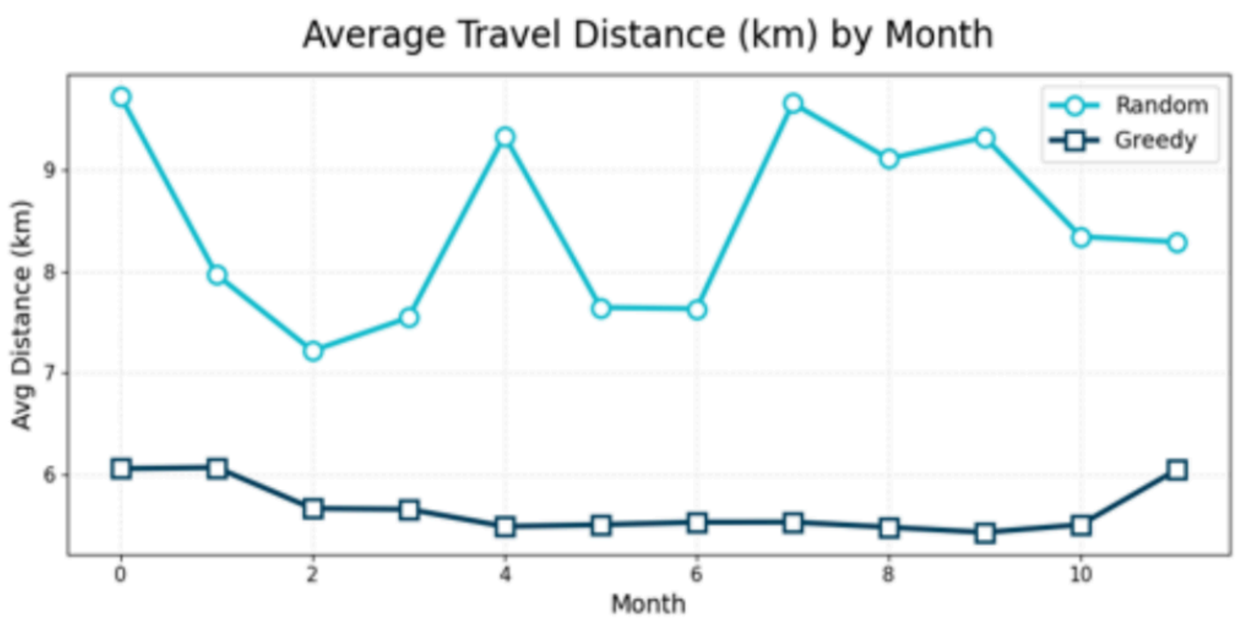
Appendix D. Unmet demand per hotspot

Month	1	2	3	4	5	6	7	8	9	10	11	12
M2N	95.879121	95.896033	95.626822	95.633188	95.391705	95.290424	95.245642	95.230525	95.106036	95.098039	95.297806	95.873453
M4Y	80.533752	80.781250	75.500000	75.374376	70.123023	67.805755	66.424682	66.120219	63.992537	63.551402	67.921147	80.157480
M5A	25.039620	25.394322	22.558923	22.857143	22.872340	23.007246	23.443223	23.345588	22.975518	23.396226	23.146474	24.801272
M5B	4.049296	4.210526	2.429907	2.798507	1.577909	1.209677	1.425662	1.428571	0.418410	0.836820	1.606426	4.063604
M4H	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000
M3N	79.513185	79.595960	78.232759	78.279570	77.045455	76.620370	76.346604	76.235294	75.662651	75.603865	76.620370	79.429735
M5T	67.355372	67.422680	65.274725	65.350877	63.425926	62.647754	62.291169	62.110312	61.083744	61.083744	62.735849	67.219917
M4X	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000
M5G	88.478261	88.552916	84.757506	84.562212	77.912621	74.937965	72.932331	72.613065	69.845361	68.992248	74.937965	88.478261
M2J	88.470067	88.520971	87.735849	87.764706	87.096774	86.802030	86.666667	86.632391	86.279683	86.279683	86.835443	88.444444
M5S	49.435666	49.549550	46.282974	46.411483	42.784810	41.085271	40.731070	40.157480	38.069705	38.172043	41.494845	49.206349
M3C	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000
M6K	34.123223	34.198113	31.909548	31.658291	29.100529	27.913279	27.049180	26.923077	26.123596	25.633803	27.837838	33.966746
M1G	75.837321	75.952381	74.300254	74.365482	72.922252	72.404372	72.022161	71.944444	71.306818	71.306818	72.404372	75.779376
M5V	23.728814	24.337349	17.223650	17.692308	12.702703	10.526316	9.776536	9.523810	6.916427	6.916427	10.773481	23.357664
M1K	85.194175	85.265700	84.278351	84.278351	83.423913	83.055556	82.913165	82.816901	82.420749	82.369942	83.102493	85.158151

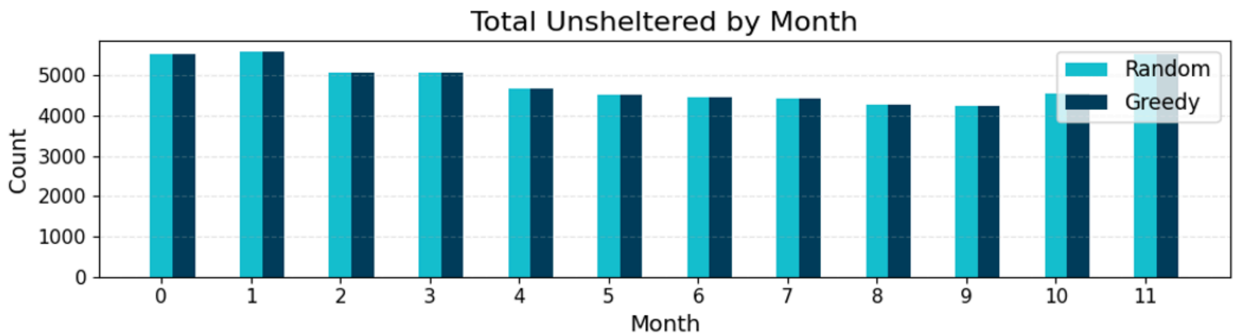
Appendix E. Hotspot vs shelters choropleth



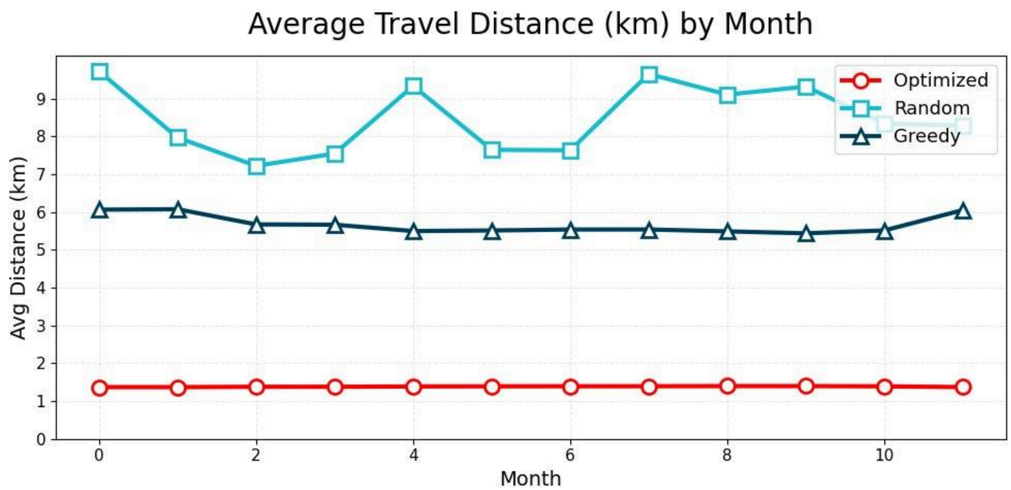
Appendix F. Average Distance Traveled by month under Greedy and Random Policy



Appendix G. Total unsheltered population per month



Appendix H. Average Distance Travelled by Month under all models



Appendix F. Total unsheltered population per month under all policies