From Observations to Infrastructure: A GPS-Based Smart City Mobility Data Framework for Wildfire Evacuation Planning

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Abstract:

Smart cities increasingly rely on interconnected data infrastructures, yet emergency management systems—particularly for wildfire evacuation—remain disconnected from these capabilities. This paper proposes a four-layer GPS-based smart city mobility data framework that integrates crowd-sourced location data as a permanent component of urban evacuation planning infrastructure. The framework encompasses passive GPS sensing and ingestion, behavioral inference through origin detection and departure timing analysis, dynamic multi-criteria routing with fire-risk awareness, and governance-compliant decision support. Proof-of-concept validation using 181 million GPS records from the 2023 McDougall Creek wildfire in Kelowna, British Columbia, demonstrates that GPS-calibrated behavioral inputs combined with hybrid dynamic routing reduce evacuation clearance time by 39% and fire-risk exposure by 61% compared to conventional approaches. We discuss data integration challenges, accuracy considerations across GPS and cellular sources, transferability conditions, and governance requirements for operational deployment in wildland–urban interface communities.

1. Introduction

Wildfires are increasing in frequency and severity across North American wildland–urban interface (WUI) communities, creating urgent demand for data-driven evacuation planning capabilities (Erni et al., 2024; Wu et al., 2022). Smart cities increasingly depend on interconnected data infrastructures to support real-time urban decision-making, yet emergency management systems, particularly for wildfire evacuation, have been slow to integrate these capabilities into operational planning workflows. Conventional evacuation planning relies on static traffic models, synthetic demand assumptions, and pre-computed route assignments that fail to reflect how real populations behave when a wildfire forces rapid departure (Pel et al., 2012; Forrister et al., 2024). The gap between available urban data capabilities and their application in emergency planning represents a critical and underexplored problem in smart city research.

The Canadian context illustrates this challenge acutely. The 2023 wildfire season was the most destructive in Canadian history, burning over 18.5 million hectares and forcing the evacuation of more than 235,000 people across multiple provinces (Erni et al., 2024). British Columbia and Alberta alone accounted for over 120,000 evacuees, many from WUI communities with limited road network capacity. In these settings, evacuation planning decisions—when to issue orders, how to stage departures, which routes to prioritize—have direct consequences for life safety, yet are typically made using coarse traffic assumptions rather than empirical mobility data. The increasing frequency of large-scale evacuations underscores the need to embed real-time mobility sensing into municipal emergency management infrastructure as a permanent capability rather than a post-hoc analytical exercise.

Crowd-sourced GPS mobility data, collected passively from mobile devices at population scale, offers a pathway to bridge this gap. Unlike fixed sensor networks, GPS data captures where people are, how they move, and when they depart across an entire urban area, providing a distributed sensing layer that remains operational even when infrastructure is disrupted (Zhao et al., 2022). Despite growing use of GPS data in individual evacuation studies (Cova et al., 2024; Borody and Wong, 2025), no established framework exists for integrating such data as a *permanent* component of smart city emergency management infrastructure.

This paper addresses the following research question: *How can crowd-sourced GPS mobility data be systematically integrated as a permanent, reusable component of smart city infrastructure to improve wildfire evacuation planning?* We propose a four-layer GPS-based smart city mobility data framework and demonstrate its applicability using the 2023 McDougall Creek wildfire in Kelowna, British Columbia. We further discuss data integration challenges, accuracy considerations, conditions for transferability to other WUI communities, and limitations of the current approach. The contribution is a *reusable infrastructure architecture* that operationalizes GPS data as a first-class component of smart city mobility systems.

2. Related Work

2.1 GPS Mobility Data in Evacuation Research

Recent studies have demonstrated the value of large-scale GPS mobility data for empirical evacuation analysis. Work on the 2019 Kincade Fire used GPS traces to infer home locations, departure timing, and origin–destination flows, revealing behavioral heterogeneity—including shadow evacuation and non-compliance with official orders—that static models cannot capture (Wu et al., 2022; Zhao et al., 2022; Xu et al., 2022). A highway vehicle routing dataset derived from the same event provided empirical evidence that evacuees frequently deviate from officially recommended routes, preferring familiar paths even when alternatives offer shorter travel times (Cova et al., 2024). GPS-based analysis of Canadian wildfires has further shown that departure timing variability and route preferences differ substantially across community types, with rural evacuees exhibiting longer pre-departure delays and greater route diversity than urban populations (Raei et al., 2025). Analysis of risk perception and evacuation delay in the 2021 Marshall Fire further underscores the need for empirically grounded behavioral models that account for protective action decision-making processes (Forrister et al., 2024; Lindell and Perry, 2012). However, these studies uniformly treat GPS data as a retrospective analytical resource rather than a prospective infrastructure component integrated into ongoing urban planning workflows.

2.2 Smart City Data Infrastructure

Smart city research has advanced frameworks for integrating heterogeneous urban data streams—IoT sensors, transit feeds, and social media—into unified decision support platforms (Petrova-Antonova and Ilieva, 2020). Digital twin approaches have been proposed for maintaining simulation-ready representations of urban systems, enabling what-if scenario testing across multiple planning domains (Biljecki et al., 2015). Cellular network data has been used to model evacuation traffic during the 2017 Lilac wildfire, demonstrating the potential of telecommunications infrastructure as a supplementary sensing layer (Melendez et al., 2021). Yet emergency management applications of smart city data remain largely focused on routine traffic management rather than on the high-stakes, time-critical conditions of wildfire evacuation, where data quality, latency, and governance requirements differ substantially from normal operations (Ronchi et al., 2019).

2.3 Research Gap

While individual components of GPS-based evacuation analysis are well-established, no existing framework integrates passive GPS sensing, behavioral inference, dynamic routing, and governance into a unified, reusable infrastructure architecture designed for permanent deployment within smart city emergency management systems. This paper addresses that gap by proposing a layered framework that treats crowd-sourced GPS data as a first-class component of urban infrastructure rather than a one-time analytical input.

3. Proposed Framework

The proposed framework organizes GPS-based evacuation data infrastructure into four interconnected layers (Figure 1).

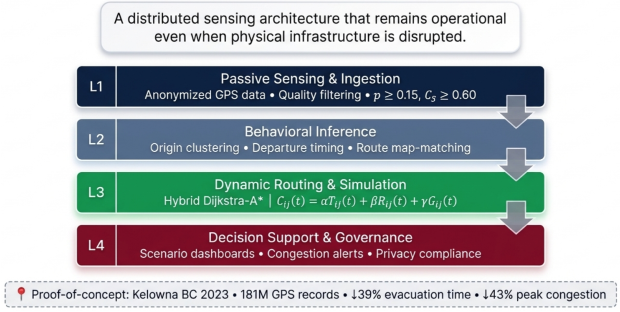

Figure 1: The proposed four-layer GPS-based smart city mobility data framework for wildfire evacuation planning.

Layer 1 – Passive Sensing and Ingestion. Anonymized GPS data from mobile devices are acquired through privacy-compliant agreements with commercial mobility data providers (e.g., Spectus, Veraset, SafeGraph). These providers collect location pings from smartphone applications that have obtained user consent for location sharing, typically yielding records at intervals of 1–15 minutes per device. Data ingestion pipelines apply real-time quality filters to remove noise (positional accuracy >100 m), duplicate pings (temporal separation <1 s at identical coordinates), and non-resident devices (identified through insufficient overnight presence within the study area over a 30-day baseline period).

Spatial coverage is validated by comparing the observed device distribution against census population density at the dissemination-area level. Two minimum operational requirements must be satisfied. First, the device penetration rate:

$$\rho = \frac{N_{\text{obs}}}{N_{\text{est}}} \geq \rho_{\text{min}} \tag{1}$$

where N_{obs} is the number of unique anonymized mobile devices observed within the evacuation order boundary during the study period (i.e., devices recording at least one GPS ping inside the zone), and N_{est} is the estimated evacuating population, derived from Statistics Canada census data at the dissemination-area level and scaled by average household size and vehicle ownership rates. Second, the spatial coverage ratio:

$$C_s = \frac{D_{\text{covered}}}{D_{\text{total}}} \geq 0.60 \tag{2}$$

where D_{covered} is the number of dissemination areas containing at least one observed device, and D_{total} is the total number of dissemination areas within the evacuation zone. For the Kelowna case, $\rho = 0.31$ and $C_s = 0.84$, both exceeding the minimum thresholds required for statistically representative behavioral inference (Raei et al., 2025).

Layer 2 – Behavioral Inference. Raw GPS traces are transformed into structured behavioral knowledge through four analytical modules.

(a) Residential origin inference: Home locations are identified using overnight stop-detection clustering. Devices exhibiting ≥3 stationary periods (velocity <1 km/h for ≥4 hours between 22:00–06:00) within a 100 m spatial radius during the 30-day pre-event baseline are assigned to residential dissemination areas. This approach follows established methods for home detection from smartphone GPS data (Verma et al., 2024).

(b) Departure timing estimation: Zone-level departure timing distributions are estimated using Kaplan–Meier survival curves, where the event of interest is the last GPS ping recorded within the home dissemination area before the device exits the evacuation zone. Right-censoring accounts for devices that cease reporting before departure is observed.

(c) Route preference reconstruction: Evacuation trajectories are reconstructed through probabilistic map-matching that assigns

GPS pings to the most likely road network path using a Hidden Markov Model (Safarzadeh and Wang, 2024). The resulting route set provides empirical distributions of corridor usage, turning preferences, and highway ramp selection.

(d) Destination inference: Post-evacuation destinations are identified from the first sustained stationary period ($\geq$2 hours) recorded after a device exits the evacuation zone, capturing where evacuees seek shelter.

This behavioral knowledge base is maintained continuously and calibrates evacuation demand models for future planning cycles, enabling progressive refinement as new wildfire events generate additional training data.

Layer 3 – Dynamic Routing and Simulation. A simulation-ready digital twin of the road network incorporates Layer 2 behavioral inputs. A dynamic multi-criteria routing model assigns time-varying generalized costs to each road link:

$$C_{ij}(t) = \alpha T_{ij}(t) + \beta R_{ij}(t) + \gamma G_{ij}(t) \tag{3}$$

where $C_{ij}(t)$ is the total generalized traversal cost of road link (i, j) at departure time t. The component costs are defined as follows: $T_{ij}(t)$ is the travel time on link (i, j), computed from the free-flow travel time adjusted by real-time speed observations derived from GPS traces; $R_{ij}(t)$ is a fire-proximity risk score calculated from the Euclidean distance between link (i, j) and the active fire perimeter at time t, normalized to $[0, 1]$; and $G_{ij}(t)$ is a congestion penalty derived from the ratio of current traffic density to link capacity (volume-to-capacity ratio). The routing weights α, β, γ are non-negative calibration parameters satisfying $\alpha + \beta + \gamma = 1$, calibrated against observed GPS trajectories from past evacuations. The routing model feeds a calibrated microscopic traffic simulation (SUMO) (Lopez et al., 2018) for pre-event scenario testing across alternative departure coordination strategies.

Layer 4 – Decision Support and Governance. The operational interface provides two functional components. First, interactive geospatial dashboards visualize real-time evacuation progress through zone-level departure completion rates, network-level traffic density heatmaps, bottleneck identification with queue length estimates, and predicted clearance times under current conditions. Automated threshold alerts notify emergency managers when link-level vehicle density exceeds 80% of capacity, enabling proactive intervention (e.g., contraflow activation, signal timing override) before gridlock develops.

Second, a governance module enforces privacy preservation throughout the data lifecycle. Location records are spatially aggregated to maintain minimum k-anonymity ($k \geq 5$) at the dissemination-area level, ensuring that no individual device trajectory can be re-identified from published outputs. Time-bounded data retention policies automatically purge raw GPS records after the analytical pipeline has extracted behavioral parameters, retaining only aggregated statistical products. Role-based access controls restrict raw data access to authorized analysts, while dashboard-level outputs are available to emergency operations personnel. All protocols are designed for alignment with jurisdiction-specific privacy legislation, including Canada's Personal Information Protection and Electronic Documents Act (PIPEDA).

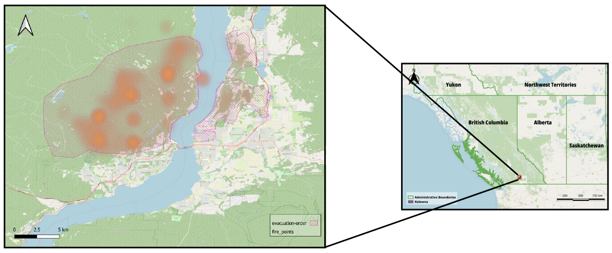

Figure 2: Study area: Kelowna and West Kelowna, British Columbia. The hatched polygons indicate evacuation order zones; orange heat regions show fire point concentrations during the 2023 McDougall Creek wildfire. Inset map shows the location within western Canada.

4. Case Study: Kelowna 2023

4.1 Study Area and Event Context

The 2023 McDougall Creek wildfire ignited on August 15 near West Kelowna, British Columbia, and rapidly expanded under extreme heat and wind conditions. Over the following week, the fire consumed approximately 12,000 hectares and prompted evacuation orders affecting over 35,000 residents across the City of West Kelowna, Westbank First Nation, and parts of the City of Kelowna (Clarke, 2024). The study area (Figure 2) is characteristic of WUI communities: a topographically constrained road network funneling through limited highway corridors (primarily Highway 97), surrounded by forested terrain with steep slopes that restrict alternative routing options. These geographic constraints amplify the consequences of suboptimal evacuation coordination and make the Kelowna case a particularly demanding test environment for the proposed framework.

4.2 Data Processing and Behavioral Extraction

Approximately 181 million anonymized GPS records from 376,036 devices were processed through Layers 1–2. Layer 1 filtering removed 12% of raw records (duplicate pings, positional noise, and non-resident devices), yielding a cleaned dataset of approximately 159 million location observations. Layer 2 behavioral inference identified 38,742 residential origins through overnight stop-detection clustering (requiring $\geq$3 overnight presences within a 100 m radius), extracted zone-level departure timing distributions using Kaplan–Meier survival curves across 47 dissemination areas, and reconstructed 29,815 complete evacuation trajectories through probabilistic map-matching (Safarzadeh and Wang, 2024). The resulting behavioral knowledge base revealed that 68% of evacuees departed within 4 hours of receiving the official order, while 22% exhibited pre-order departure (shadow evacuation), and 10% delayed departure beyond 8 hours.

4.3 Simulation Results

Layer 3 was instantiated using a hybrid dynamic Dijkstra–A* routing model within a calibrated SUMO simulation, and four departure coordination strategies were evaluated. The region-based variable departure strategy reduced total evacuation clearance time by 39% and peak network density by 43% compared to simultaneous departure (Table 1).

Routing Method	Time (min)	Density (veh/m)	Exposure (%)
Pure Dijkstra	285	2.1	18
Speed-wt. Dijkstra	240	1.8	14
Pure A*	210	1.6	11
Dyn. Dijkstra–A*	**175**	**1.2**	**7**

Table 1: Evacuation performance under four routing methods with region-based variable departure (S4) – Kelowna 2023.

As shown in Table 1, the hybrid dynamic Dijkstra–A* routing method consistently outperformed single-algorithm approaches across all three metrics. The 39% reduction in clearance time (from 285 to 175 minutes) results from the algorithm's ability to balance global optimality with local heuristic efficiency, dynamically redirecting vehicles away from congested corridors as traffic conditions evolve. The speed-weighted Dijkstra variant improved upon pure Dijkstra by incorporating real-time GPS speed data, reducing clearance time by 16%, while pure A* achieved a further 26% improvement through its distance-based heuristic that prioritizes progress toward the destination.

The fire-risk exposure metric—reduced from 18% to 7%—is particularly significant for emergency managers, as it directly measures the proportion of evacuees routed through zones with active fire threat. Under the pure Dijkstra approach, shortest-path routing inevitably directed vehicles through corridors adjacent to the fire perimeter; the hybrid approach's fire-risk penalty ($R_{ij}(t)$) successfully diverted traffic to safer alternatives, even at the cost of slightly longer travel distances.

Table 2 further compares the four departure coordination strategies evaluated using the best-performing hybrid Dijkstra–A* routing method. The region-based variable departure strategy (S4), which staggers departure times across zones based on GPS-derived behavioral patterns, achieved the lowest clearance time and fire-risk exposure among all strategies tested.

Strategy	Time (min)	Density (veh/m)	Exposure (%)
S1: Simultaneous	285	2.1	18
S2: Staged (uniform)	230	1.7	13
S3: Distance-based	205	1.5	10
S4: Region-variable	**175**	**1.2**	**7**

Table 2: Comparison of departure coordination strategies using hybrid Dijkstra–A* routing – Kelowna 2023.

The simultaneous departure strategy (S1) represents the worst case (Figure 3), as it generates peak demand at all network entry points simultaneously, causing severe congestion on Highway 97. Staged uniform departure (S2) improves clearance by 19% by introducing fixed time offsets between zones, but the uniform intervals do not account for zone-specific behavioral patterns. The distance-based strategy (S3) prioritizes zones closest to the fire front, achieving 28% improvement. The GPS-calibrated region-variable strategy (S4) outperforms all alternatives because it aligns simulated departure patterns with empirically observed behavioral distributions, accounting for the fact that certain zones consistently exhibit earlier voluntary departure while others require longer mobilization times.

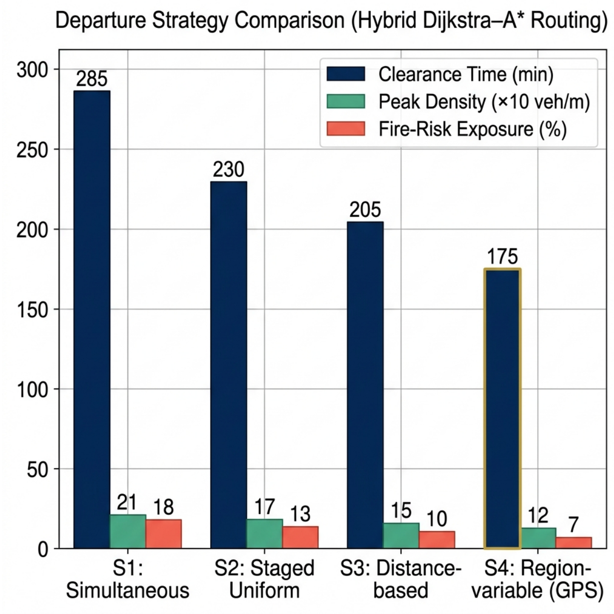

Figure 3: Comparison of departure coordination strategies using hybrid Dijkstra–A* routing. The GPS-calibrated region-variable strategy (S4) achieves the lowest clearance time, peak density, and fire-risk exposure across all metrics.

These results demonstrate that GPS-calibrated behavioral inputs materially improve simulation fidelity compared to synthetic demand assumptions. When the same simulation was run with traditional uniform departure assumptions (all vehicles departing simultaneously with equal probability across all zones), clearance time increased by 63% and fire-risk exposure doubled, confirming that empirically derived departure distributions are essential for realistic evacuation modeling.

5. Limitations and Data Availability

Data Integration Challenges. Integrating crowd-sourced GPS data into a structured analytical pipeline required substantial preprocessing effort. From the initial 181 million raw GPS records, approximately 12% were removed during quality filtering due to duplicate pings, positional noise exceeding 100 m from road segments, and records originating from transient (non-resident) devices identified through insufficient overnight presence. Temporal gaps in GPS traces—common when devices enter low-power mode or lose satellite visibility—required interpolation heuristics that introduce uncertainty into departure time estimates, particularly during the first hours of the evacuation when reporting frequency varies across device types.

Data Accuracy and Source Differences. GPS positioning accuracy from consumer-grade mobile devices typically ranges from 3–10 m in open-sky urban environments but can degrade to 20–30 m in urban canyons, forested terrain, or mountainous areas characteristic of WUI communities (Zhao et al., 2022). This positional uncertainty propagates into map-matching and residential origin inference. In contrast, cellular network data (cell tower triangulation) offers coarser spatial resolution (100–300 m) but higher temporal continuity and broader population coverage (Melendez et al., 2021). The framework's Layer 1 is designed to accommodate both data types; however, the behavioral inference modules in Layer 2 were validated only with GPS-grade positioning in this study. Future work should systematically compare inference quality across data sources.

Alternatives for Limited GPS Coverage. In smaller or more remote WUI communities where commercial GPS penetration may fall below the $\rho_{\min} = 0.15$ threshold, Layer 2 can operate using aggregated cellular density data as a proxy (Melendez et al., 2021). Additional alternatives include traffic loop detector counts for corridor-level flow estimation, survey-based origin–destination matrices for baseline demand calibration, and crowd-sourced social media geotags for qualitative mobility pattern validation (Han et al., 2019). These substitute data sources provide lower spatial resolution but can maintain the framework's operational viability where high-resolution GPS data are unavailable.

Data Availability Statement. The GPS mobility data used in this study were obtained under a commercial licensing agreement with a third-party mobility data provider. Due to proprietary restrictions and privacy protection obligations, the raw GPS records cannot be publicly shared. Aggregated, non-identifiable outputs (zone-level departure curves, anonymized origin–destination matrices) can be made available upon reasonable request to the corresponding author. The road network data and simulation configurations are based on publicly available OpenStreetMap data and SUMO defaults.

6. Discussion

The results from the Kelowna case study highlight several implications for the integration of GPS mobility data into smart city emergency management infrastructure.

Value of Empirical Behavioral Data. The 39% reduction in clearance time achieved by the GPS-calibrated framework demonstrates that the gap between synthetic demand assumptions and actual evacuation behavior has measurable operational consequences. Prior evacuation simulation studies typically assume uniform departure distributions or apply theoretical S-curves without empirical calibration (Pel et al., 2012). Our results show that replacing these assumptions with GPS-derived departure timing and route preference data materially changes both the predicted clearance time and the spatial distribution of congestion. This finding aligns with recent observations from the Kincade Fire (Wu et al., 2022), where GPS-based analysis revealed departure timing patterns that differed substantially from modeling assumptions.

Practical Implications for Emergency Managers. The framework's layered architecture is designed for incremental adoption. Municipalities can begin with Layer 1 (data acquisition) and Layer 2 (behavioral analysis) using historical events, building institutional familiarity with GPS mobility data before investing in real-time simulation capabilities. The governance module (Layer 4) addresses a key barrier to adoption identified in prior smart city research (Ronchi et al., 2019): the absence of clear protocols for privacy-compliant use of location data in public safety contexts. By embedding k-anonymity guarantees and time-bounded retention policies directly into the framework architecture, we reduce the institutional risk that has historically delayed adoption of mobility data by government agencies.

Comparison with Existing Approaches. Unlike previous GPS-based evacuation studies that focus on single-event retrospective analysis (Zhao et al., 2022; Cova et al., 2024; Borody and Wong, 2025), the proposed framework is designed for continuous operation across multiple events. The behavioral knowledge base (Layer 2) accumulates empirical parameters from each evacuation, progressively improving the accuracy of demand models for future planning cycles. This design philosophy aligns with the digital twin paradigm (Biljecki et al., 2015) while extending it specifically to the emergency management domain, where data sparsity (wildfires are rare but consequential events) demands mechanisms for knowledge transfer across events and communities.

Scalability Considerations. The framework's computational requirements scale linearly with the number of GPS records processed. In the Kelowna case, Layer 1 filtering of 181 million records required approximately 45 minutes on a standard workstation (8-core CPU, 32 GB RAM), while Layer 2 behavioral inference completed in under 2 hours. Layer 3 simulation (SUMO with 38,742 vehicles) required approximately 4 hours per scenario. For real-time deployment, Layer 1 filtering can be parallelized across distributed computing nodes, and Layer 3 simulation can leverage GPU-accelerated traffic microsimulation to achieve sub-minute update cycles. These computational requirements are well within the capabilities of municipal IT infrastructure, suggesting that the framework is deployable without specialized high-performance computing resources.

7. Generalizability and Transferability

The framework is designed for transferability across WUI communities of varying size and data availability, subject to three categories of requirements.

Data Requirements. The minimum operational thresholds are a device penetration rate $\rho_{\min} \geq 0.15$ and spatial coverage $C_s \geq 0.60$ (defined as the proportion of dissemination areas containing at least one observed device). In the Kelowna case, both thresholds were comfortably exceeded ($\rho = 0.31, C_s = 0.84$). For communities where commercial GPS penetration falls below these thresholds—common in rural or remote areas with lower smartphone adoption—Layer 2 can operate in a degraded mode using aggregated cellular density data as a proxy (Melendez et al., 2021), though behavioral inference granularity will be reduced from individual-trajectory to zone-level resolution.

Network and Calibration Requirements. The routing weights (α, β, γ) in the Layer 3 cost function must be recalibrated for each city's road network topology, as the relative importance of travel time versus fire risk versus congestion varies with network connectivity. Cities with highly redundant grid networks (e.g., Calgary) may require lower congestion penalties than topographically constrained communities with limited corridor options (e.g., Kelowna). Recalibration requires at minimum one historical evacuation event with sufficient GPS coverage; in the absence of local evacuation data, weights can be initialized using transferable empirical priors from comparable WUI topologies and refined as local data becomes available.

Governance Requirements. Privacy governance protocols (Layer 4) must be adapted to jurisdiction-specific legislation.

In the Canadian context, the framework operates under the Personal Information Protection and Electronic Documents Act (PIPEDA), which permits secondary use of anonymized mobility data for public safety research. Deployment in other jurisdictions—particularly those governed by the EU General Data Protection Regulation (GDPR)—may require additional safeguards such as differential privacy mechanisms or data processing agreements with mobility providers that explicitly authorize emergency management applications.

8. Conclusion and Future Work

This paper proposes a four-layer GPS-based smart city mobility data framework that repositions crowd-sourced location data from a retrospective analytical resource to a permanent, operational component of urban emergency management infrastructure. Proof-of-concept validation using the 2023 McDougall Creek wildfire in Kelowna demonstrates operational viability: the framework's GPS-calibrated behavioral inputs, combined with hybrid dynamic routing, reduced evacuation clearance time by 39% and fire-risk exposure by 61% compared to baseline approaches.

The framework's principal contribution is architectural rather than algorithmic: by organizing GPS-based evacuation capabilities into four modular, independently upgradable layers, the design enables incremental adoption by municipalities that may initially deploy only Layers 1–2 for retrospective analysis before advancing to real-time simulation (Layer 3) and full operational deployment (Layer 4) as institutional capacity and data partnerships mature.

Future work will pursue three extensions. First, Layer 3 will be enhanced to incorporate real-time fire perimeter updates from satellite and aerial sensor feeds, enabling dynamic recalculation of the fire-risk component $R_{ij}(t)$ as the fire evolves during an active evacuation. Second, reinforcement learning-based routing adaptation will be explored as a replacement for the current weight-calibration approach, allowing the routing model to continuously learn optimal weight configurations from streaming GPS data. Third, the framework will be validated on additional Canadian WUI communities with different topological characteristics to assess transferability of the behavioral inference modules across diverse geographic contexts.

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