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A Novel Heuristic Approach for Simplifying Urban Risk Zones in Distribution Route Planning

Método heurístico para la simplificación de zonas de riesgo urbano en la planificación de rutas de distribución

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Technological innovation: A geometric risk-aware routing framework is proposed that transforms heterogeneous urban incident data into circular conflict zones and integrates them into a Vehicle Routing Problem through a secant-based arc–zone interaction mechanism.

Industrial application: The proposed methodology enables logistics operators to incorporate urban accident and crime exposure into route planning, reducing operational risk while maintaining acceptable transportation efficiency in real-world distribution networks.

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Resumen

Las operaciones logísticas urbanas están expuestas a accidentes de tránsito e incidentes delictivos que pueden afectar la eficiencia del transporte y la seguridad operacional. Este trabajo propone un marco heurístico geométrico para incorporar estructuras de riesgo urbano dentro de un Problema de Ruteo de Vehículos con Capacidad (CVRP). La metodología integra registros georreferenciados de accidentes y robos, técnicas de agrupamiento espacial, análisis de empalmes, transformación de regiones irregulares en zonas circulares de riesgo y un mecanismo secante para evaluar la exposición de las rutas. Las zonas de riesgo se incorporan al modelo mediante una penalización multiplicativa que permite equilibrar costo y riesgo. La metodología fue evaluada utilizando datos reales de la ciudad de Irapuato, México, correspondientes al periodo 2020–2025 y una red de distribución de 97 clientes. Los resultados muestran que el enfoque propuesto identifica estructuras persistentes de conflicto urbano y las incorpora al proceso de optimización. El análisis de sensibilidad evidenció una reducción de los cruces por zonas de conflicto de seis a cero con un incremento moderado en la distancia recorrida. Los hallazgos demuestran la utilidad de la heurística propuesta para la planificación logística urbana sensible al riesgo.

Palabras clave: Ruteo Vehicular, Riesgo Urbano, Agrupamiento Espacial, Heurística Geométrica, Logística Sensible al Riesgo.

Abstract

Urban logistics operations are increasingly affected by traffic accidents and criminal incidents that may compromise transportation efficiency and operational safety. This study proposes a geometric heuristic framework for incorporating urban risk structures into a Capacitated Vehicle Routing Problem (CVRP). The methodology combines georeferenced accident and robbery records, spatial clustering, overlap analysis, transformation of irregular conflict regions into circular risk zones, and a secant-based mechanism for evaluating route exposure to risk. The resulting zones are integrated into the routing model through a multiplicative penalty structure that balances transportation cost and risk avoidance. The framework was evaluated using real-world data from Irapuato, Mexico, including accident and crime records collected between 2020 and 2025 and a distribution network of 97 customers. Results show that the proposed methodology successfully identifies urban conflict structures and incorporates them into routing decisions. Sensitivity analysis revealed a clear trade-off between routing efficiency and risk exposure, reducing conflict-zone crossings from six to zero with a moderate increase in routing cost. The findings demonstrate the practical applicability of the proposed geometric heuristic for risk-aware urban logistics planning.

Keywords: Vehicle Routing Problem, Urban Risk, Spatial Clustering, Geometric Heuristics, Risk-Aware Logistics.

Introduction

The vehicle routing problem (VRP) has been a fundamental area of research in logistics (Sar & Ghadimi, 2023) and operational optimization, particularly in contexts where efficiency in distribution and transportation is critical for improving performance and reducing costs. Since its original formulation by Dantzig and Ramser (1959), a wide range of extensions have been proposed to better represent real-world logistics systems, including capacitated variants, multi-depot configurations, time windows, and stochastic demand structures (Tang et al., 2015; Vidal et al., 2015; Güner et al., 2017). More recent applications have expanded toward urban logistics and e-commerce distribution systems, where operational constraints and service requirements are increasingly complex (Torres et al., 2022).

The main contribution of this work is the proposal of a geometric heuristic framework capable of transforming heterogeneous urban accident and crime data into circular risk zones, integrating them directly into a vehicle routing model. This approach enables the simultaneous consideration of efficiency and safety when planning routes in complex urban environments.

A relevant stream within this literature considers the incorporation of heterogeneous cost structures and operational restrictions into the routing process. In particular, VRP variants with route penalties have been proposed to discourage the use of certain arcs or regions of the network, thereby promoting compliance with regulatory constraints or improving operational safety. These formulations typically introduce additional costs associated with specific edges or nodes, rather than explicitly removing them from the feasible solution space (Wen & Eglese, 2014; Xiong et al., 2024). However, despite their flexibility, most of these approaches assume that such penalties are exogenously defined and spatially static.

In parallel, the increasing complexity of urban systems has led to the consideration of spatially explicit restrictions within logistics planning. Urban freight distribution is associated with externalities such as congestion, noise, and environmental pollution, as well as public health impacts (Haarstad et al., 2024; Yang et al., 2025; Zhao et al., 2025; Espadaler-Clapés et al., 2023). Given the uneven spatial distribution of these impacts, policy instruments such as zoning regulations, low-emission zones, congestion pricing schemes, and time-window restrictions have been widely implemented to regulate freight mobility in cities (Fried et al., 2025; Ma et al., 2025). These interventions effectively transform classical routing problems into constrained VRP variants that incorporate spatial, temporal, and environmental restrictions (Şahin & Yaman, 2024; Boriboonsomsin et al., 2023; Álvarez-Horcajo, et al., 2024; Bruglieri et al., 2025).

While these approaches have been extensively studied in European and Asian contexts, Latin American cities present additional challenges associated with heterogeneous infrastructure conditions and uneven urban development patterns. In these settings, infrastructure limitations and road safety issues significantly affect distribution efficiency. For instance, Barrera-Jiménez and Stevenson (2025) show that urban structure and road infrastructure quality influence traffic safety outcomes and enable the identification of collision-prone zones. Similarly, recent studies highlight that congestion, informal circulation patterns, and regulatory variability further complicate urban freight operations in these environments (Rodríguez et al., 2026; Román-Cedillo & Bautista-Hernández, 2026).

Within this context, the identification and representation of spatial risk zones has emerged as a complementary research direction in urban logistics optimization. Rather than treating risk regions as predefined inputs, recent studies emphasize the importance of deriving such structures from spatial data distributions. In this regard, clustering techniques have been widely used to extract meaningful spatial groupings from georeferenced data, which can subsequently be incorporated into optimization models (Tiwari et al., 2023). Among these methods, k-means clustering has been extensively adopted due to its computational efficiency and its ability to produce compact and interpretable partitions defined by centroids (Zhang, 2022; Zhang et al., 2025). However, its assumption of convex and isotropic cluster geometry limits its representational flexibility in complex urban environments.

Density-based methods such as DBSCAN have been proposed as an alternative due to their ability to detect arbitrarily shaped clusters (Tu et al., 2022). Nevertheless, their performance is sensitive to parameter selection and varying density distributions, which may reduce robustness in heterogeneous urban contexts (Khan et al., 2018). In comparison, k-means provides a more stable and computationally efficient framework, particularly when the objective is not only pattern detection but also the integration of spatial structures into optimization models as operational constraints or cost modifiers.

Motivated by these considerations, this study adopts k-means as the basis for the identification of spatial risk structures. To overcome its geometric limitations, cluster centroids are transformed into circular influence zones representing localized risk areas. These regions are then integrated into the routing problem through a geometric intersection mechanism between network arcs and risk zones, enabling an explicit evaluation of route exposure to urban risk.

The resulting formulation extends the classical VRP by introducing cost structures that depend not only on distance or travel time but also on the spatial interaction between vehicle trajectories and endogenous risk regions. Accordingly, the proposed method can be interpreted as a VRP with geometry-dependent penalties, where route feasibility and cost are influenced by intersection with dynamically generated risk zones. This framework allows the direct integration of spatial analytics into routing optimization without relying exclusively on exogenous or static spatial restrictions.

This article addresses a VRP with route penalties defined by spatially generated risk zones. A heuristic is proposed to construct such zones based on clustering and geometric transformation of spatial data, and to incorporate them into the routing model through arc-level penalty adjustments. The objective is to minimize total routing cost, including both travel distance and penalties associated with the traversal of high-risk areas, which is particularly relevant for urban freight applications in environments characterized by heterogeneous infrastructure and elevated spatial uncertainty.

The remainder of this paper is organized as follows. The Methodology section describes the proposed heuristic framework and its technical components in detail. The Results section presents the application of the model to a real-world urban distribution case study. Finally, the Conclusion section discusses the main findings, the limitations of the proposed approach, and potential directions for future research.

Methodology

This study proposes a spatially informed heuristic framework for incorporating urban risk structures into a Vehicle Routing Problem (VRP). The methodology integrates georeferenced incident data, clustering-based spatial abstraction, geometric transformation of risk regions, and arc-level penalization within a routing optimization model.

The central idea is to transform heterogeneous urban risk observations into continuous geometric structures that can be evaluated directly within a network representation of the transportation system. This allows the routing model to incorporate spatial exposure effects without relying on predefined administrative boundaries or static risk maps.

The methodological framework consists of six sequential stages: (i) collection and georeferencing of urban incident data, (ii) spatial clustering using k-means, (iii) identification of overlapping risk structures, (iv) transformation of irregular spatial patterns into circular risk zones, (v) geometric evaluation of route–zone interactions through a secant-based approach, and (vi) integration of risk penalties into a capacitated VRP model.

Figure 1 illustrates the overall framework adopted in this research.

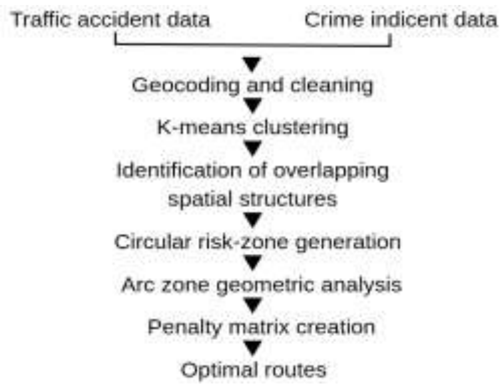

Figure 1. Proposed methodological framework.

Two independent datasets were employed to characterize urban risk conditions:

1. Traffic accident records.
2. Crime incident records associated with robbery events.

Both datasets were obtained from governmental open-data repositories through public information access mechanisms. Since the original records contained textual location descriptions, a georeferencing procedure was implemented in Python to convert addresses into geographic coordinates. Each observation was georeferenced and represented by:

$$x_i = (\alpha_i, \beta_i) \in \mathbb{R}^2$$

Sets and parameters:

$N: set\ of\ nodes$
$V = \{0, 1, \dots, n\}: set\ of\ customers$
$A = \{(i,j) \mid i,j \in N, i \neq j\}: set\ of\ arcs$
$S = \{1, \dots, m\}: set\ of\ vehicles$
$K = \{1, \dots, L\}: set\ of\ risk\ zones$
$\alpha_i: latitude\ of\ node\ i$
$\beta_i: longitude\ of\ node\ i$
$P_i: position\ of\ node\ i$
$c_k = (h_k, l_k): center\ of\ risk\ zone\ k$
$h_k: x - coordinate\ of\ center$
$l_k: y - coordinate\ of\ center$
$r_k: radus\ of\ risk\ zone\ k$
$\lambda: risk\ sensitivity\ parameter$
$\delta_{ij}^k: intersection\ indicator$
$\gamma_i^k: node\ inclusion\ indicator$
$for\ each\ node\ i \in N: x_i = (\alpha_i, \beta_i) \in \mathbb{R}^2$
$Risk\ zone\ k \in K: Z_k = \{x \in \mathbb{R}^2: \|x - c_k\|^2 \leq r_k\}$
$q_i = demand\ of\ customer\ i$
$Q = vehicle\ capacity$
$d_{ij} = Harvesine\ distance\ between\ nodes$
$c_{ij} = base\ travel\ cost$
$x_{ijs} \in \{0,1\}: decision\ variable, 1\ if\ vehicle\ s\ traverses\ arc\ (i,j), 0\ otherwise$

Let:

$D^{acc} = \{x_i^{acc}\}_{i=1}^{n_1}: traffic\ accident\ dataset$
$D^{inc} = \left\{x_j^{inc}\right\}_{j=1}^{n_2}: crime\ incident\ dataset$

The geocoding process was implemented in Python and transformed textual addresses into geographic coordinates.

To identify latent spatial structures of risk, k-means clustering is independently applied to each dataset.

For accidents:

$$C^{acc} = \left\{C_1^{acc}, \dots, C_{k_1}^{acc}\right\}$$

For crime incidents:

$$C^{inc} = \left\{C_1^{inc}, \dots, C_{k_1}^{inc}\right\}$$

Each cluster is characterized by its centroid:

$$c_k = \frac{1}{|C_k|} \sum_{x \in C_k} x$$

To capture overlapping slaping risk patterns, clusters from both datasets are intersected in the spatial domain.

Let:

$$C^* = \{C_p^{acc} \cap C_q^{inc} \neq 0\}$$

Every composite region C_k^* is transformed into a circular approximation to ensure computational tractability within the routing model.

The centroid of each region is computed as:

$$c_k = (\alpha_k, \beta_k)$$

The radius is defined as:

$$r_k = max_{x \in C_k^*} \|x - c_k\|$$

Thus, each risk region is represented as a circular zone:

$$Z_k = \{x \in \mathbb{R}^2 : \|x - c_k\|^2 \leq r_k\}$$

This approximation allows complex spatial polygons to be embedded into a tractable geometric structure compatible with routing evaluation.

To define the arc-zone interaction model, the transportation network is defined as a directed graph:

$$G = (N, A)$$

Where each arc $(i, j) \in A$ represents a potential route segment.

For the geometric evaluation of arc-zone intersections, let P_i and P_j be the coordinates of nodes i and j. Each arc is represented as a line segment $\overline{P_i P_j}$. For each zone Z_k, the minimum distance between its center c_k and the segment is computed using a projection-based operator:

$$t_{ij}^k = \frac{(c_k - P_i) \cdot (P_j - P_i)}{\|P_j - P_i\|^2}$$

The closest point on the segment is:

$$P^* = \begin{cases} P_i + t_{ij}^k (P_j - P_i), & 0 \leq t_{ij}^k \leq 1 \\ \arg\min(\|c_k - P_i\|, \|c_k - P_j\|), & otherwise \end{cases}$$

The distance to the zone is:

$$d_k(i, j) = \|c_k - P^*\|^2$$

An arc is considered to intersect a risk zone if:

$$\delta_{ij}^k = \begin{cases} 1 & if\ d_k(i, j) \leq r_k \\ 0 & otherwise \end{cases}$$

This defines a secant-based risk interaction mechanism.

Let γ_i^k indicate whether node i lies within zone k:

$$\gamma_i^k = \begin{cases} 1 & if\ P_i \in Z_k \\ 0 & otherwise \end{cases}$$

Nodes located inside risk zones must be serviced regardless of route penalties, ensuring feasibility of the VRP solution.

The final penalty associated with arc (i,j) is defined as:

$$p_{ij} = 1 + \lambda \sum_{k \in K} \delta_{ij}^k \left(1 - \max(\gamma_i^k, \gamma_j^k)\right)$$

This formulation ensures that arcs crossing risk zones are penalized unless they connect mandatory nodes within the same zone. The parameter λ controls the importance assigned to risk avoidance during route construction. When λ = 0, the model reduces to a classical capacitated VRP and no risk consideration is incorporated. As λ increases, route segments intersecting risk zones become progressively less attractive, encouraging the optimization model to select alternative trajectories whenever feasible. A sensitivity analysis was conducted using different λ values to evaluate the trade-off between transportation cost and risk exposure.

A multiplicative penalty structure is adopted (Table 1) instead of a classical Big-M formulation to avoid numerical instability and excessive dominance of risk terms in the objective function. This formulation allows a continuous trade-off between travel cost and risk exposure, which is more consistent with real-world urban logistics decision-making.

Table 1. Interpretation.

Situation	Penalized
Arc outside the circle	No
Secant arc and no customer inside	Yes
Secant arc and destination customer inside	No
Secant arc and both customers inside	No

The geographical coordinates associated with customers and depot locations were used to construct the transportation network. Since the nodes are represented by latitude and longitude coordinates, the distance between nodes was calculated using the Haversine formulation, which accounts for the curvature of the Earth and provides more accurate estimates than Euclidean distances when working with geospatial data.

The resulting problem is formulated as a capacitated VRP with spatially dependent arc cost:

Objective function

$$\min Z = \sum_{s\in S} \sum_{(i,j)\in A} x_{ijs}\, c_{ij}\, p_{ij}$$

Subject to

Customer assignment:

$$\sum_{j\in N} \sum_{s\in S} x_{ijs} = 1 \quad \forall_i \in V$$

Flow conservation:

$$\sum_{j\in N} x_{ijs} - \sum_{j\in N} x_{jis} = 0$$

Depot constraint:

$$\sum_{j\in N} x_{0js} = 1 \ \ \forall_s \in S$$

Capacity constraint:

$$\sum_{i\in V} q_i \sum_{j\in N} x_{0js} \leq Q$$

The proposed methodology is implemented through a sequential heuristic composed of clustering, geometric processing and routing optimization stages. The following algorithm summarizes the procedure.

Algorithm: Risk-Zone Routing Heuristic
Step 1. Import accident records.
Step 2. Import robbery records.
Step 3. Geocode all observations.
Step 4. Apply k-means clustering to accident data.
Step 5. Apply k-means clustering to crime data.
Step 6. Detect overlapping clusters.
Step 7. Compute centroids of overlapping regions.
Step 8. Calculate maximum-distance radius.
Step 9. Generate circular risk zones.
Step 10. Construct the set of route arcs.
Step 11. Evaluate arc-circle intersections.
Step 12. Compute penalty coefficients.
Step 13. Calculate Haversine distances.
Step 14. Generate penalized cost matrix.
Step 15. Solve the capacitated VRP.
Step 16. Return optimal routes.

To ensure the reproducibility of the proposed approach, the clustering process was conducted by evaluating fifteen different configurations, with 20 clusters ultimately selected as the optimal representation of urban incidents. Outliers were removed by excluding observations located more than 5 km from the global centroid, thereby improving cluster compactness. The radius of each circular risk zone was defined as the maximum distance between the cluster centroid and its farthest observation, ensuring a consistent representation of the spatial extent of risk. The CVRP model was configured with a network of 93 customers and a homogeneous fleet of vehicles, incorporating multiplicative penalties according to the level of exposure to risk zones.

From a practical perspective, the sensitivity analysis showed that setting $\lambda = 1$ achieved a balanced solution by reducing route crossings through risk zones at the cost of a 13.9% increase in total travel distance. Increasing the penalty to $\lambda = 3$ completely eliminated crossings while requiring an additional increase of less than 1 km compared with the previous scenario. Therefore, the appropriate penalty value should be selected according to the desired trade-off between a substantial reduction in risk exposure and a moderate increase in travel distance. The secant-based mechanism improves the accuracy of the exposure assessment by explicitly evaluating the interaction between route segments and circular risk zones, thereby avoiding overestimation. Although representing irregular risk regions as circles simplifies the computational process, it also introduces a geometric approximation of the actual spatial distribution of risk.

Results

The proposed methodology was evaluated using a real-world urban logistics scenario in the city of Irapuato, Guanajuato, Mexico. Traffic accident and robbery records collected between 2020 and 2025 were obtained through public information access mechanisms and subsequently georeferenced. The routing network considered 97 customer locations distributed throughout the urban area. After applying the proposed clustering and overlap procedure, six risk zones were identified and incorporated into the routing model.

The present study employs traffic accident and robbery records collected between 2020 and 2025 to identify urban conflict zones. The objective of the proposed methodology is not to predict future incidents but rather to detect persistent spatial structures associated with elevated operational risk. Consequently, a multi-year observation window was adopted to reduce the influence of short-term fluctuations and isolated events.

Using a longer temporal horizon offers two methodological advantages. First, it increases the statistical robustness of the clustering process by incorporating a larger number of observations. Second, it allows the identification of recurring spatial patterns that remain relatively stable over time and therefore are more representative of the structural characteristics of the urban environment.

From a logistics perspective, routing decisions are typically designed considering medium-term operational conditions rather than temporary incident concentrations. Therefore, zones repeatedly associated with accidents and criminal activity over several years constitute more reliable indicators of exposure risk than hotspots derived from a single year of observations.

For these reasons, the period 2020–2025 was considered adequate to identify stable conflict zones capable of supporting strategic routing decisions within the proposed vehicle routing framework (Figure 2).

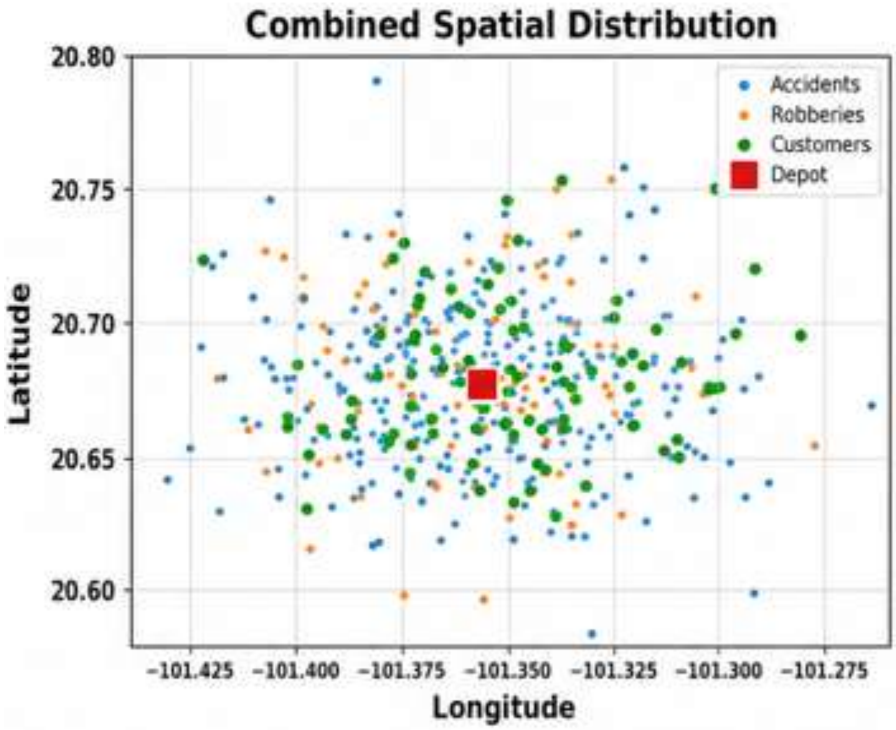

Figure 2. Combined Spatial Distribution.

To identify an appropriate representation of urban risk structures, multiple clustering configurations were evaluated. Since the proposed approach relies on transforming spatial clusters into circular penalty zones, the selection of the number of clusters has direct implications for the resulting radius sizes and, consequently, for the behavior of the routing model. A very small number of clusters tends to generate excessively large circles that overestimate risk exposure, whereas an excessive number of clusters produces fragmented regions with limited practical relevance for route planning.

A total of fifteen clustering configurations were evaluated. Each experiment was assessed according to the spatial coherence of the resulting clusters, the resulting radius lengths, and the interpretability of the identified risk zones. Among the tested configurations, Experiment 6, corresponding to 20 clusters, provided the most balanced representation of the spatial distribution of incidents.

Prior to the final clustering stage, observations located more than 5 km from the global centroid of the dataset were excluded. These observations represented isolated events with low spatial density and exhibited a strong influence on centroid allocation. Their inclusion generated clusters with disproportionately large radii and reduced the spatial discrimination capacity of the model. Consequently, removing these outliers improved cluster compactness and produced risk zones more consistent with the actual spatial concentration of incidents.

Figure 3 and Table 2 summarize the results obtained during the clustering calibration process. The selected configuration generated twenty spatial clusters that adequately captured the main concentration patterns of urban incidents while maintaining manageable radius values for subsequent integration into the routing model.

Table 2. Representative cluster characteristics.

Cluster	Points	Centrolid lat	Centroid lon	Max radius (km)
1	30	20.679710	-101.353250	1.50
2	14	20.630728	-101.375326	1.78
3	25	20.690042	-101.335087	1.58
4	18	20.680632	-101.400713	2.53

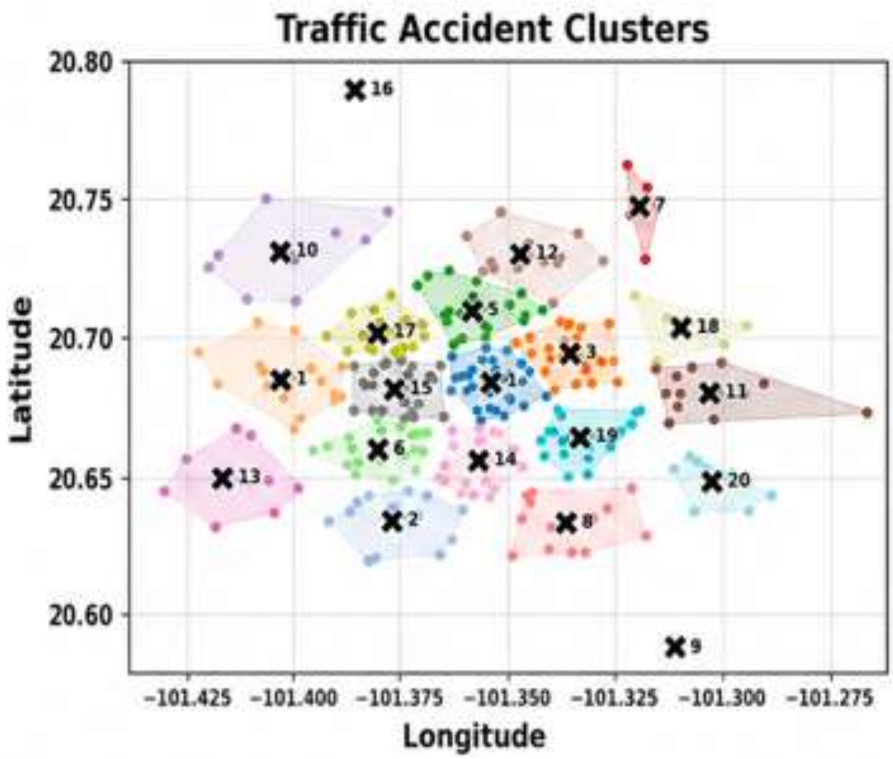

Figure 3. Traffic accident clusters.

Figure 3 presents the final assignment of incident observations to the twenty clusters. At this stage, only the cluster centroids and their associated observations are identified. The geometric boundaries of the future penalty zones are not yet defined, as the objective of this phase is solely to detect latent spatial structures within the incident data.

A more detailed visualization of the cluster geometry is presented in Figure 4. The figure illustrates the irregular spatial distributions generated by the clustering process, highlighting the heterogeneous nature of urban risk patterns. These irregular structures constitute the basis for the subsequent overlap analysis.

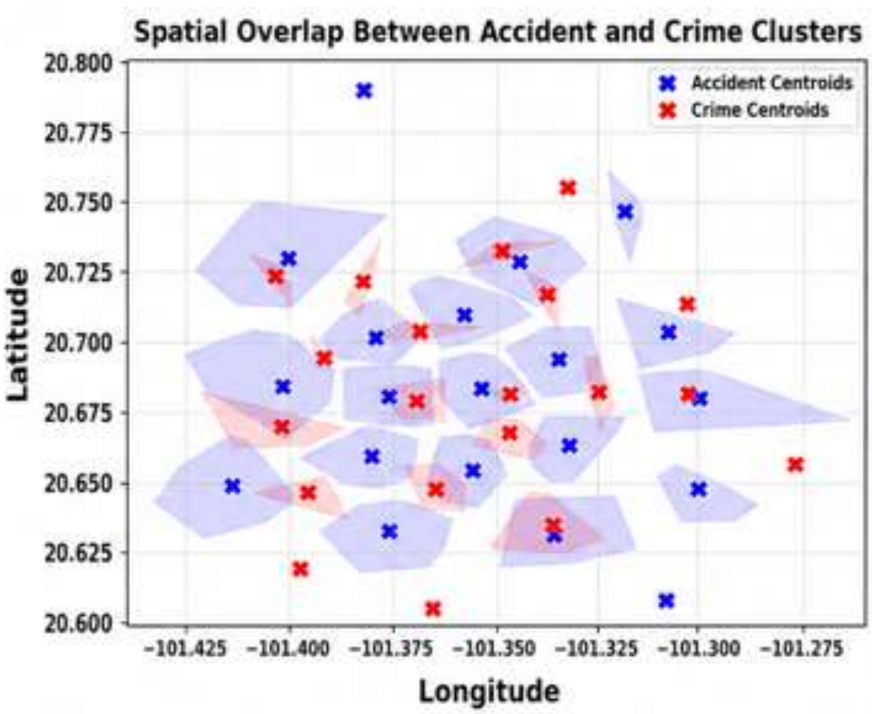

Figure 4. Spatial overlap.

Figure 5 presents the spatial overlap between accident clusters and robbery clusters. The overlapping areas represent locations where multiple sources of urban risk coexist simultaneously. These regions are particularly relevant from a logistics perspective because they combine elevated accident exposure with security-related concerns, increasing the operational risk associated with vehicle movements.

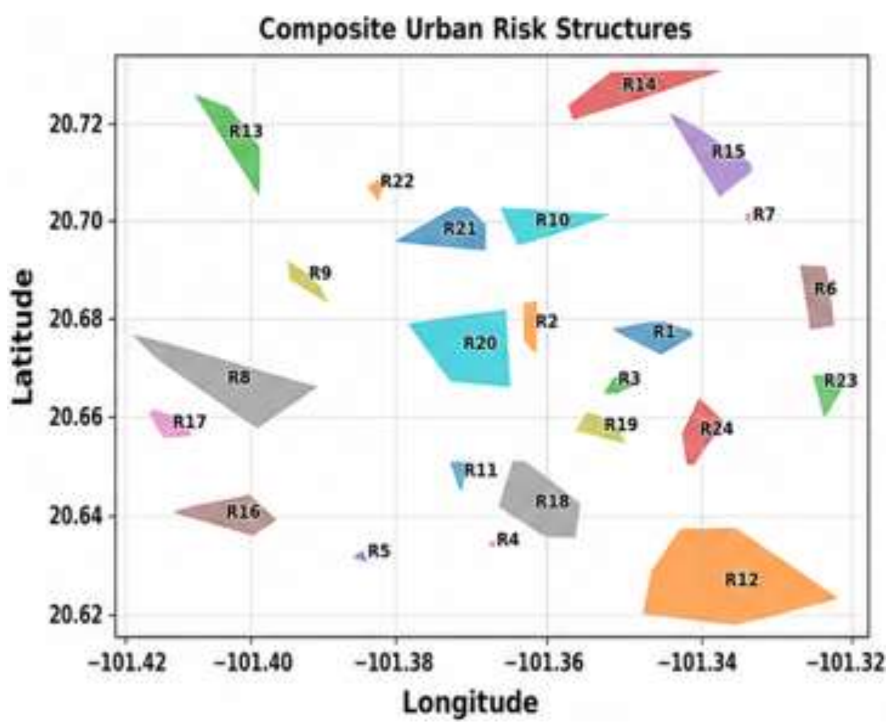

Figure 5. Intersections.

The intersection regions identified in Figure 5 were subsequently processed to calculate a new centroid and a representative radius. Specifically, a composite spatial structure was generated from each overlap area, and the maximum distance between the new centroid and the outermost point of the composite structure was used to define the radius of influence.

Figure 6 illustrates the resulting circular risk zones generated through this procedure. The resulting circles constitute the final penalty regions employed in the routing model. Unlike administrative boundaries or predefined restricted areas, these zones emerge directly from historical urban risk patterns and therefore provide a data-driven representation of the spatial conditions faced by distribution vehicles. This characteristic allows the proposed methodology to dynamically adapt the routing process to local urban risk structures while maintaining computational tractability within the VRP formulation.

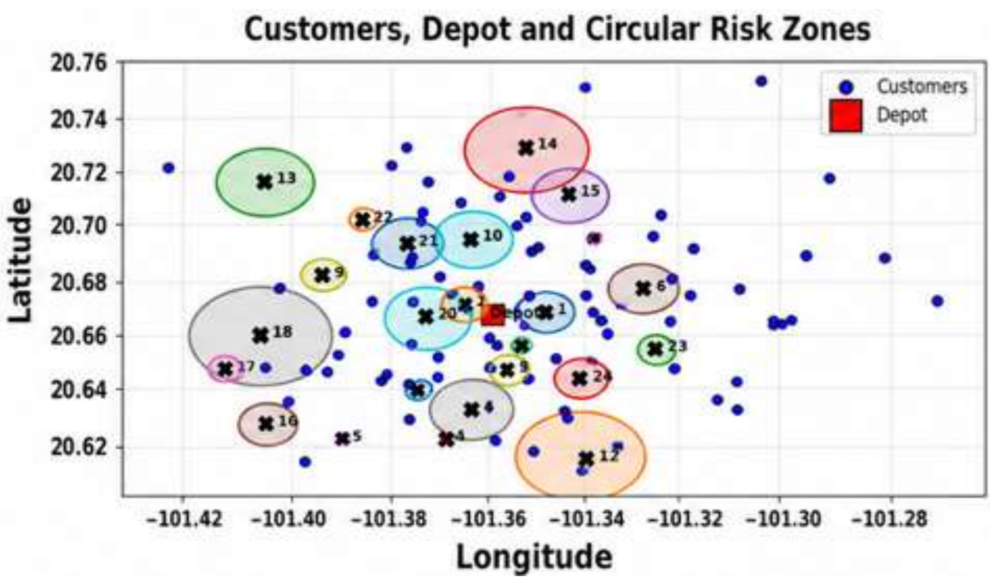

Figure 6. Risk zones.

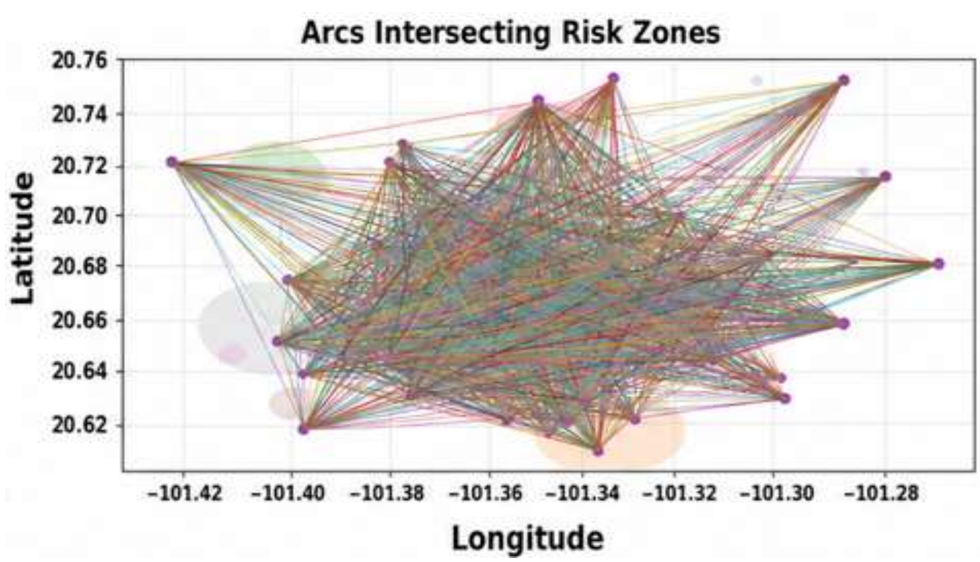

Figure 7. Arcs.

Figure 7 illustrates the complete set of potential route segments generated from the transportation network together with the circular risk zones identified from overlapping accident and crime structures. Each line represents a candidate arc connecting two network nodes, while the shaded circles correspond to the risk zones incorporated into the routing model.

A multiplicative penalty structure is adopted instead of a classical Big-M formulation to avoid numerical instability and excessive dominance of risk terms in the objective function. This formulation allows a continuous trade-off between travel cost and risk exposure, which is more consistent with real-world urban logistics decision-making.

The resulting solution demonstrates how the proposed methodology modifies route construction in response to the spatial distribution of urban risk. Rather than treating risk zones as prohibited areas, the model incorporates them as penalized regions within the objective function. Consequently, routes tend to avoid conflict zones whenever economically feasible, while still allowing traversal when the additional detour would generate a disproportionate increase in transportation cost or when customers located near risk zones must be serviced. The figure illustrates the balance achieved between transportation efficiency and risk avoidance, showing that the proposed framework can incorporate urban conflict structures into routing decisions without compromising network feasibility.

The sensitivity analysis revealed a clear trade-off between transportation efficiency and risk exposure. Increasing the risk weight from $\lambda=0$ to $\lambda=1$ reduced the number of risk-zone crossings from six to two, at the expense of a 13.9% increase in total routing cost. Further increasing the risk weight to $\lambda=3$ completely eliminated all risk-zone crossings while increasing the routing cost by less than 1 km compared to $\lambda=1$. These results suggest the existence of an operational equilibrium where substantial reductions in risk exposure can be achieved with relatively limited increases in transportation cost.

Table 3. Sensitivity analysis.

Lambda	Total cost (km)	Risk crossings
0	112.81	6
1	128.45	2
3	129.41	0

For the selected risk sensitivity level ($\lambda = 1$), the routing solution reduced the number of conflict-zone crossings from six to two while maintaining a feasible three-vehicle configuration. This result confirms that the proposed geometric penalization mechanism effectively influences route selection and encourages safer trajectories throughout the distribution network.

The resulting solution demonstrates how the proposed methodology modifies route construction in response to the spatial distribution of urban risk. Rather than treating risk zones as prohibited areas, the model incorporates them as penalized regions within the objective function. Consequently, routes tend to avoid conflict zones whenever economically feasible, while still allowing traversal when the additional detour would generate a disproportionate increase in transportation cost or when customers located near risk zones must be serviced.

Figure 8 presents the optimal routing solution obtained after incorporating the proposed risk penalization mechanism into the VRP model. The red square denotes the depot location, while blue points represent customer locations. The shaded circles correspond to the circular risk zones derived from overlapping accident and robbery structures.

The colored routes represent the tours assigned to the three vehicles.

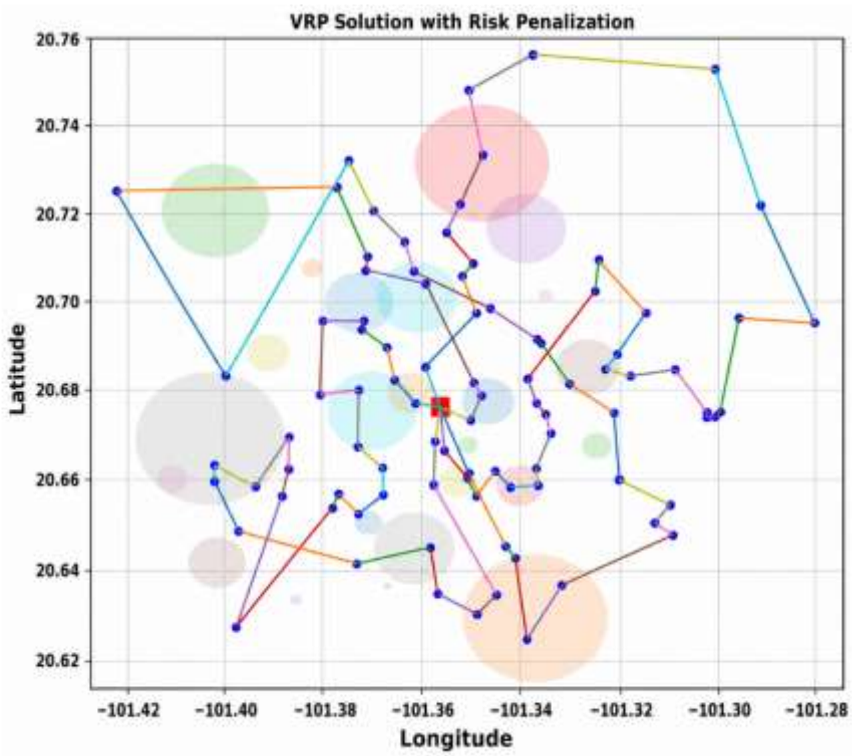

Figure 8. VRP solution.

Vehicle 1: [0, 48, 78, 35, 30, 34, 72, 84, 6, 68, 42, 37, 85, 28, 86, 11, 14, 60, 62, 8, 76, 77, 67, 26, 79, 58, 21, 59, 4, 0]

Vehicle 2: [0, 40, 54, 31, 25, 20, 15, 43, 2, 70, 45, 9, 74, 91, 17, 16, 89, 65, 80, 64, 69, 90, 50, 83, 73, 22, 56, 71, 92, 18, 0]

Vehicle 3: [0, 87, 82, 41, 55, 49, 66, 10, 63, 3, 88, 53, 24, 13, 75, 29, 19, 7, 57, 47, 33, 23, 38, 36, 27, 32, 39, 81, 51, 52, 12, 1, 44, 5, 61, 46, 0]

Although the proposed methodology discourages route segments intersecting conflict zones, some penalized arcs remained in the optimal solution. This behavior is expected because the penalty mechanism does not prohibit risk exposure but rather incorporates it as an additional cost component. Consequently, when the detour required to avoid a conflict zone becomes disproportionately large, the optimization process may still select a penalized arc. This characteristic reflects realistic logistics decision-making, where complete risk avoidance is often impractical and must be balanced against operational efficiency.

Conclusion

This study proposed and evaluated a geometric heuristic framework for incorporating urban risk structures into a Vehicle Routing Problem (VRP). The primary objective was to develop a methodology capable of transforming heterogeneous urban incident data into spatially explicit risk representations that could be directly integrated into routing decisions. The results obtained demonstrate that this objective was successfully achieved.

The proposed framework combines georeferenced accident and robbery records, clustering techniques, spatial overlap analysis, geometric abstraction, and route optimization. Starting from historical urban incident data, the methodology identifies latent spatial risk structures, detects overlapping regions associated with multiple risk sources, and transforms these irregular spatial patterns into circular risk zones suitable for integration within a capacitated VRP model. This transformation constitutes one of the main contributions of the study, as it provides a practical mechanism for converting complex urban risk information into computationally tractable routing inputs.

A second contribution is the development of a secant-based geometric interaction mechanism that evaluates whether a route segment intersects a risk zone. Unlike approaches that rely on administrative boundaries or predefined restricted areas, the proposed formulation allows risk exposure to be quantified directly from the geometric relationship between route arcs and data-driven conflict zones. This provides a flexible and transferable framework that can be adapted to different urban environments and risk sources.

The computational experiments conducted using real-world data from the city of Irapuato, Mexico, confirmed the practical applicability of the methodology. The clustering and overlap procedures successfully identified persistent urban conflict structures, which were subsequently incorporated into the routing model through a multiplicative penalty mechanism. The resulting framework preserved computational feasibility while allowing risk considerations to influence route construction.

The sensitivity analysis demonstrated a clear trade-off between transportation efficiency and risk exposure. The classical VRP solution ($\lambda = 0$) generated six crossings through conflict zones and a total routing cost of 112.81 km. Introducing moderate risk sensitivity ($\lambda = 1$) reduced the number of crossings to two while increasing routing cost by approximately 13.9%. Increasing the risk parameter to $\lambda = 3$ completely eliminated all crossings through conflict zones while requiring less than one additional kilometer compared with the $\lambda = 1$ scenario. These results provide empirical evidence that the proposed heuristic is capable of significantly reducing exposure to urban risk while maintaining acceptable transportation efficiency.

An important characteristic of the proposed approach is that risk zones are not treated as prohibited regions. Instead, risk is incorporated as a continuous cost component that allows the optimization process to balance safety considerations and operational efficiency. Consequently, the methodology reflects realistic logistics decision-making environments in which complete risk avoidance may not always be economically justified.

Overall, the results demonstrate that the proposed geometric heuristic constitutes a useful and effective mechanism for integrating urban risk information into vehicle routing decisions. The methodology enables the identification of meaningful spatial conflict structures, their transformation into tractable geometric representations, and their incorporation into route optimization models through a mathematically consistent framework.

Future research may extend the proposed methodology in several directions. A particularly promising avenue consists of integrating predictive spatial-risk models based on machine learning techniques to generate dynamic risk zones derived from anticipated accident and crime patterns rather than solely historical observations. Additional extensions may include time-dependent risk representations, multi-objective formulations that explicitly balance transportation cost and risk exposure, and the incorporation of additional urban risk factors such as traffic congestion, flooding events, infrastructure disruptions, or social disturbances. These developments could further enhance the ability of routing systems to operate under complex and evolving urban conditions.

Although the results confirm the usefulness of the proposed heuristic framework, several limitations should be acknowledged. The methodology relies on historical data, whose validity may be affected by dynamic changes in the road infrastructure. In the case study analyzed, the identified urban conflict patterns reflect persistent spatial structures; however, their representativeness may decrease if substantial modifications occur in the transportation network. The moderate increase in travel distance is offset by the elimination of route crossings through risk zones, representing an acceptable trade-off in exchange for improved operational safety. When scaling the model to megacities with higher traffic density and more complex crime patterns, adjustments to the clustering model will likely be required to preserve the quality of the risk representation. Finally, the effectiveness of the proposed framework depends on the timely updating of georeferenced risk data, as delays in data acquisition or reporting may reduce the accuracy of the resulting risk zones.

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