

Sample: Corporate security and travel risk, Mexico City: report

Project: Sample: Corporate security and travel risk, Mexico City

Goal: Describe the project Sample: Corporate security and travel risk, Mexico City: run the analyses that tell the most about its data, draw every result, and write a cited report.

Run: 294d550b-9eea-4398-b429-6280256992ba (running, 11 agent run(s))

Generated: 2026-10-18T05:29:33Z, version 1

Model cost: USD 0.0000 over 0 model call(s)

Data used

Data	Kind	Rows	Time span	Summary	Source
Company sites	vector, Point	8		8 point features; 'type' has 4 values (top: office 3, warehouse 2, client 2); 'security_level' has 2 values (top: standard 6, enhanced 2); 'staff' 8 to 420 (mean 97.5); named by 'name' (e.g. Head office, Distribution center, Sales office Norte); extent -99.1652,19.4107 to -99.1046,19.4578. Point locations of Company sites by type.	[107]
Hotels	vector, Point	30		30 point features; 'approved' has 2 values (top: True 17, False 13); 'stars' 3 to 5 (mean 4.067); named by 'name' (e.g. Hotel Los Pinos 1, Hotel El Cerro 2, Hotel La Fuente 3); extent -99.1728,19.4108 to -99.1024,19.4643. Point locations of Hotels by approved.	[108]
Travel routes	vector, LineString	10		10 line features; 'mode' has 2 values (top: approved taxi 8, company car 2); 'typical_min' 19 to 44 (mean 30.2); named by 'name' (e.g. Airport to Head office, Airport to Hotel Los Pinos 1, Hotel Los Pinos 1 to Head office); total length 51.24 km; extent -99.1652,19.4105 to -99.0901,19.4643. Lines (Travel routes) such as routes or networks.	[109]
Security incidents	vector, Point	1,700	2025-10-01 to 2026-09-30	1,700 point features; dated by 'occurred_at' from 2025-10-01 to 2026-09-30; 'type' has 8 values (top: robbery 456, theft 390, vandalism 252); 'severity' has 3 values (top: low 832, medium 610, high 258); extent -99.1802,19.3971 to -99.0859,19.4682. Dated point events by type: where and when Security incidents happen.	[2]
Risk zones	vector, Polygon	14		14 polygon (area) features; 'night_travel' has 3 values (top: escort 5, allowed 5, avoid 4); 'risk_score' 1 to 10 (mean 6.143); named by 'name' (e.g. La Ribera, Los Pinos, El Cerro); total area 80.06 km2; extent -99.1809,19.3964 to -99.0856,19.4688. Areas (Risk zones) with risk_score to compare and map.	[110]
Hospitals	vector, Point	15		15 point features; 'english_speaking' has 2 values (top: False 9, True 6); 'trauma_level' 1 to 3 (mean 1.6); named by 'name' (e.g. Hospital Las Acacias, Hospital El Puerto Viejo, Hospital La Alameda); extent -99.1691,19.4018 to -99.0923,19.4672. Point locations of Hospitals by english_speaking.	[111]
Safe havens	vector, Point	12		12 point features; 'type' has 4 values (top: partner office 4, embassy 4, hotel 3); 'open_24h' has 2 values (top: True 6, False 6); extent -99.1732,19.4029 to -99.0999,19.4675. Point locations of Safe havens by type.	[112]

Data	Kind	Rows	Time span	Summary	Source
Protest events	vector, Point	80	2026-01-05 to 2026-09-28	80 point features; dated by 'date' from 2026-01-05 to 2026-09-28; 'size' has 3 values (top: large 32, small 28, medium 20); 'theme' has 4 values (top: education 23, water 22, labor 21); extent -99.1465,19.4258 to -99.1195,19.4519. Dated point events by size: where and when Protest events happen.	[3]
Travel log	table	400	2025-10-01 to 2026-09-30	Table of 400 rows and 6 columns without geometry; dated by 'date' from 2025-10-01 to 2026-09-30; 'incident_reported' has 2 values (top: False 390, True 10); 'travellers' 1 to 4 (mean 2.56); 'delay_min' 0 to 24 (mean 6.668). A table of Travel log without locations.	[4]
Site guard roster	table	16		Table of 16 rows and 4 columns without geometry; 'shift' has 2 values (top: day 8, night 8); 'armed' has 2 values (top: False 15, True 1); 'guards' 1 to 6 (mean 4.188). A table of Site guard roster without locations.	[113]
Country security briefing	document			1-page pdf document 'Country security briefing'; language en; mentions 7 place(s): Head office to Distribution center (1), Head of (1), Distribution (1), La Ribera (1), Head office (1). A document about Head office to Distribution center, Head of, Distribution.	[114]
Hotel security assessment	document			1-page md document 'Hotel security assessment'; language en; mentions 4 place(s): Hotel Los Pinos 1 (1), Hotel El Cerro 2 (1), Head office (1), Hotel La Fuente 3 (1). A document about Hotel Los Pinos 1, Hotel El Cerro 2, Head office.	[115]
Sample: Corporate security and travel risk, Mexico City	record				[116]
Hot spot analysis: Protest events	layer, Polygon	29			[117]
Hot spot analysis: Hotels	layer, Polygon	14			[118]
Hot spot analysis: Security incidents	layer, Polygon	353			[119]
Emerging hot spots: Protest events	layer, Polygon	14			[120]
Emerging hot spots: Security incidents	layer, Polygon	108			[121]
Repeat and near repeat classification: Protest events	layer, Point	80			[122]
Summarize within: Risk zones	layer, Polygon	14			[123]
Summarize within: Risk zones	layer, Polygon	14			[124]
Summarize within: Risk zones	layer, Polygon	14			[125]
Find point clusters: Hospitals	layer, Point	15			[126]
Find point clusters: cluster hulls	layer, Polygon	1			[127]
Find point clusters: Safe havens	layer, Point	12			[128]

Data	Kind	Rows	Time span	Summary	Source
Find point clusters: cluster hulls	layer, Polygon	2			[129]
Find point clusters: Protest events	layer, Point	80			[130]
Find point clusters: cluster hulls	layer, Polygon	1			[131]
Calculate density: Protest events	layer, Polygon	386			[132]
Calculate density: Hotels	layer, Polygon	82			[133]
Calculate density: Security incidents	layer, Polygon	2,240			[134]
Find outliers: Risk zones	layer, Polygon	14			[135]
Find nearest: Hospitals	layer, Point	14			[136]
Find nearest: Hospitals	layer, Point	14			[137]
Find nearest: Hospitals	layer, Point	6			[138]

Timeline

Timeline: events per week by dataset

Per week: 53 weeks from 2025-09-29 to 2026-09-28; trend +0.105 per week; first half 1,078, second half 1,079 (+0.1%)

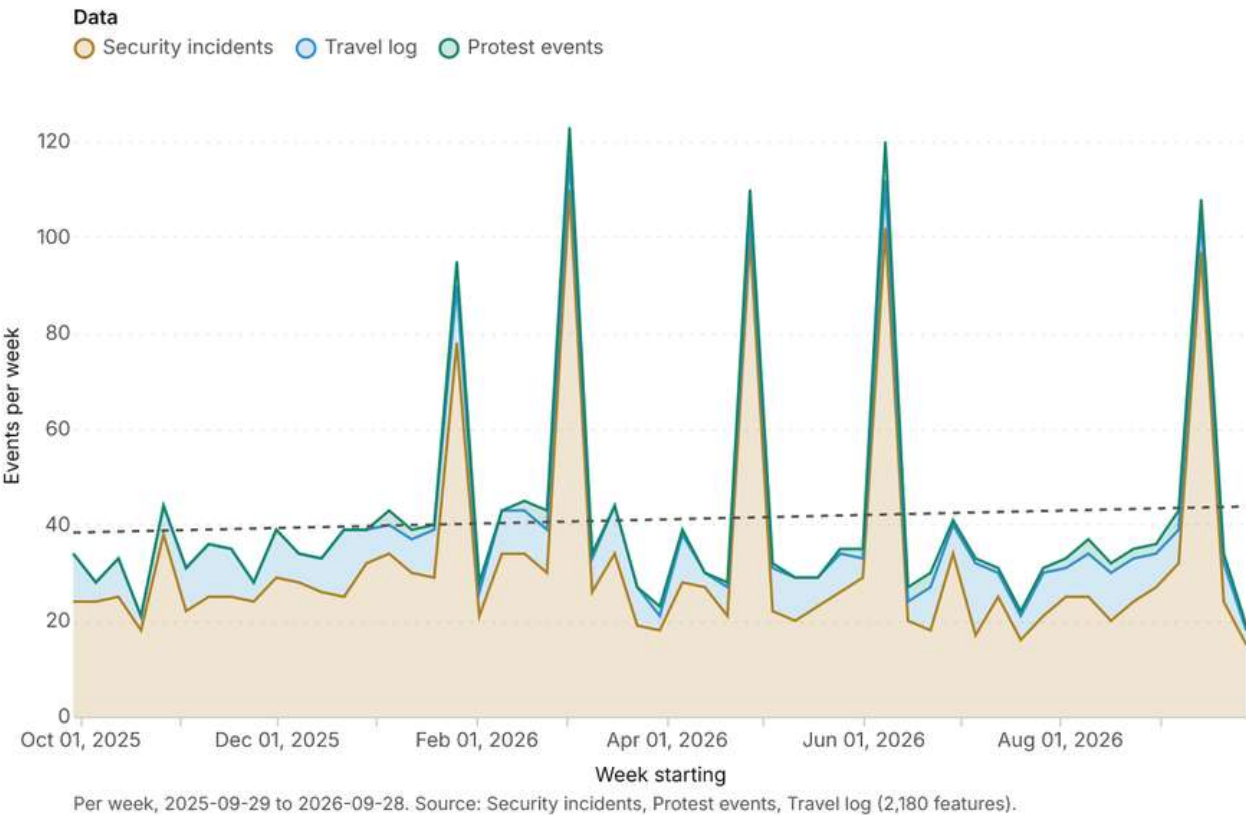


Figure 1. Timeline: events per week by dataset [1]. Per week, 2025-09-29 to 2026-09-28. Source: Security incidents, Protest events, Travel log (2,180 features). The data is in the appendix.

The timeline counts 2,180 dated events in Security incidents, Protest events, Travel log per week, from week of 2025-09-29 to week of 2026-09-28 [1][2][3][4]. By dataset: Security incidents 1,700; Travel log 400; Protest events 80

[1]. The trend is +0.105 events per week; the second half of the weeks has 1,079 against 1,078 in the first (+0.1%) [1].

Busiest weeks

- week of 2026-03-02: 123 events [1]
- week of 2026-06-08: 120 events [1]
- week of 2026-04-27: 110 events [1]

Quietest weeks

- week of 2026-09-28: 19 events [1]
- week of 2025-10-20: 21 events [1]
- week of 2026-07-20: 22 events [1]

Hot spots

What this analysis is. Hot spot analysis: Getis-Ord Gi* hot and cold spots with z-scores, p-values and confidence bins [5]. In ArcGIS it is Find Hot Spots or Hot Spot Analysis (Getis-Ord Gi*); in QGIS, qgis:hotspot (plugin) [5].

Why it was run on this data. 80 points: Getis-Ord Gi* tests whether the concentrations in Protest events are statistically significant [6].

What it found. Hot spots on Protest events: Hot spot analysis: 1 layer saved: Hot spot analysis: Protest events (29 features) [7][8]. It reported result, bins 29; result, count 29; result, elapsed ms 5; result, cell size m 500; result, incidents used 80; result, distance band m 1,000 [7].

Result	Value
result, bins	29
result, count	29
result, elapsed ms	5
result, cell size m	500
result, incidents used	80
result, distance band m	1,000
billing, cost	0.0516
billing, list price	0.0516
billing, upstream cost	0

Findings

Evidenced: Hot spots on Protest events: Hot spot analysis: 1 layer saved: Hot spot analysis: Protest events (29 features) [7][8].

Evidenced: It reported result, bins 29; result, count 29; result, elapsed ms 5; result, cell size m 500; result, incidents used 80; result, distance band m 1,000 [7].

A model draft was discarded because a sentence did not cite a source of this section.

Tool gp_hot_spots; parameters {"project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "features": {"layer": "Protest events (cf75e6b1)"}, "aggregation": "hexagon", "cell_size_m": 500.0, "distance_band_m": 1000.0}

Hot spots

What this analysis is. Hot spot analysis: Getis-Ord Gi* hot and cold spots with z-scores, p-values and confidence bins [5]. In ArcGIS it is Find Hot Spots or Hot Spot Analysis (Getis-Ord Gi*); in QGIS, qgis:hotspot (plugin) [5].

Why it was run on this data. 30 points: Getis-Ord Gi* tests whether the concentrations in Hotels are statistically significant [9].

What it found. The hot spot analysis generated 14 features [10] after processing the Hotels layer [11]. The analysis used 30 incidents and set both the distance band and cell size to 2,000 m [10]. The process completed quickly, taking 2 ms [10]. The billing for this analysis was 0.0506 [10].

Result	Value
result, bins	14
result, count	14
result, elapsed ms	2
result, cell size m	2,000
result, incidents used	30
result, distance band m	2,000
billing, cost	0.0506
billing, list price	0.0506
billing, upstream cost	0

Findings

Evidenced: Hot spots on Hotels: Hot spot analysis: 1 layer saved: Hot spot analysis: Hotels (14 features) [10][11].

Evidenced: It reported result, bins 14; result, count 14; result, elapsed ms 2; result, cell size m 2,000; result, incidents used 30; result, distance band m 2,000 [10].

Tool gp_hot_spots; parameters {"project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "features": {"layer": "Hotels (28842e9c)"}, "aggregation": "hexagon", "cell_size_m": 2000.0, "distance_band_m": 2000.0}

Hot spots

What this analysis is. Hot spot analysis: Getis-Ord Gi* hot and cold spots with z-scores, p-values and confidence bins [5]. In ArcGIS it is Find Hot Spots or Hot Spot Analysis (Getis-Ord Gi*); in QGIS, qgis:hotspot (plugin) [5].

Why it was run on this data. 1700 points: Getis-Ord Gi* tests whether the concentrations in Security incidents are statistically significant [12].

What it found. Hot spots on Security incidents: Hot spot analysis: 1 layer saved: Hot spot analysis: Security incidents (353 features) [13][14]. It reported result, bins 353; result, count 353; result, elapsed ms 18; result, cell size m 500; result, incidents used 1,700; result, distance band m 500 [13].

Result	Value
result, bins	353
result, count	353
result, elapsed ms	18
result, cell size m	500
result, incidents used	1,700
result, distance band m	500
billing, cost	0.084
billing, list price	0.084
billing, upstream cost	0

Findings

Evidenced: Hot spots on Security incidents: Hot spot analysis: 1 layer saved: Hot spot analysis: Security incidents (353 features) [13][14].

Evidenced: It reported result, bins 353; result, count 353; result, elapsed ms 18; result, cell size m 500; result, incidents used 1,700; result, distance band m 500 [13].

Tool gp_hot_spots; parameters {"project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "features": {"layer": "Security incidents (afb5d90c)"}, "aggregation": "hexagon", "cell_size_m": 500.0, "distance_band_m": 500.0}

Space time hot spots

What this analysis is. Emerging hot spots: Where hot spots are new, consecutive, intensifying, persistent, diminishing, sporadic, oscillating or historical over time [15]. In ArcGIS it is Emerging Hot Spot Analysis or Create Space Time Cube [15].

Why it was run on this data. Protest events carry dates in 'date': emerging hot spot analysis finds new, intensifying and fading hot spots per week [16].

What it found. Space time hot spots on Protest events: Emerging hot spots: 1 layer saved: Emerging hot spots: Protest events (14 features) [8][17]. It reported result, count 14; result, elapsed ms 4; result, resolution 8; result, features used 80; result, time neighbors 0; billing, cost 0.104 [17].

Result	Value
result, count	14
result, elapsed ms	4
result, resolution	8
result, features used	80
result, time neighbors	0
billing, cost	0.104
billing, list price	0.104
billing, upstream cost	0

Findings

Evidenced: Space time hot spots on Protest events: Emerging hot spots: 1 layer saved: Emerging hot spots: Protest events (14 features) [8][17].

Evidenced: It reported result, count 14; result, elapsed ms 4; result, resolution 8; result, features used 80; result, time neighbors 0; billing, cost 0.104 [17].

A model draft was discarded because a sentence did not cite a source of this section.

Tool gp_space_time_hot_spots; parameters {"project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "features": {"layer": "Protest events (cf75e6b1)"}, "interval": "week", "bin_shape": "h3", "resolution": 8, "time_field": "date"}

Space time hot spots

What this analysis is. Emerging hot spots: Where hot spots are new, consecutive, intensifying, persistent, diminishing, sporadic, oscillating or historical over time [15]. In ArcGIS it is Emerging Hot Spot Analysis or Create Space Time Cube [15].

Why it was run on this data. Security incidents carry dates in 'occurred_at': emerging hot spot analysis finds new, intensifying and fading hot spots per week [18].

What it found. Space time hot spots on Security incidents: Emerging hot spots: 1 layer saved: Emerging hot spots: Security incidents (108 features) [14][19]. It reported result, count 108; result, elapsed ms 21; result, resolution 8; result, features used 1,700; result, time neighbors 0; billing, cost 0.185 [19].

Result	Value
result, count	108
result, elapsed ms	21
result, resolution	8
result, features used	1,700
result, time neighbors	0
billing, cost	0.185
billing, list price	0.185

Result	Value
billing, upstream cost	0

Findings

Evidenced: Space time hot spots on Security incidents: Emerging hot spots: 1 layer saved: Emerging hot spots: Security incidents (108 features) [14][19].

Evidenced: It reported result, count 108; result, elapsed ms 21; result, resolution 8; result, features used 1,700; result, time neighbors 0; billing, cost 0.185 [19].

Tool gp_space_time_hot_spots; parameters {"project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "features": {"layer": "Security incidents (afb5d90c)"}, "interval": "week", "bin_shape": "h3", "resolution": 8, "time_field": "occurred_at"}

Near repeat

What this analysis is. Repeat and near repeat classification: Classify incidents as originators, repeats (same place) or near repeats within a distance and time window, with a Knox test table [20]. In ArcGIS it is Repeat and Near Repeat Classification or Near Repeat Calculator [20].

Why it was run on this data. Near repeat analysis tests whether Protest events close in space also follow each other within 27 days [21].

What it found. The tool executed used the Protest events data [8] to classify near repeats [22]. The resulting dataset contained a count of 80 pairs [22], with 11 total chains identified [22]. Furthermore, 15 pairs were linked, and the average distance was reported as 200 m [22].

Result	Value
result, days	27
result, count	80
result, chains	11
result, distance m	200
result, elapsed ms	4
result, pairs linked	15
billing, cost	0.0524
billing, list price	0.0524
billing, upstream cost	0

Findings

Evidenced: Near repeat on Protest events: Repeat and near repeat classification: 1 layer saved: Repeat and near repeat classification: Protest events (80 features) [8][22].

Evidenced: It reported result, days 27; result, count 80; result, chains 11; result, distance m 200; result, elapsed ms 4; result, pairs linked 15 [22].

Tool gp_near_repeat; parameters {"days": 27, "project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "features": {"layer": "Protest events (cf75e6b1)"}, "distance_m": 200.0, "time_field": "date"}

Summarize within

What this analysis is. Summarize within: Count and aggregate the features inside each polygon (or bin), proportionally for lines and polygons [23]. In ArcGIS it is Summarize Within or Aggregate Points; in QGIS, native:countpointsinpolygon or native:sumlinelengths [23].

Why it was run on this data. Count Hospitals inside each feature of Risk zones by english_speaking; the counts map as a choropleth (natural breaks, sequential colors) [24].

What it found. Summarize within on Hospitals, Risk zones: Summarize within: 1 layer saved: Summarize within: Risk zones (14 features) [25][26][27]. It reported result, count 14; result, elapsed ms 0; billing, cost 0.0106; billing, list price 0.0106; billing, upstream cost 0 [25].

Result	Value
result, count	14
result, elapsed ms	0
billing, cost	0.0106
billing, list price	0.0106
billing, upstream cost	0

Findings

Evidenced: Summarize within on Hospitals, Risk zones: Summarize within: 1 layer saved: Summarize within: Risk zones (14 features) [25][26][27].

Evidenced: It reported result, count 14; result, elapsed ms 0; billing, cost 0.0106; billing, list price 0.0106; billing, upstream cost 0 [25].

Tool gp_summarize_within; parameters {"stats": [{"stat": "sum", "field": "trauma_level"}], "project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "features": {"layer": "Hospitals (8a96a3d4)", "group_by": "english_speaking", "polygons": {"layer": "Risk zones (a4d2e294)"}}

Summarize within

What this analysis is. Summarize within: Count and aggregate the features inside each polygon (or bin), proportionally for lines and polygons [23]. In ArcGIS it is Summarize Within or Aggregate Points; in QGIS, native:countpointsinpolygon or native:sumlinelengths [23].

Why it was run on this data. Count Hospitals inside each feature of Risk zones by english_speaking; the counts map as a choropleth (natural breaks, sequential colors) [24].

What it found. Summarize within on Safe havens, Risk zones: Summarize within: 1 layer saved: Summarize within: Risk zones (14 features) [27][28][29]. It reported result, count 14; result, elapsed ms 0; billing, cost 0.01052; billing, list price 0.01052; billing, upstream cost 0 [28].

Result	Value
result, count	14
result, elapsed ms	0
billing, cost	0.01052
billing, list price	0.01052
billing, upstream cost	0

Findings

Evidenced: Summarize within on Safe havens, Risk zones: Summarize within: 1 layer saved: Summarize within: Risk zones (14 features) [27][28][29].

Evidenced: It reported result, count 14; result, elapsed ms 0; billing, cost 0.01052; billing, list price 0.01052; billing, upstream cost 0 [28].

Tool gp_summarize_within; parameters {"stats": [], "project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "features": {"layer": "Safe havens (d7ec6bb0)", "group_by": "type", "polygons": {"layer": "Risk zones (a4d2e294)"}}

Summarize within

What this analysis is. Summarize within: Count and aggregate the features inside each polygon (or bin), proportionally for lines and polygons [23]. In ArcGIS it is Summarize Within or Aggregate Points; in QGIS, native:countpointsinpolygon or native:sumlinelengths [23].

Why it was run on this data. Count Hospitals inside each feature of Risk zones by english_speaking; the counts map as a choropleth (natural breaks, sequential colors) [24].

What it found. The analysis employed the `gp\_summarize\_within` tool [30], accepting Protest events [8] and Risk zones [27] as inputs [30]. This process yielded a result count of 14 [30].

Result	Value
result, count	14
result, elapsed ms	0
billing, cost	0.01188
billing, list price	0.01188
billing, upstream cost	0

Findings

Evidenced: Summarize within on Protest events, Risk zones: Summarize within: 1 layer saved: Summarize within: Risk zones (14 features) [8][27][30].

Evidenced: It reported result, count 14; result, elapsed ms 0; billing, cost 0.01188; billing, list price 0.01188; billing, upstream cost 0 [30].

Tool gp_summarize_within; parameters {"stats": [], "project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "features": {"layer": "Protest events (cf75e6b1)"}, "group_by": "size", "polygons": {"layer": "Risk zones (a4d2e294)"}}

Find point clusters

What this analysis is. Find point clusters: Density-based clusters (DBSCAN, HDBSCAN or OPTICS, optionally space-time) with hulls and noise [31]. In ArcGIS it is Find Point Clusters or Density-based Clustering; in QGIS, native:dbscanclustering or native:stdbscanclustering [31].

Why it was run on this data. DBSCAN finds dense groups of Hospitals and separates noise [32].

What it found. Find point clusters on Hospitals: Find point clusters: 2 layers saved: Find point clusters: Hospitals (15 features); Find point clusters: cluster hulls (1 feature) [26][33]. It reported result, count 15; result, noise 4; result, distance m 2,000; result, elapsed ms 2; result, min points 3; billing, cost 0.0503 [33].

Result	Value
result, count	15
result, noise	4
result, distance m	2,000
result, elapsed ms	2
result, min points	3
billing, cost	0.0503
billing, list price	0.0503
billing, upstream cost	0

Findings

Evidenced: Find point clusters on Hospitals: Find point clusters: 2 layers saved: Find point clusters: Hospitals (15 features); Find point clusters: cluster hulls (1 feature) [26][33].

Evidenced: It reported result, count 15; result, noise 4; result, distance m 2,000; result, elapsed ms 2; result, min points 3; billing, cost 0.0503 [33].

Tool gp_find_point_clusters; parameters {"method": "dbscan", "project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "features": {"layer": "Hospitals (8a96a3d4)"}, "distance_m": 2000.0, "min_points": 3}

Find point clusters

What this analysis is. Find point clusters: Density-based clusters (DBSCAN, HDBSCAN or OPTICS, optionally space-time) with hulls and noise [31]. In ArcGIS it is Find Point Clusters or Density-based Clustering; in QGIS, native:dbscanclustering or native:stdbscanclustering [31].

Why it was run on this data. DBSCAN finds dense groups of Safe havens and separates noise [34].

What it found. The tool saved 2 layers: Find point clusters: Safe havens found 12 features, and Find point clusters: cluster hulls found 2 features [35]. The process resulted in 12 points, with 4 points categorized as noise [35].

Result	Value
result, count	12
result, noise	4
result, distance m	2,000
result, elapsed ms	1
result, min points	3
billing, cost	0.05024
billing, list price	0.05024
billing, upstream cost	0

Findings

Evidenced: Find point clusters on Safe havens: Find point clusters: 2 layers saved: Find point clusters: Safe havens (12 features); Find point clusters: cluster hulls (2 features) [29][35].

Evidenced: It reported result, count 12; result, noise 4; result, distance m 2,000; result, elapsed ms 1; result, min points 3; billing, cost 0.05024 [35].

Tool gp_find_point_clusters; parameters {"method": "dbscan", "project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "features": {"layer": "Safe havens (d7ec6bb0)"}, "distance_m": 2000.0, "min_points": 3}

Find point clusters

What this analysis is. Find point clusters: Density-based clusters (DBSCAN, HDBSCAN or OPTICS, optionally space-time) with hulls and noise [31]. In ArcGIS it is Find Point Clusters or Density-based Clustering; in QGIS, native:dbscanclustering or native:stdbscanclustering [31].

Why it was run on this data. DBSCAN finds dense groups of Protest events and separates noise [36].

What it found. Find point clusters on Protest events: Find point clusters: 2 layers saved: Find point clusters: Protest events (80 features); Find point clusters: cluster hulls (1 feature) [8][37]. It reported result, count 80; result, noise 3; result, distance m 500; result, elapsed ms 2; result, min points 3; billing, cost 0.0516 [37].

Result	Value
result, count	80
result, noise	3
result, distance m	500
result, elapsed ms	2
result, min points	3
billing, cost	0.0516
billing, list price	0.0516
billing, upstream cost	0

Findings

Evidenced: Find point clusters on Protest events: Find point clusters: 2 layers saved: Find point clusters: Protest events (80 features); Find point clusters: cluster hulls (1 feature) [8][37].

Evidenced: It reported result, count 80; result, noise 3; result, distance m 500; result, elapsed ms 2; result, min points 3; billing, cost 0.0516 [37].

Tool gp_find_point_clusters; parameters {"method": "dbscan", "project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "features": {"layer": "Protest events (cf75e6b1)"}, "distance_m": 500.0, "min_points": 3}

Calculate density

What this analysis is. Calculate density: Kernel density per square kilometer on a grid [38]. In ArcGIS it is Calculate Density or Kernel Density; in QGIS, native:heatmapkerneldensityestimation [38].

Why it was run on this data. 80 points in Protest events: a density surface shows where they concentrate [39].

What it found. Calculate density on Protest events: Calculate density: 1 layer saved: Calculate density: Protest events (386 features) [8][40]. It reported result, count 386; result, elapsed ms 11; result, bandwidth m 1,000; result, cell size m 200; result, excluded null 0; result, max density per km2 29.94 [40].

Result	Value
result, count	386
result, elapsed ms	11
result, bandwidth m	1,000
result, cell size m	200
result, excluded null	0
result, max density per km2	29.94
billing, cost	0.0516
billing, list price	0.0516
billing, upstream cost	0

Findings

Evidenced: Calculate density on Protest events: Calculate density: 1 layer saved: Calculate density: Protest events (386 features) [8][40].

Evidenced: It reported result, count 386; result, elapsed ms 11; result, bandwidth m 1,000; result, cell size m 200; result, excluded null 0; result, max density per km2 29.94 [40].

Tool gp_calculate_density; parameters {"kernel": "quartic", "project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "features": {"layer": "Protest events (cf75e6b1)"}, "bandwidth_m": 1000.0, "cell_size_m": 200.0}

Calculate density

What this analysis is. Calculate density: Kernel density per square kilometer on a grid [38]. In ArcGIS it is Calculate Density or Kernel Density; in QGIS, native:heatmapkerneldensityestimation [38].

Why it was run on this data. 30 points in Hotels: a density surface shows where they concentrate [41].

What it found. The density calculation was run on the Hotels layer [11] by utilizing the `gp\_calculate\_density` tool [42].

Result	Value
result, count	82
result, elapsed ms	3
result, bandwidth m	2,000
result, cell size m	1,000
result, excluded null	0
result, max density per km2	1.819
billing, cost	0.0506
billing, list price	0.0506

Result	Value
billing, upstream cost	0

Findings

Evidenced: Calculate density on Hotels: Calculate density: 1 layer saved: Calculate density: Hotels (82 features) [11][42].

Evidenced: It reported result, count 82; result, elapsed ms 3; result, bandwidth m 2,000; result, cell size m 1,000; result, excluded null 0; result, max density per km2 1.819 [42].

Tool gp_calculate_density; parameters {"kernel": "quartic", "project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "features": {"layer": "Hotels (28842e9c)"}, "bandwidth_m": 2000.0, "cell_size_m": 1000.0}

Calculate density

What this analysis is. Calculate density: Kernel density per square kilometer on a grid [38]. In ArcGIS it is Calculate Density or Kernel Density; in QGIS, native:heatmapkerneldensityestimation [38].

Why it was run on this data. 1700 points in Security incidents: a density surface shows where they concentrate [43].

What it found. Calculate density on Security incidents: Calculate density: 1 layer saved: Calculate density: Security incidents (2240 features) [14][44]. It reported result, count 2,240; result, elapsed ms 60; result, bandwidth m 500; result, cell size m 200; result, excluded null 0; result, max density per km2 267.9 [44].

Result	Value
result, count	2,240
result, elapsed ms	60
result, bandwidth m	500
result, cell size m	200
result, excluded null	0
result, max density per km2	267.9
billing, cost	0.084
billing, list price	0.084
billing, upstream cost	0

Findings

Evidenced: Calculate density on Security incidents: Calculate density: 1 layer saved: Calculate density: Security incidents (2240 features) [14][44].

Evidenced: It reported result, count 2,240; result, elapsed ms 60; result, bandwidth m 500; result, cell size m 200; result, excluded null 0; result, max density per km2 267.9 [44].

Tool gp_calculate_density; parameters {"kernel": "quartic", "project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "features": {"layer": "Security incidents (afb5d90c)"}, "bandwidth_m": 500.0, "cell_size_m": 200.0}

Outliers

What this analysis is. Find outliers: Anselin local Moran's I: HH, LL clusters and HL, LH outliers [45]. In ArcGIS it is Find Outliers or Cluster and Outlier Analysis (Anselin Local Moran's I) [45].

Why it was run on this data. Local Moran's I maps clusters and outliers of 'risk_score' [46].

What it found. Outliers on Risk zones: Find outliers: 1 layer saved: Find outliers: Risk zones (14 features) [27][47]. It reported result, count 14; result, elapsed ms 2; result, permutations 199; result, excluded null 0; result, distance band m 2,548; billing, cost 0.05042 [47].

Result	Value
result, count	14

Result	Value
result, elapsed ms	2
result, permutations	199
result, excluded null	0
result, distance band m	2,548
billing, cost	0.05042
billing, list price	0.05042
billing, upstream cost	0

Findings

Evidenced: Outliers on Risk zones: Find outliers: 1 layer saved: Find outliers: Risk zones (14 features) [27][47].

Evidenced: It reported result, count 14; result, elapsed ms 2; result, permutations 199; result, excluded null 0; result, distance band m 2,548; billing, cost 0.05042 [47].

Tool gp_outliers; parameters {"field": "risk_score", "project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "features": {"layer": "Risk zones (a4d2e294)"}, "aggregation": "hexagon"}

Spatial autocorrelation

What this analysis is. Spatial autocorrelation: Global Moran's I: is the pattern clustered, dispersed or random [48]. In ArcGIS it is Spatial Autocorrelation (Global Moran's I) [48].

Why it was run on this data. Global Moran's I says whether similar values of 'risk_score' sit next to each other [49].

What it found. The spatial autocorrelation tool was run using the Risk zones input [27], completing without generating a map output [50].

Result	Value
result, n	14
result, p value	0.6185
result, z score	-0.498
result, morans i	-0.2235
result, variance	0.08664
result, elapsed ms	1
result, expected i	-0.07692
result, excluded null	0
result, distance band m	2,548
result, p value normality	0.6003
result, z score normality	-0.5239
result, variance normality	0.0783
billing, cost	0.02
billing, list price	0.02
billing, upstream cost	0

Findings

Evidenced: Spatial autocorrelation on Risk zones: Spatial autocorrelation: done; no map output [27][50].

Evidenced: It reported result, n 14; result, p value 0.6185; result, z score -0.498; result, morans i -0.2235; result, variance 0.08664; result, elapsed ms 1 [50].

Tool gp_spatial_autocorrelation; parameters {"field": "risk_score", "project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "features": {"layer": "Risk zones (a4d2e294)"}}

Find nearest

What this analysis is. Find nearest: The k nearest features for each input, with geodesic distance and bearing [51]. In ArcGIS it is Find Nearest or Near; in QGIS, native:joinbynearest or native:nearestneighbouranalysis [51].

Why it was run on this data. The nearest of Travel routes to each of Hospitals, with distances [52].

What it found. Find nearest on Travel routes, Hospitals: Find nearest: 1 layer saved: Find nearest: Hospitals (14 features) [26][53][54]. It reported result, count 14; result, elapsed ms 10; billing, cost 0.0105; billing, list price 0.0105; billing, upstream cost 0 [53].

Result	Value
result, count	14
result, elapsed ms	10
billing, cost	0.0105
billing, list price	0.0105
billing, upstream cost	0

Findings

Evidenced: Find nearest on Travel routes, Hospitals: Find nearest: 1 layer saved: Find nearest: Hospitals (14 features) [26][53][54].

Evidenced: It reported result, count 14; result, elapsed ms 10; billing, cost 0.0105; billing, list price 0.0105; billing, upstream cost 0 [53].

Tool gp_find_nearest; parameters {"k": 1, "to": {"layer": "Travel routes (17118d2e)"}, "from": {"layer": "Hospitals (8a96a3d4)"}, "project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "max_distance_m": 2000.0}

Find nearest

What this analysis is. Find nearest: The k nearest features for each input, with geodesic distance and bearing [51]. In ArcGIS it is Find Nearest or Near; in QGIS, native:joinbynearest or native:nearestneighbouranalysis [51].

Why it was run on this data. The nearest of Travel routes to each of Hospitals, with distances [52].

What it found. Find nearest on Safe havens, Hospitals: Find nearest: 1 layer saved: Find nearest: Hospitals (14 features) [26][29][55]. It reported result, count 14; result, elapsed ms 1; billing, cost 0.01054; billing, list price 0.01054; billing, upstream cost 0 [55].

Result	Value
result, count	14
result, elapsed ms	1
billing, cost	0.01054
billing, list price	0.01054
billing, upstream cost	0

Findings

Evidenced: Find nearest on Safe havens, Hospitals: Find nearest: 1 layer saved: Find nearest: Hospitals (14 features) [26][29][55].

Evidenced: It reported result, count 14; result, elapsed ms 1; billing, cost 0.01054; billing, list price 0.01054; billing, upstream cost 0 [55].

Tool gp_find_nearest; parameters {"k": 1, "to": {"layer": "Safe havens (d7ec6bb0)"}, "from": {"layer": "Hospitals (8a96a3d4)"}, "project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "max_distance_m": 2000.0}

Find nearest

What this analysis is. Find nearest: The k nearest features for each input, with geodesic distance and bearing [51]. In ArcGIS it is Find Nearest or Near; in QGIS, native:joinbynearest or native:nearestneighbouranalysis [51].

Why it was run on this data. The nearest of Travel routes to each of Hospitals, with distances [52].

What it found. The `gp\_find\_nearest` tool was utilized with Protest events [8] and Hospitals [26] [56]. This process found 6 results [56]. The execution was quick, completing in 1 elapsed ms [56]. The billing cost associated with this operation was 0.0119 [56].

Result	Value
result, count	6
result, elapsed ms	1
billing, cost	0.0119
billing, list price	0.0119
billing, upstream cost	0

Findings

Evidenced: Find nearest on Protest events, Hospitals: Find nearest: 1 layer saved: Find nearest: Hospitals (6 features) [8][26][56].

Evidenced: It reported result, count 6; result, elapsed ms 1; billing, cost 0.0119; billing, list price 0.0119; billing, upstream cost 0 [56].

Tool gp_find_nearest; parameters {"k": 1, "to": {"layer": "Protest events (cf75e6b1)"}, "from": {"layer": "Hospitals (8a96a3d4)"}, "project": "188436ed-c19a-4e7c-ab43-b58fe7291e56", "max_distance_m": 2000.0}

Maps and charts

The run also made 23 map image(s)

[57][58][59][60][61][62][63][64][65][66][67][68][69][70][71][72][73][74][75][76][77][78][79] and 27 chart(s) [80][81][82][83][84][85][86][87][88][89][90][91][92][93][94][95][96][97][98][99][100][101][102][103][104][105][106].

Hot spot analysis: Protest events

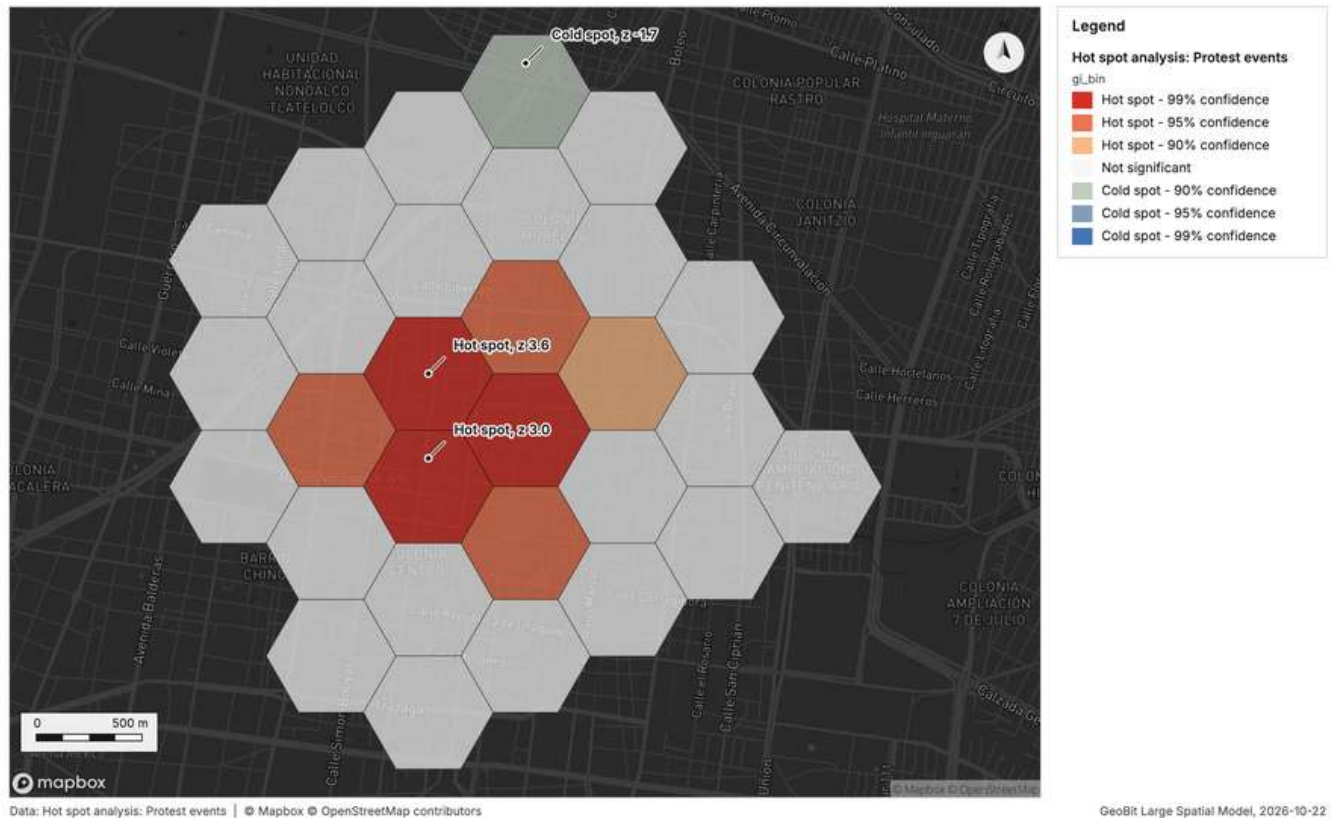


Figure 2. Hot spot analysis: Protest events [57]

Hot spot analysis: Hotels

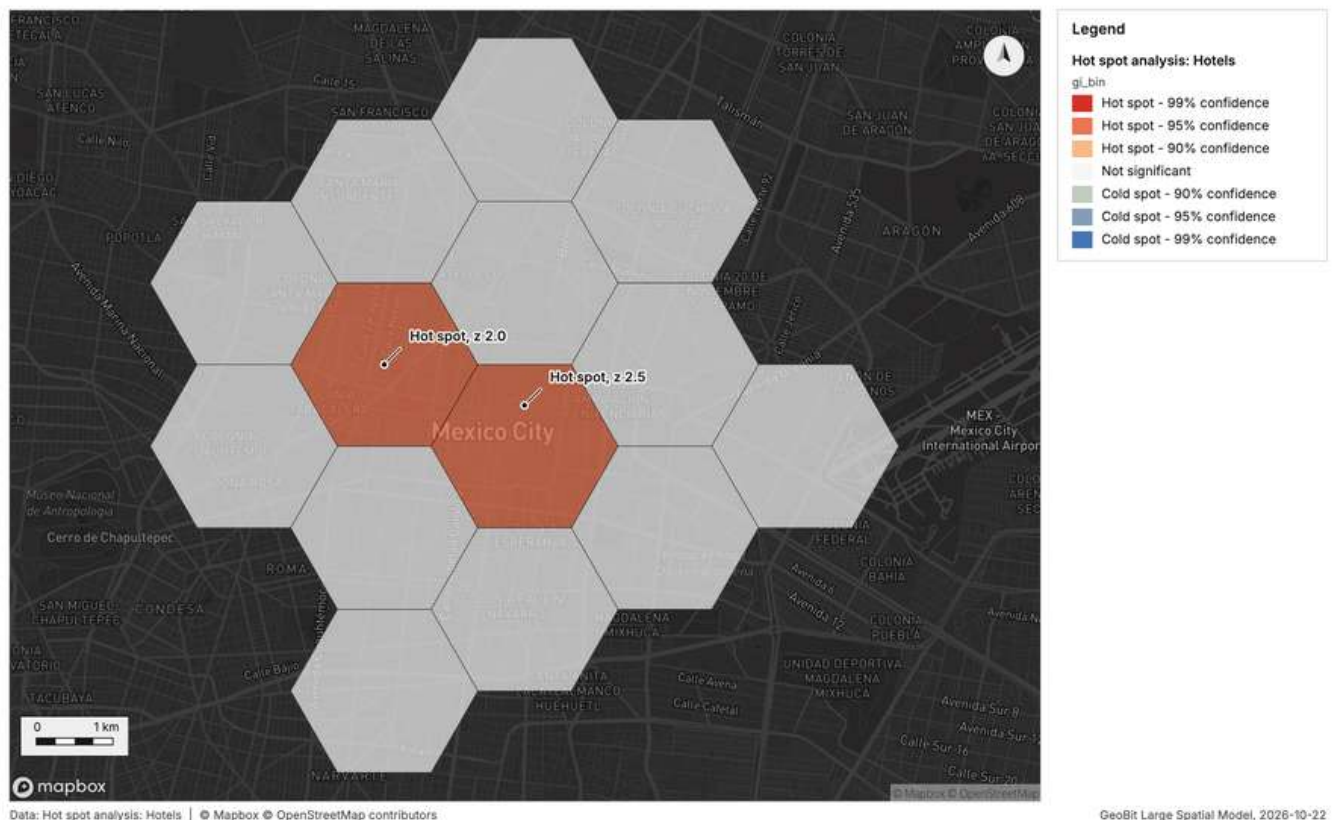


Figure 3. Hot spot analysis: Hotels [58]

Hot spot analysis: Security incidents

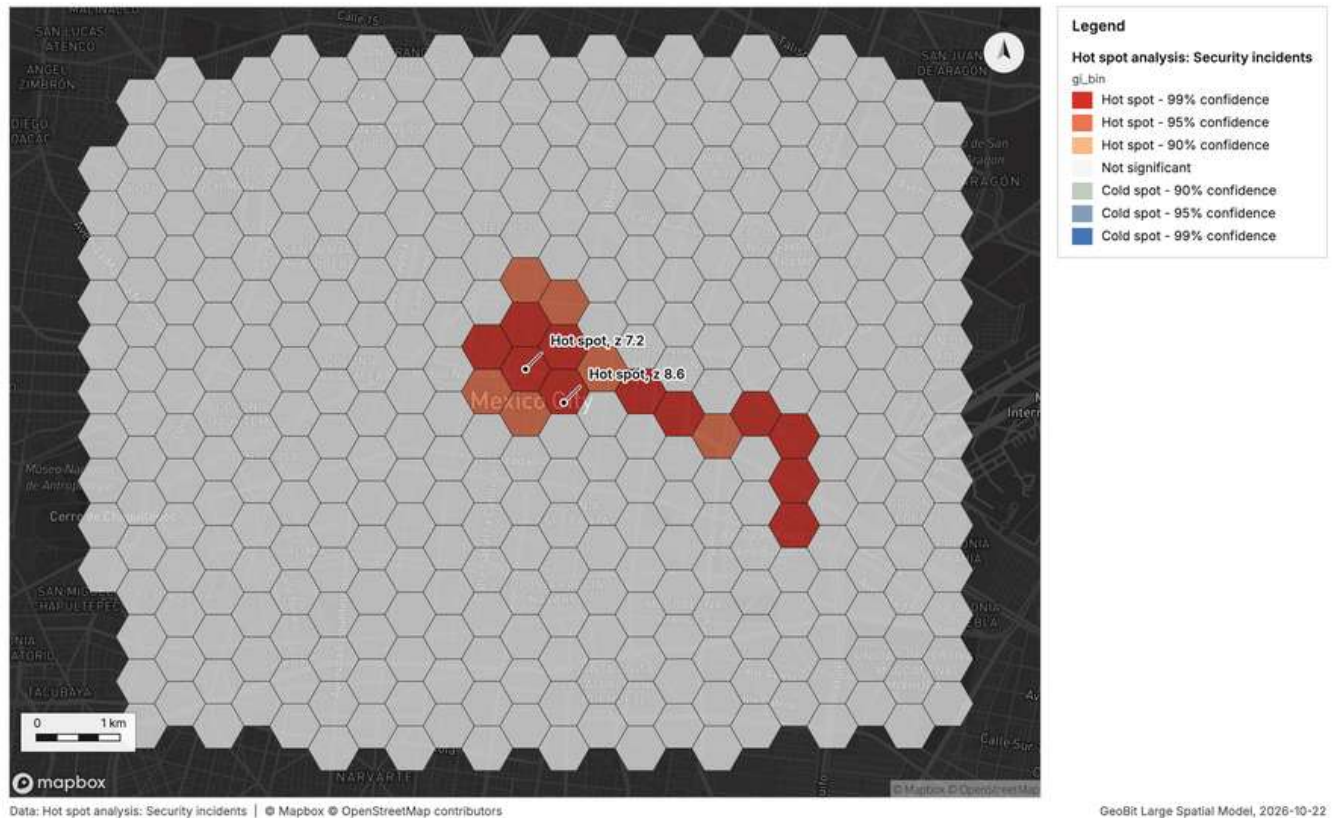


Figure 4. Hot spot analysis: Security incidents [59]

Emerging hot spots: Protest events

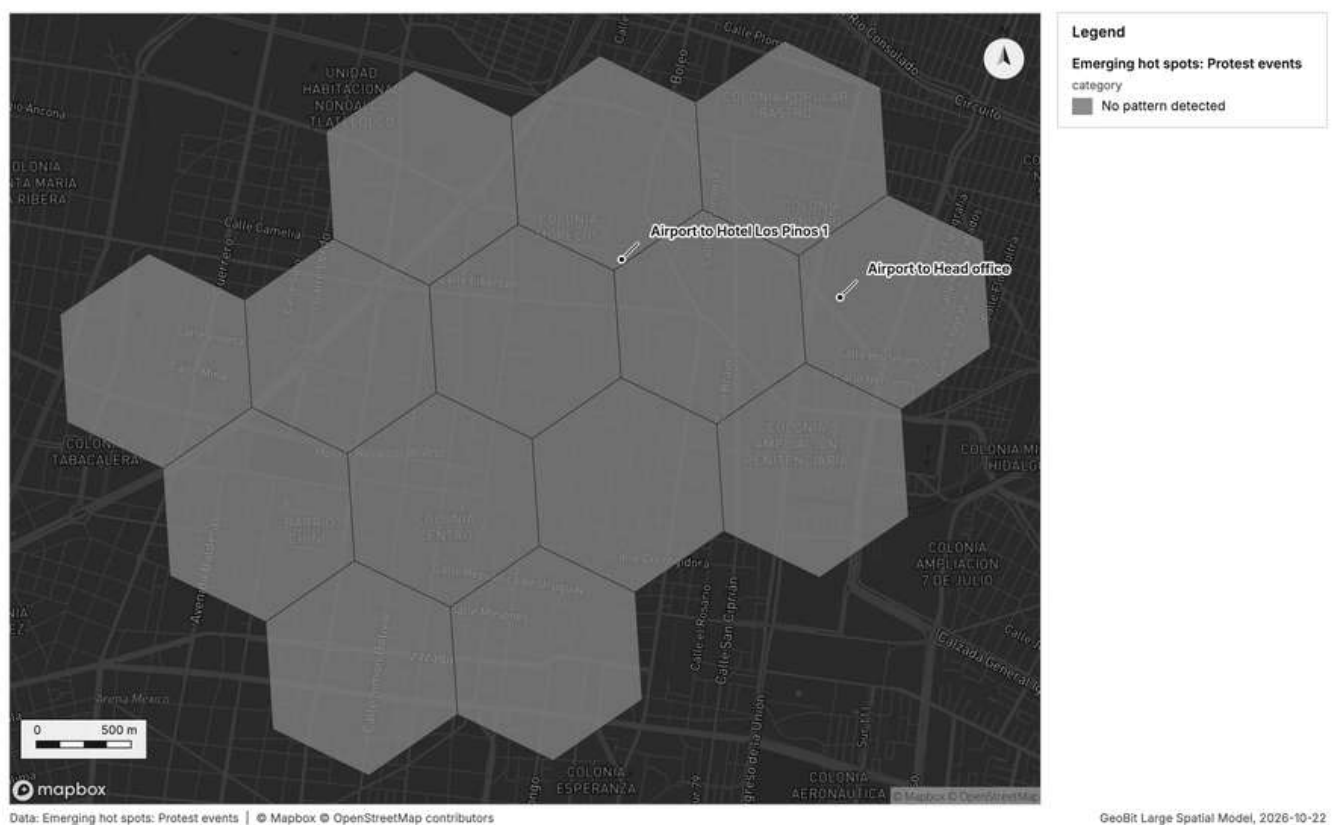


Figure 5. Emerging hot spots: Protest events [60]

Emerging hot spots: Security incidents

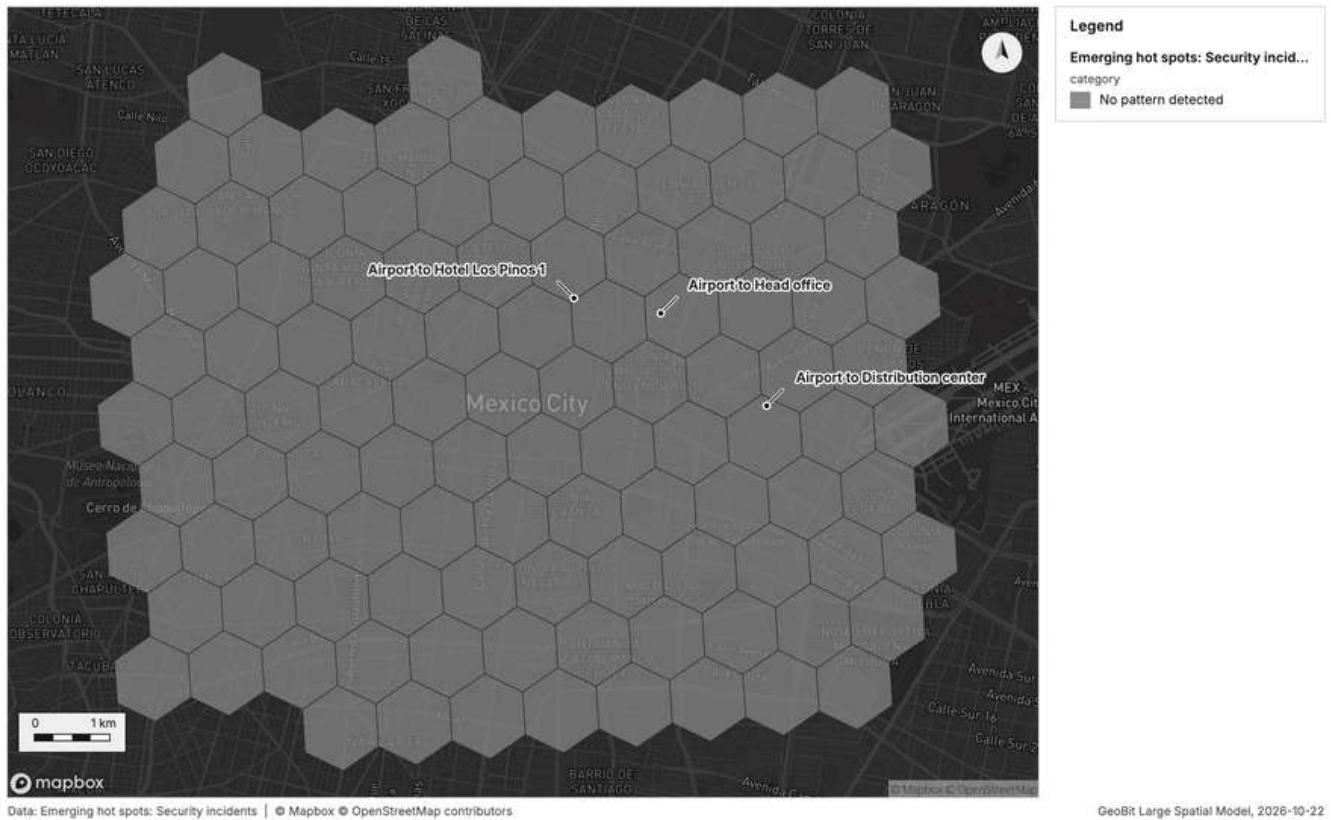


Figure 6. Emerging hot spots: Security incidents [61]

Repeat and near repeat classification: Protest events



Figure 7. Repeat and near repeat classification: Protest events [62]

Summarize within: Risk zones

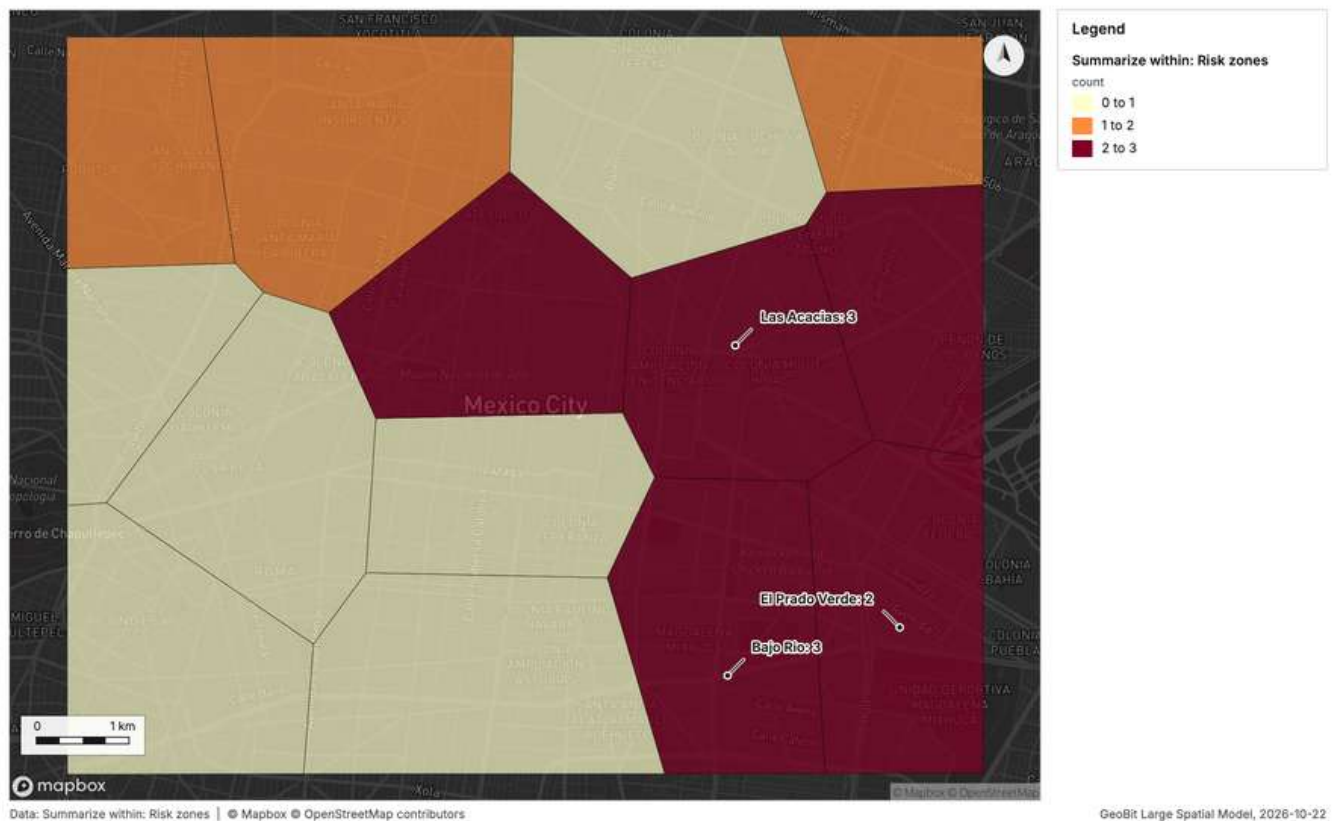


Figure 8. Summarize within: Risk zones [63]

Summarize within: Risk zones

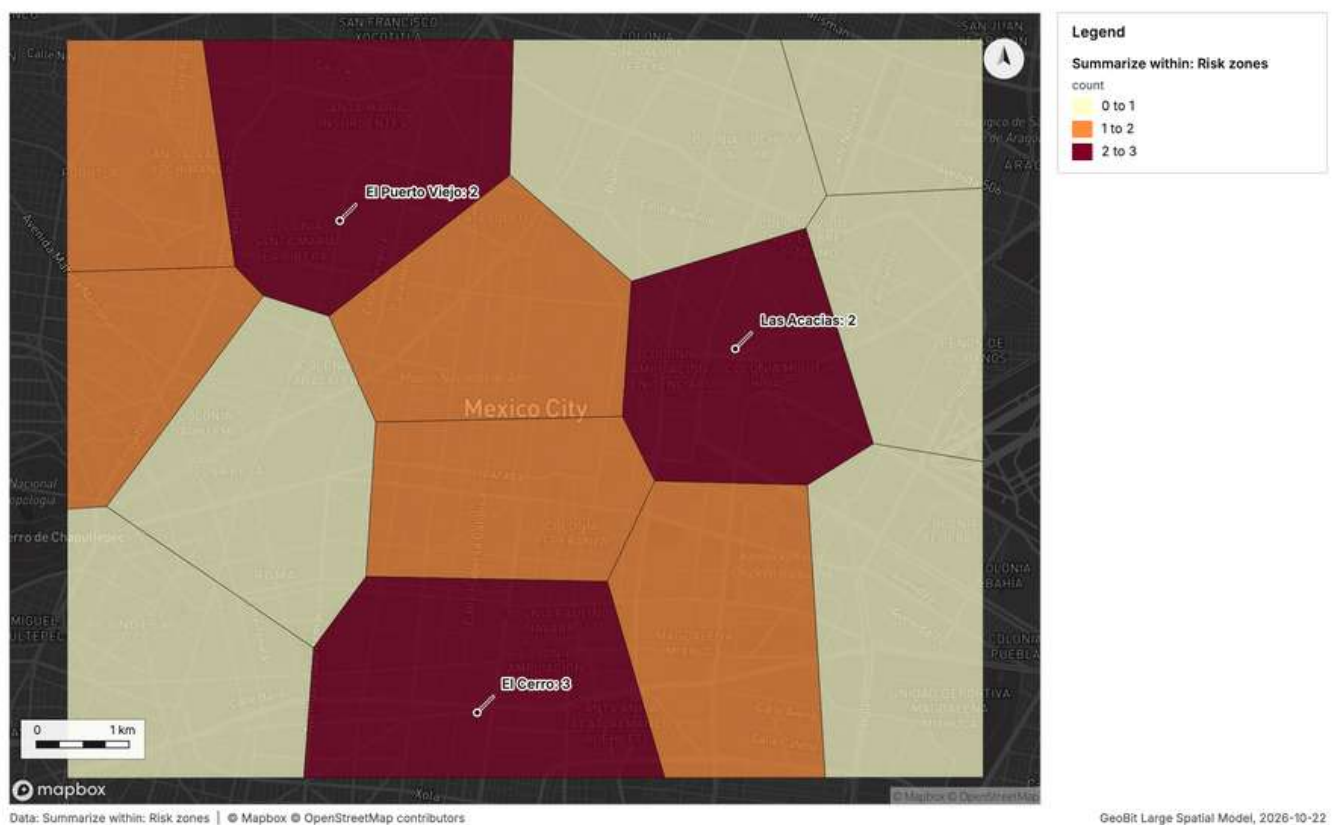


Figure 9. Summarize within: Risk zones [64]

Summarize within: Risk zones

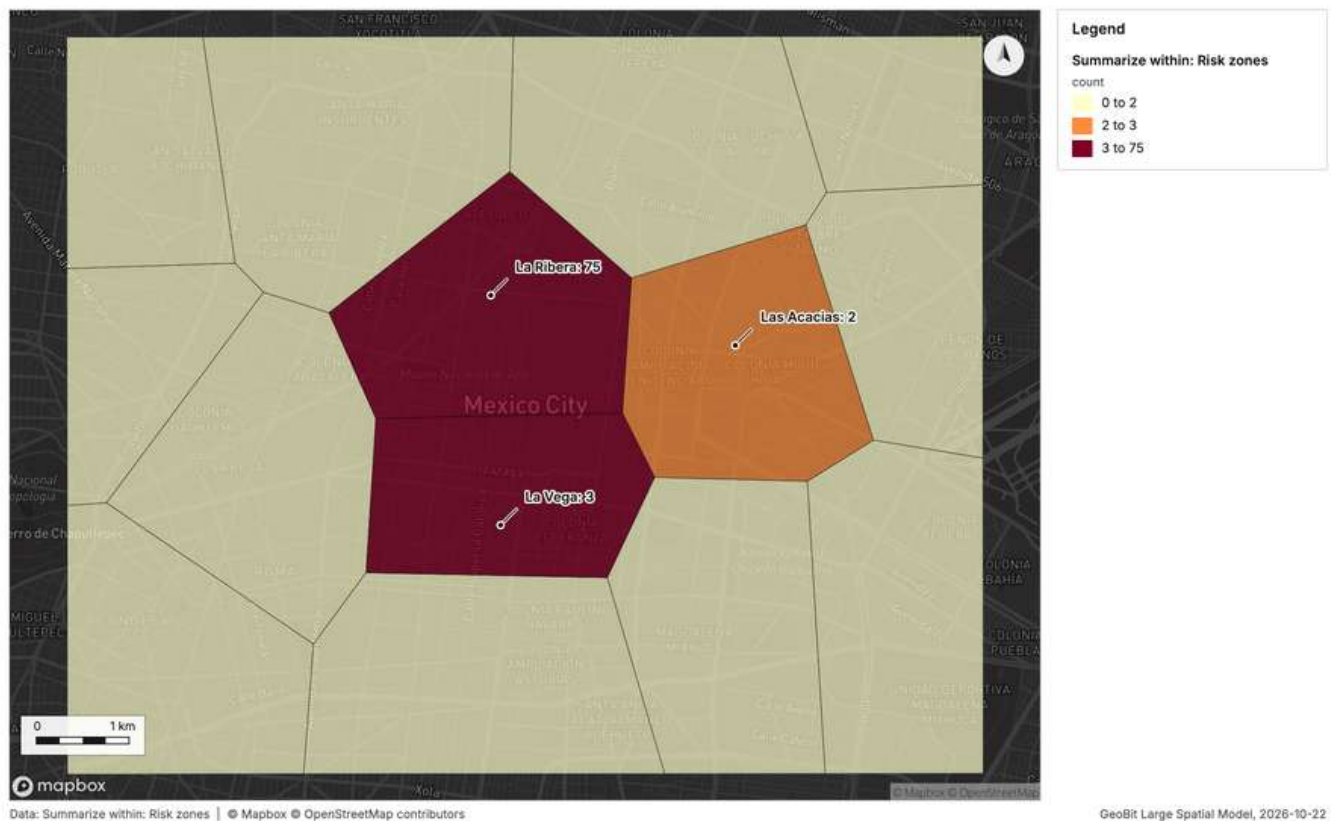


Figure 10. Summarize within: Risk zones [65]

Find point clusters: Hospitals

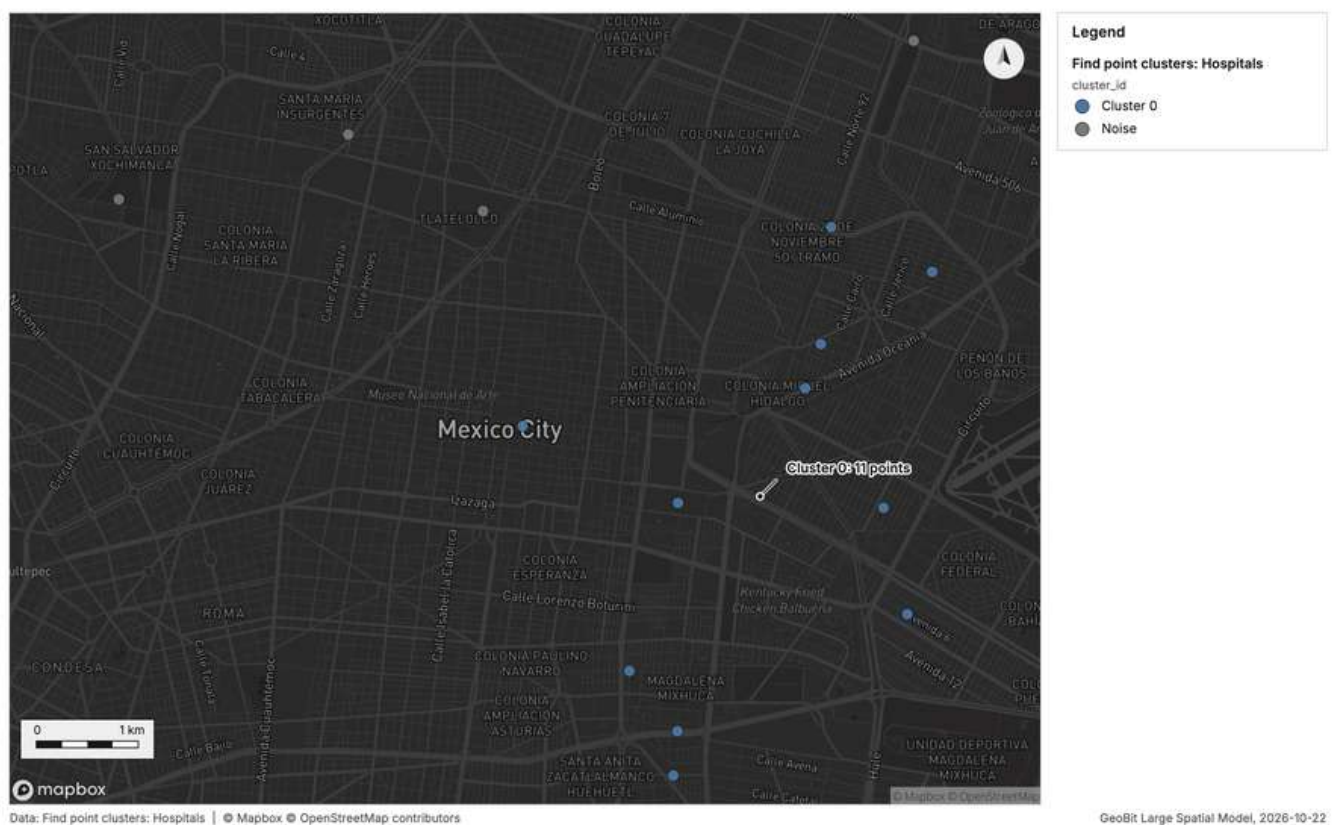


Figure 11. Find point clusters: Hospitals [66]

Find point clusters: cluster hulls



Figure 12. Find point clusters: cluster hulls [67]

Find point clusters: Safe havens

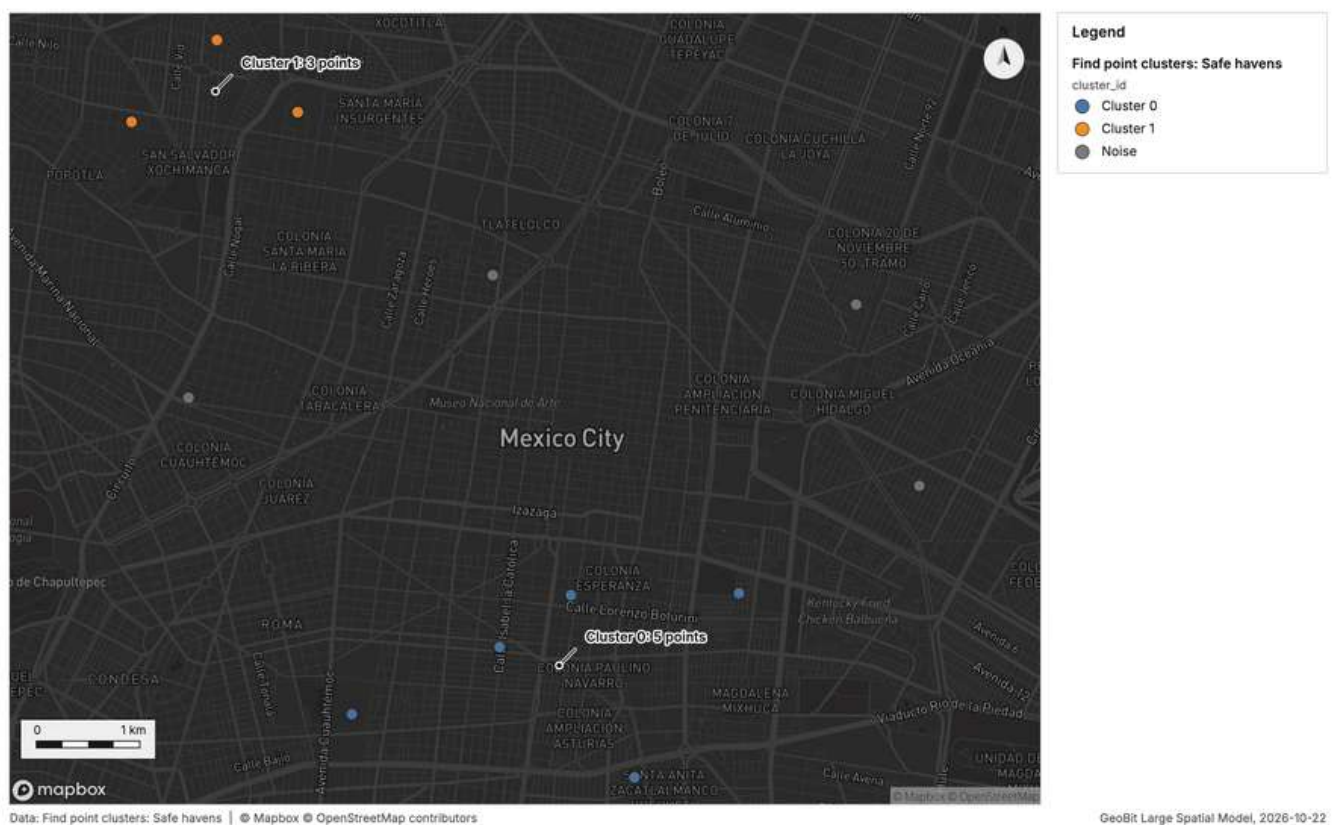


Figure 13. Find point clusters: Safe havens [68]

Find point clusters: cluster hulls

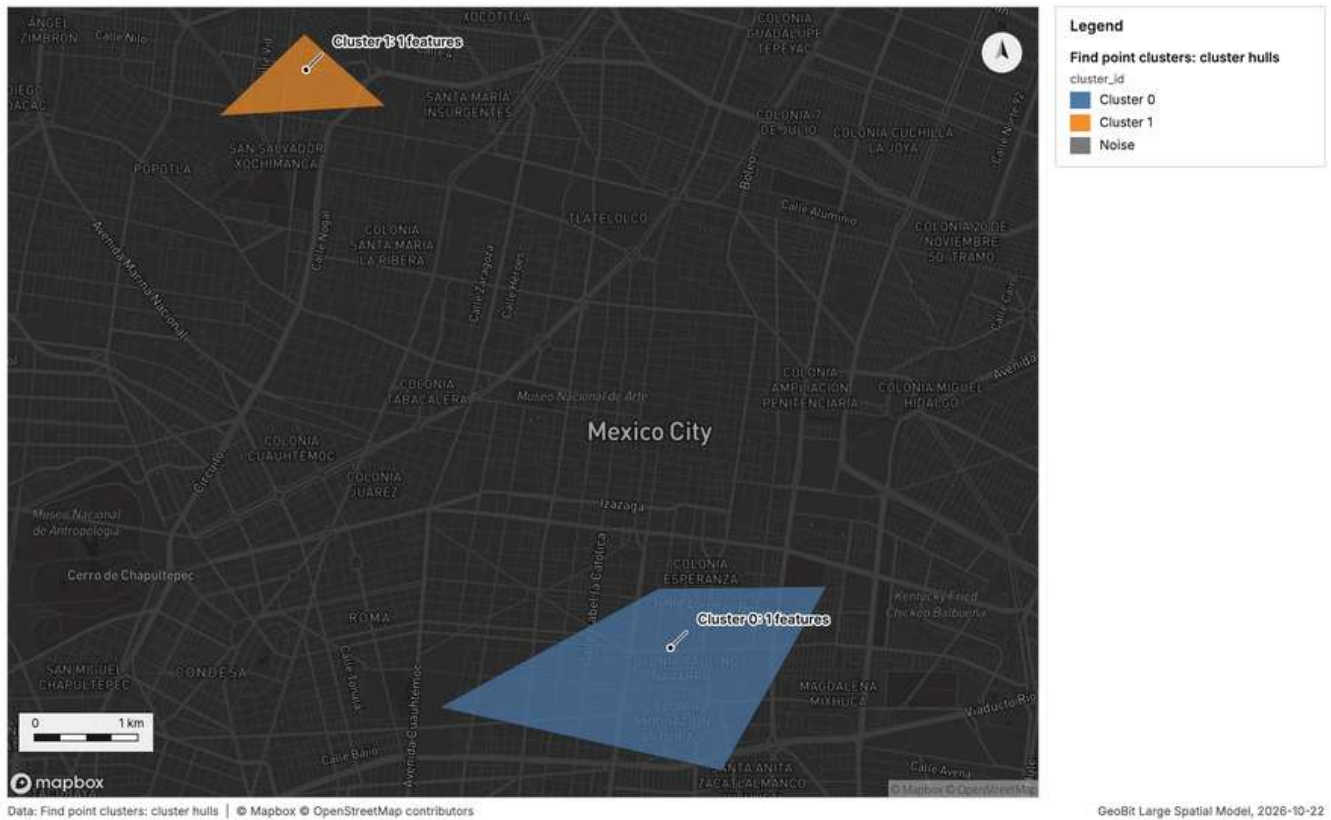


Figure 14. Find point clusters: cluster hulls [69]

Find point clusters: Protest events



Figure 15. Find point clusters: Protest events [70]

Find point clusters: cluster hulls

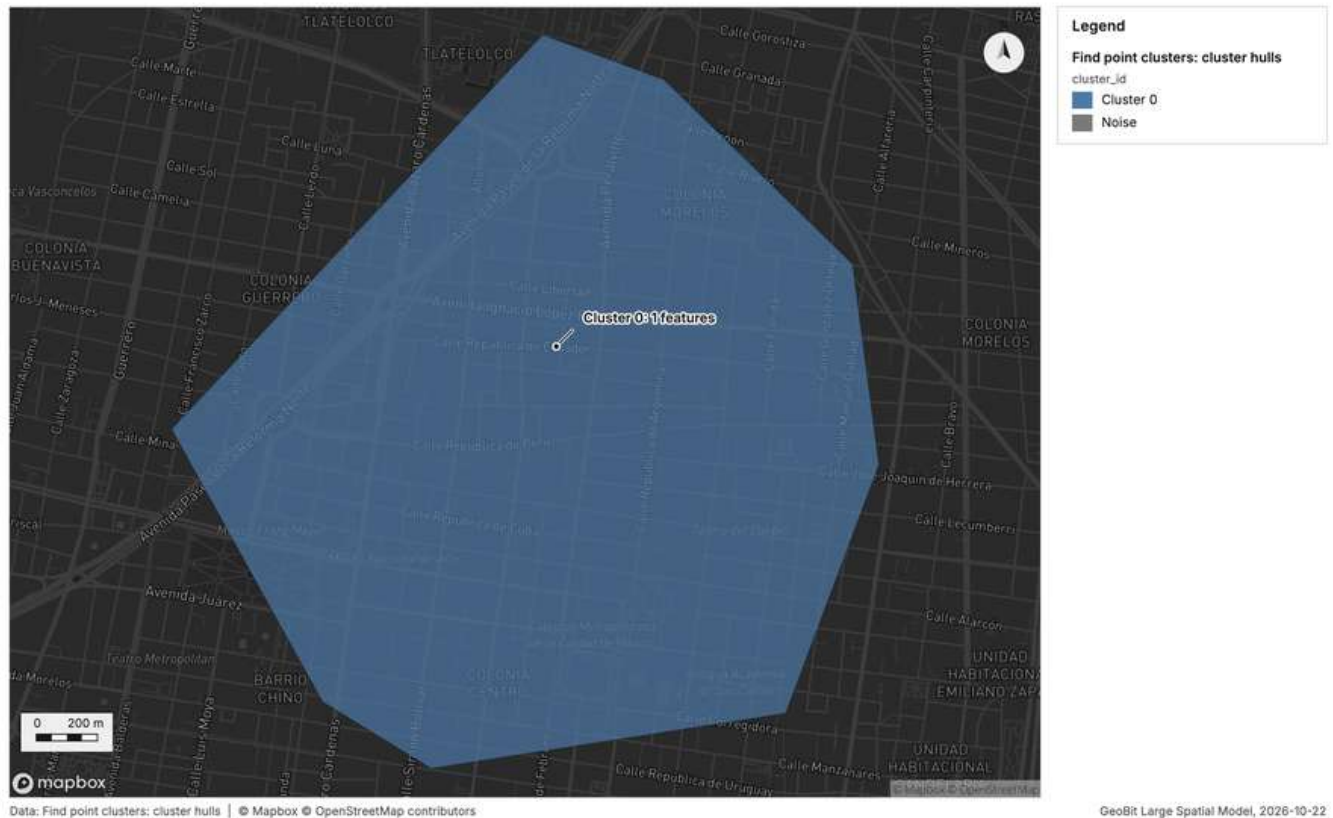


Figure 16. Find point clusters: cluster hulls [71]

Calculate density: Protest events

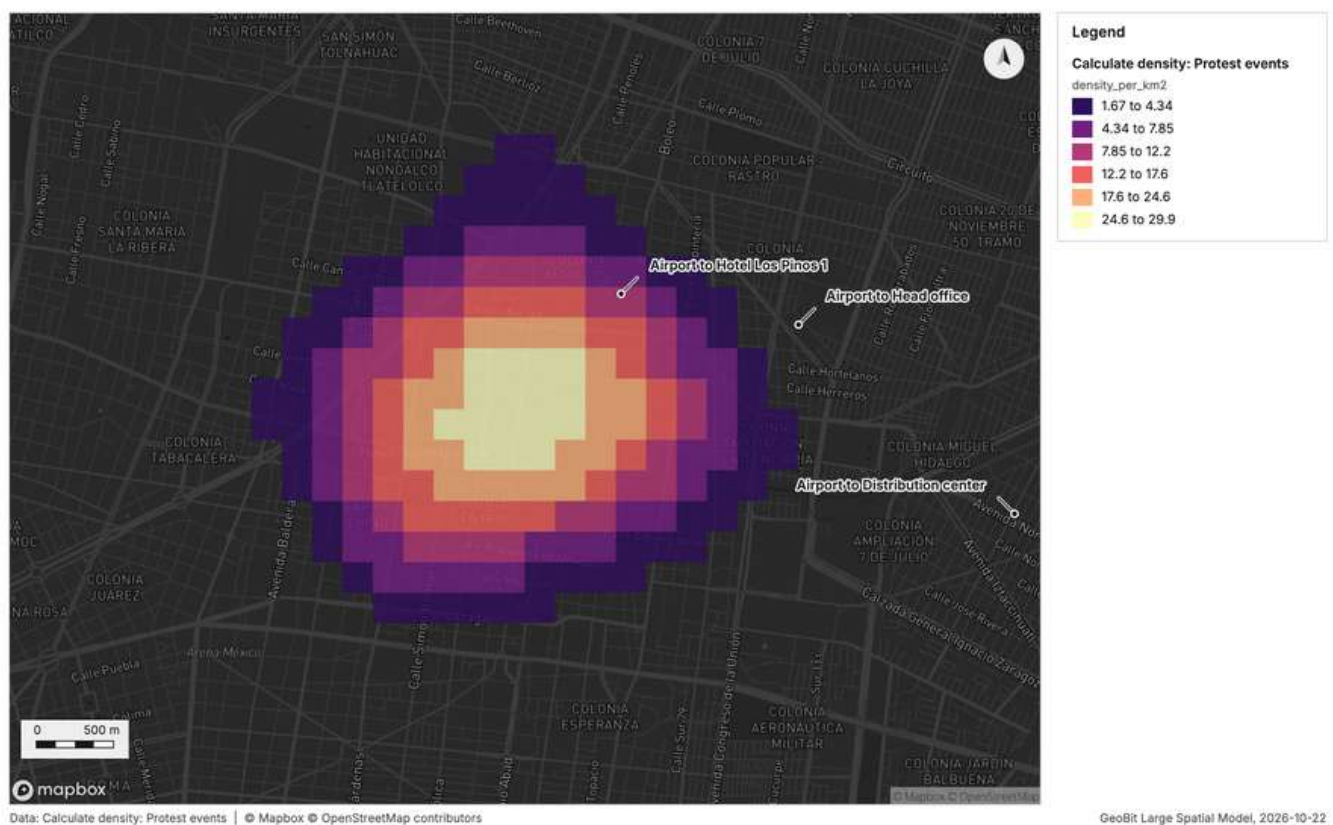


Figure 17. Calculate density: Protest events [72]

Calculate density: Hotels



Figure 18. Calculate density: Hotels [73]

Calculate density: Security incidents



Figure 19. Calculate density: Security incidents [74]

Risk zones by risk_score

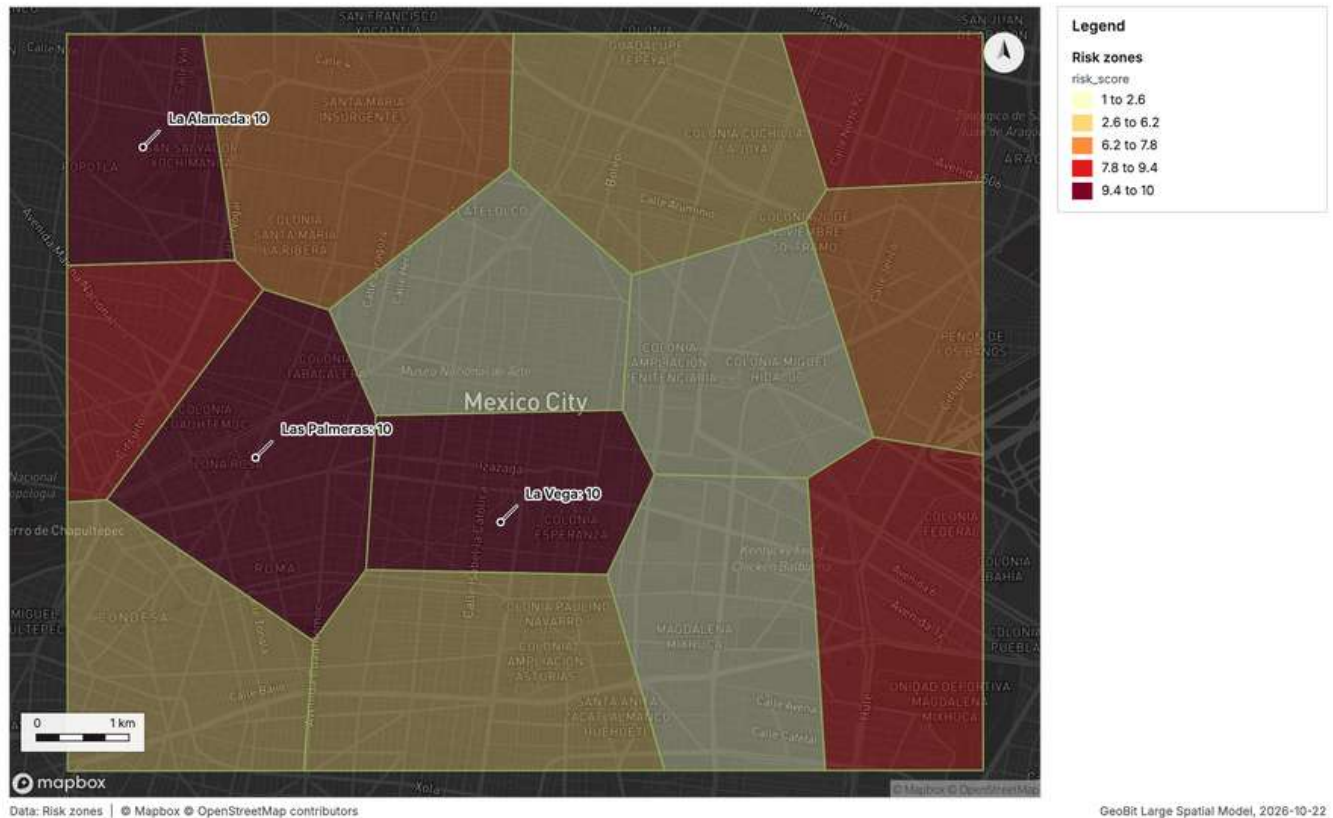


Figure 20. Risk zones by risk_score [75]

Find outliers: Risk zones



Figure 21. Find outliers: Risk zones [76]

Find nearest: Hospitals



Figure 22. Find nearest: Hospitals [77]

Find nearest: Hospitals

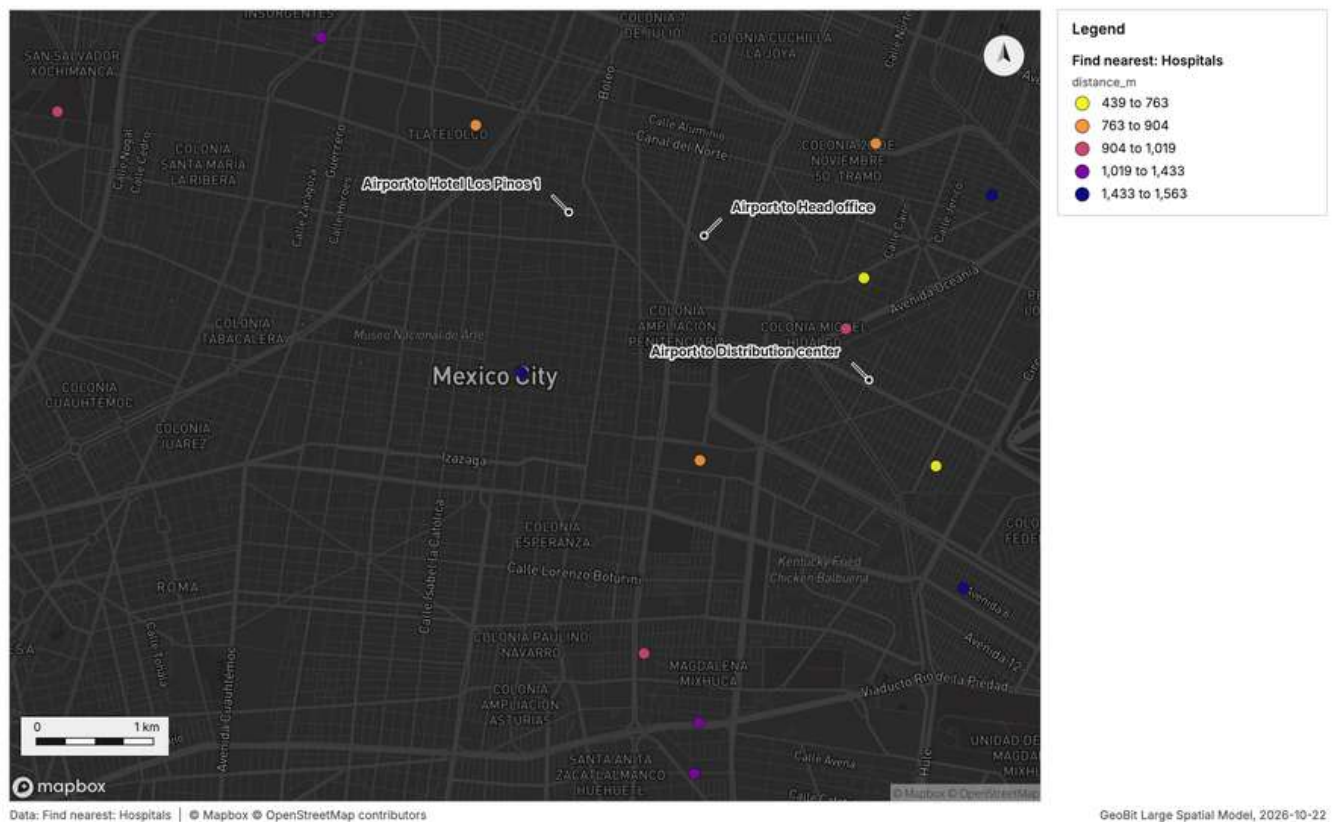


Figure 23. Find nearest: Hospitals [78]

Find nearest: Hospitals

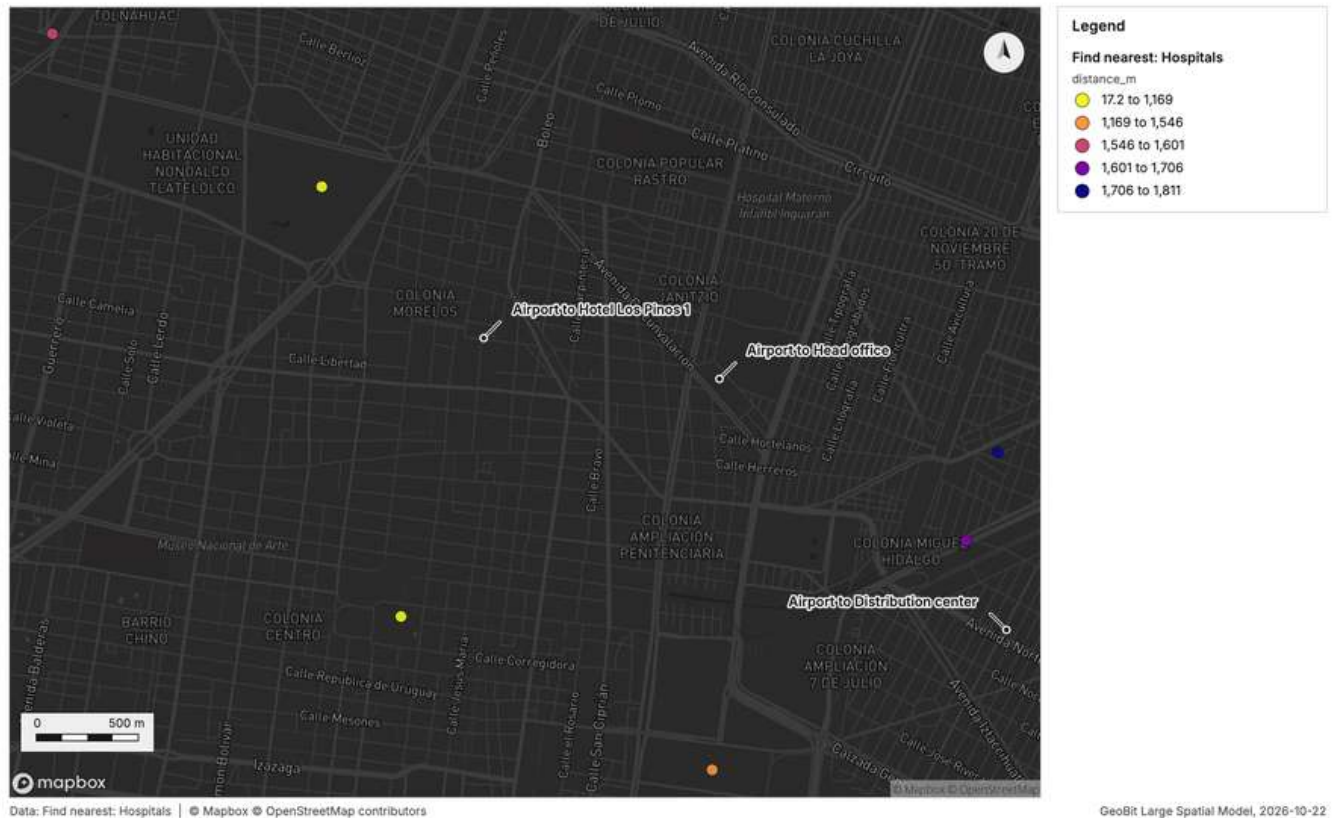


Figure 24. Find nearest: Hospitals [79]

What the map shows. This map, titled "Emerging hot spots: Protest events," analyzes a specific geographic area running from longitude -99.15818 to -99.10583 and latitude 19.41925 to 19.45709. The analysis indicates that there is no identifiable pattern of "Emerging [60]

Inferred: read from the image by gemma4:e4b, not evidence.

Count per week by occurred_at and type

Per week: 53 weeks from 2025-09-29 to 2026-09-28; trend +0.0702 per week; first half 844, second half 838 (-0.7%)

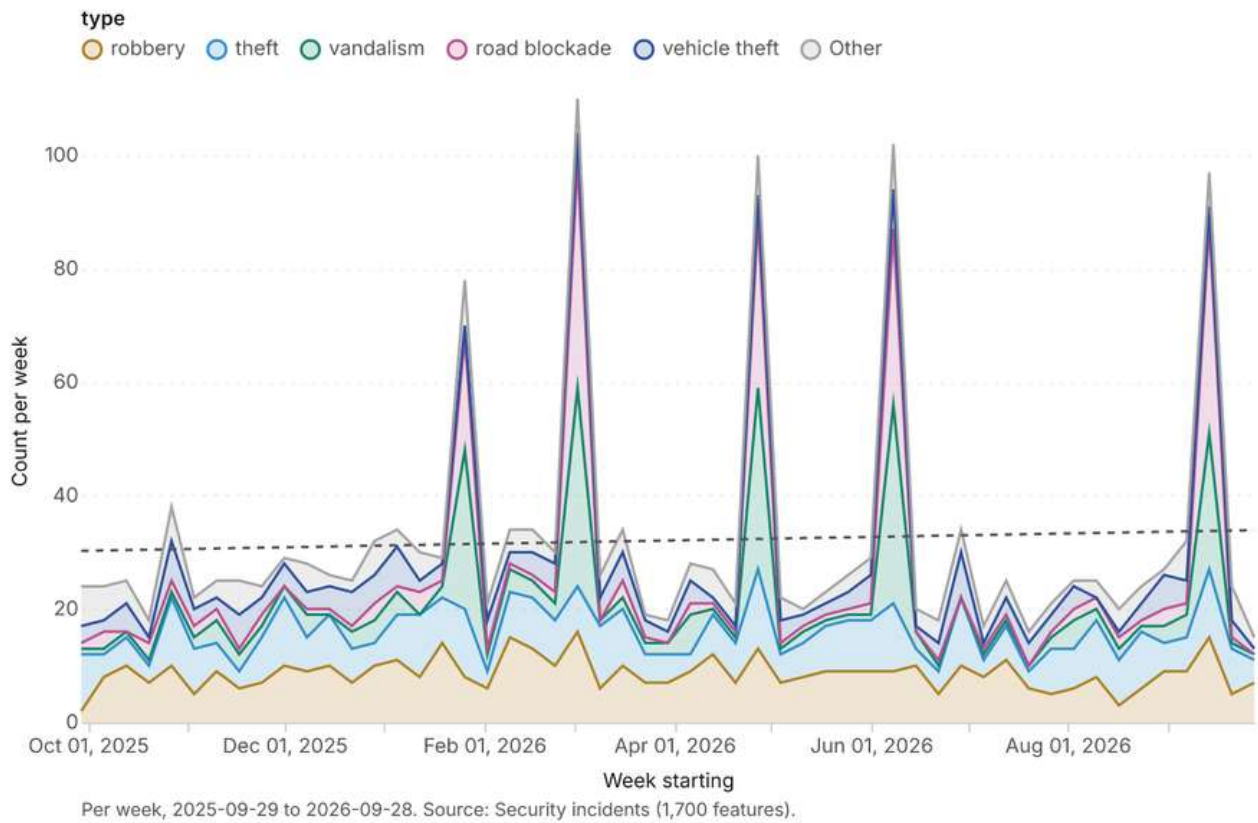


Figure 25. Security incidents over time (occurred_at) [80]. Per week, 2025-09-29 to 2026-09-28. Source: Security incidents (1,700 features). The data is in the appendix.

Count per week by date and size

Per week: 39 weeks from 2026-01-05 to 2026-09-28; trend +0.00283 per week; first half 36, second half 44 (+22.2%)

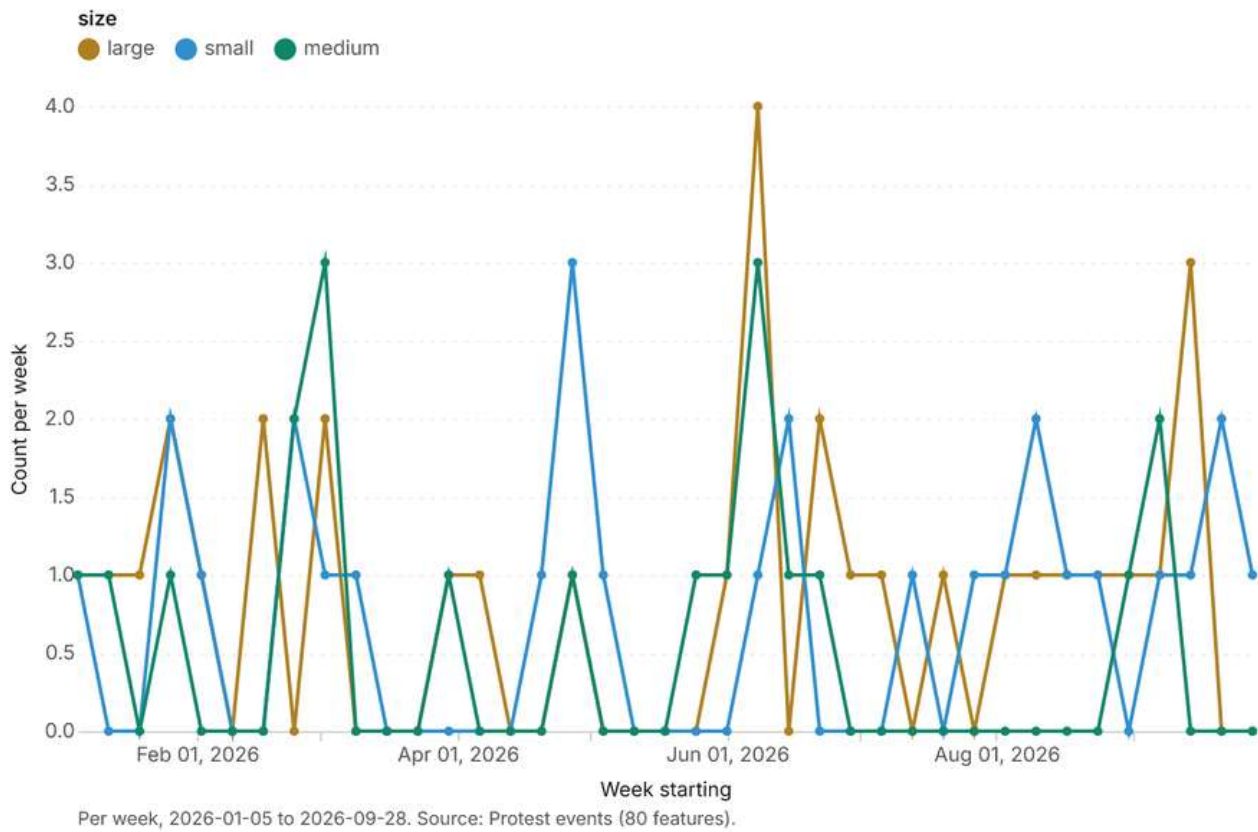


Figure 26. Protest events over time (date) [81]. Per week, 2026-01-05 to 2026-09-28. Source: Protest events (80 features). The data is in the appendix.

Count per week by date and incident_reported

Per week: 53 weeks from 2025-09-29 to 2026-09-28; trend -0.0118 per week; first half 208, second half 189 (-9.1%)

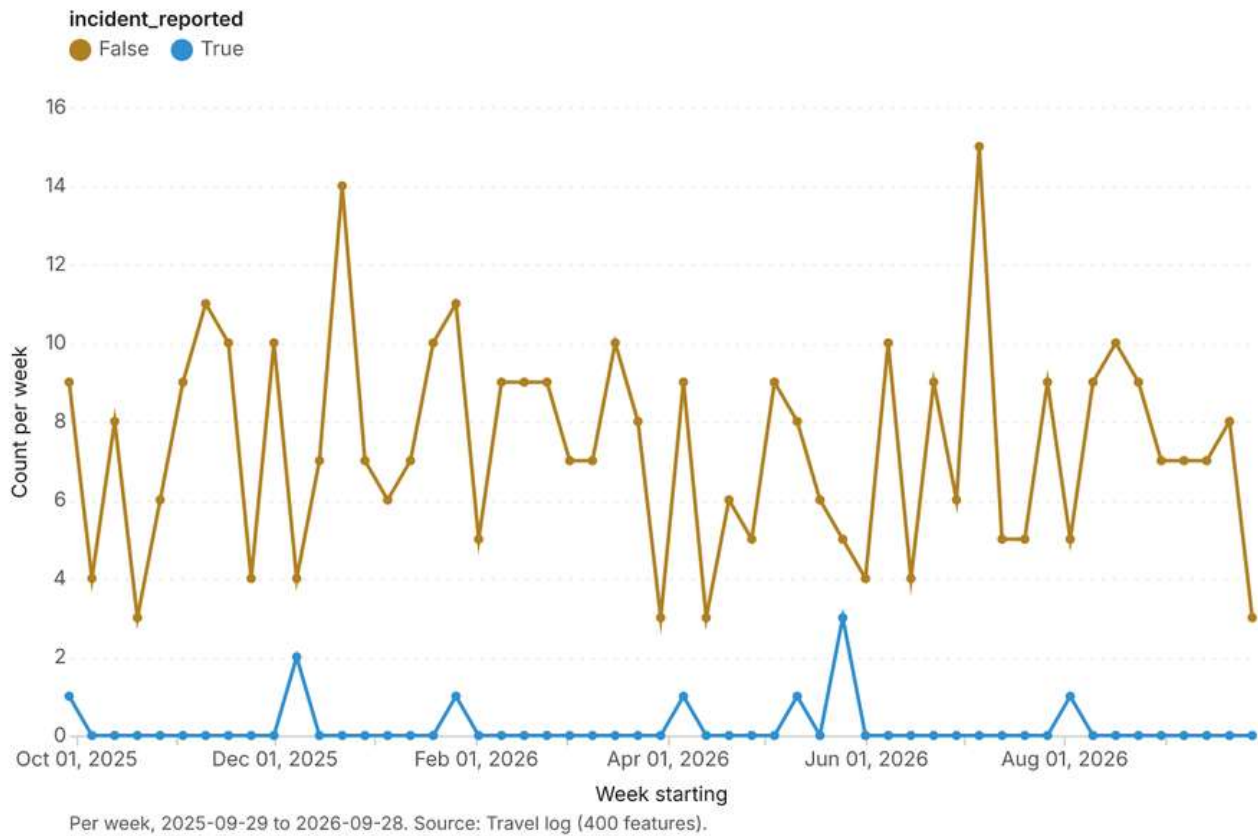


Figure 27. Travel log over time (date) [82]. Per week, 2025-09-29 to 2026-09-28. Source: Travel log (400 features). The data is in the appendix.

Gi* z-score distribution

29 features: 7 hot and 1 cold at 90% confidence or more

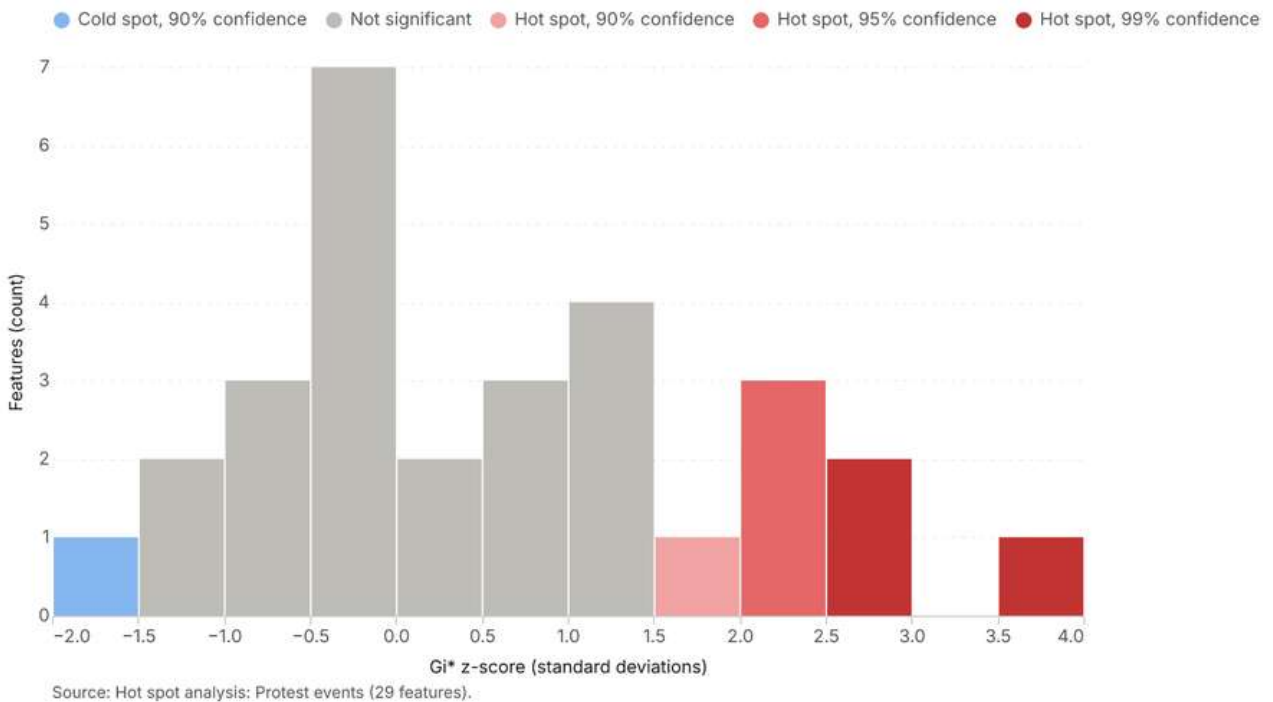


Figure 28. Hot spot analysis: Protest events [83]. Source: Hot spot analysis: Protest events (29 features). The data is in the appendix.

Gi* z-score distribution

14 features: 2 hot and 0 cold at 90% confidence or more

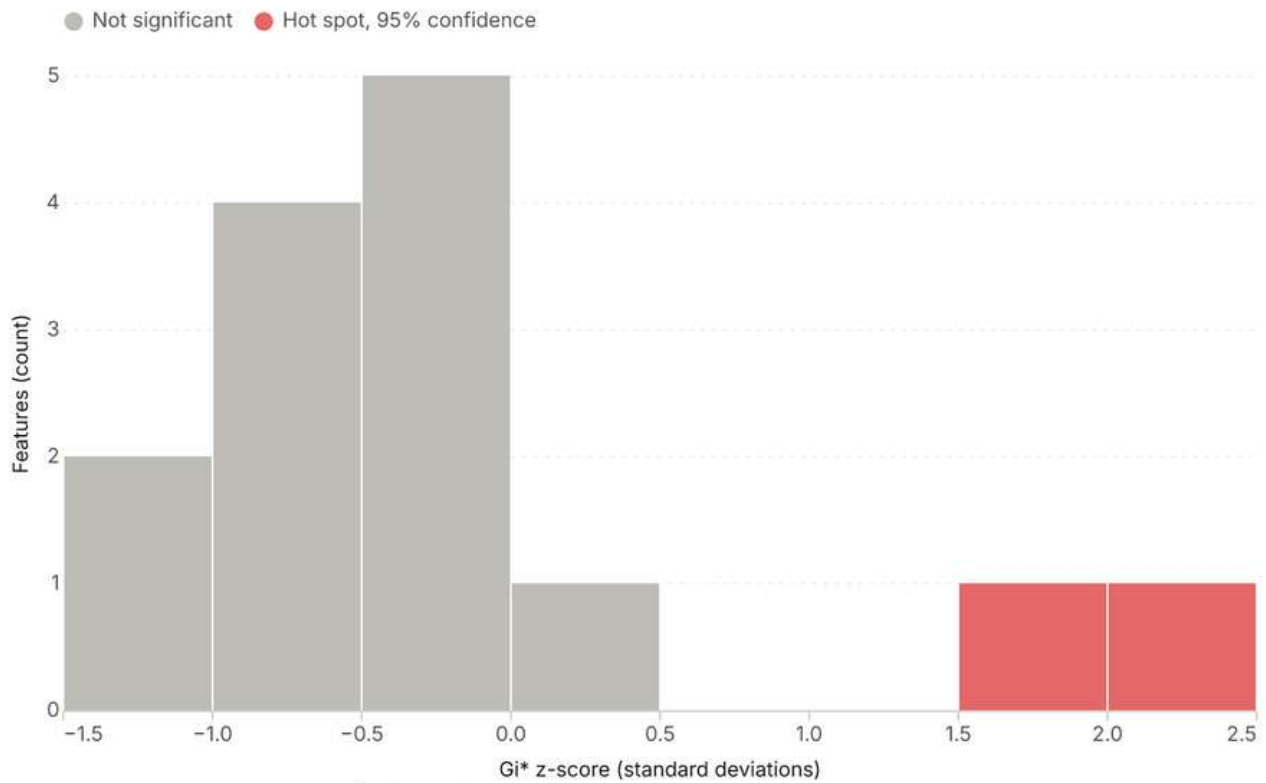


Figure 29. Hot spot analysis: Hotels [84]. Source: Hot spot analysis: Hotels (14 features). The data is in the appendix.

Gi* z-score distribution

353 features: 17 hot and 0 cold at 90% confidence or more

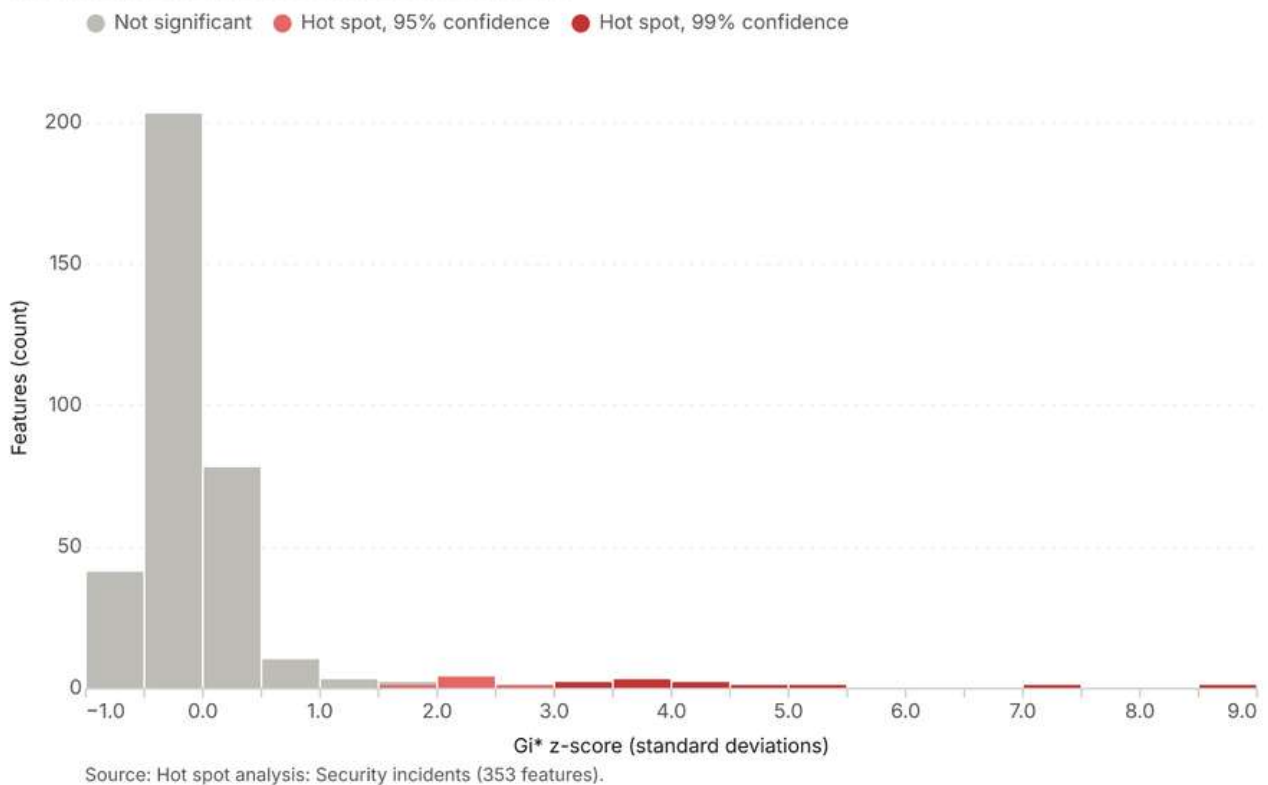
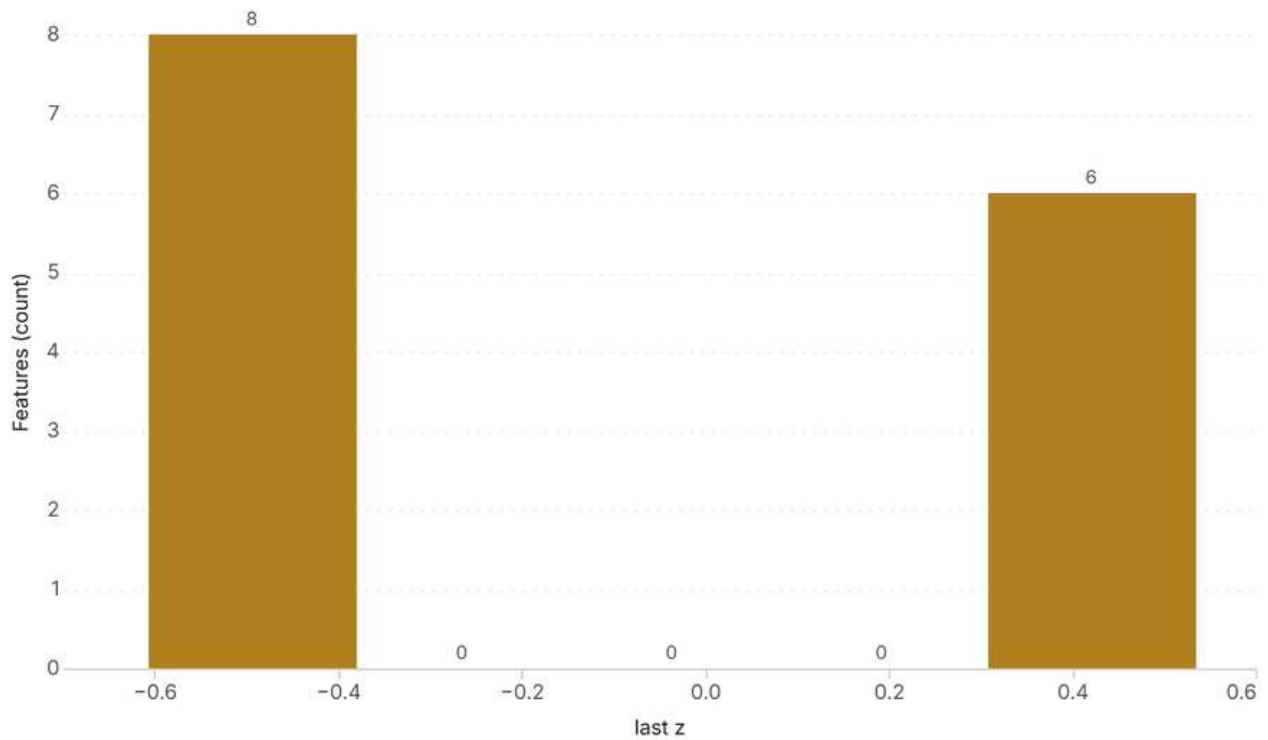


Figure 30. Hot spot analysis: Security incidents [85]. Source: Hot spot analysis: Security incidents (353 features). The data is in the appendix.

Distribution of last_z

14 values in 5 bins

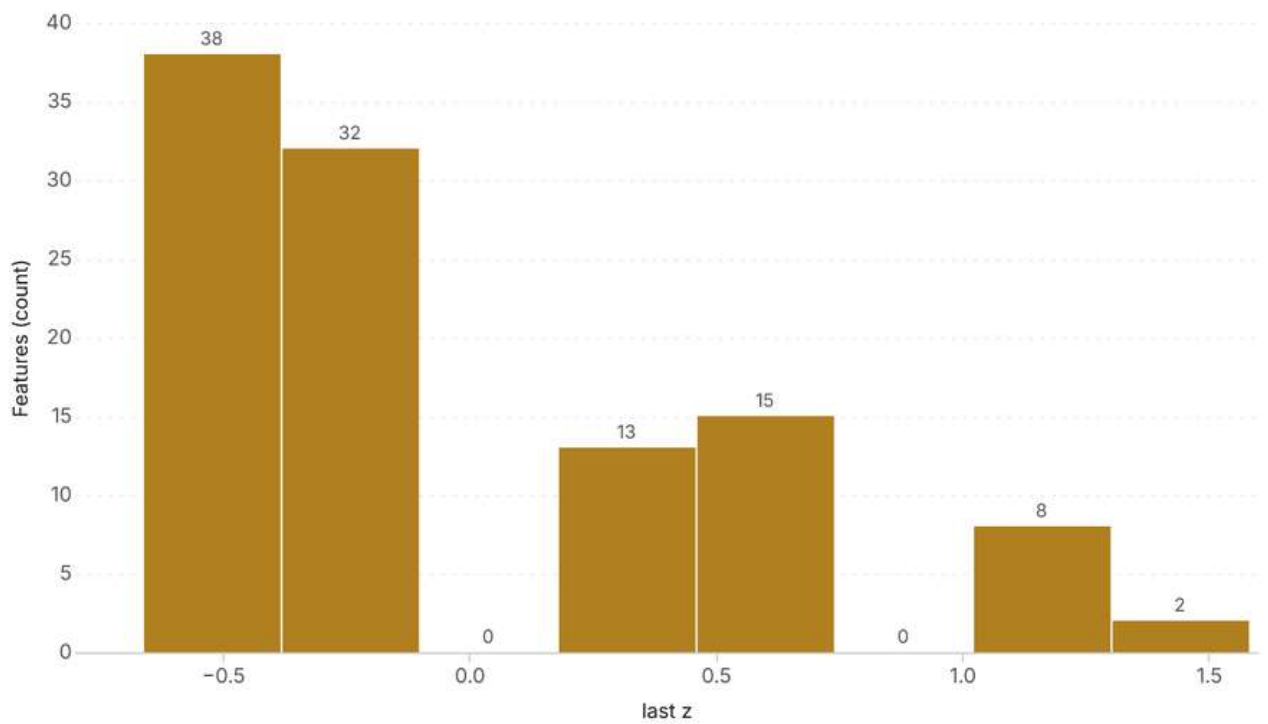


Source: Emerging hot spots: Protest events (14 features).

Figure 31. Emerging hot spots: Protest events [86]. Source: Emerging hot spots: Protest events (14 features). The data is in the appendix.

Distribution of last_z

108 values in 8 bins



Source: Emerging hot spots: Security incidents (108 features).

Figure 32. Emerging hot spots: Security incidents [87]. Source: Emerging hot spots: Security incidents (108 features). The data is in the appendix.

Count per week by date and size

Per week: 39 weeks from 2026-01-05 to 2026-09-28; trend +0.00283 per week; first half 36, second half 44 (+22.2%)

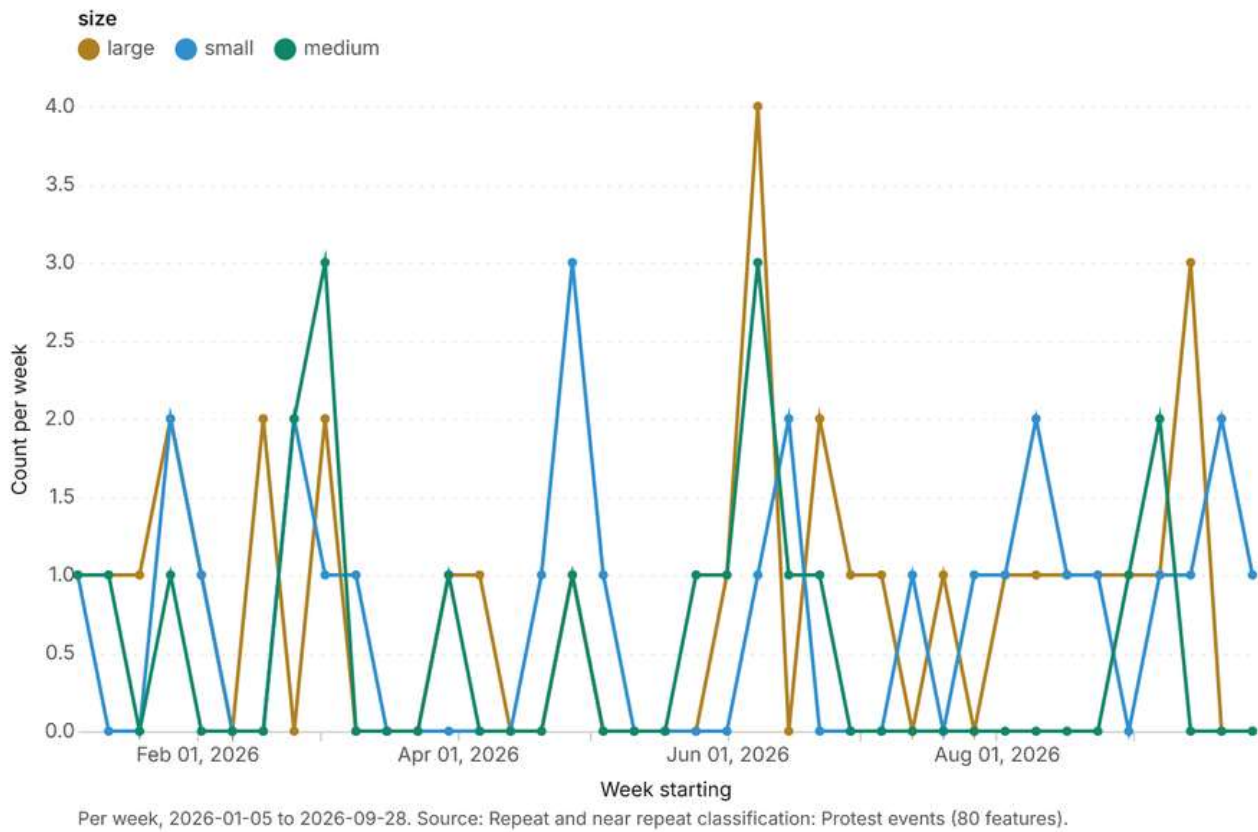


Figure 33. Repeat and near repeat classification: Protest events [88]. Per week, 2026-01-05 to 2026-09-28. Source: Repeat and near repeat classification: Protest events (80 features). The data is in the appendix.

Distribution of count

14 values in 5 bins

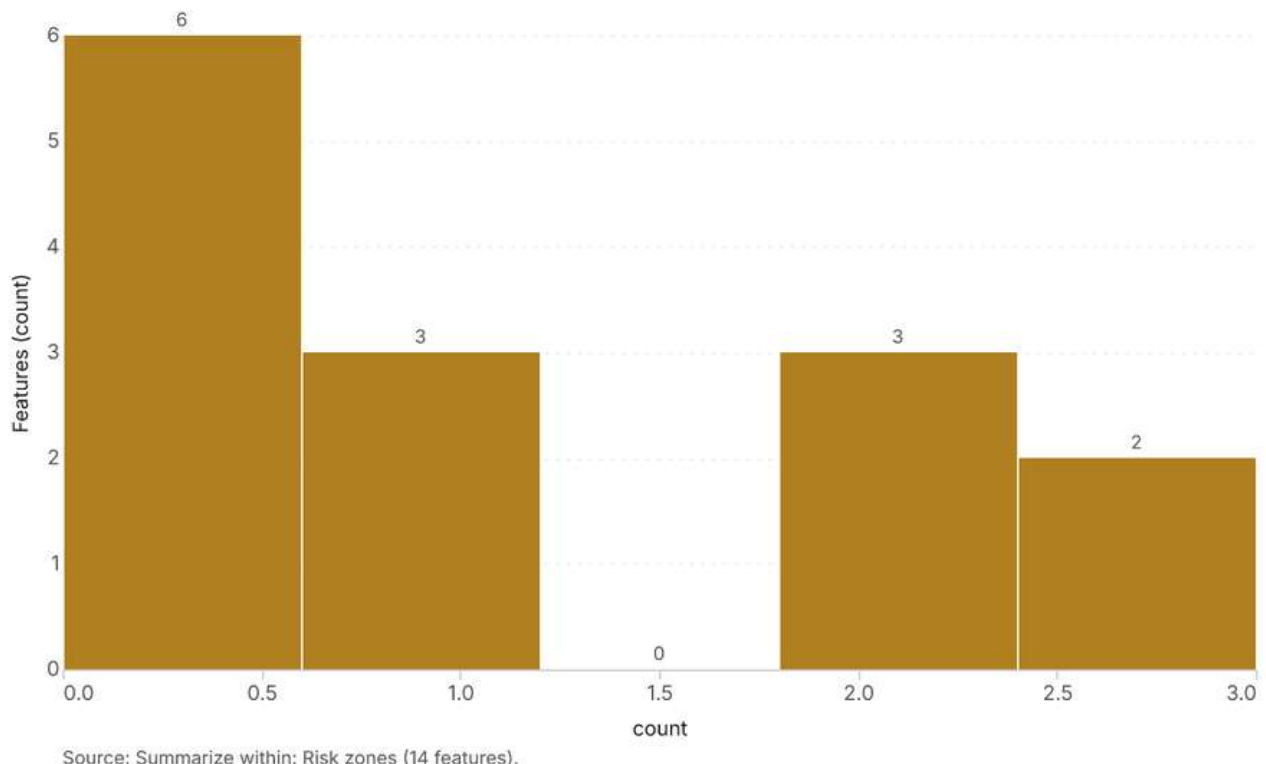


Figure 34. Summarize within: Risk zones [89]. Source: Summarize within: Risk zones (14 features). The data is in the appendix.

Distribution of count

14 values in 5 bins

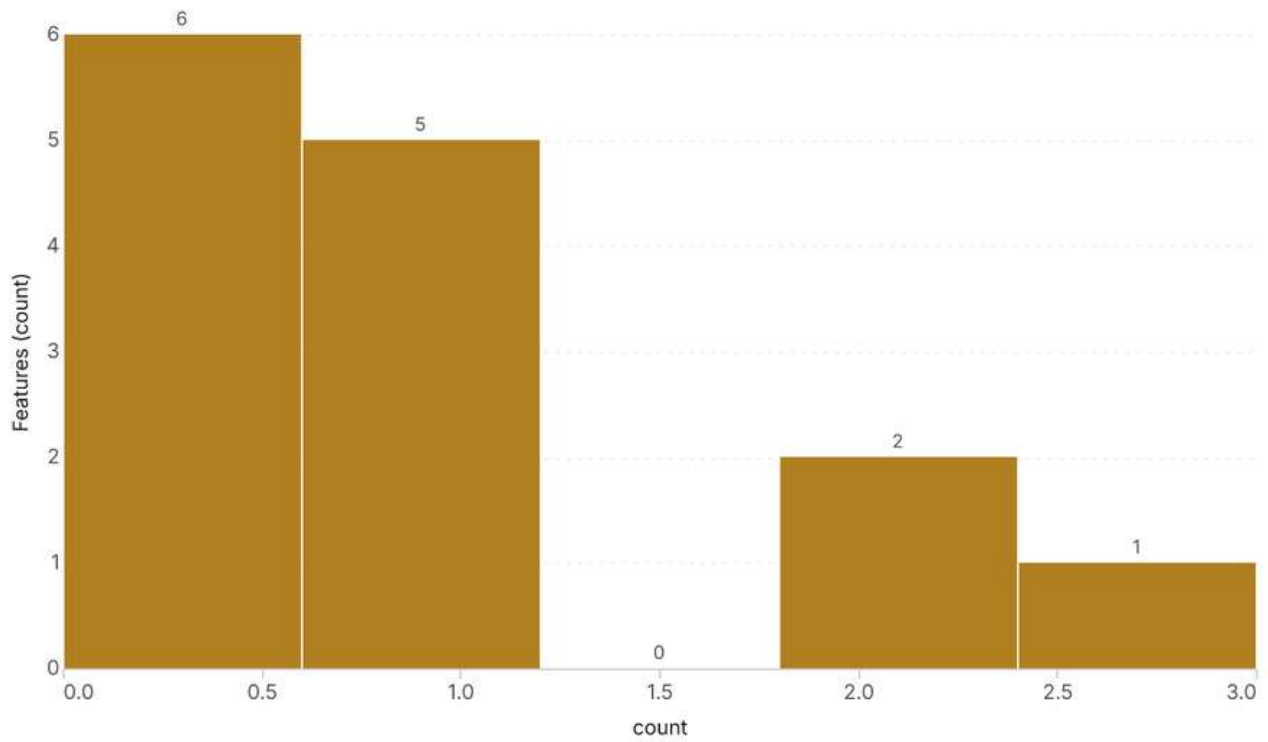


Figure 35. Summarize within: Risk zones [90]. Source: Summarize within: Risk zones (14 features). The data is in the appendix.

Distribution of count

14 values in 5 bins

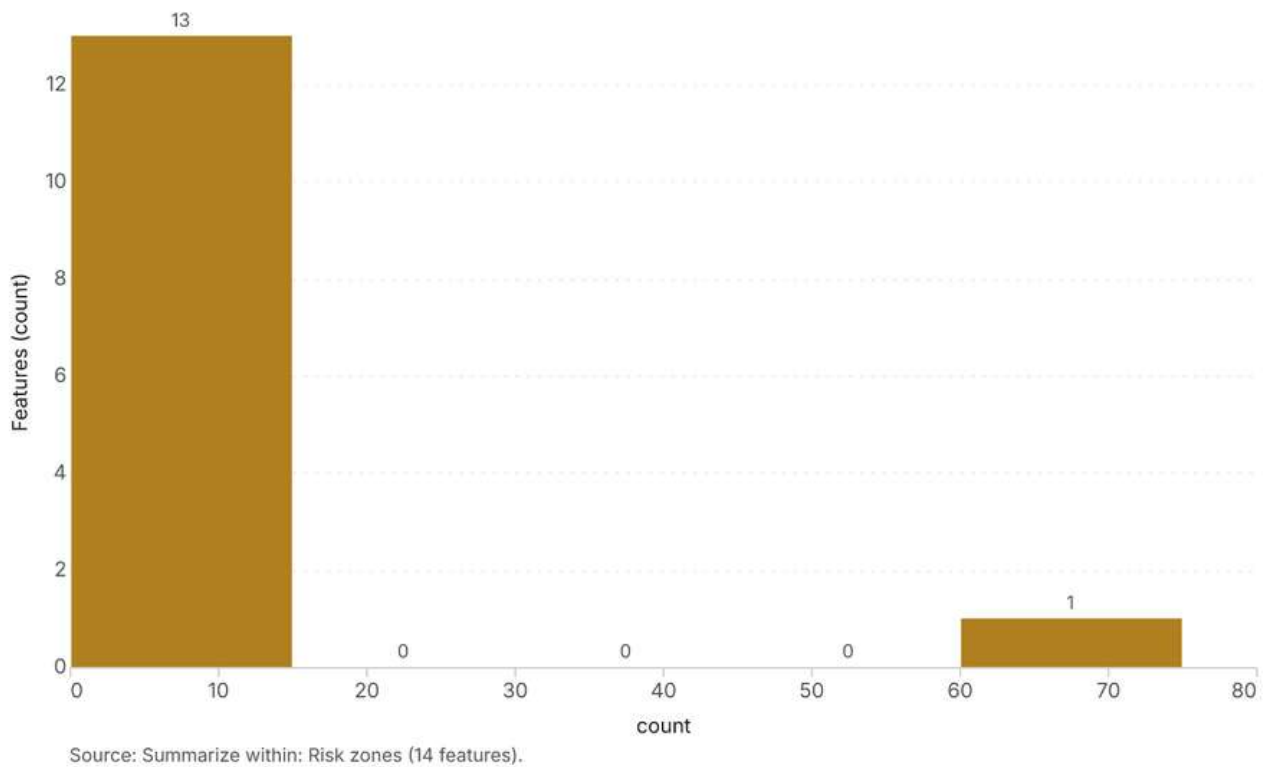


Figure 36. Summarize within: Risk zones [91]. Source: Summarize within: Risk zones (14 features). The data is in the appendix.

Cluster sizes

1 clusters over 15 features

cluster	features	share
0	11	73.3%
Noise	4	26.7%

Source: Find point clusters: Hospitals (15 features).

Figure 37. Find point clusters: Hospitals [92]. Source: Find point clusters: Hospitals (15 features). The data is in the appendix.

Cluster sizes

1 clusters over 1 features

cluster	features	share
0	1	100.0%

Source: Find point clusters: cluster hulls (1 features).

Figure 38. Find point clusters: cluster hulls [93]. Source: Find point clusters: cluster hulls (1 features). The data is in the appendix.

Cluster sizes

2 clusters over 12 features

cluster	features	share
0	5	41.7%
Noise	4	33.3%
1	3	25.0%

Source: Find point clusters: Safe havens (12 features).

Figure 39. Find point clusters: Safe havens [94]. Source: Find point clusters: Safe havens (12 features). The data is in the appendix.

Cluster sizes

2 clusters over 2 features

cluster	features	share
0	1	50.0%
1	1	50.0%

Source: Find point clusters: cluster hulls (2 features).

Figure 40. Find point clusters: cluster hulls [95]. Source: Find point clusters: cluster hulls (2 features). The data is in the appendix.

Cluster sizes

1 clusters over 80 features

cluster	features	share
0	77	96.2%
Noise	3	3.8%

Period: 2026-01-05 to 2026-09-28 (date). Source: Find point clusters: Protest events (80 fea...

Figure 41. Find point clusters: Protest events [96]. Period: 2026-01-05 to 2026-09-28 (date). Source: Find point clusters: Protest events (80 features). The data is in the appendix.

Cluster sizes

1 clusters over 1 features

cluster	features	share
0	1	100.0%

Source: Find point clusters: cluster hulls (1 features).

Figure 42. Find point clusters: cluster hulls [97]. Source: Find point clusters: cluster hulls (1 features). The data is in the appendix.

Distribution of col

386 values in 10 bins

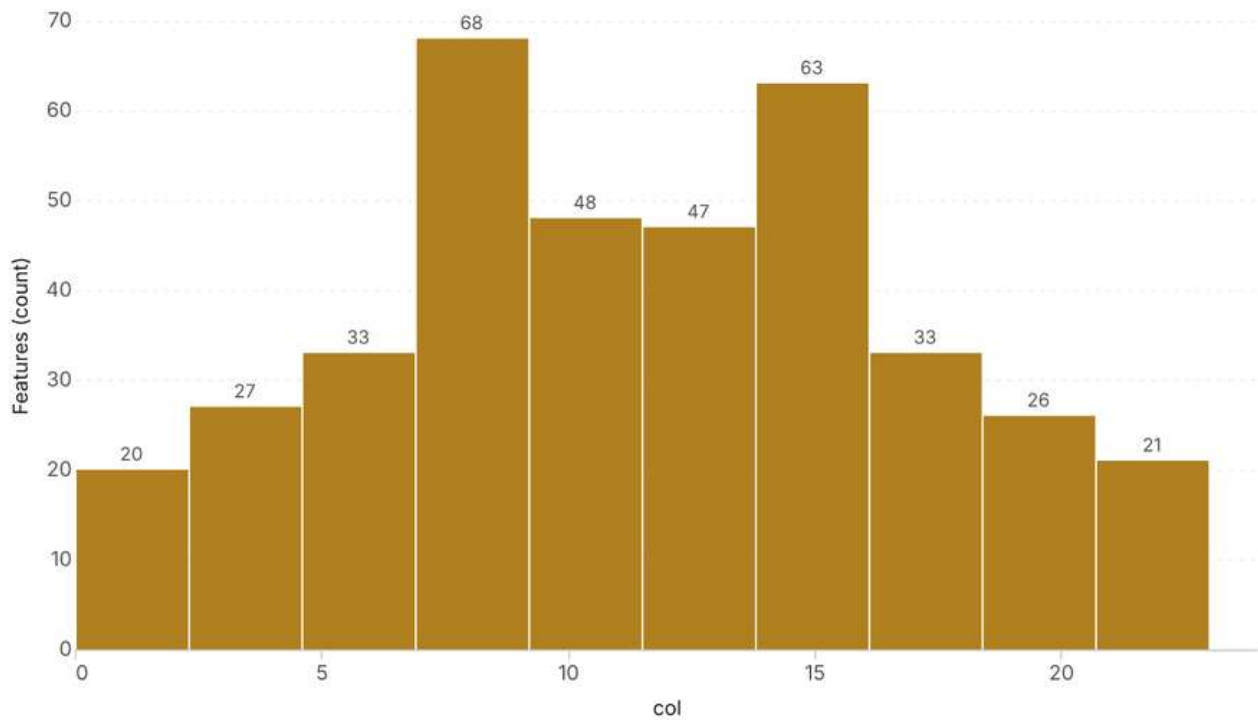


Figure 43. Calculate density: Protest events [98]. Source: Calculate density: Protest events (386 features). The data is in the appendix.

Distribution of density_per_km2

82 values in 8 bins

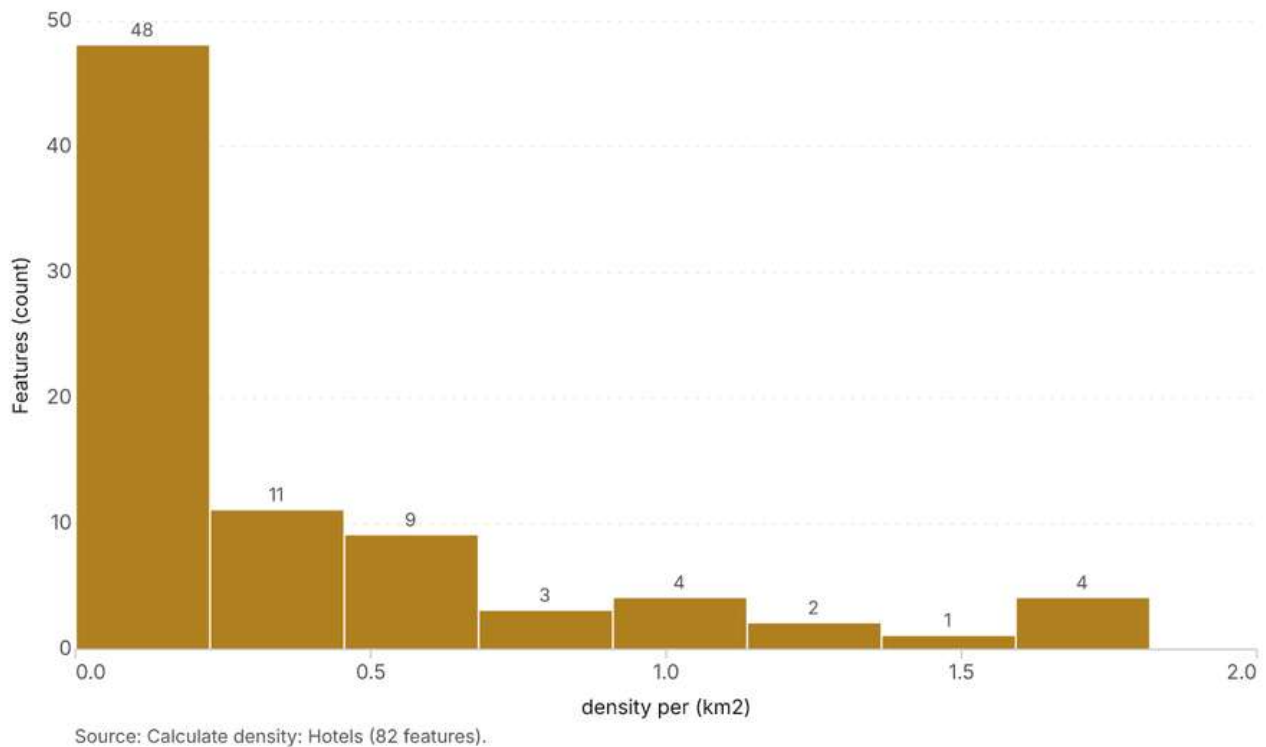


Figure 44. Calculate density: Hotels [99]. Source: Calculate density: Hotels (82 features). The data is in the appendix.

Distribution of col

2,240 values in 13 bins

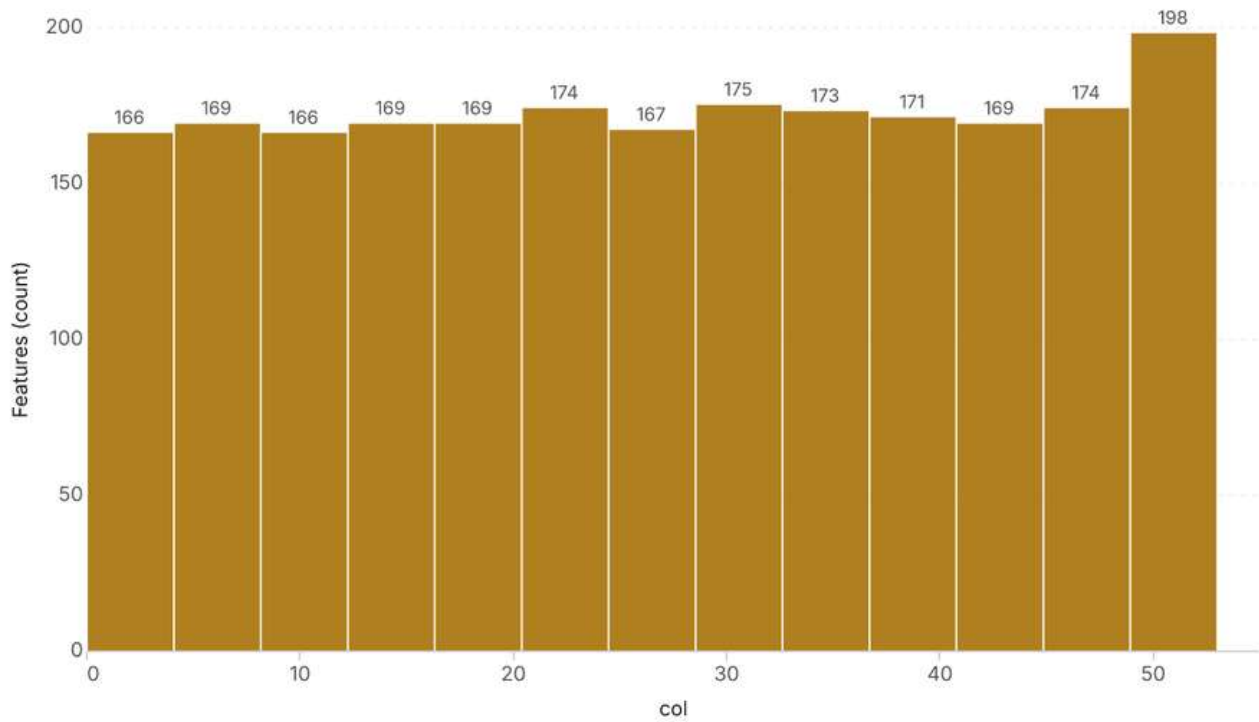
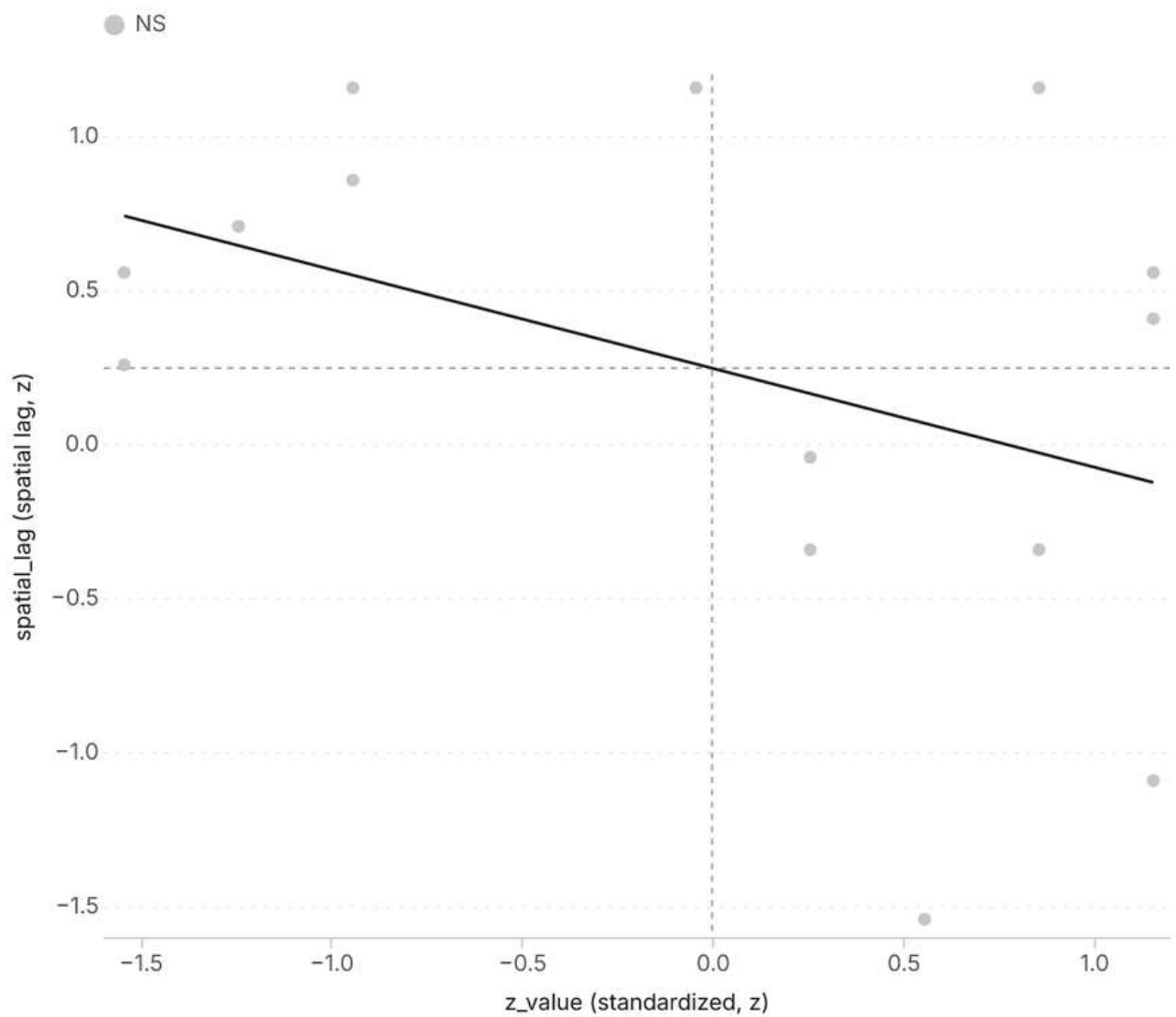


Figure 45. Calculate density: Security incidents [100]. Source: Calculate density: Security incidents (2,240 features). The data is in the appendix.

Moran scatter

14 features; slope -0.321 (the Moran's I of these standardized values)



Source: Find outliers: Risk zones (14 features).

Figure 46. Find outliers: Risk zones [101]. Source: Find outliers: Risk zones (14 features). The data is in the appendix.

Ranked by rank
Top 14 of 14 (smallest first)

rank	name
1	approved taxi
1	approved taxi
1	approved taxi
1	approved taxi
1	approved taxi
1	approved taxi
1	approved taxi
1	approved taxi
1	approved taxi
1	approved taxi
1	approved taxi
1	company car
1	approved taxi

Source: Find nearest: Hospitals (14 features).

Figure 47. Find nearest: Hospitals [102]. Source: Find nearest: Hospitals (14 features). The data is in the appendix.

Ranked by rank

Top 14 of 14 (smallest first)

rank	name
1	embassy
1	embassy
1	hotel
1	embassy
1	partner office
1	hotel
1	partner office
1	hotel
1	partner office
1	embassy
1	partner office
1	partner office
1	partner office
1	hotel

Source: Find nearest: Hospitals (14 features).

Figure 48. Find nearest: Hospitals [103]. Source: Find nearest: Hospitals (14 features). The data is in the appendix.

Count per week by to_date and to_size

Per week: 22 weeks from 2026-01-26 to 2026-06-22; trend +0.00903 per week; first half 3, second half 3 (+0.0%)

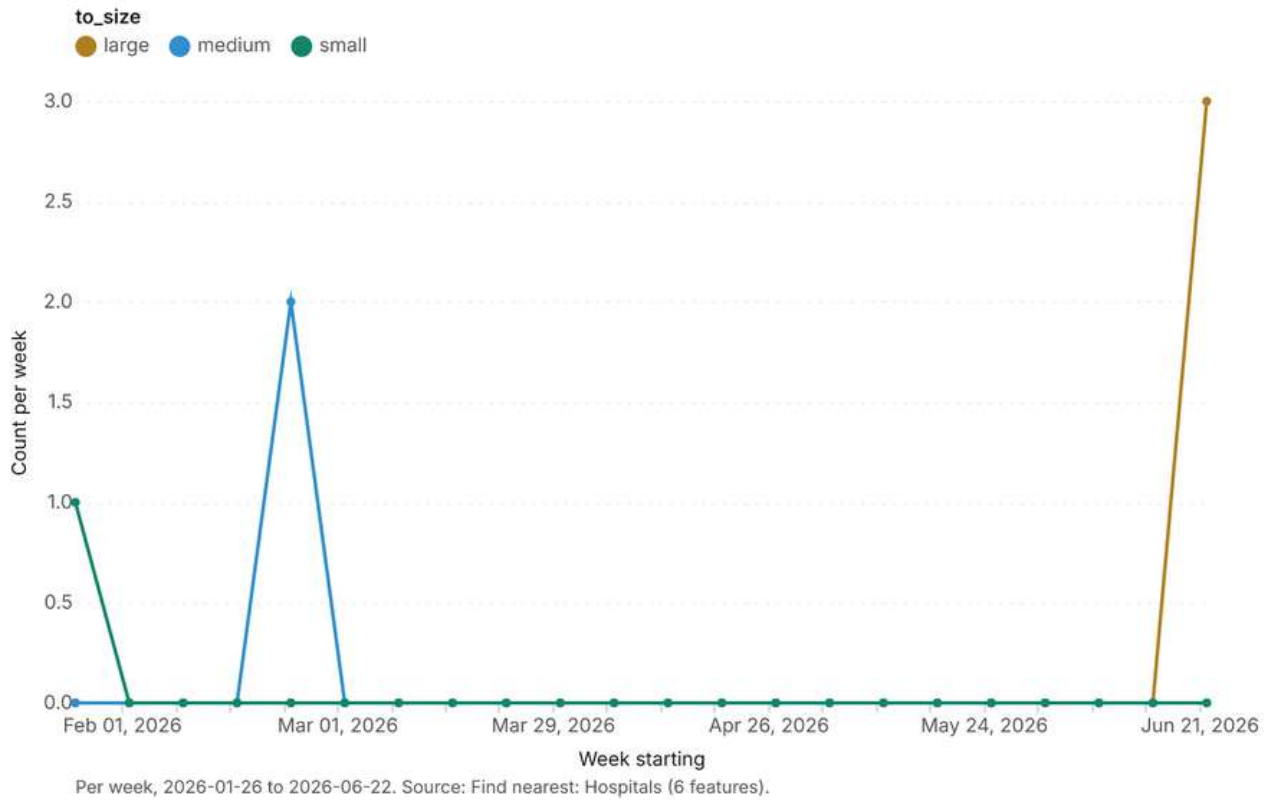


Figure 49. Find nearest: Hospitals over time [104]. Per week, 2026-01-26 to 2026-06-22. Source: Find nearest: Hospitals (6 features). The data is in the appendix.

Count per week by date and size

Per week: 39 weeks from 2026-01-05 to 2026-09-28; trend +0.00283 per week; first half 36, second half 44 (+22.2%)

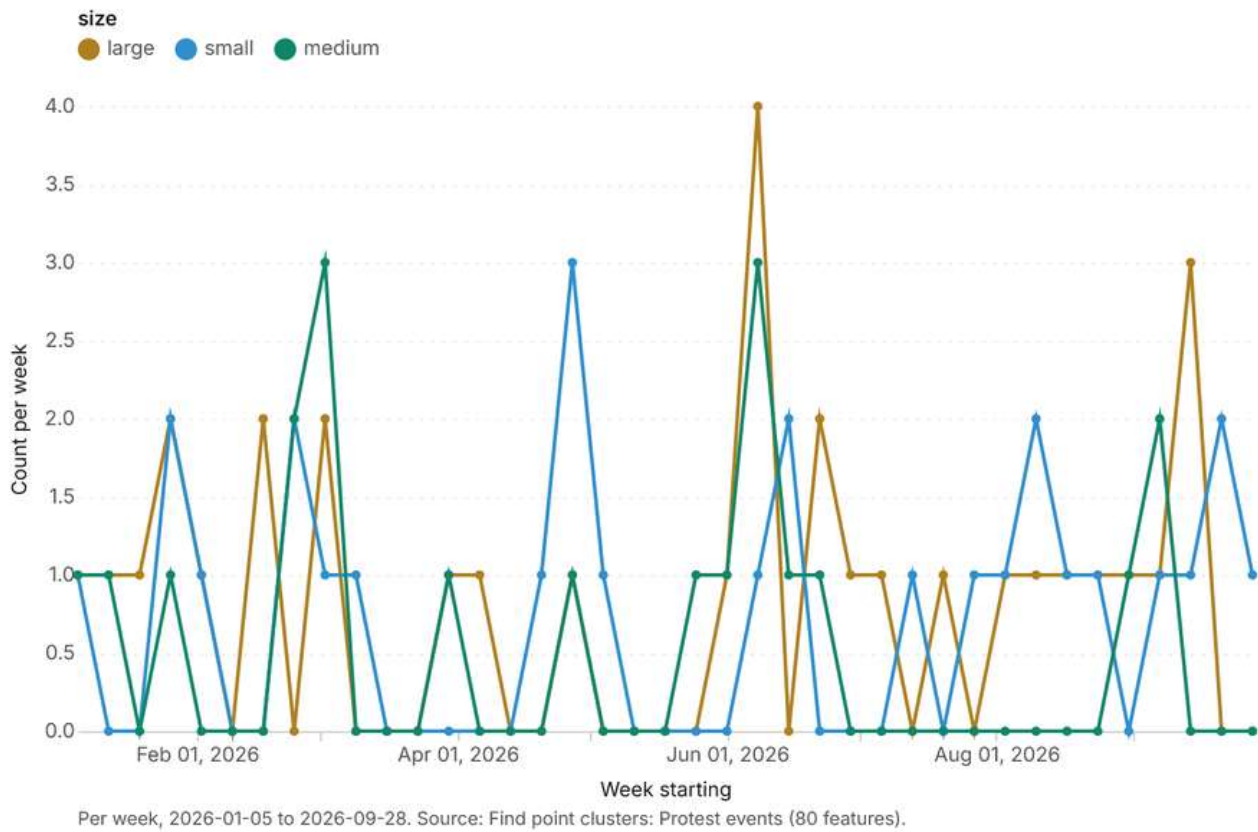


Figure 50. Find point clusters: Protest events over time [105]. Per week, 2026-01-05 to 2026-09-28. Source: Find point clusters: Protest events (80 features). The data is in the appendix.

Count per week by date and size

Per week: 39 weeks from 2026-01-05 to 2026-09-28; trend +0.00283 per week; first half 36, second half 44 (+22.2%)

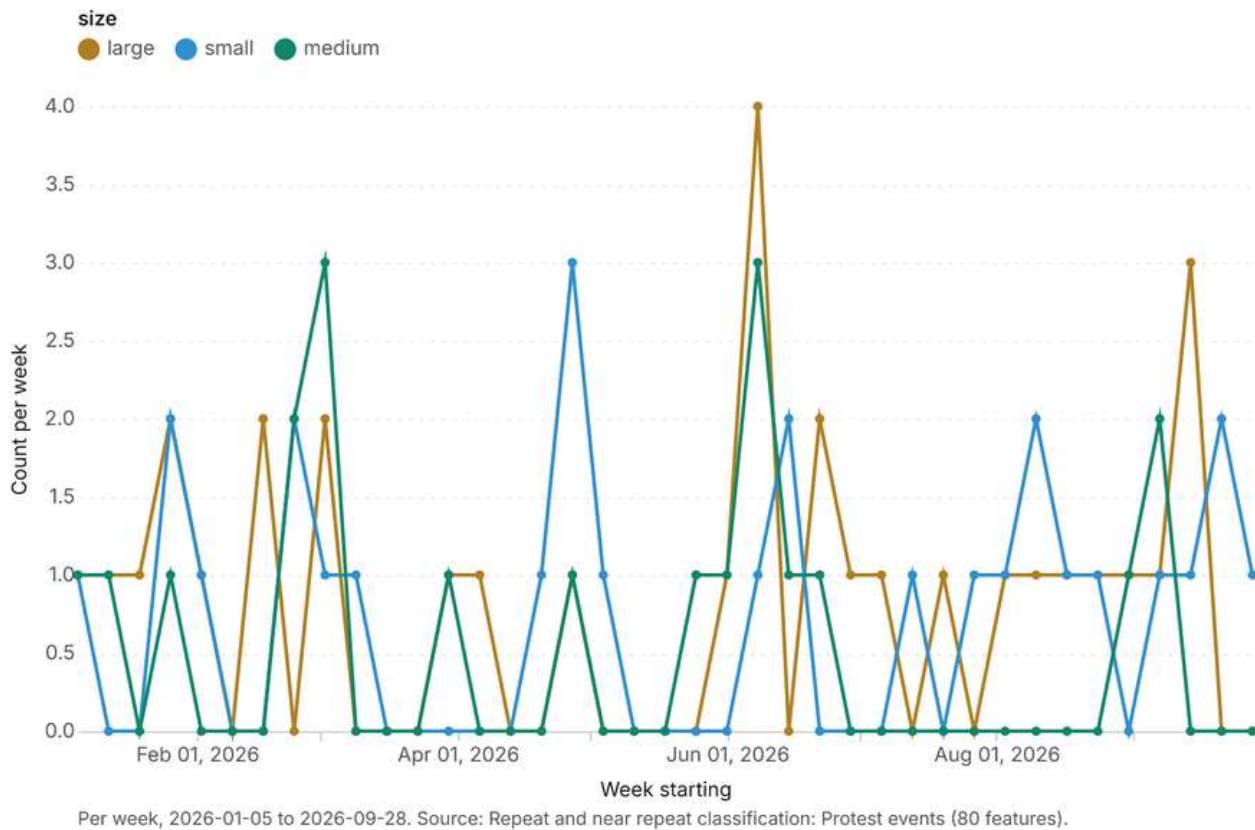


Figure 51. Repeat and near repeat classification: Protest events over time [106]. Per week, 2026-01-05 to 2026-09-28. Source: Repeat and near repeat classification: Protest events (80 features). The data is in the appendix.

Changes since the last run

This is the first report of this project.

Sources

- [1] Rendering: Chart: Timeline: events per week by dataset. 159 rows (id f07ed5b6-9486-4c24-a7ad-e2c1b9a45323)
- [2] Dataset: Security incidents. vector, 1700 rows (id e157aa87-0056-48e2-affe-2abe8c8f035b)
- [3] Dataset: Protest events. vector, 80 rows (id 61b11bf6-a94e-410d-bc75-a441daea9e2e)
- [4] Dataset: Travel log. table, 400 rows (id 91769657-5256-4993-90ae-bea93e5d9277)
- [5] Catalog: Hot spot analysis (operation catalog, gp_hot_spots). Getis-Ord Gi* hot and cold spots with z-scores, p-values and confidence bins. ArcGIS: Find Hot Spots, Hot Spot Analysis (Getis-Ord Gi*). QGIS: qgis:hotspot (plugin). (id gp_hot_spots)
- [6] Plan: Hot spots of Protest events (the Start plan's candidate c_e4c60efa6297). 80 points: Getis-Ord Gi* tests whether the concentrations in Protest events are statistically significant. (id 2f94775f-544a-4c5f-9cbe-3a9e3ee974e2:c_e4c60efa6297)
- [7] Tool result: gp_hot_spots, step 0. Hot spot analysis: 1 layer saved: Hot spot analysis: Protest events (29 features). (id cb954b77-a9f1-40f9-ba2a-8936e0981670:0)
- [8] Layer: Protest events. 80 features (id cf75e6b1-838e-4795-85d8-20e39702882e)
- [9] Plan: Hot spots of Hotels (the Start plan's candidate c_d9214e0b2e9c). 30 points: Getis-Ord Gi* tests whether the concentrations in Hotels are statistically significant. (id 2f94775f-544a-4c5f-9cbe-3a9e3ee974e2:c_d9214e0b2e9c)
- [10] Tool result: gp_hot_spots, step 1. Hot spot analysis: 1 layer saved: Hot spot analysis: Hotels (14 features). (id cb954b77-a9f1-40f9-ba2a-8936e0981670:1)
- [11] Layer: Hotels. 30 features (id 28842e9c-fa0f-4fa0-ab60-50616b38e2eb)
- [12] Plan: Hot spots of Security incidents (the Start plan's candidate c_2cf7cb199846). 1700 points: Getis-Ord Gi* tests whether the concentrations in Security incidents are statistically significant. (id 2f94775f-544a-4c5f-9cbe-3a9e3ee974e2:c_2cf7cb199846)

[13] Tool result: gp_hot_spots, step 2. Hot spot analysis: 1 layer saved: Hot spot analysis: Security incidents (353 features). (id cb954b77-a9f1-40f9-ba2a-8936e0981670:2)

[14] Layer: Security incidents. 1,700 features (id afb5d90c-b04a-45b5-86de-02dd48a97b15)

[15] Catalog: Emerging hot spots (operation catalog, gp_space_time_hot_spots). Where hot spots are new, consecutive, intensifying, persistent, diminishing, sporadic, oscillating or historical over time. ArcGIS: Emerging Hot Spot Analysis, Create Space Time Cube. (id gp_space_time_hot_spots)

[16] Plan: Space time hot spots of Protest events (the Start plan's candidate c_7097f355a4d8). Protest events carry dates in 'date': emerging hot spot analysis finds new, intensifying and fading hot spots per week. (id 2f94775f-544a-4c5f-9cbe-3a9e3ee974e2:c_7097f355a4d8)

[17] Tool result: gp_space_time_hot_spots, step 0. Emerging hot spots: 1 layer saved: Emerging hot spots: Protest events (14 features). (id 4ce981f8-e618-4a52-ab5e-deb572cf8a18:0)

[18] Plan: Space time hot spots of Security incidents (the Start plan's candidate c_333ac7b0a6a6). Security incidents carry dates in 'occurred_at': emerging hot spot analysis finds new, intensifying and fading hot spots per week. (id 2f94775f-544a-4c5f-9cbe-3a9e3ee974e2:c_333ac7b0a6a6)

[19] Tool result: gp_space_time_hot_spots, step 1. Emerging hot spots: 1 layer saved: Emerging hot spots: Security incidents (108 features). (id 4ce981f8-e618-4a52-ab5e-deb572cf8a18:1)

[20] Catalog: Repeat and near repeat classification (operation catalog, gp_near_repeat). Classify incidents as originators, repeats (same place) or near repeats within a distance and time window, with a Knox test table. ArcGIS: Repeat and Near Repeat Classification, Near Repeat Calculator. (id gp_near_repeat)

[21] Plan: Near repeat of Protest events (the Start plan's candidate c_f95b4db5e496). Near repeat analysis tests whether Protest events close in space also follow each other within 27 days. (id 2f94775f-544a-4c5f-9cbe-3a9e3ee974e2:c_f95b4db5e496)

[22] Tool result: gp_near_repeat, step 2. Repeat and near repeat classification: 1 layer saved: Repeat and near repeat classification: Protest events (80 features). (id 4ce981f8-e618-4a52-ab5e-deb572cf8a18:2)

[23] Catalog: Summarize within (operation catalog, gp_summarize_within). Count and aggregate the features inside each polygon (or bin), proportionally for lines and polygons. ArcGIS: Summarize Within, Aggregate Points. QGIS: native:countpointsinpolygon, native:sumlinelengths. (id gp_summarize_within)

[24] Plan: Hospitals per feature of Risk zones (the Start plan's candidate c_6520524d187a). Count Hospitals inside each feature of Risk zones by english_speaking; the counts map as a choropleth (natural breaks, sequential colors). (id 2f94775f-544a-4c5f-9cbe-3a9e3ee974e2:c_6520524d187a)

[25] Tool result: gp_summarize_within, step 0. Summarize within: 1 layer saved: Summarize within: Risk zones (14 features). (id 4db35232-a32c-47e1-9154-89fbc3620126:0)

[26] Layer: Hospitals. 15 features (id 8a96a3d4-1867-4c29-8033-2a6817b92b2c)

[27] Layer: Risk zones. 14 features (id a4d2e294-c13c-4572-b6fc-2b8ef4e9c955)

[28] Tool result: gp_summarize_within, step 1. Summarize within: 1 layer saved: Summarize within: Risk zones (14 features). (id 4db35232-a32c-47e1-9154-89fbc3620126:1)

[29] Layer: Safe havens. 12 features (id d7ec6bb0-8b36-474d-8157-931bdc40122a)

[30] Tool result: gp_summarize_within, step 2. Summarize within: 1 layer saved: Summarize within: Risk zones (14 features). (id 4db35232-a32c-47e1-9154-89fbc3620126:2)

[31] Catalog: Find point clusters (operation catalog, gp_find_point_clusters). Density-based clusters (DBSCAN, HDBSCAN or OPTICS, optionally space-time) with hulls and noise. ArcGIS: Find Point Clusters, Density-based Clustering. QGIS: native:dbscanclustering, native:stdbscanclustering. (id gp_find_point_clusters)

[32] Plan: Cluster points of Hospitals (the Start plan's candidate c_65a1f33e9e5e). DBSCAN finds dense groups of Hospitals and separates noise. (id 2f94775f-544a-4c5f-9cbe-3a9e3ee974e2:c_65a1f33e9e5e)

[33] Tool result: gp_find_point_clusters, step 0. Find point clusters: 2 layers saved: Find point clusters: Hospitals (15 features); Find point clusters: cluster hulls (1 feature). (id 86c36cc2-95cb-4bfa-aac6-db9cc2913cc1:0)

[34] Plan: Cluster points of Safe havens (the Start plan's candidate c_5ba3c571cd04). DBSCAN finds dense groups of Safe havens and separates noise. (id 2f94775f-544a-4c5f-9cbe-3a9e3ee974e2:c_5ba3c571cd04)

[35] Tool result: gp_find_point_clusters, step 1. Find point clusters: 2 layers saved: Find point clusters: Safe havens (12 features); Find point clusters: cluster hulls (2 features). (id 86c36cc2-95cb-4bfa-aac6-db9cc2913cc1:1)

[36] Plan: Cluster points of Protest events (the Start plan's candidate c_ae60a45625a8). DBSCAN finds dense groups of Protest events and separates noise. (id 2f94775f-544a-4c5f-9cbe-3a9e3ee974e2:c_ae60a45625a8)

[37] Tool result: gp_find_point_clusters, step 2. Find point clusters: 2 layers saved: Find point clusters: Protest events (80 features); Find point clusters: cluster hulls (1 feature). (id 86c36cc2-95cb-4bfa-aac6-db9cc2913cc1:2)

[38] Catalog: Calculate density (operation catalog, gp_calculate_density). Kernel density per square kilometer on a grid. ArcGIS: Calculate Density, Kernel Density. QGIS: native:heatmapkerneldensityestimation. (id gp_calculate_density)

[39] Plan: Kernel density of Protest events (the Start plan's candidate c_7c8acce6dd51). 80 points in Protest events: a density surface shows where they concentrate. (id 2f94775f-544a-4c5f-9cbe-3a9e3ee974e2:c_7c8acce6dd51)

[40] Tool result: gp_calculate_density, step 0. Calculate density: 1 layer saved: Calculate density: Protest events (386 features). (id 72e7e894-08fe-429b-84d0-f973eac006a1:0)

[41] Plan: Kernel density of Hotels (the Start plan's candidate c_fb39ef5f9446). 30 points in Hotels: a density surface shows where they concentrate. (id 2f94775f-544a-4c5f-9cbe-3a9e3ee974e2:c_fb39ef5f9446)

[42] Tool result: gp_calculate_density, step 1. Calculate density: 1 layer saved: Calculate density: Hotels (82 features). (id 72e7e894-08fe-429b-84d0-f973eac006a1:1)

[43] Plan: Kernel density of Security incidents (the Start plan's candidate c_8b75d0e8f5bf). 1700 points in Security incidents: a density surface shows where they concentrate. (id 2f94775f-544a-4c5f-9cbe-3a9e3ee974e2:c_8b75d0e8f5bf)

[44] Tool result: gp_calculate_density, step 2. Calculate density: 1 layer saved: Calculate density: Security incidents (2240 features). (id 72e7e894-08fe-429b-84d0-f973eac006a1:2)

[45] Catalog: Find outliers (operation catalog, gp_outliers). Anselin local Moran's I: HH, LL clusters and HL, LH outliers. ArcGIS: Find Outliers, Cluster and Outlier Analysis (Anselin Local Moran's I). (id gp_outliers)

[46] Plan: Local morans i of Risk zones (the Start plan's candidate c_b57bb9ae247a). Local Moran's I maps clusters and outliers of 'risk_score'. (id 2f94775f-544a-4c5f-9cbe-3a9e3ee974e2:c_b57bb9ae247a)

[47] Tool result: gp_outliers, step 0. Find outliers: 1 layer saved: Find outliers: Risk zones (14 features). (id 8804c2f2-0669-4232-a6ea-33b246fdbbe10:0)

[48] Catalog: Spatial autocorrelation (operation catalog, gp_spatial_autocorrelation). Global Moran's I: is the pattern clustered, dispersed or random. ArcGIS: Spatial Autocorrelation (Global Moran's I). (id gp_spatial_autocorrelation)

[49] Plan: Global morans i of Risk zones (the Start plan's candidate c_e8c49b66ee35). Global Moran's I says whether similar values of 'risk_score' sit next to each other. (id 2f94775f-544a-4c5f-9cbe-3a9e3ee974e2:c_e8c49b66ee35)

[50] Tool result: gp_spatial_autocorrelation, step 1. Spatial autocorrelation: done; no map output. (id 8804c2f2-0669-4232-a6ea-33b246fdbbe10:1)

[51] Catalog: Find nearest (operation catalog, gp_find_nearest). The k nearest features for each input, with geodesic distance and bearing. ArcGIS: Find Nearest, Near, Generate Near Table. QGIS: native:joinbynearest, native:nearestneighbouranalysis. (id gp_find_nearest)

[52] Plan: Find nearest of Hospitals and Travel routes (the Start plan's candidate c_6c9de7d7d3b4). The nearest of Travel routes to each of Hospitals, with distances. (id 2f94775f-544a-4c5f-9cbe-3a9e3ee974e2:c_6c9de7d7d3b4)

[53] Tool result: gp_find_nearest, step 0. Find nearest: 1 layer saved: Find nearest: Hospitals (14 features). (id d72a65fe-570d-4b7e-bb1f-3397ddd3dff0:0)

[54] Layer: Travel routes. 10 features (id 17118d2e-4c8a-4e58-a365-56ed0dcccdeb)

[55] Tool result: gp_find_nearest, step 1. Find nearest: 1 layer saved: Find nearest: Hospitals (14 features). (id d72a65fe-570d-4b7e-bb1f-3397ddd3dff0:1)

[56] Tool result: gp_find_nearest, step 2. Find nearest: 1 layer saved: Find nearest: Hospitals (6 features). (id d72a65fe-570d-4b7e-bb1f-3397ddd3dff0:2)

[57] Rendering: Map: Hot spot analysis: Protest events (id 500df2bf-0773-4df4-997b-e52faf1d7b86)

[58] Rendering: Map: Hot spot analysis: Hotels (id a9b20642-0e6f-4981-a664-da575f4c0f47)

[59] Rendering: Map: Hot spot analysis: Security incidents (id dfc0443f-8eec-4850-bcf5-b167e4b25bb2)

[60] Rendering: Map: Emerging hot spots: Protest events (id 0099fe22-7871-4a15-a0e8-1feae00a5bfe)

[61] Rendering: Map: Emerging hot spots: Security incidents (id ac12c726-afc7-4f73-bcad-180032253879)

[62] Rendering: Map: Repeat and near repeat classification: Protest events (id 88da8834-5528-4120-a9c9-c2d8f343794a)

[63] Rendering: Map: Summarize within: Risk zones (id 00bc1476-064e-4f9d-b9df-58b7176702f7)

[64] Rendering: Map: Summarize within: Risk zones (id 097e7003-7459-4810-8b27-5f7a0070cb99)

[65] Rendering: Map: Summarize within: Risk zones (id 0f0f8452-fff5-40e3-9da5-e4b1a4e0c9c3)

[66] Rendering: Map: Find point clusters: Hospitals (id 47eb8a01-1990-4474-b495-5bf2f8a9ea58)

[67] Rendering: Map: Find point clusters: cluster hulls (id 9199cde6-d3cd-466f-bbdb-c545c614f5d9)

[68] Rendering: Map: Find point clusters: Safe havens (id b7163651-cc15-45dd-85df-b9a1e1a0c2ab)

[69] Rendering: Map: Find point clusters: cluster hulls (id b07c64b4-3212-4751-b9fe-884c92e2af0b)

[70] Rendering: Map: Find point clusters: Protest events (id 09c181e5-fd50-4a4d-8fb9-c372f05b7087)

[71] Rendering: Map: Find point clusters: cluster hulls (id 837965dd-bd8f-4eda-8fc0-9ce4211449eb)

[72] Rendering: Map: Calculate density: Protest events (id 26c2dd95-9903-4e3a-9502-b9d59a00d91f)

[73] Rendering: Map: Calculate density: Hotels (id 87642b35-e16d-4168-a04d-24944d0ea7c8)

[74] Rendering: Map: Calculate density: Security incidents (id db714770-2476-4110-af9b-826c0fda7266)

[75] Rendering: Map: Risk zones by risk_score (id acd51039-768b-4034-9aa3-0fa9355f4884)

[76] Rendering: Map: Find outliers: Risk zones (id 5323e5c1-28e1-44b3-8f9c-44f34efbf17f)

[77] Rendering: Map: Find nearest: Hospitals (id a1567a83-3fb0-4dcf-8d6c-71ba8b4ed7d7)

[78] Rendering: Map: Find nearest: Hospitals (id b16977bf-56c6-43a5-bf88-4d5b01a2648c)

[79] Rendering: Map: Find nearest: Hospitals (id 11bfd2f1-7879-4693-a32a-915be104a231)

[80] Rendering: Chart: Security incidents over time (occurred_at). 318 rows (id e4bbd9ee-6938-4976-afea-98b10b22455f)

[81] Rendering: Chart: Protest events over time (date). 117 rows (id f828e7a2-d14d-4bc3-b257-85cd520ee1ef)

[82] Rendering: Chart: Travel log over time (date). 106 rows (id 66c88c61-6c69-4dc0-a55d-5c961369ab06)

[83] Rendering: Chart: Hot spot analysis: Protest events. 11 rows (id 66439a0c-ac69-4219-b24e-6f7ff88f70d2)

[84] Rendering: Chart: Hot spot analysis: Hotels. 6 rows (id c52e7b32-d25d-4aed-abe8-9ebb7f603bfd)

[85] Rendering: Chart: Hot spot analysis: Security incidents. 16 rows (id ca9f7204-df1a-4b6c-b63a-414bc07961a3)

[86] Rendering: Chart: Emerging hot spots: Protest events. 5 rows (id a0edbd15-0e36-4d00-9145-33631fafb0d4)

[87] Rendering: Chart: Emerging hot spots: Security incidents. 8 rows (id 0b5d890b-d25b-4e32-8200-951dc01149f7)

[88] Rendering: Chart: Repeat and near repeat classification: Protest events. 117 rows (id 2306aa49-d791-4cd3-8d4c-28e6660067db)

[89] Rendering: Chart: Summarize within: Risk zones. 5 rows (id c94ab553-318c-4a5e-bfe3-5ceb6088a6d2)

[90] Rendering: Chart: Summarize within: Risk zones. 5 rows (id 67037acd-9bb9-4174-b327-02e297418724)

[91] Rendering: Chart: Summarize within: Risk zones. 5 rows (id 923af0d1-ab6e-4ce5-b3d9-81d29ab8cc03)

[92] Rendering: Chart: Find point clusters: Hospitals. 2 rows (id 20d9b93a-9f38-4502-8832-0c3847923a24)

[93] Rendering: Chart: Find point clusters: cluster hulls. 1 rows (id f9da01d9-7689-4ba1-b714-0a48053eb1ae)

[94] Rendering: Chart: Find point clusters: Safe havens. 3 rows (id b1d7e3a3-1643-4aea-87c6-3d0616a865de)

[95] Rendering: Chart: Find point clusters: cluster hulls. 2 rows (id 4093c918-1c9f-481a-8b57-2adef8395ab8)

[96] Rendering: Chart: Find point clusters: Protest events. 2 rows (id 83853866-50d0-468b-8c71-7faa0aa71c50)

[97] Rendering: Chart: Find point clusters: cluster hulls. 1 rows (id e5bfd36e-59ac-4d44-805f-ba7f25c9358d)

[98] Rendering: Chart: Calculate density: Protest events. 10 rows (id 73671b82-b4a3-42c0-a8ae-b1d27cba0ec2)

[99] Rendering: Chart: Calculate density: Hotels. 8 rows (id c0aefbfb-9735-4f03-a2e6-d27fabd30313)

[100] Rendering: Chart: Calculate density: Security incidents. 13 rows (id a8231907-9048-4318-9575-1e7364e4238a)

[101] Rendering: Chart: Find outliers: Risk zones. 14 rows (id 491c699f-46c0-4622-98ad-1183374f76e1)

[102] Rendering: Chart: Find nearest: Hospitals. 14 rows (id 9cc7d0a7-efe8-4e46-9c45-e42681c0944f)

[103] Rendering: Chart: Find nearest: Hospitals. 14 rows (id e56bd3f0-499e-402f-a74a-cca2f35b3bc9)

[104] Rendering: Chart: Find nearest: Hospitals over time. 66 rows (id 51a6266c-78a0-4146-87ab-d79e4d6ba260)

[105] Rendering: Chart: Find point clusters: Protest events over time. 117 rows (id 86bdb528-cab1-4fff-aa57-5ee0311a2b43)

[106] Rendering: Chart: Repeat and near repeat classification: Protest events over time. 117 rows (id 4dfde3d2-01b3-45b2-90c2-09129de0912c)

[107] Dataset: Company sites. vector, 8 rows (id a57e5e2e-a25d-409d-9272-6ca1c1ae23ab)

[108] Dataset: Hotels. vector, 30 rows (id 960da6f9-a119-47d2-8c4c-73faa6425317)

[109] Dataset: Travel routes. vector, 10 rows (id 1008679c-3d12-45ea-a8ce-be53355c90d8)

[110] Dataset: Risk zones. vector, 14 rows (id a6555125-2ca1-45ce-8a48-57ce5705423b)

[111] Dataset: Hospitals. vector, 15 rows (id 03c9ffea-5a0a-4d80-8965-c0709759aff3)

[112] Dataset: Safe havens. vector, 12 rows (id 511f2fd6-d838-46cc-a47c-c29f431a83c0)

[113] Dataset: Site guard roster. table, 16 rows (id 19276383-dfed-4594-b706-1f9d7ba7b072)

[114] Dataset: Country security briefing. document, ? rows (id f20d3f16-9057-4bc4-a33a-b2d8b53657a0)

[115] Dataset: Hotel security assessment. document, ? rows (id e794bded-1be4-41a5-bbf2-086e1a0791f3)

[116] Record: Sample: Corporate security and travel risk, Mexico City (id 188436ed-c19a-4e7c-ab43-b58fe7291e56)

[117] Layer: Hot spot analysis: Protest events. 29 features (id db1e7e50-0b84-4c23-a7f1-70d712d84483)

[118] Layer: Hot spot analysis: Hotels. 14 features (id 236b49e6-718b-468e-9414-fec05e2fd046)

[119] Layer: Hot spot analysis: Security incidents. 353 features (id 354043da-a305-407a-bbe0-c2d077f68fed)

[120] Layer: Emerging hot spots: Protest events. 14 features (id d4e930d7-f5cc-45e0-b105-ee6ff35846d6)

[121] Layer: Emerging hot spots: Security incidents. 108 features (id 7d258e9e-7357-4428-8775-a97375d60dd3)

[122] Layer: Repeat and near repeat classification: Protest events. 80 features (id c15ea26d-f7bf-43bf-987f-05e0d75a4a76)

[123] Layer: Summarize within: Risk zones. 14 features (id 46424976-b4de-430a-93e8-53723336e3a7)

[124] Layer: Summarize within: Risk zones. 14 features (id 66d57619-49ef-4eb7-831b-bedc47b571d1)

[125] Layer: Summarize within: Risk zones. 14 features (id 705e651a-1e75-493d-a532-0c8927aa40cd)

[126] Layer: Find point clusters: Hospitals. 15 features (id 991c0297-f207-49c1-9361-29e0d01cd1f5)

[127] Layer: Find point clusters: cluster hulls. 1 features (id e06a131f-7989-4c9a-bad5-98f65d8d13ee)

[128] Layer: Find point clusters: Safe havens. 12 features (id 1da076c5-d608-4691-b2c6-0458f1989d7e)

[129] Layer: Find point clusters: cluster hulls. 2 features (id cb9419c5-0ee1-4dba-a62a-5b39176bab51)

[130] Layer: Find point clusters: Protest events. 80 features (id 84d6cdb7-cfe3-4875-8ab3-4c85027ca7be)

[131] Layer: Find point clusters: cluster hulls. 1 features (id baa8dcc7-143d-4f94-a316-947abdb534cf)

[132] Layer: Calculate density: Protest events. 386 features (id 54008367-d33a-4511-b5e1-8c4a55915ad0)

[133] Layer: Calculate density: Hotels. 82 features (id c4eba0a4-6712-445b-bc6c-cf0c26bb9cac)

[134] Layer: Calculate density: Security incidents. 2,240 features (id 57bb3eed-15a3-4c3d-b425-89ac6f7edeaf)

[135] Layer: Find outliers: Risk zones. 14 features (id e8ee4af5-2649-4990-8578-af9a7ca2a1e6)

[136] Layer: Find nearest: Hospitals. 14 features (id cc3abbbe-dedb-4bf4-a08f-10d4882a63d2)

[137] Layer: Find nearest: Hospitals. 14 features (id 39cac909-2a3f-47b4-9123-524c237e05eb)

[138] Layer: Find nearest: Hospitals. 6 features (id 5b28ce74-706d-460a-b867-4b1ce5f6ed98)

Appendix: the data behind the charts

Figure 1. Timeline: events per week by dataset [1]

period	series	value
2025-09-29	Security incidents	24
2025-09-29	Travel log	10
2025-09-29	Protest events	0
2025-10-06	Security incidents	24
2025-10-06	Travel log	4
2025-10-06	Protest events	0
2025-10-13	Security incidents	25
2025-10-13	Travel log	8
2025-10-13	Protest events	0
2025-10-20	Security incidents	18
2025-10-20	Travel log	3
2025-10-20	Protest events	0
2025-10-27	Security incidents	38
2025-10-27	Travel log	6
2025-10-27	Protest events	0
2025-11-03	Security incidents	22
2025-11-03	Travel log	9
2025-11-03	Protest events	0
2025-11-10	Security incidents	25

period	series	value
2025-11-10	Travel log	11
2025-11-10	Protest events	0
2025-11-17	Security incidents	25
2025-11-17	Travel log	10
2025-11-17	Protest events	0
2025-11-24	Security incidents	24
2025-11-24	Travel log	4
2025-11-24	Protest events	0
2025-12-01	Security incidents	29
2025-12-01	Travel log	10
2025-12-01	Protest events	0
2025-12-08	Security incidents	28
2025-12-08	Travel log	6
2025-12-08	Protest events	0
2025-12-15	Security incidents	26
2025-12-15	Travel log	7
2025-12-15	Protest events	0
2025-12-22	Security incidents	25
2025-12-22	Travel log	14
2025-12-22	Protest events	0
2025-12-29	Security incidents	32
2025-12-29	Travel log	7
2025-12-29	Protest events	0
2026-01-05	Security incidents	34
2026-01-05	Travel log	6
2026-01-05	Protest events	3
2026-01-12	Security incidents	30
2026-01-12	Travel log	7
2026-01-12	Protest events	2
2026-01-19	Security incidents	29
2026-01-19	Travel log	10
2026-01-19	Protest events	1
2026-01-26	Security incidents	78
2026-01-26	Travel log	12
2026-01-26	Protest events	5
2026-02-02	Security incidents	21
2026-02-02	Travel log	5
2026-02-02	Protest events	2
2026-02-09	Security incidents	34
2026-02-09	Travel log	9
2026-02-09	Protest events	0
2026-02-16	Security incidents	34
2026-02-16	Travel log	9

period	series	value
2026-02-16	Protest events	2
2026-02-23	Security incidents	30
2026-02-23	Travel log	9
2026-02-23	Protest events	4
2026-03-02	Security incidents	110
2026-03-02	Travel log	7
2026-03-02	Protest events	6
2026-03-09	Security incidents	26
2026-03-09	Travel log	7
2026-03-09	Protest events	1
2026-03-16	Security incidents	34
2026-03-16	Travel log	10
2026-03-16	Protest events	0
2026-03-23	Security incidents	19
2026-03-23	Travel log	8
2026-03-23	Protest events	0
2026-03-30	Security incidents	18
2026-03-30	Travel log	3
2026-03-30	Protest events	2
2026-04-06	Security incidents	28
2026-04-06	Travel log	10
2026-04-06	Protest events	1
2026-04-13	Security incidents	27
2026-04-13	Travel log	3
2026-04-13	Protest events	0
2026-04-20	Security incidents	21
2026-04-20	Travel log	6
2026-04-20	Protest events	1
2026-04-27	Security incidents	100
2026-04-27	Travel log	5
2026-04-27	Protest events	5
2026-05-04	Security incidents	22
2026-05-04	Travel log	9
2026-05-04	Protest events	1
2026-05-11	Security incidents	20
2026-05-11	Travel log	9
2026-05-11	Protest events	0
2026-05-18	Security incidents	23
2026-05-18	Travel log	6
2026-05-18	Protest events	0
2026-05-25	Security incidents	26
2026-05-25	Travel log	8
2026-05-25	Protest events	1

period	series	value
2026-06-01	Security incidents	29
2026-06-01	Travel log	4
2026-06-01	Protest events	2
2026-06-08	Security incidents	102
2026-06-08	Travel log	10
2026-06-08	Protest events	8
2026-06-15	Security incidents	20
2026-06-15	Travel log	4
2026-06-15	Protest events	3
2026-06-22	Security incidents	18
2026-06-22	Travel log	9
2026-06-22	Protest events	3
2026-06-29	Security incidents	34
2026-06-29	Travel log	6
2026-06-29	Protest events	1
2026-07-06	Security incidents	17
2026-07-06	Travel log	15
2026-07-06	Protest events	1
2026-07-13	Security incidents	25
2026-07-13	Travel log	5
2026-07-13	Protest events	1
2026-07-20	Security incidents	16
2026-07-20	Travel log	5
2026-07-20	Protest events	1
2026-07-27	Security incidents	21
2026-07-27	Travel log	9
2026-07-27	Protest events	1
2026-08-03	Security incidents	25
2026-08-03	Travel log	6
2026-08-03	Protest events	2
2026-08-10	Security incidents	25
2026-08-10	Travel log	9
2026-08-10	Protest events	3
2026-08-17	Security incidents	20
2026-08-17	Travel log	10
2026-08-17	Protest events	2
2026-08-24	Security incidents	24
2026-08-24	Travel log	9
2026-08-24	Protest events	2
2026-08-31	Security incidents	27
2026-08-31	Travel log	7
2026-08-31	Protest events	2
2026-09-07	Security incidents	32

period	series	value
2026-09-07	Travel log	7
2026-09-07	Protest events	4
2026-09-14	Security incidents	97
2026-09-14	Travel log	7
2026-09-14	Protest events	4
2026-09-21	Security incidents	24
2026-09-21	Travel log	8
2026-09-21	Protest events	2
2026-09-28	Security incidents	15
2026-09-28	Travel log	3
2026-09-28	Protest events	1

Figure 25. Security incidents over time (occurred_at) [80]

period	series	value
2025-09-29	robbery	2
2025-09-29	theft	10
2025-09-29	vandalism	1
2025-09-29	road blockade	1
2025-09-29	vehicle theft	3
2025-09-29	Other	7
2025-10-06	robbery	8
2025-10-06	theft	4
2025-10-06	vandalism	1
2025-10-06	road blockade	3
2025-10-06	vehicle theft	2
2025-10-06	Other	6
2025-10-13	robbery	10
2025-10-13	theft	5
2025-10-13	vandalism	1
2025-10-13	road blockade	0
2025-10-13	vehicle theft	5
2025-10-13	Other	4
2025-10-20	robbery	7
2025-10-20	theft	3
2025-10-20	vandalism	1
2025-10-20	road blockade	3
2025-10-20	vehicle theft	1
2025-10-20	Other	3
2025-10-27	robbery	10
2025-10-27	theft	12
2025-10-27	vandalism	1
2025-10-27	road blockade	2
2025-10-27	vehicle theft	7
2025-10-27	Other	6

period	series	value
2025-11-03	robbery	5
2025-11-03	theft	8
2025-11-03	vandalism	2
2025-11-03	road blockade	2
2025-11-03	vehicle theft	3
2025-11-03	Other	2
2025-11-10	robbery	9
2025-11-10	theft	5
2025-11-10	vandalism	4
2025-11-10	road blockade	2
2025-11-10	vehicle theft	2
2025-11-10	Other	3
2025-11-17	robbery	6
2025-11-17	theft	3
2025-11-17	vandalism	3
2025-11-17	road blockade	1
2025-11-17	vehicle theft	6
2025-11-17	Other	6
2025-11-24	robbery	7
2025-11-24	theft	8
2025-11-24	vandalism	2
2025-11-24	road blockade	2
2025-11-24	vehicle theft	3
2025-11-24	Other	2
2025-12-01	robbery	10
2025-12-01	theft	12
2025-12-01	vandalism	2
2025-12-01	road blockade	0
2025-12-01	vehicle theft	4
2025-12-01	Other	1
2025-12-08	robbery	9
2025-12-08	theft	6
2025-12-08	vandalism	4
2025-12-08	road blockade	1
2025-12-08	vehicle theft	3
2025-12-08	Other	5
2025-12-15	robbery	10
2025-12-15	theft	9
2025-12-15	vandalism	0
2025-12-15	road blockade	1
2025-12-15	vehicle theft	4
2025-12-15	Other	2
2025-12-22	robbery	7

period	series	value
2025-12-22	theft	6
2025-12-22	vandalism	3
2025-12-22	road blockade	1
2025-12-22	vehicle theft	6
2025-12-22	Other	2
2025-12-29	robbery	10
2025-12-29	theft	4
2025-12-29	vandalism	4
2025-12-29	road blockade	3
2025-12-29	vehicle theft	5
2025-12-29	Other	6
2026-01-05	robbery	11
2026-01-05	theft	8
2026-01-05	vandalism	4
2026-01-05	road blockade	1
2026-01-05	vehicle theft	7
2026-01-05	Other	3
2026-01-12	robbery	8
2026-01-12	theft	11
2026-01-12	vandalism	0
2026-01-12	road blockade	4
2026-01-12	vehicle theft	2
2026-01-12	Other	5
2026-01-19	robbery	14
2026-01-19	theft	8
2026-01-19	vandalism	2
2026-01-19	road blockade	1
2026-01-19	vehicle theft	3
2026-01-19	Other	1
2026-01-26	robbery	8
2026-01-26	theft	12
2026-01-26	vandalism	28
2026-01-26	road blockade	20
2026-01-26	vehicle theft	2
2026-01-26	Other	8
2026-02-02	robbery	6
2026-02-02	theft	3
2026-02-02	vandalism	3
2026-02-02	road blockade	1
2026-02-02	vehicle theft	5
2026-02-02	Other	3
2026-02-09	robbery	15
2026-02-09	theft	8

period	series	value
2026-02-09	vandalism	4
2026-02-09	road blockade	1
2026-02-09	vehicle theft	2
2026-02-09	Other	4
2026-02-16	robbery	13
2026-02-16	theft	9
2026-02-16	vandalism	3
2026-02-16	road blockade	1
2026-02-16	vehicle theft	4
2026-02-16	Other	4
2026-02-23	robbery	10
2026-02-23	theft	8
2026-02-23	vandalism	3
2026-02-23	road blockade	2
2026-02-23	vehicle theft	5
2026-02-23	Other	2
2026-03-02	robbery	16
2026-03-02	theft	8
2026-03-02	vandalism	35
2026-03-02	road blockade	40
2026-03-02	vehicle theft	5
2026-03-02	Other	6
2026-03-09	robbery	6
2026-03-09	theft	11
2026-03-09	vandalism	1
2026-03-09	road blockade	0
2026-03-09	vehicle theft	4
2026-03-09	Other	4
2026-03-16	robbery	10
2026-03-16	theft	10
2026-03-16	vandalism	2
2026-03-16	road blockade	3
2026-03-16	vehicle theft	5
2026-03-16	Other	4
2026-03-23	robbery	7
2026-03-23	theft	5
2026-03-23	vandalism	2
2026-03-23	road blockade	1
2026-03-23	vehicle theft	3
2026-03-23	Other	1
2026-03-30	robbery	7
2026-03-30	theft	5
2026-03-30	vandalism	2

period	series	value
2026-03-30	road blockade	0
2026-03-30	vehicle theft	2
2026-03-30	Other	2
2026-04-06	robbery	9
2026-04-06	theft	3
2026-04-06	vandalism	7
2026-04-06	road blockade	2
2026-04-06	vehicle theft	4
2026-04-06	Other	3
2026-04-13	robbery	12
2026-04-13	theft	7
2026-04-13	vandalism	1
2026-04-13	road blockade	1
2026-04-13	vehicle theft	1
2026-04-13	Other	5
2026-04-20	robbery	7
2026-04-20	theft	7
2026-04-20	vandalism	1
2026-04-20	road blockade	1
2026-04-20	vehicle theft	1
2026-04-20	Other	4
2026-04-27	robbery	13
2026-04-27	theft	14
2026-04-27	vandalism	32
2026-04-27	road blockade	30
2026-04-27	vehicle theft	4
2026-04-27	Other	7
2026-05-04	robbery	7
2026-05-04	theft	5
2026-05-04	vandalism	1
2026-05-04	road blockade	1
2026-05-04	vehicle theft	4
2026-05-04	Other	4
2026-05-11	robbery	8
2026-05-11	theft	6
2026-05-11	vandalism	2
2026-05-11	road blockade	1
2026-05-11	vehicle theft	2
2026-05-11	Other	1
2026-05-18	robbery	9
2026-05-18	theft	8
2026-05-18	vandalism	1
2026-05-18	road blockade	1

period	series	value
2026-05-18	vehicle theft	2
2026-05-18	Other	2
2026-05-25	robbery	9
2026-05-25	theft	9
2026-05-25	vandalism	1
2026-05-25	road blockade	1
2026-05-25	vehicle theft	3
2026-05-25	Other	3
2026-06-01	robbery	9
2026-06-01	theft	9
2026-06-01	vandalism	1
2026-06-01	road blockade	2
2026-06-01	vehicle theft	5
2026-06-01	Other	3
2026-06-08	robbery	9
2026-06-08	theft	12
2026-06-08	vandalism	35
2026-06-08	road blockade	31
2026-06-08	vehicle theft	7
2026-06-08	Other	8
2026-06-15	robbery	10
2026-06-15	theft	3
2026-06-15	vandalism	3
2026-06-15	road blockade	0
2026-06-15	vehicle theft	1
2026-06-15	Other	3
2026-06-22	robbery	5
2026-06-22	theft	4
2026-06-22	vandalism	1
2026-06-22	road blockade	1
2026-06-22	vehicle theft	3
2026-06-22	Other	4
2026-06-29	robbery	10
2026-06-29	theft	12
2026-06-29	vandalism	0
2026-06-29	road blockade	0
2026-06-29	vehicle theft	8
2026-06-29	Other	4
2026-07-06	robbery	8
2026-07-06	theft	3
2026-07-06	vandalism	1
2026-07-06	road blockade	1
2026-07-06	vehicle theft	1

period	series	value
2026-07-06	Other	3
2026-07-13	robbery	11
2026-07-13	theft	6
2026-07-13	vandalism	1
2026-07-13	road blockade	1
2026-07-13	vehicle theft	3
2026-07-13	Other	3
2026-07-20	robbery	6
2026-07-20	theft	3
2026-07-20	vandalism	1
2026-07-20	road blockade	0
2026-07-20	vehicle theft	4
2026-07-20	Other	2
2026-07-27	robbery	5
2026-07-27	theft	8
2026-07-27	vandalism	2
2026-07-27	road blockade	1
2026-07-27	vehicle theft	3
2026-07-27	Other	2
2026-08-03	robbery	6
2026-08-03	theft	7
2026-08-03	vandalism	5
2026-08-03	road blockade	2
2026-08-03	vehicle theft	4
2026-08-03	Other	1
2026-08-10	robbery	8
2026-08-10	theft	10
2026-08-10	vandalism	2
2026-08-10	road blockade	2
2026-08-10	vehicle theft	0
2026-08-10	Other	3
2026-08-17	robbery	3
2026-08-17	theft	8
2026-08-17	vandalism	2
2026-08-17	road blockade	2
2026-08-17	vehicle theft	1
2026-08-17	Other	4
2026-08-24	robbery	6
2026-08-24	theft	10
2026-08-24	vandalism	1
2026-08-24	road blockade	1
2026-08-24	vehicle theft	3
2026-08-24	Other	3

period	series	value
2026-08-31	robbery	9
2026-08-31	theft	5
2026-08-31	vandalism	3
2026-08-31	road blockade	3
2026-08-31	vehicle theft	6
2026-08-31	Other	1
2026-09-07	robbery	9
2026-09-07	theft	6
2026-09-07	vandalism	4
2026-09-07	road blockade	2
2026-09-07	vehicle theft	4
2026-09-07	Other	7
2026-09-14	robbery	15
2026-09-14	theft	12
2026-09-14	vandalism	24
2026-09-14	road blockade	37
2026-09-14	vehicle theft	3
2026-09-14	Other	6
2026-09-21	robbery	5
2026-09-21	theft	8
2026-09-21	vandalism	1
2026-09-21	road blockade	1
2026-09-21	vehicle theft	3
2026-09-21	Other	6
2026-09-28	robbery	7
2026-09-28	theft	4
2026-09-28	vandalism	1
2026-09-28	road blockade	0
2026-09-28	vehicle theft	1
2026-09-28	Other	2

Figure 26. Protest events over time (date) [81]

period	series	value
2026-01-05	large	1
2026-01-05	small	1
2026-01-05	medium	1
2026-01-12	large	1
2026-01-12	small	0
2026-01-12	medium	1
2026-01-19	large	1
2026-01-19	small	0
2026-01-19	medium	0
2026-01-26	large	2
2026-01-26	small	2

period	series	value
2026-01-26	medium	1
2026-02-02	large	1
2026-02-02	small	1
2026-02-02	medium	0
2026-02-09	large	0
2026-02-09	small	0
2026-02-09	medium	0
2026-02-16	large	2
2026-02-16	small	0
2026-02-16	medium	0
2026-02-23	large	0
2026-02-23	small	2
2026-02-23	medium	2
2026-03-02	large	2
2026-03-02	small	1
2026-03-02	medium	3
2026-03-09	large	0
2026-03-09	small	1
2026-03-09	medium	0
2026-03-16	large	0
2026-03-16	small	0
2026-03-16	medium	0
2026-03-23	large	0
2026-03-23	small	0
2026-03-23	medium	0
2026-03-30	large	1
2026-03-30	small	0
2026-03-30	medium	1
2026-04-06	large	1
2026-04-06	small	0
2026-04-06	medium	0
2026-04-13	large	0
2026-04-13	small	0
2026-04-13	medium	0
2026-04-20	large	0
2026-04-20	small	1
2026-04-20	medium	0
2026-04-27	large	1
2026-04-27	small	3
2026-04-27	medium	1
2026-05-04	large	0
2026-05-04	small	1
2026-05-04	medium	0

period	series	value
2026-05-11	large	0
2026-05-11	small	0
2026-05-11	medium	0
2026-05-18	large	0
2026-05-18	small	0
2026-05-18	medium	0
2026-05-25	large	0
2026-05-25	small	0
2026-05-25	medium	1
2026-06-01	large	1
2026-06-01	small	0
2026-06-01	medium	1
2026-06-08	large	4
2026-06-08	small	1
2026-06-08	medium	3
2026-06-15	large	0
2026-06-15	small	2
2026-06-15	medium	1
2026-06-22	large	2
2026-06-22	small	0
2026-06-22	medium	1
2026-06-29	large	1
2026-06-29	small	0
2026-06-29	medium	0
2026-07-06	large	1
2026-07-06	small	0
2026-07-06	medium	0
2026-07-13	large	0
2026-07-13	small	1
2026-07-13	medium	0
2026-07-20	large	1
2026-07-20	small	0
2026-07-20	medium	0
2026-07-27	large	0
2026-07-27	small	1
2026-07-27	medium	0
2026-08-03	large	1
2026-08-03	small	1
2026-08-03	medium	0
2026-08-10	large	1
2026-08-10	small	2
2026-08-10	medium	0
2026-08-17	large	1

period	series	value
2026-08-17	small	1
2026-08-17	medium	0
2026-08-24	large	1
2026-08-24	small	1
2026-08-24	medium	0
2026-08-31	large	1
2026-08-31	small	0
2026-08-31	medium	1
2026-09-07	large	1
2026-09-07	small	1
2026-09-07	medium	2
2026-09-14	large	3
2026-09-14	small	1
2026-09-14	medium	0
2026-09-21	large	0
2026-09-21	small	2
2026-09-21	medium	0
2026-09-28	large	0
2026-09-28	small	1
2026-09-28	medium	0

Figure 27. Travel log over time (date) [82]

period	series	value
2025-09-29	False	9
2025-09-29	True	1
2025-10-06	False	4
2025-10-06	True	0
2025-10-13	False	8
2025-10-13	True	0
2025-10-20	False	3
2025-10-20	True	0
2025-10-27	False	6
2025-10-27	True	0
2025-11-03	False	9
2025-11-03	True	0
2025-11-10	False	11
2025-11-10	True	0
2025-11-17	False	10
2025-11-17	True	0
2025-11-24	False	4
2025-11-24	True	0
2025-12-01	False	10
2025-12-01	True	0
2025-12-08	False	4

period	series	value
2025-12-08	True	2
2025-12-15	False	7
2025-12-15	True	0
2025-12-22	False	14
2025-12-22	True	0
2025-12-29	False	7
2025-12-29	True	0
2026-01-05	False	6
2026-01-05	True	0
2026-01-12	False	7
2026-01-12	True	0
2026-01-19	False	10
2026-01-19	True	0
2026-01-26	False	11
2026-01-26	True	1
2026-02-02	False	5
2026-02-02	True	0
2026-02-09	False	9
2026-02-09	True	0
2026-02-16	False	9
2026-02-16	True	0
2026-02-23	False	9
2026-02-23	True	0
2026-03-02	False	7
2026-03-02	True	0
2026-03-09	False	7
2026-03-09	True	0
2026-03-16	False	10
2026-03-16	True	0
2026-03-23	False	8
2026-03-23	True	0
2026-03-30	False	3
2026-03-30	True	0
2026-04-06	False	9
2026-04-06	True	1
2026-04-13	False	3
2026-04-13	True	0
2026-04-20	False	6
2026-04-20	True	0
2026-04-27	False	5
2026-04-27	True	0
2026-05-04	False	9
2026-05-04	True	0

period	series	value
2026-05-11	False	8
2026-05-11	True	1
2026-05-18	False	6
2026-05-18	True	0
2026-05-25	False	5
2026-05-25	True	3
2026-06-01	False	4
2026-06-01	True	0
2026-06-08	False	10
2026-06-08	True	0
2026-06-15	False	4
2026-06-15	True	0
2026-06-22	False	9
2026-06-22	True	0
2026-06-29	False	6
2026-06-29	True	0
2026-07-06	False	15
2026-07-06	True	0
2026-07-13	False	5
2026-07-13	True	0
2026-07-20	False	5
2026-07-20	True	0
2026-07-27	False	9
2026-07-27	True	0
2026-08-03	False	5
2026-08-03	True	1
2026-08-10	False	9
2026-08-10	True	0
2026-08-17	False	10
2026-08-17	True	0
2026-08-24	False	9
2026-08-24	True	0
2026-08-31	False	7
2026-08-31	True	0
2026-09-07	False	7
2026-09-07	True	0
2026-09-14	False	7
2026-09-14	True	0
2026-09-21	False	8
2026-09-21	True	0
2026-09-28	False	3
2026-09-28	True	0

Figure 28. Hot spot analysis: Protest events [83]

bin_start	bin_end	band	band_label	count
-2	-1.5	cold_90	Cold spot, 90% confidence	1
-1.5	-1	not_significant	Not significant	2
-1	-0.5	not_significant	Not significant	3
-0.5	0	not_significant	Not significant	7
0	0.5	not_significant	Not significant	2
0.5	1	not_significant	Not significant	3
1	1.5	not_significant	Not significant	4
1.5	2	hot_90	Hot spot, 90% confidence	1
2	2.5	hot_95	Hot spot, 95% confidence	3
2.5	3	hot_99	Hot spot, 99% confidence	2
3.5	4	hot_99	Hot spot, 99% confidence	1

Figure 29. Hot spot analysis: Hotels [84]

bin_start	bin_end	band	band_label	count
-1.5	-1	not_significant	Not significant	2
-1	-0.5	not_significant	Not significant	4
-0.5	0	not_significant	Not significant	5
0	0.5	not_significant	Not significant	1
1.5	2	hot_95	Hot spot, 95% confidence	1
2	2.5	hot_95	Hot spot, 95% confidence	1

Figure 30. Hot spot analysis: Security incidents [85]

bin_start	bin_end	band	band_label	count
-1	-0.5	not_significant	Not significant	41
-0.5	0	not_significant	Not significant	203
0	0.5	not_significant	Not significant	78
0.5	1	not_significant	Not significant	10
1	1.5	not_significant	Not significant	3
1.5	2	hot_95	Hot spot, 95% confidence	1
1.5	2	not_significant	Not significant	1
2	2.5	hot_95	Hot spot, 95% confidence	4
2.5	3	hot_95	Hot spot, 95% confidence	1
3	3.5	hot_99	Hot spot, 99% confidence	2
3.5	4	hot_99	Hot spot, 99% confidence	3
4	4.5	hot_99	Hot spot, 99% confidence	2
4.5	5	hot_99	Hot spot, 99% confidence	1

bin_start	bin_end	band	band_label	count
5	5.5	hot_99	Hot spot, 99% confidence	1
7	7.5	hot_99	Hot spot, 99% confidence	1
8.5	9	hot_99	Hot spot, 99% confidence	1

Figure 31. Emerging hot spots: Protest events [86]

bin_start	bin_end	count
-0.608	-0.3794	8
-0.3794	-0.1508	0
-0.1508	0.0778	0
0.0778	0.3064	0
0.3064	0.535	6

Figure 32. Emerging hot spots: Security incidents [87]

bin_start	bin_end	count
-0.663	-0.3824	38
-0.3824	-0.1017	32
-0.1017	0.1789	0
0.1789	0.4595	13
0.4595	0.7401	15
0.7401	1.021	0
1.021	1.301	8
1.301	1.582	2

Figure 33. Repeat and near repeat classification: Protest events [88]

period	series	value
2026-01-05	large	1
2026-01-05	small	1
2026-01-05	medium	1
2026-01-12	large	1
2026-01-12	small	0
2026-01-12	medium	1
2026-01-19	large	1
2026-01-19	small	0
2026-01-19	medium	0
2026-01-26	large	2
2026-01-26	small	2
2026-01-26	medium	1
2026-02-02	large	1
2026-02-02	small	1
2026-02-02	medium	0
2026-02-09	large	0
2026-02-09	small	0
2026-02-09	medium	0

period	series	value
2026-02-16	large	2
2026-02-16	small	0
2026-02-16	medium	0
2026-02-23	large	0
2026-02-23	small	2
2026-02-23	medium	2
2026-03-02	large	2
2026-03-02	small	1
2026-03-02	medium	3
2026-03-09	large	0
2026-03-09	small	1
2026-03-09	medium	0
2026-03-16	large	0
2026-03-16	small	0
2026-03-16	medium	0
2026-03-23	large	0
2026-03-23	small	0
2026-03-23	medium	0
2026-03-30	large	1
2026-03-30	small	0
2026-03-30	medium	1
2026-04-06	large	1
2026-04-06	small	0
2026-04-06	medium	0
2026-04-13	large	0
2026-04-13	small	0
2026-04-13	medium	0
2026-04-20	large	0
2026-04-20	small	1
2026-04-20	medium	0
2026-04-27	large	1
2026-04-27	small	3
2026-04-27	medium	1
2026-05-04	large	0
2026-05-04	small	1
2026-05-04	medium	0
2026-05-11	large	0
2026-05-11	small	0
2026-05-11	medium	0
2026-05-18	large	0
2026-05-18	small	0
2026-05-18	medium	0
2026-05-25	large	0

period	series	value
2026-05-25	small	0
2026-05-25	medium	1
2026-06-01	large	1
2026-06-01	small	0
2026-06-01	medium	1
2026-06-08	large	4
2026-06-08	small	1
2026-06-08	medium	3
2026-06-15	large	0
2026-06-15	small	2
2026-06-15	medium	1
2026-06-22	large	2
2026-06-22	small	0
2026-06-22	medium	1
2026-06-29	large	1
2026-06-29	small	0
2026-06-29	medium	0
2026-07-06	large	1
2026-07-06	small	0
2026-07-06	medium	0
2026-07-13	large	0
2026-07-13	small	1
2026-07-13	medium	0
2026-07-20	large	1
2026-07-20	small	0
2026-07-20	medium	0
2026-07-27	large	0
2026-07-27	small	1
2026-07-27	medium	0
2026-08-03	large	1
2026-08-03	small	1
2026-08-03	medium	0
2026-08-10	large	1
2026-08-10	small	2
2026-08-10	medium	0
2026-08-17	large	1
2026-08-17	small	1
2026-08-17	medium	0
2026-08-24	large	1
2026-08-24	small	1
2026-08-24	medium	0
2026-08-31	large	1
2026-08-31	small	0

period	series	value
2026-08-31	medium	1
2026-09-07	large	1
2026-09-07	small	1
2026-09-07	medium	2
2026-09-14	large	3
2026-09-14	small	1
2026-09-14	medium	0
2026-09-21	large	0
2026-09-21	small	2
2026-09-21	medium	0
2026-09-28	large	0
2026-09-28	small	1
2026-09-28	medium	0

Figure 34. Summarize within: Risk zones [89]

bin_start	bin_end	count
0	0.6	6
0.6	1.2	3
1.2	1.8	0
1.8	2.4	3
2.4	3	2

Figure 35. Summarize within: Risk zones [90]

bin_start	bin_end	count
0	0.6	6
0.6	1.2	5
1.2	1.8	0
1.8	2.4	2
2.4	3	1

Figure 36. Summarize within: Risk zones [91]

bin_start	bin_end	count
0	15	13
15	30	0
30	45	0
45	60	0
60	75	1

Figure 37. Find point clusters: Hospitals [92]

cluster	features	fraction	share
0	11	0.7333	73.3%
Noise	4	0.2667	26.7%

Figure 38. Find point clusters: cluster hulls [93]

cluster	features	fraction	share
0	1	1	100.0%

Figure 39. Find point clusters: Safe havens [94]

cluster	features	fraction	share
0	5	0.4167	41.7%
Noise	4	0.3333	33.3%
1	3	0.25	25.0%

Figure 40. Find point clusters: cluster hulls [95]

cluster	features	fraction	share
0	1	0.5	50.0%
1	1	0.5	50.0%

Figure 41. Find point clusters: Protest events [96]

cluster	features	fraction	share
0	77	0.9625	96.2%
Noise	3	0.0375	3.8%

Figure 42. Find point clusters: cluster hulls [97]

cluster	features	fraction	share
0	1	1	100.0%

Figure 43. Calculate density: Protest events [98]

bin_start	bin_end	count
0	2.3	20
2.3	4.6	27
4.6	6.9	33
6.9	9.2	68
9.2	11.5	48
11.5	13.8	47
13.8	16.1	63
16.1	18.4	33
18.4	20.7	26
20.7	23	21

Figure 44. Calculate density: Hotels [99]

bin_start	bin_end	count
0.0002631	0.2276	48
0.2276	0.455	11
0.455	0.6823	9
0.6823	0.9096	3
0.9096	1.137	4
1.137	1.364	2
1.364	1.592	1
1.592	1.819	4

Figure 45. Calculate density: Security incidents [100]

bin_start	bin_end	count
0	4.077	166
4.077	8.154	169

bin_start	bin_end	count
8.154	12.23	166
12.23	16.31	169
16.31	20.38	169
20.38	24.46	174
24.46	28.54	167
28.54	32.62	175
32.62	36.69	173
36.69	40.77	171
40.77	44.85	169
44.85	48.92	174
48.92	53	198

Figure 46. Find outliers: Risk zones [101]

value	lag	type
-1.242	0.7068	NS
0.257	-0.3427	NS
-0.9424	1.157	NS
0.8567	1.157	NS
-1.542	0.257	NS
0.257	-0.0428	NS
1.157	0.5569	NS
-0.0428	1.157	NS
0.8567	-0.3427	NS
1.157	-1.092	NS
-0.9424	0.8567	NS
-1.542	0.5569	NS
1.157	0.4069	NS
0.5569	-1.542	NS

Figure 47. Find nearest: Hospitals [102]

rank	name
1	approved taxi
1	approved taxi
1	approved taxi
1	approved taxi
1	approved taxi
1	approved taxi
1	approved taxi
1	approved taxi
1	approved taxi
1	approved taxi
1	approved taxi
1	company car

rank	name
1	approved taxi

Figure 48. Find nearest: Hospitals [103]

rank	name
1	embassy
1	embassy
1	hotel
1	embassy
1	partner office
1	hotel
1	partner office
1	hotel
1	partner office
1	embassy
1	partner office
1	partner office
1	partner office
1	hotel

Figure 49. Find nearest: Hospitals over time [104]

period	series	value
2026-01-26	large	0
2026-01-26	medium	0
2026-01-26	small	1
2026-02-02	large	0
2026-02-02	medium	0
2026-02-02	small	0
2026-02-09	large	0
2026-02-09	medium	0
2026-02-09	small	0
2026-02-16	large	0
2026-02-16	medium	0
2026-02-16	small	0
2026-02-23	large	0
2026-02-23	medium	2
2026-02-23	small	0
2026-03-02	large	0
2026-03-02	medium	0
2026-03-02	small	0
2026-03-09	large	0
2026-03-09	medium	0
2026-03-09	small	0
2026-03-16	large	0
2026-03-16	medium	0

period	series	value
2026-03-16	small	0
2026-03-23	large	0
2026-03-23	medium	0
2026-03-23	small	0
2026-03-30	large	0
2026-03-30	medium	0
2026-03-30	small	0
2026-04-06	large	0
2026-04-06	medium	0
2026-04-06	small	0
2026-04-13	large	0
2026-04-13	medium	0
2026-04-13	small	0
2026-04-20	large	0
2026-04-20	medium	0
2026-04-20	small	0
2026-04-27	large	0
2026-04-27	medium	0
2026-04-27	small	0
2026-05-04	large	0
2026-05-04	medium	0
2026-05-04	small	0
2026-05-11	large	0
2026-05-11	medium	0
2026-05-11	small	0
2026-05-18	large	0
2026-05-18	medium	0
2026-05-18	small	0
2026-05-25	large	0
2026-05-25	medium	0
2026-05-25	small	0
2026-06-01	large	0
2026-06-01	medium	0
2026-06-01	small	0
2026-06-08	large	0
2026-06-08	medium	0
2026-06-08	small	0
2026-06-15	large	0
2026-06-15	medium	0
2026-06-15	small	0
2026-06-22	large	3
2026-06-22	medium	0
2026-06-22	small	0

Figure 50. Find point clusters: Protest events over time [105]

period	series	value
2026-01-05	large	1
2026-01-05	small	1
2026-01-05	medium	1
2026-01-12	large	1
2026-01-12	small	0
2026-01-12	medium	1
2026-01-19	large	1
2026-01-19	small	0
2026-01-19	medium	0
2026-01-26	large	2
2026-01-26	small	2
2026-01-26	medium	1
2026-02-02	large	1
2026-02-02	small	1
2026-02-02	medium	0
2026-02-09	large	0
2026-02-09	small	0
2026-02-09	medium	0
2026-02-16	large	2
2026-02-16	small	0
2026-02-16	medium	0
2026-02-23	large	0
2026-02-23	small	2
2026-02-23	medium	2
2026-03-02	large	2
2026-03-02	small	1
2026-03-02	medium	3
2026-03-09	large	0
2026-03-09	small	1
2026-03-09	medium	0
2026-03-16	large	0
2026-03-16	small	0
2026-03-16	medium	0
2026-03-23	large	0
2026-03-23	small	0
2026-03-23	medium	0
2026-03-30	large	1
2026-03-30	small	0
2026-03-30	medium	1
2026-04-06	large	1
2026-04-06	small	0
2026-04-06	medium	0
2026-04-13	large	0

period	series	value
2026-04-13	small	0
2026-04-13	medium	0
2026-04-20	large	0
2026-04-20	small	1
2026-04-20	medium	0
2026-04-27	large	1
2026-04-27	small	3
2026-04-27	medium	1
2026-05-04	large	0
2026-05-04	small	1
2026-05-04	medium	0
2026-05-11	large	0
2026-05-11	small	0
2026-05-11	medium	0
2026-05-18	large	0
2026-05-18	small	0
2026-05-18	medium	0
2026-05-25	large	0
2026-05-25	small	0
2026-05-25	medium	1
2026-06-01	large	1
2026-06-01	small	0
2026-06-01	medium	1
2026-06-08	large	4
2026-06-08	small	1
2026-06-08	medium	3
2026-06-15	large	0
2026-06-15	small	2
2026-06-15	medium	1
2026-06-22	large	2
2026-06-22	small	0
2026-06-22	medium	1
2026-06-29	large	1
2026-06-29	small	0
2026-06-29	medium	0
2026-07-06	large	1
2026-07-06	small	0
2026-07-06	medium	0
2026-07-13	large	0
2026-07-13	small	1
2026-07-13	medium	0
2026-07-20	large	1
2026-07-20	small	0

period	series	value
2026-07-20	medium	0
2026-07-27	large	0
2026-07-27	small	1
2026-07-27	medium	0
2026-08-03	large	1
2026-08-03	small	1
2026-08-03	medium	0
2026-08-10	large	1
2026-08-10	small	2
2026-08-10	medium	0
2026-08-17	large	1
2026-08-17	small	1
2026-08-17	medium	0
2026-08-24	large	1
2026-08-24	small	1
2026-08-24	medium	0
2026-08-31	large	1
2026-08-31	small	0
2026-08-31	medium	1
2026-09-07	large	1
2026-09-07	small	1
2026-09-07	medium	2
2026-09-14	large	3
2026-09-14	small	1
2026-09-14	medium	0
2026-09-21	large	0
2026-09-21	small	2
2026-09-21	medium	0
2026-09-28	large	0
2026-09-28	small	1
2026-09-28	medium	0

Figure 51. Repeat and near repeat classification: Protest events over time [106]

period	series	value
2026-01-05	large	1
2026-01-05	small	1
2026-01-05	medium	1
2026-01-12	large	1
2026-01-12	small	0
2026-01-12	medium	1
2026-01-19	large	1
2026-01-19	small	0
2026-01-19	medium	0
2026-01-26	large	2

period	series	value
2026-01-26	small	2
2026-01-26	medium	1
2026-02-02	large	1
2026-02-02	small	1
2026-02-02	medium	0
2026-02-09	large	0
2026-02-09	small	0
2026-02-09	medium	0
2026-02-16	large	2
2026-02-16	small	0
2026-02-16	medium	0
2026-02-23	large	0
2026-02-23	small	2
2026-02-23	medium	2
2026-03-02	large	2
2026-03-02	small	1
2026-03-02	medium	3
2026-03-09	large	0
2026-03-09	small	1
2026-03-09	medium	0
2026-03-16	large	0
2026-03-16	small	0
2026-03-16	medium	0
2026-03-23	large	0
2026-03-23	small	0
2026-03-23	medium	0
2026-03-30	large	1
2026-03-30	small	0
2026-03-30	medium	1
2026-04-06	large	1
2026-04-06	small	0
2026-04-06	medium	0
2026-04-13	large	0
2026-04-13	small	0
2026-04-13	medium	0
2026-04-20	large	0
2026-04-20	small	1
2026-04-20	medium	0
2026-04-27	large	1
2026-04-27	small	3
2026-04-27	medium	1
2026-05-04	large	0
2026-05-04	small	1

period	series	value
2026-05-04	medium	0
2026-05-11	large	0
2026-05-11	small	0
2026-05-11	medium	0
2026-05-18	large	0
2026-05-18	small	0
2026-05-18	medium	0
2026-05-25	large	0
2026-05-25	small	0
2026-05-25	medium	1
2026-06-01	large	1
2026-06-01	small	0
2026-06-01	medium	1
2026-06-08	large	4
2026-06-08	small	1
2026-06-08	medium	3
2026-06-15	large	0
2026-06-15	small	2
2026-06-15	medium	1
2026-06-22	large	2
2026-06-22	small	0
2026-06-22	medium	1
2026-06-29	large	1
2026-06-29	small	0
2026-06-29	medium	0
2026-07-06	large	1
2026-07-06	small	0
2026-07-06	medium	0
2026-07-13	large	0
2026-07-13	small	1
2026-07-13	medium	0
2026-07-20	large	1
2026-07-20	small	0
2026-07-20	medium	0
2026-07-27	large	0
2026-07-27	small	1
2026-07-27	medium	0
2026-08-03	large	1
2026-08-03	small	1
2026-08-03	medium	0
2026-08-10	large	1
2026-08-10	small	2
2026-08-10	medium	0

period	series	value
2026-08-17	large	1
2026-08-17	small	1
2026-08-17	medium	0
2026-08-24	large	1
2026-08-24	small	1
2026-08-24	medium	0
2026-08-31	large	1
2026-08-31	small	0
2026-08-31	medium	1
2026-09-07	large	1
2026-09-07	small	1
2026-09-07	medium	2
2026-09-14	large	3
2026-09-14	small	1
2026-09-14	medium	0
2026-09-21	large	0
2026-09-21	small	2
2026-09-21	medium	0
2026-09-28	large	0
2026-09-28	small	1
2026-09-28	medium	0