

Sample: Education, Toronto: report

Project: Sample: Education, Toronto

Goal: Describe the project Sample: Education, Toronto: run the analyses that tell the most about its data, draw every result, and write a cited report.

Run: 95849996-3ab1-4ed0-9250-b76a5d0b816f (running, 11 agent run(s))

Generated: 2026-10-18T06:06:03Z, version 1

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

Data used

Data	Kind	Rows	Time span	Summary	Source
Schools	vector, Point	45		45 point features; 'level' has 3 values (top: elementary 30, middle 8, secondary 7); 'capacity' 350 to 1,597 (mean 663.3); 'enrolment' 266 to 1,355 (mean 603); 'built_year' 1,918 to 2,019 (mean 1965); named by 'name' (e.g. Southgate Elementary School, Eastfield Elementary School, Westbrook Elementary School); extent -79.4521,43.6511 to -79.3505,43.7074. Point locations of Schools by level.	[109]
School catchments	vector, Polygon	45		45 polygon (area) features; 'children_5_17' 924 to 5,561 (mean 2113); named by 'name' (e.g. Southgate Elementary School catchment, Eastfield Elementary School catchment, Westbrook Elementary School catchment); total area 63.02 km2; extent -79.4566,43.6477 to -79.3433,43.7123. Areas (School catchments) with children_5_17 to compare and map.	[110]
Student homes	vector, Point	2,500	2023-08-01 to 2026-09-30	2,500 point features; dated by 'enrolled_on' from 2023-08-01 to 2026-09-30; 'transport' has 4 values (top: walk 1125, bus 740, car 497); 'grade' 0 to 12 (mean 6.081); 'distance_km' 0.01 to 1.35 (mean 0.4847); named by 'student_ref' (e.g. ST000001, ST000002, ST000003); extent -79.4552,43.6481 to -79.3453,43.7112. Dated point events by transport: where and when Student homes happen.	[2]
Bus stops	vector, Point	80		80 point features; 'school_run' has 2 values (top: True 45, False 35); 'routes' 1 to 4 (mean 2.425); extent -79.4545,43.6514 to -79.3453,43.7096. Point locations of Bus stops by school_run.	[111]
Childcare centers	vector, Point	60		60 point features; 'spaces' 22 to 118 (mean 75.68); 'waitlist' 0 to 79 (mean 43.85); extent -79.4542,43.6525 to -79.3469,43.7106. Point locations of Childcare centers.	[112]
Housing developments	vector, Point	40	2023-03-01 to 2027-11-01	40 point features; dated by 'completion_month' from 2023-03-01 to 2027-11-01; 'units' 53 to 629 (mean 243.4); 'family_units_pct' 11 to 59 (mean 33.98); extent -79.4441,43.6566 to -79.3486,43.7079. Dated point events: where and when Housing developments happen.	[3]
Major roads	vector, LineString	22		22 line features; 'lanes' 4 to 4 (mean 4); named by 'name' (e.g. Bloor Nova Street, Dundas Nova Street, Front Street); total length 133.7 km; extent -79.4555,43.6484 to -79.3453,43.7111. Lines (Major roads) such as routes or networks.	[113]

Data	Kind	Rows	Time span	Summary	Source
Enrollment by school and year	table	270	2021-09-01 to 2026-09-01	Table of 270 rows and 6 columns without geometry; dated by 'school_year' from 2021-09-01 to 2026-09-01; 'enrolment' 266 to 1,389 (mean 593.7); 'capacity' 350 to 1,597 (mean 663.3); 'utilization_pct' 72 to 134.5 (mean 90.88). A table of Enrollment by school and year without locations.	[4]
Staffing	table	45		Table of 45 rows and 4 columns without geometry; 'teachers' 12 to 61 (mean 26.89); 'support_staff' 2 to 14 (mean 8.267); 'portables' 0 to 8 (mean 0.8667). A table of Staffing without locations.	[114]
School capacity review	document			1-page md document 'School capacity review 2026'; language en; mentions 4 place(s): Maple Cross Elementary School (1), Parkside Middle School (1), Wren Park Elementary School (1), 43.69843, -79.36600 (1). A document about Maple Cross Elementary School, Parkside Middle School, Wren Park Elementary School.	[115]
Sample: Education, Toronto	record				[116]
Emerging hot spots: Student homes	layer, Polygon	96			[117]
Emerging hot spots: Housing developments	layer, Polygon	22			[118]
Repeat and near repeat classification: Student homes	layer, Point	2,500			[119]
Summarize within: School catchments	layer, Polygon	45			[120]
Summarize within: School catchments	layer, Polygon	45			[121]
Summarize within: School catchments	layer, Polygon	45			[122]
Hot spot analysis: Student homes	layer, Polygon	281			[123]
Hot spot analysis: Childcare centers	layer, Polygon	20			[124]
Hot spot analysis: Housing developments	layer, Point	40			[125]
Calculate density: Student homes	layer, Polygon	1,838			[126]
Calculate density: Childcare centers	layer, Polygon	112			[127]
Calculate density: Housing developments	layer, Polygon	80			[128]
Find point clusters: Student homes	layer, Point	2,500			[129]
Find point clusters: cluster hulls	layer, Polygon	1			[130]
Find point clusters: Childcare centers	layer, Point	60			[131]
Find point clusters: cluster hulls	layer, Polygon	8			[132]

Data	Kind	Rows	Time span	Summary	Source
Find point clusters: Housing developments	layer, Point	40			[133]
Find point clusters: cluster hulls	layer, Polygon	1			[134]
Find outliers: School catchments	layer, Polygon	45			[135]
Find nearest: Student homes	layer, Point	2,500			[136]
Find nearest: Student homes	layer, Point	2,500			[137]
Find nearest: Student homes	layer, Point	2,251			[138]

Timeline

Timeline: events per quarter by dataset

Per quarter: 26 quarters from 2021-07-01 to 2027-10-01; trend +2.84 per quarter; first half 1,101, second half 1,709 (+55.2%)

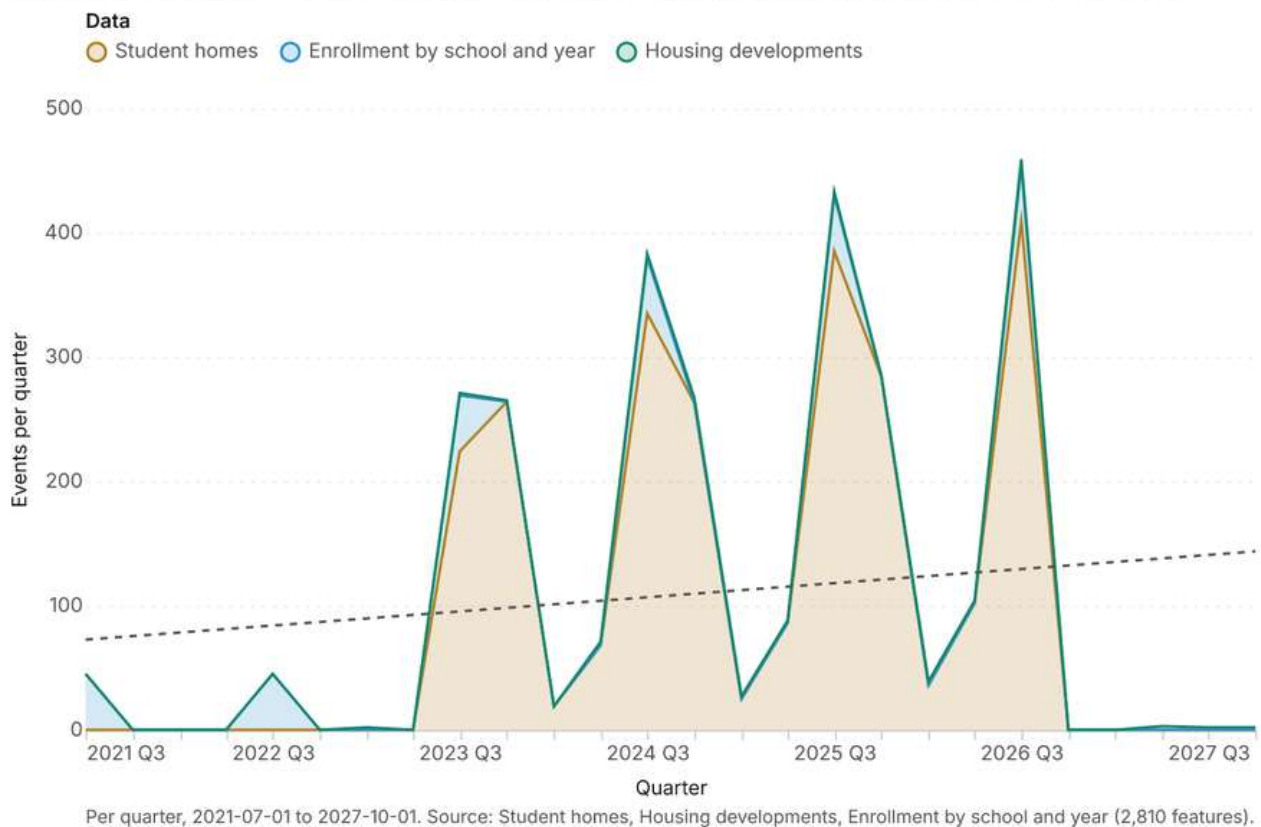


Figure 1. Timeline: events per quarter by dataset [1]. Per quarter, 2021-07-01 to 2027-10-01. Source: Student homes, Housing developments, Enrollment by school and year (2,810 features). The data is in the appendix.

The timeline counts 2,810 dated events in Student homes, Housing developments, Enrollment by school and year per quarter, from Q3 2021 to Q4 2027 [1][2][3][4]. By dataset: Student homes 2,500; Enrollment by school and year 270; Housing developments 40 [1]. The trend is +2.84 events per quarter; the second half of the quarters has 1,709 against 1,101 in the first (+55.2%) [1]. 7 of the 26 quarters had no events [1].

Busiest quarters

- Q3 2026: 459 events [1]
- Q3 2025: 433 events [1]

- Q3 2024: 383 events [1]

Quietest quarters with events

- Q1 2023: 2 events [1]

- Q3 2027: 2 events [1]

- Q4 2027: 2 events [1]

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 [5]. In ArcGIS it is Emerging Hot Spot Analysis or Create Space Time Cube [5].

Why it was run on this data. Student homes carry dates in 'enrolled_on': emerging hot spot analysis finds new, intensifying and fading hot spots per month [6].

What it found. The analysis generated 96 features for the "Emerging hot spots: Student homes" layer [7].

Result	Value
result, count	96
result, elapsed ms	19
result, resolution	8
result, features used	2,500
result, time neighbors	0
billing, cost	0.225
billing, list price	0.225
billing, upstream cost	0

Findings

Evidenced: Space time hot spots on Student homes: Emerging hot spots: 1 layer saved: Emerging hot spots: Student homes (96 features) [7][8].

Evidenced: It reported result, count 96; result, elapsed ms 19; result, resolution 8; result, features used 2,500; result, time neighbors 0; billing, cost 0.225 [7].

Tool gp_space_time_hot_spots; parameters {"project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "features": {"layer": "Student homes (05789208)"}, "interval": "month", "bin_shape": "h3", "resolution": 8, "time_field": "enrolled_on"}

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 [5]. In ArcGIS it is Emerging Hot Spot Analysis or Create Space Time Cube [5].

Why it was run on this data. Housing developments carry dates in 'completion_month': emerging hot spot analysis finds new, intensifying and fading hot spots per month [9].

What it found. The analysis processed the Housing developments layer [11], resulting in an Emerging hot spots layer containing 22 features [10].

Result	Value
result, count	22
result, elapsed ms	4
result, resolution	7
result, features used	40

Result	Value
result, time neighbors	0
billing, cost	0.102
billing, list price	0.102
billing, upstream cost	0

Findings

Evidenced: Space time hot spots on Housing developments: Emerging hot spots: 1 layer saved: Emerging hot spots: Housing developments (22 features) [10][11].

Evidenced: It reported result, count 22; result, elapsed ms 4; result, resolution 7; result, features used 40; result, time neighbors 0; billing, cost 0.102 [10].

Tool gp_space_time_hot_spots; parameters {"agg": "sum", "project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "features": {"layer": "Housing developments (afc1332b)"}, "interval": "month", "bin_shape": "h3", "resolution": 7, "time_field": "completion_month", "value_field": "units"}

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 [12]. In ArcGIS it is Repeat and Near Repeat Classification or Near Repeat Calculator [12].

Why it was run on this data. Near repeat analysis tests whether Student homes close in space also follow each other within 30 days [13].

What it found. Near repeat on Student homes: Repeat and near repeat classification: 1 layer saved: Repeat and near repeat classification: Student homes (2500 features) [8][14]. It reported result, days 30; result, count 2,500; result, chains 284; result, distance m 200; result, elapsed ms 61; result, pairs linked 1,594 [14].

Result	Value
result, days	30
result, count	2,500
result, chains	284
result, distance m	200
result, elapsed ms	61
result, pairs linked	1,594
billing, cost	0.125
billing, list price	0.125
billing, upstream cost	0

Findings

Evidenced: Near repeat on Student homes: Repeat and near repeat classification: 1 layer saved: Repeat and near repeat classification: Student homes (2500 features) [8][14].

Evidenced: It reported result, days 30; result, count 2,500; result, chains 284; result, distance m 200; result, elapsed ms 61; result, pairs linked 1,594 [14].

Tool gp_near_repeat; parameters {"days": 30, "project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "features": {"layer": "Student homes (05789208)"}, "distance_m": 200.0, "time_field": "enrolled_on"}

Summarize within

What this analysis is. Summarize within: Count and aggregate the features inside each polygon (or bin), proportionally for lines and polygons [15]. In ArcGIS it is Summarize Within or Aggregate Points; in QGIS, native:countpointsinpolygon or native:sumlinelengths [15].

Why it was run on this data. Count Student homes inside each feature of School catchments by transport; the counts map as a choropleth (natural breaks, sequential colors) [16].

What it found. Summarize within on Student homes, School catchments: Summarize within: 1 layer saved: Summarize within: School catchments (45 features) [8][17][18]. It reported result, count 45; result, elapsed ms 6; billing, cost 0.06092; billing, list price 0.06092; billing, upstream cost 0 [17].

Result	Value
result, count	45
result, elapsed ms	6
billing, cost	0.06092
billing, list price	0.06092
billing, upstream cost	0

Findings

Evidenced: Summarize within on Student homes, School catchments: Summarize within: 1 layer saved: Summarize within: School catchments (45 features) [8][17][18].

Evidenced: It reported result, count 45; result, elapsed ms 6; billing, cost 0.06092; billing, list price 0.06092; billing, upstream cost 0 [17].

Tool gp_summarize_within; parameters {"stats": [{"stat": "sum", "field": "grade"}], "project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "features": {"layer": "Student homes (05789208)", "group_by": "transport", "polygons": {"layer": "School catchments (534622c6)"}}

Summarize within

What this analysis is. Summarize within: Count and aggregate the features inside each polygon (or bin), proportionally for lines and polygons [15]. In ArcGIS it is Summarize Within or Aggregate Points; in QGIS, native:countpointsinpolygon or native:sumlinelengths [15].

Why it was run on this data. Count Student homes inside each feature of School catchments by transport; the counts map as a choropleth (natural breaks, sequential colors) [16].

What it found. Summarize within on Childcare centers, School catchments: Summarize within: 1 layer saved: Summarize within: School catchments (45 features) [18][19][20]. It reported result, count 45; result, elapsed ms 1; billing, cost 0.01212; billing, list price 0.01212; billing, upstream cost 0 [19].

Result	Value
result, count	45
result, elapsed ms	1
billing, cost	0.01212
billing, list price	0.01212
billing, upstream cost	0

Findings

Evidenced: Summarize within on Childcare centers, School catchments: Summarize within: 1 layer saved: Summarize within: School catchments (45 features) [18][19][20].

Evidenced: It reported result, count 45; result, elapsed ms 1; billing, cost 0.01212; billing, list price 0.01212; billing, upstream cost 0 [19].

Tool gp_summarize_within; parameters {"stats": [{"stat": "sum", "field": "spaces"}], "project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "features": {"layer": "Childcare centers (9489916f)", "polygons": {"layer": "School catchments (534622c6)"}}

Summarize within

What this analysis is. Summarize within: Count and aggregate the features inside each polygon (or bin), proportionally for lines and polygons [15]. In ArcGIS it is Summarize Within or Aggregate Points; in QGIS,

native:countpointsinpolygon or native:sumlinelengths [15].

Why it was run on this data. Count Student homes inside each feature of School catchments by transport; the counts map as a choropleth (natural breaks, sequential colors) [16].

What it found. Summarize within on Housing developments, School catchments: Summarize within: 1 layer saved: Summarize within: School catchments (45 features) [11][18][21]. It reported result, count 45; result, elapsed ms 1; billing, cost 0.01172; billing, list price 0.01172; billing, upstream cost 0 [21].

Result	Value
result, count	45
result, elapsed ms	1
billing, cost	0.01172
billing, list price	0.01172
billing, upstream cost	0

Findings

Evidenced: Summarize within on Housing developments, School catchments: Summarize within: 1 layer saved: Summarize within: School catchments (45 features) [11][18][21].

Evidenced: It reported result, count 45; result, elapsed ms 1; billing, cost 0.01172; billing, list price 0.01172; billing, upstream cost 0 [21].

Tool gp_summarize_within; parameters {"stats": [{"stat": "sum", "field": "units"}], "project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "features": {"layer": "Housing developments (afc1332b)", "polygons": {"layer": "School catchments (534622c6)"}}

Hot spots

What this analysis is. Hot spot analysis: Getis-Ord Gi* hot and cold spots with z-scores, p-values and confidence bins [22]. In ArcGIS it is Find Hot Spots or Hot Spot Analysis (Getis-Ord Gi*); in QGIS, qgis:hotspot (plugin) [22].

Why it was run on this data. 2500 points: Getis-Ord Gi* tests whether the concentrations in Student homes are statistically significant [23].

What it found. Hot spots on Student homes: Hot spot analysis: 1 layer saved: Hot spot analysis: Student homes (281 features) [8][24]. It reported result, bins 281; result, count 281; result, elapsed ms 23; result, cell size m 500; result, incidents used 2,500; result, distance band m 500 [24].

Result	Value
result, bins	281
result, count	281
result, elapsed ms	23
result, cell size m	500
result, incidents used	2,500
result, distance band m	500
billing, cost	0.1
billing, list price	0.1
billing, upstream cost	0

Findings

Evidenced: Hot spots on Student homes: Hot spot analysis: 1 layer saved: Hot spot analysis: Student homes (281 features) [8][24].

Evidenced: It reported result, bins 281; result, count 281; result, elapsed ms 23; result, cell size m 500; result, incidents used 2,500; result, distance band m 500 [24].

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

Tool gp_hot_spots; parameters {"project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "features": {"layer": "Student homes (05789208)"}, "aggregation": "hexagon", "cell_size_m": 500.0, "distance_band_m": 500.0}

Hot spots

What this analysis is. Hot spot analysis: Getis-Ord Gi* hot and cold spots with z-scores, p-values and confidence bins [22]. In ArcGIS it is Find Hot Spots or Hot Spot Analysis (Getis-Ord Gi*); in QGIS, qgis:hotspot (plugin) [22].

Why it was run on this data. 60 points: Getis-Ord Gi* tests whether the concentrations in Childcare centers are statistically significant [25].

What it found. Hot spots on Childcare centers: Hot spot analysis: 1 layer saved: Hot spot analysis: Childcare centers (20 features) [20][26]. It reported result, bins 20; result, count 20; result, elapsed ms 2; result, cell size m 2,000; result, incidents used 60; result, distance band m 2,000 [26].

Result	Value
result, bins	20
result, count	20
result, elapsed ms	2
result, cell size m	2,000
result, incidents used	60
result, distance band m	2,000
billing, cost	0.0512
billing, list price	0.0512
billing, upstream cost	0

Findings

Evidenced: Hot spots on Childcare centers: Hot spot analysis: 1 layer saved: Hot spot analysis: Childcare centers (20 features) [20][26].

Evidenced: It reported result, bins 20; result, count 20; result, elapsed ms 2; result, cell size m 2,000; result, incidents used 60; result, distance band m 2,000 [26].

Tool gp_hot_spots; parameters {"project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "features": {"layer": "Childcare centers (9489916f)"}, "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 [22]. In ArcGIS it is Find Hot Spots or Hot Spot Analysis (Getis-Ord Gi*); in QGIS, qgis:hotspot (plugin) [22].

Why it was run on this data. 40 points: Getis-Ord Gi* tests whether the concentrations in Housing developments are statistically significant [27].

What it found. The hot spot analysis was performed using the Housing developments layer [11] and saved one layer, "Hot spot analysis: Housing developments," containing 40 features [28]. This execution step resulted in an elapsed time of 1 ms [28]. The analysis also generated a result set with 0 excluded null values [28], and total billing costs for the process amounted to 0.0508 [28].

Result	Value
result, count	40
result, elapsed ms	1
result, excluded null	0
result, distance band m	2,000
billing, cost	0.0508
billing, list price	0.0508

Result	Value
billing, upstream cost	0

Findings

Evidenced: Hot spots on Housing developments: Hot spot analysis: 1 layer saved: Hot spot analysis: Housing developments (40 features) [11][28].

Evidenced: It reported result, count 40; result, elapsed ms 1; result, excluded null 0; result, distance band m 2,000; billing, cost 0.0508; billing, list price 0.0508 [28].

Tool gp_hot_spots; parameters {"field": "units", "project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "features": {"layer": "Housing developments (afc1332b)"}, "aggregation": "hexagon", "cell_size_m": 2000.0, "distance_band_m": 2000.0}

Calculate density

What this analysis is. Calculate density: Kernel density per square kilometer on a grid [29]. In ArcGIS it is Calculate Density or Kernel Density; in QGIS, native:heatmapkerneldensityestimation [29].

Why it was run on this data. 2500 points in Student homes: a density surface shows where they concentrate [30].

What it found. The density calculation was performed using the Student homes dataset [31]. This process analyzed 1,838 features and reported a maximum density per km2 of 388.8 [31].

Result	Value
result, count	1,838
result, elapsed ms	59
result, bandwidth m	500
result, cell size m	200
result, excluded null	0
result, max density per km2	388.8
billing, cost	0.1
billing, list price	0.1
billing, upstream cost	0

Findings

Evidenced: Calculate density on Student homes: Calculate density: 1 layer saved: Calculate density: Student homes (1838 features) [8][31].

Evidenced: It reported result, count 1,838; result, elapsed ms 59; result, bandwidth m 500; result, cell size m 200; result, excluded null 0; result, max density per km2 388.8 [31].

Tool gp_calculate_density; parameters {"kernel": "quartic", "project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "features": {"layer": "Student homes (05789208)"}, "bandwidth_m": 500.0, "cell_size_m": 200.0}

Calculate density

What this analysis is. Calculate density: Kernel density per square kilometer on a grid [29]. In ArcGIS it is Calculate Density or Kernel Density; in QGIS, native:heatmapkerneldensityestimation [29].

Why it was run on this data. 60 points in Childcare centers: a density surface shows where they concentrate [32].

What it found. Calculate density on Childcare centers: Calculate density: 1 layer saved: Calculate density: Childcare centers (112 features) [20][33]. It reported result, count 112; result, elapsed ms 3; result, bandwidth m 2,000; result, cell size m 1,000; result, excluded null 0; result, max density per km2 1.453 [33].

Result	Value
result, count	112

Result	Value
result, elapsed ms	3
result, bandwidth m	2,000
result, cell size m	1,000
result, excluded null	0
result, max density per km2	1.453
billing, cost	0.0512
billing, list price	0.0512
billing, upstream cost	0

Findings

Evidenced: Calculate density on Childcare centers: Calculate density: 1 layer saved: Calculate density: Childcare centers (112 features) [20][33].

Evidenced: It reported result, count 112; result, elapsed ms 3; result, bandwidth m 2,000; result, cell size m 1,000; result, excluded null 0; result, max density per km2 1.453 [33].

Tool gp_calculate_density; parameters {"kernel": "quartic", "project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "features": {"layer": "Childcare centers (9489916f)"}, "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 [29]. In ArcGIS it is Calculate Density or Kernel Density; in QGIS, native:heatmapkerneldensityestimation [29].

Why it was run on this data. 40 points in Housing developments: a density surface shows where they concentrate [34].

What it found. Calculate density on Housing developments: Calculate density: 1 layer saved: Calculate density: Housing developments (80 features) [11][35]. It reported result, count 80; result, elapsed ms 3; result, bandwidth m 2,000; result, cell size m 1,000; result, excluded null 0; result, max density per km2 881.6 [35].

Result	Value
result, count	80
result, elapsed ms	3
result, bandwidth m	2,000
result, cell size m	1,000
result, excluded null	0
result, max density per km2	881.6
billing, cost	0.0508
billing, list price	0.0508
billing, upstream cost	0

Findings

Evidenced: Calculate density on Housing developments: Calculate density: 1 layer saved: Calculate density: Housing developments (80 features) [11][35].

Evidenced: It reported result, count 80; result, elapsed ms 3; result, bandwidth m 2,000; result, cell size m 1,000; result, excluded null 0; result, max density per km2 881.6 [35].

Tool gp_calculate_density; parameters {"kernel": "quartic", "project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "features": {"layer": "Housing developments (afc1332b)"}, "bandwidth_m": 2000.0, "cell_size_m": 1000.0, "weight_field": "units"}

Find point clusters

What this analysis is. Find point clusters: Density-based clusters (DBSCAN, HDBSCAN or OPTICS, optionally space-time) with hulls and noise [36]. In ArcGIS it is Find Point Clusters or Density-based Clustering; in QGIS, native:dbscanclustering or native:stdbcanclustering [36].

Why it was run on this data. DBSCAN finds dense groups of Student homes and separates noise [37].

What it found. Find point clusters on Student homes: Find point clusters: 2 layers saved: Find point clusters: Student homes (2500 features); Find point clusters: cluster hulls (1 feature) [8][38]. It reported result, count 2,500; result, noise 1,490; result, distance m 200; result, elapsed ms 32; result, min points 20; billing, cost 0.1 [38].

Result	Value
result, count	2,500
result, noise	1,490
result, distance m	200
result, elapsed ms	32
result, min points	20
billing, cost	0.1
billing, list price	0.1
billing, upstream cost	0

Findings

Evidenced: Find point clusters on Student homes: Find point clusters: 2 layers saved: Find point clusters: Student homes (2500 features); Find point clusters: cluster hulls (1 feature) [8][38].

Evidenced: It reported result, count 2,500; result, noise 1,490; result, distance m 200; result, elapsed ms 32; result, min points 20; billing, cost 0.1 [38].

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

Tool gp_find_point_clusters; parameters {"method": "dbscan", "project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "features": {"layer": "Student homes (05789208)"}, "distance_m": 200.0, "min_points": 20}

Find point clusters

What this analysis is. Find point clusters: Density-based clusters (DBSCAN, HDBSCAN or OPTICS, optionally space-time) with hulls and noise [36]. In ArcGIS it is Find Point Clusters or Density-based Clustering; in QGIS, native:dbscanclustering or native:stdbcanclustering [36].

Why it was run on this data. DBSCAN finds dense groups of Childcare centers and separates noise [39].

What it found. Find point clusters on Childcare centers: Find point clusters: 2 layers saved: Find point clusters: Childcare centers (60 features); Find point clusters: cluster hulls (8 features) [20][40]. It reported result, count 60; result, noise 1; result, distance m 1,000; result, elapsed ms 3; result, min points 3; billing, cost 0.0512 [40].

Result	Value
result, count	60
result, noise	1
result, distance m	1,000
result, elapsed ms	3
result, min points	3
billing, cost	0.0512
billing, list price	0.0512
billing, upstream cost	0

Findings

Evidenced: Find point clusters on Childcare centers: Find point clusters: 2 layers saved: Find point clusters: Childcare centers (60 features); Find point clusters: cluster hulls (8 features) [20][40].

Evidenced: It reported result, count 60; result, noise 1; result, distance m 1,000; result, elapsed ms 3; result, min points 3; billing, cost 0.0512 [40].

Tool gp_find_point_clusters; parameters {"method": "dbscan", "project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "features": {"layer": "Childcare centers (9489916f)"}, "distance_m": 1000.0, "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 [36]. In ArcGIS it is Find Point Clusters or Density-based Clustering; in QGIS, native:dbscanclustering or native:stdbscanclustering [36].

Why it was run on this data. DBSCAN finds dense groups of Housing developments and separates noise [41].

What it found. Find point clusters on Housing developments: Find point clusters: 2 layers saved: Find point clusters: Housing developments (40 features); Find point clusters: cluster hulls (1 feature) [11][42]. It reported result, count 40; result, noise 3; result, distance m 2,000; result, elapsed ms 1; result, min points 3; billing, cost 0.0508 [42].

Result	Value
result, count	40
result, noise	3
result, distance m	2,000
result, elapsed ms	1
result, min points	3
billing, cost	0.0508
billing, list price	0.0508
billing, upstream cost	0

Findings

Evidenced: Find point clusters on Housing developments: Find point clusters: 2 layers saved: Find point clusters: Housing developments (40 features); Find point clusters: cluster hulls (1 feature) [11][42].

Evidenced: It reported result, count 40; result, noise 3; result, distance m 2,000; result, elapsed ms 1; result, min points 3; billing, cost 0.0508 [42].

Tool gp_find_point_clusters; parameters {"method": "dbscan", "project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "features": {"layer": "Housing developments (afc1332b)"}, "distance_m": 2000.0, "min_points": 3}

Outliers

What this analysis is. Find outliers: Anselin local Moran's I: HH, LL clusters and HL, LH outliers [43]. In ArcGIS it is Find Outliers or Cluster and Outlier Analysis (Anselin Local Moran's I) [43].

Why it was run on this data. Local Moran's I maps clusters and outliers of 'children_5_17' [44].

What it found. The `gp\_outliers` tool was executed using the `School catchments` layer [18]. The process generated 45 results [45], completing with an elapsed time of 4 ms [45]. Furthermore, the analysis utilized 199 permutations [45] and established a distance band of 1,430 m [45].

Result	Value
result, count	45
result, elapsed ms	4
result, permutations	199
result, excluded null	0
result, distance band m	1,430

Result	Value
billing, cost	0.05135
billing, list price	0.05135
billing, upstream cost	0

Findings

Evidenced: Outliers on School catchments: Find outliers: 1 layer saved: Find outliers: School catchments (45 features) [18][45].

Evidenced: It reported result, count 45; result, elapsed ms 4; result, permutations 199; result, excluded null 0; result, distance band m 1,430; billing, cost 0.05135 [45].

Tool gp_outliers; parameters {"field": "children_5_17", "project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "features": {"layer": "School catchments (534622c6)"}, "aggregation": "hexagon"}

Spatial autocorrelation

What this analysis is. Spatial autocorrelation: Global Moran's I: is the pattern clustered, dispersed or random [46]. In ArcGIS it is Spatial Autocorrelation (Global Moran's I) [46].

Why it was run on this data. Global Moran's I says whether similar values of 'children_5_17' sit next to each other [47].

What it found. Spatial autocorrelation on School catchments: Spatial autocorrelation: done; no map output [18][48]. It reported result, n 45; result, p value 0.4896; result, z score 0.6909; result, morans i 0.05071; result, variance 0.0113; result, elapsed ms 2 [48].

Result	Value
result, n	45
result, p value	0.4896
result, z score	0.6909
result, morans i	0.05071
result, variance	0.0113
result, elapsed ms	2
result, expected i	-0.02273
result, excluded null	0
result, distance band m	1,430
result, p value normality	0.5075
result, z score normality	0.6627
result, variance normality	0.01228
billing, cost	0.02
billing, list price	0.02
billing, upstream cost	0

Findings

Evidenced: Spatial autocorrelation on School catchments: Spatial autocorrelation: done; no map output [18][48].

Evidenced: It reported result, n 45; result, p value 0.4896; result, z score 0.6909; result, morans i 0.05071; result, variance 0.0113; result, elapsed ms 2 [48].

Tool gp_spatial_autocorrelation; parameters {"field": "children_5_17", "project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "features": {"layer": "School catchments (534622c6)"}}

Find nearest

What this analysis is. Find nearest: The k nearest features for each input, with geodesic distance and bearing [49]. In ArcGIS it is Find Nearest or Near; in QGIS, native:joinbynearest or native:nearestneighbouranalysis [49].

Why it was run on this data. The nearest of Major roads to each of Student homes, with distances [50].

What it found. Find nearest on Major roads, Student homes: Find nearest: 1 layer saved: Find nearest: Student homes (2500 features) [8][51][52]. It reported result, count 2,500; result, elapsed ms 1,073; billing, cost 0.06044; billing, list price 0.06044; billing, upstream cost 0 [51].

Result	Value
result, count	2,500
result, elapsed ms	1,073
billing, cost	0.06044
billing, list price	0.06044
billing, upstream cost	0

Findings

Evidenced: Find nearest on Major roads, Student homes: Find nearest: 1 layer saved: Find nearest: Student homes (2500 features) [8][51][52].

Evidenced: It reported result, count 2,500; result, elapsed ms 1,073; billing, cost 0.06044; billing, list price 0.06044; billing, upstream cost 0 [51].

Tool gp_find_nearest; parameters {"k": 1, "to": {"layer": "Major roads (f801bcde)"}, "from": {"layer": "Student homes (05789208)"}, "project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "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 [49]. In ArcGIS it is Find Nearest or Near; in QGIS, native:joinbynearest or native:nearestneighbouranalysis [49].

Why it was run on this data. The nearest of Major roads to each of Student homes, with distances [50].

What it found. Find nearest on Childcare centers, Student homes: Find nearest: 1 layer saved: Find nearest: Student homes (2500 features) [8][20][53]. It reported result, count 2,500; result, elapsed ms 129; billing, cost 0.0612; billing, list price 0.0612; billing, upstream cost 0 [53].

Result	Value
result, count	2,500
result, elapsed ms	129
billing, cost	0.0612
billing, list price	0.0612
billing, upstream cost	0

Findings

Evidenced: Find nearest on Childcare centers, Student homes: Find nearest: 1 layer saved: Find nearest: Student homes (2500 features) [8][20][53].

Evidenced: It reported result, count 2,500; result, elapsed ms 129; billing, cost 0.0612; billing, list price 0.0612; billing, upstream cost 0 [53].

Tool gp_find_nearest; parameters {"k": 1, "to": {"layer": "Childcare centers (9489916f)"}, "from": {"layer": "Student homes (05789208)"}, "project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "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 [49]. In ArcGIS it is Find Nearest or Near; in QGIS, native:joinbynearest or native:nearestneighbouranalysis [49].

Why it was run on this data. The nearest of Major roads to each of Student homes, with distances [50].

What it found. The `gp\_find\_nearest` tool was utilized with Housing developments [11] and Student homes [8] as inputs [54]. The operation successfully generated 2,251 results [54]. Specific performance metrics showed the elapsed time was 118 ms [54]. Furthermore, the recorded billing cost for this process was 0.0608 [54].

Result	Value
result, count	2,251
result, elapsed ms	118
billing, cost	0.0608
billing, list price	0.0608
billing, upstream cost	0

Findings

Evidenced: Find nearest on Housing developments, Student homes: Find nearest: 1 layer saved: Find nearest: Student homes (2251 features) [8][11][54].

Evidenced: It reported result, count 2,251; result, elapsed ms 118; billing, cost 0.0608; billing, list price 0.0608; billing, upstream cost 0 [54].

Tool gp_find_nearest; parameters {"k": 1, "to": {"layer": "Housing developments (afc1332b)"}, "from": {"layer": "Student homes (05789208)"}, "project": "89129455-9e05-4edb-9cc1-dcfb440cc5ba", "max_distance_m": 2000.0}

Maps and charts

The run also made 23 map image(s)

[55][56][57][58][59][60][61][62][63][64][65][66][67][68][69][70][71][72][73][74][75][76][77] and 31 chart(s) [78][79][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][107][108].

Emerging hot spots: Student homes

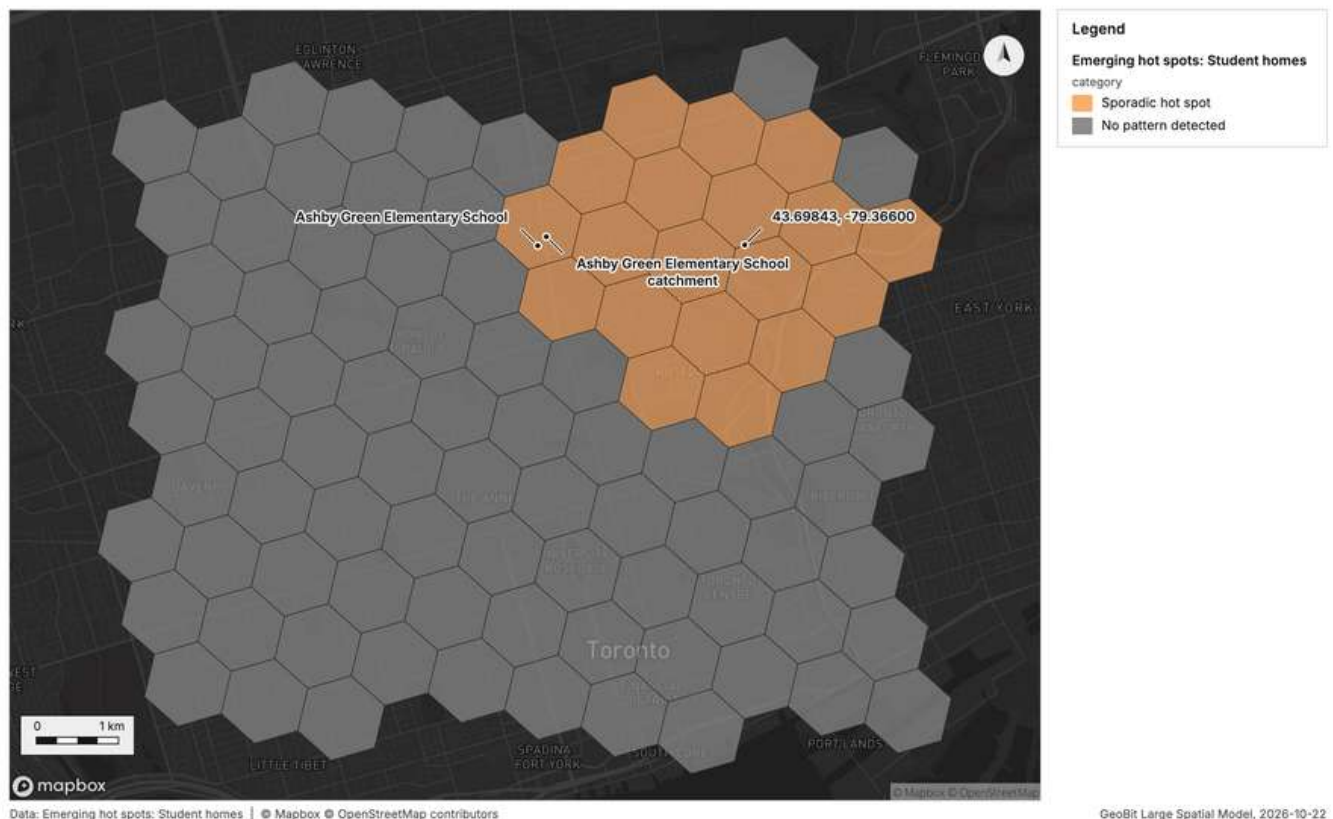


Figure 2. Emerging hot spots: Student homes [55]

Emerging hot spots: Housing developments

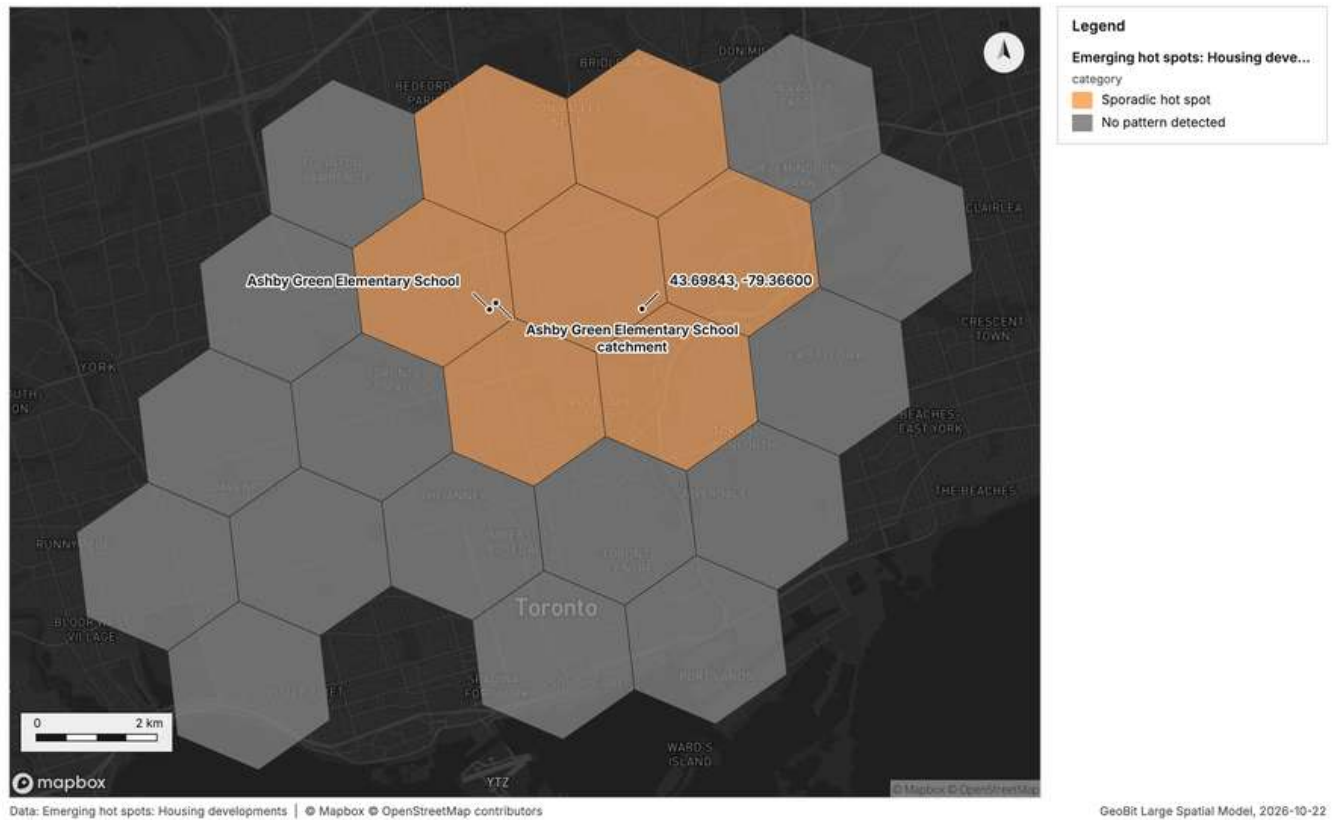


Figure 3. Emerging hot spots: Housing developments [56]

Repeat and near repeat classification: Student homes

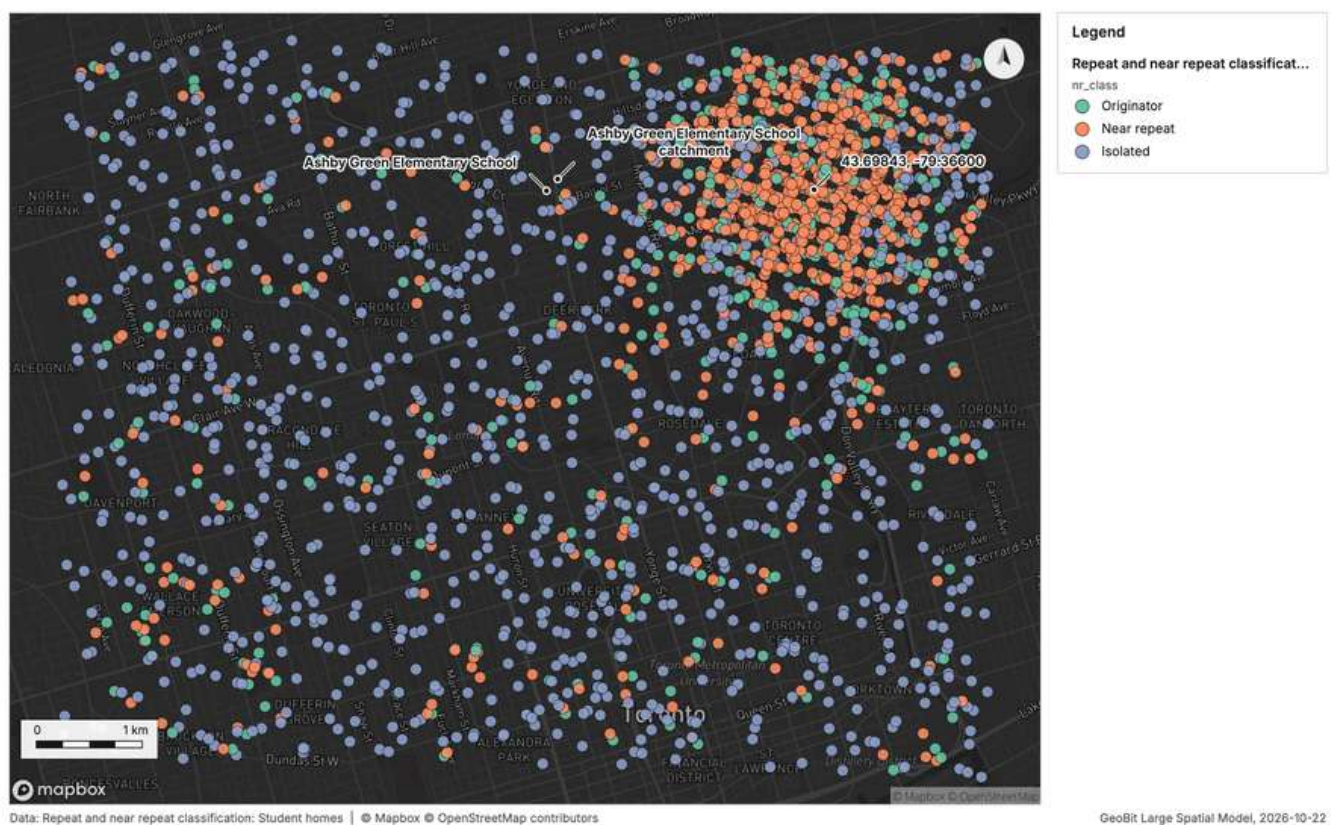


Figure 4. Repeat and near repeat classification: Student homes [57]

Summarize within: School catchments

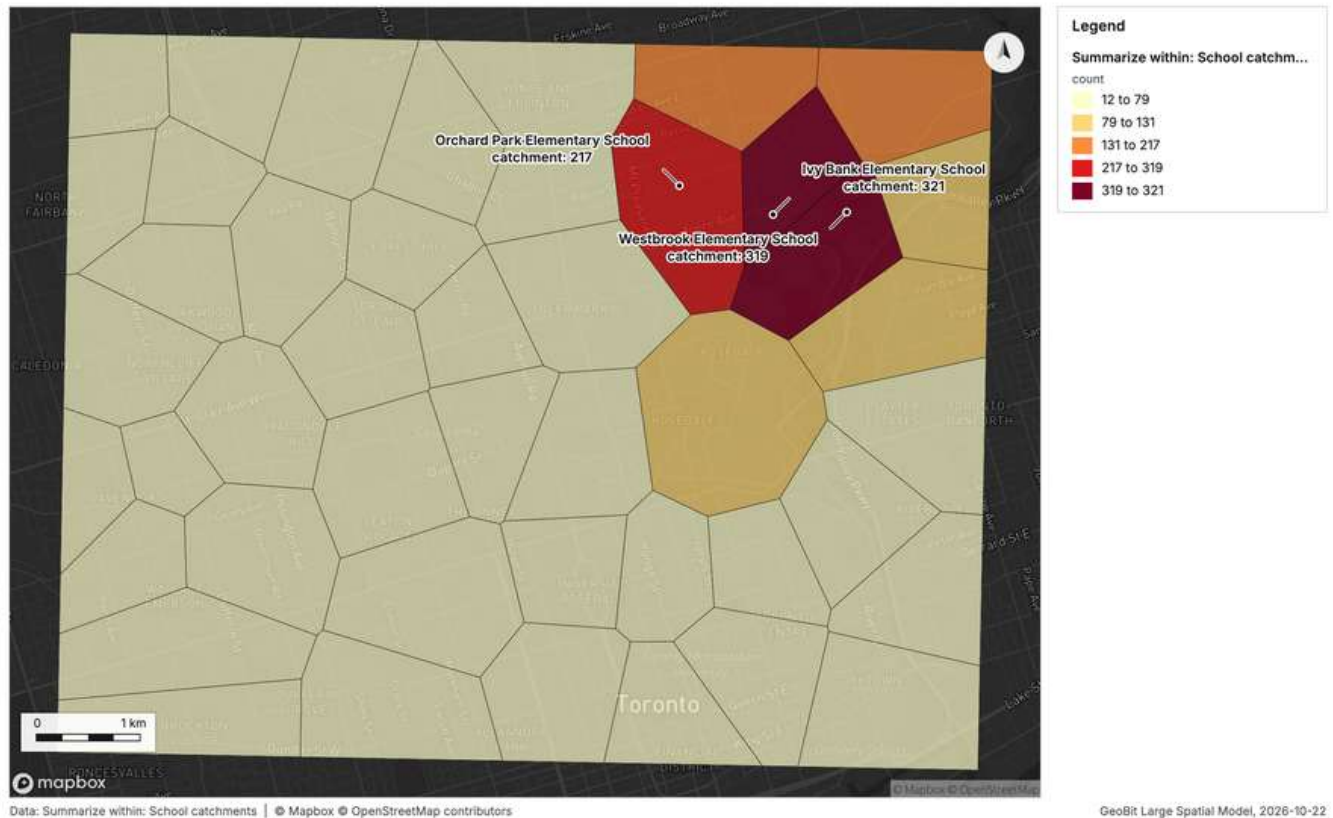


Figure 5. Summarize within: School catchments [58]

Summarize within: School catchments

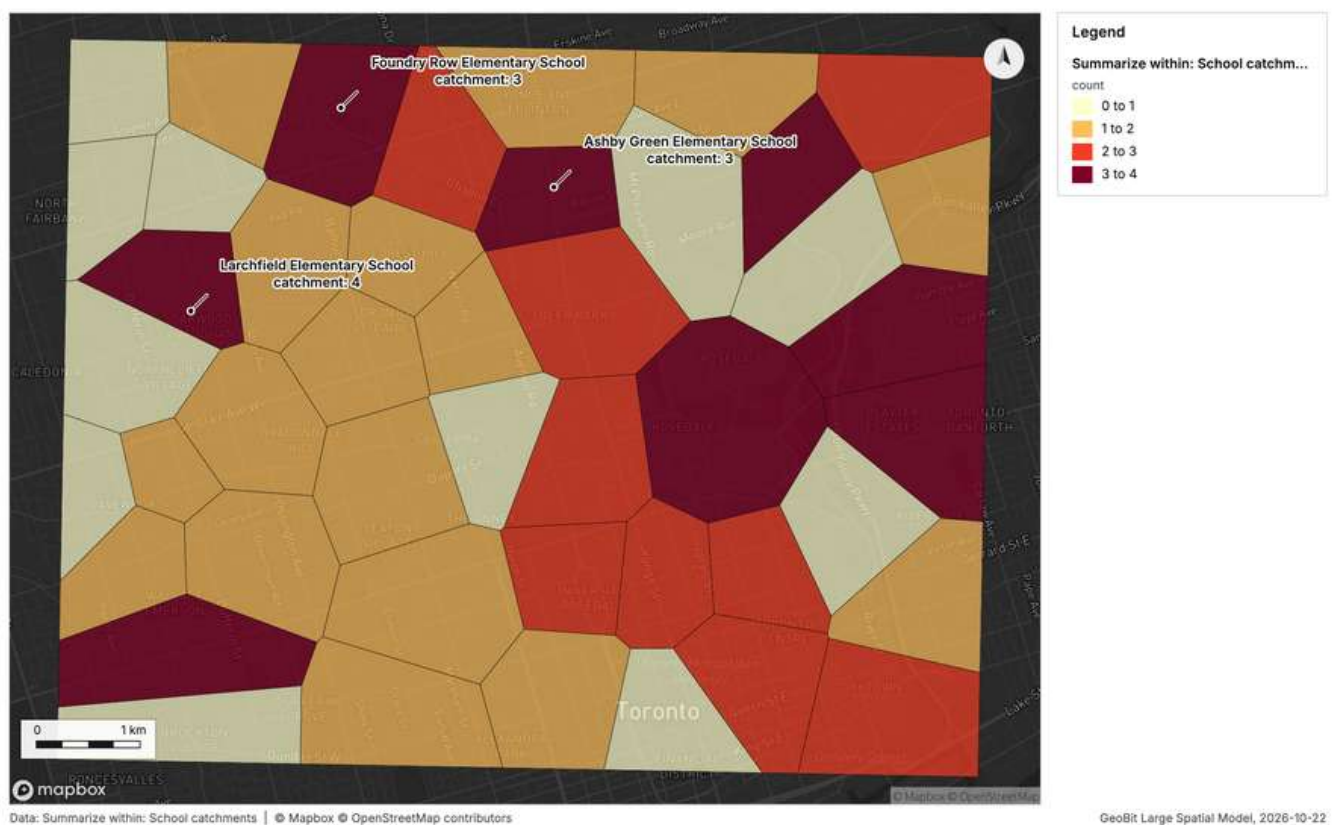


Figure 6. Summarize within: School catchments [59]

Summarize within: School catchments

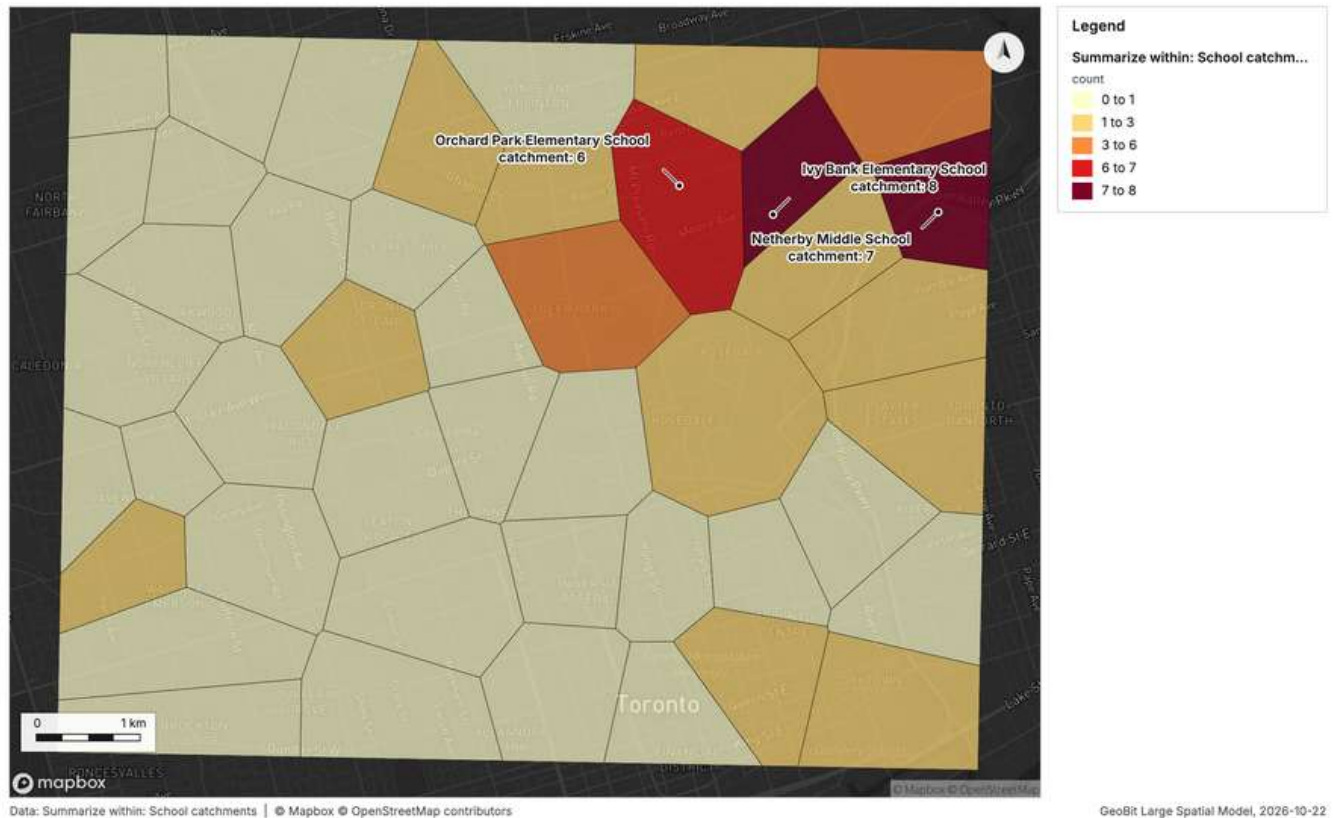


Figure 7. Summarize within: School catchments [60]

Hot spot analysis: Student homes

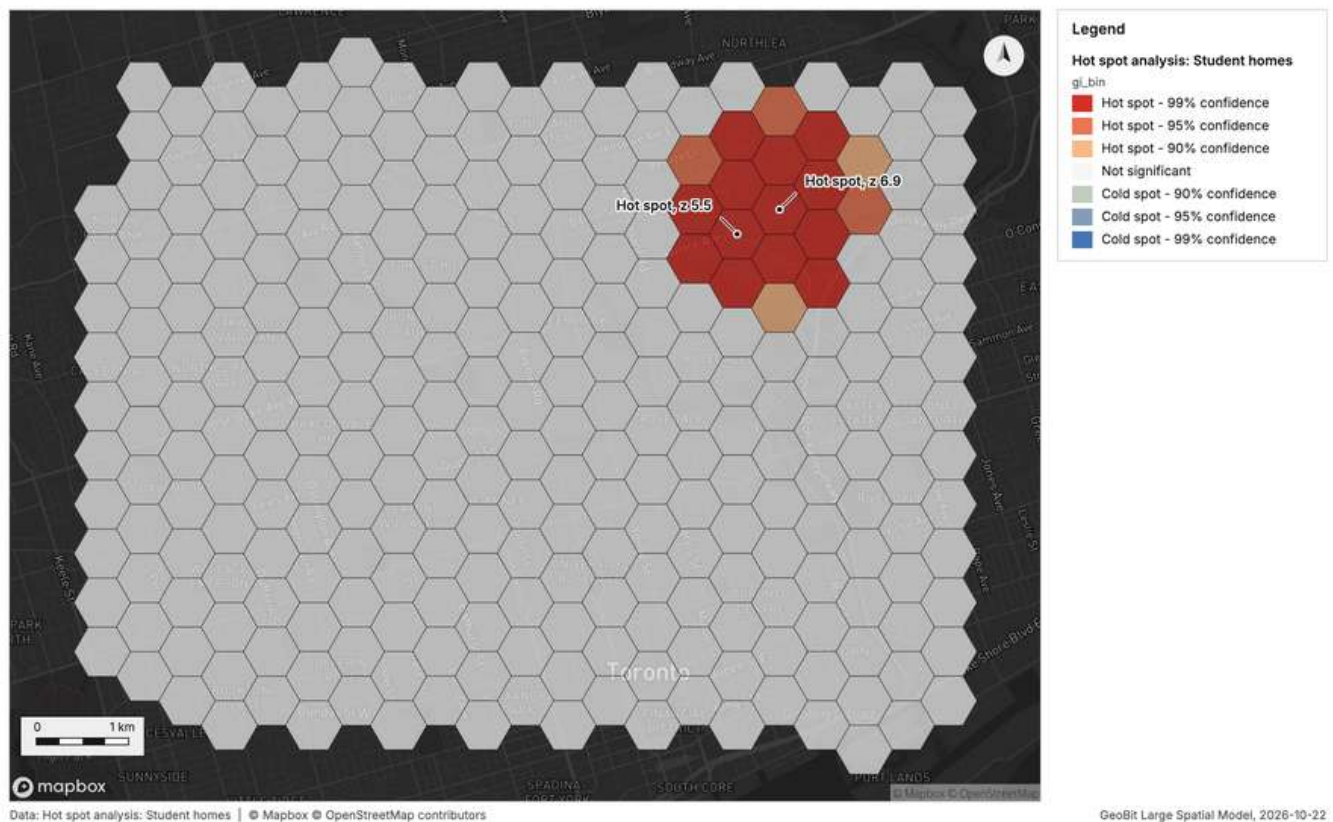


Figure 8. Hot spot analysis: Student homes [61]

Hot spot analysis: Childcare centers



Figure 9. Hot spot analysis: Childcare centers [62]

Hot spot analysis: Housing developments

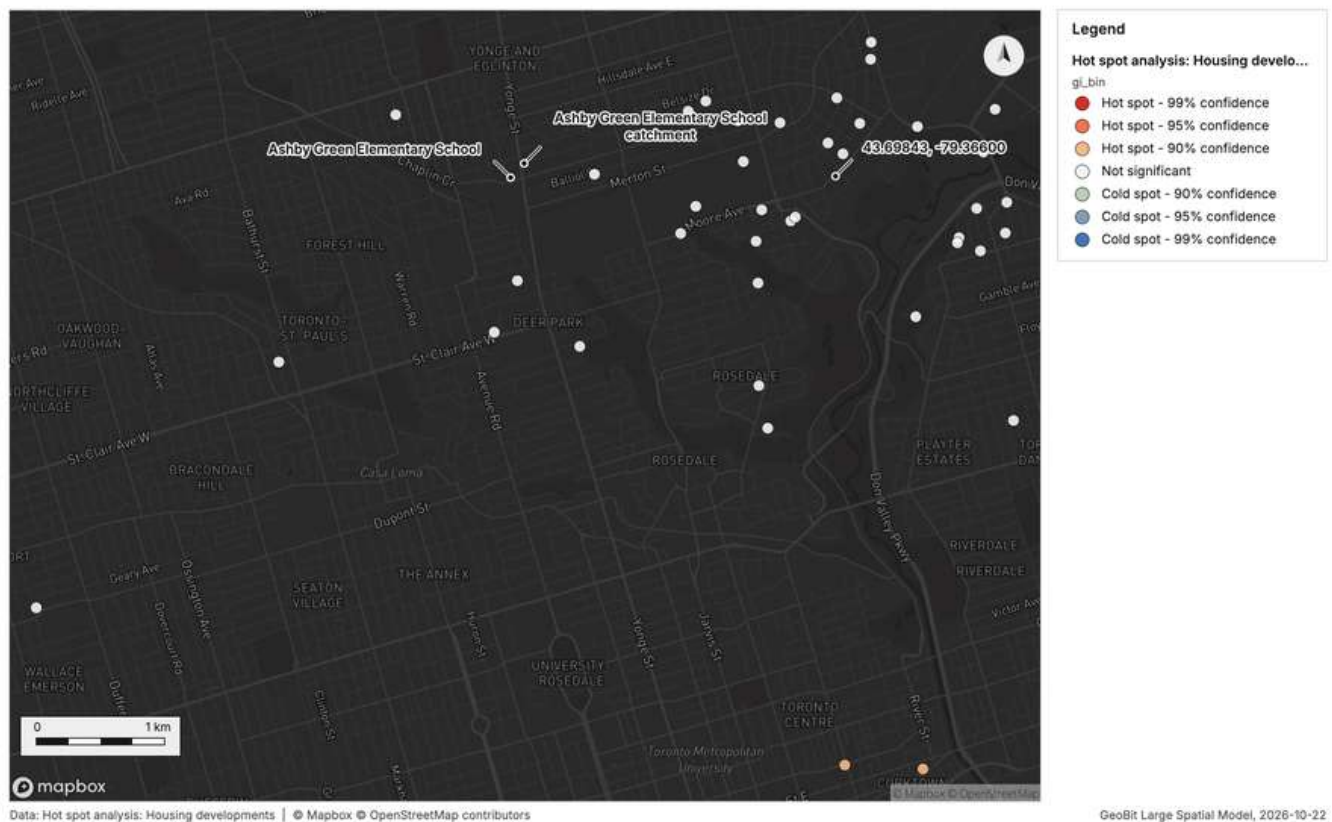


Figure 10. Hot spot analysis: Housing developments [63]

Calculate density: Student homes

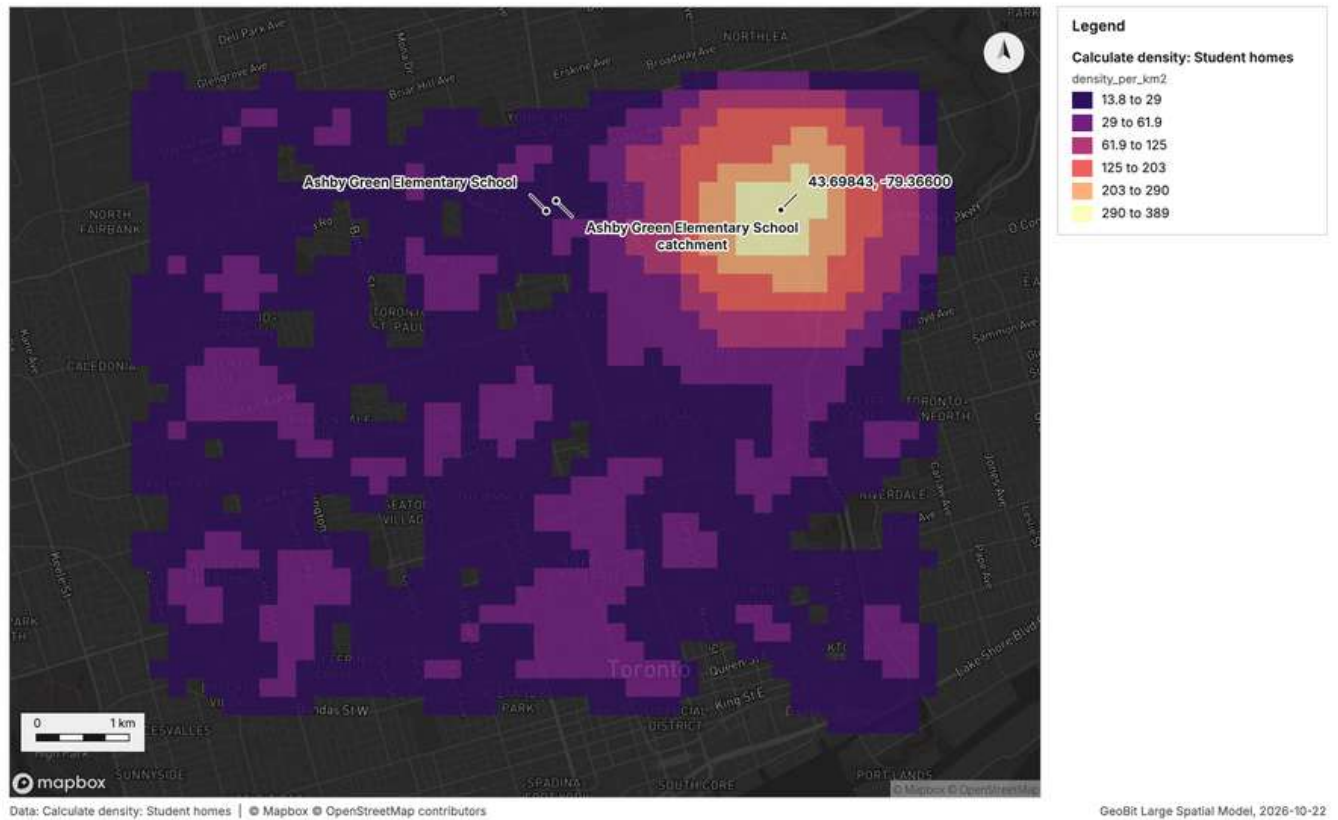


Figure 11. Calculate density: Student homes [64]

Calculate density: Childcare centers



Figure 12. Calculate density: Childcare centers [65]

Calculate density: Housing developments



Figure 13. Calculate density: Housing developments [66]

Find point clusters: Student homes

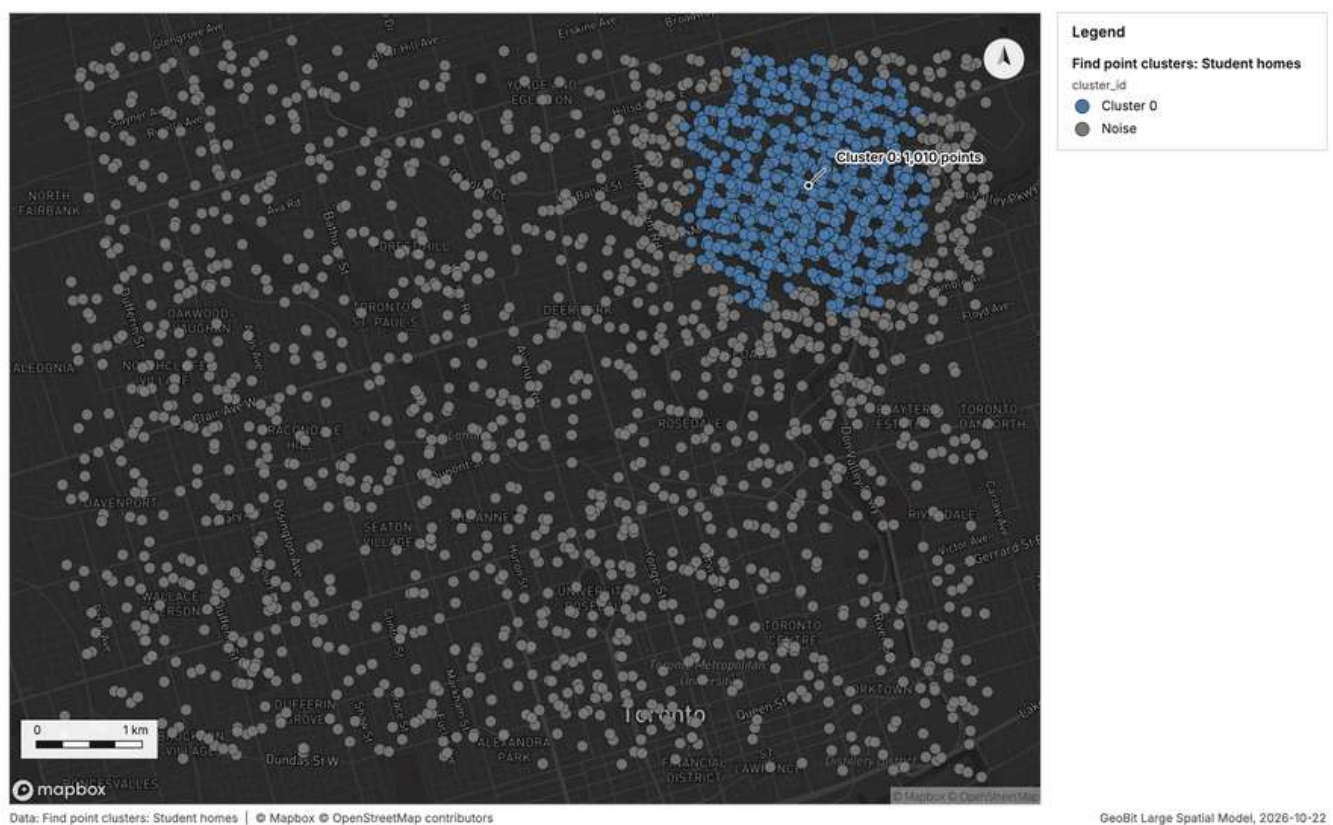


Figure 14. Find point clusters: Student homes [67]

Find point clusters: cluster hulls

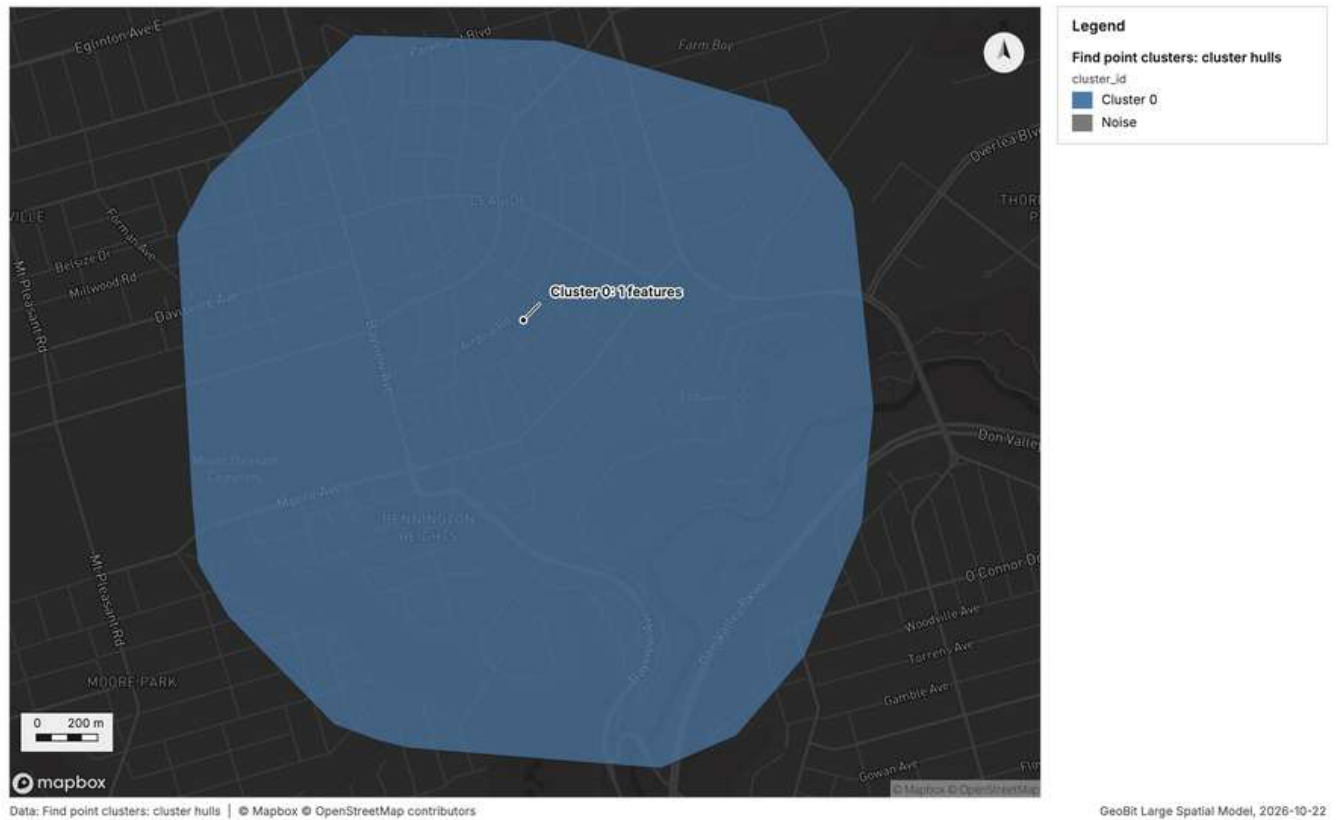


Figure 15. Find point clusters: cluster hulls [68]

Find point clusters: Childcare centers

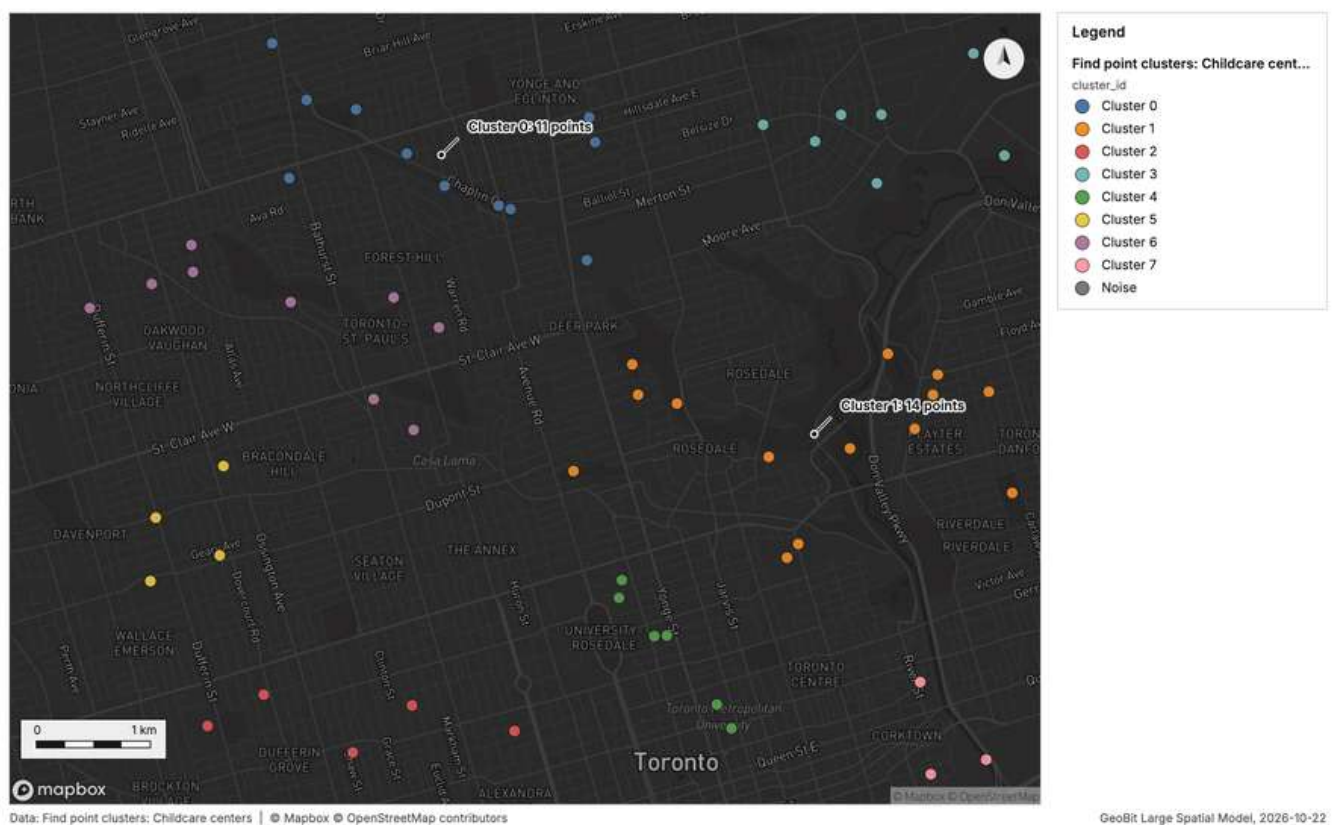


Figure 16. Find point clusters: Childcare centers [69]

Find point clusters: cluster hulls



Figure 17. Find point clusters: cluster hulls [70]

Find point clusters: Housing developments

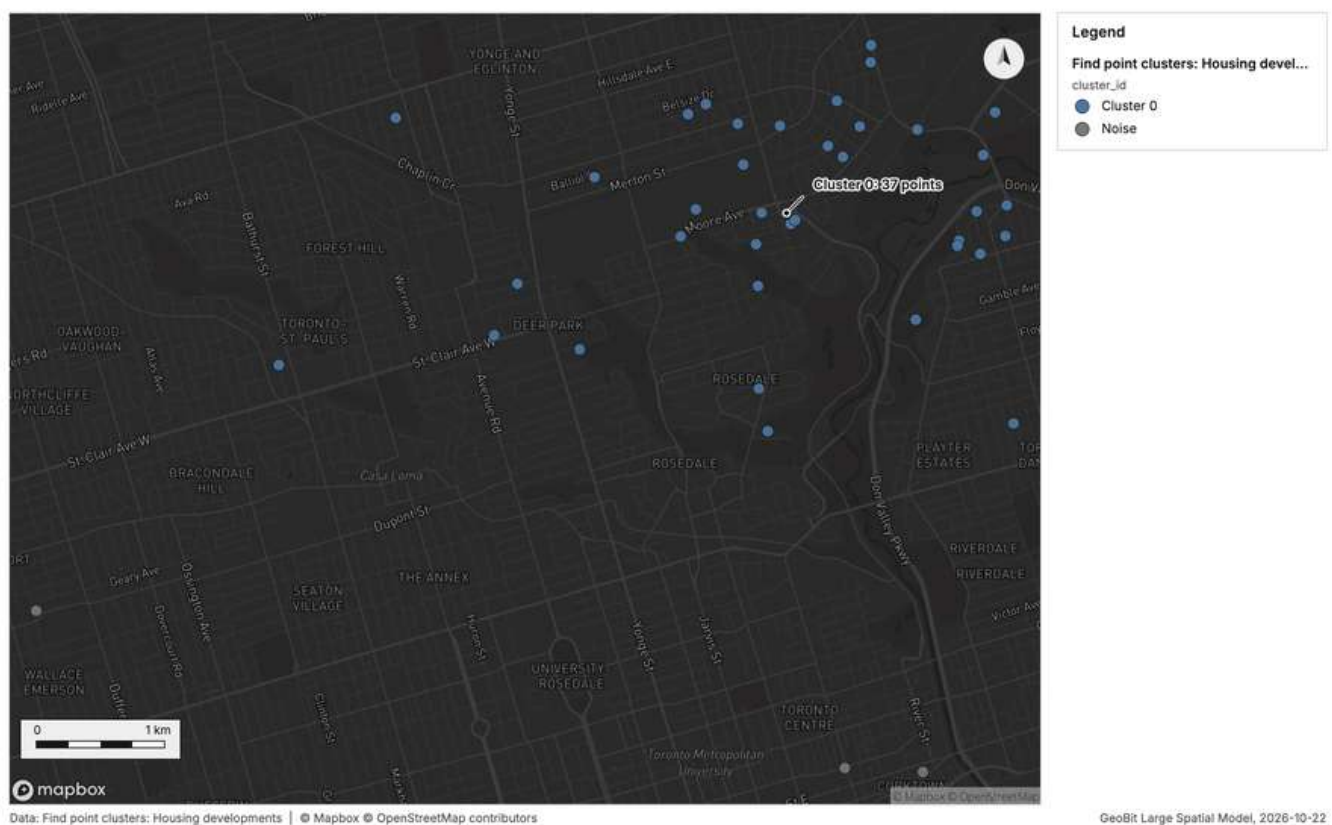


Figure 18. Find point clusters: Housing developments [71]

Find point clusters: cluster hulls



Figure 19. Find point clusters: cluster hulls [72]

School catchments by children_5_17

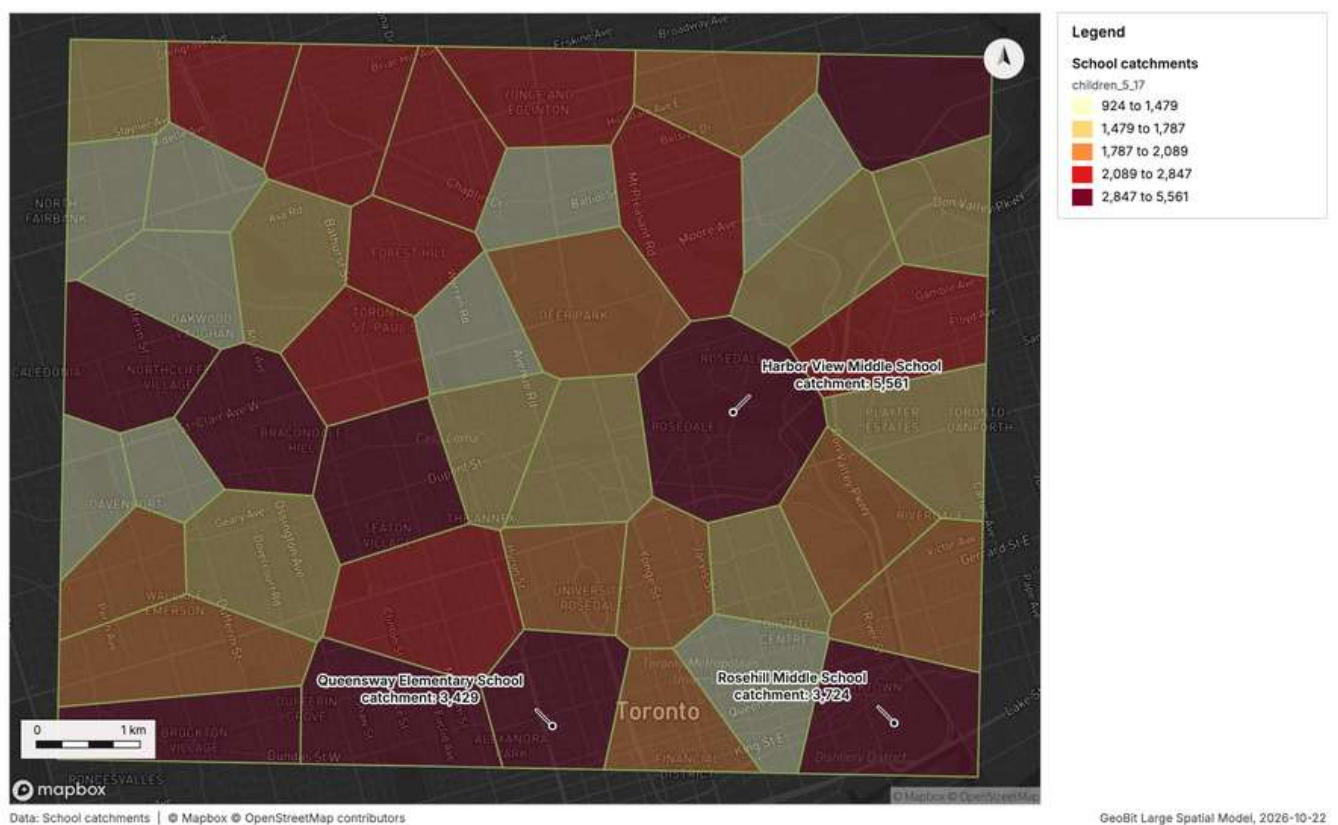


Figure 20. School catchments by children_5_17 [73]

Find outliers: School catchments

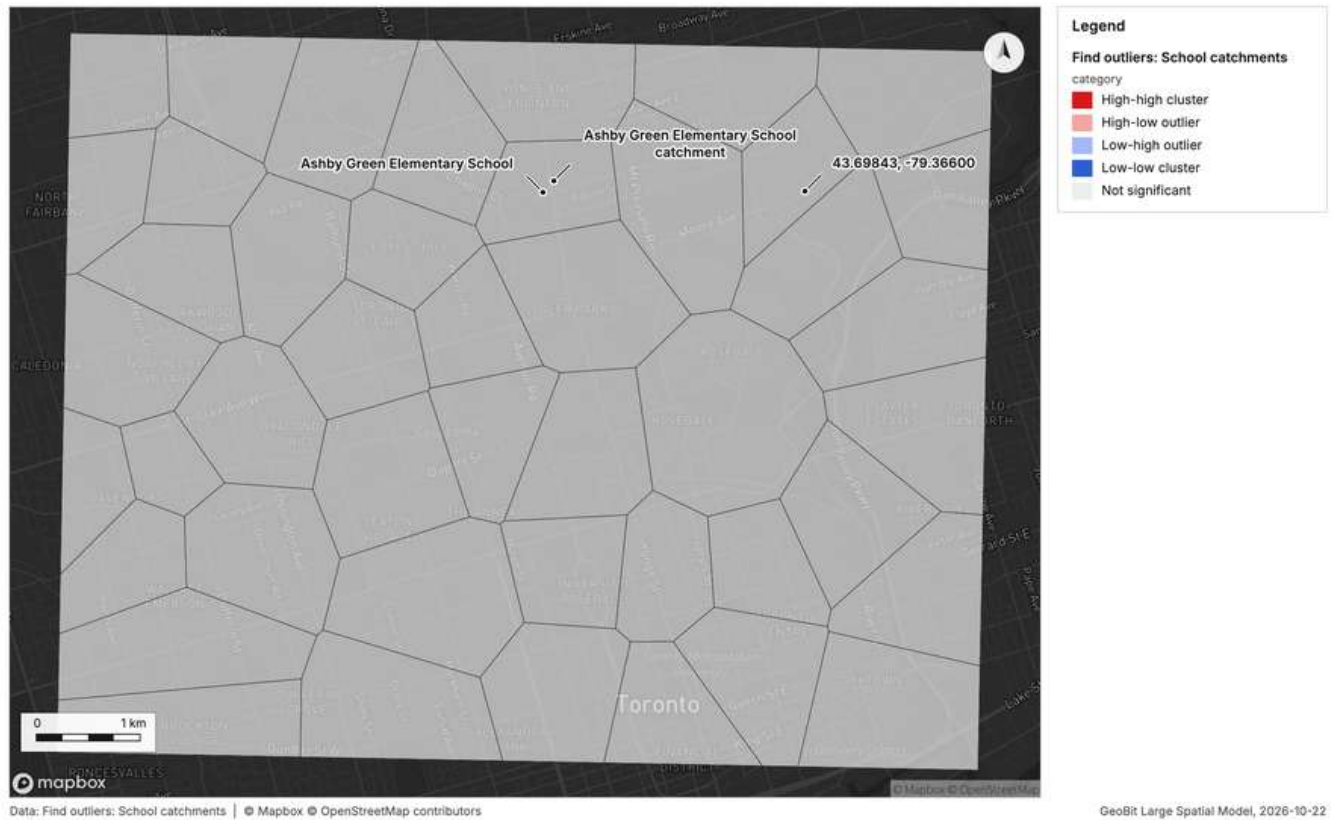


Figure 21. Find outliers: School catchments [74]

Find nearest: Student homes

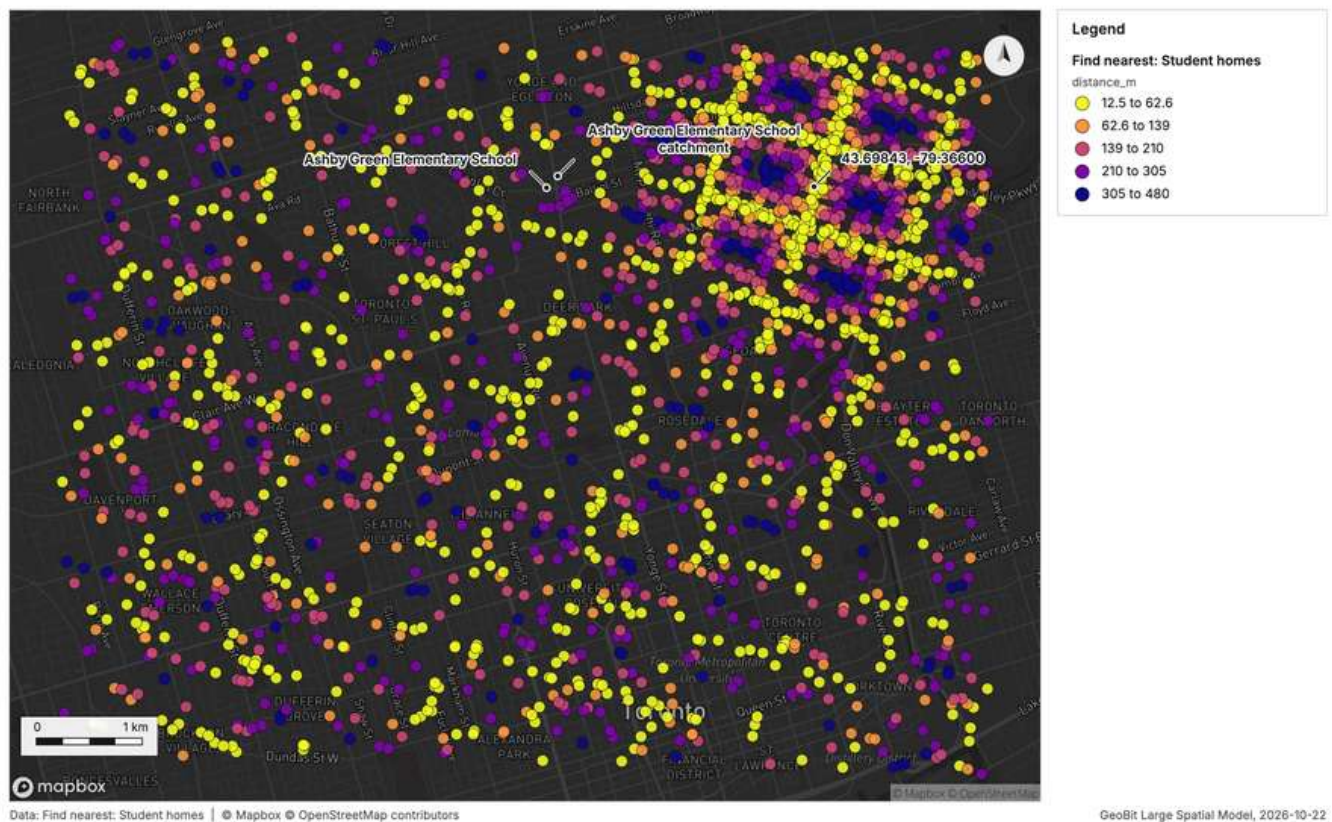


Figure 22. Find nearest: Student homes [75]

Find nearest: Student homes

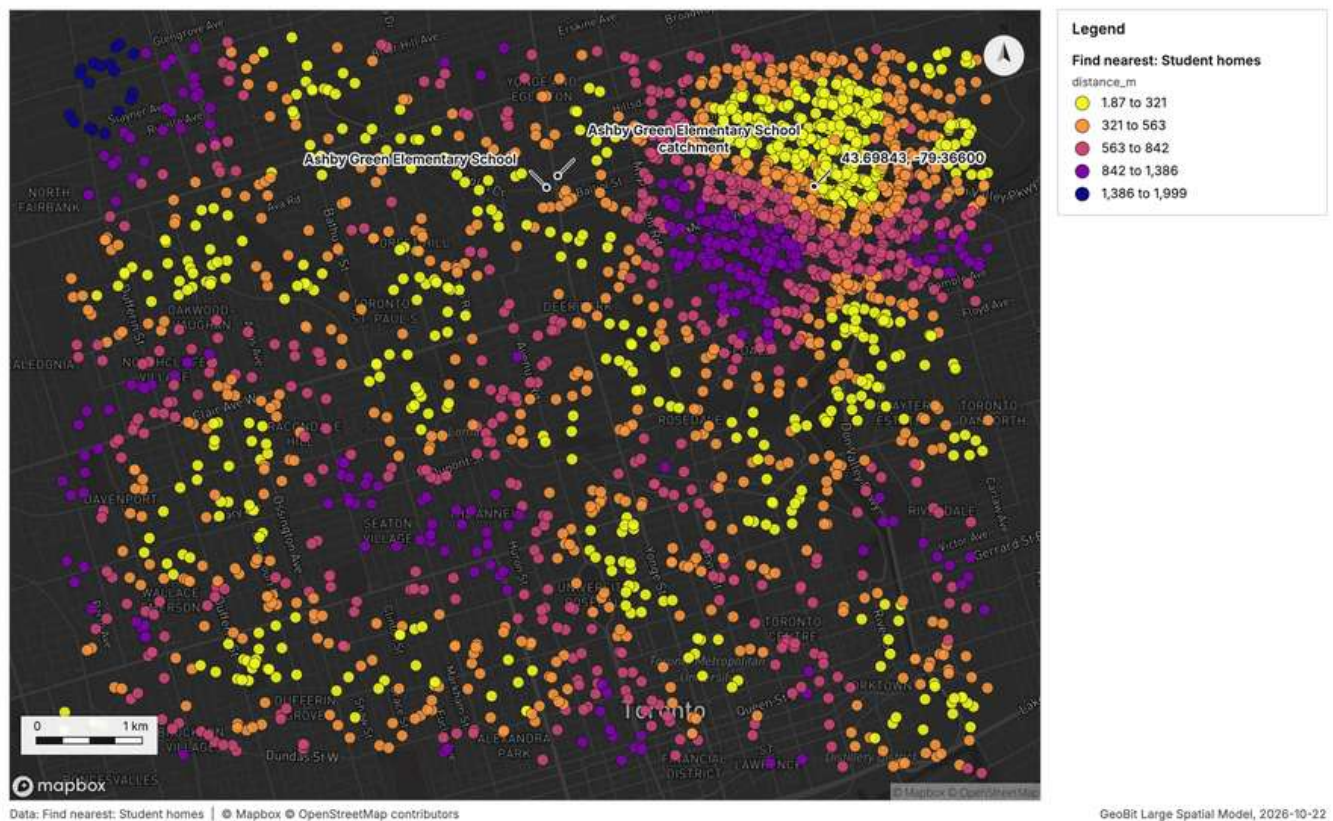


Figure 23. Find nearest: Student homes [76]

Find nearest: Student homes



Figure 24. Find nearest: Student homes [77]

What the map shows. The map displays the emerging hot spots for student homes across a grid area. A distinct, concentrated cluster of "Sporadic hot spot" areas, colored orange, is visible in the upper-central portion of the map. The majority of the geographical area is colored gray, corresponding to [55]

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

Distribution of capacity

45 values in 7 bins

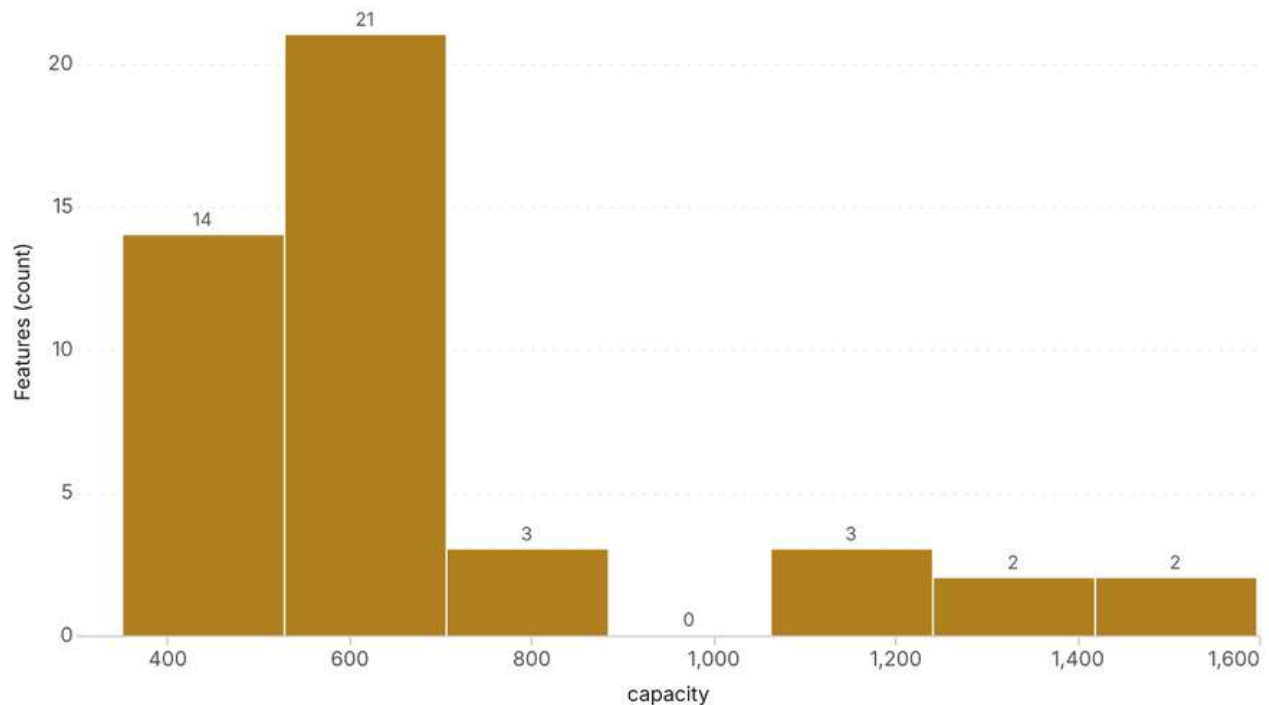


Figure 25. Schools over time (built_year) [78]. Source: Schools (45 features). The data is in the appendix.

Sum of units per quarter by completion_month

Per quarter: 20 quarters from 2023-01-01 to 2027-10-01; trend +13 per quarter; first half 4,668, second half 5,070 (+8.6%)

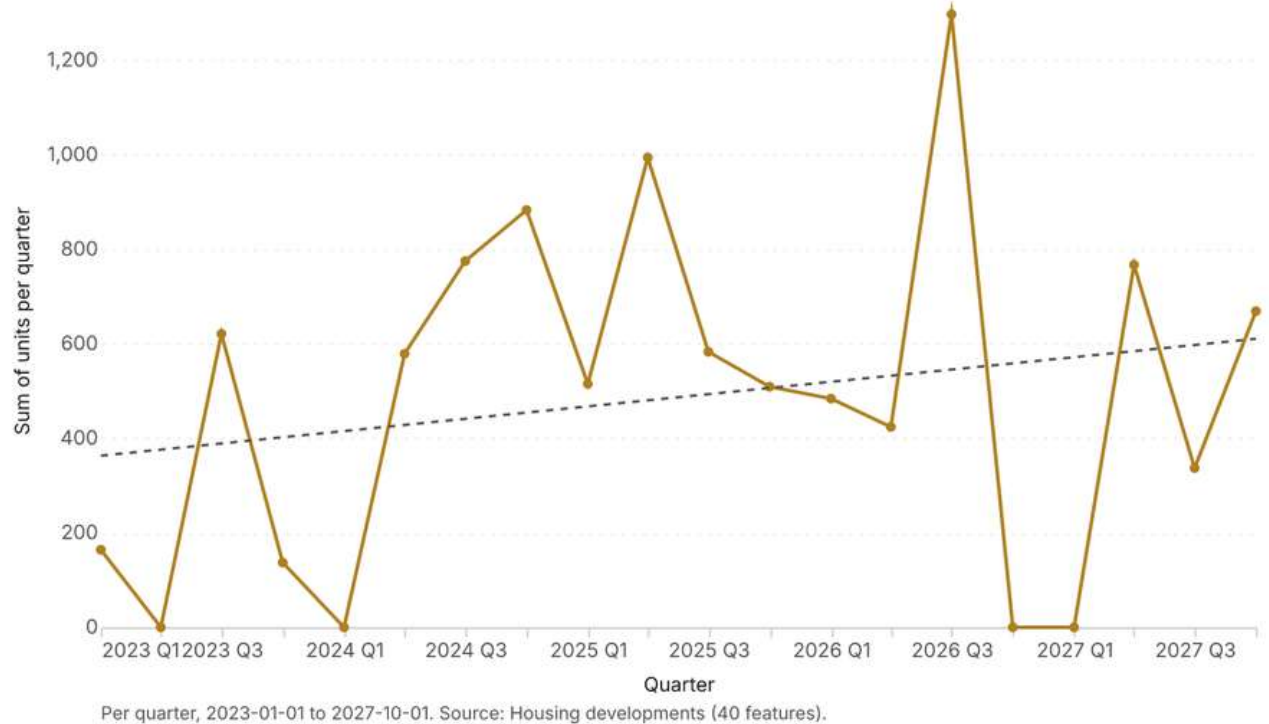
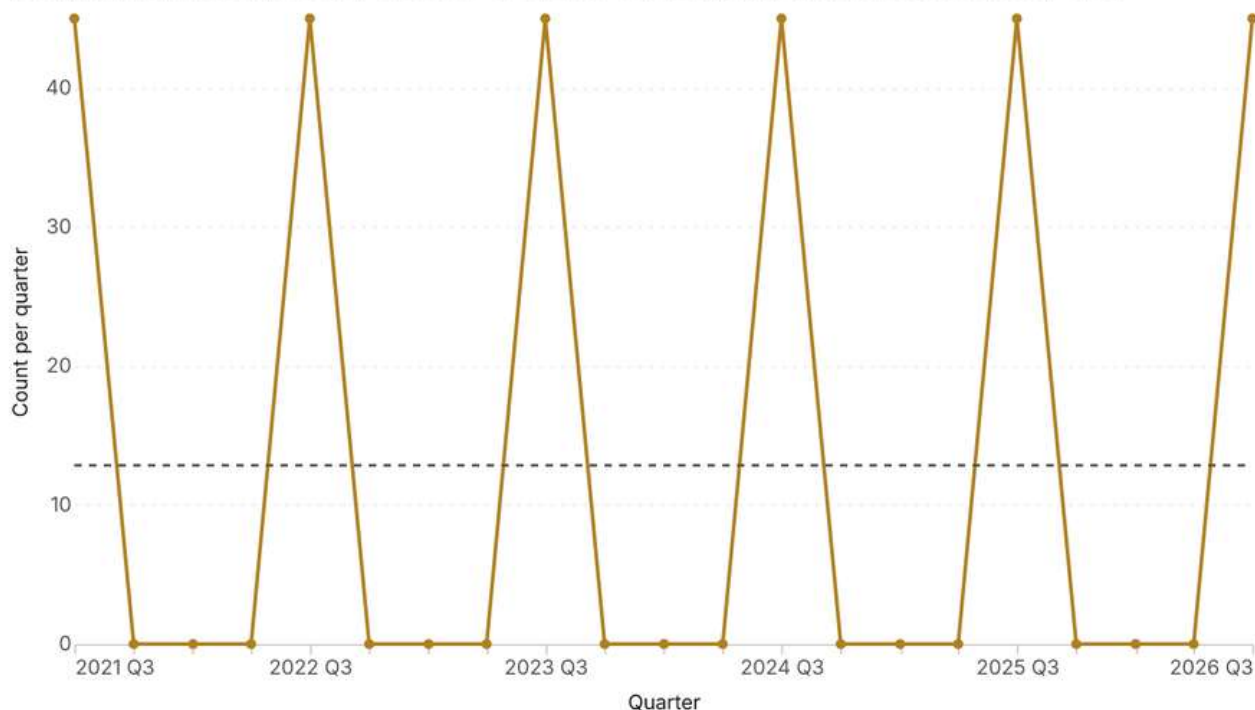


Figure 26. Housing developments over time (completion_month) [79]. Per quarter, 2023-01-01 to 2027-10-01. Source: Housing developments (40 features). The data is in the appendix.

Count per quarter by school_year

Per quarter: 21 quarters from 2021-07-01 to 2026-07-01; trend +0 per quarter; first half 135, second half 135 (+0.0%)

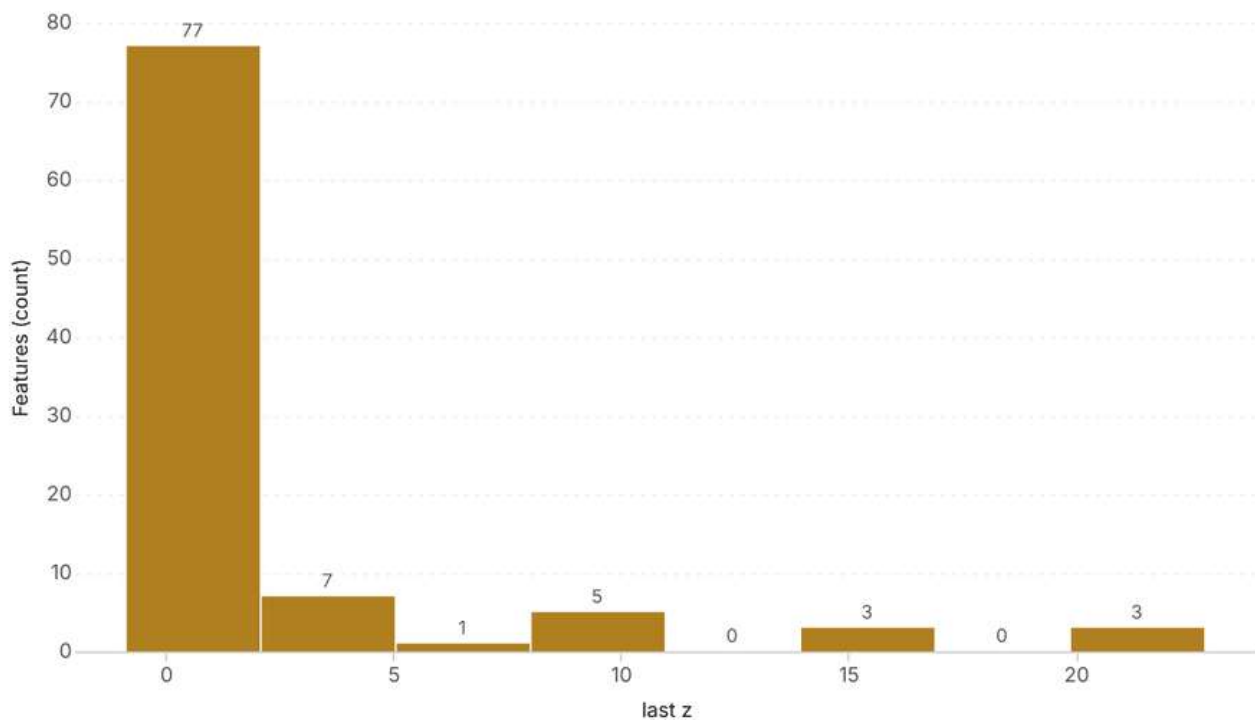


Per quarter, 2021-07-01 to 2026-07-01. Source: Enrollment by school and year (270 features).

Figure 27. Enrollment by school and year over time (school_year) [80]. Per quarter, 2021-07-01 to 2026-07-01. Source: Enrollment by school and year (270 features). The data is in the appendix.

Distribution of last_z

96 values in 8 bins

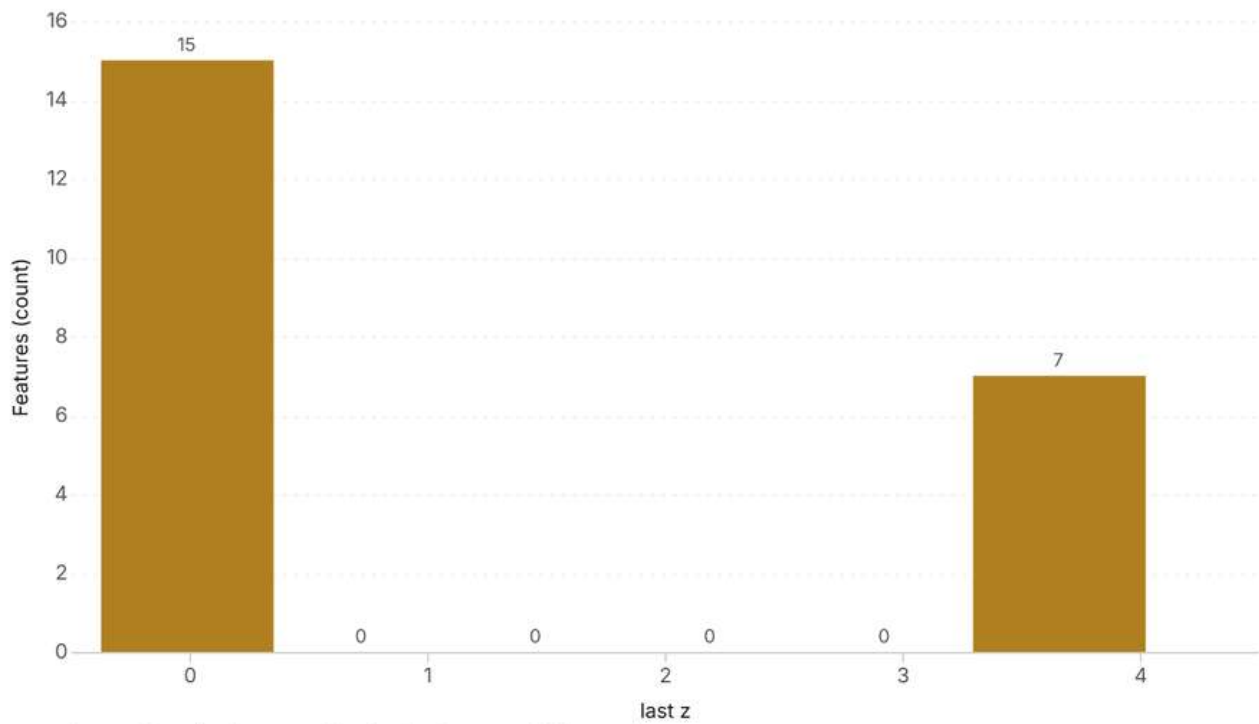


Source: Emerging hot spots: Student homes (96 features).

Figure 28. Emerging hot spots: Student homes [81]. Source: Emerging hot spots: Student homes (96 features). The data is in the appendix.

Distribution of last_z

22 values in 6 bins



Source: Emerging hot spots: Housing developments (22 features).

Figure 29. Emerging hot spots: Housing developments [82]. Source: Emerging hot spots: Housing developments (22 features). The data is in the appendix.

Ranked by distance_km

Top 20 of 2,500 (smallest first)

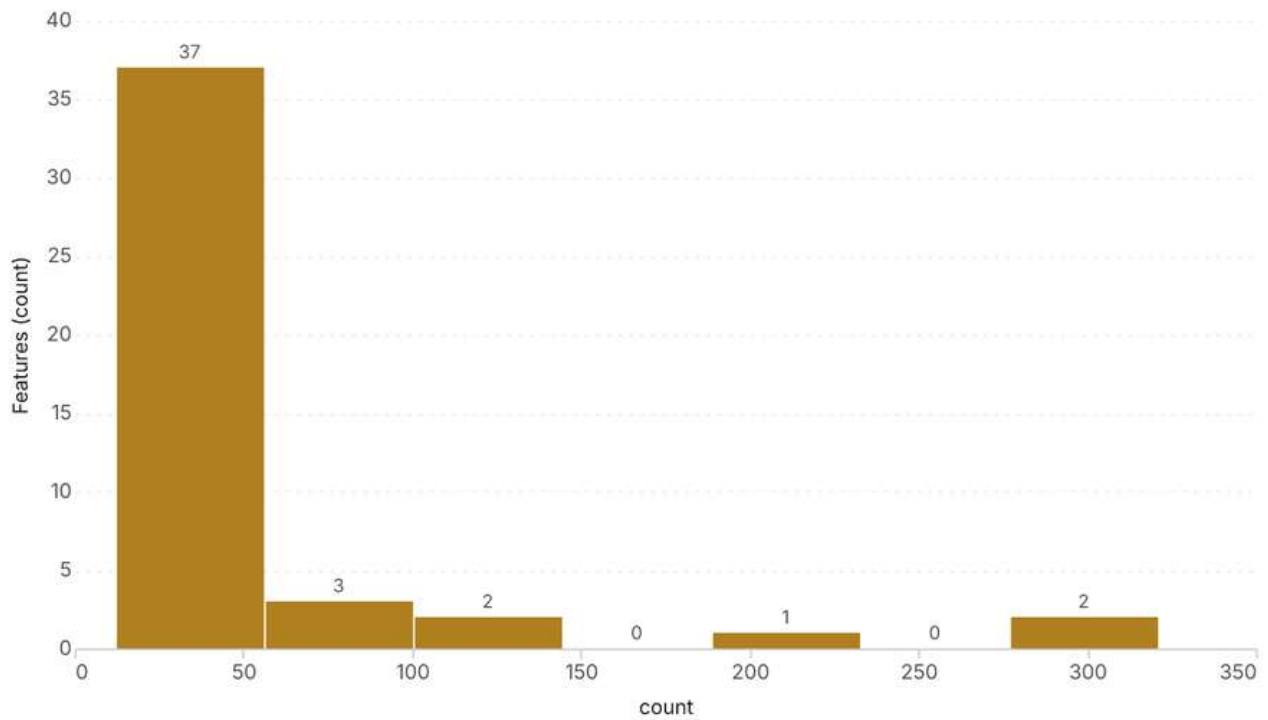
rank	name	distance_km
1	near_repeat	0.01
2	isolated	0.02
3	isolated	0.02
4	isolated	0.02
5	originator	0.03
6	isolated	0.03
7	near_repeat	0.03
8	isolated	0.03
9	near_repeat	0.04
10	near_repeat	0.04
11	originator	0.05
12	isolated	0.05
13	originator	0.05
14	near_repeat	0.05
15	isolated	0.05
16	originator	0.05
17	near_repeat	0.05
18	near_repeat	0.06
19	near_repeat	0.06
20	isolated	0.06

Period: 2023-08-01 to 2026-09-30 (enrolled_on). Source: Repeat and near repeat classificati...

Figure 30. Repeat and near repeat classification: Student homes [83]. Period: 2023-08-01 to 2026-09-30 (enrolled_on). Source: Repeat and near repeat classification: Student homes (2,500 features). The data is in the appendix.

Distribution of count

45 values in 7 bins

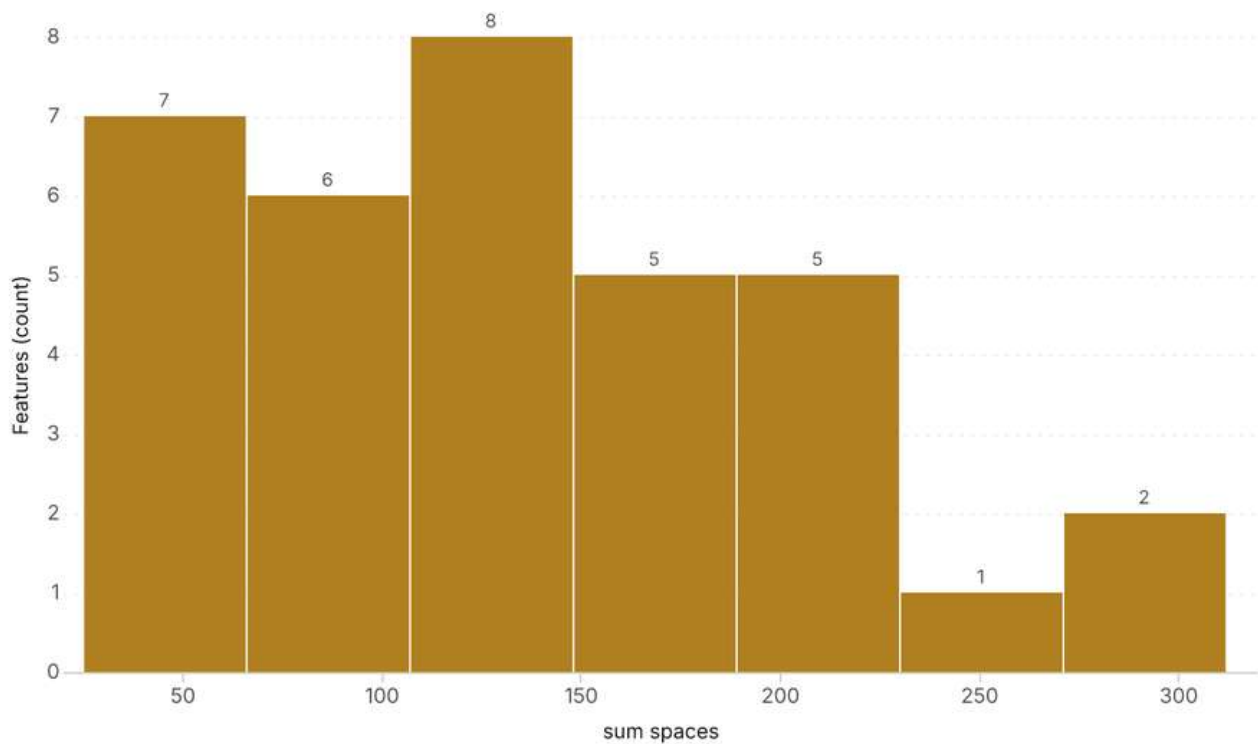


Source: Summarize within: School catchments (45 features).

Figure 31. Summarize within: School catchments [84]. Source: Summarize within: School catchments (45 features). The data is in the appendix.

Distribution of sum_spaces

34 values in 7 bins

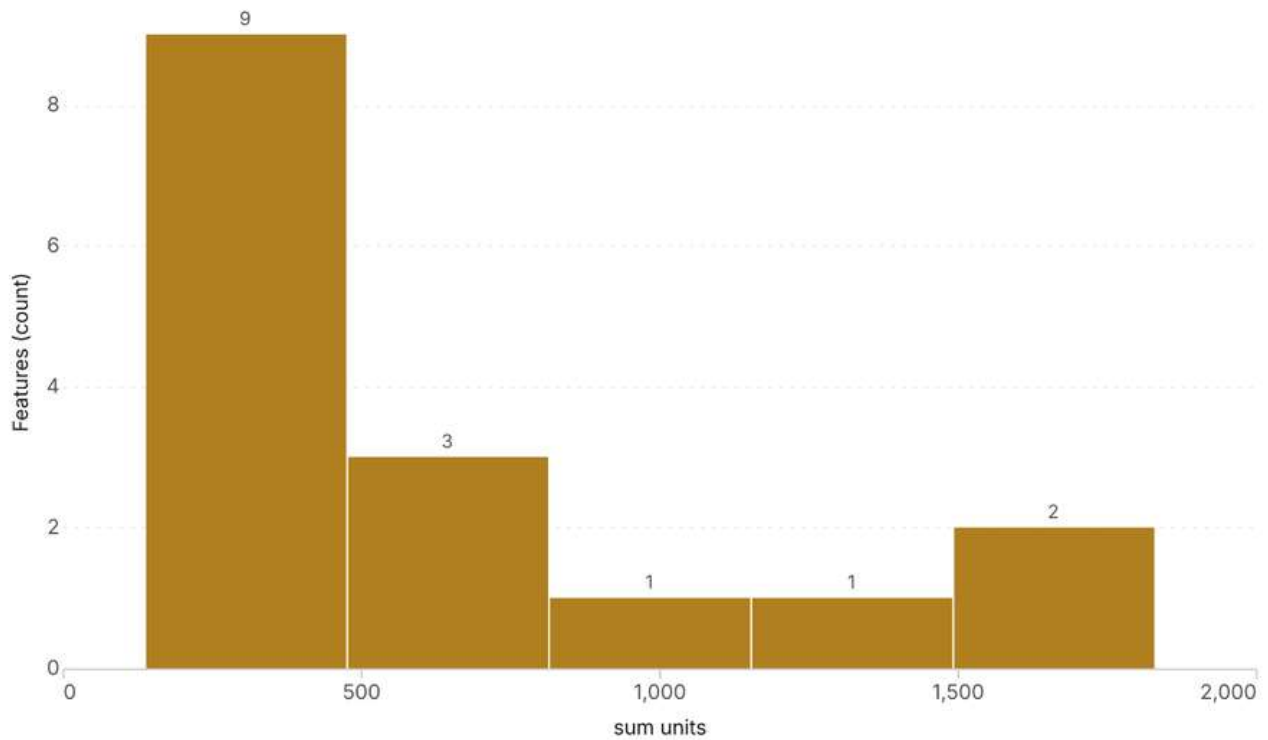


Source: Summarize within: School catchments (45 features).

Figure 32. Summarize within: School catchments [85]. Source: Summarize within: School catchments (45 features). The data is in the appendix.

Distribution of sum_units

16 values in 5 bins

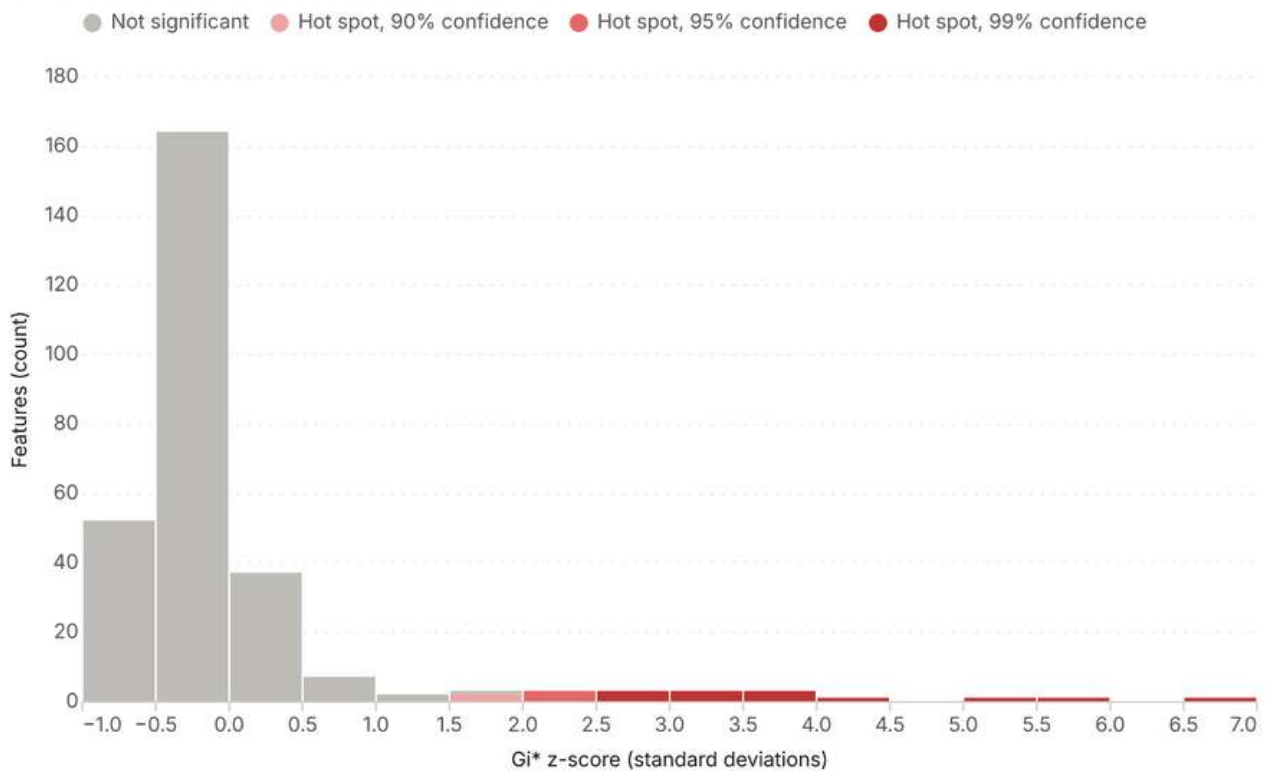


Source: Summarize within: School catchments (45 features).

Figure 33. Summarize within: School catchments [86]. Source: Summarize within: School catchments (45 features). The data is in the appendix.

Gi* z-score distribution

281 features: 18 hot and 0 cold at 90% confidence or more



Source: Hot spot analysis: Student homes (281 features).

Figure 34. Hot spot analysis: Student homes [87]. Source: Hot spot analysis: Student homes (281 features). The data is in the appendix.

Gi* z-score distribution

20 features: 2 hot and 3 cold at 90% confidence or more

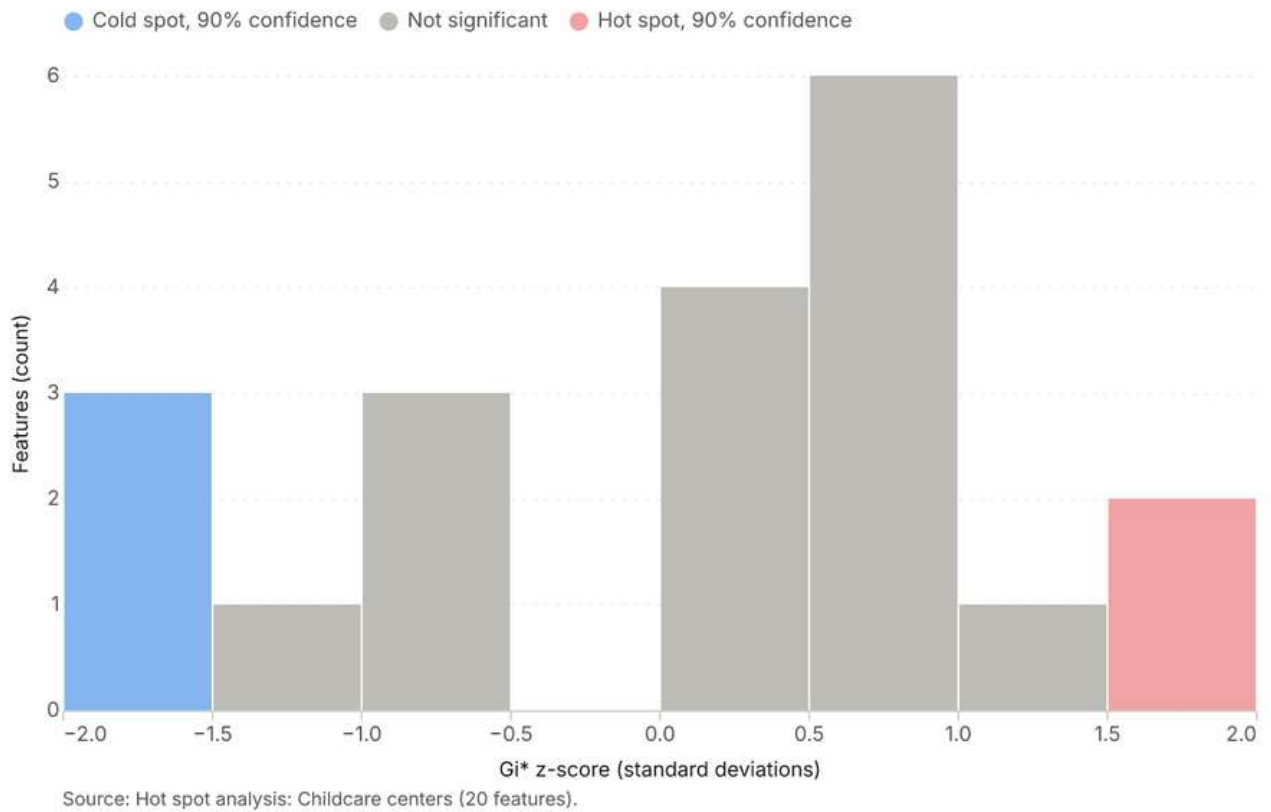


Figure 35. Hot spot analysis: Childcare centers [88]. Source: Hot spot analysis: Childcare centers (20 features). The data is in the appendix.

Gi* z-score distribution

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

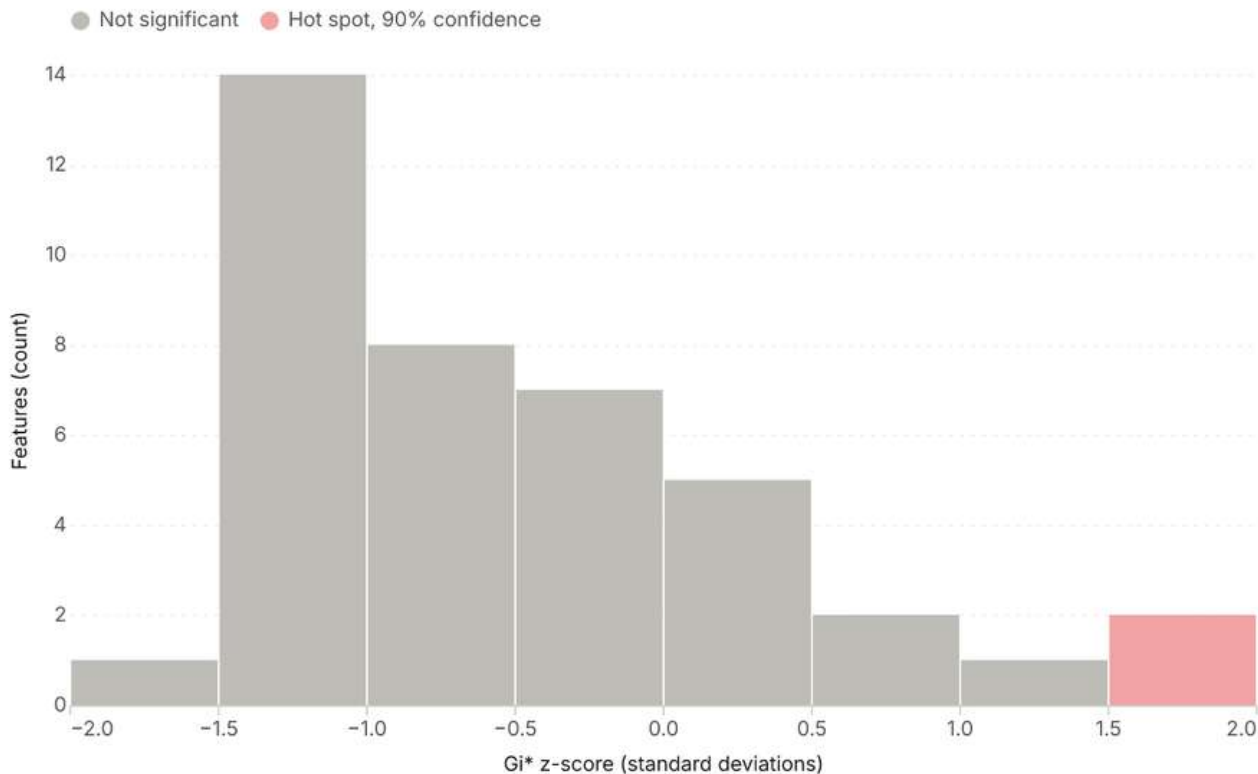


Figure 36. Hot spot analysis: Housing developments [89]. Period: 2023-03-01 to 2027-11-01 (completion_month). Source: Hot spot analysis: Housing developments (40 features). The data is in the appendix.

Distribution of col

1,838 values in 12 bins

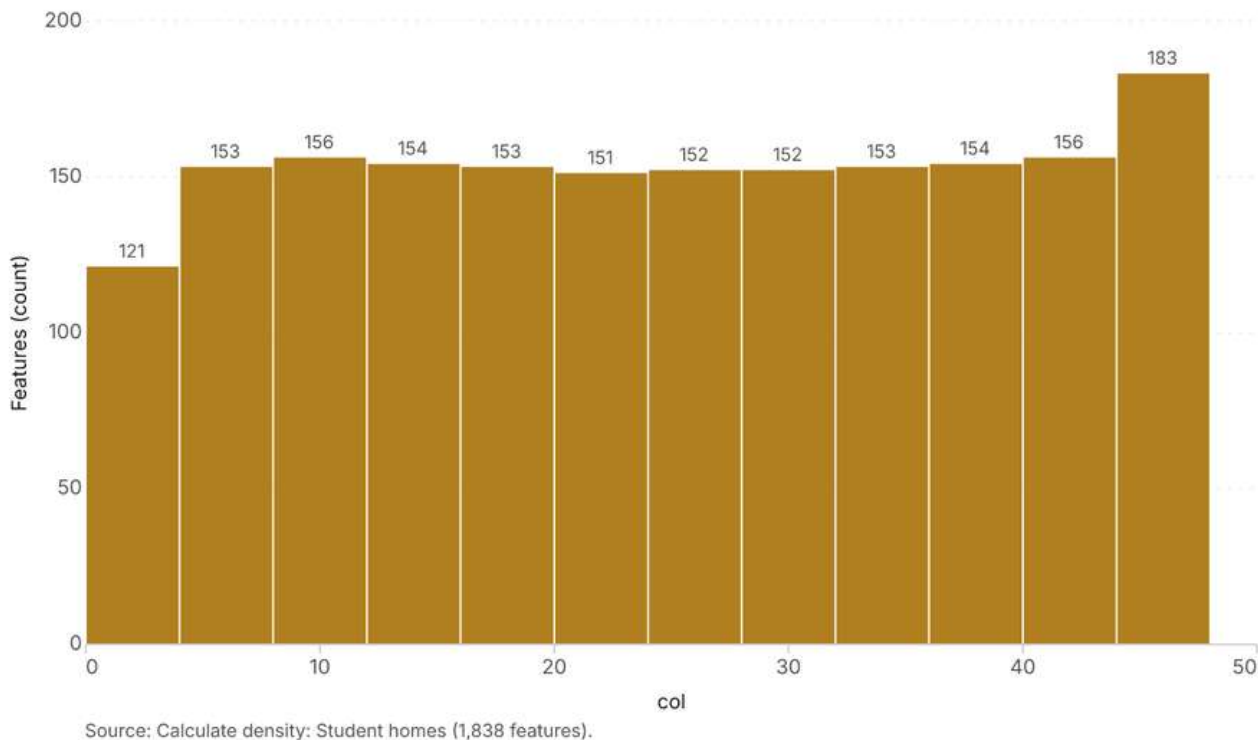
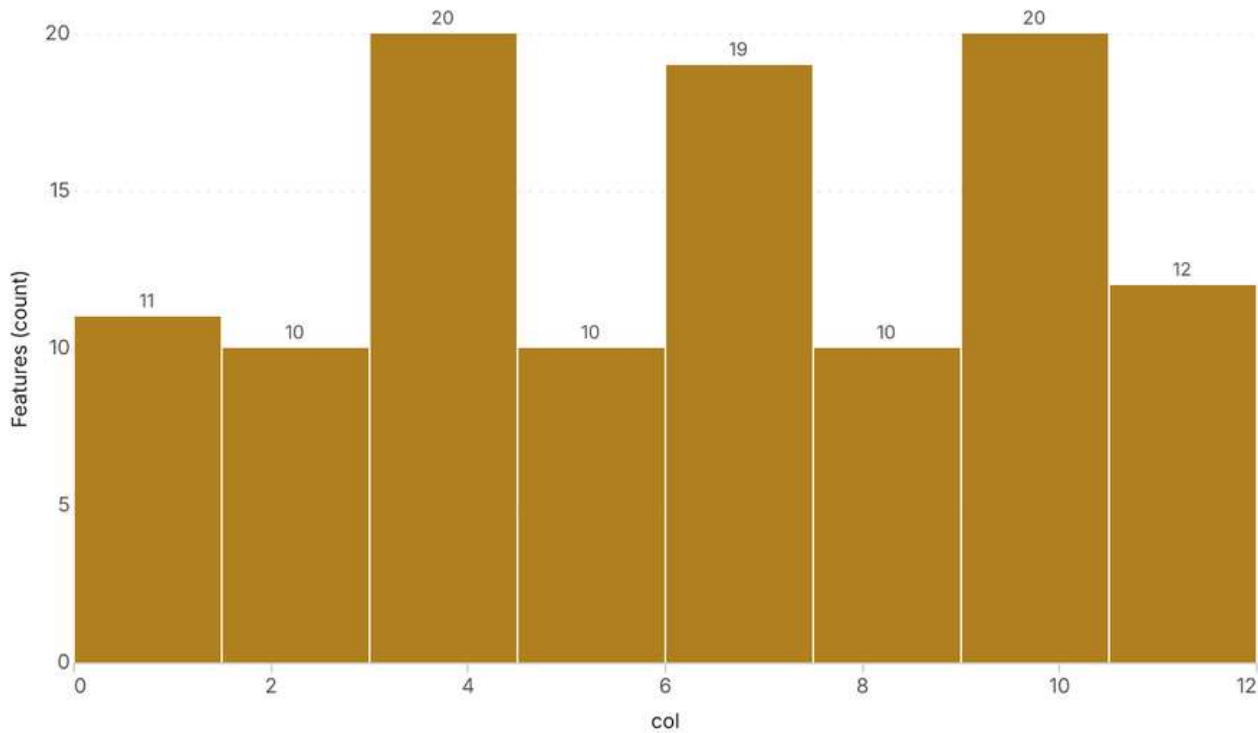


Figure 37. Calculate density: Student homes [90]. Source: Calculate density: Student homes (1,838 features). The data is in the appendix.

Distribution of col

112 values in 8 bins

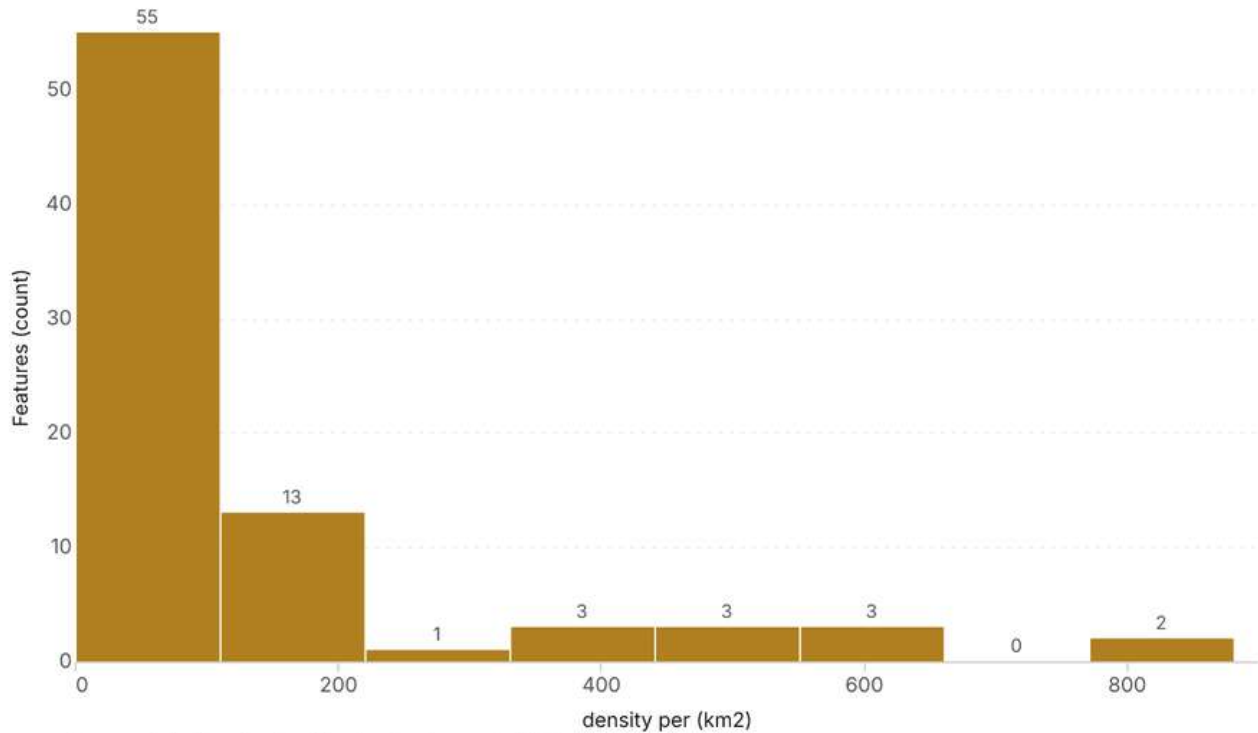


Source: Calculate density: Childcare centers (112 features).

Figure 38. Calculate density: Childcare centers [91]. Source: Calculate density: Childcare centers (112 features). The data is in the appendix.

Distribution of density_per_km2

80 values in 8 bins



Source: Calculate density: Housing developments (80 features).

Figure 39. Calculate density: Housing developments [92]. Source: Calculate density: Housing developments (80 features). The data is in the appendix.

Cluster sizes

1 clusters over 2,500 features

cluster	features	share
Noise	1,490	59.6%
0	1,010	40.4%

Period: 2023-08-01 to 2026-09-30 (enrolled_on). Source: Find point clusters: Student homes ...

Figure 40. Find point clusters: Student homes [93]. Period: 2023-08-01 to 2026-09-30 (enrolled_on). Source: Find point clusters: Student homes (2,500 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 41. Find point clusters: cluster hulls [94]. Source: Find point clusters: cluster hulls (1 features). The data is in the appendix.

Cluster sizes

8 clusters over 60 features

cluster	features	share
1	14	23.3%
0	11	18.3%
6	9	15.0%
3	7	11.7%
4	6	10.0%
2	5	8.3%
5	4	6.7%
7	3	5.0%
Noise	1	1.7%

Source: Find point clusters: Childcare centers (60 features).

Figure 42. Find point clusters: Childcare centers [95]. Source: Find point clusters: Childcare centers (60 features). The data is in the appendix.

Cluster sizes

8 clusters over 8 features

cluster	features	share
0	1	12.5%
1	1	12.5%
2	1	12.5%
3	1	12.5%
4	1	12.5%
5	1	12.5%
6	1	12.5%
7	1	12.5%

Source: Find point clusters: cluster hulls (8 features).

Figure 43. Find point clusters: cluster hulls [96]. Source: Find point clusters: cluster hulls (8 features). The data is in the appendix.

Cluster sizes

1 clusters over 40 features

cluster	features	share
0	37	92.5%
Noise	3	7.5%

Period: 2023-03-01 to 2027-11-01 (completion_month). Source: Find point clusters: Housing ...

Figure 44. Find point clusters: Housing developments [97]. Period: 2023-03-01 to 2027-11-01 (completion_month). Source: Find point clusters: Housing developments (40 features). The data is in the appendix.

Cluster sizes

1 clusters over 1 features

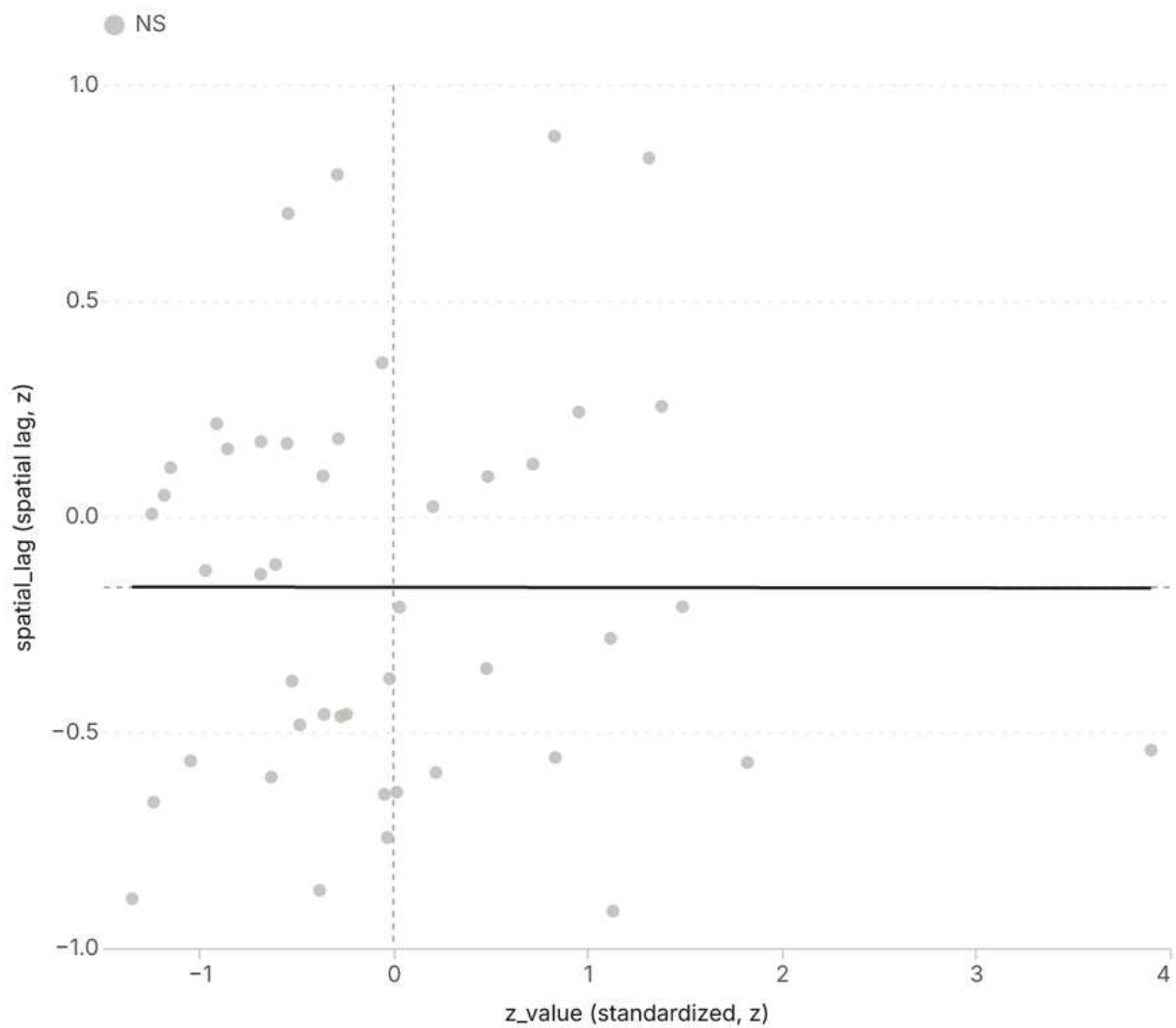
cluster	features	share
0	1	100.0%

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

Figure 45. Find point clusters: cluster hulls [98]. Source: Find point clusters: cluster hulls (1 features). The data is in the appendix.

Moran scatter

45 features; slope -0.000 (the Moran's I of these standardized values)



Source: Find outliers: School catchments (45 features).

Figure 46. Find outliers: School catchments [99]. Source: Find outliers: School catchments (45 features). The data is in the appendix.

Ranked by rank

Top 20 of 2,500 (smallest first)

rank	name
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1

Period: 2023-08-01 to 2026-09-30 (from_enrolled_on). Source: Find nearest: Student homes ...

Figure 47. Find nearest: Student homes [100]. Period: 2023-08-01 to 2026-09-30 (from_enrolled_on). Source: Find nearest: Student homes (2,500 features). The data is in the appendix.

Ranked by rank

Top 20 of 2,500 (smallest first)

rank	name
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1

Period: 2023-08-01 to 2026-09-30 (from_enrolled_on). Source: Find nearest: Student homes ...

Figure 48. Find nearest: Student homes [101]. Period: 2023-08-01 to 2026-09-30 (from_enrolled_on). Source: Find nearest: Student homes (2,500 features). The data is in the appendix.

Count per month by from_enrolled_on and from_transport

Per month: 38 months from 2023-08-01 to 2026-09-01; trend +0.429 per month; first half 1,067, second half 1,184 (+11.0%)

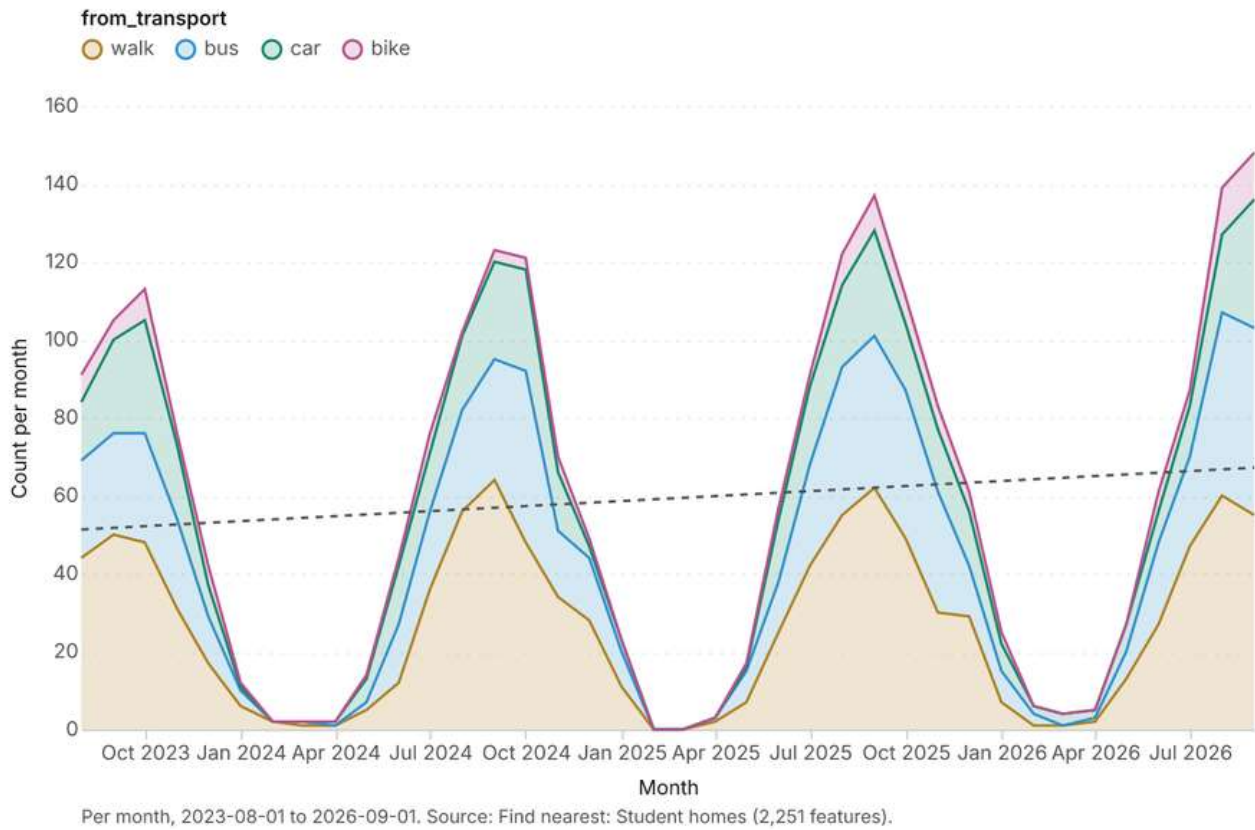


Figure 49. Find nearest: Student homes over time [102]. Per month, 2023-08-01 to 2026-09-01. Source: Find nearest: Student homes (2,251 features). The data is in the appendix.

Count per month by from_enrolled_on and from_transport

Per month: 38 months from 2023-08-01 to 2026-09-01; trend +0.381 per month; first half 1,198, second half 1,302 (+8.7%)

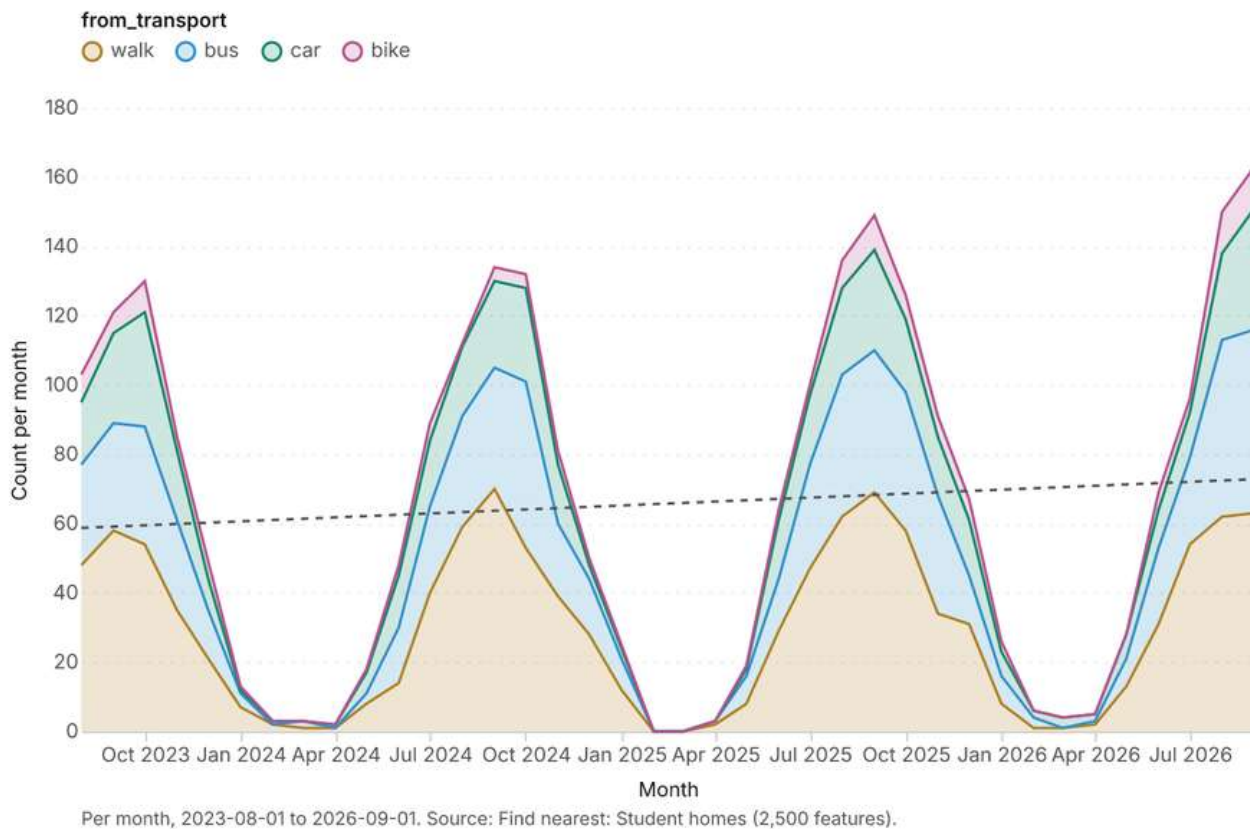


Figure 50. Find nearest: Student homes over time [103]. Per month, 2023-08-01 to 2026-09-01. Source: Find nearest: Student homes (2,500 features). The data is in the appendix.

Count per month by from_enrolled_on and to_name

Per month: 38 months from 2023-08-01 to 2026-09-01; trend +0.381 per month; first half 1,198, second half 1,302 (+8.7%)

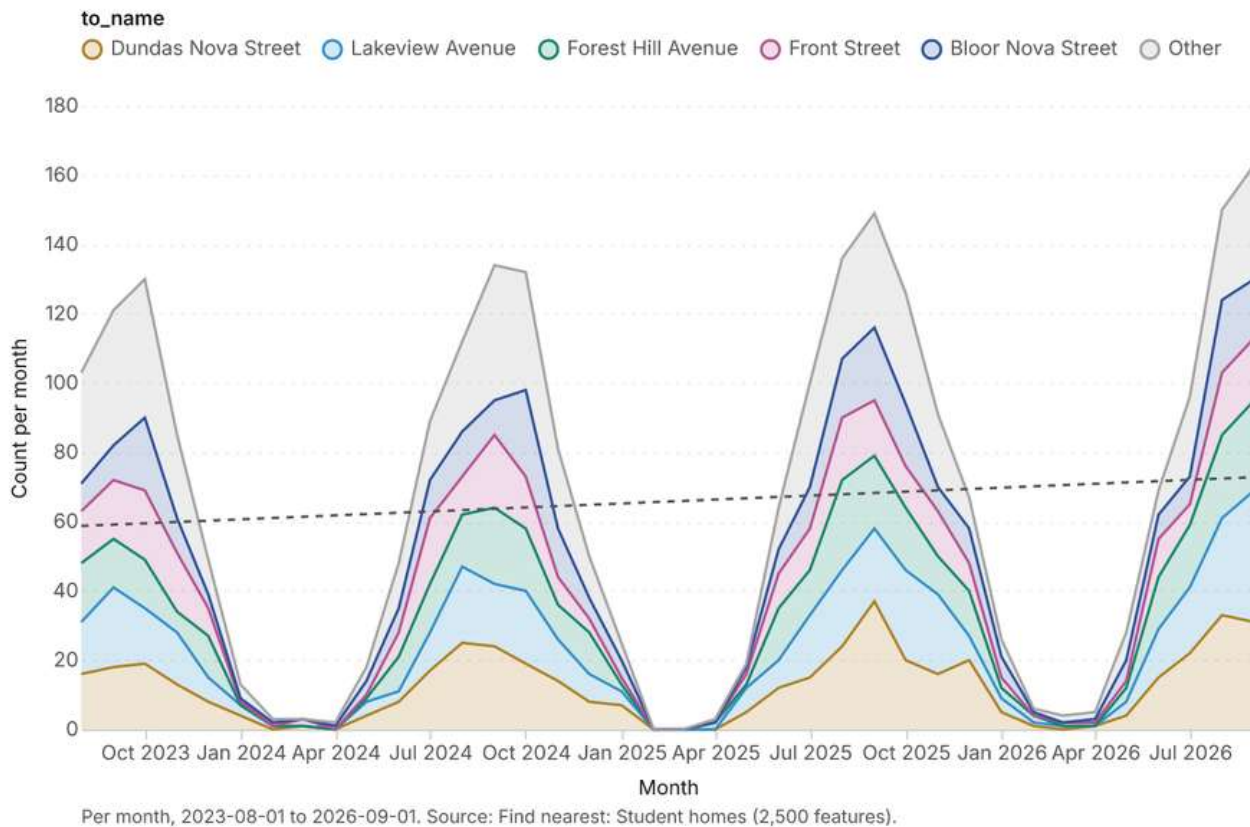


Figure 51. Find nearest: Student homes over time [104]. Per month, 2023-08-01 to 2026-09-01. Source: Find nearest: Student homes (2,500 features). The data is in the appendix.

Count per quarter by completion_month and is_noise

Per quarter: 20 quarters from 2023-01-01 to 2027-10-01; trend +0.0301 per quarter; first half 19, second half 21 (+10.5%)

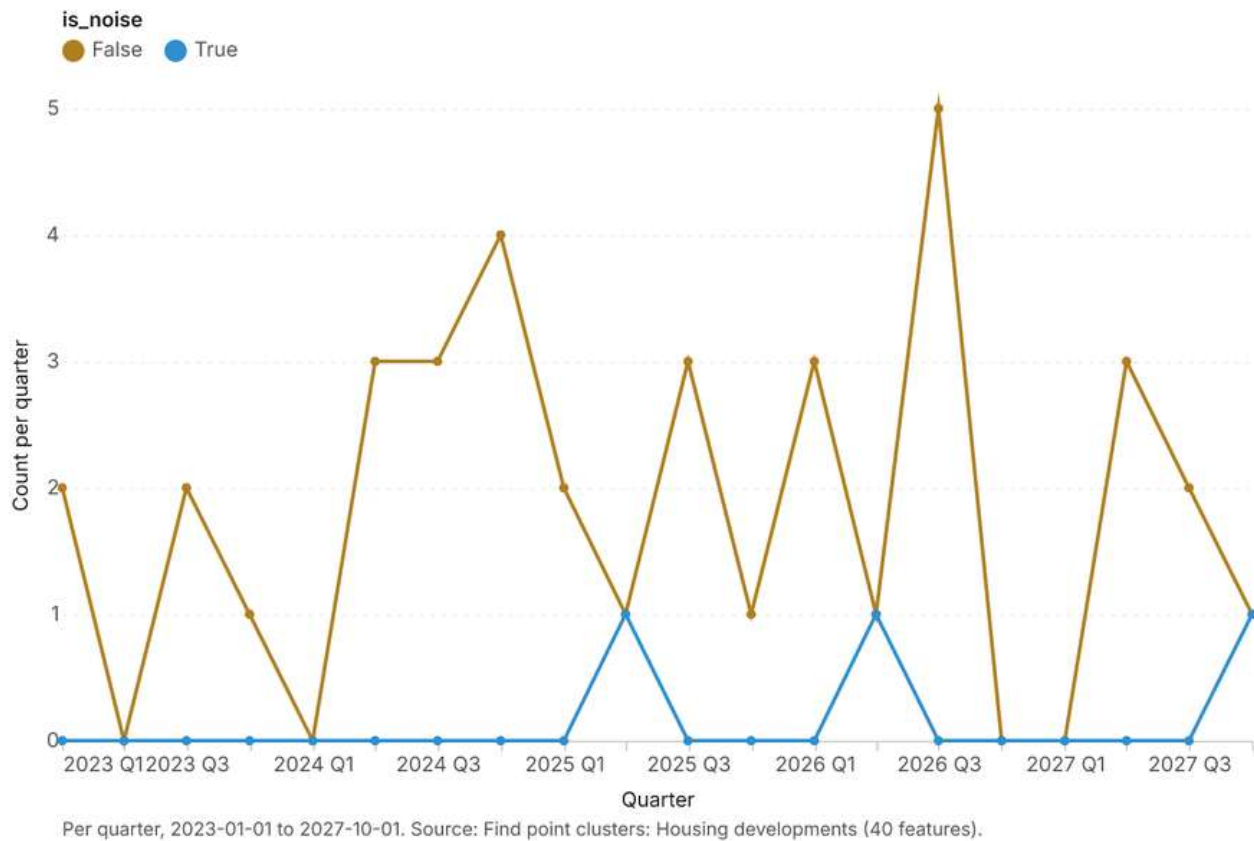
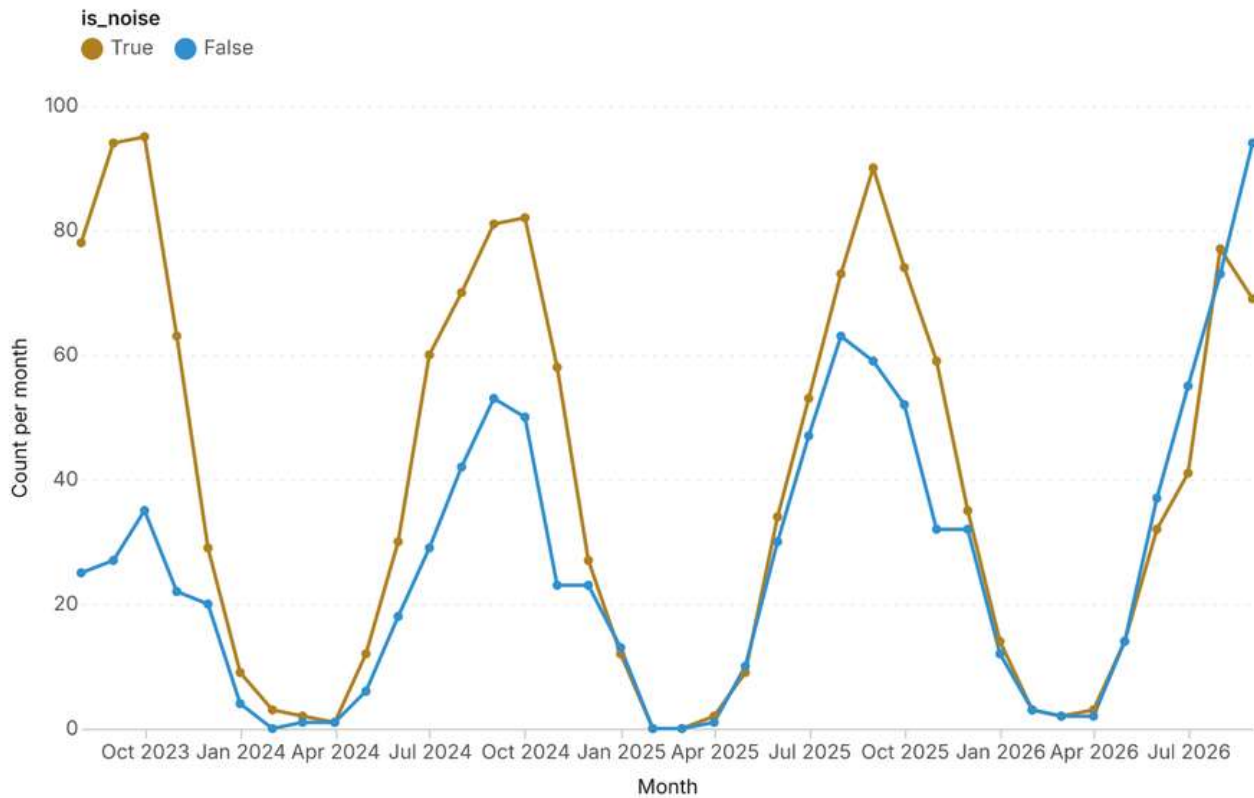


Figure 52. Find point clusters: Housing developments over time [105]. Per quarter, 2023-01-01 to 2027-10-01. Source: Find point clusters: Housing developments (40 features). The data is in the appendix.

Count per month by enrolled_on and is_noise

Per month: 38 months from 2023-08-01 to 2026-09-01; trend +0.381 per month; first half 1,198, second half 1,302 (+8.7%)



Per month, 2023-08-01 to 2026-09-01. Source: Find point clusters: Student homes (2,500 features).

Figure 53. Find point clusters: Student homes over time [106]. Per month, 2023-08-01 to 2026-09-01. Source: Find point clusters: Student homes (2,500 features). The data is in the appendix.

Count per quarter by completion_month and gi_bin

Per quarter: 20 quarters from 2023-01-01 to 2027-10-01; trend +0.0301 per quarter; first half 19, second half 21 (+10.5%)

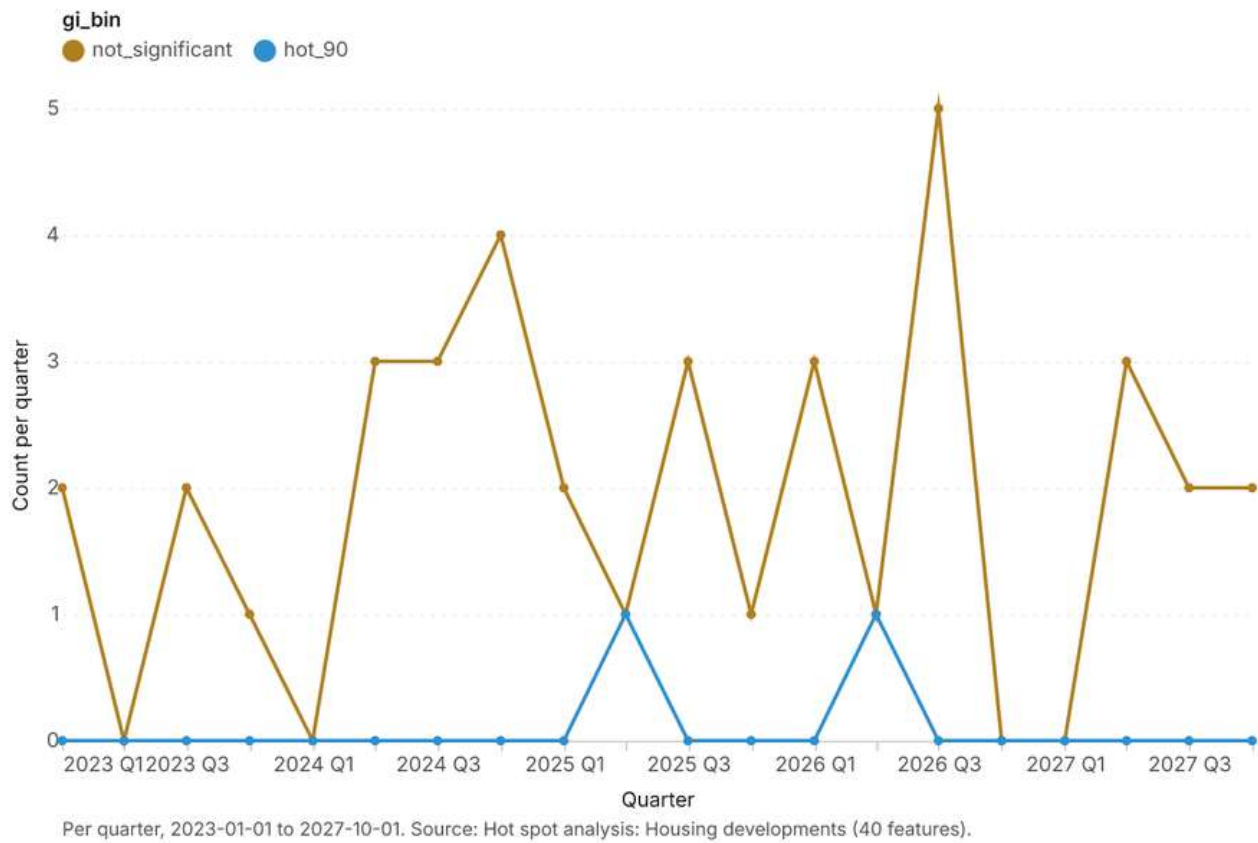


Figure 54. Hot spot analysis: Housing developments over time [107]. Per quarter, 2023-01-01 to 2027-10-01. Source: Hot spot analysis: Housing developments (40 features). The data is in the appendix.

Count per month by enrolled_on and nr_class

Per month: 38 months from 2023-08-01 to 2026-09-01; trend +0.381 per month; first half 1,198, second half 1,302 (+8.7%)

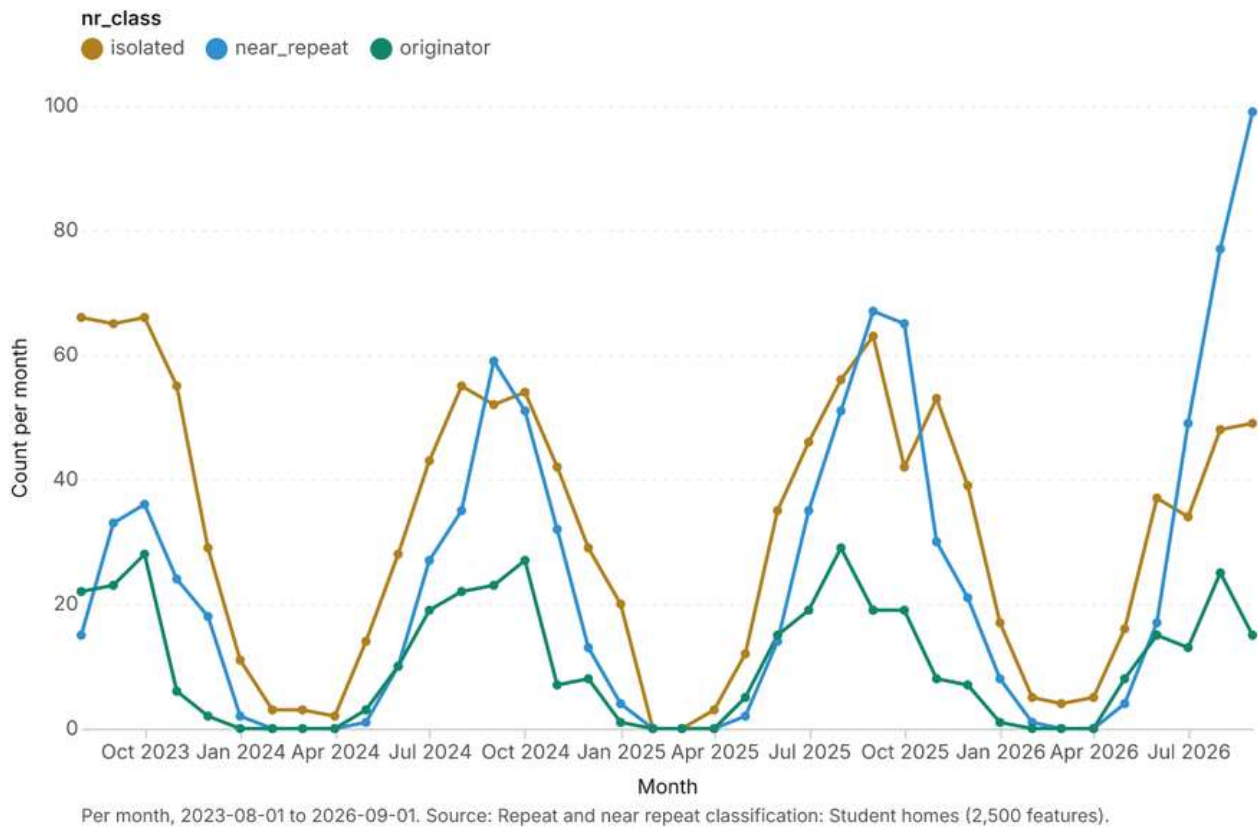


Figure 55. Repeat and near repeat classification: Student homes over time [108]. Per month, 2023-08-01 to 2026-09-01. Source: Repeat and near repeat classification: Student homes (2,500 features). The data is in the appendix.

Changes since the last run

This is the first report of this project.

Sources

- [1] Rendering: Chart: Timeline: events per quarter by dataset. 78 rows (id 79388dbd-a74a-40df-b300-c9c05078ac9c)
- [2] Dataset: Student homes. vector, 2500 rows (id 28ef32ad-fdbf-4e64-879d-ef97c69d99c8)
- [3] Dataset: Housing developments. vector, 40 rows (id 9073798d-0507-463a-99b0-0f74516b77ea)
- [4] Dataset: Enrollment by school and year. table, 270 rows (id af8cf345-1c02-4892-beda-cb8f239c4cd1)
- [5] 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)
- [6] Plan: Space time hot spots of Student homes (the Start plan's candidate c_7f1ecb93fe03). Student homes carry dates in 'enrolled_on': emerging hot spot analysis finds new, intensifying and fading hot spots per month. (id da4c2c71-fa66-4f6d-b51a-fc46626d4137:c_7f1ecb93fe03)
- [7] Tool result: gp_space_time_hot_spots, step 0. Emerging hot spots: 1 layer saved: Emerging hot spots: Student homes (96 features). (id 9aff1884-9259-4a26-929a-88629da03a75:0)
- [8] Layer: Student homes. 2,500 features (id 05789208-552f-4f37-be96-0e77b9279a4e)
- [9] Plan: Space time hot spots of Housing developments (the Start plan's candidate c_e422a5866706). Housing developments carry dates in 'completion_month': emerging hot spot analysis finds new, intensifying and fading hot spots per month. (id da4c2c71-fa66-4f6d-b51a-fc46626d4137:c_e422a5866706)
- [10] Tool result: gp_space_time_hot_spots, step 1. Emerging hot spots: 1 layer saved: Emerging hot spots: Housing developments (22 features). (id 9aff1884-9259-4a26-929a-88629da03a75:1)
- [11] Layer: Housing developments. 40 features (id afc1332b-5445-4ac2-9d98-ebb6b1520bd2)

[12] 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)

[13] Plan: Near repeat of Student homes (the Start plan's candidate c_a7cb51bb85b3). Near repeat analysis tests whether Student homes close in space also follow each other within 30 days. (id da4c2c71-fa66-4f6d-b51a-fc46626d4137:c_a7cb51bb85b3)

[14] Tool result: gp_near_repeat, step 2. Repeat and near repeat classification: 1 layer saved: Repeat and near repeat classification: Student homes (2500 features). (id 9aff1884-9259-4a26-929a-88629da03a75:2)

[15] 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)

[16] Plan: Student homes per feature of School catchments (the Start plan's candidate c_525cc89e9df7). Count Student homes inside each feature of School catchments by transport; the counts map as a choropleth (natural breaks, sequential colors). (id da4c2c71-fa66-4f6d-b51a-fc46626d4137:c_525cc89e9df7)

[17] Tool result: gp_summarize_within, step 0. Summarize within: 1 layer saved: Summarize within: School catchments (45 features). (id 0c3a09c9-8654-4d86-b171-2c58372abb46:0)

[18] Layer: School catchments. 45 features (id 534622c6-56d8-4348-94c9-c424e61a442d)

[19] Tool result: gp_summarize_within, step 1. Summarize within: 1 layer saved: Summarize within: School catchments (45 features). (id 0c3a09c9-8654-4d86-b171-2c58372abb46:1)

[20] Layer: Childcare centers. 60 features (id 9489916f-d13f-4283-b308-ff5bcae62a0d)

[21] Tool result: gp_summarize_within, step 2. Summarize within: 1 layer saved: Summarize within: School catchments (45 features). (id 0c3a09c9-8654-4d86-b171-2c58372abb46:2)

[22] 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)

[23] Plan: Hot spots of Student homes (the Start plan's candidate c_7a39d826a935). 2500 points: Getis-Ord Gi* tests whether the concentrations in Student homes are statistically significant. (id da4c2c71-fa66-4f6d-b51a-fc46626d4137:c_7a39d826a935)

[24] Tool result: gp_hot_spots, step 0. Hot spot analysis: 1 layer saved: Hot spot analysis: Student homes (281 features). (id 9c081bf6-6d02-4b46-93ef-d4823a0030c1:0)

[25] Plan: Hot spots of Childcare centers (the Start plan's candidate c_0bdc4dd83b93). 60 points: Getis-Ord Gi* tests whether the concentrations in Childcare centers are statistically significant. (id da4c2c71-fa66-4f6d-b51a-fc46626d4137:c_0bdc4dd83b93)

[26] Tool result: gp_hot_spots, step 1. Hot spot analysis: 1 layer saved: Hot spot analysis: Childcare centers (20 features). (id 9c081bf6-6d02-4b46-93ef-d4823a0030c1:1)

[27] Plan: Hot spots of Housing developments (the Start plan's candidate c_6f57933191fe). 40 points: Getis-Ord Gi* tests whether the concentrations in Housing developments are statistically significant. (id da4c2c71-fa66-4f6d-b51a-fc46626d4137:c_6f57933191fe)

[28] Tool result: gp_hot_spots, step 2. Hot spot analysis: 1 layer saved: Hot spot analysis: Housing developments (40 features). (id 9c081bf6-6d02-4b46-93ef-d4823a0030c1:2)

[29] 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)

[30] Plan: Kernel density of Student homes (the Start plan's candidate c_4c71448e6d05). 2500 points in Student homes: a density surface shows where they concentrate. (id da4c2c71-fa66-4f6d-b51a-fc46626d4137:c_4c71448e6d05)

[31] Tool result: gp_calculate_density, step 0. Calculate density: 1 layer saved: Calculate density: Student homes (1838 features). (id a4a004d3-3ba6-400d-932e-b8110651d1ff:0)

[32] Plan: Kernel density of Childcare centers (the Start plan's candidate c_069e6a20b03a). 60 points in Childcare centers: a density surface shows where they concentrate. (id da4c2c71-fa66-4f6d-b51a-fc46626d4137:c_069e6a20b03a)

[33] Tool result: gp_calculate_density, step 1. Calculate density: 1 layer saved: Calculate density: Childcare centers (112 features). (id a4a004d3-3ba6-400d-932e-b8110651d1ff:1)

[34] Plan: Kernel density of Housing developments (the Start plan's candidate c_441f3db47c68). 40 points in Housing developments: a density surface shows where they concentrate. (id da4c2c71-fa66-4f6d-b51a-fc46626d4137:c_441f3db47c68)

[35] Tool result: gp_calculate_density, step 2. Calculate density: 1 layer saved: Calculate density: Housing developments (80 features). (id a4a004d3-3ba6-400d-932e-b8110651d1ff:2)

[36] 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)

[37] Plan: Cluster points of Student homes (the Start plan's candidate c_e4e6b0b009c4). DBSCAN finds dense groups of Student homes and separates noise. (id da4c2c71-fa66-4f6d-b51a-fc46626d4137:c_e4e6b0b009c4)

[38] Tool result: gp_find_point_clusters, step 0. Find point clusters: 2 layers saved: Find point clusters: Student homes (2500 features); Find point clusters: cluster hulls (1 feature). (id d27977c5-a8cd-4f40-9af6-797ca9424ec9:0)

[39] Plan: Cluster points of Childcare centers (the Start plan's candidate c_43ed026ce5e0). DBSCAN finds dense groups of Childcare centers and separates noise. (id da4c2c71-fa66-4f6d-b51a-fc46626d4137:c_43ed026ce5e0)

[40] Tool result: gp_find_point_clusters, step 1. Find point clusters: 2 layers saved: Find point clusters: Childcare centers (60 features); Find point clusters: cluster hulls (8 features). (id d27977c5-a8cd-4f40-9af6-797ca9424ec9:1)

[41] Plan: Cluster points of Housing developments (the Start plan's candidate c_ac70f2a99d9b). DBSCAN finds dense groups of Housing developments and separates noise. (id da4c2c71-fa66-4f6d-b51a-fc46626d4137:c_ac70f2a99d9b)

[42] Tool result: gp_find_point_clusters, step 2. Find point clusters: 2 layers saved: Find point clusters: Housing developments (40 features); Find point clusters: cluster hulls (1 feature). (id d27977c5-a8cd-4f40-9af6-797ca9424ec9:2)

[43] 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)

[44] Plan: Local morans i of School catchments (the Start plan's candidate c_98e5a5704b62). Local Moran's I maps clusters and outliers of 'children_5_17'. (id da4c2c71-fa66-4f6d-b51a-fc46626d4137:c_98e5a5704b62)

[45] Tool result: gp_outliers, step 0. Find outliers: 1 layer saved: Find outliers: School catchments (45 features). (id 2d7fd4ea-3928-4276-820c-93cbaa5d8370:0)

[46] 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)

[47] Plan: Global morans i of School catchments (the Start plan's candidate c_62c90091b007). Global Moran's I says whether similar values of 'children_5_17' sit next to each other. (id da4c2c71-fa66-4f6d-b51a-fc46626d4137:c_62c90091b007)

[48] Tool result: gp_spatial_autocorrelation, step 1. Spatial autocorrelation: done; no map output. (id 2d7fd4ea-3928-4276-820c-93cbaa5d8370:1)

[49] 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)

[50] Plan: Find nearest of Student homes and Major roads (the Start plan's candidate c_b5e7bf8242db). The nearest of Major roads to each of Student homes, with distances. (id da4c2c71-fa66-4f6d-b51a-fc46626d4137:c_b5e7bf8242db)

[51] Tool result: gp_find_nearest, step 0. Find nearest: 1 layer saved: Find nearest: Student homes (2500 features). (id 96f791ed-0415-4640-9ce5-4a248513b9be:0)

[52] Layer: Major roads. 22 features (id f801bcde-56b2-4e61-ba19-14d0273cc0a8)

[53] Tool result: gp_find_nearest, step 1. Find nearest: 1 layer saved: Find nearest: Student homes (2500 features). (id 96f791ed-0415-4640-9ce5-4a248513b9be:1)

[54] Tool result: gp_find_nearest, step 2. Find nearest: 1 layer saved: Find nearest: Student homes (2251 features). (id 96f791ed-0415-4640-9ce5-4a248513b9be:2)

[55] Rendering: Map: Emerging hot spots: Student homes (id 99865f9e-61ae-4a54-8e71-4f24fa9e045e)

[56] Rendering: Map: Emerging hot spots: Housing developments (id c6a807f2-4f43-4cf7-bbdd-0d94e82be22b)

[57] Rendering: Map: Repeat and near repeat classification: Student homes (id f7b40372-ed14-4b51-9886-d46e8380e886)

[58] Rendering: Map: Summarize within: School catchments (id 16071de3-2db4-4d2a-9f22-069707921f74)

[59] Rendering: Map: Summarize within: School catchments (id 6880f2c7-fb2a-402c-b96c-562b236be148)

[60] Rendering: Map: Summarize within: School catchments (id 7370b20e-f371-4cfd-b692-ca80e8c8b321)

[61] Rendering: Map: Hot spot analysis: Student homes (id 81a795ec-10a3-41fe-8418-bb2735586194)

[62] Rendering: Map: Hot spot analysis: Childcare centers (id d79041bc-d5c3-40bc-9a8b-1efee804ea40)

[63] Rendering: Map: Hot spot analysis: Housing developments (id 53ecf3c1-e4a9-4b9b-9614-b876299daf76)

[64] Rendering: Map: Calculate density: Student homes (id bfebe2b5-1bfa-44c5-b02d-d31e232f58c2)

[65] Rendering: Map: Calculate density: Childcare centers (id 4d64bc05-4b18-466d-9916-7cbaaba82672)

[66] Rendering: Map: Calculate density: Housing developments (id 9939a26d-3d46-4228-a88e-6276ccbbfce9)

[67] Rendering: Map: Find point clusters: Student homes (id 61cf32ac-295f-43d1-b073-76ae493477dd)

[68] Rendering: Map: Find point clusters: cluster hulls (id a6559fb3-821b-4fe4-ba92-a09934cf2f3c)

[69] Rendering: Map: Find point clusters: Childcare centers (id ece220ce-fe57-4bdc-a842-471ae4c94bed)

[70] Rendering: Map: Find point clusters: cluster hulls (id f519a030-b3a6-484c-93cf-8681144e4a8b)

[71] Rendering: Map: Find point clusters: Housing developments (id d14109fd-c380-468c-85e3-d7337bbf109e)

[72] Rendering: Map: Find point clusters: cluster hulls (id 078cb00b-7d37-4f3e-a204-57bd1a525b99)

[73] Rendering: Map: School catchments by children_5_17 (id a27302ad-817f-4696-a735-0a3a66fbb8ef)

[74] Rendering: Map: Find outliers: School catchments (id da831d0f-f5f9-4acb-b0cd-29083c443756)

[75] Rendering: Map: Find nearest: Student homes (id 40e2475f-79fa-4fc0-b95d-0920bd10ac82)

[76] Rendering: Map: Find nearest: Student homes (id 70ebd047-6948-4216-9cf9-75b35e49c830)

[77] Rendering: Map: Find nearest: Student homes (id 5b49f3b5-9a72-4fd4-96f3-f2c2703027ab)

[78] Rendering: Chart: Schools over time (built_year). 7 rows (id 880207dc-7868-40f4-b250-d08848fe4f7c)

[79] Rendering: Chart: Housing developments over time (completion_month). 20 rows (id ee6bae39-81ad-4908-93f3-48e4b8dab2f3)

[80] Rendering: Chart: Enrollment by school and year over time (school_year). 21 rows (id 3c99d290-2ab6-4f32-bf72-5e28a47a0305)

[81] Rendering: Chart: Emerging hot spots: Student homes. 8 rows (id c2759717-bd77-4ab7-80f2-0ff5624d1d0d)

[82] Rendering: Chart: Emerging hot spots: Housing developments. 6 rows (id 9da321f7-d9db-457c-b398-aadc13a51b1d)

[83] Rendering: Chart: Repeat and near repeat classification: Student homes. 20 rows (id e9d40fe4-2dcb-4274-a637-c4492395395e)

[84] Rendering: Chart: Summarize within: School catchments. 7 rows (id ed117d61-c2b8-4711-8e6b-6162a4f09bdd)

[85] Rendering: Chart: Summarize within: School catchments. 7 rows (id 538dd834-8935-4acf-aa77-c6b3e48cbffe)

[86] Rendering: Chart: Summarize within: School catchments. 5 rows (id eb2e00b9-1335-4b02-9b76-1e583e9b01a0)

[87] Rendering: Chart: Hot spot analysis: Student homes. 15 rows (id 12fec60a-bec0-4c49-8e09-a74a94fa49f5)

[88] Rendering: Chart: Hot spot analysis: Childcare centers. 7 rows (id 40554f68-7964-4f45-a1ac-19d17066ae79)

[89] Rendering: Chart: Hot spot analysis: Housing developments. 8 rows (id 01cab3a4-6f58-49af-8dd9-3f246085fc6b)

[90] Rendering: Chart: Calculate density: Student homes. 12 rows (id e75022eb-77cc-4f13-ae4e-64fa1d81fa6d)

[91] Rendering: Chart: Calculate density: Childcare centers. 8 rows (id 6c204cf8-7a68-44be-80f5-4f7cde56072e)

[92] Rendering: Chart: Calculate density: Housing developments. 8 rows (id ca34157f-9a27-457d-81e1-29b86f4f275e)

[93] Rendering: Chart: Find point clusters: Student homes. 2 rows (id e0334377-b051-4859-a2cd-6fbb987551b4)

[94] Rendering: Chart: Find point clusters: cluster hulls. 1 rows (id ef7a2223-1d85-448d-b093-0c2513affca5)

[95] Rendering: Chart: Find point clusters: Childcare centers. 9 rows (id 29ef1518-618b-4ea4-a5ee-2c96e1ec5827)

[96] Rendering: Chart: Find point clusters: cluster hulls. 8 rows (id 208e1927-bbe9-4755-a5ef-4f46a24d4689)

[97] Rendering: Chart: Find point clusters: Housing developments. 2 rows (id 40ab1fbd-7eab-4e95-ba32-5f9e4781e9d4)

[98] Rendering: Chart: Find point clusters: cluster hulls. 1 rows (id e4c8befa-2e05-41d0-bb8c-8fe8283edd90)

[99] Rendering: Chart: Find outliers: School catchments. 45 rows (id a50e1dab-42b9-4ff9-ae70-a9480fc0b696)

[100] Rendering: Chart: Find nearest: Student homes. 20 rows (id 4fc59395-9d71-4f81-958d-f88bf5cb6659)

[101] Rendering: Chart: Find nearest: Student homes. 20 rows (id 0852c0c8-a586-4261-b871-7d8105dd7e1b)

[102] Rendering: Chart: Find nearest: Student homes over time. 152 rows (id 75d40924-ed16-40d7-b9b0-3c4a873dd613)

[103] Rendering: Chart: Find nearest: Student homes over time. 152 rows (id b06f7c1c-a6b8-4ca2-8124-9b931b6d16b9)

[104] Rendering: Chart: Find nearest: Student homes over time. 228 rows (id 1007cf6f-af9a-4bc4-a5e5-aba4c425e396)

[105] Rendering: Chart: Find point clusters: Housing developments over time. 40 rows (id 96ec5cd7-6530-4341-a797-33f6a56e2fb7)

[106] Rendering: Chart: Find point clusters: Student homes over time. 76 rows (id 8bc71da9-95da-46d6-9855-df0cfc359e93)

[107] Rendering: Chart: Hot spot analysis: Housing developments over time. 40 rows (id 9cfa00e8-1d3c-4faa-95d0-f0720805090f)

[108] Rendering: Chart: Repeat and near repeat classification: Student homes over time. 114 rows (id b240dc06-1b76-4e65-bbc3-8914c9a85bb6)

[109] Dataset: Schools. vector, 45 rows (id febb26e1-84d6-4ddb-9a3f-f5e1f0b7f795)

[110] Dataset: School catchments. vector, 45 rows (id ad5953fb-dbca-4073-bc92-0e08c51e1651)

[111] Dataset: Bus stops. vector, 80 rows (id bb1e7508-4720-407c-b71c-a26b23a4f915)

[112] Dataset: Childcare centers. vector, 60 rows (id 4fef3ba9-e30d-4b7d-a5d6-605ce87f7d10)

[113] Dataset: Major roads. vector, 22 rows (id 2a9a4d23-28ed-4b9f-9748-91ea14603b7a)

[114] Dataset: Staffing. table, 45 rows (id afb73c89-d4b1-4d19-a074-f8a824e6cbbc)

[115] Dataset: School capacity review. document, ? rows (id 4d0bbaf0-8f67-45ac-b564-ab860018c60d)

[116] Record: Sample: Education, Toronto (id 89129455-9e05-4edb-9cc1-dcfb440cc5ba)

[117] Layer: Emerging hot spots: Student homes. 96 features (id 7dda31be-8b88-4be6-9357-f49b99e0ad3f)

[118] Layer: Emerging hot spots: Housing developments. 22 features (id 967c6193-6c0c-406a-a2c6-546a83bbbc65)

[119] Layer: Repeat and near repeat classification: Student homes. 2,500 features (id 4b593664-c2f4-4a80-95fe-f240335119a6)

[120] Layer: Summarize within: School catchments. 45 features (id d0384b31-144b-4c4f-a178-ec4c53caae50)

[121] Layer: Summarize within: School catchments. 45 features (id 478d8495-5caf-48d5-b6fa-eb6fb6b4293d)

[122] Layer: Summarize within: School catchments. 45 features (id 975d2d0e-1edb-42ad-b028-67b76335136f)

[123] Layer: Hot spot analysis: Student homes. 281 features (id a502e8fe-ffa2-4e21-9f58-9ec29380391f)

[124] Layer: Hot spot analysis: Childcare centers. 20 features (id 1b0dfd64-2343-44f2-94d6-e1605b181217)

[125] Layer: Hot spot analysis: Housing developments. 40 features (id e4d2879f-df41-457c-becc-2143c520d6c0)

[126] Layer: Calculate density: Student homes. 1,838 features (id 0a6f63b2-6a88-4993-a597-e2734a63f13a)

[127] Layer: Calculate density: Childcare centers. 112 features (id 9a43b28a-a83c-403a-89b3-276f72a30159)

[128] Layer: Calculate density: Housing developments. 80 features (id db78cd56-46ef-4a6b-8256-28f6fbc19e9)

[129] Layer: Find point clusters: Student homes. 2,500 features (id 6619977a-546f-41cf-a5d9-f9fa92133533)

[130] Layer: Find point clusters: cluster hulls. 1 features (id 93e7b932-a3f4-42f8-9d0a-b4d8266c9326)

[131] Layer: Find point clusters: Childcare centers. 60 features (id 394eb585-c105-412b-8add-e49c4579ae41)

[132] Layer: Find point clusters: cluster hulls. 8 features (id eac0e935-66fc-4c67-b7eb-367618a58b3c)

[133] Layer: Find point clusters: Housing developments. 40 features (id e8272a5f-e728-40d3-9f70-cc41284df4b6)

[134] Layer: Find point clusters: cluster hulls. 1 features (id e315ede4-4e6c-4399-b511-158bba19ae68)

[135] Layer: Find outliers: School catchments. 45 features (id c01d8927-0a79-40f8-ac32-3d74384c6f2c)

[136] Layer: Find nearest: Student homes. 2,500 features (id 9df5c370-c651-40e7-be15-05353e74ecf7)

[137] Layer: Find nearest: Student homes. 2,500 features (id a2c749a0-1ba4-4b20-92aa-88c388a66e07)

[138] Layer: Find nearest: Student homes. 2,251 features (id f6524eb3-a994-493f-8273-4c78a1381cac)

Appendix: the data behind the charts

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

period	series	value
2021-07-01	Student homes	0
2021-07-01	Enrollment by school and year	45
2021-07-01	Housing developments	0
2021-10-01	Student homes	0
2021-10-01	Enrollment by school and year	0
2021-10-01	Housing developments	0
2022-01-01	Student homes	0
2022-01-01	Enrollment by school and year	0
2022-01-01	Housing developments	0
2022-04-01	Student homes	0
2022-04-01	Enrollment by school and year	0
2022-04-01	Housing developments	0
2022-07-01	Student homes	0
2022-07-01	Enrollment by school and year	45
2022-07-01	Housing developments	0
2022-10-01	Student homes	0
2022-10-01	Enrollment by school and year	0
2022-10-01	Housing developments	0
2023-01-01	Student homes	0

period	series	value
2023-01-01	Enrollment by school and year	0
2023-01-01	Housing developments	2
2023-04-01	Student homes	0
2023-04-01	Enrollment by school and year	0
2023-04-01	Housing developments	0
2023-07-01	Student homes	224
2023-07-01	Enrollment by school and year	45
2023-07-01	Housing developments	2
2023-10-01	Student homes	264
2023-10-01	Enrollment by school and year	0
2023-10-01	Housing developments	1
2024-01-01	Student homes	19
2024-01-01	Enrollment by school and year	0
2024-01-01	Housing developments	0
2024-04-01	Student homes	68
2024-04-01	Enrollment by school and year	0
2024-04-01	Housing developments	3
2024-07-01	Student homes	335
2024-07-01	Enrollment by school and year	45
2024-07-01	Housing developments	3
2024-10-01	Student homes	263
2024-10-01	Enrollment by school and year	0
2024-10-01	Housing developments	4
2025-01-01	Student homes	25
2025-01-01	Enrollment by school and year	0
2025-01-01	Housing developments	2
2025-04-01	Student homes	86
2025-04-01	Enrollment by school and year	0
2025-04-01	Housing developments	2
2025-07-01	Student homes	385
2025-07-01	Enrollment by school and year	45
2025-07-01	Housing developments	3
2025-10-01	Student homes	284
2025-10-01	Enrollment by school and year	0
2025-10-01	Housing developments	1
2026-01-01	Student homes	36
2026-01-01	Enrollment by school and year	0
2026-01-01	Housing developments	3
2026-04-01	Student homes	102
2026-04-01	Enrollment by school and year	0
2026-04-01	Housing developments	2
2026-07-01	Student homes	409
2026-07-01	Enrollment by school and year	45

period	series	value
2026-07-01	Housing developments	5
2026-10-01	Student homes	0
2026-10-01	Enrollment by school and year	0
2026-10-01	Housing developments	0
2027-01-01	Student homes	0
2027-01-01	Enrollment by school and year	0
2027-01-01	Housing developments	0
2027-04-01	Student homes	0
2027-04-01	Enrollment by school and year	0
2027-04-01	Housing developments	3
2027-07-01	Student homes	0
2027-07-01	Enrollment by school and year	0
2027-07-01	Housing developments	2
2027-10-01	Student homes	0
2027-10-01	Enrollment by school and year	0
2027-10-01	Housing developments	2

Figure 25. Schools over time (built_year) [78]

bin_start	bin_end	count
350	528.1	14
528.1	706.3	21
706.3	884.4	3
884.4	1,063	0
1,063	1,241	3
1,241	1,419	2
1,419	1,597	2

Figure 26. Housing developments over time (completion_month) [79]

period	value
2023-01-01	164
2023-04-01	0
2023-07-01	621
2023-10-01	137
2024-01-01	0
2024-04-01	579
2024-07-01	775
2024-10-01	883
2025-01-01	515
2025-04-01	994
2025-07-01	583
2025-10-01	509
2026-01-01	484
2026-04-01	424
2026-07-01	1,297

period	value
2026-10-01	0
2027-01-01	0
2027-04-01	767
2027-07-01	337
2027-10-01	669

Figure 27. Enrollment by school and year over time (school_year) [80]

period	value
2021-07-01	45
2021-10-01	0
2022-01-01	0
2022-04-01	0
2022-07-01	45
2022-10-01	0
2023-01-01	0
2023-04-01	0
2023-07-01	45
2023-10-01	0
2024-01-01	0
2024-04-01	0
2024-07-01	45
2024-10-01	0
2025-01-01	0
2025-04-01	0
2025-07-01	45
2025-10-01	0
2026-01-01	0
2026-04-01	0
2026-07-01	45

Figure 28. Emerging hot spots: Student homes [81]

bin_start	bin_end	count
-0.896	2.069	77
2.069	5.033	7
5.033	7.998	1
7.998	10.96	5
10.96	13.93	0
13.93	16.89	3
16.89	19.86	0
19.86	22.82	3

Figure 29. Emerging hot spots: Housing developments [82]

bin_start	bin_end	count
-0.379	0.3548	15
0.3548	1.089	0

bin_start	bin_end	count
1.089	1.823	0
1.823	2.556	0
2.556	3.29	0
3.29	4.024	7

Figure 30. Repeat and near repeat classification: Student homes [83]

rank	name	distance_km
1	near_repeat	0.01
2	isolated	0.02
3	isolated	0.02
4	isolated	0.02
5	originator	0.03
6	isolated	0.03
7	near_repeat	0.03
8	isolated	0.03
9	near_repeat	0.04
10	near_repeat	0.04
11	originator	0.05
12	isolated	0.05
13	originator	0.05
14	near_repeat	0.05
15	isolated	0.05
16	originator	0.05
17	near_repeat	0.05
18	near_repeat	0.06
19	near_repeat	0.06
20	isolated	0.06

Figure 31. Summarize within: School catchments [84]

bin_start	bin_end	count
12	56.14	37
56.14	100.3	3
100.3	144.4	2
144.4	188.6	0
188.6	232.7	1
232.7	276.9	0
276.9	321	2

Figure 32. Summarize within: School catchments [85]

bin_start	bin_end	count
25	66	7
66	107	6
107	148	8
148	189	5
189	230	5

bin_start	bin_end	count
230	271	1
271	312	2

Figure 33. Summarize within: School catchments [86]

bin_start	bin_end	count
137	475.6	9
475.6	814.2	3
814.2	1,153	1
1,153	1,491	1
1,491	1,830	2

Figure 34. Hot spot analysis: Student homes [87]

bin_start	bin_end	band	band_label	count
-1	-0.5	not_significant	Not significant	52
-0.5	0	not_significant	Not significant	164
0	0.5	not_significant	Not significant	37
0.5	1	not_significant	Not significant	7
1	1.5	not_significant	Not significant	2
1.5	2	hot_90	Hot spot, 90% confidence	2
1.5	2	not_significant	Not significant	1
2	2.5	hot_95	Hot spot, 95% confidence	3
2.5	3	hot_99	Hot spot, 99% confidence	3
3	3.5	hot_99	Hot spot, 99% confidence	3
3.5	4	hot_99	Hot spot, 99% confidence	3
4	4.5	hot_99	Hot spot, 99% confidence	1
5	5.5	hot_99	Hot spot, 99% confidence	1
5.5	6	hot_99	Hot spot, 99% confidence	1
6.5	7	hot_99	Hot spot, 99% confidence	1

Figure 35. Hot spot analysis: Childcare centers [88]

bin_start	bin_end	band	band_label	count
-2	-1.5	cold_90	Cold spot, 90% confidence	3
-1.5	-1	not_significant	Not significant	1
-1	-0.5	not_significant	Not significant	3
0	0.5	not_significant	Not significant	4
0.5	1	not_significant	Not significant	6
1	1.5	not_significant	Not significant	1
1.5	2	hot_90	Hot spot, 90% confidence	2

Figure 36. Hot spot analysis: Housing developments [89]

bin_start	bin_end	band	band_label	count
-2	-1.5	not_significant	Not significant	1
-1.5	-1	not_significant	Not significant	14
-1	-0.5	not_significant	Not significant	8
-0.5	0	not_significant	Not significant	7
0	0.5	not_significant	Not significant	5
0.5	1	not_significant	Not significant	2
1	1.5	not_significant	Not significant	1
1.5	2	hot_90	Hot spot, 90% confidence	2

Figure 37. Calculate density: Student homes [90]

bin_start	bin_end	count
0	4	121
4	8	153
8	12	156
12	16	154
16	20	153
20	24	151
24	28	152
28	32	152
32	36	153
36	40	154
40	44	156
44	48	183

Figure 38. Calculate density: Childcare centers [91]

bin_start	bin_end	count
0	1.5	11
1.5	3	10
3	4.5	20
4.5	6	10
6	7.5	19
7.5	9	10
9	10.5	20
10.5	12	12

Figure 39. Calculate density: Housing developments [92]

bin_start	bin_end	count
0.0577	110.2	55
110.2	220.4	13
220.4	330.6	1
330.6	440.8	3
440.8	551	3
551	661.2	3
661.2	771.4	0

bin_start	bin_end	count
771.4	881.6	2

Figure 40. Find point clusters: Student homes [93]

cluster	features	fraction	share
Noise	1,490	0.596	59.6%
0	1,010	0.404	40.4%

Figure 41. Find point clusters: cluster hulls [94]

cluster	features	fraction	share
0	1	1	100.0%

Figure 42. Find point clusters: Childcare centers [95]

cluster	features	fraction	share
1	14	0.2333	23.3%
0	11	0.1833	18.3%
6	9	0.15	15.0%
3	7	0.1167	11.7%
4	6	0.1	10.0%
2	5	0.08333	8.3%
5	4	0.06667	6.7%
7	3	0.05	5.0%
Noise	1	0.01667	1.7%

Figure 43. Find point clusters: cluster hulls [96]

cluster	features	fraction	share
0	1	0.125	12.5%
1	1	0.125	12.5%
2	1	0.125	12.5%
3	1	0.125	12.5%
4	1	0.125	12.5%
5	1	0.125	12.5%
6	1	0.125	12.5%
7	1	0.125	12.5%

Figure 44. Find point clusters: Housing developments [97]

cluster	features	fraction	share
0	37	0.925	92.5%
Noise	3	0.075	7.5%

Figure 45. Find point clusters: cluster hulls [98]

cluster	features	fraction	share
0	1	1	100.0%

Figure 46. Find outliers: School catchments [99]

value	lag	type
-0.9672	-0.1255	NS
1.383	0.255	NS

value	lag	type
-0.6288	-0.6039	NS
-0.0459	-0.6442	NS
0.7193	0.1212	NS
1.317	0.8302	NS
-0.0572	0.3557	NS
0.0175	-0.639	NS
-0.5212	-0.3817	NS
-0.356	-0.459	NS
0.4873	0.0922	NS
0.2043	0.0226	NS
-0.9095	0.2148	NS
-0.2881	0.7917	NS
0.9559	0.2419	NS
-0.2405	-0.4586	NS
-0.6061	-0.1115	NS
-0.2824	0.1801	NS
-1.147	0.1129	NS
-1.243	0.0056	NS
-1.18	0.049	NS
-1.044	-0.5665	NS
1.131	-0.9146	NS
-0.0311	-0.7442	NS
0.2201	-0.5934	NS
-0.3798	-0.8665	NS
1.49	-0.2094	NS
1.824	-0.5705	NS
-0.0198	-0.3756	NS
0.8348	-0.5589	NS
0.0322	-0.2103	NS
-0.5473	0.169	NS
-1.234	-0.6621	NS
-0.5416	0.7018	NS
-0.4816	-0.4831	NS
-1.345	-0.8861	NS
-0.3617	0.0937	NS
-0.8529	0.1562	NS
-0.2711	-0.4635	NS
3.903	-0.5416	NS
-0.6831	-0.1341	NS
0.8302	0.8808	NS
1.119	-0.2824	NS
-0.682	0.1734	NS
0.4805	-0.3526	NS

Figure 47. Find nearest: Student homes [100]

rank	name
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1

Figure 48. Find nearest: Student homes [101]

rank	name
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1
1	1

Figure 49. Find nearest: Student homes over time [102]

period	series	value
2023-08-01	walk	44
2023-08-01	bus	25
2023-08-01	car	15
2023-08-01	bike	7
2023-09-01	walk	50
2023-09-01	bus	26
2023-09-01	car	24
2023-09-01	bike	5
2023-10-01	walk	48
2023-10-01	bus	28
2023-10-01	car	29
2023-10-01	bike	8
2023-11-01	walk	31
2023-11-01	bus	23
2023-11-01	car	19
2023-11-01	bike	3
2023-12-01	walk	17
2023-12-01	bus	12
2023-12-01	car	8
2023-12-01	bike	5
2024-01-01	walk	6
2024-01-01	bus	4
2024-01-01	car	1
2024-01-01	bike	1
2024-02-01	walk	2
2024-02-01	bus	0
2024-02-01	car	0
2024-02-01	bike	0
2024-03-01	walk	1
2024-03-01	bus	1
2024-03-01	car	0
2024-03-01	bike	0
2024-04-01	walk	1
2024-04-01	bus	0
2024-04-01	car	1
2024-04-01	bike	0
2024-05-01	walk	5
2024-05-01	bus	2
2024-05-01	car	6
2024-05-01	bike	1
2024-06-01	walk	12
2024-06-01	bus	15
2024-06-01	car	15

period	series	value
2024-06-01	bike	2
2024-07-01	walk	36
2024-07-01	bus	20
2024-07-01	car	15
2024-07-01	bike	5
2024-08-01	walk	56
2024-08-01	bus	26
2024-08-01	car	19
2024-08-01	bike	1
2024-09-01	walk	64
2024-09-01	bus	31
2024-09-01	car	25
2024-09-01	bike	3
2024-10-01	walk	48
2024-10-01	bus	44
2024-10-01	car	26
2024-10-01	bike	3
2024-11-01	walk	34
2024-11-01	bus	17
2024-11-01	car	15
2024-11-01	bike	4
2024-12-01	walk	28
2024-12-01	bus	16
2024-12-01	car	3
2024-12-01	bike	2
2025-01-01	walk	11
2025-01-01	bus	9
2025-01-01	car	3
2025-01-01	bike	0
2025-02-01	walk	0
2025-02-01	bus	0
2025-02-01	car	0
2025-02-01	bike	0
2025-03-01	walk	0
2025-03-01	bus	0
2025-03-01	car	0
2025-03-01	bike	0
2025-04-01	walk	2
2025-04-01	bus	1
2025-04-01	car	0
2025-04-01	bike	0
2025-05-01	walk	7
2025-05-01	bus	8

period	series	value
2025-05-01	car	1
2025-05-01	bike	1
2025-06-01	walk	25
2025-06-01	bus	13
2025-06-01	car	16
2025-06-01	bike	3
2025-07-01	walk	42
2025-07-01	bus	26
2025-07-01	car	20
2025-07-01	bike	3
2025-08-01	walk	55
2025-08-01	bus	38
2025-08-01	car	21
2025-08-01	bike	8
2025-09-01	walk	62
2025-09-01	bus	39
2025-09-01	car	27
2025-09-01	bike	9
2025-10-01	walk	49
2025-10-01	bus	38
2025-10-01	car	17
2025-10-01	bike	7
2025-11-01	walk	30
2025-11-01	bus	31
2025-11-01	car	16
2025-11-01	bike	6
2025-12-01	walk	29
2025-12-01	bus	13
2025-12-01	car	14
2025-12-01	bike	5
2026-01-01	walk	7
2026-01-01	bus	8
2026-01-01	car	7
2026-01-01	bike	3
2026-02-01	walk	1
2026-02-01	bus	3
2026-02-01	car	2
2026-02-01	bike	0
2026-03-01	walk	1
2026-03-01	bus	0
2026-03-01	car	3
2026-03-01	bike	0
2026-04-01	walk	2

period	series	value
2026-04-01	bus	1
2026-04-01	car	2
2026-04-01	bike	0
2026-05-01	walk	13
2026-05-01	bus	7
2026-05-01	car	7
2026-05-01	bike	0
2026-06-01	walk	27
2026-06-01	bus	21
2026-06-01	car	8
2026-06-01	bike	5
2026-07-01	walk	47
2026-07-01	bus	23
2026-07-01	car	13
2026-07-01	bike	4
2026-08-01	walk	60
2026-08-01	bus	47
2026-08-01	car	20
2026-08-01	bike	12
2026-09-01	walk	55
2026-09-01	bus	48
2026-09-01	car	33
2026-09-01	bike	12

Figure 50. Find nearest: Student homes over time [103]

period	series	value
2023-08-01	walk	48
2023-08-01	bus	29
2023-08-01	car	18
2023-08-01	bike	8
2023-09-01	walk	58
2023-09-01	bus	31
2023-09-01	car	26
2023-09-01	bike	6
2023-10-01	walk	54
2023-10-01	bus	34
2023-10-01	car	33
2023-10-01	bike	9
2023-11-01	walk	35
2023-11-01	bus	26
2023-11-01	car	20
2023-11-01	bike	4
2023-12-01	walk	21
2023-12-01	bus	14

period	series	value
2023-12-01	car	9
2023-12-01	bike	5
2024-01-01	walk	7
2024-01-01	bus	4
2024-01-01	car	1
2024-01-01	bike	1
2024-02-01	walk	2
2024-02-01	bus	0
2024-02-01	car	1
2024-02-01	bike	0
2024-03-01	walk	1
2024-03-01	bus	2
2024-03-01	car	0
2024-03-01	bike	0
2024-04-01	walk	1
2024-04-01	bus	0
2024-04-01	car	1
2024-04-01	bike	0
2024-05-01	walk	8
2024-05-01	bus	3
2024-05-01	car	6
2024-05-01	bike	1
2024-06-01	walk	14
2024-06-01	bus	16
2024-06-01	car	15
2024-06-01	bike	3
2024-07-01	walk	40
2024-07-01	bus	25
2024-07-01	car	19
2024-07-01	bike	5
2024-08-01	walk	59
2024-08-01	bus	32
2024-08-01	car	20
2024-08-01	bike	1
2024-09-01	walk	70
2024-09-01	bus	35
2024-09-01	car	25
2024-09-01	bike	4
2024-10-01	walk	53
2024-10-01	bus	48
2024-10-01	car	27
2024-10-01	bike	4
2024-11-01	walk	39

period	series	value
2024-11-01	bus	21
2024-11-01	car	17
2024-11-01	bike	4
2024-12-01	walk	28
2024-12-01	bus	16
2024-12-01	car	4
2024-12-01	bike	2
2025-01-01	walk	12
2025-01-01	bus	9
2025-01-01	car	3
2025-01-01	bike	1
2025-02-01	walk	0
2025-02-01	bus	0
2025-02-01	car	0
2025-02-01	bike	0
2025-03-01	walk	0
2025-03-01	bus	0
2025-03-01	car	0
2025-03-01	bike	0
2025-04-01	walk	2
2025-04-01	bus	1
2025-04-01	car	0
2025-04-01	bike	0
2025-05-01	walk	8
2025-05-01	bus	8
2025-05-01	car	2
2025-05-01	bike	1
2025-06-01	walk	29
2025-06-01	bus	15
2025-06-01	car	17
2025-06-01	bike	3
2025-07-01	walk	47
2025-07-01	bus	30
2025-07-01	car	20
2025-07-01	bike	3
2025-08-01	walk	62
2025-08-01	bus	41
2025-08-01	car	25
2025-08-01	bike	8
2025-09-01	walk	69
2025-09-01	bus	41
2025-09-01	car	29
2025-09-01	bike	10

period	series	value
2025-10-01	walk	58
2025-10-01	bus	40
2025-10-01	car	21
2025-10-01	bike	7
2025-11-01	walk	34
2025-11-01	bus	34
2025-11-01	car	17
2025-11-01	bike	6
2025-12-01	walk	31
2025-12-01	bus	14
2025-12-01	car	16
2025-12-01	bike	6
2026-01-01	walk	8
2026-01-01	bus	8
2026-01-01	car	7
2026-01-01	bike	3
2026-02-01	walk	1
2026-02-01	bus	3
2026-02-01	car	2
2026-02-01	bike	0
2026-03-01	walk	1
2026-03-01	bus	0
2026-03-01	car	3
2026-03-01	bike	0
2026-04-01	walk	2
2026-04-01	bus	1
2026-04-01	car	2
2026-04-01	bike	0
2026-05-01	walk	13
2026-05-01	bus	8
2026-05-01	car	7
2026-05-01	bike	0
2026-06-01	walk	31
2026-06-01	bus	22
2026-06-01	car	11
2026-06-01	bike	5
2026-07-01	walk	54
2026-07-01	bus	25
2026-07-01	car	13
2026-07-01	bike	4
2026-08-01	walk	62
2026-08-01	bus	51
2026-08-01	car	25

period	series	value
2026-08-01	bike	12
2026-09-01	walk	63
2026-09-01	bus	53
2026-09-01	car	35
2026-09-01	bike	12

Figure 51. Find nearest: Student homes over time [104]

period	series	value
2023-08-01	Dundas Nova Street	16
2023-08-01	Lakeview Avenue	15
2023-08-01	Forest Hill Avenue	17
2023-08-01	Front Street	15
2023-08-01	Bloor Nova Street	8
2023-08-01	Other	32
2023-09-01	Dundas Nova Street	18
2023-09-01	Lakeview Avenue	23
2023-09-01	Forest Hill Avenue	14
2023-09-01	Front Street	17
2023-09-01	Bloor Nova Street	10
2023-09-01	Other	39
2023-10-01	Dundas Nova Street	19
2023-10-01	Lakeview Avenue	16
2023-10-01	Forest Hill Avenue	14
2023-10-01	Front Street	20
2023-10-01	Bloor Nova Street	21
2023-10-01	Other	40
2023-11-01	Dundas Nova Street	13
2023-11-01	Lakeview Avenue	15
2023-11-01	Forest Hill Avenue	6
2023-11-01	Front Street	17
2023-11-01	Bloor Nova Street	10
2023-11-01	Other	24
2023-12-01	Dundas Nova Street	8
2023-12-01	Lakeview Avenue	7
2023-12-01	Forest Hill Avenue	12
2023-12-01	Front Street	8
2023-12-01	Bloor Nova Street	4
2023-12-01	Other	10
2024-01-01	Dundas Nova Street	4
2024-01-01	Lakeview Avenue	3
2024-01-01	Forest Hill Avenue	0
2024-01-01	Front Street	1
2024-01-01	Bloor Nova Street	1
2024-01-01	Other	4

period	series	value
2024-02-01	Dundas Nova Street	0
2024-02-01	Lakeview Avenue	1
2024-02-01	Forest Hill Avenue	0
2024-02-01	Front Street	0
2024-02-01	Bloor Nova Street	1
2024-02-01	Other	1
2024-03-01	Dundas Nova Street	1
2024-03-01	Lakeview Avenue	0
2024-03-01	Forest Hill Avenue	0
2024-03-01	Front Street	2
2024-03-01	Bloor Nova Street	0
2024-03-01	Other	0
2024-04-01	Dundas Nova Street	0
2024-04-01	Lakeview Avenue	0
2024-04-01	Forest Hill Avenue	0
2024-04-01	Front Street	0
2024-04-01	Bloor Nova Street	1
2024-04-01	Other	1
2024-05-01	Dundas Nova Street	4
2024-05-01	Lakeview Avenue	4
2024-05-01	Forest Hill Avenue	1
2024-05-01	Front Street	1
2024-05-01	Bloor Nova Street	4
2024-05-01	Other	4
2024-06-01	Dundas Nova Street	8
2024-06-01	Lakeview Avenue	3
2024-06-01	Forest Hill Avenue	10
2024-06-01	Front Street	7
2024-06-01	Bloor Nova Street	7
2024-06-01	Other	13
2024-07-01	Dundas Nova Street	17
2024-07-01	Lakeview Avenue	11
2024-07-01	Forest Hill Avenue	14
2024-07-01	Front Street	19
2024-07-01	Bloor Nova Street	11
2024-07-01	Other	17
2024-08-01	Dundas Nova Street	25
2024-08-01	Lakeview Avenue	22
2024-08-01	Forest Hill Avenue	15
2024-08-01	Front Street	11
2024-08-01	Bloor Nova Street	13
2024-08-01	Other	26
2024-09-01	Dundas Nova Street	24

period	series	value
2024-09-01	Lakeview Avenue	18
2024-09-01	Forest Hill Avenue	22
2024-09-01	Front Street	21
2024-09-01	Bloor Nova Street	10
2024-09-01	Other	39
2024-10-01	Dundas Nova Street	19
2024-10-01	Lakeview Avenue	21
2024-10-01	Forest Hill Avenue	18
2024-10-01	Front Street	15
2024-10-01	Bloor Nova Street	25
2024-10-01	Other	34
2024-11-01	Dundas Nova Street	14
2024-11-01	Lakeview Avenue	12
2024-11-01	Forest Hill Avenue	10
2024-11-01	Front Street	8
2024-11-01	Bloor Nova Street	14
2024-11-01	Other	23
2024-12-01	Dundas Nova Street	8
2024-12-01	Lakeview Avenue	8
2024-12-01	Forest Hill Avenue	12
2024-12-01	Front Street	4
2024-12-01	Bloor Nova Street	6
2024-12-01	Other	12
2025-01-01	Dundas Nova Street	7
2025-01-01	Lakeview Avenue	4
2025-01-01	Forest Hill Avenue	2
2025-01-01	Front Street	2
2025-01-01	Bloor Nova Street	5
2025-01-01	Other	5
2025-02-01	Dundas Nova Street	0
2025-02-01	Lakeview Avenue	0
2025-02-01	Forest Hill Avenue	0
2025-02-01	Front Street	0
2025-02-01	Bloor Nova Street	0
2025-02-01	Other	0
2025-03-01	Dundas Nova Street	0
2025-03-01	Lakeview Avenue	0
2025-03-01	Forest Hill Avenue	0
2025-03-01	Front Street	0
2025-03-01	Bloor Nova Street	0
2025-03-01	Other	0
2025-04-01	Dundas Nova Street	0
2025-04-01	Lakeview Avenue	0

period	series	value
2025-04-01	Forest Hill Avenue	2
2025-04-01	Front Street	0
2025-04-01	Bloor Nova Street	0
2025-04-01	Other	1
2025-05-01	Dundas Nova Street	5
2025-05-01	Lakeview Avenue	7
2025-05-01	Forest Hill Avenue	1
2025-05-01	Front Street	3
2025-05-01	Bloor Nova Street	2
2025-05-01	Other	1
2025-06-01	Dundas Nova Street	12
2025-06-01	Lakeview Avenue	8
2025-06-01	Forest Hill Avenue	15
2025-06-01	Front Street	10
2025-06-01	Bloor Nova Street	7
2025-06-01	Other	12
2025-07-01	Dundas Nova Street	15
2025-07-01	Lakeview Avenue	18
2025-07-01	Forest Hill Avenue	13
2025-07-01	Front Street	12
2025-07-01	Bloor Nova Street	12
2025-07-01	Other	30
2025-08-01	Dundas Nova Street	24
2025-08-01	Lakeview Avenue	22
2025-08-01	Forest Hill Avenue	26
2025-08-01	Front Street	18
2025-08-01	Bloor Nova Street	17
2025-08-01	Other	29
2025-09-01	Dundas Nova Street	37
2025-09-01	Lakeview Avenue	21
2025-09-01	Forest Hill Avenue	21
2025-09-01	Front Street	16
2025-09-01	Bloor Nova Street	21
2025-09-01	Other	33
2025-10-01	Dundas Nova Street	20
2025-10-01	Lakeview Avenue	26
2025-10-01	Forest Hill Avenue	18
2025-10-01	Front Street	12
2025-10-01	Bloor Nova Street	18
2025-10-01	Other	32
2025-11-01	Dundas Nova Street	16
2025-11-01	Lakeview Avenue	23
2025-11-01	Forest Hill Avenue	11

period	series	value
2025-11-01	Front Street	13
2025-11-01	Bloor Nova Street	7
2025-11-01	Other	21
2025-12-01	Dundas Nova Street	20
2025-12-01	Lakeview Avenue	7
2025-12-01	Forest Hill Avenue	13
2025-12-01	Front Street	8
2025-12-01	Bloor Nova Street	10
2025-12-01	Other	9
2026-01-01	Dundas Nova Street	5
2026-01-01	Lakeview Avenue	4
2026-01-01	Forest Hill Avenue	3
2026-01-01	Front Street	3
2026-01-01	Bloor Nova Street	6
2026-01-01	Other	5
2026-02-01	Dundas Nova Street	1
2026-02-01	Lakeview Avenue	1
2026-02-01	Forest Hill Avenue	2
2026-02-01	Front Street	0
2026-02-01	Bloor Nova Street	1
2026-02-01	Other	1
2026-03-01	Dundas Nova Street	0
2026-03-01	Lakeview Avenue	1
2026-03-01	Forest Hill Avenue	0
2026-03-01	Front Street	1
2026-03-01	Bloor Nova Street	0
2026-03-01	Other	2
2026-04-01	Dundas Nova Street	1
2026-04-01	Lakeview Avenue	0
2026-04-01	Forest Hill Avenue	0
2026-04-01	Front Street	1
2026-04-01	Bloor Nova Street	1
2026-04-01	Other	2
2026-05-01	Dundas Nova Street	4
2026-05-01	Lakeview Avenue	4
2026-05-01	Forest Hill Avenue	4
2026-05-01	Front Street	2
2026-05-01	Bloor Nova Street	6
2026-05-01	Other	8
2026-06-01	Dundas Nova Street	15
2026-06-01	Lakeview Avenue	14
2026-06-01	Forest Hill Avenue	15
2026-06-01	Front Street	11

period	series	value
2026-06-01	Bloor Nova Street	7
2026-06-01	Other	7
2026-07-01	Dundas Nova Street	22
2026-07-01	Lakeview Avenue	19
2026-07-01	Forest Hill Avenue	18
2026-07-01	Front Street	6
2026-07-01	Bloor Nova Street	8
2026-07-01	Other	23
2026-08-01	Dundas Nova Street	33
2026-08-01	Lakeview Avenue	28
2026-08-01	Forest Hill Avenue	24
2026-08-01	Front Street	18
2026-08-01	Bloor Nova Street	21
2026-08-01	Other	26
2026-09-01	Dundas Nova Street	31
2026-09-01	Lakeview Avenue	38
2026-09-01	Forest Hill Avenue	26
2026-09-01	Front Street	18
2026-09-01	Bloor Nova Street	17
2026-09-01	Other	33

Figure 52. Find point clusters: Housing developments over time [105]

period	series	value
2023-01-01	False	2
2023-01-01	True	0
2023-04-01	False	0
2023-04-01	True	0
2023-07-01	False	2
2023-07-01	True	0
2023-10-01	False	1
2023-10-01	True	0
2024-01-01	False	0
2024-01-01	True	0
2024-04-01	False	3
2024-04-01	True	0
2024-07-01	False	3
2024-07-01	True	0
2024-10-01	False	4
2024-10-01	True	0
2025-01-01	False	2
2025-01-01	True	0
2025-04-01	False	1
2025-04-01	True	1
2025-07-01	False	3

period	series	value
2025-07-01	True	0
2025-10-01	False	1
2025-10-01	True	0
2026-01-01	False	3
2026-01-01	True	0
2026-04-01	False	1
2026-04-01	True	1
2026-07-01	False	5
2026-07-01	True	0
2026-10-01	False	0
2026-10-01	True	0
2027-01-01	False	0
2027-01-01	True	0
2027-04-01	False	3
2027-04-01	True	0
2027-07-01	False	2
2027-07-01	True	0
2027-10-01	False	1
2027-10-01	True	1

Figure 53. Find point clusters: Student homes over time [106]

period	series	value
2023-08-01	True	78
2023-08-01	False	25
2023-09-01	True	94
2023-09-01	False	27
2023-10-01	True	95
2023-10-01	False	35
2023-11-01	True	63
2023-11-01	False	22
2023-12-01	True	29
2023-12-01	False	20
2024-01-01	True	9
2024-01-01	False	4
2024-02-01	True	3
2024-02-01	False	0
2024-03-01	True	2
2024-03-01	False	1
2024-04-01	True	1
2024-04-01	False	1
2024-05-01	True	12
2024-05-01	False	6
2024-06-01	True	30
2024-06-01	False	18

period	series	value
2024-07-01	True	60
2024-07-01	False	29
2024-08-01	True	70
2024-08-01	False	42
2024-09-01	True	81
2024-09-01	False	53
2024-10-01	True	82
2024-10-01	False	50
2024-11-01	True	58
2024-11-01	False	23
2024-12-01	True	27
2024-12-01	False	23
2025-01-01	True	12
2025-01-01	False	13
2025-02-01	True	0
2025-02-01	False	0
2025-03-01	True	0
2025-03-01	False	0
2025-04-01	True	2
2025-04-01	False	1
2025-05-01	True	9
2025-05-01	False	10
2025-06-01	True	34
2025-06-01	False	30
2025-07-01	True	53
2025-07-01	False	47
2025-08-01	True	73
2025-08-01	False	63
2025-09-01	True	90
2025-09-01	False	59
2025-10-01	True	74
2025-10-01	False	52
2025-11-01	True	59
2025-11-01	False	32
2025-12-01	True	35
2025-12-01	False	32
2026-01-01	True	14
2026-01-01	False	12
2026-02-01	True	3
2026-02-01	False	3
2026-03-01	True	2
2026-03-01	False	2
2026-04-01	True	3

period	series	value
2026-04-01	False	2
2026-05-01	True	14
2026-05-01	False	14
2026-06-01	True	32
2026-06-01	False	37
2026-07-01	True	41
2026-07-01	False	55
2026-08-01	True	77
2026-08-01	False	73
2026-09-01	True	69
2026-09-01	False	94

Figure 54. Hot spot analysis: Housing developments over time [107]

period	series	value
2023-01-01	not_significant	2
2023-01-01	hot_90	0
2023-04-01	not_significant	0
2023-04-01	hot_90	0
2023-07-01	not_significant	2
2023-07-01	hot_90	0
2023-10-01	not_significant	1
2023-10-01	hot_90	0
2024-01-01	not_significant	0
2024-01-01	hot_90	0
2024-04-01	not_significant	3
2024-04-01	hot_90	0
2024-07-01	not_significant	3
2024-07-01	hot_90	0
2024-10-01	not_significant	4
2024-10-01	hot_90	0
2025-01-01	not_significant	2
2025-01-01	hot_90	0
2025-04-01	not_significant	1
2025-04-01	hot_90	1
2025-07-01	not_significant	3
2025-07-01	hot_90	0
2025-10-01	not_significant	1
2025-10-01	hot_90	0
2026-01-01	not_significant	3
2026-01-01	hot_90	0
2026-04-01	not_significant	1
2026-04-01	hot_90	1
2026-07-01	not_significant	5
2026-07-01	hot_90	0

period	series	value
2026-10-01	not_significant	0
2026-10-01	hot_90	0
2027-01-01	not_significant	0
2027-01-01	hot_90	0
2027-04-01	not_significant	3
2027-04-01	hot_90	0
2027-07-01	not_significant	2
2027-07-01	hot_90	0
2027-10-01	not_significant	2
2027-10-01	hot_90	0

Figure 55. Repeat and near repeat classification: Student homes over time [108]

period	series	value
2023-08-01	isolated	66
2023-08-01	near_repeat	15
2023-08-01	originator	22
2023-09-01	isolated	65
2023-09-01	near_repeat	33
2023-09-01	originator	23
2023-10-01	isolated	66
2023-10-01	near_repeat	36
2023-10-01	originator	28
2023-11-01	isolated	55
2023-11-01	near_repeat	24
2023-11-01	originator	6
2023-12-01	isolated	29
2023-12-01	near_repeat	18
2023-12-01	originator	2
2024-01-01	isolated	11
2024-01-01	near_repeat	2
2024-01-01	originator	0
2024-02-01	isolated	3
2024-02-01	near_repeat	0
2024-02-01	originator	0
2024-03-01	isolated	3
2024-03-01	near_repeat	0
2024-03-01	originator	0
2024-04-01	isolated	2
2024-04-01	near_repeat	0
2024-04-01	originator	0
2024-05-01	isolated	14
2024-05-01	near_repeat	1
2024-05-01	originator	3
2024-06-01	isolated	28

period	series	value
2024-06-01	near_repeat	10
2024-06-01	originator	10
2024-07-01	isolated	43
2024-07-01	near_repeat	27
2024-07-01	originator	19
2024-08-01	isolated	55
2024-08-01	near_repeat	35
2024-08-01	originator	22
2024-09-01	isolated	52
2024-09-01	near_repeat	59
2024-09-01	originator	23
2024-10-01	isolated	54
2024-10-01	near_repeat	51
2024-10-01	originator	27
2024-11-01	isolated	42
2024-11-01	near_repeat	32
2024-11-01	originator	7
2024-12-01	isolated	29
2024-12-01	near_repeat	13
2024-12-01	originator	8
2025-01-01	isolated	20
2025-01-01	near_repeat	4
2025-01-01	originator	1
2025-02-01	isolated	0
2025-02-01	near_repeat	0
2025-02-01	originator	0
2025-03-01	isolated	0
2025-03-01	near_repeat	0
2025-03-01	originator	0
2025-04-01	isolated	3
2025-04-01	near_repeat	0
2025-04-01	originator	0
2025-05-01	isolated	12
2025-05-01	near_repeat	2
2025-05-01	originator	5
2025-06-01	isolated	35
2025-06-01	near_repeat	14
2025-06-01	originator	15
2025-07-01	isolated	46
2025-07-01	near_repeat	35
2025-07-01	originator	19
2025-08-01	isolated	56
2025-08-01	near_repeat	51

period	series	value
2025-08-01	originator	29
2025-09-01	isolated	63
2025-09-01	near_repeat	67
2025-09-01	originator	19
2025-10-01	isolated	42
2025-10-01	near_repeat	65
2025-10-01	originator	19
2025-11-01	isolated	53
2025-11-01	near_repeat	30
2025-11-01	originator	8
2025-12-01	isolated	39
2025-12-01	near_repeat	21
2025-12-01	originator	7
2026-01-01	isolated	17
2026-01-01	near_repeat	8
2026-01-01	originator	1
2026-02-01	isolated	5
2026-02-01	near_repeat	1
2026-02-01	originator	0
2026-03-01	isolated	4
2026-03-01	near_repeat	0
2026-03-01	originator	0
2026-04-01	isolated	5
2026-04-01	near_repeat	0
2026-04-01	originator	0
2026-05-01	isolated	16
2026-05-01	near_repeat	4
2026-05-01	originator	8
2026-06-01	isolated	37
2026-06-01	near_repeat	17
2026-06-01	originator	15
2026-07-01	isolated	34
2026-07-01	near_repeat	49
2026-07-01	originator	13
2026-08-01	isolated	48
2026-08-01	near_repeat	77
2026-08-01	originator	25
2026-09-01	isolated	49
2026-09-01	near_repeat	99
2026-09-01	originator	15