

Grid-Based Semantic Enrichment of Human Mobility Data for Urban Spatial Patterns Profiling: Hotspot and Service Gap Area Detection in Kota Yogyakarta, Indonesia

Iswari, L.,^{1,2} Permanasari, A. E.,^{1*} Fauziati, S.¹ and Widyawan¹

¹Department of Electrical and Information Engineering, Universitas Gadjah Mada, Yogyakarta, Indonesia
E-mail: adhitya@ugm.ac.id*

²Department of Informatics, Universitas Islam Indonesia, Yogyakarta, Indonesia
E-mail: lizdaiswari@mail.ugm.ac.id, ORCID ID: <https://orcid.org/0000-0002-5812-5370>

*Corresponding Author

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Abstract

Understanding urban spatial patterns from human mobility data requires semantic context beyond raw trajectory analysis. Existing approaches face three key limitations: grid size selection relies on empirical judgment rather than systematic evaluation, semantic enrichment assigns a single dominant label without quantifying degrees of dominance, and hotspot detection relies solely on demand-side density without considering urban facility supply. This study proposes a grid-based semantic enrichment framework for urban spatial pattern detection, comprising four components: a multi-criteria grid-size evaluation framework, confidence-score-based semantic enrichment, supply-demand synthesis for hotspot identification, and service gap identification. The framework was applied to Kota Yogyakarta, Indonesia, using over 4.6 million trajectory points from 130,395 mobile users. A grid size of 500 m was identified as optimal across ten evaluated resolutions. Supply-demand synthesis was applied to 342 grid cells. Results show that only 10.5% of cells qualify as full hotspots, concentrated in the central-eastern urban area and dominated by functionally mixed zones. Unmet demand is the primary service gap type, covering 24% of the study area, more than four times the proportion of underutilized supply (5.6%), suggesting the presence of informal activity not captured in spatial datasets. These findings demonstrate that the proposed framework provides a systematic methodology for extracting meaningful urban insights from large-scale human mobility data, with practical implications for evidence-based urban planning in mid-sized Indonesian cities.

Keywords: Grid Segmentation, Human Trajectory, Spatial Profiling, Urban Demand, Urban Supply

1. Introduction

Urban mobility analysis is a developed research area for understanding how citizens move and interact within cities. With the adoption of smartphones and location-based services, large-scale human mobility datasets are now available for analyzing movement patterns, identifying activity centers, and supporting urban planning decisions [1][2] and [3]. These datasets provide rich spatiotemporal information that can reveal where citizens gather, how long they stay, and what urban functions attract them. Understanding these patterns is essential for effective city management, transportation planning, and distribution of urban services [4] and [5]. However, existing trajectory analysis methods face fundamental limitations in

semantic understanding. Most current approaches focus on spatial clustering or density estimation without involving contextual information about what urban functions exist at the detected locations [6] and [7]. Methods such as kernel density estimation (KDE) and density-based clustering (DBSCAN) can identify where people gather, but cannot explain why those areas attract citizens or what services are available there [8] and [9]. Furthermore, existing methods rely on demand-side trajectory data alone without considering the supply-side availability of urban facilities, making it impossible to distinguish between well-served areas and areas where citizen demand is unmet [10] and [11].

Semantic enrichment of trajectory data is a promising approach to address these limitations. By attaching contextual information, semantic enrichment transforms raw movement records into meaningful representations of citizen activity [6] and [12]. Semantically enriched trajectory data enable researchers not only to identify where citizens gather but also to characterize the functional attributes of gathering areas, revealing patterns that pure spatiotemporal analysis cannot achieve [13] and [14]. Grid-based spatial segmentation has been widely adopted as a framework for organizing trajectory data and attaching semantic attributes from the third-party data provider, as it provides uniform spatial units that enable data analysis across large urban areas [15] and [16].

Despite these developments, several critical gaps remain in existing grid-based semantic enrichment approaches. First, grid size selection in existing studies relies on empirical judgment rather than quantitative evaluation, which limits the reproducibility and transferability of the framework [15] and [17]. Second, existing enrichment methods assign a single dominant semantic label to each grid cell without quantifying the degree of semantic dominance, potentially losing important information about mixed-use urban areas [13] and [14]. Third, region-of-interest detection in existing studies is based solely on demand-side trajectory density, without considering the supply-side availability of urban facilities, and may prevent the identification of service gaps where supply and demand are misaligned [5][11] and [18]. These gaps collectively indicate the need for a systematic computational framework that integrates multi-criteria grid evaluation, confidence-based semantic enrichment, and supply-demand synthesis to enable more comprehensive profiling of urban spatial patterns from large-scale human mobility data.

To address these limitations, this study proposes a grid-based semantic enrichment framework to profile urban spatial patterns in hotspot and service gap areas, applied to Kota Yogyakarta, Indonesia. The framework provides four contributions. First, a four-criteria quantitative evaluation framework for grid size selection that assesses data completeness, coverage, reliability, and diversity across multiple grid resolutions and provides objective grid size recommendations. Second, a confidence-scoring data classification that assigns four levels of semantic enrichment to grid cells for both POI and land use data. This classification provides a grid-based semantic complexity from functionally specialized to mixed-use areas. Third, a supply-demand synthesis framework that combines urban

facility supply with citizen activity demand for region-of-interest detection and distinguishes among full hotspots, partial hotspots, and non-hotspots. Fourth, a service gap identification framework that reveals spatial mismatches between urban facility supply and citizen demand, identifying both underutilized areas and unmet demand areas.

Kota Yogyakarta, Indonesia, is selected as the case study area because it represents a mid-sized Indonesian city with a diverse urban structure that includes commercial, educational, residential, and culturally significant areas. Evidence from mid-sized Indonesian cities is largely absent from the urban computing literature, which tends to focus on large metropolitan areas with commercially dense data coverage [13] and [17].

2. Related Works

2.1 Semantic Trajectory Enrichment

Raw trajectory data provide the spatiotemporal dimensions of human movement, but they lack contextual meaning about what users are doing at visited locations. Semantic enrichment addresses this limitation by attaching meaningful contextual attributes, such as POI types, land use classifications, and activity labels [6] and [7]. This enrichment enables the extraction of meaningful behavioral patterns, including activity sequences, such as "home → office → restaurant" and functional characterizations of visited locations [19] and [20]. Various approaches have been proposed for semantic enrichment, including stop-point extraction combined with POI matching [6], grid-based semantic region-of-interest mining with contextual annotations [7] and multi-semantic category assignment using external databases [20]. Early work established the conceptual framework of transforming raw GPS data into semantic episodes through stop identification and geographic annotation [21]. Despite these advances, existing enrichment methods mostly assign a single dominant semantic label to each spatial unit without quantifying the degree of semantic dominance, thereby losing important information about functionally mixed or heterogeneous urban areas. Additionally, most approaches enrich individual trajectory points rather than spatial grid units, limiting their scalability to large-scale datasets.

2.2 Grid-Based Spatial Segmentation

Grid-based spatial segmentation divides a study area into uniform rectangular cells, providing a structured and computationally efficient framework for organizing trajectory data and semantic attributes [15] and [22]. Grid-based methods have

been adopted in urban mobility analysis because they offer consistent spatial units that enable comparison across the study area and avoid the parameter sensitivity issues associated with density-based clustering approaches [16] and [23]. Grid size significantly affects the accuracy of urban functional area identification and spatial pattern detection. Studies have demonstrated that different grid resolutions capture different scales of urban spatial patterns, from building-level detail at fine resolutions to neighborhood-scale patterns at coarser resolutions [15]. POI density and spatial heterogeneity within grid cells have been used to characterize urban functional areas at various spatial scales [14] and [17]. However, existing grid-based studies select grid sizes based on empirical judgment or prior literature without having a quantitative evaluation across multiple criteria. No existing study proposes a multi-criteria scoring framework that simultaneously evaluates the completeness, coverage, reliability, and diversity of semantic enrichment across grid resolutions, thereby limiting the reproducibility and transferability of grid-size recommendations.

2.3 Urban Hotspot Detection and Service Gap Analysis

Urban hotspot detection identifies areas of concentrated citizen activity within cities [2] and [16]. Existing studies define hotspots primarily by trajectory point density, in which areas exceeding a specified threshold are classified as hotspots [16] and [22]. Some studies refine this by incorporating hierarchical density classification based on percentile thresholds [9] and [23]. More recent work has extended hotspot definitions by incorporating POI data and land use information to characterize the functional nature of detected areas [13] and [24]. Service gap analysis examines the spatial mismatch between the supply of urban facilities and the demand from the population they serve [5] and [18]. Existing studies typically use population density, demographic models, or fixed distance thresholds as demand measures, without incorporating actual human mobility data [11] and [25]. Studies of facility accessibility have used spatial proximity metrics and population distributions to identify underserved areas, but have not measured actual utilization [18]. POI-based distribution analyses have mapped facility locations but have not identified areas where informal demand is not captured by formal records [25] and [26].

A shared limitation across both hotspot detection and service gap studies is the reliance on a single dimension of analysis. Hotspot methods use only

demand-side density and do not consider supply-side facility availability. Service gap methods use static population or administrative data, without incorporating actual mobility stop points. Neither approach can simultaneously distinguish well-served areas, underutilized supply, and unmet demand at the grid cell level [5] and [11].

3. Methods

3.1 Data Sources and Study Area

The mobility dataset was obtained through a formal data-sharing agreement with a telecommunications provider in Indonesia. The dataset covers December 2021 and contains 11,088,800 trajectory points from 370,191 unique users. Each record contains four attributes: Mobile Advertising ID (MAID), latitude, longitude, and timestamp, as shown in Table 1. MAIDs are unique 36-character pseudonymous identifiers assigned to mobile devices for advertising purposes. All records were provided in anonymized form. No, personally identifiable information was collected or processed in this study.

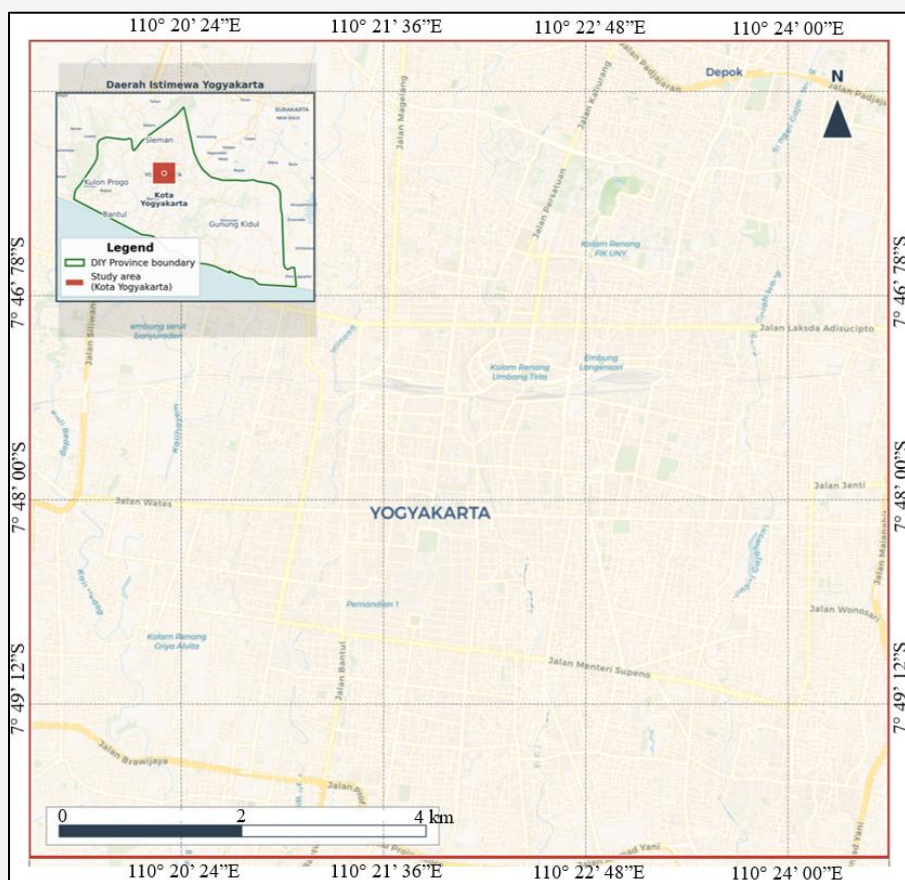
MAID-based mobility data is collected via Software Development Kits (SDKs) embedded in mobile applications that have active location permissions [27]. This dataset represents a specific user segment: individuals who actively use smartphones and have granted location permissions, primarily consisting of working-age individuals with consistent device engagement [28]. This characteristic is important for acknowledging potential sampling biases that limit generalizability to the broader population [2]. The study area is Kota Yogyakarta, Indonesia. This city represents a mid-sized Indonesian city with a diverse urban structure, including commercial districts, educational zones, residential neighborhoods, and cultural heritage areas. The area is defined by the bounding box: 110.325°E to 110.410°E and -7.835°S to -7.755°S, covering approximately 9.5 km × 8.9 km, as illustrated in Figure 1.

3.2 Research Framework

This study proposes a two-phase computational framework for detecting urban spatial patterns by integrating a semantically enriched spatial grid and extracted activity from human mobility data. The first phase identifies the optimal grid resolution. The framework consists of four steps: data preparation, grid semantic enrichment, segmentation evaluation, and enrichment method comparison, as illustrated in Figure 2. The second phase detects urban spatial patterns.

Table 1: Sample of human mobility data

Maid	Latitude	Longitude	Datetime	Geometry
b74fb520-8f92-47fe-9771-affc32c6af5d	-7.794260	110.368910	2021-12-01 00:00:00	POINT (110.36891 - 7.79426)
b74fb520-8f92-47fe-9771-affc32c6af5d	-7.794240	110.368912	2021-12-01 00:00:00	POINT (110.3689117431641 -7.79424)
b74fb520-8f92-47fe-9771-affc32c6af5d	-7.794260	110.368912	2021-12-01 00:00:00	POINT (110.3689117431641 -7.79426)
b74fb520-8f92-47fe-9771-affc32c6af5d	-7.794250	110.368919	2021-12-01 00:00:00	POINT (110.3689193725586 -7.79425)
b74fb520-8f92-47fe-9771-affc32c6af5d	-7.794240	110.368912	2021-12-01 00:00:00	POINT (110.3689117431641 -7.79424)

**Figure 1:** Study area in Kota Yogyakarta

The framework for detecting urban spatial patterns. This phase consists of zone mapping, supply characterization, demand characterization, and supply-demand synthesis, including hotspot and service gap identification, as illustrated in Figure 3. The framework processes two main inputs: human trajectory data and OpenStreetMap (OSM) data. In Phase 1 (Figure 2), OSM data is enriched onto grid cells, producing enriched grids.

In parallel, trajectory data is processed into stop points. These two outputs become the inputs for Phase 2 (Figure 3). Enriched grids are used for supply characterization, while stop points are used for demand characterization. Both supply and demand profiles are then combined to profile urban spatial patterns, producing hotspot and service gap areas as the final output.

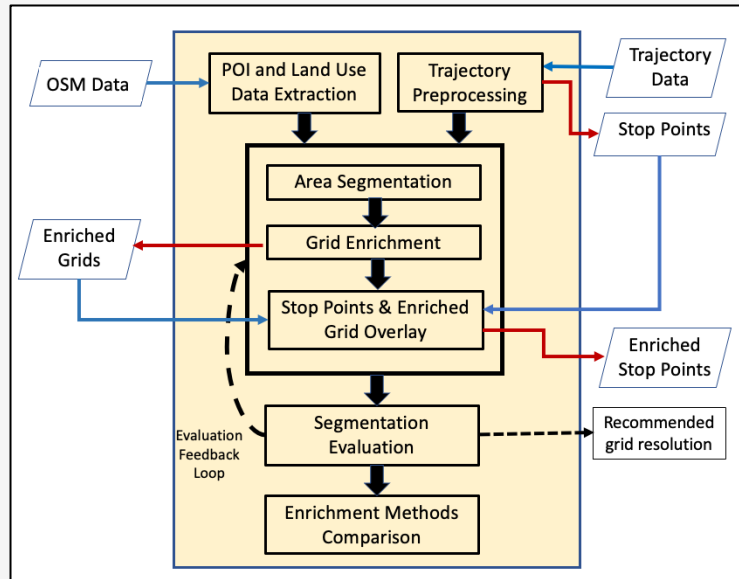


Figure 2: Framework for finding optimal grid resolution

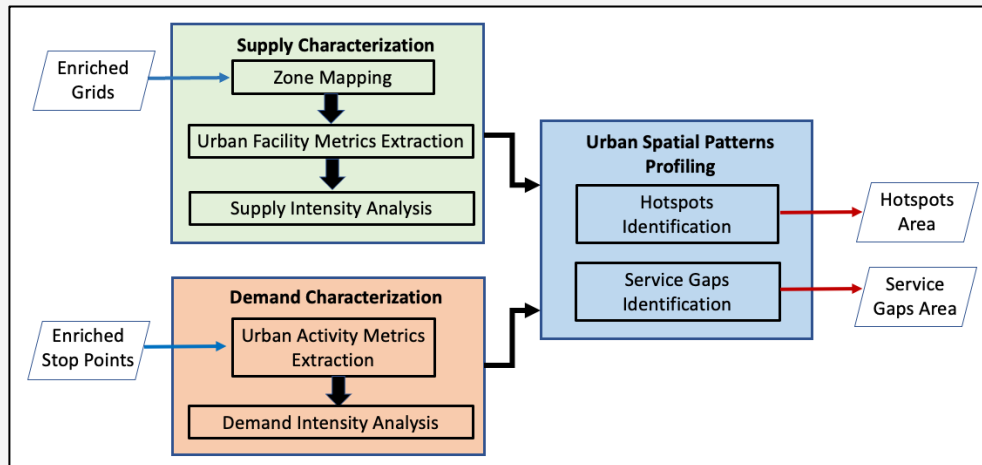


Figure 3: Framework of urban spatial patterns detection

3.2.1 Data preparation

Geographic context data were extracted from OpenStreetMap (OSM) within the study area bounding box [29]. Two types of data were retrieved: Points of Interest (POI) as point data and land use as polygon data. POI data describe urban facilities, such as restaurants, schools, and places of worship [14]. Land use data describe functional zones, such as residential, commercial, and agricultural areas [13]. Trajectory preprocessing consists of duplicate removal and stop-point filtering. Duplicate records are points that share identical MAID, latitude, longitude, and timestamp. When duplicate records are detected, only the first occurrence is retained. Raw trajectory data contains both movement points and stationary points. To focus the analysis on locations where users actually stop and stay, only stop points are retained. A stop

point is defined as a location where a user remains within a 200-meter radius for at least 20 minutes [30][31] and [32]. Points that do not meet both conditions are considered transient movement points and are removed.

3.2.2 Grid semantic enrichment

The study area covers approximately 82.95 km². Grid size significantly affects the identification accuracy of urban functional areas and spatial patterns [15] and [16]. A finer grid captures more spatial detail but may result in sparse data per cell, while a coarser grid aggregates more data per cell but may lose spatial specificity. Ten grid sizes were tested at 100-meter intervals, ranging from 100 m to 1000 m. The smaller resolutions (100-300 m) capture building-level and street-level detail, with 100 m approximating individual building size and

200-300 m representing pedestrian-scale accessibility [13] [15] and [33]. The medium resolutions (400-600 m) operate at block-level scale, with 500 m validated for human mobility trajectory analysis and mixed-functional area identification [15] and [34]. Larger resolutions (700-1000 m) capture neighborhood-scale patterns in broader activity spaces [15] and [16]. This systematic comparison enables empirical determination of the most effective resolution for identifying urban spatial patterns. Each grid cell is assigned contextual attributes from OSM data. The enrichment process consists of three steps: dominant type identification, confidence score calculation, and semantic label assignment. For each grid cell, the dominant POI type is identified as the amenity type with the highest frequency within the cell boundary. The dominant land use is the one with the largest total intersection area within the cell. The dominance of each semantic type is quantified using a confidence score, calculated as shown in Equations 1 and 2:

$$POI_conf_i = \max_j \left(\frac{n_{i,j}}{n_{t,i}} \right) \cdot 100 \quad \text{Equation 1}$$

$$LU_conf_i = \max_k \left(\frac{a_{i,k}}{a_{t,i}} \right) \cdot 100 \quad \text{Equation 2}$$

Where:

- POI_conf_i = POI confidence score for grid cell i (%)
- LU_conf_i = LU confidence score for grid cell i (%)
- $n_{i,j}$ = count of POI type j in grid cell i
- $n_{t,i}$ = total count of POI features in grid cell i
- $a_{i,k}$ = area of land use type k in grid cell i (m^2)
- $a_{t,i}$ = total area of grid cell i (m^2)
- $\max_j$ = maximum values across all POI types j present in a grid cell
- $\max_k$ = maximum values across all land use types k present in a grid cell

Each cell is assigned a semantic label based on four confidence levels, as summarized in Table 2. A threshold of 50% distinguishes semantically dominant from semantically mixed cells [15] and [35]. High-confidence cells receive a single label representing homogeneous or clear functional specialization. Medium-confidence cells receive dual labels for the first- and second-ranked types. These cells represent areas with transient or moderate semantic diversity. Low-confidence cells

are labeled "Mixed-Use," indicating high semantic heterogeneity. Cells with no OSM data are assigned "NA."

3.2.3 Segmentation evaluation

To identify the optimal grid size, each grid resolution is evaluated using four criteria: data completeness ($C1$), data coverage ($C2$), data reliability ($C3$), and data diversity ($C4$) [15]. Data completeness measures the proportion of grid cells and stop points receiving at least one semantic attribute, calculated as the average of grid and point completeness. Data coverage measures the intensity and spatial quality of semantic information, calculated as the average of land use coverage and normalized POI density. Data reliability measures the certainty of semantic classification using confidence scores from Equations 1 and 2. Data diversity measures the proportion of unique semantic types captured relative to the total types available in the dataset. The four criteria and the final weighted total score are calculated as shown in Equations 3 to 7:

$$C1 = \frac{1}{G} \sum_{i=1}^G \left[0.5 \cdot \frac{n_{types,i}}{2} + 0.5 \cdot \frac{P_{classified,i}}{P_i} \right] \cdot 100 \quad \text{Equation 3}$$

$$C2 = \frac{1}{G} \sum_{i=1}^G \frac{1}{2} \left[\frac{\sum_{j=1}^{m_i} a_{i,j}}{A_i} + \frac{n_i}{\rho_{max}} \right] \cdot 100 \quad \text{Equation 4}$$

$$C3 = \frac{1}{G} \sum_{i=1}^G \frac{1}{2} [POI_conf_i + LU_conf_i] \quad \text{Equation 5}$$

$$C4 = \frac{1}{G} \sum_{i=1}^G \frac{T_i}{N_{total}} \cdot 100 \quad \text{Equation 6}$$

$$TS = w_1 \cdot C1 + w_2 \cdot C2 + w_3 \cdot C3 + w_4 \cdot C4 \quad \text{Equation 7}$$

Where:

- G = total number of grid cells
- $n_{types,i}$ = number of semantic data types within grid cell i
- $P_{classified,i}$ = number of stop points that have at least one semantic value within grid cell i
- P_i = total number of stop points within grid cell i

- $a_{i,j}$ = area of land use polygon j in grid cell i
 A_i = total area of grid cell i
 m_i = number of land use polygons intersecting within grid cell i
 n_i = number of POI features within grid cell i
 ρ_{max} = maximum POI density across all grid resolutions evaluated
 T_i = number of unique semantic types (POI and land use) within grid cell i
 N_{total} = total number of unique semantic types in the reference dataset
 w_1, w_2, w_3, w_4 = weights assigned to C1, C2, C3, and C4 respectively

Equal weighting is adopted as the primary evaluation scheme, as it provides an unbiased baseline that treats all criteria equally. Two additional weighting schemes are applied as sensitivity analyses to verify that the optimal grid recommendation remains consistent under alternative assumptions, as summarized in Table 3. The grid size achieving the highest total score under Scheme 1 is recommended as the optimal resolution. Schemes 2 and 3 are used to verify the robustness of this recommendation.

3.2.4 Enrichment method comparison

The proposed grid-based approach is compared against DBSCAN clustering and Kernel Density Estimation (KDE). All three methods share the same objective: attaching semantic attributes from OSM data to stop points. However, they differ in how they organize space to achieve this enrichment. The three methods are evaluated on four criteria: trajectory coverage, completeness, diversity, and

processing time. All experiments were conducted in a Python 3.10 environment using pandas, NumPy, and scikit-learn for data processing and clustering. The system used a Linux server with 251 GB of RAM.

DBSCAN groups stop points into clusters using a distance threshold (epsilon) and a minimum point count, then assigns dominant semantic labels based on POI and land use data within each cluster's convex hull [36] and [37]. DBSCAN is widely used for trajectory analysis due to its ability to identify clusters of arbitrary shape without requiring a predefined number of clusters. However, it has limitations of sensitivity to parameter settings and a tendency to produce broad hotspot areas that reduce analytical precision. KDE computes a continuous density surface for each semantic type and assigns the dominant label at each location based on the maximum density value [2] and [38]. KDE is also widely used in trajectory analysis for its ability to produce smooth, continuous representations of spatial density. However, KDE is sensitive to bandwidth selection, and its results can be significantly affected by this parameter choice.

3.2.5 Zone mapping.

Raw OSM semantic types are numerous and fine-grained. To enable meaningful analysis, individual POI and land use types are mapped to broader functional-zone categories, as widely used in semantic trajectory analysis [13] and [17]. POI amenity types are grouped into seven functional zones (Table 4), and land use types into six functional zones (Table 5). This reduces the number of semantic categories from 88 raw POI types and 21 land use types to more interpretable functional zones.

Table 2: Confidence level and semantic label assignment

Confidence Score	Confidence Level	Semantic Category	Semantic Value
> 50%	High	Homogeneous	Dominant type
30% - 50%	Medium	Transient	Dual-label
< 30%	Low	Heterogenous	Mixed-use
0%	No Class	No Data	NA

Table 3: Weighting schemes for grid evaluation

Scheme	C1(%)	C2(%)	C3(%)	C4(%)	Rationale
Scheme 1	25	25	25	25	Equal importance and unbiased baseline
Scheme 2	40	20	20	20	Prioritizes completeness as the most critical dimension
Scheme 3	30	30	30	10	De-emphasize diversity and prioritizes data classification

Table 4: POI zone mapping

POI Zone	POI Type
Commercial	ATM, bank, cafe, fast food, internet cafe, karaoke box, restaurant, shop, spa, studio, theatre
Industrial or Logistics	Post box, post office, waste disposal
Transport or Mobility	Bench, bus station, car rental, car wash, fuel, motorcycle parking, parking space, shelter, ticket validator
Educational or Institutional	College, community center, conference center, courthouse, government, kindergarten, library, prep school, prison, school, townhall, university
Religious	Grave yard, place of mourning, place of worship
Health service	Clinic, dentist, doctors, hospital, pharmacy
Residential	Rumah susun

Table 5: Land use zone mapping

Land Use Zone	Land Use Type
Agriculture or Green	Aquaculture, brownfield, farmland, farmyard, flowerbed, forest, grass, greenery, greenfield, meadow, orchard
Space	
Residential	Residential
Commercial	Commercial, recreation ground, retail
Transport or Mobility	Railway
Educational	Civic admin, education, institutional, military
Religious	Cemetery, religious

Table 6: Supply-demand intensity classification rules

Class	Threshold	Supply Intensity Interpretation	Demand Intensity Interpretation
High	Value $\geq$ Q3	Well-supplied area with strong facility presence	High citizen activity, frequently visited or long-stay area
Medium	Q1 < Value < Q3	Moderately supplied area	Moderate citizen activity
Low	0 < Value $\leq$ Q1	Poorly supplied area with limited facilities	Low citizen activity, rarely visited or brief-stay area
Empty	Value = 0	No facility data recorded in OSM	No stop points recorded in this cell

3.2.6 Supply and Demand characterization

Urban facility metrics quantify urban supply in each grid cell. They describe the facilities available in an area, regardless of whether citizens actually visit them. Three metrics are used to quantify urban facility supply: POI density, land use coverage, and semantic type variety. POI density measures the concentration of urban facilities and is widely used in hotspot detection and urban functional zone analysis [23] and [39]. Land use coverage captures the physical infrastructure and zoning characteristics of each cell [16]. Semantic type variety measures functional diversity, which is associated with greater urban attractiveness and potential for citizen gathering [13].

Urban activity metrics quantify urban demand based on the stop point in each cell. Demand characteristics describe how citizens actually use urban space, independent of what facilities are available. Four metrics are used to quantify urban activity profiles: visit frequency, unique users, mean

dwel duration, and return rate. Visit frequency is the total number of stop points per cell. This metric indicates location accessibility and attractiveness [16] and [22]. Unique users is the count of distinct user IDs per cell, representing the diversity of visitors. Mean dwell duration is the average stay duration per cell and distinguishes transit behavior from extended engagement [6] and [12]. Return rate is the ratio of visits to unique users and distinguishes routine-oriented from destination-oriented behavior. Each supply and demand metric is classified into four levels using quartile-based thresholds. Quartile-based classification adapts to the actual distribution of values, avoiding the limitations of arbitrary fixed thresholds [15] and [16]. The classification rules are summarized in Table 6. Each grid cell receives three supply-class labels and four demand-class labels, providing a comprehensive multidimensional profile of urban supply and demand.

3.2.7 Hotspot identification

A hotspot is defined as a grid cell that simultaneously shows high supply and high demand. Three criteria are applied, using Q3 as the threshold: POI density and semantic type variety as supply-side criteria, and visit frequency as the demand-side criterion. Using a single criterion produces two types of false positives: cells with high POI density but low visits indicate underutilized facilities, while cells with high visits but low POI density may reflect transit behavior rather than genuine gathering.

Each grid cell is assigned one of four classification levels based on the number of criteria met. Full hotspots meet all three criteria, representing genuine urban gathering areas with strong supply-demand alignment. Partial hotspots meet two of three criteria. Weak signal cells meet only one criterion. Non-hotspots meet none. This four-level classification captures the hierarchy of urban activity intensity, distinguishing genuine gathering areas from areas of lower functional significance. The dominant POI zone label of each hotspot cell is reported to provide functional context for each identified area. This four-level classification captures the hierarchy of urban activity intensity, distinguishing genuine gathering areas from areas of lower functional significance [16] and [20].

3.2.8 Service gap identification

Service gaps are identified through a supply-demand contrast logic that reveals spatial mismatches between available urban facilities and actual citizen activity. Identifying service gaps has direct implications for urban planning, as it reveals where facilities are underutilized and where new facilities may be needed to meet unmet citizen demand [26]. A supply-demand mismatch matrix classifies each cell based on the combination of POI density class and visit frequency class (Figure 4). Four categories are defined. First, Balanced Active: high or medium level of both POI density and visit frequency, indicating a well-served area. Second, Type 1 Underutilized Supply: high or medium POI density but low visits, indicating that facilities exist but attract limited human activity. This may reflect poor physical accessibility or a mismatch between the facility type and the community's actual needs. Third, Type 2 Unmet Demand: high or medium visits but low or empty POI density, indicating active areas with scarce formal facilities. This may reflect informal activity or areas requiring new facility provision. Fourth, Balanced Inactive: low or empty POI density and low visits, representing peripheral areas with minimal urban activity on both

supply and demand sides. The land use zone of each cell is examined to provide additional spatial context, linking supply-demand mismatches to the physical characteristics of the surrounding urban environment. Together, the supply-demand synthesis produces four analytical outputs per grid cell: hotspot level, service gap type, dominant POI zone label, and dominant land use zone label.

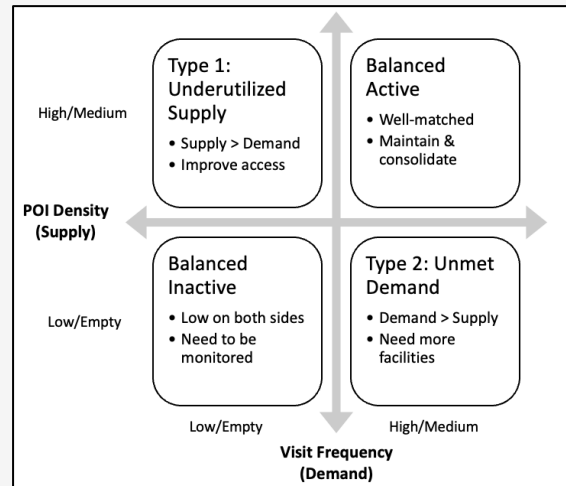


Figure 4: Supply-demand mismatch matrix

4. Results and Discussion

4.1 Data Preprocessing

The original dataset contains 11,088,800 trajectory points from 370,191 unique users. Duplicate removal eliminated 35.7% of records, reducing the dataset to 7,127,812 points. This high duplication rate is consistent with known characteristics of SDK-based location data, where mobile applications may log repeated signals at fixed intervals when the device is stationary [27]. Stop-point filtering using a 200-meter radius and 20-minute minimum stop duration retained 301,084 genuine stop points from 130,395 unique users, derived from 4,629,167 trajectory points. This confirms that a large proportion of raw trajectory data reflects transient movement rather than genuine stationary activity.

OSM data extraction provides 3,261 POI features across 86 unique amenity types. The three dominant categories are restaurants (21.6%), places of worship (14.5%), and schools (10.0%). The land use dataset contains 584 features across 24 unique types, dominated by farmland (25.8%), residential areas (17.4%), and cemeteries (16.7%). The dominance of farmland and cemeteries reflects Kota Yogyakarta's mid-sized city character, where urban development coexists with agricultural and cultural land uses. To examine spatial distribution, the study area was divided into nine sub-areas using a 3×3 decomposition, as summarized in Table 7 and

illustrated in Figure 5. Three patterns are identified. First, human activity is strongly concentrated in the central area. The Center accounts for the highest stop-point density (21.8%), followed by East (18.2%) and North-East (13.2%). Together, these three sub-areas contain 53.2% of all stop points while covering only one-third of the study area. Second, POI distribution partially aligns with the stop-point distribution, but there are misalignments.

The North accounts for 19% of POIs but only 8.3% of stop points, suggesting an underutilized supply. The East accounts for 18.2% of stop points but only 11% of POIs, suggesting unmet demand. Third, land use coverage does not track human activity patterns. The North-West has the highest land use coverage (9.61%) despite the lowest stop-point density (4.5%). These coarse-scale misalignments provide the basis for the grid-level service gap findings in Section 4.6.

Table 7: Stop points distribution on 3x3 sub-areas

Sub-Areas	Stop Points Density	POI Density	Land Use Coverage
North-West	13,663 (4.5%)	64 (2%)	88.56ha (9.61%)
North	24,980 (8.3%)	622 (19%)	31.25ha (3.39%)
North-East	39,889 (13.2%)	520 (16%)	61.59ha (6.69%)
West	21,575 (7.2%)	146 (4%)	32.37ha (3.51%)
Center	65,769 (21.8%)	798 (24%)	59.97ha (6.51%)
East	54,890 (18.2%)	364 (11%)	63.41ha (6.88%)
South-West	27,598 (9.2%)	137 (4%)	72.77ha (7.90%)
South	18,663 (6.2%)	410(13%)	16.02ha (1.74%)
South-East	34,057 (11.3%)	200(6%)	49.92ha (5.42%)
Total	301,084	3,261	475.86 ha

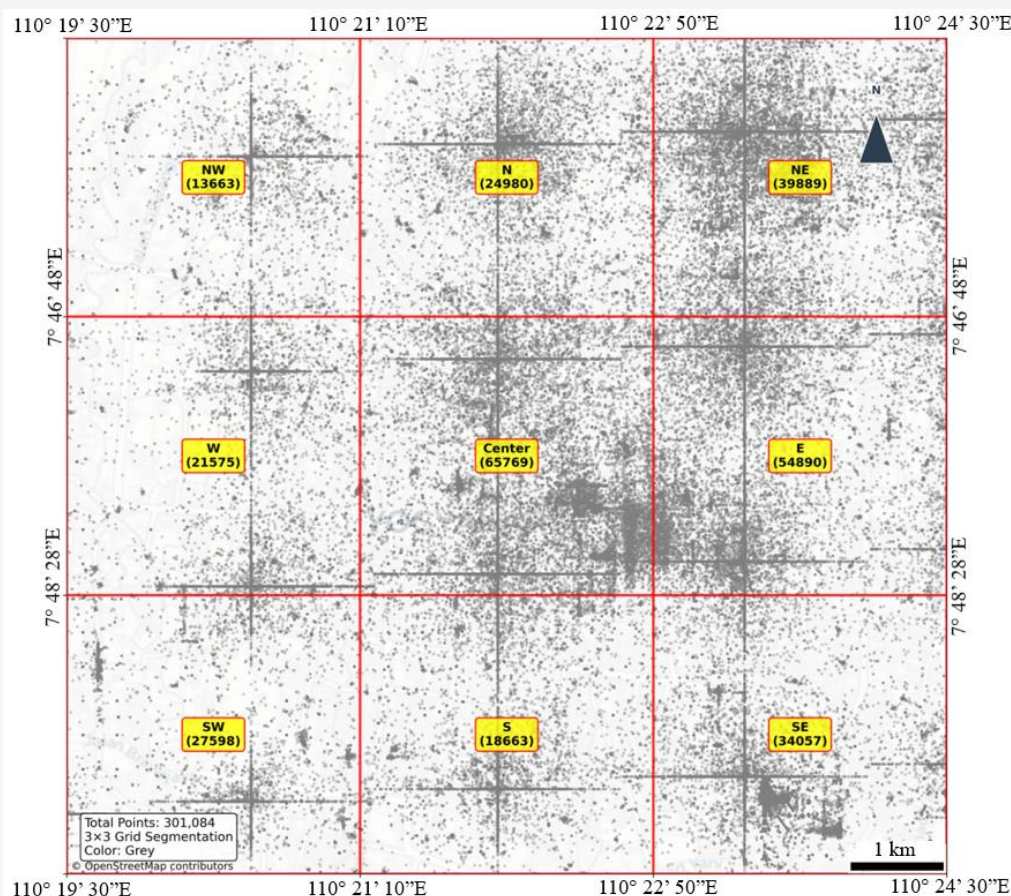


Figure 5: Spatial distribution of stop points

4.2 Grid-based Area Segmentation

The study area was segmented into ten grid sizes from 100 m to 1000 m. As shown in Table 8, fully classified grids increase from 6.42% at 100 m to 95.56% at 1000 m, while empty grids decrease from 56.55% at 100 m to 0% at 900 m and 1000 m. This confirms a fundamental trade-off: finer grids provide spatial granularity but suffer from low semantic completeness, while coarser grids achieve higher coverage but reduce spatial detail. To illustrate how grid resolution affects spatial pattern

detection, Figure 6 presents a map vignette comparing land use coverage at 300 m, 500 m, 700 m, and 900 m grid sizes for a selected area. At 300 m, land use polygons are fragmented across many small cells, resulting in lower completeness per cell. At 500 m resolution, cells capture more complete land use information while still preserving spatial detail. At 700 m and 900 m, cells aggregate larger areas, which increases completeness but reduces the ability to distinguish neighboring functional zones.

Table 8: Basic Grid Profile

Grid Size (m)	Total Grids	Fully Classified (%)	Partially Classified (%)	Empty Grids (%)
100	8366	6.42	37.03	56.55
200	2115	20.43	50.54	29.03
300	960	35.73	48.44	15.83
400	552	49.82	39.67	10.51
500	342	64.62	29.82	5.56
600	240	71.25	25.83	2.92
700	182	84.07	12.09	3.85
800	144	85.42	12.50	2.08
900	110	90.91	9.09	0.00
1,000	90	95.56	4.44	0.00

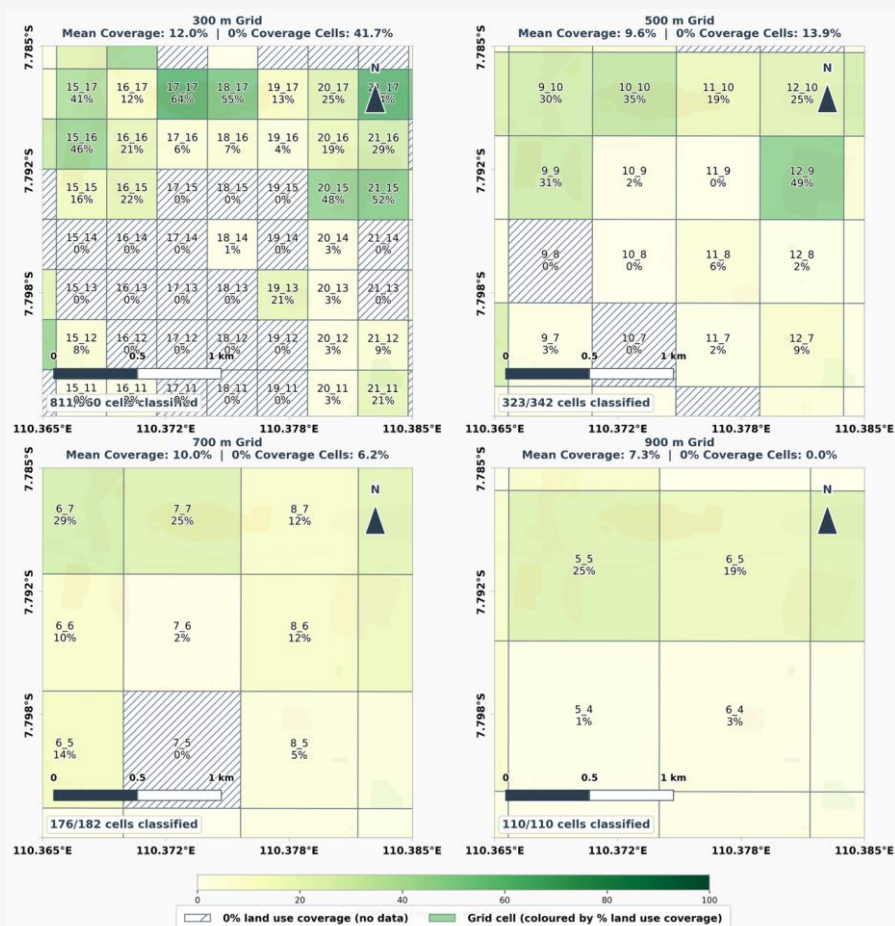


Figure 6: Land use coverage comparison across several grid resolutions

4.2.1 Grid enrichment and evaluation

The evaluation results across all ten grid sizes are presented in Table 9. Data completeness ($C1$, Equation 3) and diversity ($C4$, Equation 6) show an inverse relationship: $C1$ increases from 41.63 at 100 m to 100.00 at 1000 m, while $C4$ decreases from 96.59 to 65.69. Data reliability ($C3$, Equation 5) peaks at mid-range resolutions (300 m –400 m) before declining at coarser resolutions, reflecting increasing semantic heterogeneity within larger cells. Data coverage ($C2$, Equation 4) remains relatively stable across all sizes. These trade-offs confirm that no single grid size optimizes all criteria simultaneously. The 500 m grid achieves the highest total score under Scheme 1 and Scheme 2, and ranks second under Scheme 3 with only a marginal difference from the top-ranked 600m grid. At the individual criteria level, the 500 m grid achieves near-complete semantic labeling ($C1$ = 96.34), stable coverage ($C2$ = 3.99), moderate reliability ($C3$ = 22.01), and high diversity ($C4$ = 83.52). The consistency of the 500 m grid as the top- or second-top-total score across all three schemes confirms the robustness of this recommendation. The 500 m grid is therefore selected as the optimal resolution for subsequent analysis.

4.2.2 Enrichment method comparison

Semantic enrichment performance was compared across grid-based, DBSCAN, and KDE methods using the optimal 500 m grid. DBSCAN used an epsilon of 150 meters and a minimum sample size of 5 points, generating 17 clusters with 0.16% noise. KDE applied Gaussian kernels with bandwidths of 200 meters for POIs and 250 meters for land use data.

As shown in Table 10, all three methods achieve high trajectory coverage, exceeding 97%. KDE gains the highest coverage (99.99%), followed by DBSCAN and the grid-based approach. For trajectory completeness, KDE and DBSCAN outperform the grid-based method because they assign labels based on surrounding density or cluster membership rather than cell classification. However, the grid-based approach achieves the highest semantic diversity (59.92%), significantly outperforming DBSCAN (17.44%) and KDE (48.03%). DBSCAN's low diversity reflects its tendency to aggregate points into homogeneous clusters, while KDE's smoothing effect homogenizes nearby semantic variations. Processing time differences are substantial: 29.84 seconds for the grid-based approach, 62.5 seconds for DBSCAN, and 453.4 seconds for KDE.

Table 9: Comparison of grid evaluation

Grid Size	C1 Data Completeness	C2 Data Coverage	C3 Data Reliability	C4 Data Variety	Total Score Schema 1*	Total Score Schema 2**	Total Score Schema 3***
100	41.63	4.60	15.53	96.59	39.59	40.00	28.19
200	72.75	4.20	22.42	94.89	48.56	53.40	39.30
300	88.59	4.04	23.28	89.77	51.42	58.86	43.75
400	93.09	3.91	23.31	84.09	51.10	59.50	44.50
500	96.34	3.99	22.01	83.52	51.47	60.44	45.06
600	98.42	3.95	22.46	77.27	50.52	60.10	45.18
700	98.08	3.82	20.44	73.08	48.85	58.70	44.01
800	98.95	3.69	20.72	72.16	48.88	58.89	44.22
900	100.00	3.81	20.21	69.67	48.42	58.74	44.17
1000	100.00	3.77	19.37	65.69	47.21	57.76	43.51

*: Equal Weights Schema (25-25-25-25) **: Prioritize Completeness Schema (40-20-20-20) ***: Low Variety Schema (30-30-30-10)

Table 10: Comparison of several enrichment methods

Criteria	Grid-based	DBSCAN	KDE
Trajectory Coverage (%)	97.00	97.72	99.99
Trajectory Completeness (%)	68.27	97.53	99.36
Trajectory Diversity (%)	59.92	17.44	48.03
Processing Time (s)	29.84	62.5	453.4

4.3 Semantic Zone Profiling

Following the zone-mapping classification, POI and land use zone labels were assigned to each grid cell based on the dominant semantic type and confidence score. Cells with more than two distinct functional categories were assigned a Mixed Zone label. Cells with one or two dominant categories received single or combined zone labels. Cells with no POI or land use data were classified as Unclassified. The distribution of POI zone classification (Table 11), shows that double- and mixed-zone classifications are dominant, covering nearly 60% of all cells for POI. This indicates that functional mixing was the dominant spatial condition rather than clear functional segregation. Among the POI type distribution (Table 12), religious facilities appear consistently across multiple zone combinations, including Commercial-Religious and Educational-Religious, together covering more than 30% of all cells. This reflects the significant role of religious infrastructure in Kota Yogyakarta's urban environment, consistent with its socio-cultural identity as a city where Islamic and Javanese traditions coexist. Spatially, Commercial Zone cells are concentrated in the north-eastern part, reflecting Kota Yogyakarta's main commercial and institutional districts, whereas unclassified cells are mainly found in the southern periphery areas (Figure 7(a)). Land use zone labels were derived from OSM land use polygon data using the same zone assignment method (Table 12). Among the classified cells, Agriculture or Green Space is the largest zone (18.13%), followed by Mixed Zone (12.28%) and Religious (8.19%), reflecting Kota

Yogyakarta's peri-urban characteristics. Spatially (Figure 7(b)), Agriculture or Green Space cells are distributed on both the northern and southern peripheries. Religious zone cells appear scattered throughout the study area with no strong spatial concentration. Unclassified cells are most dense in the eastern and south-eastern part, suggesting that OSM land use data coverage is weakest in these areas. The most notable observation in Table 11 is that the land use classification shows a higher proportion of unclassified cells (28.07%) than POIs (12.9%). This reflects the limited OSM land use coverage in mid-sized cities, where formal land use mapping is less complete than in large metropolitan areas [17]. Given the high proportion of unclassified land use cells, POI data is treated as the primary semantic input for supply characterization, while land use data serves as a contextual layer that provides additional spatial interpretation where coverage is available.

Two limitations of the zone profiling results should be noted. First, the 500m grid resolution may not capture detailed variations within each cell, as a single cell may contain multiple functional activities that are not fully represented by the dominant zone label. Second, Unclassified cells in the land use classification do not necessarily indicate the absence of land use activity. They may instead reflect gaps in OSM data coverage rather than genuinely empty areas. OSM data quality tends to be better in urban centers than in peripheral areas [17]. These limitations are acknowledged in the interpretation of supply characterization and service gap findings in Sections 4.4 and 4.6.

Table 11: POI and land use zone classification

Category	POI Label	Land Use Label
Single Zone (1 type)	100 cells (29.2%)	133 (38.9%)
Double Zone (2 types)	111 cells (32.5%)	71 (20.8%)
Mixed Zone (>2 types)	87 (25.4%)	42 (12.3%)
Unclassified	44 (12.9%)	96 (28.1%)

Table 12: Top zone classification

POI Zone Type	Cell Count	Land Use Zone Type	Cell Count
Mixed Zone	87 (25.44%)	Agriculture/green space	62 (18.13%)
Commercial Zone	47 (13.74%)	Mixed zone	42 (12.28%)
Educational - Religious	33 (9.65%)	Religious	28 (8.19%)
Commercial - Religious	31 (9.06%)	Agriculture - Religious	26 (7.60%)
Religious	27 (7.89%)	Residential	25 (7.31%)
Commercial - Educational	22 (6.43%)	Agriculture - Residential	10 (2.92%)
Educational - Health Service	20 (5.85%)	Religious - Residential	9 (2.63%)
Others	31 (9.10%)	Others	44 (12.86%)
Unclassified / No Data	44 (12.87%)	Unclassified / No Data	98 (28.07%)

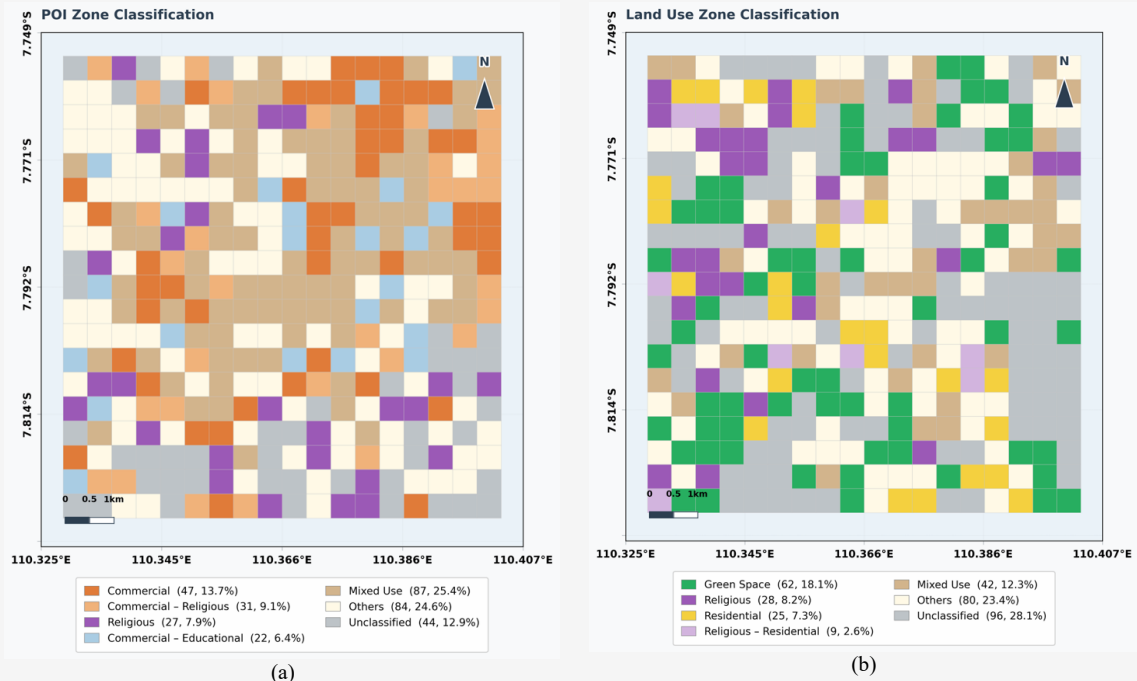


Figure 7: Spatial distribution of zone classification for: (a) POI and (b) land use

Table 13: Supply intensity classification summary

Metric	Classified Cells	Empty Cells	Q1	Q2	Q3	High Cells	Medium Cells	Low Cells
POI Density	298 (87.2%)	44 (12.9%)	12 POI/km ²	32 POI/km ²	64 POI/km ²	78 (22.8%)	144 (42.1%)	76 (22.2%)
Land Use Coverage	246 (71.9%)	96 (28.1%)	0.89%	3.00%	9.15%	62 (18.1%)	122 (35.7%)	62 (18.1%)
Type Variety	323 (94.4%)	19 (5.6%)	3 types	6 types	10 types	89 (26.0%)	137 (40.1%)	97 (28.3%)

4.4 Supply and Demand Characterization

Supply characterization uses three metrics across 342 grid cells with each classification threshold (Table 13). POI density indicates that 87.2% of cells contain at least one POI, indicating broad urban facility coverage. High-density cells are concentrated in the central and north-eastern parts, reflecting Kota Yogyakarta's urban core (Figure 8(a)). Semantic type variety closely mirrors the POI density pattern, with high-variety cells concentrated in the central and eastern parts (Figure 8(b)). This spatial correlation suggests that facility intensity and functional diversity reinforce each other rather than operating as independent dimensions. Land use coverage differs from the other two metrics, with 28% empty cells, the highest among all supply metrics, reflecting OSM data incompleteness noted in Section 4.3.2. Among non-zero cells, Q3 is only 9.15%, indicating that most grid cells are only partially covered by land use polygons. The spatial distribution of land use coverage classes is more

scattered and fragmented, with no clear geographic concentration of high-coverage cells (Figure 8(c)).

Demand characterization was conducted across all 342 grid cells using 301,084 aggregated stop points. All four activity metrics exhibit right-skewed distributions (Table 14), with skewness values ranging from 2.72 (return rate) to 5.64 (visit frequency). This skewness confirms that quartile-based classification is an appropriate approach, which avoids invalid normality assumptions and eliminates the need for data transformation. This approach is also transferable to other cities with unknown mobility data distributions. Visit frequency is the primary demand variable in cross-classification because it most directly measures citizens' demand intensity. Table 15 presents three key patterns. First, visit frequency and unique users are strongly aligned: 83 of 86 high-visit cells are also high-user cells, indicating that visit volume is driven primarily by user breadth rather than repeat visits. Second, return rate shows no consistent

alignment with visit volume, indicating that revisiting behavior is independent of overall activity level. Third, high-visit cells tend toward shorter mean dwell durations, with only 7 of 86 high-visit

cells recording long dwell durations. This suggests that high-visit cells serve as transit or brief-stop destinations, while lower-visit cells support activities that require longer stays.

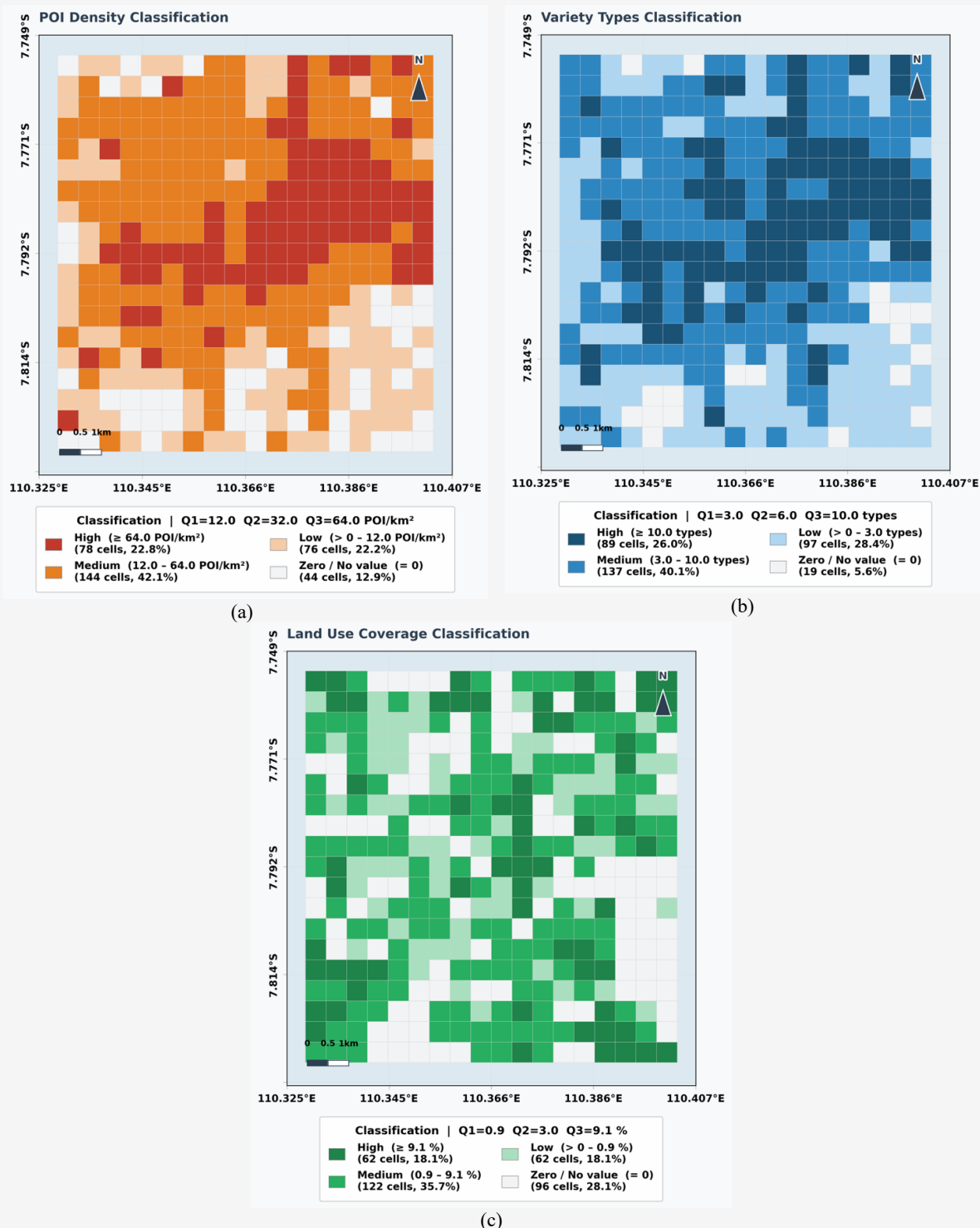


Figure 8: Spatial distribution of urban facility classification: (a) POI density; (b) variety types; and (c) land use coverage

Table 14: Demand intensity statistics

Metric	Mean	Std. Dev	Skewness	Q1	Q2	Q3
Visit Frequency (visits)	880.36	2128.40	5.64	113.25	237.50	595.25
Unique Users (users)	524.01	1078.35	3.72	66.25	159.50	396.75
Mean Dwell Duration (minute)	168.97	55.20	3.67	143.06	160.75	180.65
Return Rate (ratio)	1.66	0.57	2.72	1.33	1.48	1.72

Table 15: Cross-classification of visit frequency vs unique users and return rate (cell counts)

Visit Level	High Users	Medium Users	Low Users	Long Duration	Medium Duration	Low Duration	High Return	Medium Return	Low Return
High	83	3	0	7	52	27	19	54	13
Medium	3	153	14	54	83	33	42	86	42
Low	0	14	72	25	35	26	25	30	31

Table 16: Hotspot intensity profiles

Level	Cell Counts	Mean POI Density	Mean Visits	Mean Variety (types)	Top 3 POI Zone
Full Hotspot (3/3)	36 (10.5%)	102.0	2,570	13.6	Mixed Zone (63.9%), Commercial Zone (11.1%), Commercial - Religious Zone (8.3%)
Partial Hotspot (2/3)	51 (15%)	105.9	734	12.3	Mixed Zone (51%), Commercial Zone (27.5%), Commercial - Educational Zone (9.8%)
Weak Signal (1/3)	72 (21%)	35.8	1,934	6.3	Mixed Zone (30.6%), Commercial Zone (15.3%), Commercial - Educational Zone (9.7%)
Non Hotspot (0/3)	183 (53.5%)	14.7	175	3.5	Unclassified (21.9%), Religious Zone (13.1%), Educational - Religious Zone (12%)

4.5 Hotspot Area Identification

A hotspot is defined as a grid cell that simultaneously exhibits high supply and high demand. Three criteria are applied using Q3 as the threshold: POI density ≥ 64 POI/km², type variety ≥ 10 unique types, and visit frequency ≥ 595 visits. As summarized in Table 16, full hotspots account for 10.5% of cells, partial hotspots for 15.0%, weak-signal cells for 21.1%, and non-hotspots for 53.5%. Full and partial hotspot cells are dominated by Mixed Zone and Commercial Zone POI labels, confirming that functional diversity and commercial activity are the primary characteristics of active urban areas. Non-hotspot cells show a different profile, dominated by Unclassified labels followed by Religious and Educational-Religious zones, reflecting areas with limited registered facilities or facilities serving specific scheduled user groups.

Analysis of the criteria met across partial hotspots and weak-signal cells reveals important patterns, as shown in Table 17. Among partial hotspot cells, 82.4% satisfy POI density and type variety but not visit frequency, indicating adequate facility supply without proportionate human activity. Among weak-signal cells, 57% meet only the visit-frequency criterion, suggesting unmet demand in certain parts of the study area. Spatially

(Figure 9(a)), full and partial hotspot cells are concentrated in the central and central-eastern areas, consistent with the high POI density and high visit-frequency zones identified in Section 4.4. Non-hotspot cells dominate the southern and north-western peripheral areas. Weak-signal cells form a transitional area surrounding the core, representing zones where either supply or demand is present but not both. These findings suggest that urban planning efforts in Kota Yogyakarta should prioritize the maintenance and enhancement of mixed-use facilities in the central-eastern core, while exploring opportunities to extend functional diversity into weak-signal transitional areas surrounding the core and to improve facility provision in the southern and north-western peripheries, where non-hotspot conditions persist.

4.6 Service Gap Area Identification

Service gap identification reveals where supply and demand are mismatched. Two types of mismatches are examined: areas where facilities exist but attract limited human activity (Type 1 Underutilized Supply) and areas where citizens are active but formal facilities are scarce (Type 2 Unmet Demand).

The distribution is summarized in Table 18 and mapped in Figure 9(b). Balanced Active cells are the most dominant at 50.9%, indicating that roughly half the study area shows alignment between facility supply and human activity. Unmet Demand is the second largest category at 24.0%, followed by Balanced Inactive at 19.6% and Underutilized Supply at 5.6%. The dominance of Unmet Demand over Underutilized Supply by more than four times indicates that the primary gap is the absence of facilities where people are already active, rather than the underuse of existing facilities. Unmet Demand cells record a very low mean POI density (9.3 POI/km²) but nearly match the mean visit values of Balanced Active cells (972.3 vs 1,241.4), confirming they are genuinely active areas. This condition may exhibit informal activity, or areas where new facilities are needed to serve existing demand. The high proportion of Unclassified labels in both the POI and land use dimensions suggests these cells likely host informal or unregistered activities, such as street markets or temporary food stalls, that generate real foot traffic but are not captured in OSM data [11] and [26]. Underutilized Supply cells record adequate POI density but very low visits (79.7), with Educational–Religious and Commercial zones as the dominant labels. These cells serve scheduled or specific-time users such as students and worshippers, whose activity patterns

may not be fully captured by the one-month dataset. Balanced Inactive cells are low on both supply and demand, dominated by Unclassified and Agriculture or Green Space zones, and are not an immediate planning priority but should be monitored as urban expansion continues.

Spatially (Figure 9(b)). Balanced Active cells are concentrated in the central and northern areas, consistent with the high POI density and high visit-frequency zones identified in Section 4.4. Unmet Demand cells are primarily found in the northern, western, and southern areas, forming a transitional zone between the active core and the inactive areas. These areas represent priority zones for new formal facility development, such as markets, community centers, or public amenities that serve the existing but underserved citizen activity.

Underutilized Supply cells are scattered in the southern and eastern areas, often adjacent to Balanced Active cells, suggesting they may be functionally overshadowed by nearby well-served areas. For these areas, the planning recommendation is not to add new facilities, but to improve their utilization through better physical access, complementary service provision, or extended operating hours. Meanwhile, Balanced Inactive cells are concentrated on the south-eastern and south-western peripheries, consistent with the low-activity pattern observed across all profiling sections.

Table 17: Criteria distribution on partial hotspots and weak signal

Partial Hotspots		Weak Signal	
Criteria Met	Cells Coverage	Criteria Met	Cells Coverage
POI Density and Type Variety	42 (82.4%)	Visit Frequency	41 (57.0%)
Visit Frequency and Type Variety	5 (9.8%)	Type Variety	16 (22.2%)
POI Density and Visit Frequency	4 (7.8%)	POI Density	15 (20.8%)

Table 18: Service gap distribution summary

Category	Cell Counts	Mean POI Density	Mean Visits	Top 3 POI Zone	Top 3 Land Use Zone
Balanced Active	174 (50.9%)	69.8	1241.4	Mixed zone (44.3%), Commercial (16.7%), Commercial - Religious (9.8%)	Unclassified (23%), Mixed Zone (19.5%), Agriculture (12%)
Type 1: Underutilized Supply	19 (5.6%)	55.8	79.7	Educational - Religious (26.3%), Commercial (26.3%), Educational - Commercial (10.5%)	Unclassified (36.8%), Religious (21%), Mixed Zone (10.5%)
Type 2: Unmet Demand	82 (24.0%)	9.3	972.3	Unclassified (20.7%), Religious (13.4%), Commercial (12.2%)	Unclassified (36.6%), Agriculture (25.6%), Religious (7.3%)
Balanced Inactive	67 (19.6%)	5.4	57.5	Unclassified (40.3%), Religious (18%), Educational - Religious (9%)	Unclassified (28.4%), Agriculture (27%), Residential (9%)

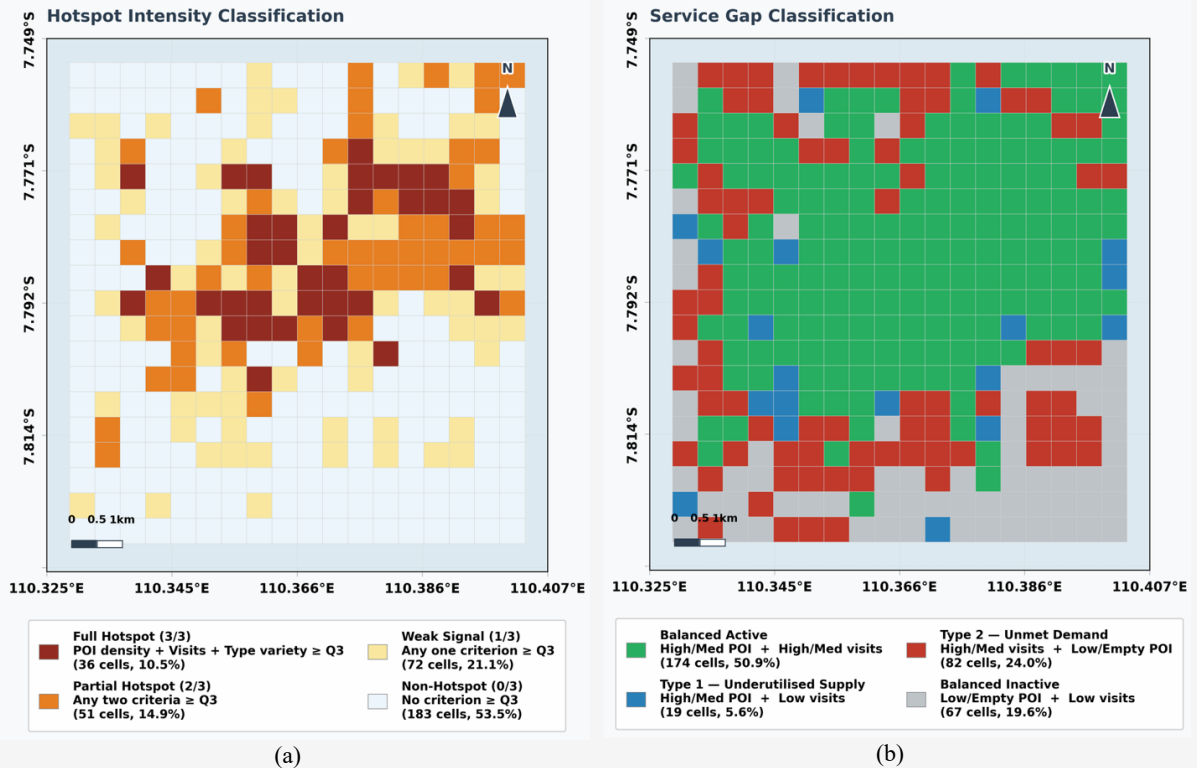


Figure 9: Spatial distribution of supply-demand characterization: (a) hotspot and (b) service gap areas

Table 19: Cross-table of service gap category vs hotspot intensity (cell count)

Category	Full Hotspot	Non-Hotspot	Partial Hotspot	Weak Signal
Balanced Active	36	46	47	45
Balance Inactive	0	67	0	0
Type 1: Underutilized Supply	0	9	4	6
Type 2: Unmet Demand	0	61	0	21

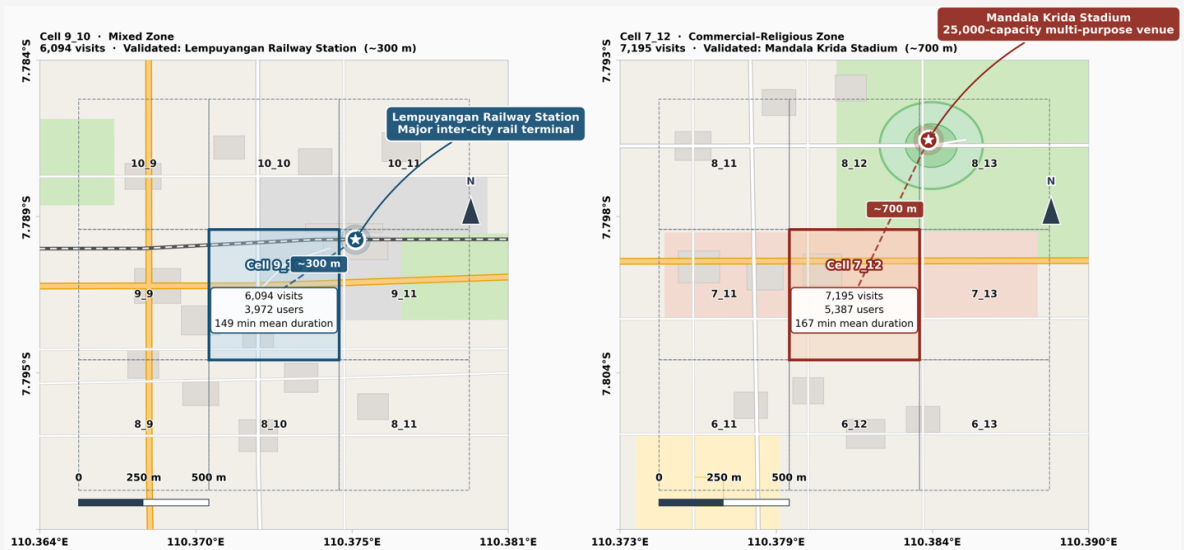
Table 19 presents cross-validation of service gap categories against hotspot intensity levels. Three observations confirm internal consistency. First, all 36 full hotspot cells are classified as Balanced Active, confirming that cells meeting all three hotspot criteria are also well-served areas. Second, all 67 Balanced Inactive cells are non-hotspots, confirming that areas with very low supply and demand never qualify as hotspots. Third, among the Unmet Demand cells, 61 are non-hotspots, and 21 are weak-signal cells. These 21 cells met the visit frequency criterion but not the supply criterion, precisely the condition that defines unmet demand. This cross-validation confirms that the hotspot and service gap classifications are methodologically coherent and produce consistent spatial characterizations of urban activity patterns across the study area.

4.7 Ground-Truth Validation Results

To assess the validity of identified hotspots, geographic centers of full hotspot cells were cross-referenced with known landmarks in Kota Yogyakarta, derived from Wikipedia and Google Maps. As summarized in Table 20, all four top full hotspot cells spatially coincide with recognized urban landmarks. Cell 8_6 corresponds to Jogja National Museum and records the highest visit count of all 342 cells (15,983 visits). Cell 9_10 falls within 300 meters of Lempuyangan Railway Station. Cell 7_12 is approximately 700 meters from Mandala Krida Stadium. Cell 14_6 aligns with the UGM campus area. The alignment between hotspot outputs and verifiable landmarks confirms that the framework identifies spatially meaningful regions of interest rather than statistical artifacts. Figure 10 illustrates the spatial ground-truth validation for cells 9_10 and 7_12.

Table 20: Full hotspot cell validation

Cell	Center Coordinates	Visit Frequency	POI Zone	Nearest Known Landmark	Distance
8_6	- 7.7966, 110.3544	15,983	Mixed Zone	Jogja National Museum (110.3534, -7.8002)	~0.5 km
14_6	-7.7695, 110.3545	7,213	Mixed Zone	UGM campus (Sleman border area)	~1.0 km
7_12	- 7.8012, 110.3816	7,195	Commercial - Religious	Mandala Krida Stadium (-7.7958, 110.3842)	~0.7 km
9_10	-7.7921, 110.3726	6,094	Mixed Zone	Lempuyangan Railway Station (-7.7902, 110.3754)	~0.3 km

**Figure 10:** Full hotspot ground truth validation

5. Conclusions and Limitations

5.1 Conclusions

This study proposed a grid-based semantic enrichment framework for detecting urban spatial patterns from human mobility data, applied to Kota Yogyakarta, Indonesia. The framework integrates stop-point filtering, multi-criteria grid evaluation, confidence-score-based semantic enrichment, and supply-demand synthesis to identify hotspot and service gap areas.

Six main conclusions are drawn. First, stop-point filtering is essential for reliable urban analysis. From 11,088,800 raw records, only 301,084 genuine stop points were retained, confirming that a large proportion of raw trajectory data reflects transient movement rather than genuine stationary activity. Second, the four-criteria evaluation framework provides a systematic and reproducible basis for grid size selection. The 500 m grid achieved the highest total score under equal weights and ranked first or near-first across all three weighting schemes, confirming the robustness of

this recommendation. Third, the grid-based enrichment method outperformed DBSCAN and KDE in semantic diversity while requiring significantly less processing time (29.84 seconds versus 62.5 and 453.4 seconds), supporting its scalability for large-scale mobility datasets. Fourth, supply and demand are spatially misaligned across the study area. POI density and type variety are concentrated in the central and eastern parts, while high visit frequency broadly mirrors but does not fully coincide with high-supply areas, confirming that single-dimension approaches are insufficient for urban spatial pattern characterization. Fifth, only 10.5% of cells qualify as full hotspots, concentrated in the central-eastern urban core. Mixed Zone dominates full hotspot cells, confirming that functional diversity is the primary driver of urban activity intensity. Sixth, unmet demand is the dominant service gap type, covering 24% of the study area and more than four times the proportion of underutilized supply (5.6%). These cells record high mean visits despite very low POI density,

suggesting informal activity not captured in OSM data and highlighting a genuine planning need for facility provision in active but underserved areas.

Together, these findings demonstrate that the proposed framework provides a systematic and replicable methodology for extracting meaningful urban insights from large-scale human mobility data. The 500 m grid is recommended as the optimal spatial resolution for urban mobility analysis in mid-sized Indonesian cities. Facility development should prioritize transitional areas where unmet demand cells are clustered, while underutilized supply cells require accessibility improvements and complementary service provision rather than additional infrastructure investment.

5.2 Limitations

Five main limitations should be considered when interpreting the findings. First, the dataset covers only one month, December 2021, which may not represent typical urban activity patterns due to holiday periods and school closures, particularly for educational and institutional zones. Second, MAID-based trajectory data represents a specific demographic segment, primarily working-age smartphone users with active location permissions. The mobility patterns of elderly residents, children, and low-income groups are not captured, limiting the generalizability of findings to the full urban population. Third, OSM data quality varies across the study area, with urban centers better mapped than peripheral areas. Some Unmet Demand cells may reflect OSM data incompleteness rather than the genuine absence of facilities, and service gap findings in peripheral areas should be interpreted with caution. Fourth, the framework was demonstrated using mobility data from Kota Yogyakarta, a medium-sized Indonesian city. Its performance may vary when applied to larger metropolitan areas or cities with different urban morphologies, higher population densities, or less complete OSM coverage. Fifth, the semantic interpretation of hotspot cells involves a degree of circularity. Hotspot cells are identified using stop-point visit frequency, and their functional characteristics are described using semantic attributes from the same spatial units, without independently confirming whether those attributes caused the activity.

Future work should consider extending temporal coverage to multiple months to capture seasonal variation, incorporating additional data sources such as social media check-ins to complement OSM supply data, and applying the framework to other mid-sized Indonesian cities to assess transferability. An adaptive or hybrid spatial segmentation

approach should also be developed to overcome the rigidity of the uniform grid structure. Additionally, independent data sources such as land value records or business revenue data should be incorporated to validate whether semantic attributes predict citizen activity levels.

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