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Are all campuses equally (digitally) visible? Crowdsourced vs. proprietary street-view coverage across Indonesian university campuses

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Abstract

Street-view imagery underpins a growing body of urban analytics, yet its availability inside semi-enclosed institutional sites such as university campuses remains largely unexamined. This study assesses street-view coverage across 40 Indonesian university campuses on a 20 m grid, comparing a crowdsourced platform (Mapillary) with a proprietary one (Google Street View) and treating disagreement between them as data rather than noise. Google reached a mean of 22.9% of grid cells against Mapillary's 3.3%; the two sources agreed on only 2.1% of cells, and 76.0% of the sampled area was reached by neither. Distance from the campus boundary explained almost none of the cell-level variation in coverage (median slope $+\mathbf{0.021}$, median $\boldsymbol{R^2} = 0.006$), indicating that physical enclosure alone does not govern where imagery exists. Coverage instead formed compact spatial clusters, plausibly along accessible routes, whereas gaps showed no comparable spatial organisation. Crowdsourced coverage depended on very few contributors, with nine campuses reliant on a single individual. Street-view availability in semi-enclosed sites is therefore shaped by internal accessibility

and individual contribution behaviour rather than boundary geometry, and the two sources capture different, non-substitutable fragments of the same space, exposing blind spots for thermal comfort and shade-equity modelling.

Keywords: street view imagery, volunteered geographic information, Google Street View, Mapillary, university campus

1 Introduction

Street view imagery (SVI) has become a standard way to observe the built environment without visiting it. Researchers use it to measure greenery, evaluate micro-scale urban heat islands, map pedestrian shade access, audit sidewalks, score walkability, and track physical change over time, often at scales that would be impossible to cover on foot [1–3]. The method rests on an assumption that is rarely stated: that imagery exists more or less wherever the analyst wants to look. Where it does not, the missing space quietly drops out of the sample, which poses a significant problem for continuous environmental phenomena like thermal exposure.

This gap between the physical environment and its visual representation particularly consequential when SVI is used to assess several environment indicators [4]. Image availability is not simply a technical matter of data coverage; it can reflect how streets are mapped, accessed, and prioritised by imagery providers [5–7]. As a result, places that are physically accessible to pedestrians may remain poorly represented in SVI datasets, creating spatial blind spots that can affect both the completeness and interpretation of environmental assessments.

University campuses are a case where that assumption is worth testing directly. Campuses are dense, heavily used, and matter for the people inside them. Campus open space affects student mental health, physical activity, thermal comfort, and the quality of daily academic life [8–11], and a growing body of work now uses SVI to evaluate campus environments at eye level [12–14]. At the same time, campuses are not ordinary urban fabric. Many are large, walled or gated, entered through a few controlled points, and served by internal roads that connect only loosely to the surrounding street network [15, 16]. In Indonesia this pattern is common enough to be a planning norm rather than an exception, with state and private universities occupying single consolidated sites of tens to hundreds of hectares in a tropical climate where daytime heat exposure heavily impacts daily pedestrian mobility [17, 18].

That combination creates a problem. SVI platforms are built around public road networks, and campuses are precisely the kind of space where the public road network stops at the gate. If coverage thins out inside campus grounds, then studies that use SVI to characterise campus environments are describing the parts of campus that happen to be reachable by a camera, not the campus itself. For climate vulnerability modeling, this risks leaving high-density pedestrian walkways unaccounted for when mapping canopy cover or shade equity [19, 20]. The coverage question therefore comes before the measurement question.

There is a second complication. SVI is no longer produced by a single actor. Proprietary platforms such as Google Street View (GSV) collect imagery through planned vehicle and trekker campaigns, while crowdsourced platforms such as Mapillary depend on whoever chooses to record and upload [7, 21]. These are different processes with different constraints, and they need not fail in the same places. Existing comparisons have mostly been run on ordinary urban street networks [5, 22]. How the two behave inside a semi-enclosed complex, where formal road access and informal pedestrian access diverge sharply, is not established.

This study compares Mapillary and GSV metadata across 40 Indonesian university campuses on a common 20 m grid. We treat the disagreement between the two sources as the object of interest rather than as a discrepancy to be reconciled, and ask three questions. First, how much of each campus does each source actually reach, and where do the two agree. Second, whether coverage decays with depth into the campus interior, as a simple enclosure argument would predict. Third, whether the crowdsourced gaps are better explained by physical access or by the small number of people who contribute at all.

2 Literature Review

2.1 Campus space, enclosure, and why coverage matters

Campuses are studied as environments in their own right, frequently functioning as de facto urban parks that provide essential green infrastructure, ecological services, and recreational space within otherwise dense cities [23, 24]. Landscape characteristics on campus are associated with student mental health offering restorative environments that reduce academic stress, alleviate cognitive fatigue, and foster social cohesion [8, 20, 25], visible greenery at eye level relates to physical activity among students [9], and open space design is treated as a lever for campus wellbeing [10]. Recent work extends this to resilience and to how legible and memorable campus nodes feel to the people who use them [13, 26]. The practical consequence is that campus interiors are exactly the spaces such research needs to see.

They are also spaces designed to be difficult to enter. Mohamed [15] describes campus life as an architecture of separation, where walls, gates, and internal hierarchies produce enclosure as a designed condition rather than a byproduct. Ali & Kim [16] asks whether a large urban campus in Cairo functions as public space at all, and finds access mediated by control points and institutional rules. The same logic appears in the wider literature on urban enclosure and enclave-making, where perimeter control reshapes who moves through a space and how [27, 28], and in the older observation that university populations form their own partially exclusive geographies within a city [29].

In Indonesia the enclosure is reinforced by scale and land tenure. Widaningrum et al. [17] characterises Indonesian urban campuses as large single-purpose sites whose spatial structure differs from the surrounding city fabric, and studentification research around Semarang shows campuses acting as anchors that reorganise the land around them while remaining internally distinct [18]. Gated forms are well established in Indonesian urban development more generally [30]. A campus of several hundred

hectares under one owner, planned as one zone, has few through-roads relative to its area whether or not anyone intended to exclude the public.

Enclosure of this kind has an obvious implication for remote observation, but it has not been measured that way [31]. If SVI platforms follow public roads, then the interior of an enclosed campus is where imagery should be scarcest, and it is also where the environmental attributes researchers care about are concentrated. Whether that scarcity actually occurs, and whether it follows distance from the perimeter or something else, is an empirical question.

2.2 Street view imagery as an observational instrument

SVI became a research instrument because it substitutes for fieldwork. Early work established that GSV could reproduce in-person neighbourhood audits with acceptable reliability [32–34], and subsequent studies used it to quantify street-level greenery [35], map urban trees with computer vision [36], measure street-level canopy cover for pedestrian shade, model micro-climate conditions such as sky-view factor and urban heat island effects [37], and audit environments for specific activities such as running [38]. Biljecki & Ito [1] review the field and document how far it now extends across urban analytics. Methods have continued to develop, including correcting camera perspective for walkability and bikeability work [39], extracting eye-level greenness from open imagery across multiple countries [40], tracking physical urban change over time [2], and also applying these methods in health research [41].

The usefulness of the method depends on properties of the imagery that vary from place to place. Hou & Biljecki [42] set out a framework for evaluating SVI quality across several dimensions, and Curtis et al. [43] showed early on that image dates are spatially and temporally unstable, so a study area is rarely observed at one moment. Zhu et al. [44] compare online imagery against on-site mobile acquisition and find that online imagery does not always represent conditions on the ground. These are not peripheral caveats. They determine what an SVI-derived measurement means.

Coverage is the most basic of these properties and has received the most recent attention. Kim & Jang [45] show that GSV coverage and image recency vary substantially in small and medium-sized cities, using a people-based rather than area-based accounting. Ha et al. [22] document uneven GSV coverage across United States metropolitan areas and argue that what is missing is itself informative. Fan et al. [4] treat coverage and bias as a mapping problem in their own right, and Zhang et al. [46] show that representation bias in imagery propagates into model predictions and replicability. Campus-scale SVI studies have generally not reported coverage first [12, 14], which leaves open how much of each campus their measurements actually describe.

2.3 Proprietary and crowdsourced imagery as different processes

Proprietary and crowdsourced platforms produce imagery under different rules. GSV is collected through planned campaigns and held under a commercial property regime that constrains how it can be used and redistributed [47, 48]. Mapillary and similar services depend on volunteers, which makes them a form of volunteered geographic

information (VGI) [49, 50] and subject to the same participation dynamics as other crowdsourced geodata [51].

Those dynamics are well documented and consistently uneven. VGI completeness varies with the socioeconomic profile of an area [6], and reviews of representativeness treat spatial bias as a defining property rather than a defect to be corrected [52]. Contribution is concentrated in a small number of active mappers [53], and user-generated geographic content clusters where connectivity and wealth already are [54]. Ferreira et al. [55] connect this directly to a digital divide operating at the intra-urban scale.

Direct comparisons between the two kinds of platform are fewer. Quinn et al. [21] compare GSV, Mapillary, and OpenStreetCam across world cities and find that Google tends toward an all-or-nothing approach to a given city while crowdsourced platforms distribute their coverage more evenly, with some neighbourhoods omitted because of barriers that are not always visible on a map. Juhász & Hochmair [5] evaluate Mapillary completeness against GSV and a reference road network and find GSV ahead on most road categories, with the exception of pedestrian and cycle paths in some cities, where volunteer capture does better. That exception is the relevant one here, because campus interiors are largely made of paths that no survey vehicle is likely to drive.

The choice between sources is also a methodological argument. Helbich et al. [48] set out why researchers might prefer open imagery over proprietary imagery on licensing and reproducibility grounds, and Danish et al. [56] build citizen-science tooling on open imagery for that reason. But an open source is only usable where it exists. If crowdsourced coverage collapses in exactly the spaces that proprietary fleets also cannot enter, the two sources are not substitutes and the gap between them carries information about the space itself. That is the gap this paper measures.

3 Data and methods

Figure 1 summarizes the overall workflow. The study first defines the campus sampling and digitises their boundaries (Section 3.1), followed by the acquisition of street-view metadata from Mapillary and GSV (Section 3.2); the cleaned metadata are subsequently integrated with a common analysis grid and used to assess imagery coverage, openness, temporal, and spatial-autocorrelation (Section 3.3). Robustness checks are then conducted separately to evaluate the stability of the results (Section 3.4).

3.1 Case study

This study uses a sample of 40 university campuses across Indonesia. Campuses were chosen as the case study because many share a distinctive spatial pattern: large, self-contained grounds with limited entry points, internal road networks only loosely connected to the surrounding city, and a mix of academic, residential, and open-space land uses enclosed within a single perimeter (Figure 2). This complex, semi-enclosed form sets campuses apart from ordinary city blocks and raises the question of how well such spaces are captured by street-view platforms, which are built around public road networks [8, 15, 16]. The 40 campuses span several islands and provinces, include both

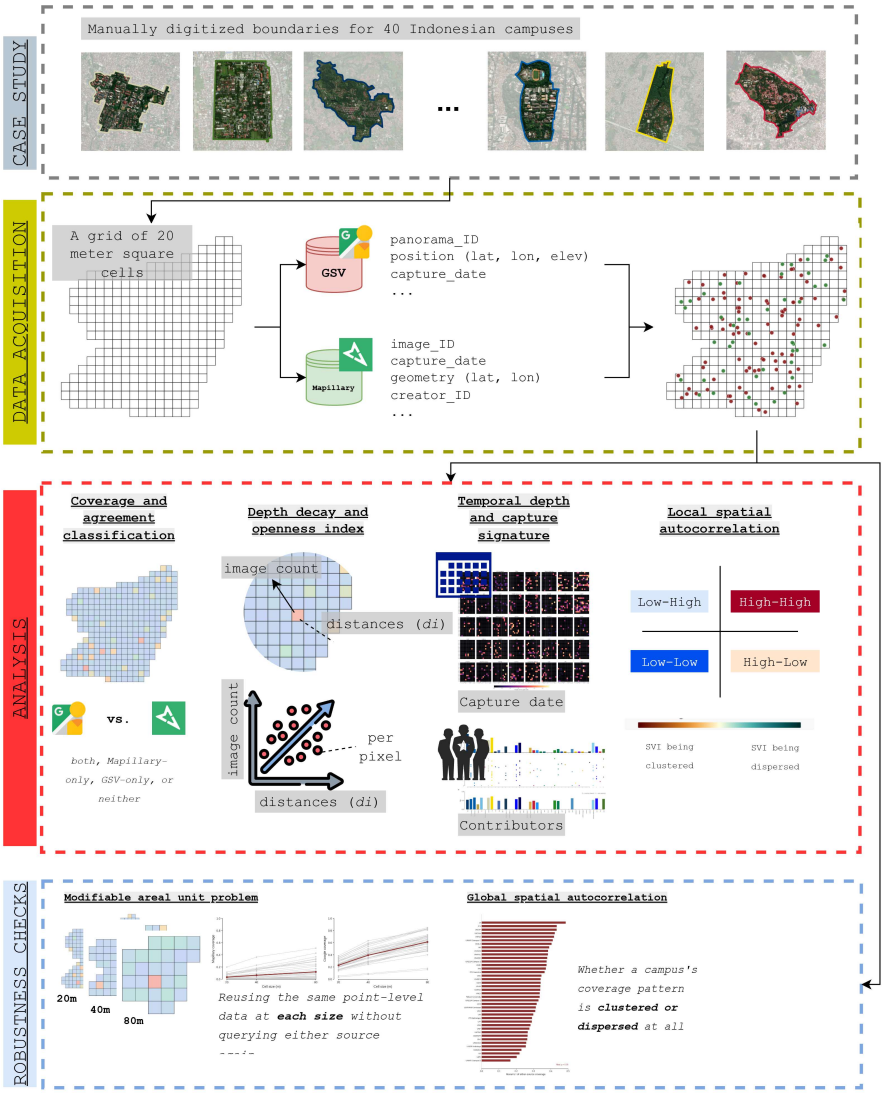

Fig. 1 Overview of the study workflow, from campus case selection and street-view metadata acquisition to coverage, openness, temporal, and spatial-autocorrelation analyses, with robustness checks across grid resolutions.

state and private universities, and cover a range of sizes and layouts, from compact single-site campuses to large multi-site universities where separate sites of the same institution are treated as distinct cases, to allow comparison across different degrees of physical enclosure rather than a single dominant campus type.

For each campus, the boundary was manually digitized as a polygon based on official campus extents, since no single consistent public dataset covers all 40 institutions; this boundary underlies every later step, including the metadata grid (Section 3.2) and

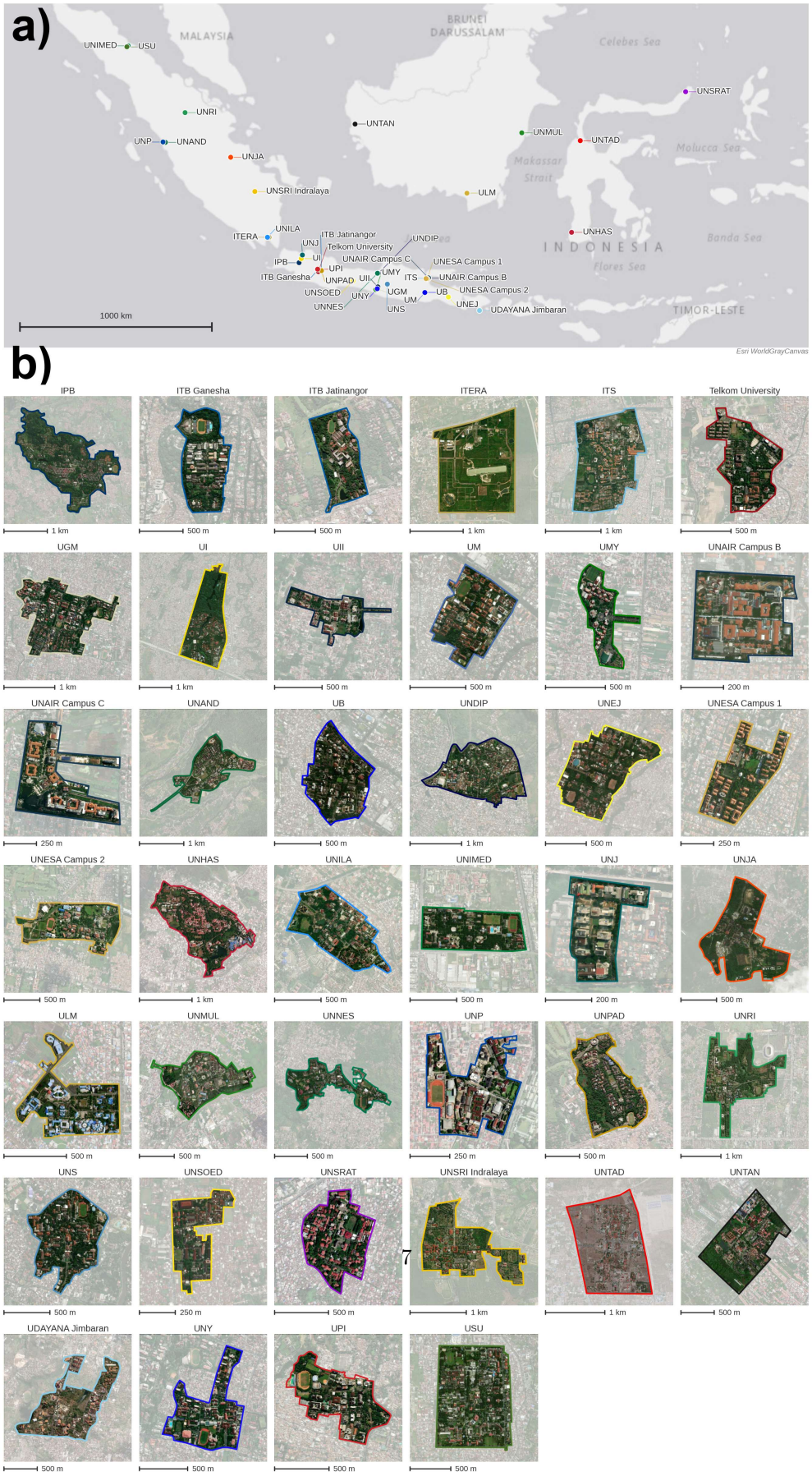

Fig. 2 Overview of the campus sample. (a) Location of all 40 campuses across Indonesia, colour-coded by institution, plotted over a national basemap by Esri WorldGrayCanvas. (b) Digitized boundary of each campus overlaid on satellite imagery by Esri World Imagery.

the distance-based openness index (Section 3.3.2). The full list of campuses, including abbreviation, official name, city and province, and centroid coordinate, is provided in the Supplementary Material (Table S1), and Figures 2a & b shows the location and boundary of each of the 40 campuses.

3.2 Data acquisition

Two sources of SVI were collected for each campus: Mapillary, a crowdsourced platform, and GSV, a proprietary one. Only metadata was collected, such as location, capture date, and platform-specific attributes[1].

For each campus, a grid of 20 meter square cells was built in the local UTM projection and clipped to the campus boundary. This grid is the common unit used to combine data from both sources (Section 3.3.1).

3.2.1 Mapillary

Mapillary metadata was collected through the Mapillary Graph API (v4), using an adaptive spatial query: each campus was queried as a single region and split into smaller sub-regions as needed until full coverage was retrieved. Table 1 lists the fields collected for each image.

Table 1 Metadata fields collected per Mapillary image.

Field	Description
Image ID	Unique image identifier
Captured-at timestamp	Capture date and time (millisecond precision)
Geometry	Longitude and latitude of the image
Compass angle	Camera heading at capture
Camera type	Capture device or projection type
Is-panoramic flag	Whether the image is a 360° panorama
Sequence ID	Groups images from one capture pass
Creator (contributor) ID	Unique contributor identifier
Organization ID	Owning organization, where one exists

3.2.2 Google Street View

GSV metadata was collected using the `streetlevel` library[2]. Collection happened in two steps:

1. A **coverage-tile query** returns the ID, position, and orientation of every panorama on each map tile (zoom level 17) that touches the campus boundary. Checking the raw output of this query directly showed it does not include a capture date at all.

[1] retrieved on 27th August 2026
[2] https://github.com/sk-zk/streetlevel

2. An **enrichment query**, run once per panorama position, returns the capture date, the capture programme (Table 2), copyright and uploader information, and, where they exist, older panoramas captured at the same spot.

Both steps were needed because location and date come from separate calls, not one.

Table 2 Metadata fields collected per GSV image.

Field	Description
Panorama ID	Unique panorama identifier
Position	Longitude, latitude, elevation
Orientation	Heading, pitch, roll
Capture date	Month precision (official); day precision (user-contributed)
Capture programme (`source`)	Car-mounted (`launch`), pedestrian (`scout`), indoor tripod (`innerspace`), or third-party upload
Copyright / uploader	Shows whether the panorama is official or user-contributed
Historical panoramas	Older captures at the same position, each with its own date

3.2.3 Deduplication and boundary clipping

Records from both sources were checked for duplicate IDs and removed, then clipped to the actual campus boundary. The cleaned points from each source were then matched to the 20 meter grid to build a per-cell summary for each campus.

3.3 Analysis

3.3.1 Coverage and agreement classification

For each grid cell i and source $k \in \{\text{Mapillary}, \text{GSV}\}$, coverage is a simple yes or no:

$$C_{i,k} = \begin{cases} 1 & \text{if at least one record of source } k \text{ falls in cell } i \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Each cell was then placed into one of four groups based on $(C_{i,\text{Mapillary}}, C_{i,\text{GSV}})$: *both* (1,1), *Mapillary-only* (1,0), *GSV-only* (0,1), or *neither* (0,0). The share of cells in each group, per campus, is what we use to compare campuses and to see where the two sources agree or disagree.

Alongside this yes-or-no measure, we also kept the raw count of records per cell, $N_{i,k}$ (images for Mapillary, panoramas for GSV). This count is heavily skewed: a small number of cells hold most of the imagery. Maps of per-cell density use a log scale for this reason, while campus totals ($\sum_i N_{i,k}$) are shown on a normal linear scale so the actual size differences between campuses and sources stay visible.

3.3.2 Depth decay and openness index

The main question behind this study is whether SVI coverage drops off as you move away from a campus's edge, toward its interior [5, 21, 22]. To test this, we measured the distance from each cell's centroid to the nearest point on the campus boundary $\partial\Omega$, and scaled it to a 0 to 1 range within each campus:

$$d_i = \frac{\text{dist}(c_i, \partial\Omega)}{\max_j \text{dist}(c_j, \partial\Omega)}, \qquad d_i \in [0, 1] \tag{2}$$

Here c_i is the centroid of cell i, and the maximum distance is taken over all cells in that same campus. A value of 0 means the cell sits right on the edge; a value of 1 means it is as deep into the campus as any cell gets. Scaling it this way means campuses of different sizes and shapes can be compared on the same axis.

For each campus, we fit a simple linear regression of coverage against this scaled distance:

$$C_i = \beta_0 + \beta_1 d_i + \varepsilon_i \tag{3}$$

where C_i is coverage from either source ($C_i = \max(C_{i,\text{Mapillary}}, C_{i,\text{GSV}})$). The slope $\hat{\beta}_1$ is what we call the **openness index**. A slope well below zero means coverage falls off sharply toward the interior, which we read as a more enclosed campus. A slope near zero means coverage stays roughly the same no matter how deep into the campus you go. This index comes only from the boundary shape and the grid, with no road data involved, so it does not inherit the gaps.

3.3.3 Temporal depth and capture signature

All dates were aggregated to the year level, which is the common resolution across both sources. For each cell and source, we counted how many distinct years appear in the records:

$$Y_{i,k} = |\{\, \text{year}(r) : r \in R_{i,k} \,\}| \tag{4}$$

where $R_{i,k}$ is the set of records of source k in cell i. At the campus level, we also summed records by year and source to see how capture activity is spread out over time, whether it happens in short bursts (which points to volunteer mapping) or more steadily (which points to a platform running its own capture programme).

For Mapillary, which is the only source where each record can be traced to a person, we also counted contributors per campus and looked at how images are split between them. To summarize this, we used the Gini coefficient of image counts per contributor:

$$G = \frac{\sum_{p=1}^{n} \sum_{q=1}^{n} |x_p - x_q|}{2n^2 \bar{x}} \tag{5}$$

where x_p is the number of images from contributor p, n is the number of contributors, and $\bar{x}$ is the average number of images per contributor. A Gini of 0 means every contributor added roughly the same amount. A Gini close to 1 means almost all the imagery comes from one person. This matters because two campuses can have

the same coverage but very different odds of that coverage being kept up over time, depending on how many people are behind it.

3.3.4 Local spatial autocorrelation

Before treating a gap in coverage as meaningful, it helps to know whether coverage is spatially clustered at all rather than scattered at random. To check this, we calculated local Moran's I for each campus. Neighbors were defined using the grid's own row and column structure (queen adjacency: any cell sharing an edge or a corner), so no external spatial-weights file was needed.

The local Moran's I for cell i is:

$$I_i = \frac{z_i}{m_2} \sum_j w_{ij} z_j, \qquad m_2 = \frac{\sum_i z_i^2}{n} \tag{6}$$

where $z_i = x_i - \bar{x}$ is the record count at cell i ($N_{i,k}$) minus the campus average, n is the number of cells in the campus, and the weights w_{ij} are row-standardized. Significance was tested with 999 permutations per cell, and any cell that did not reach $p < 0.05$ was marked not significant.

Cells were sorted into four types based on their own value and their neighbors' average value: *High-High* (a well-covered cell surrounded by well-covered cells), *Low-Low* (a gap surrounded by gaps), and two outlier types, *High-Low* and *Low-High*. High-High clusters mark solid pockets of coverage. Low-Low clusters mark solid pockets of missing coverage, which is what we are most interested in when asking whether parts of a campus are being systematically left out.

3.4 Robustness checks

3.4.1 Modifiable areal unit problem

Grid-based coverage numbers can change depending on how big the grid cells are. To check how much this matters, every coverage analysis (Section 3.3.1) was repeated at three cell sizes, $s \in \{20\,m, 40\,m, 80\,m\}$ (Table 3), reusing the same point-level data at each size without querying either source again. We checked whether campuses kept roughly the same ranking, and whether the gap between the two sources stayed about the same size, across all three grids.

Table 3 Grid sizes used to test sensitivity to cell size.

Cell size (m)	Cell area (m^2)	Role
20×20	400	Main analysis grid
40×40	1600	Mid-range check
80×80	6400	Coarse check

3.4.2 Global spatial autocorrelation

As a check on the local clustering results in Section 3.3.4, we also calculated global Moran's I for each campus:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \cdot \frac{\sum_i \sum_j w_{ij} z_i z_j}{\sum_i z_i^2} \tag{7}$$

using the same neighbor structure and the same permutation test (999 permutations per campus) as before. This tells us whether a campus's coverage pattern is clustered at all, before we look at where the clusters actually are.

4 Results

4.1 Coverage and source agreement

Across the 40 sampled campuses, GSV reached a mean of 22.9% of grid cells (median 23.1%, range 3.3%–38.5%), while Mapillary reached a mean of only 3.3% (median 1.2%, range 0%–20.0%) (Table 4). This difference is visible directly in the per-cell density maps: GSV panoramas (Figure 3) form a near-continuous presence across most campus grids, whereas Mapillary images (Figure 4) appear as sparse, isolated pockets. The campus-level totals in Figure 5 make the same asymmetry concrete in absolute terms rather than proportions.

GSV coverage was roughly seven times higher than Mapillary on average, and the two distributions differed in shape as well as magnitude: GSV coverage was fairly evenly spread across campuses (interquartile range 19.6%–26.5%), whereas Mapillary coverage was heavily right-skewed, with three-quarters of campuses below 5.4% and a small number of outliers, UNMUL (20.0%), UNDIP (11.5%), and IPB (9.0%), pulling the mean well above the median.

Nine campuses (UMY, UNAIR Campus C, UNAND, UNEJ, UNESA Campus 1, UNJA, ULM, UNRI, UNTAD) returned zero Mapillary images despite having Google coverage; a further seven fell below 1%. In total, 16 of 40 campuses (40%) had effectively negligible Mapillary presence, meaning any analysis restricted to Mapillary data (Section 4.4) draws on an effective sample closer to $n = 31$, not the full 40. This same set of nine campuses recurs below and is treated as a structural feature of the sample rather than noted separately each time.

The cell-level agreement classification (Figure 6) shows the same pattern spatially. Averaged across the sample, cells classified as *both* accounted for only 2.1% of area, *Mapillary-only* for 1.2%, *Google-only* for 20.8%, and *neither* for 76.0%.

Reordering campuses by the size of their *both* class rather than total coverage reshuffles the ranking meaningfully (Figure S1 Supplementary Material). UNMUL leads not because it has the most combined coverage but because it is the one campus where Mapillary and GSV substantively overlap (9.6% both, plus a further 10.4% Mapillary-only, the largest crowdsourced-exclusive share in the sample), followed by UNDIP (8.6% both), USU (6.8%), UB (6.5%), and UNNES (6.2%). At the opposite

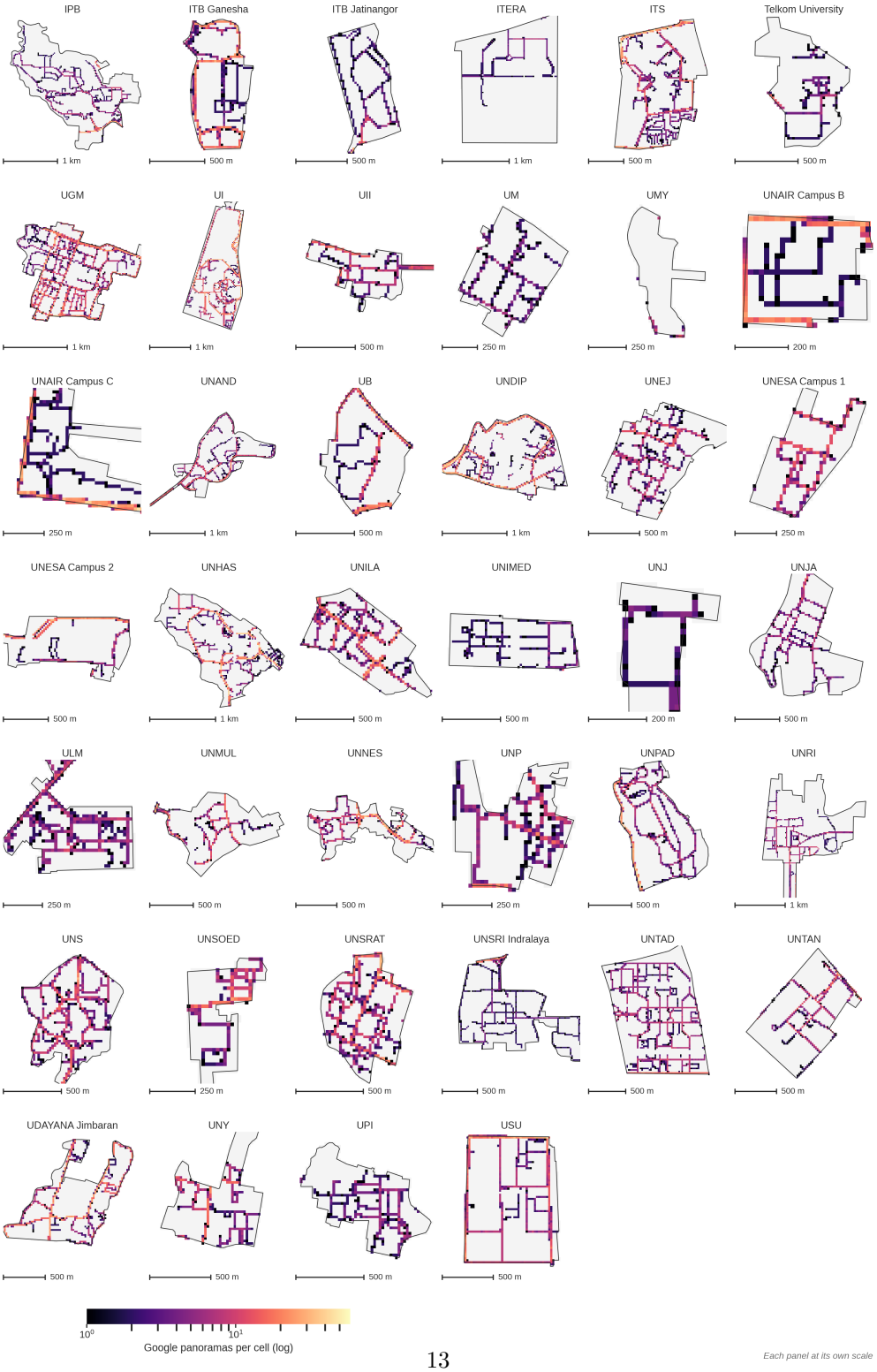

Fig. 3 GSV images per grid cell, log-scale, per campus.

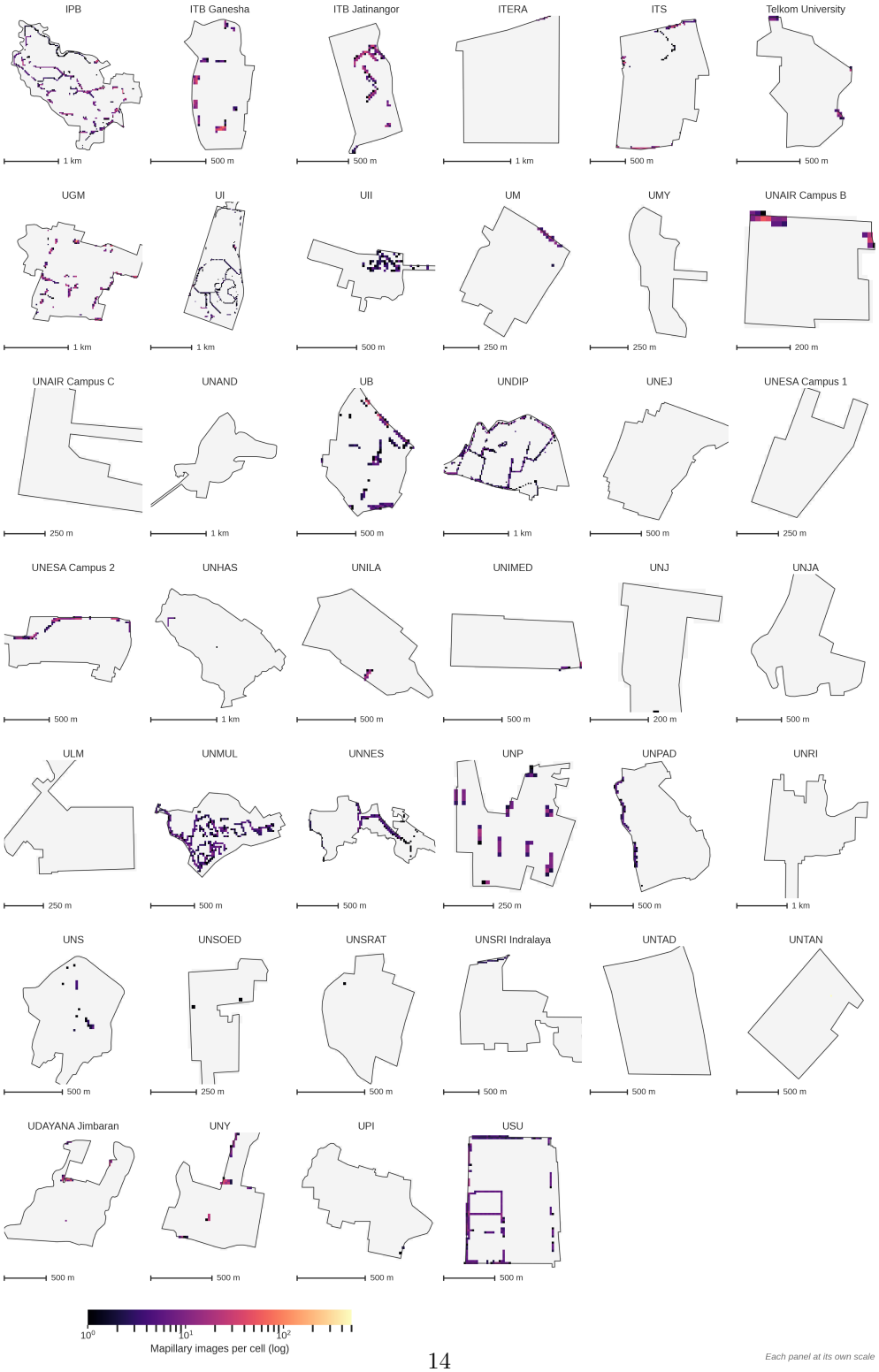

Fig. 4 Mapillary images per grid cell, log-scale, per campus.

Table 4 Coverage summary: campuses with the five highest and five lowest either-source coverage ratios, out of 40. Full table in Table S2 Supplementary Material.

Campus	Mapillary coverage	GSV coverage	Either-source coverage
Highest either-source coverage			
ULM	0.000	0.385	0.385
UII	0.089	0.328	0.376
UGM	0.050	0.357	0.366
UNSRAT	0.001	0.362	0.362
UNS	0.012	0.338	0.345
Lowest either-source coverage			
UNESA Campus 2	0.044	0.153	0.162
UNTAN	0.000	0.153	0.154
UNRI	0.000	0.137	0.137
ITERA	0.002	0.053	0.055
UMY	0.000	0.033	0.033
$n = 40$			
Mean	0.033	0.229	0.240

end, campuses such as ITERA, UNTAN, UNRI, and UMY show almost no Mapillary-only or both coverage at all; their profiles are functionally a two-class split between Google-only and neither.

This confirms that source overlap is not just rare in aggregate, it is concentrated in a handful of campuses, while for most of the sample the two sources behave as though they were surveying different populations of space entirely: where SVI exists, it is overwhelmingly attributable to GSV alone, and the majority of every campus's interior remains unreached by either source simultaneously [22, 48]

4.2 Enclosure and openness

The relationship between coverage and depth into the campus interior was weak and inconsistent across the sample. As Figure 7(a) shows, individual campus profiles scatter widely around a nearly flat sample mean. The median openness slope was +0.021, not negative, and only 18 of 40 campuses (45%) showed the expected negative slope, meaning coverage more often held steady or rose slightly toward the interior than decayed as hypothesized. Explanatory power was low throughout: the median R^2 was 0.006, and no campus exceeded $R^2 \approx 0.06$ (Table 5), indicating that normalized depth alone explains very little of the cell-to-cell variation in coverage for any individual campus.

The ranked slopes in Figure 7b identify which campuses anchor each end of the distribution. The most negative, most enclosure-consistent, slopes were at UNJ ($\hat{\beta}_1 = -0.382$, edge coverage 37.0% falling to core coverage 13.3%), UNDIP (−0.348, 36.9% → 15.9%), UNESA Campus 2 (−0.296), ITB Ganesha (−0.286), and UNAIR Campus B (−0.277). The most positive slopes, where coverage was actually higher in the interior than at the edge, were UNEJ (+0.385), UNMUL (+0.372), UPI (+0.303), UNILA (+0.264), and UNRI (+0.194).

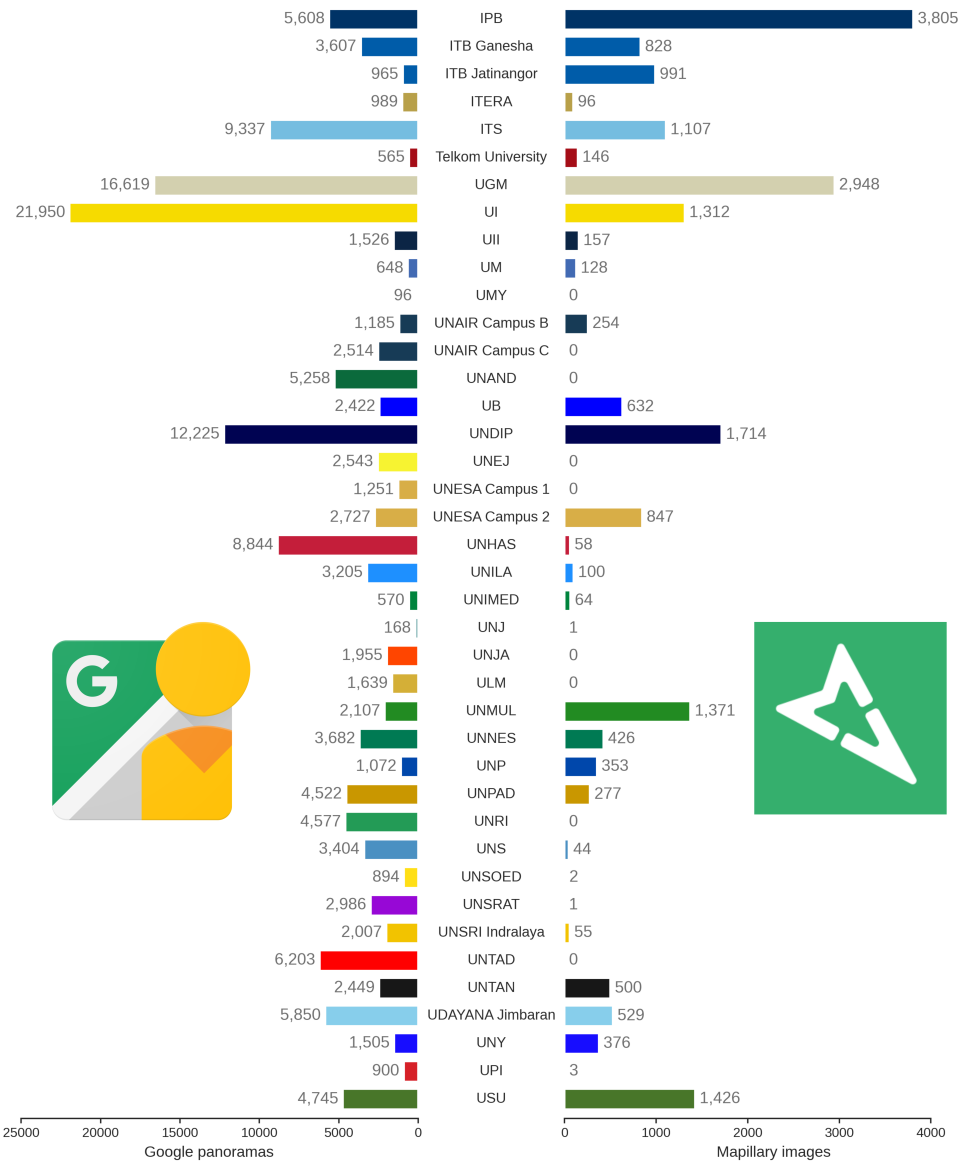

Fig. 5 Total Google and Mapillary street view images per campus.

Averaged across all 40 campuses, mean coverage barely changed from edge to core (25% → 26%, +1.2 percentage points), essentially flat overall.

Taken together, a simple linear decay from the boundary does not capture the dominant spatial pattern of coverage for most campuses in this sample. This is itself a finding worth noting: it suggests that physical enclosure, distance from the perimeter, is not the primary force shaping where SVI does and does not exist within a campus.

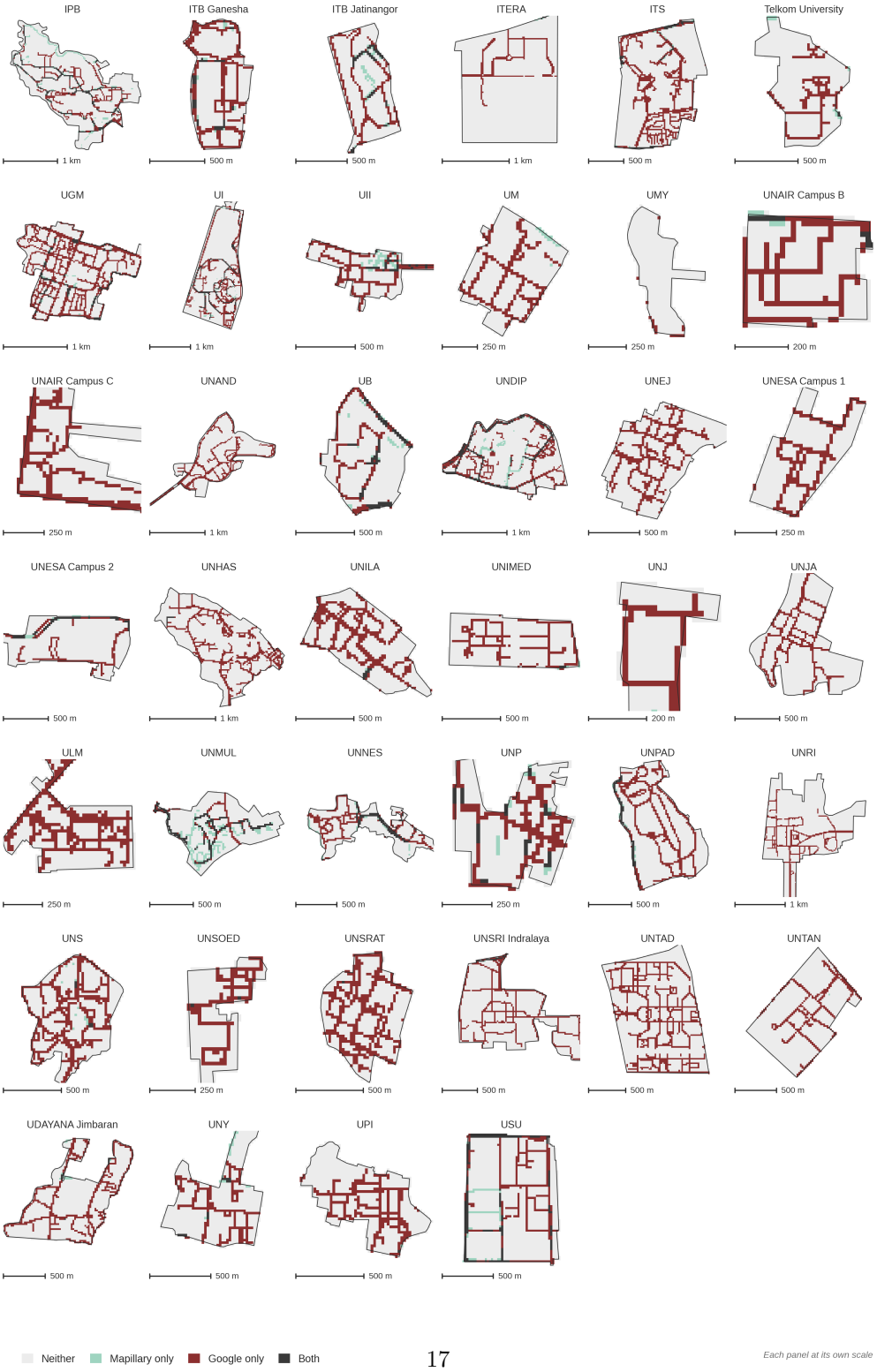

Fig. 6 Cell-level source agreement per campus: neither, Mapillary only, Google only, or both.

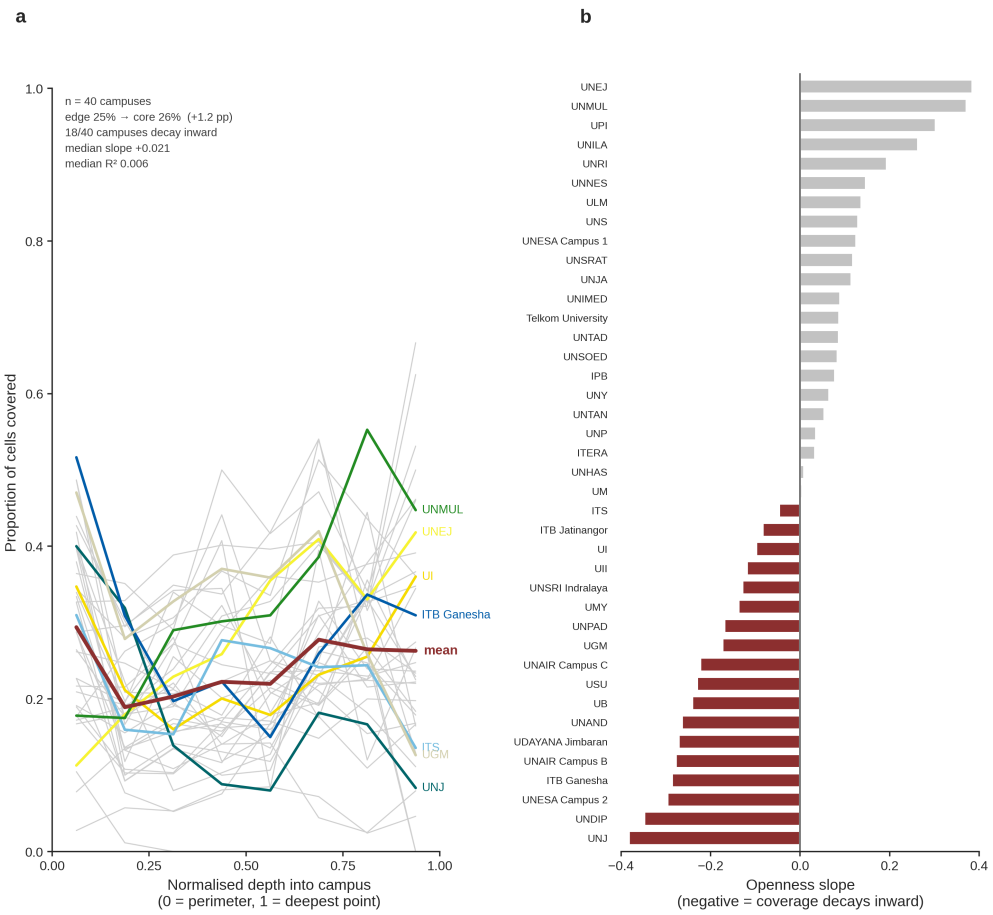

Fig. 7 (a) Coverage against normalised depth into campus, every campus in grey with the sample mean in red; (b) openness index (regression slope) per campus, sorted by value.

Section 4.3 shows instead that coverage organizes around specific accessible routes rather than decaying smoothly with distance, a structurally different mechanism than the one the openness index was built to detect.

4.3 Local clustering of coverage

The local (cell-level) LISA analysis was run separately on each source's own density surface, and the two produce meaningfully different pictures.

Google Street View. Because GSV has non-trivial density in every campus, its LISA classification (Figure 8; Table 6) is defined for the full sample of 40. On average, 6.3% of cells were significant High-High and 11.4% were significant overall. UNAIR Campus C had the highest High-High share (10.1%), followed by UNILA (9.9%) and UNDIP (9.8%); IPB (3.1%), UNSRI Indralaya (2.8%), and ITB Jatinangor (3.3%)

Table 5 Openness index: campuses with the five most negative (enclosure-consistent) and five most positive slopes, out of 40. Full ranking in Table S3.

Campus	Slope $\hat{\beta}_1$	Edge coverage	Core coverage	R^2
Most negative (enclosure-consistent)				
UNJ	−0.382	0.370	0.133	0.061
UNDIP	−0.348	0.369	0.159	0.038
UNESA Campus 2	−0.296	0.246	0.048	0.048
ITB Ganesha	−0.286	0.428	0.329	0.026
UNAIR Campus B	−0.277	0.373	0.175	0.024
Most positive				
UNRI	+0.194	0.102	0.240	0.018
UNILA	+0.264	0.214	0.373	0.024
UPI	+0.303	0.172	0.380	0.034
UNMUL	+0.372	0.177	0.518	0.042
UNEJ	+0.385	0.141	0.359	0.053
$n = 40$				
Median	+0.021	—	—	0.006

had the lowest, indicating that even campuses with substantial overall GSV coverage (Section 4.1) can show relatively diffuse rather than tightly clustered coverage. Considering total significant clustering rather than High-High alone, ITB Ganesha (16.6%), UNAIR Campus C (14.8%), UNSOED (14.8%), and UNAIR Campus B (14.8%) stood out. Critically, ULM was the only campus in the entire sample, on either source, to show any statistically significant Low-Low clustering (1.1% of cells): every other campus, across both Google and Mapillary, showed a Low-Low share of exactly zero.

Table 6 Local Moran's I (LISA) cluster shares, computed on GSV density, defined for all 40 campuses: highest and lowest High-High shares.

Campus	% HH	% LH	% significant
Highest High-High share			
UNAIR Campus C	10.1	4.8	14.8
UNILA	9.9	4.4	14.3
UNDIP	9.8	3.9	13.7
Lowest High-High share			
UMY	1.9	2.9	4.8
UNSRI Indralaya	2.8	2.0	4.8
IPB	3.1	2.2	5.3
$n = 40$			
Mean	6.3	5.4	11.4

Mapillary. The local analysis is only meaningfully defined where Mapillary imagery exists, restricting this part of the analysis to the 31 campuses identified in

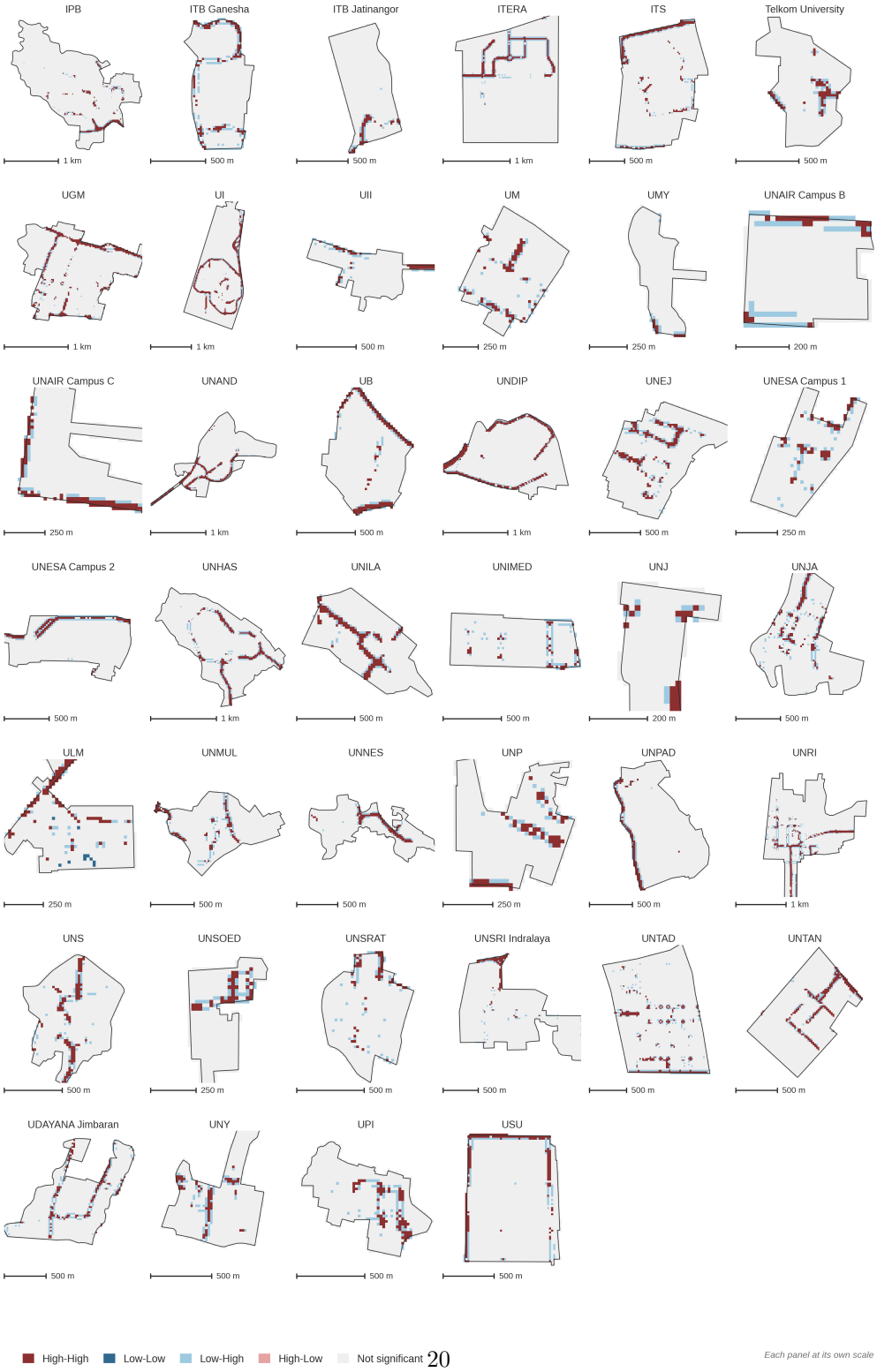

Fig. 8 LISA cluster quadrants (High-High, Low-High, Low-Low, High-Low, not significant) for Google panorama density, per campus.

Section 4.1. The LISA classification (Figure 9; Table 7) again showed clustering concentrated in High-High and Low-High categories, with no Low-Low clustering in any of the 31. UNMUL (7.5% High-High), USU (4.6%), and ITB Jatinangor (4.9%) showed the highest shares of significant High-High cells, consistent with the same small set of campuses that dominate Mapillary volume overall (Section 4.1). The nine campuses with zero Mapillary presence show, by construction, no significant local clustering of any type; this is a direct consequence of there being no density surface to test, not a spatial finding in its own right.

Table 7 Local Moran's I (LISA) cluster shares, computed on Mapillary image density: campuses with the highest share of significant High-High cells, and the nine campuses with no significant clustering (zero Mapillary presence).

Campus	**% HH**	**% LH**	**% significant**	n **cells**
Highest High-High share				
UNMUL	7.5	5.7	13.2	1802
USU	4.6	5.8	10.3	2826
ITB Jatinangor	4.9	3.3	8.3	1356
No significant clustering (zero Mapillary presence)				
UMY, UNAIR C, UNAND, UNEJ, UNESA 1, UNJA, ULM, UNRI, UNTAD	0.0	0.0	0.0	—

Comparing the two sources directly, Google's local clustering was both more consistently detectable, since it is defined for all 40 campuses rather than 31, and, on average, somewhat weaker in intensity per cell (mean High-High share 6.3% for Google versus a comparable range concentrated in fewer campuses for Mapillary). More importantly, the two sources' High-High clusters are not concentrated in the same campuses: UNAIR Campus C and UNILA lead on Google despite having negligible or zero Mapillary presence, while UNMUL and USU lead on Mapillary despite unremarkable Google clustering. This divergence indicates that the two sources are not simply weaker and stronger versions of the same spatial pattern; they trace different clusters of accessible space within the same campuses.

Across both sources, the near-total absence of Low-Low clustering, ULM alone, at 1.1% on Google, being the single exception in the entire sample, indicates that interior coverage gaps are not spatially contiguous "dead zones" so much as an absence of any organized signal at all, while the coverage that does exist forms compact, statistically distinguishable clusters, plausibly tracing accessible routes or specific mapping passes rather than distance-based decay.

Read alongside Section 4.2, this reframes the enclosure question: where clustering is detectable, coverage is organized by proximity to specific accessible routes or mapping efforts rather than by distance from the boundary, a pattern the depth-decay model cannot see because it treats all directions from the boundary as equivalent.



Fig. 9 LISA cluster quadrants for Mapillary image density (High-High, Low-High, Low-Low, High-Low, not significant), per campus.

4.4 Temporal signatures and contributor structure

The year-by-month calendar heatmaps reveal a clear divergence between the two sources' temporal behaviour that a simple annual total would flatten out. On the Google side (Figure 10; per-cell distinct-year counts detailed in Figure S2 Supplementary Material), five campuses stand out as unusually dense: UI, UNDIP, IPB, and ITB Ganesha all show sustained, multi-year blocks of high-intensity capture rather than isolated bright cells, indicating repeated, systematic re-surveying rather than a single pass.

UGM is a distinct case within this group: its active period is comparatively narrow, capture is concentrated into fewer calendar windows, yet the intensity within those windows is considerable, so the campus registers less spread across the calendar but a comparably large absolute volume when it does capture. This distinguishes two forms of Google intensity that a single coverage percentage would conflate: sustained-breadth capture (UI, UNDIP) versus concentrated-depth capture (UGM).

On the Mapillary side (Figure 11; per-cell distinct-year counts detailed in Figure S3 Supplementary Material), the pattern inverts in an important way. IPB, ITB Ganesha, UI, UGM, and UNDIP again surface as the standout campuses, but here the calendar footprint is comparatively sparse: activity clusters into a handful of scattered months rather than sustained blocks, and yet these same five campuses still out-contribute every other campus in the sample by a wide margin.

In other words, the campuses that dominate Mapillary volume do so through short, disproportionately productive bursts rather than through sustained temporal presence, a signature consistent with a small number of individually motivated mapping efforts rather than routine, ongoing community contribution [6, 52]. This is corroborated directly by the contributor data below: the campuses that dominate Mapillary volume are exactly the campuses with the highest contribution concentration.

Contributor structure could be assessed for 31 of 40 campuses with at least one identifiable Mapillary contributor; the remaining 9 had zero Mapillary images (Section 4.1). Among these 31, the mean number of contributors was 3.97 (median 3, range 1–15), and contribution was highly concentrated, with a mean Gini coefficient of 0.358 and a mean top-contributor share of 79.0% (Table 8). This concentration is visible directly in Figures 12(a) & (b), where a small number of campuses show both high contributor counts and steep drop-offs in per-contributor volume.

The most concentrated campuses were UI, with a Gini of 0.730 across 12 contributors (Figure 12(c)), indicating a long tail beneath one dominant contributor, followed by UNDIP (0.681, 8 contributors) and ITB Jatinangor (0.664), where a single contributor supplied 99.7% of that campus's 991 images from only 3 total contributors. ITS (0.658) and UGM (0.657, the campus with the most contributors overall at 10) complete the top five. Nine campuses had exactly one identifiable contributor, meaning their entire Mapillary presence, however large, rests on a single person's activity.

Read together, the Mapillary-only outliers identified earlier (UNMUL, UNDIP, IPB; Section 4.1), the local clustering results (Section 4.3), and this section's contributor concentration point to the same underlying mechanism: Mapillary coverage in this sample is not a smooth crowdsourced layer building incrementally over time, but

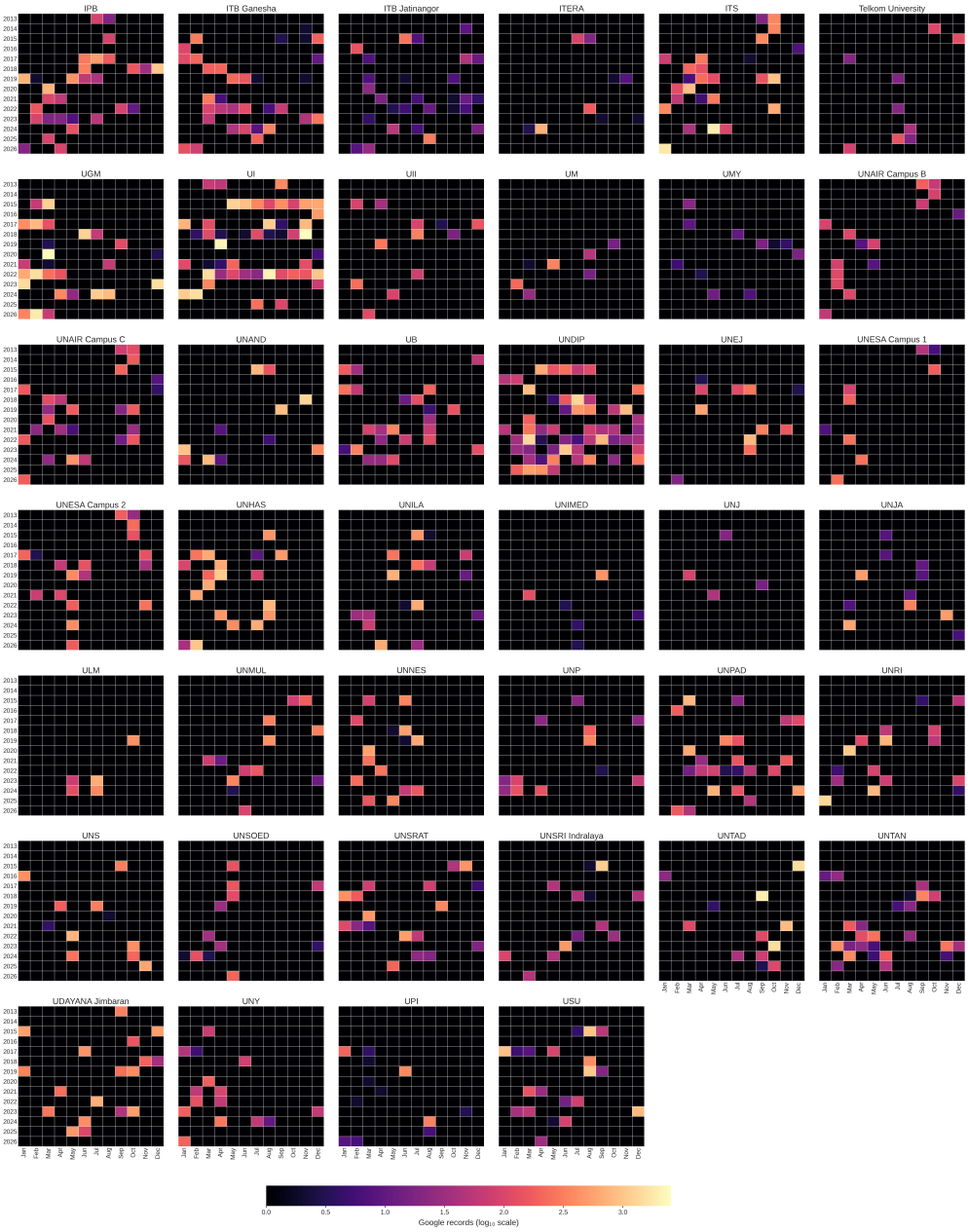

Fig. 10 GSV capture activity by year and month, per campus, $\log_{10}$ scale.

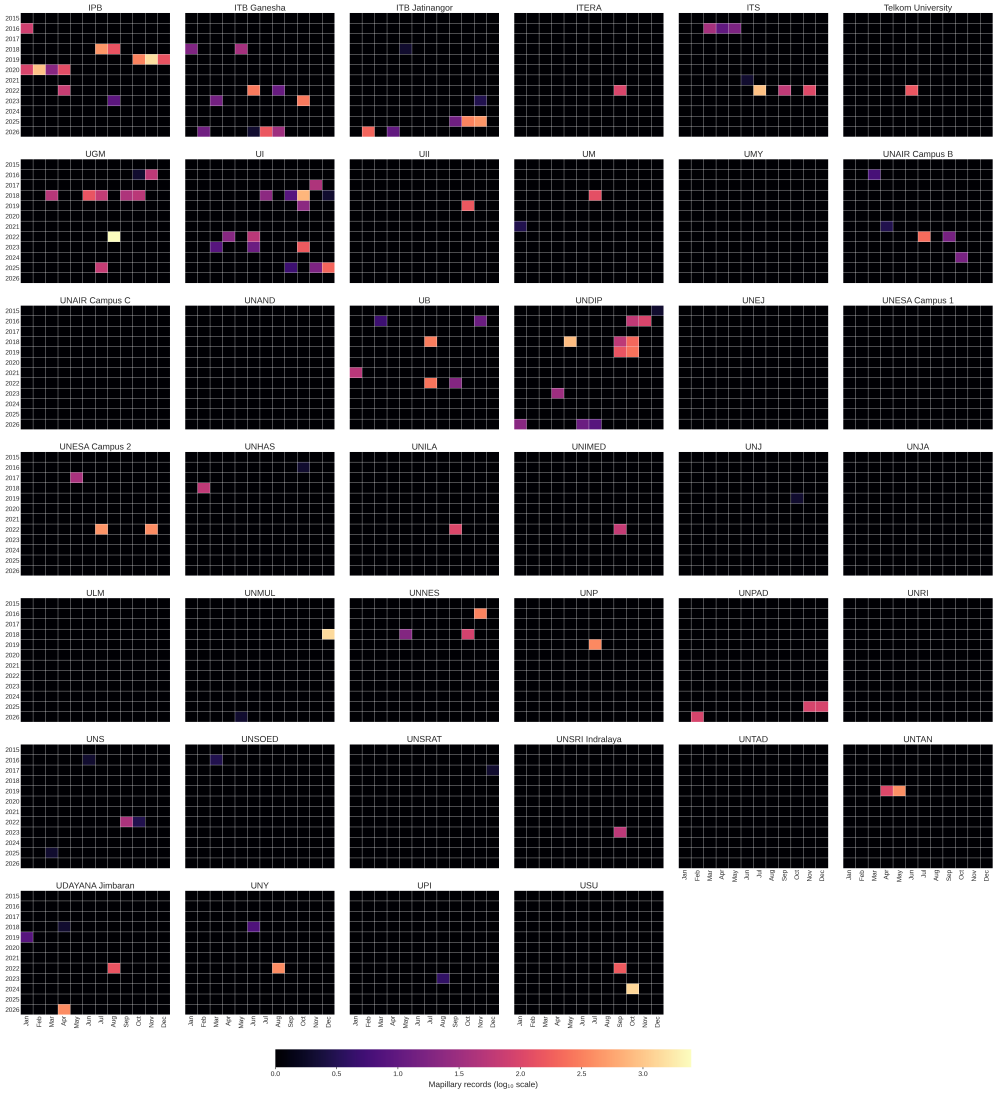

Fig. 11 Mapillary capture activity by year and month, per campus, $\log_{10}$ scale.

a small number of individually driven mapping episodes, concentrated in specific campuses, specific short windows, and often specific people. This is a materially different data-generating process from Google's, and is central to the discrepancy this paper examines: the two sources are not two noisy measurements of the same underlying "true" coverage, but two structurally different processes that happen to be measured on the same scale.

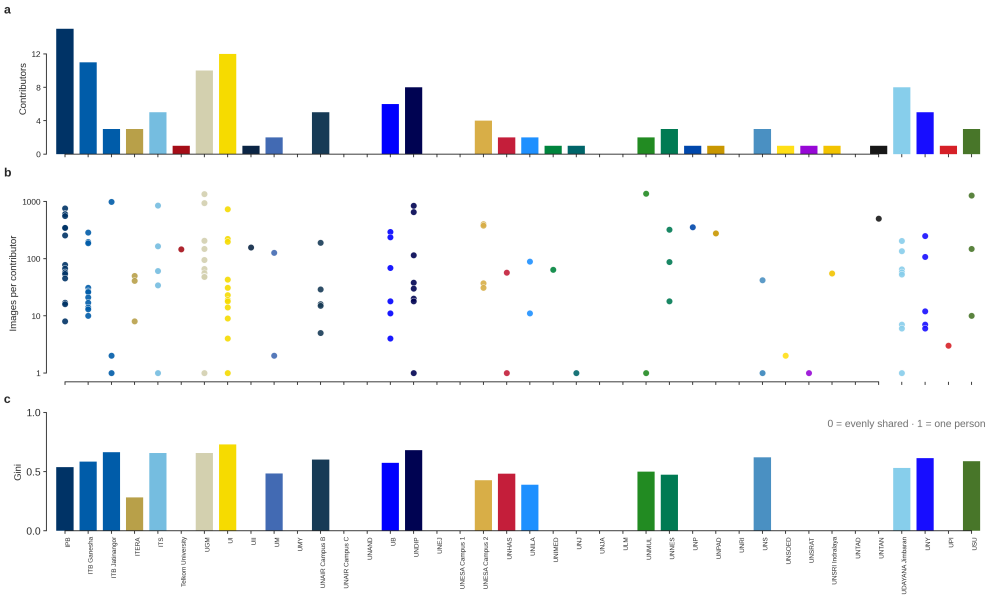

Fig. 12 (a) Number of Mapillary contributors per campus; (b) images per contributor; and (c) Gini coefficient of contribution concentration per campus, where values closer to 0 indicate more evenly distributed contributions and higher values indicate greater concentration among fewer contributors.

Table 8 Contributor concentration: the five campuses with the highest Gini coefficient, among the 31 with at least one identifiable Mapillary contributor.

Campus	Contributors	Images	Gini
UI	12	1315	0.730
UNDIP	8	1716	0.681
ITB Jatinangor	3	991	0.664
ITS	5	1108	0.658
UGM	10	2949	0.657
$n = 31$			
Mean	3.97	—	0.358

4.5 Robustness checks

Coverage ratios rose substantially with cell size, as expected. Mean Mapillary coverage increased from 3.3% at 20 m to 6.4% at 40 m and 12.1% at 80 m; mean Google coverage rose from 22.9% to 39.5% to 61.2% over the same range (Table 9). This pattern is visible for every individual campus in Figure 13, not only in the sample average.

Despite this level shift, campus rankings were highly stable: the Spearman rank correlation between 20 m and 80 m coverage was $\rho = 0.985$ for Mapillary and $\rho = 0.891$

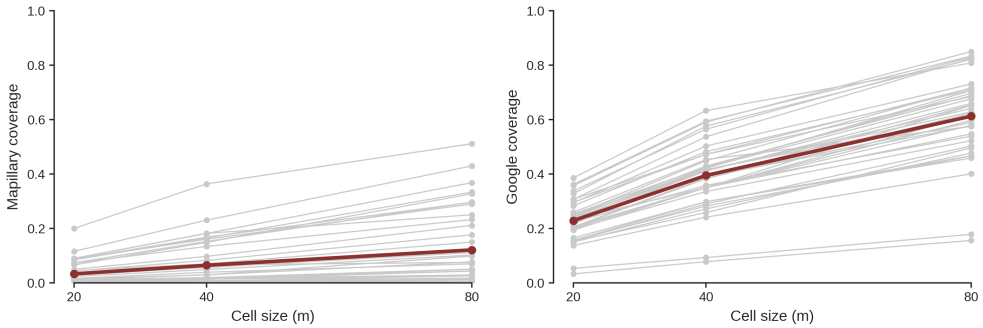

Fig. 13 Coverage at three grid resolutions (20, 40, 80 m). Every campus in grey, sample mean in red.

Table 9 Mean coverage across the sample at each MAUP resolution, and rank-correlation stability between the finest (20 m) and coarsest (80 m) grids.

	20 m	**40 m**	**80 m**
Mean Mapillary coverage	0.033	0.064	0.121
Mean Google coverage	0.229	0.395	0.612
	Spearman ρ (20 m vs. 80 m)		
Mapillary ranking	0.985 ($p < 0.001$)		
Google ranking	0.891 ($p < 0.001$)		

for Google, both significant at $p < 0.001$. Which campuses are relatively well- or poorly-covered therefore does not depend on the choice of grid resolution, even though the absolute percentages do.

Global Moran's I, computed on either-source binary coverage (Figure 14), showed statistically significant spatial clustering in all 40 campuses. UI recorded the strongest clustering ($I = 0.485$), followed by ITS (0.437) and UNDIP (0.436); UNAIR Campus B recorded the weakest, though still significant, clustering ($I = 0.166$). Because this statistic is computed on either-source coverage rather than on a single source, it is defined and significant for every campus in the sample, including those with negligible Mapillary presence.

5 Discussion

5.1 Coverage, enclosure, and detachment from the surrounding city

GSV reached 22.9% of grid cells on average against Mapillary's 3.3%, the two sources agreed on only 2.1%, and 76.0% of the sampled area was reached by neither. Uneven street-view coverage is well documented across cities and metropolitan areas [4, 21, 22, 45]; what the campus scale exposes is that the unevenness persists inside a single

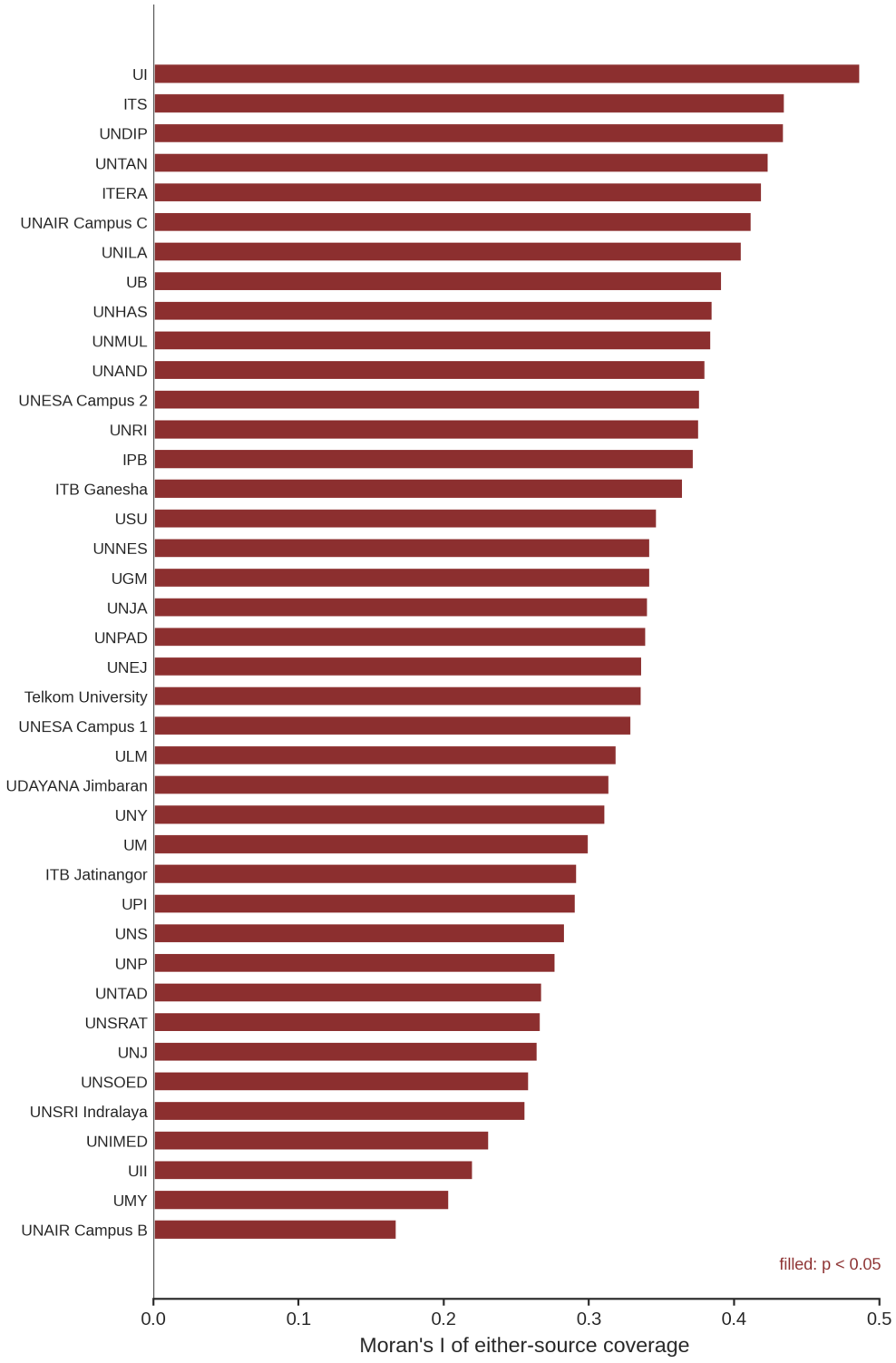

Fig. 14 Global Moran's I of either-source coverage per campus. All 40 campuses are significant at $p < 0.05$.

parcel of a few square kilometres. The depth-decay test did not behave as the enclosure hypothesis predicted: the median openness slope was +0.021, the median R^2 was 0.006, and only 18 of 40 campuses decayed inward at all. Distance from the perimeter, taken alone, explains almost none of the cell-level variation.

The subset that did decay is more informative than the aggregate. The steepest negative slopes belong to UNJ ($\hat{\beta}_1 = -0.382$, edge coverage 37.0% falling to 13.3%), UNDIP (−0.348), UNESA Campus 2 (−0.296), ITB Ganesha (−0.286), and UNAIR Campus B (−0.277), all embedded in dense urban fabric, while the most positive belong to peripheral sites such as UNEJ (+0.385) and UNMUL (+0.372). This suggests the gradient is produced by what surrounds the campus rather than by the interior: where a campus sits inside a well-covered city, perimeter cells inherit imagery from adjacent public roads and coverage falls away past the gate; where the hinterland is itself unmapped, no edge premium exists and the slope flattens. The boundary is legible in the imagery record, but chiefly at campuses whose surroundings are mapped, which gives measurable form to accounts of Indonesian campuses as enclaves developing separately from their host cities [15–18, 28–30]. The clustering results agree: global Moran's I was significant in all 40 campuses (0.166–0.485), yet High-High and Low-High clusters dominated and Low-Low clustering was effectively absent, appearing only at ULM (1.1% of cells). Coverage forms compact clusters along accessible corridors; its absence has no organised spatial structure for a distance-based model to detect.

5.2 Temporal depth and the contributors behind it

Coverage ratios describe where imagery exists, not when it was captured or how often renewed. Google's record on the better-covered campuses is a record of repeat visits: UI, UNDIP, IPB, and ITB Ganesha show sustained multi-year capture, while UGM concentrates comparable volume into a narrower window. Instability in Google capture dates is a known constraint [43, 45], but Google's gaps are gaps in a series, and the platform returns. Mapillary's record is not a thinner version of that series. It is a scatter of isolated months, empty at nine campuses and negligible at sixteen, reducing the effective sample for crowdsourced analysis to 31. The campuses carrying substantial Mapillary volume reached it through short, disproportionately productive bursts rather than continuous accumulation. For examples, see Figure 15.

The contributor data explains those bursts. Across the 31 campuses with any identifiable contributor, the mean was 3.97 contributors, the mean Gini coefficient 0.358, and the mean top-contributor share 79.0%; concentration peaks at the campuses with the most imagery, including UI ($G = 0.730$), UNDIP (0.681), and ITB Jatinangor (0.664, where one contributor supplied 99.7% of that campus's 991 images). Nine campuses depend on a single person. This matches established findings that a small number of highly active participants generate most volunteered geographic information [5, 49, 50, 53] and that such data is spatially uneven [6, 51, 52, 54, 55]. The practical consequence is that 9.0% coverage at IPB and 0.0% at UNEJ are not two measurements of one quantity: the first is the residue of a few mapping episodes, the second records that none occurred. Neither is a stable property of the site, and both can lapse as easily as they appeared.

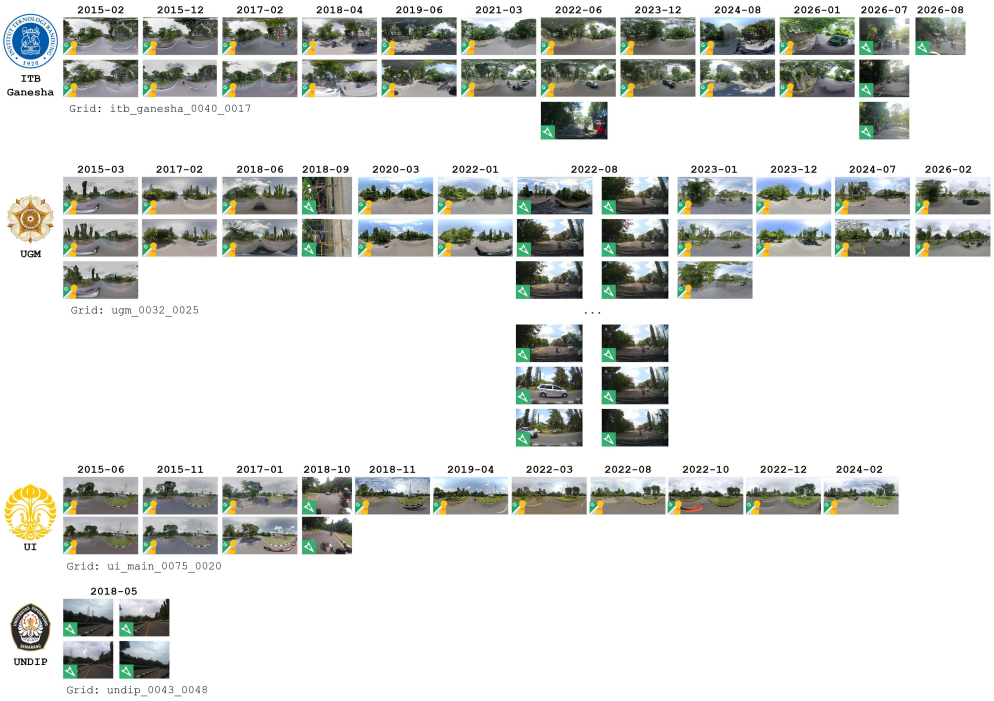

Fig. 15 Examples of retrieved SVIs within a representative grid at each campus: ITB Ganesha Campus, UGM, UI, and UNDIP (from top to bottom).

5.3 The case for independent street-view acquisition

If neither platform covers most of the campus and the crowdsourced source rests on a handful of people, institutions that need street-level data about their own grounds cannot wait for it to arrive. Independent, openly licensed acquisition becomes the practical route, consistent with arguments that reliance on proprietary imagery carries methodological and licensing costs open alternatives avoid [7, 47, 48] and with toolkits already built to make open collection tractable [40, 56].

Three benefits follow. Computer vision research needs coverage where the phenomenon occurs: semantic segmentation underpins greenery indices [35, 36], visual composition modelling [31], and perception studies [20, 32], and models trained on unevenly distributed imagery inherit that unevenness, degrading replicability across sites [46]. The people exposed to these environments are students and staff, and their exposure occurs on interior paths rather than the ring road: eye-level greenery is associated with student physical activity [9] and campus landscape with mental health [8, 10], and street-view methods have been applied to campus space quality [12], imageability [13], and open-space resilience [26], all requiring interior imagery that our results show to be scarcest. Finally, self-collected imagery can serve as a repeatable audit instrument, extending established systematic-observation practice [33, 34, 38, 41]

and change-tracking work [2] into a defined institutional cycle suited to sustainability reporting [14, 25].

5.4 Visual openness as an institutional choice

The pattern is not only technical. Google's coverage is a commercial product following drivable access and corporate priorities [47], and a gated campus is not obliged to admit a survey vehicle; Mapillary's requires someone on the ground willing to record and publish. The near-absence of crowdsourced imagery at 16 of 40 campuses therefore admits two caveats, that nobody has undertaken the effort or that the institutional setting does not encourage open sharing of campus visual data. Our data cannot separate them, and we do not claim to.

This distinction also suggests that SVI coverage should not be interpreted simply as a measure of physical accessibility. A campus may be highly accessible and intensively used while remaining poorly represented in publicly available street-level imagery because accessibility to people does not necessarily translate into accessibility to mapping platforms or imagery contributors. The resulting discrepancy is important because it introduces a form of observational bias: areas with limited imagery may appear less studied or less environmentally relevant, when in fact they may simply be less visible through the available data infrastructure.

The consequence holds either way. This sits awkwardly with institutions that participate in sustainability rankings and open-science commitments presupposing exactly this kind of environmental documentation, and with accounts of campuses functioning as quasi-public space in developing-country metropolises [16]. Making campus imagery openly available is a low-cost decision with direct research value [48, 56], particularly for micro-climate studies, where open street-level datasets enable accurate mapping of canopy shade, sky-view factors, and pedestrian thermal comfort to target heat-mitigation interventions where students actually walk [37], and it rests with the institutions rather than with either platform. The spatial distinctiveness that makes Indonesian campuses interesting as study sites [15, 17] is the same distinctiveness that keeps them out of datasets built on public roads.

5.5 Limitations and future work

Four limitations bound these results. The sample of 40 campuses spans several islands, both public and private institutions, and a wide size range, but is not a probability sample; some campuses cover several square kilometres, so a campus-level statistic such as the openness slope averages across internally heterogeneous territory, and cross-campus comparison here is descriptive rather than inferential. We measure the existence of imagery, not its quality: a cell counts as covered if one record falls within it, regardless of resolution, obstruction, angle, or age. Quality assessment frameworks exist [42], on-site comparisons show online imagery does not always represent conditions faithfully [44], and perspective differences between platforms affect downstream measurement [39], so a campus recorded as covered may still be unusable. Date precision also differs between sources, so all temporal analysis was conducted at year

level, and the acquisition relies on undocumented platform endpoints, making this a snapshot retrieved in August 2026 by a method that may not remain valid.

Several directions follow. Assessing imagery quality rather than presence would establish how much recorded coverage around Indonesian campuses is actually usable. Pairing cluster geometry with mapped internal path networks would test directly whether coverage follows accessible corridors, which our results imply but do not demonstrate. Repeating the acquisition periodically would convert this snapshot into a monitoring series and reveal whether crowdsourced coverage grows or decays once its initiating contributor stops. Extending the approach to hospitals, industrial estates, and gated residential developments would test whether the pattern is specific to campuses or general to semi-enclosed institutional sites.

6 Conclusion

This study measured street-view imagery availability across 40 Indonesian university campuses on a 20 m grid, comparing crowdsourced (Mapillary) against proprietary (GSV) sources and treating their disagreement as the object of analysis. Coverage was scarce and highly asymmetric: Google reached 22.9% of cells on average and Mapillary 3.3%, while the two agreed on 2.1%, and 76.0% of the sampled area was reached by neither. Distance from the boundary does not explain where coverage occured, with a median slope of +0.021 and median R^2 of 0.006. The campuses that showed decay inward were predominantly those embedded in dense, well-mapped cities, suggesting the gradient reflects the coverage differential across the boundary rather than enclosure alone. Coverage clusters in every campus, but only within its covered fraction, with Low-Low clustering effectively absent.Crowdsourced coverage depended on very few people: a mean of 3.97 contributors, a mean Gini of 0.358, and nine campuses dependent on one individual.

Together these results indicate that street-view availability in semi-enclosed institutional sites is governed by internal accessibility and individual contribution decisions rather than perimeter geometry, and that the two sources are not substitutes but different data-generating processes reporting on different fragments of the same space. The practical implication is direct: institutions needing street-level environmental data for their own grounds, whether for sustainability auditing, open-space planning, or vision-model training, should not expect either platform to supply it, and independent openly licensed acquisition is the tractable route within their own control.

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Declarations

- Funding: This research, entitled "Cooling Cities, Warming Communities: Quantifying Climate Resilience in Urban Parks Through Anthropomorphic Mapping and Place Attachment," is funded by Universitas Indonesia under Contract No. PKS-357/UN2.RST/HKP.05.00/2025. This research is funded by the Indonesian Endowment Fund for Education (LPDP) on behalf of the Indonesian Ministry of Higher Education, Science and Technology and managed under the Global Reach Program (Contract No. 0791/DIRBAGA/V/2026 and 146/PKS/R/UI/2026).

- Competing interests: The authors have no competing interests to declare.
- Data availability: The shareable data generated in this study are available on Hugging Face at https://doi.org/10.57967/hf/11294. Google Street View and Mapillary metadata were obtained through their respective APIs and are subject to the terms and conditions of the respective providers. The code developed for this study is publicly available on GitHub at [https://github.com/AditPradana36/campus-svi-availability.git].
- Author contribution: **M.R.P.:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Visualization, Writing – original draft. **J.M.S.:** Conceptualization, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition. **N.M.:** Writing – review & editing, Supervision, Project administration. **N.S.R.:** Writing – review & editing, Supervision, Project administration.

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