Mechanisms contributing to road network growth in volunteered street view imagery data

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Keywords: Data coverage, Mapillary, Volunteered geographic information, Spatial distribution, Crowdsourced data.

Abstract

This study focuses on the growth of road networks in volunteered street view imagery (VSVI) data, using data from the Mapillary platform in Tokyo as a case study. The results demonstrate that VSVI data extends outward from the city center and is governed by two fundamental spatial processes, *densification* and *exploration*, as observed for OpenStreetMap in previous studies. Among these, *densification* becomes more dominant as dataset grows, rising from 76.8% to 91.4% of total contributions. Furthermore, bivariate regression analyses indicated relationships between the number of image contributions and road coverage, as well as the growth rate of road networks for various road types. Specifically, the growth in coverage for National Expressways follows a logarithmic model, whereas other road types are better represented by linear models with higher-grade roads exhibiting greater growth rates. This study represents the first attempt to explore the links between the number of contributions and spatial distribution in VSVI, thereby providing new insights into its dynamic growth patterns and future development trends.

1. Introduction

Citizen participation has been demonstrated as an effective means of collecting various types of geographic information (Goodchild, 2007), playing a crucial role in supporting data-driven initiatives in smart cities. Among these, volunteered street view imagery (VSVI), which is a dataset of street-level images contributed by volunteers, has proven to be a valuable resource for acquiring timely and detailed streetscape information through a fully open and cost-free approach (d’Andrimont et al., 2018; Zhang et al., 2021; Tsutsumida and Funada, 2023). VSVI holds significant potential for supporting automatic mapping, enabling dynamic urban monitoring, and informing urban environmental policymaking. However, its practical application remains limited, partly because of the inherent spatial heterogeneity of VSVI contributions (Juhász and Hochmair, 2015; Juhász and Hochmair, 2016; Ma et al., 2019; Mahabir et al., 2020) and unknown mechanisms governing the spatial distribution of data.

As a type of crowdsourced data, the VSVI allows users to upload street-level images captured at any time, location, or device. Due to the uncertainty of contribution locations, many recent studies have sought to explore the mechanisms influencing the spatial distribution of such data. Existing research has examined spatial distribution differences at the national, city, and road levels, revealing relationships between VSVI distribution and factors such as social (e.g., population density) and physical environments (e.g., land use), and the availability of other commercial street-level imagery data (Juhász and Hochmair, 2015; Juhász and Hochmair, 2016; Ma et al., 2019; Mahabir et al., 2020; Seto and Nishimura, 2022). Zheng and Amemiya (2024) explored the relationship between the number of street revisits and VSVI data quality at the road level without investigating the intrinsic mechanisms contributing to the spatial distribution. Because VSVI does not guarantee data coverage, understanding place selection patterns across different contribution stages and the statistical relationships between contribution volume and coverage rate could provide new insights into the dynamics of VSVI mapping and help estimate future development trends.

The growth patterns of road networks have been explored in other types of crowdsourced data, particularly in OpenStreetMap (OSM) (Corcoran and Mooney, 2013; Corcoran et al., 2013; Elias et al., 2023; Minaei, 2020; Zhao et al., 2015). However, these results may not apply to VSVI because, unlike OSM, which allows users to contribute data remotely via the Internet, VSVI requires contributors to physically visit locations and upload photographs taken on-site. As a result, the spatial choices of contributions as well as the patterns and speed of data expansion may differ significantly. Therefore, it is important to investigate VSVI within the framework of the existing theories to better understand its unique characteristics and dynamics.

Therefore, we performed an intrinsic analysis of the evolution of a network of roads containing VSVI with increasing contributions. For spatial expansion patterns, we hypothesized that, considering city centers as primary areas of activity for citizens, the distance from the city center may influence the priority of a location being contributed to. Moreover, the two sequentially dominant expansion patterns of *exploration* (expansion of the network into new areas) and *densification* (increase in the local density of the street network) observed in OSM street network representations (Corcoran et al., 2013) may also apply to VSVI because high-grade roads are often more accessible, more likely to attract on-site contribution behaviors, and thereby cover roads faster than low-grade roads. Regarding the statistical relationships between the volume number and coverage rate, we assume that the results vary by road type owing to the different travel speeds of the dominant travel modes across road types. To assess the above assumptions, the analysis observed the spatial expansion process at different contribution stages, considering the distance to the city center and road types, as well as exploring the growth rate of road coverage along with contribution volumes for different road types. Specifically, we explored imagery data on the Mapillary platform (launched in 2014), which was the first website to share geotagged photos contributed by a crowd. With exponential growth in data, more than two billion street-level images from over 190 counties are available on this platform (https://www.mapillary.com/).

2. Methods

2.1 Overview of analysis

Tokyo was selected as the study area because it is a hotspot for Mapillary activities in Japan. Specifically, we first conducted a qualitative observation of the spatial expansion of road networks containing Mapillary data at different contribution levels and across varying distances from the city center to examine the influence of location on place selection. We then quantified the volume of the two expansion patterns of *exploration* (defined as the contribution length for high-grade roads) and *densification* (defined as the contribution length for low-grade roads) to explore the sequential transition between them (Section 3.3). Furthermore, to estimate the rate of network growth, we fit linear, logarithmic, and logistic bivariate regression models using the number of contributions as the independent variable for all road segments and types (Section 3.4). To note, the contribution volume was calculated based on the number of unique image IDs in the study area. The spatial coverage values (D_i) at different contribution stages were calculated as the ratio of the total length of the road segments containing data (L_{road_data}) to the total road length (L_{total}) in Tokyo for all road segments or specific road types.

$$D_j = \frac{L_{road\_data}}{L_{total}}$$

2.2 Data description

2.2.1 Map imagery data: A total of 5,626,656 imagery data points were downloaded from the Mapillary API for Tokyo on the date of data collection, that is, July 18, 2022. To this end, a bounding box covering the entire area of Tokyo was created and all imagery data up to the retrieval date (July 16–18, 2022) were downloaded. GeoJSON files containing the coordinates of the image nodes, sequence ID of the image, image ID, and timestamp were then retrieved and transferred into point shape files in ArcGIS Pro 3.0.0 for further analysis. To facilitate temporal analysis, images without timestamps and those taken before the launch of Mapillary in 2014 were excluded. Images more than 55 m from the road centerline (the sum of half the maximum road width (35 m; based on road data) and the assumed GPS drift (20 m)) were removed because they were deemed to not have been captured along roads. Additionally, we excluded points located on railways that were not included in this study. These procedures were performed in ArcGIS using the "closest facility" tool to match the image points with roads. After these steps, 5,264,258 map points remained for analysis.

2.2.2 Reference road data: Reference roads were used to evaluate the spatial distribution of the data and data attributes. The reference roads for evaluation were obtained from the centerline road data of the Digital Map (Basic Geospatial Information) 2021 provided by the Geospatial Information Authority of Japan. The roads were categorized into five groups: National Expressways, National Highways, Prefectural Roads, Municipal Roads, and Parkways/Garden Paths. Road segments, used as the unit of measurement for road length covered by data, were generated by dividing roads at intersections. However, for National Expressways, tunnels, and road segments exceeding 1 km in length with few intersections, segmentation was performed at 100-meter intervals (a method commonly adopted in urban audit studies; Li et al., 2015; Li, 2021) to ensure comparability in segment length. After preprocessing, a total of 767,228 road segments were used to construct a road network for data connections. The average length of each segment was 52 m. After matching Mapillary points, 185,832 road segments were found to contain Mapillary data.

3. Results

3.1 Monthly growth of Mapillary contributions

Figure 1 illustrates the development of Mapillary contributions in Tokyo in the form of continuous contributions during the study period. Most of these contributions were made after 2016. The Mapillary dataset for Tokyo reached more than one million contributions in March 2018, and five million contributions in December 2021.

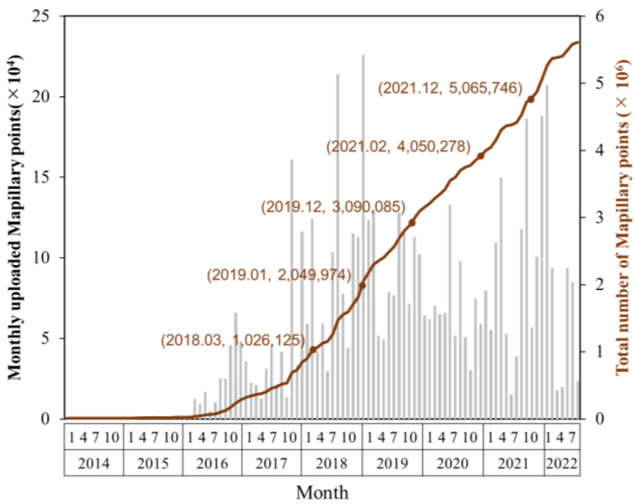

Figure 1. Monthly growth of Mapillary contributions in Tokyo. The upper row on the x-axis shows months. Values in brackets show example dates and total contributions at that date.

3.2 Spatial coverage

Based on the calculations performed in ArcGIS, the total length of the reference road network in Tokyo is 39,440.5 km. After more than eight years of contribution, the length of the segments containing Mapillary image data was 10,769 km, which was almost one-third of the total length (27.3%; Figure 2). In terms of road type, the highest road coverage was found for National Expressways (90.9%; Figure 3 (*b*)), followed by National Highways (90.3%; Figure 3 (*c*)) and Prefectural Roads (73.5%; Figure 3 (*d*)). The values were relatively low for Municipal Roads (24.0%; Figure 3 (*e*)) and Parkways/Garden Paths (16.7%; Figure 3 (*f*)).

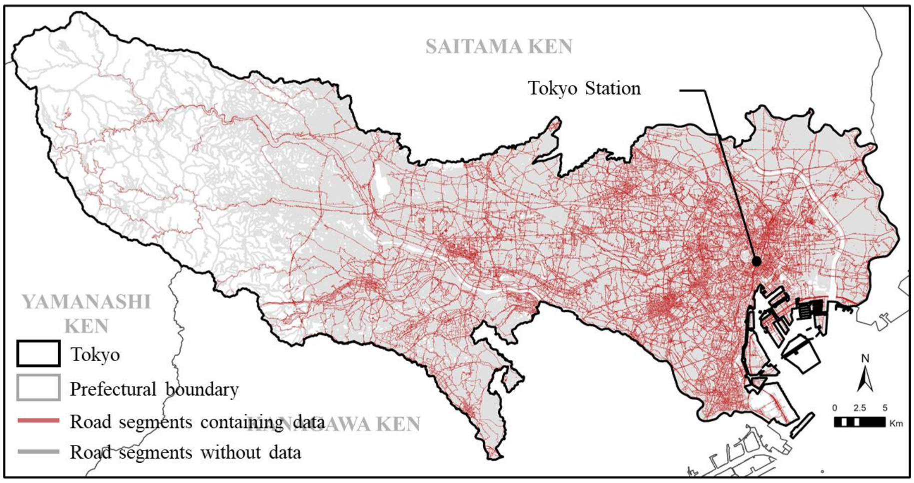

Figure 2. Spatial distribution of road segments with Mapillary data (red lines) and without Mapillary data (gray lines) for all road segments.

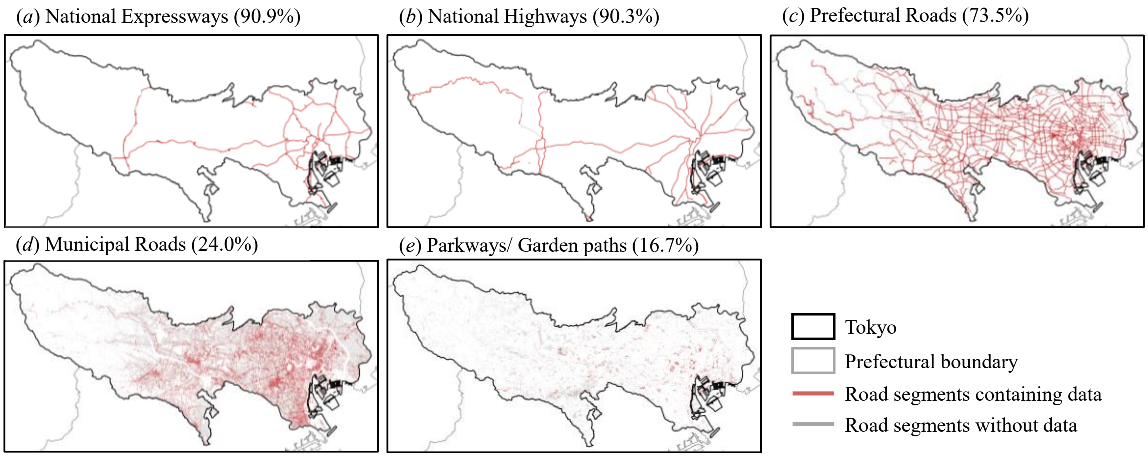

Figure 3. Spatial distribution of road segments with Mapillary data (red lines) and without Mapillary data (gray lines) across all road types.

3.3 Spatial expansion process

Figure 4 shows the spatial expansion of the Mapillary street network in Tokyo, in parallel with an increase in the number of contributions (N_c). Generally, coverage gradually increased from the center of Tokyo (Tokyo Station) to its outskirts. In the early stage, when the total number of image contributions was less than two million (Figure 4 (*a* and *b*)), road network expansion primarily occurred within a 10 km radius from the city center, with only a small number of contributions beyond the range. In the later stages, when the contributions exceeded two million Figure 4 (*c, d,* and *e*), there were noticeably fewer contributions within the 10 km zone, whereas more contributions appeared in the 10-20 km range and– 20-50 km range.

To quantitatively examine whether a similar pattern found in OSM (Corcoran et al., 2013; as described in Section 1) was observed for the VSVI, we calculated the percentage of the length of each road type among the road segments newly mapped at each N_c level. As shown in Figure 5, this percentage for high-grade road types (National Expressways, National Highways, and Prefectural Roads), which represent *exploration*, decreased from 43.5 to 9.4%, whereas the ratio for low-grade roads (Municipal Roads and Parkways/Garden Paths), representing *densification*, increased from 76.8 to 91.4% with an increase in N_c.

3.4 Rate of network growth

Regressions were carried out for all road segments and each road type using the number of image contributions as an independent variable and spatial coverage in Tokyo at corresponding contribution levels as the dependent variable. Table 1 and Figure 6 present the best-fitting models (selected based on Akaike Information Criterion values). For all road segments, the top model had a coefficient of 5.3, indicating an approximately 5.3% increase in coverage per million contributions (Figure 6 (*a*)). For National Expressways (Figure 6 (*b*)), a logarithmic model provided the best fit, whereas a linear model was most suitable for other road types (Figure 6 (*c*–*f*)), with coefficient values ranging from 3.1 for Parkways/Garden Paths (Figure 6 (*f*)) to 18.0 for National Highways (Figure 6 (*c*)).

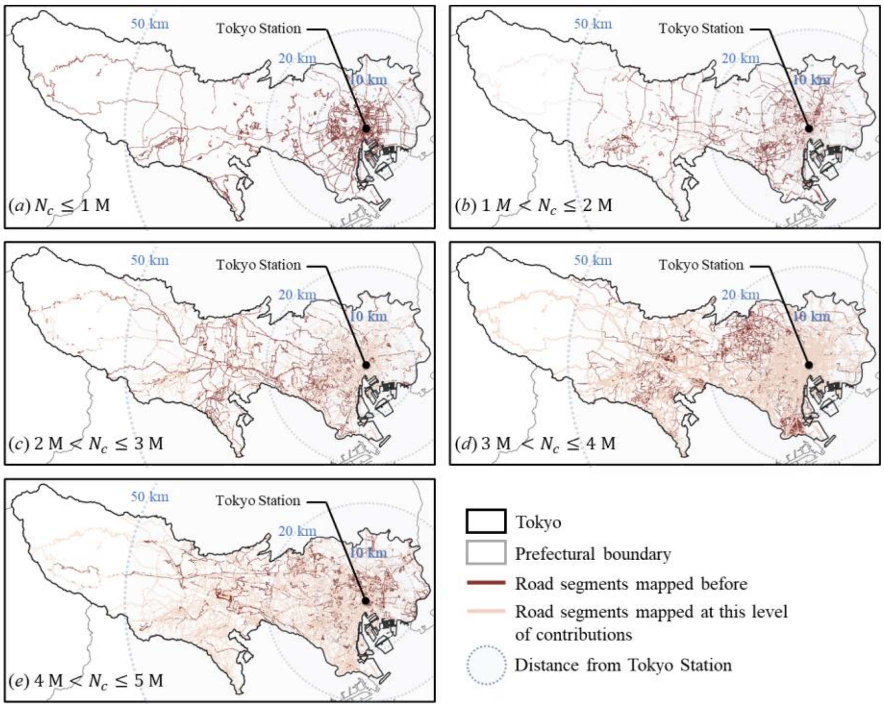

Figure 4. Spatial expansion process of the Mapillary road network at different levels of contributions

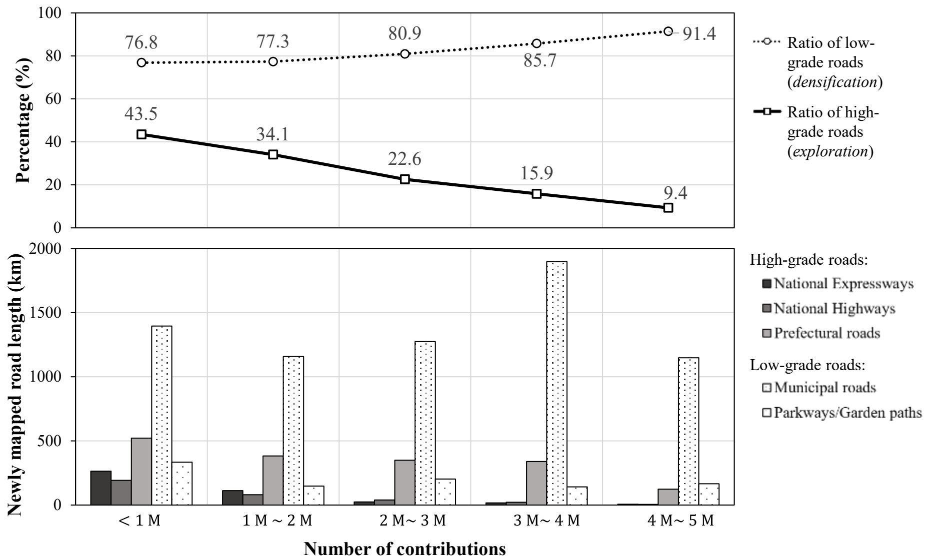

Figure 5. Percentages of newly mapped road lengths of road segments for different road types at different contribution levels.

Table 1. Model parameters for the best-fitting regression models of road coverage with the number of street revisits as the independent variable.

Road types	Equation	R^2	Sig.	Parameter Estimates Const.		B	
All road segments	Linear	0.995	< 0.001	0.912	***	5.259	***
National Expressways	Logarithmic	0.934	< 0.001	67.282	***	11.885	***
National Highways	Linear	0.856	< 0.001	18.749	***	17.951	***
Prefectural Roads	Linear	0.98	< 0.001	3.098	***	15.323	***
Municipal Roads	Linear	0.998	< 0.001	0.195	***	4.524	***
Parkways/ Garden Paths	Linear	0.982	< 0.001	1.013	***	3.149	***

Note.: *** $p < 0.001$

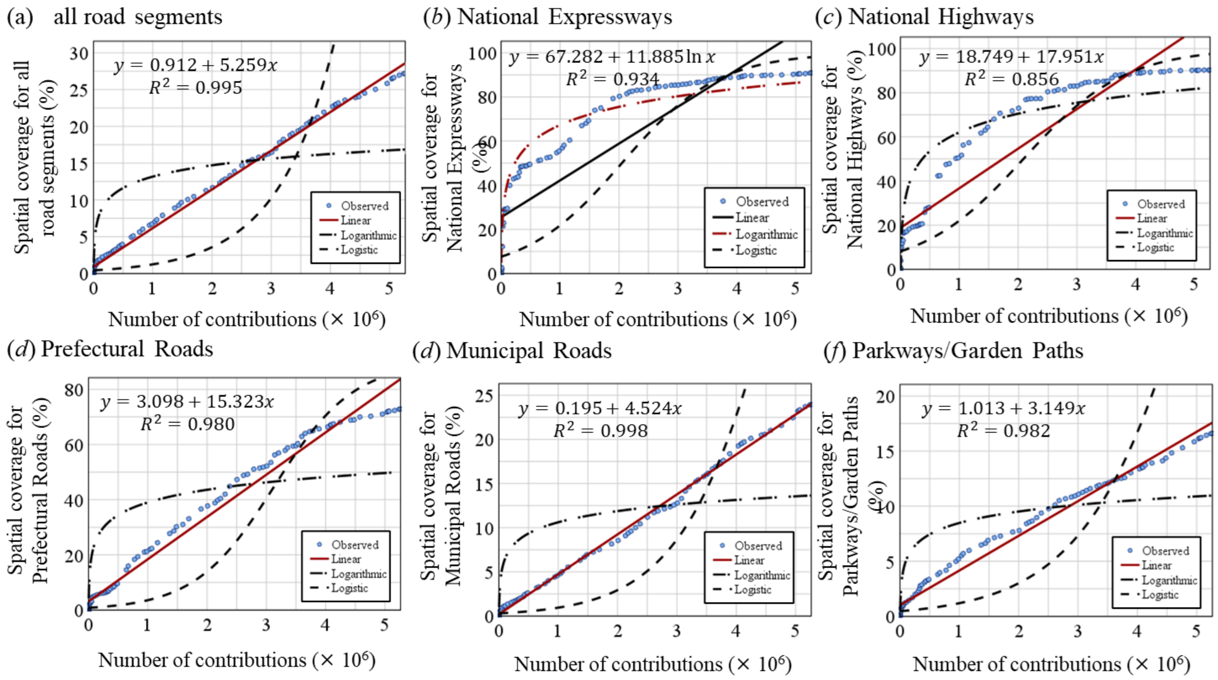

Figure 6. Regression models of the relationship between spatial coverage and number of contributions for each road type. The best-fit model is indicated in red.

4. Discussion

As a potential data source for streetscape information generated through citizen engagement to support data-driven urban policy-making, this study addresses a key challenge in the application of volunteered street view imagery (VSVI): the uncertainty in its spatial distribution. To address this, we established a novel link between the contribution volume and the spatial distribution patterns.

The results of the expansion process support our assumption that when the number of contributions is low in the early stage of VSVI development in a district, road segments with available data tend to be concentrated in the city center area. As the number of contributions increases, more road segments containing data are found on the outskirts. These results are consistent with those of previous studies, showing that higher spatial coverage is found in densely populated areas (Mahabir et al., 2020; Seto and Nishimura, 2023), which is thought to be due to a higher number of potential contributors. For spatial expansion on the outskirts (the Tama area in Tokyo), hotspot enclaves appeared randomly at different levels of contribution in addition to some major roads. This was likely due to the mapping events conducted by some organizations, such as the Mapillary community in Japan or for education in the field of GIS, as well as the personal preferences of some power users to achieve full data coverage in a specific area.

In terms of road network expansion, a similar pattern was found in Mapillary and OpenStreetMap (Corcoran et al., 2013). *Exploration* (contributions to high-grade roads) tended to occur primarily at an earlier stage, whereas *densification* (contributions to low-grade roads) maintained a stable increase during the study period, leading to a later dominance. Unlike OpenStreetMap, a similar phenomenon observed in Mapillary was more likely driven by higher accessibility and traffic volume. The similarities in data-expansion patterns across different forms of crowdsourced data provide insights into the potential for identifying common mechanisms or patterns underlying the expansion processes of other similar datasets.

Regarding the current state of spatial coverage, the results indicate that after nearly eight years of contributions in Tokyo, Mapillary—despite not achieving full road coverage—provides relatively comprehensive coverage on higher-grade roads. This level of coverage is comparable to that of Google Street View, a representative example of traditional street view imagery services. Notably, Google Street View has been reported to have an average spatial coverage of 90.5% across 45 small- and medium-sized cities in the U.S. (Kim & Jang, 2023). These findings suggest that even an unstructured, citizen-driven VSVI contribution approach can generate a dataset comparable to commercial SVI services, particularly for high-grade roads. As for the growth rate, differences were found between road types, as assumed. High-grade roads were best described using a logarithmic model with a high starting rate that decreased when a certain high level of coverage was reached. This later stage may indicate the completion of the mapping. In contrast, the relationship for low-grade roads is best described by a linear function with a stable growth rate.

Differences between road types in this respect may be due to platform characteristics of VSVI mapping behavior, where volunteers must physically travel along roads to collect data. As a result, high-grade roads with greater accessibility tend to attract more contributors. The higher travel speeds and relatively shorter total length of these roads facilitate the rapid and long-distance expansion of VSVI data. Therefore, we suggest that although the number of contributions in an area has been widely used as a metric of the level of VSVI development in that area, studies/audits must account for the large differences between geographic and social environments and different road types.

Based on our analysis of road network growth on Mapillary platform, we proposed a novel proxy measure for evaluating the level of VSVI data availability–an essential requirements for smart city applications–based on its stages of development. Specifically, in the early stages, VSVI are more likely to capture information on high-grade roads. In contrast, coverage of low-grade roads tends to emerge later and at a slower pace, typically following a spatial sequence from the city center to the outskirts. Furthermore, we offer several recommendations for VSVI platforms to improve spatial completeness. As contributions grow, areas frequently visited by citizens are likely to become well represented quickly, since contributors must physically visit locations to take photos. However, gaps in coverage–particularly in areas or along road types with lower traffic volumes (e.g., suburban areas or low-grade roads)–should be addressed by increasing user motivation or offering targeted incentives. Potential strategies include game-like challenge tasks and reward systems calibrated to the difficulty of coverage.

Our study had some limitations. First, the method used to locate points on roads relied on the closest distance, which may have introduced map-matching errors, especially at intersections and in areas where roads overlap. The 55-meter threshold may have included points that were not on roads or excluded valid ones. Additionally, analyzing the relationship between coverage and contribution alone does not provide a proxy measure that can be used to evaluate coverage in other regions. Future studies should explore the role of the ratio of contribution to area size or total road length in determining data completeness. Finally, patterns of duplicate posting, which tend to enhance the spatial and temporal resolution of streetscape information (Zheng and Amemiya, 2024), should be examined further in future work.

5. Conclusions

This study presents an initial analysis of the relationship between contribution volume and street network growth in VSVI. Specifically, we identify the spatial characteristics of network expansion on the Mapillary platform, highlight shifts in dominant patterns, and reveal the relationship between contribution volume and growth in spatial coverage across different road types. These findings provide a theoretical basis for predicting VSVI data availability in smart city applications, taking into account road types and regional characteristics at different stages of development. The results are expected to promote the broader use of such data in practical applications and enhance our understanding of the effectiveness of citizen participation in data collection.

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