# Analysis of Building 3D Attribute Coverage and Spatial Disparity of Editing Activities in OpenStreetMap

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**Abstract**

This study analyzed the completeness and spatial distribution of three-dimensional (3D) building attributes within OpenStreetMap (OSM) data across Japan, along with an examination of the characteristics of editing activities. A data extraction and analysis pipeline was developed to assess the spatial coverage of 3D attributes and patterns of editing activity at the multi-scale. The key findings are as follows: (1) only 4.7% of OSM buildings in Japan possess height attributes, with notable regional disparities in 3D attribute coverage. (2) editing activities are highly concentrated, as evidenced by average Gini coefficient of 0.949, with 38.3% of prefectures exhibiting a high concentration (HHI > 2500). (3) urban areas tend to exhibit more diverse editor participation, whereas rural areas are heavily reliant on a limited number of editors. (4) the import of government 3D city model data significantly enhanced the 3D attribute coverage in certain municipalities. (5) sustainability challenges are present, particularly in rural areas that are dependent on a few editors. The results underscore the necessity of targeted efforts to enhance 3D data completeness and editor participation, especially in underrepresented regions. This analysis provides insights to support the sustainable development of OSM 3D building data in Japan.

## 1. Introduction

In recent years, the demand for three-dimensional (3D) urban models has rapidly increased in the fields of urban planning, disaster prevention, and smart city construction. In Japan, the development of 3D urban models is being led by the government, as exemplified by "Project PLATEAU," a 3D urban model development project promoted by the Ministry of Land, Infrastructure, Transport and Tourism (Seto et al., 2023). However, the development of high-precision data is costly and time consuming. OpenStreetMap (OSM), a representative example of volunteer geographic information (VGI), has attracted attention as an alternative solution to this problem. OSM is the world's largest open-source geographic information platform launched in 2004, with a cumulative total of approximately 10 million registered users as of February 2025. It provides fundamental geospatial information from around the world in the XML format under an open license. The OSM building data has been confirmed to contain approximately 510 million buildings worldwide. In addition to conventional 2D information, 3D attributes, such as height, number of floors (building:levels), number of underground floors (building:levels: underground), minimum height (min_height), and elevation (ele), can be recorded in the model.

However, owing to the characteristics of VGI, issues such as regional disparities and editor dependence have been highlighted in the quality and completeness of OSM data (Seto et al., 2020). Accuracy, attribute accuracy, temporal accuracy, and logical consistency (Senaratne et al., 2017), Most of the existing studies have mainly focused on quality assessment at the city level and analysis of 2D data (Brovelli et al., 2018; Herfort et al., 2023), with limited analysis of the coverage of 3D attributes (Biljecki et al., 2023). Regarding the continuity of activities of contributors (editors) in maintaining the quality of VGI data, a global analysis of the distribution of OSM editors revealed an oligopoly of a few active editors (Neis & Zipf, 2012), and a qualitative study of the relationship between editors' motivation and continuity of A qualitative study on the relationship between editors' motives and continuity revealed the importance of intrinsic motivation (Budhathoki & Haythornthwaite, 2013).

In contrast, OSM studies in Japan include a questionnaire-based analysis of editors (Yamashita et al., 2019), the quality evaluation of mountain place names (Yamashita et al., 2022), and Seto et al. (2023) evaluate the completeness of OSM building data in the Tokyo by comparing with the Ministry of Land, Infrastructure, Transport and Tourism's "Project PLATEAU" data. Although the completeness of the data was evaluated by comparing it with PLATEAU data, no analysis of buildings with 3D attributes was conducted at the national level. Therefore, in this study, to quantitatively analyze the completeness and spatial unevenness of OSM building 3D attribute data covering all of Japan, as well as the characteristics of editing activities, a script for data extraction and analysis was developed to evaluate the spatial coverage of 3D attributes and the continuity and concentration of editing activities throughout Japan. The purpose of this project is to evaluate the spatial coverage of 3D attributes and the continuity and concentration of editing activities in Japan.

## 2. Methods

The study area covered the entire country of Japan and OpenStreetMap (OSM) data as of February 1, 2025, were analyzed. Spatial analysis was conducted primarily at the prefectural level (n = 47) to identify regional disparities in the data. However, some analyses were conducted at the municipal level (N = 1,905). Figure 1 shows the data processing flow for aggregation and analysis. Phase 1 involved data extraction and import. Phase 2 consisted of data aggregation and output to the CSV. The data were mapped and analyzed using QGIS.

The analysis used OpenStreetMap (OSM) data covering the entire country of Japan (editor attribute dump data as of February 1, 2025, provided by Geofabrik) and the administrative area data. Table 1 shows the items in the aggregation table output from the procedure shown in Figure 1 and introduces the analysis results: 3d_coverage.csv, prefecture_analysis.csv, and editor_stats.csv.

| file Name | item summary |
|---|---|
| 3d_coverage.csv (9 items) | prefcode, total_buildings, height_count, levels_count, min_height_count, underground_count, ele_count, height_coverage, levels_coverage |
| prefecture_analysis.csv (14 items) | prefcode, building_count, editor_count, gini_coefficient, top_editor, top_editor_share, top5_editor_share, top10pct_editor_share, hhi, height_count, height_coverage_rate, levels_count, levels_coverage_rate, first_edit_date, last_edit_date |
| editor_stats.csv (11 items) | uid, first_edit, last_edit, total_edits, building_edits, active_prefectures, building+height, building_types, height_edits, levels_edits, height_edit_rate |

Table 1. Aggregate items for 3D building attributes.

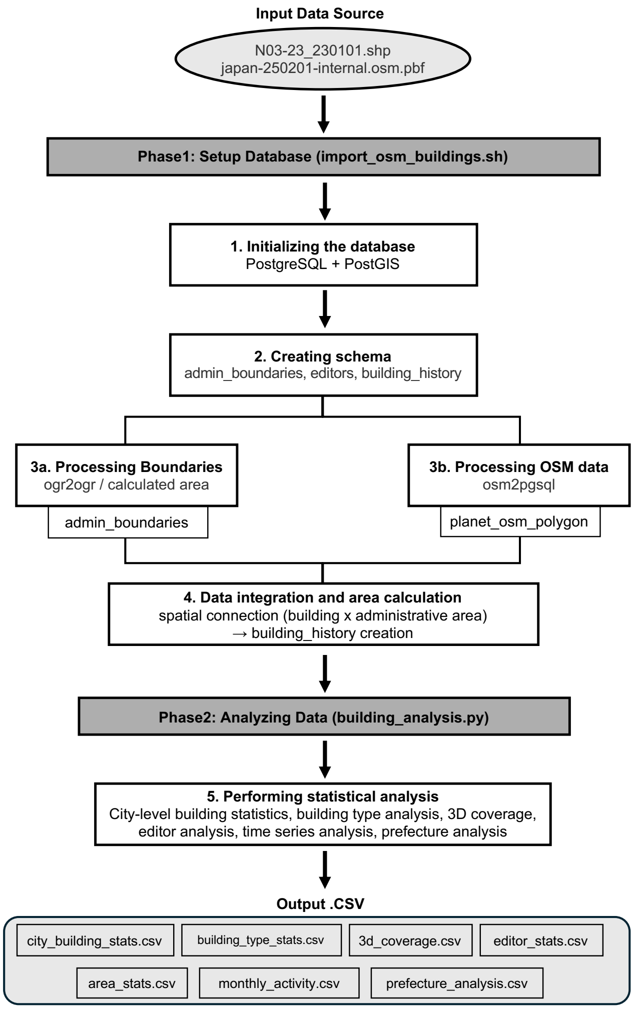


Figure 1. Data processing flow for analysis.

The extraction of 3D attributes in the building data was performed for height, building:levels, min_height, building:levels:underground, and ele, so that the data could be aggregated into spatial units of 47 prefectures or 1905 municipalities. To quantitatively evaluate the concentration of editorial activities, this study applied the Gini coefficient, which is used in economics to measure income inequality, and the Herfindahl-Hirschman index (HHI), which is used to measure market concentration, to the analysis of editors' contributions. These indices have been used in previous studies to measure community participation imbalances (Chikoto et al., 2015).

The Gini coefficient was calculated using the following formula, where $x_i$ and $x_j$ represent the number of building edits by editors $i$ and $j$, $n$ is the total number of editors, and μ is the average number of building edits. The Gini coefficients were distributed in the range of 0 (perfect equality) to 1 (perfect inequality), with disparities generally greater than 0.4.

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left|x_i - x_j\right|}{2n^2\mu}$$

The HHI was calculated using the following formula, where *Si* represents the market share (%) of editor *i*: The output of the HHI was calculated by squaring the share, and the maximum value was 10,000. Generally, a value greater than 2,500 is considered a highly concentrated. The 3D attribute coverage and editorial activity characteristics of OSM building data across Japan were quantitatively analyzed.

$$HHI = \sum_{i=1}^{n} s_i^2$$

## 3. Data Constraints

### 3.1 Overview of OSM Building Data and 3D Attributes

The following results were obtained using the developed analysis method. The national OSM database contains 24,183,256 buildings, of which 3D attributes were recorded as follows: height (1,125,395; 4.7%), number of floors (1,104,648; 4.6%), minimum height (563; 0.002%), number of basement floors (563; 0.002%), underground floors (1,104,648; 4.6%), and elevation (1,111,850; 4.6%). The average area of a building was 288.5 m$^2$, and when restricted to buildings with 3D attributes, the average area was 1260.3 m$^2$. Therefore, landmarks with 3D attributes tend to be large buildings.

The number of buildings with more than 10,000 buildings (15 types, accounting for 99% of all buildings) and the number of buildings containing 3D attributes were summarized according to the building type. It was found that 21,019,547 buildings with unknown building use (building=yes) accounted for 86.9% of all the buildings (Table 2). However, these buildings did not contain many 3D attributes, with only 388,685 buildings (1.85%) having a height attribute, and 254,883 buildings (1.21%) having a level attribute. In the case of houses, which represent residences, 1,704,721 (7.05%) houses were found to be the most common, with 529,163 (2.19%) in the height attribute and 487,023 (2.01%) in the level attribute. Other public buildings with a relatively large number of entries for height and level were industrial (68,468; 0.28%), commercial (36,058; 0.15%), and public (26,431; 0.11%); however, the absolute numbers were small.

In light of the nationwide situation concerning the assignment of 3D attributes by building type, a Pearson correlation analysis was subsequently conducted to examine the relationships among the number of buildings, number of editors, and 3D attribute coverage rate at the prefectural level. This analysis confirmed the presence of a significant relationship. (1) The number of buildings and editors ($r=0.608$, $p<0.05$), (2) the height coverage rate and floor coverage rate ($r=0.602$, $p<0.05$), and (3) the number of editors and floor coverage rate ($r=0.328$, $p<0.05$). However, no significant correlation was found between the number of editors and the height coverage ($r=0.256$, $p\geq0.05$). This suggests that the factors in the editing process and the skills of specific editors are more important than the number of editors in the development of the height data.

| Rank | building_type | count | height | levels | underground | ele | avg_height | avg_levels | avg_area_sqm |
|---|---|---|---|---|---|---|---|---|---|
| 1 | yes | 21,019,547 | 388,685 | 254,883 | 56,518 | 382,107 | 6.2 | 7.28 | 132.63 |
| 2 | house | 1,704,721 | 529,163 | 487,023 | 53,975 | 527,392 | 7.08 | 1.93 | 88.81 |
| 3 | detached | 349,641 | 264 | 57,466 | 8 | 118 | 7.45 | 2.07 | 87.92 |
| 4 | apartments | 277,299 | 57,692 | 126,101 | 2,420 | 56,399 | 12.13 | 4.09 | 302.8 |
| 5 | residential | 183,740 | 31,137 | 30,226 | 2,089 | 30,827 | 8.12 | 2.39 | 122.4 |
| 6 | greenhouse | 126,243 | 546 | 9,868 | 0 | 67 | 1.91 | 1 | 392.86 |
| 7 | roof | 85,623 | 748 | 4,890 | 22 | 465 | 8.27 | 1.07 | 103.92 |
| 8 | industrial | 68,468 | 27,063 | 22,986 | 2,821 | 26,959 | 7.27 | 1.56 | 1320.7 |
| 9 | retail | 68,067 | 16,629 | 22,946 | 1,708 | 16,179 | 8.07 | 2.05 | 836.75 |
| 10 | school | 39,365 | 1,872 | 4,210 | 50 | 1,725 | 13.17 | 2.82 | 991.39 |
| 11 | farm_auxiliary | 36,934 | 21 | 123 | 0 | 22 | 6.86 | 1.46 | 140.74 |
| 12 | commercial | 36,058 | 17,577 | 21,028 | 1,057 | 17,079 | 10.68 | 3.34 | 411.57 |
| 13 | warehouse | 27,504 | 14,988 | 14,918 | 689 | 14,753 | 5.56 | 1.23 | 661.29 |
| 14 | public | 26,431 | 22,012 | 16,536 | 2,217 | 21,982 | 7.54 | 1.71 | 344.66 |
| 15 | garage | 20,831 | 65 | 6,805 | 7 | 20 | 4.34 | 1.06 | 74.01 |

Table 2. Number of buildings by type and 3D attributes.

### 3.2 Basic Characteristics and Time-series Changes

During the study period (May 11, 2008, to February 1, 2025), 24,394 editors contributed to the compilation of OSM building data, but there were significant temporal and regional differences in their activities. After 2016, the number of editors exceeded 1,000 every year owing to the spread of OSM activities in Japan and building data compilation progressed. The development of 3D attributes, such as height and number of floors, tended to be relatively low until around 2021; however, the high input ratio of the number of floors compared to the height makes it easier for OSM editors to reflect the data from field surveys. The overall development of 3D attribute data will not occur until after 2022, which coincides with the time when data are imported for Project PLATEAU. The number of users who intensively conducted their editing activities in one prefecture was the highest at 19,287 (78.9%), whereas the number of building edits was only 3,367,714 (14%), suggesting that editors who are active in multiple prefectures may be more active in their editing activities. The relationship between the number of editors and number of editors was not statistically significant.

| first_edit | Editors | building_edits | height_edits | levels_edits |
|---|---|---|---|---|
| 2008 | 7 | 548,574 | 640 | 1,745 |
| 2009 | 13 | 438,135 | 96 | 19,308 |
| 2010 | 36 | 832,260 | 366 | 69,426 |
| 2011 | 254 | 1,449,119 | 155 | 5,117 |
| 2012 | 352 | 3,930,337 | 5,734 | 23,358 |
| 2013 | 440 | 582,171 | 229 | 19,814 |
| 2014 | 645 | 542,740 | 28,545 | 22,380 |
| 2015 | 828 | 1,375,713 | 408 | 21,062 |
| 2016 | 2,359 | 2,751,621 | 258 | 37,343 |
| 2017 | 1,875 | 2,036,606 | 551 | 68,097 |
| 2018 | 3,148 | 2,352,174 | 1,465 | 47,797 |
| 2019 | 4,007 | 2,145,502 | 4,990 | 66,343 |
| 2020 | 2,081 | 983,599 | 1,282 | 12,478 |
| 2021 | 2,757 | 923,435 | 665 | 30,152 |
| 2022 | 1,369 | 2,193,776 | 971,584 | 635,280 |
| 2023 | 1,550 | 662,933 | 104,439 | 15,147 |
| 2024 | 2,494 | 438,208 | 3,974 | 9,615 |

Table 3. Activity period.

### 3.3 Distribution of Buildings by Region and Spatial Uneven of 3D Attributes

The spatial distribution trend of the number of buildings by prefecture is shown in Figure 2. Hokkaido (2,688,753 buildings; 11.12%), Aichi Prefecture (1,694,860 buildings; 7.01%), and Osaka Prefecture (1,651,393 buildings; 6.83%) occupied the top three positions in the total number of buildings, indicating that OSM building-editing activities are relatively active in these three major metropolitan areas in Japan and Hokkaido. However, a marked regional difference was observed in the coverage rate of 3D attributes, with Nagano (46.2%), Aichi (46.2%), Ibaraki (27.2%), and Osaka (21.7%) in the top three for coverage including height and levels attributes, while Hokkaido, on the contrary, had a low coverage rate of 0.7%. The presence of 18 prefectures where the coverage rate, encompassing height and level attributes, is less than 1% of the total number of buildings suggests that numerous regions in Japan still lack 3D attributes despite the comprehensive development of building data.

Next, when analyzed by municipality (Figure 3), which is a more mesoscale spatial unit, the percentage of 3D attributes in the total number of OSM building data was significantly higher in Saku City (99.7% of 87,006), Chino City (99.9% of 68,373), and Okaya City (99.9% of 34,149) in Nagano Prefecture. This was followed by Hokota City, Ibaraki Prefecture (99.9% of 62,823); Ukiha City, Fukuoka Prefecture (99.8% of 24,813); Asago City, Hyogo Prefecture (89.8% of 7,776); and Miyoshi City, Hyogo Prefecture (86.1% of 63,767). Among the three metropolitan areas, seven of the 16 wards in Nagoya City, Aichi Prefecture, were the most highly developed with a content rate of over 90%. Common to these municipalities, with the exception of Nagoya City, is that they have little existing OSM data and have imported and integrated PLATEAU data into the OSM data, which is also outlined in OSMWiki.

When examining the distribution of buildings within Nagano Prefecture, particularly where there is a significant presence of 3D attributes (Figure 4), it is evident that the majority of OSM building data include these 3D attributes. In Saku, Chino, and Okaya, comprehensive data were compiled for buildings across all areas of these cities. Conversely, in the surrounding regions, despite the presence of urban districts, OSM building data are often compiled sporadically. Therefore, it cannot be conclusively stated that the overall state of the OSM building data compilation in the Nagano Prefecture is reliable.

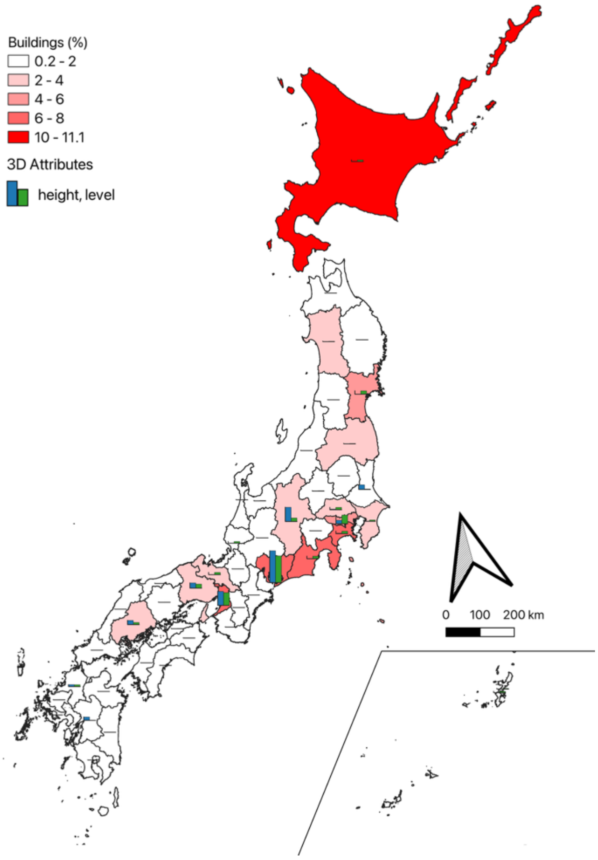


Figure 2. Number of OSM buildings (%) and 3D attributes by prefecture.

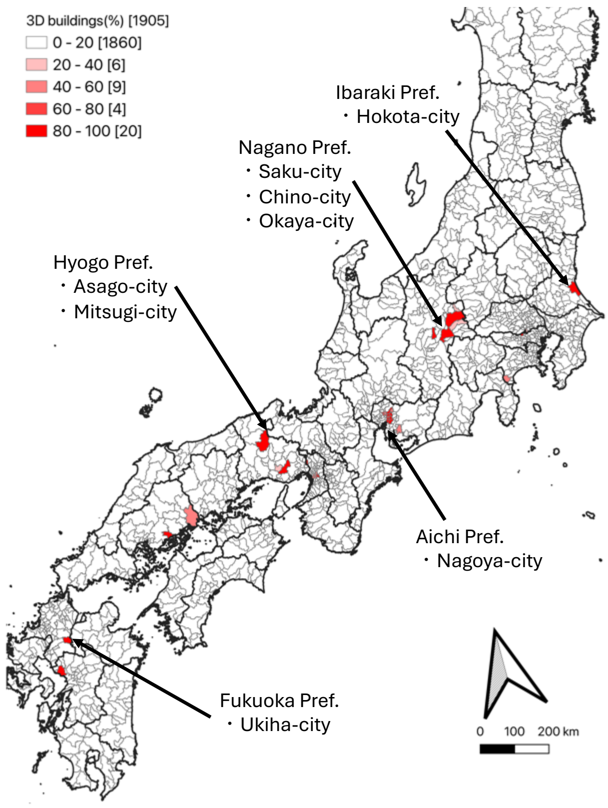


Figure 3. Percentage of OSM buildings with 3D attributes in number of OSM buildings by municipality (%).

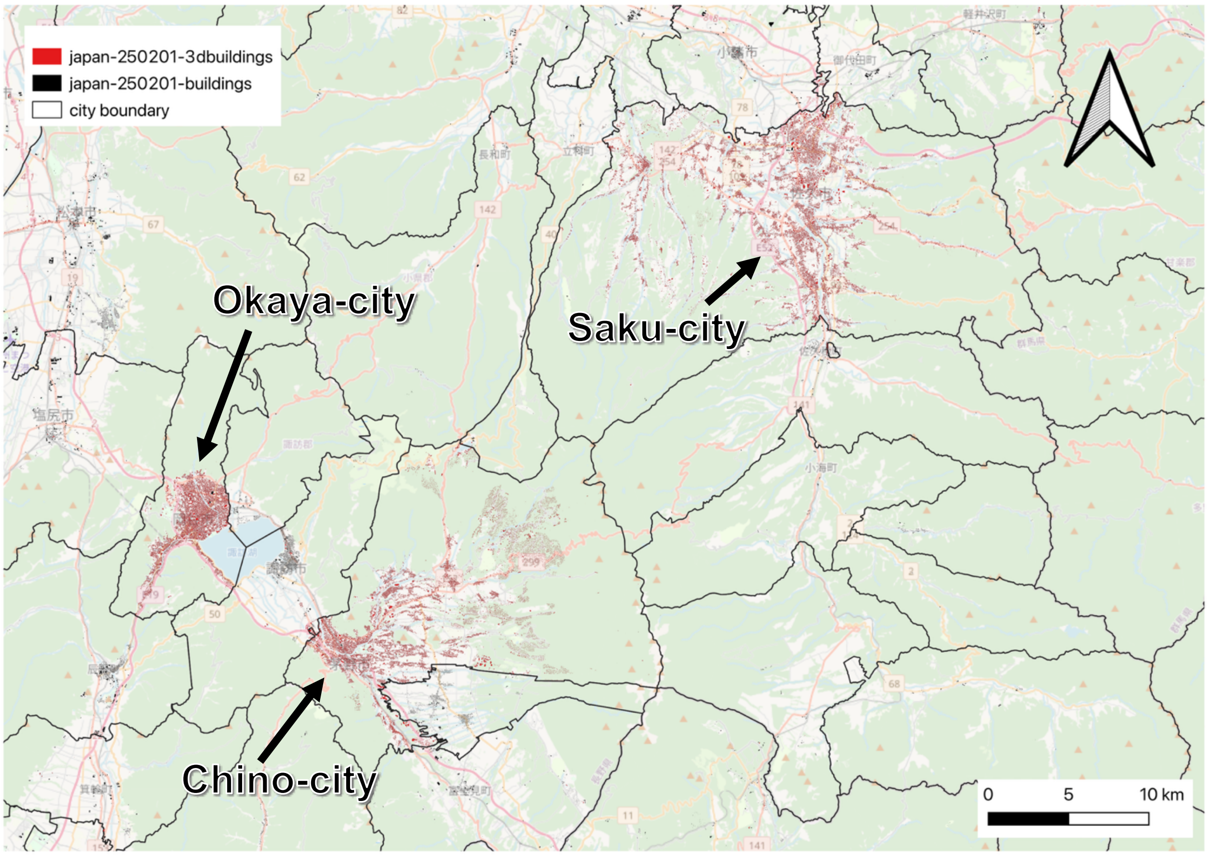


Figure 4. Spatial distribution of OSM buildings with 3D attributes in Nagano prefecture.


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The above analysis revealed an uneven regional distribution of 3D attributes. The pattern and concentration of editors' activities were considered to have a significant impact on this spatial disparity. Subsequently, it examined the continuity and concentration of editorial activities.

### 3.4 Concentration of Editorial Activity and Regional disparities

To obtain a more detailed picture of regional disparities in editorial activities, we analyzed the distribution and concentration of editors by prefecture. The analysis of the share of top editors, shown in Figure 5, reveals that the national average is 35.3%, but large disparities exist among regions. Specifically, the share of top editors ranged from a minimum of 5.5% (809 editors in Oita Prefecture) to a maximum of 84.2% (208 editors in Akita Prefecture), a gap of approximately 15 times. On the other hand, the total number of editors per prefecture averaged 854 (there may be overlaps among prefectures), ranging from a minimum of 195 (Miyazaki Prefecture) to a maximum of 3,276 (Tokyo), a difference of approximately 17. Notably, there was an inverse correlation between these two indices. In the prefectures with the largest number of editors (the metropolitan areas of Tokyo, Kanagawa, and Osaka), the share of top editors is low at around 10-15%, indicating that editing activities are distributed among many participants. By contrast, in regional prefectures with a small number of editors, the share is very high, ranging from 50 to 80%, and the structure is highly dependent on one editor in particular. This trend indicates that, while a variety of participants are active in urban areas, rural areas rely on intensive activities by a limited number of participants.

The Gini coefficient, which measures the concentration of editing, was extremely high at 0.949, close to 1.0, indicating unevenness. The distribution of editors in 29 prefectures (61.7%) showed a Gini coefficient of 0.95, indicating an extremely large disparity in the amount of editing by each editor. In the six prefectures with the highest inequality (Akita, Shizuoka, Hokkaido, Aichi, Kyoto, and Nara), the average number of editors was 772 and the share of top editors ranged from 51.9% to 84.2%, indicating that an oligopoly of a few editors was evident. In the five prefectures with the lowest Gini coefficients of 0.9 to 0.82 (Ishikawa, Okayama, Fukuoka, Kumamoto, and Oita), the average number of editors was 1261, and the top editors' share ranged from 5.5% to 13.6%, showing generally low results.

Figure 6 shows the same regional distribution expressed in terms of HHI, with higher values indicating a higher concentration of editorial activity. The national average HHI is 2,075, indicating a moderate level of concentration, but the regional distribution shows clear polarization: 22 (46.8%) prefectures have a low concentration of less than 1,500, whereas 18 (38.3%) have a high concentration of more than 2500. The characteristics of regions with extreme concentrations are particularly noteworthy. In the six prefectures showing high concentrations (Akita, Saga, Yamaguchi, Nara, Yamanashi, and Tottori) with an HHI > 4,000, indicating oligopoly, the average number of editors is as low as 376, and the share of one top editor reaches 61.8% to 84.2%. In contrast, in the 15 prefectures with an HHI < 1,000, the average number of editors is as large as 1,381, and the share of one top editor is relatively low, averaging 5.0%~27.1%. This indicates a clear relationship, whereby editorial activities are dispersed and share concentration decreases as the number of editors increases. Thus, the HHI analysis results also show that the degree of editorial dependence on a particular editor differs between regions with many and few OSM editors.

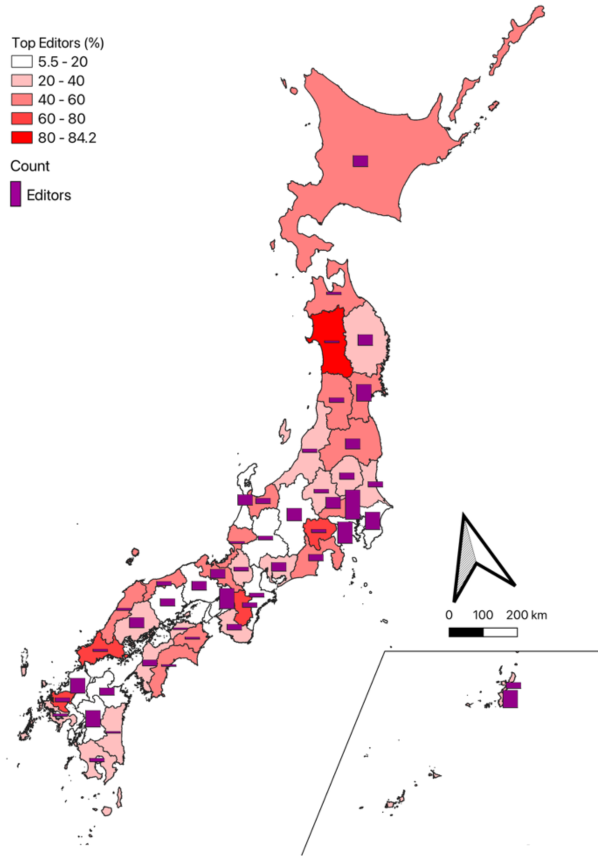


Figure 5. Percentage of OSM buildings edited in the top editors.

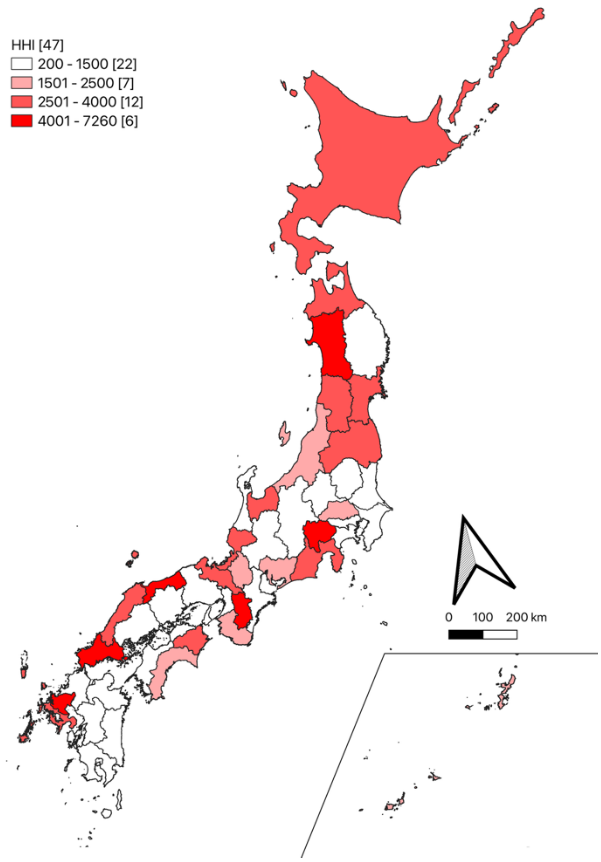


Figure 6. HHI analysis of editorial occupancy of OSM buildings

# 4. Discussion

## 4.1 Regional Disparities in Editorial Activity and Concentration

The results of the previous chapter's analysis revealed quantitative regional disparities and a concentration of editing activities in Japan's OSM building data. The factors underlying these results are examined below. Prefectures with a 3D attribute coverage rate of less than 1% and more than 100,000 buildings were identified, including Hokkaido (coverage rate: 0.7%; buildings: 2.68 million), Miyagi (coverage rate: 0.8%; buildings: 890,000), and Tochigi (coverage rate: 0.9%; buildings: 910,000). These regions have the potential for future development; however, they lack 3D attributes, making them ideal targets for concentrated data-development efforts.

The Gini coefficient analysis showed a national average of 0.949, which is very high and close to 1.0, indicating an uneven distribution. A total of 89.4% of the prefectures had a Gini coefficient of 0.9 or higher, indicating a large disparity in the amount of editing among editors nationwide. The HHI analysis also revealed a polarized structure, with 46.8% of prefectures having no oligopoly and 38.3% being highly concentrated. These indicators highlight the structural problem of establishing a cooperative system with diverse participants, mainly in urban areas, whereas rural areas rely on concentrated activities of a limited number of editors.

## 4.2 Sustainability Issues and Factor Analysis

An extreme concentration of editing activities, as indicated by a Gini coefficient of 0.9 or higher and an HHI > 4,000, poses serious challenges to the sustainability of the OSM community. In rural areas, the departure of a top editor can significantly reduce editing activities. This issue stems from the inherent characteristics of VGI, namely voluntariness" and "heterogeneity." The "1% rule," as pointed out by Haklay (2016), is more pronounced in regional data with geographical limitations. In these regions, promoting the participation of new editors and supporting the skill development of existing editors should be prioritized. Structural factors contributing to urban bias include the geographical concentration of the editing community and practical need for 3D building data. Project PLATEAU was also identified as a significant factor. For example, Saku (99.7%) and Chino (99.9%) achieved high 3D attribute coverage rates.

# 5. Conclusions

As the first comprehensive analysis of OSM building 3D data covering all of Japan, this study provides important academic and practical findings with the following major results. First, the analysis of 47 prefectures in Japan as a spatial unit confirmed a clear inverse correlation between the share of top editors and the total number of editors, and a polarized structure by HHI, which quantitatively confirmed the geographical disparity. Second, the analysis revealed serious concerns about sustainability in terms of the risk of editor departure in regions that show a high dependence on specific editors.

These findings reveal the intrinsic characteristics of VGI and limitations of data maintenance based on voluntary contributions. Simultaneously, regions with high data coverage were found to have a diversity of editors and an environment that enables them to utilize open basic data entering Project PLATEAU, and regions with a rich dataset were found even in rural areas. The data processing flow for tabulation and analysis developed in this study clarifies the status of OSM data maintenance and editor continuity and can be used to prioritize data maintenance and plans for the revitalization of the editing community.

An important future research direction is a comparative analysis of Overture Maps, which contains Microsoft building data and has 3D attributes estimated by machine learning, and a comparison of the properties of bottom-up VGI and top-down commercial data. In particular, resources outside the OSM can be utilized for further enrichment of the 3D attributes identified in this study. The analytical framework and statistical findings of this study are applicable not only to OSM but also to the evaluation and improvement of other VGI platforms, and will contribute to the development of an open geospatial information infrastructure and the construction of a sustainable editing community.

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**References**

Biljecki, F., Chow, Y. S., Lee, K.: 2023. Quality of crowdsourced geospatial building information: a global assessment of OpenStreetMap attributes. *Building and Environment*, 237, 110295. doi.org/10.1016/j.buildenv.2023.110295

Brovelli, M.A., Zamboni, G.: 2018. A new method for the assessment of spatial accuracy and completeness of OpenStreetMap building footprints. *ISPRS Int. J. Geo-Inf.*, 7(8), 289. doi.org/10.3390/ijgi7080289

Budhathoki, N. R., Haythornthwaite, C.: 2012. Motivation for open collaboration: crowd and community models and the case of OpenStreetMap. *American Behavioral Scientist*, 57(5), 548-575. doi.org/10.1177/0002764212469364.

Chikoto, G., Ling, Q., Neely, D.: 2015. The adoption and use of the Hirschman–Herfindahl index in nonprofit research: does revenue diversification measurement matter?. *International Journal of Voluntary and Nonprofit Organizations*, 27, 1425-1447. doi.org/10.1007/s11266-015-9562-6.

Haklay, M.: 2016. Why is participation inequality important?. In: Capineri, C, Haklay, M, Huang, H, Antoniou, V, Kettunen, J, Ostermann, F and Purves, R. (eds.) *European Handbook of Crowdsourced Geographic Information*, 35-44. London: Ubiquity Press.

Herfort, B., Lautenbach, S., Porto de Albuquerque, J., Anderson, J., Zipf, A. 2023.: A spatio-temporal analysis investigating completeness and inequalities of global urban building data in OpenStreetMap. *Nat Commun*, 14, 3985. doi.org/10.1038/s41467-023-39698-6.

Labetski, A., Vitalis, S., Biljecki, F., Arroyo Ohori, K., Stoter, J.: 2022. 3D building metrics for urban morphology. *International Journal of Geographical Information Science*, 37(1), 36–67. doi.org/10.1080/13658816.2022.2103818.

Lei, B., Stouffs, R., Biljecki, F.: 2022. Assessing and benchmarking 3D city models. *International Journal of Geographical Information Science*, 37(4), 788–809. doi.org/10.1080/13658816.2022.2140808.

Neis, P., Zipf, A.: 2012. Analyzing the contributor activity of a volunteered geographic information project: the case of OpenStreetMap. *ISPRS Int. J. Geo-Inf.*, 1(2), 146-165. doi.org/10.3390/ijgi1020146.

Seto, T., Kanasugi, H., Nishimura, Y.: 2020. Quality verification of volunteered geographic information using OSM notes data in a global context. *ISPRS Int. J. Geo-Inf.*, 9(6), 372. doi:10.3390/ijgi9060372.

Seto, T., Furuhashi, T., Uchiyama, Y.: 2023. The role of 3D city model data as an open digital commons: a case study of openness in Japan's digital twin "Project PLATEAU". *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.*, XLVIII-4/W1-2023, 201-208. doi.org/10.5194/isprs-archives-XLVIII-4-W7-2023-201-2023.

Yamashita, J., Seto, T., Nishimura, Y., Iwasaki, N.: 2019. VGI contributors' awareness of geographic information quality and its effect on data quality: a case study from Japan. *International Journal of Cartography*, 5(2–3), 214-224. doi:10.1080/23729333.2019.1613086.

Yamashita, J., Seto, T., Iwasaki, N., Nishimura, Y.: 2022. Quality assessment of volunteered geographic information for outdoor activities: an analysis of OpenStreetMap data for names of peaks in Japan. *Geo-Spatial Information Science*, 26(3), 333-345. doi.org/10.1080/10095020.2022.2085188.

## Appendix

The source code for the data processing script and aggregation results is available at GitHub repository.
https://github.com/tossetolab/osm-3d-stat/