ASSESSING THE QUALITY OF BUILDING FOOTPRINTS ON OPENSTREETMAP: A CASE STUDY IN TAIWAN

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Abstract

In recent years, an emerging trend in the information community is the growing use of web applications to collect and share geographic information. Such initiatives have increased the accessibility of geodata. Collaborative mapping platforms such as OpenStreetMap (OSM) have become important sources of geodata and potentially complementary with any Spatial Data Infrastructure initiatives. However, as volunteered geodata were generated by people with varying skill levels, quality issues such as missing details and incomplete content are inevitable with this approach.

In this study, we aimed to understand both the weakness and potential of OSM building footprints from three criteria: completeness, topological errors, and geometric accuracy. Case study areas were set in two major metropolitan areas of Taiwan, Taipei City and Taichung City. We compared OSM quality with a reference dataset from authority. The completeness assessment was computed in different scales by unit-based and object-based methods. We found the object-based method more appropriate for assessing our data. The completeness of corresponding building footprints ($C_{overlap}$) was 15.8% in Taipei and 11.7% in Taichung respectively; the highest complete location was Dari district of Taichung ($C_{overlap}$ = 66.2%). Completeness results were mixed between high-density and low-density districts. Generally, the central business districts had higher completeness than low-density areas and the variation was significant. An interesting finding was that the resolution of OSM building footprints in several districts of Taichung was higher than the reference dataset. Based on an inquiry of the OSM contributor community, we believe the high-resolution footprints were likely due to the promotion of university education in those areas.

Subsequently, we assessed topological errors and found that 2.9% of OSM building footprints in Taipei and 2.0% in Taichung had overlapping errors. In contrast, the reference dataset had no errors. Then, 384 OSM building footprints with a 1:1 relation to the reference building identified by the overlap method were randomly sampled to measure geometric accuracy. Using a turning function, the geometric accuracy assessment identified that 12% were very similar to reference buildings yet 10% were highly dissimilar. Through visual analysis and computing the sum of the number of vertices, we concluded that the reference dataset was more complex in building representation.

As the Taiwanese OSM contributor community intended to tag building footprints for evacuation, we tried to identify the completeness of evacuation buildings in the two cities. The results showed that 47.1% of evacuation buildings can be identified on OSM.

This all indicates that the general completeness of OSM building footprints is not consistent, and they are mostly under-represented. Nevertheless, OSM building footprints in several districts of Taichung possess higher resolution than authoritative data, and the completeness of both building footprints and evacuation centres is higher than 50%. This shows OSM has a great potential for field use, particularly in a scenario of disaster management. OSM can be a better source for a large-scale SDI platform and help to enable a resilient and prepared society.

Keywords: Data Quality, Volunteered Geographic Information, Building Footprint, Spatial Data Infrastructures

1. SETTING THE SCENE

The innovations of information and communication technologies (ICTs) have brought numerous benefits to the real world. Instant and content-rich spatial data from websites and mobile apps are easy to share and access on the Internet. Today geographic information is not only produced by authoritative organizations but also by lay people without professional cartographic skills. This phenomenon, termed Volunteered Geographic Information (VGI), encapsulates the idea of collecting, maintaining, and distributing geographic information by volunteers (Goodchild, 2007).

There is no fixed form of VGI. It may be citizen-generated geographic content including images, videos, and textual information (Craglia et al., 2012; Dransch et al., 2013). In terms of vector data to represent physical features such as roads and buildings, OpenStreetMap (OSM) is the most famous of VGI initiatives. OSM is a collaborative mapping platform wherein volunteers can digitalize features based on high-resolution imagery, or leverage Global Positioning System (GPS) tracks to create a street map. As it is free and open, it has been an alternative geodata source to authoritative venues. In contrast, authoritative geodata from Spatial Data

Infrastructure (SDI) initiatives are expensive to create and update; in addition, users are often required to pay fees for access to authoritative data.

OSM has therefore played a critical role in areas without a good quality digital map and where geodata are limited by access. For example, after the devastating earthquake in Haiti in 2010, OSM became the default basemap for responding organizations (Zook et al., 2010). In recent years, the number of OSM registered user has risen rapidly, increasing tenfold between 2010 and 2016, reaching 2.4 million. Yet as OSM data are contributed by volunteers with various motivations and skills, quality issues such as vandalism, missing details, and incomplete content are inevitable and have been critical research problems.

In our experience using OSM, the quality of building data is highly uncertain. Buildings comprise one of the most important physical elements of human society. The need for building data is high in many domains such as urban planning (e.g. analysis of land use change) and emergency management (e.g. developing an evacuation system or damage assessment). We therefore conducted a case study to assess the quality of OSM building footprints in regions of Taiwan. We measured completeness, topological errors, and geometric accuracy in OSM building footprints by comparing OSM data with authoritative data and the GIS analyzer. Moreover, as recent studies pointed out that VGI could be used for pre-disaster planning and preparation (Haworth and Bruce, 2015; Schelhorn et al., 2014) and the Taiwanese OSM's contributor community has begun annotating evacuation locations, there was a need to obtain complete information on OSM regarding evacuation buildings. This study integrates several existing methods to understand both the weakness and potential of OSM building footprints from the aspects of internal and external quality.

The remainder of the paper is organized as follows: Section 2 provides a brief review of quality elements and methods of OSM quality assessment. Section 3 describes the methodology of the study. Section 4 demonstrates the results of data quality assessment. In section 5, we discuss our results compared to similar studies, draw conclusions, and provide insight into OSM quality issues.

2. QUALITY ISSUE OF OPENSTREETMAP

2.1. Quality Issues of VGI

Spatial data and services are usually provided by authorities with sufficient knowledge, technology, and labor for capture, analysis, and digitalization through a top-down approach. However, the cost of production, integration, updating, and delivery is expensive. And most SDIs typically deploy only participants who have professional spatial information skills, leaving a large part of society with a nominal role (Budhathoki et al., 2008; Ho and Rajabifard, 2010). These issues can potentially be complemented by VGI. As VGI is a bottom-up approach in which citizens act as sensors; data are usually free and open access. It is beneficial specifically where authoritative data fall short in satisfying the needs of a particular situation (Feick and Roche, 2013).

Though VGI has many advantages, it lacks structured sampling and rigorous measurement methods; data quality is a major concern (Goodchild and Glennon, 2010; Goodchild et al., 2012). Generally, data quality represents for the user the fitness of the dataset for a potential application (Aalders, 2002). As data holds a perceivable level of similarity between the data produced and the real-world phenomena described, assessing quality in relation to the absence of errors in the data is the measurement of internal quality (Devillers et al., 2007; Fisher, 1999; Guptill and Morrison, 1995). Common quality elements have been defined by standard organizations. For example, ISO 19113 described five elements including completeness, logical consistency, positional accuracy, temporal accuracy, and thematic accuracy. Another aspect of data quality is external quality. It represents how well internal specifications fulfill the user needs. The assessment relies on measures of internal criteria and explicit objectives for intended use (Poser and Dransch, 2010).

When using authoritative data, quality criteria are often documented in the metadata. This helps end users realize data quality. However, when using VGI, these criteria are absent in the metadata, so quality is uncertain and has become a barrier for OSM for end-users. In this study, we measured three criteria of OSM building footprints: completeness, topological errors, and geometric accuracy. Completeness is a measure of presence and absence of features. It describes the relationship between objects and the abstract universe of all such objects (Goodchild, 2008; ISO, 2013; Veregin, 1999). Geometric accuracy assesses the positioning and geometric resolution from the ground reality. In OSM quality assessment, the two criteria often use a reference dataset for comparison (e.g. Girres and Touya, 2010). Topological errors often occur due to a fallible mapping which violates predefined rules of geometry and results in logical inconsistency. Possible polygon errors include (1) unclosed rings, (2) gaps and overlapping between polygons, and (3) self-intersection (Servigne et al., 2000).

2.2. Assessment Methods

Methods for OSM quality assessment differ in features and criteria. The comparison method, which assesses quality by comparing OSM data with similar high-accuracy data, is essential and widely applied in the literature. For example, to assess positional accuracy of OSM road networks in England, Haklay (2010) used a buffer zone to calculate the percentage of overlap between VGI and authoritative data; the results showed OSM had approximately 80% overlap. Haklay (2010) also calculated the total length of OSM roads, and compared the values with the authoritative dataset in grid units for the completeness assessment. Besides this, OSM studies have measured quality at different scales and times (e.g. Zielstra and Zipf, 2010), or focused on automated feature matching comparison (e.g. Koukoletsos et al., 2012). Various methods of quality assessment have been developed. Results showed that OSM data can be very rich with good quality, but it is heterogeneous in the details of features. The researcher also concluded that OSM quality should be evaluated both locally and globally (Zheng and Zheng, 2014).

With regard to assessing quality of polygon features, researchers have developed several methods related to our objective criteria. For example, Hecht et al. (2013) developed unit- and object-based (i.e. feature matching) methods for measuring completeness of OSM building footprints. Targeting geometric accuracy, Girres and Touya (2010) calculated polygonal granularity (i.e. the shortest segment) and compactness of lake features, and the result demonstrated a great difference in granularity between OSM features and references. However, the two methods lack a good way to interpret results. Methods such as the Hausdorff distance or surface distance were also used (Eckle and de Albuquerque, 2015). Comparing these methods, we found that shape similarity is a better measure for geometric accuracy. This measure uses the turning function developed by Arkin et al. (1991) and has been tested (e.g. Mooney et al., 2010; Fan et al., 2014). As for topological errors, assessment does not require reference data, and tools with robust algorithms are available. A case in point is Sehra et al. (2016) investigated topological errors on line and polygon features on OSM and found a large number of errors.

In this section, we briefly introduced the assessment methods and findings in the literature. Note that as quality assessment usually requires a reference dataset for comparison and mass processing and measurement, the OSM quality control among contributors still relies on crowdsourcing and social approaches (Goodchild and Li, 2012). Several free online quality assessment and assurance tools (e.g. OSM Notes) have been developed to get detailed OSM quality information from users.

3. THE STUDY AREA AND ASSESSMENT METHODOLOGY

This section describes the data used in this study and the assessment methodology. We integrate several existing methods from previous research on OSM quality (e.g. Hecht et al., 2013; Mooney et al., 2010; Fan et al., 2014).

3.1. Study Area and Data Collection

The areas selected for this study were two major metropolitan areas of Taiwan, Taipei City and Taichung City. As OSM data quality highly depends on the density of OSM contributors, we assumed that the quality of building data was potentially better than other administrative districts since contributor density in the urban districts of Taipei and Taichung was high (Chuang et al., 2013, Haklay et al., 2010a). Additionally, Taichung is composed of four areas with great variance of population density. The assessment results in the low-density areas (Shanxian and Haixian) provide a reflection of other such urban areas.

Figure 1: The study area: Taipei City and Taichung City

The OSM dataset (shapefiles) was extracted from the OSM data provider Geofabrik[1], which was updated to 12 March 2016. The reference dataset used as a baseline for assessment was the Taiwan Electronic Map, supplied by the National Land Surveying and Mapping Centre (NLSC) at a scale of 1:2500. Through visual comparison between the reference dataset and Satellite Map, it was highly complete. This comparison can be seen in a web mapping platform[2]. The data were not free to the public currently; a Web Map Service (WMS) was provided.

3.2. The Unit-Based Completeness Assessment

The basic completeness measurement was built on the unit-based method defined by Hecht et al. (2013). It measures the proportion of total number or area of OSM building footprints and references within a given unit. There are two indicators of completeness. C_{No} measures the completeness of total number and C_{Area} measures the completeness of total area. The definitions of C_{No} and C_{Area} are:

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[1] https://www.geofabrik.de/ [accessed 12 March 2016]
[2] http://emap.nlsc.gov.tw/gis103/ [accessed 1 July 2016]

$$C_{No} = \frac{\sum BuildingNoOSM}{\sum BuildingNoRef} \qquad (1)$$

$$C_{Area} = \frac{\sum BuildingAreaOSM}{\sum BuildingAreaRef} \qquad (2)$$

In this study, we used the administrative districts as defined units and assessed the completeness at three scales: city, township, and village. The results would be presented by tables in the township units and maps in the village units

3.3. The Object-Based Assessment

The unit-based method does not consider feature-matching relation. Building data production requires huge manual processing, and the outcome has different standards. A building footprint can represent several buildings, or a single building. Therefore, there are six relations existing between reference polygons and OSM building polygons: 1:1, 1:n, 1:0, 0:1, n:1, and n:m. Identification of OSM building footprints corresponding to at least one reference building (1:1, 1:n, n:1, or n:m) enables the assessment to be calculated in relation to their representatives.

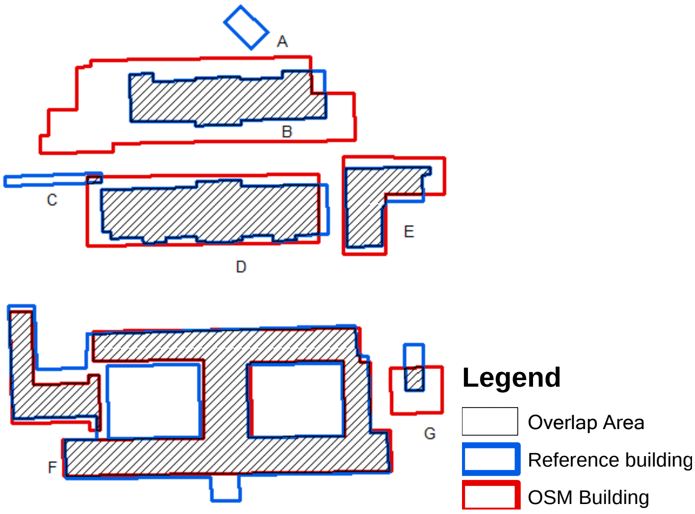
The feature-matching rule is an important research setting in an object-based method. In our previous study, we used an attribute similarity ratio and a buffer search for the corresponding public property (Kalantari and La, 2015). However, this was not applicable to building footprints, as a name attribute was absent. Therefore we used the overlap method, which computes the overlap area between two polygons. We defined that the ratio of the overlap area in the minimum footprint area between OSM and reference had to reach 30% to be regarded as corresponding features (Hecht et al., 2013; Fan et al., 2014). Otherwise, it was regarded as non-matching (1:0 or 0:1). Completeness based on the overlap method ($C_{overlap}$) is defined as:

$$\text{For corresponding building, } \frac{BuildingOverlapArea}{\min(Area(OSM_i), Area(Ref\,j))} > 30\%,$$

$$C_{overlap} = \frac{\sum CorrespondingBuildingAreaOSM}{\sum BuildingAreaRef} \qquad (3)$$

Figure 2 is an example of the identification of corresponding features. The seven reference building footprints in blue line were marked as A to F. The reference building C was a non-matching feature since the overlap area was only 9% of the reference building area. By contrast, other overlap areas (B and D~G) matched more than 30% of the minimal footprint area. Thus associated building footprints were regarded as matching.

Figure 2: An example of using the overlap method for feature matching, the reference building C has 9% overlap area, thus it is non-matching.



3.4. Methods for Geometric Accuracy and Topological Error Assessment

As mentioned, there are several methods used for geometric accuracy assessment in the literature. In this study, we measured to what extent OSM shape is similar to the reference shape. The method used in this study was based on the similarity algorithm (i.e. turning function) developed by Arkin et al. (1991). It transforms a polygon as a list of angle–length vertices in a counterclockwise direction and the perimeter is rescaled as 1. The similarity between two polygon shapes can be defined as the distance between their turning functions. This distance is normalized to the range [0, 1]. Through visual analysis, Mooney et al. (2010) defined the similarity between two shapes by normalizing the distance into a similarity value, where 1 represents identical shapes, and the lower the value, the less similarity. Corresponding polygons have a very similar shape while a similarity value is greater than or equal to 0.8, and a value of 0.5 or less represents very dissimilar shapes. The major limitation of this method is that it is independent of the size of the shape.

For the shape similarity assessment, we implemented the source code provided by Gene Ressler[3] on ArcGIS. As the calculation requires much manual manipulation to assign matching IDs of the corresponding polygon with a 1:1 relation, we used simple random sampling to extract the OSM buildings. Sampled buildings in various locations were identified by the overlap method mentioned in

[3] https://www3.cs.stonybrook.edu/~algorith/implement/turn/distrib/sim.c [accessed 12 March 2016]

the previous section. The sampling size was determined at the 95% Confidence Level (CL) and 5% Margin of Error (MOE) commonly used in statistics. By applying the geometric accuracy assessment, we were able to measure differences in building footprint representation between OSM and the reference dataset.

As for topological error detection, the OSM data used in this study were shapefiles. A shapefile is a non-topological data structure that does not explicitly store topological relationships. According to the specifications, shapefile polygons do not pose the problem of self-intersection[4]. Therefore, we investigated unclosed rings and overlapping between polygons. The topological errors were assessed by the ArcGIS topology tool with cluster tolerance at 0.001 m.

3.5. Completeness of the Evacuation Centres

In February 2016, a devastating Earthquake struck Taiwan (Tainan City) and caused numerous injuries and deaths. How to use OSM as a disaster information map for civic resilience became a serious topic in the Taiwanese OSM's contributor community. They decided to identify evacuation centres and tag them on OSM buildings.

In correspondence to this action, we were interested in how many evacuation buildings could actually be identified. We therefore conducted a survey on the completeness of evacuation buildings in OSM in Taipei and Taichung. The evacuation locations were extracted from the governmental Open Data platform[5] and then converted to point data in GIS. Evacuation locations in open space such as parks were manually excluded. The unit-based method (C_{No}) was adopted to measure completeness. We computed the portion of the number of evacuation locations intersecting OSM building footprints and the total number of evacuation locations within the city and township units. This was defined as:

$$\mathrm{C}_{\mathrm{evacuation}} = \frac{\sum EvacuationLocationIntersectNo}{\sum EvacuationLocationNo} \qquad (4)$$

4. QUALITY ASSESSMENT PROCESS AND RESULTS

4.1. Preprocessing

There were several preprocessing steps before the assessments. First, the coordinate systems of the two datasets were different. To make a comparison, the coordinate system of the OSM dataset was transformed to 2-degree Transverse

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[4] http://support.esri.com/white-paper/279 [accessed 24 August 2016]
[5] http://portal.emic.gov.tw/pub/DSP/OpenData/EEA/Shelter.xml [accessed 12 March 2016]

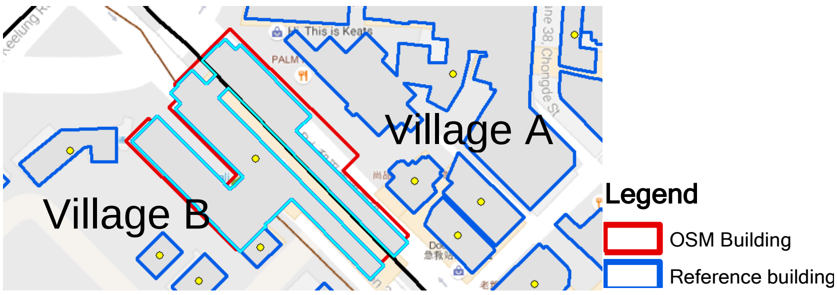
Mercator projection (TWD97 TM2, EPSG Code 3826), the same as the reference dataset.

Second, as both datasets were mainly digitalized from remote sensing images, there were some small polygons which were not building footprints. These features were mainly a cabin, garage, or public toilet on the map. For example, Figure 3 shows that a polygon in the reference dataset was actually not a building. To exclude non-building features, we removed building footprints with an area smaller than 20 m^{2}, in accordance with findings from a previous experiment (Hecht et al., 2013).

Figure 3: An example of building footprint area under 20 m^2 in the reference dataset (Base Map/ Street View data ©2016 Google)

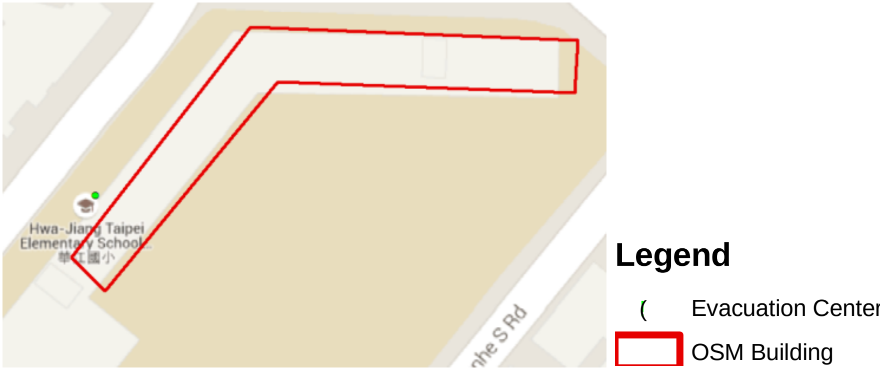
Third, all the building footprints were spatially joined with the administrative districts to assign the district name. As there were a small number of buildings located on the boundary of the administrative district (e.g. MRT station), the value was null after the join. We determined the value by the location of the centroid for assigning the district name. Figure 4 demonstrates that the MRT building was located on the boundary between two villages. As its centroid is located in Village B, the building was labelled as Village B.

Figure 4: A MRT station across two districts is labeled in the district of its centroid (Base Map ©2016 Google)



Additionally, our preliminary evaluation found that the coordinates of the evacuation locations (point data) were not precise enough, in that some evacuation locations do not intersect with building footprints (Figure 5). Because of this, we used a 20-meter buffer circle instead of the point of evacuation location in the measurement of $C_{evacuation}$.

Figure 5: Positional accuracy issue of evacuation location (Base Map data ©2016 Google)



4.2. Completeness Assessment

After preprocessing, the total number of reference building footprints was 62,823 in Taipei, and 198,276 in Taichung. By comparison, the total number from OSM was 7,638 in Taipei, and 102,958 in Taichung. The completeness of total numbers (C_{No}) was 12.2% in Taipei against 51.9% in Taichung. However, when computing the completeness of total area (C_{area}), the result was contrary. The total area was 17.4% complete in Taipei, and 12.8% complete in Taichung. By assessing completeness in higher granularity and visual inspection, we found that the total number of building footprints in several districts of Taichung was more than the reference dataset (e.g. Central, East, and Nantung district of the inner city), that C_{No} was higher than 100%. This caused opposite results between C_{No} and C_{area} in the city units. Due to the resolution of building footprints, C_{No} was not appropriate to be used in Taichung.

After the assessment of the unit-based method, completeness was re-calculated by the object-based method. $C_{overlap}$ was 15.8% in Taipei and 11.7% in Taichung. Between C_{area} and $C_{overlap}$, we tried to identify which measure was more appropriate to interpret completeness. We concluded that $C_{overlap}$ can exclude part of the topological errors (see: Discussion and Conclusion). Here we present $C_{overlap}$ in detail. Table 1 summarizes the result in the township units of the two cities. The spatial distributions of $C_{overlap}$ in village units are presented in Figure 6.

Table 1: The completeness assessment of the OSM building ($C_{overlap}$)

a. Taipei City

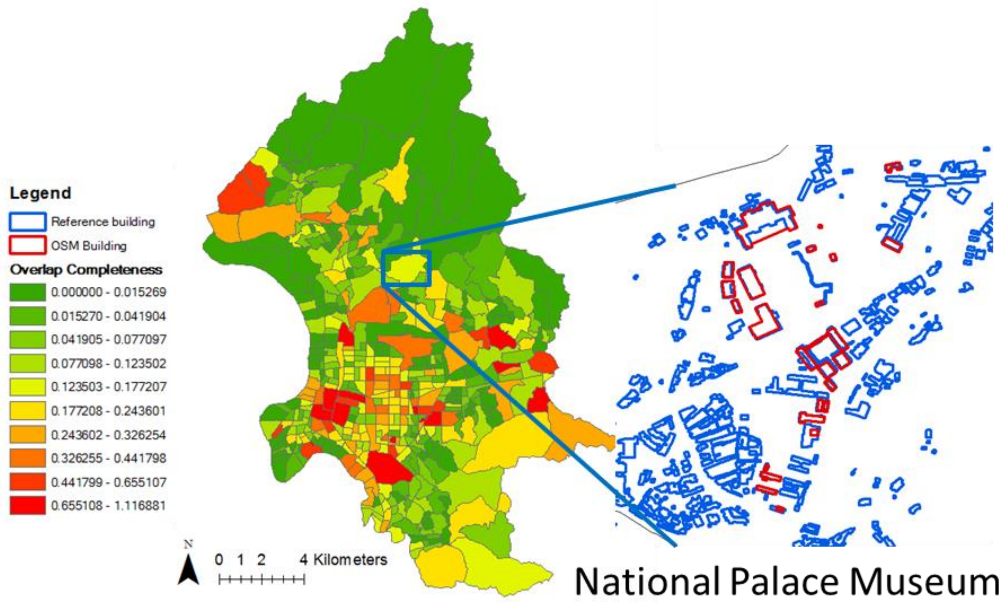
	Beitou	Zhongshan	Zhongzheng	Neihu	Nangang	Shilin
$C_{overlap}$	16.2%	19.8%	38.1%	18.4%	24.6%	8.2%
	Datong	Daan	Wenshan	Songshan	Xinyi	Wanhua
$C_{overlap}$	9.1%	26.2%	11.2%	17.4%	21.6%	13.4%

b. Taichung City

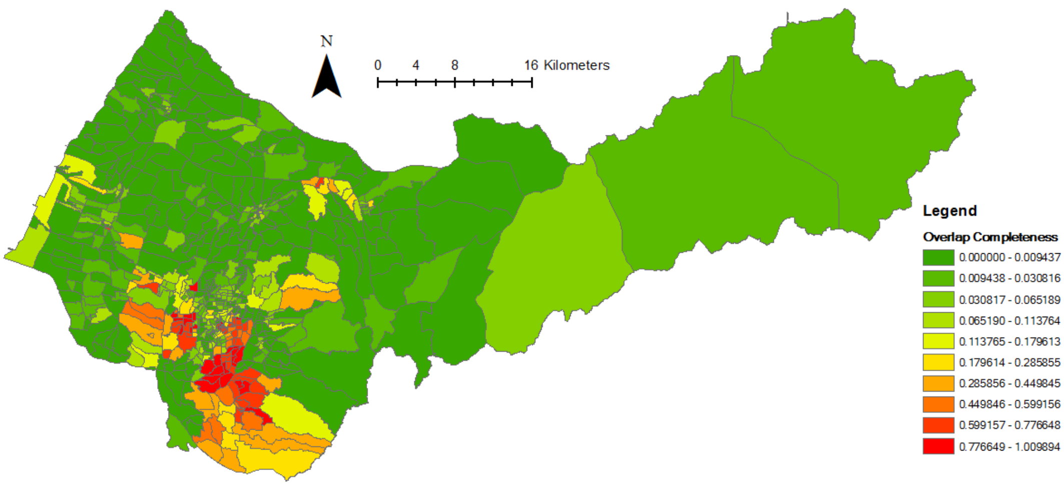
Inner city	Central	East	West	South	North	Xitun	Nantun	Beitun	
$C_{overlap}$	62.0%	58.8%	4.7%	6.9%	5.5%	8.7%	58.5%	5.1%	
Tuen Mun	Wufeng	Dari	Taiping	Wuri					
$C_{overlap}$	42.2%	66.2%	1.1%	4.6%					
Haixian	Qingshui	Dajia	Shalu	Wuqi	Daan	Dadu	Longjing	Waipu	
$C_{overlap}$	2.0%	0.01%	3.4%	3.2%	0.01%	0.01%	2.7%	1.2%	
Shanxian	Fengyuan	Donshi	Daya	Houli	Tanzi	Shigang	Shengang	Heping	Xinshe
$C_{overlap}$	1.0%	1.0%	0.01%	0.9%	1.1%	25.1%	0.2%	1.8%	0.2%

Figure 6: The map of OSM building footprints completeness assessment

a. Taipei City



b. Taichung City



By examining the values across the townships and villages of Taipei, the central business districts (CBDs) exhibited higher completeness than other areas (Figure 6). These areas were Zhongzheng, Daan, and Nangang (Table 1). Important traffic and education facilities such as Taipei Railway Station, National Taiwan University, and Academia Sinica were located in these districts. On the other hand, completeness was low in low-density areas. For example, Shilin had the lowest completeness ($C_{overlap}$ = 8.2%) as it contained a large mountain area. The building footprints were not quite complete and only important facilities were mapped. A visual comparison of the building footprints around the National Palace Museum in Shilin is illustrated in Figure 6a.

In the case of Taichung, $C_{overlap}$ of several townships was even higher than any district in Taipei. Generally, building footprints in these townships had higher resolution as compared to the reference dataset. For example, $C_{overlap}$ in the districts around Chaoyang University of Technology and Taichung Railway Station was very high. Nevertheless, in most districts, even West and South of the inner city (CBD), $C_{overlap}$ was under 7%, and it was under 4% in the low-density areas (most districts in Haixian and Shanxian). The variance of the completeness in Taichung was more significant.

In summary, the completeness of OSM building footprints in the two cities demonstrated mixed results. The variation is significant. $C_{overlap}$ reached 30%~75% in a few specific districts, but it was often low (under 10%) in low-density areas. We concluded that OSM does not represent a complete record in its current state in Taiwan. Nevertheless, the high-resolution building footprints in several districts of Taichung can be an advantage. Building footprints in these districts can benefit the user who requires a detailed edge of a specific building.

4.3. Topological Errors and Geometric Accuracy Assessment

In the topological error assessment, we found there were 182 and 3,956 overlapping errors in Taipei and Taichung respectively. The percentage was 2.9% in Taipei and 2.0% in Taichung. By contrast, there were no errors in the reference dataset. Polygons in the two datasets had no unclosed rings. The results indicated that overlapping errors were still common in OSM building footprints. Two of the most common overlapping issues identified are illustrated in Figure 7.

As for the geometric assessment, 384 buildings with a 1:1 relation to the reference dataset were sampled randomly in various locations, manually, according to 95% CL and 5% MOE. We further examined the geometric accuracy of OSM building footprints (i.e. shape similarity). Using the turning function to measure the similarity ratio, the values of the 384 sampled building footprints ranged from 0.254 to 0.929. The mean was 0.641 and the standard deviation was 0.124. We used visual analysis to check results and confirmed the threshold defined by Mooney et al (2010). Our assessment showed that only 12% of OSM building footprints with a value greater than 0.8 were very similar to the reference building. 77% of OSM building footprints with a value between 0.5 and 0.8 were regarded as dissimilar and 11% of OSM building footprints with a value under 0.5 were very dissimilar. Figure 8 shows three examples of different similarity ratios.

Figure 7: Examples of the topological errors

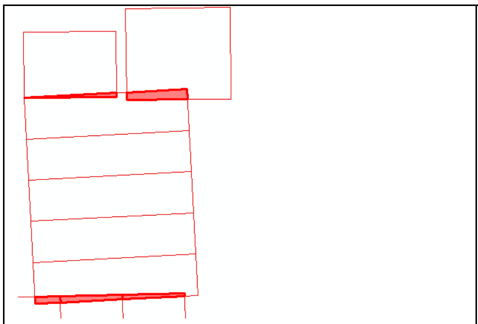
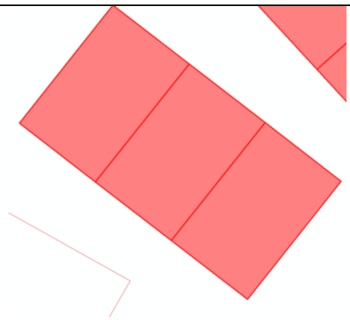
	
a. Overlapping between adjacent building footprints	b. Duplicated polygons with various resolution (3 small building footprints within the big one)

Figure 8: Examples of the shape similarity assessment (Base Map ©2016 Google)

		
Value = 0.9182	Value = 0.6413	Value = 0.2680
“Very Similar”	“Dissimilar”	“Very dissimilar”

In addition to the computation of similarity ratios, we found that the number of vertices in OSM polygons was only 35% as compared to the reference dataset. Considering topological errors, the ratio of dissimilar building footprints, and the number of vertices in OSM polygons, we concluded that the OSM building footprints are mostly under-represented. The reference dataset is more complex in its building representation.

4.4. Completeness Assessment of Evacuation Centres

In the final assessment, we aimed to know how many evacuation buildings have been mapped on OSM. The results showed that 58.0% in Taipei (246 out of 424) and 36.8% in Taichung (165 out of 448) of the evacuation buildings could be identified from OSM building footprints respectively. In summary, 47.1% of the evacuation buildings were mapped.

When we further investigated the cause of the incompleteness, the main reason was the activity centre of each village was not mapped. In contrast, the evacuation building in education facilities (schools and universities) were mostly mapped on OSM. For example, 82% of the evacuation buildings were education facilities in Nangang of Taipei and 71% were mapped.

To use OSM as a disaster information map for evacuation, the completeness of OSM building footprints might be below user expectation (i.e. around 35%~50%). Yet, if the OSM contributor community can be made aware of the reason for incompleteness and start an action to map to specify building footprints such as activity centres, it still has a great potential to reach acceptable completeness.

5. DISCUSSION AND CONCLUSION

OSM are regarded as a potential complementary source for any SDI initiative yet its quality is a major concern. tTo understand the weakness and potential, this paper conducted a case study of OSM quality assessment from multi-criteria: completeness, topological errors, geometric accuracy; the case study area was set in Taiwan.

Our completeness assessment used both unit-based and object-based methods. As we found that there were duplicated polygons with various resolutions (Figure 7b), we concluded that the object-based method can deal with such errors better and reflect actual completeness. A reminder here is that processing to delete duplicated polygons can increase the accuracy of results. Future refinement of the overlap method should consider this issue. This processing might also be a requirement for the OSM contributor community.

As for completeness in different areas, we found that the areas with highest completeness were located in the CBDs, particularly a district with important transport and education facilities. Comparing our results to a previous study in Germany (Hecht et al., 2013), the completeness of building footprints in Taiwan was a bit lower; a visible difference can be perceived on OSM. Since the population density in Taipei and Taichung is much higher than the German states, this indicates that the Taiwanese OSM's contributor community has lacked sufficient motivation to map building footprints.

An interesting finding is that OSM building footprints have higher resolution than the reference dataset in several districts of Taichung. Figure 9 shows a visual comparison between OSM and the reference dataset around the Nantung district. Using the OSM dataset, a user can locate a specific building easily. Some building footprints even possess an address tag. The high-resolution building footprints in Taichung can provide more utility in the scenario of disaster management. For example, the emergency sectors need building data in high resolution to locate an exact building boundary for operations. The reference datasets do not fulfill this need (i.e. current building data in Taiwanese emergency management information system are provided by the private sector). Although the completeness of OSM building footprints is not good enough, they have great potential for research use, as high-resolution building data are often limited by access.

Figure 9: The OSM building footprints have higher resolution than the reference dataset in Taichung (Base Map ©2016 Bing, ©2016 Google)

	
OSM	The reference dataset

Further checking the production process of these building footprints through an inquiry in the OSM contributor community, we found that the features were mapped from a project by the Department of Landscape and Urban Design at the Chaoyang University of Technology. The students used the JOSM (Java OpenStreetMap Editor) governmental address data service, and Google Maps with ground surveys to digitalize the building footprints. The integration of various data and techniques helped contributors map high-resolution data. This implies that the education system itself might be the key to quality improvement of OSM. However, these high-resolution data are only available in a few districts and most building areas outside CBDs are not mapped. This causes inconsistency. Besides, from our topological error and geometric accuracy assessment, we addressed two issues: (1) various topological errors, particularly duplicated polygons, and (2) the fact that most building footprints are under-represented. The simplified OSM building representation raises a complicated question: how good is good enough (see: Figure 9)? We further applied visual analysis of OSM in several cities, supposing that under-representation was a common issue. Perhaps OSM must develop a better standard for building representation and mapping.

Although the quality of OSM building footprints is not as great as authoritative data, it still has the advantages of open and free access. This study addresses that OSM data have the potential for finer resolution than other data sources. One lesson learned from this case study is that promoting OSM in education can enhance its quality. For example, if high school students can learn the fundamentals of OSM skills to edit and map evacuation buildings on OSM, this can help students learn about their living environment for disaster prevention. This strategy can help achieve the vision of OSM, that everyone and anyone can access underlying geodata freely, as well as enabling a resilient society. While from the point of view of geospatial education, we have to remind ourselves that such teaching plans must be promoted in both the global and local OSM communities.

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