International Journal of Applied Earth Observations and Geoinformation 115 (2022) 103094

Contents lists available at ScienceDirect

International Journal of Applied Earth Observation and Geoinformation

journal homepage: www.elsevier.com/locate/jag

A comprehensive framework for evaluating the quality of street view imagery

Yujun Hou [a], Filip Biljecki [a,b,*]

[a] Department of Architecture, National University of Singapore, Singapore
[b] Department of Real Estate, National University of Singapore, Singapore

ARTICLE INFO

Keywords:
Street-level imagery
Crowdsourcing
Geospatial data
Quality assessment framework
Heterogeneity

ABSTRACT

Street view imagery (SVI) is increasingly in competition with traditional remote sensing sources and assuming its domination in myriads of studies, mainly thanks to the omnipresence of commercial services such as Google Street View. Similar to other spatial data, SVI may be of variable quality and burdened with a variety of errors. Recently, this concern has been amplified with the rise of volunteered SVI such as Mapillary and KartaView, which – akin to other instances of Volunteered Geographic Information (VGI) – are of heterogeneous quality. However, unlike with many other forms of spatial data, there has not been much discussion about the quality of SVI datasets, let alone a standard and mechanism to assess them. Further, current spatial data quality standards are not entirely applicable to SVI due to its particularities. Following a multi-pronged method, we establish a comprehensive framework for describing and assessing the quality of SVI. We present a categorised set of 48 elements that suggest the quality of imagery and associated data such as geographic information and metadata. The framework is applicable to any source of SVI, including both commercial and crowdsourcing services. In the implementation, which we release open-source, we assess several quality elements of SVI datasets across 9 cities. The results expose varying quality of SVI and affirm the importance of the work. Given the exponential volume of studies taking advantage of SVI, but largely overlooking quality aspects, this work is a timely contribution that will benefit data providers, contributors, and users. It may also be applied on other forms of image-based VGI, and underpin establishing a formal international standard in the future. On a broader perspective, while providing an overdue definition of SVI, this work also reveals issues and open questions that impede delineating and assessing this diverse form of urban and terrestrial imagery.

1. Introduction

In recent years, street view imagery (SVI) has become an increasingly prevalent and important source of ground-level geographic information, adding to the variety of datasets that describe the complex and ever-changing urban environment (Kang et al., 2018; Ma et al., 2019; Laumer et al., 2020; Mahabir et al., 2020; Biljecki and Ito, 2021; Yin et al., 2021). While initially engaged mostly for viewing urban landscape, navigation, and qualitative assessment of the physical environment, recent advances in image processing technologies such as computer vision led to SVI being increasingly used for quantitative research (Biljecki and Ito, 2021). A multitude of applications based on SVI have emerged, touching on a wide range of domains including spatial data infrastructure (Yin et al., 2021; Hosseini et al., 2022; Ning et al., 2022a), urban health (Kang et al., 2020), built environment quality (Li et al., 2021b), urban activities (Zhang et al., 2020; Yao et al., 2021; Hawes et al., 2022), urban change (Naik et al., 2017; Byun and Kim, 2022), urban mobility (Zhang et al., 2019; Li et al., 2022), urban perception (Dubey et al., 2016; Kruse et al., 2021; Guan et al., 2022; Inoue et al., 2022; Qiu et al., 2022; Wei et al., 2022), urban climate (Ignatius et al., 2022), flood vulnerability assessment (Ning et al., 2022b), transportation (Wang et al., 2022), energy (Sun et al., 2022), safety (HE et al., 2022), building risk assessment (Pelizari et al., 2021), greenery (Branson et al., 2018), 3D reconstruction (Pang and Biljecki, 2022), geo-localisation (Cheng et al., 2018), geospatial artificial intelligence (Liu and Biljecki, 2022) and so on.

SVI is available through both commercial and crowdsourcing services. Well-known commercial SVI services (e.g. Google Street View) rely on systematic and standardised data acquisition approaches and cover about 100 countries. Crowdsourcing services have appeared as well, giving rise to volunteered street view imagery (VSVI) (Mahabir et al., 2020). These are prominently Mapillary and KartaView, which embrace a different model — images are irregularly contributed by a

* Corresponding author.
E-mail address: filip@nus.edu.sg (F. Biljecki).

https://doi.org/10.1016/j.jag.2022.103094
Received 27 July 2022; Received in revised form 19 October 2022; Accepted 30 October 2022

decentralised network of volunteers around the world, akin to other forms of Volunteered Geographic Information (VGI), and the uploaded images are free and open for anyone to use. Other than commercial SVI and VSVI, some researchers opt for own data collection for various reasons, e.g. to have imagery from a specific time of the day or weather season, to maintain consistency, and acquire imagery from study areas that are not covered by commercial or crowdsourcing services (Peng et al., 2018; Verma et al., 2019; Ao et al., 2019; Bochkarev and Smirnov, 2019; Gorgul et al., 2019; He et al., 2020; Wang et al., 2021; Ogawa et al., 2021; Kim and Lee, 2022).

While SVI arguably achieved the status of a key geospatial dataset and its importance across dozens of use cases shows no sign of waning, quality has surprisingly not been much subject of research. The main research gap is that, despite spatial data quality playing a prominent role in remote sensing, VGI, and spatial data infrastructures (SDI), there has been no quality standard that establishes quality elements of SVI and enables their assessment.

Further, the recent traction of VSVI has catalysed an increasingly pressing need to address the aforementioned lack of a quality standard for SVI, as its data quality inevitably becomes more heterogeneous following the expansion of volunteered data. For example, Mapillary,[1] a prominent platform to provide VSVI, currently has more than 1.5 billion images gathered since its public inception in early 2014 (Juhász and Hochmair, 2016). However, similar to other forms of VGI (Goodchild, 2007), VSVI data are heterogeneous in quality and suffer from issues such as inaccuracy, incompleteness, and inconsistency. While data quality challenges for the conventional types of VGI (e.g. OpenStreetMap, Flickr images, geotagged tweets, etc.) have been extensively discussed in literature (Goodchild, 2007; Haklay, 2010; Goodchild and Li, 2012; Keßler and de Groot, 2013; Ali and Schmid, 2014; Barron et al., 2014; Antoniou and Skopeliti, 2015; Fonte et al., 2017; Jonietz et al., 2017; Langley et al., 2017; Senaratne et al., 2017; Seto et al., 2020; Biljecki, 2020; Yan et al., 2020), VSVI presents as one emerging and distinct form of VGI with its own unique data quality challenges, which have rarely been addressed in the literature. Although some studies have examined the completeness and user contribution patterns of VSVI (Juhász and Hochmair, 2016; Ma et al., 2019; Quinn and Alvarez León, 2019; Mahabir et al., 2020), there still lacks a comprehensive framework to address thoroughly the various data quality challenges found in VSVI, together with the properties of imagery. This topic is also important because such errors can propagate and affect downstream analyses and applications.

Fig. 1 illustrates an example of multiple issues and properties of SVI, and how further use may be affected by these, similar to the topic of error propagation with other types of spatial data (Ranacher et al., 2016; Bruno and Roncella, 2019; Mocnik and Westerholt, 2021). First, an image (A) may be blurry and of poor quality, leading to unreliable analyses. Second, in an image (E) collected by another contributor on the same road, the sight of roadside greenery is obstructed by a vehicle, and when such image is processed (i.e. image segmentation; see G) and used in an analysis (e.g. estimation of the amount of visible greenery, a common application of SVI), it may lead to underestimation (cf. the adequate image D taken at the same location as E and segmented (F)). Note that this influence is subject to the application scenario — for example, if the application is identifying vehicle types (instead of estimating the amount of visible greenery), the vehicle in (E) would probably not be considered obstructing. Third, the image A is lateral and non-panoramic, not facing the front view of the road as it is in more common cases (see D and E), but such information is not always available in the metadata, which is potentially consequential when used in automated analyses in which such imagery is not expected. Further, it is important to understand the timeliness and positional accuracy (see B and C) of the data to establish its fitness for purpose.

[1] https://www.mapillary.com/

In this paper, we comprehensively discuss the topic of quality of SVI and propose a framework to define its quality-related properties. In practice, the specific types and combinations of quality issues encountered by SVI users could differ depending on the application scenario. Thus, while the framework is comprehensive, it is also designed to be general such that it can be tailored flexibly when applied to specific scenarios. The framework has several benefits, e.g. establishing a common and formalised understanding for SVI quality, facilitating the evaluation of 'fitness for purpose' of an SVI dataset, and enabling comparative quality analyses for different datasets and geographies. Further, in our overarching paper we define SVI to facilitate the discourse on quality, provide examples of the implementation of the framework, and discuss potential applications of the framework in practice to address SVI quality. While our work is motivated by heterogeneous VSVI, it is generic, applicable to any SVI source including commercial services. The framework serves as an overview guide and can be tailored and applied with flexibility to different application scenarios, as understandably, the quality issues faced in different scenarios could be different.

2. Background and related work

2.1. Availability, collection, and uses of SVI

Discussing the quality of SVI first requires an overall understanding of how the data is collected and used. The former reveals potential sources of uncertainty, while the latter indicates the potential ways for quality issues to affect usability.

Google Street View (GSV) is the most frequently used data source for SVI-based urban studies (Biljecki and Ito, 2021), unsurprisingly given its prevalence around the world. GSV images are collected in a standardised way: car-mounted panoramic camera systems are used for capturing public drivable roads; and in some areas, backpack-mounted cameras are used to supplement the coverage of narrow paths, especially those within landmarks and open spaces (e.g. public parks), as well as certain indoor spaces (Anguelov et al., 2010). Moreover, images are usually collected in the daytime and under good weather and lighting conditions, and they tend to be consistent in coverage, following an *all-or-nothing* approach (Quinn and Alvarez León, 2019). In some countries in which GSV is not available, e.g. China, similar services have emerged, e.g. Tencent Street View or Baidu Total View.

In contrast, Mapillary and KartaView have surfaced as popular VSVI platforms. The images are captured in various weather conditions, seasons and times of the day, using different imaging devices (e.g. mobile phones, tablets, action cameras, professional capturing rigs, etc.), and by differently experienced contributors (Neuhold et al., 2017). Such diversity leads to heterogeneous quality. The intermittent nature of contribution also means that coverage is not consistent, both geographically and temporally.

Researchers have employed SVI for various use cases, such as enriching spatial data infrastructure, assessing urban health, understanding urban perception, analysing transportation, estimating urban greenery and so on (Biljecki and Ito, 2021). Most of these studies involved, as an essential part of their methodology, extracting relevant features from the images (either manually or automatically using computer vision), and subsequently using these features together with the image metadata (e.g. location, time of capture) or other datasets (e.g. socioeconomic data) for further analysis. For example, in numerous walkability and bikeability studies, researchers have utilised SVI in place of field assessments to detect the relevant physical environment features; subsequently, these features were used to evaluate accessibility (Hara et al., 2012, 2015; Ito and Biljecki, 2021), inventory walking or cycling infrastructure (Ferster et al., 2020; Ding et al., 2021; Venkatesh et al., 2021; Kang et al., 2021; Ning et al., 2022a), or study how perceived walkability affects health (Wang et al., 2019; Zhou et al., 2019). Thus, conceivably, aspects including but not limited to image quality, spatial coverage, timeliness, and metadata availability are key to the quality of SVI and can affect its usability.

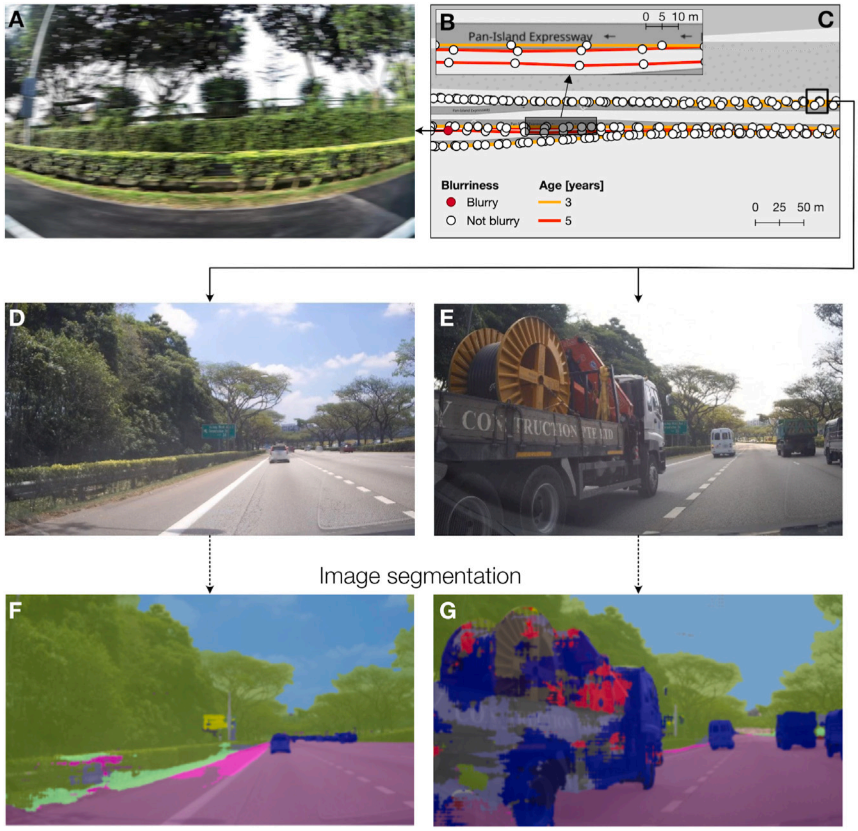

Fig. 1. Examples of some quality issues and characteristics of SVI. In our work, we provide a comprehensive series of quality elements and establish a framework to characterise the properties of SVI. Many of the quality aspects will have an adverse affect (i.e. error propagation) on a spatial analysis (e.g. obstructions may affect the estimation of greenery in streetscapes).
Source: A, D, E, F, G — downloaded from Mapillary and processed; B, C — OpenStreetMap contributors.

2.2. SVI quality challenges documented in research

Here we have reviewed and gathered various prominent quality challenges faced in SVI-driven research, which we adopt in our framework.

Image quality. Common issues include poor lighting conditions, blurriness and variable weather conditions, and in some cases, outdoor images could be mixed with indoor images such as those taken inside tunnels and shops, making it difficult to select the suitable images for a use case (Li et al., 2018; Law et al., 2019; Lauko et al., 2020; Miranda et al., 2020). A significant amount of distortion could be present in some images, especially those with equirectangular projection. Using these images directly without correction for geometric measurements could yield inaccurate results (Yin et al., 2015).

Obstruction. Obstruction by dynamic objects is another frequently cited issue, where objects of interest are blocked by passing traffic and people (Najafizadeh and Froehlich, 2018; Bin et al., 2020; Hu et al., 2020; Novack et al., 2020).

Coverage. Unbalanced spatial coverage occurs on both commercial and crowdsourcing platforms. For crowdsourcing platforms, as contributions are intermittent and uncoordinated, not all roads are captured and some areas might lack contributors. At the smaller scale, collection also tends to favour major roads (Szczepańska and Pietrzyk, 2020).

Timeliness. The temporal coverage of SVI is another consideration, as it is often heterogeneous and updates may be sporadic. In the same city, some parts could be updated more frequently than others, which could lead to inconsistent coverage as the places are not captured in the same period. Update frequency is also a common issue encountered (Miranda et al., 2020; He et al., 2020). Infrequent data collection makes it hard to gather up-to-date information and conduct temporal analyses such as change detection. Time is an important consideration also because there may be mismatch between the collection time of imagery and the targeted period of a study, leading to biases and inaccurate results (Larkin and Hystad, 2019; Chen et al., 2020). For example, images taken in winter are not suitable for greenery studies that involve measuring the amount of visible greenery (He et al., 2020).

Metadata availability. The image metadata provides useful information that can be used to filter unsuitable images. Applications such as built environment audit require images that are looking at specific places, so information including location, heading, and pitch would be useful in facilitating the selection of suitable images (Rundle et al., 2011). In general, the topic of metadata of SVI does not seem as developed as it is for some other types of spatial data (Labetski et al., 2018; Quarati et al., 2021).

2.3. Existing work on SVI quality

While quality issues have been briefly mentioned in many studies that use SVI as the data source, as shown in Section 2.2, there are currently few studies that focus predominantly on the topic of SVI quality, and these studies mostly zero in on a few selected aspects (i.e. spatial coverage and user contribution patterns) instead of providing a comprehensive quality evaluation framework (Juhász and Hochmair, 2016; Ma et al., 2019; Quinn and Alvarez León, 2019; Mahabir et al., 2020; Fry et al., 2020).

Juhász and Hochmair (2016) conducted a global assessment on the spatial completeness of Mapillary along the major roads. A more detailed evaluation was done comparing the coverage of Mapillary and GSV for 11 areas in the US and northern Europe, along various road types (i.e. main, residential, pedestrian or cycle paths) on OpenStreetMap (OSM). Contributor behaviour was also analysed, examining factors such as duration of active mapping, mapping distance, etc.

It was not until a few years later that the state of Mapillary was examined again, by Ma et al. (2019), featuring an exploratory analysis of the contributor behaviour. The study found inequality in Mapillary contribution, as a large amount of data was contributed by a small number of users, and the geographical distribution of data and users was unbalanced. Greater seasonal variations were observed in Mapillary than in OSM, as mapping can be done remotely (e.g. using aerial images) but SVI has to be captured in the field (i.e. on the streets). The study also found that the time property of many images were inaccurate, suggesting that inaccuracy of metadata could be a concern, among other quality issues.

Quinn and Alvarez León (2019) conducted a comparative assessment of the spatial coverage of GSV, Mapillary and OpenStreetCam (currently known as KartaView), in 24 cities around the world. A more detailed case study was carried out in 25 Brazilian cities. Differing from other studies, the assessment was qualitative in nature and manually conducted by three evaluators independently. It was found that while GSV often has either almost full or no coverage for a place, VSVI offers more evenly distributed coverage.

Mahabir et al. (2020) compared Mapillary and KartaView in terms of spatial coverage and contribution patterns, for four US cities. Differing from other studies, the coverage was not calculated in terms of how much of the street network is covered, but the cumulative length of all available sequences in each 1 x 1 km grid cell. It was shown that coverage patterns vary spatially, and most contributions were found along local roads and in populated areas. The amount of data per cell was found to be significantly positively related to the population density per cell.

Fry et al. (2020) assessed the spatial availability, image age, and image age variance of GSV in Latin American cities. Among a regularly spaced grid of 530,308 near-road points, it was found that GSV was available at 45.1% of the points, while wide variations in availability were observed in different cities and countries. Areas with better socioeconomic conditions were found to have more and newer images with greater age variances. This unequal spatial and temporal availability could induce biases in SVI-based research.

It seems that spatial coverage is an aspect that has been consistently examined in all of these studies, and most studies involving VSVI quality also investigate user contribution patterns. As present in Section 2.2, there are more quality issues in practice that challenge the usability of SVI, yet they are not included in the existing SVI quality research. With the growing popularity of SVI in urban research and the rise of VSVI, there is thus a strong call for a comprehensive framework to holistically describe and assess the quality of SVI. In our research, we approach the topic in a holistic manner and considerably expand the state of the art outlined in this section. Taking into account related work, we have identified further dozens of properties and issues, well beyond the scope of the state of the art and the examples in Fig. 1, and present a comprehensive SVI quality framework.

2.4. Related data quality standards

To conceptualise the data quality dimensions for SVI, and to assess to what extent existing standards could be applied to SVI, we reviewed related quality standards for spatial data, mainly ISO 19157, ISO 19130, ISO 19115, QA4EO (Quality Assurance Framework for Earth Observation), as well as seminal work on VGI quality.

ISO 19157 (Geographic information — Data Quality) (ISO 19157:2013) provides an overarching standard for geographic information data quality, and includes six quality dimensions: completeness, thematic accuracy, logical consistency, temporal quality, positional accuracy and usability. Each dimension consists of several sub-elements, e.g. commission and omission, conceptual and topological consistency, etc. Datasets can be evaluated against the criteria set based on the different dimensions, through either quantitative or qualitative measures. While the standard could serve as an umbrella guideline for SVI quality and certainly provide foundational knowledge for this work, a tailored and more detailed framework catering to SVI is needed, as dimensions such as completeness could have different meanings for different data types. For example, while it is fairly straightforward to understand omission errors in SVI (places lacking coverage), it is rather disputable what should be considered as commission errors in SVI, because virtually anywhere on the Earth could be photographed; this is different from, for example, road datasets in which a road can be mapped where it does not exist in real life. Another element, thematic accuracy, which typically refers to how accurately a classified land use or land cover category matches with the 'ground truth', might not be directly applicable to SVI data either.

ISO 19115 (Geographic information — Metadata) (ISO 19115:2014) instructs that data providers should supply sufficient metadata to describe their products, so that users can understand the assumptions and limitations of the data and assess its fitness for their intended use. Metadata is thus an important consideration when we devise the framework. Considering the photogrammetric applications of SVI (e.g. 3D reconstruction, geolocating features), we also reviewed ISO 19130 (Geographic information — Imagery sensor models for geopositioning) (ISO 19130:2014). The standard specifies that geographic data should come with sufficient information and documentation to support geopositioning, which determines the ground coordinates of an object from image coordinates. Aspects such as image overlap and interior orientation parameters are also considered.

The QA4EO (CEOS, 2010) was established by the Committee on Earth Observation Satellites (CEOS) as an international quality assurance framework for satellite remote sensing data. Derived from best practices, the framework provides key principles for how to achieve an internationally harmonised and consistent quality assessment process, through the use of documented and quantifiable Quality Indicators at each stage of the data processing chain (i.e. collection, processing, and delivery), so that all users could readily assess whether a RS product is suitable for their specific application (i.e. 'fit for purpose'). The data quality dimensions discussed in the literature include accuracy, completeness, resolution, redundancy, readability, accessibility, consistency, and trust of sources (Batini et al., 2017; Barsi et al., 2019). However, these dimensions are not entirely transferable to SVI. For example, privacy could be a significant issue for SVI as it captures details such as human faces and number plates much more clearly, and thus should be prominently featured in the framework.

In VGI research, the data types commonly discussed include map-based VGI (geometries and their associated attributes created by contributors to represent geographic objects, e.g. OSM, Wikimapia), image-based VGI (mainly referring to standalone geotagged photographs of geographic objects uploaded to the internet by contributors, e.g. Flickr), and text-based VGI (e.g. geotagged tweets) (Senaratne et al., 2017). Various quality assurance methods have also been proposed (Goodchild and Li, 2012; Ali and Schmid, 2014; Antoniou and Skopeliti, 2015; Fonte et al., 2017; Senaratne et al., 2017; Biljecki, 2020). However, they are not entirely applicable to SVI, because of the peculiarities of SVI as a distinct data form, as explained later in Section 2.5.

While not related to spatial data, ISO 12232 (Photography — Digital still cameras) (ISO 12232:2019) was also included in the research, in an effort to understand the current standards for photographic image quality. ISO 12232 specifies how ISO speed ratings, standard output sensitivity values and recommended exposure index should be assigned and reported for digital still cameras, providing a standard mechanism for comparing the photographic sensitivity of different cameras. Although camera quality can affect image quality, our work focuses primarily on quality elements of the SVI data. Thus, this guideline is not considered applicable to the framework proposed in Section 4.

While none of the standards is fully applicable to SVI, we learn from the efforts presented in this section and adopt some concepts in our framework, such as logical consistency.

Table 1
Differences between SVI and other image-based data.

Aspects	Street view imagery	Remote sensing imagery	Image-based VGI (excluding VSVI)
Perspective	Ground-level	Aerial	Unconstrained
Point-of-view	Objective	Objective	Mostly subjective
Collection regime	Commercial: centralised; VSVI: decentralised	Centralised	Decentralised
Contributors	Commercial: various organisations; VSVI: differently experienced private individuals contributing to various platforms	National and international agencies	Differently experienced private individuals
Temporal sampling	Commercial: update as and when needed, with constrained frequency; VSVI: irregular, with unconstrained frequency	Regular, with constrained frequency	Irregular, with unconstrained frequency
Spatial sampling	Connected and ordered sequences of points, with rather ad hoc coverage	Connected areas, with known and consistent coverage, but the concept of ordered sequence is less important	Unconnected and unordered points, with irregular coverage
Quality control	Commercial: guidelines vary from company to company, usually consistently followed; VSVI: subject to the platform's own quality control mechanism, which is usually rather basic and relatively poorly documented	Strict, well-documented, following internationally established principles	Little to no quality control
Image quality	Commercial: mostly consistent; VSVI: heterogeneous	Consistent and stable	Heterogeneous

2.5. SVI as an emerging and distinct data form

Existing spatial data quality standards such as ISO 19157 (ISO 19157:2013) are versatile and provide yardsticks for spatial data quality. While they provide a valuable basis, we argue that SVI is a distinct form of spatial data and these standards might not be fully transferable to it and capture all relevant properties.

The differences between SVI and other types of image-based data are detailed in Table 1. Compared to remote sensing data of which the collection follows internationally established scientific and engineering principles, SVI (especially VSVI) has a rather ad hoc or even decentralised collection regime, making it prone to heterogeneous quality (Yin et al., 2021). In contrast with point-based geotagged images and area-based remote sensing imagery, SVI is typically presented as a connected, ordered sequence of points (images), providing continuous observation along a trajectory traversed. Hence, characteristics such as the sequence length, sampling interval, sequential order, and spatial continuity (i.e. whether the sequence could provide connected, uninterrupted observation along the trajectory) are unique to SVI and crucially influence its quality, but are not important to other forms of image-based data and not covered by existing quality norms in GIS. SVI is also systematically prone to motion blur (Fig. 1), especially among VSVI, considering that the data is usually collected while the imaging device is moving, unlike other data types. Taking photos behind a windshield, as it is common in SVI, could also cause out-of-focus blurriness if the camera focuses on the windshield instead. For timeliness, the collection of SVI is not constrained by a fixed frequency, unlike the case for remote sensing, and can thus be potentially used to update authoritative spatial data, akin to other VGI data (Zhang et al., 2018), but the ad hoc and irregular collection could also lead to other timeliness issues. Privacy concern is also greater for SVI than for remote sensing imagery as SVI captures far more details on the ground, often including people's faces and vehicle licence plates.

While devising the framework for SVI quality, we are also aware of the differences between commercial and volunteered SVI. Owing to different collection regimes, sources of quality issues could differ for the two types of SVI. For VSVI, it is useful to examine the contributors (the data sources) so as to understand potential sources of errors and biases, and consequently conceive better mechanisms for quality control. However, this aspect is not so applicable to commercial SVI such as GSV, where data collection is standardised and managed. Ideally, to facilitate comparative evaluation, the quality elements considered for the framework should be universally applicable to various SVI sources. We reckon that, while quality issues could have varying roots for different SVI services and providers, the expectations for what is considered a 'usable' dataset from the data user's perspective should be arguably consistent across various data sources, which could provide a common basis for cross-platform comparison. With this reasoning in consideration, our framework is conceptualised primarily based on what a user would likely expect of the data itself, with regards to its quality at the post-production stage and usability, instead of how the data is collected.

Therefore, considering the uniqueness of SVI as a distinct form of spatial data, with its own quality challenges differing from those of others, and the current lack of a comprehensive quality framework for SVI, a new and refined framework describing the quality elements of SVI data is necessary.

3. Method

3.1. Overview

The study was conducted with a multi-pronged method, which includes reviewing related literature and data quality standards, understanding current practices by the main SVI providers, and combing through tens of thousands of images on our own. Setting the scene for the development of the framework, we provide our definition of SVI (Section 3.2) and discuss the various levels of spatial scales, another particularity of SVI (Section 3.3).

Fig. 2. Various examples of quality issues and unconventional SVI found in practice. In this work, we outline the potential quality issues and provide the means to their formalisation.
Source: A, B, C, D, E, F, H — Mapillary; G — KartaView.

As far as the method goes, building on related work that partially addresses this topic (Section 2.3), we looked into the existing quality assurance practices by the main SVI providers, by searching for information to understand what has been in place so far. The details are presented in Section 3.4. Afterwards, we employed a literature review of papers mentioning SVI, potentially exposing quality aspects researchers may have encountered (Section 2.2). We have also given attention to papers that involve own data collection (Peng et al., 2018; Verma et al., 2019; Ao et al., 2019; Bochkarev and Smirnov, 2019; Gorgul et al., 2019; He et al., 2020; Wang et al., 2021; Ogawa et al., 2021; Kim and Lee, 2022), as they may reveal further particularities about SVI, e.g. expose quality issues and metadata. To understand what existing standards are in place, how transferable they are to SVI data, and how they can act as a guideline to derive SVI data quality elements, we reviewed related data quality standards (Section 2.4). Next, we have visually examined a multitude of images on different platforms to supplement our findings from the literature review by revealing quality issues we might not have previously encountered, as well as to obtain a detailed, first-hand understanding of the heterogeneity in quality especially for VSVI. Some examples of the images examined are shown in Fig. 2.

Following the methodology, we conceptualised a framework entailing 7 quality categories and encompassing 48 elements, to describe and assess the quality of SVI datasets.

3.2. Definition

Before discussing the framework of SVI quality, it is pivotal to provide a definition for SVI, so that any quality elements would be derived based on this common understanding of what is actually considered as SVI, a surprising omission from the body of knowledge.

After reviewing literature and extensively combing through images, we found out that while many have referred to SVI as a sequence of geotagged images, the spatial continuity in SVI data (whether the sequence provides spatially continuous observation) is also another essential characteristic that makes SVI stand out as a unique form of data, but this aspect has almost never been specifically mentioned. We thus arrived at a definition that we consider includes all crucial aspects of SVI:

> Street view imagery (SVI) is typically a sequence of geotagged, ground-level photographs taken along a trajectory, providing spatially continuous observation of its vicinity.

Although mostly being in the form of a sequence of connected photographs, it is possible to find single street view photographs that do not belong to a sequence, and they could be considered as SVI as well, if their content is relevant (i.e. portraying the overall streetscape). SVI has been frequently taken from a moving car, bicycle, pedestrian, and so on, and it is commonly taken at a consistent angle (or panoramically) along the moving trajectory. Common imaging devices include panoramic cameras, car-mounted dashcams, and smartphones, largely depending on the service being commercial (e.g. Google Street View, Baidu Total View) or crowdsourcing (e.g. Mapillary, KartaView).

3.3. Scale and hierarchy

Various spatial concepts are intertwined with SVI. For example, a single street-level image is an independent piece of data (see Figs. 1 and 2), but it also belongs to a sequence, which may lead to other considerations. In our work, we define the following scales: image, sequence (containing multiple images), street segment (on which zero or more sequences are collected), and aggregated units (grid cell and administrative areas, e.g. a city). The quality metrics we develop can be either directly assessed or aggregated at these levels, or both. Understandably, not all SVI data is distributed along the streets, and some may be found within areas such as squares, parks and so on. For this type of data, it is possible to analyse its quality at the aggregated units level instead. We elaborate further on this topic of scale and hierarchy in the definition of the framework (Section 4).

3.4. Existing quality assurance practices by various SVI services

Though being a commercial platform, Google allows users to contribute their own panoramic images for any location, whether as impartial individuals, or as 'Street View trusted photographers' who can be hired by businesses to help them capture 360-degree photos for marketing purposes. Thus, currently, the GSV images displayed on their interface, or accessible through their static API, are a mix of both Google-acquired and user-contributed content (though the volume of the former dwarfs the latter). Google has a set of image quality policies regarding user-contributed photos, from which the quality standard for their own images could be implied, as presumably, the prime objective is to ensure consistent quality standard across various sources. The quality requirements include three aspects: image quality (i.e. image size, aspect ratio, gaps in image, stitching errors, sharpness, and exposure), connectivity (i.e. line-of-sight clarity between connected photos, 1-meter and 3-meter intervals for indoors and outdoors shooting respectively), and appropriateness (i.e. consent from people or places being photographed, authenticity, geographically accurate placement, legal content). For privacy protection, Google employs face and licence plate blurring algorithms on all of their own images, and any video content uploaded by users. However, the blurring is not applied on non-video content contributed by users, which includes panoramas. Instead, users can optionally apply blurring on their own, by using the blurring tool in the application. The assumption is, for images uploaded without blurring, the photographer has obtained consent from the people being photographed, but the company does not ascertain whether that is the case.

Mapillary adopted a different approach by introducing a neural network-based quality scoring system (not openly released and with limited information available publicly), based on a combination of several image properties including blurriness, occlusion (e.g. by camera mount and water drops), windshield reflections, exposure condition, weather condition, time of capture, and capturing properties (i.e. penalising close-up or non-street level images). The images were automatically rated discretely from 1 to 5 (with 5 representing the best overall quality). The resulting quality scores were published on the platform, and users could filter images based on the scores. However, this system seems to have been removed, as the scores are no longer displayed. While KartaView also seems to have an internal image quality scoring system, as related metrics could be found in the metadata of certain images, no documentation describing this approach has been found either. Both Mapillary and KartaView allow users to report images with quality issues or inappropriate content.

Despite the various quality assurance mechanisms by services, quality issues can be observed in SVI in practice (as detailed in Section 2.2). A potential reason could be that the policies are not always strictly enforced, or it may be challenging to detect certain quality issues automatically, as they are extrinsic and may not be assessed on their own, e.g. positional errors, inaccurate camera parameters.

4. Framework

We conceptualised a comprehensive framework that contains 48 quality elements grouped in 7 categories (image quality, metadata availability and accuracy, spatial quality, temporal quality, logical consistency, redundancy, privacy) to describe and assess the quality of SVI data. Table 2 summarises the elements and maps it to the levels (Section 3.3) at which they could be applied. Each element is described in the continuation. In our framework, we take the approach of ISO 19157 (ISO 19157:2013), which in its core defines spatial data quality elements in a descriptive manner, but does not mandate specific data quality measures on how to measure and express them. However, we give examples of potential measures and indicators both in the framework and in the implementation in the next section.

4.1. Image quality (A)

An image should convey an adequate amount of information and detail to be considered of acceptable quality. In this category, we define 8 elements that pertain to the visual characteristics of the photo: image size, blurriness, obstruction, illumination condition, noise, capture settings, distortion, and stitching errors. All these elements are evaluated at the level of the image.

Image size (A1) refers to the resolution of the photo. This element is important because a small image size could limit the amount of detail shown. Second, blurriness (A2), which could be motion blur, out-of-focus blur, or even artificial blur (e.g. unnecessary masking), could also cause an image to lose detail (Fig. 2A and example in Fig. 1). Third, obstruction (A3) occurs when a significant portion of the image has been blocked, such as by a passing vehicle or signboard (Fig. 2B). Objects that are not intended to appear in the image could obstruct the view of the street too, such as camera mount, water drops, falling snowflakes or leaves, car window edge or the interior of vehicle in general, etc. Sometimes, objects that are expected to be present in a street view image could also cause obstruction if they are not the focus of study, e.g. roadside trees obstructing buildings; in this case, the realisation of the framework could also be tailored accordingly and reflect these objects as obstruction instead. Illumination condition (A4), such as too much or too little light, or whether the camera is pointing towards the light source, could cause over- or under-exposure, and affect the contrast of the image, sometimes causing glare and reflections as well. These conditions could cause the image to lose a significant amount of detail. Sometimes, if a camera is placed behind a tinted window glass, the accuracy of colours could be affected too. Next, the level of noise (A5) reflects how grainy an image is. Further, bad capture settings (A6) could also affect image quality, e.g. the image is taken close-up instead of giving a full street view, is tilted or inverted, or is taken (or edited) with filters or distracting effects. The distortion (A7) could be present in wide angle or equirectangularly projected images, or could also be caused by water drops on the glass window (Fig. 2E). Finally, panoramas could be imperfectly stitched at times (A8), resulting in loss of information.

4.2. Metadata availability and accuracy (B)

Metadata provides useful information about the properties and characteristics of SVI data, serving various purposes including data access, determining fitness of use, and so on (ISO 19115:2014). There are 20 elements we identify in this category.

A unique identifier (ID) may be assigned to an image or sequence (B1), and its order index in the sequence may be provided. The same goes for the contributor (B2) of the imagery and sequence. This element is also relevant for commercial sources, as it may indicate the company or user who collected the data.

Timestamps (B3) are important for understanding the age and relevance of the data (e.g. when studying greenery, it may be useful to exclude imagery taken during winter). It is important to note that in practice, this information could be available at different levels of precision. For example, GSV provides the month and year in which an image was taken, while Mapillary and KartaView provide the exact date and time of capture.

Exterior orientation parameters (B4) include latitude, longitude, elevation, heading, pitch, tilt, and the height of camera relative to the ground. On the other hand, interior orientation parameters (B5), including focal length, position of principal point, and distortion parameters, could provide useful information for distortion correction and photogrammetric applications.

The field of view (B6) refers to the vertical and horizontal angles of the shooting, and suggests whether an image is panoramic. Camera projection type (B7) indicates whether the projection used for imaging is perspective, fisheye, spherical, or equirectangular. Device name (B8) provides brand and model information of the imaging device, and it sheds light on the acquisition approach.

The width and height of the image (B9) should also be provided in the metadata. It should be noted that this element differs from A1 which is about whether the image size is appropriate for a specific use case (e.g. by specifying a threshold). File URL (B10) from which the image can be downloaded is often provided in practice. For a sequence, it is also useful to provide the number of images (B11) it contains and its total length (B12).

Apart from the usual metadata attributes commonly provided by various SVI services, we also include in our framework other attributes that could indicate the characteristics of an image, such as the weather condition shown in the image (B13), the type of carrier (e.g. vehicle, bicycle, or pedestrian) from which an image is taken (B14), and the view direction of an image (B15; i.e. whether a non-panoramic image is looking at the front, the back, or the side of the road), as they could give useful information for selecting relevant images for a certain use case. For instance, in bikeability studies, images taken from a bicycle would better approximate the perspective of a cyclist compared to those taken from a vehicle or pedestrian. In urban perception studies, researchers may want to avoid using images taken under different

Table 2
SVI quality elements of the developed framework and the matching level.

Quality aspects			Level and hierarchy			
Categories		Elements	Image	Sequence	Street	Grid/Admin
A. Image quality	A1	Image size	✓			
	A2	Blurriness	✓			
	A3	Obstruction	✓			
	A4	Illumination condition	✓			
	A5	Noise	✓			
	A6	Capture settings	✓			
	A7	Distortion	✓			
	A8	Stitching errors	✓			
B. Metadata availability and accuracy	B1	Unique identifier	✓	✓		
	B2	Contributor	✓	✓		
	B3	Timestamp	✓			
	B4	Exterior orientation parameters	✓			
	B5	Interior orientation parameters	✓			
	B6	Field of view	✓			
	B7	Camera projection type	✓	✓		
	B8	Device name	✓	✓		
	B9	Image dimensions	✓			
	B10	File URL	✓			
	B11	Number of images in sequence		✓		
	B12	Total length of sequence		✓		
	B13	Weather condition	✓			
	B14	Carrier type	✓	✓		
	B15	View direction	✓			
	B16	Matched road	✓			
	B17	Attachments	✓			
	B18	Quality score or metrics	✓	✓		
	B19	Proper documentation	✓	✓		
	B20	Licence	✓	✓		
C. Spatial quality	C1	Spatial coverage			✓	✓
	C2	Two-way coverage			✓	
	C3	Panorama coverage			✓	✓
	C4	Spatial continuity		✓	✓	
	C5	Count			✓	✓
	C6	Positional accuracy	✓			
	C7	Rotational accuracy	✓			
D. Temporal quality	D1	Age of the most recent coverage			✓	✓
	D2	Age of the first available coverage			✓	✓
	D3	Number of years covered			✓	✓
	D4	Number of months covered			✓	✓
	D5	Time elapsed between coverage			✓	✓
	D6	Temporal accuracy	✓			
E. Logical consistency	E1	Order of images		✓		
	E2	Temporal validity	✓			
	E3	Positional validity	✓			
F. Redundancy	F1	Duplicates	✓	✓		
	F2	Content relevancy	✓			
G. Privacy	G1	Masking of human faces	✓			
	G2	Masking of vehicle registration plates	✓			

weather conditions which could influence human perception. Images facing the front of the road may be more useful for estimating urban form (e.g. estimating the street canyon) compared to images facing the side of the road.

If an image is taken on a road (i.e. excluding off-road or indoor coverage), the name or ID of the road that the image is matched to could also be given (B16). For example, images on KartaView are matched to OSM roads and the matched road ID is available in the metadata of the image. Some SVI datasets might come with additional data products as attachments (B17), such as point clouds associated with the photograph, which are useful for photogrammetric applications. The point clouds could be obtained by a lidar scanner that scans the depth information of the surroundings while the photograph is taken, or be derived from photogrammetric techniques such as structure from motion. Other possible attachments include features detected from the image using computer vision (e.g. traffic signs, light poles, etc.), as well as manually labelled annotations (e.g. for object detection, semantic segmentation, etc.), which are useful for various applications including geospatial analysis and developing computer vision algorithms. The availability of these attachments could widen the applicability of SVI data and make it more versatile. SVI platforms might adopt their own schemes to measure or score the quality of images and sequences (B18). In this case, there should be proper documentation (B19) that explains clearly how the scores are derived and should be interpreted. Proper documentation of all other metadata attributes, explaining what they represent, how they are obtained, and how precise and accurate they are, should also be available. The licence under which the image is released should be provided as well (B20).

Furthermore, it is important that these metadata attributes are not only available, but also accurate. The availability and accuracy of all these aspects can be directly assessed at either image or sequence level, and the analysis could be aggregated to higher levels as well (e.g. percentage of imagery in a district that has information on the B6 Field of view).

4.3. Spatial quality (C)

Spatial quality can be examined from both completeness and positional accuracy aspects.

Spatial coverage (C1), referring to the availability of SVI across space, can be calculated at both street and grid level, where the former indicates for each street how much percentage of it is covered with SVI, and the latter indicates how many grid cells in the study area have SVI available. Ideally, roads should be covered in both directions (if they are not panoramically covered), as useful objects such as building facades can only be fully viewed if they are covered in both ways. Thus, the element C2 suggests two-way coverage.

A panorama provides more complete observation at any point, it is thus useful to define it as a separate quality element (C3), such as by calculating how many images available are panoramas, how much percentage of each street is covered with panoramas, or how many grid cells contain panoramas. The count of photos per street or per grid cell implies density of SVI (C5).

Spatial continuity (C4) is a unique and essential characteristic of SVI. It can be assessed by calculating the spacing interval between images, at both sequence and street levels, which could indicate how close the images are to each other and reflect the sampling rate. Fig. 2G shows an example of a discontinuous sequence. For non-panoramas, it is also important to check if images in the same sequence are taken at a relatively consistent angle to the path so that the view is likely consistent and connected. This aspect could be checked by comparing the rotational parameters of images to the bearing of the road. Image overlap is another aspect of spatial continuity. When there are sufficient images at the same place that are taken close enough to each other, it is more likely to achieve sufficient image overlap to form stereoscopic images, which are necessary for transferring 2D image coordinates to 3D space coordinates in photogrammetry. A consistent view is also an assumption underlying many SVI-based urban environment studies. For example, studies that involve quantifying the proportional presence of objects in images (e.g. estimating green view index, sky view factor, etc.) assume the street is being viewed at a consistent angle throughout the images.

Positional accuracy (C6) could affect to what extent we can associate the information derived from an image with its reported location (i.e. latitude, longitude, elevation). The positional error is determined as the difference between the recorded location and the ground truth. Fig. 2F shows an example of positional error. Rotational accuracy (C7) refers to the accuracy of heading, pitch, and tilt of an image, and is determined by the difference between the reported values and the ground truth.

4.4. Temporal quality (D)

Similar to spatial quality, temporal quality includes both completeness and accuracy. The age of the most recent coverage (D1) indicates recency or outdatedness, while the age of the first available coverage (D2) indicates when a place was first imaged. These two combined indicate the temporal span of the coverage at a place, an element that may be relevant for longitudinal studies and change detection. The numbers of years (D3) and months (D4) in which a place has been covered indicate whether the place has been imaged in multiple points in time, across different years, seasons and months. By calculating the average time elapsed between successive coverage trips (D5), we can understand on average, how frequently a place has been imaged, while calculating the variance of time elapsed between successive coverage trips could give insight on how regularly the place has been imaged (i.e. higher variance suggests higher irregularity). All these metrics could be evaluated at both street and grid levels. Temporal accuracy (D6) refers to how accurately the capture time of the image is reported, and is determined by the difference between the reported capture time and the ground truth. Similar to positional and rotational accuracy, this element can only be directly evaluated at the image level, but the analysis could be aggregated at higher levels.

4.5. Logical consistency (E)

Data should also be checked against any violations of logical consistency. In the case of SVI, images in the same sequence have to be correctly ordered (E1), which is especially important for applications such as navigation and 3D reconstruction. Fig. 2D illustrates an example where the images have been wrongly ordered. The temporal (E2) and positional (E3) validity complete this category of elements. For example, the capture time should not exceed the current date and time, and an image visibly captured on land should not be found in the middle of water on the map. While it may appear that these elements are not necessary, we found imagery with clearly inconsistent timestamps, e.g. from years such as 2073.

4.6. Redundancy (F)

Duplicate images or sequences may exist in a SVI dataset, possibly due to upload error, creating redundant data. The content of some images could be irrelevant and as a result these images should not be even considered to be street view images. For example, Fig. 2H shows a few sequences of aerial images. Although also providing useful information about the earth surface, they are not street view images. Using SVI for analysis without filtering out such redundant data could lead to inaccurate results.

4.7. Privacy (G)

Human faces (F1) and vehicle registration plates (F2) are in principle blurred in SVI to preserve privacy. Fig. 2C shows an example where not all pedestrians' faces have been entirely concealed due to presumably an imperfect privacy assurance mechanism.

5. Implementation and examples

To demonstrate the application of the developed framework to describe the quality of SVI in practice and to suggest their realisation with specific data quality measures, we provide an implementation for several elements: blurriness (A2), spatial coverage (C1), count (C5), average time elapsed between coverage (D5), age of the most recent and the first available coverage (D1 and D2), and number of years and months covered (D3 and D4). These metrics are intrinsic, i.e. they do not require a reference dataset, such as positional accuracy (C6) does. They were evaluated at both the street and grid levels in the Kowloon area of Hong Kong, to demonstrate different levels (Section 3.3). To demonstrate applicability worldwide and use for comparative studies, one of these metrics – spatial coverage (C1) – was estimated for 8 additional study areas around the world: Singapore, Nagoya, Chicago, Panama, Santiago, Zagreb, Cairo, and Melbourne. We have released the implementation as open-source code (Python), in the form of an interactive notebook, at https://github.com/ualsg/SVI-Quality-Checker. The results are given predominantly as maps.

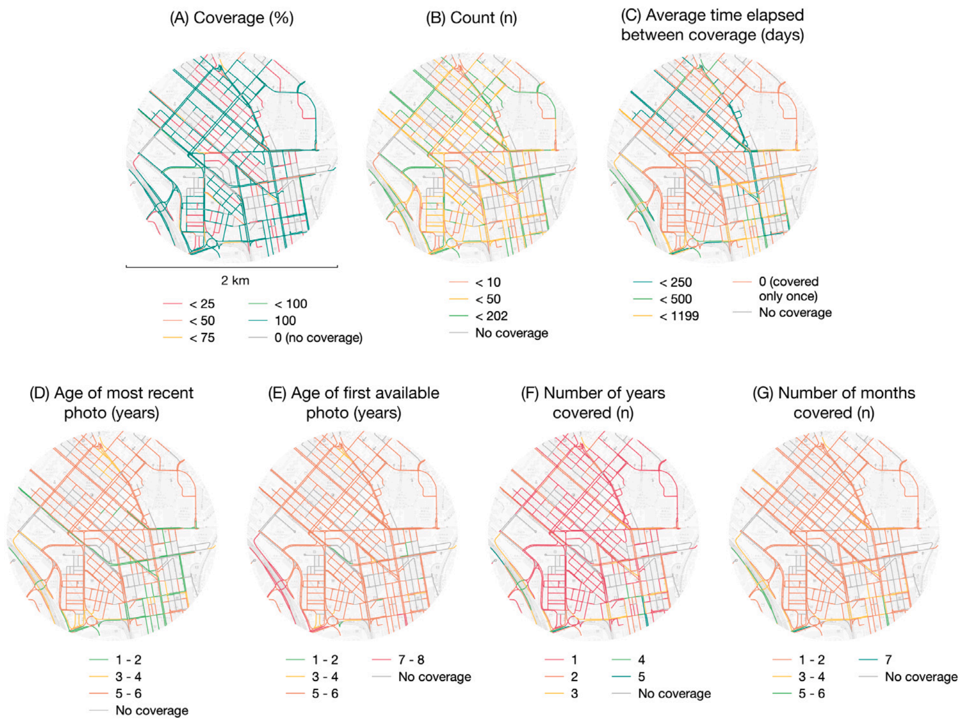

Fig. 3. Seven elements (C1, C5, D1, D2, D3, D4, D5) calculated for Mapillary data in Kowloon, Hong Kong at the level of each street segment.

5.1. Data

We used data obtained from Mapillary for the implementation. For each city, point locations of all images found in the study area, together with their associated metadata, were downloaded from Mapillary via their API; while for Kowloon, the actual images were also downloaded for blurriness detection (A2). The street networks within the study area, which were used for the street-level analysis, were obtained from OSM using the Python package OSMnx (Boeing, 2017). To aid the interpretation of the results and give more context in conjunction with other data, for the grid-level analysis, we distinguish populated areas, which we obtained from gridded population datasets from WorldPop (Tatem, 2017).

5.2. Spatial processing

For all street-level analyses, points were first snapped to their nearest roads within 10 m (this buffer radius could be varied), as not all images would be exactly located on the street network due to various reasons (e.g. positional errors). As such, the points have been spatially grouped by the different streets they are snapped to. For all grid-level analyses, each image was associated to a particular cell.

5.3. Results of the implemented quality elements

Coverage. Coverage can be calculated by various methods as documented in Section 2.3. For this implementation, we have provided our own method for calculating coverage at both the street and grid levels.

For street-level coverage, we calculate for each street the proportion of its full length that is covered with SVI. After snapping points to roads, each road is split at the snapped points. The lengths of all resulting segments are calculated, and those longer than 50 m are removed, as we consider only the street portions where the images are not further than 50 m apart as SVI-covered. The lengths of all remaining segments are summed to give the total SVI-covered distance for the street; this number is then divided by the total street length to derive the coverage percentage for the street. Fig. 3A shows the coverage percentage calculated for the streets in Kowloon. Fig. 6 shows the coverage percentage calculated for the streets in all 9 cities.

For grid-level coverage, after overlaying the points with the grid, we evaluate the presence and absence of SVI in each populated cell. The cells without SVI coverage are further distinguished by whether they contain roads so as to provide further information to aid interpretation. Nonetheless, it does not mean that cells with no roads are not expected to be SVI-covered, as off-road street view images do exist, and may be covering paths that are not already mapped. Fig. 4A shows the grid-based coverage calculated for Kowloon.

Count. At the street level, the SVI count for each street is the total number of points associated with that street. At the grid level, the total number of points in each cell is calculated as the count. Figs. 3B and 4B show the count calculated respectively at the street and grid levels in Kowloon. The figures double as an example of the different approaches to spatial scales when assessing the quality.

Average time elapsed between coverage. The ages, in days, of all images on each street (or in each cell) are first calculated. These images are then grouped by their age (those taken on the same day are considered same group or same coverage trip), and the difference between the maximum and minimum ages is thus the total time elapsed between the first and last coverage trips. This difference is then averaged by the total number of periods elapsed between these groups to give the average time elapsed between coverage trips. Figs. 3C and 4C show the average time elapsed calculated respectively at the street and grid levels in Kowloon.

Age of the most recent and age of the first available coverage. For each street and each cell, the ages of all images are calculated, with the minimum being the age of the most recent coverage for that street or cell, and the maximum being the age of the first available coverage for that street or cell. Figs. 3D and 3E show, respectively, the age of the most recent photo and the age of the first available photo in each street in Kowloon. Figs. 4D and 4E show the corresponding grid-level analysis.

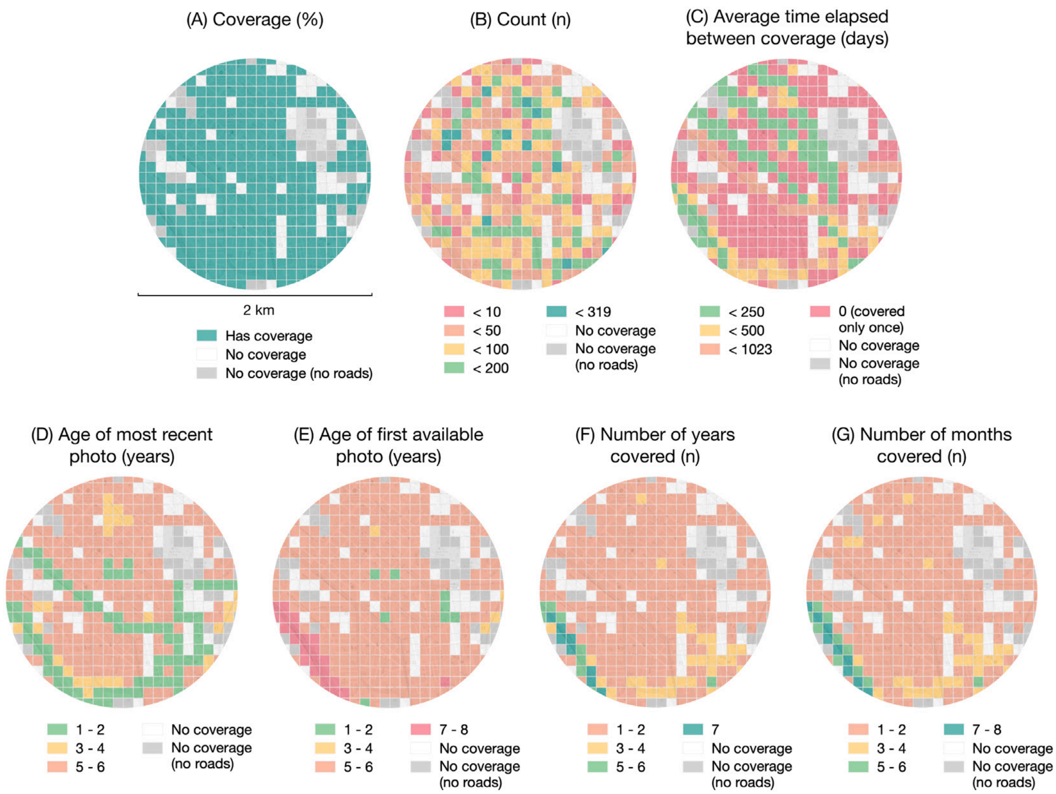

Fig. 4. The same elements as in the previous figure, calculated at another level (grid) in the hierarchy.

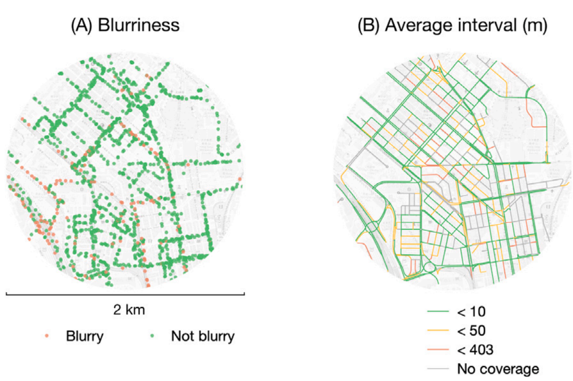

Fig. 5. Example of the assessment of two elements (A2 and C4). Unlike examples so far, the element on the left is assessed at the image level.

Numbers of years and months covered. For each street and cell, the years and months that the images were captured in are obtained, and the numbers of unique years and months covered are calculated. Figs. 3F and 3G show respectively the numbers of years and months in which the streets in Kowloon have been SVI-covered. Figs. 4F and 4G show the corresponding grid-level analysis.

Blurriness. This metric is only evaluated at the image (point) level. A method based on the variance of the Laplacian is used to automatically detect the amount of blur in an image, using the package OpenCV (Bradski, 2000). As the Laplacian operator is often used for edge detection, a high variance indicates a heterogeneous presence of both edge-like and non-edge like responses, typical of an in-focus image, while a low variance indicates a low amount of edges, typical of a blurry image. The variance is then compared to an empirically-determined threshold to determine whether an image is considered blurry. Fig. 5A shows the spatial distribution of blurry and non-blurry images in Kowloon.

Average spacing interval. This metric is only evaluated at the street level, and is calculated by dividing the total street length by the total count of images on that street. The calculation result is shown in Fig. 5B.

6. Discussion

The framework and the results have been discussed in detail in the sections hitherto. Here we postulate further applications of the work and expose limitations.

Besides general quality assessment studies applicable to both commercial and crowdsourcing sources, such as the one in Section 5, more specific applications of the framework and its implementation are possible. For example, in the context of VSVI, the work may be used to associate the quality metrics to each contributor (a quality contribution score can be assigned to reflect trustworthiness and effort of different contributors) and to detect vandalism, a topic that gained interest in other instances of VGI (Neis et al., 2012; Li et al., 2021a). Further, the derived quality elements may be adopted by services and help users filter for imagery suitable for their analysis and help contributors identify areas in need of data of better quality or updated coverage.

A potential limitation of the methodology is *survivorship bias* in the portion in which we manually checked thousands of images to identify issues. As SVI services have internal quality assurance mechanisms, we have access to only imagery *after* such quality control have been applied, i.e. data that *survived* such process.

An impediment of the framework is that certain metrics are difficult to measure automatically. For example, it can be challenging to judge whether the positional information of an image is accurate just from looking at the image and its location on the map. It is also not possible to assess positional accuracy by merely comparing how far a trajectory

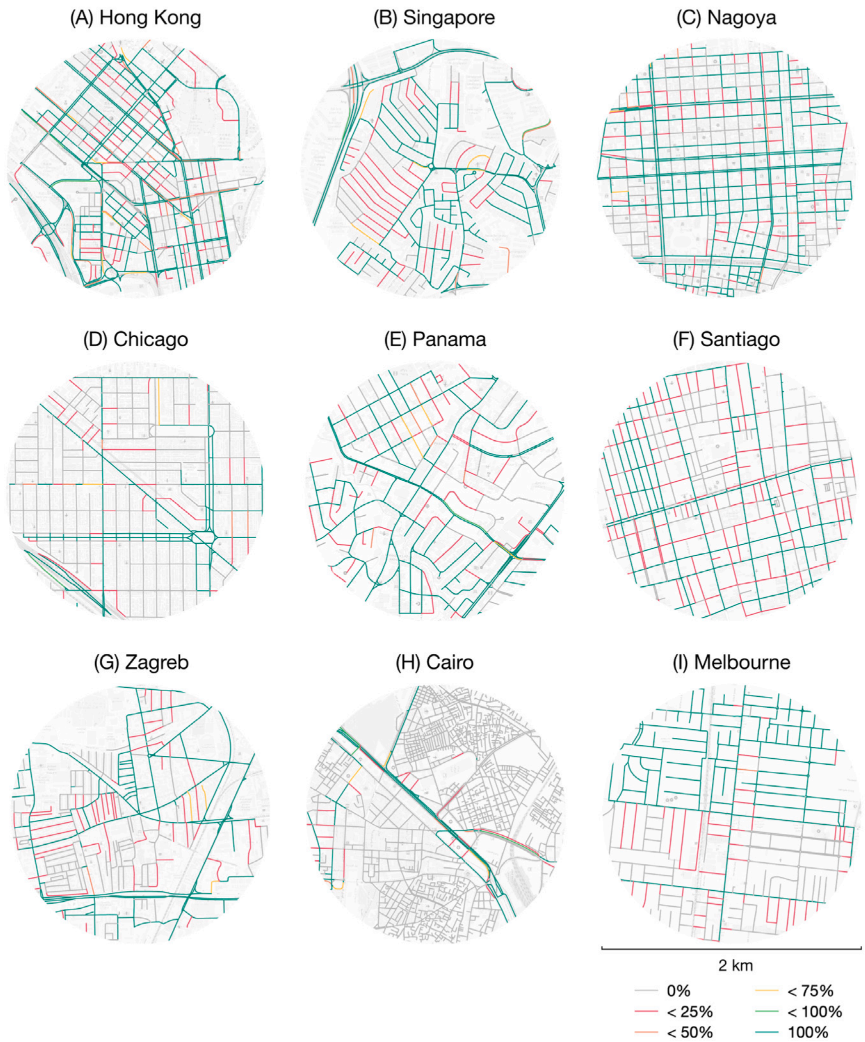

Fig. 6. Street-based coverage (C1) for nine cities. The results expose heterogeneous spatial quality around the world, affirming the importance of establishing a framework for assessing the quality of street view imagery. This quality element has a few applications: understanding whether a study area has a sufficiently complete dataset for a spatial analysis, detecting undermapped areas in VSVI, and comparative analyses on SVI data collection patterns and practices.

deviates from a road to which it may be matched, without understanding whether the trajectory was even recorded in that particular street. For example, it is possible that a sequence was acquired in a parallel street or a footpath next to a matched road, or even off-road. This limitation is in line with other spatial data quality assessment approaches, which regularly require a ground truth reference dataset.

Much of the SVI nowadays is collected by cars on roads, but there are some unconventional and off-road SVI, such as imagery collected on hiking trails and cycle paths. Our framework is able to accommodate any SVI, but it should be acknowledged nevertheless that the research was driven by the orthodox platform of SVI (i.e. imagery collected from cars on roads), potentially leaving some particularities pertaining to unconventional platforms overlooked.

7. Conclusions

As street view imagery is now an established dataset in the geospatial community, it is also increasingly heterogeneous with the growing services, coverage, and the emergence of crowdsourced platforms. Quality, an inescapable topic in the geospatial realm, has been largely overlooked in the SVI research community, and there are neither standards nor holistic quality assessment frameworks or procedures developed for SVI.

For the first time, we propose a thorough set of SVI quality elements to characterise the multifaceted characteristics of SVI data that have implications on their use and are compatible with existing spatial data quality guidelines. Our framework is comprehensive, encompassing dozens of quality aspects pertinent to SVI, and their different scales: from individual images and sequences to streets and districts. We also provide an open-source toolkit, which may be used to assess a subset of the metrics that do not require external validation and it is applicable for any location worldwide. Another contribution of our work to the fundamentals of the field is the definition of SVI (Section 3.2) and its position in the landscape of image-based geoinformation (Section 2.5). Much of our work, while tailored for SVI, may be applied also in the domain of image-based VGI other than SVI (e.g. Flickr) (Hu et al., 2015), mobile mapping systems (Yang, 2019), and UAV (Luo et al., 2022).

As this work may provide a basis for a formal standard, a viable direction for future work is the development of a markup language to store the metadata and quality results in a standardised way and propose it to an organisation such as OGC or ISO for standardisation. Further, as it establishes the foundation of the quality of SVI, there are a few viable research lines we put forward. First, the investigation of error propagation in SVI based on some of the identified metrics when the imagery is used in downstream analyses (e.g. Fig. 1 gives a hint of the idea). Second, the implementation can be scaled into a multivariate global analysis, considerably expanding related work beyond their focus on completeness (Section 2). Third, further research is needed for the automated detection of issues in SVI that are challenging to implement. Such work would not only be useful for large-scale assessment of SVI datasets, but also for other purposes. For example, determining a suitable set of images to reconstruct 3D building models (Pang and Biljecki, 2022) and to ensure the consistency of quality of imagery for longitudinal studies in which the quality will inevitably vary (Li et al., 2022).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The code and sample dataset used in this research have been released openly on https://github.com/ualsg/SVI-Quality-Checker

Acknowledgements

We thank the editor and the reviewers for their comments. We appreciate the valuable contributions of the VGI community. We thank our colleagues at the NUS Urban Analytics Lab for the discussions. This research is part of the projects (i) Large-scale 3D Geospatial Data for Urban Analytics, which is supported by the National University of Singapore under the Start Up Grant R-295-000-171-133; and (ii) Multi-scale Digital Twins for the Urban Environment: From Heartbeats to Cities, which is supported by the Singapore Ministry of Education Academic Research Fund Tier 1.

References

Ali, A.L., Schmid, F., 2014. Data Quality Assurance for Volunteered Geographic Information. In: Duckham, M., Pebesma, E., Stewart, K., Frank, A.U. (Eds.), Geographic Information Science. In: Lecture Notes in Computer Science, Springer International Publishing, Cham, pp. 126–141. http://dx.doi.org/10.1007/978-3-319-11593-1_9.

Anguelov, D., Dulong, C., Filip, D., Frueh, C., Lafon, S., Lyon, R., Ogale, A., Vincent, L., Weaver, J., 2010. Google Street View: Capturing the World at Street Level. Computer 43 (6), 32–38. http://dx.doi.org/10.1109/MC.2010.170.

Antoniou, V., Skopeliti, A., 2015. Measures and indicators of VGI quality: an overview. In: ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences. II-3/W5. http://dx.doi.org/10.5194/isprsannals-II-3-W5-345-2015.

Ao, Y., Wang, J., Zhou, M., Lindenbergh, R.C., Yang, M.Y., 2019. Fully convolutional networks for street furniture identification in panorama images. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XLII-2/W13, 13–20. http://dx.doi.org/10.5194/isprs-archives-xlii-2-w13-13-2019.

Barron, C., Neis, P., Zipf, A., 2014. A Comprehensive Framework for Intrinsic OpenStreetMap Quality Analysis. Trans. GIS 18 (6), 877–895. http://dx.doi.org/10.1111/tgis.12073.

Barsi, Á., Kugler, Z., Juhász, A., Szabó, G., Batini, C., Abdulmuttalib, H., Huang, G., Shen, H., 2019. Remote sensing data quality model: From data sources to lifecycle phases. Int. J. Image Data Fusion 10 (4), 280–299. http://dx.doi.org/10.1080/19479832.2019.1625977.

Batini, C., Blaschke, T., Lang, S., Albrecht, F., Abdulmutalib, H.M., Barsi, Á., Szabó, G., Kugler, Z., 2017. Data Quality in Remote Sensing. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XLII-2/W7, 447–453. http://dx.doi.org/10.5194/isprs-archives-XLII-2-W7-447-2017.

Biljecki, F., 2020. Exploration of open data in southeast Asia to generate 3D building models. ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. VI-4/W1-2020, 37–44. http://dx.doi.org/10.5194/isprs-annals-vi-4-w1-2020-37-2020.

Biljecki, F., Ito, K., 2021. Street view imagery in urban analytics and GIS: A review. Landsc. Urban Plan. 215, 104217. http://dx.doi.org/10.1016/j.landurbplan.2021.104217.

Bin, J., Gardiner, B., Li, E., Liu, Z., 2020. Multi-source urban data fusion for property value assessment: A case study in Philadelphia. Neurocomputing 404, 70–83. http://dx.doi.org/10.1016/j.neucom.2020.05.013.

Bochkarev, K., Smirnov, E., 2019. Detecting advertising on building façades with computer vision. Procedia Comput. Sci. 156, 338–346. http://dx.doi.org/10.1016/j.procs.2019.08.210.

Boeing, G., 2017. OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. Comput. Environ. Urban Syst. 65, 126–139. http://dx.doi.org/10.1016/j.compenvurbsys.2017.05.004.

Bradski, G., 2000. The OpenCV Library. Dr. Dobb's J. Softw. Tools.

Branson, S., Wegner, J.D., Hall, D., Lang, N., Schindler, K., Perona, P., 2018. From Google Maps to a fine-grained catalog of street trees. ISPRS J. Photogramm. Remote Sens. 135, 13–30. http://dx.doi.org/10.1016/j.isprsjprs.2017.11.008.

Bruno, N., Roncella, R., 2019. Accuracy assessment of 3D models generated from Google Street View imagery. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci. XLII-2/W9, 181–188. http://dx.doi.org/10.5194/isprs-archives-XLII-2-W9-181-2019.

Byun, G., Kim, Y., 2022. A street-view-based method to detect urban growth and decline: A case study of Midtown in Detroit, Michigan, USA. PLoS One 17 (2), e0263775. http://dx.doi.org/10.1371/journal.pone.0263775.

CEOS, 2010. A Quality Assurance Framework for Earth Observation (QA4EO). Technical Report, Group on Earth Observations/Committee on Earth Observation Satellites, QA4EO.

Chen, L., Lu, Y., Sheng, Q., Ye, Y., Wang, R., Liu, Y., 2020. Estimating pedestrian volume using Street View images: A large-scale validation test. Comput. Environ. Urban Syst. 81, 101481. http://dx.doi.org/10.1016/j.compenvurbsys.2020.101481.

Cheng, L., Yuan, Y., Xia, N., Chen, S., Chen, Y., Yang, K., Ma, L., Li, M., 2018. Crowd-sourced pictures geo-localization method based on street view images and 3D reconstruction. ISPRS J. Photogramm. Remote Sens. 141, 72–85. http://dx.doi.org/10.1016/j.isprsjprs.2018.04.006.

Ding, X., Fan, H., Gong, J., 2021. Towards generating network of bikeways from Mapillary data. Comput. Environ. Urban Syst. 88, 101632. http://dx.doi.org/10.1016/j.compenvurbsys.2021.101632.

Dubey, A., Naik, N., Parikh, D., Raskar, R., Hidalgo, C.A., 2016. Deep Learning the City: Quantifying Urban Perception at a Global Scale. In: Leibe, B., Matas, J., Sebe, N., Welling, M. (Eds.), Computer Vision – ECCV 2016. In: Lecture Notes in Computer Science, Springer International Publishing, Cham, pp. 196–212. http://dx.doi.org/10.1007/978-3-319-46448-0_12.

Ferster, C., Fischer, J., Manaugh, K., Nelson, T., Winters, M., 2020. Using OpenStreetMap to inventory bicycle infrastructure: A comparison with open data from cities. Int. J. Sustain. Transp. 14 (1), 64–73. http://dx.doi.org/10.1080/15568318.2018.1519746.

Fonte, C., Antoniou, V., Bastin, L., Estima, J., Jokar Arsanjani, J., Laso Bayas, J., See, L., Vatseva, R., 2017. Assessing VGI Data Quality. In: Mapping and the Citizen Sensor. Ubiquity Press, London, pp. 137–163. http://dx.doi.org/10.5334/bbf.g.

Fry, D., Mooney, S.J., Rodríguez, D.A., Caiaffa, W.T., Lovasi, G.S., 2020. Assessing Google Street View Image Availability in Latin American Cities. J. Urban Health 97 (4), 552–560. http://dx.doi.org/10.1007/s11524-019-00408-7.

Goodchild, M.F., 2007. Citizens as sensors: The world of volunteered geography. GeoJournal 69 (4), 211–221. http://dx.doi.org/10.1007/s10708-007-9111-y.

Goodchild, M.F., Li, L., 2012. Assuring the quality of volunteered geographic information. Spatial Stat. 1, 110–120. http://dx.doi.org/10.1016/j.spasta.2012.03.002.

Gorgul, E., Chen, C., Wu, K.K., Guo, Y., 2019. Measuring street enclosure and its influence to human physiology through wearable sensors. In: Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2019 ACM International Symposium on Wearable Computers. ACM, http://dx.doi.org/10.1145/3341162.3343794.

Guan, F., Fang, Z., Wang, L., Zhang, X., Zhong, H., Huang, H., 2022. Modelling people's perceived scene complexity of real-world environments using street-view panoramas and open geodata. ISPRS J. Photogramm. Remote Sens. 186, 315–331. http://dx.doi.org/10.1016/j.isprsjprs.2022.02.012.

Haklay, M., 2010. How Good is Volunteered Geographical Information? A Comparative Study of OpenStreetMap and Ordnance Survey Datasets. Environ. Plan. B: Plann. Des. 37 (4), 682–703. http://dx.doi.org/10.1068/b35097.

Hara, K., Azenkot, S., Campbell, M., Bennett, C.L., Le, V., Pannella, S., Moore, R., Minckler, K., Ng, R.H., Froehlich, J.E., 2015. Improving Public Transit Accessibility for Blind Riders by Crowdsourcing Bus Stop Landmark Locations with Google Street View: An Extended Analysis. ACM Trans. Access. Comput. 6 (2), 5:1–5:23. http://dx.doi.org/10.1145/2717513.

Hara, K., Le, V., Froehlich, J., 2012. A feasibility study of crowdsourcing and google street view to determine sidewalk accessibility. In: Proceedings of the 14th International ACM SIGACCESS Conference on Computers and Accessibility. In: ASSETS '12, Association for Computing Machinery, New York, NY, USA, pp. 273–274. http://dx.doi.org/10.1145/2384916.2384989.

Hawes, J.K., Gounaridis, D., Newell, J.P., 2022. Does urban agriculture lead to gentrification? Landsc. Urban Plan. 225, 104447. http://dx.doi.org/10.1016/j.landurbplan.2022.104447.

He, H., Lin, X., Yang, Y., Lu, Y., 2020. Association of street greenery and physical activity in older adults: A novel study using pedestrian-centered photographs. Urban For. Urban Green. 55, 126789. http://dx.doi.org/10.1016/j.ufug.2020.126789.

HE, Z., Wang, Z., Xie, Z., Wu, L., Chen, Z., 2022. Multiscale analysis of the influence of street built environment on crime occurrence using street-view images. Comput. Environ. Urban Syst. 97, 101865. http://dx.doi.org/10.1016/j.compenvurbsys.2022.101865.

Hosseini, M., Miranda, F., Lin, J., Silva, C.T., 2022. Citysurfaces: City-scale semantic segmentation of sidewalk materials. Sustainable Cities Soc. 79, 103630. http://dx.doi.org/10.1016/j.scs.2021.103630.

Hu, Y., Gao, S., Janowicz, K., Yu, B., Li, W., Prasad, S., 2015. Extracting and understanding urban areas of interest using geotagged photos. Comput. Environ. Urban Syst. 54, 240–254. http://dx.doi.org/10.1016/j.compenvurbsys.2015.09.001, cited By 4.

Hu, F., Liu, W., Lu, J., Song, C., Meng, Y., Wang, J., Xing, H., 2020. Urban Function as a New Perspective for Adaptive Street Quality Assessment. Sustainability 12 (4), 1296. http://dx.doi.org/10.3390/su12041296.

Ignatius, M., Xu, R., Hou, Y., Liang, X., Zhao, T., Chen, S., Wong, N., Biljecki, F., 2022. Local Climate Zones: Lessons from Singapore and potential improvement with street view imagery. ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci. X-4/W2-2022, 121–128. http://dx.doi.org/10.5194/isprs-annals-X-4-W2-2022-121-2022.

Inoue, T., Manabe, R., Murayama, A., Koizumi, H., 2022. Landscape value in urban neighborhoods: A pilot analysis using street-level images. Landsc. Urban Plan. 221, 104357. http://dx.doi.org/10.1016/j.landurbplan.2022.104357.

ISO 12232:2019, 2019. Photography – Digital Still Cameras – Determination of Exposure Index, ISO Speed Ratings, Standard Output Sensitivity, and Recommended Exposure Index. Vol. 2019. Standard, International Organisation for Standardisation, Geneva, CH.

ISO 19115:2014, 2014. Geographic Information – Metadata – Part 1: Fundamentals. Vol. 2014. Standard, International Organisation for Standardisation, Geneva, CH.

ISO 19130:2014, 2014. Geographic Information – Imagery Sensor Models for Geopositioning – Part 2: SAR, InSAR, Lidar and Sonar. Vol. 2014. Standard, International Organisation for Standardisation, Geneva, CH.

ISO 19157:2013, 2013. Geographic Information – Data Quality. Vol. 2013. Standard, International Organisation for Standardisation, Geneva, CH.

Ito, K., Biljecki, F., 2021. Assessing bikeability with street view imagery and computer vision. Transp. Res. C 132, 103371. http://dx.doi.org/10.1016/j.trc.2021.103371.

Jonietz, D., Antonio, V., See, L., Zipf, A., 2017. Highlighting Current Trends in Volunteered Geographic Information. ISPRS Int. J. Geo-Inf. 6 (7), 202. http://dx.doi.org/10.3390/ijgi6070202.

Juhász, L., Hochmair, H.H., 2016. User Contribution Patterns and Completeness Evaluation of Mapillary, a Crowdsourced Street Level Photo Service. Trans. GIS 20 (6), 925–947. http://dx.doi.org/10.1111/tgis.12190.

Kang, J., Körner, M., Wang, Y., Taubenböck, H., Zhu, X.X., 2018. Building instance classification using street view images. ISPRS J. Photogramm. Remote Sens. 145, 44–59. http://dx.doi.org/10.1016/j.isprsjprs.2018.02.006.

Kang, B., Lee, S., Zou, S., 2021. Developing Sidewalk Inventory Data Using Street View Images. Sensors 21 (9), 3300. http://dx.doi.org/10.3390/s21093300.

Kang, Y., Zhang, F., Gao, S., Lin, H., Liu, Y., 2020. A review of Urban physical environment sensing using street view imagery in public health studies. Ann. GIS 26 (3), 261–275. http://dx.doi.org/10.1080/19475683.2020.1791954.

Keßler, C., de Groot, R.T.A., 2013. Trust as a Proxy Measure for the Quality of Volunteered Geographic Information in the Case of OpenStreetMap. In: Vandenbroucke, D., Bucher, B., Crompvoets, J. (Eds.), Geographic Information Science At the Heart of Europe. Springer International Publishing, Cham, pp. 21–37. http://dx.doi.org/10.1007/978-3-319-00615-4_2.

Kim, S.-N., Lee, H., 2022. Capturing reality: Validation of omnidirectional video-based immersive virtual reality as a streetscape quality auditing method. Landsc. Urban Plan. 218, 104290. http://dx.doi.org/10.1016/j.landurbplan.2021.104290.

Kruse, J., Kang, Y., Liu, Y.-N., Zhang, F., Gao, S., 2021. Places for play: Understanding human perception of playability in cities using street view images and deep learning. Comput. Environ. Urban Syst. 90, 101693. http://dx.doi.org/10.1016/j.compenvurbsys.2021.101693.

Labetski, A., Kumar, K., Ledoux, H., Stoter, J., 2018. A Metadata ADE for CityGML. Open Geosp. Data Softw. Standards 3 (1), 42. http://dx.doi.org/10.1186/s40965-018-0057-4.

Langley, S.A., Messina, J.P., Moore, N., 2017. Using meta-quality to assess the utility of volunteered geographic information for science. Int. J. Health Geogr. 16 (1), 40. http://dx.doi.org/10.1186/s12942-017-0113-9.

Larkin, A., Hystad, P., 2019. Evaluating street view exposure measures of visible green space for health research. J. Expo. Sci. Environ. Epidemiol. 29 (4), 447–456. http://dx.doi.org/10.1038/s41370-018-0017-1.

Lauko, I.G., Honts, A., Beihoff, J., Rupprecht, S., 2020. Local color and morphological image feature based vegetation identification and its application to human environment street view vegetation mapping, or how green is our county? Geo-Spatial Inf. Sci. 23 (3), 222–236. http://dx.doi.org/10.1080/10095020.2020.1805367.

Laumer, D., Lang, N., van Doorn, N., Aodha, O.M., Perona, P., Wegner, J.D., 2020. Geocoding of trees from street addresses and street-level images. ISPRS J. Photogramm. Remote Sens. 162, 125–136. http://dx.doi.org/10.1016/j.isprsjprs.2020.02.001.

Law, S., Paige, B., Russell, C., 2019. Take a Look Around: Using Street View and Satellite Images to Estimate House Prices. ACM Trans. Intell. Syst. Technol. 10 (5), 54:1–54:19. http://dx.doi.org/10.1145/3342240.

Li, Y., Anderson, J., Niu, Y., 2021a. Vandalism detection in OpenStreetMap via user embeddings. In: Proceedings of the 30th ACM International Conference on Information Knowledge Management. ACM, http://dx.doi.org/10.1145/3459637.3482213.

Li, S., Ma, S., Tong, D., Jia, Z., Li, P., Long, Y., 2021b. Associations between the quality of street space and the attributes of the built environment using large volumes of street view pictures. Environ. Plann. B Urban Anal. City Sci. 239980832110563. http://dx.doi.org/10.1177/23998083211056341.

Li, X., Ratti, C., Seiferling, I., 2018. Quantifying the shade provision of street trees in urban landscape: A case study in Boston, USA, using Google Street View. Landsc. Urban Plan. 169, 81–91. http://dx.doi.org/10.1016/j.landurbplan.2017.08.011.

Li, M., Sheng, H., Irvin, J., Chung, H., Ying, A., Sun, T., Ng, A.Y., Rodriguez, D.A., 2022. Marked crosswalks in US transit-oriented station areas, 2007–2020: A computer vision approach using street view imagery. Environ. Plann. B Urban Anal. City Sci. 239980832211121. http://dx.doi.org/10.1177/23998083221112157.

Liu, P., Biljecki, F., 2022. A review of spatially-explicit GeoAI applications in Urban geography. Int. J. Appl. Earth Obs. Geoinf. 112, 102936. http://dx.doi.org/10.1016/j.jag.2022.102936.

Luo, J., Zhao, T., Cao, L., Biljecki, F., 2022. Semantic Riverscapes: Perception and evaluation of linear landscapes from oblique imagery using computer vision. Landsc. Urban Plan. 228, 104569. http://dx.doi.org/10.1016/j.landurbplan.2022.104569.

Ma, D., Fan, H., Li, W., Ding, X., 2019. The State of Mapillary: An Exploratory Analysis. ISPRS Int. J. Geo-Inf. 9 (1), 10. http://dx.doi.org/10.3390/ijgi9010010.

Mahabir, R., Schuchard, R., Crooks, A., Croitoru, A., Stefanidis, A., 2020. Crowdsourcing Street View Imagery: A Comparison of Mapillary and OpenStreetCam. ISPRS Int. J. Geo-Inf. 9 (6), 341. http://dx.doi.org/10.3390/ijgi9060341.

Miranda, F., Hosseini, M., Lage, M., Doraiswamy, H., Dove, G., Silva, C.T., 2020. Urban Mosaic: Visual Exploration of Streetscapes Using Large-Scale Image Data. In: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems. Association for Computing Machinery, New York, NY, USA, pp. 1–15. http://dx.doi.org/10.1145/3313831.3376399.

Mocnik, F.-B., Westerholt, R., 2021. The effect of tectonic plate motion on georeferenced long-term global datasets. Int. J. Appl. Earth Obs. Geoinf. 94, 102183. http://dx.doi.org/10.1016/j.jag.2020.102183.

Naik, N., Kominers, S.D., Raskar, R., Glaeser, E.L., Hidalgo, C.A., 2017. Computer vision uncovers predictors of physical Urban change. Proc. Natl. Acad. Sci. 114 (29), 7571–7576. http://dx.doi.org/10.1073/pnas.1619003114.

Najafizadeh, L., Froehlich, J.E., 2018. A Feasibility Study of Using Google Street View and Computer Vision to Track the Evolution of Urban Accessibility. In: Proceedings of the 20th International ACM SIGACCESS Conference on Computers and Accessibility. ACM, Galway Ireland, pp. 340–342. http://dx.doi.org/10.1145/3234695.3240999.

Neis, P., Goetz, M., Zipf, A., 2012. Towards automatic vandalism detection in OpenStreetMap. ISPRS Int. J. Geo-Inf. 1 (3), 315–332. http://dx.doi.org/10.3390/ijgi1030315.

Neuhold, G., Ollmann, T., Bulò, S.R., Kontschieder, P., 2017. The Mapillary Vistas Dataset for Semantic Understanding of Street Scenes. In: 2017 IEEE International Conference on Computer Vision. ICCV, pp. 5000–5009. http://dx.doi.org/10.1109/ICCV.2017.534.

Ning, H., Li, Z., Wang, C., Hodgson, M.E., Huang, X., Li, X., 2022a. Converting street view images to land cover maps for metric mapping: A case study on sidewalk network extraction for the wheelchair users. Comput. Environ. Urban Syst. 95, 101808. http://dx.doi.org/10.1016/j.compenvurbsys.2022.101808.

Ning, H., Li, Z., Ye, X., Wang, S., Wang, W., Huang, X., 2022b. Exploring the vertical dimension of street view image based on deep learning: a case study on lowest floor elevation estimation. Int. J. Geogr. Inf. Sci. 36 (7), 1317–1342. http://dx.doi.org/10.1080/13658816.2021.1981334.

Novack, T., Vorbeck, L., Lorei, H., Zipf, A., 2020. Towards Detecting Building Facades with Graffiti Artwork Based on Street View Images. ISPRS Int. J. Geo-Inf. 9 (2), 98. http://dx.doi.org/10.3390/ijgi9020098.

Ogawa, Y., Oki, T., Chen, S., Sekimoto, Y., 2021. Joining Street-View Images and Building Footprint GIS Data. In: Proceedings of the 1st ACM SIGSPATIAL International Workshop on Searching and Mining Large Collections of Geospatial Data. ACM, Beijing China, pp. 18–24. http://dx.doi.org/10.1145/3486640.3491395.

Pang, H.E., Biljecki, F., 2022. 3D building reconstruction from single street view images using deep learning. Int. J. Appl. Earth Obs. Geoinf. 112, 102859. http://dx.doi.org/10.1016/j.jag.2022.102859.

Pelizari, P.A., Geiß, C., Aguirre, P., María, H.S., Peña, Y.M., Taubenböck, H., 2021. Automated building characterization for seismic risk assessment using street-level imagery and deep learning. ISPRS J. Photogramm. Remote Sens. 180, 370–386. http://dx.doi.org/10.1016/j.isprsjprs.2021.07.004.

Peng, Z., Gao, S., Xiao, B., Guo, S., Yang, Y., 2018. CrowdGIS: Updating digital maps via mobile crowdsensing. IEEE Trans. Autom. Sci. Eng. 15 (1), 369–380. http://dx.doi.org/10.1109/tase.2017.2761793.

Qiu, W., Zhang, Z., Liu, X., Li, W., Li, X., Xu, X., Huang, X., 2022. Subjective or objective measures of street environment, which are more effective in explaining housing prices? Landsc. Urban Plan. 221, 104358. http://dx.doi.org/10.1016/j.landurbplan.2022.104358.

Quarati, A., Martino, M.D., Rosim, S., 2021. Geospatial Open Data Usage and Metadata Quality. ISPRS Int. J. Geo-Inf. 10 (1), 30. http://dx.doi.org/10.3390/ijgi10010030.

Quinn, S., Alvarez León, L., 2019. Every single street? Rethinking full coverage across street-level imagery platforms. Trans. GIS 23 (6), 1251–1272. http://dx.doi.org/10.1111/tgis.12571.

Ranacher, P., Brunauer, R., Trutschnig, W., Van der Spek, S., Reich, S., 2016. Why GPS makes distances bigger than they are. Int. J. Geogr. Inf. Sci. 30 (2), 316–333. http://dx.doi.org/10.1080/13658816.2015.1086924.

Rundle, A.G., Bader, M.D., Richards, C.A., Neckerman, K.M., Teitler, J.O., 2011. Using Google Street View to Audit Neighborhood Environments. Am. J. Prev. Med. 40 (1), 94–100. http://dx.doi.org/10.1016/j.amepre.2010.09.034.

Senaratne, H., Mobasheri, A., Ali, A.L., Capineri, C., Haklay, M.M., 2017. A review of volunteered geographic information quality assessment methods. Int. J. Geogr. Inf. Sci. 31 (1), 139–167. http://dx.doi.org/10.1080/13658816.2016.1189556.

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. http://dx.doi.org/10.3390/ijgi9060372.

Sun, M., Han, C., Nie, Q., Xu, J., Zhang, F., Zhao, Q., 2022. Understanding Building Energy Efficiency with Administrative and Emerging Urban Big Data by Deep Learning in Glasgow. Energy Build. 112331. http://dx.doi.org/10.1016/j.enbuild.2022.112331.

Szczepańska, A., Pietrzyk, K., 2020. An Evaluation of Public Spaces with the Use of Direct and Remote Methods. Land 9 (11), 419. http://dx.doi.org/10.3390/land9110419.

Tatem, A.J., 2017. WorldPop, open data for spatial demography. Sci. Data 4 (1), 170004. http://dx.doi.org/10.1038/sdata.2017.4.

Venkatesh, G.M., Pereira, B., Little, S., 2021. Urban Footpath Image Dataset to Assess Pedestrian Mobility. In: Proceedings of the 1st International Workshop on Multimedia Computing for Urban Data. ACM, Virtual Event China, pp. 23–30. http://dx.doi.org/10.1145/3475721.3484313.

Verma, D., Jana, A., Ramamritham, K., 2019. Machine-based understanding of manually collected visual and auditory datasets for urban perception studies. Landsc. Urban Plan. 190, 103604. http://dx.doi.org/10.1016/j.landurbplan.2019.103604.

Wang, C., Antos, S.E., Triveno, L.M., 2021. Automatic detection of unreinforced masonry buildings from street view images using deep learning-based image segmentation. Autom. Constr. 132, 103968. http://dx.doi.org/10.1016/j.autcon.2021.103968.

Wang, M., Chen, Z., Rong, H.H., Mu, L., Zhu, P., Shi, Z., 2022. Ridesharing accessibility from the human eye: Spatial modeling of built environment with street-level images. Comput. Environ. Urban Syst. 97, 101858. http://dx.doi.org/10.1016/j.compenvurbsys.2022.101858.

Wang, R., Lu, Y., Zhang, J., Liu, P., Yao, Y., Liu, Y., 2019. The relationship between visual enclosure for neighbourhood street walkability and elders' mental health in China: Using street view images. J. Transp. Health 13, 90–102. http://dx.doi.org/10.1016/j.jth.2019.02.009.

Wei, J., Yue, W., Li, M., Gao, J., 2022. Mapping human perception of Urban landscape from street-view images: A deep-learning approach. Int. J. Appl. Earth Obs. Geoinf. 112, 102886. http://dx.doi.org/10.1016/j.jag.2022.102886.

Yan, Y., Feng, C.-C., Huang, W., Fan, H., Wang, Y.-C., Zipf, A., 2020. Volunteered geographic information research in the first decade: A narrative review of selected journal articles in GIScience. Int. J. Geogr. Inf. Sci. 34 (9), 1765–1791. http://dx.doi.org/10.1080/13658816.2020.1730848.

Yang, B., 2019. Developing a mobile mapping system for 3D GIS and smart city planning. Sustainability 11 (13), 3713. http://dx.doi.org/10.3390/su11133713.

Yao, Y., Zhang, J., Qian, C., Wang, Y., Ren, S., Yuan, Z., Guan, Q., 2021. Delineating urban job-housing patterns at a parcel scale with street view imagery. Int. J. Geogr. Inf. Sci. 35 (10), 1–24. http://dx.doi.org/10.1080/13658816.2021.1895170.

Yin, L., Cheng, Q., Wang, Z., Shao, Z., 2015. 'Big data' for pedestrian volume: Exploring the use of Google Street View images for pedestrian counts. Appl. Geogr. 63, 337–345. http://dx.doi.org/10.1016/j.apgeog.2015.07.010.

Yin, J., Dong, J., Hamm, N.A.S., Li, Z., Wang, J., Xing, H., Fu, P., 2021. Integrating remote sensing and geospatial big data for Urban land use mapping: A review. Int. J. Appl. Earth Obs. Geoinf. 103, 102514. http://dx.doi.org/10.1016/j.jag.2021.102514.

Zhang, F., Wu, L., Zhu, D., Liu, Y., 2019. Social sensing from street-level imagery: A case study in learning spatio-temporal Urban mobility patterns. ISPRS J. Photogramm. Remote Sens. 153, 48–58. http://dx.doi.org/10.1016/j.isprsjprs.2019.04.017.

Zhang, X., Yin, W., Yang, M., Ai, T., Stoter, J., 2018. Updating authoritative spatial data from timely sources: A multiple representation approach. Int. J. Appl. Earth Obs. Geoinf. 72, 42–56. http://dx.doi.org/10.1016/j.jag.2018.05.022.

Zhang, F., Zu, J., Hu, M., Zhu, D., Kang, Y., Gao, S., Zhang, Y., Huang, Z., 2020. Uncovering inconspicuous places using social media check-ins and street view images. Comput. Environ. Urban Syst. 81, 101478. http://dx.doi.org/10.1016/j.compenvurbsys.2020.101478.

Zhou, H., He, S., Cai, Y., Wang, M., Su, S., 2019. Social inequalities in neighborhood visual walkability: Using street view imagery and deep learning technologies to facilitate healthy city planning. Sustainable Cities Soc. 50, 101605. http://dx.doi.org/10.1016/j.scs.2019.101605.