CHAPTER 7

Assessing VGI Data Quality

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Abstract

Uncertainty over the data quality of Volunteered Geographic Information (VGI) is the largest barrier to the use of this data source by National Mapping Agencies (NMAs) and other government bodies. A considerable body of literature exists that has examined the quality of VGI as well as proposed methods for quality assessment. The purpose of this chapter is to review current data quality indicators for geographic information as part of the ISO 19157 (2013) standard and how these have been used to evaluate the data quality of VGI in the past. These indicators include positional, thematic and temporal accuracy, completeness, logical consistency and usability. Additional indicators that have

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been proposed for VGI are then presented and discussed. In the final section of the chapter, the idea of integrated indicators and workflows of quality assurance that combine many assessment methods into a filtering system is highlighted as one way forward to improve confidence in VGI.

Keywords

Spatial data quality, ISO 19157, positional accuracy, thematic accuracy, usability

1 Introduction and Background

Quality is a key component of any dataset. Decisions on using a spatial dataset for a certain purpose are heavily based on quality measures such as positional accuracy, thematic quality, completeness and usability. This also applies to Volunteered Geographic Information (VGI), a new and growing source of data, contributed by citizens, that can take many different forms, e.g. geotagged photographs through sites such as Panoramio and Flickr, online maps such as OpenStreetMap (OSM) and Wikimapia, and 3D VGI such as OSM-3D and OSM2World. For a more detailed overview of the diverse range of current VGI data sources, see Chapter 2 (See et al., 2017).

A set of elements is specified in the ISO 19157 standard for spatial data quality (ISO, 2013). This framework adequately serves communities such as National Mapping Agencies (NMAs), which have professional staff following rigorous protocols and multiple quality control processes so as to produce high-quality products of a minimum acceptable specification. However, these spatial data quality guidelines have not been developed with any consideration of the nature of VGI. The data quality of VGI brings new challenges into the quality assessment field, and therefore it is possible to consider VGI data quality using this standard and then recommend additional measures that take the specific nature of VGI into account.

One characteristic of VGI is its heterogeneous nature, e.g. there is often a spatial bias in the information, with more data collected in urban than in rural areas (Estima et al., 2014; Neis and Zielstra, 2014; Ma et al., 2015) or a bias towards specific types of features, influenced by the interests of the volunteers (Bégin et al., 2013). Moreover, even inside the urban fabric, the more popular and touristic areas are getting more attention, and thus more data with higher detail, than obscure and fairly unknown urban areas (Antoniou and Schlieder, 2014; Estima et al., 2014). These biases can be further influenced by access to, and knowledge of, digital resources, the language of the VGI application, cultural differences and how much time users have to participate (Holloway et al., 2007; Zook and Graham, 2007).

Another issue with VGI is the lack of rigorous data specifications of the kind that accompany more authoritative Geographic Information (GI), an issue which can lead to heterogeneous data quality (Hochmair and Zielstra, 2012). While collaborative mapping can improve data quality to a certain extent (Haklay et al., 2010), frequent changes to the same features can deteriorate the overall quality and usability of the data; examples of this phenomenon can be found in location-based services (Mooney and Corcoran, 2012) and gazetteers (Antoniou et al., 2016b). Moreover, the fact that there is no standard way in which the data are collected, as well as data specifications that vary between and also within initiatives, means that quality will vary over space and time; see e.g. OSM, where free tagging of features is possible.

For some types of VGI applications, such as OSM or Instagram, the volunteers may contribute information in any location. However, some VGI campaigns have been promoted with a more specific objective in mind and consequently have employed a statistical sampling system to make sure that the data are collected where they are needed, that a more global coverage is obtained or that more accurate results are achieved. These campaigns have been promoted to citizen scientists, eliciting their help with specific goals, e.g. quantifying human impact (See et al., 2013) or assessing cropland and other land use area estimates (Waldner et al., 2015), or even collecting photographs around the world, such as for the Degree Confluence Project[1]. Some of the statistical sampling systems used include systematic allocation of points in a grid; and random or stratified random samples, whether these are points, polygons or pixels. One of the key advantages of using statistical samples includes having a stricter control on what data the users can contribute and where, allowing for more straight-forward measures of quality, e.g. through estimation of statistical uncertainties and determination of possible sample augmentation to reduce these uncertainties. Additionally, and depending on the design of these systems, comparisons between users are easier to do, since the location is fixed and shared between the contributors. A key disadvantage of predetermined sampling systems, however, might be precisely their strictness, e.g. bounding the users to a pre-defined set of geographic locations, with usually little possibility of reporting local and sometimes more relevant characteristics from the surroundings that might contribute to a better understanding and achievement of a given objective; this, in itself, could be detrimental to the quality of the information by providing information that is very precise but off-target.

VGI quality has been the subject of a considerable amount of research, particularly with regard to the quality of OSM. For example, a number of studies have tried to assess VGI quality based on comparisons with authoritative data provided by NMAs or commercial companies (e.g. Girres and Touya, 2010; Haklay, 2010; Zielstra and Zipf, 2010; Antoniou, 2011; Estima and Painho, 2013; Fan et al., 2014). These comparisons are based on the belief that authoritative data are always of a minimum, acceptable quality and created according to high standards and that it is thus reasonable to assume that authoritative data can play the role of reference datasets during a quality evaluation process of VGI datasets. In these studies, a number of methods are used, e.g. data matching, generalisation evaluation, etc., that consider different elements of data quality such as positional or thematic accuracy. However, the application of these methods is not always possible, because of limited data availability, licence restrictions or the lack of access to costly authoritative datasets. Moreover, as VGI datasets are often richer than their authoritative counterparts, and will only continue to increase in richness, the use of authoritative data as a reference dataset for quality evaluation may no longer be the most valid choice. In some parts of the world, VGI is more complete and more accurate than authoritative datasets (Neis et al., 2011; Vandecasteele and Devillers, 2015), which poses challenges to the assessment of VGI data quality.

This chapter provides a review of data quality indicators for geographic information that are part of the ISO 19157 (2013) standard, of how these have been used to evaluate the data quality of VGI in the past and of other approaches that could be used. Additional indicators that have been proposed for VGI in particular are also presented, as well as initiatives to develop quality assessment frameworks combining several quality measures and indicators.

2 Measures and Indicators to Assess VGI Quality

ISO 19157 is the latest release (2013) of a data quality standard among the internationally known standards for describing spatial data quality, e.g. the International Cartographic Association (ICA), Federal Geographic Data Committee (FGDC) and Committee on Standardization (CEN) standards. It attempts to define a set of measures for evaluating and reporting data quality. The conceptual model for geodata quality as specified in ISO 19157 represents data quality by a series of data quality elements, e.g. positional accuracy. Each data quality element is then further described by measures that allow the data quality to be evaluated, and the results of the evaluation can be documented and reported to any interested party. The ISO 19157 standard does not attempt to define any minimum acceptable levels of quality for spatial data, and it considers only conventional datasets without proposing any data quality elements or measures specific to VGI. The next subsection outlines the different spatial data quality elements that are part of ISO 19157 and how they can be used to measure VGI quality, drawing upon examples from the literature and VGI practices.

2.1 ISO Quality Measures Applicable to VGI

The first five spatial data quality elements of ISO 19157 (Sections 2.1.1 to 2.1.5) are focused on the quality of the product from a producer's point of view, or on what is termed the 'internal quality' of a dataset (Devillers and Jeansoulin, 2006). The sixth spatial data quality element (Section 2.1.6) is focused on the user needs and requirements and is referred to as the 'external quality' of a dataset (Devillers and Jeansoulin, 2006). Thus there may be situations where the internal quality is high (i.e. it is produced according to a set of specifications) but the external quality poor (i.e. it does not fulfil a particular purpose from a user's perspective). The same will apply to VGI, so the fact that a VGI dataset is created according to some initial specifications does not necessarily mean that it can be used to cover all or any requirements stated by potential end users. This is of particular importance when we consider that in many implicit VGI sources, the existing specifications might have no direct relation to spatial or geomatics aims. Some additional quality elements have been proposed for crowdsourced data that fall in between internal and external quality (Meek et al., 2014), corresponding to what the authors called the stakeholder model; these additional quality elements have also been referred to as quality indicators (Antoniou and Skopeliti, 2015) and are discussed in more detail in Section 2.2.

2.1.1 Positional Accuracy

Positional accuracy refers to the accuracy of the position of features (i.e. points, lines or areas) within a spatial reference system, and is usually assessed by comparing the position of features with their counterparts in reference data, which are considered to represent the 'true' position. This assessment, however, requires the existence of reference data with similar characteristics and a valid time frame to make the comparison.

The use of portable data collection technologies, such as Global Navigation Satellite Systems (GNSS) receivers embedded in smartphones, is one of the most common methods to collect the geographic position associated with crowdsourced data. Previously, these technologies were capable of delivering a spatial precision exceeding ±10m (Coleman, 2010). However, the precision is continuously improving, and accuracies of 2–3 m or even higher can now be achieved, depending on the receivers used, the observation method or the observation conditions (Pesyna et al., 2015). When combined with the increasing availability of Web-based maps and imagery (in some cases with very high spatial resolution) that can be used, for example, as digitising backdrops, it is not surprising that the positional accuracy of VGI has increased, and is now appropriate for a wide range of applications.

Several studies have been conducted to assess the positional accuracy of VGI data. An analysis of positional accuracy of OSM in relation to Google Maps and Bing Maps was undertaken by Ciepłuch et al. (2010) for sites in Ireland, and concluded that in some locations there were differences of up to 10m (for Google Maps) between these sources, although only for some types of features, which seemed to result from digitisation over low-resolution images. For a set of OSM road features compared to the UK's Ordnance Survey data, the average errors identified were 5.8m (Haklay, 2010) – a distance unlikely to be seriously problematic for most land cover maps, but one which could cause small or narrow features (ponds, hedges, riparian habitats, etc.) to be missed or misplaced. Canavosio-Zuzelski et al. (2013) performed a positional accuracy assessment of OSM as part of a vector adjustment correction. However, in this case, rather than accepting official survey data as truth, both official data and OSM data were assessed against independent stereo imagery, which means the technique can be applied to other national agency and topographic datasets and has the potential to identify areas where the VGI surpasses the accepted dataset. Thus the authors were able to assess OSM against USGS (United States Geological Survey) and TIGER (Topologically Integrated Geographic Encoding and Referencing) road data on a more-or-less equal footing – albeit for a very small area for which the aerial imagery was available. In general, the availability of such accurate benchmarking data is restricted, and this (or a requirement for very current information) may be the very reason why VGI is being elicited. The most successful examples of such quality control analyses are where feedback is given to the volunteers to enable them to improve their contributions, e.g. in OSM.

The positional accuracy of points representing geotagged photographs may also be considered and analysed, once the specifications are available regarding what feature should be positioned. In Hochmair and Zielstra (2012), the location associated with the Flickr and Panoramio photographs was compared to the location of the photograph as determined by the authors analysing what was represented in the photograph. Several aspects were identified that may influence positional quality; for example, the position assigned to some photographs was the location from which the photograph was taken, while for others it was the position of what was represented in the photograph (potentially some distance away), without any additional indication of what the position represented. Another aspect identified that influenced the positional accuracy was the confusion between similar features that are present in the region (such as different bridges over a river close to each other), which became apparent when the location of the photographs was viewed on a satellite image or digital map.

The assessment of the positional accuracy or the extent mapping of patchy vegetation, highly-textured land use types and ecotones presents much more of a challenge. For land cover mapping, it is often the case that categorical labels (or degrees of similarity to those labels) are being elicited from contributors for attachment to user-supplied location points or to predefined polygon features. Absolute positional accuracy is still important, but more often relates to boundaries between mapped areas or to the location of single survey points, and the predominant source of inaccuracy is thematic misclassification (to which, of course, these positional inaccuracies can contribute).

Other approaches may, however, be considered for assessing or increasing positional accuracy of VGI, due to the amount of data available and their dynamic characteristics (Section 2.2). To correct and quantify positional errors, conflation approaches that use a set of reference features are common for discrete data that fit an existing taxonomy (Coleman, 2010; Girres and Touya, 2010; Haklay, 2010).

2.1.2 Thematic Accuracy

Thematic accuracy refers to the accuracy of classes or thematic tags associated with specific locations or objects placed in geographic space, such as classes assigned to pixels in a land cover map or tags assigned to a vector-encoded entity, e.g. a highway, river, building or green area. The assessment of thematic accuracy in VGI may be performed using a traditional approach, where the information is compared to reference data, e.g. satellite imagery or authoritative data, by experts. For instance, Estima and Painho (2013; 2015) and Jokar Arsanjani et al. (2015b) investigated the thematic accuracy of the classification of OSM features using the Corine Land Cover database and the pan-European GMESUA dataset as authoritative reference data, respectively. However, the assessment of the thematic accuracy of VGI raises new challenges, due to the lack of strict specifications, the characteristics of the contributors and contributions, and the type of thematic information at stake. Therefore, additional quality indicators may be used, which are further explained in Section 2.2. The assignment of thematic information in VGI has many similarities to the extensive tagging and relevance assessment of documents by volunteers or paid contractors working via systems such as Amazon's Mechanical Turk. Many land cover mapping challenges are effectively labelling problems, where predefined pixels or spatial features must be assigned to particular classes; therefore, some of the work developed in these areas of application to assure data quality may be applied to VGI.

Currently, the majority of VGI is contributed for free, by volunteers, but there is an increasing interest in contracting out classification tasks such as land cover labelling to paid workers in the cloud. In such contexts, spam and errors are common, whether these stem from a lack of skill or from deliberate attempts to mislead (including attempts to cheat the system in a way that cannot be easily detected). A number of strategies have been proposed and evaluated for getting the best value out of contracted labellers, and in particular for trading off the value of new information about unlabelled entities against the value of reinforcing or correcting information about entities that have been labelled repeatedly (Ipeirotis et al., 2014). This corresponds to the use of additional quality indicators, which are further addressed in Section 2.2. One consideration when deciding between accuracy improvement and new data acquisition must be the possible impact of errors when a dataset is used in the real world – a balancing act similar to the calculation of ROC (Receiver Operating Characteristic) curves or sensitivity/specificity calculations for classifiers and prediction algorithms. The problem of risk and liability, when considered in the VGI world, is usually sidestepped through the use of disclaimers, but if VGI begins to seriously underpin Spatial Data Infrastructures (SDIs) – see Chapter 12 (Demetriou et al., 2017) – and commercial products, the issue will become more pressing.

Many of the non-VGI labelling tasks described have marked parallels to VGI problems: for example, data points are often being collected, like 'ground truth', in order to carry out a supervised classification, and in many cases the labelling is not simply binary or categorical. In such cases, when redundant observations exist for each particular item, the variation between labellers is not simply noise; often, the uncertainty and disagreement, if recorded and analysed, can yield important information about the real world. In the case of VGI, this could include conditions on the ground such as vegetation succession, change of ownership or mixing of land covers. Many papers in the field also note the importance of training for labellers as well as for models (e.g. Clark and Aide, 2011; Fritz et al., 2012), and show the sorts of learning curves that are possible with varying quantities and qualities of reference data.

Of course, even well trained users vary in their accuracy, and differences between experts and non-experts are also likely to exist. A comparison of the quality results of expert and non-expert volunteers for tag assignment was done by See et al. (2013). The results showed that in some types of tags (in this particular case, 'human impact'), non-expert volunteers produced results as good as the experts, probably because the concept was new to both non-experts and experts alike so both had the same learning curves. However, for some land cover classes, the experts (some of whom had considerable experience in image classification) performed better, but the non-experts showed improvements over time, especially when feedback on the quality of their results was provided to them.

2.1.3 Completeness

Completeness refers to the presence or absence of features, of their attributes and of relationships compared to the product's specification; it is divided into a) commission, which explains excess data presence in a dataset, and b) omission, which explains data absence from a dataset. Completeness is of major concern/importance in VGI, since many volunteered datasets are demonstrably biased towards particular spatial regions (see e.g. Haklay, 2010), but also towards certain features that are easier to measure or towards themes or 'pet features' (Bégin et al., 2013) that are of particular interest to the contributing individual, or even motivated by accessibility or digital inclusion (Zielstra and Zipf, 2010). This reliance on the motivation of individual volunteers will determine the resolution, homogeneity, representativity and domain consistency of the resulting data. Where a principled sampling strategy can be imposed on volunteers, e.g. a probabilistic schema or the systematic, even grid of the Degree Confluence Project, the volunteered data have the potential to be more broadly applicable, but the value of the data will depend on the coverage by volunteers, meaning that many platforms must actively direct users to the desired locations, trading off potentially rich information elsewhere against an even placement of observations.

The lack of specifications and the nature of VGI makes, in some cases, the assessment of completeness a complex process, which cannot rely only on direct unit-based comparisons, and instead requires the development of new approaches. Moreover, in many areas, the number of digitised VGI features may exceed that found in an authoritative dataset (Neis et al., 2011), making a simple comparison of feature counts inappropriate, and requiring a subtler consideration of commission and omission (Jackson et al., 2013). Koukoletsos et al. (2012) present a method that holds promise for such contexts, combining geometric and attribute constraints to match road segments in OSM with those found in an authoritative dataset, and to achieve a tile-by-tile completeness assessment. In another study, Hecht et al. (2013) proposed an object-based approach to assess the completeness of building footprints. Haklay (2010) identified a bias in UK OSM data coverage towards more affluent areas, and relates this to the fact that socially marginal (and less-mapped) areas may be the very locations where charities and agencies requiring free data are operating. Brovelli et al. (2017) developed a web application to compare OSM road data with authoritative road data, enabling the assessment of completeness and positional accuracy of OSM data. Ciepłuch et al. (2010) also compared the spatial coverage of OSM to that of Google Maps and Bing Maps, and identified regions with different levels of coverage in the three datasets. Globally, this bias is being somewhat redressed by the volunteers' own efforts to improve coverage, and by focused initiatives such as KompetisiOSM in Indonesia[2] , but it remains the case that coverage is extremely heterogeneous in VGI, both spatially and thematically, and that the absence of information in an area makes it difficult to draw robust conclusions about trends. Brunsdon and Comber (2012) specifically addressed the lack of experimental design in a volunteered dataset recording the first flowering date of lilacs in the USA by applying random coefficient modelling and bootstrapping approaches to tease out more reliable information on phenological trends.

2.1.4 Temporal Quality

Temporal quality refers to the quality of the temporal attributes, such as date of collection, date of publication, update frequency, last update or temporal validity (also referred to as currency), and also to relationships between the temporal validity of features. Currency is one aspect of traditional data quality where VGI can be expected to surpass authoritative data, especially in dynamically changing environments, given the large numbers of citizens who are acting as sensors at any one time. However, there is often a trade-off between currency and other facets of data quality. The issue of representativeness becomes even more vexed when the spatial domain is extended to the spatio-temporal domain, and, unless a temporal sampling scheme is also imposed upon contributors, the density and coverage of a VGI dataset over a small time range can be very limited. For citizen sensor networks, which are largely made up of automated instruments, such as the Weather Underground, the observation pattern across time is fairly consistent. However, in other contexts (e.g. presence-only species observations and the mapping of urban infrastructure), a user will need to carefully consider the ranges of data that are appropriate for their purpose, and whether cumulative observations are valuable. In making this decision, they will probably require metadata on the individual features, e.g. date stamps and data on feature updates. An important consideration here is that the date stamp should reflect the time at which the measurement or observation was made, rather than the time at which it was uploaded or digitised, depending on the application to which the data are applied (see e.g. Antoniou et al., 2016a).

Even though the potential of VGI to provide updated information is large, it is relevant to notice that a large heterogeneity is likely to occur over space and for different types of phenomena or features to be mapped, since VGI is dependent on the availability of interested volunteers to collect each particular type of data at the required locations.

2.1.5 Logical Consistency

Logical consistency refers to the degree of adherence to logical rules of data structure, attribution and relationships as described in a product's specifications. Logical consistency of an observation makes little sense in isolation: it must usually be assessed with reference to other data from the same source, or from independent (and sometimes authoritative) data, and lends itself to automated quality assessment – for example, to the use of rules such as 'forest fires are highly unlikely in dense urban areas'. Hashemi and Ali Abbaspour (2015) used the concept of spatial similarity in a multi-representation data combination to build a framework to determine the probable inconsistencies in OSM, aiming to help in evaluating the logical consistency of VGI data. Bonter and Cooper (2012) discuss the use of a smart filter system in the context of species identification in Project FeederWatch: when participants enter counts of species that are too high or species that do not normally appear on standard lists, the filter is activated and users are informed of unusual observations, thereby correcting potential errors in real-time. Similar smart filters could be devised and put into place in other types of VGI projects, thereby addressing some aspects of logical consistency.

2.1.6 Usability

As mentioned above, usability (or fitness-for-use) refers to the external quality of a dataset and is focused on the needs of the user. The five aforementioned data quality elements may be aggregated in order to describe the overall usability of a specific dataset for a particular use, i.e., fitness-for-purpose. In other words, usability acts as a complementary element by linking both user requirements and data quality measures to check whether the data for a specific application can be used (Guptill and Morrison, 1995; Devillers et al., 2007).

Table 1 summarises the requirements and specific aspects regarding the application of ISO quality measures to VGI. In Section 3, establishing workflows and combining quality indices to assess VGI quality in order to assess usability is further developed.

2.2 Quality Measures Specific to VGI

When considering VGI, other data quality indicators are required to supplement those proposed in the ISO framework. This occurs not only because in many situations comparison with authoritative datasets is not possible, but also because the characteristics and nature of VGI enable the use of indicators that do not usually make sense when applied to data created by professionals. These indicators may provide valuable information even though in most situations they do not assess accuracy but instead assess data reliability or credibility (which are considered as synonyms in this chapter). As these indicators may

Table 1: ISO quality elements, their requirements and issues related to their use with VGI.

ISO quality elements		Requirements	Issues for the application to VGI
Internal quality	Positional accuracy	• Data specification • Existence of reference data with similar characteristics and valid time frame	• Lack of specifications • Dynamic nature of VGI • Inexistence of comparable reference data • Spatial and thematic heterogeneity
	Thematic accuracy		
	Completeness		
	Temporal Quality		
	Logical Consistency	• Other data of the same source or independent data	• Applicable to VGI • May enable automatic validation checks
External quality	Usability	• Specification of user needs	• May be assessed by combining quality measures and indicators

provide data that allow quality estimation in real-time or near real-time, they enable the development of automated approaches that may be used to improve the process of data collection, requiring, for example, confirmation and/or additional checks by the contributors.

Different suggestions have been put forth regarding what these indicators might look like (Table 2). For example, Goodchild and Li (2012) provide three broad categories of measures to ensure VGI data quality: i) crowdsourcing revision, where data quality can be ensured by multiple contributors; ii) social measures, which focus on the assessment of contributors themselves as a proxy measure for the quality of their contributions; and iii) geographic consistency, through an analysis of the consistency of contributed entities. Meek et al. (2014) provide three models of data quality, where the stakeholder model sits in between the more traditional internal (producer) and external (consumer) quality indicators, and they suggest a number of different quality elements, including vagueness, ambiguity, judgement, reliability, validity and trust. Bordogna et al. (2014) also provide a set of quality indicators for VGI that are arranged into internal and external quality, where the internal quality measures are grouped by type of VGI, i.e. measurements or text-based VGI, and the external quality measures are grouped by reliability of the individual and reputation of the organisation. Senaratne et al. (2016) review VGI quality assessment methods and separate them into measures and indicators of quality, where the former correspond to the traditional accuracy assessment measures described in the previous section, and the latter are referred to as qualitative and more abstract quality indicators, such as local knowledge, experience and reputation. They also suggest that an additional approach to ensure data quality, referred to as 'data mining', should be added to the ones proposed by Goodchild and Li (2012). Antoniou and Skopeliti (2015) propose the aggregation of the quality indicators into three broad categories: i) data indicators; ii) demographic and other socio-economic indicators; and iii) indicators about the contributors. These may be considered to integrate the types of indicators mentioned in the above different frameworks and are developed further in this chapter.

Table 2: Categories of quality measures proposed for VGI.

Goodchild and Li (2012)	Meek et al. (2014)	Bordogna et al. (2014)	Antoniou and Skopeliti (2015)	Senaratne et al. (2016)
• Crowdsourcing revision • Social measures • Geographic consistency	• Internal quality indicators • Stakeholder model • External quality indicators	• Internal quality • External quality	• Data indicators • Demographic and socio-economic indicators • Contributor indicators	• Measures of quality • Indicators of quality • Data mining

2.2.1 Data-based Indicators

One important group of quality indicators of VGI are those that involve comparison with other sources of crowdsourced data (Table 3). One possibility is to measure the 'agreement' to the corresponding data, which we define here as the coherence of the data with other sources of crowdsourced data. Agreement can be measured between datasets using a Boolean measure or a continuous variable with traditional measures such as distance between corresponding elements, attribute comparisons, etc., and may be considered an indicator of data reliability. Logical consistency of data available in different data sources can also be used to estimate data reliability, identifying if, according to the types of features present in all available data sources, a particular contribution is likely to be correct or not. As stressed by Sui et al. (2013), approaches that compare data based on their geographic location have not yet been developed enough. Note, however, that all these indicators may be used to measure data reliability, but not to assess data accuracy if none of the data under comparison can be considered as reference data.

Another set of indicators can also be calculated that could reveal VGI quality by solely examining the VGI dataset itself and the associated metadata (Table 3). The work in this area has focused primarily on assessing OSM data quality. Such indicators could include the total length of features and the point density in a square-based grid, as calculated by Ciepłuch et al. (2010), or the number of versions, the stability against changes and the corrections and rollbacks of features, as examined by Keßler and de Groot (2013). The provenance of features contributed to OSM (i.e. whether the data were captured using a GPS, were manually digitised or resulted from a bulk import) has been the

Table 3: Data-based quality indicators proposed for VGI.

Indicators Category	Indicators	Description / Examples
Data-based indicators (assess data reliability)	Coherence with other sources of corresponding data (not considered as reference)	Compare, for example, geometric attributes such as distance between corresponding elements or overlaps
	External logical consistency	Logical consistency of VGI with non-corresponding data available in other data sources
	Internal logical consistency	Logical consistency of the VGI dataset itself
	VGI metadata	Number of versions, features corrections, stability against changes, observation methods, used equipment, date of observation

focus of the quality-related work of Van Exel et al. (2010). Finally, Barron et al. (2014) have developed iOSMAnalyzer, which uses more than 25 methods and indicators to assess OSM data quality based solely on data history. Although some of these indicators are related to the aforementioned quality component of completeness (Section 2.1.3), completeness in authoritative GI would not be measured in this way. Hence there is a need to find completeness and other data indicators that are customised to the nature of VGI.

Some of the facets of traditional metadata are of particular interest in assessing and using VGI. For example, the lineage of a record or dataset may include its edit history and information on how it was measured, and can be especially important in the automated assessment of VGI fitness-for-use. Examples of metadata potentially useful for VGI are equipment used in measurements; data about the volunteer (contributor indicator); date and time of data collection; or atmospheric conditions at the time a particular observation was taken. Individual metadata about heterogeneous observations can be extremely useful in identifying bias and likely trustworthiness, as seen, for example, in the context of amateur weather monitoring (Bell et al., 2013) and digitised trails (Esmaili et al., 2013). However, metadata are often not available for VGI, which limits, to some extent, the use of these approaches. To overcome this difficulty, methodologies have already been proposed to create metadata for VGI (Kalantari et al., 2014).

2.2.2 Demographic and Socio-economic Indicators

Empirical studies have revealed that there is a correlation between the demographics of an area and the completeness and positional accuracy of the data (Mullen et al., 2015). It has also been shown that areas with lower population density (i.e. rural areas) can have a negative effect on the completeness of VGI data (Zielstra and Zipf, 2010). At the same time, population density correlates positively with the number of contributions, thus affecting data completeness

Table 4: Demographic and Socio-economic quality indicators proposed for VGI.

Indicators Category	Indicators	Relevance
Demographic and Socio-economic indicators of the region (indicators of data quality)	Demographics	Show correlation with data quality parameters
	Population density	
	Social deprivation	
	Socio-economic reality	
	Income	
	Population age	

or positional accuracy (see e.g. Zielstra and Zipf, 2010; Haklay, 2010; Haklay et al., 2010; Jokar Arsanjani and Bakillah, 2015) .

Closely related to demographics are other socio-economic factors, which may also influence the overall quality (Tulloch, 2008; Elwood et al., 2013). For example, it has been shown that social deprivation and the underlying socio-economic reality of an area can have a considerable effect on completeness and positional accuracy of OSM data (Haklay et al., 2010; Antoniou, 2011). Similarly, other factors such as high income and low population age can result in a higher number of contributions and therefore higher VGI quality in terms of positional accuracy and completeness (Girres and Touya, 2010; Jokar Arsanjani and Bakillah, 2015).

Thus, if census or social survey data are available for an area, they might be used to make inferences about the quality of VGI data over geographic space. Table 4 summarises the above mentioned indicators.

2.2.3 Contributor Indicators

Quality indicators can include the history of contributions, the profiling of contributors or the experience, recognition and local knowledge of the individual (van Exel et al., 2010; Table 5). Moreover, the number of contributors in certain areas or features has been examined, and has been positively correlated with data completeness and positional accuracy (Keßler and de Groot, 2013). Methods for the automatic computation of contributor reliability regarding

Table 5: Contributor quality indicators proposed for VGI.

Indicators Category	Indicators	Description	Relevance
Contributor indicators (assess contributor reliability)	Contributors' interests	Infer contributor bias to particular features	Expected correlation with data reliability
	Contributors' history of contributions	Infer contributor trustworthiness	
	Contributors' recognition by other contributors	Infer contributor reliability	
	Contributors' location	Infer contributor local knowledge	
	Contributors' behaviour	Infer contributor difficulty in contributing	
	Contributors' education	Infer contributor expertise	
	Profiling of contributors	Created by aggregating several contributor indicators	

thematic information in VGI have been proposed by several authors. Haklay et al. (2010) and Tang and Lease (2011) stress the need for multiple observations and observers to enable consensus-based data quality assessments. Foody and Boyd (2012) and Foody et al. (2013) proposed a method for using these repeated observations to concretely assess the quality of VGI contributors using a latent class analysis of VGI in relation to land cover.

Differences between volunteers are always likely to exist, and, therefore, in the examples of 'social' quality assessment described above, known individuals could be identified and given a more trusted status, and these individuals could then be actively responsible for reviewing the work of others. However, when considering thematic quality, the issue of contributor reliability can be more complicated than a single ranking. Some contributors excel at labelling particular types of objects or habitats, but perform poorly elsewhere in the problem domain. Knowledge of the strengths and weaknesses of the volunteers allows a more nuanced consideration of the trustworthiness of their contributions, but often requires independent reference data to be computed. For example, Comber et al. (2013) calculated the consistency and skill of each volunteer in relation to each land cover class, using a number of control points for which the land cover had been independently determined by experts, and demonstrated that at least some concerns about the quality of VGI can be addressed through careful data collection, the use of control points to evaluate volunteer performance and spatially explicit analyses.

In the context of labelling for commercial gain, the workers do not see the submissions of others, and it is necessary to automate the process of identifying trustworthy experts against whom the work of others can be benchmarked (Raykar and Yu, 2012). Vuurens and de Vries (2012) tackle this issue by deriving patterns from the behaviour of different worker types, and attempt to diagnose the nature, and thus the likely error rate, of particular workers. For example, they note that 'diligent' workers are less likely to differ in their votes by more than one step on an ordinal scale of labels, and they exploit this fact to interpret the difference between contributors' judgements to identify their trustworthiness. However, there are many contexts where no natural ordering is present in the labels from which a contributor can choose.

Some of the facets of metadata regarding the volunteer, such as age, address, level of education or interests, are of interest in assessing VGI reliability. It is also possible to construct metadata based on the past behaviour of a user or the number of times their contributions have been identified as erroneous by other volunteers, which requires the storing of all alterations and changes made to the system. This may enable, through the definition of a set of rules, the automatic extraction of quality information, which may be used as an initial indicator of credibility, enabling the exclusion of some VGI from an analysis based on the likelihood that it might be less trustworthy. An example of these procedures is the approach proposed by Lenders et al. (2008), where the contributor's reliability is assessed using the information about the volunteer's location and the time of the contribution. These types of approaches may be particularly useful for NMAs (see Chapter 13 by Olteanu-Raimond et al., 2017), for example, to identify which contributions are more reliable and therefore worthy of allocations of resources for their validation, as all crowdsourced data used by NMAs need to be validated by professionals (Fonte et al., 2015a).

It is also possible to measure the 'vagueness' of contributions, defined by Meek et al. (2014) as the inability of a contributor to make a clear-cut decision. For example, when volunteers are asked to interpret satellite imagery in Geo-Wiki, they attach a confidence rating to their choice, which ranges from highly uncertain to full confidence in their answer (Fritz et al., 2012). These vagueness measures can be used as filters on the data or to apply weights to those answers with higher vagueness.

3 Developing Quality Assurance Workflows and Combining Indicators

Although many different quality indicators and measures for VGI have been emerging over the last decade, combining these indicators into an integrated quality assessment is an ongoing area of VGI data quality research. For example, Bishr and Mantelas (2008) have proposed a 'trust and reputation model', where these two concepts together are proxies for data quality (Figure 1). Users rate each other's contributions on a score range of 1 to 10, which makes up the reputation component. Users are also linked to one another through a social network, which can be used to measure the strength of the relationship between two individuals. These two components are combined and then divided by the logarithm of the distance between a contributor's location and the observation to calculate a trust rating. This trust model therefore takes both spatial context and reputation, through user ratings and the relationships between contributors, into account. The model remains theoretical and was not applied in the paper cited above, but an example of data collection for an urban growth scenario was outlined. The inclusion of relationships via social networking could give greater weight to the ratings of certain individuals.

Jokar Arsanjani et al. (2015a) have for their part proposed a multivariate indicator, referred to as the contribution index (CI), that combines diverse classic quality indicators, as well as user perspectives of data, including the number of volunteers involved in mapping a particular feature along with the frequency of contributions (Figure 2).

However, the main problem with the assessment of VGI based on fitness-for-use is that many methods and measures are designed to assess a specific VGI dataset or a single use case, and are not generalisable or transferable to other VGI datasets or purposes. However, some papers have appeared in which quality assurance workflows have been proposed. For example, Bordogna et al. (2015) propose a flexible system that allows users to specify minimum acceptable quality levels based on their requirements (Figure 3). The system contains a series of quality indicators, including both standard

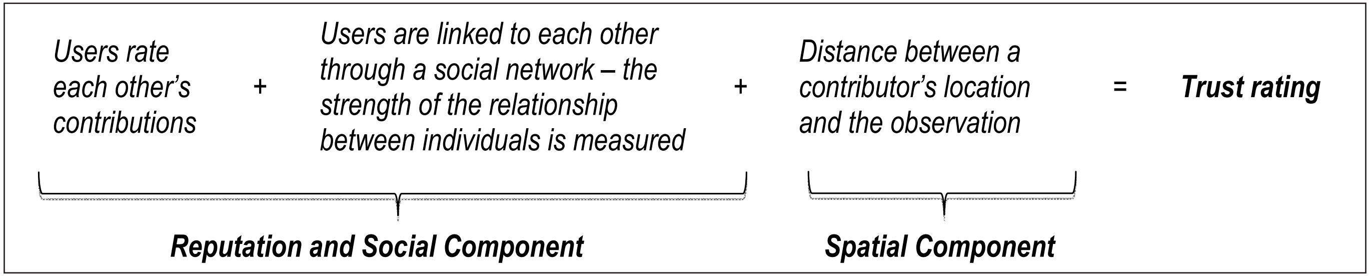

Fig. 1: Scheme of the trust and reputation model proposed by Bishr and Mantelas (2008).

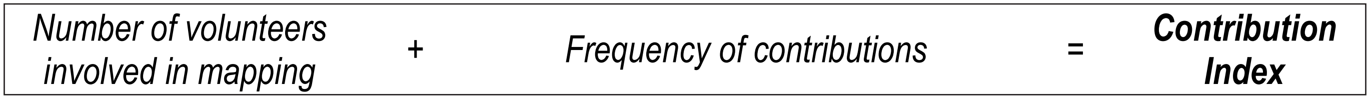

Fig. 2: Scheme of the determination of the contribution index proposed by Jokar Arsanjani et al. (2015a).

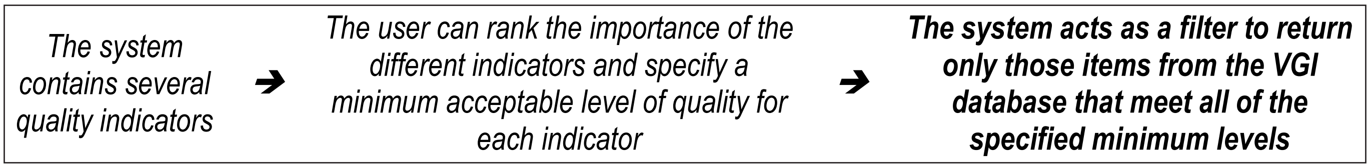

Fig. 3: Scheme of the system proposed by Bordogna et al. (2015) that allows users to specify minimum acceptable quality levels based on their requirements.

internal quality measures such as positional accuracy and ones specifically geared towards VGI (see Section 2.2). The user can rank the importance of the different indicators and specify a minimum acceptable level of quality for each indicator, and then the system acts as a filter to return only those items from the VGI database that meet all of these minimum levels; the authors perform a demonstration of the system on a VGI dataset of glaciological observations.

The creation of workflows that allow for the assessment of different aspects of quality has also been proposed. The framework proposed by COBWEB includes a quality assessment workflow that uses some automatic validation procedures to obtain data quality indicators to insert in the information metadata (Meek et al., 2016), while Ballatore and Zipf (2015) have proposed a multidimensional framework to assess conceptual quality.

The need to assess fitness-for-use has been present even without considering VGI, and methodologies to make this assessment have already been proposed in other contexts. For example, Lush (2015) proposed the creation of a GEO label that aims to be a mechanism to assist users to determine the fitness-for-use of datasets: a visual tool was developed that aggregates information about the producer, data lineage, compliance with standards, existence of quality information, user's feedback, expert reviews and citation information. These types of tools may be adapted to the characteristics of VGI and generate user friendly tools that can assist the user in identifying which data are appropriate for each application, according to their needs.

This is an area of research that we anticipate will continue to grow in the future.

4 Conclusions

This chapter considered the quality of VGI from the perspective of ISO 19157 and then presented additional quality measures designed to handle the specific nature of VGI, e.g. data-specific indicators, demographic and socio-economic indicators, and indicators related to the contributors. Authoritative data and VGI have similarities, i.e. both are examples of spatial data that can be assessed using the measures set out in ISO 19157. However, there are also some differences between these two data sources that require new ways of quality assessment, since the specific nature of VGI presents some problematic issues as well as new challenges. These issues and challenges include the heterogeneity of the data and contributors, spatial bias, lack of specifications, the dynamic nature in which the data are updated, the patchiness of the contributions and the lack of authoritative data, all of which have driven the development of new assessment methods for VGI. For example, the lack of reference data (as well as the static nature of reference data) has led to studies that have moved away from the need to use authoritative data to assess the quality of VGI; this has resulted in the creation of new data indicators, e.g. consistency related to multiple contributions at the same place or agreement of multiple contributions of the same set of features. At the same time, the social element of VGI has led to research into socio-economic and demographic indicators, while the pivotal role of the contributor in VGI has stimulated research around a diverse set of indicators related to quantifying them.

Another area of more recent VGI quality-related research has been in combining indicators, either as a way to visualise the quality using graphical approaches, such as through a GEO label (Lush, 2015), or to create workflows that allow for the assessment of different aspects of quality. However, few attempts have yet been implemented that use automated processes to assess VGI quality in addition to the use of the crowd self-correction or of selected volunteers for data validation (Fonte et al., 2015b). Nevertheless, these combinations are particularly desirable due to the dynamic characteristic of VGI, which makes the use of traditional approaches, which take time and require expert intervention, less suitable.

Although VGI has many similarities to authoritative GI, one of the main difference is the much more relaxed nature of the data collection protocols. The need for more VGI protocols, including the need for a framework that considers quality as one element, is addressed in Chapter 10 (Minghini et al., 2017). Chapter 10 also considers how quality assurance can be influenced by technological solutions that can help to seamlessly enforce protocols and thereby increase data quality, while recognising the trade-offs between the complexity of the protocol and participant motivation and retention.

The quality of VGI will continue to be one of the most important barriers to the integration of VGI to authoritative data, and developing generic and flexible solutions such as the system proposed by Bordogna et al. (2015) represents one tangible step forward; thus, we envisage that workflow developments will be a key area of research in the future. Standards agencies also need to recognise that there are new sources of spatial data and that existing standards must be adapted to include these sources or new standards must be developed. A first step in this direction has been made by the W3C with a document (currently in a draft form; Tandy et al., 2016) on best practices that should be taken into consideration when publishing and using spatial data on the Web. The document highlights another aspect, and, in a sense, extends the notion of usability, by drawing attention to the discoverability and accessibility of the spatial data published.

Notes

[1] http://confluence.org/

[2] https://www.hotosm.org/projects/indonesia-0

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