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RESEARCH ARTICLE

Maximizing the value of a volunteer: A novel method for prioritizing humanitarian VGI activities

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Abstract: As a consequence of their reliance on a scarce volunteer resource, humanitarian mapping organizations must prioritize their mapping activities. For mapping in anticipation of a crisis or mapping in support of long-term crises, the only method available to organizations is an estimation of the "completeness" of the map, with organizations directing volunteers to map areas where data are missing. Whilst this method is suitable for organizations that focus on general map improvement, for those who create data for a specific reason (e.g., drinking water provision) the method is sub-optimal. In this article, we present a new method of humanitarian mapping prioritization, that considers the purpose of map data collection. The method identifies locations where contributions by volunteers are expected to have the biggest impact on the desired use of the map data and therefore maximizes the value gained from volunteer contributions. We explain our method using the example of measuring distance to healthcare and demonstrate its superior ability to consider the context of map data over generic estimations of map "completeness". Our method provides humanitarian mapping organizations with an easily reproducible and low cost method and an opportunity to make better informed decisions about mapping prioritization, when the purpose of map data collection is known. Using our method, organizations will be able to maximize the value gained from a scarce volunteer resource and increase the efficiency of humanitarian map data production.

Keywords: Volunteered geographic information, crisis mapping, OpenStreetMap, humanitarian

1 Introduction

Map data are critical to humanitarian organizations. They provide situational awareness to humanitarian organizations to support location-specific planning and response and provide an understanding of the location of populations who are vulnerable to the impacts of humanitarian crises [48]. However, map data are costly to produce and maintain, and consequently are often lacking in areas where populations are vulnerable to the impacts of humanitarian crises [26, 51]. Volunteered geographic information (VGI), as a usually free source of easily updatable geographic information, is widely recognized as a valuable alternative source of map data to humanitarian organizations [26, 28]. Here, we use the term VGI to refer to data with explicit spatial properties produced knowingly by a group of volunteers, an example being map data produced by the OpenStreetMap (OSM) community. Volunteers have varied reasons for producing VGI, but in the context of humanitarian mapping, volunteers are often driven to donate their time and skills by altruism (i.e., their desire to help others) [21,30,50]. Since volunteers first produced geographic information in support of a humanitarian crisis in the aftermath of the 2010 Haiti earthquake [60], VGI has been produced in support of a number of event-centric (e.g., Typhoon Haiyan in 2013, the 2014 West Africa Ebola outbreak; the 2023 Turkey-Syria earthquake) and long-term chronic (e.g., response to post-conflict limb loss in Northern Uganda; see [32, 33]) crises.

Though VGI is a valuable source of map data, producing VGI for humanitarian purposes can be difficult. Humanitarian volunteers are a relatively scarce resource. OSM has over 10 million contributors but less than three percent (303,000) have contributed to humanitarian mapping projects [29]. Additionally, humanitarian volunteers, as with many other OSM contributors, often do not maintain their contributions over the long-term. Most humanitarian volunteers, who typically join in response to a rapid-onset crisis (e.g., an earthquake), withdraw from humanitarian mapping projects within 28 days [23, 38]. Consequently, humanitarian mapping organizations must rely upon a small number of volunteers to complete most of the mapping work, particularly in the case of organizations seeking to undertake prospective mapping in support of chronic crises or mapping in preparation for potential future crises [8, 24]. Because of the scarcity of the volunteer resource, humanitarian mapping organizations must prioritize where mapping is most needed and direct volunteers to map these locations.

Currently, the only tool available to humanitarian organizations to prioritize mapping in support of chronic humanitarian crises or crisis preparation is using generic notions of map "completeness". "Completeness" describes a wide range of methods intended to estimate the omission (missing) and commission (extra) of real-world features on the map [12]. For humanitarian mapping organizations whose aims are to fill in blank spots on the map, prioritization of mapping using generic estimations of "completeness" is suitable. However, "completeness" is contextual and difficult to define [36,45,47], which poses a problem for humanitarian organizations who map with a specific purpose in mind. In this article, we argue that estimates of generic map "completeness" provide a sub-optimal approach to location prioritization when mapping is carried out for a specific purpose, because the value of new data is dependent on the desired use-case, not merely the overall "completeness" of the map. We therefore present a new method for the prioritization of humanitarian mapping activities that focuses on maximizing the expected impact of new map data in context of the specific purpose for which it is being collected, as opposed to merely where the map appears to be the most "incomplete". Our approach can be used by humanitarian mapping organizations with particular purposes of map data collection in mind, for example the YouthMappers organization, who create map data in support of achieving the Sustainable Development Goals (SDGs) [7], or Community Mapping Uganda (https://communitymapping.org), who collect data to aid in the distribution of health services in remote regions [33,56], to direct volunteers; and will enable mapping organizations to optimize the value gained from a given amount of "mapping effort".

2 Background

2.1 Humanitarian VGI: Volunteer scarcity and mapping prioritization

Producing VGI can be difficult, time consuming and at times, repetitive and boring [56][55,56]. Current VGI mapping platforms (such as the OSM iD editor) often have steep learning curves, which can be off-putting to first time mappers and require a significant investment of volunteer time to master VGI contribution [15, 49, 55]. Most humanitarian mapping organizations also prefer VGI to be contributed manually by volunteers, as opposed to with the help of machine learning (ML) algorithms, for example [33]. Even though the use of ML to improve the ease and speed of mapping has been evaluated [56] and an emergent ML-augmented platform (RAPiD) was introduced by Facebook Labs in 2019, mapping remains time consuming [53]. Mapping can also be repetitive, especially in rural locations, which can lead to volunteer boredom and fatigue [53]. Alternative methods of encouraging humanitarian mapping enjoyment have been evaluated [56], but are yet to be widely adopted by humanitarian mapping organizations. When platforms are difficult, time consuming and repetitive to use, drivers of initial contributions such as altruism are often outweighed by feelings of boredom [53, 56]. Consequently, humanitarian volunteers usually only contribute for a short period of time after their initial recruitment and studies have demonstrated that most volunteers withdraw from their chosen humanitarian mapping project within 28 days of joining [23, 38]. Humanitarian organizations therefore rely upon a scarce volunteer resource to produce map data.

Due to the difficulties retaining volunteers and reliance upon a scarce volunteer resource, humanitarian mapping organizations must prioritize where mapping takes place. To understand how humanitarian mapping organizations prioritize locations we must understand the three scenarios where map data are required:

1. After a rapid onset event-centric crisis, for example an earthquake where data are needed urgently for activities such as search and rescue (e.g., Humanitarian OSM Team (HOT), Map Action).
2. In anticipation of an event-centric crisis for a vulnerable population, map data are needed to assist with planning and resilience (e.g., MissingMaps, HOT).
3. During (or following) a long-term chronic crisis, for example a civil war, where data are needed to plan and implement interventions (e.g., Community Mapping Uganda, Map Action, HOT).

For scenario one, map data are usually produced in relatively small regions undergoing the crisis for a specific purpose (e.g., search and rescue), which dictates where mapping is needed. For scenarios two and three, which typically focus on large rural areas, suitable approaches for prioritizing the location of volunteer mapping efforts are less clear. Currently humanitarian mapping organizations use the only method available to them: identifying where the map is "incomplete". For example, the Gap Detection Tool, which can be used by members of the HOT community to identify "incomplete" locations and propose these locations as new HOT projects. Prioritizing mapping using generic estimations of "completeness" is common amongst the largest humanitarian mapping organizations (e.g., HOT, MissingMaps) who usually have more general mapping aims that focus on map "completeness". For example, in 2019 HOT announced its three-year strategic plan which was developed to align with the SDGs aim of "leaving no-one behind". An important aim of the strategic plan includes adding an area home to one billion people to the map [31], which requires mapping in areas where building data are missing.

However, "completeness" can be difficult to estimate and quantify. Usually "completeness" is estimated extrinsically by comparing a VGI dataset to another dataset (usually an authoritative dataset) that is assumed to be "complete" (see [11, 41, 59]). Despite its popularity, comparison to another dataset is only possible when a reference dataset exists, which is not always available in lower income countries [9,10]. If a reference dataset is unavailable (which is usually the case in areas where humanitarian VGI is required), "completeness" is commonly estimated through comparison to a dataset produced using machine learning approaches (e.g., OSM Gap Detection Tool, [43]). Alternatively, intrinsic methods (using only the data itself) can be used to estimate dataset "completeness". Examples include studying the historical growth of the dataset and estimating "completeness" based upon the hierarchical classification of the features within the dataset and the number of volunteers contributing [11, 12]; estimation of feature saturation over time [17]; and predicting "completeness" based upon sociodemographic indicators [39].

Even if "completeness" can be quantified, as a concept it is highly contextual. "Completeness" is scale- and context-dependent [45]. Defining "completeness" embeds decisions on what types of features should be considered, as well as whether they can be appropriately represented [36, 45, 47]. Using "completeness" to prioritize mapping where map data are being collected for a specific reason (i.e., context) is therefore sub-optimal. "Completeness" is also a highly dynamic concept: a mapping organization or volunteer may reach their goal of "completeness" and stop mapping, but updated satellite imagery and the appearance (or disappearance) of features in the landscape will change the "completeness" level over time. For example, in 2017 OSM added Maxar Premium imagery to its mapping platforms, which is more recent than the Bing imagery that was previously used, meaning that areas once considered to be "complete" became once again "incomplete". Events such as this limit the effectiveness of intrinsic methods of "completeness" estimation described above (e.g., those based on number of contributors or number of features mapped; [12, 17]), as a lack of activity resulting from assumed "completeness" could produce misleading results, discouraging further mapping in the region. Mapping at high levels of data "completeness" is also difficult, and volunteers can spend large amounts of time searching for features to be added or removed [13]. With only this method available to them, humanitarian mapping organizations are forced to prioritize mapping effort using a hard to quantify metric that fails to consider the purpose of data collection, leading to an inefficient use of a scarce volunteer resource.

To allow humanitarian organizations to prioritize mapping activities more effectively, we propose an alternative method that considers the purpose of map data collection (i.e., the context of map data use, for example estimating access to water, providing internet access), rather than generic notions of "completeness". We propose that if an organisation has a specific reason for collecting data, humanitarian mapping should be prioritized where further volunteer contributions will have the greatest expected impact and be most valuable to the humanitarian organisation. Our method helps humanitarian mapping organizations with a specific purpose of data collection in mind, to best utilize their scarce volunteer resource and organize mapping in an efficient and impactful way.

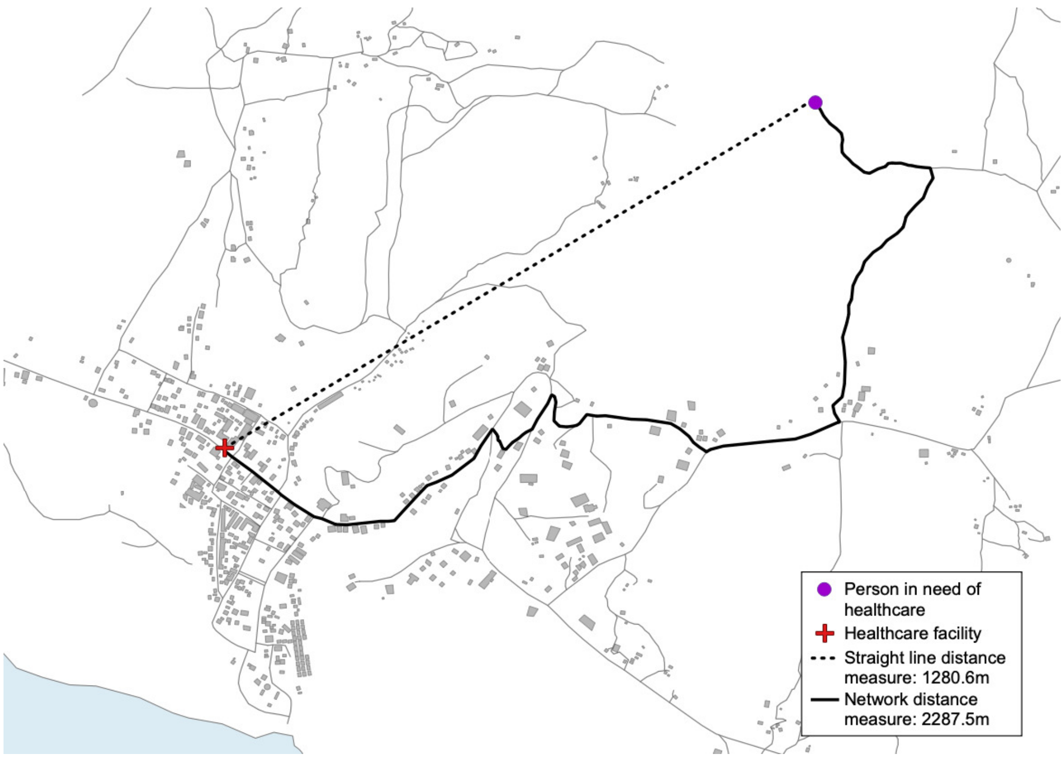

Figure 1: Comparison of straight line and network measures of distance to healthcare in Côtes-de-Fer, Haiti. In this example, the straight line method underestimates distance to healthcare by over 1 km, making the journey appear to be c.56% of its true distance.

2.2 Case study background: Estimating access to healthcare

The assessment of access to healthcare provides a common example of an application for which VGI is commonly used. To help conceptualize access to healthcare, authors have sought to identify the dimensions of access, which work together to prevent the realization of access. Three dimensions of access are now widely recognized: availability, affordability and acceptability [35, 44]. Whilst all dimensions are important and work together to prevent realized access to healthcare, it is often spatial variations in availability, describing the distribution of available healthcare facilities and the route travelled to access them, that significantly impede realized access [35,37,57]. Availability is also the dimension of access that is reliant upon datasets of road and path networks. Road and path networks are required for the calculation of distance to healthcare, known as network distance. Network distance is often the preferred method for estimating distance to healthcare as simple straight-line distances (which measure the length of a line drawn directly between the service user and the healthcare provider), often result in underestimations (Figure 1; [34, 54]). Measuring distance to healthcare is therefore a useful case study to demonstrate how humanitarian mapping should be prioritized based upon the end use of map data and the value of volunteer contributions.

To improve the prioritization of humanitarian mapping activities, we develop a method that measures how contributions of map data by volunteers change the outcomes of map data use (mean distance to healthcare, in this case). Our method prioritizes locations where changes in the outcomes of map data use are largest and consequently prioritizes locations where volunteer contributions have the highest expected impact. To illustrate the method, we measure distance to healthcare on an artificially degraded VGI road network in 27 countries. This is intended to reflect a typical use case for humanitarian mapping data in which organizations have identified a number of countries or regions to include in a mapping campaign and wish to prioritize the allocation of volunteer resources. We perform our method and examine (i) how measures of distance to healthcare change with increasing contributions of map data and (ii) how changes in measures of distance to healthcare can be used to prioritize humanitarian mapping.

3 Methods

3.1 Study areas

Our method was evaluated using 27 countries (Figure 2) that were selected using three inclusion criteria:

1. Countries classified as "Developing" by the United Nations Development Report (based on their Human Development Index), as countries where people are most likely to face distance-based barriers to healthcare access [52].
2. Countries with a population of more than one million, to allow for sufficient sample points per country.
3. Countries with a reported OSM road network "completeness" of around 70% or over as estimated by [11], which facilitates a clearer illustration of our iterative degradation approach (though an estimate of the "completeness" is not necessary for the method itself).

A full list of countries selected and their estimated OSM road network "completeness" can be found in the supplementary materials (S1).

3.2 Data

All data were freely available under an open data licence, which serves to minimize costs to humanitarian organizations associated with adoption of this method and promote reproducibility. Road and path networks for each country were downloaded from the OSM database via the Geofabrik Download server [46], converted to a Structured Query Language (SQL) file using osm2po [2] and loaded into a single PostGIS [4] database. Only

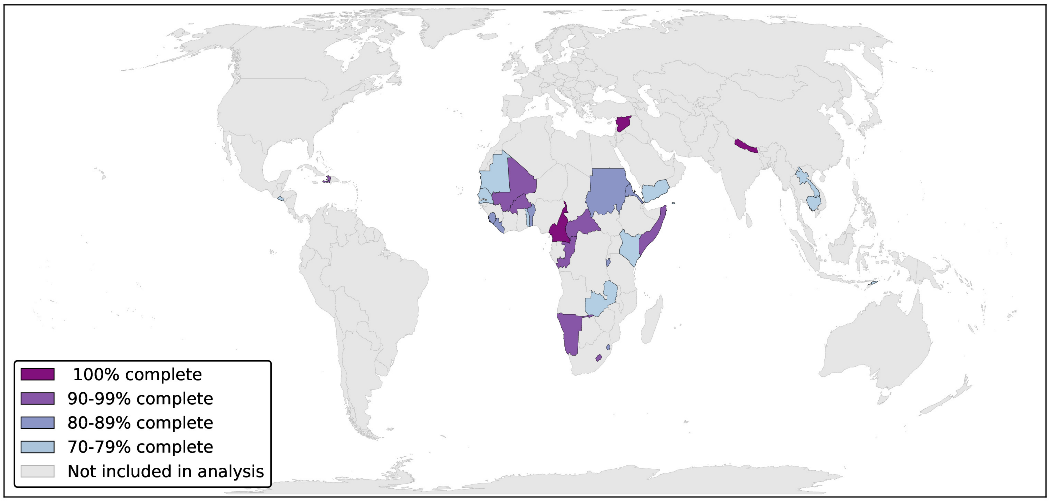

Figure 2: Countries used in the sensitivity analysis and their “completeness” as estimated by Barrington-Leigh and Millard-Ball [11].

network types that were passable on foot or by motor vehicle were included. To simplify analysis road types were reclassified, reducing the number of network feature types from 18 to 5 classes: primary, secondary, tertiary, unclassified and path. Healthcare facility data were also downloaded for each country from the OSM database via the Geofabrik Download Server and loaded into the same PostGIS database as road and path networks using osm2pgsql [1]. For analysis purposes, only primary health care facilities (health care clinic, doctor or hospital) were selected as these facilities represent “points of entry” to healthcare services [27]. Gridded population count estimates for the year 2020, at a resolution of 100m, were downloaded in raster format for each country from the WorldPop repository [5].

3.3 Approach

The proposed approach comprises an iterative process of running the desired analysis for a sample of population locations, degrading the dataset, and then re-running the analysis until no data remains. By recording the result at each “step” in this process, the relationship between the result and level of degradation can be examined. For example, here we are concerned with accessibility to primary health care facilities, for which we are calculating the mean distance between the sample points and their nearest health care location. In this example, we will be degrading the dataset in increments of 10% of the original value and calculating the mean distance value for each increment, to see how the result is affected by the degradation process.

To sample the population points, random populated locations on the gridded population raster were chosen (where the raster value was greater than zero). The sample size was proportional to the individual country’s population, with one population point sampled per 100,000 people. Sample sizes ranged from 11 in Eswatini to 537 in Kenya (S1). Distance between each population point and its nearest healthcare facility was calculated using the

Djikstra shortest path algorithm in pgRouting software [3], plus the straight line distance between the population point and its nearest network node and between the health care facility and its nearest network node. The Djikstra algorithm calculates the shortest path by weighting edges (e.g., individual road segments) based upon their length and finding a sequence of connected edges that provide the lowest total weight (distance) between two locations [22]. If a connected sequence of road segments could not be found due to missing segments in the road network, the straight-line distance was calculated directly between the population point and nearest health care facility, which is commonly used to estimate distance to healthcare when road network datasets are unavailable (e.g. [40, 58]). Given that the focus of this study is the relative impact of data "completeness" on measuring distance to healthcare, rather than accurate estimation of access to healthcare in a country, we have elected to only calculate distance travelled rather than travel time. Whilst travel time provides a more realistic estimation of healthcare availability [6, 25], it requires an understanding of travel modes and behaviors in each country, which is beyond the scope of this study.

For each country, the total number of road and path network features was calculated and a set of degradation values representing 10% of the total number of features in each class of network feature type (primary, secondary, tertiary, unclassified and path) is calculated. Starting with the full road and path network (total number of features), the distance between each sampled population point and its nearest healthcare facility was then calculated and the mean distance to healthcare was recorded alongside road and path network coverage. The road and path network for the country was then degraded by removing a number of features equal to the 10% degradation value for each class (resulting in a stratified degradation), and the process is then repeated until all of the data have been removed. Each sequence of degradation was repeated 100 times per country to account for stochasticity in the selection of population points and degradation of the road and path network, with the network reset each time. The mean of these 100 iterations was then calculated and used to construct a plot comparing the number of features (i.e., decreasing levels of degradation, up to the current road and path network) against mean distance to healthcare for each country. This approach is summarized as pseudocode in Algorithm 1. The source code for the analysis (implemented in Python 3) can be found at https://gitlab.com/kirstywatkinson/vgi-prioritization. The method is made open source to increase its reproducibility and to enable humanitarian mapping organizations to be more transparent about the way they prioritize mapping efforts.

Following plot construction, the mean absolute rate of change in distance between the current road and path and the first level of degradation (i.e. the slope of the line segment at the far right of the plot) is calculated. This value will be known herein as MARC and demonstrates the level of impact that the most recent mapping activity has had upon the analysis. The MARC is calculated as the change in distance divided by the change in number of features. When comparing different countries, it is then possible to make an assumption about the level of impact that would be expected from the next mapping activity. For example, where the MARC is very high, it is likely that further mapping activity will have a significant impact upon the results of the analysis. Conversely, where the MARC is very low, it is likely that further mapping activity will have less impact upon the results of the analysis. In such a case, where a decision had to be made about prioritizing mapping, for an organisation interested in measuring healthcare availability, priority would be given to the country or region with the highest rate of change.

To demonstrate that generic estimates of map "completeness" provide a sub-optimal indication of mapping priority when humanitarian mapping organizations have specific reasons for map data collection, MARC obtained for each country were correlated against estimated level of road network "completeness" [11] using a Spearman's rank correlation coefficient test. We expected no correlation between the two variables (i.e., "completeness" does not explain mapping priority).

Algorithm 1 A pseudocode representation of the proposed approach.

```
// input datasets and values
roadNetwork =                // road network dataset
roadClasses =                // road classes ('motorway', 'A road', etc.)
healthcareFacilities =       //primary health care facilites dataset
degradePercent =             // percentage of features to degrade each iteration
countries =                  // list of countries to be analysed
// initialize list to store results
allResults = []
// loop through each country
for for each country in countries do
    nFeatures = roadNetwork.length
    meanDistances = []
    n = country.population * 0.1
    results = []
    results.append(country)

    // repeat until the road network is entirely degraded
    while nFeatures > 0 do
        popPoints = population.randomSample(n)
        distances = []

        // get the distance to the nearest healthcare point
        for each point in popPoints do
            nearestHealthcare = point.nearest(healthcareFacilities)
            distances.append(point.distance(nearestHealthcare)
        end for

        //calculate mean distance travelled and append to a dectionary
        meanDistance = distances.sum / popPoints.length
        results.append(meanDistance)

    end while
    allResults.append(results)

    // degrade the network by class
    for each class in roadClasses do
        nClass = roadNetwork.getClass(class).length
        degradationValue = nClass / 100 * degradationPercent
        roadNetwork.randomSample(degredationValue).delete

        Export allResults to a dataframe

    end for
end for
```

4 Results

Inspection of plots comparing mean distance to healthcare and number of road and path network features revealed considerable variation between countries. Although variation in the shape of plots comparing mean distance to healthcare and number of road and path features was observed between countries, the resulting curves from the 27 countries could be categorized by shape into three general categories: sigmoidal, convex and linear. Most countries (n=15) had sigmoidal curves (i.e., they resembled the letter "S"), with examples including Nepal, Eswatini and Burundi (Figure 3a). Sigmoidal curves were characterized by initially shallow slopes (likely caused by an unconnected road network preventing network distance calculation), followed by a steepening (as roads and paths became connected allowing network distance calculations, rapidly increasing the mean distance as is demonstrated in Figure 1), and finally a shallowing again (as changes to the road network become increasingly minor, thus having a reduced impact upon the resulting curve). A smaller number of countries (n=7) had convex curves, with examples including Haiti, Republic of the Congo and Central African Republic (Figure 3b). The convex curve may be seen as a variation on the sigmoidal curve, in which a similar pattern to the sigmoidal curve is initially followed (slope is shallow, then increases as network distance calculations become possible). However, in this case, the addition of further network data actually reduces the mean distance in comparison with less complete versions of the network (though not, of course, in comparison with the straight line distance, which is not possible). This is simply the result of shorter routes being created by the addition of further detail, which would be expected in many countries, but is highly dependent upon network topology and the distribution of primary health care facilities, which is, in turn dependent upon a range of topographic, demographic and socio-economic variables. It is, of course possible that some sigmoidal curves would follow this pattern with the addition of further data. Finally, a small number of countries (n=4) exhibited linear curves (Figure 3c). It is likely that this is simply a less developed version of the sigmoidal or convex curve, and the curve would be expected to either flatten (becoming sigmoidal) or dip (becoming convex) depending on a number of factors relating to the network topology and distribution of primary health care centers. The curve shapes for all 27 countries are listed in Table 1, along with the MARC and estimated completeness level from [11].

The MARC for each country is listed in Table 1, which shows that they also vary between countries. Timor-Leste had the highest MARC, with a 190.66 m increase in mean distance to healthcare for every 100 features added (Table 1). Nepal had the smallest MARC, with only a 0.07 m increase in mean distance to healthcare for every 100 features added (Table 1). Using our method, from inspection of the curves comparing mean distance to healthcare and road network "completeness" and comparison of MARC we ranked the mapping priority of the 27 countries studied (Table 1). Those countries with the highest MARC are those for which contributions of map data are expected to be most impactful and therefore should be prioritized. Conversely, those with the lowest MARC represent the countries where contributions of map data are expected to be least impactful and therefore are less likely to be prioritized. It is noteworthy that as expected there is no relationship between the MARC and the estimated "completeness" of the countries (Figure 4; Spearman's rank correlation coefficient of -0.12). Several countries with the highest MARC (Eswatini, Namibia, Burkina Faso) had higher estimated "completeness" than countries (Togo, Kenya) with the lowest MARC (Table 1). Though as is expected most countries with an estimated "completeness" of 100% were ranked as the lowest mapping priority, a notable exception was Cameroon, which ranked 19th out of 27. This has clear implications for prioritization in the allocation of mapping resources, irrespective of the estimated or perceived level of "completeness".

Country	Curve shape	Mean absolute rates of distance change (m per 100 features)	Estimated completeness
Timor-Leste	Linear	190.66	69.13
Swaziland	Sigmoidal	18.67	82.07
Namibia	Convex	18.37	92.72
Republic of the Congo	Convex	14.44	92.28
Eritrea	Convex	12.30	81.97
Burkina Faso	Sigmoidal	9.35	93.45
Cambodia	Sigmoidal	8.95	74.57
Somalia	Convex	7.94	97.8
Benin	Sigmoidal	7.48	82.09
Central African Republic	Sigmoidal	6.73	98.87
Sierra Leone	Sigmoidal	4.06	83.92
Haiti	Convex	3.78	94.18
Burundi	Sigmoidal	3.45	86.74
Lao People's Democratic Republic	Sigmoidal	2.63	77.88
El Salvador	Sigmoidal	2.52	74.56
Zambia	Sigmoidal	1.75	71.82
Lesotho	Sigmoidal	1.71	98.81
Sudan	Convex	1.70	86.80
Cameroon	Sigmoidal	1.59	100
Liberia	Linear	1.51	87.28
Yemen	Linear	1.22	73.22
Senegal	Sigmoidal	1.13	70.07
Togo	Linear	1.13	77.39
Mali	Sigmoidal	0.45	94.3
Kenya	Sigmoidal	0.43	71.18
Syria	Sigmoidal	0.25	100
Nepal	Sigmoidal	0.07	100

Table 1: Summary of curve shape for each country and the associated MARC.

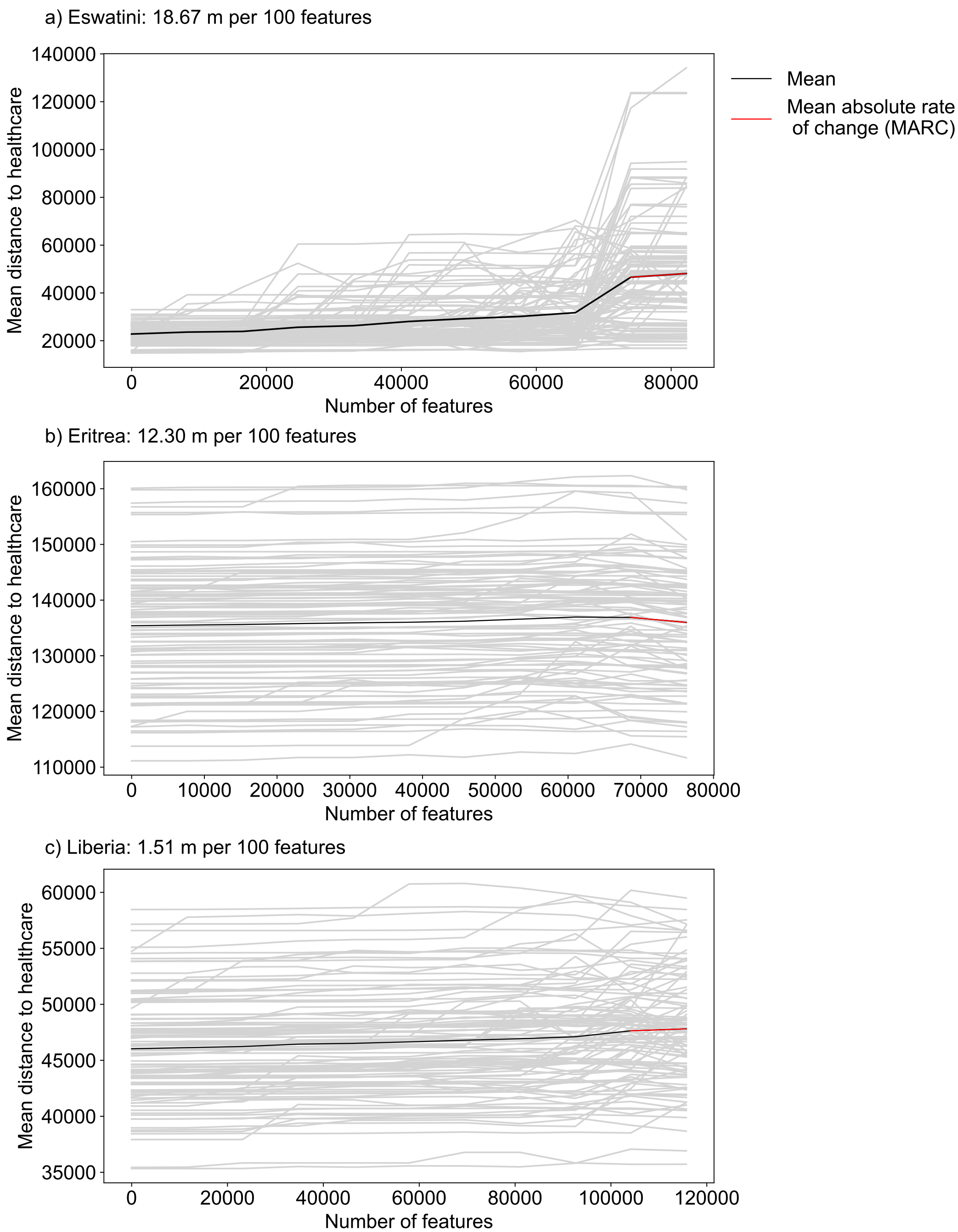

Figure 3: Three different curve shapes: a) Sigmoidal (Eswatini); b) Convex (Eritrea); c) concave (Liberia).

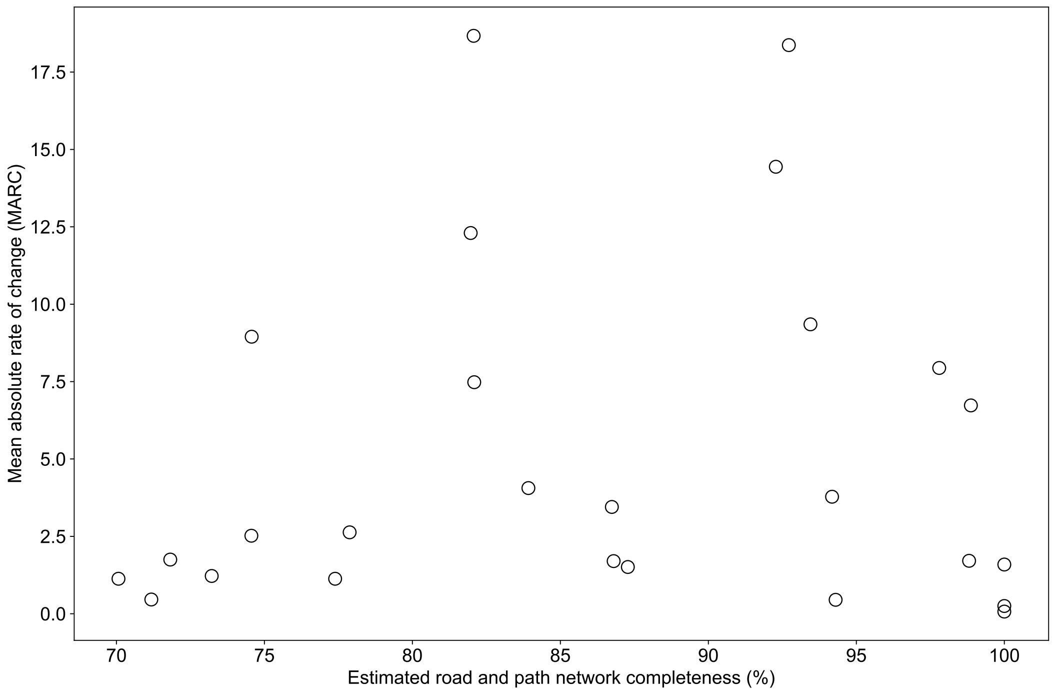

Figure 4: Correlation between MARC and estimated road and path network "completeness". A Spearman's rank correlation coefficient of -.012 was obtained. An outlier is omitted from the figure, with an estimated 'completeness' value of 69.14% and MARC value of 190.66m

5 Discussion

VGI is a valuable source of map data to humanitarian organizations. Though the ambition of many VGI organizations and volunteers is to produce a "complete" map, the reality of a finite volunteer resource means that organizations have to prioritize locations to which they will direct volunteers. The only method currently available to support this prioritization mapping is the use of generic estimates of map "completeness". The method is undoubtedly useful for mapping organizations whose aims are to fill in "blanks on the map" (e.g., HOT), however, "completeness" is highly contextual, difficult to quantify and does not reflect the value of new data for specific map data uses [36,45]. As a result, such measures are less well-suited to the needs of organizations who are mapping in support of a particular analysis or activity (e.g., YouthMappers, Community Mapping Uganda), and result in sub-optimal prioritization of resources, limiting the impact of mapping activities. In this article, we have presented a new approach to the prioritization of humanitarian mapping activity, in which mapping is targeted in locations where contributions by volunteers are expected to have the largest impact on the intended use of the map data.

Using the example of a healthcare availability assessment (a common use-case for humanitarian VGI), we have demonstrated how this approach can be used to prioritize humanitarian mapping activities based upon their likely impact on the analysis itself. In doing so, we have revealed a considerable variation in the relationship between the estimated "completeness" of a dataset and mean distance to healthcare between countries, which serves to illustrate the importance of context-specific approaches such as those presented here. We have also demonstrated the lack of any relationship between the MARC and estimated level of "completeness", demonstrating that such generic measures are not a suitable proxy for "usefulness" for a given analytical purpose. For example, several countries with high MARC (e.g., Burkina Faso and Namibia), had higher estimated "completeness" (93.45% and 92.72% respectively) than countries with lower MARC (e.g., El Salvador with an estimated "completeness" of 74.56%). If mapping priority was determined based upon estimated "completeness" alone, El Salvador would be prioritized, which would be expected to increase the mean distance to healthcare by an average of approximately 2.52 m per 100 features added to the map. Using the method presented here, however, Burkina Faso would be prioritized, which would be expected to increase the mean distance to healthcare by an average of approximately 9.35 m per 100 features added to the map. In cases where data are being collected for a specific use-case, our context-specific method for mapping prioritization has a clear advantage over the use of estimations of generic "completeness".

Using MARC, we ranked the countries to indicate mapping priority against an evaluation of mean distance to primary healthcare (Table 1). Timor-Leste, Eswatini, Namibia, Congo and Eritrea were identified as countries for which additional mapping would have the greatest immediate impact. The countries had the highest MARC and are therefore the locations where further contributions by volunteers are expected to lead to the biggest changes in distance to healthcare. Targeting such locations would enable humanitarian mapping organizations collecting health related map data to send their scarce volunteer resources to map in areas where their contributions will have the biggest purpose specific impact, maximising the value gained from each period of time donated by a volunteer.

To demonstrate how our method could be used by humanitarian organizations to prioritize health-related mapping, we will use two countries that were reported by [11] to have a similar estimated road network "completeness" (Timor-Leste and Kenya) and determine which country should be prioritized for mapping activity in support of a healthcare availability assessment. The plots for Timor-Leste and Kenya produced using our approach are shown in Figure 5. Comparing the plots, we can visually identify that Timor-Leste has a higher MARC: 190.66 m per 100 features compared to Kenya's 0.47 m per 100 features. The humanitarian mapping organisation would therefore direct most volunteers to map Timor-Leste, where their contributions are expected to have a much greater impact on estimations of access to healthcare. The organisation would then carry out mapping and repeat the analysis. It may be that Timor-Leste still has the highest MARC and should continue to be prioritized. However, as the curve starts to flatten (the MARC reduces), then the MARC of Kenya (or another country) may be greater than that of Timor-Leste, and so it would be prioritized instead. In this way, our method therefore provides humanitarian mapping organizations with a tool to identify which location(s) would have the greatest impact for their given purpose, which is continually updated as mapping progresses. This therefore constitutes a powerful tool to enable humanitarian mapping organizations to direct a scarce and small volunteer resource in the most efficient way possible.

Our method complements existing methods (e.g., using generic estimates of map "completeness") for the prioritization of volunteer mapping activities. Only open and freely available software and data are used, helping to minimize the cost to humanitarian mapping organisation. A reference implementation of our method is available at https://gitlab.com/kirstywatkinson/vgi-prioritization, meaning that the method is easily reproducible. Our method offers those humanitarian mapping organizations who are collecting data for a particular analytical purpose to make informed decisions about which locations will have the most significant impact upon their results. However, it is important to consider that some countries with a low MARC may increase with more contributions (for example a country with a sigmoidal curve becoming convex), and so the analysis should be repeated at regular intervals. For this reason, we would also recommend that (as per our example above) some volunteer resource is directed to lower priority countries, particularly those with apparently poorly developed curves, which (along with contributions from individuals and organizations with different priorities) will allow such patterns to be identified.

Not only does our method provide a new method for prioritizing humanitarian mapping in locations where contributions are expected to have the greatest impact (for a given analytical purpose), but it may also have positive implications for volunteer retention. Humanitarian mapping campaigns often struggle to retain volunteers over the long-term [23, 24, 38], with most volunteers withdrawing from projects due to a loss of interest, lack of time or repetition-induced fatigue [53]. Volunteers are commonly motivated to join projects by a desire to learn, develop skills or an interest in the project [18,20]. If volunteers were deployed to new locations more regularly, there would be increased opportunity to learn about new locations and features to map. Opportunities for learning could promote continued engagement in mapping activities and reduce the likelihood of volunteer withdrawal from mapping campaigns. Moving to new locations may also attract new volunteers located in those regions, increasing the number of volunteers and the amount of data produced in support of humanitarian mapping campaigns.

5.1 Limitations and future work

Though the purpose of this article is to propose a general method to identify priority mapping locations, there are some limitations specific to our case study (measuring mean distance to primary healthcare) that would benefit from further investigation. Our method of measuring distance to healthcare was dependent upon a dataset of primary healthcare locations from OSM. It is therefore likely that the primary health care dataset is "incomplete", and that the extent of missing, outdated or otherwise incorrect data will vary between countries. Though this should be mitigated to some extent by our use of estimated "completeness" as one of our inclusion criteria for countries, the results are nevertheless dependent upon the quality of this dataset. Future work might therefore include a sensitivity analysis to explore the impact of health care facility dataset "completeness", or the incorporation of additional datasets (e.g., healthsites.io [66]). It is also important that the estimates of road network "completeness" that we have used date from 2017 [11] and estimated "completeness" would likely be higher at the time of writing were the values re-calculated. The use of other completeness estimates (both extrinsic and intrinsic) would also be worthwhile.

The creation of map data, particularly roads, tends to follow particular patterns, as opposed to being random. For example it has been demonstrated that road mapping on OSM sometimes begins with the mapping of primary roads (e.g., motorways), followed by sec-

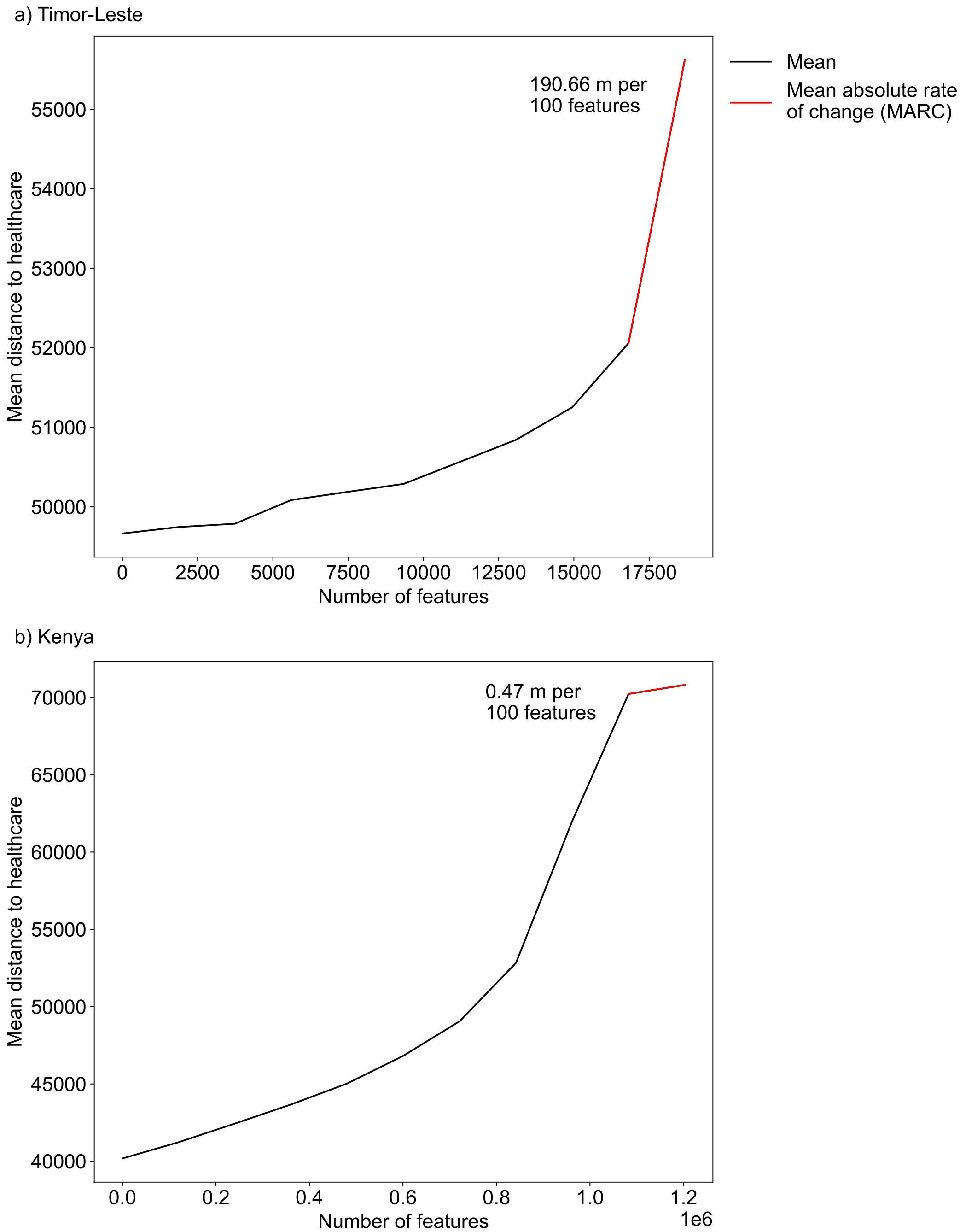

Figure 5: Changes in mean distance to healthcare with increasing number of road and path network features for a) Timor-Leste and b) Kenya. Comparison of the plots and MARC demonstrate further contributions of road and path network data with add most value to Timor-Leste (highest MARC) and should be prioritized over Kenya.

ondary roads, tertiary roads and finally paths [14,19]. Our method, where network features are randomly removed in a stratified manner (i.e., with features removed from all classes of road at each stage of degradation), does not reflect this pattern. Although directed humanitarian mapping activities in which volunteers are assigned a particular "zone" using a task manager to avoid duplication are unlikely to follow this pattern, future work could nevertheless consider different approaches to weighting by road hierarchy when removing features from the road and path network. For example, one could prioritize the degradation of lower-level network features first, as opposed to degrading all classes equally as in this research.

It is also important to acknowledge the limitations and biases of the algorithm used to calculate network distance. Though the Djikstra algorithm has a number of advantages, including its relative computational efficiency [16], it follows a Greedy approach in which a node cannot be reconsidered once visited [16,42], even if a shorter path exists, which can lead to sub-optimal results. Though this would be a rare occurrence in practice (and hence should be addressed by the multiple iterations for each country), future applications of our approach in a similar application area (e.g., measuring distance to water) could explore the use of other algorithms to measure network distance. Future work could also explore reproducing our case study on a different set of countries, such as higher income countries, for example.

As well as exploring ways to overcome the outlined limitations, the method should be evaluated by humanitarian mapping organizations to help understand their ability to use the method and their willingness to adopt it. Such evaluations may also reveal ways in which the method can be adapted to best suit the needs of those organizations. The applicability of the method to non-humanitarian applications of mapping should also be investigated, as we believe the method will be suitable for any application where map data are required. An example application could be the provision of services such as schools, transport links, and shops within urban areas, where road and path data are required to measure travel distances for local residents.

6 Conclusion

Map data are critical to humanitarian organizations. However, they are costly to produce and maintain and the production of alternative sources of map data such as VGI must be prioritized due to the reliance of humanitarian mapping organizations upon a scarce volunteer resource [8]. Currently, the only method available for the prioritization of locations for mapping activity is the use of generic estimates of map "completeness". Such approaches are suitable for some humanitarian mapping organizations (i.e., those wishing to "fill in the blanks", such as HOT), but is sub-optimal for humanitarian mapping organizations who are collecting data for a particular analytical purpose (e.g., Community Mapping Uganda).

In this article we have proposed a new method for prioritizing humanitarian use-case specific mapping activities based upon the expected impact on the results of a given analysis, as opposed to generic estimates of "completeness". Our method involves performing an analysis related to the purpose of map data collection (e.g., measuring distance to water) on an increasingly degraded dataset for each candidate mapping location and examining changes in the results of the analysis. Priority locations are identified where the mean absolute rate of change (MARC) in the analysis results is highest. Our case study also revealed considerable variation in the response of countries to changes in the number of features mapped and no relationship between MARC and estimated network "completeness". This clearly demonstrates that generic estimates of "completeness" are not a suitable method of prioritization where there is a specific reason for map data collection, and that the proposed method provides an optimal alternative.

This research provides humanitarian mapping organizations with a new method that can be used either in isolation or as a complement to other approaches to prioritization (e.g., donor priorities, perceived urgency etc.) to make informed choices about mapping prioritization. In doing so, such organizations can maximize the value gained from the contributions by scarce volunteer resources, leading to greater positive outcomes from humanitarian mapping activities.

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References

[1] osm2pgsql, 2022. https://github.com/openstreetmap/osm2pgsql.

[2] osm2po, 2022. https://osm2po.de/.

[3] pgRouting, 2022. https://github.com/pgRouting/website.

[4] PostGIS, 2022. http://postgis.net/.

[5] WorldPop, 2022. www.worldpop.org.

[6] AHMED, S., ADAMS, A. M., ISLAM, R., HASAN, S. M., AND PANCIERA, R. Impact of traffic variability on geographic accessibility to 24/7 emergency healthcare for the urban poor: A GIS study in Dhaka, Bangladesh. *PLOS ONE 14*, 9 (2019). 10.1371/journal.pone.0222488.

[7] ANDERSON, J., BLEVINS, C., COWAN, N., CARNEY-NEDELMAN, D., CLARK, C., CRINO, M., ENGSTROM, R., HINTON, R., MANN, M., MCCUSKER, B., NEALON, R., SOLÍS, P., AND ZEBALLOS, M. Reflecting on the YouthMappers Movement. In *Open Mapping towards Sustainable Development Goals: Voices of YouthMappers on Community Engaged Scholarship*, P. Solís and M. Zeballos, Eds., Sustainable Development Goals Series. Springer International Publishing, Cham, 2023, pp. 365–370. doi:10.1007/978-3-031-05182-1_33.

[8] ANDERSON, J., SODEN, R., KEEGAN, B., PALEN, L., AND ANDERSON, K. M. The Crowd is the Territory: Assessing Quality in Peer-Produced Spatial Data During Disasters. *International Journal of Human-Computer Interaction 34*, 4 (2018), 295–310. doi:10.1080/10447318.2018.1427828.

[9] BAARIU, S. N. *Analysis and Modelling of Cartographic Services Among the East African Community Member States*. Thesis, University of Nairobi, 2020.

[10] BAARIU, S. N., MULAKU, G. C., AND SIRIBA, D. N. State of Cartographic Services among the East African Community Member States. *Journal of Geographic Information System 11*, 01 (2019), 56. doi:10.4236/jgis.2019.111005.

[11] BARRINGTON-LEIGH, C., AND MILLARD-BALL, A. The world's user-generated road map is more than 80% complete. *PLOS ONE 12*, 8 (2019), e0180698. doi:10.1371/journal.pone.0180698.

[12] BARRON, C., NEIS, P., AND ZIPF, A. A Comprehensive Framework for Intrinsic OpenStreetMap Quality Analysis. *Transactions in GIS 18*, 6 (2014), 877–895. doi:10.1111/tgis.12073.

[13] BASTANI, F., HE, S., ABBAR, S., ALIZADEH, M., BALAKRISHNAN, H., CHAWLA, S., AND MADDEN, S. Machine-assisted map editing. Association for Computing Machinery, pp. 23–32. doi:10.1145/3274895.3274927.

[14] BÉGIN, D., DEVILLERS, R., AND ROCHE, S. Assessing Volunteered Geographic Information (VGI) quality based on contributors' mapping behaviours. vol. XL-2/W1. doi:10.5194/isprsarchives-XL-2-W1-149-2013.

[15] BEHRENS, J., VAN ELZAKKER, C. P. J. M., AND SCHMIDT, M. Testing the Usability of OpenStreetMap's iD Tool. *The Cartographic Journal 52*, 2 (Apr. 2015), 177–184. doi:10.1080/00087041.2015.1119457.

[16] BONDY, J. A., AND MURTY, U. S. R. Graph and subgraphs. In *Graph theory with applications*, vol. 290. Macmillan London, 1976.

[17] BRÜCKNER, J., SCHOTT, M., ZIPF, A., AND LAUTENBACH, S. Assessing shop completeness in OpenStreetMap for two federal states in Germany. *AGILE: GIScience Series 2* (2021), 1–7. doi:10.5194/agile-giss-2-20-2021.

[18] BUDHATHOKI, N. R., AND HAYTHORNTHWAITE, C. Motivation for Open Collaboration: Crowd and Community Models and the Case of OpenStreetMap. *American Behavioral Scientist 57*, 5 (May 2013), 548–575. doi:10.1177/0002764212469364.

[19] CIEPLUCH, B., MOONEY, P., AND WINSTANLEY, A. C. Building Generic Quality Indicators for OpenStreetMap.

[20] COLEMAN, D., GEORGIADOU, Y., AND LABONTE, J. Volunteered Geographic Information: the nature and motivation of produsers. *International Journal of Spatial Data Infrastructures Research 4*, 4 (2009), 332–358.

[21] CONVERGNE, E., AND SNYDER, M. R. Making Maps to Make Peace: Geospatial Technology as a Tool for UN Peacekeeping. *International Peacekeeping 22*, 5 (2015), 565–586. doi:10.1080/13533312.2015.1094193.

[22] DIJKSTRA, E. W. A note on two problems in connexion with graphs. *Numerische Mathematik 1*, 1 (1959), 269–271. 10.1007/BF01386390.

[23] DITTUS, M., QUATTRONE, G., AND CAPRA, L. Social Contribution Settings and Newcomer Retention in Humanitarian Crowd Mapping. E. Spiro and Y.-Y. Ahn, Eds., Springer International Publishing, pp. 179–193.

[24] DITTUS, M., QUATTRONE, G., AND CAPRA, L. Mass Participation During Emergency Response: Event-centric Crowdsourcing in Humanitarian Mapping. Association for Computing Machinery, pp. 1290–1303. doi:10.1145/2998181.2998216.

[25] DOS ANJOS LUIS, A., AND CABRAL, P. Geographic accessibility to primary healthcare centers in Mozambique. *International Journal for Equity in Health 15*, 1 (2016), 173–185. doi:10.1186/s12939-016-0455-0.

[26] EROS, E. Putting 200 Million People "on the Map": Evolving Methods and Tools. In *Technologies for Development*, S. Hostettler, Ed. 2018. doi:10.1007/978-3-319-91068-0_15. Section: 15.

[27] GUAGLIARDO, M. F. Spatial accessibility of primary care: concepts, methods and challenges. *International Journal of Health Geographics 3*, 1 (2004), 3. 10.1186/1476-072X-3-3.

[28] HAWORTH. Emergency management perspectives on volunteered geographic information: Opportunities, challenges and change. *Computers, Environment and Urban Systems 57* (May 2016), 189–198. doi:10.1016/j.compenvurbsys.2016.02.009.

[29] HEIGIT. Statistics, 2023.

[30] HERFORT, B., LAUTENBACH, S., PORTO DE ALBUQUERQUE, J., ANDERSON, J., AND ZIPF, A. The evolution of humanitarian mapping within the OpenStreetMap community. *Scientific Reports 11*, 1 (2021), 3037. doi:10.1038/s41598-021-82404-z.

[31] HOTOSM. Strategic Plan, 2023. https://www.hotosm.org/strategic-plan.

[32] HUCK, J. J., ATIM, P., MORO, E. B., AND NIRMALAN, M. Prevalence and Spatial Patterns of Major Limb Loss in the Acholi Sub-Region of Uganda. *Prosthesis 4*, 3 (2022), 369–382. 10.3390/prosthesis4030030.

[33] HUCK, J. J., PERKINS, C., HAWORTH, B. T., MORO, E. B., AND NIRMALAN, M. Centaur VGI: A Hybrid Human-Machine Approach to Address Global Inequalities in Map Coverage. *Annals of the American Association of Geographers 111*, 1 (2021). doi:10.1080/24694452.2020.1768822.

[34] IHANTAMALALA, F. A., HERBRETEAU, V., RÉVILLION, C., RANDRIAMIHAJA, M., COMMINS, J., ANDRÉAMBELOSON, T., RAFENOARIMALALA, F. H., RANDRIANAMBININA, A., CORDIER, L. F., BONDS, M. H., AND GARCHITORENA, A. Improving geographical accessibility modeling for operational use by local health actors. *International Journal of Health Geographics 19*, 27 (2020). doi:10.1186/s12942-020-00220-6.

[35] IYER, H. S., FLANIGAN, J., WOLF, N. G., SCHROEDER, L. F., HORTON, S., CASTRO, M. C., AND REBBECK, T. R. Geospatial evaluation of trade-offs between equity in physical access to healthcare and health systems efficiency. *BMJ Global Health 5*, 10 (2020). doi:10.1136/bmjgh-2020-003493.

[36] KITCHIN, R., PERKINS, C., AND DODGE, M. Thinking About Maps. In *Rethinking Maps: New Frontiers in Cartographic Theory*. Routledge, London, 2011.

[37] LINDHOLM, D., JAMES, S., LAGERQVIST, B., HLATKY, M. A., AND VARENHORST, C. New Method for Assessing the Effect of Driving Distance to Hospital Care. *Circulation: Cardiovascular Quality and Outcomes 10*, 9 (Sept. 2017), e003850. doi:10.1161/CIRCOUTCOMES.117.003850.

[38] MAHMUD, Z., CHAUHAN, A., SARKAR, D., AND SODEN, R. Revisiting Engagement in Humanitarian Mapping: An Updated Analysis of Contributor Retention in OpenStreetMap. In *Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems* (New York, NY, USA, 2022), CHI EA '22, Association for Computing Machinery, pp. 1–6. 10.1145/3491101.3519728.

[39] MASHHADI, A., QUATTRONE, G., AND CAPRA, L. The impact of society on volunteered geographic information: The case of OpenStreetMap. In *In: Arsanjani, JJ and Zipf, A and Mooney, P and Helbich, M, (eds.) OpenStreetMap in GIScience Experiences, Research, and Applications. (pp. 125-141). Springer: Cham, Switzerland. (2015)*, J. J. Arsanjani, A. Zipf, P. Mooney, and M. Helbich, Eds. Springer, Cham, Switzerland, 2015, pp. 125–141. doi:10.1007/978-3-319-14280-7_7.

[40] MOISE, I. K., KALIPENI, E., AND ZULU, L. C. Analyzing Geographical Access to HIV Sentinel Clinics in Relation to Other Health Clinics in Zambia. *Journal of Map & Geography Libraries 7*, 3 (2011), 254–281. 10.1080/15420353.2011.599756.

[41] NEIS, P., ZIELSTRA, D., AND ZIPF, A. The Street Network Evolution of Crowdsourced Maps: OpenStreetMap in Germany 2007-2011. *Future Internet 4*, 1 (2012), 1–21. doi:10.3390/fi4010001.

[42] NOTO, M., AND SATO, H. A method for the shortest path search by extended Dijkstra algorithm. In *SMC 2000 conference proceedings. 2000 IEEE international conference on systems, man and cybernetics.* (2000), vol. 3, pp. 2316–2320. 10.1109/ICSMC.2000.886462.

[43] OPENSTREETMAP. Gap Detection. https://osm-analytics.org/#/gaps.

[44] PETERS, D. H., GARG, A., BLOOM, G., WALKER, D. G., BRIEGER, W. R., AND RAHMAN, M. H. Poverty and access to health care in developing countries. *Annals of the New York Academy of Sciences 1136* (2008), 161–171. doi:10.1196/annals.1425.011.

[45] QUINN, S., AND LEÓN, L. A. Every single street? Rethinking full coverage across street-level imagery platforms. *Transactions in GIS 23*, 6 (2019), 1251–1272. doi:10.1111/tgis.12571.

[46] RAMM, F., KARCH, C., MCCANN, M., REICHERT, M., AND TOPF, J. Geofabrik, 2022. https://download.geofabrik.de.

[47] ROTH, R. E., BREWER, C. A., AND STRYKER, M. S. A typology of operators for maintaining legible map designs at multiple scales. *Cartographic Perspectives*, 68 (2011), 29–64. doi:10.14714/CP68.7.

[48] SAN MARTIN, R., AND PAINHO, M. Geospatial preparedness: Empirical study of the joint effort to provide geospatial support to disaster response. *Transactions in GIS 23*, 3 (2019), 481–494. doi:10.1111/tgis.12537.

[49] SCHMIDT, M., AND KLETTNER, S. Gender and Experience-Related Motivators for Contributing to OpenStreetMap. *Online proceedings of the ACTIVITY workshop* (2013). doi:20.500.12708/43113.

[50] STUKAS, A. A., SNYDER, M., AND CLARY, E. G. Understanding and encouraging volunteerism and community involvement. *The Journal of Social Psychology 156*, 3 (2016), 243–255. doi:10.1080/00224545.2016.1153328.

[51] SUI, D., GOODCHILD, M., AND ELWOOD, S. Volunteered Geographic Information, the Exaflood, and the Growing Digital Divide. In *Crowdsourcing Geographic Knowledge: Volunteered Geographic Information (VGI) in Theory and Practice*, D. Sui, S. Elwood, and M. Goodchild, Eds. Springer Netherlands, Dordrecht, 2013, pp. 1–12. doi:10.1007/978-94-007-4587-2_1.

[52] TANSER, F. C., AND LE SUEUR, D. The application of geographical information systems to important public health problems in Africa. *International Journal of Health Geographics 1*, 1 (Dec. 2002), 4. doi:10.1186/1476-072X-1-4.

[53] VARGAS MUNOZ, J., TUIA, D., AND FALCÃO, A. X. Deploying machine learning to assist digital humanitarians: making image annotation in OpenStreetMap more efficient. *International Journal of Geographical Information Science* (2021), 1–21. doi:10.1080/13658816.2020.1814303.

[54] VERMA, V., AND DASH, U. Geographical accessibility and spatial coverage modelling of public health care network in rural and remote India. *PloS one* (2020). doi:10.1371/journal.pone.0239326.

[55] VOGLER, R., HENNIG, S., AND FERBER, N. Redressing the Exclusiveness. Challenges which Prevent New Users from Contributing to OSM. In *GI_Forum* (2017), vol. 1, pp. 294–299. doi:10.1553/giscience2017_01_s294.

[56] WATKINSON, K., HUCK, J. J., AND HARRIS, A. Centaur VGI: An Evaluation of Engagement, Speed, and Quality in Hybrid Humanitarian Mapping. *Annals of the American Association of Geographers 0*, 0 (2022), 1–20. doi:10.1080/24694452.2022.2058907.

[57] WEISS, D. J., NELSON, A., VARGAS-RUIZ, C. A., GLIGORIĆ, K., BAVADEKAR, S., GABRILOVICH, E., BERTOZZI-VILLA, A., ROZIER, J., GIBSON, H. S., SHEKEL, T., KAMATH, C., LIEBER, A., SCHULMAN, K., SHAO, Y., QARKAXHIJA, V., NANDI, A. K., KEDDIE, S. H., RUMISHA, S., AMRATIA, P., ARAMBEPOLA, R., CHESTNUTT, E. G., MILLAR, J. J., SYMONS, T. L., CAMERON, E., BATTLE, K. E., BHATT, S., AND GETHING, P. W. Global maps of travel time to healthcare facilities. *Nature Medicine 26*, 12 (2020), 1835–1838. doi:10.1038/s41591-020-1059-1.

[58] ZAFRI, N. M., NURULLAH, M., NEEMA, M. N., AND WALIULLAH, M. Spatial accessibility to healthcare facilities in coastal region of Bangladesh. *The International Journal of Health Planning and Management 36*, 3 (2021), 643–655. 10.1002/hpm.3107.

[59] ZIELSTRA, D., AND ZIPF, A. A comparative study of proprietary geodata and volunteered geographic information for Germany. vol. 2010, Guimarães Portugal, pp. 1–15.

[60] ZOOK, M., GRAHAM, M., SHELTON, T., AND GORMAN, S. Volunteered Geographic Information and Crowdsourcing Disaster Relief: A Case Study of the Haitian Earthquake. *World Medical & Health Policy 2* (2010). doi:10.2202/1948-4682.1069.