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Crowdsourced Validation and Updating of Dynamic Features in OpenStreetMap

An analysis of Shelter Mapping after the 2015 Nepal Earthquake

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ABSTRACT

The paper presents results from a validation process of OpenStreetMap (OSM) rapid mapping activities using crowdsourcing technology in the aftermath of the Gorkha earthquake 2015 in Nepal. We present a framework and tool to iteratively validate and update OSM objects. Two main objectives are addressed: first, analyzing the accuracy of the volunteered geographic information (VGI) generated by the OSM community; second, investigating the spatio-temporal dynamics of spontaneous shelter camps in Kathmandu. Results from three independent validation iterations show that only 10 % of the OSM objects are false positives (no shelter camps). Unexpectedly, previous mapping experience only had a minor influence on mapping accuracy. The results further show that it is critical to monitor the temporal dynamics. Out of 4,893 identified shelter camps, 54% were already empty/closed six days after the first mapping. So far, updating geographical features during humanitarian crisis is not properly addressed by the existing crowdsourcing approaches.

Keywords

OpenStreetMap, validation, disaster shelter, Nepal earthquake, crowdsourcing.

INTRODUCTION

Earthquakes pose a serious unpredictable threat to people living in hazard prone areas worldwide. Especially urban agglomerations in seismically active areas are in danger to sustain serious damages on property, critical lifeline systems, and livelihoods, often causing alarming death tolls. Earthquake damages are estimated to cause economic losses between \$ 253 and \$ 522 billion annually, with countries in the global south bearing the largest proportion of casualties (J. E. Daniell *et al.*, 2011). Alongside physical damages and a large number of casualties and economic losses, the immediate and often long-term effects of earthquakes include large numbers

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of Internal Displaced People (IDP) seeking refuge in makeshift shelters. Several reasons exist for people being fearful of going back into their houses, mainly due to secondary hazards such as landslides or further collapses due to aftershocks. Frequently, people do not have any other housing option left due to the severe damages they experienced.

The European Emergency Management Service and the United Nations Institute for Training and Research (UNITAR) provide rapid mapping using satellite imagery to produce spatial data during humanitarian crisis situation. Such officially endorsed datasets have the advantage of being authorized within the international emergency response system (European Commission, 2016, UNITAR, 2016). The mapping services thus provide various levels of detail based on user demand and requests from early responders in the field. All map products follow some quality checks prior to publication, which means they have a high reliability. However, since this is a costly and laborious process, and given the urgency of the information needs of relief workers, there have been attempts in the past few years to resort to crowdsourcing approaches in this context.

The Humanitarian OpenStreetMap Team (HOT) shows how Volunteered Geographic Information (VGI) can help response organizations to navigate within data scarce environments and provide useful information for agencies including governments on the ground. This is accomplished in the immediate aftermath of a disaster by volunteers spread all over the world through the generation of spatial information from the analysis of satellite imagery (HOT, 2015a, Soden and Palen, 2014a, Zook *et al.*, 2010).

So far there have been studies analyzing OSM data accuracy (Girres and Touya, 2010, Haklay, 2010, Neis *et al.*, 2013). Most of them use administrative or commercial datasets as a reference.

The quality of OSM contributions by their users has been investigated by Arsanjani *et al.* (2013). Eckle and Porto de Albuquerque (2015) also assessed the quality of remote mapping vis-à-vis local expert mappers. However, in crisis situations such reference data is often not available or does not cover event-related dynamic objects (e.g. damaged buildings or spontaneous camps). In such situations, mapping projects like OSM mainly focus on providing basic information like buildings, streets, and landuse. Monitoring of dynamic features often happens through field surveys carried out by crisis responders rather than by the OSM community. As of today, only in few cases remote mappers provided status updates. Westrope *et al.* (2014) used ground truthing to assess the quality of damaged buildings mapping. Others use Unmanned Aerial Vehicles (UAV) to collect high-resolution data (Meier, 2015a, b).

During the Gorkha Earthquake in Nepal in April 2015, there has been a significant response by the OSM community (Clark, 2015, Poiani *et al.*, 2016), in which thousands of spontaneous IDP camps were mapped by local and remote OSM mappers through different HOT tasks. In this paper, we use this as a case study to make the following two analyses:

1. Assess the classification accuracy of features that are critical to emergency responders, as well as the potential influence of OSM mapping experience and the task instructions and guidelines;
2. Investigate the temporal dynamics of inherent attributes (status) of the mapped features.

Therefore, the paper is structured as follows: first, we explain the crowdsourcing approach used to validate accuracy and acquire information on temporal dynamics of spontaneous IDP camps. Second, we provide some background information on the shelter situation in Nepal, datasets used, and analysis performed. After that, we show the results of this study, discuss them and provide some concluding remarks.

RESEARCH APPROACH

In this paper we present a methodology to evaluate the accuracy of geographical features that are critical to emergency responders by leveraging crowdsourcing techniques. Figure 1 depicts the conceptual framework we apply. Our method utilizes as a starting point a GIS database containing geographical features, their geometries and feature attributes (t_0 , left-hand side of Figure 1). From this database, critical features that are of interest in the ongoing crisis situation and the disaster response are selected based on hazard characteristics and requests from disaster responders or the reconstruction community (t_1 in Figure 1). These selected features are validated iteratively through a simple crowdsourcing task (upper flowchart sequence in Figure 1). This task fulfills two steps at a time, validation of the initial mapping accuracy and updating the feature properties (t_2 in Figure 1). Validation is done using the same sources as the ones available for volunteers of the initial mapping task. In contrast, feature property updates use new information sources, e.g. from photos, aerial or satellite imagery. The updated geographical features are again stored in the database.

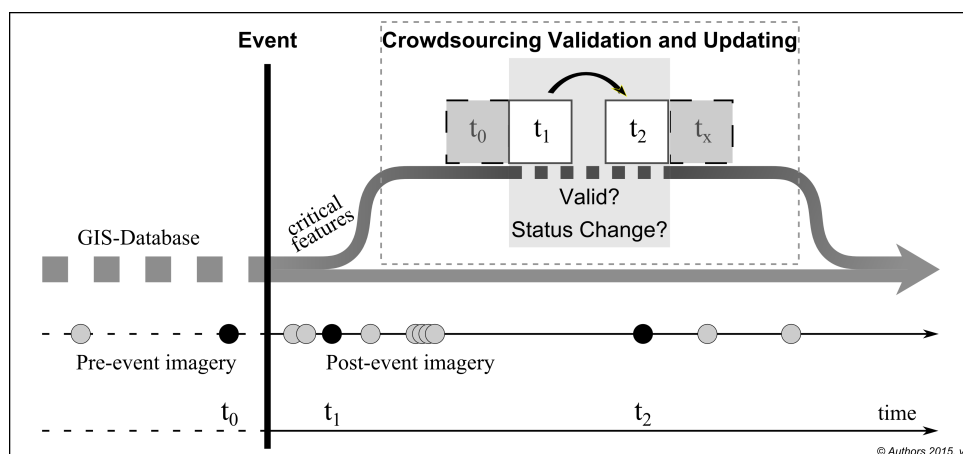


Figure 1. Conceptual Framework

Crowdsourcing techniques are applied in several studies especially regarding the classification of information gathered from social media (Goodchild and Glennon, 2010, Zook *et al.*, 2010), however to the best of our knowledge this approach was not yet used for evaluating geographical features of collaborative maps such as OpenStreetMap. Critical geographic features may have been stored in the OSM database already before the disaster event, such as hospitals, bridges or critical lifelines. It may also be possible that critical features are added to the database during the crisis immediately after the event, e.g. shelter sites that emerge as part of peoples immediate coping mechanisms. In both cases, emergency responders will benefit from timely validation and update of feature properties.

We apply the presented conceptual framework to the case study of spontaneous IDP camps that emerged after the Nepal earthquake. The validation provides insights on features that are by mistake tagged as camps (false positives), while the updating offers information on the actual (more up-to-date) status.

CASE STUDY: SHELTERS AFTER EARTHQUAKES

The Gorkha Earthquake of April 25, 2015 led to more than 600,000 damaged buildings and more than 8,700 deaths (GoN, 2015). The event with a magnitude of 7.8 M_w and a maximum Mercalli Intensity of IX caused widespread destruction in 31 districts of which 14 were declared most affected. Hundreds of strong aftershocks, including a 6.9 M_w (26th April, Sindupalchowk), and 6.8 M_w (12th May, Dolakha), caused fear and further destruction in other areas (National Planning Commission, 2015). Consequently, around 2.3 million people were initially displaced, while according to the International Organization of Migration (IOM) as of September 2015, almost 60,000 remained in 120 displacement sites hosting more than 20 households (IOM, 2015a).

These numbers only reflect people from camps that are monitored through the Displacement Tracking Matrix (DTM). The DTM is used as an information management tool for monitoring people's movement after major disasters and to ensure timely provision of basic needs (IOM, 2015b). The information collected comprises basic socio-economic indicators to more specific camp-management related issues and it is coupled to the general UN-Cluster approach (UN OCHA, 2015). Nevertheless, there is a large number of people unaccounted for living in small makeshift shelters of varying sizes and configurations, which are unregistered. In many cases, this has been due to difficulties to reach and assess most affected areas in a timely manner. A detailed household-level survey conducted by German researcher institutions revealed that there are large differences among the people from rural and urban areas (Khazai, Anhorn, Brink, *et al.*, 2015, Khazai, Anhorn, Girard, *et al.*, 2015). In the most affected districts, people had to cope with completely collapsed buildings and lack of suitable land, building their immediate shelters in close vicinity. In contrast, the urban population of the Kathmandu Valley often had a choice between multiple options. Managed camps were first established in Kathmandu, where larger open spaces are available for the relative small number of people in need compared with previously modelled scenarios with thousands of IDPs in the valley (Anhorn and Khazai, 2015). Immediately after the main shock on April 25, 2015, HOT started to launch mapping tasks to improve OSM data availability for disaster response. Previous engagement with the Kathmandu Living Labs (KLL) team, a local Non-Governmental Organization (NGO) promoting the use of OSM data, led to the formulation of tasks relevant to and in coordinating with local relief organizations including the government (HOT, 2015a, KLL,

2015, Soden and Palen, 2014). Tasks comprised mostly of mapping of buildings, streets, and other physical features, but also more relief-oriented tasks, such as identifying potential helipads. One of the first HOT tasks was located in the Kathmandu valley and aimed at mapping IDP camps spontaneously evolving across the country and is identified as #1008 in the microtasking tool used to coordinate mapping volunteers called “Tasking Manager” (HOT, 2015b). With more and more volunteers engaging in the mapping activities and more post-disaster imagery becoming available during the Nepal crisis, IDP camp mapping became one of the core duties of remote mappers (e.g. see tasks identified as #1010, #1024, #1030, #1044, #1046, #1058, #1060, #1062).

METHODOLOGY

Datasets Used

In our case study, we used the OSM database to gather critical geographical features within Nepal. This database contains information on several object types, e.g. streets, buildings and other critical infrastructure. They are stored with geometric representation as nodes, ways or relations with several attributes in a key-value structure. The OSM database further contains information about which user created or edited the object and stores the timestamp of such actions.

The OSM tasking manager (HOT, 2015b) functions as the main instrument to connect field requests to the global OSM and crisis-mapper community. The tasks in the manager thus can give insights on spatial information needs in the crisis-hit area. Furthermore, contribution to the tasks is announced and promoted through the HOT electronic mailing list. In our study, we focus on IDP spontaneous camp features mapped in Task #1008. Thus, we filtered the OSM database using the key value structure proposed in the mapping task. All geographical features tagged with “idp:camp_site=spontaneous_camp” were extracted within the given extent of the task (in total 5,412 objects). Figure 2 shows the spatial distribution of all extracted objects.

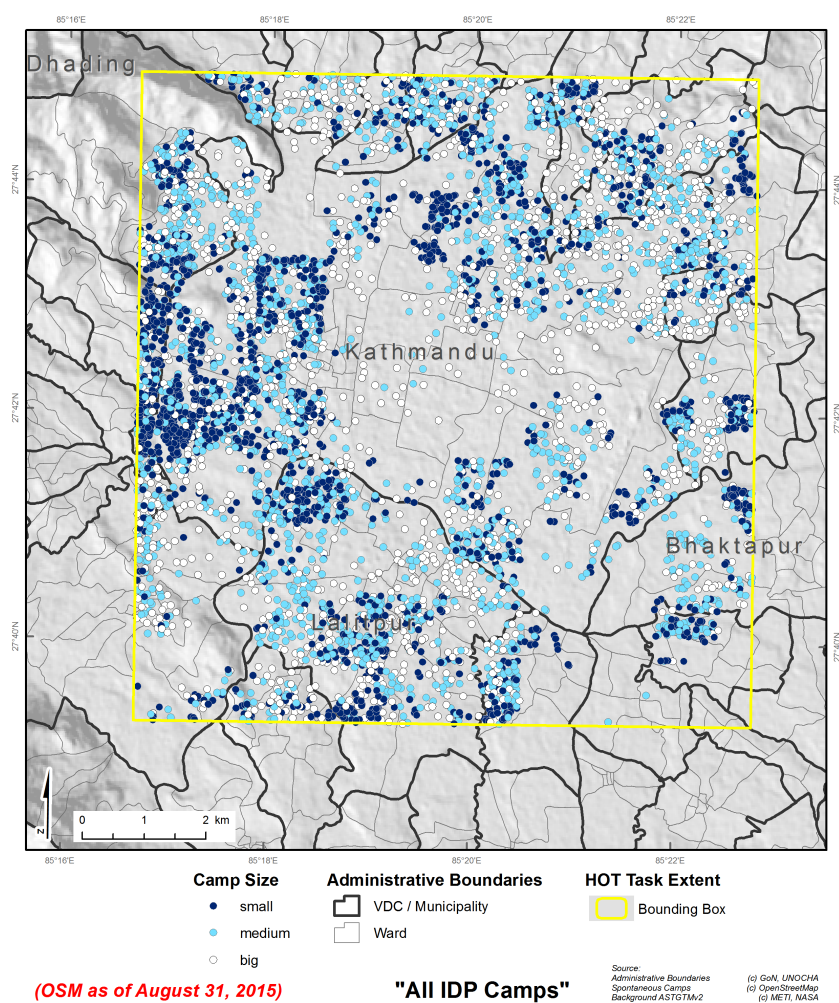


Figure 2. OSM dataset used.

All pre- and post-event information was derived from satellite imagery provided by several companies. In the crowdsourcing task we utilized two Pleiades[®] satellite imagery provided by CNES Airbus showing the pre-disaster situation as of November 29, 2014 and the post-disaster situation as of April 27, 2015 with a spatial resolution of 0.5m. All Pleiades[®] imagery are available under the “Airbus DS / OSM-FR License Acknowledgement” for the OSM/HOT activities. We also use Worldview-3 imagery provided by DigitalGlobe[®] as of April 27, 2015 with a spatial resolution of 0.3m. They also provided access to satellite imagery as of May 3, 2015 based on GeoEye-1 with a spatial resolution of 0.5m. All DigitalGlobe[®] imagery is available under the Open Database license (ODbL).

Data Preparation

To understand the accuracy of mapped spontaneous IDP camps and to investigate the temporal dynamics, we developed a crowdsourcing tool to engage experienced and trained OSM mappers. The Graphical User Interface (GUI, see Figure 3) of this crowdsourcing tool has been implemented based on PyBossa, an open source solution for crowdsourcing of information (PyBossa, 2015).

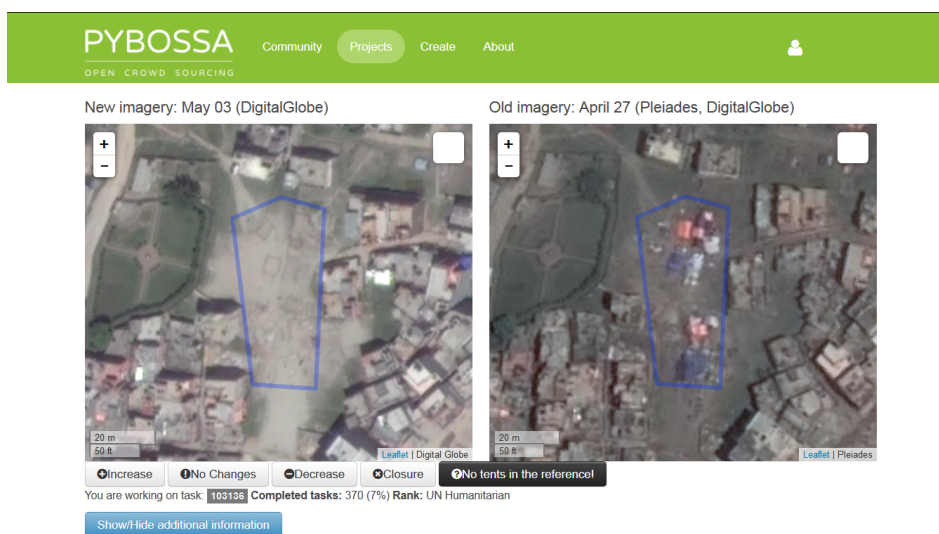


Figure 3. The Crowdsourcing Tool GUI implemented in PyBossa.

The crowdsourcing tool allows seeing each individual feature (in our case spontaneous IDP shelter sites) on two different satellite imagery: on the right-hand side of the GUI, the reference image is presented (i.e. the same source as for the initial HOT mapping task), whereas on the left-hand side, a “newer image” is shown. The validation is based on the reference imagery (two days after the main shock), while feature property updates also incorporate the consideration of the left-hand side imagery (eight days after the main shock). We address our two research objectives by classifying the objects using the scheme in Table 1. Figure 4 provides examples for each of the possible crowdsourced classifications. Each feature is classified by exactly three independent users recruited through various OSM and disaster mapper groups.

Classification		Description
True positive	Increase	The feature shows more tents in the new image compared to the reference.
	No change	The feature shows the same amount of tents.
	Decrease	The feature shows less tents in the new image than in the reference.
	Closure	The feature shows tents in the reference image, but not in the new image.
False positive	No tents	The reference image does not show any IDP camps.

Table 1. Feature classification scheme.

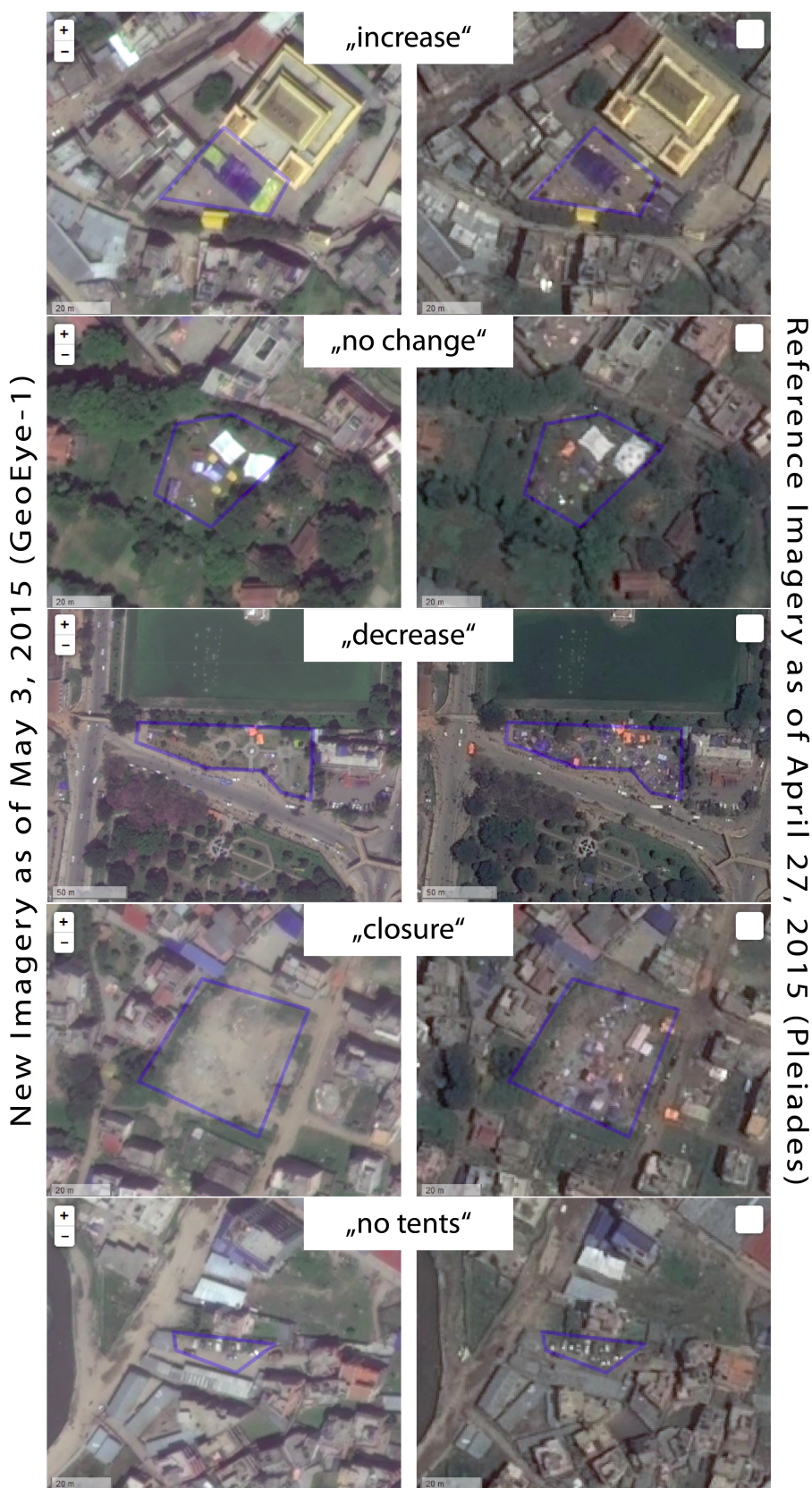


Figure 4. Examples for different feature classifications.

Data Analysis Methods

Over one hundred users (115) contributed to the crowdsourcing validation and updating analysis. They iteratively classified all features between October 12, 2015 until November 19, 2015. All features received at least 3 independent classifications.

To address our first research objective, we only distinguished between true and false positives. For each category, we further differentiate between “high” and “medium” validity. High validity corresponds to a high cross-user confidence, which is achieved if the results of all crowdsourced classifications match (e.g. 3 times “true positive”). Medium validity is achieved if only two users agree (e.g. “false positive”, “false positive”, and “true positive”).

To assess the influence of mapping experience on the quality of the mapping results, statistics were collected through the “How did you contribute to OpenStreetMap?” Tool (Neis, 2015). All but 12 mappers that contributed to the mapping of our selected features could be identified using this tool. Mappers were classified in three equally-sized groups using the overall number of nodes they created in OSM. This value functions as a proxy to assess their mapping experience. We calculated the distribution of objects that are created by mappers with three levels of experience: low (< 4248 nodes), medium (up to 127,155 nodes) and high (> 127,155 nodes). We also conducted a qualitative analysis of all false positives by examining these features to detect common mapping errors. The mapping guidelines provided in the original HOT tasks were evaluated as to whether they included information to avoid such errors or not. This analysis gives insights about the impact of the used mapping instructions and tagging guidelines.

To understand the temporal dynamics of spontaneous IDP camps (second research objective), we analysed all features labeled as “true positives”. For each status change (“increase”, “no change”, “decrease”, and “closure”), we differentiate again between “high” and “medium” validity. Additionally, “ambiguous validity” was used to classify features with three different classifications. According to the classification presented in Table 1, we further used the area of each object to analyze spatial trends. Spontaneous IDP camps were therefore classified as regards to their size in three equal groups: small (< 112 sqm), medium (up to 384 sqm), and large (> 384 sqm) camps. Figure 5 provides some insights to the camp size distribution of all OSM objects. These groups were used to calculate the distribution of objects according to their status.

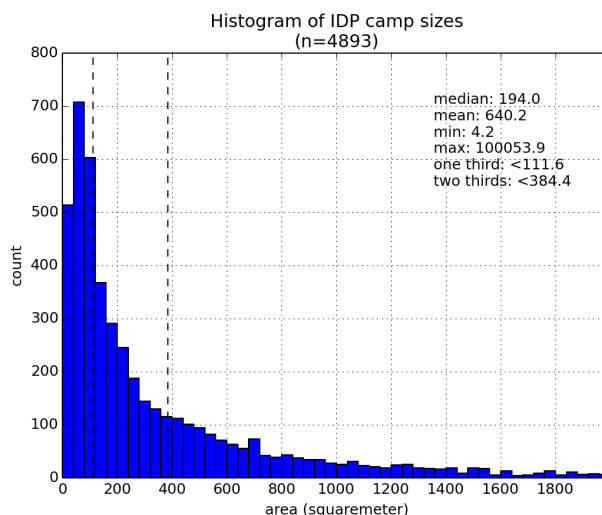


Figure 5. Distribution of IDP camp sizes.

RESULTS

The following section presents the results of the outlined analysis method, divided according to the first (mapping accuracy) and the second (temporal dynamics) research objective of this study.

Mapping Accuracy

This section describes the results from the analytical steps described in the previous section. Out of the final

sample, 4,893 (90%) are spontaneous IDP camps (true positives), while 519 (10%) are actually not showing camps (false positives). Out of all true positives, 4,123 (84%) have a high validity and so do 120 (23%) of the false positives (see Figure 6).

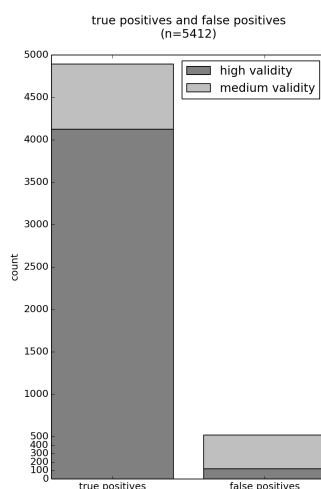


Figure 6. Number of true and false positives by validity.

The level of experience of remote OSM mappers in relation these results is visible in Figure 7. In total 52% of the mapping contribution is generated by highly experienced mappers, whereas only 15% is mapped by low experienced ones. Comparing the distribution of true and false positives reveals that low experienced mappers contribute almost equally to both (15% versus 13%). But so do also highly experienced mappers (53% versus 48%) and medium experienced mappers (32% versus 39%). In general, the classification accuracy of the initial mapping only varies slightly according to OSM experience. Mappers with low mapping experience do not map less accurate in our sample. Moreover, the contribution of highly experienced mappers does not show significant higher quality.

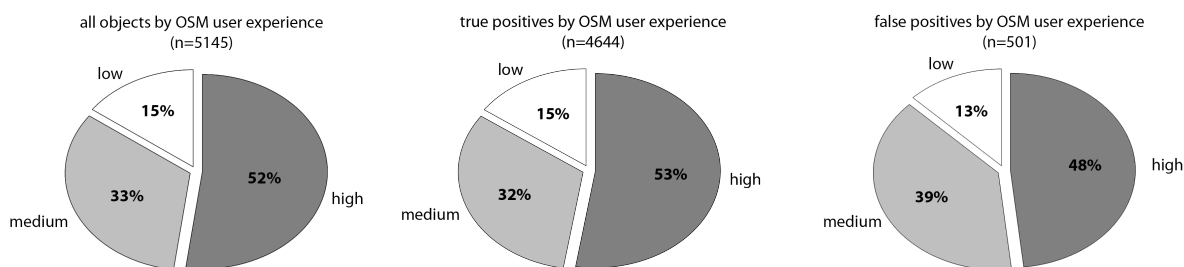


Figure 7. Number of true positives and false positives features by OSM mapper experience.

According to the individual feedback received from the volunteers and cross-checking with the OSM database, some common mapping errors are described in the following paragraph. Figure 8 represents some examples of these common errors, which were identified through the crowdsourcing validation. The main factors in incorrectly identifying spontaneous IDP camps leading to false positives comprise of

- a) Roofing materials (Figure 8, upper part):
 Many spontaneous camps are made of plastic tarpaulin in mainly two colors, blue and orange/red. Nepalese roof types also include Corrugated Galvanized Iron (CGI) sheets which are in some cases painted blue, green or show weathering effects (rusty=red). Additionally, in day-to-day construction tarpaulin is used for smaller sheds, temporary roofing of construction sites or to cover possessions stored outside. Therefore, typical roofing materials are the same or look the same as compared to those used for spontaneous IDP camps. Hence, distinguishing them from satellite imagery can often be quite difficult.

Sometimes the OSM database includes buildings with such roofing materials, even though the provided pre-event imagery for the initial mapping does show that the features already existed and by contrast they could have been identified as not event-related.

b) Mobile features (Figure 8, lower part):

In many cases cars and trucks on roads or parked alongside, or other mobile features were incorrectly mapped as tents. Such mobile features are difficult to interpret using bi-temporal visual change detection. It seems that many OSM mappers did not consider new features in the post-event imagery as potentially unrelated to the earthquake event.



Figure 8. Common mapping errors.

The HOT task description and the “IDP Collection Guidance” provided to HOT contributors do not explicitly mention or depict the previously mentioned common errors. The instructions provide three different ways of delineating spontaneous IDP camps. The actual spatial representation we find in the OSM database is in accordance with these guidelines and summarized as follows (see Table 2 and Figure 9):

Table 2. Comparison of different mapping instructions.

Source	Description	Representation in the database
HOT Task Description	“For each campsite you find, draw an area around the entire campsite”	OSM mappers circumvented groups of tents more broadly and enclosed open spaces in-between them. Single tents function as vertices of the resulting polygon.
IDP Collection Guidance	“single tents are located in small areas not large enough to hold more than one or two total tents. There often isn’t much surrounding open area, in these cases just trace the outline of the tent”	OSM mappers mapped individual tents marking the exact outer boundary resulting in a few square meters total area only.
IDP Collection Guidance	“An Area IDP settlement will usually have 5 or more tents. Please trace the extent of the entire open area.”	In some cases, the mapped object is not just covering the outer boundaries of multiple tents, but includes a larger area around. This complete area might be considered as the “potential camp space”.



Figure 9. Spatial representation of different camp structures.

Temporal Dynamics

The second objective of this study is to analyze the temporal dynamics of spontaneous IDP camps in Kathmandu. Figure 10 provides an overview of the different transitions of camps between April 27 and May 3. As described earlier, camps were classified as increased, not changed, decreased or closed using the above mentioned classification scheme (Table 1). Out of 4,893 camps assessed, 2,593 (53%) have been closed, 1,054 (22%) decreased, 801 (16%) did not change, only 95 (2%) increased, and 350 (7%) were ambiguous. The level of high validity per class varies: 67% for “closure”, 51% for “decrease”, 49% for “no change”, 25% for “increase”. Hence, determining “closure” was unequivocal to volunteers. However, identifying increasing camps was more difficult.

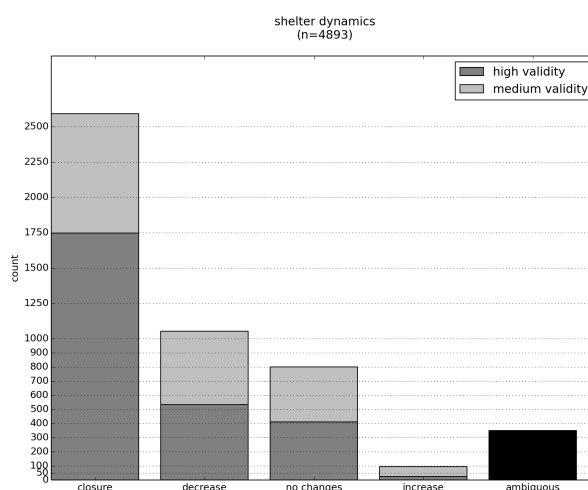


Figure 10. Temporal shelter dynamics.

The dynamics according to shelter size shows the following patterns. The vast majority of small camps were closed (63%). About a quarter (24%) did not change over time. Only a few decreased (4%) or increased (1%). Medium size camps showed slightly different dynamics: More than half (54%) of the camps closed, one-fifth (20%) decreased or remained unchanged (17%). Only 2% increased. Big camps closed (42%) or decreased (41%) in almost equal terms. Merely 3% increased and 8% did not change. If we compare the temporal dynamics across camp sizes, some trends are evident: The tendency to remain unchanged shrinks from small to big camp size, while decreasing probability rises. The number of camps that were closed declines with larger sizes. Only 29% of all small camps still exist after eight days, compared to more than half (52%) of the big camps. Thus, those camps remaining are more likely the big ones.

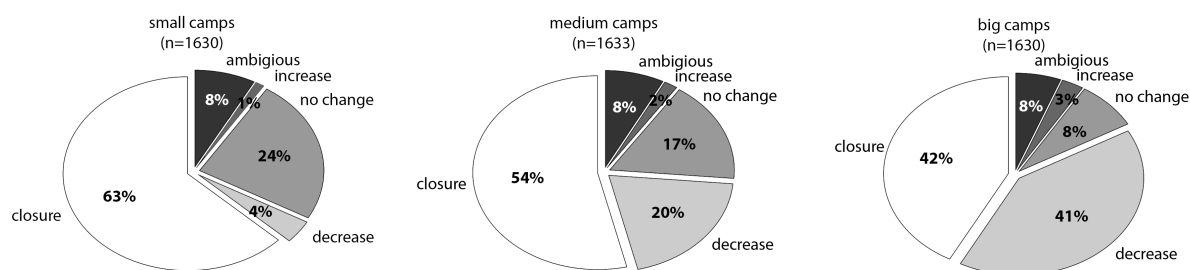


Figure 11. Temporal shelter dynamics by camp size.

DISCUSSION

The presented framework to validate crowdsourced mapping and its application to the case study of critical OSM features is innovative and similar analyses have not been conducted before. The validation of OSM objects mapped show comparatively good results even though no ground-truthing was conducted.

The analysis of OSM mapping accuracy needs to be framed by the overall process of rapid-mapping activities during an unfolding crisis. Most OSM users contributing to HOT tasks do not have first-hand experience of the crisis area under investigation (Dittus *et al.*, 2016). One-tenth of the mapped spontaneous IDP camps have been false positives in our sample, despite the fact, that the HOT tasking mechanism includes a first validation step for all tiles. Task #1008 has been almost finished (99%) in less than two days and validated to 69% after three days. However, the results of our study show that the validation process of the initial mapping performed by the OSM community did not lead to the complete absence of false positives.

Westrope *et al.* (2014) analyzed the accuracy of OSM damage mapping with ground truthing. Damaged buildings were either heavily over- or underrepresented depending on the used damage classification. It needs to be clarified, that damage detection from satellite imagery in general is considered a difficult task even to experts (Kerle, 2013). Compared to damage assessment, the identification of spontaneous IDP camps is a task that seems better suited to the expertise of remote mappers. This is mainly due to the fact that the respective features (tents) are already known to them.

Despite being a task proposed by the HOT community for “experienced users” only, our results show that the low experienced users did not contribute to a greater extent to false positives. In contrast to other studies (Barron *et al.*, 2014), mapping experience of the OSM user only had minor influence on accuracy in our case. However, differences between overall OSM experience and HOT mapping experience should be evaluated in more detail. Reasons for errors in the final sample used for this study may be found in the instructions and guidelines provided, as they only depict true positives (Dittus *et al.*, 2016). Likewise, ambiguous specifications in the documentation led to different interpretations of how to delineate tents and camps. Depending on the intended use of the GIS database, such interpretation differences hamper further spatial analysis, e.g. studies incorporating camp areas to calculate occupancy rates. The predominant part of remote mappers does not possess local knowledge and often faces difficulties in recognizing objects that are unfamiliar to them. Improving the instructions provided to remote mappers to include examples for false positives and clarify the right way of delineating objects might thus help reducing mapping errors. However, further investigation on the influence of improved guidelines is still necessary.

Regarding the temporal fluctuations of spontaneous IDP camps and their inhabitants, our analysis reveals some very high dynamics. More than half of the camps closed during this very short timeframe. Individual (small size) camps are more likely to close with inhabitants either moving back to their houses or seeking for temporary housing somewhere else. This is supported by the government’s strategy to build larger camps where provision of critical services (water & sanitation, food, and non-food items) can be managed more effectively (Shelter Cluster Nepal, 2014). The dynamics we observed through the crowdsourcing assessment is in agreement with other studies like the intention survey conducted by IOM (2015c) and the household survey of Khazai, Anhorn, Brink, *et al.* (2015). Updating the GIS database is crucial given this high temporal dynamics, especially after disastrous events, when up-to-date information is fundamental to potentially life-saving decision-making.

With more and more satellite imagery becoming available from the worst hit areas in Nepal, the focus of HOT activities also shifted to provide base map information for these regions. Due to these circumstances, additional tasks for updating the previously mapped spontaneous IDP camps were not launched. Unfortunately, the

previously generated data became outdated quickly, although new imagery was also available for Kathmandu. As a result, emergency responders could only benefit from the information about shelters generated by the OSM community in the beginning of the crisis.

CONCLUSION

Crowdsourcing methods are more and more used for disaster management purposes (Goodchild and Glennon, 2010, Palen *et al.*, 2015). Likewise, the OSM data and built upon geo-services provide first responders with valuable information. Nevertheless, spatial quality and temporal resolution are critical issues, especially if their dynamics is inherent to the mapped features. Furthermore, initial reports from the field suggest that there were spontaneous camps evolving all over in the valley, with various materials in use (James E. Daniell *et al.*, 2015, Khazai, Anhorn, Girard, *et al.*, 2015). They were characterized by very high temporal dynamics. Therefore, we need to consider some margin of un-detected camps having been existent at times for which there was no satellite imagery available. Also, cases of missed camps might have occurred during the OSM mapping. In this paper we did not consider these undetected camps.

Our analysis shows that the accuracy and temporal dynamics of critical features in GIS databases can be assessed using crowdsourcing techniques. It is clear that crowdsourced volunteers were able to identify true and false positives with high confidence. Nevertheless, the still small number of iterations is a limitation to the present case study, which should be addressed in future work.

In comparison with the OSM mapping exercise itself, the task might be considered easy, as not the whole satellite scene needs to be scanned manually. To further improve the quality of crowdsourcing, future work should concentrate on distinguishing reliable and un-reliable classification volunteers. For example, the *Cohen's kappa coefficient* (Cohen, 1968) could be used to determine inter-rater agreement for qualitative features. Further research is also needed on how to provide guidelines and instructions for remote mappers including false positives to foster improved mapping results.

Hitherto updating geographical features during humanitarian crisis is not addressed within the OSM community. Nevertheless, we think the proposed framework herein also might also allow an improvement in validation and updating of crowdsourced geographical features beyond disasters. The tool can be used, not just for critical features, but also for regular features that show high dynamics. With more and more information becoming available through a larger variety of sensors (satellite, aerial, drones, etc.) (Meier, 2015c), it could be interesting to expand the bi-temporal comparison of images in our framework to include more images of different time stamps.

We think with a clearly structured tagging scheme behind, the current OSM database would be able to represent more dynamic features. We are not suggesting to have multiple tags with timestamp(s) which would be one option, but introduce a tool that allows to regularly update existing features which are critical for example for emergency response capacities. With more and more tools becoming available to allow for dynamic content and users looking for the most up-to-date information, the challenge ahead remains in structuring these efforts but also ensure qualitative integrity.

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