Centaur VGI: Evaluating a human-machine workflow for increased productivity during humanitarian mapping campaigns

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Summary

The spatial and temporal distribution of global map data is highly unequal, with large areas of the world suffering from a paucity of data. Volunteered geographic information (VGI) has been vaunted as a potential solution, but is also criticised for reinforcing rather than alleviating inequalities. Human-machine workflows have been suggested to improve the speed and quality of VGI production for poorly mapped regions, but this ability is yet to be fully evaluated. This paper provides the first detailed evaluation of a human-machine workflow, testing its ability to produce high quality, timely data in remote regions often neglected by humanitarian mapping campaigns.

KEYWORDS: Volunteered geographic information, machine learning, humanitarian mapping, mapping inequalities

1. Introduction

1.1. Mapping inequalities

Globally an inequality in the coverage, currency and consistency of map data persists (Huck et al., 2020). Higher income, technologically advanced countries benefit from highly detailed, up-to-date maps, whilst lower income, technologically disadvantaged countries face addressing humanitarian and developmental challenges with outdated, poor quality and inconsistent data (Scott and Rajabaford, 2017). The reasons for this disparity are manifold and include historic control of data by past-colonial powers (Graham et al., 2014), the digital divides (Schradie, 2011) and the ability of higher income countries to afford maintenance and production of authoritative map data. Inequalities are not only observed between higher and lower income countries but within countries themselves. Urban areas are often advantaged by accurate, thematically-rich data due to their relatively higher affluence and ICT penetration compared to rural areas (Young et al., 2020). Despite the promise of advancements in digital mapping and the introduction of VGI to lower cost and skill barriers of map data production, it has been argued that these technologies can reinforce, rather than alleviate, many of these inequalities (Perkins, 2014). Consequently, populations without access to maps data are often left vulnerable to the impacts of humanitarian crises, with responses hampered by a lack of data on the location of affected populations and infrastructure required to plan responses.

1.2. Human-machine mapping workflows

Human-machine mapping workflows, specifically the integration of machine learning (ML) into VGI workflows, have been suggested as a solution to alleviate inequalities in map data and overcome motivational and practical challenges of mapping in remote, rural areas (Huck et al., 2020; Vargaz-

Munoz et al., 2020). The integration of ML is said to improve existing volunteer engagement by reducing volunteer effort (Vargas-Munoz et al., 2020), helping to attract new types of volunteers (Huck et al., 2020) and increasing the quality and speed of data production (Vargas-Munoz et al., 2020). Several human-machine mapping workflows have since been suggested (see Huck et al., 2020; Vargas-Munoz et al., 2020; Bastani et al. 2019; Herfort et al., 2019), although the extent of ML integration varies between workflows.

One particular approach, known as 'Centaur VGI' (Huck et al., 2020), suggests sharing mapping tasks between the machine and human volunteers throughout the mapping process, seeking to improve volunteer engagement, increase efficiency and improve the thematic and positional accuracy of data. The machine is tasked with identifying and classifying features, whilst the human is asked to verify the machine output, improving machine performance and ensuring all data uploaded is accurate and correct. An illustrated comparison of the Centaur VGI workflow and a traditional VGI workflow (e.g. OpenStreetMap (OSM) is given in Figure 1.

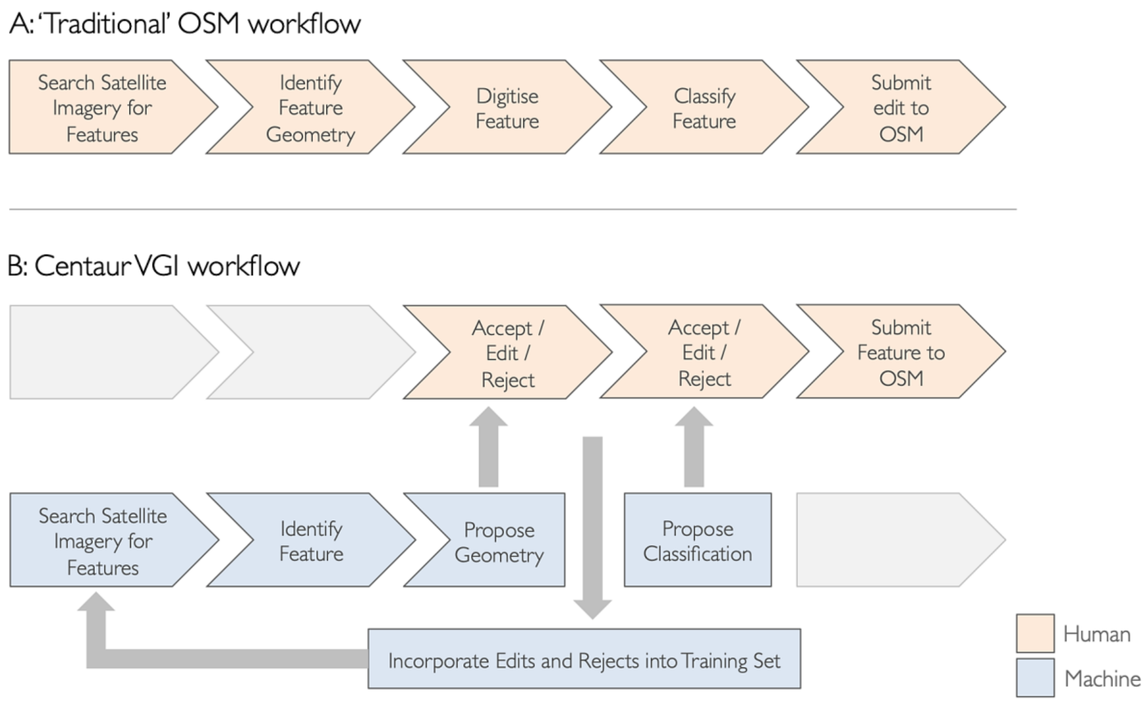

Figure 1: Labour division between the human volunteer and the machine in (A) a traditional VGI workflow (e.g. OpenStreetMap), and (B) the Centaur VGI workflow, *reproduced from Huck et al. (2020).*

However, a thorough user evaluation of the Centaur VGI approach has yet to be undertaken, meaning the proposed benefits cannot be verified. The purpose of this research is therefore to evaluate the potential of the Centaur VGI approach to improve:

- The thematic and geometric accuracy of resulting data.
- Volunteer mapping efficiency.
- Volunteer engagement.
- The user experience of mapping platforms (particularly first time mappers).

2. Methods

To evaluate the Centaur VGI workflow (Figure 1b) an online mapping platform was developed based on the workflow, which asked website users to decide if a machine proposed geometry was a building or not, and if necessary edit the geometry before uploading. The platform can then feedback user input to the machine, incrementally improving machine performance. The website was used by participants who provided insight into platform usability through 'think-aloud' commentary and questionnaire responses.

2.1. Implementation of the Centaur VGI workflow

The Centaur VGI workflow (Figure 1b) was implemented using JavaScript and connected to the live OSM database via the OSM APIv3[1] and the Overpass API[2]. Due to the focus upon user experience and engagement with the platform (and in order to keep costs down), we used a static database containing pre-generated machine-detected building geometries for the country of Uganda[3], rather than a 'live' ML service generating building footprints concurrent with website use. This had no bearing on the user experience. Figure 2 outlines the interaction between website user and background website operations allowing the user to approve, edit or reject the machine generated geometries. An example of the mapping interface can be seen in Figure 3.

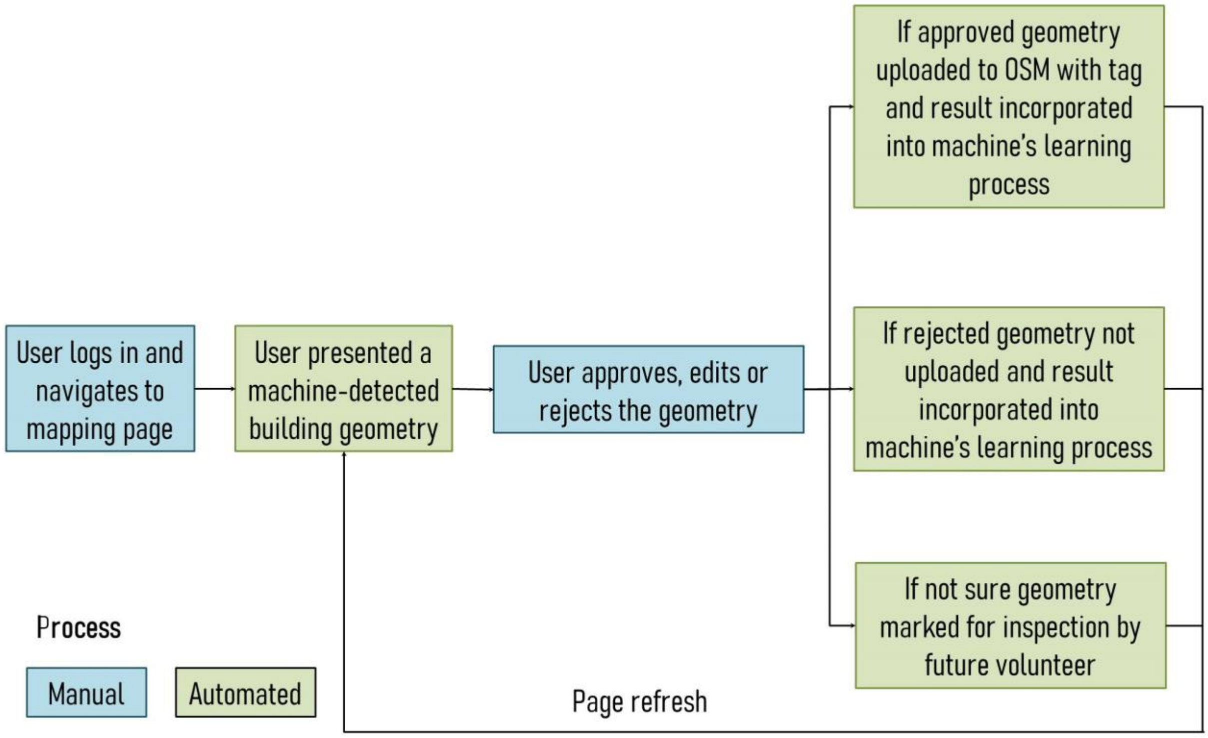

Figure 2: Client(user)-server interaction for the Centaur VGI platform

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[1] https://wiki.openstreetmap.org/wiki/API_v0.3
[2] https://wiki.openstreetmap.org/wiki/Overpass_API
[3] https://github.com/microsoft/Uganda-Tanzania-Building-Footprints

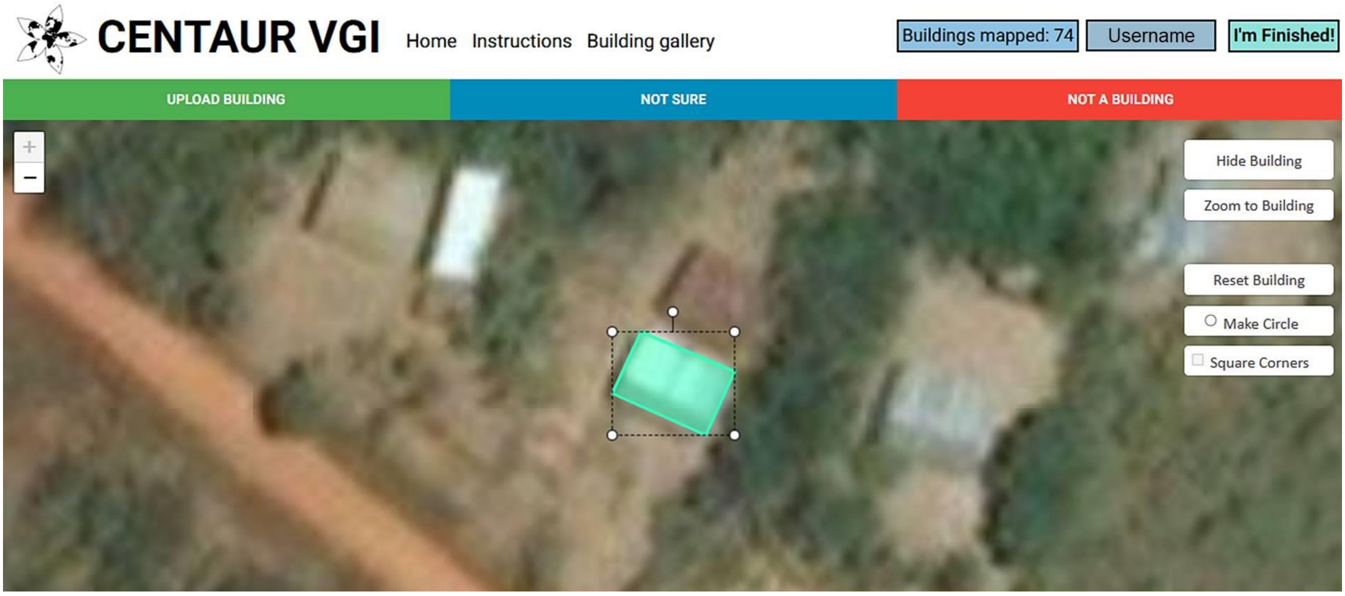

Figure 3: Centaur VGI mapping(user) interface

2.2. Comparative platform

A pre-existing VGI platform[4] was used to compare the efficiency, engagement, repetitiveness and accuracy of the Centaur VGI platform. In contrast to the Centaur platform, the platform uses a traditional workflow, with a task manager assigning unmapped areas of land to volunteers, who then manually map them using the OSM iD editor[5] (Figure 1a). Upon completion of mapping the area is marked as complete and the volunteer is given a new area to map.

2.3. Participant recruitment and demographics

In total 34 participants were recruited to complete the evaluation. Participants were sought from the postgraduate, academic and alumni population of the University of Manchester and reflected a range of demographics. Participants ranged in age from 18 to 65 (Figure 4), mainly identified as women, and exhibited a variety of levels of prior experience in producing VGI and technical (computer and Internet) experience. The majority had previously taken part in at least one mapathon, which is largely as a result of high-profile mapathons run by this research group in recent years (Figure 5).

[4] https://communitymapping.org
[5] https://www.openstreetmap.org/edit

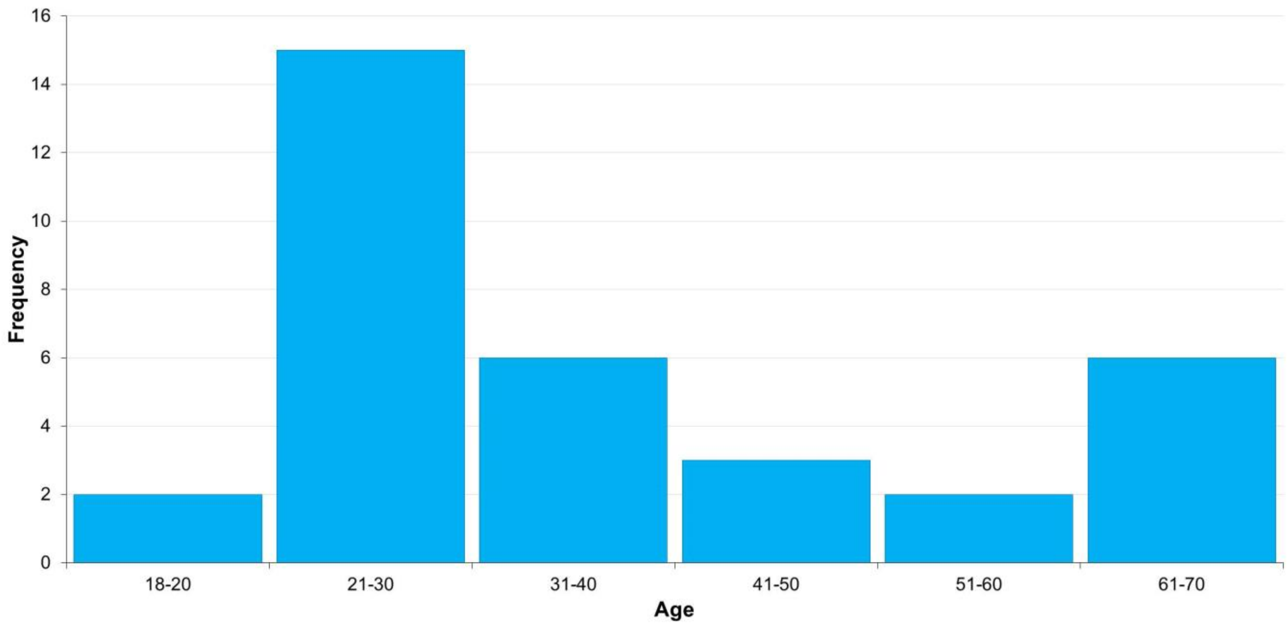

Figure 4: Participant ages

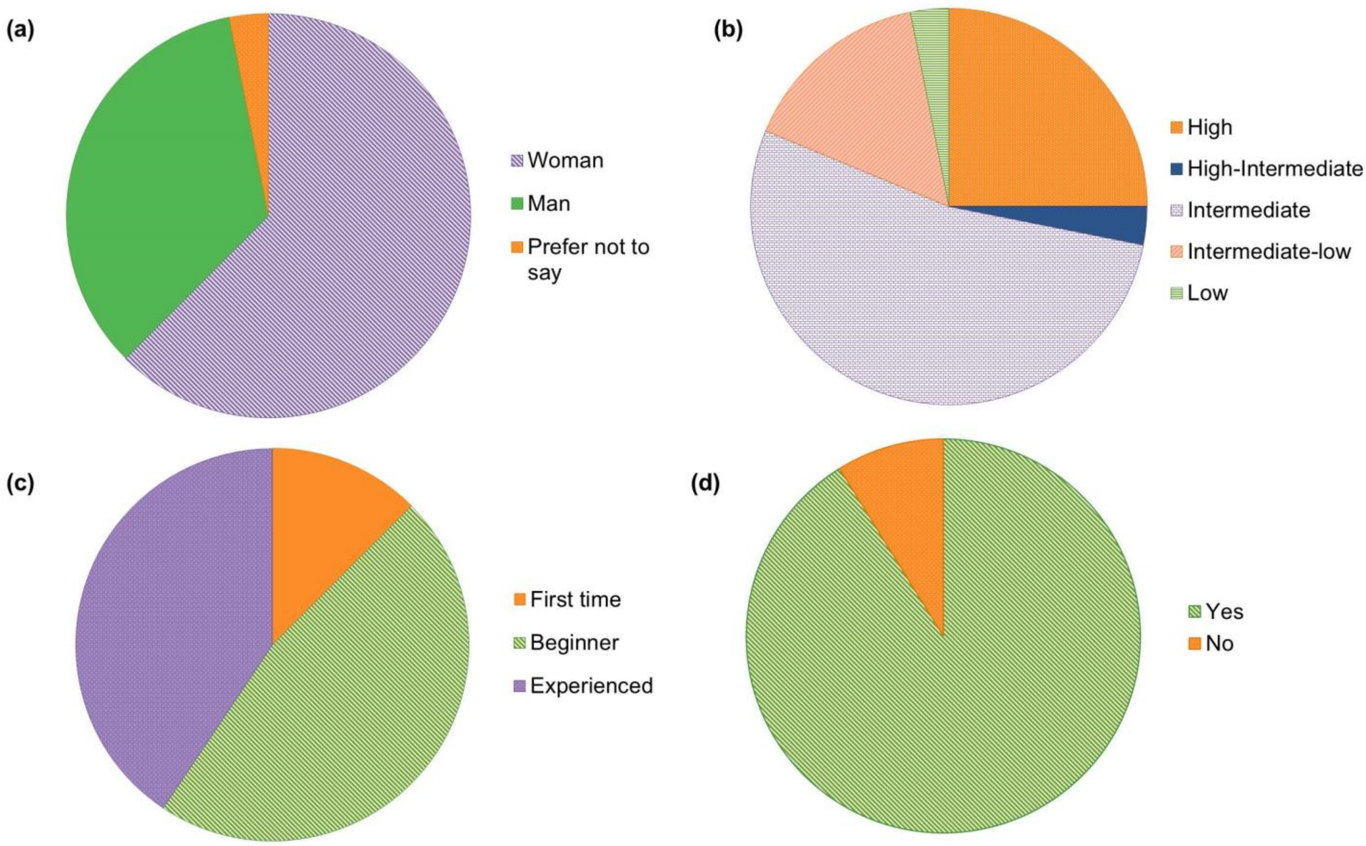

Figure 5: Participant demographics (a) Identified gender (b) Technical experience (c) Experience producing VGI (d) Previous participation in a mapathon

2.4. Platform evaluation

Each participant took part in a 1:1 mapping session conducted via Skype. Each participant was asked to map as many buildings as possible in ten minutes using each platform, the order of which was randomised in order to mitigate bias. Whilst mapping participants were asked to 'think-aloud', explaining what they were doing and why; and commenting on their likes and dislikes in relation to each platform. After each ten minutes the total number of buildings mapped was recorded. Participants were then asked to complete a questionnaire which collected limited demographic data (age, gender and education), information on technical experience, experience with VGI and motivations for mapping and asked questions about individual and comparative platform usability (adapted from Ballatore et al., 2020). Participants were also asked to verbally provide further detailed information about their experience of each platform. Verbal comments made during and after each ten-minute mapping activity were recorded and transcribed prior to analysis.

3. Proposed analysis

3.1. Mapping rate and accuracy calculation

To explore the ability of the Centaur VGI workflow to produce timely, high quality data the data produced using each platform will be evaluated by the calculation of a number of quantitative accuracy and efficiency measures:

1) Statistical measures of the number of buildings produced per participant.
2) Statistical measures of the rate of buildings mapped per participant.
3) Total number of true and false positive buildings produced by all participants.
4) Total number of true and false negative buildings produced by all participants.

In the absence of 'authoritative' data with which to compare, measures 3 and 4 will be calculated based upon comparison with the same satellite imagery as was used by the participants[6].

3.2. Questionnaire analysis

In order to understand the ease of use of each platform, a usability score (Ballatore et al. (2020)) was generated for each platform based on each participant's response to the 15 usability questions asked in the questionnaire. Each question response scored as follows: "strongly agree" scored as 4,"agree" as 3, "neutral" as 2, "disagree" as 1 and "strongly disagree" as 0 (maximum score of 60). Following this a number of statistical measures will be calculated based on individual platform usability scores.

Usability scores will be compared between the platforms to investigate variations in perception of usability based on participant characteristics such as age, identified gender, technical experience, motivation and order of platform use.

3.3. Transcript analysis

Verbatim transcripts will be categorised into 9 topics, classifying the type of verbalisation made (Action description (what they are doing), action explanation (why they are doing), description of observed feature(s), observation of the platform, opinion about the platform, platform redesign proposal, user experience, other (adapted from Hertzum et al. (2015)).The topics will then be further

[6]https://docs.microsoft.com/en-gb/bingmaps/rest-services/imagery/

categorised based on valence (positive or negative) to provide insight into the participants' emotions whilst using the platform (Seo et al., 2015).

4. Conclusion

By completing the outlined evaluation and analysis of the 'Centaur VGI' workflow, a detailed understanding of its ability to produce timely, high quality data in remote, rural regions can be gained. This is important, as such areas are typically overlooked by volunteer mappers and organisations. The evaluation will reveal the efficacy, accuracy and usability of the workflow in comparison to the familiar, traditional VGI workflow.

5. References and Citations

BALLATORE, A., MCCLINTOCK, W., GOLDBERG, G. & KUHN, W. 2020. Towards a Usability Scale for Participatory GIS. *Geospatial Technologies for Local and Regional Development Proceedings of the 22nd AGILE Conference on Geographic Information Science*, 327-348.

BASTANI, F., HE, S., JAGWANI, S., PARK, E., ABBAR, S., ALIZADEH, M., BALAKRISHNAN, H., CHAWLA, S., MADDEN, S. SADEGHI, M. 2019. Inferring and Improving Street Maps with Data-Driven Automation. https://arxiv.org/abs/1910.04869

GRAHAM, M., HOGAN, B., STRAUMANN, R. K. MEDHAT, A. 2014. Uneven Geographies of User-Generated Information: Patterns of Increasing Informational Poverty. *Annals of the Association of American Geographers*, **104**(4), 746-764.

HERFORT, B., LI, H., FENDRICH, S., LAUTENBACH, S. ZIPF, A. 2019. Mapping Human Settlements with Higher Accuracy and Less Volunteer Efforts by Combining Crowdsourcing and Deep Learning. *Remote Sensing*, **11**, 1799-1819.

HERTZUM, M., BORLUND, P. KRISTOFFERSEN, K. 2015. What Do Thinking-Aloud Participants Say? A Comparison of Moderated and Unmoderated Usability Sessions. *International Journal of Human-Computer Interaction*, **31**(9). pg 557-570

HUCK, J. J., PERKINS, C., HAWORTH, B. T., MORO, E. B. NIRMALAN, M. 2020. Centaur VGI: A Hybrid Human–Machine Approach to Address Global Inequalities in Map Coverage. *Annals of the American Association of Geographers*, **111**(1), 231-251.

PERKINS, C. 2014. Plotting practices and politics: (im)mutable narratives in OpenStreetMap. *Transactions of the Institute of British Geographers*, **39**(2), 304-317.

SCHRADIE, J. 2011. The digital production gap: The digital divide and Web 2.0 collide. *Poetics*, **39**(2), 145-168.

SCOTT, G. RAJABIFARD, A. 2017. Sustainable development and geospatial information: a strategic framework for integrating a global policy agenda into national geospatial capabilities. *Geo-spatial Information Science*, **20**(2), 59-76.

SEO, K.-K., LEE, S., CHUNG, B. D. PARK, C. 2015. Users' Emotional Valence, Arousal, and Engagement Based on Perceived Usability and Aesthetics for Web Sites. *International Journal of Human–Computer Interaction*, **31**(1), 72-87.

VARGAS MUÑOZ, J. E., TUIA, D. FALCÃO, A. X. 2020. Deploying machine learning to assist digital humanitarians: making image annotation in OpenStreetMap more efficient. *International Journal of Geographical Information Science*, 1-21.

YOUNG, J. C., LYNCH, R., BOAKYE-ACHAMPONG, S., JOWAISAS, C., SAM, J. NORLANDER, B. 2020. Volunteer geographic information in the Global South: barriers to local implementation of mapping projects across Africa. *GeoJournal*.

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Biographies

Kirsty Watkinson is a PhD student in the Department of Geography at the University of Manchester researching the application of machine learning and offline technologies to support and improve the production of volunteered geographic information during humanitarian mapping campaigns.

Jonathan Huck is a Senior Lecturer in Geographical Information Science in the Department of Geography at the University of Manchester. He is interested in the application of maps, GIS and emergent technologies to geographical problems, particularly in the areas of health and conflict.

Angela Harris is a Senior Lecturer in Remote Sensing in the Department of Geography at the University of Manchester. Angela is interested in the innovative application of remote sensing to monitor the impact of environmental change on vegetation communities and improve our understanding of ecosystem physical processes.

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