ISPRS Journal of Photogrammetry and Remote Sensing 142 (2018) 380–388

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

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

Slavery from Space: Demonstrating the role for satellite remote sensing to inform evidence-based action related to UN SDG number 8

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ARTICLE INFO

Article history:
Received 16 August 2017
Received in revised form 14 February 2018
Accepted 15 February 2018
Available online 2 March 2018

Keywords:
Slavery
Sustainable Development Goals
Google Earth
High resolution data
Sampling
Volunteers
Brick Kilns
Emissions
CO_2

ABSTRACT

The most recent Global Slavery Index estimates that there are 40.3 million people enslaved globally. The UN's Agenda 2030 for Sustainable Development Goal number 8, section 8.7 specifically refers to the issue of forced labour: ending modern slavery and human trafficking, including child labour, in all forms by 2025. Although there is a global political commitment to ending slavery, one of the biggest barriers to doing so is having reliable and timely, spatially explicit and scalable data on slavery activity. The lack of these data compromises evidence-based action and policy formulation. Thus, to meet the challenge of ending modern slavery new and innovative approaches, with an emphasis on efficient use of resources (including financial) are needed. This paper demonstrates the fundamental role of remote sensing as a source of evidence. We provide an estimate of the number of brick kilns across the 'Brick Belt' that runs across south Asia. This is important because these brick kilns are known sites of modern-day slavery. This paper reports the first rigorous estimate of the number of brick kilns present and does so using a robust method that can be easily adopted by key agencies for evidence-based action (i.e. NGOs, etc.) and is based on freely available and accessible remotely sensed data. From this estimate we can not only calculate the scale of the slavery problem in the Brick Belt, but also calculate the impact of slavery beyond that of the enslaved people themselves, on, for example, environmental change and impacts on ecosystem services – this links to other Sustainable Development Goals. As the process of achieving key Sustainable Development Goal targets will show, there are global benefits to ending slavery - this will mean a better world for everyone: safer, greener, more prosperous, and more equal. This is termed here a Freedom Dividend.

1. Introduction

The Global Slavery Index (GSI) defines modern slavery in terms of "situations of exploitation that a person cannot refuse or leave because of threats, violence, coercion, abuse of power or deception" (GSI, 2016; page 158). The most recent estimate from the GSI (2017) indicates that there are currently 40.3 million people enslaved globally, including more than 30 million slaves in the 22 Organisation for Economic Co-operation and Development (OECD) Development Assistance Committee (DAC)-list of recipient countries for which there is uniform, comparable, representative data (www.globalslaveryindex.org). In recognition of the need to address this situation, the United Nations' Agenda 2030 for Sustainable Development Goal (SDG) number eight which refers to the provision of 'decent work and economic growth' by specifically promoting full productive employment and decent work for all people (United Nations, 2016a), has an addition, section 8.7 (which was adopted as a SDG in 2015), which specifically refers to the issue of forced labour. Section 8.7 aims to end modern slavery and human trafficking including ending child labour in all forms by 2025 (United Nations, 2016b). This is a global target that requires all nations to put forward assets and people in order to eradicate slavery once and for all.

There is a global political commitment to ending slavery, however, accurate information on slavery activity is not easy to come by and as such is one of the biggest barriers to a successful end to slavery. Therefore, what is required in the pursuit to meeting SDG 8.7 is reliable, timely, spatially explicit and scalable data on slavery activity. The lack of these data compromises

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https://doi.org/10.1016/j.isprsjprs.2018.02.012
0924-2716/

evidence-based action and policy formulation. Thus, to meet the challenge of ending modern slavery, new and innovative approaches, with an emphasis on efficient use of resources (including financial) are required. The potential of remote sensing to inform efforts to tackle humanitarian issues, including slavery, has been noted (Bales, 2007:163). Indeed, a range of humanitarian issues have been shown to benefit from remote sensing, including poverty studies (Jean et al., 2016; Watmough et al., 2016) and supporting international peace and security (Jasani et al., 2009). Further, the Harvard Humanitarian Initiative, a unique system-wide network dedicated to improving humanitarian performance through increased learning and accountability, has recognised the added value of remotely sensed data (http://www.alnap.org/). Amnesty International are purchasing medium to high resolution imagery from satellite companies and then employing analysts to assess what the images are showing as a visual investigation for areas that are inaccessible to humanitarian and human rights organisations – they have created a programme for imagery analysis for human rights issues: Science for Human Rights Programme for Digital Globe (www.amnesty.org/). There is significant benefit to be gained from conducting assessments of human rights abuses using high resolution satellite remote sensing in particular, and this combined with eye-witness accounts from the ground can be extremely useful. These benefits are manifest in helping to track abuses and identify crises, as well as hopefully leading to the prosecution of those carrying out the abuses (Lavers et al., 2009) or enabling fast responses to humanitarian crises when they occur (Piesing, 2011; Witharana et al., 2014). Other work, still in its infancy but specifically looking at slavery, includes the mapping of fish farms suspected of using forced labour in the Sundarbans National Park (McGoogan and Rashid, 2016). The use of remote sensing for the detection of slavery activity is clearly a potential application area ripe for exploration.

In this paper we build on the aforementioned potential and present for the first time an estimate of the number of brick kilns across the so-called 'Brick Belt' region of south Asia. The focus on brick kilns is important since they are known sites of modern-day slavery. Research points to the ongoing and widespread abuse and exploitation of brick kiln workers, including children, and situations of forced labour, with many trafficked into situations of bonded labour slavery. The workforce in these kilns are predominantly migrants and from socially excluded and economically marginalised communities. A lack of both relevant preventative action and prosecution means that little is being done to prevent such practices (Bales, 1999, 2005; Kara, 2014; Khan and Qureshi, 2016). Although there are regional estimates of the number of brick kilns and thus slaves working within them, the full scale of the number of brick kilns and, by proxy, slavery is unknown. For example, the NGO Anti-Slavery International, reports that the National Sample Survey Organisation (NSSO) estimated that in 2009–2010, brick kilns employed more than 5% of India's 460 million workers; which would equate to more than 23 million brick kiln workers, with an estimated ~70% of the labour force in these kilns working under force. Others have offered estimates regarding the number of children who work under conditions of debt bondage, including within the brick making industry; Save the Children (2007) suggests that there are '250,000 children' who are living and working in Pakistani brick kilns. This is part of the enslaved workforce that means Pakistan can produce 8% of the world's bricks (Baum, 2010) as they take on a number for jobs within the kilns such as mixing mud, collecting water, carrying bricks and helping to fire them (Bales, 1999). This statistic is further supported by the International Labour Organisation (2005) report which found that around 40% of all brick kiln workers (both children and adults) within the Punjab region of Pakistan are working within bonded labour practices.

In this paper an initial step in providing data needed to inform action is presented. High resolution satellite remotely sensed data are used to make a rigorous and credible estimate of the number of brick kilns across the 'Brick Belt', using a straight-forward and reproducible method – based on freely available and accessible satellite data that will facilitate future work and the monitoring of progress in addressing the UN's SDG number 8.

2. Study area

The brick making industry is a large part of the development of the infrastructure and economy within these nations (Hawksley and Pradesh, 2014) and production appears to be increasing to cope with demand for building material (Baum, 2010). The areal extent of the 'Brick Belt' is 1,551,997 km^2 and crosses country and regional borders, thus calling for the use of a method of study such as remote sensing that can freely cross such boundaries. The core aim of this paper was to provide an estimate of the total number of brick kilns in the 'Brick Belt'. However, in achieving this goal we also wished to provide evidence to support the quality of the estimate derived. To do this we also study in detail a small region, an area of 250 km^2 in the northern Indian State of the Rajasthan. Ground intelligence from NGOs informs that a high occurrence of brick kilns exist in this region. The 'Brick Belt' itself is an unofficial region of Pakistan, northern India, Nepal and Bangladesh, that encompasses a large proportion of the brick kilns that can be found globally (Fig. 1).

There are several types of brick kilns that can be found in different areas of the world, however, there is one dominant type that can be found within the 'Brick Belt' and that is the large oval kiln (perimeter of around 217 m), known as the Bull's Trench Kiln (BTK); it is these BTKs that are the most likely to use an enslaved workforce (Bales, 1999) due to their sheer size (Patil, 2016).

3. Data and methods

A methodology was adopted based on high resolution satellite data provided by the geographic browser Google Earth. The open access satellite imagery provided has been used in a considerable number of studies and has many virtues for the study of the Earth's surface at a range of scales (Yu and Gong, 2012; Bastin et al., 2017). As stated already, the brick kilns are large, particularly with respect to the spatial resolution of high resolution satellite data such as WorldView, Pléiades, GeoEye-1, and QuickBird. Moreover, the kilns have a distinct spectral and spatial form and are thus readily visible on the high resolution colour satellite data available in the Google Earth geobrowser. Examples of different kiln types can be seen in Fig. 2. In this study, brick kilns were identified via visual interpretation of the imagery - the most recent satellite data from the geobrowser were used and the locations of fully formed kilns were mapped. The date range of the high resolution RGB imagery used (captured by WorldView-2 and Pléiades-1A/1B satellites, with a spatial resolution of 0.46 m and 0.5 m respectively) was between 05/11/14 and 03/12/16.

In order to generate an estimate of the number of brick kilns across the entire 'Brick Belt', a sampling approach was adopted as it was impractical within this study to undertake a complete survey of the entire region. A rigorous means to obtain a statistically credible and unbiased estimate of the number of kilns is to base the analysis on a probability sample drawn from the study region (Cochran, 2007). With little prior knowledge on the likely locations or abundance of brick kilns in the region a simple random sampling based approach was adopted in order to yield a credible estimate of the total number of kilns in the area. A grid of 100 km^2 square cells was overlaid on the 'Brick Belt' and a sample of grid

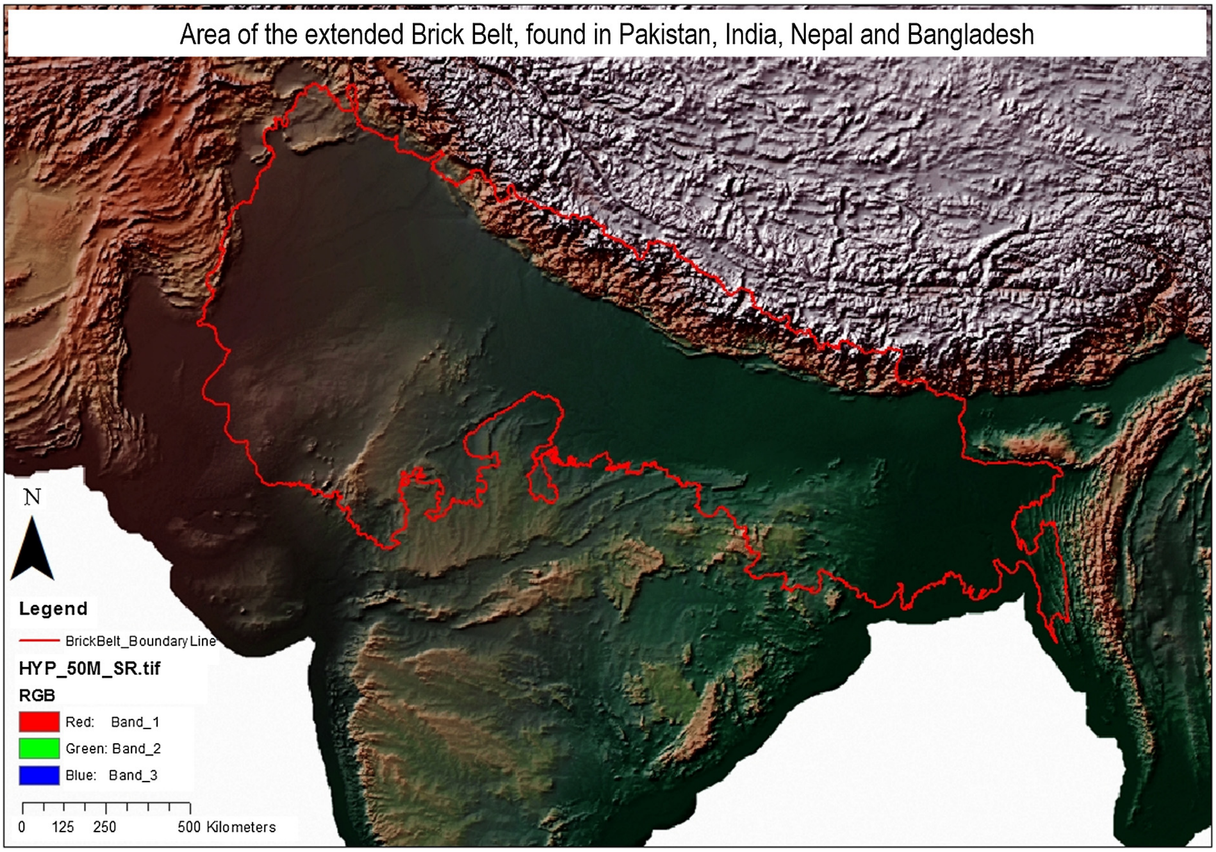

Fig. 1. The 'Brick Belt' is an unofficial area that encompasses much of the Brick-making industry globally. It covers the areas of Pakistan, Northern India, Nepal and Bangladesh.

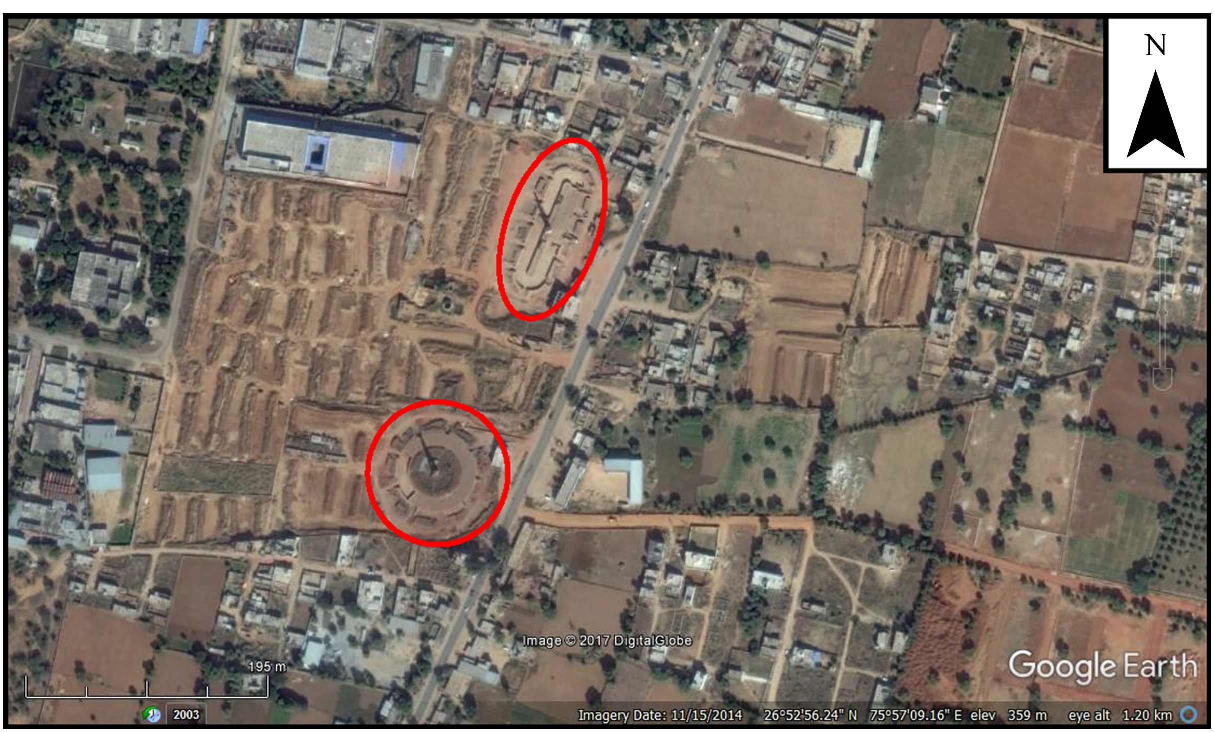

Fig. 2. An image featuring two brick kilns. One is a traditional Bull's Trench Kiln (BTK) and the other is a circular kiln. Surrounding these kilns is a number of clay fields that are used in the production of the bricks themselves before the firing of the bricks in the kilns. These fields are commonly found close to the kilns although sometimes they are not directly adjacent to the kilns.

cells obtained upon which to base an estimate for the total 'Belt' region. With no planning values to inform the sample design (Neter et al., 1993; Cochran, 2007), a random sample of 30 grid cells was selected to obtain information to inform the study design. The image data for each of these selected grid cells was visually interpreted and a count of the number of kilns present made. This approach is referred to here as expert visual interpretation. From this sample, the standard deviation of kiln numbers per cell was estimated to be 4.6. This latter value was used to determine the required sample size to estimate the average number of kilns per grid cell ±0.5 with a simple random sampling design at the 95% level of confidence using basic sampling theory (Neter et al., 1993; Cochran, 2007). The values used are rather arbitrary, balancing competing pressures and demands on resources while seeking to ensure that a credible estimate of average kiln abundance per 100 km^2 grid cell may be derived, which in turn may be scaled to give an estimate of the total in the 'Brick Belt'. The required sample size was determined to be 320 cells and an online random number generator was used to select this sample of cells from the imagery. The image extract for each selected grid cell was then visually interpreted and the locations of brick kilns highlighted. The average number of kilns per cell was calculated and then multiplied by the number of cells making up the 'Brick Belt' to yield an estimate of the total number of kilns.

To evaluate the accuracy of the estimate obtained by visual interpretation, a comparison of the kilns identified for the 250 km^2 region of Rajasthan was undertaken. For this comparison volunteers via crowd-sourcing were tasked to identify brick kilns in the imagery of this area in the State of Rajasthan. Volunteers analysed image extracts presented randomly from the 396 image extracts that covered the region. Each image extract was viewed and annotated by at least 15 volunteers to aid quality assessment and reduce the potential for negative impacts arising from sources such as spammers (Foody, 2014), but also to ensure that the entire region was covered. Once 15 volunteers had viewed an image extract that extract was withdrawn from the set available for annotation. In that way each image was viewed multiple times but also each and every image was viewed to give complete spatial coverage.

The online citizen science platform Zooniverse (Bowyer et al., 2015) was used to task the volunteers. The platform currently has around 1.6 million registered users and hosts a variety of projects that seek volunteers to support data-processing tasks; it was chosen because of the speed at which it is possible to disseminate a project and reach such a wide, varied audience, in addition to the relevance of the data captured about the volunteers' annotations. The "Slavery from Space" site consists of a landing page with a "Get Started" button, which navigates users to a classification page where they mark the centres of brick kilns in Google Earth satellite images (Fig. 3). The viewing resolution of the images will have varied according to the volunteers' device, operating system, and browser.

In May 2017 the Slavery from Space project was tested with participants in a Massive Open Online Course (MOOC) developed by the University of Nottingham on Ending Slavery on the Future-Learn.org website. The project was then promoted on social media, and some members of the Zooniverse discussion forums also participated. The project was picked up by the *New Scientist* (Reynolds, 2017), which enthused a new audience, and resulted in the project's completion in the last week of June when all 396 images had been seen by at least 15 volunteers. The Zooniverse website does not require users to register to participate in a project, so the number of individual volunteers must be estimated with the internet protocol (IP) address tagged to each classification; in this case around 120 independent volunteers contributed their time to the project. To analyse resultant volunteered data, a script was deployed (available at https://github.com/zooniverse/aggregation-for-caesar/releases/tag/0.1) which uses a nearest neighbour clustering algorithm to count and locate aggregated markings made by four or more independent volunteers when located within five pixels of each other. Thus, a kiln was identified and labelled as such when at least 4 of the volunteers who views an image extract suggested the same or similar location for its centre. Although not ideal, this approach is similar to that used in

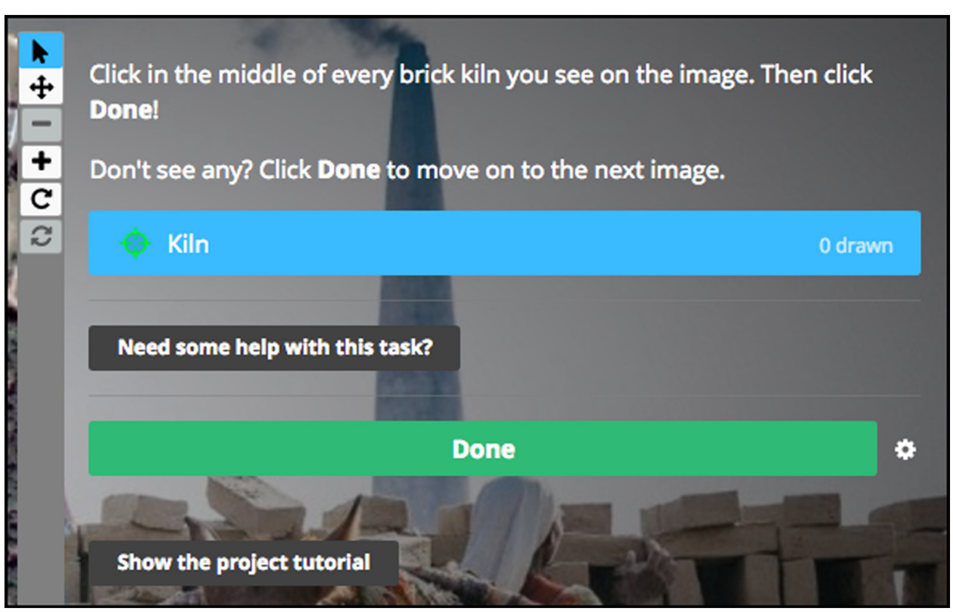

Fig. 3. The Slavery from Space task, with the Help, Done and Tutorial buttons below the question text. The images can be manipulated for closer inspection using the image controls seen to the left (e.g. zooming and panning). The classification page first presents volunteers with a tutorial that describes the task's steps. Google Earth images are presented alongside the question text and a tool for marking kilns on the image, which volunteers operate by clicking with their left-hand mouse button. Below the marking tool volunteers can click on a help button for detailed task instructions and example images. When volunteers have marked all the kilns on an image, they click on a green "Done" button to see a summary of their response and then a "Next" button to load a new image. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

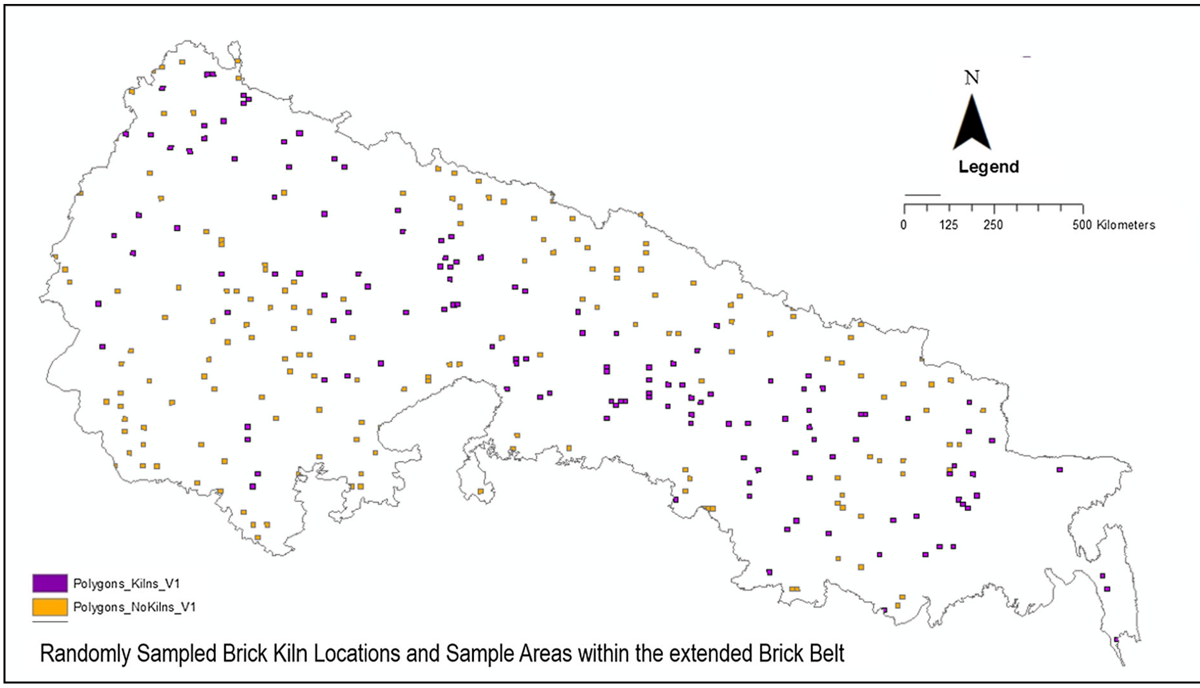

Fig. 4. Location of the randomly generated 320 100 km^2 sample cells, illustrating which had brick kilns and which had none, across the Brick Belt. A standard probability sample design, simple random sampling, was used here which allows unbiased estimation. A cell with multiple kilns has the exact same inclusion probability as a cell with one or even no kilns present. The approach adopted allows an estimate of the total of kilns over the entire study area. A file containing the border of the 'Brick Belt' as well as those locations (polygons depicting sample cells) where brick kilns were found is provided to visualise in the Interactive Map Viewer (http://www.elsevier.com/googlemaps). This allows the imagery used for mapping to be perused too.

other studies in which volunteers have been used to identify simple land cover information from high resolution imagery (Foody et al., 2015). Crowd sourcing has considerable potential to support studies such as this that require simple visual interpretation of imagery. The crowd is often motivated by tasks that are deemed worthy and serve a public good purpose, the task is straightforward and requires only modest instruction and the power of the crowd enables large data sets to be surveyed in a short period. It is, therefore, unsurprising that volunteers have an increasingly important role to play in mapping activity (See et al., 2016). Inevitably there are concerns with crowdsourced data as there is potential for error and uncertainty arising from sources ranging from spammers to simple genuine mistakes but the use of multiple interpreters may help address such data quality concerns (Foody, 2014; Foody et al., 2013).

Finally, the image extracts were also subjected to annotation by an independent adjudicator (the lead author) who followed a rigorous labelling protocol and whose labels were taken to be the most authoritative of the set derived. These latter labels were used as the 'ground truth' in terms of expressing the accuracy of the initial expert interpreter who studied the entire 'Brick Belt' and the labelling derived from the volunteers.

4. Results and discussion

Brick kilns were unevenly distributed and often tended to occur in clusters of varying size. Just over half the grid cells sampled (173 cells) contained no kilns (Fig. 4) while two contained over 30 kilns each (Fig. 5). In total, the expert identified a total of 1142 kilns across the 320 grid cells sampled (Fig. 4). This suggests an average of 0.0357 kilns per km^2 which when scaled over the entire area of the Brick Belt yields an estimated total number of kilns of 55,387 (Table 1). There is no directly comparable estimate to compare this

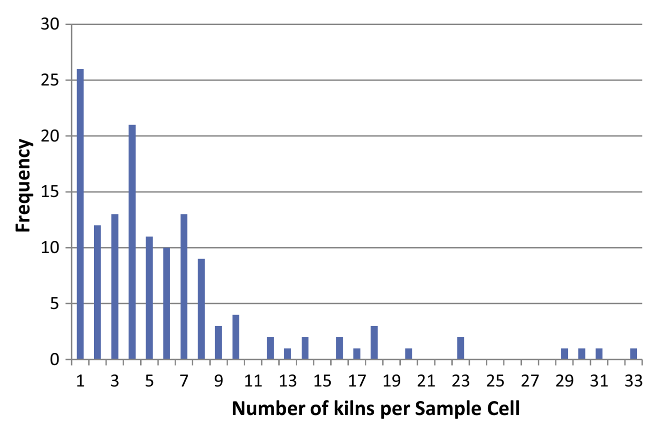

Fig. 5. Frequency distribution of number of brick kilns per sample cell. Note that 1142 kilns were found across the 320 sample cells with 43% of those cells featuring one or more brick kilns.

Table 1
Results and important statistics from the sampling process.

Statistic	Results
Total number of cell samples	320
Total number of kilns	1142
Mean number of kilns in each cell	3.569
Estimated number of kilns in Brick Belt[a]	55,387
Average density of kilns (per km^2)	0.03758

[a] Based on the estimated mean number of kilns per cell and rounded to nearest whole number. Note that the standard deviation was 6.3731 and the associated 95% confidence interval for the mean number of kilns per cell was 2.87–4.27 which would yield lower and upper estimates of the total number of kilns across the Brick Belt of 44,542 and 66,270 respectively.

to, hence the need for this study. Other estimates of brick kiln numbers have a lack of source and credibility in their estimates. For example, the Pakistan Institute of Labour Education and Research estimated that there are 11,000 brick kilns in Pakistan (Khan, 2010), but information on how this estimate was made is not given. Anti-Slavery International (2015) reported that "It is estimated that there at least 100,000 functioning brick kilns in India...", but again the source of this figure is not given (and note the Brick Belt only encompasses a small part of India). Sonia Awale (2015) in the Nepali Times estimates "1100 or so brick kilns in

Fig. 6. Examples of markings made by volunteers. A: Example of an image with 7 kilns are the correct identification of them by the volunteers (as denoted by their clustering); B: An example of a disused kiln identified by some volunteers; C: An example of wrongly identified feature (a roundabout, though notice a minimal marking in the cluster) and D: one lone marking of a feature associated with the Brick making industry (a clay field), a feature associated with the Brick making industry (note the 4 clusters correctly mark brick kilns).

Nepal" again with no citation as to a source of this estimate. The key point of these diverse 'guestimations' is that no reliable methodology, and indeed one that is transferable over space and time, has previously been used to estimate the number of kilns in the 'Brick Belt'. Thus our estimate with a rigorous methodology as its provenance should be used to inform future work on brick kiln numbers.

During the check on the quality of kiln mapping by way of the detailed study of the 250 km^2 region of Rajasthan it was apparent that where there were clustering of markings by individual volunteers in the Zooniverse project this clearly matched the brick kilns identified by the expert interpreter, illustrated in Fig. 6A. This was also the case for the kilns identified by the independent adjudicator. The volunteers, expert, and independent adjudicator all agreed on the same 262 kilns. However, 1 and 17 additional features were identified as kilns by the independent adjudicator and volunteers respectively (Table 2). The feature identified by both the adjudicator and volunteers was determined to be a brick kiln that had been missed by the expert visual interpreter. Taking the adjudicator's labelling to be the 'ground truth', the accuracy of the expert labelling was estimated to be 99.6%. The other 16 features marked by the volunteers were commission errors and related to footprints of old kilns (Fig. 6B), half built kilns and other circular features such as roundabouts (Fig. 6C). Other lone markings by volunteers also featured (e.g., Fig. 6D showed a marking for features relating to the brick making industry, but not a kiln itself) but these were excluded from analyses since they were not selected by the clustering algorithm. With 263 brick kilns, this area of India has an average density of 1.052 kilns per km^2. This is higher than that of the estimated average across the 'Brick Belt' but matches what we know from NGOs working in this area about the concentration of kilns in the Rajasthan area. This also informs us that elsewhere in the 'Brick Belt' the density of brick kilns is typically lower.

It is acknowledged that these estimates on brick kiln numbers are not fully spatially explicit for the entire 'Brick Belt': The obvious next step is to map the actual locations of all brick kilns to provide spatially explicit information on brick kilns. The locations of the kilns in each of the 320 sampled cells and the 250 km^2 region of Rajasthan may be used to inform future work in this regard. Going forward and building on this work research will take a number of avenues. The first avenue is to liaise with those on the ground, both governmental agencies and local antislavery non-governmental organisations, working to free slaves. Only by working with these organisations can the estimate produced in this paper be used to calculate the number of slaves working in this industry across the belt. Moreover, we can also examine the impact of slavery beyond that of the enslaved people themselves. For example, more precise estimates of how much environmental impact results from slavery activity, or loss of ecosystem services, are possible, as well as suggestions of alternative brick making technologies with lower carbon emissions (Luby et al., 2015) that might then be adopted by free workers and businesses not involved in the use of enslaved labour. Fig. 7 illustrates clearly the emissions from the fixed chimney of a Bull's trench kiln. This illustrates well a case in point: Focussing on carbon dioxide (CO_2) emissions, Maheshwari and Jain (2017) calculated the carbon footprint of all operations and activity of fixed chimney brick kilns in India; Tahir and Rafique (2009) analysed data suggesting that 4000 brick kilns in the Punjab region of Pakistan released 525,440 tonnes of CO_2 each year. If we use their estimate of an average 131 tonnes of CO_2 per kiln, then the 'Brick Belt' is responsible for emitting 7,255,697 tonnes of CO_2 each year. It is also important to note that brick kilns also account for an additional increase in global warming by the type of smoke they produce. This particularly damaging type of smoke is called black soot, or sometimes "black carbon." As Elisabeth Rosenthal (2009) explained in the New York Times: "While carbon dioxide may be the No. 1 contributor to rising global temperatures, scientists say black carbon has emerged as an important No. 2, with recent studies estimating that it is responsible for 18 percent of the planet's warming, compared with 40 percent for carbon dioxide." We are currently unable to estimate the amount of 'black soot' within the overall CO_2 calculation, but the fundamental point is this: in addition to being a scene of serious human rights abuses, the nature of the existing brick making technology significantly contributes to CO_2 emissions and thereby the process of climate change. The closely related nature of these two global problems suggests that they could well be addressed simultaneously rather than separately.

Table 2
Identified brick kilns in the Rajasthan area by the volunteers, expert and independent adjudicator and the error margin of the expert and volunteers.

	Expert	Volunteers	Independent Adjudicator
Number of ID BK	262	279	263
Error (relative to independent adjudicator)	0.4%	6.1%	n/a

The second avenue relates to geospatial methods and related technologies, all of which can be thought of under the umbrella term of crowd computing (Brown and Yarberry, 2009) within the context of the Digital Earth 2020 (Craglia et al., 2012). All of this work is underpinned by the advances in the closely related fields of Web 2.0 which emphasises user-generated content, citizen science, geobrowsers serving up remotely sensed data and machine learning (Cheng and Han, 2016). Future work will continue to exploit developments in these fields, but crucial to this is the high resolution satellite data from which the features relating to slavery activity, in this case brick kilns, can be extracted. The recent launches of low-cost nano satellites (e.g., Houberg and McCabe, 2016) are of interest, as are the ESA Copernicus Sentinel-2 whose free and assured data could potentially be enhanced with respect to spatial resolution to match those of the features to be extracted through super resolution analyses (e.g., Ling et al., 2016). Super resolution analyses could also be applied to the Landsat archive to provide an historical perspective to the kilns. All these datasets could be mined using deep learning methods (e.g., Yu et al., 2016; Zhong et al., 2017; Weng et al., 2017), which promise to improve feature detection by automated methods (Gong and Junwei, 2016). The openness of high resolution satellite data via the Google Earth geobrowser has been key in this study and will be going forward, particularly to organisations for whom resources are limited, such as NGOs and local government (Lehmann et al., 2017). Moreover, the ability to process the large amounts of these data for regional to global analyses via new cloud solutions that dovetail with the open data, for example Google Earth, but also ESA Cloud Toolbox and NASA Earth Exchange (Klein et al., 2017) is important. Also important will be to continue to harness the power of the crowd; after all sustainable development is everyone's business (Walters, S. - https://theconversation.com/the-sdgs-wont-be-met-without-active-citizens-fortified-with-new-knowledge-81279). Dissemination of key findings can be accomplished using the aforementioned geobrowers - having "virtual globes" enables communication of data and research findings in an intuitive three-dimensional (3D) global perspective worldwide (Yu and Gong, 2012; Gorelick et al., 2017). Reaching out to citizens is also important from a data collection point of view. As has been demonstrated in this paper the power of the crowd can assist in the mapping effort. This work extends the growing literature on the value of crowdsourcing linked to analyses of remotely sensed data that benefits from a range of online platforms (e.g. Heipke, 2010; Bastin et al., 2013; See et al., 2015).

Fig. 7. An example of a Fixed Chimney Bull's Trench brick kiln @31.5385546, 75.9813821 – note the emissions from the chimney stack. From Digital Globe's WorldView-2 satellite system; pan-sharpened natural colour at 50 cm resolution; captured in November 2015. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Despite these promising research avenues there are challenges ahead in linking the statistical estimation reported here to slavery activity. This requires follow through, but at least, for the first time the scale and specific locations of the industry are now known. The only other investigation of this nature was conducted on Lake Volta by Tomnod and this deemed very important as it helped to provide external and verified evidence that slavery was occurring. It had already been noted that child slavery is a major issue in the fishing industry of this lake and this study using remotely sensed data was hugely important as it corroborated a survey conducted by the Ghanaian Government which estimated that 35,000 children are involved in the fishing sector with a significant proportion working in conditions of modern slavery, as children are seen as a cheap, malleable and easily disposable source of labour (Tomond and World Freedom Fund, 2015). Wall-to-wall high spatial remotely sensed data was crucial and the methods in using these data are transferable. Indeed, there are examples of slave labour in other known industries that could benefit from remote sensing analyses, such as quarrying, mining, and illegal deforestation.

5. Conclusion

This work presents the first rigorous estimate of the number of brick kilns present across the 1,551,997 km^2 area of south Asia known as the 'Brick Belt'. The estimate of 55,387 kilns, averaging 0.03575 kilns per km^2, was produced using a robust method that can be easily adopted by key agencies for evidence-based action (i.e. NGOs, etc.) and was based on freely available and accessible high resolution satellite sensor data. Through this study, we have taken an initial step in work to support the global political commitment to ending modern slavery, as set out by the United Nations' Agenda 2030 for Sustainable Development Goal (SDG) number eight, section 8.7. The work here should contribute to a wider effort that requires all nations to put forward assets and people to be used in efforts to eradicating slavery once and for all. By using remotely sensed data, and associated geospatial science and technology, the lack of reliable and timely, spatially explicit and scalable data on slavery activity that has been a major barrier could be overcome. Indeed this is just one of many examples of how crucial remotely sensed data are to achieving a more sustainable world (Esch et al., 2017; Xiao et al., 2018).

There are many research avenues to pursue to ensure that there is an appropriate and fit-for-purpose data platform that helps meet the challenge of ending modern slavery. These avenues have been discussed with a caution that an emphasis on efficient use of resources (including financial) is key. There is a long way to go; nonetheless it is hoped that through this initial work a small contribution to the effort has been accomplished. As the process of achieving key Sustainable Development Goal targets will show, there are global benefits to ending slavery, for economies, peace, health, and the environment (which link a number of SDGs together). Ending slavery will mean a better world for everyone: safer, greener, more prosperous, and more equal. Critically, remote sensing has a major role to play in achieving this "Freedom Dividend".

Acknowledgements

This publication uses data generated via the Zooniverse.org platform, development of is which funded by generous support, including a Global Impact Award from Google, and by a grant from the Alfred P. Sloan Foundation. We are also grateful to Google for the opportunity afforded by their platform and the Rights Lab (Beacon of Excellence), University of Nottingham for funding. The reviewers (including Mike Steven) are thanked for their supportive feedback as are the volunteers who participated in the "Slavery from Space" project on Zooniverse.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.isprsjprs.2018.02.012. These data include Google maps of the most important areas described in this article.

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