Slavery from Space: An analysis of the modern slavery-environmental degradation nexus using remote sensing data

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BSc (Hons)

Thesis submitted to the University of Nottingham
for the degree of Doctor of Philosophy

March 2020

Acknowledgements

There are many people to thank for their assistance and support throughout the production of this thesis. When I first began more than three years ago I was starting a Research Masters and through the wonderful opportunities I have been afforded by the University of Nottingham I am instead producing a thesis for the submission of a degree of Doctor of Philosophy. I would therefore like to take this opportunity to thank Zoe Trodd and Todd Landman for offering the funds to cover a conversion of my 'never-completed' Masters project to a fully funded PhD which has opened many doors and seen me join the Rights Lab as a PhD Student and now Research Associate. Within the Rights Lab I would also like to thank my colleagues for their advice, guidance and support throughout the research process; special shout-outs to Jacqui and Nathalie whom I am constantly bombarding with questions but they never hesitate to help with my queries as I figure this whole 'being an academic' thing out.

I would like to take the opportunity to thank my fellow co-authors on my publications: Chloe Brown, Christopher Ives, Stuart Marsh, Sarah Owen, and Jessica Wardlaw. Further, I would like to thank Jessica Sparks for her mentorship and insight into the fisheries sector, collaborative know-how and encouragement and support throughout not only my PhD but also my employment – I look forward to working more in the future. Special mention goes to Giles Foody who was my supervisor in my first year and has provided sound advice regarding numerous remote sensing methods throughout the course of my studies. Moreover, I wish to thank Xiaodong Li and David Brown respectively, for their knowledge of machine learning which enabled some of the work in this thesis to take place, and their work on the modern slavery-environment nexus, which has paved the way for this research output and hopefully many more to come.

Furthermore, my fellow co-authors and supervisors Professor Doreen Boyd and Professor Kevin Bales. Doreen has shown great support throughout all of my University studies, being my Undergraduate tutor, my remote sensing lecturer, Undergraduate Dissertation Supervisor, and finally my PhD Supervisor. She has quite literally taught me everything that I know about remote sensing and it has been a pleasure and privilege to work for and alongside her within the School of Geography and the Rights Lab during the infancy of the ‘Slavery from Space’ work. She has also been a great mentor in allowing changes of direction and supporting my movements into the study of modern slavery-environmental impacts. Kevin has provided a clinical eye, and great insight into modern slavery – I can always rely on an email and his books, and without his pioneering work on modern slavery, the environment, and the need to apply remote sensing data, this thesis would not be possible. Therefore I am wholly grateful for the support, wisdom and help you have both provided.

Special thanks to Professor Suzanne McGowan and Dr Gary Watmough for conducting the *viva voce* and providing feedback; and thanks to Dr Michela Mariani for moderating the session.

Finally, I wish to thank my family and friends who have supported me being a ‘perpetual student’ and explaining that no ‘she works at the University now too!’ To my friends Alicia, Bethany and Emmelia who have shown great support and always asking how it’s going, I appreciate you taking time out of your busy schedules to ask. Last, to my Mum, Dad, brother Reece, and Nan – thank you for all your support, dealing with my stressful outbursts and reading through all of my work even if you don’t really know what it is about. This would not have been possible without you and I will be forever grateful that I have such a wonderful support network around me.

This thesis is dedicated to my Nannan – who saw me start University but never saw me finish. Here I am doing it a second time.

Abstract

Modern slavery has been connected to degradation of the environment, and has been found to contribute to anthropogenic climate change. Three sectors have been investigated using satellite Earth Observation (EO) data in order to provide a unique insight into the modern slavery-environmental degradation nexus. Remote sensing affords a unique ability to measure and understand these ecological changes over large timescales, and vast geographical areas. A local, regional, and global assessment of sectors known to heavily use modern slavery practices within their workforce has been undertaken using a variety of remotely sensed data sources and products. Fish-processing, brick kilns, and tree loss associated with multiple sectors, have all been analysed.

Levels of environmental damage in the affected sectors have been noted, and measured using satellite EO data. These effects have included: tree loss of mangroves and tropical forests for fish-processing camps and oil palm plantations; the emission of pollutants which contribute to atmospheric climate change; the extraction of resources, such as groundwater and good-quality topsoil; and changes to landcover and land-use in areas that are important for production of food and economic support for large populations.

Over the course of this investigation, ten post-harvest fish-processing camps have been located, and the first replicable methodology for estimating the number of brick kilns in the South Asian ‘Brick Belt’ region has been provided – where open access satellite EO data enabled the estimation of 55,387 brick kilns. The latter has since enabled machine learning methodologies to provide accurate locations and kiln ages which have assisted in the environmental assessment of this large-scale transnational industry. Furthermore, if modern slavery practices were eliminated from this industry, the environmental impact of the brick-making could be reduced by the equivalent of almost 10,000 kilns. Finally, tree loss has been quantified and the policy implications of deforestation and forest degradation as a result of modern slavery have been explored in four countries. Ultimately, there are a large variety of environmentally degrading activities known to use modern slavery practices that may be explored using satellite EO data. Remote sensing throughout this thesis has enabled the exploration of these implications for some sectors, and proved the proof of concept that additional data acquisition from remotely sensed sources, can support in the overall goal of assisting in the understanding and eradication of modern slavery.

Satellite EO is an underutilised methodology within the antislavery community and, as shown within this thesis, there is the power to investigate the environmental implications of these sectors which have had numerous documented cases of modern slavery. In order to achieve the Sustainable Development Goals (SDGs) – particularly target 8.7 which aims to end modern slavery by 2030 – multiple avenues of investigation are required to understand, locate, and eradicate modern slavery. Applying remote sensing to assess the ecological impact of these cases is one such avenue that can provide information to assist in this achievement, and support the success of multiple SDGs.

The author would like to acknowledge that they have written the thesis from the starting point of being a non-survivor.

Contents

List of Figures

List of Tables

Chapter 1: Introduction (Extended Abstract)

Modern slavery (defined in Table 1.1) is a global, and yet hidden, problem that is estimated to affect 40.3 million people (ILO 2017a) – approximately 15% of those people are subjected to modern slavery undertaking activities thought to be linked to environmentally degrading activities (ILO 2017a: 32). As the issue is hidden, there is little hard evidence regarding modern slavery; rectification of this issue has begun as modern slavery is included within the United Nations' (UN) Sustainable Development Goals (SDGs) (UN 2016a) (Table 1.1). The SDGs serve to promote multiple linking goals and interactions to achieve sustainable development by 2030. Modern slavery can therefore be addressed through multiple lenses of investigation. Within this thesis the emphasis is upon the impact of environmental degradation associated with sectors known to use modern slavery. Addressing modern slavery can provide benefits for environmental protection, and vice versa.

Table 1.1: Table of definitions for some of the key terms and ideas used throughout the thesis.

Term	Definition
Modern Slavery	As noted in the Bellagio-Harvard Guidelines, modern slavery is the status or condition of a person over whom control, tantamount to possession, is exercised (Research Network on the Legal Parameters of Slavery 2012). This includes threats, violence, coercion and abuse of power, or deception (Walk Free 2016: 158). This is an umbrella term which is recognised in the United Kingdom's antislavery legislation and includes varied forms of exploitation, such as: institutions and practices similar to slavery, the slave trade, slavery, forced labour, servitude and human trafficking.[a]
Remote Sensing	Monitoring of the Earth's surface from a distance (in this case using satellite Earth Observation (EO) data) with sensors that measure electromagnetic radiation emitted from features upon the ground; thus yielding useful information to understand a number of Earth systems (adapted from Curran 1985).

Sustainable Development Goals	Adopted in September 2015, and launched 1 January 2016, the SDGs are the United Nations' flagship development policy working toward ending poverty, protecting the planet and ensuring peace and prosperity by 2030 (UNDP 2019). 17 goals are noted, requiring integrated solutions, including the use of geospatial technologies (UN 2012: 70).

[a] The term 'modern slavery' has received criticism over time as it encompasses a number of different exploitative practices and can be conflated with other forms of abuses which fall under a 'spectrum of exploitation'. For example, whilst modern slavery is a term commonly used within the UK, within the United States, the term human trafficking is more prolific, this is despite the legislation often referring to the same forms of exploitation. It can therefore be suggested that as a dynamic phenomenon it is difficult to define the nuances of exploitation in such a term (Mende 2019). Others believe that the term is 'vague' and is used 'selectively' (Martins Jr. 2016); something which many in the antislavery community disagree with (Gupta 2016), and which is supported by the definitional use within national legislation and international guidance (such as the SDGs).

Whilst there are a number of further reasons against the use of the term 'modern slavery' – outlined, for example, by Dottridge (2017); and there is need for the inclusion of survivors within the definitional process (Nicholson *et al.* 2018) – the widespread use of the umbrella term was deemed appropriate in the context of the following papers contained in this thesis.

Finally, it is important to note that the SDGs link modern slavery and child labour within the same goal (SDG target 8.7) despite child labour being a separate issue and one that contains critiques related to the western ideals of children and their role within society (Wijen 2015). This is despite children being a key part of household income contribution within many countries globally. Child labour is not investigated as part of this thesis specifically but is an adjacent problem that must be kept in mind when assessing issues of exploitation.

This thesis aims to assess the impacts of modern slavery on the natural world; achievement of this requires a methodology which can address this impact at a global scale and across time to provide further context to the relationship between modern slavery and environmental damage. The chosen methodology – remote sensing (see Table 1.1) – can be used to analyse uncertain and dangerous areas for partner organisations on the ground, assess the prevalence of industries, and assist in understanding the changing relationship between industries using workers subjected to modern slavery and their impact on the environment. Modern slavery awareness and understanding began to increase in the 1990s, however it is only since the launch of the

SDGs that there has been a clear effort to collect data. Therefore gaps exist. Remote sensing can be used to investigate the implications of modern slavery on the environment across a global scale. Furthermore, since there are at least 50 years of data available in the satellite EO data archives, a look back in time across the Anthropocene is possible. As a result, to understand the modern slavery-environmental degradation nexus (Brown *et al.* 2019) it is suggested within this thesis that Earth Observation (EO) data be used.

The thesis uses a range of remotely sensed data types, and their derived products as a proxy, to investigate the environmental impacts of modern slavery (Table 1.2). Remote sensing has historically been focused toward applications of environmental assessment (Boyd and Foody 2011), yet can also provide insight into the modern slavery-environment nexus. Indeed geospatial technologies were touted as an important form of data capture during the formulation of the SDGs (UN 2012: 70). Emphasis is placed on the environmental goals; therefore application of this methodology is possible. As shown in the sensors and available data, EO has a wide number of applications – from landcover mapping to monitoring atmospheric conditions – that can be used to assess the juncture between modern slavery and ecological systems. Applying remote sensing to these industries allows the production of data to support evidence-based decision-making and contribute to the growing body of data relating to the integration of EO with SDG targets and indicators (Anderson *et al.* 2017; Scott and Rajabifard 2017; Andries *et al.* 2018; Kussul *et al.* 2019; Lehmann *et al.* 2019; Masó *et al.* 2019; Revilla 2019; Estoque 2020). As already stated, remote sensing provides global (almost daily) coverage of the planet, this capability enables the identification of trends on the ground and within the atmosphere often in remote and hard to access locations. The industries assessed here occur in several areas, on differing scales. However, by assessing these sectors using satellite EO data we can provide timely insight for ongoing monitoring as well as a historical assessment to support the understanding of industries using modern slavery over space and time. Combining data sources can assist in the ‘sat-truthing’ of high-risk sectors where ground-truth data are currently unavailable or inaccessible; identifying risks to ecological systems, and locating possible sites of modern slavery.

The three industries investigated were chosen due to their known involvement in the degradation of the environment as a result of modern slavery (Figure 1.1). Evidence for the nexus within these sectors – fish-processing camps, brick kilns, and tree loss – has been identified previously (see Bales 2012, 2016; Jensen 2013; Brickell *et al.* 2018; Brown *et al.* 2019).

Table 1.2: Details of the satellite sensor data accessed and used within the analyses of this thesis; as well as the derived data products which were used. Data have been split into optical, atmospheric and derived products.

Optical Data							
Satellite	Sensor	Bands[a]	Resolution Spatial (m)[b]	Provider	Analysis Chapter/Paper	Accessed	Literature
Landsat 7	Enhanced Thematic Mapper Plus (ETM+)	7(1)	30	USGS	3/2	EarthExplorer	USGS (2016)
Landsat 8	Operational Land Imager (OLI)	8(1)	30				
Doves	PlanetScope	4	3	Planet Labs	3/2	Planet Explorer	Planet Labs (2019)
RapidEye	–	5	5				
Sentinel-2	Multispectral Imager (MSI)	13	10	ESA		Copernicus Open Access Hub	Drusch *et al.* (2012)
WorldView Series	–	4-8(1)	0.31	Digital Globe	3/2	Google Earth Pro[c]	DigitalGlobe (2018)
GeoEye-1	–	4(1)	0.41		4/3		
QuickBird	–	4(1)	0.65				ESA (2019a)
SPOT Series	–	4(1)	1.5	CNES/Airbus	3/2	Google Earth Pro[c]	ESA (2019b)
Pléiades-1A/B	–	4(1)	0.5		4/3		ESA (2019c)
Atmospheric Data							
Sentinel-5 Precursor (5p)	Tropospheric Monitoring Instrument (TROPOMI)	14	7500×7500	ESA	5/4	Copernicus Open Access Hub	Veefkind *et al.* (2012)
Orbiting Carbon Observatory-2	OCO-2	3	1290×2250	NASA	5/4	Jet Propulsion Laboratory (JPL)	Osterman *et al.* (2018)
Derived Data Products							
Source	Data Component	Measures					

Global Forest Watch (GFW)	Landsat (5, 7 and 8)	Global Tree Cover	–	–	World Resources Institute	6/5	Global Forest Watch Google Earth Engine[c]	Hansen *et al.* (2013)
MODIS Landcover Data	MODIS	Land Cover	–	500	NASA	5/5	Earth Explorer	Sulla-Menashe *et al.* (2019)

[a] Bands are the total number of bands measured plus a note if there is a panchromatic band measured: denoted in values as multi (pan).

[b] The most common spatial-resolution of the data are included for the visible and multispectral bands; they are often smaller for the panchromatic; more details can be found in the literature and mission sites for each of these programmes.

[c] Google Earth Pro (Yu and Gong 2012) and Google Earth Engine (GEE) (Gorelick *et al.* 2017) both represent the development of "virtual globes" to enable all users to access and analyse freely available satellite EO data sources, and create replicable methodologies without the cost of purchasing the data or software. These data sources have been chosen as they provide methodologies and data that are open and available to other researchers across the antislavery space to increase understanding of the modern slavery-environmental degradation nexus (Brown *et al.* 2019) at a global scale, even if funds are limited.

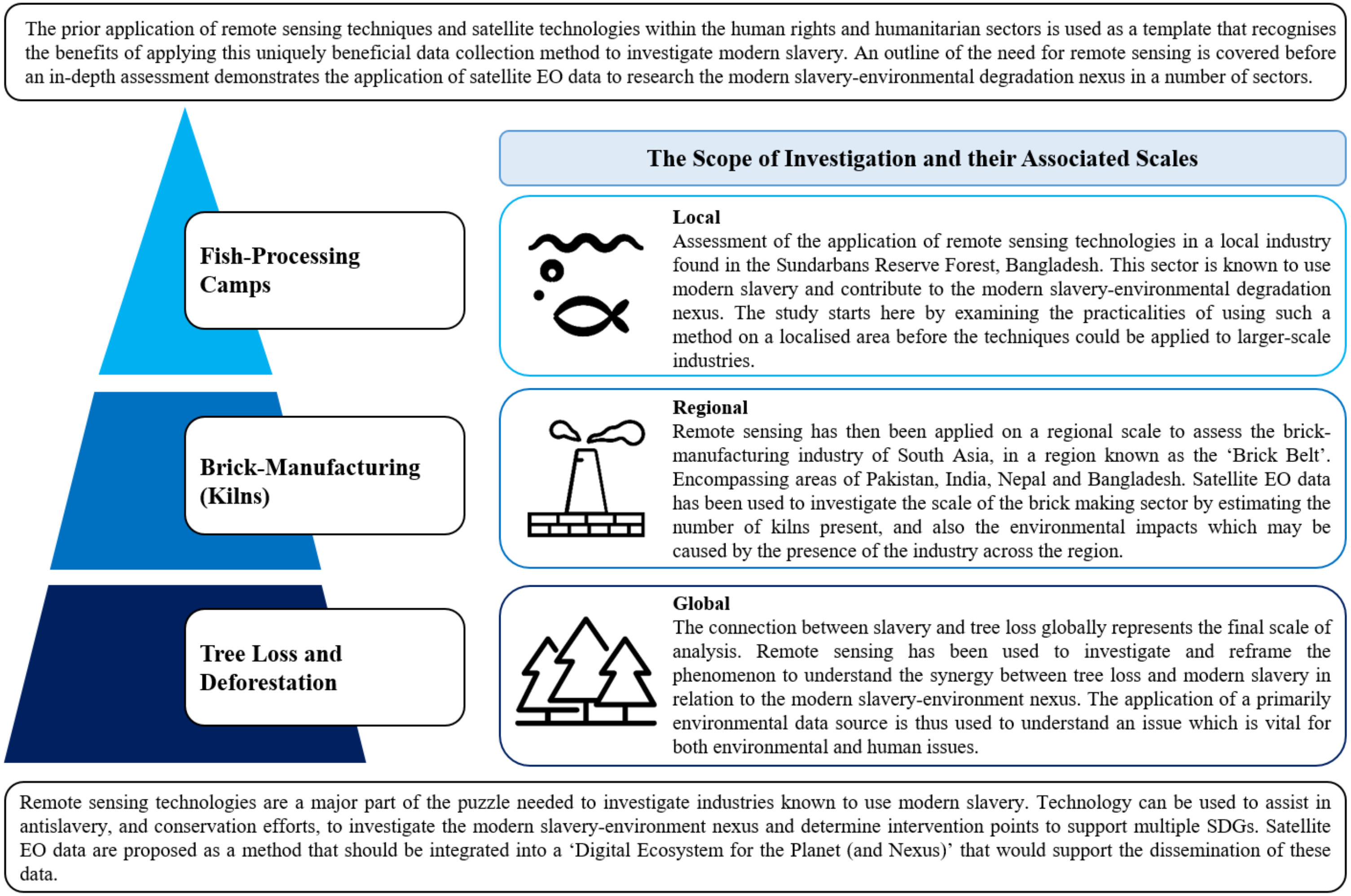

Figure 1.1: Detailed structure of the thesis. Exploring the application of remote sensing for the modern slavery-environment nexus in three industries (fish-processing camps, brick kilns, and tree loss) across varying scales.

These industries are operating in protected conservation areas (such as mangrove removal for the development of fish camps in the Sundarbans, and the loss of tropical forest for oil palm and cattle ranching); and/or at large scales, contributing to peaks in air pollution and emissions influencing climate change (for example brick-manufacturing in South Asia). The scale and scope of these sectors mean investigating the modern slavery-environment nexus is only truly possible at present through remote sensing. To fully understand the environmental implications of modern slavery, remote sensing must be incorporated into the study of the issue; without ending modern slavery, the associated environmental damage will be not be fully eradicated and the cycle of degradation is likely to continue. Moreover, multiple SDGs are interconnected with these industries (Figure 1.2). Therefore, investigating the social-ecological dimensions of modern slavery may provide data to support the achievement of these targets.

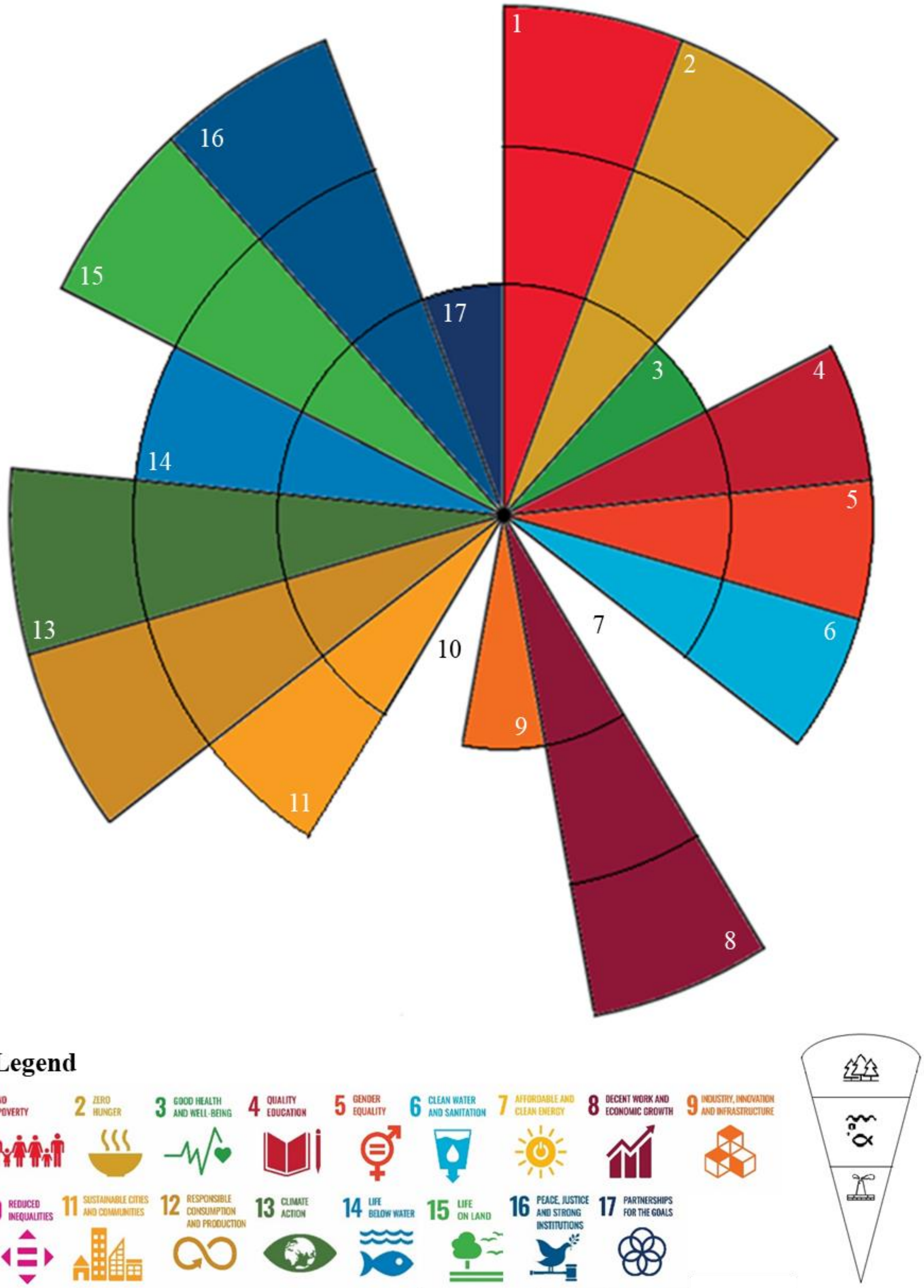

Figure 1.2: Sustainable Development Goals which link to the industries researched within this thesis. All are linked to SDG 8 and SDG 16 as they reference both modern slavery and human trafficking respectively. This is along with several others. SDGs 7 and 10 are not connected with any sectors within this thesis. The interior circles denotes the brick-manufacturing sector, followed by the fish-processing camps, finally the outer circle represents those SDG targets and indicators which are linked to tree loss and deforestation throughout this thesis. Colours and numbers denoted the relevant SDGs.

The thesis addresses the problem of the modern slavery-environment nexus in the three sectors, at three scales: local, regional and global (Figure 1.1) – fulfilling the aim of:

Identifying the environmental impacts of sectors known to use practices of modern slavery via the application of satellite EO data within three specified sectors. Thus determining the viability of remote sensing to support antislavery research.

This is undertaken by demonstrating the unique role of satellite remote sensing data to investigate the modern slavery-environmental degradation nexus (Brown *et al.* 2019). Applying these data has a myriad of benefits. EO data are important due to their historical observations of the Earth, their ability to monitor large geographic areas in remote locations, and over long timescales. Therefore, they will prove useful in achieving the overall goals of the interconnected social-ecological SDGs.

Five papers are included in the thesis (see Table 1.3), summarised and explored in the 'Discussion and Recommendations' section (Figure 1.3). Paper 1 provides an overview of the application of remote sensing for the wider study of modern slavery and the integration of the methodology within the antislavery community; as well as noting the types of industries which may be investigated to further understand the modern slavery-environment nexus. This is followed by the first original piece of research; Paper 2 investigates the social-ecological impacts of post-harvest fish-processing camps within the Sundarbans mangrove forest, Bangladesh – identifying the location, number and environmental damage caused by the camps and linking this to the issue of modern slavery. Both Papers 3 and 4 investigate the brick-manufacturing sector of South Asia within a region commonly known as the 'Brick Belt'. The first estimates the prevalence of the kilns – as without this information there is no way to understand the environmental impacts of the sector. The second addresses these environmental impacts, looking at the extraction of natural resources, changes to landcover and assessing the impact of the pollutants released from the kilns. Finally, Paper 5 analyses the co-occurrence of tree loss and modern slavery by linking environmental protections and prevalence of modern slavery, alongside insights into previous, and forecast, measures of tree loss and illegal logging.

Table 1.3: List of Papers included in the thesis with the associated Chapters in which they are included. Author contributions for all Papers (and proposed Papers) are also included. Full copies of the published Papers are available in the Appendices.

Chapter/ Paper No.	Title, Authors, and Author Contributions	Status	**Journal** *(Target Journal)*
2/1	Analysing slavery through satellite technology: How remote sensing could revolutionise data collection to help understand the socio-ecological dimensions of modern slavery (**Appendix A**) – *Bethany Jackson, Kevin Bales, Sarah Owen, Jessica Wardlaw and Doreen S. Boyd* BJ led the production of the manuscript including concept development, primary literature searching, and the write-up and editing of the full manuscript. SO took the lead on the environmental nexus portion with assistance from BJ. JW led the crowdsourcing section. DB and KB provided additional resources, guidance on ideas and structure, and provided annotated edits of the drafts.	Published (2018)	Journal of Modern Slavery
3/2	Remote sensing of fish-processing in the Sundarbans Reserve Forest, Bangladesh: An insight into the modern slavery-environment nexus in the coastal fringe – *Bethany Jackson, Doreen S. Boyd, Christopher D. Ives, Jessica L. Decker Sparks, Giles M. Foody, Stuart Marsh and Kevin Bales* BJ conducted the analysis of the remote sensing data for the fish-processing camps in the Sundarbans under guidance from DB, GF and SM. The work used data collected by KB as the basis for the ground-truthing of the work. Development of the manuscripts' narrative was assisted by CI and JS. Supplementary materials and the connections between modern slavery and environmental vulnerability were produced structured and formed by BJ and CI. Finally extensive comments and were provided by all authors, in particular DB, CI and JS.	Submitted For Review	*Maritime Studies (MAST)*
4/3	Slavery from Space: Demonstrating the role for satellite remote sensing to inform evidence-based action related to UN SDG number 8 (**Appendix B**) – *Doreen S. Boyd, Bethany Jackson, Jessica Wardlaw, Giles M. Foody, Stuart Marsh and Kevin Bales* Primary analysis and data collection from the estimation phase was undertaken by BJ with guidance from DB and GM. The primary application of remote sensing to estimate the number of kilns was developed by BJ, DB, GM and KB. The crowdsourcing data and experiment was devised and assessed by BJ, JW, GM and SM. The expert comparison was conducted by BJ, the independent adjudication by DB and the crowd analysis by JW. Write-up completed by DB with assistance, and editing, by BJ.	Published (2018)	ISPRS Journal of Photogrammetry and Remote Sensing

5/4	Using remote sensing to analyse the modern slavery-environment nexus of the South Asian brick-manufacturing industry: A slavery from space investigation – *Bethany Jackson, Doreen S. Boyd and Kevin Bales* Concept design was developed by BJ and DS; with the primary data collection and analysis being conducted by BJ. The write-up of the analysis was completed by BJ, with edits by DB and KB.	In Prep	*Sustainability*
6/5	Understanding the co-occurrence of tree loss and modern slavery to improve efficacy of conservation actions and policies (**Appendix C**) – *Bethany Jackson, Jessica L. Decker Sparks, Chloe Brown and Doreen S. Boyd* Concept development and write-up was completed by BJ and JS. Primary analysis was undertaken by BJ, with assistance on the Mozambique section by CB. DS provided the method for the analysis of the EPI/GSI which drove the direction of the paper, as well as feedback and edits on the manuscript.	Published (2020)	Conservation Science and Practice

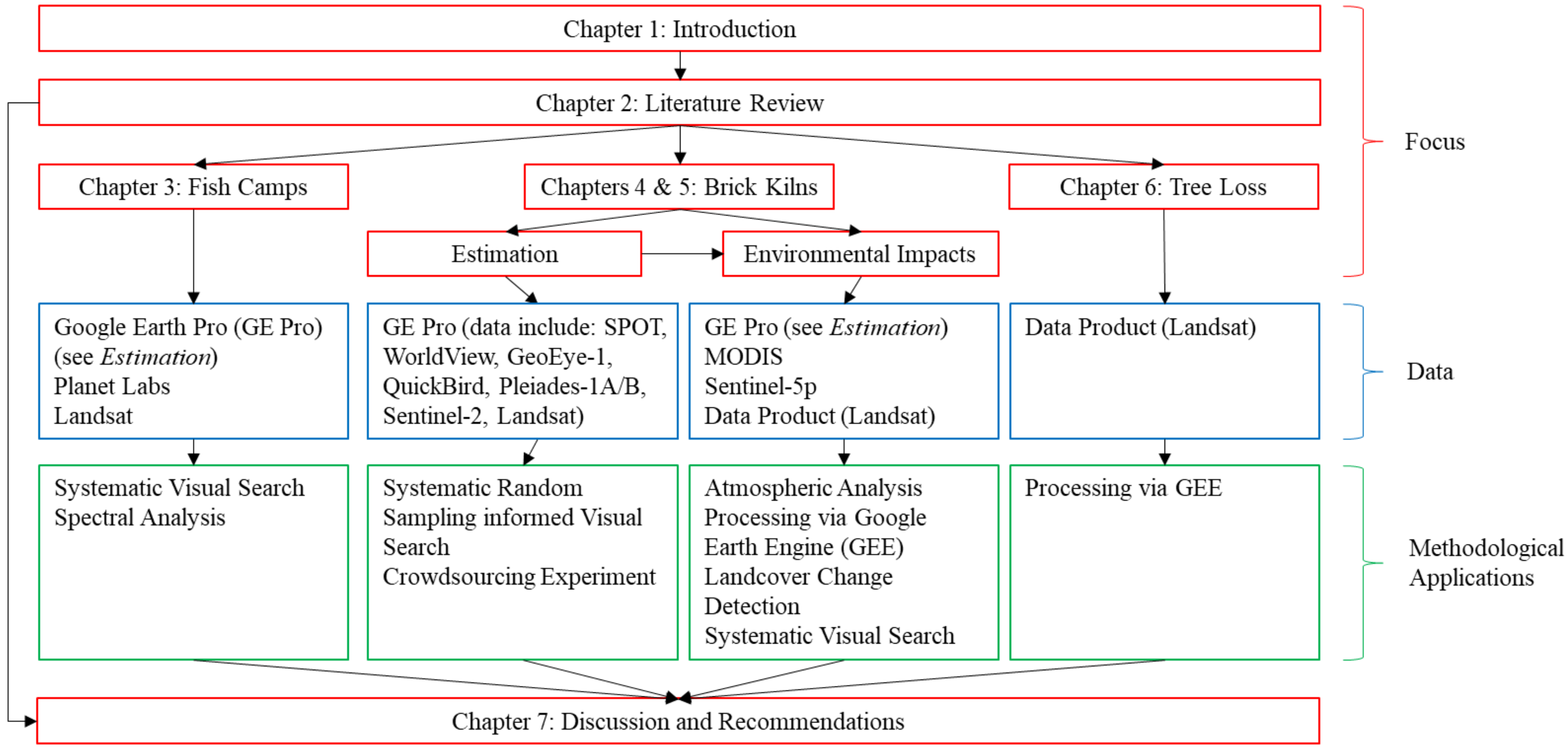

Figure 1.3: Flow Chart showing the linkages between the Chapters/Papers noted in Table 1.3 with relation to the methods and data used as part of the analyses.

Overall, the research contained in this thesis has demonstrated that there is an environmental impact by modern slavery causing negative effects upon the Earth's landscape (such as soil degradation, pollution of water and the ground, tree loss, and over-extraction of natural resources) and atmosphere (for example, via the release of greenhouse gas emissions (GHGs), and limiting of climate change mitigation as a result of tree loss). Remote sensing has been successfully used to assess the scale, location and damage caused to the mangrove forest of Bangladesh by the operation of fish-processing camps. Additionally, the scale of the brick-making industry in South Asia has been established, which made it possible to determine the degradation caused across the region from the extraction of groundwater and topsoil, moreover addressing GHGs emission and the impact of kilns on landcover – suggesting that brick kilns using modern slavery may be in conflict with several SDGs. Finally, low environmental protections are likely linked to higher levels of modern slavery as a result of criminal actors being able to exploit the land and people with impunity (Bales 2016). This has been assessed in relation to the global issue of tree loss where efforts need to be made to combat the removal of trees to limit the impacts of climate change and modern slavery. Consequently, satellite EO data is a beneficial tool which can be used to investigate the modern slavery-environment nexus; this must be combined with other technological and traditional data collection methods to establish the true scale of modern slavery as part of a 'Digital Ecosystem for the Planet (and Nexus)'.[1] Remote

[1] The 'Digital Ecosystem for the Planet' is a proposal from the United Nations Environmental Programme (UNEP) which seeks to provide a platform that will draw together key environmental datasets, geospatial data and experts to tackle global environmental issues (UNEP 2018; Campbell and Jensen 2019). Proposals at present contain references to indigenous communities and the monitoring of environmentally degrading activities by people, but at present they ignore the possible impact of modern slavery. In Chapter 7 it is proposed that the concept of the modern slavery-environmental degradation nexus (Brown *et al.* 2019) can also be combined with this system to support the environmental SDGs.

sensing is a vital addition to the study of the nexus and should continue to be incorporated to assist further ground-data collection relating to the social-ecological effects of modern slavery across many other sectors, at varying scales, both temporal and spatial.

Chapter 2: Literature Review

This Chapter/Paper (see Table 1.3) has been adapted and updated (with recent relevant literature) from its original published version in the *Journal of Modern Slavery* which is contained in Appendix A.

Analysing slavery through satellite technology: How remote sensing could revolutionise data collection to help understand the socio-ecological dimensions of modern slavery

Globally an estimated 40.3 million people are currently engaged in conditions of modern slavery (24.9 million in forced labour, and 15.4 million in forced marriage), a quarter of whom are children (ILO 2017a, 2017b; Walk Free 2018).[2] As many as 15-

[2] This figure was first estimated in 2017 when the International Labour Organization (ILO) partnered with Walk Free, the producers of the Global Slavery Index (GSI). The figure is the most current reliable global estimate available, and was determined using surveys, interviews and datasets. The global estimate was first produced for the 'Global Estimates of Modern Slavery' report published by the ILO (2017a, 2017b). These results were then expanded upon in the 2018 edition of the GSI which provides a breakdown on figures by country (Walk Free 2018). However, there have been a number of critiques of the GSI approach from the start of the project (see Gallagher 2014), particularly regarding the methodologies used in the Index, and the alterations of the definitions of 'modern slavery' used within each edition (Guth *et al.* 2014; Gallagher 2017; Mügge 2017). These critical comments also apply to the expansion of regional level data to country level analyses within this version of the GSI (Silverman 2018) where the accuracy for these estimates are not provided. For example, a multiple systems estimate (MSE) for the UK estimated between 10,000-13,000 people found under conditions of modern slavery (Silverman 2014; Bales *et al.* 2015); whereas by the 2018 GSI this had increased to 136,000 (Walk Free 2018). Whilst there are criticisms of the application of MSE to measure modern slavery (Whitehead *et al.* 2019) this rise in modern slavery victims is a ten-fold increase, and is likely to be an overestimation – when assessed on a national level – due to the extrapolation of sampling from developing countries to those in developed Asia, Western Europe and North America, where no primary samples were undertaken for the 2018 GSI (Silverman 2018). Moreover, issues of bi-directionality, lack of direct

30% of the overall estimate could be engaged in environmentally degrading activities (ILO 2017a) equating to 6-12 million people.[3] To tackle modern slavery, and a number of other developmental challenges, the United Nations (UN) created the Sustainable Development Goals (SDGs), which came into force on 1 January 2016, replacing the Millennium Development Goals (MDGs) (World Bank and UNDP 2015). The MDGs aimed to remove people from situations of poverty, whereas the SDGs aim to provide an environment that will keep them out of poverty for good. The remote sensing community has long worked to tackle issues within the SDGs, primarily those related to the environment. However, an increasing number of applications relate to targets and indicators that have social and cultural implications for sustainability across a number of fields (Weng 2016). One target that could benefit from the use of geospatial information, is target 8.7 (part of SDG 8), which aims to tackle forms of modern slavery and child labour. Target 8.7 stipulates society must:

> Take immediate and effective measures to eradicate forced labour, end modern slavery and human trafficking… and by 2025 end child labour in all its forms. (United Nations 2016a: 24, 2016b)

application, and the changing methodology to measure forced labour and forced marriage have been noted (Bermudez and Stewart 2018).

[3] Figures are based on the environmentally degrading sectors and the proportion of forced labour contained within them from the GEMS (ILO 2017a: 32). The lower estimate (15%) is made up of the proportion of labour contained in the agricultural, forest and fishing sectors (11% combined), as well as mining and quarrying activities (4%). The upper estimate (30% of exploitative labour being environmentally damaging) includes those sectors previously noted, in addition to manufacturing (15%). Whilst these figures may be inaccurate, they are the best indication that we have at present to enable understanding on the links between the modern slavery-environment nexus (Brown *et al.* 2019). These figures are particularly important as data assessing this interaction are currently lacking.

With the goal firmly set, governments, businesses and campaigners have joined the fourth antislavery movement to help eradicate modern slavery for good.[4] However, technological advancements for data collection on modern slavery could hold the key to end this fight; particularly when seeking to understand the environmental implications of modern slavery.

The use of satellite Earth Observation (EO) data for tackling the SDGs is a recent and growing phenomenon (Trinder *et al.* 2018) that is being touted as a data source that can observe the entire 'human-environment nexus' – as promoted by organisations such as the Group on Earth Observations (GEO) – in relation to the SDGs (Sudmanns *et al.* 2019). Here it is suggested that remote sensing could be an important form of data acquisition to enhance understanding of the social-ecological investigation of modern slavery. Anderson *et al.* (2017) explored a range of possible uses for remote sensing technology and the SDGs, such as: measuring the impact of environmental change, ecosystem monitoring, measuring climatic variables, and investigating the implications of varied population dynamics. These examples barely touched on Goal 8, only briefly mentioning other economic indicators within the goal but never explicitly referring to target 8.7; however, they can be used as a basis to support the investigation of the nexus between modern slavery and environmental degradation (Brown *et al.* 2019). Moreover, the use of remote sensing exploring cultural heritage has been examined (Xiao *et al.* 2018). The work by Xiao *et al.* (2018) is built upon a range of studies that had developed methods to investigate archaeological sites using remotely sensed data,

[4] The fourth antislavery movement is one of the key drivers of current antislavery scholarship: see Trodd (2017) "Introducing the Rights Lab", http://blogs.nottingham.ac.uk/rights/2017/08/04/walkfree7/ (retrieved 20 August, 2018); and Bales (2016-2019) "The Antislavery Usable Past" Arts & Humanities Research Council, https://ahrc.ukri.org/research/casestudies/the-antislavery-usable-past/ (retrieved 20 August, 2018).

which are commonly conducted using radar, LiDAR and imagery analysis from Unmanned Aerial Vehicles (UAVs) or satellite EO data. Their study expressed the importance of these methods in the context of supporting elements of both SDG 8 and SDG 11 which both include references to cultural heritage. Overall Xiao *et al.*'s (2018) study demonstrates the benefit of remote sensing technology to protect cultural heritage, and suggests where such technology can be used in the future. The studies mentioned show a clear movement in the remote sensing field to produce research which supports the SDGs and the associated 169 indicators. Others have also noted the link between satellite EO data and the SDGs (e.g. Andries *et al.* 2018; Kussul *et al.* 2018; Masó *et al.* 2019). Moreover, applications to investigate direct and adjacent SDG issues, such as poverty and literacy rates, have been combined with satellite EO data (see Watmough *et al.* 2013a, 2013b, 2016, 2019); thus, providing data to support the SDGs.

While there is limited, but growing, information referring to geospatial technology and the SDGs, there have been many uses of remote sensing data for humanitarian and human rights research and practice, with new innovations in the types of data used for analysis (Larsson 2016; Pierro *et al.* 2017). Non-governmental organisations (NGOs) are beginning to invest in the use of these technologies to tackle human rights violations, for example the work of Amnesty Decoders (Amnesty International 2018a). The development of these applications represents an important step towards the use of remote sensing for social challenges.

2.1 Remote Sensing for Humanitarian and Human Rights Cases

Remote sensing is the practice of collecting data predominantly passively (using reflected sunlight from the Earth's surface to measure the reflectance of features on the ground to determine their properties) from a distance (see also Table 1.1). Since the first satellite was launched in the 1950s, capabilities to monitor the Earth have continued to develop. There were more than 600 EO and earth science satellites orbiting the planet in 2017 collecting large volumes of data with untapped potential to investigate industries, known to be utilising modern slavery practices, from above (Union of Concerned Scientists 2017). There are large temporal sets of data, for instance, the U.S. Landsat mission. The data from this mission were made freely available in 2008, providing an archive of imagery spanning more than 40 years (Borowitz 2017). The Landsat missions have a medium spatial-resolution (30m pixels), allowing for vast data collection at a reasonable level of detail across the entire planet. However, the continuing availability of the imagery is uncertain (Popkin 2018). Other satellites, with even higher spatial-resolutions, allow us to view features on the Earth's surface in detail, such as DigitalGlobe and Planet Labs, both commercial satellite data providers. Increasingly data are improving in all resolutions – source (as in laser, radar, optical), spatial (different pixel sizes), spectral (different wavebands), temporal (collected on different dates) and radiometric (data content of the pixel). Data are also becoming free at the point of access, particularly from satellites owned and operated by national space agencies; greatly increasing the range of possible uses.

Remote sensing comes from three primary platforms: UAVs, airborne (for instance aircraft) and satellites. In the fight against modern slavery it is satellite EO data that is the most appropriate, not only because of the vast abundance of data, but also for two other key reasons. First, it provides detail (in the form vast temporal- and spatial-resolution data) which is cost-effective compared to the relative-expense of launch, collection and processing. For example, the Landsat open access archive has substantially increased the output of EO research (Zhu *et al.* 2019) and regularly provides US $2 billion to the U.S. economy which dwarfs the US $80 million budget for the programme (Popkin 2018), leading to more government satellite programmes (e.g. ESA's Copernicus Constellation) providing open access imagery (Drusch *et al.* 2012). Second, it protects vulnerable people's privacy should they be subjected to modern slavery because they are not visible at the spatial-resolutions available. Rather, satellite EO data works as a proxy to provide additional insights to address the social and environmental impacts of modern slavery on the ground. Coarser imagery, such as those which are available freely, are therefore beneficial as they prevent perpetrators from identifying workers and locations which may lead them to take harmful actions against those who are subjected to modern slavery. Higher spatial-resolution data (from commercial providers such as DigitalGlobe's WorldView constellation and Airbus' Pléiades satellites) would also be beneficial, but precautions should be taken in order to anonymise these data and prevent the open access availability of the raw spatial datasets to limit possible risks of negative consequences for workers subjected to modern slavery. This means that data should be shared with trusted partners, and where published, should not be done so in full to minimise vulnerabilities. Cost-effective, open access, data affords NGOs, academics and policy makers the opportunity to conduct analysis with a focus on modern slavery over large spatial and temporal scales. Monitoring cases of human rights violations and humanitarian crises with satellite data have become common (AAAS 2014), however, these platforms have never been used within the modern antislavery movement; this is despite the scope of data being directly applicable to the study of modern slavery impact from an environmental lens.

UAVs, a recent technological development, have taken the practice of remote sensing to the mainstream. However, imagery collected from the small cameras placed on board (known as the payload) have primarily been used in humanitarian cases; such as in disaster hit areas to help develop clear plans for delivering aid and assessing damage within remote areas before aid workers arrive (Leetaru 2015). When a camera is situated in the payload imagery can be captured and used in a number of contexts. For example, refugee camps have grown large in number and size across the Middle East, particularly since the start of the Syrian conflict in 2011. Satellite data has revealed rapid expansion of the UN's refugee camps and can help to protect those within the camp in conflict situations (Belliveau 2016). Despite the registration process upon entering a camp, population monitoring can be difficult, and analysis of data collected by an on board UAV camera, or a satellite image, can provide a more accurate estimation of the number of residents, thus assisting registrars on the ground. These methods use tents and shelters to estimate the number of people present which is vital as it informs the volume and scale of provisions required for each camp (Checchi *et al.* 2013; Lang *et al.* 2010; Meier 2015a).

Whilst the use of UAVs may be beneficial in some contexts they may not be for all. For example, UAVs fly close to the ground, thus they can capture a lot of detailed images; features such as people and vehicles are visible. Airborne sensors fly higher – each offering a unique perspective (see Chapter 2 Figure 2.1 in Choi-Fitzpatrick 2020), but they also carry sensors which may put people at risk, these features are also becoming common in commercial satellite data. For example DigitalGlobe's 'WorldView' satellites have a spatial-resolution of up to 31cm (high enough to view and detect the model of a car, but not so high as to identify people) which is available commercially for the first time since changes to U.S. law (Koziol 2014). It is therefore important to consider the ethics of using remote sensing for a human rights issue such as modern slavery, as high levels of detail in the future may put vulnerable people at risk of further harm. There is no guarantee that imagery will not be used nefariously, however these high resolution data are restricted to those who have the financial means, or are restricted by governments (Florini and Dehqanzada 1999). The technology is already available and there appears to be very little will to restrict access again. Data providers must consider to whom data are released, whilst users must carefully consider which data are required, and why, when engaging in remote sensing investigations of sectors where vulnerable populations reside. This is likely to become more of a concern as the technological developments of satellite-based remote sensing continue into the future.

2.1.1 Further Considering these Ethical Implications

The ethics of remote sensing have been considered since the first high spatial-resolution satellite was launched in the 1990s (Slonecker *et al.* 1998). More recently Notley and Webb-Gannon (2016) have explored the issues of remote sensing and privacy with special reference to the application of remote sensing for human rights analysis. There are a number of concerns about the use of satellite EO data for tackling human rights violations, including modern slavery. NGOs do not want to endanger vulnerable people should cases of modern slavery be identified, and the perpetrators somehow become aware of this (Boyd *et al.* 2017, *unpublished*). The community of analysts and NGOs must be aware of the possible risks to those they are trying to help, to protect them from further harm. Similar ethical considerations have been noted with reference to required regulations that prevent the marginalisation and targeting of vulnerable groups within society (Finn and Wright 2012).

These ideas are considered further by Choi-Fitzpatrick (2014: 28-30) who argues that researchers and organisations using, in this case, UAVs to enable societal change for good need to prioritise six key concepts: subsidiarity, physical and material security, the ‘do no harm’ principle (balancing the situation being monitored and the risks involved to those producing, using and featured within the data collected), the public good, respect for privacy and respect for data. It is important that a strict code of ethics, common to the field of remote sensing and study of modern slavery, is adhered to in order to mitigate risk of further distress, harm of violation to workers subjected to modern slavery through the use of the technology – bearing in mind the ‘do no harm’ aspect of the work.

Some of the issues of privacy may also apply to very high spatial-resolution satellite EO data. The sensors that supply this type of data tend to be commercially owned; therefore the data can be extremely expensive. This is where tradeoffs regarding satellite data selection are often made. In the case of investigating industries using modern slavery practices, the most vital consideration is the protection of vulnerable populations, these must also be considered alongside costs and the level of detail needed within these data in order to conduct meaningful analysis. Whilst the majority of open-source data have pixel resolutions of around 30m, the European Space Agency (ESA) Copernicus programmes’ Sentinel-2 satellites have 10m spatial-resolution and a revisit rate of 5 days; these pixels are still large enough, however, to diminish the risk of privacy violations (ESA 2015; Drusch *et al.* 2012) – the same can be applied to the 3m spatial-resolution Doves operated by Planet Labs. Consequently, satellite EO data is seen as the most applicable form of data to help analyse sectors known to have an environmental impact and contain practices of modern slavery.

2.2 Remote Sensing Modern Slavery

There is precedent for the use of remote sensing in a range of human rights applications (AAAS 2014) but there has not been a concerted effort to apply these practices to instances of modern slavery. The idea for using satellite EO data in the effort to measure and enhance knowledge of modern slavery was first mooted by Kevin Bales (2007: 163) when visiting the UN's Office for Outer Space Affairs (UNOOSA). He recognised how satellite technology could help to target the remotest of areas where modern slavery often takes place, and has continued to advocate for its inclusion (Drejer and Bales 2018: 136-140). This is an important benefit as data can help support antislavery NGOs on the ground by providing detailed maps of industries in remote areas which may have previously been inaccessible, or even unknown (as has occurred with the developments of mapping for the brick-manufacturing industry in South Asia: see Chapter 4/Paper 3/Appendix B; Foody *et al.* 2019; Li *et al.* 2019). Although remote sensing methods may not be applicable to collect data on all forms of exploitation listed under 'modern slavery', the use of remotely sensed imagery provides an additional resource to enhance understanding of numerous industries, especially their ecological impacts – framed within the structure of the modern slavery-environment nexus (Brown *et al.* 2019). However, this does not mean the method will replace interactions with survivors and organisations on the ground working to end modern slavery – rather it is a data acquisition method that assists in understanding the modern slavery-environment nexus, providing data to assist in SDG 8.7's overall goal of ending modern slavery. EO data would provide additional support to more established antislavery methodologies (e.g. interviews, and survivor narratives). Industries where satellite EO data would be applicable include: brick kilns (see Chapter's 4 (Appendix B) and 5/Paper's 3 and 4), agriculture, quarries, mines, charcoal camps (which effect forest environments: see Chapter 6/Paper 5/Appendix C), fish-processing camps (Chapter 3/Paper 2) and fishing (in both land-based open water and oceans). The problem of modern slavery is so widespread and the collection of remotely sensed imagery is so frequent, that the technology would be beneficial as an additional methodological tool to use in this field.

2.2.1 Assessing Modern Slavery with Satellites in Research

At the time of writing only a few published research papers have used remotely sensing imagery and data products to provide information on modern slavery (Boyd *et al.* 2018 – see Chapter 4/Paper 3/Appendix B; Foody *et al.* 2019; Li *et al.* 2019; Jackson *et al.* 2020 – see Chapter 6/Paper 5/Appendix C), but there has been a growth in the number of studies specifically investigating modern slavery.[5] Boyd *et al.* (2018) estimated the number of brick kilns in South Asia using open source imagery available through Google Earth Pro geobrowser. This is an important piece of research as it assesses an industry that is known to use bonded and child labour. Previously, little was known about the extent of the South Asian brick manufacturing industry, and the development of this estimate would not have been possible without geospatial technology due to the size of the region being investigated. The work contained in the Boyd *et al.* (2018) paper (see Chapter 4/Paper 3/Appendix B) is a beneficial development in the possible use of technology for human rights analysis but is also important for NGOs and local governments, as the information can be used to help with the decision-making process when abolishing modern slavery practices and developing environmental policy within brick-manufacturing, as well as establishing compliance with current regulations. Moreover, the study embraces crowdsourcing to collect data and demonstrates the engagement of civil society with the SDGs – which is key to ensuring they are sustained and successful – whilst processing large volumes of data quickly. Further detail and investigation into the South Asian 'Brick Belt' can be found in Chapter 4/Paper 3 (Appendix B), followed by an environmental assessment in Chapter 5/Paper 4.

[5] Details of research on modern slavery occurring within the UK are available through a database supported by the Independent Anti-Slavery Commissioner and the Rights Lab; the database is accessible via http://iascresearch.nottingham.ac.uk/

Researchers at the University of Nottingham have also been investigating the impact of illegal fish-processing camps within the UN Educational, Scientific and Cultural Organization (UNESCO) protected Sundarbans Reserve Forest (SRF), Bangladesh (see Chapter 3/Paper 2; McGoogan and Rashid 2016). These sites are known to use modern slavery and child labour (Jensen 2013). They are also understood to have an adverse ecological impact on the mangroves in which they are situated (Bales 2016). Geospatial technology in this case can be used to protect the environment and help to support the liberation of workers subjected to modern slavery through the provision of evidence to encourage government and UN-led action.

2.2.1.1 The Modern Slavery-Environmental Degradation Nexus in Research

Satellites are, and have been, used extensively to monitor the Earth System's environment, providing a robust and continuous method to measure and monitor our anthropogenic footprint (Tatum *et al.* 2008; Boyd and Foody 2011), thus the application to investigate the nexus from this lens is encouraged. The knowledge acquired through the analysis of satellite EO data provides information to support management of the environment, limit damaging actions, and establish measures of the relative successes, or failures, of environmental policies which have been employed to mitigate damage. The environmental destruction of our planet is documented daily by EO satellites, creating an extensive and valuable archive of data. These data are used to inform practice and improve environmental awareness, but the question remains, how may they also be used to assist in the eradication of modern slavery due to the increased understanding of the social-ecological connection of exploitation (something the aim of this thesis strives to achieve).

The destruction of the environment and the presence of modern slavery are entwined in a 'deadly dance' (Bales 2016). Those subject to modern slavery are often involved in dangerous and destructive practices that have the potential to etch large physical signatures upon the landscape, in as many as 15% of cases according to ILO estimates (ILO 2017a: 32). Deforestation of the Amazon is a clear example of this (Fearnside 2008). Bales (2016: 10) notes that:

> "If modern slavery were an American state it would have the population of California and the economic output of the District of Columbia, but it would be the world's third-largest producer of CO_2, after China and the United States."[6]

Yet, little emphasis has been placed on the study of the powerful linkage between such social and physical variables until recently. Exploited labourers that are commonly linked with high environmental impacts include forestries, fisheries, factories and farming (Brown *et al.* 2019) – three of which are explored within this thesis; see Chapters' 3/Papers' 2 (fish-processing), 4/3 (Appendix B) and 5/4 (on brick kilns), and finally Chapter 6/Paper 5 (examining tree loss – Appendix C).

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[6] Bales (2016: 10) based his calculations on estimates using modern slavery figures from the 2014 Global Slavery Index (Walk Free 2014) by adding together all slave-based deforestation and other CO_2-producing crimes (such as mining, brick-making, quarrying, aquaculture, and agriculture) to produce these estimates. There are now clearer environmental assessments and figures for each sectors which can be used (e.g. ILO 2017a, 2017b, 2017c); but Bales' 2016 estimate was a positive initial assessment to encourage understanding of the connection between modern slavery and environmental degradation.

Some of the products from these exploitative activities end up with the domestic market, for example the dried fish from the Sundarbans (Jensen 2013; Bales 2016); whereas others such as beef and timber can enter the international supply chains, travelling from places such as Brazil to the UK (Emberson *et al.* 2019a, 2019b). Therefore, the issues of the modern slavery-environmental degradation nexus (Brown *et al.* 2019) is a global one that must be considered as such.

The brick kiln industry is widespread across South Asia, as discussed previously, but the true scale of the industry's environmental impacts have not yet been realised (see Chapters/Papers' 4/3 and 5/4 for an investigation of these impacts). At present, the volume of emissions have been explored, as has the extraction of clay, used to produce the bricks, which strips the land reducing the fertility thus pushing those reliant on agriculture into further vulnerability, particularly poverty restricting the successful achievement of SDG 1 (Boyd *et al.* 2018 – see Chapter 4/Paper 3/Appendix B; Skinder *at al.* 2014a; Skinder *et al.* 2015; Pariyar *et al.* 2013) – the scale of this and further conflicts that may arise due to this impact are explored in Chapter 5/Paper 4. Similarly, mining releases a variety of heavy metals via the extraction of particular ores. The use of mercury is common across gold mining in West Africa and South America (Clifford 2017; Gerson *et al.* 2018). Planet Labs satellites, for example, have captured evidence of extensive gold mining in Peru (Planet Labs 2018). Elsewhere, mercury can have devastating health effects, and in the Eastern Congo, illegal mining impacts water quality, increases deforestation (thus increasing the risk of modern slavery; see Chapter 6/Paper 5/Appendix C) and contributes to poaching and species loss (Bales 2016; Salazar-Camacho *et al.* 2017). The environmental damage caused by industries known to heavily use modern slavery practices are perpetuating a socially and ecologically damaging cycle, increasing the risk of populations becoming vulnerable to modern slavery.

Aquaculture farms and post-harvest fish-processing camps in the Sundarbans use workers subjected to modern slavery to remove coastal mangroves, as discussed above (Bales 2016; see Chapter 3/Paper 2). These forests are globally important carbon sinks, and a key defence against erosion and natural disasters (Bales 2016; Gillis *et al.* 2017). The cyclicity between human vulnerability and its exploitation, and environmental vulnerability and its exploitation, continues to be exacerbated. In Brazil, the agricultural industry plays a large role for those living in modern slavery. Illegal deforestation for logging and cattle ranch land clearance are common, despite tough antislavery laws (Brazilian Penal Code 2003) – which are being limited by the Bolsonaro administration – and the climate protection offered by the rainforest, which is being threatened by tree removal and forest fires (see Jackson *et al.* 2020 - Chapter 6/Paper 5/Appendix C). There is growing evidence of a modern slavery-environmental destruction nexus (Brown *et al.* 2019). Exploring the interactions between the two is important not only to preserve the environment from serious threats such as climate change, but also to protect those at risk of modern slavery.

These examples demonstrate synergies within environmental signatures that have the potential to be located in satellite EO data. Primary visual signatures such as the shapes and patterns of industries, and secondary signatures held within the environment can be explored. Visual signals for instance include the distinct oval kilns and rows of drying bricks in the 'Brick Belt' (Boyd *et al.* 2018 – Chapter 4/Paper 3/Appendix B; Foody *et al.* 2019; Li *et al.* 2019), these also apply to the extraction of resources and the effect of pollutant emissions (Chapter 5/Paper 4). Whereas secondary signatures can include land-use change, alteration of vegetation health and flood frequencies, among others (Foody 2003; Giri 2016; Sonter *et al.* 2017). Remote sensing technology is already capable of detecting many of these signatures at differing scales; hence the application to assess environmentally degrading sectors that have documented examples of modern slavery within their workforce. There are a number of remotely sensed data products available which can be adapted and utilised to investigate the impact of the modern slavery-environment nexus (as utilised in this thesis; Table 1.2); this is particularly relevant when assessing tree loss and assessing the co-occurrence with the presence of modern slavery (Jackson *et al.* 2020 – Chapter 6/Paper 5/Appendix C). Products such as the Global Forest Watch (GFW) global tree loss dataset can be re-evaluated alongside illegal logging data (a proxy for modern slavery) and the presence of forest degrading activities. Deforestation caused by agricultural practices, mining, and fishing related activities (explored in the removal of mangroves in Chapter 3/Paper 2) have all caused tree loss which is compounded by the continued presence of modern slavery.

Satellite EO data provides a unique line of enquiry, with remote sensing methodologies enabling evidence-based decisions for both social and environmental science policy. Indeed, such cross disciplinary projects are beginning to explore these themes.[7] Projects at Stanford University are utilizing remote sensing data to assess the environmental output of brick kilns pollution in Bangladesh (Jordan 2017, 2019) – this has been explored for the whole of the 'Brick Belt' in Chapter 5/Paper 4 – and the University of Nottingham's Rights Lab has investment in the field with their 'Data and Measurement' and 'Ecosystems and the Environment' programmes (University of Nottingham 2017, 2020), researching the uses of remote sensing to measure modern slavery and assess its impact on the Earth's environmental systems (University of Nottingham 2017, 2020; Landman 2018). Quantification of the potential environmental damage that can be mitigated is important in the approach to understanding the socio-ecological nexus of modern slavery and ecosystems – undertaken previously by Bales (2012, 2016), but also applied for sectors in this thesis (see Chapter 5/Paper 4).

The link between climate change, poverty and forced labour is well documented, yet the ability to conduct local analyses efficiently to provide action to limit the impacts of

[7] Such as Royal Holloway's Blood Bricks project (www.projectbloodbricks.org/project) and the University of Nottingham's Rights Lab (https://www.nottingham.ac.uk/research/beacons-of-excellence/rights-lab/index.aspx /)

these issues is poor due to the remoteness of locations, lack of resources and limited enforcement of laws to protect people and the environment – satellites can be used to identify these potential vulnerabilities, prior to entrapment (Kaye and McQuade 2007). By highlighting spatial patterns and causal variables at high temporal-resolutions, remote sensing allows the development of monitoring programmes via a social-ecological lens to tackle the nexus and support multiple SDGs (Figure 1.2). For Cambodia – ranked second in the list of climate vulnerable countries – the relationship between changing work opportunities, due to climate forced landscape alterations, and migration, which often leads to debt bondage, is closely studied (Blood Bricks 2017; Brickell *et al.* 2018; Brickell *et al.* 2019; Natarajan *et al.* 2019). The Blood Bricks project us one such study that is examining how climate change is facilitating modern slavery (Brickell *et al.* 2018; Blood Bricks 2017). The combination of local ground intelligence, coupled with analysis of satellite EO data showing environmental change provides a powerful opportunity to analyse spatial, physical and human pressures which may increase vulnerability. Similar trends have been noted across the sectors explored within this thesis by Brown *et al.* (2019) whom link modern slavery, environmental degradation and climate change within fisheries, forests, fields, and factory environments. It is possible to use satellite EO data to both understand past patterns and model future modern slavery-environment damage scenarios so support can be provided to strengthen security and provide assistance to vulnerable communities across these regions.

Documenting the scale of these environmental impacts are the first steps in being able to evaluate the damaging contribution of modern slavery on the environment (i.e. the nexus). With space agencies continually responding to the demand for satellite data to monitor Earth’s environment, advances in sensor design and delivery of knowledge products (that enable a user to easily access information); there is no reason to believe that a satellite derived ‘Geospatial Environmental Slavery Index’ – which could integrate with a ‘Digital Ecosystem for the Planet (and Nexus)’ (explored in Chapter 7: Discussion and Recommendations) – product would not be achievable which could support understanding of modern slavery and assist in data provision which may lead to the achievement of SDG target 8.7. This is alongside a number of environmental SDGs including numbers 14 and 15; addressing terrestrial and aquatic ecosystems (Figure 1.2).

2.2.1.2 Further Developments in Academic Research

Work undertaken at organisations such as the Harvard Humanitarian Initiative (HHI), and the Satellite Sentinel Project (SSP) combine evidence from satellite data and witness testimony, to draw together details to assess humanitarian crises and human rights violations (Card and Baker 2014). This is a common form of analysis in this field, and was demonstrated successfully when SSP collaborated with DigitalGlobe to assess the impacts of the Sundanese Conflict (The Enough Project and Satellite Sentinel Project 2013). Piecing together multiple analysis methods allows NGOs to create a holistic story surrounding an event, although many do not seek to address the environmental implications of these activities. [8] Although these studies do not specifically relate to modern slavery, the humanitarian crises analysed by the HHI and SSP contain risk factors that may lead to increased vulnerability to modern slavery (Bales 2005). Poverty can often lead to subjection to modern slavery, which can be impacted by disasters, conflict and population growth (Kaye and McQuade 2007; Bales 2010). Many of these risks overlap with the work of humanitarian agencies.

[8] For example Forensic Architecture https://www.forensic-architecture.org

Combining multiple data acquisition methods is something academics should consider for the study of modern slavery going forward. Remote sensing techniques are producing an increasing volume of data, which can be used alongside a myriad of other sources – including survivor testimony, supply chain analysis, and survey data – to refine global estimates of modern slavery, and determine the location, scale and volume of environmental degradation caused by this exploitation. Additional benefits from satellite EO data may include locational analysis of industries known to use an exploited workforce. By combining data sources the exact locations of modern slavery activity may be identified. Despite the field being in its infancy, using satellite data to track slaved-based industries is an important step in the effort to end all forms of modern slavery by the 2030 deadline (United Nations 2012, 2016a).

2.2.2 Use of Satellites to Investigate Modern Slavery by the Media

Journalists have a major role in increasing the awareness of global social issues, and modern slavery is no exception. Larger press organisations, such as Thomson Reuters and the Associated Press (AP), have also been enhancing their reporting with the use of satellite data to capture instances of modern slavery, exposing criminality and corruption; often this overlooks the impact of these activities upon ecological systems.

The AP Pulitzer Prize-winning investigative report into the state of seafood supply chains within Southeast Asia included geospatial analysis to bring to light the working practices people subjected to modern slavery were forced to endure.[9] The articles noted how labourers were trafficked to work in the Thai fishing industry and could be trapped on numerous boats in the Indian Ocean processing catches on board before being moved

[9] Details of the AP investigation are available via https://www.ap.org/explore/seafood-from-slaves/index.html#main-section

(McDowell *et al.* 2015a; Mason and Mendoza 2015). The investigation also found evidence of mass graves where workers subjected to modern slavery had been buried, and captured the movement of fishing vessels across the ocean using satellite data (McDowell *et al.* 2015b; Newitz 2017).

The investigation conducted by the AP raised the concept that you 'cannot hide from space'. Some forms of exploitation, such as domestic servitude and those occurring within carpet weaving factories, are not viable for investigation through the use of satellite EO data as the nature of the subjection to modern slavery occurs indoors. This is the major limiting factor of remote sensing and demonstrates why a number of methodologies are required. Where industries can be viewed by remote sensing methods, the addition of these data could prove beneficial – enabling insight into regions which have previously been inaccessible, such as the global fishing industry. As a result of the investigation, the Thai fishing industry came under intense scrutiny for its labour practices, and awareness of exploitation in these supply chains caused changes to law internationally (Mendoza 2016). It is clear that the global fishing industry is one with serious labour practice issues, and the exploitation evident in the workforce is being investigated in detail by a number of sectors including NGOs (such as the Environmental Justice Foundation), academia (e.g. Sparks 2018; Tickler *et al.* 2018) and the media (McGoogan and Rashid 2016). However, land-based post-harvest processing activities have often been overlooked, despite these sectors being vulnerable to exploitative work practices and causing degradation to ecosystems (as explored in the fish-processing camps of Bangladesh in Chapter 3/Paper 2). It is feasible that geospatial technology can be included in other studies of supply chain transparency in visible industries, contributing evidence to support reforms to worker's rights and industry mines, charcoal camps, cotton and agriculture among others. So far these industries have not been explored using remote sensing data or techniques (Bales 2016).

2.2.3 Use of Satellite Data by NGOs to Investigate Modern Slavery

A number of NGOs have begun to embrace satellite technology and imagery to demonstrate evidence of human rights violations. However, the use of geospatial imagery by the human rights NGO community has been criticised for the distance it can create from the complex realities on the ground (Perkins and Dodge 2009). Thus when analysing modern slavery from space, it is important to build a network of *in situ* contacts, crucially antislavery NGOs, so that evidence from satellite data can impact upon direct-action and influence the implementation of policy.

Amnesty International has been one of the most prolific at using these resources, creating a visual evidence base that supports survivor and witness testimony, enabling satellite data to be given as evidence in court; more recently investigating Myanmar Military action within Rakhine State (Amnesty International 2018b). A number of high-profile campaigns have capitalised on the vast amount of data available from geospatial technology and the organisation now employs its own team of analysts. Specific attention to modern slavery has been hidden within other human rights abuses but this does not mean that the work that Amnesty has carried out using this technology is not beneficial. Their work has looked closely at the village of Baga, in Nigeria, after the atrocities committed by Boko Haram; assessing the scale of the destruction was vital to establish the story of the hundreds of women and girls who were kidnapped and subjected to modern slavery by their captors (Amnesty International 2015; Koettl 2015). This analysis used traditional environmental assessments to determine the social destruction that had occurred, but vitally demonstrated the versatility of satellite EO analysis to provide information on social-ecological connections; these activities may then be applied to understand the modern slavery-environment nexus. Additionally, there have been extensive investigations by Amnesty into North Korea's well-documented human rights abuses in labour camps and detention centres (Amnesty International 2013a; 2013b). Amnesty International used satellite EO data to assess the size of the camps and identify features that indicate whether there are increased agricultural activities that use forced labour occurring in these locations, noting that camps were often in working order and expanding capacity for housing prisoners and agricultural activities (Amnesty International 2016). More recently Human Rights Watch (HRW) have used satellite data to support reporting around political abuses in the Xinjiang province of China (Dholakia and Wang 2018) and detentions camps at the U.S.-Mexico border (HRW 2018).

The utilisation of geospatial technology in these cases has proved invaluable in raising awareness of NGO campaigns, but there are only limited technical analyses, often relying on the identification of features and comparison of images before and after an event. For example, the assessment of Boko Haram destruction in Nigeria (Amnesty International 2015) and the development of prison camps in North Korea (Amnesty International 2013a, 2013b). This information is still beneficial for an organisations' purposes, but utilising more technical details could help to provide new data that may have previously been overlooked, such as producing more detailed temporal analyses which may identify features in the lead up to a human rights abuse in order to predict when an abuse may be likely to occur in the future. In addition, combining witness testimony, imagery from the ground, satellite EO data and legal frameworks can add value to an investigation. This may be possible in the context of modern slavery. For example, the application of survivor narrative analyses and the antislavery legislation database can be used in conjunction with other data sources to address this specific human rights abuse.[10] It is important to look at these data holistically; this will be vital when applying satellite EO data to a complex human rights issue such as modern slavery. Work by HRW, a non-profit organisation which investigates human rights abuses, is being revolutionised by new partnerships with emerging EO companies (HRW 2018). Commercial satellite providers, such as Planet Labs, are moving from large-scale singular and expensive satellites to the launch and operation of multiple small satellites. These constellations of satellites collect a vast amount of data for global coverage at reduced costs compared to other commercial operators, and can be flexible in their applications (Harebottle 2017; Zolli 2018a). Recognising the need for data in the human rights sector, Planet Labs has the intention of creating a new kind of global observatory whereby philanthropists provide the funds, Planet Labs and other companies provide the data and scientists and researchers come together to tackle modern slavery in a collaborative manner (Zolli 2018b, 2018c). This is a plan shared by the Delta 8.7 platform and its parent body Alliance 8.7 – a United Nations programme which assess the progress towards SDG target 8.7 – which was explored at the 'Code 8.7' conference (Landman *et al.* 2019). It is often the cost of the equipment, data and expertise required to analyse imagery that can be prohibitive to the humanitarian sector; this is increasingly being considered by EO companies, who often have an emphasis on providing free data for humanitarian purposes (Wolfinbarger 2016). Other organisations, such as DigitalGlobe, use the power of people to sift through vast amounts of information to help with specific issues (known as

[10] Two open access databases have recently been launched that draw on data to assist in the achievement of SDG 8.7. These comprise of a new survivor narrative database called 'VOICES: Narratives by Survivors of Modern Slavery' (http://antislavery.ac.uk/ - Narratives) and the new 'Legislation Database' (https://antislaverylaw.ac.uk/).

crowdsourcing). For the frequently unsafe and unmapped areas where humanitarian organisations work, remote sensing offers cross-national, time series data (Meier 2015b).

2.2.3.1 Crowdsourcing/Citizen Science

Recent developments in the crowdsourcing sector have reiterated the importance of the method in filling data gaps and providing evidence for the SDGs (Fritz *et al.* 2019). For the study of modern slavery, crowdsourcing the analysis of satellite EO data has three key benefits in these circumstances. First, the datasets are 'big data', characterised by their volume, variety, and rapid rate of capture, which the remote sensing community is increasingly unequipped to manage alone (Chi *et al.* 2016). Issues specific to satellite EO data, in this context, include: technology, data processing, data access, and the applications/users (Sudmanns *et al.* 2019). Remote sensing data is varied and can be multi-source, multi-temporal, and multi-resolution. Second, satellite EO data analysis needs validation, because poor data comes with economic and ethical costs. Estimates of the prevalence and impact of modern slavery inform policy and, when derived from satellite data, mis-estimates could impact the resources made available to tackle modern slavery, and its ecological effects, on the ground; data accuracy is important so as not to further endanger vulnerable people (Foody 2015a; Foody 2015b). Crowdsourced data can be validated in a variety of ways, according to how that data will be used (Senaratne *et al.* 2017; Wiggins *et al.* 2011). Third, and finally, human analysts are more creative and flexible in their assessment of satellite EO data than computers, and online volunteers can increase the efficiency of data processing and analysis sat less cost (Haklay *et al.* 2018). In fact, it may assist in strengthening machine-based learning methods.

The crowdsourcing of data for the humanitarian sector has been embraced both in the field, such as OpenStreetMap, CrisisMappers and Digital Humanitarians, and online, for instance, MicroMappers, Zooniverse, and Tomnod (Fritz *et al.* 2017). Industries known to employ practices of modern slavery have been analysed, (Boyd *et al.* 2018 – methodology included in Chapter 4/Paper 3/Appendix B; Foody *et al.* 2019). The humanitarian crowdsourcing project Tomnod and the Global Fund to End Slavery, also employed these techniques to track instances of fishing activity on Lake Volta, Ghana (Tomnod and World Freedom Fund 2015); an area where there are reports of the prevalent use of child labour (IJM 2016). The study employed the crowd to look for instances of buildings on the lake shore where vulnerable children may be being housed, boats on the lake, and fish cages in the water. Overall, the study recorded 244,006 instances of fishing paraphernalia and building across the lake and its banks (Tomnod and World Freedom Fund 2015: 11-13). Mapping Lake Volta was invaluable for the NGOs that contributed to the project, allowing resources to be targeted more effectively and helping support children subjected to possible forms of modern slavery. However, recent backlash against the branding of child exploitation within the Lake Volta fishing sector has been raised by people within the region (Mensah and Okyere 2019), and this must be investigated further to establish the true situation on the ground.

2.3 Conclusion

Remote sensing for human rights analysis is developing at a rapid rate due to the frequent and widespread collection of satellite EO data. Efforts to apply remote sensing principles have commonly been used to provide resources to humanitarian crises, information regarding remote locations and conflict zones, as well as the management of disasters, as the examples in this Chapter (Paper 1/Appendix A) illustrate. The success of these studies have demonstrated that it is entirely feasible to apply these methods to the study of modern slavery, and in particular the environmental effects of these practices through the lens of the modern slavery-environmental degradation nexus (Brown *et al.* 2019). Findings from the employment of remotely sensed data to understanding the nexus and reduce labour exploitation and environmental damage are already being used by NGOs to inform interventions on the ground, and indeed it is hoped that these resources would lead to long-term monitoring and legislative change supporting survivor rights and understanding the socio-ecological implications of modern slavery (University of Nottingham 2017, 2020). Focus on the use of remotely sensed data specifically for the study of modern slavery has begun, but there is more that needs to be explored, including a range of data in several industries.

At present remotely sensed data cannot account for the precise locations where modern slavery practices are occurring, but insights can be provided into industries which can then be used as a resource by those locally undertaking direct action. Remote sensing can never replace the data that is collected *in situ* by people regarding such an important social issue as modern slavery. However, satellite EO data can be used to support these methods and provide data on a scale that may not be feasible on the ground. Therefore, multiple methods of data collection are needed to successfully advance the fourth antislavery movement, develop knowledge of the modern slavery-environment nexus, and eradicate modern slavery in line with the SDGs 2030 target and for humanity to benefit from the 'freedom dividend' it would provide (Bales 2012: xxix; Landman 2018). The use of satellite EO data could revolutionise the way we think about the hidden crime of modern slavery and its effect on the environment – as space technologies provide a unique perspective of the globe, uninterrupted and with many avenues of analysis that are yet to be explored. Throughout this thesis, these themes are addressed via the application of satellite EO data to investigate, and increase understanding, around the linked social-ecological systems (SES) of modern slavery and the environment.

Chapter 3: Fish Camps

This Chapter/Paper (see Table 1.3) has been submitted to *Maritime Studies (MAST)* and is currently under-review.

Remote sensing of fish-processing in the Sundarbans Reserve Forest, Bangladesh: An insight into the modern slavery-environment nexus in the coastal fringe

3.1 Introduction

Globally, there is growing recognition of the potential for remote sensing data to expose environmentally damaging and illegal fishing activities, which exacerbate environmental degradation (Al-Abdulrazzak and Pauly 2014; Belhabib *et al.* 2016; Oozeki *et al.* 2018; Kurekin *et al.* 2019; Young 2019). However, to date, this focus has mostly been placed on marine fishing activities at the production phase. There is a knowledge-gap with respect to land-based activities along the coastal fringe – including production through aquaculture and post-harvest fish-processing.

Remote sensing can provide evidence to assess environmental activities (Boyd and Foody 2011), support conservation, and achieve sustainable protection of marine and terrestrial ecosystems (Anderson *et al.* 2017; Pettorelli *et al.* 2018). This has been applied to investigate mangrove environments (Richards and Friess 2016; Lucas *et al.* 2017; Gandhi and Jones 2019); and is a suitable data source to understand the environmental impacts of the fisheries sector. In the coastal zone, measurements of environmental degradation have quantified mangrove deforestation rates (Hamilton and Casey 2016; Richards and Friess 2016), monitored erosion (Rahman *et al.* 2011; Payo *et al.* 2016), and assessed marine ecosystems e.g. coral reefs (Hedley *et al.* 2016; Foo and Asner 2019). With multiple vulnerability frameworks for the coast also being noted (Aswani *et al.* 2018). Remote sensing can also expose illegal environmental activity (Lega *et al.* 2014). The application of remotely sensed data to investigate the connection between illegal activities, including human rights abuses such as modern slavery, have been demonstrated (Boyd *et al.* 2018 – Chapter 4/Paper 3/Appendix B; Jackson *et al.* 2020 – Chapter 6/Paper 5/Appendix C). Others have advocated for an increased use of remote sensing to assess the environmental impacts of slavery-supported activities (Jackson *et al.* 2018 – Chapter 2/Paper 1/Appendix A; Jackson 2019).

This study has documented prohibited activities occurring in protected areas of the Sundarbans mangrove forest in Bangladesh, causing damage which subverts the intention of these protections. This is the first step in enabling the identification modern slavery using satellite EO data – at present only the sectors can be identified (Boyd *et al.* 2018; Landman 2018; Landman *et al.* 2019), yet as noted in previous ground-based studies in the Sundarbans (Jensen 2013; Bales 2016) environmental damage occurs alongside modern slavery cases. Thus, the first step towards identification of modern slavery cases from remotely sensed data alone is to identify those sectors which are likely to be utilising these practices based on proxy measures, such as compliance with environmental regulations. Triangulation of satellite EO, ground, and secondary data sources measuring the social and ecological conditions of the region (e.g. interviews, surveys etc.) should be combined in order to provide a more holistic distinction between cases of modern slavery and labour exploitation, and those where illegal activities are exclusively occurring. There will be occasions where illegality and modern slavery occur alongside one another, but identifying overall sector traits supports baseline data collection that supports the training and identification of remote sensing as a tool to eventually identify modern slavery cases automatically. The complex nature of modern slavery is reflected in the varied human activities across the forest, which include deforestation, village construction, the operation of fish-processing camps, and aquaculture development. Remotely sensed data enables the combined investigation of environmental and human issues. There is particular potential to combine ground-data relating to associated fisheries crimes, with remote sensing data to 'sat-truth' irregular activities, such as modern slavery, as part of a wider strategy of data triangulation.

Knowledge of land-based fishing activities is limited. For example, many rudimentary land-based fishing activities occur in remote coastal areas, primarily in developing countries; therefore ground-data are often limited at these sites, meaning seasonality, scale of environmental degradation, and the length of operational activity at these sites are unknown. Access to ground-data collection can be hindered by the physical conditions of the mangroves; including shallow waters, and extensive root networks. Moreover, many land-based activities are associated with other forms of fisheries crime. There have been cases of other illegal environmental activity, including: poaching of endangered species (Saif and MacMillan 2016); logging; collection of shrimp fry (Ahmed *et al.* 2019); and child labour and modern slavery in post-harvest fish-processing (Jensen 2013; Bales 2016) and shrimp production (EJF 2014; Verité 2016, 2017a). Efforts have been made by the Food and Agriculture Organization (2018a) (FAO) to tackle child labour in the marine and aquaculture segments; however, this overlooks other forms of exploitation. Limited information on fish-processing is compounded by the lack of modern slavery data in fisheries. There has been an overwhelming focus on marine capture fisheries with some research connecting human rights and environmental damage (Tickler *et al.* 2018; Walk Free 2018; Sparks 2018), and illegal, unreported and unregulated (IUU) fishing (EJF 2019a, 2019b); with little focus on other segments.

The elimination of modern slavery (defined in the Bellagio-Harvard Guidelines as the exploitation of a person(s) through coercion, threat of, or actual violence; Research Network on the Legal Parameters of Slavery 2012) and the sustainability of fisheries are both included in the United Nations' (UN) (2016a) Sustainable Development Goals (SDGs). To meet targets contained within SDG 8.7 (eradication of modern slavery), the drivers of exploitation, and the locations in which they occur, need to be understood. Remote sensing can be a tool to understand the nature of the links between modern slavery and the environment in the fisheries sector. Particularly within South and Southeast Asia where integrated human dependence on marine ecosystems – for nutritional, economic (e.g. fish-processing and aquaculture), and coastal protection, for example from climate change impacts – are noted as medium to high (Selig *et al.* 2018). Within Bangladesh they are high in both the nutritional and economic assessments (Selig *et al.* 2018: 4). Monitoring progress of the SDGs therefore requires remotely sensed data (Anderson *et al.* 2017; Andries *et al.* 2018; Kussul *et al.* 2019; Masó *et al.* 2019). Applying these data to assess often neglected land-based fishing activities enables further understanding of the impacts on SDG 14 ("Life below Water") and 15 ("Life on Land") in the coastal fringe. The presence of processing activities in these localities can lead to erosion and reduced sedimentation, deforestation, prohibited coastal development, and run-off affecting the delta, mangrove forest, and ocean. By using satellite earth observation (EO) data, the evolution of land-based fishing activities in the SRF can address fish-processing camps' contributions to coastal damage, as achieved in the marine environment (see Belhabib *et al.* 2019).

Modern slavery is highly likely to be linked to environmental degradation in the Sundarbans; for example, through the removal of mangrove trees which limits the capacity of the delta to grow, as well as leading to habitat loss for protected species such as the Bengal tiger. Previous interactions support this assertion as the modern slavery-environment nexus has been highlighted by both Jensen (2013) – and expanded upon by Brown *et al*. (2019) – and Bales (2016) in the mangrove forest. Moreover, the environmental impacts of human activities linked to fish-processing and possible labour exploitation have been known since the early 2000s (Jalais 2004). These risks are unlikely to abate in the future as these camps continue to operate. Whilst the distinction between illegal activity and modern slavery are hard to differentiate at present, the distinction of clear environmental zones, mean that environmental crimes are easier to identify and address within the SRF. Moving forward, the collection of further primary ground-data will enable the identification of factors which can identify the difference between illegal environmental crimes, and those sectors which are utilising modern slavery practices in their workforce. These risks warrant further investigation, particularly in under-represented land-based fishing activities. Addressing these concerns should allow greater understanding of the emerging modern slavery-environmental degradation nexus (Brown *et al.* 2019) which is predicated upon a linked social-ecological system (SES).

Drivers of exploitation in land-based fishing activities, often prey on a lack of economic opportunities (Figure 3.1). Small-scale aquaculture has been seen as an alternative livelihood approach to support rural development (Garcia *et al.* 2018; FAO 2018b) that may follow fish stock declines linked to overfishing and climate change (FAO 2016a); evidence suggests aquaculture itself could also be related to stock collapses in Asia (Garcia *et al.* 2018). Therefore, the vulnerability of small-scale and subsistence fishers is likely to increase (FAO 2016a); raising poverty levels, which may lead to marginalisation and exploitation of people (Islam and Chuenpagdee 2013; Galappaththi and Nayak 2017; Bavinck 2018). Moreover, climate change and environmental stressors (i.e. cyclones, erosion, increasing soil salinity, and flooding) impact upon peoples livelihoods (Ahmed *et al.* 2019); affected people then require work which may lead to them becoming trapped in forced criminal activity (Ahmed *et al.* 2019) or lead to migration where they become vulnerable to trafficking and forced labour (IOM 2016; Molinari 2017). Climate change has also been associated with the movement of people into illegal livelihood activities, such as using banned nets to collect shrimp fry, and logging of the mangrove forest (Ahmed *et al.* 2019). The presence of modern slavery enables illegal activity to persist, causing further environmental damage, in turn leading to increased vulnerability.

Bangladesh is used as a case study to highlight the utility of remote sensing to fill some of these data-gaps, by: 1) addressing the extent of human activity in the Sundarbans, including fish-processing camps; 2) determining the trends in camp operations over time; and 3) assessing the environmental impact of the fish-processing sites within the lens of the modern slavery-environment nexus. Our work advances the understanding of the nexus, and provides a clearer picture of the threats to people and ecosystems within the SRF. Moreover, evidence has been provided demonstrating how satellites may be used to help combat modern slavery and environmental degradation.

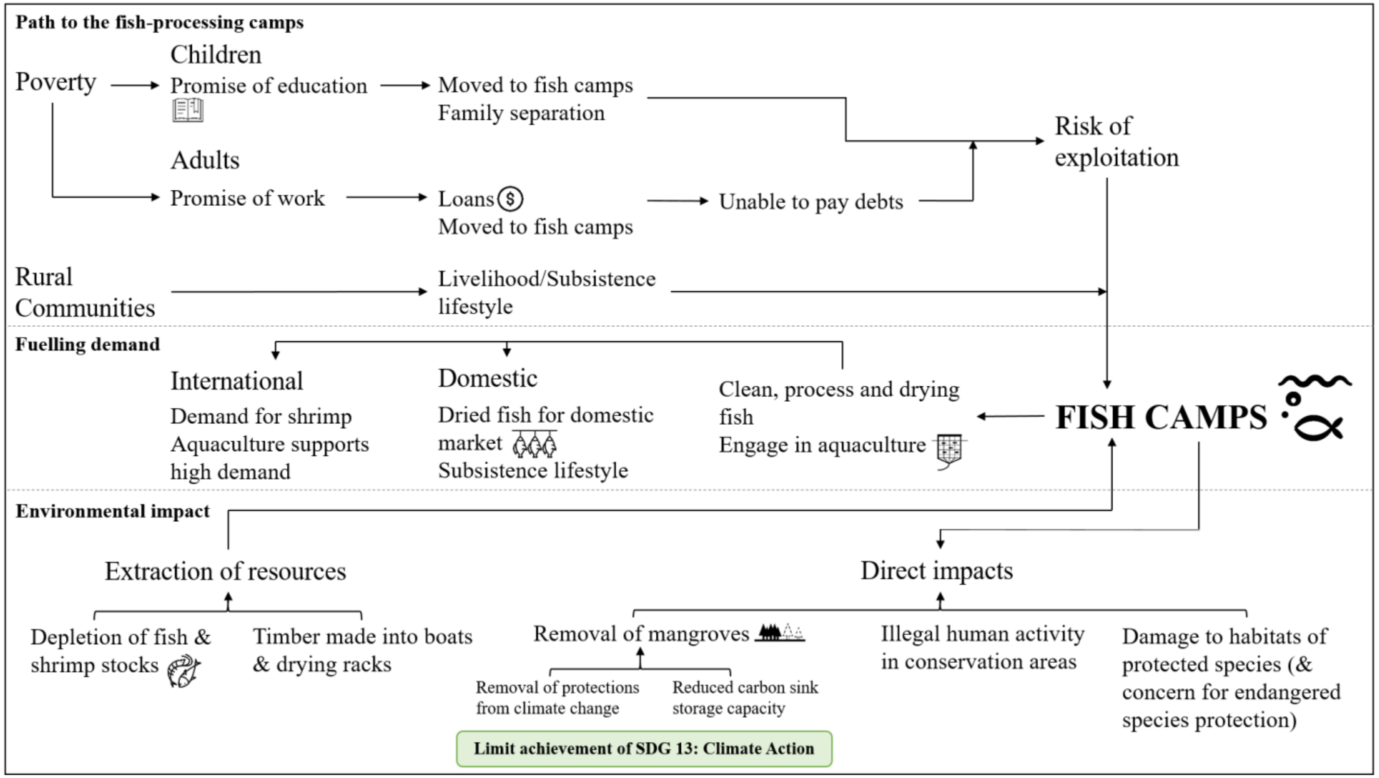

Figure 3.1: Demonstrating the relationship between modern slavery and the natural mangrove ecosystem in relation to fish-processing camps, and why it is important to combat modern slavery due to the negative impacts which can be exerted on the environment as part of the nexus. This explores the path to exploitation, the drivers fuelling modern slavery, and the environmental impacts of these phases. Information from a number of sources were used to develop the relationships which have been noted here; details associated with the path to fish processing were obtained from Jensen (2013), Bales (2016), and Brown *et al.* (2019); demand was noted by sources such as Bales (2016), Hernandez *et al.* (2018), and Dhar *et al.* (2020); finally the environmental impact of these camps are identified in the results of this Chapter/Paper, but also Bales (2016). These links are simplified and are likely to be impacted by further issues, however, these connections are the dominant paths noted in key literature related to land-based fishing activities. The pathway is based upon Brickell *et al.*'s (2018: 16-17) exploration of the pathway to exploitation within the Cambodian brick industry.

3.2 Study Area

The Bangladesh SRF, is part of the largest continuous mangrove forest in South Asia, covering a 6,017 km^2 area of land (Rahman *et al.* 2015). Ramsar and UNESCO World Heritage sites were established in 1992 and 1997 respectively. The 'reserved forest' status allows for the continued extraction of resources in some locations. Three zones permit no human activity: Sundarbans West, South, and East (Ramsar 2003). These mangroves support the livelihoods of those living in, and around, the forest due to the abundance of services (supplementary material is available in Appendix D, Table D.1). Local rural populations are the primary beneficiaries; many use traditional fishing practices, foraging and trapping, farming and aquaculture to support subsistence lifestyles.

Fish-processing camps are present in the reserve, with some located in villages. They consist of mangrove-cleared areas with structures for landing, cleaning and drying fish. The dominant market for processed fish is domestic. There have been reports of hazardous working conditions and exploitative practices in the camps (Jensen 2013; Bales 2016). Additional revenues can be gained through the operation of aquaculture ponds, farming shrimp and mud crabs (Ahmed *et al.* 2017; Rahman *et al.* 2017). Drivers of exploitation in the SRF include the promise of work to support subsistence for those in the remote villages, and the promise of education (Figure 3.1); as well as associated environmental drivers, such as climate change and unsustainable fish stocks.

3.3 Methods

Several satellite EO data types were integrated to provide an assessment of the environmental implications of fish-processing in the SRF. Data available on Google Earth Pro (provided by DigitalGlobe – WorldView; and CNES/Airbus – SPOT and Pléiades 1A/1B) underwent a gridded systematic visual search of all data from 2000-

2018 by an image interpreter following a sampling protocol similar to that employed by Boyd *et al.* (2018). Evidence of human activities were documented, including: processing camps, boats villages and earthen ponds (Figure 3.1). These were determined through: 1) the presence of human-made structures (both on the land and bridging the water e.g. buildings, earthen ponds – that can be used for both aquaculture (Ahmed *et al.* 2017; Rahman *et al.* 2017) and drinking water purposes (Øhlenschlæger *et al.* 2016) – and jetties); 2) the removal of mangrove areas in uniformed areas (e.g. rectangular clearings, or areas cleared the presence of camps and earthen ponds); and 3) evidence of transport infrastructure such as boats and shipping lanes. All of which were very different from the natural landscape of mangrove trees, waterways and sand. They were chosen as similar features are noted in the literature addressing modern slavery in the fish camps (Jensen 2013; Bales 2016), and they were identified in a preliminary search of the region in order to assess the possible benefits of instigating a research project using the Google Earth Pro geobrowser platform. Features were easily identifiable due to the high spatial-resolution data available on the platform from DigitalGlobe (Maxar Technologies) and Airbus which provided clear imagery which could be used to highlight these features. However, it is important to note that not all activity occurring in the marine environment may have been captured due to the sporadic nature of data uploaded to Google Earth Pro. Terrestrial activity were also more likely to be captured as the impact is more permanent. Recording the extent of all human activity is important for future conservation and management.

Areas of mangrove loss and erosion located at the camp sites were calculated using measurement tools available in the software (utilising the polygon function to annotate the Google Earth Pro data by calculating the area of the camps/mangrove forest removal; and the change in location i.e. erosion) by manually measuring the total area of the camps, and comparing the change in geographic area across the years with available data. The extent to which erosion was measured involved taking the furthest extent of the camp for each year, and measuring the extent of land that has been lost at the camp locations.

High temporal-resolution data from Planet Labs – which specialises in the development, launch, and operation of a high spatial-resolution (3m) 'CubeSat' Doves constellation (Hand 2015) using the 4-band PlanetScope sensor – were used to understand the seasonal trends of the camps; including when the peak operating periods are and when the periods for vegetation recovery occur. Data were accessed via a partnership with the University of Nottingham. The three-month PlanetScope mosaic data for the 2018 were downloaded for the Sundarbans to determine the seasonality of the camps. Moreover, Landsat data (30m spatial-resolution in the optical – red, green, blue, and near-infrared bands; 15m in the panchromatic – a single channel combining the measurements from the red, green and blue channels) were used to provide an estimated formation date for each camp – such as when the camp first appeared within the SRF using data from the peak processing period (November-December). Data from 1999-2018 were downloaded for each year during these months. The locations of the camps as identified by the systematic visual search and the information noted by Jensen (2013) and Bales (2016) informed the spectral sampling of the Landsat data to estimate the age of the camps. These data analysed spanned two Landsat sensors – Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager (OLI); data were analysed spectrally, using reflectance (red, green, blue and NIR; and the panchromatic band), to estimate camp age in ERDAS Imagine 2018 (Licensed by the University of Nottingham). Random sample points for spectral comparison were taken from the camps, the surrounding mangrove forest, and water. Differences in the spectral reflectance graphs were noted; the earliest year in which there were spectral differences at the camp locations were recorded as the estimated year of formation. These findings were assessed against Google Earth Pro data to support the estimated year of formation assertion. A trade-off was made between the spatial-resolution and time-series to analyse the 15m panchromatic band.

3.4 Results

Ten land-based fish-processing camps were located in the SRF from 2000-2018 (Figure 3.2); their size and occupation period varied (Table 3.1) – thus the area of mangroves affected differed annually. All camps were found on the southern coastal fringe; some are likely to be obscured from ground view along smaller channels, but are visible in satellite EO data. A number of camps were identified near the Indian border; they were smaller and more secluded than the eastern sites. These camps were briefly present, within the conservation areas (Sundarbans West and South) (Ramsar 2003), and are likely to have been removed because of the breach in conservation regulation. The camps in the east are larger, typically containing hundreds of drying racks. Site 5 is the largest camp, and is connected to the village of *Alorkol* on the island of Dublar Char.

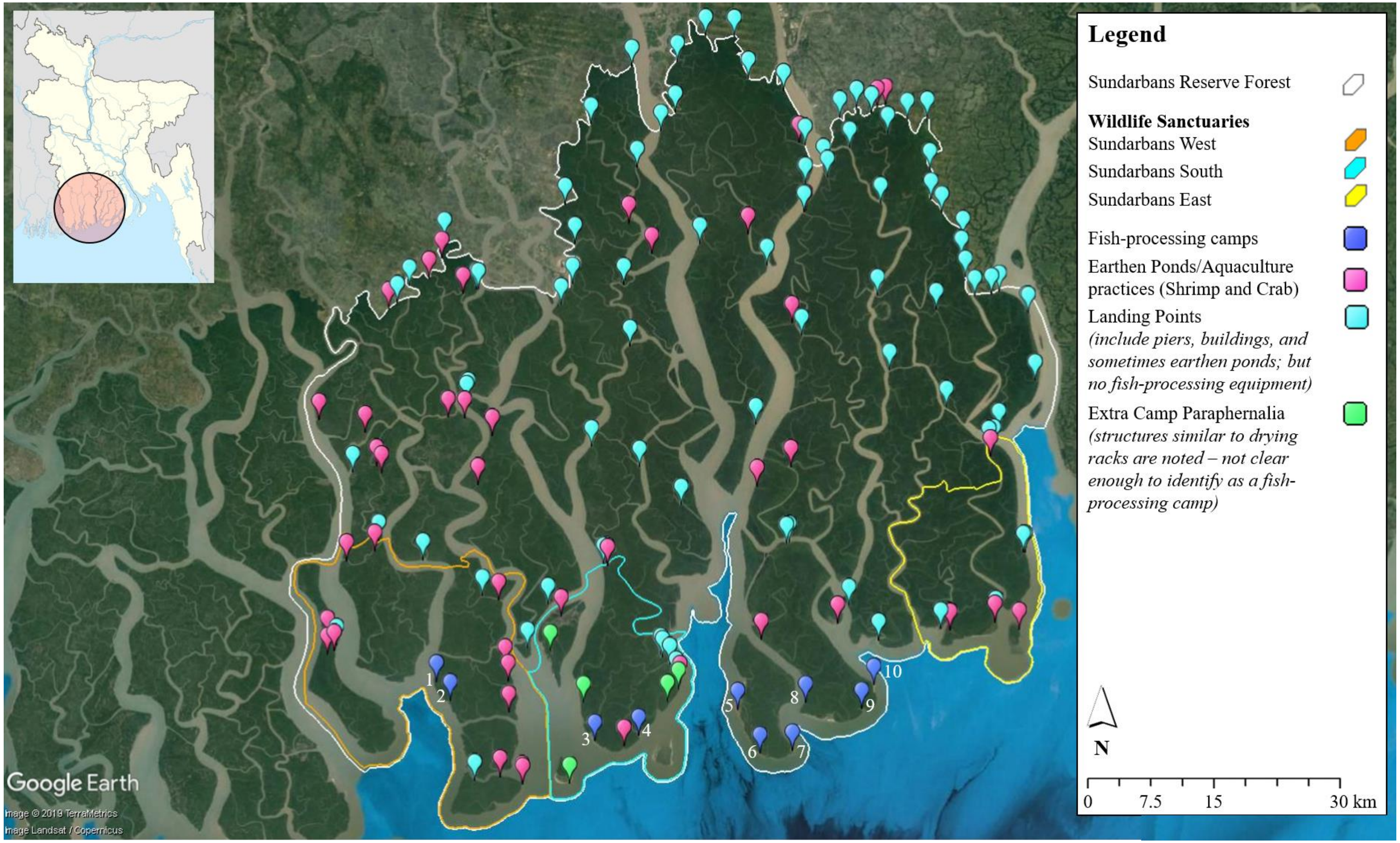

Figure 3.2: Map of human activity evident in the Sundarbans Reserve Forest, Bangladesh. This includes 10 fish-processing camps to the South of the reserve (numbered). The three protected wildlife sanctuaries are also visible (Ramsar 2003), their extent has been shown within the SRF boundary. Map data from Google: Landsat/Copernicus (2019).

Table 3.1: Area of mangrove forest (ha) that the fish-processing camps covered across the SRF as measure in the high spatial-resolution data available on the Google Earth Pro platform. Not all years are available (no data marked –) due to irregular updates to the platform, and some camps only have partial coverage (marked *).[a]

Fish-Processing Site	Year Imagery Available (Google Earth Pro)						
	2002	2006	2010	2011	2013	2014	2016
1	–	–	–	–	0.66	0.61	0.62
2	–	–	–	–	1.04	1.02	0.75
3	–	–	–	–	–	0.42	0.36
4	–	–	–	–	0.02	0.17	0.13
5	–	139.98	–	110.91	97.92*	106.61	80.34*
6	26.35	24.83*	25.06	24.51	–	19.71	9.56*
7	29.40	54.25	40.80	36.39	29.64	28.21	23.00
8	–	1.99	–	1.26	1.59	1.96	1.81
9	–	1.52*	–	8.26	9.44	9.41	8.16
10	–	17.99	–	17.17	18.85	17.46	15.59
Total area affected by fish camps ha per year	55.75	240.56	65.86	198.49	159.17	185.59	140.32

[a] Data gaps in the archive can be addressed in future analysis by building partnerships/gaining funding to access the archives of those data providers (DigitalGlobe and Airbus) used by Google to supply their platform. This would enable archival data searches to full in those early data-gaps for some of the camps and complete hopefully provide complete coverage for those years in which not all data were available for the area of interest.

Earthen ponds (pools of impounded water along the river channels) (Hossain *et al.* 2013) were the most common human-made feature after the drying racks (too numerous to quantify visually); present at five camps, predominantly in the east of the SRF. There is evidence that these ponds are used for both the growth in aquaculture (Ahmed *et al.* 2017; Rahman *et al.* 2017); and providing access to drinking water (Øhlenschlæger *et al.* 2016) for camp workers. Overall, 81 landing sites or small settlements were identified from 2000-2018; including villages, some of which had ponds – all found to the north of the SRF (Figure 3.2). Moreover, 187 independent earthen pond structures were recorded (2000-2018). One such pond formed before the development of Site 3 (to the north of the camp) and evidence of further pond development for aquaculture is visible at Site 9 during the 2016-2017 fish-processing season (Figure 3.3).

Figure 3.3: Formation of the second aquaculture pond at Site 9 (top-left of the image) in the Dove PlanetScope data from the 2016-2017 season; projected in true colour (red, green and blue bands used). Data courtesy of Planet Labs (Planet Team 2018).

Both Sites 6 and 7 reduced in size and moved inland approximately 315m (2002-2016) and 200m (2006-2016) respectively, as erosion occurred; visible in the Google Earth

Pro data. The formation of a second earthen pond at Site 9 may be explained by the partial collapse of the original structure; fluctuations in sedimentation upstream may affect the stability of the camps. Predicted destabilisation of the delta corresponds to locations where mangrove removal has occurred for camp development (Rahman *et al.* 2011; Payo *et al.* 2016).

Seasonal changes to the camps were visible in Planet Labs' '3-month mosaic' data (Figure 3.4); most notably at Site 5. The village of *Alorkol* found adjacent to this site is the only feature remaining once the camp has been dismantled following the processing season. Partial vegetation recovery occurs between April-September. The camps are fully operational during the post-monsoon winter months, when fishing conditions are improved (Kay *et al.* 2018); visible in the high-temporal Planet Labs data.

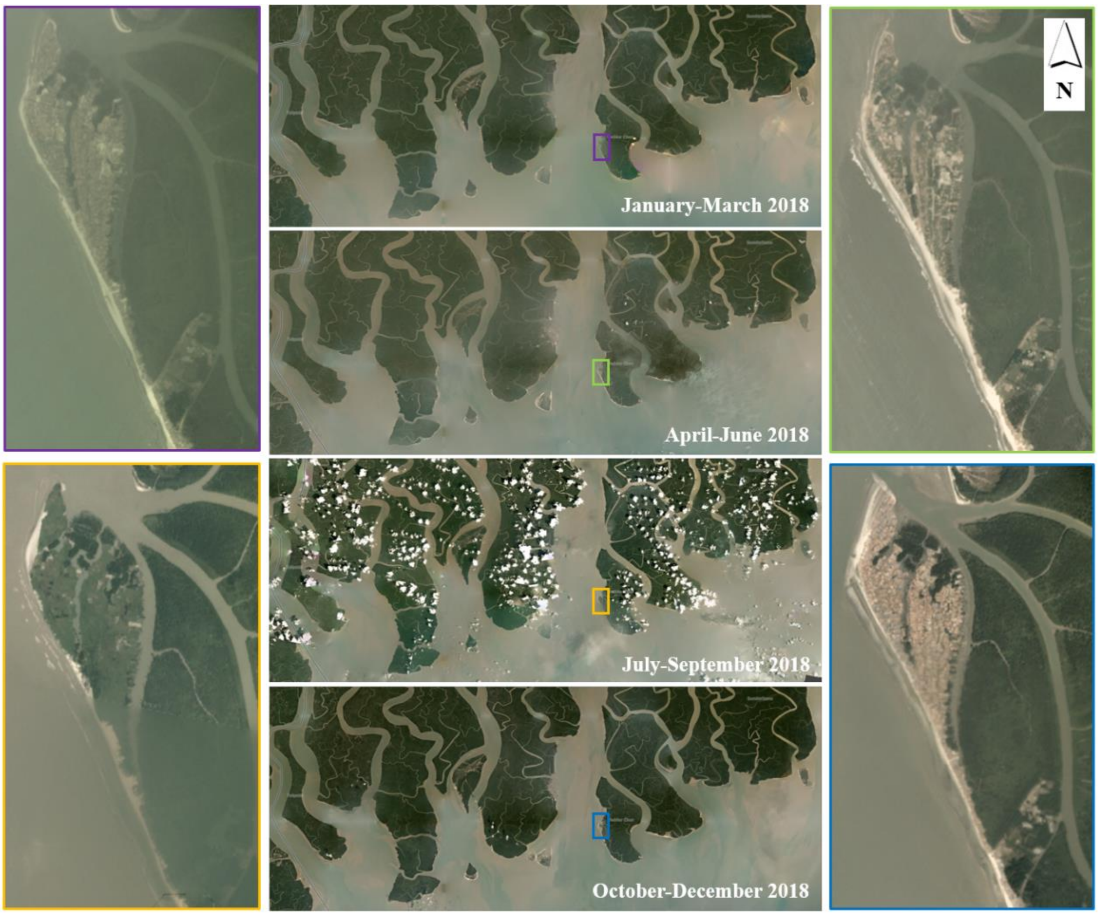

Figure 3.4: The seasonal variation of the fish-processing camps in SRF seen in the '3-month Dove 4-band PlanetScope mosaics' from Planet Labs – projected in the red, green and blue bands as a true colour image (Data courtesy of Planet Labs - Planet Team 2018). Surrounded by close shots of Site 5 at the village of *Alorkol* where the variation is clear – colours of the images denote the season they were captured, visible in the wider SRF view.

Supply of fish to the camps is often conducted using small boats predominantly used for small-scale fishing (Figure 3.5).

Figure 3.5: Example of the fishing boats which were identified in the Sundarbans, available to view on the Google Earth Pro, with imagery provided by Google: CNES/Airbus, captured 29.11.2016.

Camp age could not be confidently determined, however, Site 5-7, 9 and 10 appear to have been present in the earliest 1999 data. Moreover, the formation of Sites 1-4 were identified in the Landsat 8 OLI data, and corroborated by Google Earth Pro (Table 3.2).

Table 3.2: Landsat data identification dates from the panchromatic band (Band 8 for both the ETM+ and OLI sensors). The earliest date in which the fish-processing camps were visible was noted. The data were downloaded via the USGS Earth Explorer platform.

Fish-processing Site	Year Fish Camp First Visible	Satellite Platform	Sensor (with panchromatic band)	Date of the Imagery Assessed
1	2013	Landsat 8	OLI	24.12.2013
2	2013	Landsat 8	OLI	24.12.2013
3	2014	Landsat 8	OLI	25.11.2014
4	2014	Landsat 8	OLI	25.11.2014
5	Before 1999	Landsat 7	ETM+	08.11.1999
6	Before 1999	Landsat 7	ETM+	08.11.1999
7	Before 1999	Landsat 7	ETM+	08.11.1999
8	2010	Landsat 7	ETM+	24.12.2010
9	Before 1999	Landsat 7	ETM+	08.11.1999
10	Before 1999	Landsat 7	ETM+	08.11.1999

Future research efforts to determine the age of the fish-processing camps should incorporate the use of classification techniques which can identify spectral changes in data. The application of a methodology similar to that used to age the brick kilns (see Li *et al.* 2019) could then be applied to Landsat 5 Thematic Mapper (TM) data to provide more insight – this was deemed not possible as the reliance on the panchromatic band in this study, a band which is not available for the earlier Landsat 5 TM sensor. This would provide a more reliable estimate of the camp ages, and the period in which they were established, increasing knowledge around seasonal trends, and environmental impact over time. Thus, establishing the legality of these camps, particularly in the protected Ramsar zones.

3.5 Discussion

Using remote sensing this investigation has demonstrated the scale of environmental damage (area of mangrove that has been removed, and the associated loss of habitat for endangered species; as well as noting some of the key areas of erosion that will continue to be effected by rising sea-levels) and seasonal trends in Bangladesh's modern slavery-supported fish-processing camps. Camp operation fluctuates to reflect the productivity of the water and the availability of fish; as fish stocks decline and become more unstable, the length of time in which these camps operate is likely to reduce; yet exploitation is likely to shift to proximal warehouses and ports where fish are processed during the off-season (Jensen 2013; Brown *et al.* 2019). People will have to adapt to support subsistence lifestyles; for some, these changes will increase vulnerability to exploitation (Figure 3.1). In response to these changes in the marine environment, evidence of aquaculture growth is evident, and likely to increase. More than 180 earthen ponds have been identified across the SRF, with several located alongside the camps suggesting a shift in current activities. In turn, future land-based aquaculture could become the dominant environmentally degrading activity in the Sundarbans, with continued risk of exploitation for vulnerable populations reliant on fish products as people move from processing activities to aquaculture. There are also other environmental risks that could come to the front through the use of fertilisers and feed to encourage growth of shrimp and crabs which may leach into the surrounding environment. Moreover, these activities will also contribute to increased destabilisation of the coastal fringe through erosion and reduced sedimentation as they require space attained through mangrove removal (see Figure 3.3); the continued degradation of the delta; and increased vulnerability (Figure 3.1) for those who rely on the mangroves.

Applying these data has been important for 'sat-truthing' the locations where previously overlooked illegal activities have occurred; building on previous efforts to address human-driven degradation in the mangroves (see Lynch *et al.* 2013; Chaussard and Kerosky 2016). These locations traditionally form the basis of 'ground-truth' data. Coupling these data will help investigations move beyond the limitations of remote sensing and ground-data alone. Remote sensing has been touted as a technical method that should be incorporated to further understand the impacts and drivers of modern slavery (Drejer and Bales 2018; Landman 2018; Landman *et al.* 2019; Jackson *et al.* 2018 – Chapter 2/Paper 1/Appendix A; Jackson 2019), increasing comprehension of the nexus, and facilitating rapid response in targeted regions.

A number of the findings identified in this study support the assertions made with regards to the modern slavery-environment nexus in other studies. For example, quantitative data related to the area of mangrove forest lost over time supports the findings of habitat loss for endangered species as documented by Bales (2016) and Jalais (2004). Furthermore, Jensen (2013) makes reference to the harsh environmental conditions in which labourers subjected to modern slavery are expected to work;

including cyclones, and factors associated with climate change such as sea-level rise, landcover change, and increase salinity (Johnson *et al.* 2016). These risks have been reiterated by Brown *et al.* (2019) in the fish-processing sector. Thus, the connection the presence of the camps is likely to impact upon the environment. However, there is evidence that the presence of environmental crimes are being addressed more so than those which contain modern slavery. For example, fish camps 1-4 were removed swiftly following their establishment in the environmentally protected regions of Sundarbans West and South. Thus, it is suggested that holistic provision of responses to these social-ecological issues, there must be 'buy-in' from the local environmental stakeholders who manage these environmentally significant areas.

The lack of response to reports of labour exploitation and modern slavery within the SRF (see Jensen 2013; Bales 2016; Brown *et al.* 2019) may be a result of the working nature of the Sundarbans. As a 'reserve' the mangrove forest is open for the most part and can be accessed by those seeking to extract resources which support their livelihood activities (Appendix D: Table D.1). In order to be able to reliably identify modern slavery activity at these sites, triangulation between satellite EO data, ground-data, and secondary (social and ecological) datasets are necessary. It is incorporating these social data that will be key, particularly as we have established that the illegal environmental activity is already being identified and prioritised. To be able to identify features using socially oriented datasets it may be important to learn about the vulnerability features from previous research projects. For example, research into livelihoods, well-being and poverty alleviation in Bangladesh (including the Sundarbans) have utilised census, satellite, and survey data to address human-environment issues (e.g. Adams *et al.* 2016; Johnson *et al.* 2016). Proposals to address these effects have included an integrated framework which addresses changing ecosystems and their impacts on sectors that are directly known to support livelihoods as noted in this study such as fisheries, aquaculture, and fish-processing (Nicholls *et al.* 2016). However, in order for any framework addressing socio-ecological issues to be successful, it will need to incorporate an understanding of the nexus. This will be important in the context of addressing the SDGs, particularly as highlighted in this study and others the increased social vulnerabilities (which will include vulnerability to labour exploitation and modern slavery; Figure 3.1) (Szabo *et al.* 2016).

Therefore, holistically addressing the nexus (Brown *et al.* 2019) requires environmental change and social justice data. Remote sensing provides the ability to understand the former; identifying trends over large spatial extents; open-access satellite sensors can capture data globally every 5 days (e.g. European Space Agency's (ESA) Sentinel-2 satellites; Drusch *et al.* 2012), whereas commercial providers, such as Planet Labs, have rapidly developing daily monitoring capabilities (Hand 2015; Planet Team 2019). Almost 50 years of data can be accessed for archival analysis, and the number of planned missions are growing. Historical data provides the opportunity to understand previous (and future) environmental change dynamics in the mangrove system (see Heumann 2011; Giri 2016; Pham *et al.* 2019). These investigations could provide evidence to track human activities, such as modern slavery and its environmental effects and can feed into vulnerability frameworks which note how changes to the marine environment can impact coastal communities (Aswani *et al.* 2018). In areas where ground-data are not historically available, satellite EO data can fill these gaps – this is vital as ground-based research cannot be retroactively conducted, whereas geospatial analysis can.

An estimated 6-12 million people are working under conditions in which they are subjected to modern slavery, undertaking environmentally degrading activities (ILO

2017a; see Chapter 2/Paper 1 Footnote 3); the remoteness of the camps in a protected area increases exploitation risk (Bales 2016). In informal processing activities, operating outside the realm of regulatory measures and enforcement capabilities, some of the poorest, and most vulnerable people are at high-risk of exploitation. Yet the focus of antislavery and environmental organisations has only slightly shifted to include processing activities; mainly focusing on Thailand (EJF 2018; 2019c, 2019d). The differences between segments, and whom they affect, is key to understanding exploitation dynamics. Ignoring land-based activities, neglects the work of women and children (see Jensen 2013; EJF 2013, 2014). Remote sensing could assist in redressing this gender-bias by elucidating high-risk areas in land-based fishing activities. One programme that addressed this was the International Labour Organization's 'Ship to Shore Rights' initiative that operated across the Thai fishing and seafood industry, and included objectives to support workers and 'victims of labour abuses, including women and children' (ILO 2019). Similar combined interventions have been proposed within the forestry sector (see Jackson *et al.* 2020/Chapter 6/Appendix C; Jackson and Decker Sparks 2020). Moreover, remote sensing can assist in the future production of antislavery initiatives, as well as providing monitoring and evaluation for these schemes.

There are several other operational benefits of applying remote sensing to investigate the SRF. First, remote sensing is scalable; this is the dominant benefit of applying these data to investigate post-harvest fish-processing, marine capture fisheries and aquaculture activities (the latter is being analysed using Sentinel-1 Synthetic-Aperture Radar (SAR): see Ottinger *et al.* 2018; Prasad *et al.* 2019) in locations where modern slavery occurrence is high-risk, or has been documented. Secondly, it is a relatively inexpensive and cost-effective data collection method (Woellert *et al.* 2011; Foody *et* *al.* 2019). However, integration of primary ground-truth data going forward is necessary to verify satellite EO data – thus moving beyond the examples from the literature (i.e. Jensen 2013; Bales 2016) that were used in this study. Finally, Verité (2016) note that operations, such as shrimp farming, often occur in dangerous and inaccessible areas; satellite sensors can provide these data in a safe manner. Including remotely sensed data would begin to readdress the neglect of land-based fishing activities, rebalancing our understanding of the social-ecological implications of these activities.

However, several limitations exist. For example, data available on Google Earth Pro was temporally sporadic and did not always provide coverage for the ten camps in the same scene, or timeframe. Only a snapshot of the SRF is provided, whilst this enables the characterisation of trends in fish-processing activities, it is not holistic. Planet Labs does not have the same spatial detail as the commercial data on Google Earth Pro despite planned sensor improvements (Planet Team 2019). Additional trade-offs are found in the temporal availability; Planet Labs has a limited data archive despite collecting data frequently. These data fill some data-gaps in the Google Earth Pro archive, but they do not completely resolve the issue of sporadic data.

Moreover, analysis of Landsat's 30m data determined little-to-no spectral difference between the camps and mangroves. Even with the 15m panchromatic band, the estimated age of the camps were difficult to determine and may have formed before 1999 but this was not identified as panchromatic data were only available from 1999 (within the ETM+ sensor). Finally, striping in the ETM+ data following the Scan Line Corrector failure (SLC-off products) (USGS 2003) obscured some sites – affecting 2007, 2011 and 2012 data.

In order to address some of these limitations, the notion of triangulating data sources will be vital – using a three-pronged approach utilising satellite EO data, ground-data, and secondary data sources; and this study should be viewed as a point of reference from which to start. For example, the identification of several camp locations have been identified, and using Landsat data we have been able to estimate the age of some camps, and view the seasonality in camp operations. However, research should not cease here; the findings from this study provide an opportunity to develop further applications of these technology in this sector. Firstly, to identify older sites and more accurately age the sites using techniques applied to sectors of similar risk (e.g. brick kilns; Li *et al.* 2019). By combining these multiple strands of data, the identification of locations which may be transitioning into more environmentally damaging activities, such as fish-processing camps and which may be utilising modern slavery practices once remotely sensed modelled are better able to identify the risks automatically (Landman *et al.* 2019). Secondly, these multiple data sources can be applied in the identification of sites which operate thus causing environmentally damaging activities – which will support the overall governance of protected regions such as the Sundarbans; and support in the identification of risk towards modern slavery, particularly as secluded regions have been linked to the presence of modern slavery (Bales 2016).

Going forward the limitations noted above should decline and opportunities for further research have been identified. Yet, there is little that can be done regarding high spatial- and temporal-resolution data access for limited cost – apart for the development of partnerships and gaining funding for the access of commercial data from providers.

3.6 Conclusion

Land-based post-harvest fish-processing activities along the coastal fringe have largely been overlooked by antislavery organisations and the marine development community.

As demonstrated here, remote sensing is an additional tool that can investigate the extent to which these activities operate over space and time. This study focused on fish camps in the Sundarbans mangroves of the Bangladesh and demonstrated the varied environmental effects of these operations in a semi-closed system. Camps were identified in areas where no human activity is permitted, and the area of deforestation and land lost through erosion has been quantified. Furthermore, additional revenue streams are being produced through small-scale aquaculture ponds. These sites have previously documented cases of modern slavery in their workforce; remote sensing has enabled insight to begin understanding the context of the modern slavery-environmental degradation nexus (Brown *et al.* 2019) within this overlooked segment.

However, to fully understand the nexus and address the SDGs, further ground-data is required; remote sensing should be applied going forward (Jackson *et al.* 2018 – Chapter 2/Paper 1/Appendix A) as part of a wider investigation approach (Jackson 2019; Landman *et al.* 2019; Scoles 2019). The benefits of ending modern slavery and protecting the environment are contained in the 'freedom dividend' (Bales 2012: xxix) – where social prospects improve, economic benefits are achieved, and the environment is protected. It is imperative that the study of the fisheries sector expands to include land-based activities, particularly when striving to address modern slavery. By achieving this in the SRF and limiting criminal activities, the ecological integrity of the mangroves can be protected, and those who rely on the SRF can be supported. Further insight into the nexus between modern slavery and the environment can be gained using satellite EO data; ultimately providing a case for continued use of these data types. Remote sensing provides an opportunity to expand our knowledge of environmental degradation, fish-processing activities, and the impact of modern slavery; supporting multiple social and environmental SDGs.

Chapter 4: Brick Kilns Estimation

This Chapter/Paper 3 (see Table 1.3) has been adapted and updated from its original published version in the *ISPRS Journal of Photogrammetry and Remote Sensing* which is contained in Appendix B.

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

4.1 Introduction

Modern slavery is defined by the Global Slavery Index (GSI) as "situations of exploitation that a person cannot refuse or leave because of threats, violence, coercion, abuse of power or deception" (Walk Free 2016: 158) (see also Table 1.1 – which refers to the 2012 Bellagio-Harvard Guidelines). Recent estimates by the International Labour Organization (ILO) (2017a) indicate there are currently 40.3 million people subjected to modern slavery globally; more than 30 million are thought to be located in the 22 Organisation for Economic Co-operation and Development (OECD) Development Assistance Committee (DAC)-list of recipient countries.[11] These nations are uniform, comparable and have representative data on the issue. Moreover, an estimate 6-12 million people are thought to be engaged in environmentally degrading sectors (ILO 2017a; see Chapter 2/Paper 1 Footnote 3). As previously noted, the Sustainable Development Goals (SDGs) have integrated the issue of modern slavery within target 8.7 (part of SDG 8 "Decent Work and Economic Growth") (UN 2016b).This is a global

[11] For current OECD DAC-list countries used in the GSI see www.globalslaveryindex.org

target that requires all nations to put forward assets and people in order to permanently end modern slavery – which would assist in achieving connected environmental targets.

Despite this global political commitment to end modern slavery, accurate information on modern slavery activity is difficult to come by and is ultimately one of the largest barriers to the permanent ending of modern slavery – the work within this research Chapter/Paper and others aims to provide data to fill this evidence-gap, with particular reference to the modern slavery-environment nexus (Brown *et al.* 2019). Reliable, timely, spatially explicit – and as demonstrated in this thesis – scalable data on modern slavery activity is required. Often to understand the issue, sector-wide data are required. 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 – see Chapter 7: 'Discussion and Recommendations' – are required.

As has been explored in detail within Chapter 2/Paper 1 (Appendix A) there is huge potential for remote sensing to inform efforts to investigate humanitarian and human rights issues; as first mooted by Bales (2007: 163) – who has continued to advocate for these forms of technological application (Drejer and Bales 2018). A range of these issues have been assisted by the use of remotely sensed data, including: poverty assessment (Jean *et al.* 2016; Watmough *et al.* 2016) and international peace and security missions (Jasani *et al.* 2009) amongst many others. As a result, previous investigations which have demonstrated unique system-wide networks dedicated to improving humanitarian and human rights responses through knowledge and accountability; Harvard Humanitarian Initiative and (HHI) and Amnesty International are good examples of organisations which are improving their understanding of crises and abuses through the added value of Earth Observation (EO) data.[12] The benefits gained from conducting assessments of human rights abuses using high resolution satellite remote sensing in particular, when combined with eye-witness testimony from the ground can be extremely useful. Gains manifest in the ability to track and identify crises, assisting in the prosecution of perpetrators (Lavers *et al.* 2009) or enabling rapid response to crises when they occur (Piesing 2011; Witharana *et al.* 2014).

The application of satellite EO data and analysis techniques to investigate modern slavery, and in particular the environmental implications of these activities are limited. The work in assessing the scale and environmental integration of modern slavery in the post-harvest fish-processing camps in the Bangladesh Sundarbans has demonstrated the use of remote sensing for the detection of modern slavery activity is clearly a potential application area ripe for exploration (refer to Chapter 3/Paper 2; McGoogan and Rashid 2016). As is the application to address tree loss (Jackson *et al.* 2020 – Chapter 6/Paper 5/Appendix C).

Throughout this Chapter (Paper 3/Appendix B) the aforementioned potential to apply satellite EO data to support antislavery action is built upon from the analysis undertaken in Chapter 3 (Paper 2), thus enabling the presentation of the first estimate for the number of brick kilns located across the 'Brick Belt' in order to support social-ecological legislation to end bonded labour, and limit environmental damage. The 'Brick Belt' is an expansive region across South Asia noted for its production of bricks due to the geological composition of the area (explored further in Chapter 5/Paper 4) and the need

[12] Programmes by HHI (http://www.alnap.org/) and Amnesty International, such as 'Science for Human Rights Programme' (via www.amnesty.org), are good examples of the remote sensing application for humanitarian and human rights. Further details of organisations using these techniques for other causes are contained in Chapter 2/Paper 1 (see also Jackson *et al.* 2018 – Appendix A).

for construction material. Investigation of the brick kilns is pertinent; these environments are known to use modern slavery practices within their workforce in around 40-70% of cases (Mitra and Valette 2017; Anti-Slavery International 2017; ILO 2005; Save the Children 2007). According to the ILO (2017a) 15% of people in the manufacturing sector (which includes brick-making) are subject to conditions of forced labour. Research points to the ongoing and widespread abuse and exploitation of brick kiln workers, including children, and situations of forced labour, with many working under conditions of debt bondage (Antislavery International 2017). Migrants are the predominant workforce, often from socially excluded and economically marginalised communities linked to the caste system (Bales 2012). These previous studies (Anti-Slavery International 2017; Bales 2012) have sought to understand the social drivers and conditions faced by kiln workers – addressing living conditions, pay, literacy rates and health; predominantly using qualitative interviews to collect data and identify areas which are more susceptible to modern slavery. Moreover, the environmental drivers of these exploitative actions are also beginning to be assessed (Bales 2016; Decker Sparks *et al. under review*); yet the inclusion of remotely sensed data is only now beginning to be applied to these industries as an additional data source to assess the social-ecological drivers of modern slavery in brick-manufacturing. Lack of understanding of these drivers, and limited preventative action and prosecution means little is currently being done to prevent such labour abuses (Bales 2005, 2012; Kara 2014; Khan and Qureshi 2016).

At present, regional estimates relating to the number of brick kilns, and thus those subjected to modern slavery working within them are unclear. The full extent of the number of kilns in the 'Belt' and, by proxy, modern slavery is unknown. For example, the non-governmental organisation (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; up to 70% of these kiln workers are thought to be labouring under of debt bondage according to research by Anti-Slavery International (2017) which focused on India. Others have offered estimates relating to the number of children working 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. These children form part of the indebted 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, 2012). This statistic is further supported by an ILO (2005) report which found that around 40% of all kiln workers (children and adults) within Punjab, Pakistan, are working as bonded labourers. It is clear then that between nations and sectors there is a difference in the estimated proportion of people being exploited – as a hidden issue, it is difficult to measure modern slavery within the workforce of these sectors as reflected in the varied estimates of exploited workers (from 40-70%). However, these estimates can be improved by developing more accurate data regarding the brick-making sector – such as estimating the number of kilns, and eventually undertaking a spatial and temporal mapping exercise to locate the kilns, as well as assessing change over time (Boyd *et al. forthcoming*; Li *et al.* 2019)

This Chapter/Paper (see Appendix B) is an initial step in providing data needed to inform action, especially before an assessment of the environmental effects of this sector can be addressed (Figure 1.3) – supporting the push from the remote sensing community to strive to produce evidence for specific targets and indicators for the achievement of the SDGs (Andries *et al.* 2018; Kussul *et al.* 2019; Masó *et al.* 2019). High spatial-resolution satellite remotely sensed data are used to make a rigorous and credible estimate of the number of kilns across the ‘Brick Belt’, using a straight-forward and reproducible method – based on freely available, accessible satellite data that will facilitate future work and the progress monitoring of UN SDG 8.

4.2 Study Area

The brick-making industry is a large part of the development of the infrastructure and economy in these nations (Hawksley and Pradesh 2014) and production appears to be increasing to cope with demand for building materials (Baum 2010). The areal extent of the ‘Brick Belt’ is approximately 1,551,997 km^2 [1,595,706 km^2 when the northern Indian State of Jammu and Kashmir is included], crossing country 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 Chapter/Paper (see Appendix B) was to provide an estimate of the total number of brick kilns in the ‘Belt’. Moreover, evidence to support the quality of the estimate was provided. Thus, a smaller study was undertaken in a 250 km^2 region, in the northern Indian State of Rajasthan. Ground intelligence from NGOs suggests a high occurrence of brick kilns exist in this region. The ‘Brick Belt’ is an unofficial region of Pakistan, northern India, Nepal and Bangladesh which is home to thousands of kilns (Figure 4.1).

Figure 4.1: 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.

There are several types of kilns, however, large oval kilns dominate the ‘Brick Belt’ (perimeter of around 217 m), known as the Bull’s Trench Kiln (BTK); it is these BTKs (and their modified cousins, the Fixed Chimney Bull’s Trench Kilns – FCBTK) that are the most likely to use workers subjected to modern slavery (Bales 1999, 2012) due to their size (Patil 2016), and analogue manufacturing techniques. Manual labour is required at all stages of the process (see Bales 2012: 152-154 and Lundgren-Kownacki *et al.* 2018: 351 for a description of the manufacturing methods).

4.2.1 Background on Brick Kilns

There are several types of brick kilns found across the ‘Brick Belt’ (Maithel *et al.* 2014), however, the three most common are Bull’s Trench Kilns (BTK) – or Fixed Chimney Bull’s Trench Kilns (FCBTK) – a circular variation of the BTK/FCBTK kilns, and finally Zig-Zag kilns which are often modified versions of the original BTK/FCBTK structures. BTK/FCBTKs are the most common kiln, they are a continuous kiln which is highly polluting due to the inefficient burning of fuels; oval in shape, they are usually found with a fixed chimney in a central location within the kiln. Circular kilns operate in a similar manner but they are smaller in size. Finally, Zig-Zag kilns are often adaptations of BTK/FCBTKs as this is more cost-effective than building a new kiln, therefore these modified kilns are of similar sizes to BTK/FCBTKs, and also operate using a continuous fire. However, Zig-Zag kilns are more energy-efficient due to the stacking of the bricks before firing which creates a pattern of air flow (a natural draft), thus enabling the fuel to burn more efficiently so less pollution (predominantly black carbon) is released during the firing of the bricks. Perhaps the most distinctive difference is that the traditional oval shape has been adapted into a rectangular one, in order to accommodate the stacking configuration of bricks required for an efficient burning cycle. Examples of these kilns as observed from above are included in Figure 4.2.

Figure 4.2: Examples of the three dominant types of kilns which are found across the 'Brick Belt'. All images were captured by WorldView satellites – DigitalGlobe/Maxar Technologies – and downloaded from Google Earth Pro (23.05.2020). A: captures a BTK which is found near Lahore, Pakistan (31 54 27.55 N, 74 13 32.88 E) and was captured during the brick-making season on 06.12.2017, hence the smoke which is visible from the centralised chimney. B: is a circular kiln found in a kiln cluster near Jaipur, India (26 54 6.23 N 75 57 14.97 E); captured 08.04.2020. Finally, C: is a Zig-Zag kiln – notable due to the rectangular shape. This kiln was captured on 25.04.2018 in a large cluster of kilns to the north of Dhaka, Bangladesh (24 1 12.01 N 90 20 27.69 E).

Kilns across the region operate in seasons. These vary across the 'Belt' as a result of slight variations in the sector and weather conditions meaning that the prime brick-making period varies per country. For example, in India and Nepal the season lasts between November and June each year (in Kathmandu Valley this is slightly shorter, from January to May); whereas in Pakistan, there are two brick-making seasons, one in the winter (November to January) and another in the spring/summer (February to June) (Mitra and Valette 2017: 18). Production is halted during the summer months due to the monsoon, and the cold climate/early evening within winter (Bales 2012: 166); these conditions are unfavourable for the drying process involved in this form of brick-making. These patterns of operation mean an estimated 1.2 trillion bricks are produced across Asia each year (Lopez *et al.* 2012: 5).

Furthermore, as a result of their sheer size, the demand for bricks, informal regulations, and lack of mechanisation; large amounts of manual labour are required to maintain operation within these structures. Migrant labour and people of lower castes are the most likely to be working within these kilns. When these conditions combine, the risk of bonded labour can increase. Each of these people have a distinct role within the kilns during brick production. From the modelling of 'green' bricks to the firing of them in the kiln. Adapted from field observations by Lundgren-Kownacki *et al.* (2018: 351) the brick-making process is noted below. Stages A-D are predominantly undertaken by women and children within the clay-fields which surround the kilns, whereas the firing and sorting of the bricks is usually completed by men. Brick-making process:

a) Material procurement: clay topsoil is extracted, then stored in the open.
b) Tempering: the clay minerals are mixed with groundwater or surface water.
c) Moulding: the clay-water mix is rolled in sand and shaped into moulding blocks by hand – predominantly by women and children. Additional materials may be added to strengthen the mix (e.g. wood, soybean husk, fly-ash and other agricultural waste) (Khan and Vyas 2008).
d) Drying: the moulded 'green' bricks are emptied and laid out on the ground for the sun to dry. Turning occurs every two days to facilitate uniformed drying.
e) Firing: the bricks are stacked in the kilns and packed with a mud-sand mix to ensure the fire heat is secure – if done incorrectly the stack can collapse. Men stand upon the bricks to light fire and stoke it through 'fire holes' (with fuels of wood, coal, used motor oil, diesel and old tyres) that are sealed afterwards to retain heat. This is a continuous process within the three kilns notes in Figure 4.2 – meaning that the fire moves around the kilns for several weeks at a time. Continuous burning is one of two operational approaches. Once fired, bricks are removed from one end of the kilns, and 'green' bricks are added at the other end ready to be fires. [13] Temperatures in the kilns can reach more than 1,500 °C (Bales 2012: 151) and occur during the brick-making seasons.

[13] A diagrammatic representation of the firing process of the kilns is available from TERI (2017: 3).

f) Sorting: once fired, the removed bricks are sorted by colour – an indication of burning and therefore the quality and price of the brick.

Whilst these are not the only types of kilns, they are the ones that are found across the 'Brick Belt'. Understanding the way in which the sector operates and the types of kilns which are found there is key to gaining knowledge about the scale of the industry, and eventually its social and environmental impacts.

4.3 Data and Methods

A methodology was adopted based on high resolution satellite data provided by the geographic browser Google Earth Pro. The open access satellite EO data provided has been used in a 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 high spatial-resolution of satellite EO 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 Pro. Examples of different kiln types found during the sampling process can be seen in Figure 4.3. In this study, brick kilns were identified via systematic visual search and 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 0.56m and 0.5m respectively) between 05.11.2014 and 03.12.2016.

Figure 4.3: An image featuring two brick kilns. One is a traditional Fixed Chimney Bull's Trench Kiln (FCBTK) and the other is a circular kiln. Surrounding these kilns are a number of clay fields used in the production of the bricks themselves before the firing of the bricks. These fields are commonly found close to the kilns although sometimes they are not directly adjacent to the kilns.

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 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 (approximately 15,500 are located across the region) 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 kilns 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 crowdsourcing were tasked to identify brick kilns in the imagery of this area in the Indian State of Rajasthan. Volunteers analysed image extracts presented randomly from the 396 image extracts downloaded from Google Earth Pro 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 a wide, varied audience, in addition to the relevance of the data captured about the volunteers' annotations. The "Slavery from Space" site consisted of a landing page with a "Get Started" button, which navigated users to a classification page where they marked the centres of brick kilns in Google Earth Pro satellite imagery.[14] 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 FutureLearn website.[15] The project was then promoted on social media, and some members of the Zooniverse discussion forums also participated. The project was promoted by the *New Scientist* (Reynolds 2017), which enthused a new audience,

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[14] The images provided for classification could be manipulated for closer inspection using the image controls (e.g. zooming and panning). The page presented volunteers with a tutorial that described the task's steps. Google Earth Pro images were presented alongside the question text and a tool for marking kilns on the image. Volunteers operated this by clicking with their left-hand mouse button. A help tool is also provided for volunteers which gave detailed task instructions and example images. When volunteers had marked all the kilns on an image, they clicked on a green "Done" button to see a summary of their response and then a "Next" button to load a new image.

[15] The MOOC 'Ending Slavery: Strategies for Contemporary Global Action' is available via the www.futurelearn.com website. The project was run by the Rights Lab, University of Nottingham. Project statistics are available: www.zooniverse.org/projects/ezzjcw/slavery-from-space

and resulted in the project's completion in the last week of June 2017 when all 396 images has 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 using a nearest neighbour clustering algorithm to count and locate aggregated markings made by four or more independent volunteers, located within five pixels of each other, was deployed.[16] Thus, a kiln was identified and labelled as such when at least 4 of the volunteers who viewed an image extract suggested the same or similar location for its centre. Although not ideal, this approach is similar to that used in other studies in which volunteers have been used to identify simple land cover information from high-spatial resolution imagery (Foody *et al.* 2015). Crowdsourcing has considerable potential to support studies such as this that require simple visual interpretation of imagery; which can then be used to support more complex applications such as machine learning (see Foody *et al.* 2019; Li *et al.* 2019). 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 datasets to be surveyed over a short period of time. 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; there is potential for error and uncertainty arising from spammers to simple,

[16] Clustering algorithm available from: https://github.com/zooniverse/aggregation-for-caesar/releases/tag/0.1

genuine mistakes – the use of multiple interpreters may help to address data quality concerns (Foody 2014; Foody *et al.* 2013).

Finally, the image extracts were subjected to annotation by an independent adjudicator who followed a rigorous labelling protocol (identifying a kiln, whether that is circular or a more traditional BTK/FCBTK, or not kiln at all based on the example images – see Figure 4.2) and whose labels were taken to be the most authoritative of the derived dataset. These latter labels were used as the 'ground truth' in terms of expressing the accuracy of the initial expert interpreter who studies the entire 'Brick Belt' and the labelling derived from the volunteers.

4.4 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 (Figure 4.4) while two contained over 30 kilns each (Figure 4.5). In total, the expert identified a total of 1,142 kilns across the 320 grid cells sampled (Figure 4.4). 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 4.1). There is no directly comparable estimate to compare this 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: 1) reported that "It is estimated that there are at least 100,000 functioning brick kilns in India…", but again the source of this figure is not given (and note the 'Belt' only encompasses a small part of India). Sonia Awale (2015) in the Nepali Times estimates "1100 or so brick kilns in

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 this estimate – with a rigorous methodology as its heart – should be used to inform future work on brick kiln numbers, location, age, environmental impact, and operational activity.

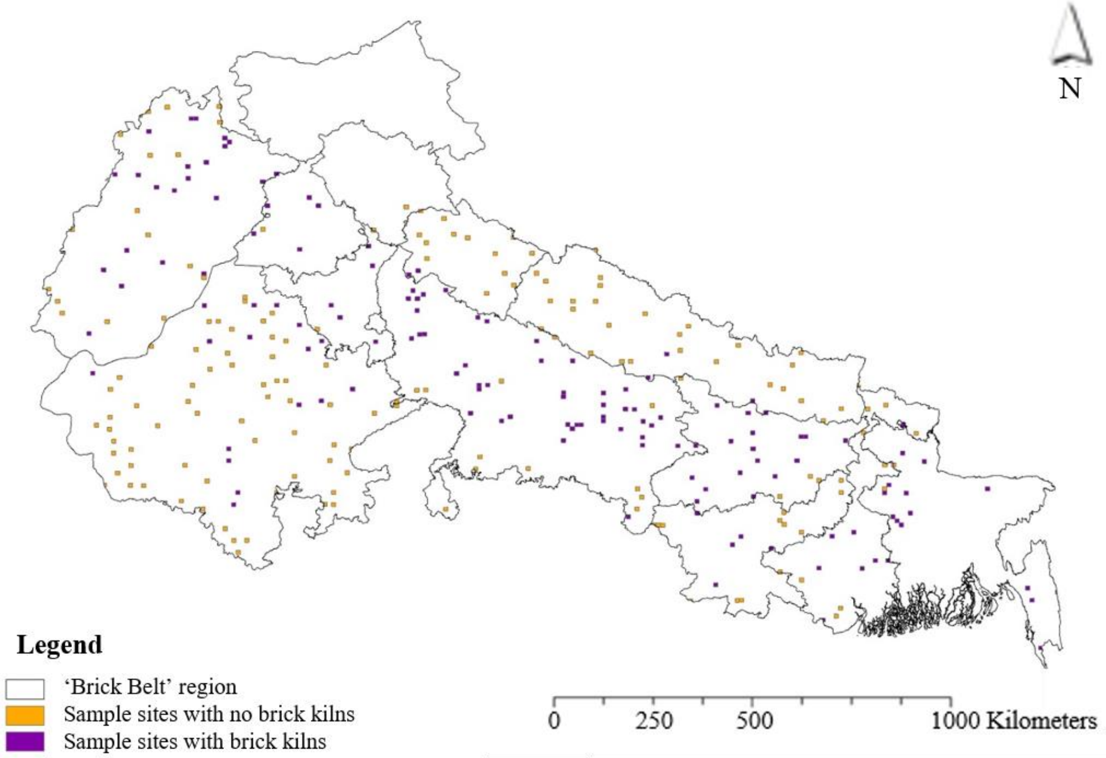

Figure 4.4: Location of the randomly generated 320, 100 km^2 sample cells, illustrating which had kilns and which did not, across the 'Belt'. A standard simple random probability sample design, was used to allow unbiased estimation. A cell with multiple kilns has the same inclusion probability as a cell with one or no kilns present. The approach adopted allows an estimate of the total of kilns over the entire study area. Note, some regions were not captured in the random sample.

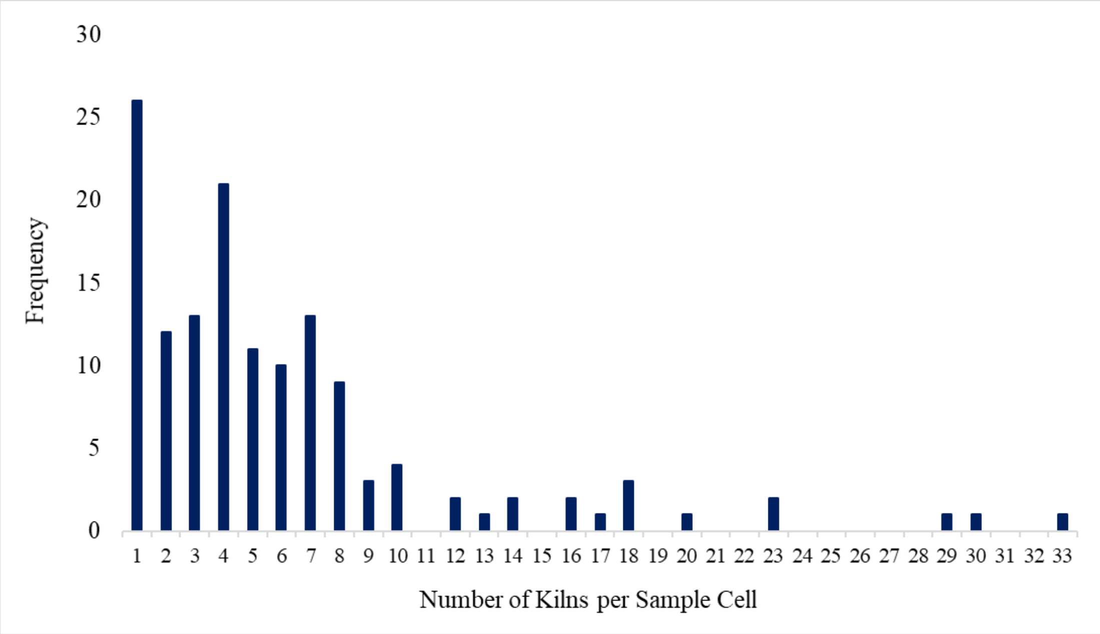

Figure 4.5: Frequency distribution of number of brick kilns per sample cell. Note that 1,142 kilns were found across the 320 sample cells with 43% of those cells featuring one or more brick kilns.

Table 4.1: Results and important statistics from the sampling process.

Statistic	**Results**
Total number of cell samples	320
Total number of kilns	1,142
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 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 kiln number for the 'Belt' of 44,542 and 66,270 respectively.

However, the random sampling undertaken as part of this estimate did contain a couple of limitations. First, some areas of the 'Belt' were not captured in the sampling process (Figure 4.4). This is a key issue of random sampling – entire regions can have missing population segments, as reflected in Bangladesh and the state of Jammu and Kashmir. This is counteracted somewhat in the estimate by the provision of lower/upper limits. However, future sampling should apply a stratified approach. For example, undertaking sampling in each country would limit the lack of sampling for entire regions and potentially provide a more accurate sample. Further sampling improvements can be determined though distance (from urban environments where the majority of kilns are located) to improve the dimensionality of data collection, particularly in continuous geographic regions, such as the 'Belt' (Morgan and Gallagher 2014). Thus, a stratified random sampling approach may be an appropriate alternative choice. Second, the sampling process did not consider landcover; as a result there were samples in the Himalayas (Nepal) and the Thar Desert (India), where kilns are unlikely to be located due to the unfavourable terrain and climate. However, these regions were all included in this initial estimation as kiln are found on the carved land in Kathmandu Valley; as well as decommissioned kilns in the Thar Desert and kilns to the north of Rajasthan, such as those noted in the data which were used to determine the accuracy of the estimate. Combining the information gained from this study with future mapping can determine additional factors such as distance to urban settlements, landcover, social and environmental factors which may increase the likelihood of kilns being established and the exploitation occurring; thus improving the sampling and enabling mapping via machine learning, such as that undertaken by Foody *et al.* (2019) and Li *et al.* (2019).

During the check on 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 that clearly matched the brick kilns identified by the expert interpreter, illustrated in Figure 4.6A. 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, one and 17 additional features were identified as kilns by the independent adjudicator and volunteers respectively; shown as a proportion of error (Table 4.2). 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 related to footprints of old kilns (Figure 4.6B), half built kilns and other circular features such as roundabouts (Figure 4.6C). Other lone markings by volunteers also featured (e.g. Figure 4.6D 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 northern Rajasthan area. This also informs us that elsewhere in the 'Brick Belt' the density of brick kilns is typically lower.

Table 4.2: 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%	–

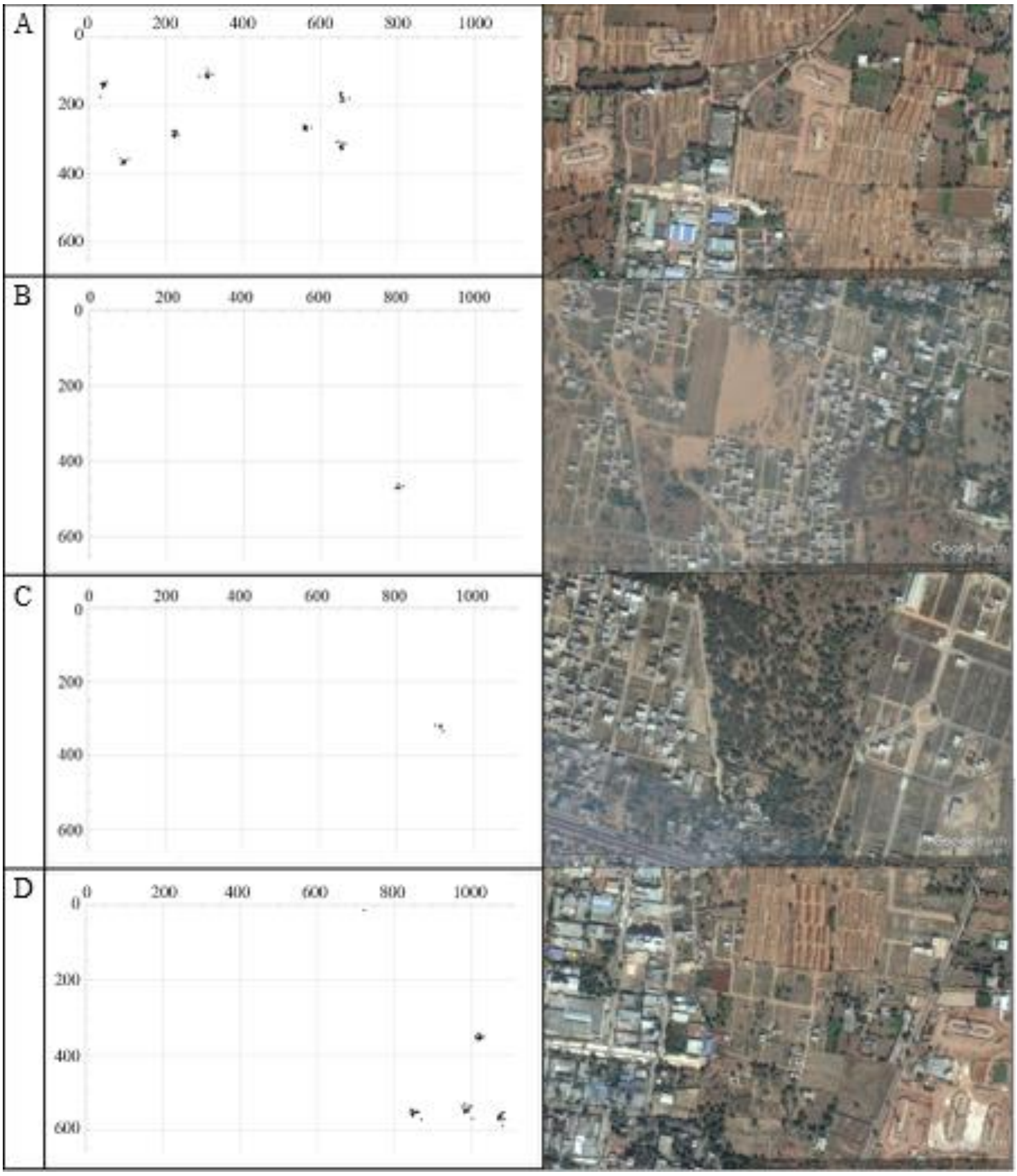

Figure 4.6: Examples of markings made by volunteers. A: Example of an image with seven kilns are the correct identification of them by the volunteers (as denoted by their clustering); B: An example of a disused kiln identified by some volunteers; C: An example of wrongly identified feature (a roundabout, though notice a minimal making in the cluster) and D: One lone marking of a feature associated with the a clay field (note the four clusters correctly marking brick kilns).

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 the brick kilns (the results from this were then used to inform machine learning analyses – such as Foody *et al.*

2019, and Li *et al.* 2019 – which provided data for the environmental analysis of the 'Brick Belt' – see Chapter 5/Paper 4). 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 NGOs, working to free slaves. Only by working with these organisations can the estimate produced in this Chapter/Paper be used to calculate the number of slaves working in this industry across the 'Belt'. Moreover, we can also examine the impact of modern slavery beyond that of the victims/survivors themselves. For example, more precise estimates of how much environmental impact results from modern 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 labourers subjected to modern slavery. Figure 4.7 illustrates clearly the emissions from the Fixed Chimney of a Bull's Trench Kiln. This illustrates well a case in point: focusing 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 4,000 brick kilns in the Punjab region of Pakistan released 525,440 tonnes of CO_2 each year. Applying their estimate of an average 131 tonnes of CO_2 per kiln, the resulting output suggests the 'Brick Belt' could be responsible for emitting 7,255,697 tonnes of CO_2 each year. It is also important to note that brick kilns account for an additional increase in global warning by the type of smoke they produce. This particularly damaging type of smoke is called black soot, or sometimes "black carbon". As 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, compare with 40 percent for carbon dioxide." We are currently unable to estimate the amount of 'black soot' within the overall CO_2 calculation. However, the fundamental point is this: in addition to being a scene of serious human right 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.

Figure 4.7: An example of a Fixed Chimney Bull's Trench Kiln (FCBTK) at 31 32 18.798 N, 75 58 52.975 E – note the emissions from the chimney stack. Image from DigitalGlobe's WorldView-2 satellite system; pan-sharpened natural colour at 50 cm spatial-resolution; captured in November 2015.

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 EO data from which the features relating to modern 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 European Space Agency's (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 Pro 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 Pro, but also ESA Cloud Toolbox and NASA Earth Exchange (Klein *et al.* 2017) is important. As is integration with wider social and environmental observatories such as a 'Global Antislavery Observatory' (ILO 2015; Landman *et al.* 2019), or a 'Digital Ecosystem for the Planet' (UNEP 2018; Campbell and Jensen 2019; Jensen et al. 2020a, 2020b). Also important will be to continue to harness the power of the crowd; after all sustainable development is everyone's business (Walters 2017). Dissemination of key findings can be accomplished using the aforementioned geobrowsers – 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 perspective. As has been demonstrated in this Chapter/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).

Despite these promising research avenues there are challenges ahead in linking the statistical estimates reported here to modern slavery activity, and in particular, the nexus (Brown *et al.* 2019). This requires follow through, but at least, for the first time the scale of the brick-making industry in the 'Belt' is known. This can be used to further investigate the spatial, temporal (Li *et al.* 2019) and environmental trends of the sector (Chapter 5/Paper 4). The only other investigation of this nature was conducted on Lake Volta by Tomnod (Tomnod and World Freedom Fund 2015; IJM 2016) and this was deemed very important as it helped to provide external and verified evidence that modern slavery was occurring (Jackson *et al.* 2018; see Chapter 2/Paper 1/Appendix A) – despite the controversy that has since arisen regarding exploitation on Lake Volta (Mensah and Okyere 2019).[17] It has already been noted that child slavery is a major

[17] The controversy surrounding the presence of child exploitation upon Lake Volta has arisen as a result of claims that these children are in fact undertaking apprenticeships (Mensah and Okyere 2019). Learning skills in order to provide an income is deemed to be more valuable for these children rather than completing traditional academic education. Therefore the accusation of child labour abuses occurring on the lake is deemed irresponsible and a projection of Western ideals as to what is beneficial for children across the world. This is a common critique of labelling child labour – often it is more useful for children to be in work or apprenticeships within developing nations, and the economic contributions of children can provide a substantial amount of support for family units (Wijen 2015). Some exploitation may be occurring in these locations, however it is important that not all child labour is labelled as exploitative when there can be no alternative for some people. Therefore, the ILO conventions on child labour should

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 (Tomnod and World Freedom Fund 2015). Wall-to-wall high spatial remotely sensed data was crucial and the methods in using these data are transferrable. Indeed, there are examples of modern slavery in other known industries that could benefit from remote sensing analyses, such as agriculture, quarrying, mining, and illegal deforestation (Jackson *et al.* 2020; see Chapter 6/Paper 5/Appendix C).

4.5 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 0.0357 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 spatial-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 SDG 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 eradicate modern slavery once and for all. This will also help to establish the environmental implications that arise from the sector and encourage investigation from an environmental perspective. By

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be applied only in the most egregious of cases, and consider differing cultural aspects when doing so, as well as adaptive strategies communities may employ in order to survive, which – as in the case of fishing on Lake Volta – may include the presence of 'child labour'.

using remotely sensed data, and associated geospatial science and technology, the lack of reliable and timely, spatially explicit and scalable data on modern 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 (Anderson *et al.* 2017; Esch *et al.* 2017; Xiao *et al.* 2018).

There are many research avenues to pursue (including an environmental assessment: Chapter 5/Paper 4) to ensure that there is an appropriate and fit-for-purpose data platform that helps meet the challenge of ending modern slavery understanding the scale of environmental degradation. These avenues have been discussed with 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 SDG targets will show, there are global benefits to ending modern slavery, for economies, peace, health, and the environment (which link a number of SDGs together). Ending modern 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’ (Bales 2012: xxix).

Chapter 5: Brick Kilns Environmental Assessment

This Chapter/Paper (see Table 1.3) is being prepared for submission to *Sustainability*.

Using remote sensing to analyse the modern slavery-environment nexus of the South Asian brick-manufacturing industry

5.1 Introduction

The application of remotely sensed data to investigate the South Asian brick kilns has been applied to provide estimates, locations, and briefly highlighting the environmental impacts (see Boyd *et al.* 2018 – Chapter 4/Paper 3/Appendix B; Foody *et al.* 2019; Li *et al.* 2019). Efforts are now also being made to directly address the emissions released from these kilns via the application of remotely sensed data (Arbain and Imasu 2019; Misra *et al.* 2019). Moreover, researchers that have previously focused on ground-based data collection for the environmental and health implications of the brick kilns (e.g. Luby *et al.* 2015) are now looking to apply remotely sensed data to investigate these effects (Jordan 2017, 2019). Thus, the benefits of satellite Earth Observation (EO) data to understand the South Asian brick-manufacturing sector can be understood. Here, brick-making is explored in relation to the modern slavery-environment nexus (Brown *et al.* 2019). Bonded labour is rife in brick-manufacturing with as many as 40-70% of workers in the sector thought to be indebted to a kiln owner (Mitra and Valette 2017; Anti-Slavery International 2017; ILO 2005; Save the Children 2007); and the ILO notes that 15% of people in manufacturing jobs are working under conditions of forced labour (ILO 2017a). As a highly extractive and emissions driven activity, brick-making is likely to have a large environmental impact that in a high proportion of cases may be linked directly to activities of exploitation. Thus impacting the achievement of environmentally focused Sustainable Development Goals (SDGs) (Decker Sparks *et al. under review*). The impact of brick kilns have consistently been raised in relation to the modern slavery-environmental degradation nexus (see Bales 2016; Brown *et al.* 2019; Brickell *et al.* 2018; Decker Sparks *et al. under review*); therefore, it is important to account for this socio-ecological impact when investigating kilns in the 'Brick Belt'.

Debt bondage specifically, is the most prevalent form of exploitation across South Asia (Bales *et al.* 2011: 33-34). Brick-making is fuelled by unfair recruitment and payment, with approximately 96% of adult males in kilns working under these conditions (Anti-Slavery International 2017: 3); often affecting the whole family who are also recruited. Recent machine learning efforts have recorded of a total of 66,634 kilns across the 'Brick Belt' (covering Pakistan, India, Nepal and Bangladesh) at 92.83% accuracy using remotely sensed data (Boyd *et al. forthcoming*).[18] This figure is roughly

[18] The location mapping to determine this definitive number of kilns was undertaken by colleagues at the University of Nottingham on the Rights Lab's Data programme and within the N-Lab. They applied a CNN-YOLO approach to high spatial-resolution data from across the 'Brick Belt' using the coordinates and imagery of the 1,142 kilns located during the sampling method of Chapter 4/Paper 3 (see also Boyd *et al.* 2018; Appendix B) to train the algorithms. Training samples were increased by rotating the kilns to provide variation within the sample dataset. The machine learning approach was then applied to determine the location of the kilns across the area (with the spatial location and density noted for a single layer). This methodology and the density of the kilns is available upon request from Doreen Boyd (Doreen.Boyd@nottingham.ac.uk) due to the sensitivity of the dataset. Further details of the methodology will be published in a forthcoming paper (Boyd *et al. forthcoming*).

These data were then processed by other colleagues to determine the year in which these kilns first formed (see Li *et al.* 2019), thus adding additional information to the original brick kiln data layer. This was undertaken by applying a break detection algorithm to data from Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI time series data (1984-2018), where random forest classifications were then used to determine a predicted age for the kiln. It is these data that have been used for the analysis of the environmental impact of the brick-making sector contained within this Chapter/Paper hence the difference in the figures from Chapter 4/Paper 3 where only an estimate was produced. These methods equivalent to the upper estimate noted by Boyd *et al.* (2018) of who estimated 55,387 kilns in the region [with lower and upper estimates of 44,542 and 66,270 respectively] (see Chapter 4, Table 4.1 – see also Paper 3/Appendix B). This accounts for around 65% of the total brick production in India (Singh and Asgher 2005). These figures have been applied as part of this Chapter as they are more accurate than the estimated figures noted in Chapter 4/Paper 3, and have geo-spatial and temporal data attached to the kilns as a result of the machine learning processes which have been applied. These kilns are spread across the Indo-Gangetic Plain, one of the most relied-upon agricultural regions in the world, supporting approximately 40% of the population of India (Pal *et al.* 2009). This area is facing pressures from rapid urbanisation and population growth, variations in agricultural production, and climate change, which is contributed to by the emission of pollutants from industrial practices (Sapkota *et al.* 2015). Brick kilns are a driver of these multiple pressures. The kilns endanger the environment from the production phase which requires the extraction of raw materials, such as water, topsoil, coal, wood and sand (Lundgren-Kownacki *et al.* 2018 explains the process of brick-making), and via the release of emissions during the firing of 'green' bricks – this is the most visible impact (see Figure 4.7 in Chapter 4/Paper 3; see also Appendix B).

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for the machine learning and aging data are currently being prepared for publication (see Boyd *et al. forthcoming*).

The algorithm for aging kilns by Li *et al.* (2019) is beneficial as it provides an accurate (83% accuracy) temporal assessment of the brick manufacturing sector; however, there are some limitations. Perhaps the main issue, and something that should be rectified with additional coding to the algorithms, is that whilst new kilns are identified, kilns that are decommissioned are not removed from the dataset. This may mean an over-count in kilns which are present as they are no longer active. Whilst it is not possible to account for these issues in the environmental assessment within this Chapter/Paper; efforts to address this limitation of the algorithm should be applied in the future.

Emission monitoring studies of kilns have often been localised and conducted via ground-surveys (see Guttikunda 2009; Guttikunda *et al.* 2013; Skinder *et al.* 2013; Skinder *et al.* 2014b; Weyant *et al.* 2014). Kiln emissions from brick-manufacturing can often be worse in kilns using modern slavery as low grade materials are common (Bales 2016) – for example, used motor oil, rubber tires and coal are among some of the most commonly used materials for fuelling (Ishaq *et al.* 2010). A range of pollutants and greenhouse gases (GHGs) are emitted including: carbon dioxide (CO_2); carbon monoxide (CO); sulphur dioxide (SO_2) and other oxides of sulphur (SO_X); methane (CH_4); particulate matter ($PM_{2.5}$); and suspended particulate matter (SPM), black carbon (BC), and oxides of nitrogen (NO_X) (Skinder *et al.* 2013). Research has often focused on the health effects of those working within, or living near, the kilns in relation to the emissions; thus data are required to support Sustainable Development Goal (SDG) 3 (“Good Health and Well-Being”). Serious health implications include cancer, cardiovascular diseases, respiratory diseases (such as asthma, chronic bronchitis, tonsillitis, acute pharyngitis and emphysema) and premature death (Joshi and Dudani 2008; Pariyar *et al.* 2013). Pollutants are not the only health concern as the heat generated by the kilns is also dangerous; as climate change affects the ‘Brick Belt’ and days become hotter, there is an increased risk of heat-induced stress within the kilns (Sett and Sahu 2014; Lundgren-Kownacki *et al.* 2018).

Atmospheric remote sensing has been operational for more than three decades since the launch of aerosol detection instruments in the 1970s (Lee *et al.* 2009) and developments have made the monitoring of atmospheric emissions possible (Fishman *et al.* 2008). The launch of the European Space Agency (ESA) Sentinel-5 Precursor (Sentinel-5p) satellite has signalled the next development in atmospheric monitoring specifically designed to provide information on emission source identification, overall air quality, climate and ozone concentration (Berger *et al.* 2012; Veefkind *et al.* 2012). The Tropospheric Monitoring Instrument (TROPOMI) on-board Sentinel-5p bridges the gap between previous atmospheric monitoring and applications toward atmospheric geo-chemistry, a key requirement in the field (Ingmann *et al.* 2012). These data can be used to assess the pollutants emitted from the region that may be attributed to the emissions released from the brick kilns.

Emissions have also led to vegetation damage within the 'Belt' (Ahmad *et al.* 2012); impacts are being recorded in agricultural soils close to kilns (Khan *et al.* 2007; Bisht and Neupane 2015; Rajonee and Uddin 2018). Additional damage is caused by heavy metals and pollutants clogging the soil. These impacts upon high-value agricultural land across the Indo-Gangetic Plain raise concerns for food security and achievement of SDGs 1 ("No Poverty") and 2 ("Zero Hunger") (UN 2016a, 2016c). Agricultural productivity has recently increased, seen in the significant levels of greening across India (Chen *et al.* 2019). Brick-manufacturing relies heavily on the same good quality topsoil, placing it in direct competition with agriculture. Reports suggest soil degradation across Asia can be accounted for by human-induced activities in 31% of inhabited land (FAO and ITPS 2015: 239). Assessing the scale of this damage will be vital for determining associated issues, such as: food security; viability of agriculture; land stability and ability to recover from natural impacts such as flooding; and resilience to landcover changes. This phenomenon is being experienced in Kathmandu Valley where population change and associated landcover alterations have occurred alongside a growth in brick manufacture, causing soil degradation, water concerns and pollution. These changes have also resulted in the need for adaptation of agriculture (Haack and Khatiwada 2007) to support more than 950 million people.

Landcover changes can also be linked to health effects (Rahman 2015) and ecological change. Remote sensing has a history of analysis regarding landcover and extrapolation of land use. Land-use/landcover (LULC) is complex, and is 'caused by the interaction between natural and social systems at different temporal and spatial scales' (Valbuena *et al.* 2008: 27). Previous analysis has assessed these changes using remote sensing to investigate brick kilns within areas across the 'Brick Belt' (see Chaurasia and Sharma 1999). As most kilns are found on the Indo-Gangetic Plain, it is expected the majority of landcover will be agricultural; therefore the development of kilns is expected to have a direct impact on the ability to produce food for a growing population. The presence of people and extractive economic activities can lead to dramatic ecosystem changes, and may lead to the migration of populations where their vulnerability to modern slavery may increase (Decker Sparks *et al. under review*).

The quality of river systems across the 'Brick Belt' has been degraded through the disposal of fired coal ash during brick manufacturing (Jamatia *et al.* 2014). Fly ash contains high concentrations of heavy metals produced during burning that settle on the ground affecting the soil, plants and water. Metals emanating from the kilns that are concerning include potassium, sodium, zinc, magnesium and iron (Sikder *et al.* 2016). The release of these metals lead to serious waste issues and are primarily linked to the burning of coal (Smith *et al.* 1998) and other low-grade materials (noted by Bales 2016). Proximity of the kilns to water bodies is a key factor in the risk of degradation. Brick kilns have been found to cause damage to the riverbanks with efforts being made to reduce the number found on the Ganga in Bihar State (Gupta 2015). Kilns also cause 'silt trapping', whereby they collect and store sediment during flood events, leading to reduced sedimentation of the river and floodplain (Mondal *et al.* 2016: 10). This problem is exacerbated by the illegal extraction of sand sediments from rivers such as the Ganga Ganges (Walker 2016).

A number of research questions have been raised, referencing the scale of pollution – both in water and the air, where emissions and pollutants are strongest and whether this corresponds to the kilns. To determine the extent of degradation to the land through a) topsoil and groundwater extraction, and b) landcover affected by kiln presence. Finally, these investigations must account for differences over time – what is the rate of increase in kiln presence and how has this affected environmental damage caused by the industry? These issues will all be considered with regards to the presence and vulnerability of modern slavery, as well as the impact of the brick kiln sector in relation to the modern slavery-environmental degradation nexus.

5.2 Methods

Three elements of environmental degradation have been assessed over time in the South Asian brick kilns. The temporal assessment was enabled through the use of data from aged kilns across the whole 'Brick Belt' from 1990-2018; totally 66,634 kilns by 2018 (equating to approximately 11,000 in Pakistan; 45,000 in India; 1,000 in Nepal; and 7,000 in Bangladesh). These data were produced by Li *et al.* following the methodology explained in their 2019 paper which ages the kilns using the extensive Landsat data archive, combined with additional data accessed via Google Earth Pro. Similar efforts are being applied using Sentinel-2 to look specifically at the emissions released during the brick-manufacturing process (Misra *et al.* 2019). The environmental elements analysed, include: the impact upon resources, damage caused to the land, and the impact on air quality. Investigation into each issue requires different methodologies. They have been applied to the aged kilns, thus assessing the environmental impacts over time, and framing them against the modern slavery-environment nexus (Brown *et al.* 2019).

5.2.1 Land and Resources

To address kiln impact on the landcover, open source landcover products produced using the Moderate Resolution Imaging Spectroradiometer (MODIS) data were downloaded for all available years (2001-2017) via the Earth Resources Observation and Science (EROS) Center; part of the MCD12Q2 Collection 6 Product (Land Cover & Surface Climate Group, n.d.; Gray *et al.* 2019; Sulla-Menashe *et al.* 2019). These data are the latest, improved MODIS landcover maps (see Friedl *et al.* 2002; Ganguly *et al.* 2010). Layer 1 of the map product was downloaded and used in the analysis; this schema contains 17 unique landcover classes known as the International Geosphere-Biosphere Programme (IGBP) classification. The scheme, developed in the 1990s (Loveland and Belward 1997), includes 14 vegetation classes, 11 natural and three human-altered, as well as three non-vegetated classes (see Table 3 in Sulla-Menashe and Friedl 2018: 7).[19] Six tiles were downloaded for each year to provide full-spatial coverage of the 'Belt'. They were intersected with the aged kiln data for each year to determine the landcover classes impacted and the rate at which this has changed over time.

Landcover is linked to resource extraction – topsoil is one of the two primary resources required. The number of bricks produced are estimated between 2 and 3.5 million per

[19] The classes denoted in the MODIS IGBP Landcover Map (taken from Sulla-Menashe and Friedl 2018: 7) were as follows: 1) evergreen needleleaf forests; 2) evergreen broadleaf forests; 3) deciduous needleleaf forests; 4) deciduous broadleaf forests; 5) mixed forests; 6) closed shrublands; 7) open shrublands; 8) woody savannas; 9) savannas; 10) grasslands; 11) permanent wetlands; 12) croplands; 13) urban and built-ups lands; 14) cropland/natural vegetation mosaics; 15) permanent snow and ice; 16) barren; and finally, 17) water bodies.

kiln per year (Gomes and Hossain 2003; Guttikunda *et al.* 2013; Saeed 2017). The lower estimate was used to determine the total number of bricks produced across the 'Brick Belt' (Equation 5.1). This is necessary for the estimates for water used to produce the bricks. Calculations were applied to the cumulative total from the aged kiln data, and for the number of kilns that were established during each annual period. Example equations to calculate the bricks are shown using the cumulative total for kilns from 2018:

(5.1) $$number\ of\ bricks\ \times number\ of\ kilns = estimated\ total\ brick\ production$$

$$2{,}033{,}784\ \times 66{,}634 = 135.52\ billion\ (bricks\ in\ 2018)$$

Before applying to known levels of topsoil extracted by kilns within India: equating to 400 million tonnes of topsoil each year (Lopez *et al.* 2012: 10; Mitra and Valette 2017: 22). These figures were extrapolated to estimate the total topsoil extracted across the region (Equation 5.2). To calculate the estimated extraction of topsoil:

(5.2) $$volume\ of\ topsoil\ sample\ study\ \div number\ of\ kilns\ sample\ study = estimated\ volume\ topsoil\ per\ kiln\ per\ year$$

$$400{,}000{,}000\ \div 100{,}000\ = 4{,}000\ tonnes\ per\ kiln\ per\ year$$

These figures were then applied to the annual total kilns identified in the aged dataset, and the cumulative total of kilns to determine the total volume of topsoil extracted. The example equation below (Equation 5.3) uses the cumulative total kilns for 2018:

(5.3) $$estimated\ volume\ topsoil\ per\ kiln\ per\ year\ \times number\ of\ kilns = total\ estimated\ volume\ of\ topsoil\ extraction\ per\ year\ in\ the\ Brick\ Belt'$$

$$4{,}000\ \times 66{,}634 =\ 266.54\ million\ tonnes$$

A similar analysis was used to determine approximately how much water is used in the production of bricks. Both surface water and groundwater have been noted as sources of the other primary brick-making resource; figures from research by Shrestha *et al.* (2013: 3) found on average 0.75 litres of groundwater are used in the production of a brick. Whereas, Kumbhar *et al.* (2014) note between 0.6-0.8 litres of water (from all sources) are used. Their study also noted that from a sample of 12 kilns, 92% were utilising water from surface sources (58.3% rivers and 33.3% streams), with the rest using groundwater sources (8%) (Kumbhar *et al.* 2014: 264). The lower estimate is applied in the case of the surface water resources to account for the fact that some of the water in the kilns sample is from the groundwater sources – being conservative should account for this variation. In order to establish the proximity of the kilns to these water sources to determine the levels of extraction and the opportunity for pollutants to enter the water supply five 1 km buffers were computed for each river or water body (such as a lake or reservoir) (Figure 5.1) and were intersected with kilns to determine the number located within this distance. Five buffers were deemed adequate as approximately 70% of kilns are located within 3 km of a water source; the additional buffers were to capture the outliers – which predominantly rely on groundwater supplies rather than river-water (Table 5.1) which is extracted through wells, boreholes, tanks, tubewells and canals, by kilns and agriculture alike (Kumbhar *et al.* 2014; Dhawan 2017).

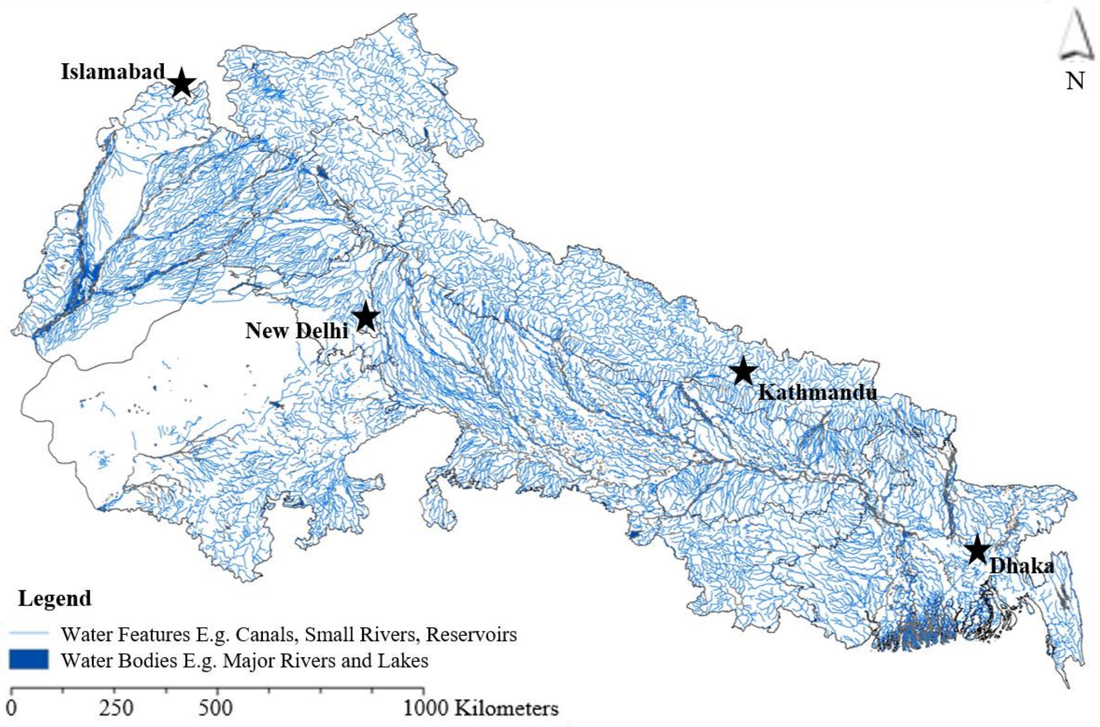

Figure 5.1: Water bodies used in the proximity analysis of the brick kilns as part of the resource extraction and pollution assessment. Open access inland water bodies' shapefile downloaded March 2019 via DIVA-GIS (DMA 1992; DMA and USGS 1996).

Table 5.1: Proximity buffers from water bodies across the 'Brick Belt' to brick kilns identified during the CNN-YOLO mapping process for the cumulative aged kiln dataset by Li *et al.* (2019) up to and including 2018.

Distance (Buffer)	**Small Rivers/ Canals (only)**	**Major Rivers, Lakes and Reservoirs**	**All Water Bodies Combined**	**Percentage of Kilns per Buffer**
< 1 km (in river channel)	–	846	846	1.27
1 km	17,883	3,526	19,559	29.35
2 km	16,967	3,772	15,899	23.86
3 km	12,313	4,498	11,249	16.88
4 km	8,391	4,547	7,515	11.28
5 km	5,403	4,326	4,366	6.55
> 5 km	4,837	44,279	6,360	9.54

In accordance with the proportion of surface water to groundwater use noted in Kumbhar *et al.* (2014) (92% to 8%), those kilns which are more than 5 km from a river are likely to use groundwater sources. When using the aged kiln dataset this is around 9% (or 6,360 kilns). Moreover, beyond a 5 km buffer distance there begins to be a significant amount of overlap, resulting in redundant data processing. Kilns found within the riverbed were also noted, this is an issue that has previously been addressed in Uttarakhand and Bihar (India) as the kilns can affect natural flood protections (Economic Times 2013; Gupta 2015). In order to calculate the amount of water extracted by these kilns – which are all calculated in bricks – the estimated total number of bricks produced within these proportion of bricks were calculated (all using the 2018 figures within these example equations) (Equation 5.4):

(5.4)

$$\frac{(estimated\ total\ brick\ production\ \div 100)\ \times 91\%\ or\ 9\%\ \ total\ number\ kilns}{1000\ for\ conversion\ into\ tonnes} = estimated\ brick\ production\ using\ surface\ water\ /groundwater\ \ (estimated\ total\ tonnes\ per\ year)$$

Therefore, the total number of bricks produced using surface water sources is:

$$(135{,}519{,}163{,}056\ \div 100) \times 91 = 123.32\ billion\ bricks$$

And the total number of bricks produced using groundwater sources is:

$$(135{,}519{,}163{,}056\ \div 100) \times 9 = 12.2\ billion\ bricks$$

These proximity findings that were applied to determine the number bricks thought to use surface water vs. groundwater were combined with the volume of water extracted from each source from the results noted by both Shesthra *et al.* (2013) and Kumbhar e*t al.* (2014) to determine an estimate of the scale of resource extraction required to manufacture bricks across the 'Brick Belt'. The equations below (Equation 5.5) apply the 2018 data in order to determine water usage:

(5.5)

$$\frac{total\ number\ of\ bricks\ for\ 91\%\ or\ 9\% \times estimated\ water\ usage\ per\ brick}{1000\ for\ conversion\ of\ volume\ into\ tonnes}$$

$$= volume\ surface\ water/groundwater\ (tonnes\ per\ year)$$

Therefore, the total estimate for the extraction of surface water:

$$\frac{(123{,}322{,}438{,}380.96\ \times 0.6)}{1000} = 73.99\ million\ tonnes$$

And finally, the total estimate for the extraction of groundwater is:

$$\frac{(12{,}196{,}724{,}675\ \times 0.75)}{1000} = 9.15\ million\ tonnes$$

5.2.2 Regional Pollutant Analysis

An analysis of the atmospheric pollutants released by the kilns has been undertaken using Sentinel-5p data made available by ESA. The TROPOMI sensor on-board measures a number of pollutants including CO, Formaldehyde (HCHO), nitrogen dioxide (NO_2), ozone (O_3) and SO_2. The mean monthly average for each pollutant was calculated using Google Earth Engine (GEE) – one of several cloud-based "virtual globe" platforms designed for use by all which promotes replicable and accessible satellite EO methodologies (Yu and Gong 2012; Gorelick *et al.* 2017), as demonstrated throughout this thesis. An overall visual assessment was used to understand the fluctuations within the brick-making cycle with limited data, as more data are accumulated, temporal trends will also be possible to determine, yet presently a baseline of these pollutants can be provided for the 'Brick Belt'. The earliest data (NO_2) are available from July 2018 on GEE, but not all, the latest is from November 2018 (CO); others became available in the intervening months. Whilst trends may not be identified with these data specifically, a baseline understanding of the sector can be reported which can support future monitoring of pollutants that may be associated with the brick kilns. Further in-depth analysis was conducted for the kilns formed in 2018.

At present, ESA does not have a sensor that measures CO_2 concentrations, therefore average global data were downloaded as a Level 3 product from NASA's Orbiting Carbon Observatory 2 (OCO-2) platform. The OCO-2 Level 3 product used for further analysis and processing within this Chapter/Paper were made available by Zammit-Mangion *et al.* (2018); the original data from their product was from their V9r (B9003r) output (OCO-2 Science Team 2018).[20] A universal kriging method was applied to these data using the SAGA package on QGIS (Version 3.2.1). This enabled the estimation of CO_2 concentrations across the 'Brick Belt' from geo-located point data in order to establish general trends in the concentrations of CO_2. Outputs of the monthly mean average calculations for all pollutants are found in Appendix E.

5.2.3 In-depth Brick Kilns Pollutant Assessment

Seasonal trends were assessed for the kilns formed in 2018 (Figure 5.2) to identify patterns in pollutant emissions at specific kiln locations across the 'Brick Belt'. These investigations used the pollutant measurements from Sentinel-5p and OCO-2. Furthermore, data from Planet Labs Doves PlanetScope and RapidEye platforms were visually analysed to determine whether pollutants were visible during the process of emission (i.e. smoke) – however the 3m and 5m spatial-resolution of these data were too coarse to glean valuable information. Therefore a systematic search of these kilns was conducted using imagery available on Google Earth Pro as the spatial-resolution is higher (up to 31cm depending on the provider). The types of kilns were also noted following the protocol which was established in Chapter 4/Paper 3 (Boyd *et al.* 2018;

[20] These data are available from https://hpc.niasra.uow.edu.au/oco2level3_b9003r/

Appendix B) where they were counted and classified as either Fixed Chimney/Bull's Trench Kilns (BTK/FCBTK), Circular Kilns or Zig-Zag Kilns (for more information see Chapter 4 Section 4.2.1 'Background on Brick Kilns').

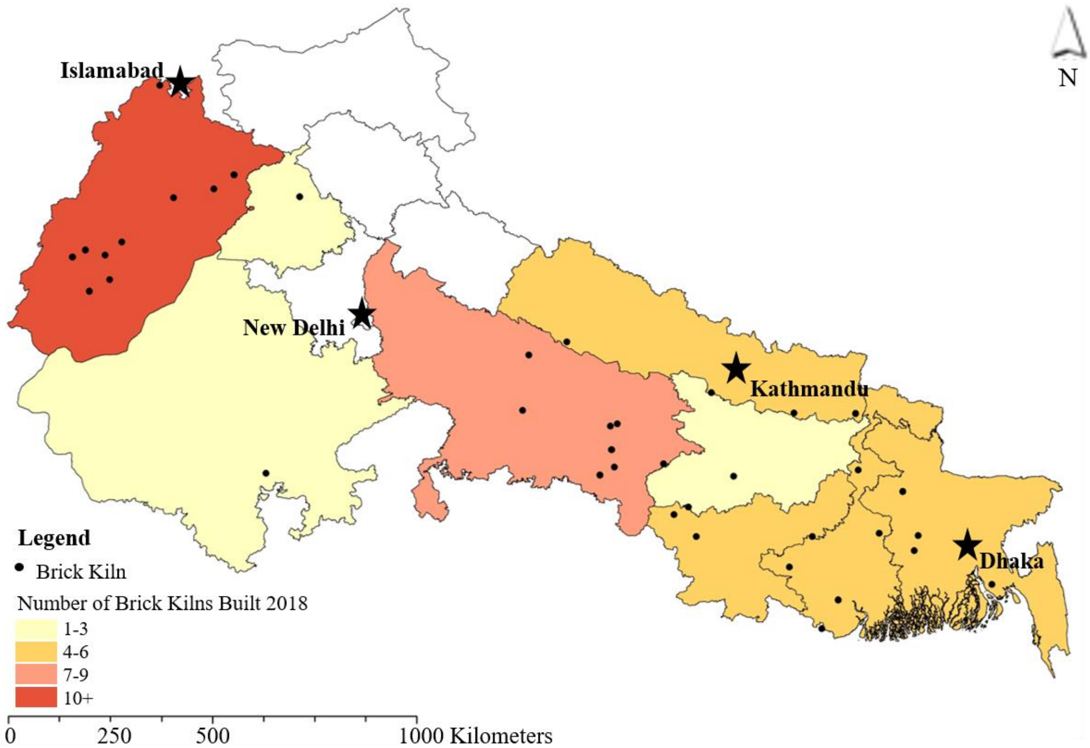

Figure 5.2: Location of the 38 brick kilns which were built in 2018 across the 'Brick Belt'. The colours denoted refer to the number of kilns which were established in that year within that region. The majority of kilns were formed in India with a lack of kilns formed in the northeast region, with the exception of Punjab, India. Punjab in Pakistan has the largest single growth in the number of kilns on a state level basis. One kiln was formed over the border from West Bengal in India, this was discounted from the analysis as it was not in the defined 'Brick Belt' region. Moreover, one kiln in Bangladesh was more industrialised, being contained in a factory setting thus reflecting the kiln types found in Southeast Asia more than the rest of the 'Brick Belt' (for example the kilns in Cambodia; see Brickell *et al.* 2018).

5.3 Results

5.3.1 Landcover Impact Assessment

The landcover occupied by kilns has undergone minimal change, with around 80% of the kilns found upon land classified as 'cropland' (Table 5.2). This may not be surprising as there are a limited number of landcover classification types found across the 'Brick Belt', and the MODIS IGBP map has a spatial resolution of 500 km in order to provide global coverage (Land Cover & Surface Climate Group, n.d.; Gray *et al.* 2019; Sulla-Menashe *et al.* 2019). Therefore, as 'cropland' covers the largest proportion of landcover in the region (an area between 930,000 km^2 in 2001 and almost 980,000 km^2 in 2017 with some fluctuation) – see Table 5.3 – the number of kilns found within this region skews toward formation on these agricultural lands. This tallies with the need for strong and fertile topsoil to produce bricks. As 'cropland' is the most likely place for these resources to be located, it is reasonable that more than 50,000 kilns were located on this landcover type by 2017. However, this denotes the risk of conflict between construction and agriculture which may limit the achievement of multiple SDGs, for example: 2; 12 ("Responsible Consumption and Production"); and 15 ("Life on Land") (UN 2016a, 2016c).

Overall, the 'Brick Belt' has shown very little variation in the landcover class location, coverage or classification type (an example of the MODIS IGBP Landcover Map is shown in Figure 5.3A); which corresponds with productive clay sediments beneath (Figure 5.3B). There has been an increase in the number of kilns present across these landcover types temporally, however, there are three classes that do not intersect with the kilns, including: deciduous needleleaf forests, closed shrubland and permanent snow and ice. The latter, in particular, is to be expected as the majority of snow in the region occurs in the mountains, an area not suitable for the construction and operation of kilns. Both the deciduous needleleaf forests and closed shrublands were not classified in the region, therefore these results are expected.

Table 5.2: The percentage of brick kilns located within each of the IGBP classification classes derived from the MODIS Landcover Product for each year between 2001 and 2017. All results are shown to 2 s.f. (Classes with no data are marked with a –). For a list of class value names see Footnote 19.

Class Value	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
1	0.02	0.02	0.03	0.02	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03
2	0.07	0.09	0.10	0.10	0.10	0.09	0.09	0.09	0.08	0.08	0.08	0.09	0.09	0.09	0.09	0.10	0.10
3	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
4	0.25	0.26	0.29	0.30	0.34	0.35	0.37	0.40	0.44	0.47	0.48	0.49	0.51	0.53	0.55	0.55	0.56
5	0.14	0.16	0.17	0.18	0.18	0.19	0.20	0.21	0.22	0.22	0.23	0.25	0.25	0.25	0.26	0.26	0.26
6	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
7	1.49	1.48	1.39	1.38	1.42	1.41	1.39	1.43	1.51	1.53	1.44	1.45	1.50	1.50	1.45	1.43	1.39
8	0.18	0.18	0.20	0.23	0.27	0.32	0.32	0.37	0.36	0.36	0.37	0.38	0.39	0.39	0.39	0.39	0.38
9	2.13	2.23	2.37	2.37	2.29	2.29	2.30	2.30	2.24	2.14	2.27	2.31	2.39	2.38	2.40	2.38	2.27
10	3.20	3.03	2.78	2.69	2.70	2.56	2.59	2.61	2.56	2.38	2.41	2.49	2.55	2.61	2.65	2.67	2.55
11	0.83	0.84	0.85	0.84	0.82	0.81	0.80	0.78	0.80	0.82	0.86	0.88	0.90	0.88	0.94	0.95	1.00
12	83.30	83.42	83.32	83.37	83.52	83.66	83.76	83.66	83.70	84.00	83.64	83.23	82.97	82.90	82.62	82.47	82.29
13	3.26	3.16	3.19	3.16	3.17	3.17	3.17	3.21	3.08	2.97	2.91	2.90	2.90	2.90	2.90	2.89	2.92
14	2.90	2.92	3.09	3.12	3.04	2.94	2.90	2.91	3.06	3.13	3.42	3.64	3.64	3.71	3.89	4.06	4.35
15	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
16	1.16	1.12	1.08	1.07	1.06	1.07	1.00	0.91	0.78	0.67	0.61	0.59	0.60	0.57	0.59	0.60	0.57
17	1.06	1.07	1.14	1.17	1.09	1.10	1.08	1.09	1.16	1.21	1.26	1.28	1.29	1.27	1.27	1.24	1.33

Table 5.3: Proportion of the ‘Brick Belt’ denoted in percentage of the landcover types present from the IGBP classification scheme between 2001 and 2017. All results are shown to 2 s.f. (Classes with no data are marked with a –; whilst anomalies of note are denoted by an *). For a list of class value names see Footnote 19.

Class Value	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
1	0.49	0.49	0.49	0.49	0.50	0.46	0.51	0.52	0.52	0.51	0.51	0.52	0.53	0.54	0.31	0.56	0.55
2	0.73	0.73	0.71	0.68	0.65	0.56	0.61	0.59	0.57	0.57	0.56	0.56	0.56	0.56	0.32	0.56	0.57
3	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
4	0.66	0.66	0.67	0.68	0.69	0.64	0.71	0.72	0.76	0.77	0.78	0.78	0.79	0.77	0.43	0.78	0.82
5	2.43	2.45	2.46	2.47	2.49	2.26	2.53	2.55	2.57	2.58	2.61	2.63	2.69	2.73	1.55	2.75	2.82
6	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
7	6.88	6.89	6.84	6.83	6.80	6.05	6.64	6.69	6.76	6.51	6.55	6.66	6.65	6.64	3.76	6.62	6.58
8	4.06	4.13	4.22	4.30	4.34	3.92	4.35	4.36	4.36	4.40	4.40	4.41	4.31	4.22	2.35	4.13	3.99
9	4.07	4.00	3.87	3.87	3.82	3.41	3.79	3.75	3.70	3.70	3.76	3.81	3.93	4.06	2.34	4.11	4.22
10	7.26	7.42	6.93	6.85	6.79	6.06	6.65	6.70	6.49	6.49	6.48	6.42	6.32	6.34	3.62	6.41	6.29
11	0.91	0.88	0.88	0.88	0.88	0.80	0.89	0.89	0.90	0.90	0.91	0.93	0.94	0.96	0.56	1.02	1.01
12	56.77	56.57	57.32	57.33	57.45	52.02	57.92	58.05	59.26	59.26	59.41	59.36	59.30	59.14	33.36*	58.97	58.78
13	1.09	1.09	1.09	1.09	1.09	0.98	1.09	1.10	1.10	1.10	1.11	1.11	1.12	1.12	0.64	1.13	1.14
14	2.28	2.24	2.16	2.15	2.16	1.94	2.13	2.11	2.04	2.04	2.08	2.11	2.16	2.23	1.31	2.40	2.52
15	0.44	0.45	0.46	0.48	0.50	0.46	0.51	0.53	0.53	0.53	0.52	0.53	0.54	0.55	0.31	0.53	0.51
16	10.87	10.91	10.80	10.79	10.73	9.63	10.56	10.34	9.53	9.53	9.19	9.08	9.04	9.02	5.06	8.94	8.97
17	1.07	1.09	1.09	1.10	1.10	10.79*	1.10	1.10	1.11	1.11	1.11	1.11	1.11	1.10	44.07*	1.09	1.22

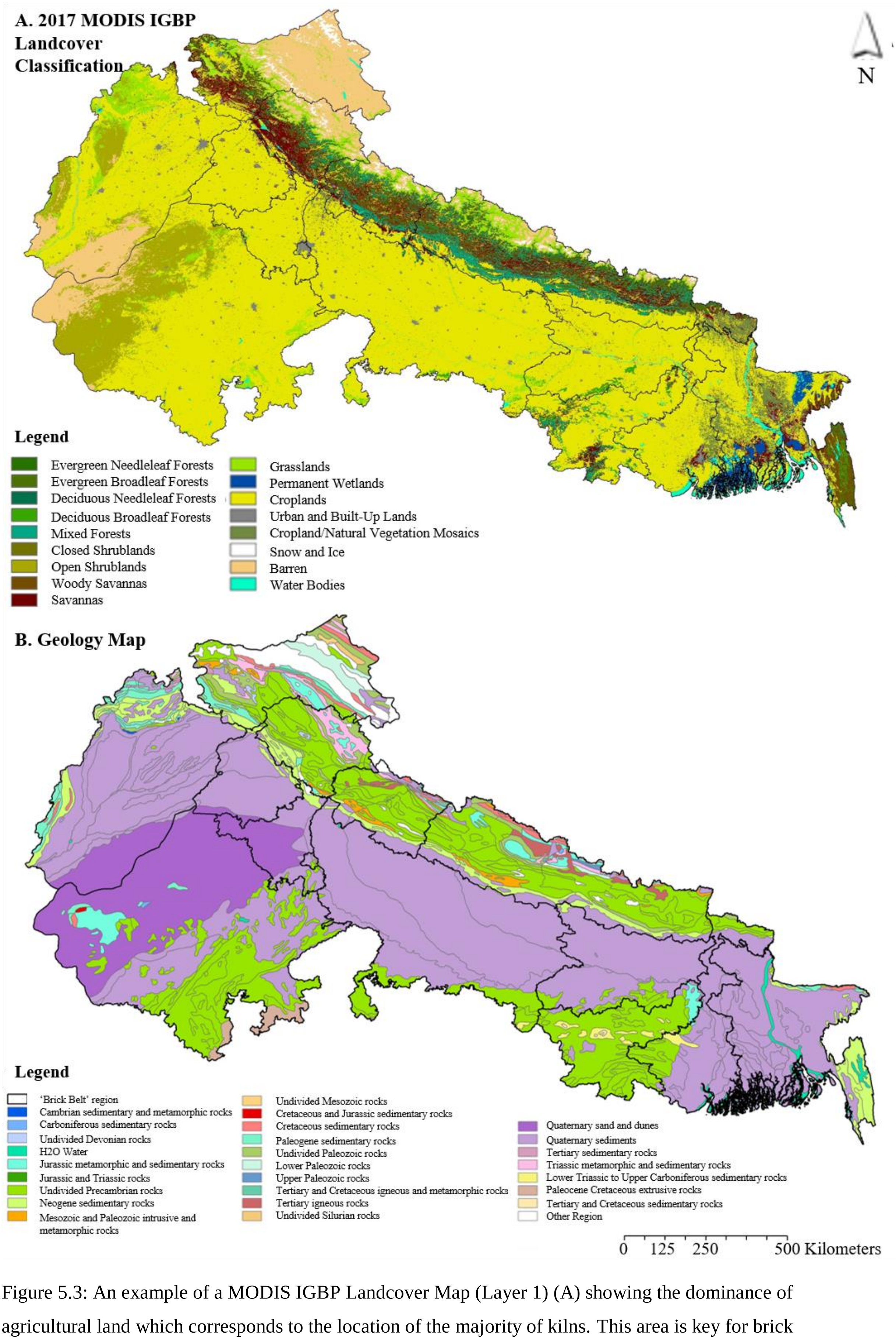

Figure 5.3: An example of a MODIS IGBP Landcover Map (Layer 1) (A) showing the dominance of agricultural land which corresponds to the location of the majority of kilns. This area is key for brick making due to the sedimentary clay beneath this region (B) (USGS – Steinhouer *et al.* 1999).

Anomalous results were noted in ‘water bodies’ (2006 and 2015); there is also a reduction in the ‘cropland’ class in 2015 which show extreme differences from the rest of the maps. One explanation could be extreme flooding across India and Bangladesh in 2006 which may have skewed the map production process. Heavy rains also led to extensive flooding in 2015 – where Bangladesh was particularly affected. Change along the major river channels of the Ganges-Brahmaputra-Meghna delta within Bangladesh are visible. This suggests that the change of landcover from ‘cropland’ to ‘water bodies’ of more than 9% between 2005 and 2006, and by almost 43% (2014-2015), are likely to be resultant of environmental change associated with these flooding events, as years where there is not significant climatic events the landcover reverts to more expected levels. Both then saw rapid reductions of a similar level in the period after this change. These results are assessed with caution and only the large reduction of ‘cropland’ area (by approximately 25% in the period 2014-2015) are of true concern as 82.62% of the brick kilns present in 2015 are located in this landcover class.

5.3.2 Resource Extraction

The rise in the number of kilns within the ‘Brick Belt’ has led to an increase in the extraction of topsoil, and both surface water and groundwater (Figure 5.4). These resources are finite and the risk to both soil and water have differing outcomes.

There is a growing risk of desertification (UN 2019) globally, associated with a reduction in fertile soils due to over-extraction. The levels of topsoil extracted vary depending on the length of kiln operation and brick-making season, and the number of people working in the kilns. Thus determining how many bricks may be produced, and whether the kiln is operating each season and year. The results here consider the average operation of a kiln (yearly production levels) and the extraction of topsoil based on a large-scale estimate for India (Lopez *et al.* 2012).

Water extraction has increased due to the number of kilns built (Figure 5.4). When the estimates for both surface water (Kumbhar *et al.* 2014) and groundwater (Shesthra *et al*. 2013) are applied to the brick kilns, approximately 1,220 tonnes of surface water and 1,525 tonnes of groundwater are used per kiln – depending on the predominant use of water source. Around 60,274 kilns are believed to use surface water, and 6,360 use groundwater according to buffer analysis (Table 5.1) which is comparable with a small ground-study of the proportion of kilns using surface water vs. groundwater by Kumbhar *et al.* (2014).

Extraction of resources at such scales diverts resources from other areas, such as agriculture and sustainable river health, and reduces water access (supported in SDG 6: "Clean Water and Sanitation") (UN 2016a, 2016c). In comparison with the impacts of agriculture in the region, the extraction by brick kilns is estimated to be around ten times smaller than topsoil extraction by the agricultural sector where it is estimated that between 30-40 tonnes per ha per year are lost in Asia as a direct result of agriculture (Pimentel and Burgess 2013). With an overall minimum and maximum area of landcover between 52.02% (in 2006) and 59.41% (in 2011) assigned to 'cropland', it is suggested that between 2.49 billion tonnes/ha/year and 3.79 billion tonnes/ha/year of topsoil could be lost as a result of agriculture. With reference to the estimates of water approximately 80% of surface and groundwater found across India is used to irrigate crops (Dhawan 2017) equating to around 1.92 million tonnes of water per year. When compared with the extraction used by the brick kilns, the use by agriculture is considerably lower (see Figure 5.4) – this may be attributed to the fact that only a third of agriculture within India relies on surface and groundwater, with almost 100 million ha reliant solely on the monsoon rains (Dhawan 2017). The estimated extraction levels may therefore increase pressures on water scarcity within the region, with Pakistan, India and Bangladesh all at risk of water supply issues where population density is high and irrigated agriculture is present (Mekonnen and Hoekstra 2016). The inclusion of extractive industries are also required when assessing water scarcity risk, particularly as the operation of the kilns also occurs at a time when the water consumption of these regions are highest, yet the water availability is also the lowest (Mekonnen and Hoekstra 2016).

The proximity analysis of all kilns and water sources showed that the vast majority are found within 5 km of a river, canal, lake or reservoir (Table 5.1). A number of these kilns were also appear to be located within the river channel (including the floodplain), subjecting them to extensive and rapidly intensifying flood events particularly during the monsoon (Loo *et al.* 2015). Flows are also enhanced by Himalayan glacial melt into rivers including the Indus and Ganges (Lutz *et al.* 2014; Sadoff *et al.* 2013: 160-161).

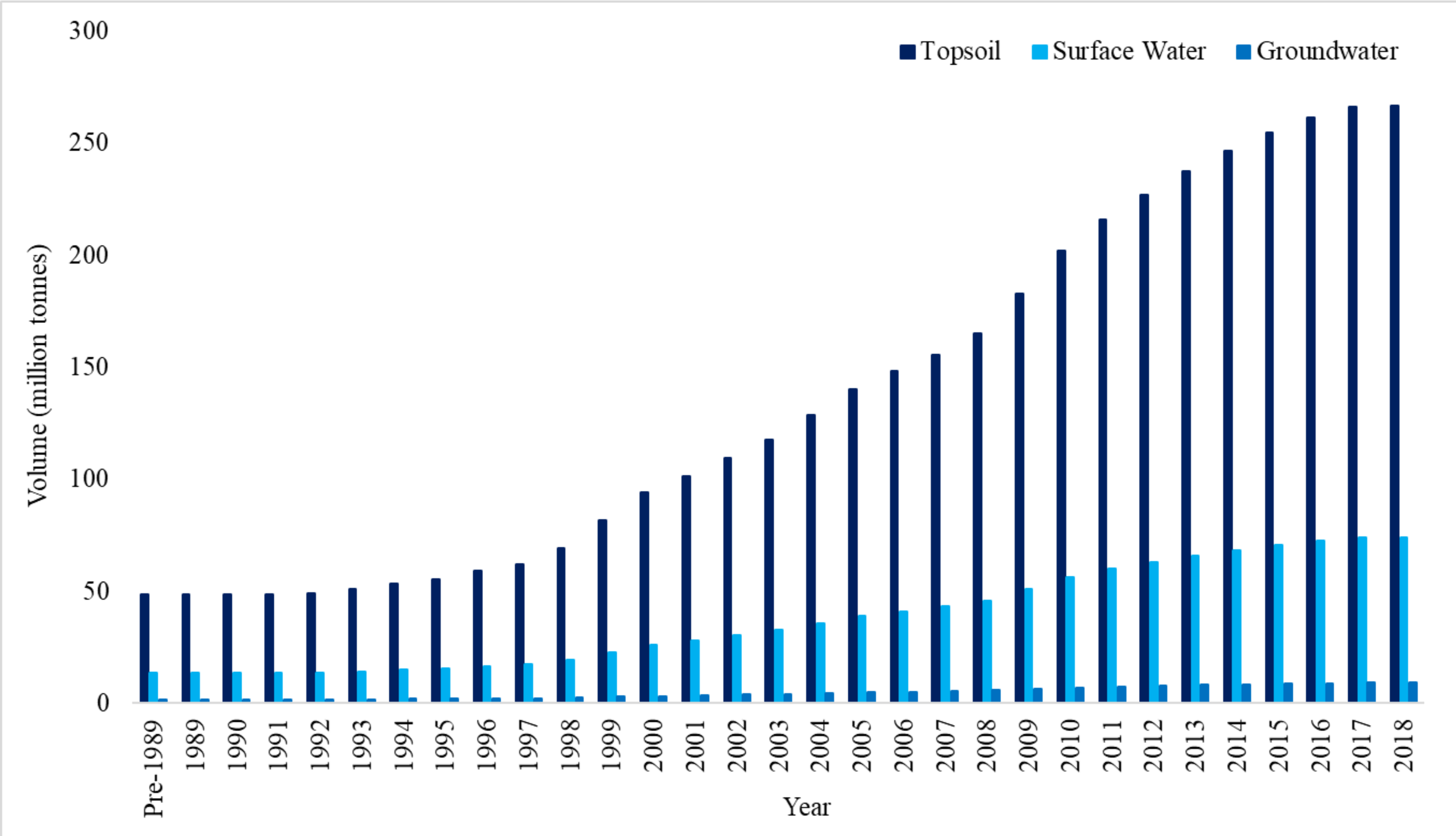

Figure 5.4: Levels of estimated resource extraction by the brick kilns, presented as extraction per year – thus increasing as the number of kilns identified in the aged kiln dataset also increased (Li *et al.* 2019). These estimates are derived from figures noted in: Lopez *et al.* (2012) and Mitra and Valette (2017) (for topsoil); and Gomes and Hossain (2003), Kumbhar *et al.* (2014) and Shresthra *et al.* (2013) – for surface water and groundwater extraction. The methodology and equations applied to establish these results are explained in Section 5.2.1.

It is important to note, in the case of resource extraction, estimates will vary, and more specific data on the volume of topsoil and water (and its source) used to produce the bricks need to be collected to provide accurate data. Moreover, the quality and content of the brick – which can include extra materials such as fly ash – may also affect the overall estimate of natural resource use. Other natural resources are also required such as coal and wood to enable the firing of the bricks which have not been calculated here. Therefore, these estimates must be considered as such; future efforts should be made to undertake large-scale ground-sampling to establish clearer data; which may then be compared against these initial estimates for across the 'Brick Belt'.

5.3.3 Air Quality Analysis

Pollution emanating from the brick kilns contribute to the wider emission of pollutants across South Asia. The 'Belt' has seasonal variations in emissions, with major urban environments influencing pollutant concentrations more when compared to rural and mountain regions. Moreover, some mountains areas have no available data. It must be acknowledged that the kilns are not the only contributing factor toward pollutant concentrations but this analysis aims to assess whether some of the pollutant concentrations may be linked to brick-manufacturing. Sentinel-5p emissions are recorded in mol. M-2 and the OCO-2 CO_2 emissions are in parts per million (ppm).

5.3.3.1 Carbon Emissions

Mean monthly emissions of carbon monoxide (CO) are high during the summer months, spreading across the whole 'Belt' after being concentrated in Bangladesh and eastern India in the preceding months (Appendix E.1). Concentrations are found over the larger cities such as New Delhi and Lahore from November 2018 onwards. West Bengal has high concentrations of CO throughout the period of observation, with slight declines here and across Bangladesh in May 2019 where the pollutant concentration is focused further north towards Bihar state before becoming trapped by the Himalayas. There are large concentrations of kilns in Bihar (of more than 8,000 in 2018) and Uttar Pradesh (approximately 20,000 kilns by 2018) and the highest CO concentrations in these states are present during the brick-making season. However, there are also high rates in the off-season (June and July 2019). The results from the Sentinel-5p CO measurements suggest that the CO produced across the 'Brick Belt' is unlikely to be linked to the production of bricks as the highest concentrations are, on the whole, inverse to the main brick production period. Limited inferences can be achieved as a result of the limited Sentinel-5p data available for use at the time of this study by this will only improve moving forward as more data are collected and made freely available. This same limitation is applied to the assessment of HCHO, O_3, NO_X, and SO_2.

The assessment of CO_2 concentrations, using the OCO-2 Level 3 data (by Zammit-Mangion *et al.* 2018; OCO-2 Science Team 2018) which had undergone a universal kriging process, suggest a limited direct correspondence with kiln operation (Appendix E.2). During the brick-making season the concentrations of CO_2 are highest toward the west of the 'Belt', with high concentrations in Punjab (Pakistan) from November-February for all years analysed (late-2014 to early-2019). Elevated concentrations of emissions for the rest of the 'Brick Belt' are concentrated in April, June and July for 2016 and 2018 in particular, suggesting an inverse trend with the operation of the kilns. The overall CO_2 concentrations are consistent with global trends with a constant level of >390 ppm for the duration observed. However, there was an anomaly in the data, showing a sharp decline in monthly averages for the November 2018, which is unlikely to relate to a reduction in pollutant concentrations. Temporal trends in the CO_2 – however limited – can still be established as five years of data are available, this is contrast to Sentinel-5p data which have been included in this analysis which has less than one year's worth of data collection.

Formaldehyde (HCHO) – formed through inefficient combustion from oil, one of several fuel types used in the kilns (Bales 2016: 109-110; Sanjel *et al.* 2016) – is emitted in high concentrations during the manufacturing season (approximately November-June, occasionally with a break during the winter months) (Appendix E.3). Emissions are concentrated in the east. High concentrations develop over Uttar Pradesh and Bihar from November through to January. As these are focused during the winter months it is likely that kilns are a contributing factor to the concentrations of HCHO as a result of limited energy efficiency in BTKs and FCBTKs (e.g. FCBTKs use on average 1.30 MJ/kg of fired bricks; Maithel *et al.* 2014: 3). The presence of HCHO also moves east over time and is dominant over Bangladesh in the spring. The overall concentrations of HCHO are rarely low; only in the Himalayas are they consistently lower.

5.3.3.2 Ozone

O_3 is a by-product of chemical interactions between NO_X and volatile organic compounds (VOCs) as a result of inefficient combustion. From October 2018 to May 2019, higher concentrations were found to the north-west of the 'Brick Belt' (Appendix E.4). This is clear in the Indian state of Jammu and Kashmir. These pollutants move south into Punjab (Pakistan) between August and September; further increases were seen across Rajasthan, Uttar Pradesh and Bihar in India. There is a short-lived fluctuation in the mean monthly average in April 2019, which recedes in May. Results suggest the emissions across the 'Belt' are contrary to the brick-making season and may be difficult to attribute directly to the kilns.

5.3.3.3 Oxides of Nitrogen

NO_2 emissions are highly concentrated during the manufacturing period (Appendix E.5). The highest are in the major urbans settlements; the summer months (May-August) experience higher emission concentrations. A band of nitrogen dioxide is found during these periods, covering the north of Pakistan's Punjab province, Punjab and Uttar Pradesh (India); a trend showing the containment of emissions in the lower portion of the 'Brick Belt' due to the confinement of the Himalayas. Intense concentrations found in Dhaka, for example, correspond with the months brick production occurs are likely to be impacted by the kilns as the city has a cluster of kilns to the north; Dhaka Division alone has 2,446 (by 2018).

5.3.3.4 Oxides of Sulphur

Monitoring of SO_2 emissions across the 'Belt' is noisy (Appendix E.6). Areas in the Himalaya have no data, whereas others have a variety of SO_2 concentrations recorded. Overall, the majority of sulphur dioxide emissions in the region are, relatively, medium to low, particularly over the autumn and winter months. By January 2019 the monthly mean concentrations begin to show an increase, corresponding to continued brick-making, however, the lack of clarity at the start of the production period suggests emissions from the kilns visible in the Sentinel-5p data may be negligible. West Bengal is the most affected. The state contains over 5,000 kilns (2018 figures), displaying increasingly high rates of SO_2 (March onwards), encroaching on Bangladesh. An inverse relationship can be inferred between higher SO_2 emissions and brick production.

5.3.3.5 2018 Brick Kilns

The assessment of the 37 viable brick kilns constructed in 2018 provided mixed results; a systematic search of high spatial-resolution data via Google Earth Pro provided evidence of activity in the kilns from the emission of white, or black, smoke from the chimneys. The kilns are spread over a wide geographic area and are found in all four sampled nations (Figure 5.2). Four of these kilns have been displayed to demonstrate some of these interactions along with data from Google Earth Pro which demonstrated that the kilns were active. All kilns had minimal concentrations of HCHO, SO_2 and CO above these kilns (Figure 5.5). Sporadic measurements of HCHO were provided for the atmosphere above all kilns (Figure 5.5 HCHO); and there was the interesting trend in SO_2 of peaks and troughs (Figure 5.5 SO_2) – however the volume of data collected was lower than those for other pollutants monitored by the Sentinel-5p TROPOMI sensor. The greatest peaks of O_3 appeared from January-March 2019 and there is extensive coverage for all four kilns shown in the example; this corresponds with the brick-making season. This is contrast to the NO_2 data where there were minimal results over time for the four kilns of interest portrayed in this example, and thus they were not 'plotable'.

For brick kilns A and B (Figure 5.5) white smoke is visible. These data were captured during the brick-making season and the atmosphere above those kilns exhibits a high level of CO_2 totalling 408-409 ppm (Figure 5.6), however this is also the case for kilns C and D (Figure 5.6). These first kilns have some measurements from the TROPOMI sensor showing high concentrations of O_3 above both (at 0.123 for Kiln A and 0.119 for Kiln B – Figure 5.5 O_3) which correspond directly to date of image acquisition. These recordings are not applicable to Kilns C and D as the data from TROPOMI was not available in the GEE software package used for analysis.

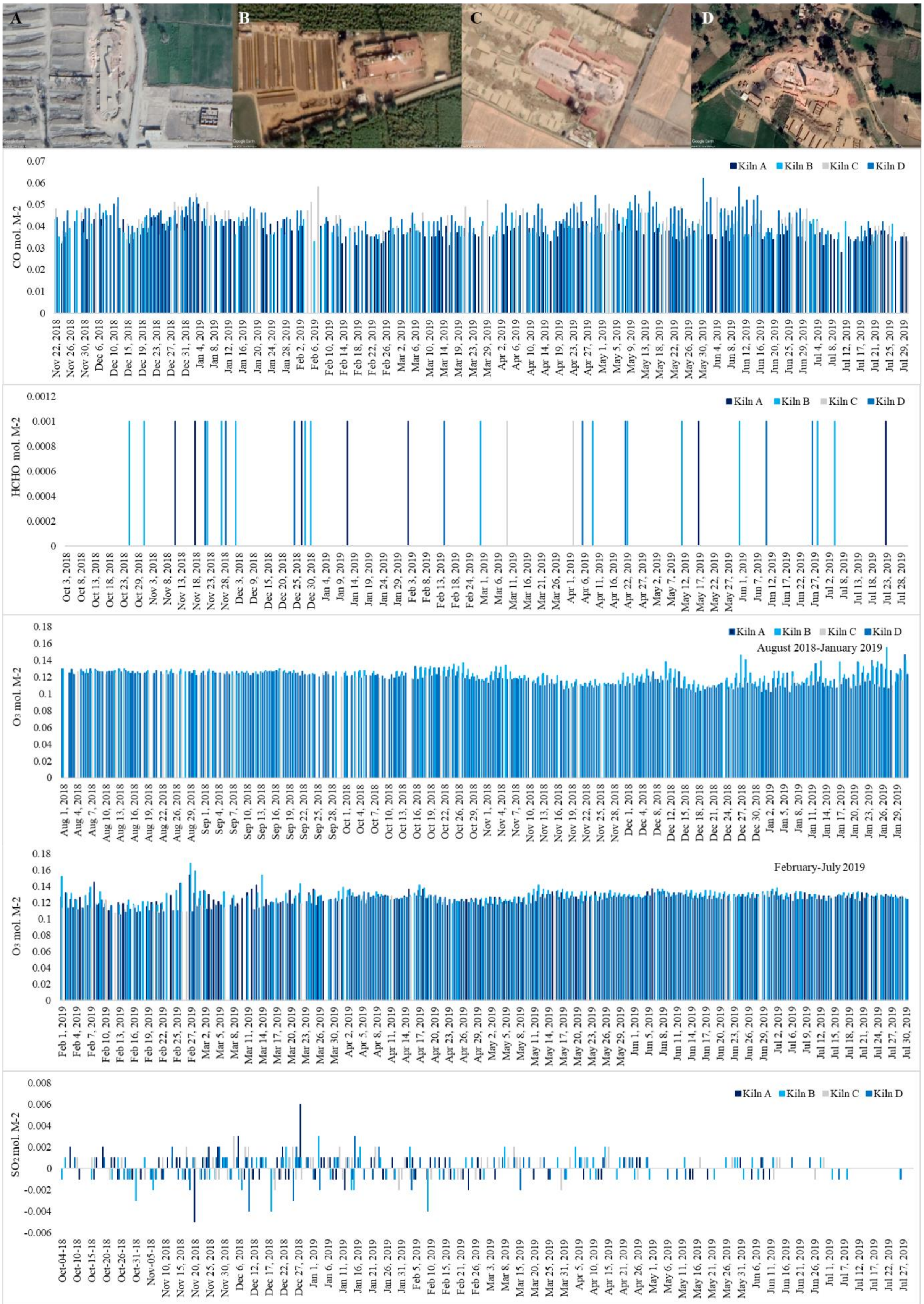

Figure 5.5: Emissions of CO, HCHO, O_3 and SO_2 as measured by the Sentinel-5p TROPOMI sensor; alongside a corresponding image from WorldView-3/4 (downloaded via Google Earth Pro) denoting the kilns that have been analysed. These images show some of the environmental impacts from kilns –

including the presence of clay fields, and the emission of smoke from the kiln chimney. These data were captured from 11.07.2018 to 21.07.2019. Emissions started to become available for analysis on GEE from 11.08.2018 (NO_2 – although not displayed in the figure as a result of the emissions in the pixels located above these four specific kilns measuring zero throughout the time period); 02.08.2018 (O_3); 04.10.2018 (for both SO_2 and HCHO), and finally 22.11.2018 (for CO). The emissions over time for the four kilns shown in the imagery are displayed on the graphs in mol. M-2.

Negative emissions values appear to be observable over the kilns for SO_2. This is a fault with the Sentinel-5p TROPOMI sensor which arises as a result of background correction errors. Background correction is calculated on a four-day moving average. When data gaps or interruptions appear in the reference radiance spectrum in the calculation for the background correction negative biases may appear which result in the SO_2 emission concentrations appearing negative in the dataset. This is likely to be the issue in the 'Brick Belt' as alternative causes of background correction errors include: contamination from volcanic SO_2 as volcanic plumes are transported into the geographical region being analysed; noise in the underlying data; and observations undertaken over particularly clean regions, or those with naturally low SO_2 emissions (Theys *et al.* 2020). These issues should be corrected on an upcoming product update.

Google Earth Pro data were recorded 20.01.2019 (Kiln A) and 24.12.2018 for Kiln B; whereas the formation of Kilns C and D were captured on 28.05.2019 and 07.03.2018 respectively. Kiln B is visibly rectangular in shape, suggesting that conversion to the more energy efficient, and thus less environmentally damaging Zig-Zag kiln has taken place. This is becoming more common across the 'Brick Belt' with seven of the 37 kilns constructed in the bounds of the 'Brick Belt' during 2018 being the newer Zig-Zag design. However, these kilns were not present within Pakistan although a quarter of the 20 kilns established in India were Zig-Zag kilns suggesting that efforts are being made to tackle the environmental effects of these kilns, if not their social implications regarding bonded labour practices.

Additionally, black smoke emissions are observed from the chimney of the Kiln C in Figure 5.5 (similar to Figure 4.7 in Chapter 4/Paper 3; see also Appendix B). This kiln was observed in May 2018, outside the usual period of kiln operation, however, the kiln is clearly active. Finally, some of the smoke is so fine that shadows are the only way to identify kiln activity for Kiln D (Figure 5.5).

CO_2 pollutant concentrations, on the other hand, are stable yet high in the vicinity of the kilns (Figure 5.6) – reflecting the global rise in carbon dioxide. There is also a longer timeframe in which these data were collected by OCO-2, but the limited variation above the kilns makes the attribution of pollutants to these kilns specifically, difficult. All kilns show an anomaly in the data – a reduction in the mean monthly average for CO_2

in November 2018 (Figure 5.6). Moreover, there are three months in which no data were available; however, when interpreting the trends in CO_2 levels in the pixels above the kiln location the loss of these data is unlikely to have a large impact.

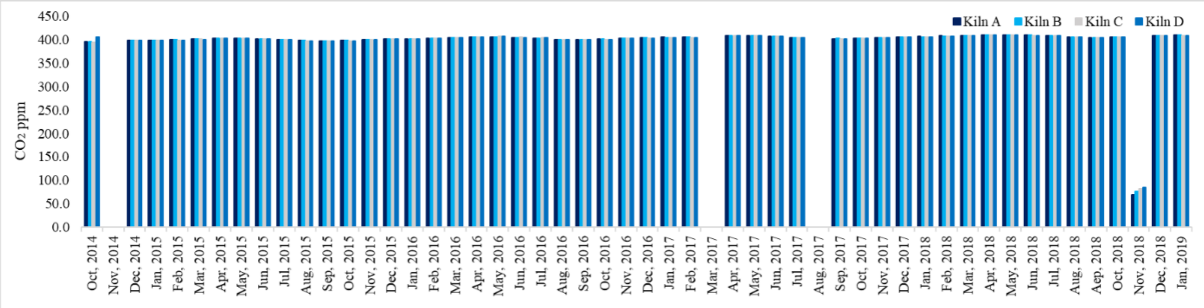

Figure 5.6: The CO_2 pollutant concentration (parts per million – ppm) of the four brick kilns highlighted in Figure 5.5. Their concentrations measured by OCO-2 and processed over these kilns (Level 3 data accessed via Zammit-Mangion *et al.* 2018; OCO-2 Science Team 2018) share extremely similar characteristics – outputs mostly overlap. There are a few of months (November 2014; March and August 2017) where there is a lack of data to establish a monthly average for the CO_2 emission, and there is a dip in the data for November 2018 which is noted across all of the dataset, indicating a universal anomaly in the data. Data were available from late-2014 to January 2019 and were analysed for this time period.

5.4 Discussion

Brown *et al.* (2019) have explored the intersection between modern slavery and the environment (i.e. the nexus) within brick-manufacturing; emphasis has been placed on debt bondage, climate change and kilns in Cambodia (Brickell *et al.* 2018; Brickell *et al.* 2019; Natarajan *et al.* 2019). These risks can also be observed in the 'Brick Belt' (see Boyd *et al.* 2018/Chapter 4/Paper 3 – Appendix B). In fact, using conservative estimates, if bonded labour were to be removed from the kilns across the 'Brick Belt' there would be a reduction of almost 10,000 kilns – ultimately this could see a reduction in topsoil and groundwater extraction of 39 million tonnes, and 1.49 billion litres, per year respectively.[21] Moreover, when comparing CO_2 emissions from the kilns using the estimated concentrations by Tahir and Rafique (2009), more than 8 million tonnes of carbon dioxide is released per year from the brick kilns – this is a more accurate estimate

[21] See Appendix F for details on the methodology and further analysis of these figures.

than those provided by Bales (2016) and Boyd *et al.* (2018 – Chapter 4/Paper 3/Appendix B) due to more accurate numbers of kilns within the region. Should modern slavery be removed from the 'Belt' there could be an annual reduction of approximately 1.3 million tonnes of CO_2 per year which would support in the efforts of Pakistan, Nepal, Bangladesh, and particularly India, to tackle climate change in accordance with the Intergovernmental Panel on Climate Change (IPCC) goals (IPCC 2018) and the Paris Climate Accord. Remote sensing plays an important role in the investigation of this nexus (Jackson 2019; Scoles 2019); and can address the concerns of the nexus whilst advising solutions. Satellite EO data has also identified changes to kiln technologies to assist in efforts to reduce emissions and make kilns more efficient has begun in India, Nepal and Bangladesh where seven of the 37 kilns established in 2018 were Zig-Zag brick kilns (for more details on the Zig-Zag kilns see Chapter 4 Section 4.2.1). However, these alterations do little to change the extractive nature of the brick-manufacturing process with regards to topsoil loss and water consumption – in order to address this, additional measures in the production phase will need to be undertaken, such as increasing the content of waste materials (e.g. fly ash) to reduce the primary extraction of topsoil (Prasad *et al.* 2014). These techniques should also be applied to reduce the water content needed to mould the bricks. Thus, to establish the true scale of the nexus and build upon those issues that have been identified within this analysis, a number of solutions will be required; yet there is the opportunity to make lasting change within the brick-making sector to reduce the environmental effects of manufacture, and the social effects of modern slavery.

5.4.1 Intersection with the Modern Slavery-Environment Nexus

Brick-manufacturing in South Asia is routinely cited as an industry that uses exploitative labour practices. The sector is largely extractive consuming resources and, in the process, damaging the environment. At present, the lack of Sentinel-5p data means that any connections or trends between kilns and pollutant concentration could not be established empirically. However, overall sectors where there is evidence of widespread dependence on fossil fuels and other natural resources will undoubtedly contribute to pollutant concentrations; at this time however it is not possible to say whether this is linked to the modern slavery-environment nexus. Bales (2016: 109-110) noted the use of alternative fuel sources that are highly damaging, thus exacerbating emissions contributing to environmental degradation and impacting health. This is commonly found at kilns with debt bondage. Whilst satellite sensor data can provide insight into the regional atmospheric composition, it cannot provide nuance into the individual kiln emissions because of the large pixel sizes. It is important that further research into the nexus include ground-data, incorporating both data sources for a holistic overview. The incorporation of ground-data will also be important when establishing the true scale of extraction for both topsoil and water in the production of these bricks, and determining any differences between kilns known to use modern slavery practices, and those that do not. Moreover, measurements from kilns known to use/not use practices of modern slavery should be recorded to establish whether changes in emissions correspond to vulnerability of exploitation. This is not currently viable as kilns utilising labour exploitation cannot be detected directly from space (Landman *et al.* 2019); but satellite EO data is a good starting point for the consideration of further research assessing the sector from an environmental lens. EO data can therefore serve as a proxy measure while ground-data are acquired.

The smoke emitted from the kiln in Figure 4.7 (Chapter 4/Paper 3; see also Appendix B) was black, and was known to use debt-bonded workers during the period of analysis. Visible smoke is often white in colour (Figure 5.5 Kilns A and B). This contrast is related to the fuel used to fire the bricks – coal and other sources are frequently used and emit vast amounts of black smoke – and kiln structure (BTK/FCBTK vs. Zig-Zag kiln). Kilns that use environmentally damaging fuel have a higher chance of illegal working practices occurring (Bales 2016: 109-110). Therefore, the kiln in Figure 5.5 Kiln C, emitting black smoke from the chimney, is at risk of these practices. The visibility of black smoke in high spatial-resolution data can be used as a proxy to identify and investigate kilns that may be at risk from modern slavery; this is assuming that those burning dirty fuel sources, such as coal, used motor oil, and tyres (Bales 2016), are also kilns that are subjecting workers to conditions of modern slavery.

5.4.2 Conflict – Failure to Achieve the SDGs

Resource extraction could lead to complications in achieving the SDGs. Water and topsoil are the primary extractive materials. Removal could have implications, including: access to water for agriculture, cleaning, sanitation and food preparation are removed due to the required levels required to make the bricks (Figure 5.4). The topsoil extracted to build the bricks directly removes resources for agriculture and food security (Figure 5.4); and thus is a direct threat to sustainable agriculture practices (Biswas *et al.* 2018). Whilst the extraction is much smaller than that of the overall agricultural sector, the two are often competing for resources directly on a local-scale and conflict could also increase as environmental change increased the likelihood of agricultural shocks, and thus livelihood precariousness in the region (Berchoux *et al.* 2019). This may have similar repercussions for water scarcity and the irrigation of crops, particularly in a changing climate. In addition to the conversion of agricultural land into clay fields, the brick kilns occupy agricultural land in almost 80% of cases (Table 5.2) – land which become unsuitable for food production once degradation by the kilns has occurred. This is likely to fuel the further selling of soil for small-scale and subsistence farmers and further reduce crop production. Biswas *et al.* (2018) note that in Bangladesh this is becoming an issue with farmers reporting 40-80% crop yield reductions and lowering of income by up to 70%. Therefore, brick kilns are in conflict with the achievement of SDG 2.4 (which specifically seeks to ensure sustainable food production systems and encourage resilient agricultural systems) and SDG 6 ("Water and Sanitation") (UN 2016a, 2016c). To achieve SDG 8.7 in the kilns, there needs to be acknowledgment that their environmental effects can have impacts on water systems and the degradation of valuable agricultural topsoil, affecting thousands.

5.4.3 Improving the Environmental Impact of Brick Kilns

Brick kilns in this region contribute to the pollution concentrations in one of the fastest developing regions in the world – this does not mean that the industry is the primary contributor, however improvements and lowering emissions from the sector are necessary to protect human and environmental health. Efforts are needed to limit, reduce and prevent future emission of serious GHGs.

Interventions to limit kiln emissions have been explored in Bangladesh (Begum *et al.* 2011; Darain *et al.* 2013; Larsen 2016). Here, there has been a push toward more sustainable manufacturing whilst limiting costs. Cost is an important factor in the changing-behaviour of brick kiln owners, particularly as competition can be high; there is an overwhelming use of debt bondage labour to reduce prices. BTKs and FCBTKs can be converted to more energy efficient, less polluting, Zig-Zag kilns (see Chapter 4 Section 4.2.1 for more details on Zig-Zag kilns), thus reducing the emission factors of the kilns (Haque *et al.* 2018). Variations on this basic design have been implemented, including: the Improved Zig-Zag kiln (IZK); natural draught kiln (Zig-Zag ND); and high/induced draught kiln (Zig-Zag HD). The latter two, are commonly found in the central region of the ‘Belt’ covering parts of India and Nepal, and Bangladesh (Maithel *et al.* 2014:5-12). Emissions reduction is the main characteristic of the Zig-Zag kiln; fuel consumption can be reduced by up to 40% (leading to reduced fuel requirement), whilst increasing the quality of bricks produced (PEC 2018). More specifically, carbon emission (CO_2, CO and BC) reduction is approximately 85% (A.P.P. 2018) – or 70% of all emissions (PEC 2018).

Improvements require investments, however costs are recuperated by the reduced volume of raw extractive materials needed for fuel (ADB 2012). An Asian Development Bank (ABD) project, provides credit to brick makers enabling them to improve standards in their current kiln or build new energy-sensitive and sustainable kilns. Overall, the energy efficiency savings are substantial (Larsen 2016: 14). At present, the majority of kiln improvements are occurring in Bangladesh (therefore only a portion of the kilns assessed in this study have been improved). These schemes are necessary for the entire ‘Brick Belt’; however, they do not address the raw extraction of materials to make the bricks – topsoil and water – only those which fire the bricks. This is something that needs to be incorporated into schemes to improve the overall efficiency of the brick kilns. Monitoring and evaluation of projects such as those noted, could be supported via satellite EO data.

Social and environmental benefits can be gained by improving traditional brick kilns according to Larsen (2016: 14-20); the costs and benefits of kiln improvements in Bangladesh’s Greater Dhaka region have been explored. Larsen’s (2016) analysis suggests that the costs of efficiency improvement are far outweighed by the benefits, which include: reduced operational costs; support for climate change mitigation; limitation of building and vegetation damage; lowering degradation to water and soil;

health benefits and a reduction in mortality levels. Thus leading to better working, and living, conditions for all.

Green technologies are now considered the only option for future kiln development in Bihar (India) (P.T.I. 2018); these considerations are also occurring across the ‘Belt’ but are yet to reach the scale seen in Bangladesh. Zig-Zag kilns may not be the most efficient – Hybrid Hoffman and Tunnel kilns are touted as the most – but the costs associated with the improvements are the most affordable and realistic (CCAC 2017). Traditional kilns can be adapted which reduces further landcover degradation, necessary for the construction of new kiln clusters; further limiting economic costs and environmental damage. Furthermore, alterations to the composition of bricks may improve their extractive burden on the environment – by incorporating waste materials the volume of topsoil required reduces (Prasad *et al.* 2014), and alternative brick production materials and methods can be promoted to reduce extraction, for example, plastic ‘eco-bricks’ (Hopkins 2014), and bricks made from ash gathered from previous firing cycles (Gadzo 2017). All of which reduce the extraction of resources in the ‘Brick Belt’ and recycle anthropogenic-made materials.

5.4.3.1 Cost vs. Benefits

Improvements to brick kilns have been proposed, including mechanisation, as a method of uplifting the industry and supporting workers, whilst reducing consumption of natural resources and increasing efficiencies. However, they are unlikely to successfully occur without state intervention due to the cost and the lack of interest from kiln owners (Bales 2012: 192-194). Whilst those improvements are beneficial for the environment, a fine line exists between progress for nature and the further exploitation of workers. Improving efficiency and limiting environmental degradation can lead to short-term cost increases; thus in kilns where debt bondage is already present, there can be further exploitation. To those workers and kiln owners who are on the cusp of using exploitative practices the price of environmental improvement could raise levels of vulnerability to exploitation.

Consequently, identification of vulnerable workers in kilns where efficiency improvements have been made, requires monitoring. Support must be provided by development actors who assist in kiln improvement initiatives to avoid workers being unduly impacted. As kilns adopt these technologies to limit their environmental footprint, those which do not must be investigated for the presence of environmentally and socially harmful practices. Whilst reducing emission concentration is vital to limiting their environmental impact, extraction levels of topsoil and water must also be addressed and moves toward sustainable brick-materials must take place.

5.4.3.2 Environmental and Social Protections

Local and national governments must support changes to kilns that move towards reductions in their environmental impact, by introducing legislation which supports changes to the sector. Legislation should reference the SDGs and be industry specific noting the inherent benefits of creating a sustainable and efficient brick-manufacturing industry in the region. Support for programmes promoting kiln efficiency improvements, and those which work to reduce modern slavery, limit environmental degradation, and support workers’ rights, should be provided.

5.5 Limitations

The study has several limitations, the most prominent being the unavailability of ground-data; to mitigate against this we utilised peer-reviewed secondary data to establish estimates for the volumes of topsoil and water extracted (Figure 5.4) in conjunction with the location data from the machine learning map (which itself used training data based on ground-reports, estimation, and crowdsourced accuracy). The use of primary data from areas around the kilns related to the environmental impacts – including pollutions, topsoil and water consumption – would be beneficial but was not available within this scoping analysis. These secondary data sources supported the analysis of brick kiln emissions from EO satellites. The pollutant analysis contains a number of limitations, including:

- Lack of detail in the CO_2 dataset – due to the coarse spatial-resolution from the OCO-2 satellite and modified data employed (by Zammit-Mangion *et al.* 2018; OCO-2 Science Team 2018), there is a lack of spatial detail for the carbon dioxide emissions compared to the pollutants analysed from the Sentinel-5p TROPOMI sensor. However, the detail obtained for CO_2 measurements is likely to be improved with the proposed launch of the ESA's 'Copernicus CO_2 Mission' in 2025. A fleet of three satellites are planned to monitor GHG emissions, providing a more detailed picture of global CO_2 emissions than at present (Mathiesen 2019).
- Meteorological factors – pollutant migration is dependent on atmospheric conditions, first demonstrated in the movement of aerosols (Kaufman *et al.* 2002). This led to the use of the mean monthly averages for overall pollutant analysis of the 'Brick Belt'. However, wind is a factor in these monthly averages as pollutants can be carried from other areas into the region, skewing the concentrations of emissions recorded above the kilns. The outputs are affected by the presence of migrating pollutants, particularly from Central Asia and the Middle East following global wind patterns. The complex nature of the atmosphere means it can be hard to attribute the pollutant to the kilns;

particularly as there appears to be an inverse relationship between higher pollutant concentrations and the brick-making season. Monsoon conditions can also transfer pollutants between the atmospheric layers (Randel *et al.* 2010); for example from the troposphere to the stratosphere and vice versa (TROPOMI specifically measures the composition of the troposphere). This may increase the volume of pollutants measured close to the planet's surface from June-September. These pollutants are unlikely to be emitted from the kilns as they do not operate during the monsoon, however previous kiln emissions may be redistributed during this period.

- Agricultural burning – commonly practiced across the Indo-Gangetic Plain is agricultural burning to clear land for new crop production; northwest India has seen an increase in the practice for the removal of rice crop residue (Shyamsundar *et al.* 2019). This elevates pollutant emissions and haze in the autumn and winter (Bikkina *et al.* 2019), corresponding to kiln operation thus making differentiation of the pollutant source difficult. Emissions in New Delhi, for example, have been elevated by the agricultural burning, kilns operating on the city outskirts, satellite settlements, industrial and construction activities and transportation (Guttikunda and Goel 2013; Guttikunda *et al.* 2013).

Further remote sensing data developments and applications may increase understanding of the environmental impacts of kilns, particularly topsoil extraction. Radar data may be used to determine the amount of subsidence that has occurred; important for establishing accurate measures of the topsoil removed to produce bricks, and determining which kilns are active and when this occurs. The availability of Sentinel-1 data (Geudtner *et al.* 2014; Torres *et al.* 2012) alongside a modelled map of clay field sites (produced in a similar manner to the brick kiln map) could provide additional insights into the brick industry.

5.6 Future Analysis Possibilities

In order to more robustly establish connections between modern slavery within the brick kilns and environmental damage, statistical approaches can and should be undertaken utilising the brick kilns dataset across the ‘Brick Belt’. There are three key issues related to the linkages between the brick-making sector and its connection to environmental degradation in this study:

- Limited data availability from the Sentinel-5p TROPOMI sensor during the period of analysis in this study.
- Limited ability to scale-up statistical analyses for the ‘Brick Belt’, both spatially and temporally.
- Future opportunities to integrate and access additional data.

First, the limited data from the Sentinel-5p sensor meant the identification of meaningful temporal trends in the emission of pollutants was not possible. This issue can be mitigated over time as increasing amounts of data are collected and become available. For example, the data used in this Chapter/Paper covered a single year (July 2018-July 2019) at most in some cases (e.g. O_3); whereas multiple years of data are now available for the pollutants monitored by Sentinel-5p. The increased volume of data enables global trends to be identified, alongside more sector specific relationships linked to modern slavery and the environment. This should enable the identification of features among the kilns that may indicate their use of illegal labour, or lawful observation of environment law. Overall, a tool may be developed as a result of the pollutant data collected which may provide insight into the nexus; one that should automatically detect changes in emissions located over kilns. This may ultimately lead to the ground-based investigation of social-ecological conditions found within the kilns.

In order to establish a usable tool for antislavery and environmental organisations, a robust statistical assessment must be applied in order to quantify the modern slavery-environment nexus. This method will be able to utilise the longer time-series data measured by the Sentinel-5p sensor. To account for possible covariance and spatial autocorrelations, this larger openly available dataset (supported by the European Space Agency's pledge to keep data 'free, full and open access'; Copernicus 2020) will be necessary. Two statistical techniques may be applied, both regression and spatial regressions. The former could be undertaken in areas where there are a large clusters of kilns, for example, Patna in Bihar State (India) or Dhaka, Bangladesh. The levels of pollutants over this area can be correlated with the number of kilns to determine where and whether the brick kilns are the dominant source of pollutant emissions in an area; with variable *x* (the number of kilns) plotted against variable *y* (volume of emission). This method can provide a statistical assessment of the relationship between brick kilns and the environmental degradation. Alternatively, understanding autocorrelation requires the application of a spatial regression (Anselin 2009). Unlike a simple or multiple regression which measures the strength, direction, and fit of a variable of interest, spatial regressions assume dependencies exist between the variables of interest and account for spatial lag within the data (Brusilovskiy n.d.). For example, the concentration of pollutants in one area can be directly impacted by those in another.

The kiln locations known as a result of the machine learning mapping method (Boyd *et al. forthcoming*) and the additional temporal analysis from the aged kiln dataset (Li *et al.* 2019) have been analysed using a simple regression. Boyd *et al.*'s (*forthcoming*) regression has analysed the relationship between the number of kilns and an alternative pollutant, $PM_{2.5}$ (particulate matter at a size of 2.5 microns in width or smaller), over a fifteen year period (2000-2015 at five year intervals) and found that there are trends in kiln numbers that are associated with increasing $PM_{2.5}$ concentrations over time. These trends can be assessed on small spatial scales to increase knowledge of the brick kilns impact on the environment.

However, these analyses may be improved by addressing the spatial-autocorrelation of brick kilns emissions and their numbers as both the location of the kilns and the number of kilns may lead to a lack of randomness in the data. Therefore a spatio-temporal analysis may be more appropriate (Rey 2001; Brusilovskiy n.d.). This technique is regularly applied to the investigation of the health effects of air pollutants (Wang *et al.* 2015; Dai and Zhou 2017; Habibi *et al.* 2017), in analyses where both spatial and temporal structures are addressed. Health implications may also be translated into the negative environmental conditions that workers may be subjected to, alongside the surrounding populations and ecological systems (Habibi *et al.* 2017).

As a result, both regression techniques – simple and auto-correlation – are applicable in the context of the brick kilns assessment, but to provide more nuanced details linking kiln emissions directly to the nexus the latter would be preferable. Particularly as lags in the pollutant data may be associated with several factors, including: kiln design, emissions from other sources, and environmental factors (e.g. wind, monsoon, and cyclones). The application of auto-correlations to analyse the emissions from brick kilns are beginning to be explored (see Rahman *et al.* 2019), and thus it is feasible that current regression techniques used to assess the kilns in the 'Brick Belt' can be expanded to incorporate those spatially explicit lags, thus supporting the measurement of the modern slavery-environment nexus.

Whilst it may not identify modern slavery *per se*, undertaking such statistical analyses can help to: 1) identify the prominent pollutants emitted from kilns; 2) track changes above areas with kiln clusters, allowing the identification of seasonality, changes in emissions and thus fuel usage – enabling the inference of social and environmental conditions within the kilns; 3) note regions where modern slavery may be a higher risk, for example, sudden increases in emission release from poor quality fuels (Bales 2012; Brickell *et al.* 2018; Crang *et al.* 2020); and finally, 4) identify geospatial differences, such as rural vs. urban kilns, and small-scale kiln presence vs. large kiln clusters. Such analyses may be applied to multiple pollutant datasets – derived from both remotely sensed data sources and ground-surveys.

Finally, to address the third issue of the study, the integration of other data sources are required. In this Chapter/Paper data that have been collected for the whole 'Brick Belt' from Sentinel-5p and OCO-2 (see Appendix E) to determine the mean monthly average for each pollutant. However, daily emissions (of the pollutants CO, HCHO, O_3, NO_2, and SO_2) may also be downloaded and analysed to provide further insight into emission patterns. Identifying temporal trends will improve as Sentinel-5p continues to orbit. Moreover, additional data measured by the Sentinel-5p TROPOMI sensor may be analysed (Veefkind *et al.* 2012) – for example, aerosols. The data collected on CO_2 emissions are limited, and whilst a regression may be possible, the application of an auto-correlation analysis is unlikely to be successful as a result of the poor-granularity of the data; the raw data may provide more scope for analysis (Zammit-Mangion *et al.* 2018; OCO-2 Science Team 2018). In addition, the quality of CO_2 data will improved going forward with the launch of the ESA CO_2 monitoring programme (due mid-2020s) (Fleming 2019; Government Europa 2019). Furthermore, as the work by Boyd *et al.* (*forthcoming*) has noted, particulate matter data ($PM_{2.5}$ and PM_{10}) may also be useful to interpret, but were not undertaken in this study as a result of the data collection parameters of the TROPOMI sensor.

Future analysis should also work to incorporate the loss of soil and water extraction for the production of bricks. The data used in this study were not adequate as estimated figures from previous studies were applied (see Figure 5.4). Thus the integration of ground-based studies on topsoil erosion, as well as rainfall levels, and the integration of LiDAR (Light Detection and Ranging) from sensors such as GEDI (Global Ecosystem Dynamics Investigation) on-board the International Space Station (ISS) – to assess ground-shift/movement (Brown *et al.* 2018) as a results of groundwater extraction and soil loss (and therefore identify the volume of resources extracted). These data provide information that would enable the assessment of any relationship between the brick kilns and the degradation of the environment in a similar manner to that of the emissions.

Whilst we cannot at present identify modern slavery within these kilns, understanding the nuances of kiln operations and their ecological impact, we may be able to begin the identification of 'high-risk' sites. Thus, the application of these statistical assessments could begin to address the scale of the modern slavery-environmental degradation-climate change connection.

5.7 Conclusion

Brick kilns undoubtedly contribute to environmental degradation, and this occurs in tandem with the exploitation of workers. Across the 'Brick Belt' it has been found that agricultural land is being re-purposed for resource extraction and converted to form kiln sites. Whilst the number of kilns being constructed has begun to slow, this does not make the industry any less damaging as fertile topsoil and water are extracted in abundance, limiting the chances of achieving SDGs 2 and 6. Therefore, it is important that SDG 8.7 is not tackled in isolation within brick-making but also encompasses the wide reaching consequences of the industry – protecting both people and nature.

The South Asian brick kilns are part of the modern slavery-environmental degradation nexus (Brown *et al.* 2019); this study has used a mix of satellite EO data products to establish the emission concentrations, landcover implications and extraction of resources affecting the region. Effort needs to be made to reduce the environmental impact of the kilns, and increase knowledge of the impact modern slavery has; overall assisting in data provision to help achieve SDG 8.7. Moving forwards, investigations into the colour of smoke emitted from kiln chimneys and radar analysis of clay fields could help determine which kilns are active and establish those using workers subjected to modern slavery. This study has established the connections between the environment and an industry which heavily uses vulnerable workers; identifying possible improvements for the sector to implement. Brick kilns are not the only industry contributing to the nexus, however it is one of the largest and most prolific. Improvements here could be used as an example case for similar industries such as fisheries, agriculture and deforestation that have also been identified as key drivers of environmental degradation and social exploitation (Brown *et al.* 2019).

Chapter 6: Tree Loss

This paper (see Table 1.3) has been adapted and updated from its original published version in *Conservation Science and Practice* which is contained in Appendix C.

Understanding the co-occurrence of tree loss and modern slavery to improve efficacy of conservation actions and policies

6.1 Introduction

Maintained forest environments have the potential to aid in achieving a number of the Sustainable Development Goals' (SDGs) socioeconomic and ecological targets: SDG 15 ("Life on Land"), SDG 13 ("Climate Action"), SDG 1 ("No Poverty"), and SDG 2 ("No Hunger") (Seymour and Busch 2016; Watson *et al.* 2018). But globally, areas where populations are most dependent on forests and their ecosystem services for subsistence and equitable sustainable development are also areas where modern slavery persists – often in activities perpetuating deforestation and similarly destructive practices that threaten biodiversity conservation (Bales 2016; FAO 2018c; Brown *et al.* 2019). Thus, this modern slavery-environmental degradation nexus may add to anthropogenic pressures on forests, compromising their ability to support the attainment of the afore-mentioned SDGs – as noted in other sectors, including brick making (Boyd *et al.* 2018 – Chapter 4/Paper 3/Appendix B), farming and fishing (Brown *et al.* 2019; see also Chapter 3/Paper 2).

Defined by the 2012 Bellagio-Harvard guidelines as "constituting control over a person in such a way as to significantly deprive that person of his or her individual liberty with the intent of exploitation through the use, management, purchase, sale, profit, transfer, or disposal of that person," (Research Network on the Legal Parameters of Slavery

2012) modern slavery is an umbrella term inclusive of varied forms of exploitation (e.g., forced labour, debt bondage, human trafficking, and slavery) (see Table 1.1). In many locations globally, the incidental biodiversity loss associated with deforestation-related tree cover loss contributes to pervasive poverty, loss of livelihoods (associated to livelihood vulnerabilities such as climate change impacts; Obeng *et al.* 2011), and food insecurity (Seymour and Busch 2016). These vulnerabilities of forested communities have contributed to the narrative that poverty leads to deforestation (Rai 2019), yet this has been shown to be more complex with studies noting that poverty can in fact reduce deforestation as people relying on the forests often protect them (Busch and Ferretti-Gallon 2017; Angelsen and Kaimowitz 1999; Angelsen and Rudel 2013). However, external threats to human security can force these already vulnerable populations to make decisions that result in them being exposed to modern slavery and participating in activities that lead to further deforestation (Bales 2016). Activities associated with tree loss, and concurrently linked with modern slavery include tree harvesting for charcoal production in the Republic of Congo and Brazil; forest clearing for conversion to cattle ranching in Brazil and farmland for oil palm plantations in Indonesia; and gold mining in the Madre de Rios region of the Amazon and the Sahel region of West Africa wherein trees are harvested for lining shafts (Verité 2017a; Brown *et al.* 2019). Additionally, many linked modern slavery-environmental degradation activities undermine conservation initiatives. For example, oil palm related deforestation, in countries such as Indonesia and Malaysia degrades habitat for endangered species; timber for charcoal production is harvested from protected Amazonian areas; and mangroves are cleared for the establishment of illegal fish-processing camps in the Sundarbans Reserve Forest (Bales 2016; Verité 2017a; Brown *et al.* 2019; Chapter 3/Paper 2).

Some estimates suggest that global forest cover decreased by approximately 3% from 41,282,694.8 km^2 to 39,991,336.2 km^2 between 1990 and 2015, with rates of tree cover loss highest in low-income countries (FAO 2016b). Tree cover loss, though, is in flux. Some cases classified as tree loss at one period in time may be re-classified as an area of gain the next measurement period because not all forest disturbances are associated with permanent conversion (i.e. deforestation rather than degradation) (Curtis *et al.* 2018). However, Global Forest Watch (GFW) data predicted that more than a quarter of global tree loss between 2001 and 2015 was associated with commodity-driven deforestation, and thus likely to be permanent and not reforested (Curtis *et al.* 2018). Should areas be reforested, attainment of the SDGs and human security may still be at risk as intact forests, rather than restored forests, may exhibit different ecosystem services than restored forests (such as carbon sequestration and biodiversity protection etc.) (Watson *et al.* 2018). Conservation of forests are vital as deforestation has been noted as a contributor to the release of greenhouse gas (GHG) emissions (IPCC 2018); placing the forest-benefits which can be gained through climate change mitigation policies, such as their role as a land-based carbon sink (Krug 2018), at risk. Forest conservation initiatives have been implemented to undertake this protection, including the United Nations' (UN) premier development scheme "Reducing Emissions from Deforestation and Forest Degradation" (REDD+) which seeks to protect forests via conservation, sustainable management, and enhancing carbon stocks. However, these policies do not yet consider modern slavery as a potential anthropogenic driver of deforestation. Preventing deforestation is a pertinent conservation goal and because of the association between deforestation and modern slavery (Verité 2017a), conservation should thus begin to consider the continued presence of modern slavery as a hurdle to overcome in management and conservation plans.

The GFW has measured and mapped tree loss yearly through remote sensing sources (Hansen *et al.* 2013). The antislavery field uses the Global Slavery Index (GSI) – national level estimates of prevalence of, and risk to, modern slavery based on Gallup-style surveys and proxies empirically associated with exploitation (ILO 2017c). While both represent data-limited fields that are reliant on and subjected to disagreements about the rigor and sensitivity of estimations and the role of politically motivated government self-reports, we purport these tools should not be used discreetly (Bales 2017; Curtis *et al.* 2018). Instead, it is more efficacious to identify synergies between tools to extrapolate more holistic understandings of conservation challenges associated with social justice concerns. While the GFW data has been demonstrating the where and when of deforestation, only recently has it started answering the question of why (Curtis *et al.* 2018). This paper extends the argument of why by integrating the GSI with the GFW and associated datasets, elucidating for the first time empirically the contribution that modern slavery could be making to deforestation-related tree cover loss and the challenges it presents for conservation management and planning. This manuscript is intended to provide insight into the connections between tree loss and modern slavery which may be relevant for conservation researchers, practitioners and the antislavery community to support multiple UN SDGs and encourage sustainable development via the indivisibility principle (UN 2016a).

6.2 Methods

Three datasets are utilised in the study: the Global Slavery Index (GSI), the Environmental Performance Index (EPI), and the Global Forest Watch (GFW) tree loss and gain data (Walk Free 2016; Hsu *et al.* 2016; Hansen *et al.* 2013). These data were used in multiple analysis methods to address the co-occurrence of modern slavery and tree loss.

Firstly, modern slavery estimates from the GSI 2016 (Walk Free 2016) were analysed using a Spearman's Rank correlation against the EPI from the same year (Hsu *et al.* 2016) (Figure 6.1).[22] The EPI is a measure of the success of 'environmental health and ecosystem vitality' which is measured via a series of metrics to gauge how ambitious and successful nations are being in establishing environmental policy goals (EPI 2018a). This dataset was used as it reflects some of the SDGs and concerns which have been previously been linked to exploitation as part of the modern slavery-environmental degradation nexus (Decker-Sparks *et al. under review*). The scoring/ranking systems of both the GSI and EPI differ. For example, in the GSI a low rank (e.g. North Korea: 1) corresponds to high prevalence of modern slavery, and a high rank (e.g. the United States) means lower prevalence of modern slavery (Walk Free 2016). Whereas for the EPI a low rank (e.g. Finland) means higher levels of environmental protections, and a higher ranked number (e.g. Mozambique: 172) suggests lower levels of protections (Hsu *et al.* 2016). Using these documented scores and ranks the Spearman's Rank correlation coefficient was undertaken using Microsoft Excel. Not every nation was included on both indices; those countries which only appeared on one were removed from the analysis at this stage meaning n = 163. A Spearman's Rank correlation was chosen as the two variables being assessed appeared to have a relationship as a result of preliminary exploration of the datasets in the form of a scatterplot. Yet when plotted on a histogram the data skewed left for the GSI and right for the EPI, suggesting non-normal data distribution which requires a non-parametric statistical test. These findings

[22] The 2016 GSI was chosen over later versions as it does not include the use of environmental indicators as a proxy for the estimation of vulnerability and prevalence to modern slavery. Therefore, by using the 2016 data, the correlation of the environmental connection between the GSI and EPI is not overstated. This practice may not be replicable in later GSI reports, but the inclusion of these data to enhance the GSI methodology has been noted (Larsen and Durgana 2017; Walk Free 2018); and as our results suggest, this is important as there is a connection between modern slavery and environmental protections.

along with other data noted below, were used to identify and determine countries of interest that require further assessment in relation to the modern slavery-environment nexus (Brown *et al.* 2019). In the case of this study, these nations experience forest degradation, however, the scatterplot (Figure 6.1) can be further used – alongside other relevant literature – to identify nations that may see environmental damage in other sectors, such as mining/quarrying, brick-making, and fishing (Decker-Sparks *et al. under review*).

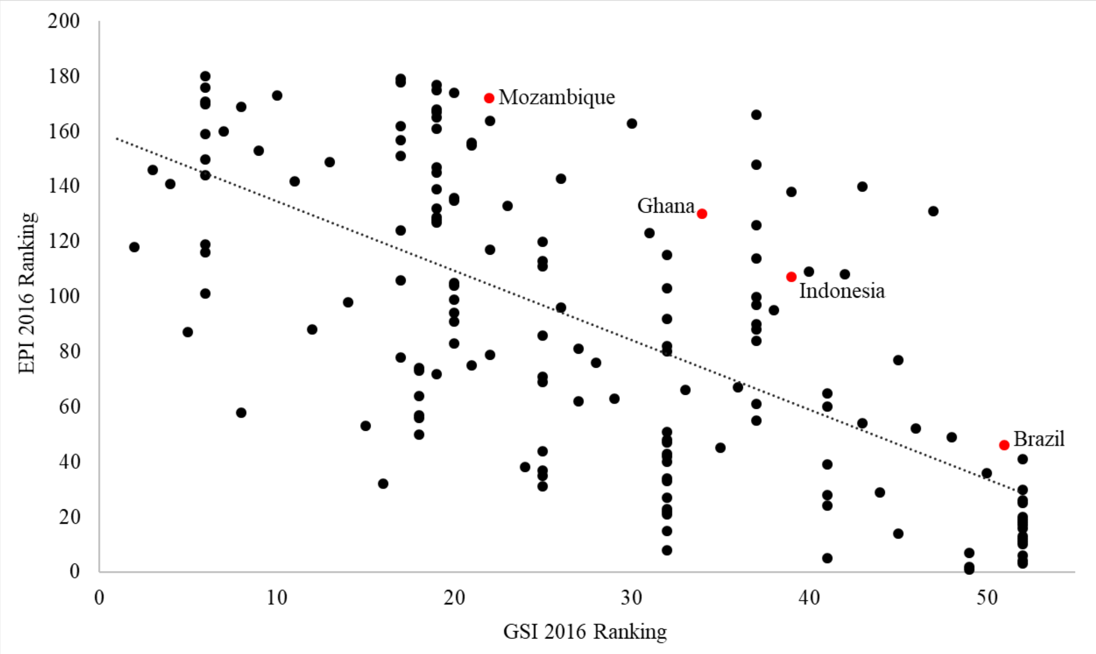

Figure 6.1: Model of the ranks Global Slavery Index (GSI) 2016 modern slavery estimates per country against the Environmental Performance Index (EPI) 2016 ranking from their scores (Walk Free 2016; Hsu *et al.* 2016). There is a strong negative correlation between countries with lower estimated levels of modern slavery and countries with higher environmental protections and vice versa. Statistical details of the scatterplot and linear trend-line are: $y = -2.5198x + 159.89$ | R^2 = 0.4334, p-value 4.98e-21.

Note that the scale for the 'GSI 2016 Ranking' has a maximum rank of 52 despite 167 countries being assessed. This is due to a number of countries receiving the same prevalence score during the sampling and extrapolation process applied in the methodology of the GSI calculations (Walk Free 2016; Larsen and Durgana 2017). This was not altered in this case as the rankings for both the GSI and EPI where kept the same as the original datasets to avoid unnecessary manipulation and distortion of these original data.

Secondly, to determine the levels of modern slavery associated with tree loss, the ILO (2017a, 2017c) estimate of people subjected to modern slavery in agricultural, forestry, quarrying and mining industries was used; totalling 15.3% of those in forced labour globally. These are industries known to contribute to tree loss and degradation. The total country estimates from the 2016 GSI were altered to determine the estimated number subjected to modern slavery within the sectors noted above (thus calculating 15.3% of the total people estimated to be subjected to modern slavery for each country where data were available). Differing levels of 'at risk' countries have been identified by categorising the output of this risk into quartile ranks based on the estimated number of people subjected to modern slavery in environmentally degrading activities, creating four categories: 'low', 'low-medium', 'medium-high' and 'high' risk.

Thirdly, these were compared with the potential losses from deforestation caused by modern slavery, where illegal logging rates were used as a proxy measure (Bales 2016). This was calculated by identifying rates of illegal logging from a number of sources (see Toyne *et al.* 2002; INDUFOR 2004: 3; Seneca Creek Associates and Wood Resources International 2004; World Bank 2006: 9; Lawson *et al.* 2014: 122; and Hoare 2015: 61-63). The lowest values from these reports for each country were used as a proxy for the presence of modern slavery – not all nations had illegal logging estimates, in cases where regional figures were available those were applied to countries in that region, some areas had no data available and thus were marked as such in the analysis. The illegal logging figures were applied to GFW data to determine the potential area of land deforested per country by modern slavery practices. The total area of tree loss per country (2001-2018) were downloaded for each country and converted into hectares; at the same time the percentage of deforestation at >30% canopy density were also extracted (Hansen *at al.* 2013). All data for this analysis was accessed via the GFW platform – these data included tree cover loss (based on Hansen *et al.* 2013) and tree cover loss by driver (based on Curtis *et al.* 2018) (GFW 2019; The Sustainability

Consortium *et al.* 2019). The total area of loss by deforestation was then calculated (Equation 6.1), followed by the estimated area that had been deforested as a result of illegal logging practices (used here as a proxy for modern slavery presence) (Equation 6.2):

(6.1) $$total\ area\ deforested = \frac{total\ area\ tree\ loss}{100} \times percentage\ of\ deforestation$$

(6.2) $$estimated\ area\ deforestation\ by\ illegal\ logging\ (proxy\ for\ slavery) = \frac{total\ area\ deforested}{100} \times percentage\ of\ illegal\ logging\ per\ country$$

These areas were then converted into the percentage of area deforested by modern slavery (using illegal logging as a proxy measure). Again, the results for these countries were split into risk categories based on the quartile ranges of the data and are presented as ‘low’ risk, ‘low-medium’, ‘medium-high’ and ‘high’ risk depending on the rank in which they fell.

Finally, the risks of modern slavery causing tree loss from the illegal logging analysis, and the modern slavery estimates were compared with predicted tree cover loss, modelled at continental and global levels by Hewson *et al.* (2019) as part of a new 1 km resolution dataset.[23] Their modelling approach included applying a multi-layer perceptron neural network to produce a global transition potential map for tree cover loss.[24] The global transition model was used in this study due to the global coverage of

[23] These data are freely available to download from http://futureclimates.conservation.org/index.html

[24] In order to establish the model of transition potential using the multi-layer perceptron neural network, Hewson *et al.* (2019: 2-6) used 25 potential tree loss variables, and modelled them alongside the 30m global tree cover map from 2000 (by Hewson *et al.* 2013), and defined tree loss as any change below the 10% threshold of tree cover. A global model, and a further six regional models were produced. The predicted transition potential was measured using a Heidke Skill score, whereby 0 meant the model was predicting better than chance alone, and +1 indicates a perfect prediction. The overall skill statistic for the global model was 0.61, with the global forest change rate under a ‘business as usual’ (BAU) scenario totalling 4.1%.

the three other datasets applied (i.e. GSI, EPI, and GFW), and the geographic scope of the four countries which are focused on in detail within the discussion. Levels of predicted loss were compared on a global scale with the area of deforested land linked to modern slavery (proxy measure) using a Spearman's Rank correlation coefficient (only those countries which were included in both datasets were used – as a number of countries in the illegal logging analysis did not have estimated illegal logging rates available, leaving n = 148). This was because the Hewson *et al.* (2019) data and the area deforested as a result of illegal logging (a proxy for modern slavery) were both heavily skewed (left); thus their assessment required a non-parametric statistical assessment. Analysis was conducted on Microsoft Excel. Additional loss and gain data from 2001-2018 were subsequently downloaded from GFW when assessing the overall drivers and predicted tree loss patterns identified for the four countries (Brazil, Ghana, Indonesia and Mozambique) investigated in more detail.

Countries where indications of high levels of predicted tree loss, moderate-high estimated modern slavery levels and illegal logging (as noted in the analyses above), as well as documented evidence of modern slavery within their forestry sectors – noted in the literature on modern slavery – were used to determine which countries were to be further assessed. These countries have experienced, and are likely to continue experiencing, tree loss associated with industries known to use modern slavery. Countries were chosen using the results from the investigations into: the levels of environmental protections and modern slavery; the estimated prevalence modern slavery in environmentally degrading sectors; the risk of illegal logging practices; predicated transitions of forests for tree loss; and literature into modern slavery and the forestry sector. Countries with higher rates of modern slavery, illegal logging, documented cases of modern slavery in the forestry sector, and a variety of environmentally degrading activities were chosen. These parameters meant Brazil, Ghana, Indonesia and Mozambique would be explored in greater detail within the context of the modern slavery-environment nexus.

A number of specific reasons these countries were selected include: 1) Indonesia's high level oil palm plantations which violate regulations (Listiyorini and Rusmana 2019); 2) Brazil has historically been seen as a place which is leading on environmental and social protections with extensive legislation related to deforestation in the Amazon and modern slavery, however the recent political climate makes it an interesting case study as a result of the erosion of these protections (Escobar 2019); 3) Ghana has a variety of environmentally degrading sectors which have been associated with forced labour, such as mining, which has been linked to extensive forest removal in protected areas (Schueler *et al.* 2011); and finally, 4) Mozambique is experiencing losses from mining and infrastructure development associated with China's 'Belt and Road' policy (EIA 2013). The variations in tree loss and the extent to which it may be connected to modern slavery within these countries makes them an interesting prospect to study.

Moreover, each have differing vulnerabilities; all are found across the tropics where Hewson *et al.*'s (2019) model predicts some of the highest losses. Past tree loss/tree gains for these countries were then extracted using the Hansen *et al.* (2013) derived dataset (GFW 2019) (accessed via Google Earth Engine (GEE)). These data covered the period 2001-2018 and were applied to the >30% tree coverage data (overall accuracy of the loss data is 75.2%: Weisse and Peterson 2015a, 2015b). Loss and gain in these scenarios is in relation to the base dataset of 'global tree coverage' for 2000. Subsequent analysis could account for these loss and gains on a per year basis to provide a more detailed understanding of the trends over time; this would also require similar temporal data for those data, or proxies, which address modern slavery – at present these data are limited but there are a few cases where this could be applied, for example in Brazil where there are annual data on modern slavery cases from 2003-2018.[25] As a result of the globally limited data on both modern slavery, illegal logging, and tree loss these overall loss and gain levels were used for this study to provide context regarding the state of the forest environments and the trends in destruction, of which some will be attributed to the exploitation of workers. Comparison with the future predicted loss for these nations was enabled, suggesting evidence of whether the pattern of degradation will continue.

6.3 Results

There is a negative relationship (rho = -0.647, *p*-value 9.912e-20) between levels of environmental protections and estimated prevalence of modern slavery (Figure 6.1) for all countries which are covered by the GSI and EPI indices from the Spearman's Rank correlation coefficient (note, only nations with ranks on both the EPI and GSI were included in the analysis: n = 163). Thus, indicating that higher environmental protections also mean lower levels of exploitation; whereas lower environmental protections are associated with higher levels of modern slavery. The four countries studied in more detail are spread along the GSI/EPI relationship with Brazil performing the best and Mozambique (which may also be considered an outlier) the worst. These findings provide important insight into the modern slavery-environment nexus, identifying a link between the two sectors which has only recently begun to be explored (Brown *et al.* 2019). Although the relationship is assessed in terms of tree loss within this paper, there is scope for analysis within other sectors known to employ practices

[25] SmartLab collated data on 'Slave Labor and Human Trafficking' in Brazil which are available to access from: https://smartlabbr.org/trabalhoescravo

of modern slavery and cause environmental damage, such as mining, quarrying, fish processing, and brick-making (see Chapter/Papers' 3/2, 4/3 (Appendix B), and 5/4). .

Hewson *et al.*'s (2019) global tree loss maps predict high rates of loss across vast swaths of the tropics, as well as Canada and Russia – where legitimate commercial logging industries dominate (Curtis *et al.* 2018); however, some of these countries exhibit lower potential risk of deforestation and tree loss associated with modern slavery activities when compared with the modified GSI figures (Figure 6.2). This does not mean that exploitation of the workforce is not taking place, it may be that it has not yet been reported. All four countries assessed in further detail have estimated rates of modern slavery in the 'medium-high' range, both overall (Table 6.1), and when assessed in relation to tree loss related activities (Figure 6.2), particularly when assessed against illegal logging levels which are used as a proxy for modern slavery activity (Figure 6.3).

When the Hewson *et al.* (2019) predicted tree loss data for all countries was assessed against the deforestation rates by illegal logging (modern slavery proxy) (seen in Figure 6.3) for those nations where these data were available; the Spearman's Rank suggested a correlation coefficient (rho) of 0.274 with a *p*-value of 0.0007. The *p*-value suggests a significant relationship between predicted loss and the area of tree removal likely to be undertaken by workers subjected to modern slavery, despite the fact that the rho could be considered low. Therefore a correlation between the two can be interpreted, but this should be taken with caution. For example, it is important to note however, that Hewson *et al.*'s (2019) dataset includes the GFW tree loss data within it model. Subsequently, this may lead to a statistical over correlation between the two variables, due to the repeated use of the data and thus the confidence in this particular correlation should consider this.

Table 6.1: Further details of the case study countries' taken directly from the Global Slavery Index (GSI) (Walk Free 2016) and the Environmental Performance Index (EPI) (Hsu *et al.* 2016). Scores relate to the overall ranks, estimated prevalence – scaled to estimate the number of people subjected to modern slavery in industries which directly impact tree loss –vulnerability, and government response scores.

Country	Prevalence Figures from GSI 2016[a]				Vulnerability Scores from GSI 2016[c]					Government Response GSI 2016[d]	EPI Figures[e]	
	2016 Global Slavery Prevalence Rank	Estimated Percent of Population in Modern Slavery	Estimated Number in Modern Slavery	Estimated Number of People in Modern Slavery Working in Activities Related to Tree Loss[b]	Civil and Political Protections	Social, Health and Economic Rights	Personal Security	Refugees and Conflict	Mean Score	Total Score	2016 Global EPI Rank	2016 Global EPI Score
Brazil	51	0.078	161,100	24,648	37.98	20.46	45.88	30.74	33.77	56.85	46	78.9
Ghana	34	0.377	103,300	15,805	51.89	38.42	47.45	28.26	41.51	28.43	130	58.89
Indonesia	39	0.286	736,100	112,623	39.15	43.35	50.38	36.01	42.22	40.61	107	65.85
Mozambique	22	0.520	145,600	22,277	39.91	48.46	54.40	35.86	44.65	40.85	172	41.82

[a] The prevalence figures from the 2016 GSI were based on data from global surveys which were conducted with Gallup via their World Poll, as has been undertaken since 2014. For the 2016 version of the GSI, the number of surveys have led to more than 42,000 respondents in 53 languages over both national and sub-national levels. The level of modern slavery prevalence is thus determined by Walk Free for those countries that have been sampled, and then extrapolated to other nations which exhibit a similar risk profile in order to determine a global assessment of prevalence (see Walk Free 2016: 13).

[b] Estimates calculated by taking the occurrence of tree loss related activities identified within the literature, including agriculture, forestry, mining and quarrying from the 'Global Estimates of Modern Slavery' (ILO 2017c: 26) occurring at a rate of 15.3% and applying these to the estimated number in modern slavery from GSI 2016. This is likely an overestimation due to the use of global figures, but provides a proportion closer to a real value that the overall modern slavery estimates for each nation. Rounded to the nearest whole number.

[c] The vulnerability measures from the GSI is based again on the collection of survey data, and responses from the interviews are modelled to provide an overall score in one of four overall categories. These data relating to the 24 variables are modelled to produce an overall vulnerability score for each categories: civil and political protections; social,

health and economic rights; personal security; and finally, refugees and conflict. These scores are then average to establish a mean vulnerability score per nation (Walk Free 2016: 13).

[d] The government response scores are based on an assessment of 98 indicators of good practice around law, victim support, and labour standards which are important in preventing and ending modern slavery practices (Walk Free 2016: 13).

[e] The EPI applies an indicator framework to determine environmental health and ecosystem vitality which are combined to establish an overall score and rank; addressing ten categories which have been identified as major issues. These include: air quality, water and sanitation, heavy metals, biodiversity and habitat, forests, fisheries, climate and energy, air pollution, water resources, and agriculture. All scores can be disaggregated at this scale. A variety of data sources are used to determine the score and rank including EO data, surveys, academic research, and government statistics among others. Indicators are constructed, aggregated into category issues, and then weighted to establish the ranks for the scores with regards to environmental health, ecosystem vitality and policy objectives. For further methodology details see Hsu *et al.* (2016: 26-33) and EPI (2018b).

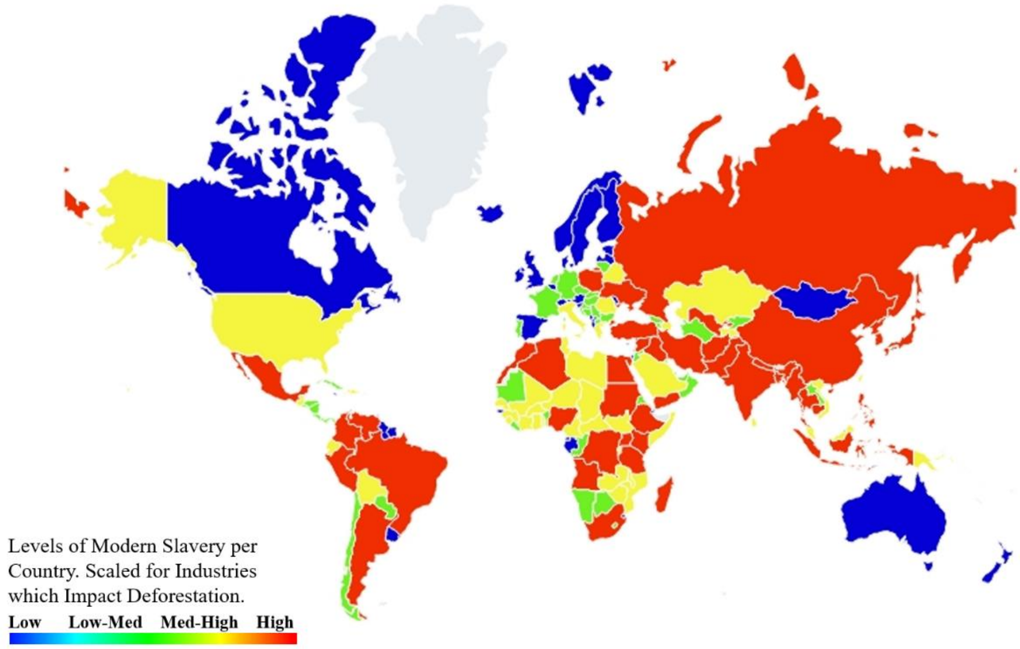

Figure 6.2: Estimated levels of modern slavery per country expected to impact levels of tree loss. Created by determining the activities which affect deforestation using the ILO (2017a, 2017c) 'Global Estimates of Modern Slavery' which equated 15.3% of those subjected to modern slavery and applying this to the 2016 GSI. Overall population estimates for those involved in environmentally damaging activities have been split into four quartile categories of risk: 'low', 'low-medium', 'medium-high', and 'high'.

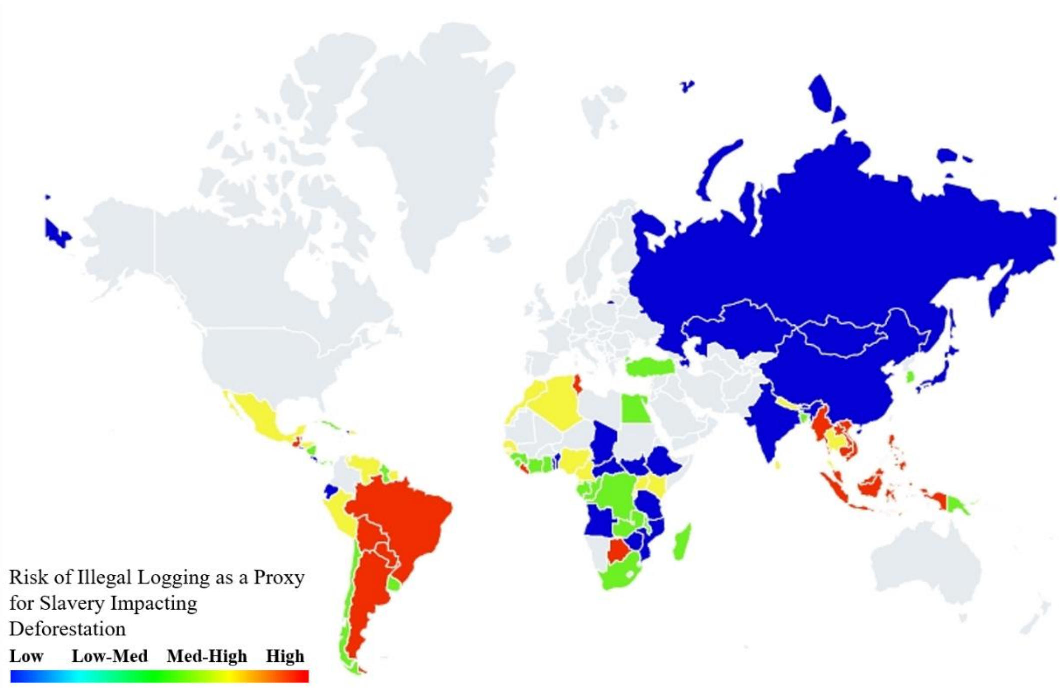

Figure 6.3: Risk of illegal logging (as a proxy for modern slavery) impacting on the proportion of deforestation measured by Global Forest Watch (GFW) 2000-2018. Overall risk of illegal logging has been split into four quartile categories of risk: 'low', 'low-medium', 'medium-high', and 'high'.

High rates of predicted tree loss by 2029 are found in Brazil (Figure 6.4) this is reflected in the illegal logging analysis (Figure 6.3). Southeast Asia is set to experience losses associated with the oil palm industry (Verité 2017a), which may be connected to illegal logging (Figure 6.3). Across central Africa high rates of tree loss are expected, despite past reductions (Rudel 2013). The drivers of previous tree loss here have been attributed to land settlements (due to population growth), agri-business, logging, and cattle-ranching. Only the very center of the Congo rainforest is likely to be lower risk. The extraction of resources to maintain living standards in the current climate crisis is also expected to have a damaging effect (Serdeczny *et al.* 2017).

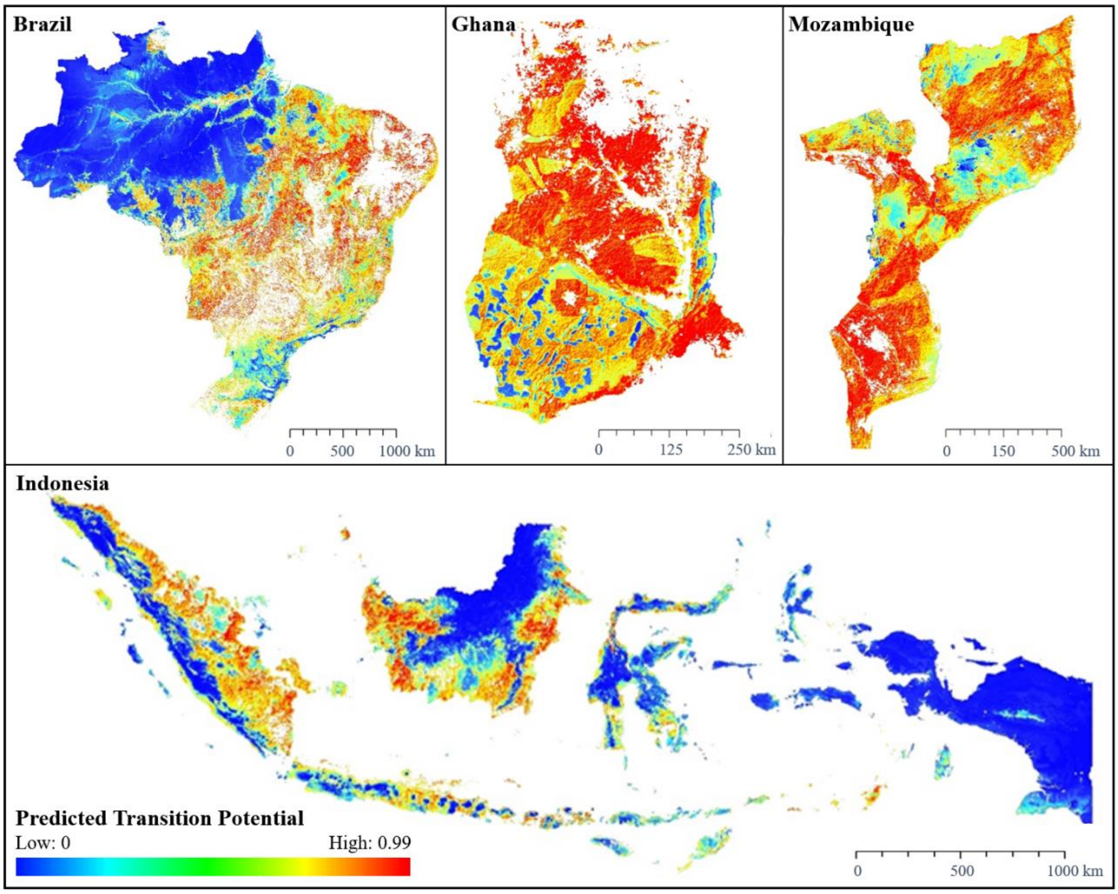

Figure 6.4: The four countries which have been investigated in the discussion. Clips of the global prediction model by Hewson *et al.* (2019) clearly demonstrate the areas of these nations which are most at risk of tree cover loss through their prediction of tree loss transitional potential. Higher levels of predicted loss are indicated in the red colours, whereas as areas of low potential tree loss are marked in blue.

Figure 6.4 shows the variation of predicted tree loss which is expansive across much of Ghana and Mozambique. Higher predicted losses within Indonesia are found in areas where oil palm plantations dominate (Figure 6.4) and illegal logging as a proxy for modern slavery is high (Figure 6.3). The inaccessibility of the protected Brazilian Amazon means that the widespread damage predicted across the rest of the country is limited in this region; however, there is clear encroachment along the southern and eastern forest edges. The Hansen *et al.* (2013) derived data from the GFW (GFW 2019) showed that all nations have experienced net-tree cover loss from 2000-2018 (Table 6.2) with little recovery indicating Hewson *et al.*'s (2019) predicted loss values are likely unless practices are altered.

Table 6.2: Tree loss and tree gain between the year 2000 and 2018 as calculated within Google Earth Engine (GEE) using the Hansen *et al.* (2013) Global Forest Watch (GFW) dataset (GFW, 2019). All displayed to 2 s.f.

Country	**Tree Loss 2000-2018 (ha)**	**Tree Gain 2000-2018 (ha)**	**Net Change 2000-2018 (ha)**
Brazil	47,000,000.00	2,864,414.32	-44,135,585.69
Ghana	671,806.76	57,439.39	-614,367.37
Indonesia	21,300,000.00	3,479,720.10	-17,820,279.90
Mozambique	1,764,314.84	55,368.62	-1,708,946.21

6.4 Discussion

Based on the results, the four nations of Brazil, Ghana, Indonesia and Mozambique were further investigated using the literature after concerns linked to the forestry sector of these nations was highlighted in the modern slavery (Figure 6.2), illegal logging (Figure 6.3), and tree loss (Table 6.2) analyses. Tree loss in these sectors associated with modern slavery are likely to continue. As a result, conservation activities that do not consider the effects of modern slavery may be less effective as modern slavery frequently provides the labour force needed to illegally clear land and deforest (Bales 2016), as explored in Figure 6.3. This must be considered when advocating for global tree restoration potential to provide benefits around, for example, climate change mitigation (Bastin *et al.* 2019), particularly within tropical forests (Brancalion *et al.* 2019). There will only be limited success without the mainstream incorporation of modern slavery impact understanding within conservation management schemes. This acknowledgement supports the achievement of interdisciplinary social justice in conservation, as advocated for by Bennett *et al.* (2017). With the addition of an antislavery framework, more narrow conceptualizations of resource users are challenged and understanding of the social justice dimensions of the relationships between people, forests, and conservation is enriched and broadened to include the often peripheral or unconsidered social domains of agency and dignity – which in the case of modern slavery and tree loss are indivisible from attaining the more frequently considered social justice objective of equality. Moreover, advocating for 'just conservation' (Vucetich *et al.* 2018) in this manner would also support the achievement of the 'freedom dividend' (Bales 2012: xxix) which promotes the economic, social, cultural and environmental benefits that may be gained from ending modern slavery. As Figure 6.1 showed there is a connection between environmental protections and modern slavery. While antislavery tools alone will not halt all tree cover loss, they could help mitigate illegal clearing and deforesting – activities that undermine conservation policies and make SDGs and targets difficult to achieve. What follows is an assessment of these areas and industries vulnerable to modern slavery in relation to tree cover, a review of their political response and where the barriers and leverage points may exist to eradicate the effects of the modern slavery-environment nexus. While focus is placed on these four nations within this paper, going forward it will be important to address the wider trends of tree loss, illegal logging and modern slavery outside of the tropics.

6.4.1 Brazil

As an upper-middle income country, Brazil has developed substantive antislavery legislation (Brazilian Penal Code 2003 Article 149) and conservation policies (e.g. protected reserves, new forests (Frederico and Anderson 2016) etc.). Yet much of Brazil's money is not distributed to large portions of the population; this inequality is necessary in the continued exploitation of people and the environment. Deforestation activities known to use exploited workers have been noted to persist in cattle-ranching (fuelling the leather and beef sectors) and the timber industry (Brown *et al.* 2019). Areas of tree loss in the protected Amazon are expected to be low as accessibility is difficult, whereas there is increasing risk along 'agriculture-forest frontiers' which is expected to have harmful long-term effects (Figure 6.4) (Garrett *et al.* 2018), thus limiting the climate change mitigation benefits that the forest provides. Contrastingly, Santos de Lima *et al.* (2018) suggest that unprotected areas are expected to experience losses of up to 40% by 2050 due to illegal harvesting, noted previously to use workers subjected to modern slavery (Bales 2016).

Brazil's comparatively high levels of environmental protections are reflected within the nation's EPI score (Table 6.1) with a rank of 46 out of 180. Although there has been some evidence of reduced deforestation (Amin *et al.* 2019), overall tree cover has declined (Table 6.2) and is predicted to continue declining (Figure 5.4) (Hewson *et al.* 2019). However, both climate change and deforestation have been noted as destabilising the Amazon rainforest ecosystem (Lenton *et al.* 2019). Additionally, Brazil's environment ministry has reported recent periods of accelerated deforestation and land clearing in Mato Grosso, Rodônia, and Amazonas states (Watts 2015; Escobar 2019). These findings are likely related to the relaxation of environmental policies amid the current socio-political context (Escobar 2019) which has also seen restrictions of the modern slavery definition (Scott *et al.* 2017) by removing the classification of 'slave-like' labour referring to those in degrading conditions – which could lead to the reduction of other abuses being identified including forced labour within the tree sector – from under the umbrella of modern slavery. This is expected to weaken the response of labour inspectors and limit the response to end economic exploitation (Mendes 2017; Philipps 2017). Despite extant legislation, Brazil is ranked 51 of 167 countries in the GSI (Table 6.1) (Walk Free 2016); Brazil's current status in the GSI/EPI rankings (Figure 6.1) could therefore change as a result of these political decisions and declining protections. Although legislation exists for both issues, a lack of resources for labour enforcement, legal loopholes, corruption, and a declining economy (Watts 2015) have stalled Brazil's progress on meeting the SDG targets to end both deforestation and modern slavery by 2030. Training provided by antislavery organisations for front-line responders undertaking labour inspections and conservation activities, to simultaneously respond to deforestation and modern slavery, would enable them to provide pastoral support and assistance to survivors of exploitation. This training would primarily support these actors with the identification of key modern slavery signs, build collaborative networks and trust between groups, and inform conservationists of which authorities to notify should they encounter exploitative practices. Following the example of integrated training in the fisheries sector of the Pacific Island states (United States Department of State 2018), could be one option for maximizing the limited resources available to reach isolated sites for enforcement purposes. Cross-sectoral collaboration could introduce more checks and balances to curb some forms of corruption; this is pertinent in light of the August 2019 Amazonian fires and the refuting of deforestation figures by President Bolsonaro (Escobar 2019).

6.4.2 Ghana

Ghana has approximately 15,000 people estimated to be working in conditions of modern slavery within activities related to tree loss (Table 6.1) – this is 'medium-high' risk when compared to our global analysis (Figure 6.2). As a lower-middle income country, agricultural forest products are highly depended upon for subsistence (Appiah *et al.* 2009). Tree losses have been widespread and will continue to be so (Figure 6.4); this is more likely as droughts occur in the region as a result of climate change where Dwomoh *et al.* (2019) found that the degraded forests had the highest burned area, concluding that both drought and degradation affected the location of the fires. Cocoa (Verité 2017a) and rubber plantations (Verité 2017b) are drivers of commodity driven deforestation and land clearing, known to use forms of modern slavery. Specifically, in the west of Ghana, mining is the dominant cause of forest loss (Schueler *et al.* 2011), often done illegally, and associated with modern slavery – including forced and child labour and human trafficking (Bales 2016; Verité 2017a). Additional losses to the forests are caused by illegal logging (estimates suggest that 34% to 70% of tree loss is caused by illegal logging practices in Ghana: Seneca Creek Associates and Wood Resources International 2004; Hoare 2015), and disturbance from fire (Janssen *et al.* 2018), which limit vegetation recovery.

The Ghanaian authorities have ratified legislative efforts, with a number focusing on child labour, and programmes to address these concerns have also been introduced (Delta 8.7 2019). However, as noted in the low GSI government response score (Table 6.1), these policies and programmes are not being fully implemented and most Ghanaian family units lack the capital to participate in the artisanal and formal mining sector; therefore, limiting the response for the largest tree loss driver in the country. As a result, adults and children are forced to work in illegal mines (Verité 2017a). In response to deforestation and land clearing, the REDD+ program is active (Forestry Commission 2016) – aiming to combat environmental destruction by reducing the burden of poverty and supporting sustainable development. Because the modern slavery-environmental degradation nexus occurs in the context of poverty and a lack of sustainable jobs, it is plausible to consider integrating antislavery tools into REDD+ frameworks to fully achieve their intended environmental and social benefits (Jackson and Decker-Sparks 2020).

6.4.3 Indonesia

The expansion of Indonesian agricultural practices are causing tree cover removal, biodiversity loss and the monopolisation of crop production in the form of oil palm – vital for this lower-middle income economy, and yet auditors assessing the oil palm sector recently found 19% of the country's plantations to be operating within forest areas without the appropriate permits (Listiyorini and Rusmana 2019). Moreover, 81% of oil palm plantations violated numerous state regulations, including operation of sites in protected areas and non-compliance with sustainable production standards (Listiyorini and Rusmana 2019), including environmental damage; such as deforestation and fires (Carlson *et al.* 2018). These factors compound the risks related to exploitation and forest degradation within Indonesia; the growth in oil palm plantations effect carbon sequestration by trees and within peatland that has been drained for production, which increases the risk of flooding thus limiting their value (Sumarga *et al.* 2016). Alongside oil palm agri-business, illegal logging is a driver of tree loss (Palmer 2001) and the risk of modern slavery activities contributing to this loss is high (Figure 6.3). The highest levels of predicted tree loss (Figure 6.4) correspond to noted locations of oil palm milling operations (FoodReg and WRI 2019), suggesting that the commodity is the primary driver of deforestation (an assertion supported by Curtis *et al.* 2018). However, since the introduction of certification schemes the rates of deforestation have declined (Carlson *et al.* 2018).

Palm oil is used extensively in the production of numerous goods, despite evidence the industry degrades the environment and workers experience conditions which leave them vulnerable to discrimination, exploitation, and modern slavery (Verité 2017a). The economic importance of this crop (Indonesia is the top producer and exporter of palm oil worldwide) belies the limited political action to lower the expansion of production (UNComtrade 2018). However, antislavery programs have been implemented to support transnational and domestic migrant workers in the sector (Hasan *et al.* 2018). Unfortunately, as the government response score indicates (Table 6.1), often only minimal protections are legislatively implemented. As there has been some impetus towards eradicating labour abuses, the Indonesian oil palm sector may present an opportunity to trial the integration of conservation actions into antislavery tools.

6.4.4 Mozambique

Mozambique is both the country with the lowest income, and lowest EPI score (Hsu *et al.* 2016), of the four nations. It also has some of the highest vulnerability scores and low government response (Table 6.1). Analysis suggests illegal logging driven by modern slavery within Mozambique is lower risk (Figure 6.3). However, the country exhibits vulnerabilities to modern slavery within the forestry sector which are high. The leading drivers of deforestation include: small-scale and commercial agriculture, construction, logging and charcoal production (Ryan *et al.* 2014). Logging has recently been the dominant cause of tree loss due in part to China's demand for timber (93% of all timber exports from Mozambique are destined for China, which contributed to 48% of the total illegal logging rate in 2012 for Mozambique: Macqueen 2018; EIA 2013) and the increased presence of Chinese companies operating in rural communities, which is leaving people vulnerable to the enhanced effects of climate change (Mambondiyani 2019). Timber is also being lost through cross-border smuggling with neighbouring nations *en route* to China (EIA 2013). Environmental protections are necessary within Mozambique as the country is increasingly dependent on forests to mitigate the effects of climate change (Serdeczny *et al.* 2017); whilst stronger legislation surrounding the movement of timber products are necessary in limiting the economic losses from the exploitation of those goods.

The lack of funds available to the Mozambique government to establish these protections is one of the reasons the removal of resources is likely to continue, particularly in the southern and north-eastern provinces (Figure 6.4) (Hewson *et al.* 2019); perpetuating a cycle of economic and environmental profiteering from outsiders and corrupt officials. China's expanding influence across Africa and the effects of the climate crisis mean landcover change and adaptation is likely to be forced, risking further vulnerabilities to exploitation associated with the modern slavery-environmental nexus (noted in: Bales 2016; Brickell *et al.* 2018; Brown *et al.* 2019). Risks include an increased level of damage from natural hazards, such as cyclones, as the forests are no longer present to limit the impact. The proportion of intense tropical storms events are likely to increase as anthropogenic climate change persists (Walsh *et al.* 2015) which is likely to raise the presence of climate-induced forced migration; this increases the risk of exploitation and has been noted in other regions affected by cyclones (IOM 2016), it is therefore also likely to occur in this region. The predicted tree loss by Hewson *et al.* (2019) in Figure 4 is a business-as-usual model, and therefore these vulnerabilities are likely to be more damaging faster, unless they are addressed within land management plans. Some of these plans are being supported by the World

Bank; they aim to protect forests, their biodiversity and ecosystem services, through programmes such as REDD+, alongside limiting climate change impact (Kaechele 2019).

6.5 Limitations

Limitations are associated with the use of secondary data and the differences in time between the two datasets was difficult to avoid. Although tree loss data is collected regularly via satellite Earth Observation (EO) data, modern slavery data is more sporadic. We do not have exact modern slavery figures at present, though the best estimates available (those from the 2016 GSI) were used. The EPI methodology (see Blanc *et al.* 2008; Hsu *et al.* 2013, 2016: 26-33; EPI 2018b) weights their analysis scores when assessing environmental performance. It was these final ranked results were used within the tree loss analysis, no additional weighting was applied at any stage. However, the EPI efforts do not account for environmental load displacement placed on the Global South, in terms of reducing environmental damage and limiting emissions, whilst the Global North, may also demand natural resources. This is a critique of the EPI and should be corrected for future use going forward.

The predicted tree loss figures were formed through a model, and the limits of the process have been noted by Hewson *et al.* (2019: 11); and the Spearman's Rank correlation results between the deforested area estimated to be using modern slavery and the global model by Hewson *et al.* (2019) is an over-correlation which must be noted when assessing that relationship. Changes to modelling method (Goldman and Weisse 2019) for the Hansen *et al.* (2013) GFW dataset dictated the scope of analysis. Moreover, there have been critiques citing that the GFW data over-estimates the loss of trees within its model, particularly within the tropics (Tropek *et al.* 2014), where differentiation is limited (i.e. distinguishing between forests and plantations); Indonesia has been specifically noted in this case (Bellot *et al.* 2017). In order to strengthen some of these limitations associated with the GFW, these data could be combined with other data sources, such as the Global Forest Resources Assessments (GFRA) (FAO 2020). However, this was not used within this assessment due to the temporal availability of the GFRA data, which is collected every five years.

The use of illegal logging as a proxy can only provide a part of the story and a deeper understanding is required going forward. Many countries had no data for illegal logging and a regional figure was used for those countries without specific rates of loss in Africa, Asia and Latin America – ultimately there are many data gaps particularly in the Global North which need to be filled in future analyses.

Finally, the countries investigated here are by no means the only ones affected by tree loss and modern slavery; nor is all tree loss deforestation. Primary data collected with ground-partners will enable the problem's scale to be fully understood.

6.6 Conclusion

The co-occurrence of modern slavery and tree cover loss – particularly that associated with illegal deforestation and land clearing – suggests a complex relationship between the phenomena that is beyond coincidental. Yet, a two-way cyclical relationship between modern slavery and tree loss within forests is present. When biological diversity decreases due to tree cover loss, vulnerability to modern slavery increases in turn raising modern slavery's contributions to tree cover and biodiversity loss. Therefore, forest related conservation actions and policy must become socially just, and account for modern slavery and its associated illegal and environmentally destructive practices. As a result of the United Nations 2030 agenda, approximately a decade remains to abolish both modern slavery (SDG 8.7) and deforestation (SDG 15.2). Thus, novel approaches to action and policy are needed in these data-limited areas. Identifying synergies between conservation and antislavery action and policy could accelerate and/or improve the likelihood of attaining the SDGs. Due to the breadth of disciplinary expertise and the presence and influence of the conservation marketing and social science working groups, such as the Society for Conservation Biology, are poised to lead the field on these innovative, transdisciplinary and cross-sectoral approaches.

Chapter 7: Discussion and Recommendations

7.1 Reviewing the Scope of the Thesis

Earth Observation (EO) has been a data type which has successfully afforded the investigation of the modern slavery-environmental degradation nexus, within factories, forests and fisheries as outlined by Brown *et al.* (2019). Here satellite remote sensing data and data products have established the environmental impacts of these three sectors of investigation – in fish-processing, brick kilns, and the forestry sector. EO has therefore enabled us to establish what the environmental impacts of modern slavery may be in industries that are heavily associated with modern slavery. The versatility of satellite EO data has enabled the study of two themes (establishing the forms and locality of environmental impacts), at three scales (local, regional, and global), in three sectors. Thus, remote sensing has been able to provide evidence to support several Sustainable Development Goals (SDGs) (Figure 1.2), and directly identify environmentally degrading activities – particularly those which limit the anthropogenic response to climate change. By applying these data, answers have been gained to support the research aim:

To identify the environmental impacts of sectors known to use practices of modern slavery via the application of satellite EO data within three specified sectors. Thus determining the viability of remote sensing to support antislavery research.

Throughout the five papers this relationship has been explored via the lens of the modern slavery-environmental degradation nexus (Brown *et al.* 2019). The novel application of remote sensing to address this cyclical relationship has enabled the assessment of the impacts of modern slavery on the natural world across this thesis.

Details of pollution levels, land-use change and soil degradation, water extraction, and tree removal, have all been identified and explored through this lens using satellite EO data and derived data products. Ultimately, remote sensing can provide timely data to assess these connections as part of a 'sat-truthing' method to enact policy change protecting both people and social-ecological systems.

A summary of the research presented in this thesis follows:

Chapter 2/Paper 1: Literature Review – this Chapter outlines the need to include remote sensing to understand human rights and humanitarian abuses; whilst noting the improvements of space technologies, the accessibility and the pioneering applications that have arisen which can support the overall aim of the thesis. The historical application of these data to provide evidence of these abuses, including modern slavery, have been noted. As are several applications to understand the modern slavery-environmental degradation nexus (Brown *et al.* 2019), including noting the possible sectors and industries that may be investigated and the approaches that can be applied (including those addressed in the thesis), across time and over differing spatial scales.

Chapter 3/Paper 2: Fish Camps – remote sensing data (accessed via Google Earth Pro, and in partnership with Planet Labs) were used in this study as a pilot methodology to support the theory that these data can be applied to investigate the spatial- and temporal-extent of the ten post-harvest fish-processing camps located in the remote Bangladesh Sundarbans. These camps have been found to environmentally degrade protected areas, cause damage to the coastal fringe, and contain practices of modern slavery (Jensen 2013; Bales 2016). Thus addressing the research question and providing data for SDG's 8, 14, and 15. Satellite EO data have demonstrated the ability to track changes over time (2000-2018), noting the area of mangroves removed thus increasing the risk of climate change related sea-level rise and erosion. Further understanding of the human activity in the region and implications for the nexus have also been noted with reference to declining fish stocks and limited climate change mitigation.

Chapter 4/Paper 3: Brick Kilns – Estimation – estimating the number of kilns within the 'Brick Belt' was vital in order to understand the true scale of the sector, determine precise kiln locations, and assess the environmental impacts. This research was vital in order to fully explore the issues of Chapter 5 (Figure 1.3). A systematic random sampling approach was undertaken using open access Google Earth Pro EO data to estimate the total number of kilns over this vast geographic area; totalling 55,387. This is the first rigorous evaluation for the number of kilns present in the region reported with a replicable methodology. Having access to the estimate assists in the understanding of brick-making in South Asia, but may also support the calculation of the scale of modern slavery, and environmental degradation in the 'Brick Belt' and understand the development of the industry over time. Thus, in order to achieve the environmental assessment, this estimate was vital.

Chapter 5/Paper 4: Brick Kilns – Environmental Assessment – data developed from those collected in Chapter 4 (Figure 1.3) were processed by partners at the University of Nottingham to determine the number and location of the kilns, which were then aged to determine the year of formation (see Li *et al.* 2019). These data were then used to assess the temporal and spatial environmental impact across the 'Belt' supporting multiple SDGs. Satellite and environmental datasets were combined to determine the rate of natural resource extraction (of topsoil and groundwater), the impact upon water ecosystems, and the atmospheric implications of the kilns (using data from Sentinel-5p and OCO-2). Patterns of environmental degradation were thus determined over time; whilst some implications were unclear (such as the inverse relationship shown in the atmospheric analysis) others were more defined. The kilns contribute to the nexus by degrading agriculturally-productive land, reducing highly-valued water sources, and releasing greenhouse gases (GHGs) which increase issues related to anthropogenic climate change. However, more ground-data are required to determine the specific impact of the kilns which use modern slavery in their workforce – at present this is not attainable (Landman *et al.* 2019). However, future research methods are suggested that may establish these connections, and support the reduction of degrading environmental activities that will help achieve multiple SDGs (Figure 1.2).

Chapter 6/Paper 5: Tree Loss – global scale open access EO data products (GFW 2019; Hansen *et al.* 2013; Curtis *et al.* 2018; Hewson *et al.* 2019) have been combined with illegal logging data, modern slavery estimates and environmental protection levels (Walk Free 2016; Hsu *et al.* 2016) to understand the co-occurrence of modern slavery and tree loss. Focus is placed on four countries: Brazil, Ghana, Indonesia, and Mozambique. Several drivers of environmental degradation linked to exploitation were noted particularly the reduction of climate change mitigation via trees which declines as forests are degraded or trees are removed illegally. The impact on both SDG 8.7 and 15.2 have been documented. Here the aim of demonstrating EO spatial benefits are highlighted regarding the shared global issues of modern slavery and tree loss. Implications for national and global conservation policy have been explored, alongside an assessment of the benefits achieved by limiting tree loss and ending modern slavery.

Throughout the thesis the benefits of applying remote sensing in sectors found to use modern slavery have been noted. An evidence-base of reliable, timely, and spatially-explicit data have been provided which may enable insight into multiple SDGs and investigate the nexus in a way that has not been utilised within the antislavery space. Numerous environmentally degrading activities have been investigated, which are likely to have negative implications for climate change mitigation going forward, such as tree removal, and emission of pollutants. The benefits of satellite EO applications have been advocated for by the United Nations in the Agenda 2030 development phase (UN 2012: 70) – and these data have the ability to support the global commitment to end exploitation and the environmental effects of modern slavery, as explored in this thesis. The scalability of remotely sensed investigations have been clear due to the unique method of EO which provides global reach, in inaccessible regions, over long timescales. This thesis has provided confirmation of these benefits as it moved from a localised study of fish-processing camps, to a regional assessment of South Asian brick-manufacturing, before finally analysing the globally destructive practices associated with tree loss. The ability to conduct such varied analysis is linked to the versatility of remote sensing applications.

All three sectors have clear links to the modern slavery-environment nexus (Brown *et al.* 2019) and provide degrading impacts to key climate change mitigation environments (e.g. tropical forests and mangroves), or directly release environmentally degrading pollutants (such as those from the brick kilns). All sectors require operational changes in order for the SDGs to be successfully achieved. There are many global benefits to ending modern slavery, ultimately leading to a better world; one that is safer, greener, more prosperous and more equal for all. One which successfully achieves the SDGs and the 'freedom dividend' (Bales, 2012: xxix). In order for this to take place however, there needs to be further cooperation between antislavery actors, governments, and academic bodies in order to capitalize on the presence of open access satellite EO data. These data should be combined with new forms of big data, technology and traditional antislavery data in order to gain a holistic view of industries known to utilise modern slavery practices, and negatively affect the environment. Incorporating the nexus into global projects which seek to apply technology to understand, and limit the social-ecological effects of, modern slavery must be undertaken. Satellite remote sensing can provide the tool to understand this connection on a global scale – it is one that should be embraced and utilised at all available opportunities.

7.2 Satellite EO to investigate the Modern Slavery-Environmental Degradation Nexus[26]

Remote sensing should be used to understand the nexus between modern slavery and the environment, but also a number of related SDGs. This thesis has sought to apply these data to increase the understanding of the environmental impacts that sectors known to use workers subjected to modern slavery (Figure 1.2). Subsequently, satellite EO data can be further developed and incorporated into antislavery interventions to support the increased knowledge of environmental degradation, environmental crimes, and illegal activities. This may ultimately lead to the establishment, or incorporation of these data into a detection, or early warning, system which identifies high-risk areas for environmental degradation in sectors that are at risk of modern slavery and labour exploitation (e.g. Digital Ecosystem for the Planet (and Nexus) – see Section 7.3).

As a data source, EO has multiple benefits which are vital to understanding the past trends in the connection, modelling future issues, and providing a method of continuous monitoring even in the most difficult of areas to access. Environmentally oriented goals have been investigated alongside the SDG target 8.7. In particular SDGs 14 and 15 have

[26] This section is adapted from an original blog written for the Delta 8.7 platform in March 2019 by the author: ‘Slavery from Space: A Remote Sensing Approach to Ending Modern Slavery’, available from https://delta87.org/2019/03/slavery-space-remote-sensing-approach-ending-modern-slavery/ (See Appendix G).

been supported. This is alongside others which relate more specifically to the sectors of investigation, including SDG 6.6 (see Chapter 3/Paper 2) and target 15.2 associated with deforestation (Chapter 6/Paper 5; Appendix C) (see Figure 1.2). The thesis has contributed to the growing number of studies providing evidence for SDG targets and indicators using remotely sensed data sources (see Anderson *et al.* 2017; Andries *et al.* 2018; Kussul *et al.* 2019; Masó *et al.* 2019). Remote sensing has been noted as a valuable tool to investigate modern slavery (Zolli 2018b; Scoles 2019), with its applications providing data which increases understanding of these sectors at varying scales (see Foody *et al.* 2019; Jackson *et al.* 2020 – see Chapter 6/Paper 5/Appendix C). Continued assessments should utilise remote sensing and the further developments of space-based technologies (which will see an increase in archival high spatial-, spectral- and temporal-resolution data; and the continued collection of these data at a lower cost for many untold applications), combined with ground-data, to provide additional research tools that can be used alongside satellite EO data to understand the implications of the modern slavery-environmental degradation nexus across vast geographic areas, long periods of time, and many industries. This in turn should promote new forms of advocacy, accountability and action at the confluence of conservation, development and antislavery initiatives. Evidence provided in this thesis supports the implementation of antislavery action and showcases the application of these data. Three areas where satellite sensor data can be applied to further support antislavery activities, by: 1) mapping 'at risk' industries associated with environmental degradation; 2) monitoring drivers of vulnerability for exploitative and environmentally degrading activities; and 3) continued investigation of the modern slavery-environment nexus.

7.2.1 Mapping 'At Risk' Sectors

Approximately 6-12 million (or 15-30%) of the total number of people subjected to modern slavery (40.3 million in recent estimates) are thought to be engaged in environmentally degrading activities (ILO 2017a; see Chapter 2/Paper 1 Footnote 3). These sectors also tend to occur in settings which make them observable from space, such as fishing, agriculture, forestry, and brick-manufacturing using kilns. Subsequently, the application of satellite EO data is a natural fit for the investigation of these issues, as noted in the aim which has been addressed using multiple sources across several sectors. The most prohibitive factor in assessing the environmental impacts of industries known to use modern slavery is the geographical extent. Remote sensing can cover these areas with ease – as demonstrated by the progression from a localised industry (fish-processing) to a regional issue (brick kilns), before assessing the global issue of tree loss (Figure 1.1). The sectors addressed are only a fraction of those which may be investigated, these include: quarrying, cotton harvesting, mining, and marine fishing activities, among others. Improvements to satellite sensors (increased spatial-, spectral- and temporal-resolution), the democratisation of space and the ability to amass free and open access data, alongside the capacity to work with commercial providers, creates opportunities to consistently monitor industries identified as 'high-risk' for social-ecological degradation. For example, the application of machine learning has been utilised in the identification of the brick kilns (Foody *et al.* 2019; Li *et al.* 2019), but this should be expanded to other sectors in order to automate identification of new features in sectors which are likely pre-disposed to the risks associated with the nexus – this is particularly applicable to post-harvest fish-processing and other land-based fishing activities, including aquaculture (Chapter 3/Paper 2).

7.2.2 Monitoring Vulnerability Factors

Remote sensing cannot presently detect the locations where workers' are being exploited (Landman *et al.* 2019), rather they are a proxy measure. Yet as stated in the aim, the benefits of satellite EO data can be used as a methodology to assist in understanding vulnerability factors associated with the modern slavery-environment nexus. Such vulnerabilities have been identified using ground-data approaches, such as Brickell *et al.*'s (2018) understanding vulnerabilities in the Cambodian brick-making industry; similar progression has been noted in post-harvest fish-processing operations (see Figure 3.2). EO data therefore enable the increased ability to comprehend and monitor vulnerability factors of modern slavery and associated environmental damage; at present, moving forward, and through retroactive application. Holistic monitoring of these connections at large geographic scales requires satellite EO data. Developments in space technologies – such as 'smallsat' and virtual constellations – will be vital for the continued monitoring of vulnerability factors associated with the nexus. Satellite EO in particular can monitor degradation levels on vast spatial- and temporal-scales, identify and track sudden ecosystem changes, and monitoring the effects of climate change which have been linked to forced-migration and increased vulnerability of modern slavery in several sectors (IOM 2016; Brickell *et al.* 2018; Brown *et al.* 2019).

However, in order to identify the full-scale of vulnerability to modern slavery, ground-data will be required. The lack of which is a clear limitation within the field of modern slavery study, but also throughout this thesis. Ground-data may come from a number of sources, for example: survivor narratives, population densities, supply chain analysis, educational data, and access to capital, and poverty rates etc. Remote sensing can only provide data for those drivers visible on the Earth's surface; although these data do provide a multitude of access to large, inaccessible regions, continuous reliable monitoring, and archival data over almost 50 years. These factors are unrivalled by other datasets available for use; hence the application of these data within this thesis in reference to the aim. However, combining data for analyses will be vital in understanding the nuances of the drivers of vulnerability which so often cause environmental degradation; but also enable this damage to be investigated as a driver of modern slavery – as noted in the nexus. Moreover, climate change is likely to have an impact upon this vulnerability. Remote sensing should be used as a tool to further understand the spatial and temporal extent of climate-associated degradation as a driver of social-ecological exploitation. The findings of this thesis have begun to achieve this, yet further applications await to be established.

7.2.3 Modern Slavery-Environmental Degradation Nexus

As noted throughout this thesis, EO has historically been applied in the investigation of ecological features (Boyd and Foody 2011); this may be incorporated into assessments regarding the modern slavery-environment nexus (Brown *et al.* 2019). This relationship needs to be fully understood to support survivors and protect ecosystems; remote sensing has the capacity to provide resources which can assist in achieving this aim. This study has provided an examination of these features from a social-ecological context, paving the way for further assessments on both the nexus and indicators which may support the SDGs. Here, and overall assessment of the connection between environmental protections and estimated levels of slavery has occurred (Figure 6.1); thus promoting the monitoring of environmental degradation globally at varying scales, which is not possible without the use of satellite EO data. Reports of modern slavery have occurred in several sectors, these negative environmental consequences have been documented using multiple remotely sensed data types and derived products (see Table

1.2). For example: mangrove removal and erosion of the coastal fringe associated with fish-processing camps (Chapter 3/Paper 2); the extraction of natural materials, and the emission of pollutants by brick kilns (Chapter 5/Paper 4); and finally, the degradation of forest cover and thus the land by industries and practices associated with tree loss, such as oil palm, agriculture, and illegal logging (Chapter 6/Paper 5 – see Appendix C). Furthermore, the benefits and continued improvements of space technologies for EO provide ample opportunities to replicate, build-upon and identify new research within many industries not examined in this thesis. This could, and should, lead to environmentally degrading conditions including the release of pollutants, deforestation, encroachment upon protected areas, and the over-extraction of resources being explored in full to build on the overall aim of this thesis. Ultimately, this should enable the antislavery community to benefit from the unique role remote sensing inhabits, capitalizing on the benefits of the data to support SDG 8.7, in addition to supporting multiple ecologically-oriented SDGs.

Remote sensing may be applied to investigate biologically significant, and often inaccessible, areas – such as Bangladesh's Sundarbans, and the Amazon basin in Brazil; these remote protected areas are believed to harbour conditions which enable criminal enterprises and exploitation to thrive (Bales 2016). By using satellite EO acquired data, these isolated regions can be, and are being, investigated particularly to monitor biodiversity levels and support environmental management and decision-making (Leidner and Buchanan 2018; Pettorelli *et al.* 2014). The work shown in Chapter 6/Paper 5 has outlined this in reference to the global issue of tree loss, and how these insights which may be gained from EO data can be used to develop understanding of drivers, and identify areas in which policy can be altered. Subsequently, using remote sensing to assess these isolated regions is important for the protection of people and nature; both in terrestrial and marine environments (Pettorelli *et al.* 2016). However, the exploitation of people, particularly in relation to modern slavery is only beginning to be addressed in these localities, and only now is this being conducted via remote sensing satellite analysis. Combined data analysis methods will need to address this neglect of the human element of the nexus; whilst also having that ability to retroactively identify trends to further understanding of environmental drivers and impacts of modern slavery. Traditional EO techniques should be incorporated into this development to monitor, and provide solutions, improving both social and ecological protections. Direct action by conservation and antislavery actors should be encouraged. Some of these lessons have been noted in this thesis, addressing brick-making and tree loss in particular (see Chapters/Papers' 5/4 and 6/5). Additional areas where investigation of human activity may drive degradation include deforestation affected regions, areas where construction has occurred, and locations where transport and communications are limited; the benefits of applying remote sensing in these cases should also be explored.

7.2.4 A Satellite EO Future for Modern Slavery Investigation

Developments, notably in the resolution (spatial, spectral, and temporal)[27] of the satellite EO data, the scale (increased frequency) and capacity of data collection and storage, alongside reduced costs (more open access and low-cost high spatial-resolution data) and processing times, have created an extensive archive of remotely sensed data

[27]EO data sources will these improvements – particularly those at high spatial-resolutions – however, they should be used with caution and risks noted/concerns raised by stakeholders and partners on the ground should be taken seriously to avoid increasing the vulnerability of labourers subjected to modern slavery. Therefore, the application of these data when assessing sectors known to use modern slavery should undergo a clear ethical review and put in place plans for safe data storage and sharing with possible partner organisations. (Also see Recommendation 5).

that has been underutilised by the antislavery community. This archive reaches-back almost 50 years which provides a unique opportunity to retroactively address modern slavery and its environmental implications. This has been used in this thesis with regards to the nexus for the application of increasing knowledge. In order to achieve a holistic understanding of the ecological implications and scale of the industries in which instances of modern slavery have been documented, remotely sensed EO data must be included. The main limitation of applying remote sensing to investigate these connections is that we cannot, at present, visibly document the exploitation happening. Rather it is the industries, and their environmental effects which are used as a proxy for modern slavery presence (Landman *et al.* 2019). However, this should not detract from the fact that satellite EO data can be used to rigorously observe and investigate those industries which are accessible, as shown across this thesis. Combining ground-data with sat-truthing sources, the social, economic and environmental impacts of modern slavery, and the nexus, can be further understood in a way which is uniquely scalable, repeatable and rooted in ecological applications (Boyd and Foody 2011). Only with these combined data, including EO sources, can a well-rounded assessment of the locality of modern slavery, and their affected sectors, be implemented to establish when and where abuses occur, and what implications arise.

7.2.4.1 Investigating the Nexus in Practice

Putting into practice the inclusion of satellite EO data to investigate and understand the effects of modern slavery upon the environment and climate change will require the integration of varied EO data sources. These responses have been noted throughout the thesis, from the integration of data available on Google Earth Pro to search for brick kilns, to those data being used to train algorithms to identify sector features (e.g. kilns), and integrate them with other data, such as atmospheric emissions. Moreover, research into the fish camps has demonstrated the process of analysis and integration of these datasets to understand the structure of a sector, its impact on a location over time. Figure 7.1 notes the integration of satellite data into a layered analysis; one that has begun in this thesis, but should continue in future analyses.

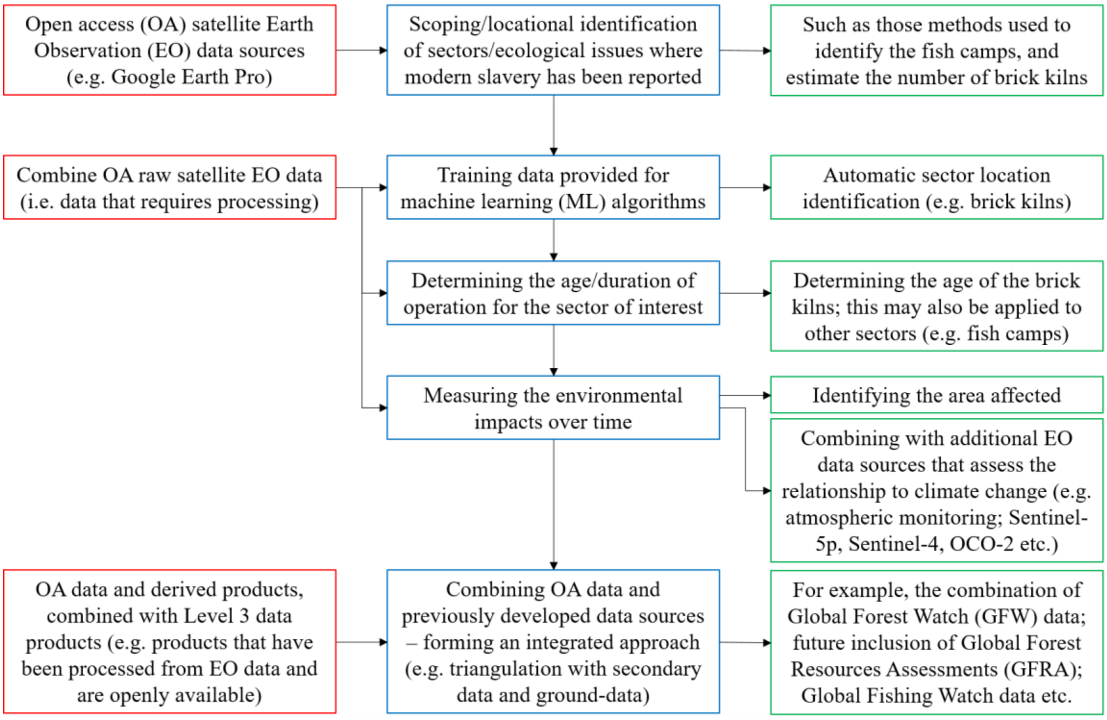

Figure 7.1: Flow chart of the layers of integration needed for remote sensing, as used in this study, and promoted for further inclusion in the development of wider systems to investigate modern slavery and its connection to environmental issues.

Whilst Figure 7.1 denotes one example of this integration it is one that can be developed further and adapted for different, sectors and application. This structure can provide a baseline for the assessment and integration of multiple satellite EO data sources in order to investigate modern slavery and its possible impact upon environmental systems. By applying such a programme of analysis sectors, and sites, that are likely to transition into more environmentally damaging activities, such as fish-processing sites. In addition, the value of the temporal data available can be used to identify seasonal trends that would highlight those transitional risks, as well as identifying activities which may be operating using environmentally degrading conditions already. Examples of possible integration methods and approaches to identify these issues of environmental degradation and modern slavery have been noted. For instance, the inclusion of Sentinel-1 Synthetic Aperture Radar (SAR) to investigate the impact of topsoil loss close to brick kilns (see Chapter 5/Paper 4) and aquaculture sites (see Chapter 3/Paper 2); as well as the integration of further longitudinal datasets to assess the relationships between tree cover and modern slavery (e.g. Global Forest Resources Assessments (GFRA); FAO 2020).

The combined integration of these remotely sensed data sources, alongside triangulation with secondary data, and primary ground-data will support the overall training for machine learning algorithms (e.g. Foody *et al.* 2019; Li *et al.* 2019; Boyd *et al. forthcoming*). Merging these data will support the ultimate aim of applying space technologies – including remote sensing – within the antislavery space: the automatic identification for modern slavery issues, and measurement of cases and environmental effects in order to provide a rapid response to labour and human rights abuses (e.g. as part of an 'Antislavery Observatory' – ILO 2015; Landman *et al.* 2019).

Moreover, the wider integration and layering of EO data can further support the success and sustainability of the SDGs. The application of satellite EO data to support these issues are linked to the multiple SDGs (Anderson *et al.* 2017; Scott and Rajabifard 2017; Andries *et al.* 2018; Kussul *et al.* 2019; Lehmann *et al.* 2019; Masó *et al.* 2019; Revilla 2019; Estoque 2020). However, few are working on the intersection between modern slavery and the environment (see Boyd *et al.* 2018 – see Chapter 4/Paper 3/Appendix B; Jackson 2019; Jackson *et al.* 2020 – see Chapter 6/Paper 5/Appendix C). This is something that a wider system of integration between remotely sensed data sources and identification of additional EO data sources may provide additional information that can make the study of the modern slavery-environment nexus a regularly viable prospect.

7.2.4.2 Remote Sensing in the Future – What is Possible when Investigating the Nexus?

There are numerous developments in remote sensing that may be applied to investigate the modern slavery-environmental degradation nexus (Brown *et al.* 2019), in particular identifying the environmental impacts. For example, Planet Labs data has already been applied in this thesis (see Chapter 3/Paper 2), yet the company recently announced improvements to the spectral-resolution of its ‘smallsats’, having launched a constellation of around 30 platforms which hold sensors with a capability of measuring eight wavebands at a spatial-resolution of 3m (Planet Team 2019). Furthermore, video satellite applications have been proposed – with one such prototype, the VividX2 (part of a proposed Vivid-I Constellation), launching in 2018 (Earth-i 2018) – this could revolutionise monitoring of suspicious or illegal activities through the provision of real-time data. For example, supporting static satellite EO data collection within sectors such as fisheries, where high resolution imagery from DigitalGlobe was previously able to identify transhipment off the coast of Papua New Guinea (McDowell *et al.* 2015).

Moreover, developments in atmospheric analysis sensors can support the further assessment of the brick kiln sector. For example, the continued launch of the Sentinel satellites from the European Space Agency’s (ESA) Copernicus programme will continue the provision of open access data regarding atmospheric composition (in particular Sentinel-4 and Sentinel-5 due for launch in 2023 and 2021 respectively) thus establishing long-term atmospheric monitoring (Ingmann *et al.* 2012). This will be achieved through a combination of geostationary and orbiting platforms – Sentinel-4 is designed to provide daily coverage over Europe (Courrèges-Lacoste *et al.* 2017), whereas Sentinel-5/-5p provide daily global coverage of atmospheric components (Stark *et al.* 2013; Sierk *et al.* 2018). In addition, the planned launch of carbon dioxide (CO_2) monitoring sensors by ESA in the mid-2020s will aim to enhance understanding of this particular pollutant and its impact on global emissions (Fleming 2019; Government Europa 2019), supporting the IPCC goal to limit global temperature increases to 1.5°C (IPCC 2018). The development of this CO_2 monitoring constellation (Mathiesen 2019) will improve the results which can be gleaned from the coarser CO_2 data currently collected using the OCO-2 platform used in the environmental assessment of the brick kilns (Chapter 5/Paper 4). These platforms will be an evolution of the current Copernicus programme, ultimately encompassing an overlooked component of atmospheric monitoring.

Finally, there are opportunities to integrate other forms of remotely acquired data to investigate the environmental effects of modern slavery. For example, LiDAR (Light Detection and Ranging), could help in the detection of mines and quarries in inaccessible areas by identifying the ground-shift below the tree canopy (Brown *et al.* 2018), and monitor forest ecosystems. This form of sensor is flexible; they can be mounted on Unmanned Aerial Vehicles (UAVs), planes, and as a payload on satellites. This has been used successfully to identify areas of cultural heritage (see Xiao *et al.* 2018) which can cause similar ground effects. Furthermore, as noted in Chapter 5/Paper 4, radar may be useful in establishing more accurate topsoil and water extraction rates for production of bricks, as well as mining, as there is a history of this source being applied to ground movement assessment – for example in natural hazards/disasters, glacial environments (Massonnet 1997) and commercial mining (Baek *et al.* 2008). The launch of ESA's EarthCARE satellite in 2021 will combine both sensor types to provide data on the Earth's atmosphere (ESA 2019) – there is nothing to say similar sensors for ground-observations cannot be invested in. Additional support can be provided from the NASA's Global Ecosystem Dynamics Investigation (GEDI) satellite on-board the International Space Station (ISS) (NASA and University of Maryland 2019); launched in 2018, it supports analysis of deforestation and its effects upon CO_2 emissions, which may strengthen further work on tree loss (as seen in Jackson *et al.* 2020 – Chapter 6/Paper 5; Appendix C). Consequently, there are many developments in remote sensing which can further knowledge of the modern slavery-environment nexus.

7.3 A Digital Ecosystem for the Planet (and Nexus)

Varied techniques are necessary to achieve the 2030 deadline of ending modern slavery (UN 2016a); both short- and long-term investigations utilising EO data are needed for the provision of reliable evidence to support fact-based decision-making which seeks to support antislavery, development, and conservation efforts. Remote sensing can support data collection at both timescales, with the added benefit of continuously improving data collection methods; structures however need to be put in place to enable the integration and development of a platform that addresses the modern slavery-environment nexus. Some systems have been suggested such as the 'Global Slavery/Antislavery Observatory' (ILO 2015; Landman *et al.* 2019) and Insight Tiles (N/Lab, University of Nottingham),[28] yet these do not include the capacity to address the nexus in the way it has been presented throughout this thesis. The inclusion of these data have been shown to be beneficial and have demonstrated the aim of the thesis

[28] The 'Insight Tiles' have developed from ground-based and satellite data processing based on a pilot project in Dar es Salaam, Tanzania. See: https://www.nottingham.ac.uk/business/businesscentres/n-lab/projects/surveying-in-dar-es-salaam.aspx

successfully. One way these factors could be integrated is via the 'Digital Ecosystem for the Planet' (UNEP 2018; Campbell and Jensen 2019).

The data collected throughout this thesis has developed the understanding of the interrelationship between modern slavery and ecological systems; showcasing the myriad benefits which can assist in providing valuable insight for the antislavery community. The connection was first noted by Bales (2016: 10) who attempted to quantify the connection, estimating that global modern slavery is the third largest emitter of CO_2 emissions. It has since been noted in other areas (see Bales 2016; Brickell *et al.* 2018; Brown *et al.* 2019; Sparks 2018) including this thesis; which primarily via the application of satellite EO data, has identified: tree loss (of both mangroves and tropical forests) (Chapter 6/Paper 5/Appendix C); erosion associated with fish-processing (Chapter 3/Paper 2) – which may be explored more in the future as precariousness in the Sundarbans increases with the effects of climate change; the extraction of high-quality topsoil for brick-making; groundwater removal and emission of heavy metals into the hydrological system; and finally, the emission of GHGs from kilns contributing to climate change (see Chapter 5/Paper 4). Furthermore, the loss of tree cover contributes CO_2 emissions and the carbon storage potential of these ecosystems is reduced. As a result, evidence for multiple SDGs have been provided, targeting SDG 15, 14 and 6. The environmental goals have been identified by the UN Environmental Programme's (UNEP) 'Digital Ecosystem for the Planet' as vital for the achievement of the 2030 Agenda (UNEP 2018; Campbell and Jensen 2019).

Whilst three sectors have been addressed within this thesis to demonstrate the unique benefits of EO data application, they are not the only environmentally damaging sectors known to use practices of modern slavery. There are a number of nuances within the co-occurrence of modern slavery and tree loss which are not as explicit as other sector drivers (such as, vulnerability drivers into brick kilns (Brickell *et al.* 2018) and fish-processing camps; Figure 3.2). Often tree loss is not the primary goal of the exploitation, but rather a necessary process before the activity in which they are exploited can be undertaken. For example, trees are removed to establish mines and quarries, clearing land for cattle ranching and agriculture (Brown *et al.* 2019), or for the establishment of fish-processing camps and small-scale aquaculture activities. Involuntary degradation of ecological systems thus occurs; yet, there is little understanding of the impacts this has on the people undertaking the work, those who live nearby, and the full extent of the impact upon ecological systems. Incorporating modern slavery into a programme such as the 'Digital Ecosystem' could increase understanding of these nuances, but this requires some adaptation of the proposed outline for the 'Digital Ecosystem'; including acknowledgment and inclusion of the fast-paced developments and applications which may be gleaned from the inclusion of EO data.

UNEP's 'Digital Ecosystem for the Planet' seeks to combine frontier technologies, including remote sensing, to provide data on SDG targets and indicators to support environmental policy and conservation measures, and understand the drivers of environmental change (Campbell and Jensen 2019). This should include the implications of modern slavery. The application of satellite EO data in this thesis has not only been used to address the scale of the sectors using modern slavery, but their environmental impacts across differing geographical and temporal scales that are unique to remotely sensed data. The use of remote sensing to investigate the environment, and the examples included here demonstrate a clear methodological link which could be combined to create holistic understanding of the social-ecological dimensions of modern slavery, whilst supporting multiple priority SDGs as identified by UNEP (SDGs 13, 14, and 15). Moreover, the inclusion of indigenous and tribal people are targeted (Jensen *et al.* 2020a); these communities are key to protecting ecosystems, yet are often isolated and at risk of exploitation – as highlighted in Chapter 6/Paper 5 (Jackson *et al.* 2020; see Appendix C). The inclusion of an additional target is proposed for 'Track 2: Environmental Stewardship' (Jensen *et al.* 2020a) which includes access to digital resources and applications that directly support, and are designed for, indigenous peoples. This should also include reference to survivors of modern slavery, providing jobs and enabling a structure to be founded which supports multiple strands of data collection. A further target relating to modern slavery could be included in Track 3 which looks at 'Indigenous Inclusion' (Target 19) (Jensen *et al.* 2020a) – some of these communities (and others identified as similarly at risk such as those in impoverishment, or rural communities) may be survivors and it is important that this additional experience is acknowledged in order to achieve sovereignty and inclusive dialogue in relation to environmental, and antislavery, initiatives which may be established. As Jensen *et al.* (2020a) note, consultation with the end-users of these data – whether that be local communities, environmental stewards, development actors or antislavery organisations – is key to successfully filling the knowledge-gaps which are present in the SDGs. It can also provide a source of ground-truthing data, gathering experiences from those who are most *au fait* with the environments and industries which are associated with the modern slavery-environmental degradation nexus. An outline of these data which may be incorporated as part of these tracks are included in Figure 7.2.

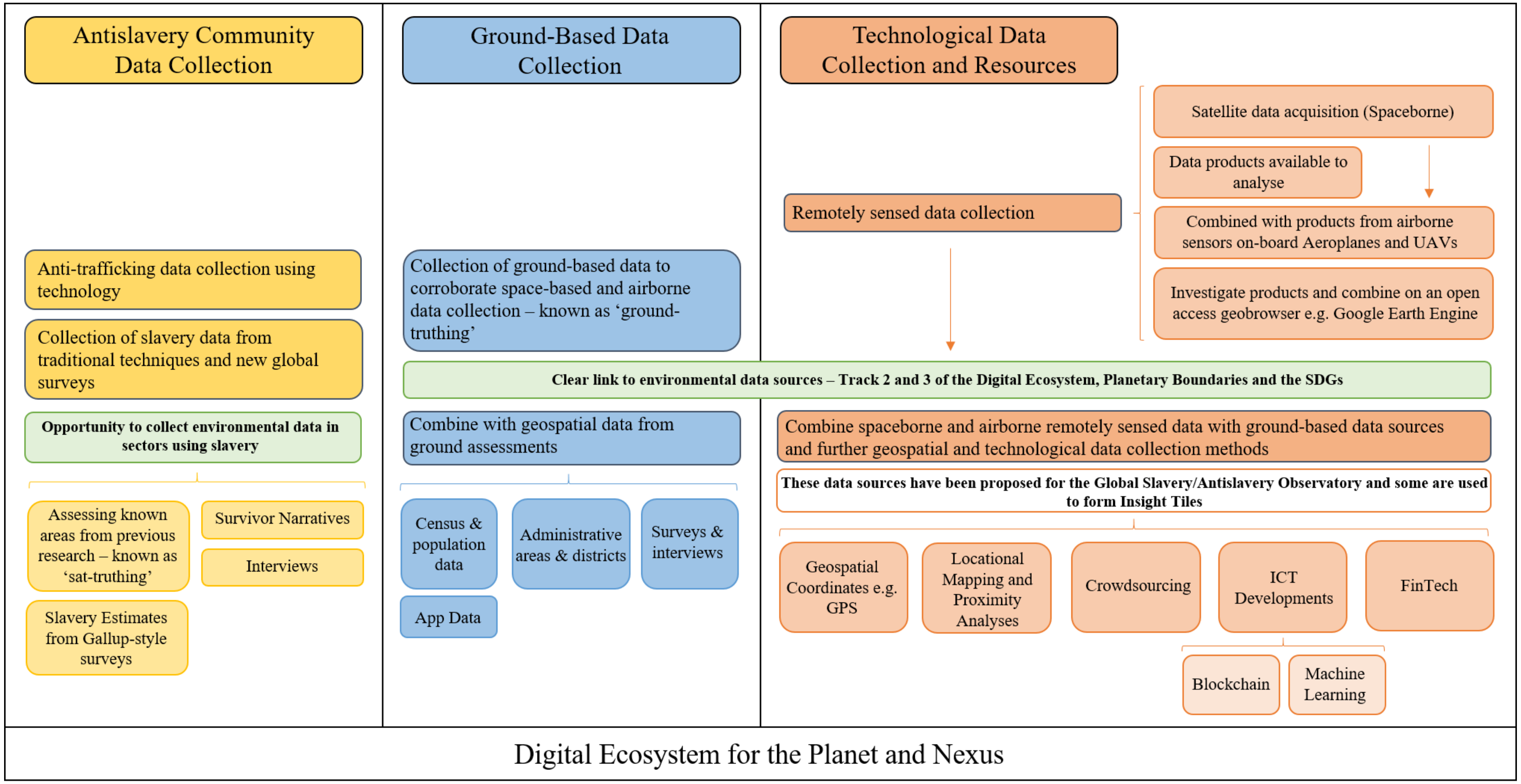

Figure 7.2: Framework of the different data strands that should be incorporated into a 'Digital Ecosystem for the Planet' which integrates the presence and effects of modern slavery and the environmental degradation nexus. This would also support the integration of a holistic antislavery tool to achieve SDG target 8.7 and make the 'freedom dividend' attainable. There are three interconnected strands (separated here to provide clarity) which address data collection techniques within the antislavery field, ground-based supporting data collection – a form of 'ground-truthing' – and an expansion of the technological data sources being used to incorporate increasing advancements in computing, remote sensing sensors and digital data collection.

68% of environmentally associated SDGs cannot be measured at present as a direct result of limited data (Campbell and Jensen 2019); this is a common problem also found in the study of modern slavery (SDG 8.7). Progress is being made to reduce these limitations, and within this thesis, satellite EO data is used to fill some of these gaps; however, issues have also been identified which must be addressed in future applications of these data sources. Whilst remote sensing can fill some of these data-gaps (Anderson *et al.* 2017; Andries *et al.* 2018; Kussul *et al.* 2019; Masó *et al.* 2019), it is clear that combined data are the only way of truly achieving the 2030 Agenda, yet remote sensing must play a key role as promoted by the UN (2012: 70). A number of geospatial technology organisations will be key to creating the Digital Ecosystem (such as the Committee of Experts on Global Geospatial Information Management, and the Group on Earth Observations (GEO)), with others seeking to incorporate the protection of human rights and human agency (e.g. UN High-Level Panel on Digital Cooperation) (Jensen *et al.* 2020b) – it is the latter that will be vital for the important understanding of the nexus and protecting social-ecological systems. When integrating these antislavery organisations should also be included, particularly those that assess the modern slavery-environment nexus, for example: Anti-Slavery International, the International Office for Migration and the U.S. Department of State. These organisations have all previously worked on the nexus (see O'Connell 2019; IOM 2016; U.S. Department of State 2018) but have failed so far to incorporate the outlined novel benefits of satellite EO data into their work; despite the knowledge that may be attained, shown in this research.

These data should work toward altering policy and ensure ecological awareness and protection are included in the development of initiatives. Additionally, integration of modern slavery into the 'Digital Ecosystem for the Planet (and Nexus)' should aim to provide evidence to support governments with the formal regulation, and place pressure on them to establish, and enforce, legislation which ensures higher ecological and social standards. To fully understand the modern slavery-environmental degradation nexus both the antislavery community, development organisations, and environmental conservation groups must be drawn together and combine efforts, including the implementation of programmes and their methods of data collection. A platform such as the 'Digital Ecosystem for the Planet (and Nexus)' could make this achievable if these data and ideas are incorporated. Subsequently, the furthering of knowledge around the modern slavery-environment nexus, should aim to encourage changes at a grassroots level (as promoted in the planned 'Digital Ecosystem' as these communities are the end-users; Jensen *et al.* 2020a), alongside the national and international governmental level. This would assist in the achievement of the 'freedom dividend' (Bales 2012: xxix), benefitting communities, the economy, and the environment. Successfully achieving the 'freedom dividend' will support the SDGs, but should be conducted within the bounds of sustainable development, as reported within the planetary boundaries (Rockström *et al.* 2009; Steffen *et al.* 2015; Randers *et al.* 2018).

7.4 Limitations

There are a number of limitations regarding the exploration of the modern slavery-environment nexus within thesis. Specific limitations for each Chapter/Paper are included for those sectors within each section. However, there are some underlying theoretical and methodological concerns which must be addressed in the future. These limitations include:

1. **Lack of ground-data** – this study hinged on the application of remote sensing as a form of 'sat-truthing' as ground-data were limited to secondary sources that

have documented cases of modern slavery and labour exploitation within the three sectors of investigation (fish-processing, brick kilns, and tree loss). It was not possible to gain access to these industries and sectors over time for this research project. Ground-truth data is noted as a key limitation throughout the thesis and in order to strengthen results in the future, more recent, geospatially reported data will be vital in order to determine the forms, and scale, of environmental degradation within these sectors. All future work should be strengthened through the collection of primary ground-data.

2. **Limited data control** – much of the data were access via Google Earth Pro (see Chapters/Papers' 3/2 and 4/3) which does not allow access to the underlying metadata, and thus spectral methods are not available to the user. This limited the analyses which could be undertaken in some of the thesis, yet was part of the trade-off between high spatial-resolution data with access to only sporadic data over which no control can be exerted, and regular, medium/high spatial-resolution data that is frequently collected but sometimes may not be available over the same temporal-scales. Moreover, a reliance on secondary ground data sources, to measure extractive processes, define the areas of investigation, and determine some of the pollutant and tree loss analysis relies on the accurate production of these original datasets which are not controlled by the researcher using them in this case. Limitations related to the specific data types and data products are included in each Chapter/Paper.
3. **Reliance on proxies** – the history of antislavery work has often relied on the presence of proxy measures to determine the scale and impact of modern slavery. The application of satellite EO data in this case is no different. Currently, we cannot determine the location of where modern slavery is

occurring via remote sensing sources (Landman *et al.* 2019), and thus proxies are the way to understand modern slavery. Assessing the environmental impacts is one method of determining the scale of specific sectors – however, this cannot be applied to all forms of modern slavery; only those sectors which are visible on the Earth's surface can be investigated using these data and this methodological technique.

7.5 Recommendations

From the findings of this study there are five recommendations to be provided to the antislavery community, conservation groups, development actors, and the field of remote sensing; promoting the further inclusion of satellite EO data to investigate modern slavery and share the beneficial applications of these data for the SDGs. Recommendations include:

1. **Transdisciplinarity** – efforts should be made to combine data collection methods to create a holistic understanding of the nexus; this will need to incorporate new satellite EO technologies and processing methods. Inclusion of key stakeholders (such as antislavery organisations, survivors, conservation groups, and international developmental/governmental groups) enables growth in the awareness of modern slavery, and creates opportunities for the targeted applications of EO data in order to locate modern slavery and further understand the relationship between modern slavery and environmental degradation. Landman (2018) outlined ways in which this is achievable; however it is vital that evidence obtained from the analysis of remotely sensed data must also include ground-data (Recommendation 2) and survivor voices (Recommendation 3). These data should be made freely available, and results

should be open access, so that relevant organisations and actors can implement appropriate strategies to end exploitation and ecological damage.

2. **Ground-data** – the major limitation of this study was the lack of ground-truthing data. Efforts should be made to increase data collection from ground sources which correspond to the satellite EO investigation. Although this study has demonstrated the benefits of 'sat-truthing' with limited ground-data, much more data are required. This is a common critique of antislavery work as data are limited across the field. Remote sensing can address this knowledge-gap in some instances, yet the goal should be to integrate these primary ground-data to verify these geospatial data.
3. **Survivor inclusion** – to successfully integrate EO data into antislavery research and understand the drivers of modern slavery and ecological damage, survivors must be included. This applies from the analysis of remotely sensed data, to the ground investigation of the modern slavery-environment nexus. At present, the inclusion of survivors has been limited in the technological sectors working to address modern slavery (see Landman *et al.* 2019). This should be rectified moving forward. To create a fully inclusive field of research, understand the nexus, and achieve SDG 8.7, we must learn from survivors, encourage collaboration, and elevate their experience to inform the application of remote sensing and ground-truthing. This must be initiated at the start of the research process, and non-survivors must acknowledge that this is the perspective from which they conducted the research; as in the case of this thesis.
4. **Integration into the 'Digital Ecosystem for the Planet'** – an outline of where and how antislavery investigations into the modern slavery-environment nexus may be incorporated has been outlined (Figure 7.2). Integration provides an

opportunity to address Recommendations 1 and 3, and create a holistic and inclusive monitoring system to identify industries and locations where modern slavery and associated environmental impacts may be occurring over long timescales, and vast geographic areas. This is unique of satellite EO data and must be embraced as it is incomparable with other sectors. Therefore geospatial, alongside ground-based data, will be required. Technological advances in space technologies should be embraced and incorporated into a 'Digital Ecosystem' in order to gain insights. However, to be successful international cooperation is necessary – which can be facilitated through a project such as the 'Digital Ecosystem for the Planet (and Nexus)'. On a local scale, this can be achieved through the layered-integration of multiple EO datasets in a framework such as that suggested in Figure 7.1.

5. **Ethical considerations** – drawing on concerns raised in Chapter 2/Paper 1 (Appendix A), further investigation is needed around the application of remote sensing for research into the nexus, particularly in areas where vulnerable populations may be at risk of exploitation. As technological and methodological applications improve, they will ultimately require a new ethical framework. These guidelines should be produced by key actors to address the modern slavery-privacy dilemma, and be accessible to all. Defining recommendations and guidance for good practice for the use of remotely sensed data before these resources become the norm should limit malpractice and demonstrate that the EO community is proactive in supporting social issues. This combined ethics is pertinent when addressing the modern slavery-environment nexus.

7.6 Concluding Remarks

Remote sensing as an application to investigate sectors that degrade the environment and rely on the presence of modern slavery, is a viable data collection and analysis method that should be promoted. It has unique properties which allow the investigation of remote, inaccessible areas, over vast geographic scales, and across a time period of almost 50 years. Throughout the thesis these benefits have been identified, proven, and evidence for the growth and promotion of satellite EO data within the antislavery space – particularly to address the modern slavery-environmental degradation nexus – has been encouraged. This is particularly important as modern slavery is the third largest emitter of CO_2 emissions (Bales 2016); with sectors increasing these forms of emissions, and modern slavery activities actively occurring in areas that are vital for climate change mitigation. Satellite EO data have been successfully applied within this thesis to investigate three industries known to use modern slavery (fish-processing camps, brick-making, and tree loss), in a method known as 'sat-truthing'. While remote sensing is not the only data collection method available, it is one that is currently the most underutilised by the antislavery community and can provide a global assessment of these environmental impacts. In order to provide a holistic picture of global modern slavery, remote sensing can assist in the provision of these data, but they should be incorporated into a global data-analysis system to thoroughly understand the drivers and implications of the modern slavery-environmental degradation nexus. Yet, it must be acknowledged that the sector should strive to integrate these data for use as part of a combined methodology. A layered methodology has been suggested, that lays out the ways in which remotely sensed data sources may be combined together to support the investigation of the modern slavery-environment nexus, and the antislavery sector more generally.

It has also been suggested that a vehicle such as the ‘Digital Ecosystem for the Planet’ could incorporate data to assess the modern slavery-environment nexus. More specifically, evidence has been provided to support the achievement of multiple SDGs – including those which are environmentally-oriented (such as SDG 14 and 15), though most pressingly target 8.7 – and help others to achieve evidence-based action led by governments, law enforcement, antislavery organisations, and conservation groups.

The research conducted in this thesis has demonstrated that satellite EO data is a methodology which is valuable for researching modern slavery, and it should be used to help understand the nexus, successfully support the SDGs, and achieve the ‘freedom dividend’ – understanding the social and ecological impacts of modern slavery via remotely sensed data acquisition (which will be vital in ending modern slavery overall) and assisting in the protection of multiple social-ecological systems.

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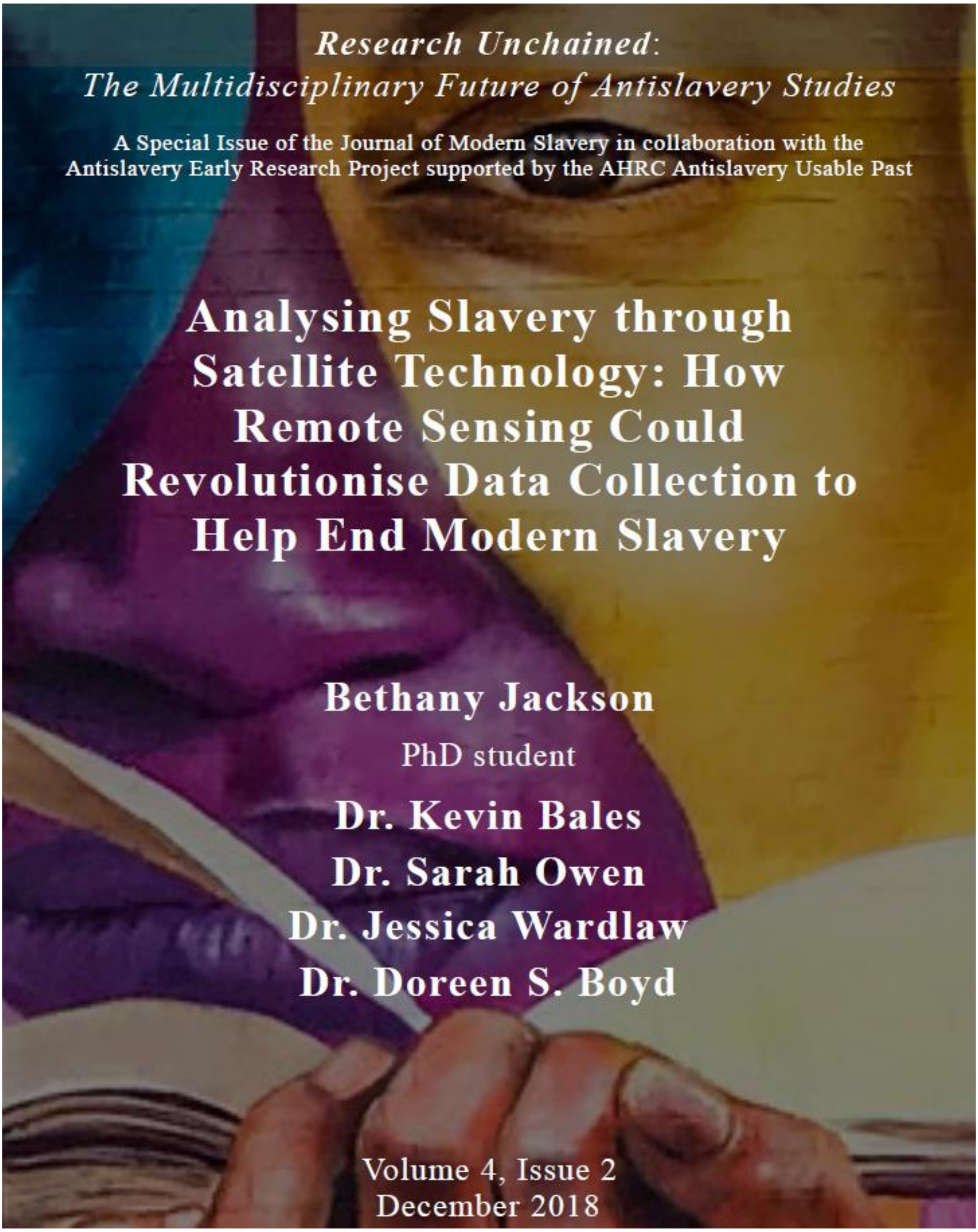
Appendix A: Analysing slavery through satellite technology: How remote sensing could revolutionise data collection to help end modern slavery (understand the socio-ecological dimensions of modern slavery)

Authors: Bethany Jackson, Kevin Bales, Sarah Owen, Jessica Wardlaw and Doreen S. Boyd

Author Contributions: BJ led the production of the manuscript including concept development, primary literature searching, and the write-up and editing of the full manuscript. SO took the lead on the environmental nexus portion with assistance from BJ. JW led the crowdsourcing section. DB and KB provided additional resources, guidance on ideas and structure, and provided annotated edits of the drafts.

Full Reference: Jackson, B., Bales, K., Owen, S., Wardlaw, J., and Boyd, D.S. (2018). Analysing Slavery through Satellite Technology: How Remote Sensing Could Revolutionise Data Collection to Help End Modern Slavery. *Journal of Modern Slavery*, 4(2), 169-199.



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A Special Issue of the Journal of Modern Slavery in collaboration with the Antislavery Early Research Project supported by the AHRC Antislavery Usable Past

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Volume 4, Issue 2
December 2018

Analysing Slavery through Satellite Technology: How Remote Sensing Could Revolutionise Data Collection to Help End Modern Slavery

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Acknowledgements

The authors would like to thank the Rights Lab for providing funding for the lead author's research and the Anti-Slavery Usable Past Postgrad Research Network (ASUP PGRN), now the Antislavery Early Research Association, for inviting submissions for the special issue following the Workshop held in Liverpool in 2017. We would also like to thank the reviewers for all of their constructive feedback. The authors would like to acknowledge that they have written the piece from the starting point as non-survivors.

Abstract

An estimated 40.3 million people are enslaved globally across a range of industries. Whilst these industries are known, their scale can hinder the fight against slavery. Some industries using slave labour are visible in satellite imagery, including mining, brick kilns, fishing and shrimp farming. Satellite data can provide supplementary details for large scales which cannot be easily gathered on the ground. This paper reviews previous uses of remote sensing in the humanitarian and human rights sectors and demonstrates how Earth Observation as a methodology can be applied to help achieve the United Nations Sustainable Development Goal target 8.7.

Key words: Crowdsourcing; Modern Slavery; Remote Sensing; Satellites; Sustainable Development Goals.

Analysing Slavery through Satellite Technology: How Remote Sensing Could Revolutionise Data Collection to Help End Modern Slavery

Globally an estimated 40.3 million people are currently trapped in modern slavery, a quarter of whom are children.[1] To tackle slavery, and a number of other developmental challenges, the United Nations (UN) created the Sustainable Development Goals (SDGs), which came into force on 1 January 2016, replacing the Millennium Development Goals (MDGs).[2] The MDGs aimed to remove people

[1] This figure was first estimated in 2017 when the International Labour Organisation (ILO) partnered with Walk Free, the producers of the Global Slavery Index (GSI). The figure is the most current estimate available, and was determined using surveys, interviews and datasets. The global estimate was first produced for the 'Global Estimates of Modern Slavery' report published by the ILO. These results were then expanded upon in the 2018 edition of the 'Global Slavery Index' which provides a breakdown of the figures by country. However, there are a number of critiques of the GSI approach, particularly regarding the methodologies used in the Index and the alterations of the definition of 'modern slavery' used within each edition (Guth *et al.* 2014; Gallagher 2017; Mügge 2017). The term 'modern slavery' is used throughout as it is the overarching term found within the United Kingdom's legislation regarding slavery, the *Modern Slavery Act* 2015 (http://www.legislation.gov.uk/ukpga/2015/30/contents). Whilst it must be acknowledged that there are a number of valid reasons against the use of this term, many of which are outlined by Michael Dottridge (2017), the widespread use of the term 'modern slavery' and the nature of exploitation described in the *Modern Slavery Act* 2015 was deemed appropriate for this manuscript. Walk Free Foundation and International Labour Organisation. "Global Estimates of Modern Slavery: Forced Labour and Forced Marriage." Geneva, 2017; ———. "Global Estimates of Child Labour: Results and Trends, 2012-2016." Geneva, 2017; Walk Free Foundation. "The Global Slavery Index 2018." Australia, 2018.

[2] World Bank and UNDP. "Transitioning from the MDGs to the SDGs." New York, 2015.

from situations of poverty, whereas the SDGs aim to provide an environment that will keep them out of poverty for good. The remote sensing community has long worked to tackle issues within the SDGs, primarily those related to the environment. However, an increasing number of applications relate to targets and indicators that have social and cultural implications for sustainability across a number of fields.[3] One target that could benefit from the use of geospatial information, is target 8.7 (part of SDG 8), which aims to tackle forms of modern slavery and child labour. Target 8.7 stipulates society must:

> Take immediate and effective measures to eradicate forced labour, end modern slavery and human trafficking… and by 2025 end child labour in all its forms.[4]

With the goal firmly set, governments, businesses and campaigners have joined the fourth anti-slavery movement to help eradicate slavery for good.[5] However, technological advancements for data collection on modern slavery could hold the key to end this fight.

The use of satellite imagery for tackling the SDGs is a recent and growing phenomenon.[6] Katherine Anderson et al. explored a range of possible uses for remote sensing technology and the SDGs, of which many examples touched upon the impact of changing environmental indicators and the effect that changes in ecosystems, climate variables and—in the most human orientated analysis—population exhibit.[7] These examples barely touched on Goal 8, only briefly mentioning other economic indicators within the goal but never explicitly referring to target 8.7. Moreover, the use of remote sensing exploring cultural heritage has been examined.[8] The work by Wen Xiao *et al*. is built upon a range of studies that had developed methods to investigate archaeological sites using remotely sensed

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[3] Qihao Weng. *Remote Sensing for Sustainability*. CRC Press: Boca Raton, 2016.

[4] "Sustainable Development Goal 8." Sustainable Development Knowledge Platform, United Nations, accessed May 18, 2017, https://sustainabledevelopment.un.org/sdg8

[5] The fourth anti-slavery movement is one of the key factors driving the current academic scholarship and developments in anti-slavery community present today: see Zoe Trodd. "Introducing the Rights Lab." University of Nottingham, accessed August 20, 2018, http://blogs.nottingham.ac.uk/rights/2017/08/04/walkfree7/; and "The Antislavery Usable Past." Arts & Humanities Research Council, accessed August 20, 2018, https://ahrc.ukri.org/research/casestudies/the-antislavery-usable-past/.

[6] John Trinder, Sisi Zlatanova, and Jie Jiang. "Editorial to Theme Section on UN Sustainable Development Goals (SDG)." *ISPRS Journal of Photogrammetry and Remote Sensing* 142 (2018):342-343.

[7] Katherine Anderson *et al*. "Earth Observation in Service of the 2030 Agenda for Sustainable Development." *Geo-spatial Information Science* 20, no. 2 (2017):77-96.

[8] Wen Xiao *et al*. "Geoinformatics for the Conservation and Promotion of Cultural Heritage in Support of the UN Sustainable Development Goals." *ISPRS Journal of Photogrammetry and Remote Sensing* 142 (2018):389-406.

data, which are commonly conducted using radar, LiDAR and imagery analysis from Unmanned Aerial Vehicles (UAVs) or satellite imagery. Their study impressed the importance of these methods in the context of supporting elements of both SDG 8 and SDG 11 which both include references to cultural heritage. Overall, Xiao *et al.*'s study demonstrates the benefit of remote sensing technology to protect cultural heritage, and suggests where such technology can be used in the future. The studies mentioned above show a clear movement in the remote sensing field to research which supports the SDGs and the associated 169 indicators.

While there is a limited amount of information referring to geospatial technology and the SDGs, there have been many uses of remote sensing for humanitarian and human rights research and practice, with new innovations in the types of data used for analysis.[9] Non-governmental organisations (NGOs) are beginning to invest in the use of these technologies to tackle human rights violations, for example, Amnesty Decoders.[10] The development of these uses represents an important step towards the use of remote sensing technology for social challenges.

Remote Sensing for Humanitarian and Human Rights Cases

Remote sensing is the practice of collecting data predominantly passively (using reflected sunlight from the Earth's surface to measure the reflectance of features on the ground to determine their properties) from a distance. Since the first satellite was launched in the 1950s, capabilities to monitor the Earth have continued to develop. There were more than 600 earth observation (EO) and earth science satellites orbiting the planet in 2017 collecting large volumes of data with untapped potential to investigate industries, known to be utilising modern slavery practices, from above.[11] There are large temporal sets of data, for instance, the U.S. Landsat mission. The data from this mission was made freely available in 2008, providing an archive of imagery spanning more than 40 years.[12] The Landsat missions have a medium spatial resolution (30m pixels), allowing for vast data collection at a reasonable level of detail across the entire planet. However, the

[9] Naomi Larsson. "How satellites are being used to expose human rights abuses." *The Guardian*, accessed May 19, 2018, https://www.theguardian.com/global-development-professionals-network/2016/apr/04/how-satellites-are-being-used-to-expose-human-rights-abuses; Robin Pierro, Tom Walker and Ben Davis. "Satellite Imagery for Human Rights Monitoring." *The Engine Room*, accessed May 19, 2018, http://library.theengineroom.org/satellite-imagery-human-rights/.

[10] "Amnesty Decoders." Amnesty International, accessed May 18, 2018, https://decoders.amnesty.org/.

[11] Union of Concerned Scientists. "UCS Satellite Database." 2017.

[12] Mariel Borowitz, *Open Space: The Global Effort for Open Access to Environmental Satellite Data*. London: MIT Press, 2017.

continuing availability of the imagery is uncertain.[13] Other satellites, with even higher resolutions, allow us to view features on the Earth's surface in detail, such as DigitalGlobe, a commercial satellite imagery provider. Increasingly data are improving in all resolutions – source (as in laser, radar, optical), spatial (different pixels sizes), spectral (different wavebands), temporal (collected on different dates) and radiometric (data content of the pixel). Data are also becoming free at the point of access, particularly from satellites owned and operated by national space agencies; greatly increasing the range of possible uses.

Remote sensing comes from three primary platforms: UAVs, airborne (for instance planes), and satellites. In the fight against modern slavery it is satellite imagery that is the most appropriate, not only because of the vast abundance of imagery, but also for two other key reasons. First, it provides detail which is cost-effective compared to launch, collection and processing costs. Second, it protects vulnerable people's privacy should they be enslaved because they are not visible at the spatial resolutions available. Coarser imagery, such as those which are available freely, are therefore beneficial as they prevent slaveholders from identifying workers and locations which may lead them to take harmful actions, impacting on those who are enslaved. Cost-effective, open access, data affords NGOs, academics and policy makers the opportunity to conduct analysis with a focus on modern slavery. Monitoring cases of human rights violations and humanitarian crises with remotely sensed data have become common, however, these platforms have never been used within the modern anti-slavery movement.[14]

UAVs, a recent technological development, have taken the practice of remote sensing to the mainstream. However, imagery collected from the small cameras placed on board (known as the payload) have primarily been used in humanitarian cases; such as in disaster hit areas to help develop clear plans for delivering aid and assessing damage within remote areas before aid workers arrive.[15] When a camera is situated in the payload imagery can be captured and has been used in a number of contexts. For example, refugee camps have grown large in number and size across the Middle East, particularly since the start of the Syrian conflict in 2011. Satellite imagery has revealed rapid expansion of the UN's refugee camps and can help to protect those within the camp in conflict

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[13] Gabriel Popkin. "US government considers charging for popular Earth-observing data." *Nature* 556 (2018): 417-418.

[14] AAAS. "Human Rights Applications of Remote Sensing: Case Studies from the Geospatial Technologies and Human Rights Project." Washington DC, 2014.

[15] Kalev Leetaru. "How Drones Are Changing Humanitarian Disaster Response." *Forbes*, accessed May 18, 2018, https://www.forbes.com/sites/kalevleetaru/2015/11/09/how-drones-are-changing-humanitarian-disaster-response/#6a39b3a0310c.

situations.[16] Despite the registration process upon entering a camp, population monitoring can be difficult, and analysis of data collected by an on board UAV camera, or a satellite image, can provide a more accurate estimation of the number of residents, thus assisting registrars on the ground. These methods use tents and shelters to estimate the number of people present which is vital as it informs the volume and scale of provisions required for each camp.[17]

Whilst the use of UAVs may be beneficial in some contexts they may not be for all. UAVs fly close to the ground, thus they can capture a lot of detailed images; features such as people and vehicles are visible. Airborne sensors fly higher, but they also carry sensors which may put people at risk, these features are also becoming common in commercial satellite data. For example DigitalGlobe's 'WorldView' satellites have a spatial resolution of up to 31cm (high enough to view and detect the model of a car, but not so high as to identify people) which is available commercially for the first time since changes to U.S. law.[18] It is therefore important to consider the ethics of using remote sensing for a human rights issue such as modern slavery, as high levels of detail in the future may put vulnerable people at risk of further harm. There is no guarantee that imagery will not be used nefariously, however, these high resolution data are still primarily commercial, limiting those who can access the data to those who have the financial means, or are restricted by governments.[19] The technology is already available and there appears to be very little will to restrict access again, but perhaps imagery providers need to consider who the data are released to and users must also play a role in thinking carefully about what data are required, and why, when engaging in remote sensing investigations of vulnerable populations.

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16 Joe Belliveau. "Humanitarian Access and Technology: Opportunities and Applications.". *Procedia Engineering* 159 (2016):300-306.

17 Francesco Checchi, Barclay T. Stewart, Jennifer J. Palmer, and Chris Grundy. "Validity and Feasibility of a Satellite Imagery-Based Method for Rapid Estimation of Displaced Populations." *International Journal of Health Geographics* 12, no. 1 (2013):4; Stefan Lang *et al*. "Earth-Observation (EO)-based *ex post* assessment of internally displaced person (IDP) camp evolution and population dynamics in Zam Zam, Darfur." *International Journal of Remote Sensing* 21, no. 21 (2010):5709-5731; Patrick Meier. "The First Ever 3D Model of a Refugee Camp Made with UAV Imagery." *iRevolutions*, accessed May 4, 2018, https://irevolutions.org/2015/08/17/first-3d-model-refugee-camp/.

18 Michael Koziol. "Lifting restrictions on satellite imagery means even closer close-ups from space." *The Sydney Morning Herald*, accessed December 4, 2018, https://www.smh.com.au/technology/lifting-restrictions-on-satellite-imagery-means-even-closer-closeups-from-space-20140618-zsdh1.html.

19 Ann M. Florini, and Yahya Dehqanzada. "Commercial Satellite Imagery Comes of Age." *Issues in Science and Technology* XVI, no. 1 (1999).

Ethical Considerations

The ethics of remote sensing have been considered since the first high spatial resolution satellite was launched in the 1990s. More recently Tanya Notley and Camellia Webb-Gannon have explored the issues of remote sensing and privacy with special reference to the application of remote sensing for human rights analysis.[20] There are a number of concerns about the use of satellite imagery for tackling human rights violations, including slavery. NGOs do not want to endanger vulnerable people should cases of slavery be identified, and the slaveholders somehow become aware of this. Concerns such as these should be considered within all remote sensing analysis that aims to protect people from human rights abuses. The community of analysts and NGOs must be aware of the possible risks to those they are trying to help, to protect them from further harm. Similar ethical considerations have been noted with reference to required regulations that prevent the marginalisation and targeting of vulnerable groups within society.[21] This idea is considered further by Austin Choi-Fitzpatrick who argues that researchers and organisations using UAVs to enable societal change for good need to prioritise six key concepts: subsidiarity, physical and material security, the 'do no harm' principle (balancing the situation being monitored and the risks involved to those producing, using and featured within the data collected), the public good, respect for privacy and respect for data.[22] It is important that a strict code of ethics, common in the field of remote sensing and study of modern slavery, is adhered to in order to mitigate risk of further distress, harm or violation to enslaved workers through the use of the technology—bearing in mind the 'do no harm' aspect of the work.

Some of the issues of privacy may also apply to very high spatial resolution satellite imagery. The sensors that supply this type of data tend to be commercially owned and therefore the data can be extremely expensive. This is where tradeoffs regarding satellite data selection are often made. In the case of investigating industries using modern slavery practices, the most vital consideration is the protection of vulnerable populations, these must also be considered alongside costs and the level of detail needed within the imagery in order to conduct meaningful analysis. Whilst the majority of open-source data have pixel resolutions of around

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[20] E. Terrence Slonecker, Denice M. Shaw, and Thomas M. Lillesand. "Emerging Legal and Ethical Issues in Advanced Remote Sensing Technology." *Photogrammetric Engineering and Remote Sensing* 64, no. 6 (1998):7; Tanya Notley, and Camellia Webb-Gannon. "Visual Evidence from Above: Assessing the Value of Earth Observation Satellites for Supporting Human Rights." *The Fibreculture Journal* 3, no. 27 (2016).

[21] R.L. Finn, and D. Wright. "Unmanned aircraft systems: Surveillance, ethics and privacy in civil applications." *Computer Law and Security Review* 28 (2012):184-194.

[22] Austin Choi-Fitzpatrick. "Drones for Good: Technological Innovations, Social Movements, and the State." *Journal of International Affairs* 68, no. 1 (2014):19-36.

30m, the new European Space Agency (ESA) Copernicus programme's Sentinel-2 satellites have 10m spatial resolution and a revisit rate of 5 days; these pixels are still large enough, however, to diminish the risk of privacy violations.[23] Consequently, satellite imagery is seen as the most applicable form of data to help analyse practices of modern slavery.

Remote Sensing Modern Slavery

There is precedent for the use of remote sensing in a range of human rights applications but there has not been a concerted effort to apply these practices to instances of modern slavery.[24] The idea for using satellite imagery in the effort to measure and end slavery was first mooted by Kevin Bales when visiting the UN's Office for Outer Space Affairs (UNOOSA).[25] He recognised how satellite technology could help to target the remotest of areas where slavery often takes place. This is an important benefit as imagery can help support anti-slavery NGOs on the ground by providing detailed maps of industries in remote areas which may have previously been inaccessible, or even unknown. Although remote sensing methods may not be applicable to collect data on all types of slavery, the use of remotely sensed imagery provides an additional resource to enhance understanding of numerous industries. However, this does not mean the method will replace interactions with survivors and organisations on the ground working to end slavery; the view would be to create additional avenues of data collection alongside these established techniques. Industries where satellite imagery would be applicable include: brick kilns (see Figure 1), quarries, mines, charcoal camps, fish-processing camps and fishing (in both open water and oceans). The problem of modern slavery is so widespread and the collection of remotely sensed imagery is so frequent, that the technology would be beneficial as an additional methodological tool to use in this field.

Satellites and Slavery in Academia

At the time of writing only one published research paper has used remotely sensed imagery to provide information on slavery within an academic setting, but there has been a growth in the number of studies specifically investigating modern

[23] ESA. "Sentinel-2 User Handbook." *European Commission*, 2015; M. Drusch *et al.* "Sentinel-2: Esa's Optical High-Resolution Mission for GMES Operational Services." *Remote Sensing of Environment* 120 (2012):25-36.

[24] AAAS. "Human Rights Applications of Remote Sensing: Case Studies from the Geospatial Technologies and Human Rights Project."

[25] Kevin Bales. *Ending slavery: how we free today's slaves*. Berkeley, CA: University of California Press, 2007:163-164.

slavery.[26] Doreen Boyd *et al*. estimated the number of brick kilns in South Asia using open source imagery available through Google Earth Pro.[27] This is an important piece of research as it assesses an industry that is known to use bonded and child labour. Previously, little was known about the extent of the South Asian brick manufacturing industry, and the development of this estimate would not have been possible without geospatial technology due to the size of the region being investigated. The work by Boyd *et al*. is a beneficial development in the possible use of technology for human rights analysis but is also important for NGOs and local governments, as the information can be used to help with the decision-making process when abolishing slavery practices within brick manufacturing.[28] Moreover, the study embraces crowdsourcing to collect data and demonstrates the engagement of civil society with the SDGs—which is key to ensuring they are sustained and successful—as well as processing large volumes of data quickly.

Building on this, researchers at the University of Nottingham have begun to investigate the impact of illegal fish-processing camps within the UN Educational, Scientific and Cultural Organization (UNESCO) protected Sundarbans Reserve Forest, Bangladesh (Figure 2).[29] These sites are known to use child labour.[30] They are also understood to have an adverse impact on the mangroves in which they are situated. Geospatial technology in this case can be used to protect the environment and help to support the liberation of enslaved workers through the provision of evidence to encourage government and UN-led action.

The Slavery-Environment Nexus in Research

Satellites are used extensively to monitor the Earth System's environment, providing a robust and continuous method to measure and monitor our anthropogenic footprint.[31] The knowledge acquired through the analysis of satellite

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26 Details of research on modern slavery occurring within the UK are available through a database supported by the Independent Anti-Slavery Commissioner and the University of Nottingham's Rights Lab; the database is accessible via http://iascresearch.nottingham.ac.uk/

27 Doreen S. Boyd *et al*. "Slavery from Space: Demonstrating the role for satellite remote sensing to inform evidence-based action related to UN SDG number 8." *ISPRS Journal of Photogrammetry and Remote Sensing* 142 (2018):380-388.

28 *Ibid*.

29 Cara McGoogan and Muktadir Rashid. "Satellites reveal 'child slave camps' in UNESCO-protected park in Bangladesh." *The Telegraph*, accessed October 26, 2016, https://www.telegraph.co.uk/technology/2016/10/23/satellites-reveal-child-slave-camps-in-unesco-protected-park-in/.

30 Kari B. Jensen "Child Slavery and the Fish Processing Industry in Bangladesh." *Focus on Geography* 56, no. 2 (2013):54-65.

31 Andrew J. Tatum, Scott J. Goetz and Simon I. Hay. "Fifty Years of Earth Observation Satellites." *Am Sci.* 96, no. 5 (2008):390-398.

imagery provides data to manage the environment, limit damaging actions, and establish measures of the relative successes, or failures, of environmental policies which have been employed to mitigate damage. The environmental destruction of our planet is documented daily by EO satellites, creating an extensive and valuable archive of data. These data are used to inform practice and improve environmental awareness, but the question remains, how may they also be used to assist in the eradication of modern slavery.

The destruction of the environment and the presence of modern slavery are entwined in a 'deadly dance'.[32] Those subject to debt bondage or forced labour are often involved in dangerous and destructive practices that have the potential to etch large physical signatures upon the landscape; deforestation of the Amazon is a clear example of this.[33] If modern slavery were a country it would be the third largest emitter of carbon dioxide (CO_2) globally, yet, little emphasis has been placed on the study of the powerful linkage between such social and physical variables.[34] Common debt bonded labours with high environmental impacts include forestries, fisheries, factories and farming.[35]

The brick kiln industry is widespread across South Asia, as discussed previously, but the true scale of the environmental impacts have not yet been realised. At present, the volume of emissions have been explored, as has the extraction of clay, used to produce the bricks, which strips the land reducing the fertility thus pushing those reliant on agriculture into further vulnerability.[36] Similarly, mining releases a variety of heavy metals via the extraction of particular ores; Mercury is common across Gold mining in West Africa and South America.[37] Planet satellites, for example, have captured evidence of extensive gold mining in

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[32] Bales. *Blood and Earth: Modern Slavery, Ecocide and the Secret to Saving the World*. New York: Speigel & Grau, 2016.

[33] Philip M. Fearnside. "The Roles and Movements of Actors in the Deforestation of Brazilian Amazonia." *Ecology and Society* 13, no. 1 (2008):23.

[34] Bales. *Blood and Earth: Modern Slavery, Ecocide and the Secret to Saving the World.*

[35] Doreen Boyd *et al.* "Modern Slavery, Environmental Destruction and Climate Change: Fisheries, Field, Forests and Factories." Rights Lab, University of Nottingham, Royal Holloway University of London and IASC, 2018.

[36] Boyd *et al*. "Slavery from Space: Demonstrating the role for satellite remote sensing to inform evidence-based action related to UN SDG number 8."; Bhat Mohd Skinder, Afeefa Qayoom Sheikh, Ashok K. Pandit and Bashir Ahmad Ganai. "Brick kiln emissions and its environmental impact: A Review." *Journal of Ecology and the Natural Environment* 6, no. 1 (2014):1-11; Bhat M Skinder *et al.* "Effect of brick kiln emissions on commonly used vegetables of Kashmir Valley." *Food Science and Nutrition* 3, no. 6 (2015):604-611; Suman Kumar Pariyar, Tapash Das and Tanima Ferdous. "Environment and Health Impact for Brick Kilns in Kathmandu Valley." *International Journal of Scientific & Technology Research* 2, no. 6 (2013):184-187.

[37] Martin J. Clifford. "Assessing releases of mercury from small-scale gold mining sites in Ghana." *The Extractive Industries and Society* 4, no. 3 (2017):497-505; Jacqueline R. Gerson, Charles T. Driscoll, Heileen Hsu-Kim and Emily S. Bernhardt. "Senegalese artisanal gold mining leads to elevated total mercury and methylmercury concentrations in soils, sediments, and rivers." *Elementa Science of the Anthropocene* 6, no. 1 (2018):11.

Peru.[38] Elsewhere, Mercury can have devastating health effects, and in the Eastern Congo, illegal mining impacts water quality, increases deforestation and contributes to poaching.[39] The environmental damage caused by industries known to heavily use modern slavery practices are perpetuating a socially and ecologically damaging cycle, increasing the risk of populations becoming vulnerable to enslavement.

Shrimp farms and fish-processing camps in the Sundarbans use slave labour to remove coastal mangroves, as discussed above.[40] These forests are a globally important carbon sink, and a key defence against erosion and natural disasters.[41] The cyclicity between human vulnerability and its exploitation, and environmental vulnerability and its exploitation, continues to be exacerbated. In Brazil, the agricultural industry plays a large role for those living in modern slavery. Illegal deforestation for logging and cattle ranch land clearance are common, despite tough anti-slavery laws and the climate protection offered by the rainforest.[42] There is growing evidence of a modern slavery-environmental destruction nexus. Exploring the interactions between the two is important not only to preserve the environment from serious threats such as climate change, but also protect those at risk of modern slavery.

These examples demonstrate synergies within environmental signatures that have the potential to be located in remote sensing imagery. Primary visual signatures such as the shapes and patterns of industries, and secondary signatures held within the environment can be explored. Visual signals for instance include the distinct oval kilns and rows of drying bricks in the 'Brick Belt'.[43] Whereas secondary signatures can include land-use change, alteration of vegetation health and flood frequencies, among others.[44] Remote sensing technology is already

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[38] Planet Labs. "Illegal Mining in Peru." *Planet*, accessed December 6, 2018, https://www.planet.com/gallery/mining-peru/.

[39] Carlos Salazar-Camacho *et al*. "Dietary human exposure to mercury in two artisanal small-scale gold mining communities of northwestern Colombia." *Environmental International* 107 (2017):47-54; Bales. *Blood and Earth: Modern Slavery, Ecocide and the Secret to Saving the World.*

[40] *Ibid*.

[41] L.G. Gillis, E.F. Belshe and G.R. Narayan. "Deforested Mangroves Affect the Potential for Carbon Linkages between Connected Ecosystems." *Estuaries and Coasts* 40, no. 4 (2017):1207-1213; Bales. *Blood and Earth: Modern Slavery, Ecocide and the Secret to Saving the World.*

[42] Brazilian Penal Code. "Article 149: Reduction to Condition Analogous to Slavery." Brasília, 2003.

[43] Boyd *et al*. "Slavery from Space: Demonstrating the role for satellite remote sensing to inform evidence-based action related to UN SDG number 8."

[44] Laura J. Sonter *et al*. "Mining drives extensive deforestation in the Brazilian Amazon." *Nature Communications* 8 (2017):1013; Chandra Giri. "Observation and Monitoring of Mangrove Forests Using Remote Sensing: Opportunities and Challenges." *Remote Sensing* 8, no. 9 (2016):783; G.M. Foody. "Remote sensing of tropical forest environments: Towards the monitoring of environmental resources for sustainable development." *International Journal of Remote Sensing* 24, no. 20 (2003):4035-4046.

capable of detecting many of these signatures at differing scales. Satellite imagery provides a unique line of enquiry, with remote sensing methodologies enabling evidence-based decisions for both social and environmental science policy. Indeed, such cross disciplinary projects are beginning to explore these themes.[45] Projects at Stanford University are utilizing remote sensing imagery to assess the environmental output of brick kiln pollution in Bangladesh, and the University of Nottingham's Rights Lab has investment in the field with their 'Data Programme', researching the uses of remote sensing to measure modern slavery and assess its impact on the Earth's environmental systems.[46]

The link between climate change, poverty and forced labour is well documented, yet the ability to conduct local analyses efficiently to provide action to limit the impacts of these issues is poor due to the remoteness of locations, lack of resources and limited enforcement of laws to protect people and the environment – satellites can be used to identify these potential vulnerabilities, prior to entrapment.[47] By highlighting spatial patterns and causal variables at high temporal resolutions, remote sensing allows the development of monitoring programmes. For Cambodia – ranked second in the list of climate vulnerable countries – the relationship between changing work opportunities, due to climate forced landscape alterations, and migration, which often leads to debt bondage, is closely studied.[48] The Blood Bricks project is one such study that is examining how climate change is facilitating modern slavery.[49] The combination of local ground intelligence, coupled with analysis of satellite imagery showing environmental change provides a powerful opportunity to analyse spatial, physical and human pressures which may increase vulnerability. It is possible to use satellites to both understand past patterns and model future modern slavery-environmental destruction scenarios so support can be provided to strengthen security and reduce vulnerability across these regions.

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[45] Such as Royal Holloway's Blood Bricks project (www.projectbloodbricks.org/project) and the University of Nottingham's Rights Lab (http://rightsandjustice.nottingham.ac.uk/).

[46] Rob Jordan. "Stanford researchers team up to reduce pollution and improve health." *Stanford News*, accessed May 16, 2018, https://news.stanford.edu/2017/09/14/stanford-researchers-team-reduce-pollution-improve-health/; Rights Lab. "Data Programme." *University of Nottingham*, accessed December 4, 2018, https://www.nottingham.ac.uk/research/beacons-of-excellence/rights-lab/programmes/data/index.aspx; Todd Landman. "Out of the Shadows: Trans-disciplinary Research on Modern Slavery." *Peace Human Rights Governance* 2, no. 2 (2018):143-162.

[47] Mike Kaye and Aidan McQuade. "Poverty, Development and the Elimination of Slavery." *Anti-Slavery International*. London, 2007.

[48] K. Brickell, L. Parsons, N. Natarajan and S. Chann. "Blood Bricks: Untold Stories of Modern Slavery and Climate Change from Cambodia." Royal Holloway University of London, 2018; Blood Bricks. "The climate change-modern slavery nexus: Why study Cambodia?" *Royal Holloway University*, accessed May 18, 2018, https://www.projectbloodbricks.org/blog/2017/7/19/blood-bricks-on-the-intersection-of-climate-change-and-modern-slavery.

[49] *Ibid.*; *Ibid.*

Documenting the scale of these environmental impacts are the first steps in being able to evaluate the damaging contribution of modern slavery on the environment. With space agencies continually responding to the demand for satellite data to monitor Earth's environment, advances in sensor design and delivery of knowledge products (that enable a user to easily access information); there is no reason to believe that a satellite derived 'Geospatial Environmental Slavery Index' product would not be achievable which could support the end of modern slavery, alongside a number of environmental SDGs.

Further Developments in Academia

Work undertaken at the Harvard Humanitarian Initiative (HHI) with the Satellite Sentinel Project (SSP) combines evidence from satellite imagery and witness testimony, to draw together details to assess humanitarian crises and human rights violations.[50] The HHI is one of the leading academic institutions looking at the way new data technologies can support humanitarian work. This was demonstrated successfully when SSP collaborated with DigitalGlobe to assess the impacts of the Sudanese conflict.[51] Piecing together multiple analysis methods allows NGOs to create a holistic story surrounding an event.[52] Although these studies do not specifically relate to modern slavery, the humanitarian crises analysed by the HHI and SSP contain risk factors that may lead to increased vulnerability to enslavement.[53] Poverty can often lead to enslavement, which can be impacted by disasters, conflict and population growth.[54] Many of these risks overlap with the work of humanitarian agencies.

Combining multiple data acquisition methods is something academics should consider for the study of modern slavery going forward. Remote sensing techniques are producing an increasing volume of data, which can be used alongside a myriad of other sources – including survivor testimony, supply chain analysis, and survey data - to refine global estimates of modern slavery. Additional benefits from satellite imagery may include locational analysis of industries known to use an enslaved workforce. By combining data sources the exact locations of

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[50] Brittany L. Card and Isaac L. Baker. "GRID: A Methodology Integrating Witness Testimony and Satellite Imagery Analysis for Documenting Alleged Mass Atrocities." *Genocide Studies and Prevention: An International Journal* 8, no. 3 (2014):49-61.

[51] The Enough Project and Satellite Sentinel Project. "Architects of Atrocity." Washington DC, 2013.

[52] For example Forensic Architecture https://www.forensic-architecture.org/.

[53] Kevin Bales. *Understanding Global Slavery: A Reader*. Berkeley, CA: University of California Press, 2005.

[54] Kaye and McQuade. "Poverty, Development and the Elimination of Slavery." London, 2007; Kevin Bales "How to combat modern slavery." *TED*, accessed September 9, 2018, https://www.ted.com/talks/kevin_bales_how_to_combat_modern_slavery/.

modern slavery activity may be identified. Despite the field being in its infancy, using satellite imagery to track slave-based industries within academia is an important step in the effort to end slavery by the 2030 deadline, noted earlier.[55]

Satellites and Slavery in the Media

Journalists have a major role in increasing the awareness of global social issues, and modern slavery is no exception. Larger press organisations, such as Thomson Reuters and the Associated Press (AP), have also been enhancing their reporting with the use of satellite imagery to capture instances of slavery, exposing criminality and corruption.

The AP Pulitzer Prize-winning investigative report into the state of seafood supply chains within South East Asia included geospatial analysis to bring to light the working practices enslaved people were forced to endure.[56] The articles noted how labourers were trafficked to work in the Thai fishing industry and could be trapped on numerous boats in the Indian Ocean processing catches on board before being moved.[57] The investigation also found evidence of mass graves where enslaved workers had been buried, and captured the movement of fishing vessels across the ocean using satellite imagery.[58]

The investigation conducted by the AP raised the concept that you 'cannot hide from space'. Some forms of slavery, such as domestic servitude and carpet weaving, are not viable for investigation through the use of satellite imagery as the nature of the enslavement occurs indoors; this is the major limiting factor of remote sensing and demonstrates why a number of methodologies are required. Where industries can be viewed by remote sensing methods, which includes a significant number, the method can be beneficial, this includes the global fishing industry. As a result of the investigation, the Thai fishing industry came under intense scrutiny for its labour practices, and awareness of exploitation in these

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[55] United Nations General Assembly. "Transforming our World: The 2030 Agenda for Sustainable Development." Geneva, 2015.

[56] Details of the award-winning AP investigation are available via https://www.ap.org/explore/seafood-from-slaves/.

[57] Robin McDowell, Martha Mendoza, and Margie Mason. "AP tracks slave boats to Papua New Guinea." *AP*, accessed March 15, 2018, https://www.ap.org/explore/seafood-from-slaves/ap-tracks-slave-boats-to-papua-new-guinea.html; Margie Mason, and Martha Mendoza. "AP Investigation Prompts New Round of Slave Rescues." *AP*, accessed March 15, 2018, https://www.ap.org/explore/seafood-from-slaves/ap-investigation-prompts-new-round-of-slave-rescues.html.

[58] Robin McDowell, Margie Mason, and Martha Mendoza. "AP Investigation: Slaves May Have Caught the Fish You Bought." *AP*, accessed March 15, 2018, https://www.ap.org/explore/seafood-from-slaves/ap-investigation-slaves-may-have-caught-the-fish-you-bought.html; Annalee Newitz. "It took less than a minute of satellite time to catch these theives red-handed." *ARS Technica*, accessed May 4, 2018, https://arstechnica.com/tech-policy/2017/02/to-catch-a-thief-with-satellite-data/.

supply chains caused changes to law internationally.[59] It is clear that the global fishing industry is one with serious labour practice issues, and the exploitation evident in the workforce is being investigated in detail by a number of sectors including NGOs, academia and the media.[60] It is feasible that geospatial technology can be included in other studies of supply chain transparency in visible industries, contributing evidence to support reforms to worker's rights and industry practices. Industries believed to use exploitative labour practices include: quarries, mines, charcoal camps, cotton and agriculture among others. So far these industries have not been explored using remote sensing techniques.[61]

Satellites and Slavery as used by NGOs

A number of NGOs have begun to embrace satellite technology and imagery to demonstrate evidence of human rights violations. However, the use of geospatial imagery by the human rights NGO community has been criticised for the distance it can create from the complex realities on the ground.[62] Thus when analysing modern slavery from space, it is important to build a network of in situ contacts, crucially anti-slavery NGOs, so that evidence from satellite imagery can impact upon direct-action and influence the implementation of policy.

Amnesty International (AI) has been one of the most prolific at using these resources, creating a visual evidence base that supports survivor and witness testimony, enabling satellite imagery to be given as evidence in court; the most recent investigation with this aim assesses Myanmar Military action within Rakhine State.[63] A number of high-profile campaigns have capitalised on the vast amount of data available from geospatial technology and the organisation now employs its own team of analysts. Specific attention to slavery has been hidden within other human rights abuses but this does not mean that the work that AI has carried out using this technology is not beneficial. Their work has looked closely at the village of Baga, in Nigeria, after the atrocities committed by Boko Haram; assessing the scale of the destruction was vital to establish the story of the

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[59] Martha Mendoza. "Obama bans US imports of slave-produced goods." *AP*, accessed March 15, 2018, https://www.ap.org/explore/seafood-from-slaves/Obama-bans-US-imports-of-slave-produced-goods.html.

[60] McGoogan and Rashid. "Satellites reveal 'child slave camps' in UNESCO-protected park in Bangladesh."

[61] Bales. *Blood and Earth: Modern Slavery, Ecocide and the Secret to Saving the World.*

[62] Chris Perkins, and Martin Dodge. "Satellite imagery and the spectacle of secret spaces." *Geoforum* 40, no. 4 (2009):546-560.

[63] Amnesty International. "'We Will Destroy Everything': Military Responsibility for Crimes against Humanity in Rakhine State, Myanmar." London, 2018.

hundreds of women and girls who were kidnapped and enslaved by their captors.[64] Additionally, there have been extensive investigations by AI into North Korea's well-documented human rights abuses in labour camps and detention centres.[65] AI used satellite imagery to assess the size of the camps and identify features that indicate whether there are increased activities occurring in these locations, noting that camps were often in working order and expanding activities.[66]

The utilisation of geospatial technology in these cases has proved invaluable for raising awareness of NGO campaigns, but there are only limited technical analyses, often relying on the identification of features and comparison of images before and after an event. This information is still beneficial for an organisations' purposes, but utilising more technical details could help to provide new data that may have previously been overlooked, such as producing more detailed temporal analyses which may identify features in the lead up to a human rights abuse in order to predict when an abuse may be likely to occur in the future. In addition, combining witness testimony, imagery from the ground, satellite imagery and legal frameworks can add value to an investigation. It is important to look at these data holistically; this will be vital when applying satellite data to a complex human rights issue such as modern slavery. Work by Human Rights Watch, a non-profit organisation which investigates human rights abuses, is being revolutionised by new partnerships with emerging EO companies.[67] Commercial satellite providers, such as Planet, are moving from larger scale singular and expensive satellites to the launch and operation of multiple small satellites. These constellations of satellites collect a vast amount of data for global coverage at a reduced cost compared to other commercial operators, and can be flexible in their applications.[68] Recognising the need for data in the human rights sector, Planet has the intention of creating a new kind of global observatory whereby philanthropists provide the

[64] "Nigeria: Satellite images show horrific scale of Boko Haram attack on Baga." Amnesty International, accessed March 13, 2018, https://www.amnesty.org/en/latest/news/2015/01/nigeria-satellite-images-show-horrific-scale-boko-haram-attack-baga/; Christoph Koettl. "The story behind the Nigeria satellite images." Amnesty International, accessed March 13, 2018, https://www.amnesty.org/en/latest/news/2015/01/the-story-behind-the-nigeria-satellite-images/.

[65] Amnesty International. "New Satellite Images Show Blurring of Political Prison Camp and Villages in North Korea." London, 2013; ---. "North Korea: New Satellite Images Show Continued Investment in the Infrastructure of Repression." London, 2013.

[66] "North Korea prison camps very much in working order." Amnesty International, accessed March 13, 2018, https://www.amnesty.org/en/latest/news/2016/11/north-korea-prison-camps-very-much-in-working-order/.

[67] "New Satellite Imagery Partnership." Human Rights Watch, accessed March 13, 2018, https://www.hrw.org/news/2017/11/30/new-satellite-imagery-partnership.

[68] Adrienne Harebottle. "Earth Observation to Capture the Mainstream Market." *Via Satellite*, accessed March 15, 2018, http://interactive.satellitetoday.com/via/may-june-2017/earth-observation-to-capture-the-mainstream-market/; Andrew Zolli. "Planet announces new, flexible emergency and disaster management." *Planet Labs*, accessed March 15, 2018, http://www.planet.com/pulse/planet-emergency-and-disaster-management-solution/.

funds, Planet and other companies provide the data and scientists and researchers come together to tackle modern slavery in a collaborative manner.[69] It is often the cost of the equipment, data, and expertise required to analyse imagery that can be prohibitive to the humanitarian sector; this is increasingly being considered by EO companies, who often have an emphasis on providing free data for humanitarian purposes.[70] Other organisations, such as DigitalGlobe, use the power of people to sift through vast amounts of information to help with specific issues (known as crowdsourcing). For the frequently unsafe and unmapped areas where humanitarian organisations work, remote sensing offers cross-national, time series data.[71]

Crowdsourcing

Crowdsourcing the analysis of satellite imagery has three key benefits in these circumstances. First, the datasets are 'Big Data', characterised by their volume, variety, and rapid rate of capture, which the remote sensing community is increasingly unequipped to manage alone.[72] Remote sensing data is varied and can be multi-source, multi-temporal, and multi-resolution. Second, satellite imagery analysis needs validation, because poor data comes with economic and ethical costs. Estimates of the prevalence and impact of modern slavery inform policy and, when derived from satellite data, mis-estimations could impact the resources made available to tackle slavery on the ground; data accuracy is important so as not to further endanger vulnerable people.[73] Crowdsourced data can be validated in a variety of ways, according to how the data will be used.[74] Third, and finally, human analysts are more creative and flexible in their assessment of satellite images than

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[69] Andrew Zolli. "Trust Conference Day 2 Keynote – Andrew Zolli." *Thomson Reuters Foundation*, accessed December 6, 2018, http://www.trustconference.com/videos/i/?id=d966ddc7-3909-4a02-9d16-0743b0946a79&confYear=2018.

[70] Susan R. Wolfinbarger. "Remote Sensing as a Tool for Human Rights Fact-Finding," in *The Transformation of Human Rights Fact-Finding* ed. Philip Alston and Sarah Knuckney. Oxford: Oxford University Press, 2016:463-478.

[71] Patrick Meier. *Digital Humanitarians*. Boca Raton, USA: CRC Press, 2015.

[72] Mingmin Chi *et al*. "Big Data for Remote Sensing: Challenges and Opportunities." *Proceedings of the IEEE* 104, 11 (2016):2207-2219.

[73] G.M. Foody. "Citizen Science in support of remote sensing research." *IEEE International Geoscience and Remote Sensing Symposium (IGARSS)* (2015):5387-5390; ———. "Valuing map validation: The need for rigorous land cover map accuracy assessment in economic valuations of ecosystem services." *Ecological Economics* 111 (2015): 13-28.

[74] Hansi Senaratne *et al*. "A review of volunteered geographic information quality assessment methods." *International Journal of Geographical Information Science* 31, no. 1 (2017):139-167; Andrea Wiggins, Greg Newman, Robert D. Stevenson and Kevin Crowston. "Mechanisms for Data Quality and Validation in Citizen Science." *IEEE Seventh International Conference on e-Science Workshops* (2011):14-19.

computers, and online volunteers can increase the efficiency of data processing and analysis at less cost.[75]

The crowdsourcing of data for the humanitarian sector has been embraced both in the field, such as OpenStreetMap, CrisisMappers and Digital Humanitarians, and online, for instance, MicroMappers and Tomnod.[76] Industries known to employ practices of modern slavery have been analysed, as previously noted in the South Asian brick manufacturing industry.[77] The humanitarian crowdsourcing project Tomnod and the Global Fund to End Slavery, also employed these techniques to track instances of fishing activity on Lake Volta, Ghana; an area where there is a prevalent use of child labour.[78] The study employed the crowd to look for instances of buildings on the lake shore where vulnerable children may be being housed, boats on the lake, and fish cages in the water. Overall, the study recorded 244,006 instances of fishing paraphernalia and buildings across the lake and its banks.[79] Mapping Lake Volta was invaluable for the NGOs that contributed to the project, allowing resources to be targeted more effectively and helping support children subjected to enslavement.

Conclusion

Remote sensing for human rights analysis is developing at a rapid rate due to the frequent and widespread collection of satellite imagery. Efforts to apply remote sensing principles have commonly been used to provide resources to humanitarian crises, information regarding remote locations and conflict zones, as well as the management of disasters, as the examples here illustrate. The success of these studies have demonstrated that it is entirely feasible to apply these methods to the study of modern slavery; findings from the employment of remotely sensed data to end modern slavery are already being used by NGOs to inform interventions on the ground, and indeed it is hoped that these resources would lead to long-term

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[75] Mordechai Haklay, Suvodeep Mazumdar, and Jessica Wardlaw. "Citizen Science for Observing and Understanding the Earth." In *Earth Observation Open Science and Innovation* ed. Pierre-Philippe Mathieu and Christoph Aubrecht. ISSI Scientific Report Series, vol 15. Cham, Switzerland: Springer, 2018:69-88.

[76] Steffen Fritz, Cidália Costa Fonte and Linda See. "The Role of Citizen Science in Earth Observation." *Remote Sensing* 9, no. 4 (2017):357.

[77] Boyd *et al.* "Slavery from Space: Demonstrating the role for satellite remote sensing to inform evidence-based action related to UN SDG number 8."

[78] International Justice Mission. "Child Trafficking into Forced Labor on Lake Volta, Ghana: A Mixed-Methods Assessment." Washington DC, 2016.

[79] Tomnod and World Freedom Fund. "Global Fund to End Slavery at Lake Volta, Ghana: Tomnod Project Report." 2015:11-13.

monitoring and legislative change supporting survivor rights.[80] Focus on the use of remotely sensed data specifically for the study of modern slavery has begun, but there is much more that needs to be explored, including a range of data sources and industries.

At present remotely sensed data cannot account for the precise locations where modern slavery practices are occurring, but insights can be provided into industries which can then be used as a resource by those locally undertaking direct action. Remote sensing can never replace the data that is collected in situ by people regarding such an important social issue as modern slavery, however, satellite imagery can be used to support these methods and provide data on a scale that may not be feasible on the ground. Therefore, multiple methods of data collection are needed to successfully advance the fourth anti-slavery movement and eradicate slavery in line with the SDGs 2030 target and for humanity to benefit from the freedom dividend it would provide.[81] The use of satellite data could revolutionise the way we think about the hidden crime of modern slavery – as you cannot hide from space.

[80] Rights Lab. "Data Programme."

[81] Kevin Bales. *Disposable People: New Slavery in the Global Economy*. Berkeley, CA: University of California Press, 2012: Preface; Landman. "Out of the Shadows: Trans-disciplinary Research on Modern Slavery."

Figures

Figure 1: An example of brick kilns located in Punjab, India – note the distinctive red colour which contrasts with the fields surrounding the structures. 4-band PlanetScope Scene projected in true colour with 3m resolution. Imagery captured September 2018. Copyright 2018 Planet Labs.[82]

[82] Planet Labs. "Planet Application Program Interface: In Space for Life on Earth." *Planet*, accessed December 6, 2018, https://api.planet.com.

Figure 2: An example of a fish-processing camp in the Sundarbans Reserve Forest, Bangladesh. Captured by RapidEye-1 in December 2017, 5m resolution projected in true colour, copyright 2018 Planet Labs.[83] The inset DigitalGlobe Worldview image is from November 2014 shows details of the camp including boats and structures, downloaded from Google Earth Pro.

[83] Ibid.

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Appendix B: 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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Author Contributions: Primary analysis and data collection from the estimation phase was undertaken by BJ with guidance from DB and GM. The primary application of remote sensing to estimate the number of kilns was developed by BJ, DB, GM and KB. The crowdsourcing data and experiment was devised and assessed by BJ, JW, GM and SM. The expert comparison was conducted by BJ, the independent adjudication by DB and the crowd analysis by JW. Write-up completed by DB with assistance, and editing, by BJ.

Full Reference: Boyd, D.S., Jackson, B., Wardlaw, J., Foody, G.M., Marsh, S., and Bales, K. (2018). Slavery from Space: Demonstrating the role for satellite remote sensing to inform evidence-based action related to UN SDG number 8. *ISPRS Journal of Photogrammetry and Remote Sensing*, 142, 380-388.

DOI: 10.1016/j.isprsjprs.2018.02.012

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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A R T I C L E I N F O

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

A B S T R A C T

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

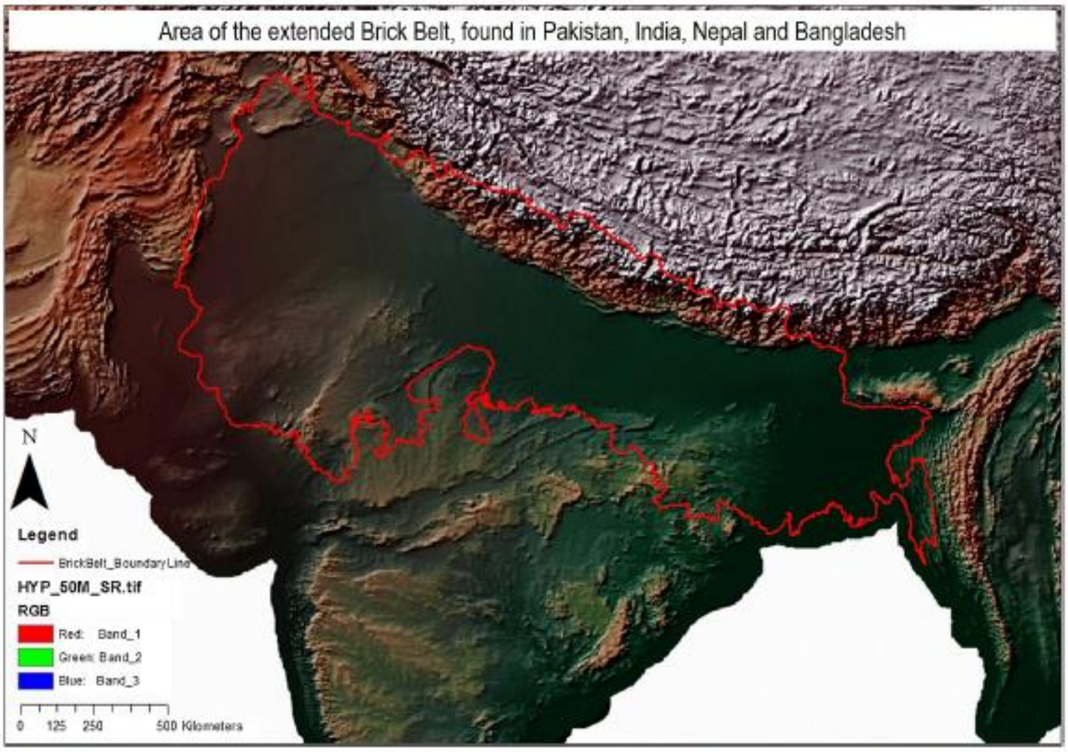

Fig. 1. The 'Brick Belt' is an unofficial area that encompasses much of the Brick-making industry globally. It covers the areas of Pakistan, Northern India, Nepal and Bangladesh.

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 FutureLearn.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

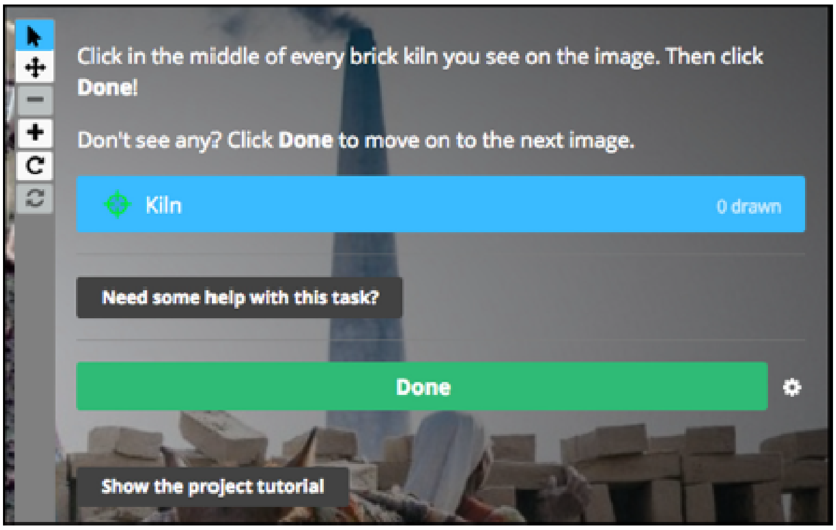

Fig. 3. The Slavery from Space task, with the Help, Done and Tutorial buttons below the question text. The images can be manipulated for closer inspection using the image controls seen to the left (e.g. zooming and panning). The classification page first presents volunteers with a tutorial that describes 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.)

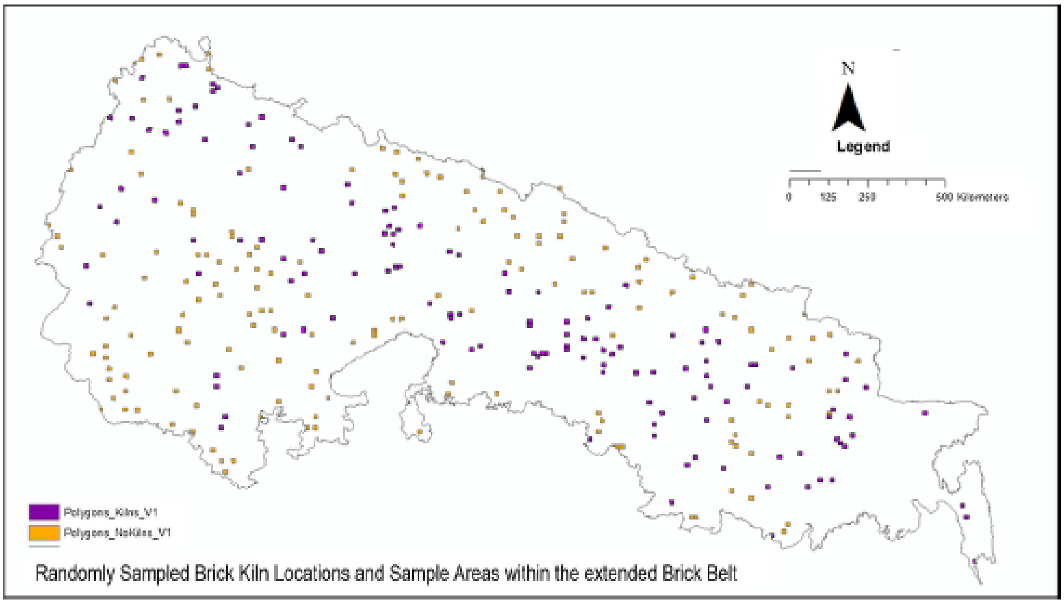

Fig. 4. Location of the randomly generated 320 100 km^2 sample cells, illustrating which had brick kilns and which had none, across the Brick Belt. A standard probability sample design, simple random sampling, was used here which allows unbiased estimation. A cell with multiple kilns has the exact same 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

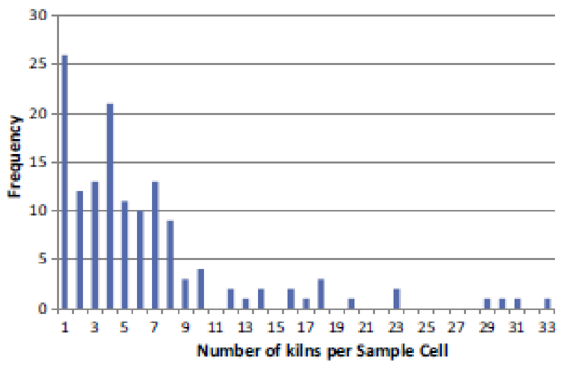

Fig. 5. Frequency distribution of number of brick kilns per sample cell. Note that 1142 kilns were found across the 320 sample cells with 43% of those cells featuring one or more brick kilns.

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

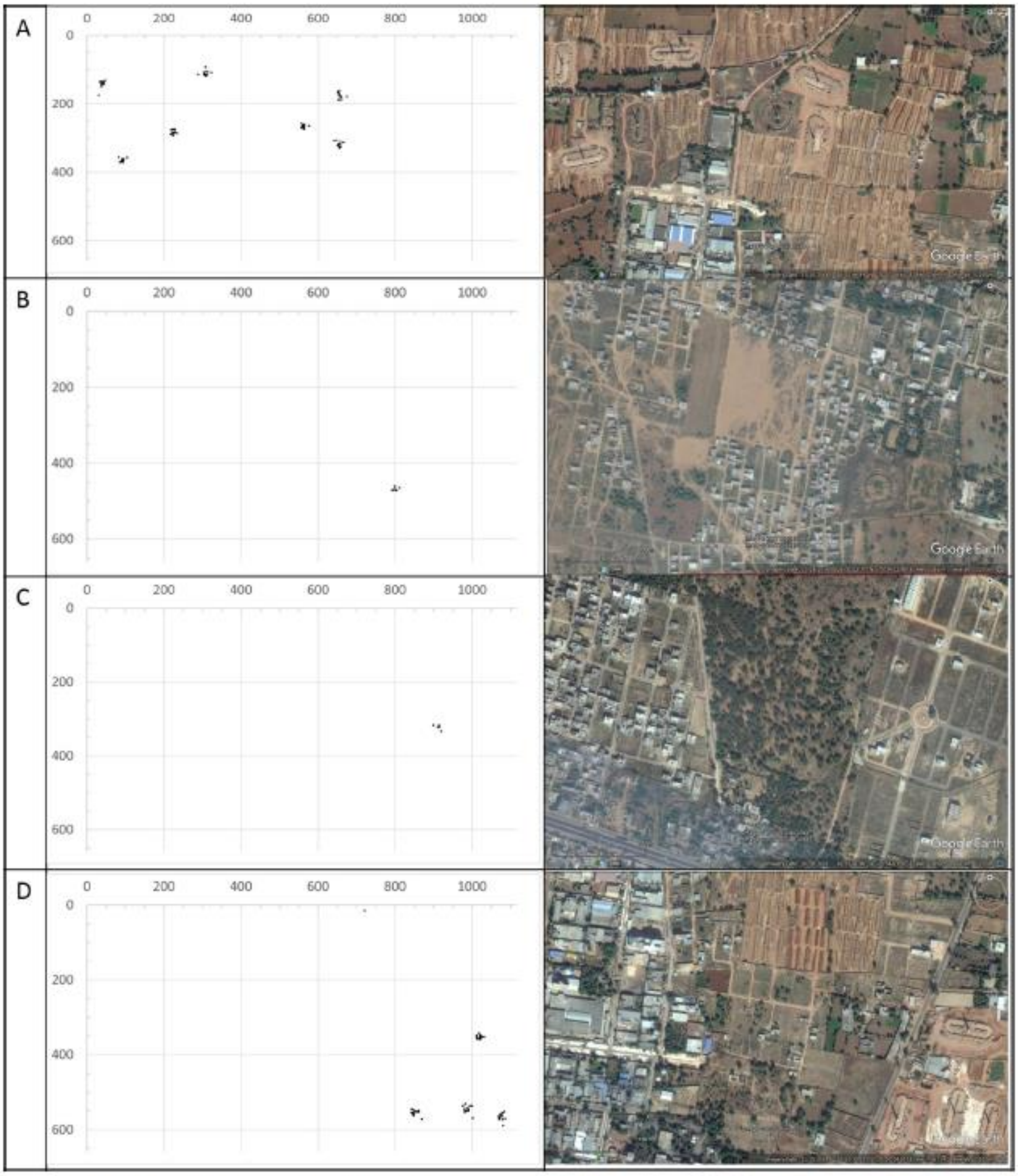

Fig. 6. Examples of markings made by volunteers. A: Example of an image with 7 kilns are the correct identification of them by the volunteers (as denoted by their clustering); B: An example of a disused kiln identified by some volunteers; C: An example of wrongly identified feature (a roundabout, though 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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Appendix C: Understanding the co-occurrence of tree loss and modern slavery to improve efficacy of conservation actions and policies

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Author Contributions: Concept development and write-up was completed by BJ and JS. Primary analysis was undertaken by BJ, with assistance on the Mozambique section by CB. DS provided the method for the analysis of the EPI/GSI which drove the direction of the paper, as well as feedback and edits on the manuscript.

Full Reference: Jackson, B., Sparks, J., Brown, C., and Boyd, D.S. (2020). Understanding the Co-Occurrence of Tree Loss and Modern Slavery to Improve Efficacy of Conservation Actions and Policies. *Conservation Science and Practice.* DOI: 10.1111/csp2.183

Received: 11 October 2019 | Revised: 16 January 2020 | Accepted: 24 January 2020
DOI: 10.1111/csp2.183

CONTRIBUTED PAPER

Conservation Science and Practice
A journal of the Society for Conservation Biology
WILEY

Understanding the co-occurrence of tree loss and modern slavery to improve efficacy of conservation actions and policies

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Funding information
Economic and Social Research Council, Grant/Award Number: ES/T501992/1

Abstract

Locations where populations are most reliant on forests and their ecosystem services for subsistence and development are also areas where modern slavery persists. These issues are noted within the Sustainable Development Goals (SDGs), both target 15.2 and 8.7 respectively. Often activities using slavery perpetuate deforestation, bolstering a slavery-environment nexus; which has been examined by comparing modern slavery estimates against environmental protection levels. This study assesses the relationship between tree loss and modern slavery focusing on four countries: Brazil, Ghana, Indonesia, and Mozambique. Previously mapped levels of tree loss and predicted future levels of loss have been compared against modern slavery estimates from the Global Slavery Index 2016 and illegal logging analyses to determine an estimate of the risk for slavery related tree loss. These results provide an insight in to the co-occurrence between modern slavery and tree loss due to a number of activities that are highlighted, including mining, illegal logging, and agricultural practices. The co-occurrence is both complex, and yet, beyond coincidental. Implications for both national and global policy are noted assessing the benefits that could be achieved by limiting tree loss and ending modern slavery; of benefit to both the conservation and antislavery communities.

KEYWORDS

conservation management and policy, deforestation, Environmental Performance Index, Global Forest Watch, Global Slavery Index, illegal logging, modern slavery, modern slavery-environment nexus, Sustainable Development Goals, tree loss

1 | INTRODUCTION

Maintained forest environments have the potential to aid in achieving a number of the Sustainable Development Goals' (SDGs) socioeconomic and ecological targets: SDG 15 ("Life on Land"), SDG 13 ("Climate Action"), SDG 1 ("No Poverty"), and SDG 2 ("No Hunger") (Seymour & Busch, 2016; Watson et al., 2018). But globally, areas where populations are most dependent on forests and their ecosystem services for subsistence and equitable sustainable development are also areas where modern slavery persists—often in activities perpetuating deforestation and similarly destructive practices that threaten biodiversity conservation (Bales, 2016; Food and Agriculture Organization [FAO], 2018; Brown et al., 2019). Thus, this modern slavery-environmental degradation nexus may add to anthropogenic pressures on forests, compromising their ability to support the attainment of the afore-mentioned SDGs—as noted in other sectors, including brick making (Boyd et al., 2018), farming, and fishing (Brown et al., 2019).

Defined by the 2012 Bellagio–Harvard guidelines as "constituting control over a person in such a way as to significantly deprive that person of his or her individual liberty with the intent of exploitation through the use, management, purchase, sale, profit, transfer, or disposal of that person," (Research Network on the Legal Parameters of Slavery, 2012) modern slavery is an umbrella term inclusive of varied forms of exploitation (e.g., forced labour, debt bondage, human trafficking, and slavery). In many locations globally, the incidental biodiversity loss associated with deforestation-related tree cover loss contributes to pervasive poverty, loss of livelihoods (associated to livelihood vulnerabilities such as climate change impacts; Obeng et al., 2011), and food insecurity (Seymour & Busch, 2016). These vulnerabilities of forested communities have contributed to the narrative that poverty leads to deforestation (Rai, 2019), yet this has been shown to be more complex with studies noting that poverty can in fact reduce deforestation as people relying on the forests often protect them (Angelsen & Kaimowitz, 1999; Angelsen & Rudel, 2013; Busch & Ferretti-Gallon, 2017). However, external threats to human security can force these already vulnerable populations to make decisions that result in them being exposed to modern slavery and participating in activities that lead to further deforestation (Bales, 2016). Activities associated with tree loss, and concurrently linked with modern slavery include tree harvesting for charcoal production in the Republic of Congo and Brazil; forest clearing for conversion to cattle ranching in Brazil and farmland for oil palm plantations in Indonesia; and gold mining in the Madre de Rios region of the Amazon and the Sahel region of West Africa wherein trees are harvested for lining shafts (Brown et al., 2019; Verité, 2017a). Additionally, many linked modern slavery-environmental degradation activities undermine conservation initiatives. For example, oil palm related deforestation, in countries such as Indonesia and Malaysia, degrades habitat for endangered species; timber for charcoal production is harvested from protected Amazonian areas; and mangroves are cleared for the establishment of illegal fish-processing camps in the Sundarbans Reserve Forest (Bales, 2016; Brown et al., 2019; Verité, 2017a).

Some estimates suggest that global forest cover decreased by approximately 3% from 41,282,694.8 sq. km to 39,991,336.2 sq. km between 1990 and 2015, with rates of tree cover loss highest in low-income countries (FAO, 2016). Tree cover loss, though, is in flux. Some cases classified as tree loss at one period in time may be reclassified as an area of gain the next measurement period because not all forest disturbances are associated with permanent conversion (i.e., deforestation rather than degradation) (Curtis, Slay, Harris, Tyukavina, & Hansen, 2018). However, Global Forest Watch (GFW) data predicted that more than a quarter of global tree loss between 2001 and 2015 was associated with commodity-driven deforestation, and thus likely to be permanent and not reforested (Curtis et al., 2018). Should areas be reforested, attainment of the SDGs and human security may still be at risk as intact forests, rather than restored forests, may exhibit different ecosystem services than restored forests (such as carbon sequestration and biodiversity protection, etc.; Watson et al., 2018). Conservation of forests are vital as deforestation has been noted as a contributor to the release of greenhouse gas emissions (Intergovernmental Panel on Climate Change, 2018); placing the forest-benefits which can be gained through climate change mitigation policies, such as their role as a land-based carbon sink (Krug, 2018), at risk. Forest conservation initiatives have been implemented to undertake this protection, including the United Nation (UN)s' premier development scheme "Reducing Emissions from Deforestation and Forest Degradation" (REDD+) which seeks to protect forests via conservation, sustainable management, and enhancing carbon stocks. However, these policies do not yet consider modern slavery as a potential anthropogenic driver of deforestation. Preventing deforestation is a pertinent conservation goal and because of the association between deforestation and modern slavery (Verité, 2017a), conservation should thus begin to consider the continued presence of modern slavery as a hurdle to overcome in management and conservation plans.

The GFW has measured and mapped tree loss yearly through remote sensing sources (Hansen et al., 2013). The antislavery field uses the Global Slavery Index (GSI)—national level estimates of prevalence of, and risk to, modern slavery based on Gallup-style surveys and proxies empirically associated with exploitation (International Labour Organization [ILO] & Walk Free, 2017). While both represent data-limited fields that are reliant on and subjected to disagreements about the rigor and sensitivity of estimations and the role of politically motivated government self-reports, we purport these tools should not be used discreetly (Bales, 2017; Curtis et al., 2018). Instead, it is more efficacious to identify synergies between tools to extrapolate more holistic understandings of conservation challenges associated with social justice concerns. While the GFW data has been demonstrating the where and when of deforestation, only recently has it started answering the question of why (Curtis et al., 2018). This paper extends the argument of why by integrating the GSI with the GFW and associated datasets, elucidating for the first time empirically the contribution that modern slavery could be making to deforestation-related tree cover loss and the challenges it presents for conservation management and planning. This manuscript is intended to provide insight into the connections between tree loss and modern slavery which may be relevant for conservation researchers, practitioners and the antislavery community to support multiple UN SDGs and encourage sustainable development via the indivisibility principle (UN, 2016).

2 | METHODS

Firstly, modern slavery estimates from the GSI 2016 (Walk Free, 2016) were modeled against the Environmental Performance Index (EPI) from the same year (Hsu et al., 2016; Figure 1). This was used to determine which countries require further assessment in relation to the slavery-environment nexus (Brown et al., 2019).

Secondly, to determine the levels of modern slavery associated with tree loss, the ILO & Walk Free (2017) estimate of people enslaved in agricultural, forestry, quarrying, and mining industries was used; totaling 15.3% of those in forced labor globally. These are industries known to contribute to tree loss and degradation. The total country estimates from the 2016 GSI were altered to determine the estimated number enslaved within the sectors noted above (Figure 2). Differing levels of "at risk" countries have been identified. Thirdly, these were compared with the potential losses from deforestation caused by slavery—calculated by identifying rates of illegal logging from a number of sources (see Hoare, 2015: pp. 61–63; INDUFOR, 2004: p. 3; Lawson et al., 2014: p. 122; Seneca Creek Associates & Wood Resources International, 2004; Toyne, O'Brien, & Nelson, 2002; World Bank, 2006: p. 9). The lowest values were used as a proxy for the presence of slavery. These figures were applied to GFW tree loss by deforestation data (2001–2018) to determine the potential area of land deforested per country by slavery practices (Figure 3). All data for this analysis was accessed via the GFW platform—these data included tree cover loss (based on Hansen et al., 2013) and tree cover loss by driver (based on Curtis et al., 2018) (GFW, 2019; The Sustainability Consortium et al., 2019). Countries were split into risk categories based on the quartile ranges of the data and are presented as "low" risk, "low-medium," "medium-high" and "high" risk depending on the rank in which they fell. Finally, the risks of slavery causing tree loss from the illegal logging analysis, and the slavery estimates (Figures 2 and 3) were compared with

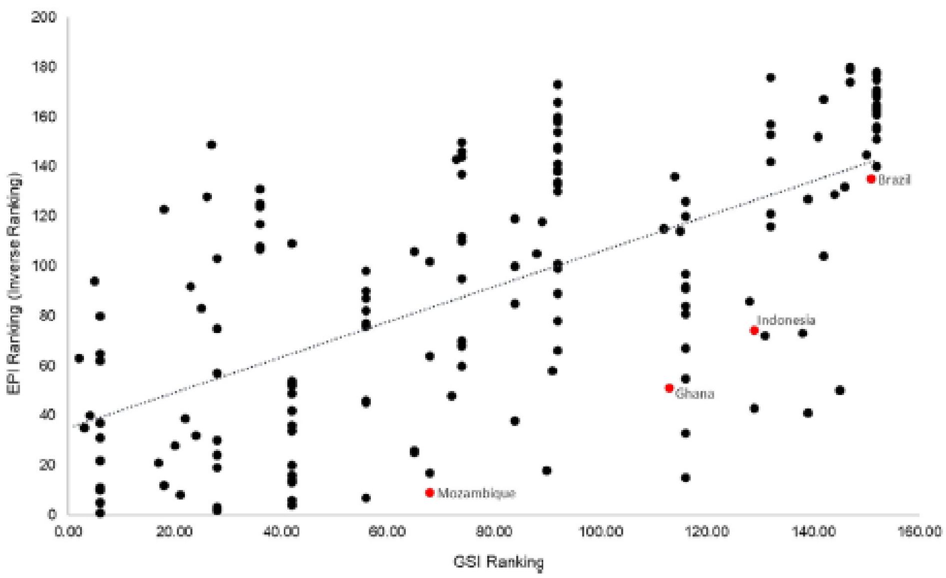

FIGURE 1 Model of the Global Slavery Index (GSI) 2016 modern slavery estimates per country against the Environmental Performance Index (EPI) 2016 score. There is a strong correlation between countries with lower estimated levels of modern slavery and countries with higher environmental protections

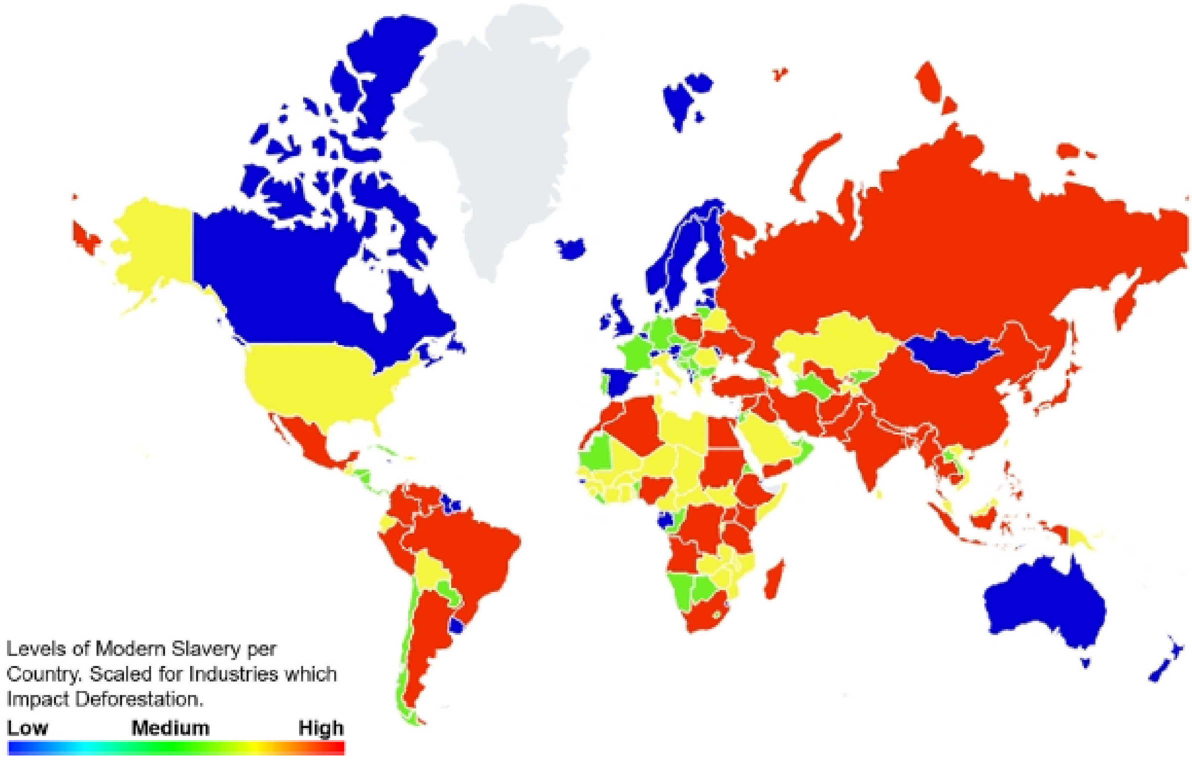

FIGURE 2 Estimated levels of slavery per country which are expected to impact levels of tree loss. Created by determining the activities which affect deforestation using the ILO & Walk Free (2017) "Global Estimates of Modern Slavery" which equated 15.3% of those enslaved and applying this to the 2016 GSI estimates

predicted tree cover loss, modeled at continental and global levels by Hewson, Crema, González-Roglich, Tabor, and Harvey (2019) as part of a new 1 km resolution dataset. These data are freely available to download (from http://futureclimates.conservation.org/index.html). Levels of predicted loss were compared on a global scale before a more detailed analysis of the predicted loss patterns was identified for the four countries investigated in more detail (shown in Figure 4).

The overlap between areas with high levels of predicted tree loss, moderate-high estimated slavery levels and illegal logging, as well as documented evidence of slavery within their forestry sectors were used to determine which countries were to be further assessed. These countries have experienced, and are likely to continue experiencing, tree loss associated with industries known to use slavery. The countries chosen using these parameters are: Brazil, Ghana, Indonesia and Mozambique. While each have differing vulnerabilities; all are found across the tropics where Hewson et al.'s (2019) model predicts some of the highest losses. Past tree loss/tree gains for these countries were then extracted using the Hansen et al. (2013) derived dataset (GFW, 2019; accessed via Google Earth Engine [GEE]). Comparison with the future predicted loss for these nations was enabled, suggesting evidence of whether the pattern of degradation will continue.

3 | RESULTS

There is a positive relationship ($R^2 = .401$) between stronger environmental protections and lower estimated cases of slavery (Figure 1). The four countries studied in more detail are spread along the GSI/EPI relationship with Brazil performing the best and Mozambique (which may also be considered an outlier) the worst. This provides an important insight into the slavery-environment nexus, identifying a link between the two sectors which has only recently begun to be explored (Brown et al., 2019). Although the relationship is assessed in terms of tree loss within this paper, there is scope for analysis within other sectors known to employ practices of modern slavery and cause environmental damage, for example, mining, quarrying, fish processing, and brick manufacture, and so forth.

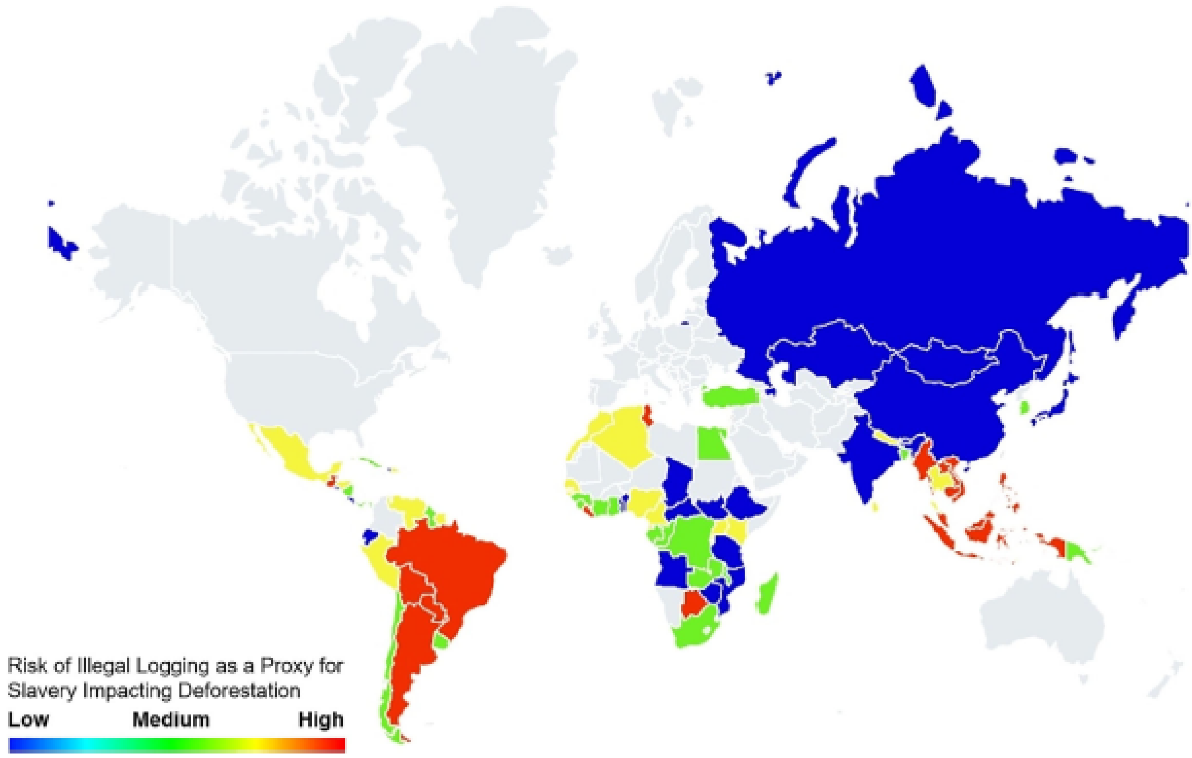

FIGURE 3 Risk of illegal logging (as a proxy for slavery) impacting on the proportion of deforestation measured by Global Forest Watch (GFW) 2001–2018

Hewson et al.'s (2019) global tree loss maps predict high rates of loss across vast swaths of the tropics, as well as Canada and Russia—where legitimate commercial logging industries dominate (Curtis et al., 2018); however, some of these countries exhibit lower risk overall when compared with the modified GSI figures (Figure 2). All four countries assessed in further detail have estimated rates of slavery in the "medium-high" range, both overall (Table 1), and when assessed in relation to tree loss related activities (Figure 2), particularly when assessed against illegal logging levels (Figure 3). High rates of predicted tree loss by 2029 are found in Brazil (Figure 4) this is reflected in the illegal logging analysis (Figure 3). Southeast Asia is set to experience losses associated with the oil palm industry (Verité, 2017a), which may be connected to illegal logging (Figure 3). Across central Africa high rates of tree loss are expected, despite past reductions (Rudel, 2013). The drivers of previous tree loss here have been attributed to land settlements (due to population growth), agri-business, logging, and cattle-ranching. Only the very center of the Congo rainforest is likely to be lower risk. The extraction of resources to maintain living standards in the current climate crisis is also expected to have a damaging effect (Serdeczny et al., 2017).

Figure 4 shows the variation of predicted tree loss that is expansive across much of Ghana and Mozambique. Higher predicted losses within Indonesia are found in areas where oil palm plantations dominate (Figure 4) and illegal logging as a proxy for slavery is high (Figure 3). The inaccessibility of the protected Brazilian Amazon means that the widespread damage predicted across the rest of the country is limited in this region; however, there is clear encroachment along the southern and eastern forest edges. The Hansen et al. (2013) derived data from the GFW (2019) showed that all nations have experienced net-tree cover loss from 2000–2018 (Table 2) with little recovery indicating Hewson et al.'s (2019) predicted loss values are likely unless practices are altered.

4 | DISCUSSION

Based on the results, the four nations of Brazil, Ghana, Indonesia, and Mozambique were further investigated. Tree loss in these sectors associated with slavery is likely to continue. As a result, conservation activities that do not consider the effects of modern slavery may be less

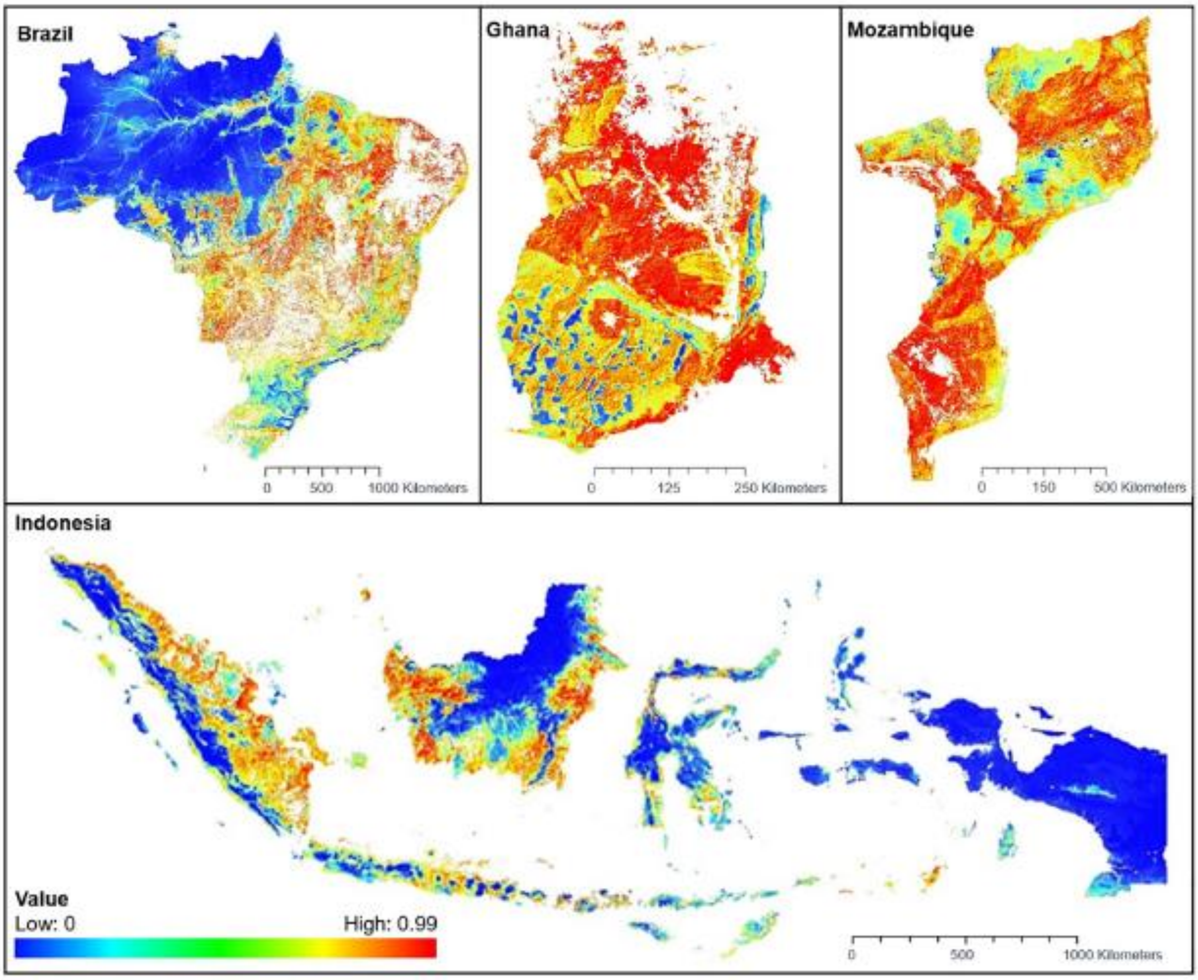

FIGURE 4 The four countries which have been investigated in the discussion. Clips of the global prediction model by Hewson et al. (2019) clearly demonstrate the areas of these nations which are most at risk of tree cover loss through their prediction of tree loss transitional potential

effective as slavery frequently provides the labor force needed to illegally clear land and deforest (Bales, 2016), as explored in Figure 3. This must be considered when advocating for global tree restoration potential to provide benefits around, for example, climate change mitigation (Bastin et al., 2019), particularly within tropical forests (Brancalion et al., 2019). There will only be limited success without the mainstream incorporation of slavery impact understanding within conservation management schemes. This acknowledgement supports the achievement of interdisciplinary social justice in conservation, as advocated for by Bennett et al. (2017). With the addition of an antislavery framework, more narrow conceptualizations of resource users are challenged and understanding of the social justice dimensions of the relationships between people, forests, and conservation is enriched and broadened to include the often peripheral or unconsidered social domains of agency and dignity—which in the case of modern slavery and tree loss are indivisible from attaining the more frequently considered social justice objective of equality. Moreover, advocating for "just conservation" (Vucetich et al., 2018) in this manner would also support the achievement of the "freedom dividend" (Bales, 2012) which promotes the economic, social, cultural and environmental benefits that may be gained from ending modern slavery. As Figure 1 showed, there is a connection between environmental protections and modern slavery. While antislavery tools alone will not halt all tree cover loss, they could help mitigate illegal clearing and deforesting—activities that undermine conservation policies and make sustainable goals and targets difficult to achieve. What follows is an assessment of

TABLE 1 Further details of the case study countries' Global Slavery Index (GSI) figures (Walk Free, 2016) and their Environmental Performance Index (EPI) scores (Hsu et al., 2016)

	Prevalence figures from GSI 2016				Vulnerability scores from GSI 2016					Government response GSI 2016	EPI figures	
Country	2016 Global slavery prevalence rank	Estimated percent of population in modern slavery	Estimated number in modern slavery	Estimated number of people in modern slavery working in activities related to tree loss[a]	Civil and political protections	Social, health and economic rights	Personal security	Refugees and conflict	Mean score	Total score	2016 Global EPI rank	2016 Global EPI score
Brazil	51	0.078	161,100	24,648	37.98	20.46	45.88	30.74	33.77	56.85	46	78.9
Ghana	34	0.377	103,300	15,805	51.89	38.42	47.45	28.26	41.51	28.43	130	58.89
Indonesia	39	0.286	736,100	112,623	39.15	43.35	50.38	36.01	42.22	40.61	107	65.85
Mozambique	22	0.520	145,600	22,277	39.91	48.46	54.40	35.86	44.65	40.85	172	41.82

[a]Estimated calculated by taking the occurrence of tree loss related activities identified within the literature, including agriculture, forestry, mining and quarrying from the "Global Estimates of Modern Slavery" (ILO & Walk Free, 2017: p. 26) occurring at a rate of 15.3% and applying these to the estimated number in modern slavery from GSI 2016. This is likely an overestimation due to the use of global figures, but provides a proportion closer to a real value that the overall slavery estimates for each nation. Rounded to the nearest whole number.

TABLE 2 Tree loss and gain between the year 2000 and 2018 as calculated within Google Earth Engine (GEE) using the Hansen et al. (2013) and Global Forest Watch (GFW) dataset (GFW, 2019)

Country	Tree loss 2000–2018 (ha)	Tree gain 2000–2018 (ha)	Net loss 2000–2018 (ha)
Brazil	47,000,000	2,864,414.315	−44,135,585.69
Ghana	671,806.7597	57,439.39172	−614,367.368
Indonesia	21,300,000	3,479,720.101	−17,820,279.9
Mozambique	1,764,314.836	55,368.62182	−1,708,946.214

these areas and industries vulnerable to modern slavery in relation to tree cover, a review of their political response and where the barriers and leverage points may exist to eradicate the effects of the modern slavery-environment degradation nexus. While focus is placed on these four nations within this article, going forward, it will be important to address the wider trends of tree loss, illegal logging and slavery outside of the tropics.

4.1 | Brazil

As an upper-middle income country, Brazil has developed substantive antislavery legislation (Brazilian Penal Code 2003 Article 149) and conservation policies (e.g., protected reserves, new forests [Frederico & Anderson, 2016] etc.). Yet much of Brazil's money is not distributed to large portions of the population; this inequality is necessary in the continued exploitation of people and the environment. Deforestation activities known to use exploited workers have been noted to persist in cattle-ranching (fuelling the leather and beef sectors) and the timber industry (Brown et al., 2019). Areas of tree loss in the protected Amazon are expected to be low as accessibility is difficult, whereas there is increasing risk along "agriculture-forest frontiers" which is expected to have harmful long-term effects (Figure 4; Garrett et al., 2018), thus limiting the climate change mitigation benefits that the forest provides. Contrastingly, Santos de Lima et al. (2018) suggest that unprotected areas are expected to experience losses of up to 40% by 2050 due to illegal harvesting, noted previously to use enslaved workers (Bales, 2016).

Brazil's comparatively high levels of environmental protections are reflected within the nation's EPI score (Table 1) with a rank of 46 out of 180. Although there has been some evidence of reduced deforestation (Amin et al., 2019), overall tree cover has declined (Table 2) and is predicted to continue declining (Figure 4; Hewson et al., 2019). However, both climate change and deforestation have been noted as destabilizing the Amazon rainforest ecosystem (Lenton et al., 2019). Additionally, Brazil's environment ministry has reported recent periods of accelerated deforestation and land clearing in Mato Grosso, Rodônia, and Amazonas states (Escobar, 2019; Watts, 2015). These findings are likely related to the relaxation of environmental policies amid the current socio-political context (Escobar, 2019) which has also seen restrictions of the modern slavery definition (Scott, De Andrade Barbosa, & Haddad, 2017) by removing the classification of forced labor from under the umbrella of modern slavery. This is expected to weaken the response of labor inspectors and limit the response to end economic exploitation (Mendes, 2017; Phillips, 2017). Despite extant legislation, Brazil is ranked 51 of 167 countries in the GSI (Table 1; Walk Free, 2016); Brazil's current status in the GSI/EPI rankings (Figure 1) could therefore change as a result of these political decisions and declining protections. Although legislation exists for both issues, a lack of resources for labor enforcement, legal loopholes, corruption, and a declining economy (Watts, 2015) have stalled Brazil's progress on meeting the SDG targets to end both deforestation and slavery by 2030. Training provided by antislavery organizations for front-line responders undertaking labor inspections and conservation activities, to simultaneously respond to deforestation and modern slavery, would enable them to provide pastoral support and assistance to survivors of exploitation. This training would primarily support these actors with the identification of key modern slavery signs, build collaborative networks and trust between groups, and inform conservationists of which authorities to notify should they encounter exploitative practices. Following the example of integrated training in the fisheries sector of the Pacific Island states (United States Department of State, 2018), could be one option for maximizing the limited resources available to reach isolated sites for enforcement purposes. Cross-sectoral collaboration could introduce more checks and balances to curb some forms of corruption; this is pertinent in light of the August 2019 Amazon fires and the refuting of deforestation figures by President Bolsonaro (Escobar, 2019).

4.2 | Ghana

Ghana has approximately 15,000 people estimated to be working in conditions of slavery within activities related to tree loss (Table 1)—this is "medium-high" risk when compared to our global analysis (Figure 2). As a lower-middle income country, agricultural forest products are highly depended upon for subsistence (Appiah et al., 2009). Tree losses have been widespread and will continue to be so (Figure 4); this is more likely as droughts occur in the region as a result of climate change where Dwomoh, Wimberly, Cochrane, and Numata (2019) found that the degraded forests had the highest burned area, concluding that both drought and degradation affected the location of the fires. Cocoa (Verité, 2017a) and rubber plantations (Verité, 2017b) are drivers of commodity driven deforestation and land clearing, known to use forms of slavery. Specifically, in the west of Ghana, mining is the dominant cause of forest loss (Schueler, Kuemmerle, & Schröder, 2011), often done illegally, and associated with slavery—including forced and child labor and human trafficking (Bales, 2016; Verité, 2017a). Additional losses to the forests are caused by illegal logging (estimates suggest that 34–70% of tree loss is caused by illegal logging practices in Ghana: Seneca Creek Associates & Wood Resources International, 2004; Hoare, 2015), and disturbance from fire (Janssen et al., 2018), which limit vegetation recovery.

The Ghanaian authorities have ratified legislative efforts, with a number focusing on child labor, and programs to address these concerns have also been introduced (Delta 8.7, 2019). However, as noted in the low GSI government response score (Table 1), these policies and programs are not being fully implemented and most Ghanaian family units lack the capital to participate in the artisanal and formal mining sector; therefore, limiting the response for the largest tree loss driver in the country. As a result, adults and children are forced to work in illegal mines (Verité, 2017a). In response to deforestation and land clearing, the REDD+ program is active (Forestry Commission, 2016)—aiming to combat environmental destruction by reducing the burden of poverty and supporting sustainable development. Because the modern slavery-environmental degradation nexus occurs in the context of poverty and a lack of sustainable jobs, it is plausible to consider integrating antislavery tools into REDD+ frameworks to fully achieve their intended environmental and social benefits.

4.3 | Indonesia

The expansion of Indonesian agricultural practices are causing tree cover removal, biodiversity loss and the monopolization of crop production in the form of oil palm—vital for this lower-middle income economy, and yet auditors assessing the oil palm sector recently found 19% of the country's plantations to be operating within forest areas without the appropriate permits (Listiyorini & Rusmana, 2019). Moreover, 81% of oil palm plantations violated numerous state regulations, including operation of sites in protected areas and noncompliance with sustainable production standards (Listiyorini & Rusmana, 2019), including environmental damage; such as deforestation and fires (Carlson et al., 2018). These factors compound the risks related to exploitation and forest degradation within Indonesia; the growth of oil palm plantations affect carbon sequestration by trees and within peatland that has been drained for production, which increases the risk of flooding thus limiting their value (Sumarga, Hein, Hooijer, & Vernimmen, 2016). Alongside oil palm agri-business, illegal logging is a driver of tree loss (Palmer, 2001) and the risk of modern slavery activities contributing to this loss is high (Figure 3). The highest levels of predicted tree loss (Figure 4) correspond to noted locations of oil palm milling operations (FoodReg & World Resources Institute, 2019), suggesting that the commodity is the primary driver of deforestation (an assertion supported by Curtis et al., 2018). However, since the introduction of certification schemes the rates of deforestation have declined (Carlson et al., 2018).

Palm oil is used extensively in the production of numerous goods, despite evidence the industry degrades the environment and workers experience conditions which leave them vulnerable to discrimination, exploitation, and modern slavery (Verité, 2017a). The economic importance of this crop (Indonesia is the top producer and exporter of palm oil worldwide) belies the limited political action to lower the expansion of production (UNComtrade, 2018). However, antislavery programs have been implemented to support transnational and domestic migrant workers in the sector (Hasan, Rukmana, Dr, & Morris, 2018). Unfortunately, as the government response score indicates (Table 1), often only minimal protections are legislatively implemented. As there has been some impetus towards eradicating labor abuses, the Indonesian oil palm sector may present an opportunity to trial the integration of conservation actions into antislavery tools.

4.4 | Mozambique

Mozambique is both the country with the lowest income, and lowest EPI score (Hsu et al., 2016), of the four nations. It also has some of the highest vulnerability scores and low government response (Table 1). Analysis suggests illegal logging driven by slavery within Mozambique is lower risk (Figure 3). However, the country exhibits vulnerabilities to enslavement within the forestry sector that are high. The leading drivers of deforestation include: small-scale and commercial agriculture, construction, logging, and charcoal production (Ryan, Berry, & Joshi, 2014). Logging has recently been the dominant cause of tree loss due in part to China's demand for timber (93% of all timber exports from Mozambique are destined for China, which contributed to 48% of the total illegal logging rate in 2012 for Mozambique: Macqueen, 2018; EIA 2013) and the increased presence of Chinese companies operating in rural communities, which is leaving people vulnerable to the enhanced effects of climate change (Mambondiyani, 2019). Timber is also being lost through cross-border smuggling with neighbouring nations en route to China (EIA, 2013). Environmental protections are necessary within Mozambique as the country is increasingly dependent on forests to mitigate the effects of climate change (Serdeczny et al., 2017); whilst stronger legislation surrounding the movement of timber products are necessary in limiting the economic losses from the exploitation of those goods.

The lack of funds available to the Mozambique government to establish these protections is one of the reasons the removal of resources is likely to continue, particularly in the southern and north-eastern provinces (Figure 4; Hewson et al., 2019); perpetuating a cycle of economic and environmental profiteering from outsiders and corrupt officials. China's expanding influence across Africa and the effects of the climate crisis mean landcover change and adaptation is likely to be forced, risking further vulnerabilities to enslavement associated with the slavery-environmental nexus (noted in: Bales, 2016; Brickell, Parsons, Natarajan, & Chann, 2018; Brown et al., 2019). Risks include an increased level of damage from natural hazards, such as cyclones, as the forests are no longer present to limit the impact. The proportion of intense tropical storms events are likely to increase as anthropogenic climate change persists (Walsh et al., 2015) which is likely to raise the presence of climate-induced forced migration; this increases the risk of exploitation and has been noted in other regions affected by cyclones (International Organisation for Migration, 2016), it is therefore also likely to occur in this region. The predicted tree loss by Hewson et al. (2019) in Figure 4 is a business-as-usual model, and therefore these vulnerabilities are likely to be more damaging faster, unless they are addressed within land management plans. Some of these plans are being supported by the World Bank; they aim to protect forests, their biodiversity and ecosystem services, through programs such as REDD+, alongside limiting climate change impact (Kaechele, 2019).

5 | LIMITATIONS

Limitations are associated with the use of secondary data and the differences in time between the two datasets were difficult to avoid. Although tree loss data are collected regularly via satellite data, modern slavery data is more sporadic. We do not have exact slavery figures at present, though the best estimates available (those from the 2016 GSI) were used. Although the EPI scores are weighted, they do not account for environmental load displacement placed on the Global South, in terms of reducing environmental damage and limiting emissions, whilst the Global North, may also demand natural resources. This is a critique of the EPI and should be corrected for future use going forward. The predicted tree loss figures were formed through a model, and the limits of the process have been noted by Hewson et al. (2019: p. 11). Changes to modeling method (Goldman & Weisse, 2019) for the Hansen et al. (2013) GFW dataset dictated the scope of analysis. Combining these analyses with other data sources, such as the Global Forest Resources Assessments (GFRA; FAO, 2020), could strengthen some of the limitations of using the GFW data. However, this was not used within this assessment due to the temporal availability of the GFRA data, which is collected every five years. The use of illegal logging as a proxy can only provide a part of the story and a deeper understanding is required going forward. Many countries had no data for illegal logging and a regional figure was used for those countries without specific rates of loss in Africa, Asia, and Latin America—ultimately there are many data gaps particularly in the Global North which need to be filled in future analyses. Finally, the countries investigated here are by no means the only ones affected by tree loss and modern slavery; nor is all tree loss deforestation. Primary data collected with ground-partners will enable the problem's scale to be fully understood.

6 | CONCLUSION

The co-occurrence of modern slavery and tree cover loss—particularly that associated with illegal deforestation and land clearing—suggests a complex relationship between the phenomena that is beyond coincidental. Yet, a two-way cyclical relationship between modern slavery and tree loss within forests is present. When biological diversity decreases due to tree cover loss, vulnerability to slavery increases in turn increasing modern slavery's contributions to tree cover and biodiversity loss. Therefore, forest related conservation actions and policy must become socially just, and account for slavery and its associated illegal and environmentally destructive practices. As a result of the United Nations 2030 agenda, approximately a decade remains to abolish both slavery (SDG 8.7) and deforestation (SDG 15.2). Thus, novel approaches to action and policy are needed in these data-limited areas. Identifying synergies between conservation and antislavery action and policy could accelerate and/or improve the likelihood of attaining the SDGs. Due to the breadth of disciplinary expertise and the presence and influence of the conservation marketing and social science working groups, the Society for Conservation Biology is poised to lead the field on these innovative, transdisciplinary, and cross-sectoral approaches.

ACKNOWLEDGMENTS AND DATA

The authors would like to thank J. Hewson, S. Crema, M. González-Roglich, K. Tabor, and C.A. Harvey for producing the predicted tree cover loss models and making them open access via Conservation International. We would also like to thank the team from the University of Maryland for the open access past tree loss data accessed via GEE. The World Resources Institute for providing free and accessible data on tree loss via the GFW Platform. Finally, we thank the reviewers for their comments. This work was supported by the UK's Economic and Social Research Council (ESRC) [ES/T501992/1].

The links to the data and code used will be uploaded to the University of Nottingham's Data Repository (https://rdmc.nottingham.ac.uk/).

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

B.J. and J.S. constructed and designed the concept for the paper, with BJ processing the data. The EPI/GSI methodology was created by DB and implemented by B.J. C.B. assisted with the Mozambique analysis. Writing was predominantly undertaken by B.J. and J.S. with assistance from C.B. and D.B.

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How to cite this article: Jackson B, Decker Sparks JL, Brown C, Boyd DS. Understanding the co-occurrence of tree loss and modern slavery to improve efficacy of conservation actions and policies. *Conservation Science and Practice*. 2020; e183. https://doi.org/10.1111/csp2.183

Appendix D: Fish Camps – Supplementary Material

Supplementary material produced as part of the land-based fish-processing activities in the Sundarbans, Bangladesh. Table D.1 shows the range of ecosystem services which may be gleaned from the mangrove forest; these are then categorised according to the ecosystem services as defined by the Millennium Ecosystem Assessment (MEA 2005). The literature used to inform these classifications were collected as part of a systematic search of the main literature databases: Web of Science, Scopus, Springer Link, Science Direct, and Google Scholar (search was undertaken on 15.01.2019). Search terms included: ‘ecosystem services* AND Sundarbans* AND Bangladesh*’. References for the literature noted from this search and included in the table are found in the main reference list.

Table D.1: An inventory of the ecosystem services found specifically within the Sundarbans Reserve Forest. These services were compiled following a search of academic literature databases (Web of Science, Scopus, Springer Link, Science Direct and Google Scholar). The results from this literature review are based on the four categories of ecosystem services defined within the Millennium Ecosystem Assessment (MEA 2005).

Ecosystem Services	Indicators	Data Sources
Provisioning Services		
Food Production	Fish – freshly caught and dried fish for the domestic and international food markets. Shrimp (and shrimp larvae); crab, molluscs. Fisheries – 678 diverse species of fish (291 species total), and other marine life; traditional artisanal fishing practices. Leaves, fruits and vegetables – crops being grown to the edges of the SRF.	Hossain *et al.* (2016) Islam *et al.* (2018); Abdullah-Al-Mamun *et al.* (2017); Uddin *et al.* (2013); Hoq (2016)
	Fishing and hunting.	Giri *et al.* (2015)
Forest Products	Logging (illegal) of protected mangroves and deforestation practices (some being used to produce fish-drying racks and buildings associated to the illegal processing of fish products by children). Fuel – both wood and charcoal. Apiculture - honey and beeswax.	Uddin *et al.* (2013); Islam *et al.* (2018); Hossain *et al.* (2016); Ahmed *et al.* (2017)
	Thatching materials – golpata (*Nypa fruticans*) and Malia grass (*Phragmites karta*).	Abdullah-Al-Mamun *et al.* (2017); Uddin *et al.* (2013)
Cultural Services		
	Medicine. Clothing – from furs and skins.	Abdullah-Al-Mamun *et al.* (2017)
Cultural Services	Artisanal fishing methods (linked to tourism). Religious festivals and temples of important cultural significance. Educational research.	Hoque Mozumder *et al.* (2018); Islam *et al.* (2018)
	Art and art products (e.g. paintings, photos etc.).	Mehvar *et al.* (2019)

Recreational Services	Tourism– promote the unique natural services available; Dublar Char commonly promoted as a tourism hotspot.	Hossain *et al.* (2016); Abdullah-Al-Mamun *et al.* (2017)
	Water transport.	Giri *et al.* (2015)
Regulatory Services		
Climate Regulation	Carbon sequestration – the largest carbon sink within South Asia, and the largest continuous mangrove system in the region. Mangroves are highest blue carbon pool (6.5 billion tonnes) globally.	Hossain *et al.* (2016) Abdullah-Al-Mamun *et al.* (2017)
	Added protection from rising sea levels associated with climate change in a low lying country.	
	Micro-climate stabilisation.	Giri *et al.* (2015)
Coastal Impacts	*Erosion*	
	Erosion of the coastline due to climate change and adverse practices causing destabilisation of the sediments within the delta due to mangrove removal; tree falling.	Ghosh *et al.* (2016)
	Loss of sediments from the Ganges delta to the Indian Ocean.	
	Accretion	
	Mangrove roots trap sediments from the ocean during tidal changes; allow for the creation of new mudflats, fertilisation of species and increasing area under the mangroves.	
	Shoreline stabilisation and wave attenuation.	Giri *et al.* (2015); Islam *et al.* (2018)
Natural Hazard Protection	Flood regulation from tidal surges, tsunamis, cyclones and monsoons – also reducing the impacts from cyclones and storms such as the intensity of the wind and subsequent storm surges.	Abdullah-Al-Mamun *et al.* (2017); Akber *et al.* (2018); Hoq (2016)
	Crop and aquaculture damage.	
	Added protection from rising sea levels associated with climate change in a low lying country (climate regulation).	
Supporting Services		

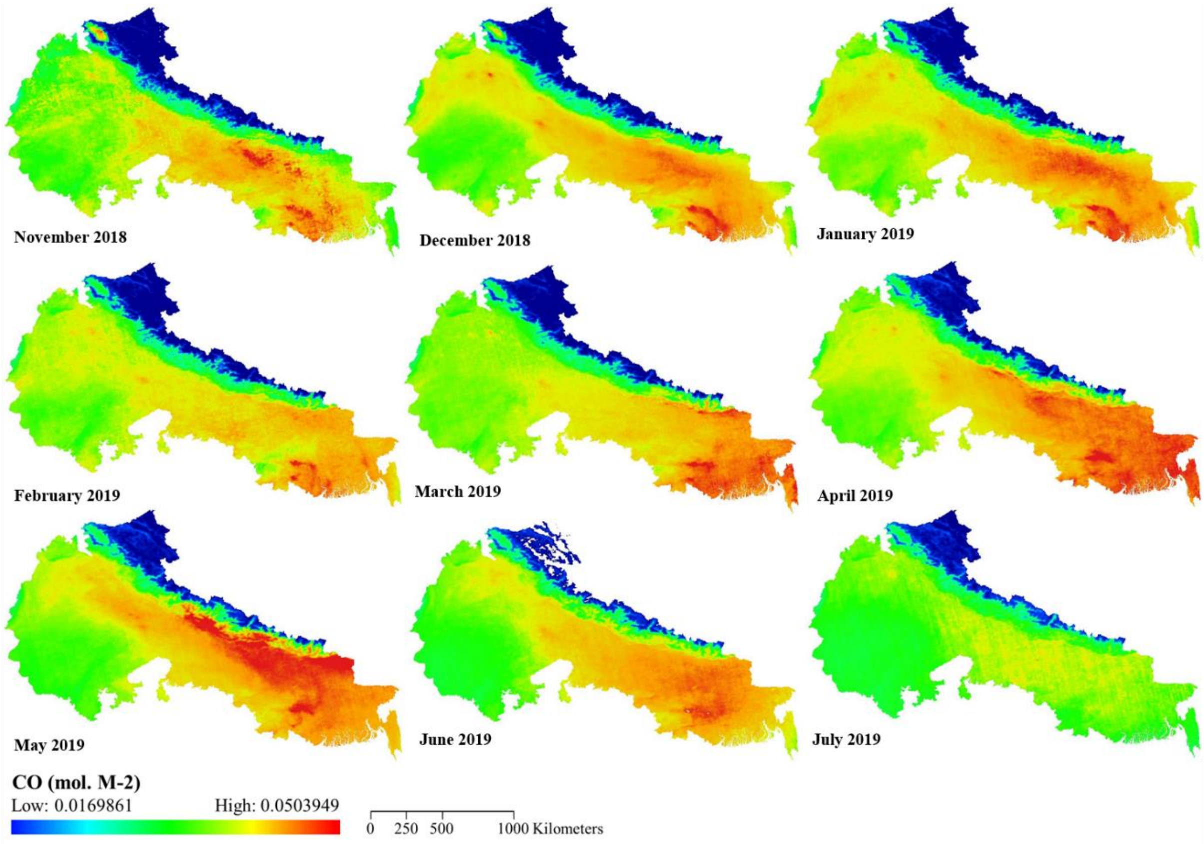
Biodiversity and Conservation Practices	UNESCO World Heritage Site and Ramsar Site – protected as it houses approximately 300 species of flora including up to 30 mangrove species (large and small tree species) and 425 species of fauna; habitat for the endangered Bengal tiger (refugia); largest continuous mangrove system within South Asia.	UNESCO (2018) ; Ramsar (2003); Islam *et al*. (2018); Uddin *et al*. (2013); Spalding *et al.* (2010); Hossain *et al.* (2016)
	Mangrove species include: *H. fomes*, *E. agallocha*, *C. decandra*, *X. mekogensis*, *S. apelatala*, *X. moluccensis*, *B. gymnorbiza* and *A. officinalis*.	
	Habitat for larger species such as the Bengal tiger, deer, monkeys, wild boars, Gangetic dolphins, Irawaddy dolphin and saltwater/estuarine crocodiles.	Abdullah-Al-Mamun *et al.* (2017)
Nutrient Cycling	Up-swell from tides and freshwater flows into the delta alternate the nutrients which are available leading to nutrient cycling and a nutrient rich environment.	
	Water quality maintenance (filtering and assimilating pollutants), groundwater recharge and discharge, flood and flow control, sediment and nutrient retention, biomass.	Hoq (2016); Giri *et al.* (2015); Ghosh *et al.* (2016)

Appendix E: Pollutant Distribution Maps

Outputs from the European Space Agency's (ESA) Sentinel-5p TROPOMI and NASA's OCO-2 data analysis over the South Asian 'Brick Belt'. Six pollutants have been analysed (see Chapter 5/Paper 4 for more details). Pollutants measured by Sentinel-5p TROPOMI included: carbon monoxide, formaldehyde, ozone, nitrogen dioxide, and sulphur dioxide. Mean monthly averages were calculated for these pollutants using Google Earth Engine (GEE); these have been standardized in their presentation. Minimum and maximum pollutant concentrations have been noted for each pollutant monitored. These data were available from July 2018 and analysed until July 2019. OCO-2 Level 3 data (by Zammit-Mangion *et al.* 2018; OCO-2 Science Team 2018) were re-processed in QGIS (Version 3.2.1) to assess carbon dioxide over the region; data were available from late-2014 to early-2019.

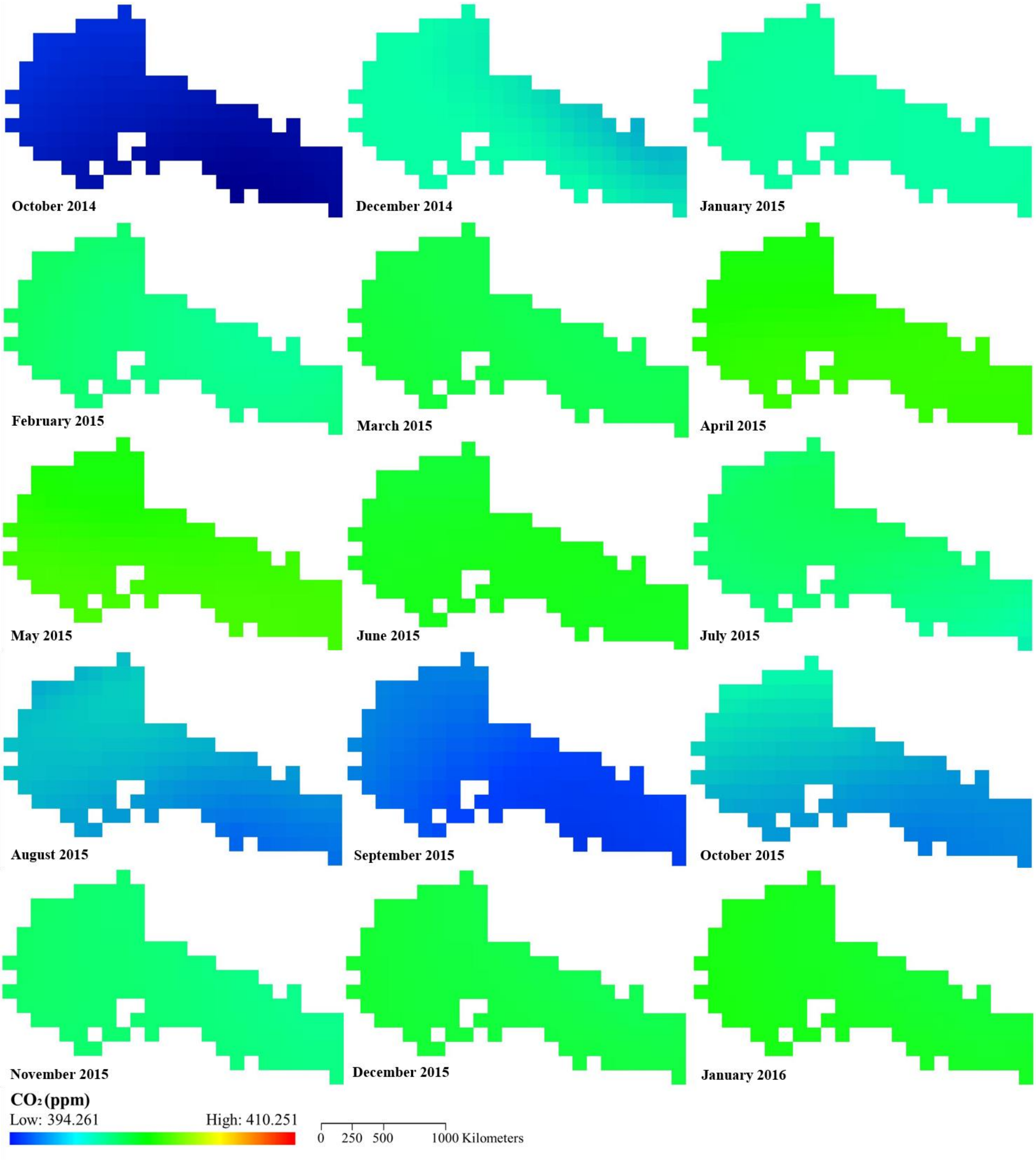
E.1 Carbon Monoxide (CO)

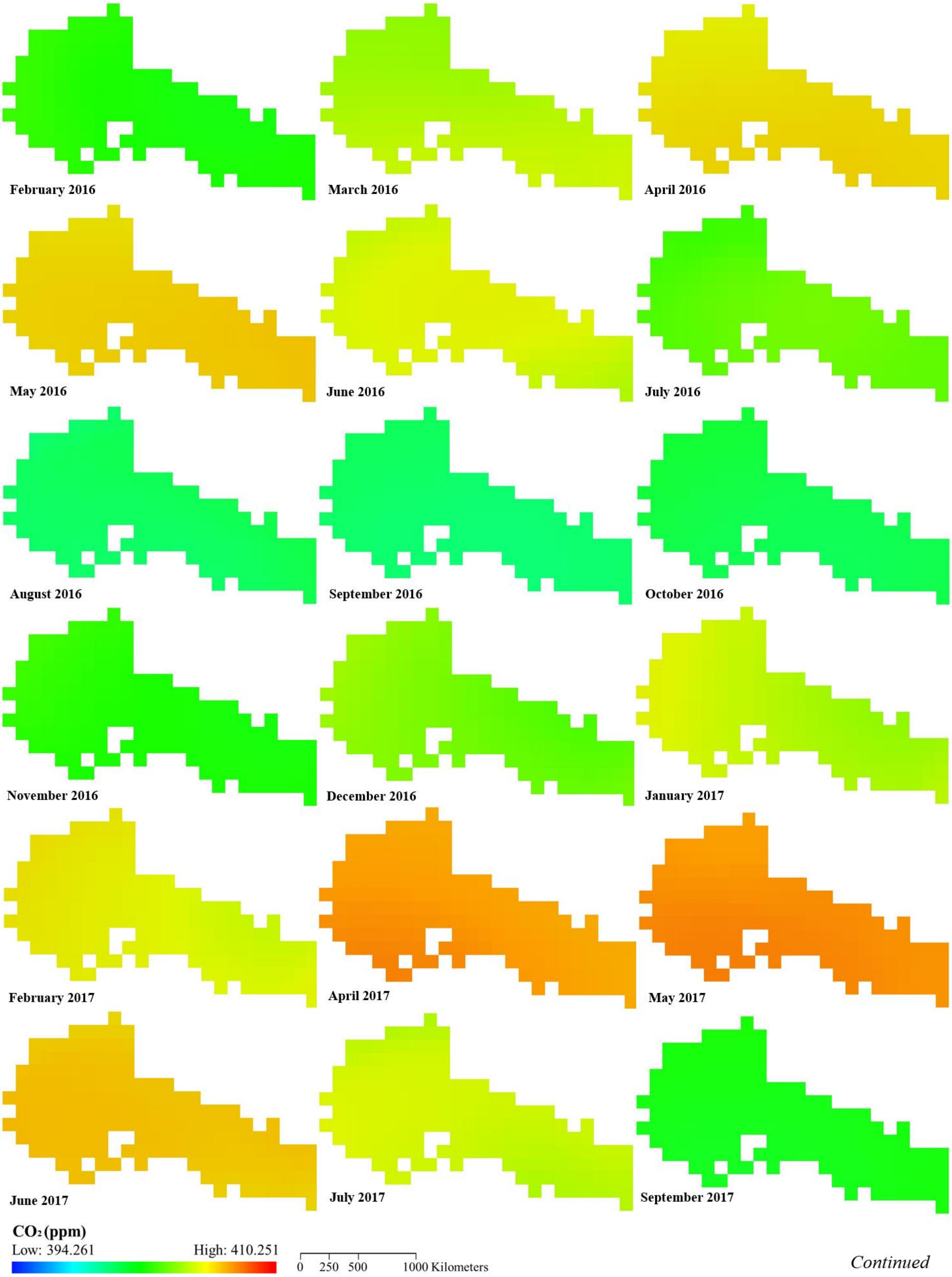
Figure E.1: Monthly mean average CO pollutant concentrations (mol. M-2) over the ‘Brick Belt’ (data measured by the Sentinel-5p TROPOMI sensor; data processed in Google Earth Engine). Minimum and maximum pollutant concentration averages were 0.0169861 and 0.0503949 mol. M-2 respectively.



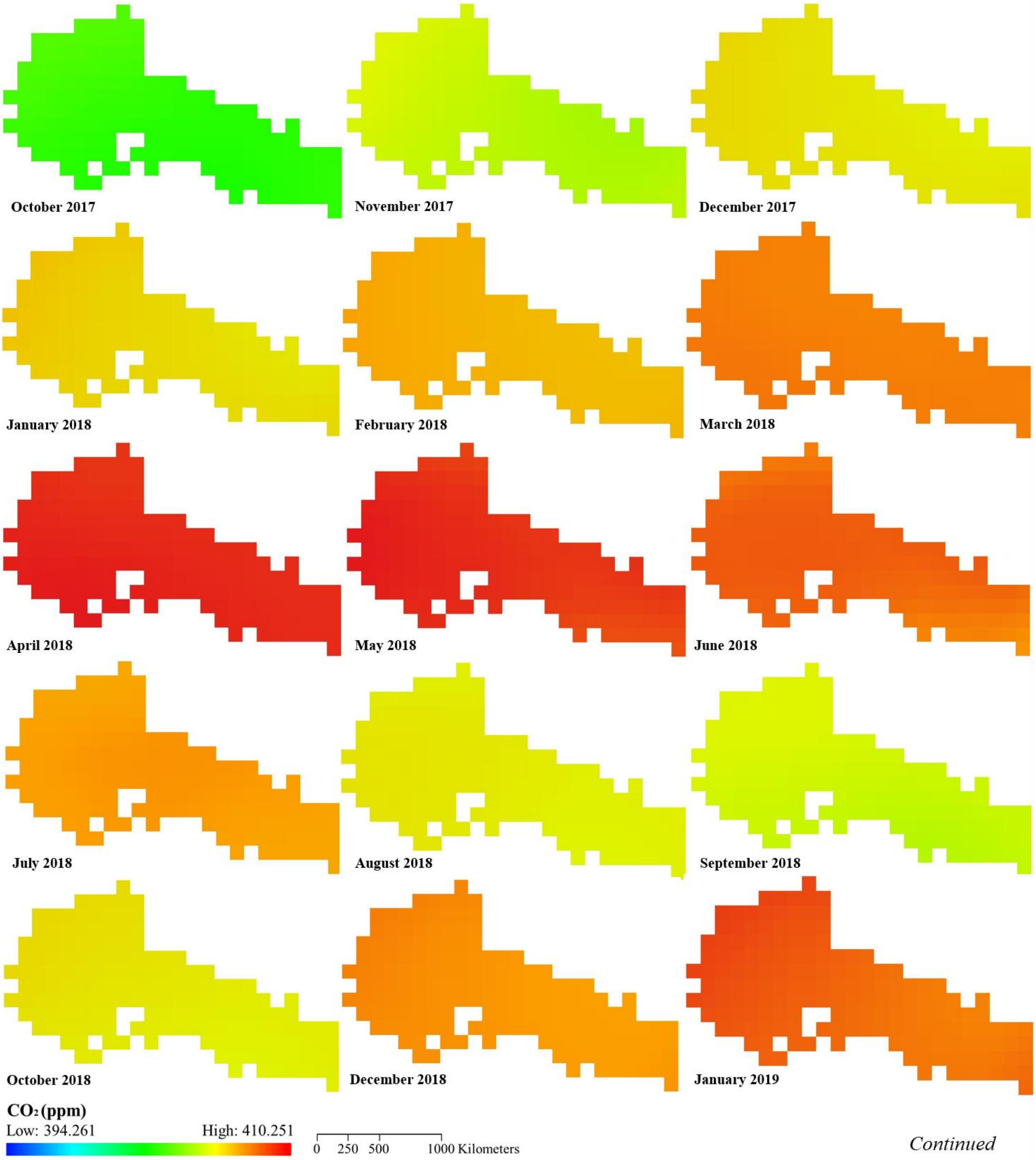
E.2 Carbon Dioxide (CO_2)

Figure E.2: Monthly mean average of CO_2 pollutant concentrations (ppm) over the 'Brick Belt' (data measured by the OCO-2 sensor; data processed in QGIS Version 3.2.1. Based on data from Zammit-Mangion *et al.* (2018) and OCO-2 Science Team (2018) from October 2014 to January 2019. Over that period three months do not have any data available. The anomalous data from November 2018 have also been removed so that the standardized presentation of the monthly averages in the figures for comparison is visible. Minimum and maximum pollutant concentration averages were 394.261 and 410.251 ppm respectively.




February 2016
March 2016
April 2016
May 2016
June 2016
July 2016
August 2016
September 2016
October 2016
November 2016
December 2016
January 2017
February 2017
April 2017
May 2017
June 2017
July 2017
September 2017
CO_2 (ppm)
Low: 394.261
High: 410.251
0 250 500 1000 Kilometers

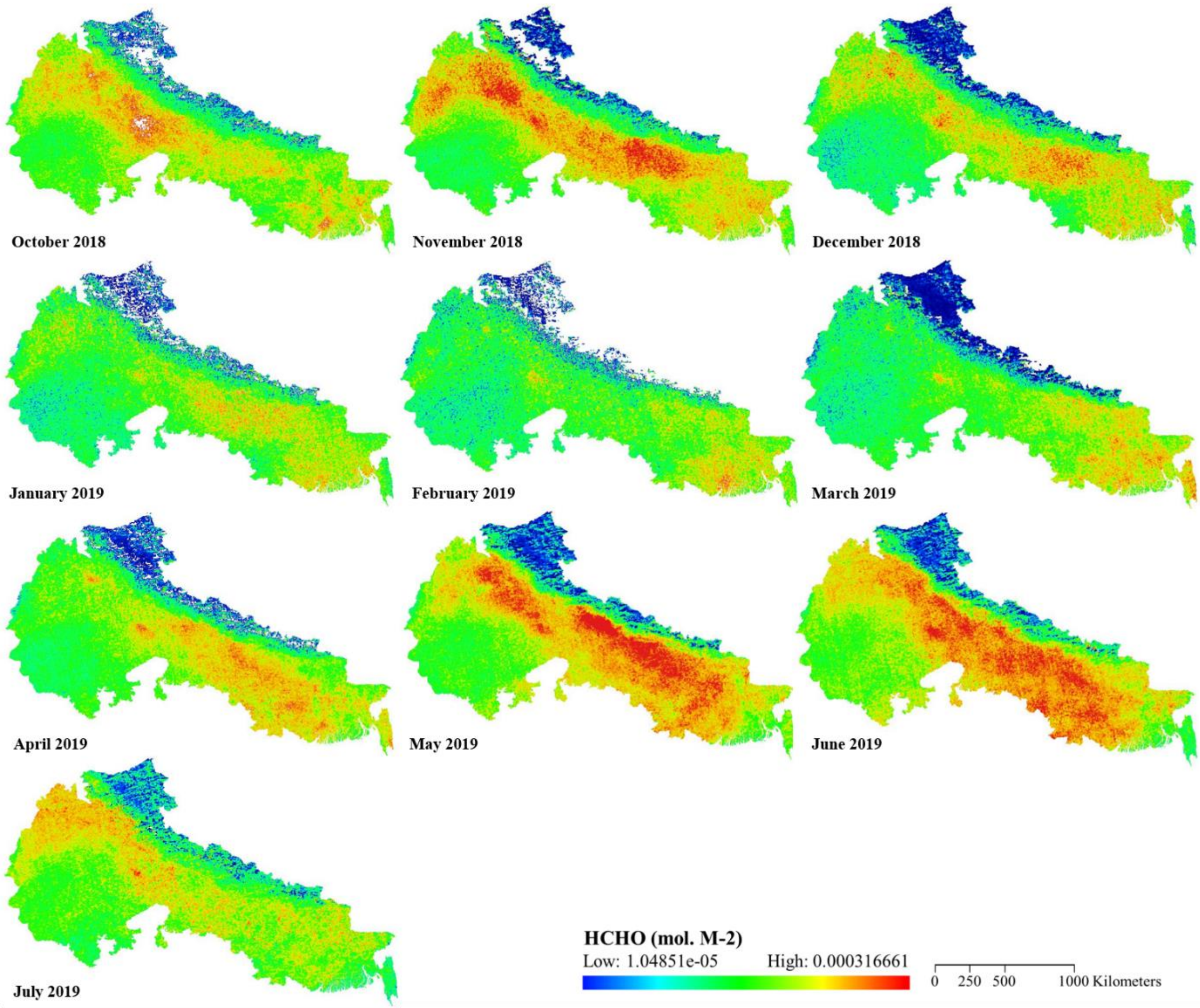
Continued


October 2017
November 2017
December 2017
January 2018
February 2018
March 2018
April 2018
May 2018
June 2018
July 2018
August 2018
September 2018
October 2018
December 2018
January 2019
CO₂ (ppm)
Low: 394.261
High: 410.251
0 250 500 1000 Kilometers

Continued

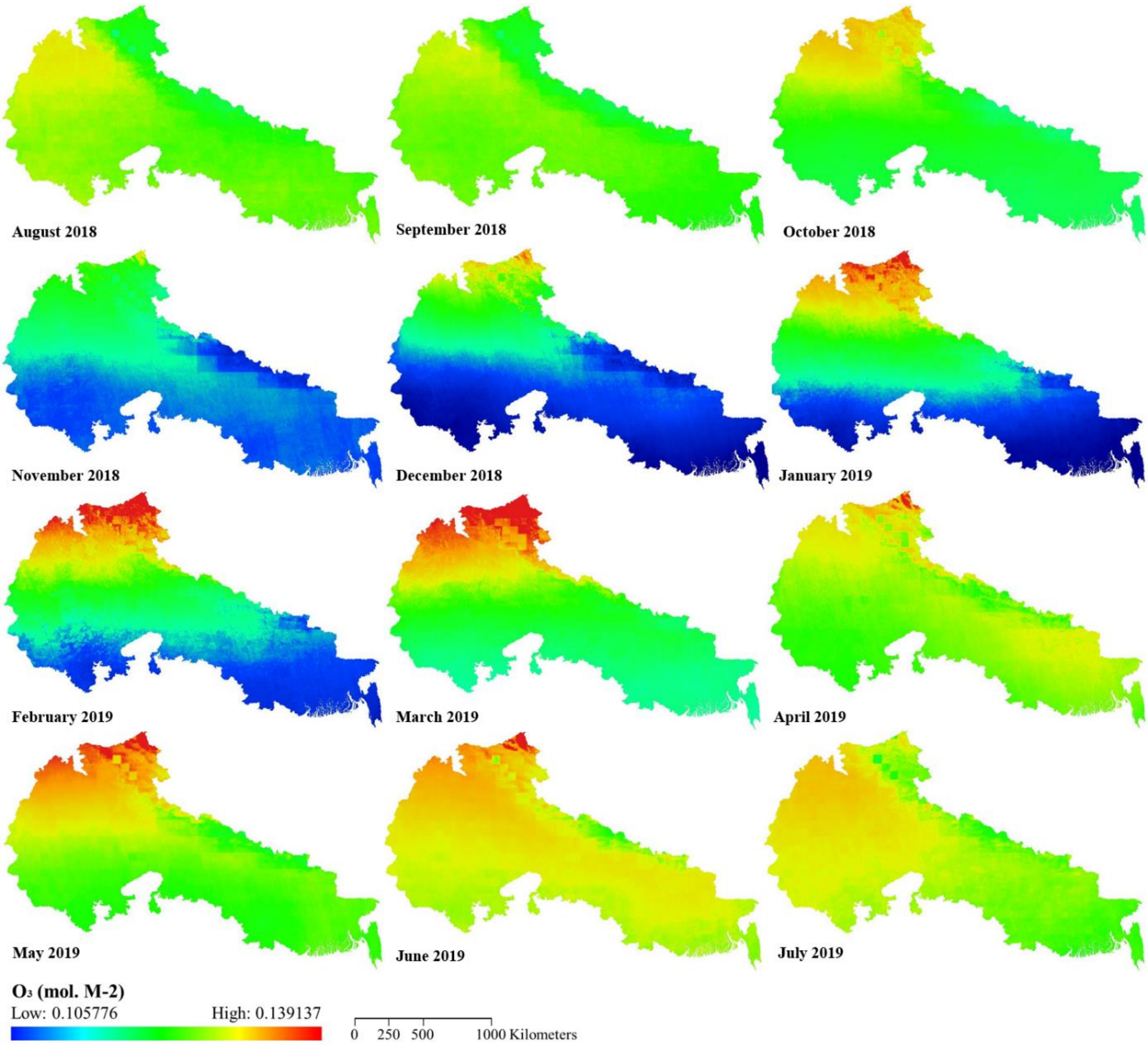
E.3 Formaldehyde (HCHO)

Figure E.3: Monthly mean average HCHO pollutant concentrations (mol. M-2) over the 'Brick Belt' (data measured by the Sentinel-5p TROPOMI sensor; data processed in Google Earth Engine). Minimum and maximum pollutant concentration averages were 1.04851e-05 and 0.000316661 mol. M-2 respectively.



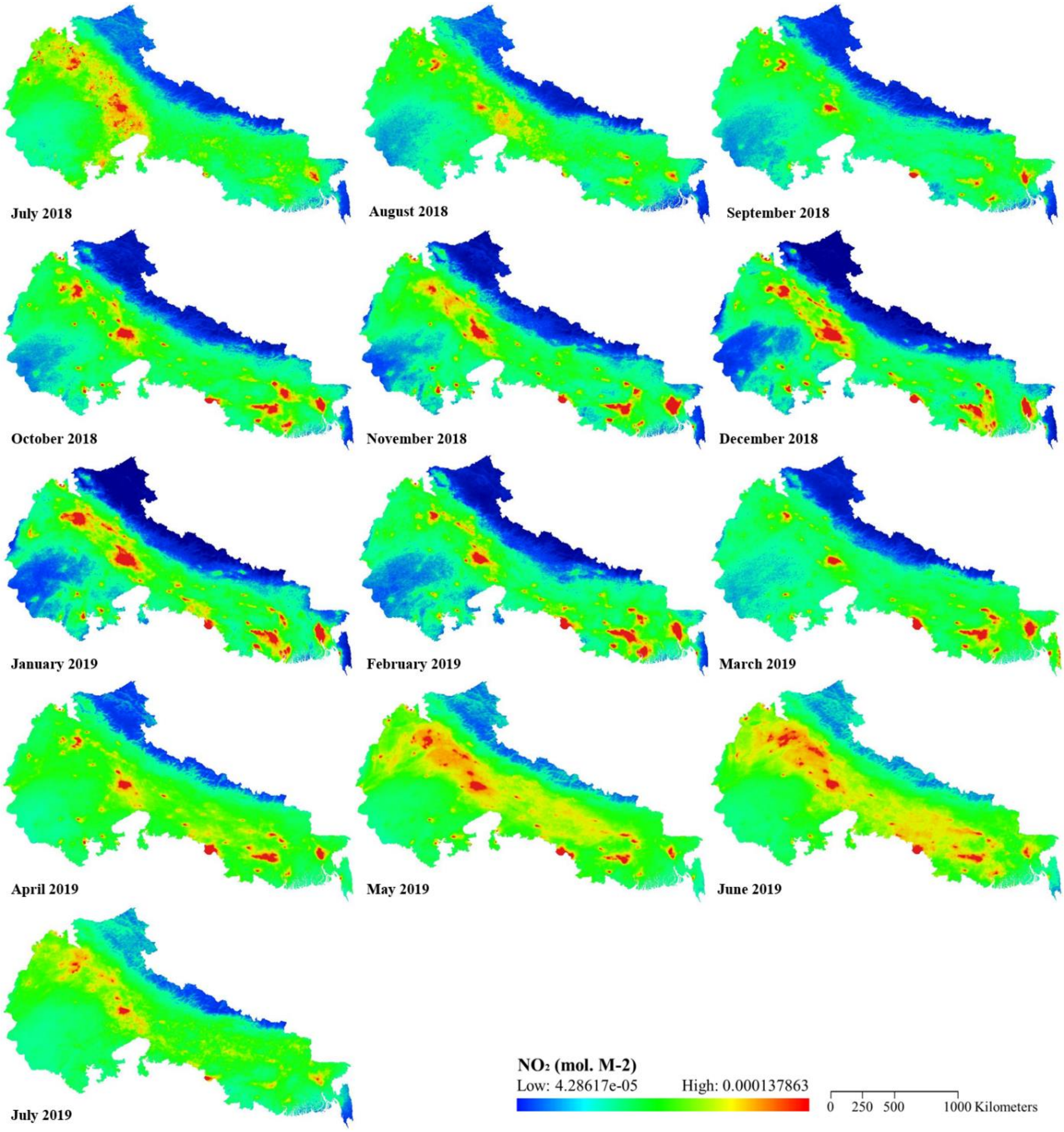
E.4 Ozone (O_3)

Figure E.4: Monthly mean average O_3 pollutant concentrations (mol. M-2) over the 'Brick Belt' (data measured by the Sentinel-5p TROPOMI sensor; data processed in Google Earth Engine). Minimum and maximum pollutant concentration averages were 0.105776 and 0.139137 mol. M-2 respectively.



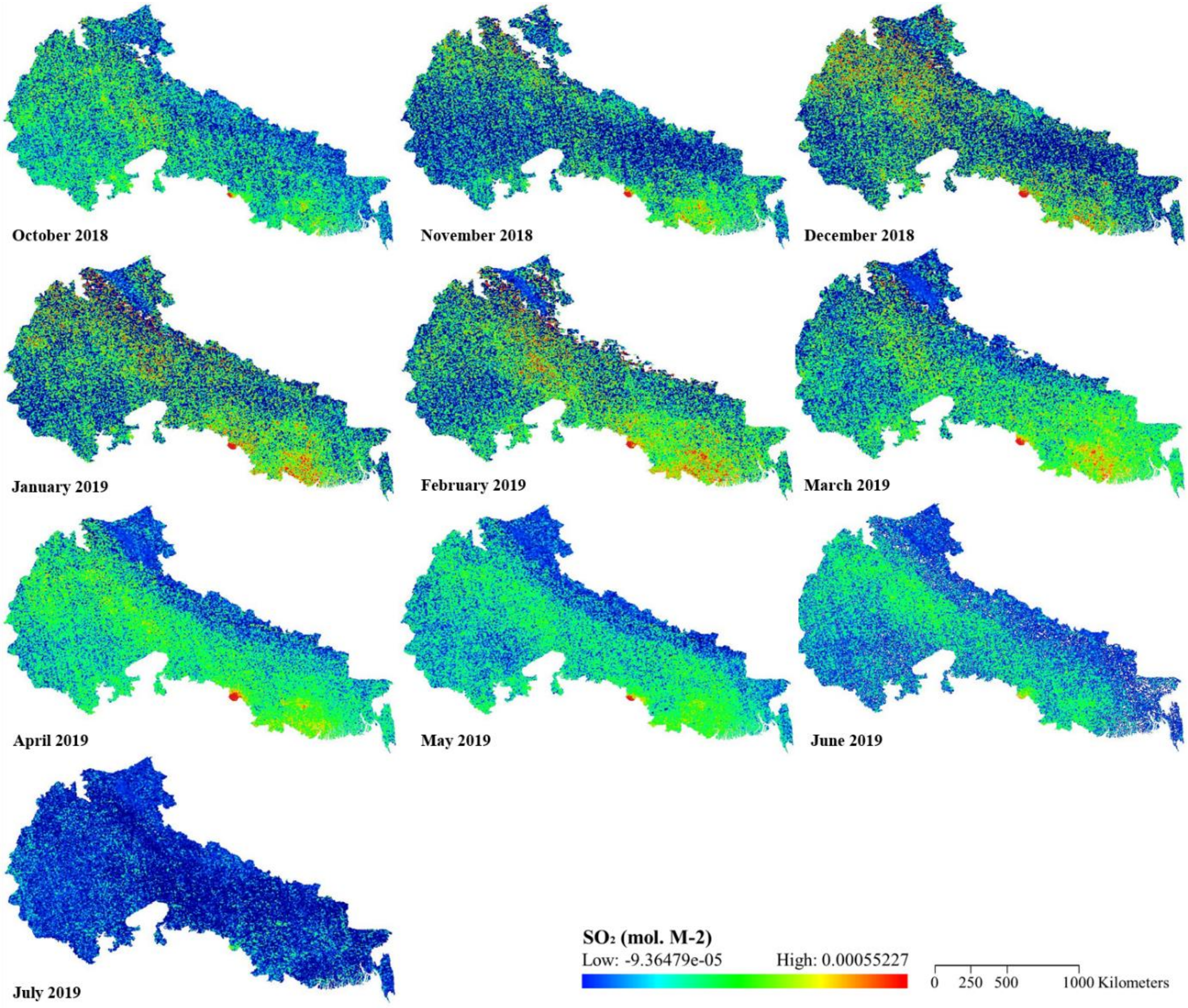
E.5 Nitrogen Dioxide (NO_2)

Figure E.5: Monthly mean average NO_2 pollutant concentrations (mol. M-2) over the 'Brick Belt' (data measured by the Sentinel-5p TROPOMI sensor; data processed in Google Earth Engine). Minimum and maximum pollutant concentration averages were 4.28617e-05 and 0.000137863 mol. M-2 respectively.



E.6 Sulphur Dioxide (SO_2)

Figure E.6: Monthly mean average SO_2 pollutant concentrations (mol. M-2) over the 'Brick Belt' (data measured by the Sentinel-5p TROPOMI sensor; data processed in Google Earth Engine). Minimum and maximum pollutant concentration averages were -9.36479e-05 and 0.00055227 mol. M-2 respectively.



Appendix F: Bonded Labour Analysis

The reduction of the environmental implications of brick-manufacturing within the 'Brick Belt' relies on the reduction of bonded labour in relation to the modern slavery-environmental nexus. In order to establish the possible reductions in extractive practices and emissions – particularly those which may be compared with previous analyses that have used the same data to produce estimated levels of carbon dioxide (CO_2) emissions (see Bales 2016; Boyd *et al.* 2018) – an assessment has been undertaken to establish the benefits of ending modern slavery in brick-making.

F.1 Method

Multiple figures have been suggested to provide an estimated number of people working within an individual brick kiln, ranging from those denoting numbers of families (Bales 2012, 2016) to those which estimate large industry-wide figures (Anti-Slavery International 2017). Conservative figures were taken to provide an estimate for the number of people estimated to be working in the brick-manufacturing kilns across the 'Brick Belt' to avoid over-exaggerating the figures. As an estimate has been calculated, it is likely that this may be an under-count of the actual figures, but this was deemed to be more useful that an over-exaggeration of the influence of exploitation in the sector.

In order to determine the estimated number of individuals per kiln, the lower estimate of 10-23 million workers (10 million) was divided by the estimated number of kilns within the whole of India (thought to be around 125,000 kilns) according to Anti-Slavery International (2017: 2). This suggests around 80 people work within a kiln – comparable with estimates by Bales (2012). This was then multiplied across the kilns found during the machine learning and aging process to determine the total number of people thought to form the workforce of these kilns annually (Figure F.1)

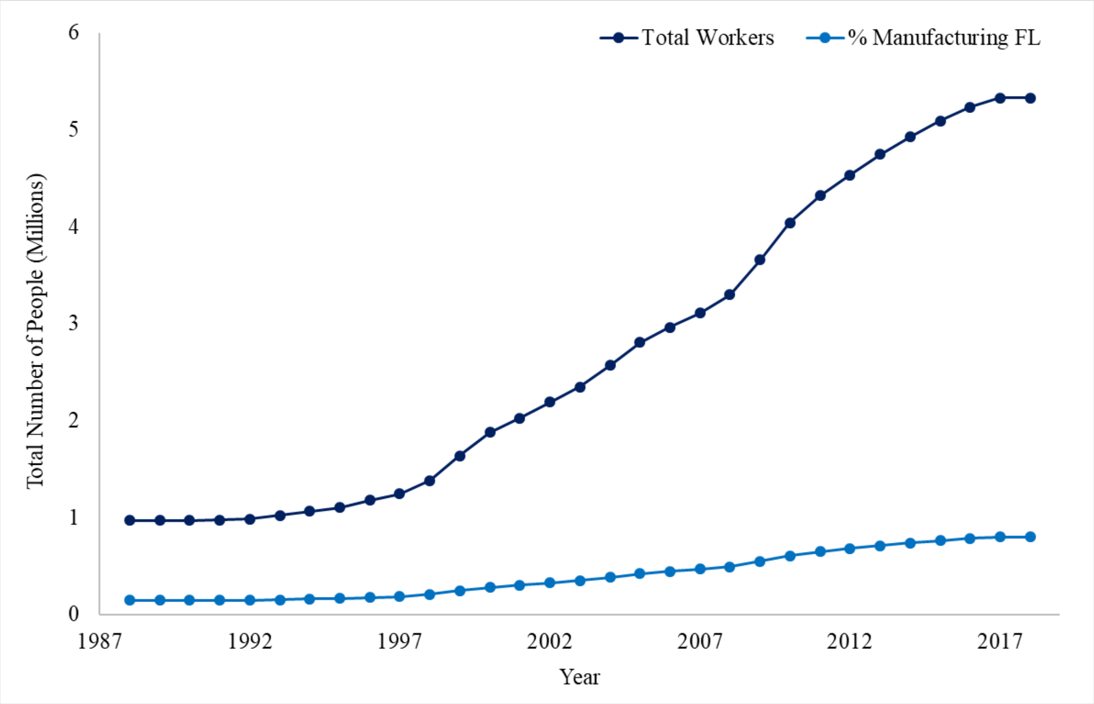


Figure F.1: Total estimated workforce, and estimated number of people working under conditions of modern slavery within that estimated workforce, for the brick-manufacturing sector of the brick kilns across the South Asian 'Brick Belt'. These figures are a conservative estimate calculated using data from the literature and applying them to the aged kiln data that are the most accurate analysis of the kilns within this region at this period in time. The data are calculated from 1988 (which includes those all those kilns which could not be aged from before this time – totalling over 12,000 within the aged-kiln dataset), starting with yearly aged data from 1989 up until 2018 when the aging analysis was concluded.

In order to gauge the estimated number of those who are working under conditions of modern slavery, the International Labour Organization's (ILO) 'Global Estimates of Modern Slavery (GEMS)' were applied. The rate of forced labour occurring in the manufacturing sector is 15% (ILO 2017a: 32).[29] This percentage was then applied to

[29]Manufacturing was chosen over construction as there are no clear definitions over the inclusion of sectors within the ILO GEMS methodology documents (ILO 2017a, 2017b, 2017c). The process occurring within the brick kilns is the processing of raw material to produce bricks that are intended for the construction industry. Therefore the more conservative figure from the 'manufacturing' sector was deemed more appropriate than the slightly higher estimated levels of forced labour in the 'construction'

the total workforce figures to provide an estimated total for the number of people working in the brick kilns under conditions of exploitation (Figure F.1).

From these data an approximation of the number of kilns which could be removed from active production should all bonded labour be eradicated was established, thus enabling the calculation of the amount of naturally extracted resources which may be saved, and producing an estimate for the level of CO_2 reduction that may be saved as a result of removing these kilns. This may be directly compared with similar calculations such as those by Bales (2016: 117). Moreover, the use of the biomass data from Tahir and Rafique (2009) – who found that 4,000 brick kilns across Pakistan emitted approximately 525,440 tonnes of CO_2 per year (131.36 tonnes per kiln per year) – was used as it could be directly compared with the estimated levels of emissions from the kilns noted in others studies (see Table F.1). However, the estimated figures produced within this analysis are more accurate as they are based on the locational analysis of the brick kilns within this region using machine learning, rather than relying on estimated figures for the number of kilns within this area – something that has not been achieved before.

Table F.1: Comparison of the estimated carbon dioxide (CO_2) emission of kilns from the environmental assessment and other studies based on figures from Tahir and Rafique (2009).

Study	**Number of Kilns**	**CO_2 Emissions Estimate (tonnes per year)**
Bales (2016: 115)	20,000	2,600,000
Boyd *et al*. (2018: 386) / Chapter/Paper 4/2 – Appendix B)	55,387	7,255,697
Chapter 5/Paper 4	66,634	8,753,042

sector. However, it cannot be denied that in the context of the South Asian 'Brick Belt' both kilns and construction are heavily entwined.

GEMS Methodology accessible via: https://www.ilo.org/wcmsp5/groups/public/---ed_norm/---ipec/documents/publication/wcms_586127.pdf

The amount of resources that may be saved, and the level of CO_2 emission reductions were estimated by removing the impact of the workforce subjected to modern slavery by converting this into an equivalent number of kilns. This assessment was conducted using the topsoil and groundwater figures calculated in Chapter 5/Paper 4 (see Table 5.3), as well as the comparable CO_2 data from the Tahir and Rafique (2009) study. These data are shown in Table F.2.

Table F.2: Details of the calculations conducted to establish the total number of people in the brick-manufacturing sectors' workforce, those people who may be working under conditions of modern slavery, and the results required to establish the reduction of some of the environmental impacts. These may be gained by the ending of modern slavery within the South Asian 'Brick Belt' using an equivalent number of kilns from the workforce subjected to modern slavery assessment – the analysis of extracted natural materials in the brick-making process and the emission of pollutants has been calculated.

Year	**Total Kilns**	**Total Workforce**	**% Total Workforce Modern Slavery**	**No. Kilns Equates to from the % Total Workforce Modern Slavery**	**Total Savings**[a]			**CO_2 Emissions Reduction (tonnes per year) (2 s.f.)**[b]
					Topsoil (tonnes per year)	Surface Water (tonnes per year)	Groundwater (tonnes per year)	
2018	66,634	5,330,720	799,608	9,995	39,980,400	11,099,019	1,372,132	1,312,956.34
2017	66,596	5,327,680	799,152	9,989	39,957,600	11,092,690	1,371,349	1,312,207.58
2016	65,413	5,233,040	784,956	9,812	39,247,800	10,895,641	1,346,989	1,288,897.75
2015	63,673	5,093,840	764,076	9,551	38,203,800	10,605,815	1,311,158	1,254,612.79
2014	61,608	4,928,640	739,296	9,241	36,964,800	10,261,854	1,268,636	1,213,924.03
2013	59,330	4,746,400	711,960	8,900	35,598,000	9,882,415	1,221,727	1,169,038.32
2012	56,677	4,534,160	680,124	8,502	34,006,200	9,440,513	1,167,096	1,116,763.61
2011	54,002	4,320,160	648,024	8,100	32,401,200	8,994,946	1,112,013	1,064,055.41
2010	50,524	4,041,920	606,288	7,579	30,314,400	8,415,627	1,040,393	995,524.89
2009	45,747	3,659,760	548,964	6,862	27,448,200	7,619,936	942,025	901,398.89
2008	41,219	3,297,520	494,628	6,183	24,731,400	6,865,721	848,784	812,179.18
2007	38,892	3,111,360	466,704	5,834	23,335,200	6,478,120	800,867	766,327.97
2006	37,017	2,961,360	444,204	5,553	22,210,200	6,165,807	762,256	729,382.97
2005	35,059	2,804,720	420,708	5,259	21,035,400	5,839,669	721,937	690,802.54
2004	32,124	2,569,920	385,488	4,819	19,274,400	5,350,795	661,499	632,971.30
2003	29,363	2,349,040	352,356	4,404	17,617,800	4,890,904	604,645	578,568.55

2002	27,367	2,189,360	328,404	4,105	16,420,200	4,558,437	563,543	539,239.37
2001	25,302	2,024,160	303,624	3,795	15,181,200	4,214,476	521,020	498,550.61
2000	23,493	1,879,440	281,916	3,524	14,095,800	3,913,156	483,769	462,906.07
1999	20,470	1,637,600	245,640	3,071	12,282,000	3,409,625	421,520	403,340.88
1998	17,302	1,384,160	207,624	2,595	10,381,200	2,881,941	356,284	340,918.61
1997	15,549	1,243,920	186,588	2,332	9,329,400	2,589,949	320,186	306,377.50
1996	14,724	1,177,920	176,688	2,209	8,834,400	2,452,531	303,198	290,121.70
1995	13,774	1,101,920	165,288	2,066	8,264,400	2,294,293	283,635	271,402.90
1994	13,319	1,065,520	159,828	1,998	7,991,400	2,218,505	274,266	262,437.58
1993	12,753	1,020,240	153,036	1,913	7,651,800	2,124,228	262,611	251,285.11
1992	12,315	985,200	147,780	1,847	7,389,000	2,051,271	253,591	242,654.76
1991	12,186	974,880	146,232	1,828	7,311,600	2,029,784	250,935	240,112.94
1990	12,129	970,320	145,548	1,819	7,277,400	2,020,290	249,761	238,989.82
1989	12,116	969,280	145,392	1,817	7,269,600	2,018,125	249,493	238,733.66
Before	12,114	969,120	145,368	1,817	7,268,400	2,017,792	249,452	238,694.26

[a] Total cumulative savings for topsoil, surface water, and groundwater were conducted for all years in this analysis. But only partial topsoil, surface water, and groundwater extraction estimates are included in Chapter 5/Paper 4 as the aging results pre-2000 are not as reliable as those post-2000 (see Li *et al.* 2019). Those coloured in red are additional results from further analysis not included in the Chapter 5/Paper 4 analysis.

[b] CO_2 emission reductions were calculated using figures from Tahir and Rafique (2009). These are the resultant savings used to form part of the assessment of the possible eradication of modern slavery within the South Asian 'Brick Belt' in order to understand the modern slavery-environmental degradation nexus (Brown *et al.* 2019). These data were used for comparison, not within the rest of the pollutant analyses that were undertaken using the European Space Agency's (ESA) Sentinel-5p satellite Earth Observation (EO) data accessed via Google Earth Engine (GEE).

Appendix G: Slavery from Space – A Remote Sensing Approach to Ending Modern Slavery

First published 7 March 2019 on the Delta 8.7 Platform in partnership with the Rights Lab, University of Nottingham. Citations have been labeled instead of the original hyperlinks (and are included in the references section) and figures removed. Accessible from: https://delta87.org/2019/03/slavery-space-remote-sensing-approach-ending-modern-slavery/

For more than half a century, satellites have been monitoring the Earth's surface. The remotely sensed data collected by sensors on these satellites have been used to investigate a myriad of features on the planet, from environmental and land cover changes to the development of cities and population growth. The ability to monitor the Earth has developed rapidly in the past 20 years, and this rich history is now frequently applied [Pierro *et al.* 2017] to work in the field of human rights.

Modern slavery is one of the most pressing human rights issues of our time. It is therefore vital that today's anti-slavery movement have access to as many tools as possible to both understand and prevent this crime. This includes harnessing available satellite technology [Walters 2019] to investigate industries, countries and regions where modern slavery practices are commonly reported. Remote sensing can provide evidence [Zolli 2018c] to support new forms of advocacy, accountability and action in the effort to prevent slavery and support survivors. In fact, remote sensing technologies are already being implemented [Scoles 2019] to support anti-slavery action.

Mapping Industries

Often the scale of industries is a prohibitive factor to ensuring the elimination of modern slavery within a workforce. This is something that remote sensing can support due to the high spatial and temporal resolution of data collection: with a combination of satellite sources, the entire Earth is mapped every day.

Through the use of freely available satellite sensor data, we produced in the Rights Lab the first statistically robust estimate [Boyd *et al.* 2018] of the number of brick kilns within the South Asian brick-manufacturing industry. As a highly unregulated industry, the true scale of brick-manufacturing has not previously been quantified. This had made it difficult to determine the exact location of individual kilns across the "Brick Belt", and to understand which of these kilns are likely to be using slave labour. This data is now being used by NGOs in the region to guide their prioritization of programme locations.

The same technology could be applied to monitor a number of other industries, including quarrying, mining, cotton harvesting, fishing and fish processing. Continued monitoring is possible due to high temporal resolutions from imagery providers such as Planet Labs [Planet Labs 2019], a commercial provider, and the European Space Agency (ESA) Sentinel [ESA 2019] series, a government provider. We are now applying artificial intelligence (AI) algorithms [Foody *et al.* 2019] to map and locate new features of interest within these industries, providing an up-to-date log for areas that are sometimes inaccessible or were previously unknown.

Monitoring Vulnerability

The abundance of satellite data means that there is a wealth of information that can be used to monitor vulnerability going forward. The amount of satellite imagery is ever-increasing, but to fully understand the risks of enslavement, we are using this imagery alongside other data such as survivor narratives, population densities, educational attainment levels and poverty rates.

The ability to monitor patterns on the surface of the Earth will only improve due to the technological innovations taking place on satellite platforms, including improvements to the spatial, spectral and temporal resolutions. Continued investigation of vulnerabilities to modern slavery will require fast responses, and AI will enable the fast processing times that we need to monitor numerous data sources and integrate them with satellite imagery to fully reveal slavery risk and vulnerability.

In addition, the costs associated with the production and operation of spacecraft are continuing to decline with the production of "smallsats" and constellations of satellites, which are beneficial to the timescales in which data are collected. Usually these are operated by commercial providers, but these companies regularly partner with humanitarian and human rights agencies [Pierro *et al.* 2017] to investigate crises and abuses.

The Nexus of Modern Slavery and Environmental Destruction

Advances in anti-slavery remote sensing also let us combine slavery and environmental data. Assessing the environmental impacts of modern slavery is important for supporting survivors and protecting natural systems. It will help us achieve an intersectional approach to the Sustainable Development Goals.

The history of remote sensing is firmly based in the monitoring of the Earth's environmental systems. As we document the connection between modern slavery and environmental destruction [IASC 2018], we are beginning to use remote sensing sources to investigate where modern slavery has been reported within the workforce and which are known to have an impact on the environment–including quarrying, mining and brick manufacturing. These impacts can include the release of pollutants, deforestation, encroachment on protected areas and the overexploitation of resources, among others.

Satellite imagery has already been used to document cases where gold mining has had drastic effects on the Amazon rainforest environment [Mascaro 2016], causing damage to protected lands. These data sources are also being used to investigate other protected regions. The risks associated with protected areas and vulnerability to enslavement are interlinked due to the remoteness of the locations and the subsequent lack of monitoring. Here satellite imagery can help to protect both people and the environment through land cover mapping and monitoring for instances of change that may indicate human activity, including areas of deforestation, buildings and structures, and the visibility of modes of transport.

Anti-Slavery Futures

Although some forms of modern slavery are not accessible through this technology, such as domestic servitude, remote sensing can support other forms of data collection on the ground. By combining remotely sensed data, other data sources and ground-truthing, we can formulate a picture of slave labour locations and industries in which modern slavery is occurring.

With a wealth of different techniques at hand, including output from satellite sensors, we can enable more evidence-based decision-making. It is this transdisciplinary approach to data collection–working with data sources that would normally be held in silos, and in partnership with NGOs, survivors and government bodies–that will ultimately provide the best insights into modern slavery around the world.