74th International Astronautical Congress (IAC), Baku, Azerbaijan, 2-6 October 2023.

IAC-23-B1.5.3

A Framework for mapping Earth Observation capabilities to the OHCHR indicators

Seonaid Rapach[a1]*, Annalisa Riccardi[a2]

[a] Department of Mechanical and Aerospace Engineering, University of Strathclyde , Glasgow
[1] seonaid.rapach.2020@uni.strath.ac.uk
[2] annalisa.riccardi@strath.ac.uk
* Corresponding Author

Abstract

Keywords: Earth Observation, Human Rights, Taxonomy,

Satellite imagery is advantageously situated to monitor human activities and environmental changes, particularly if the target is remote and across large spatial areas. In some instances in-situ data collection is not possible, this is for example if the target is isolated or the political stance of the country prevents ground access. Human rights research can faces these obstacles when trying to collect and use traditional in-situ data methods. This paper focuses on the human rights and security sector, by presenting a systematic framework developed and used to understand and explore the applicability of satellite imagery to human rights monitoring. An extensive literature review of research papers and development projects was conducted to identify all the capabilities of Earth Observation (EO), by also suggesting relevant missions, supplementary data products, algorithms and analytical processes. An outline of the review is presented in the paper through a taxonomy of all relevant satellite applications that meet the Office of the United Nations High Commissioner for Human Rights (OHCHR) framework on human rights indicators. Overall, this research aims to ensure that this data source is maximized for its full potential in the field, to ensure that effective human rights studies are conducted. The vast scope of EO data applications is made clear through this paper, however future developments in space technology and future planned missions are also discussed to understand which human rights insights can be met in the future with more frequent and higher spatial and spectral resolution information. Despite the essential need for EO data in the sector and the advancement of the Space industry, it also comes with its own limitations, which are discussed in detail in the paper.

1. Introduction

The field of collecting satellite imagery is expanding rapidly and has already been integrated into various applications, with particular emphasis on monitoring changes in the environment, including deforestation [1], rising sea-level [2], and weather [3]. The urgent need to address climate change has driven the demand for Earth Observation (EO) satellites, which provide crucial data illustrating the evolving environment. This encompasses the documentation of increasing greenhouse gas emissions [4], the tracking of gradual environmental degradation like desertification [5] and droughts [6] [7], as well as swift responses to natural disasters [8]. Satellite imagery is firmly integrated into international reporting and environmental frameworks. Notably, the International Charter Space and Major Disasters, recognized by the UN and numerous international relief organizations, as well as the Intergovernmental Panel on Climate Change (IPCC), have designated satellite data as a vital tool for conducting climate change studies and assessing its impacts [9].

Beyond environmental applications, satellite imagery has proven to be an invaluable source of information in social and economic studies. It finds utility in various domains such as GDP forecasting [10], urban planning [11], and poverty mapping [12]. Several characteristics make it conducive to societal research, including its regular orbital cycle with very high to medium spatial resolution. EO satellites typically operate in low-earth orbit, enabling them to observe nearly the entire Earth's surface during their orbits, facilitating data collection in remote and inaccessible areas like the Amazon or isolated regions like the Arctic. This attribute also renders satellite imagery apt for human rights research, where information collection can be hindered by political restrictions or remoteness. Locating the progression of conflicts and human rights abuses has been an application of EO data, building upon the concept that dates back to reconnaissance planes during World War II. The first publicly documented use of satellite imagery as evidence in a trial occurred in the International Criminal Tribunal for the former Yugoslavia (ICTY) [13]. Notable examples also include monitoring the expansion of Uyghur 're-education' camps in China through high-resolution imagery [14] [15]. These instances have gained prominence in the public-eye as they offer tangible evidence of suspected atrocities, corroborating eyewitness accounts.

Though there are clearly numerous opportunities for Earth Observation (EO) data in human rights research, the integration of such data is not consistent across all human rights institutions, and there is currently no overarching framework bridging these seemingly disparate domains. Notably, the Office of the United Nations High Commissioner for Human Rights (OHCHR) has devised a comprehensive framework encompassing all human rights indicators categorized under the 16 fundamental human rights principles. These indicators are employed by the OHCHR to assess compliance with human rights commitments, monitor developmental progress, and compile reports on potential rights violations [16]. While this framework primarily finds utility within the United Nations, which also hosts the Satellite Centre (UNOSAT), enabling streamlined utilization of satellite imagery for investigations, it possesses broader applicability. Third-party investigators can adopt OHCHR indicators, and organizations can develop internal indicators, particularly in cases where the full potential of satellite imagery remains untapped. Consequently, this paper embarks on an exploration, outlining the extensive potential inherent in EO data for human rights research. It does so by delineating a taxonomy that equips researchers, non-governmental organizations (NGOs), and the interested public with a comprehensive understanding of how EO data can be seamlessly integrated into their endeavours.

Similar work has been conducted by the UN but in regard to the UN’s Sustainable Development Goals (SDG). The goals serve as a blueprint for member states to improve the health and prosperity of people and the planet. Comprising 17 distinct SDGs, they encompass all paths that countries need to take to make systemic changes to society and the environment from reducing inequalities to preserving our oceans and forests. In 2020, 5 years after the publication and adoption of the SDGs, the European Space Agency (ESA) formulated a framework outlining how various types of satellite imagery can contribute to measuring progress towards these SDGs [17]. This framework categorizes the relevance of EO data based on several factors, including the maturity of EO technologies, scalability, technical capabilities, and other pertinent indicators and considerations.

The primary focus of the following research is to establish key data sources and important assimilation techniques through the taxonomy while acknowledging any potential limitations in their application. The requirements for utilising satellite imagery in the study are broken down into distinct points including analysing the completeness of the application, dissecting the trends across each imagery type, addressing related additional information required and spatial resolution requirements. To illustrate the points, selected OHCHR indicators are analysed in the context of each section.

It is worth noting that the OHCHR framework makes reference to numerous SDGs in its own set of indicators, resulting in some overlap between the research conducted by O'Conner in 2020 and the present study [17]. Nevertheless, even in cases where indicators are linked to the SDGs, the report establishes connections to EO research that may not have been previously explored.

2. Background

2.1 OHCHR Framework

In 2012, the Office of the United Nations High Commissioner for Human Rights (OHCHR) developed a set of indicators with the primary aim of facilitating standardized and robust investigative procedures in cases of suspected human rights violations. The OHCHR delineated these indicators across the 16 distinct Human Rights, resulting in a total of 514 unique indicators spanning all these rights. However, these indicators are not evenly distributed among the rights, and certain indicators are duplicated across multiple rights. For instance, the indicator 'Life expectancy at birth or age 1' is applicable to both the *Right to the enjoyment of the highest attainable standard of physical and mental health* and the *Right to life*, albeit with a slight variation as the former right includes 'health-adjusted life expectancy.' To enhance the clarity of the taxonomy organization, each duplicated indicator is assigned to the right with which it shares a closer correlation to, although we acknowledge the relevance of all rights when assessing the impact of EO data on each right individually. Each indicator was labelled to simplify referencing in the paper (Appendix A lists selected referenced indicators).

2.2 Remote Sensing Principles

Remote sensing is a process of capturing electromagnetic (EM) radiation from the Earth’s surface and its surrounding atmosphere. The rays are typically reflected rays from the Sun, otherwise known as ‘passive sensors’. The most common form of passive sensors is multispectral imagery, which most commonly collects visible (red, green, blue) and near-infrared (VNIR) EM radiation, but many missions also expand their capabilities to collect across additional infrared (IR) and microwave (MW) bands. This form of imagery is very versatile as it can be used to visualise an area of interest, but also be processed to for numerical analysis in a variety of ways, including index calculations and machine learning algorithms.

Hyperspectral imagery shares similarities with multispectral imagery, as it captures passive EM radiation across VNIR, IR and MW spectra. However, hyperspectral instruments collect across a larger number of finer spectral bands, on the order of 10-100. This form of technology is particularly useful for recording the spectral signature of a site, allowing for finer identification and analysis. There are instances where hyperspectral missions are tuned to a particular feature, including gases in the atmosphere. This is versatile across a number of gases including greenhouse gases CO_2, CH_4 and trace gases SO_2, NO_x, CO.

In contrast to passive sensors, 'active' sensors function by emitting electromagnetic radiation toward the Earth's surface and then capturing the reflected radiation. Synthetic Aperture Radar (SAR) is a form of active sensing because it emits radar pulses to measure changes on the Earth's surface. SAR systems operate at various frequencies, influencing their ability to penetrate surfaces and impacting their spatial resolution. For instance, X-band SAR sensors exhibit limited penetration but offer high spatial resolution, making them valuable for detecting surface changes on land or in water bodies. Conversely, P-band SAR, with its lower frequency and enhanced penetration capabilities, finds application in biomass and soil studies.

Satellite-based meteorological missions are also a widely used dataset because they provide a plethora of information on the climate at a regional to global scale. Precipitation satellites, such as the Tropical Rainfall Measuring Mission (TRMM) and the Global Precipitation Measurement Mission (GPM), are ubiquitous, playing pivotal roles in diverse applications encompassing weather forecasting, natural disaster prediction, and agricultural investigations. These meteorological satellites amalgamate a diverse array of sensors, including visible, near-infrared (VNIR), microwave technology, and radar imaging imagery, thereby enabling the identification of crucial elements within weather phenomena.

Beyond the individual satellite missions that closely monitor weather patterns, there exist comprehensive meteorological datasets that amalgamate satellite imagery with ground-based station data, offering an enriched source of meteorological information. Noteworthy examples of such datasets include the Climate Hazards Center InfraRed Precipitation with Station Data (CHIRPS) and the Multi-Source Weighted Ensemble Precipitation (MSWEP) dataset. Both of these datasets integrate daily gauge observations with satellite-derived imagery to deliver high-performance precipitation products, enhancing the accuracy and utility of meteorological data. Given the distinctive derivation process of meteorological data, it warrants classification as a distinct imagery type for the purposes of this paper.

3. EO-OHCHR Taxonomy

The following research adopts a similar approach to O'Conner (2020), where the research analysed if EO can suitably be applied to monitor the goal of each SDG indicator. However, the research puts focus on the type of imagery that are best suited to meeting the needs of the specific goal. The selected EO types for taxonomy are as follows are multispectral (VNIR), multispectral (MW), hyperspectral, SAR, and meteorological data. Of the 16 human rights outlined by the OHCHR, 12 have the potential to ingest satellite imagery for human rights investigations albeit to varying degrees. Therefore, the taxonomy has outlines the degree to which EO data can meet the goal of each indicator, by assessing whether it can 'fully' or 'partially' contribute.

Although EO imagery can impact 75% of the OHCHR rights, it is determined that 52 specific indicators can be monitored with satellite imagery, weighted mostly to indicators featured in *right to adequate food, right to enjoyment of highest attainable standard of physical and mental health* (will refer to as 'right to health'), *right to adequate housing, right to life* and *right to water*. A clear connection between these rights, and their associated indicators is they have a spatial determinant, which is key for satellite imagery. Since the imagery collects EM information over large swathes of land, this lends itself well to monitoring surrounding environment, which many directly or indirectly impact communities in that vicinity. The environment could include a natural landscape, such as water bodies or forests, or built-up settlements, such as cities.

3.1 Full vs. Partial applications

Each indicator is assessed whether the goal can be fully or partially met with EO and this primarily considers the objective of said indicator. For example, OHCHR 1.4.5 has the objective to measure the 'proportion of agricultural area under productive and sustainable agriculture [2.4.1]'. The main objective of this indicator is to quantify the amount agriculture land, and to determine whether the farming practices ensure healthy and resilient crops. Multispectral imagery is a key contributor, as seen in table 1, because it can fulfil both objectives, including detecting and classifying agricultural land. Land use and land cover (LULC) classification is the method of determining the type of landscape in an image and a variety of techniques that can be employed to classify landscapes include manual labelling [18] or machine learning algorithms [19] [20]. This methodology lends itself well to indicator 1.4.5 because it can classify by land types based on its spectral signature, by separating agricultural land from over landcover types [19] [20] [21] and even separating agricultural land based upon type of crop grown [22] [23]. SAR is another data source that is used in LULC and crop classification of agricultural land because it is sensitive to changes on the ground and is not obscured by weather events, such as cloud. However, this form of data is normally integrated with multispectral imagery because it is not able to differentiate classes of land or crop on its own [19] [23] [24].

The next aspect of the indicator is the quantify if the land is tended with sustainable methods. 'Sustainable agriculture' can have many interpretations and so a variety of methodologies can be applied to quantify it. Multispectral imagery can be used in a number of ways to meet this purpose, such as by quantifying the productivity [19] [25] and susceptibility to drought [6] [7]. Other forms of imagery can also play a role in monitoring the health and productivity of crops, whether as sole data source, such as hyperspectral imager [26] [27] [28] and SAR [29] imagery, or in combination with other assimilated data such as meteorological data [6].

Under evaluation of the expectations of the indicator and considering all possible EO research opportunities to meet its needs, each imagery types for indicator 1.4.5 are either is either labelled as fully or partially observable under the taxonomy in Table 1, with green and yellow respective labelling. Since multispectral imagery (VNIR) can be used to measure the area of land and also determine if the land is under sustainable practices, thus achieving all requirements for this indicator and so is labelled as full observable, whereas the other applicable imagery types are labelled as partial because they can be only used for one of the requirements of the indicator, or both to a limited degree.

Table 1: Referenced OHCHR indicators, with selected indicators for EO research highlighted

RIGHT TO ADEQUATE FOOD																																
1.1.1	1.1.2	1.1.3	1.1.4	1.1.5	1.1.6	1.2.1	1.2.2	1.2.3	1.2.4	1.3.1	1.3.2	1.3.3	1.3.4	1.4.1	1.4.2	1.4.3	1.4.4	1.4.5	1.4.6	1.4.7	1.4.8	1.4.9	1.4.10	1.4.11	1.5.1	1.5.2	1.5.3	1.5.4	1.5.5	1.5.6	1.6.1	1.6.2
RIGHT TO ADEQUATE FOOD								RIGHT TO ADEQUATE HEALTH																								
1.7.1	1.8.1	1.8.2	1.9.1	1.9.2	1.9.3	1.10.1	1.10.2	2.1.1	2.1.2	2.1.3	2.1.4	2.2.2	2.2.3	2.2.4	2.2.5	2.2.6	2.2.7	2.2.8	2.2.9	2.2.10	2.2.11	2.3.1	2.3.1	2.3.2	2.3.3	2.3.4	2.3.5	2.3.6	2.3.7	2.3.8	2.3.9	2.3.10
RIGHT TO ADEQUATE HEALTH (CONT)																																
2.4.1	2.4.2	2.4.3	2.4.4	2.5.1	2.5.2	2.5.3	2.5.4	2.5.5	2.5.6	2.5.7	2.5.8	2.5.9	2.6.1	2.6.2	2.6.3	2.6.4	2.7.1	2.7.2	2.7.3	2.8.1	2.8.2	2.8.3	2.8.4	2.8.5	2.9.1	2.9.2	2.9.3	2.9.4	2.9.5	2.9.6	3.1.1	3.1.2
RIGHT NOT TO BE SUBJECTED TO TORTURE OR TO CRUEL, INHUMAN OR DEGRADING TREATMENT OR PUNISHMENT																																
3.1.3	3.2.1	3.2.2	3.2.3	3.1.3	3.2.1	3.2.2	3.2.3	3.2.4	3.3.1	3.3.2	3.3.3	3.4.1	3.4.2	3.4.3	3.4.4	3.4.5	3.4.6	3.4.7	3.5.1	3.5.2	3.5.3	3.5.4	3.6.1	3.7.1	3.7.2	3.7.3	3.7.4	3.7.5	3.8.1	3.8.2	3.8.3	4.1.1
RIGHT TO PARTICIPATE IN PUBLIC AFFAIRS																								RIGHT TO EDUCATION								
4.2.1	4.2.2	4.2.3	4.2.4	4.2.5	4.2.6	4.3.1	4.3.2	4.3.3	4.3.4	4.3.5	4.3.6	4.4.1	4.4.2	4.4.3	4.4.4	4.4.5	4.5.1	4.5.2	4.6.1	4.6.2	4.6.3	4.7.1	4.7.2	5.1.1	5.1.2	5.1.3	5.2.1	5.2.2	5.2.3	5.2.4	5.2.5	5.2.6
RIGHT TO EDUCATION (CONT)																																
5.2.7	5.2.8	5.2.9	5.3.1	5.3.2	5.3.3	5.3.4	5.3.5	5.3.6	5.3.7	5.3.8	5.4.1	5.4.2	5.4.3	5.4.4	5.4.5	5.4.6	5.5.1	5.5.2	5.5.3	5.5.4	5.5.5	5.5.6	5.5.7	5.6.1	5.6.2	5.6.3	5.7.1	5.7.2	5.7.3	5.8.1	5.9.1	5.10.1
	RIGHT TO ADEQUATE HOUSING																															
5.11.1	6.1.1	6.1.2	6.1.3	6.1.4	6.1.5	6.2.1	6.2.2	6.2.3	6.2.4	6.2.5	6.2.6	6.2.7	6.3.1	6.3.2	6.4.1	6.4.2	6.4.3	6.5.1	6.5.2	6.5.3	6.5.4	6.6.1	6.6.2	6.6.3	6.6.4	6.7.1	6.7.2	6.7.3	6.7.4	6.7.6	6.8.1	6.8.2
	RIGHT TO WORK																															
6.9.1	7.1.1	7.1.2	7.1.3	7.1.4	7.2.1	7.2.2	7.2.3	7.2.4	7.2.5	7.2.6	7.3.1	7.3.2	7.3.3	7.4.1	7.4.2	7.4.3	7.5.1	7.5.2	7.5.3	7.5.4	7.5.5	7.6.1	7.6.2	7.6.3	7.6.4	7.6.5	7.7.1	7.7.2	7.7.3	7.8.1	7.8.2	7.8.3
RIGHT TO WORK (CONT)					RIGHT TO SOCIAL SECURITY																											
7.8.4	7.9.2	7.9.3	7.9.4	7.10.1	8.1.1	8.1.2	8.1.3	8.1.4	8.1.5	8.1.6	8.2.1	8.2.2	8.2.3	8.2.4	8.3.1	8.3.2	8.3.3	8.4.1	8.4.2	8.4.3	8.5.1	8.5.2	8.5.3	8.5.4	8.6.1	8.6.2	8.7.1	8.7.2	8.7.3	8.7.4	8.8.1	8.9.1
	RIGHT TO FREEDOM OF OPINION AND EXPRESSION																									RIGHT TO A FAIR TRIAL						
8.10.1	9.1.1	9.1.2	9.1.3	9.1.4	9.2.1	9.2.2	9.2.3	9.2.4	9.2.5	9.2.6	9.2.7	9.3.1	9.3.2	9.3.3	9.3.4	9.3.5	9.3.6	9.4.1	9.4.2	9.4.3	9.5.1	9.6.1	9.6.2	9.7.1	9.8.1	10.1.1	10.1.2	10.1.3	10.2.1	10.2.2	10.2.3	10.2.4

Table 1 (continued): Referenced OHCHR indicators, with selected indicators for EO research highlighted

RIGHT TO A FAIR TRIAL (CONT)																																
10.2.6	10.3.1	10.3.2	10.3.3	10.3.4	10.3.5	10.3.6	10.4.1	10.4.2	10.4.3	10.4.4	10.3.5	10.3.6	10.4.1	10.4.2	10.4.3	10.4.4	10.5.5	10.5.6	10.6.1	10.6.2	10.6.3	10.7.1	10.7.2	10.8.1	10.8.2	10.9.1	10.9.2	10.10.1	10.10.2	10.11.1	10.12.1	10.12.2
		VIOLENCE AGAINST WOMEN																														
10.12.3	10.12.4	11.1.1	11.1.2	11.1.3	11.1.4	11.2.1	11.2.2	11.2.3	11.3.1	11.3.2	11.3.3	11.3.4	11.4.1	11.4.2	11.4.3	11.5.1	11.5.2	11.5.3	11.5.4	11.6.1	11.6.2	11.6.3	11.6.4	11.7.3	11.8.1	11.9.1	11.10.1	11.10.2	11.11.1	11.12.1	11.12.2	11.12.3
	RIGHT TO NON-DISCRIMINATION AND EQUALITY																												RIGHT TO LIFE (CONT)			
11.12.4	12.1.1	12.1.2	12.2.1	12.2.2	12.2.3	12.2.4	12.2.5	12.3.1	12.3.2	12.3.3	12.3.5	12.4.1	12.4.2	12.4.3	12.4.4	12.5.1	12.5.2	12.5.3	12.6.1	12.6.2	12.7.1	12.7.2	12.8.2	12.9.1	12.9.2	12.10.1	12.10.2	12.11.1	13.1.1	13.2.1	13.2.2	13.2.3
RIGHT TO LIFE																																
13.2.4	13.2.5	13.2.6	13.2.7	13.3.1	13.3.2	13.3.3	13.3.4	13.3.5	13.4.1	13.4.4	13.4.5	13.4.6	13.4.7	13.5.1	13.5.2	13.5.3	13.5.4	14.5.5	13.6.1	13.6.2	13.6.3	13.7.1	13.7.2	13.8.1	13.8.3	13.8.4	13.9.1	13.9.2	13.10.2	14.1.1	14.1.2	14.1.3
RIGHT TO ADEQUATE WATER AND SANITATION																								RIGHT TO FREEDOM OF PEACEFUL ASSEMBLY AND ASSOCIATION								
14.1.4	14.1.5	14.1.6	14.2.1	14.2.2	14.2.3	14.3.1	14.3.2	14.3.3	14.3.4	14.4.1	14.4.2	14.5.1	14.5.2	14.6.1	14.6.2	14.7.1	14.8.1	14.9.1	14.9.2	14.10.1	14.10.2	14.10.3	14.10.4	15.1.1	15.1.2	15.2.1	15.2.2	15.2.3	15.3.1	15.3.2	15.4.1	15.4.2
RIGHT TO FREEDOM OF PEACEFUL ASSEMBLY AND ASSOCIATION (CONT)																					RIGHT TO LIBERTY AND SECURITY OF PERSON											
15.5.4	15.5.5	15.5.6	15.5.7	15.6.1	15.6.2	15.6.3	15.6.4	15.7.1	15.7.2	15.7.3	15.8.1	15.8.2	15.9.1	15.9.2	15.10.1	15.10.2	15.11.1	15.11.2	15.12.1	15.13.1	15.13.3	16.1.1	16.1.2	16.2.1	16.2.2	16.2.3	16.3.1	16.3.2	16.3.3	16.3.4	16.3.5	16.3.6
RIGHT TO LIBERTY AND SECURITY OF PERSON (CONT)																																
16.4.1	16.4.2	16.4.3	16.4.5	16.4.6	16.4.7	16.5.1	16.5.2	16.6.1	16.6.2	16.7.3	16.7.4																					

3.1.1. Broad indicator requirements

The taxonomy presented in table 1 demonstrates the variety of applications that satellite imagery in documenting potential violations of human rights. However, an aspect that that is clear from the table is that satellite imagery only provides partial information for the majority of indicators. Some indicators listed cover many broad features, such as OHCHR 13.8.4, which outlines ‘Prevalence of and death rates associated with communicable and non-communicable diseases (e.g., HIV/AIDS [3.3.1], malaria, tuberculosis [3.3.2], [3.3.3], and hepatitis b [3.3.4])’. The indicator does list some possible disease that need to be mapped, but this is not a of possible communicable and non-communicable diseases that need to be covered. Satellite data is very effective for predicting the occurrence of some diseases, predominately derived from nature e.g. malaria [30] [31], cholera [32], tuberculosis [33] and meningitis [34]. These diseases are predictable for satellites imagery as they are dependent on their surrounding environment, such as malaria with is correlated with heavy rainfall in dry climates. There are some instances where the improvement of satellite technology and processing techniques can open up more possibilities in epidemiology research, such as the improvement of aerosol optical depth measurements from sensors [35], which in turn will improve the measurements of particulate matter monitoring in cardiac and respiratory research [36]. However, in many instances diseases are not traceable.

Table 3: Taxonomy of OHCHR indicators mapped to applicable EO imagery.

	Right to adequate food								Right to health					
	1.4.2	1.4.5	1.4.8	1.4.10	1.4.11	1.5.3	1.5.6	1.9.3	2.2.11	2.3.2	2.3.9	2.5.2	2.8.2	2.9.1
Multispectral (VIR)														
Multispectral (MW)														
Hyperspectral														
SAR														
Meteorological datasets														

	*1		*2		Right to adequate housing													
	3.2.1	3.5.2	5.4.1	5.8.1	6.2.1	6.2.3	6.2.5	6.2.6	6.6.1	6.6.2	6.6.3	6.6.4	6.7.1	6.7.2	6.7.3	6.7.4
Multispectral (VIR)																
Multispectral (MW)																
Hyperspectral																
SAR																
Meteorological datasets																

	Right to work					*3			*4	*5	Right to life					Right to water						
	7.3.1	7.6.4	7.5.2	7.9.3	7.9.4	8.5.4	8.9.1	8.10.1	9.3.3	12.9.1	13.4.7	13.6.2	13.8.4	13.9.2	13.10.2	14.1.2	14.2.1	14.3.3	14.3.4	14.5.1	14.6.1	14.10.2
Multispectral (VIR)																						
Multispectral (MW)																						
Hyperspectral																						
SAR																						
Meteorological datasets																						

SUPERSCRIPT

*1 Right not to be subjected to torture or to cruel, inhuman or degrading treatment or punishment

*2 Right to education

*3 Right to social security

*4 Right to freedom of opinion and expression (OHCHR 9)

*5 Right to non-discrimination and equality

Level of contribution EO satellite imagery has to OHCHR indicator

Full contribution of EO data

Partial contribution of EO data

3.1.2. Combination with other data sources

Indicator 13.8.4 has a broad range of requirements for the indicator and so it cannot be fully monitored with satellite data, but it also demonstrates the general limitation of satellite technology in this field because of its reliance to integrate other data sources for a meaningful result. The specific indicator requires a range of different data sources, including health records [31] [32] [34] and survey data [33] to substantiate the hypothesis. Other indicators also adopt other forms of data to train models [37] refine models with expert knowledge [38] with forms of data that include in-situ measurements, official statistics or eye witness accounts. This, however, is a limitation of all forms of data, where it can only provide information on one perspective. The think-tank 'Betterplace Labs' states that human rights research requires 'both quantitative and qualitative research methods' and so there will always be a need to collect information from many resources to conduct a thorough investigation [39].

An alternative way of viewing satellite imagery is it another type of data that can assist in delivering further insights that were not possible. When describing the role that remote sensing can play in modern slavery investigations, Jackson (2019) outlines that EO cannot be used for all types slavery studies, but can provide information 'in remote areas which may have previously been inaccessible, or even unknown'. This is demonstrated in OHCHR 3.5.2, 'Reported cases of inhuman methods of execution and treatment of persons sentenced to death /incarcerated in the reporting period'. The basis for this indicator's analysis is taken from research into reports of North Korea's inhumane detention centres. North Korea isolates itself from most of the world, with personal accounts of brutality and extremism, which include illegal imprisonments and brutal killings Satellite imagery presents a unique vantage to validate the testimonies of escaped population. Son (2020) explores the work done by NGO 'the Mapping project', which aims to report on the alleged atrocities the North Korean Government has put on its people. The work uncovers the location of burial sites of victims of state-sponsored killings. They describes that satellite imagery improves the quality of the interviews because the images can 'contextualise the testimony' [40] [41] [42]. Clearly there is relevance of mixed methods analysis is vital for this research because it help identify common patterns [43].

3.1.3 Spatial resolution requirements

The OHCHR indicators cover a wide range of spatial scales, from discerning individual buildings to aggregating on a national level. Therefore, the satellite mission spatial resolution needs to match the level of detail required in the investigation. With some commercial satellite missions achieving resolution down to 20cm, this broadens the possibility for ingesting EO data in human rights research. This level of resolution is greatly needed for indicators that require find details. OHCHR 13.6.2, 13.9.2 and 13.10.2 all relate to determining the proportion of people killed by execution, from imprisonment or conflict, such as war. In instances of extreme violations like war crimes or illegal executions, mass graves are likely to be the method of disposal of bodies, and their mere detection can serve as compelling evidence in human rights investigations. While satellite imagery cannot provide an exact count of victims of such heinous acts, it can supply timely information regarding the location, timing, and frequency of these graves [41] [44] [45] [46].

Lavers (2009) emphasizes the preference for high-resolution satellite imagery in human rights research whenever feasible [47]. There is a variety of options in multispectral VNIR imagery options from commercial missions that reach with resolutions <1m, but there are options to use open-source imagery that can achieve resolution at approximately 10m, such as ESA's Copernicus programme or NASA's Landsat programme. Throughout the taxonomy, both options are explored and referenced wherever possible, such as OHCHR 6.2.3 which estimates reclaimed hazardous sites. Soil contamination can render a site hazardous, and multispectral imagery can detect and quantify this by identifying distinct spectral signatures in contaminated soil compared to healthy soil. This application can be served using commercial imagery, open-source data [48], or a combination of both [49], with open-source imagery sometimes offering suitable resolutions, albeit contingent on the size of the monitored land. In contrast to multispectral VNIR imagery, SAR imagery, although relatively newer in comparison, also has the capability to achieve very high spatial resolutions.

In an ideal situation, the highest resolution satellite imagery is optimal because it can provides the most detail in an image and so more accurate results can be obtained [50]. However, attaining such resolution may prove unfeasible in many circumstances because the user will always be limited by storage and budgetary restrictions. These limitations are prominent in many areas of the public and charity sector, which is also where these investigations take place. For commercial satellite imagery that can reach equal or less than 1m spatial resolution currently cost on average $22.5/km^2 [51], which becomes expensive if generating a time-series analysis across a large area. This type of imagery is necessary for studies that require this level of detail, but there are many open-source data options that can provide high spatial and spectral resolution, including the Sentinel-2, Sentinel-3 (ESA), Landsat, Terra and Aqua (NASA) missions. Furthermore, noncommercial research can also obtain VHR imagery is available with no cost if applying to specialised grants.

Not all imagery forms have as many options as multispectral VNIR and SAR, including passive microwave satellites that are limited in varieties and abundance. Table 1 demonstrates that passive microwave radiometers are primarily applicable in research related to the health of natural and agricultural landscapes because it interacts uniquely with water, which occur over large scales and so very high-resolution imagery is not required. Nevertheless, studies are limited to AOI that can be resolved within the current standards of satellite. NASA's Soil Moisture Active-Passive Mission (SMAP) is one of the leading passive (and active) microwave satellites and achieves a resolution of 9 km after resampling, limiting chosen FOV to areas that can be resolved at this resolution. Studies on air pollution and weather also bare this problem where they are limited by the resolution of data. Monitoring capabilities of GHG gases is expanding due to the demand of industries to meet net-zero targets. GHGSat, commercial satellite data provider, offers data down to 50m, but at a cost. Unlike multispectral imagery, there is a large gap in capabilities between commercial data and open-source data, as ESA's Sentinel-5 provides resolution at approximately 5.5 x 3.5 km.

3.2 Comparison of sensors

3.2.1 Multispectral imagery

Based on the findings of the taxonomic analysis, multispectral VNIR imagery emerges as the most pertinent tool for addressing the specified OHCHR indicators. This makes it extremely important to identify important features in human rights studies, such as mass graves or destroyed landscapes. Manual identification is a well-used method because it is the easiest to interpret and so can be widely understood by the general public. This makes it extremely important for identifying important features in human rights studies, such as mass graves or destroyed landscapes. Notably, organizations like the UN Satellite Centre (UNOSAT) have relied on this method, utilizing it, for instance, in their efforts to verify the presence of mass graves in Libya's Marqub District [52]. This method is effective in detecting very slight disturbances to the Earth's surface, where details are very fine fine or if a training dataset is not available. However, manual classification can be unreliable as it includes human error and is time consuming [53].

Spectral indices constitute another prominent aspect of multispectral (VNIR/MW) research, primarily because they enable the selective enhancement of specific target features through the choice of complementary wavelengths. Spectral indices typically involve the computation of differences between distinct wavelengths, such as the Difference Vegetation Index (DVI) which is the difference between the near-infrared (NIR) and red bands. The Normalised Difference Vegetation Index (NDVI) is a slight variation on the DVI, but is important to compare vicinity and health of vegetation and so is used widely in taxonomy in a number of ways including assessing irrigation on arable land [54] [55] [56], disease mapping [57] and identifying locations of labour exploitation [58].

Machine learning (ML) algorithms are another form to process satellite imagery, and can be applied to many applications in human rights investigations. ML classification algorithms are notably used in LULC because they can compute varied and complex data sources for fast and digestible output. This is particularly important in the context of human rights research where ML LULC algorithms can be applied to research including agricultural land under sustainable practices [19] [20], water quality parameters [59], and urban environments [60]. ML classification also has applications in identifying specific features such as roads [61] [62], impoverished communities [63] or damaged houses after a disaster [64].

Multispectral imagery is also an important tool in assessing the concentration of particulate matter, particles that are a by-product of combustion, in the atmosphere and so are prevalent in urban areas or near industrial activities. The particles have severe effects on health, particularly on heart [65]and respiratory disease [66]. Indicator 2.3.9 addresses it by specifying monitoring capabilites of particulate matter ('Annual mean levels of fine particulate matter (e.g. PM2.5 and PM10) in cities (population weighted) [11.6.2]'). Particulate matter research applies multispectral imagery in a unique way, where the aerosol optical depth (AOD) or aerosol optical thickness (AOT) is used. AOD measures the amount of light lost from aerosols in the atmosphere and so this is a key feature needed to measure particulate matter. The MODIS instrument aboard NASA's Terra and Aqua satellites is the most widely used instrument in these studies [67] [68]. Satellite-derived particulate matter estimations can also be used in combination with other data sources, such as public health data or imagery from natural disasters, to derive its direct impact on surrounding communities [69] [70] [71].

3.2.2 Passive microwave

Passive microwave imagery represents a subset of multispectral data, typically distinct from visible near-infrared (VNIR) multispectral satellite missions. However, there are noteworthy exceptions to this pattern, exemplified by NASA's Aqua satellite, which carries both a microwave radiometer (AMSR-E) and a spectro-radiometer designed to monitor the VNIR/SWIR spectrum (MODIS). Nevertheless, the majority of missions, such as SMOS (ESA), SMAP, and HYRDOS (NASA), remain separated due to their specialized applications. These applications primarily focus on soil moisture studies, as water content is a dominant factor that affects the signal. This information is critical for agricultural studies that centre on irrigation [72] [73] and crop health [7], but can also be extended to applications in human health and safety, from vector-borne diseases [74] and natural disasters [75]. Therefore, passive MW is a vital foundation to *right to adequate food*, *right to health* and *right to housing*.

3.2.3 Hyperspectral imagery

Hyperspectral imagery plays a prominent role in various research domains, and its significance is particularly pronounced in endeavors aimed at the identification of specific substances, whether they are situated on land, within aquatic environments, or in the atmosphere. Within the realm of agricultural studies, hyperspectral imagery stands out due to its capacity to tailor wavelength selection for the precise detection of crop productivity and health [27] [28] [76]. This capability enables a nuanced spectral analysis, setting it apart from multispectral remote sensing, which exhibits limited spectral diversity [27]. Consequently, hyperspectral imagery emerges as an ideal tool for addressing indicators related to the right to Adequate Food, particularly indicators 1.4.5, 1.4.8, 1.4.10, 1.4.11, and 1.9.3.

As well as crop studies, hyperspectral imagery is capable of determining pollution concentration in soil, a critical component of determining habitability of land and investigations into poor industrial practices. Notably, heavy metals, which pose severe environmental threats and often result from industrial and mining activities, have been subject to hyperspectral analysis, including arsenic [77], Chromium [49], Zinc [78], Nickel [78] and Copper [78]. Pollution can also infiltrate water supplies and so hyperspectral imagery can also measure the water quality in instances where water system may be compromised [79] [80] [81] [82].

Some hyperspectral missions are adapted to specifically measure gas column-densities in the atmosphere, which allows for studies on GHG and trace gas emission studies. The term ‘air pollution’ encompasses a variety of different gases, of which satellites are able to monitor many, including CO_2, SO_2, NO_X and CO. OHCHR indicators 2.3.2 and 2.8.2 directly assess air pollution levels (the former only measures CO_2 levels) and so the results can be directly obtained from emission-specific missions, such as Sentinel-5 and OCO-2/3 [83] [84] [85] [86]. Gas emissions can also be used as an indirect indicator for research in GDP forecasting [87], and wildfire damage mapping [88].

3.2.4 Synthetic Aperture Radar

Synthetic Aperture Radar (SAR) imagery stands out as a widely employed imaging modality in the realm of OHCHR investigations. Its versatility, driven by a broad spectrum of operating wavelengths and spatial resolutions, enables it to have a wide range of applications. A distinction attribute of SAR imagery that makes it particularly important for human rights research, demonstrated through the taxonomy, is its sensitivity to different textures as this determines the reflectance angle of the radar signal. It is especially sensitive to water because it responds to water very differently than other materials. This means it is very important for studies on the *right to water and sanitation*, including measuring water content in soil [89], locating offshore oil spills [90] [91] and wastewater disposal [92].

SAR sensitivity also extends to impervious surfaces, which are typically found in built-up areas like towns and cities. Therefore, it’s very useful in providing information to indicators found in *right to adequate housing*. Applications of SAR for this purpose are detecting the expansion of urban cities [93] [94] [95], but also detecting fragilities to infrastructure, which could ultimately make buildings unsafe [96] [97] [98].

Notably, SAR sensors exhibit clear sensitivity to surface displacements on the Earth's surface. Coupled with its capacity to discriminate between surface features, SAR imaging emerges as an invaluable tool for natural disaster mapping. This attribute aligns with the OHCHR indicators 8.5.4 and 8.9.1, which necessitate the mapping of disasters to assess direct economic losses and the number of individuals directly affected, respectively. SAR imagery serves as a potent means of quantifying the impacts of both natural and man-made disasters by enabling the detection of structural changes in buildings before and after such events occur [99] [100] [101].

3.2.6 Meteorology datasets

Site-specific rainfall measurements are required in hydrological studies of agricultural land (addressing indicators 1.4.2, 1.4.5, 1.4.10, 1.5.3 and 1.9.3). In these applications, data derived directly from satellites, and supplemented with site-specific rainfall gauge measurements, are applied [102] [103] [73] to refine the accuracy at a site-specific level. CHIRPS is an alternative dataset that can also be applied in agricultural studies, and proves useful if in-situ gauge measurements are not manageable [104] [6] [105]. There is overlap between passive MW and meteorological research as both provide information on rainfall and moisture parameters. Therefore, meteorological datasets are insightful for studies of disease mapping [31] [34] [106], poverty estimates [107] [108] and natural disaster management [109]

[110], covering *right to health, right to housing* and *rights to non-discrimination and equality*.

4. Future of the field

This study clearly demonstrates the benefit that satellite imagery already contributes to human rights research, spanning a wide range applications including environmental, health, agriculture and conflict, albeit not officially documented. The taxonomy therefore provides a framework that interested parties can adopt into their own human rights research, whether by Government officials, NGOs or public advocacy groups. Furthermore, professionals in EO services and analytics can use the taxonomy as a tool for understanding and expanding the potential for EO to feature in more human rights applications in the future, as they have the skills enhance and expand upon the techniques already discussed. Lack of trained analysts is a potential risk to the sector [111], but transparency and awareness of this unique data source will gradually mitigate this concern.

However, it is important to acknowledge a limitation of this technology: certain forms of satellite imagery may lack the requisite sophistication to capture intricate details within a specific scene. Unmanned aerial vehicles (UAVs) and aerial imagery represent alternative remote sensing technologies that hold significance in humanitarian research, particularly in contexts such as natural disaster assessment, conflict analysis, and pollution monitoring. These imaging modalities are often preferred due to their ability to provide high-resolution data and flexible flight scheduling. Nevertheless, they too encounter limitations associated with airspace permissions, potentially impeding observations in restricted areas. Geostationary satellites offer continuous monitoring capabilities but are constrained to the specific areas covered by their missions. The pace of technological advancement in satellite missions, with private missions leading the way in major strides in frequency and high spatial resolution, promises ongoing progress. Public missions, on the other hand, are instrumental in ensuring widespread access through open-source data dissemination. The evolution of satellite technology will likely continue in parallel with the integration of multiple imaging sources, harnessing the advantages of each to provide the spatial resolution of UAVs combined with the scalability and regularity of satellite imagery. This approach has already found application in precision agriculture studies [112] [113] and natural disaster assessments [114] [115], aligning with the requirements of the OHCHR indicators and holding potential for expansion into diverse applications in the future.

Following the completion of an investigation, findings can be communicated through various channels, including official reports and media coverage. However, the most significant and consequential use of this information lies in legal processes aimed at holding perpetrators accountable. The International Criminal Tribunal for the former Yugoslavia (ICTY) marked a pivotal moment by incorporating satellite imagery as evidence to depict the extent of devastation caused. Since then, such imagery has been introduced in numerous civil, national, and international court cases, serving not only to set the scene for juries but also as substantive evidence. It is important to note that the predominant use of satellite imagery in legal contexts has largely been confined to visual inspection of high-resolution multispectral imagery due to lawyers[1] limited familiarity with alternative imagery types and techniques. Several challenges must be surmounted to facilitate the admissibility of EO data as evidence, including the standardization of satellite imagery and associated techniques. Equally critical is raising awareness within the legal community, as a deeper understanding of the diverse technologies available can bolster lawyers confidence in presenting new techniques in court.

5. Conclusions

The distinctive and indispensable role of satellite imagery in human rights investigations arises from its capacity for comprehensive and timely coverage of the Earth's surface. Despite its adoption in select investigations, its full potential remains largely untapped. Consequently, the presented taxonomy offers a comprehensive overview of the myriad possibilities offered by this technology. The foundation of this study is built upon the OHCHR human rights indicators, chosen for their all-encompassing nature, widespread adoption, and their alignment with the United Nations' Sustainable Development Goals—a connection that is extensively explored using satellite imagery.

The proposed taxonomy outlines the various types of satellite imagery that can aid in fulfilling each relevant indicator, while also indicating the extent to which such imagery can address the specific demands of each indicator. It is worth noting that most applications of Earth observation (EO) technology only provide partial contributions to the OHCHR indicators, as these indicators entail complex requirements and both EO data and other data sources offer only one perspective. Nonetheless, the taxonomy has illuminated the diverse array of applications spanning the OHCHR indicators and has shed light on how satellite imagery can bridge critical data gaps.

[1] Interview with expert witness of satellite imagery in court, Online, 24th May 2023

Multispectral imagery stands as the most well-known and widely employed form of satellite imagery in human rights-related investigations. This popularity stems from its ease of interpretation by the general public, its prevalence as the most commonly used sensor type aboard satellites in orbit, and the availability of numerous algorithms for data processing. Nevertheless, the taxonomy underscores the spectrum of applications within the OHCHR indicators and underscores the capacity of satellite imagery to address information deficiencies.

Acknowledgements

This study was half-funded by ESA under the OSIP Co-Sponsored PhD activity: “EO4HR: Earth Observation for Human Rights Monitoring" No. 4000138000 (part of the ESA Discovery EISI Framework). The authors would also like to acknowledge the support of ESA and project partner MindEarth through the Research Fellow program. Thank you also to Lars Bromley, Specialist at the United Nations Institute for Training and Research (UNITAR), for providing their expertise in the field

Appendix A: Selected Labelled Indicators

Rights	Indicators	Reference
Right to adequate food (OHCHR 1)	Arable irrigated land per person	**1.4.2**
	Proportion of agricultural area under productive and sustainable agriculture [2.4.1]	**1.4.5**
	Volume of production per labour unit by classes of farming/pastoral/forestry enterprise size [2.3.1]	**1.4.8**
	Cereal import dependency ratio in the reporting period	**1.4.10**
	Proportion of fish stocks within biologically sustainable levels [14.4.1]	**1.4.11**
	Proportion of targeted population that was brought above the poverty line in the reporting period [1.2.1, 1.2.2]	**1.5.3**
	Proportion of the rural population who live within 2 km of an all-season road [9.1.1]	**1.5.6**
	Indicator of food price anomalies [2.c.1]	**1.9.3**
	Proportion of targeted population that was extended access to safely managed drinking water source[6.1.1] in the reporting period	**14.10.2***
Right to the enjoyment of the highest attainable standard of physical and mental health (OHCHR 2)	Proportion of the target population covered by all vaccines included in their national programme, including children immunized against vaccine-preventable diseases [3.b.1]	**2.2.11**
	Proportion of population using safely managed drinking water [6.1.1] and sanitation services [6.2.1]	**14.10.2***
	CO2 emission per unit of value added [9.4.1]	**2.3.2**
	Proportion of population or households living or working in or near hazardous conditions rehabilitated	**6.6.3***
	Annual mean levels of fine particulate matter (e.g. PM2.5 and PM10) in cities (population weighted) [11.6.2]	**2.3.9**
	Hazardous waste generated per capita and proportion of hazardous waste treated, by type of treatment[12.4.2]	**6.6.4***
	(Improvement in) Density and distribution of medical and paramedical personnel, hospital beds and other primary health-care facilities [3.c.1]	**2.5.2**
	Coverage of essential health services (defined as the average coverage of essential services based on tracer interventions that include reproductive, maternal, new born and child health, infectious diseases, noncommunicable diseases and service capacity and access, among the general and the most disadvantaged population) [3.8.1]	**2.5.9***
	Mortality rate attributed to household and ambient air pollution [3.9.1]	**2.8.2**
	Number of deaths, missing persons and directly affected persons attributed to disasters per 100,000 population [11.5.1/13.1.1]	**8.9.1***
	Death rate associated with and incidence of new HIV infections per 1,000 uninfected population [3.3.1], and incidence of tuberculosis [3.3.2], malaria [3.3.3] and hepatitis B [3.3.4] per 1,000 population, by sex, age and key population	**2.9.1**
Right not to be subjected to torture or to cruel, inhuman or degrading treatment or punishment (OHCHR 3)	Actual prison occupancy as a proportion of prison capacity in accordance with relevant United Nations instruments on prison conditions	**3.2.1**
	Proportion of detained and imprisoned persons in accommodation meeting legally stipulated requirements(e.g., drinking water, cubic content of air, minimum floor space, heating)	**3.2.2**
	Reported cases of inhuman methods of execution and treatment of persons sentenced to death /incarcerated in the reporting period	**3.5.2**
	Incidence and prevalence of death, physical injury and communicable and non-communicable diseases (e.g., HIV/AIDS [3.3.1], tuberculosis [3.3.2], malaria [3.3.3], and mental impairment) in custody	**2.9.1***
Right to education (OHCHR 5)	Proportion of schools with access to (a) electricity; (b) the Internet for pedagogical purposes; (c) computers for pedagogical purposes; (d) adapted infrastructure and materials for students with disabilities; (e) basic drinking water; (f) single-sex basic	**5.4.1**

	sanitation facilities; and (g) basic handwashing facilities (as per the WASH indicator definitions) [4.a.1]	
	(Improvement in) Density of primary, secondary and higher education facilities in the reporting period	**5.8.1**
Right to adequate housing (OHCHR 6)	Proportion of homes(cities, towns and villages) brought under the provisions of building codes and by-laws in the reporting period	**6.2.1**
	Habitable area (sq. m.) added through reclamation, including of hazardous sites and change in land-use pattern, in the reporting period	**6.2.3**
	Ratio of land consumption rate to population growth rate [11.3.1]	**6.2.5**
	Average share of the built-up area of cities that is open space for public use for all, by sex, age and persons with disabilities [11.7.1]	**6.2.6**
	Proportion of population with sufficient living space (persons per room or rooms per household) or average number of persons per room among target households	**6.6.1**
	Proportion of households living in permanent structure in compliance with building codes and by-laws	**6.6.2**
	Proportion of households living in or near hazardous conditions	**6.6.3**
	Hazardous waste generated per capita and proportion of hazardous waste treated, by type of treatment [12.4.2]	**6.6.4**
	Proportion of urban population living in slums, informal settlements or inadequate housing [11.1.1]	**6.7.1**
	Proportion of population using safely managed drinking water [6.1.1], sanitation services [6.2.1], electricity [7.1.1] and waste disposal [11.6.1]	**6.7.2**
	Proportion of population living in households with access to basic services[1.4.1]	**6.7.3**
	Proportion of population that has convenient access to public transport, by sex, age and persons with disabilities [11.2.1]	**6.7.4**
	Proportion of the rural population who live within 2 km of an all-season road [9.1.1]	**1.5.6***
Right to work (OHCHR 7)	Proportion and frequency of enterprises inspected for conformity with labour standards and proportion of inspections resulting in administrative action or prosecution	**7.3.1**
	Proportion of children in productive activity	**7.5.2**
	Proportion of workers in precarious employment(e.g.,short-,fixed-term, casual, seasonal workers)	**7.6.4**
	Number of victims of human trafficking per 100,000 population, by sex, age and form of exploitation [16.2.2]	**7.9.3**
	Reported cases of violation of the right to work, including forced labour, discrimination and unlawful termination of employment and proportion of victims who received adequate compensation	**7.9.4**
Right to social security (OHCHR 8)	Direct economic loss attributed to disasters in relation to global gross domestic product (GDP) [1.5.2]	**8.5.4**
	Proportion of population in specific situations of need receiving social assistance for food, housing, health care, education, emergency or relief services Number of deaths, missing persons and directly affected persons attributed to disasters per 100,000 population [1.5.1]	**8.9.1**
	Proportion of individuals in the formal or informal economy below national poverty line before and after social transfers	**8.10.1**
Right to freedom of opinion and expression (OHCHR 9)	Proportion of population with access to TV and radio broadcasts	**9.3.3**
Rights to non-discrimination and equality (OHCHR 12)	Proportion of population using safely managed drinking water [6.1.1], sanitation services [6.2.1], electricity [7.1.1] and waste disposal [11.6.1]	**6.7.2***
	Proportion of targeted populations below national poverty line [1.2.1](and Gini indices) before and after social transfers	**12.9.1**
Right to life (OHCHR 13)	Proportion of population using safely managed drinking water services [6.1.1]	**14.10.2***
	Coverage of essential health services (defined as the average coverage of essential services based on tracer interventions that include reproductive, maternal, newborn and child health, infectious diseases, non-communicable diseases and service capacity and access, among the general and the most disadvantaged population) [3.8.1]	**13.4.7**
	Number of deaths in custody per 1,000 detained or imprisoned persons, by cause of death(e.g.,illness, suicide, homicide)	**13.6.2**
	Prevalence of and death rates associated with communicable and non-communicable diseases (e.g., HIV/AIDS [3.3.1], malaria, tuberculosis [3.3.2], [3.3.3], and hepatitis b [3.3.4])	**13.8.4**
	Number of executions (under death penalty)	**13.9.2**
	Proportion of population using safely managed drinking water services [6.1.1]	**14.10.2***

	Number of conflict-related deaths per 100, 000 population by sex, age and cause [16.1.2]	**13.10.2**
Right to water and sanitation (OHCHR 14)	Change in water-use efficiency over time [6.4.1]	**14.1.2**
	Proportion of schools with access to (e) basic drinking water; (f) single-sex basic sanitation facilities; and(g) basic handwashing facilities (as per the WASH indicator definitions) [4.a.1]	**14.2.1**
	Proportion of bodies of water with good ambient water quality [6.3.2]	**14.3.3**
	Proportion of wastewater safely treated [6.3.1]	**14.3.4**
	Proportion of health centres, prisons and other institutions with access to safe drinking water, sanitation and hand-washing facilities (e.g. with facilities for persons with disabilities, older persons)	**14.5.1**
	Mortality rate attributed to unsafe water, unsafe sanitation and lack of hygiene (exposure to unsafe Water, Sanitation and Hygiene for All (WASH) services) [3.9.2]	**14.6.1**
	Proportion of population using safely managed drinking water services [6.1.1] and safely managed sanitation services, including a hand-washing facility with soap and water [6.2.1]	**14.10.2**
Right to freedom of peaceful assembly and association (OHCHR 15)	Proportion of population covered by a mobile network, by technology [9.c.1]	**9.3.4***

Bibliography

[1] M. Finer, S. Novoa, M. J. Weisse, R. Petersen, J. Mascaro, T. Souto, F. Stearns and R. G. Martinez, "Combating deforestation: From satellite to intervention," *Science,* vol. 360, no. 6359, pp. 1303-1305, 2018.

[2] E. Berthier, E. Schiefer, G. K. C. Clarke, B. Menounos and F. Remy, "Contribution of Alaskan glaciers to sea-level rise derived from satellite imagery," *Nature Geoscience,* vol. 3, pp. 92-95, 2010.

[3] P. Lynch, "The origins of computer weather prediction and climate modeling," *Journal of Computational Physics,* vol. 227, no. 7, pp. 3431-3444, 2008.

[4] R. DeFries, F. Achard, S. Brown, M. Herold, D. Murdiyarso, B. Schlamadinger and C. de Souza Jr, "Earth observations for estimating greenhouse gas emissions from deforestation in developing countries," *Environmental Science & Policy,* vol. 10, no. 4, pp. 385-394, 2007.

[5] L. Hein and N. de Ridder, "Desertification in the Sahel: a reinterpretation," *Global Change Biology,* vol. 12, no. 5, pp. 751-758, 2006.

[6] N. Alahacoon, M. Edirisinghe and M. Ranagalage, "Satellite-Based Meteorological and Agricultural Drought Monitoring for Agricultural Sustainability in Sri Lanka," *Sustainability,* vol. 13, no. 3427, 2021.

[7] M. Le Page and M. Zribi, "Analysis and Predictability of Drought In Northwest Africa Using Optical and Microwave Satellite Remote Sensing Products," *Scientific Reports,* vol. 9, no. 1466, 2019.

[8] T. W. Gillespie, J. Chu, E. Frankenberg and D. Thomas, "Assessment and Prediction of Natural Hazards from Satellite Imagery," *Prog Phys Geogr. ,* vol. 31, no. 5, pp. 459-470, 2007.

[9] ESA, "Satellite data provide valuable support for IPCC climate report," ESA, 31 08 2021. [Online]. Available: https://www.esa.int/Applications/Observing_the_Earth/Space_for_our_climate/Satellite_data_provide_valuable_support_for_IPCC_climate_report. [Accessed 30 07 2023].

[10] J. Wu, Z. Wang, W. Li and J. Peng, "Exploring factors affecting the relationship between light consumption and GDP based on DMSP/OLS nighttime satellite imagery," *Remote Sensing of Environment,* vol. 134, pp. 111-119, 2013.

[11] S. I. Deliry, Z. Y. Avdan and U. Avdan, "Extracting urban impervious surfaces from Sentinel-2 and Landsat-8 satellite data for urban planning and environmental management," *Environmental Science and Pollution Research,* vol. 28, pp. 6572-6586, 2021.

[12] G. R. Watmough, P. M. Atkinson, A. Saikia and C. W. Hutton, "Understanding the Evidence Base for Poverty–Environment Relationships using Remotely Sensed Satellite Data: An Example from Assam, India," *World Development,* vol. 78, pp. 188-203, 2016.

[13] A. Wolffenbuttel, "MH-17 Trial: U.S. Satellite Imagery and Foreign Confidential Intelligence in a Public Trial," 27 04 2021. [Online]. Available: http://opiniojuris.org/2021/04/27/mh-17-trial-u-s-satellite-imagery-and-foreign-confidential-intelligence-in-a-public-trial/. [Accessed 01 09 2023].

[14] J. Sudworth, "China's hidden camps," BBC, 2018.

[15] E. Robinson and S. Mann, "Investigating the Growth of Detention Facilities in Xinjiang Using Nighttime Lighting," RAND, 2021.

[16] OHCHR, "OHCHR Assessment of human rights concerns in the Xinjiang Uyghur Autonomous Region, People’s Republic of China," OHCHR, 2022.

[17] B. O'Connor, K. Moul, B. Pollini, X. de Lamo, W. Simonson, H. Allison, F. Albrecht, R. M. Guzinski, H. Larsen, J. McGlade and M. Paganini, "Earth Observation for SDG," 05 2020. [Online]. Available: https://eo4society.esa.int/wp-content/uploads/2021/01/EO_Compendium-for-SDGs.pdf. [Accessed 18 11 2022].

[18] A. Alshari and B. W. Gawali, "Development of classification system for LULC using remote sensing," *Global Transitions Proceedings,* vol. 2, pp. 8-17, 2021.

[19] N. Kussul, M. Lavreniuk, A. Kolotii, S. Skakun, O. Rakoid and L. Shumilo, "A workflow for Sustainable Development Goals indicators assessment based on high-resolution satellite data," *International Journal of Digital Earth,* vol. 13, no. 2, 2020.

[20] S. Talukdar, P. Singha, S. Mahato, Shahdahad, S. Pal, Y. Liou and A. Rahman, "Land-Use Land-Cover Classification by Machine Learning Classifiers for Satellite Observations—A Review," *Remote Sens.,* vol. 12, no. 1135, 2020.

[21] O. Akar and O. Gungor, "Classification of multispectral images using Random Forest algorithm," *Journal of Geodesy and Geoinformation,* vol. 1, no. 2, pp. 105-112, 2012.

[22] C. M. Sicre, R. Fieuzal and F. Baup, "Contribution of multispectral (optical and radar) satellite images to the classification of agricultural surfaces," *International Journal of Applied Earth Observation and Geoinformation,* vol. 84, no. 101972, 2020.

[23] K. Kussul, G. Lemoine, F. J. Gallego, S. V. Skakun, M. Lavreniuk and A. Y. Shelestov, "Parcel-Based Crop Classification in Ukraine Using Landsat-8 Data and Sentinel-1A Data," *IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING,* vol. 9, no. 6, 2016.

[24] V. N. Mishra, R. Prasad, P. Kumar, D. K. Gupta and P. K. Srivastava, "Dual-polarimetric C-band SAR data for land use/land cover classification by incorporating textural information," *Environmental Earth Sciences,* vol. 76, no. 26, 2017.

[25] A. C. Das, R. Noguchi and T. Ahamed, "Integrating an Expert System, GIS, and Satellite Remote Sensing to Evaluate Land Suitability for Sustainable Tea Production in Bangladesh," *Remote Sens,* vol. 12, no. 4136, 2020.

[26] I. Mariotto, P. S. Thenkabail, A. Huete, E. T. Slonecker and A. Platonov, "Hyperspectral versus multispectral crop-productivity modeling and type discrimination for the HyspIRI mission," *Remote Sensing of Environment,* vol. 139, pp. 291-305, 2013.

[27] M. Teke, H. S. Deveci, O. Haliloglu, S. Z. Gurbuz and U. Sakarya, "A Short Survey of Hyperspectral Remote Sensing Applications in Agriculture," in *6th International Conference on Recent Advances in Space Technologies (RAST)*, Istanbul, Turkey, 2013.

[28] C. B. Panda and K. N. Mohair, "Application of Hyperspectral Remote Sensing Role in Precision Farming and Sustainable Agriculture Under Climate Change: A Review," in *Climate Change Impacts on Natural Resources, Ecosystems and Agricultural Systems*, Springer Climate. Springer, Cham., 2023, pp. 503-520.

[29] G. Wiseman, H. McNairn, S. Homayouni and J. Shang, "RADARSAT-2 Polarimetric SAR Response to Crop Biomass for Agricultural Production Monitoring," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* vol. 7, no. 11, pp. 4461-4471, 2014.

[30] N. Minakawa, S. Munga, F. Atieli, E. Mushinzimana, G. Zhou, A. K. Githeko and G. Yan, "SPATIAL DISTRIBUTION OF ANOPHELINE LARVAL HABITATS IN WESTERN KENYAN HIGHLANDS: EFFECTS OF LAND COVER TYPES AND TOPOGRAPHY," *Am. J. Trop. Med. Hyg,* vol. 73, no. 1, pp. 157-165, 2005.

[31] M. C. Wimberly, D. M. Nekorchuk and R. R. Kankanala, "Cloud-based applications for accessing satellite Earth observations to support malaria early warning," *Scientific Data,* vol. 9, no. 208, 2022.

[32] B. Lobitz, L. Beck, A. Huq, B. Wood, G. Fuchs, A. S. G. Garuque and R. Colwell, "Climate and infectious disease: Use of remote sensing for detection of Vibrio cholerae by indirect measurement," *PROCEEDINGS OF THE NATIONAL ACADEMY OF SCIENCES,* vol. 97, no. 4, 2000.

[33] J. B. Kaneene, C. S. Bruning-Fann, L. M. Granger, R. Miller and B. A. Porter-Spalding, "Environmental and farm management factors associated with tuberculosis on cattle farms in northeastern Michigan," *Scientific Reports: Original Study,* vol. 221, no. 6, 2002.

[34] M. C. Thomson, A. M. Molesworth, M. H. Djingarey, K. R. Yameogo, F. Belanger and L. Cuevas, "Potential of environmental models to predict meningitisepidemics in Africa," *Tropical Medicine and International Health,* vol. 11, no. 6, pp. 781-788, 2006.

[35] L. A. Remer, R. C. Levy and J. V. Martins, "Opinion: Aerosol Remote Sensing Over The Next Twenty Years," *EGUsphere,* 2023.

[36] Z. Hu, "Spatial analysis of MODIS aerosol optical depth, PM2.5, and chronic coronary heart disease," *International Journal of Health Geographics,* vol. 8, no. 27, 2009.

[37] N. M. Kussul, A. Y. Shelestov, B. Yailymov, L. L. Shumilo, H. O. Yailymova, M. S. Lavreniuk, L. M. Kolos, L. V. Pidgorodetska and Y. V. Bilokonska, "Urban Atlas for Ukrainian cities on the basis of high-resolution satellite data," *Space Sci. & Technol.,* vol. 25, no. 6, pp. 51-60, 2019.

[38] Zylshal, S. Sulma, F. Yulianto, J. T. Nugroho and P. Sofan, "A support vector machine object based image analysis approach on urban green space extraction using Pleiades-1A imagery," *Modeling Earth Systems and Environment,* vol. 2, no. 54, 2016.

[39] S. Nabulega, "Research methods in human rights work: Some basics you need to know," betterplace Lab, 18 05 2020. [Online]. Available: https://www.betterplace-lab.org/research-methods-in-human-rights-work-some-basics-you-need-to-know. [Accessed 01 09 2023].

[40] S. A. Son, "Watching North Korea from the sky: Remote sensing and documenting human rights in the Democratic People's Republic of Korea," *Political Geography,* vol. 92, no. 102525, 2022.

[41] S. A. Son, D. Bielefield, H. Yang, H. Lee, S. Oh, S. Stevens, Y. Choi, E. H.-S. Shin, D. Yoon and C. E. Olesen, "Mapping the Fate of the Dead: Killings and Burials in North Korea," Transitional Justice Working Group (TJWG), Seoul, 2019.

[42] A. Park, D. Bielefeld, H. Y. Lee, S. Stevens, Y. Choi, E. H.-S. Shin, J. Kang, A. S.-A. Park, S. Song, D. Yoon and S. Kunnuwong, "MAPPING KILLINGS UNDER KIM JONG-UN: North Korea's Response to International Pressure," Seoul: Transitional Justice Working Group, Seoul, 2021.

[43] D. Congram, M. Kenyhercz and A. G. Green, "Grave mapping in support of the search for missing persons in conflict contexts," *Forensic Science International,* vol. 278, pp. 260-268, 2017.

[44] A. Froehlich and C. M. Tāiatu, "Bosnian Mass Graves," in *Space in Support of Human Rights*, Vienna, European Space Policy Institute, 2020, pp. 65-78.

[45] Amnesty International, "Burundi: Satellite evidence supports witness accounts of mass graves," Amnesty International, 28 01 2016. [Online]. Available: https://www.amnesty.org/en/latest/news/2016/01/burundi-satellite-evidence-supports-witness-accounts-of-mass-graves/#:~:text=The%20imagery%2C%20dating%20from%20late,day%20of%20Burundi's%20escalating%20crisis.. [Accessed 20 01 2023].

[46] B. L. Card and I. L. Baker, "GRID: A Methodology Integrating Witness Testimony and Satellite Imagery Analysis for Documenting Alleged Mass Atrocities," *Genocide Studies and Prevention: An International Journal,* vol. 8, no. 3, pp. 49-61, 2014.

[47] C. Lavers, O. Bishop, O. Hawkins, E. Grealey, C. Cox, D. Thomas and S. Trimel, "Application of satellite imagery to monitoring Human Rights abuse of vulnerable communities, with minimal risk to relief staff," *Journal of Physics: Conference Series,* vol. 178, no. 012039, 2009.

[48] Y. Fang, L. Xu, A. Wong and D. A. Clausi, "Multi-Temporal Landsat-8 Images for Retrieval and Broad Scale Mapping of Soil Copper Concentration Using Empirical Models," *Remote Sens.,* vol. 14, no. 2311, 2022.

[49] V. Khosravi, F. D. Ardejani, A. Gholizadeh and M. Saberioon, "Satellite Imagery for Monitoring and Mapping Soil Chromium Pollution in a Mine Waste Dump," *Remote Sensing,* vol. 13, no. 1277, 2021.

[50] S. Basheer, X. Wang, A. A. Forooque, R. A. Nawaz, K. Liu, T. Adekanmbi and S. Liu, "Comparison of Land Use Land Cover Classifiers Using Different Satellite Imagery and Machine Learning Techniques," *Remote Sens,* vol. 14, no. 4978, 2022.

[51] Statista, "Commercially available satellite imagery worldwide in 2022, by cost per square kilometer," Statista, 03 2022. [Online]. Available: https://www.statista.com/statistics/1293877/commercial-satellite-imagery-cost-worldwide/. [Accessed 7 09 2023].

[52] UNOSAT, "UNOSAT satellite imagery-based analysis of disturbed earth near Tarhuna, in Marqub District, Tripolitania Region, Libya on behalf of the Independent Fact-Finding Mission on Libya," 15 09 2021. [Online]. Available: https://www.ohchr.org/sites/default/files/Documents/HRBodies/HRCouncil/FFM-Libya/UNOSAT.pdf. [Accessed 10 02 2023].

[53] A. Cheriyadat, E. Bright, D. Potere and B. Bhaduri, "Mapping of settlements in high-resolution satellite imagery using high performance computing," *GeoJournal,* vol. 69, pp. 119-129, 2007.

[54] M. J. Cheema and W. G. Bastiaanssen, "Land use and land cover classification in the irrigated Indus Basin using growth phenology information from satellite data to support water management analysis," *Agricultural Water Management,* vol. 97, no. 10, pp. 1541-1552, 2010.

[55] H. Bazzi, N. Baghadadi, D. Ienco, M. El Hajj, M. Zribi, H. Belhouchette, M. J. Escorihuela and V. Demarez, "Mapping Irrigated Areas Using Sentinel-1 Time Series in Catalonia, Spain," *Remote Sens.,* vol. 11, no. 1836, 2019.

[56] N. Jin, B. Tao, W. Ren, M. Feng, R. Sun, L. He, W. Zhuang and Q. Yu, "Mapping Irrigated and Rainfed Wheat Areas Using Multi-Temporal Satellite Data," *Remote Sens.,* vol. 8, no. 207, 2016.

[57] A. Midekisa, G. Senay, G. M. Henebry, P. Semuniguse and M. C. Wimberly, "Remote sensing-based time series models for malaria early warning in the highlands of Ethiopia," *Malaria Journal,* vol. 11, no. 165, 2012.

[58] I. Kougkoulos, M. S. Cakir, N. Kunz, D. S. Boyd, A. Trautrims, K. Hatzinikolaou and S. Gold, "A Multi-Method Approach to Prioritize Locations of Labor Exploitation for Ground-Based Interventions," *Production and Operations Management,* vol. 30, no. 12, pp. 4396-4411, 2021.

[59] X. Chen, Y. S. Li, Z. Liu, K. Yin, Z. Li, O. W. Wai and B. King, "Integration of multi-source data for water quality classification in the Pearl River estuary and its adjacent coastal waters of Hong Kong," *Continental Shelf Rsearch,* vol. 24, no. 16, pp. 1827-1843, 2004.

[60] T. S. Aung, I. Overland, R. Vakulchuk and Y. Xie, "Using satellite data and machine learning to study conflict-induced environmental and socioeconomic destruction in data-poor conflict areas: The case of the Rakhine conflict," *Environ. Res. Commun.,* vol. 3, no. 025005, 2021.

[61] D. German and B. Jedynak, "An active testing model for tracking roads in satellite images," *IEEE,* vol. 18, no. 1, 1996.

[62] C. Unsalan and B. Sirmacek, "Road Network Detection Using Probabilistic and Graph Theoretical Methods," *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING,* vol. 50, no. 11, 2012.

[63] N. Jean, M. Burke, M. Xie, M. Davis, D. Lobell and S. Ermon, "Combining satellite imagery andmachine learning to predict poverty," *Science,* vol. 353, no. 6301, pp. 790-794, 2016.

[64] E. Weber and H. Kan, "BUILDING DISASTER DAMAGE ASSESSMENT IN SATELLITE IMAGERY WITH MULTI-TEMPORAL FUSION," in *ICLR 2020 AI For Earth Sciences Workshop*, 2020.

[65] A. Peters, "Particulate matter and heart disease: Evidence from epidemiological studies," *Toxicology and Applied Pharmacology,* vol. 207, no. 2, pp. 477-482, 2005.

[66] S. Y. Kyung and S. H. Jeong, "Particulate-Matter Related Respiratory Diseases," *Tuberculoisis and Respiratory Diseases,* vol. 83, pp. 116-121, 2020.

[67] S. A. Christopher and P. Gupta, "Satellite Remote Sensing of Particulate Matter Air Quality: The Cloud-Cover Problem," *Journal of the Air & Waste Management Association,* vol. 60, no. 5, pp. 596-602, 2010.

[68] Y. Guo, Q. Tang, D.-Y. Gong and Z. Zhang, "Estimating ground-level PM2.5 concentrations in Beijing using a satellite-based geographically and temporally weighted regression model," *Remote Sensing of Environment,* vol. 198, pp. 140-149, 2017.

[69] S. Faridi, R. Bayat, A. J. Cohen, E. Sharafkhani, J. R. Brook, S. Niazi, M. Shamsipour, H. Amini, K. Naddafi and M. S. Hassanvand, "Health burden and economic loss attributable to ambient PM2.5 in Iran based on the ground and satellite data," *Scientific Report,* vol. 12, no. 14386, 2022.

[70] S. C. Anenberg, P. Achakulwisut, M. Brauer, D. Moran, J. S. Apte and D. K. Henze, "Particulate matter-attributable mortality and relationships with carbon dioxide in 250 urban areas worldwide," *Scientific Reports,* vol. 9, no. 11552, 2019.

[71] H. K. Preisler, D. Schweizer, R. Cisneros, T. Procter, M. Ruminski and L. Tarnay, "A statistical model for determining impact of wildland fires on Particulate Matter (PM2.5) in Central California aided by satellite imagery of smoke," *Environmental Pollution,* vol. 205, pp. 340-349, 2015.

[72] E. Jalilvand, M. Tahirishy, S. A. G. Z. Hashemi and L. Brocca, "Quantification of irrigation water using remote sensing of soil moisture in a semi-arid region," *Remote Sensing of Environment,* vol. 231, no. 111226, 2019.

[73] L. Brocca, A. Tarpanelli, P. Filippucci, W. Dorigo, F. Zaussinger, A. Gruber and D. Fernandez-Prieto, "How much water is used for irrigation? A new approach exploiting coarse resolution satellite soil moisture products," *International Journal of Applied Earth Observation and Geoinformation,* vol. 73, pp. 752-766, 2018.

[74] T. W. Chuang, G. M. Henebry, J. S. Kimball, D. L. VanRoekel-Patton, M. B. Hildreth and M. C. Wimberly, "Satellite microwave remote sensing for environmental modeling of mosquito population dynamics," *Remote. Sens. Environ.,* vol. 125, pp. 147-156, 2012.

[75] T. D. Groeve, "Flood monitoring and mapping using passive microwave remote sensing in Namibia," *Geomatics, Natural Hazards and Risk,* vol. 1, no. 1, pp. 19-35, 2010.

[76] I. Mariotto, P. S. Thenkabail, A. Huete, E. T. Slonecker and A. Platonov, "Hyperspectral versus multispectral crop-productivity modeling and type discrimination for the HyspIRI mission," *Remote Sensing of Environment,* vol. 139, pp. 291-305, 2013.

[77] X. Jia and D. Hou, "Mapping soil arsenic pollution at a brownfield site using satellite hyperspectral imagery and machine learning," *Science of the Total Environment,* vol. 857, no. 159387, 2023.

[78] Zhang, B. Guo, B. Zou, W. Wei, Y. Lei and T. Li, "Retrieving soil heavy metals concentrations based on GaoFen-5 hyperspectral satellite image at an opencast coal mine, Inner Mongolia, China," *Environmental Pollution,* vol. 300, no. 118981, 2022.

[79] K. Song, L. Li, L. P. Tedesco, S. Li, B. E. Hall and J. Du, "Remote quantification of phycocyanin in potable water sources through an adaptive model," *ISPRS,* vol. 95, pp. 68-80, Journal of Photogrammetry.

[80] V. E. Brando and A. G. Dekker, "Satellite hyperspectral remote sensing for estimating estuarine and coastal water quality," *IEEE Transactions on Geoscience and Remote Sensing,* vol. 41, no. 6, pp. 1378-1387, 2003.

[81] V. Sagan, K. T. Peterson, M. Maimaitijiang, P. Sidike, J. Sloan, B. A. Greeling, S. Maalouf and C. Adams, "Monitoring inland water quality using remote sensing: potential and limitations of spectral indices, bio-optical simulations, machine learning, and cloud computing," *Earth-Science Reviews,* vol. 205, no. 103197, 2020.

[82] N. Chang, S. Imen and B. Vannah, "Remote Sensing for Monitoring Surface WaterQuality Status and Ecosystem State in Relationto the Nutrient Cycle: A 40-Year Perspective," *Critical Reviews in Environmental Science and Technology,,* vol. 45, pp. 101-166, 2015.

[83] L. Zhang, C. S. Lee, R. Zhang and L. Chen, "Spatial and temporal evaluation of long term trend (2005–2014) of OMI retrieved NO2 and SO2 concentrations in Henan Province, China," *Atmospheric Environment,* vol. 154, pp. 151-166, 2017.

[84] D. A. Potts, E. J. S. Ferranti, R. Timmis, A. S. Brown and J. D. V. Hey, "Satellite Data Applications for Site-Specific Air Quality Regulation in the UK: Pilot Study and Prospects," *Atmosphere,* vol. 12, no. 1659, 2021.

[85] L. Yurganov and V. Rakitin, "Two Decades of Satellite Observations of Carbon Monoxide Confirm the Increase in Northern Hemispheric Wildfires," *Atmosphere,* vol. 13, no. 1479, 2022.

[86] W. Su, Q. Hu, Y. Chen, J. Lin, C. Zhang and C. Liu, "Inferring global surface HCHO concentrations from multisource hyperspectral satellites and their application to HCHO-related global cancer burden estimation," *Environment International,* vol. 170, no. 107600, 2022.

[87] S. kumar and P. K. Muhuri, "A novel GDP prediction technique based on transfer learning using CO2 emission dataset," *Applied Energy,* vol. 253, no. 113476, 2019.

[88] S. Xulu, N. Mbatha and K. Peerbhay, "Burned Area Mapping over the Southern Cape Forestry Region, South Africa Using Sentinel Data within GEE Cloud Platform," *ISPRS Int. J. Geo-Inf,* vol. 10, no. 511, 2021.

[89] M. A. Shareef, A. Khenchaf and A. Toumi, "Integration of Passive and Active Microwave Remote Sensing to Estimate Water Quality Parameters," in *IEEE Radar Conference (RadarConf)*, Philadelphia, PA, USA, 2016.

[90] O. Garcia-Pineda, I. MacDonald, C. Hu, J. Svejkovsky, M. Hess, D. Dukovskoy and S. L. Morey, "Detection of Floating Oil Anomalies From the Deepwater Horizon Oil Spill With Synthetic Aperture Radar," *Oceanography,* vol. 26, no. 2, pp. 124-137, 2013.

[91] G. Chen, Y. Li, G. Sun and Y. Zhang, "Application of Deep Networks to Oil Spill Detection Using Polarimetric Synthetic Aperture Radar Images," *Appl. Sci.,* vol. 968, p. 7, 2017.

[92] M. G. M, B. H, R. Trinh, J. Pan and R. Christine, "Satellite detection of wastewater diversion plumes in Southern California," *Estuarine, Coastal and Shelf Science,* vol. 186, pp. 171-182, 2017.

[93] T. Esch, W. Heldens, A. Hirner, M. Keil, M. Marconcini, A. Roth, J. Zeilder, S. Dech and E. Strano, "Breaking new ground in mapping human settlements from space – The," *ISPRS Journal of Photogrammetry and Remote Sensing,* vol. 134, pp. 30-42, 2017.

[94] M. Marconcini, A. Metz-Marconini, S. Ureyen, D. Palacios-Lopez, W. Hanke, F. Bachofer, J. Zeidler, T. Esch, N. Gorelick, A. Kakarla, M. Paganini and E. Strano, "Outlining where humans live, the World Settlement Footprint 2015," *Scientific Data,* vol. 7, no. 242, 2020.

[95] I. H. Holobaca, J. Benedek, C. D. Ursu, M. Alexe and K. Temerdek-Ivan, "Ratio of Land Consumption Rate to Population Growth Rate in the Major Metropolitan Areas of Romania," *Remote Sensing,* vol. 14, no. 6016, 2022.

[96] F. Dell'Acqua and P. Gamba, "Unstructured Human Settlement Mapping with SAR Sensors," in *roceedings of the IEEE Geoscience and Remote Sensing Symposium, IGARSS 2006*, New York, 2006.

[97] G. Delo, M. Civera, E. Lenticchia, G. Miraglia, C. Surace and R. Ceravolo, "Interferometric Satellite Data in Structural Health Monitoring: An Application to the Effects of the Construction of a Subway Line in the Urban Area of Rome," *Applied Sciences,* vol. 12, no. 1658, 2022.

[98] X. Hao, B.-G. Hu, T. Kun, H. Wei and K. Peng, "Application of Satellite Interference Imaging Technology in Building Safety Monitoring," in *ICSINC 2018: Signal and Information Processing, Networking and Computers*, 2018.

[99] T. G. J. Rudner, M. Rubwurm, K. Fil, R. Pelich, B. Bischke, V. Kopackova and P. Bilinski, "Multi3Net: Segmenting Flooded Buildings via Fusion of Multiresolution, Multisensor, and Multitemporal Satellite Imagery," in *Proceedings of the AAAI Conference on Artificial Intelligence*, 2019.

[100] M. Matsuoka and F. Yamazaki, "Use of Satellite SAR Intensity Imagery for Detecting Building Areas Damaged Due to Earthquakes," *Earthquake Spectra,* vol. 20, no. 3, 2004.

[101] M. Gahler, "Remote Sensing for Natural or Man-made Disasters and Environmental Changes," *Environmental Applications of Remote Sensing,* 2016.

[102] M. W. van Eekelen, W. G. Bastiaanssen, C. Jarmain, B. Jackson, F. Ferreira, P. van der Zaag, A. S. Okello, J. Bosch, P. Dye, E. Bastidas-Obando, R. J. Dost and W. M. Luxemburg, "A novel approach to estimate direct and indirect water withdrawals from satellite measurements: A case study from the Incomati basin," *Agriculture, Ecosystems & Environment,* vol. 200, pp. 126-142, 2015.

[103] T. Foster, T. Mieno and Brozović, "Satellite-Based Monitoring of Irrigation Water Use:Assessing Measurement Errors and TheirImplications for Agricultural WaterManagement Policy," *Water Resources Research,* vol. 56, 2020.

[104] S. Ragettli, T. Herberz and T. Siegfried, "An Unsupervised Classification Algorithm for Multi-Temporal Irrigated Area Mapping in Central Asia," *Remote Sens.,* vol. 10, no. 1823, 2018.

[105] A. Wolanin, G. Mateo-Garcia, G. Camps-Valls, L. Gomez-Chova, M. Meroni, G. Duveiller, Y. Liangzhi and Guanter L, "Estimating and understanding crop yields with explainable deep learning in the Indian Wheat Belt," *Environ. Res. Lett.,* vol. 15, no. 024019, 2020.

[106] G. C. de Magney, R. Murtugudde, M. R. Sapiano, A. Nizam, C. W. Brown, A. J. Busalacchi, M. Yunus, G. B. Nair, A. I. Gil, C. F. Lanata, J. Calkins, B. Manna, K. Rajendran, M. K. Bhattacharya, A. Huq, R. B. Sack and R. R. Colwell, "Environmental signatures associated withcholera epidemics," *PNAS,* vol. 105, no. 46, pp. 17676-17681, 2008.

[107] J. Hersh, R. Engstrom and M. Mann, "Open data for algorithms: mapping poverty in Belize using open satellite derived features and machine learning," *Information Technology for Development,* vol. 27, no. 2, 2021.

[108] E. T. R. T. Rogers D, "Povertymapping in Uganda: an analysis using remotelysensed and other environmental data," 2006. [Online]. Available: https://royalsocietypublishing.org/doi/epdf/10.1098/rsif.2016.0690. [Accessed 25 08 2023].

[109] Y. Hong, R. F. Adler, A. Negri and G. J. Huffman, "Flood and landslide applications of near real-time

satellite rainfall products," *Natural Hazards,* vol. 43, pp. 285-294, 2007.

[110] R. L. Ray and J. M. Jacobs, "Relationships among remotely sensed soil moisture, precipitation and landslide events," *Natural Hazards,* vol. 43, pp. 211-222, 2007.

[111] N. Witjes and P. Olbrich, "A fragile transparency: satellite imagery," *Science and Public Policy,* vol. 44, no. 4, pp. 524-534, 2017.

[112] M. Maimaitijiang, V. Sagan, P. Sidike, A. M. Daloye, H. Erkbol and F. B. Fritschi, "Crop Monitoring Using Satellite/UAV Data Fusion and Machine Learning," *Remote sens.,* vol. 12, no. 1357, 2020.

[113] A. Jenerowicz and Woroszkiewicz, "The pan-sharpening of satellite and UAV imagery for agricultural applications," in *Proceedings Volume 9998, Remote Sensing for Agriculture, Ecosystems, and Hydrology XVIII*, Edinburgh, Scotland, 2016.

[114] M. Kakooei and Y. Baleghi, "Fusion of satellite, aircraft, and UAV data for automatic disaster damage assessment," *International Journal of Remote Sensing,* vol. 38, no. 8-10, 2017.

[115] Y. Li, W. Hu, H. Dong and X. Zhang, "Building Damage Detection from Post-Event Aerial Imagery Using Single Shot Multibox Detector," *Appl. Sci.,* vol. 9, no. 1128, 2019.