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Review

Earth observation technology's alignment with OHCHR indicators for strengthening human rights breach investigations and adjudication

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A R T I C L E I N F O

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A B S T R A C T

Human rights investigations demand reliable data sources to substantiate alleged events, and satellite imagery offers diverse options crucial for evidential support. This paper delineates how Earth Observation (EO) imagery can be tailored to align with the requirements outlined by the Office of the United Nations High Commissioner for Human Rights (OHCHR) indicators, facilitating stakeholders in optimising their studies with applicable technological applications. To streamline EO technology, the paper categorises it into six primary payloads capable of observing such events: multispectral visible. multispectral infrared, passive microwave, hyperspectral, synthetic aperture radar, and meteorological datasets. Given variations in versatility across applications, the study further segregates each into 'full' and 'partial' applications. As shown here, EO data is an emerging form of digital evidence in legal proceedings for human rights breaches. The paper outlines the current trends in court cases and then outlines future opportunities for applications, based on the OHCHR taxonomy. This paper encourages investigators to fully consider the range of EO technology available, and the likely challenges to its relevance and admissibility, in such proceedings.

1. Introduction

A pivotal moment in human history occurred in 1948, marked by the collective action of member states of the United Nations who defined the Universal Declaration of Human Rights (UDHR) in response to the widespread atrocities witnessed during the Second World War. Comprising 30 articles, the UDHR delineates the fundamental human rights inherent to all individuals. This framework is a cornerstone because it underpins over 80 international human rights treaties and declarations [1]. Among these is the European Convention on Human Rights, established in 1959, which led to the creation of the European Court of Human Rights (ECtHR), the first of its kind. Comparable human rights tribunals, such as the International Criminal Court (ICC) and the International Court of Justice (ICJ), have since emerged with the shared objective of safeguarding human rights and holding perpetrators of violations legally accountable.

Despite the existence of mechanisms aimed at proving or disproving allegations, many investigators face limitations in accessing the area of interest (AOI), particularly in regions governed by sensitive political regimes or where alleged events occur discreetly [2]. Furthermore, courts have long relied heavily on eyewitness accounts, which are valuable but often challenged on the premise of bias in the witnesses or in gathering accounts that may be unreliable [3]. This challenge is not unique to international human rights courts but is prevalent across legal proceedings.

However, the advent of technology has brought about a revolution in the availability of information and data. This transformation has been leveraged to the court's advantage, including proliferation of in surveillance and traffic imagery, 3D modelling and GPS. These technological tools offer unprecedented opportunities to enhance the evidentiary basis of court proceedings, providing potentially more reliable and objective means of verifying claims and holding perpetrators accountable.

Remote sensing is another technology that is an invaluable data source for these purposes. Initially guarded by military facilities for observing conflicts, remote sensing has witnessed significant development over the past four decades, with a rise in public and commercial programs to serve the broader public. There are various forms of remote sensing: ground-based remote sensing occurs where a sensor collects data on the ground, such as thermometers. Aerial remote sensing is a

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sophisticated way of gathering information from aircraft and has proved very important for human rights investigations and court proceedings. Significantly, during the International Criminal Tribunal for the former Yugoslavia, aerial photography, notably imagery from U2 spy planes, played a crucial role in locating mass graves and regroupment areas for the proceedings [4]. However, a challenge associated with aerial remote sensing is navigating airspace regulations, particularly in restricted areas. This obstacle presents significant difficulties when attempting to observe politically sensitive regions.

In contrast, satellite remote sensing circumvents such limitations because satellite orbits are not bound by national airspace restrictions, thus offering global and consistent coverage across multiple spectral bands. These characteristics render satellite remote sensing crucial for human rights studies and as evidence, given the reliability and objectivity of the information it provides. However, despite the multitude benefits of utilising Earth Observation (EO) data in human rights investigations, its adoption has been uneven due to a lack of widespread understanding within both the observation and legal communities. This knowledge gap similarly affects the full utilisation of EO data in court proceedings. Thus, this paper aims to examine and structure the historical precedents and future potentials of satellite imagery in this field. To achieve this, the paper first proposes a taxonomy that categorises EO cases from five different satellite sensors (namely multispectral visible-infrared, passive microwave, hyperspectral, synthetic aperture radar, and meteorological datasets). It then links these with indicators outlined by the Office of the High Commissioner for Human Rights (OHCHR). Finally, the organisational framework explores historical applications of satellite imagery in court cases and compares these with the utilisation within the OHCHR taxonomy, to identify gaps in research, and how investigators could better or more appropriately use EO data to aid their work.

1.1. Satellite imagery overview

Satellite Earth Observation (EO) technology utilises various payloads to observe the Earth's surface across different wavelengths of electromagnetic (EM) radiation, each interacting uniquely with the Earth's surface and atmosphere. These spectral bands offer distinct applications relevant to environmental and socioeconomic research. Five primary forms of satellite imagery are commonly used: multispectral visible, multispectral infrared, passive microwave (MW), hyperspectral, synthetic aperture radar (SAR), and meteorological data.

Multispectral imagery collects data from specific portions of the electromagnetic spectrum, with the red, green, and blue (RGB) bands being the most commonly used. These bands are particularly versatile because they produce images similar to what the human eye perceives, making them easy and intuitive to interpret. This accessibility allows non-specialists to understand and analyze the images as well. When combined with NIR bands in VNIR (Visible and Near-Infrared) imagery, the versatility of RGB imagery expands, enhancing many applications, including vegetation health assessment [5], urban development analysis [6], and environmental studies [7]. This form of sensing is called 'passive sensing' because it passively observes and measures natural phenomena signals from Earth. Extending beyond visible bands, infrared imaging also covers mid-infrared (MIR) and shortwave infrared (SWIR), enabling applications beyond the capabilities of visible light alone.

Another form of passive sensing is passive microwave sensors, which specialise in sensing across the microwave section of the electromagnetic spectrum. While their applications may be narrower than multispectral imaging, they are crucial for sea ice monitoring [8] and hydrology studies, including soil moisture assessment [9] and surface water phenology [10].

Hyperspectral sensing operates slightly differently from VNIR and microwave by collecting information across many finer spectral bands. Unlike multispectral imagery, which typically captures data in just a few bands, hyperspectral sensors gather data across hundreds of bands. This capability detects specific spectral signatures, making hyperspectral sensing valuable for tasks like geological [11] and agricultural studies [12].

In contrast to passive sensing, some satellites utilise active sensing methods, such as Synthetic Aperture Radar (SAR). SAR sends signals to Earth and detects the reflected signals, allowing for imaging in various weather conditions. SAR is versatile and finds applications across environmental, agriculture, disaster monitoring, and other fields.

While many weather satellites incorporate some of the sensing bands to the bands mentioned above, they are primarily optimised to collect atmospheric data for generating weather maps, tracking storms, and analysing weather patterns. Although not directly impacting individual human rights, extreme weather events such as floods or droughts can pose significant dangers to human safety and well-being.

All of these sensing methods—multispectral (visible), multispectral (infrared), passive microwave, hyperspectral, SAR, and meteorological data—span a range of applications across environmental and social studies. Together, they provide a robust foundation for the taxonomy, supporting diverse research and practical applications.

1.2. OHCHR and human rights courts

The development of human rights indicators began at the World Conference on Human Rights in Vienna in 1993, where international organisations and states curated the Vienna Declaration and Programme of Action, a plan to improve human rights globally. The Office of the United Nations High Commissioner for Human Rights (OHCHR) was also created as a result of the conference. The office drew on the expertise of non-governmental organisations (NGOs) and international agencies to articulate human rights in a set of indicators. The framework was subsequently published in 2012 with the primary aim of facilitating standardised and robust investigative procedures in cases of suspected human rights violations, drawn in line with the Universal Declaration of Human Rights (UDHR). The indicators are captured in three groups: structural, process and outcome, with specific purposes supporting the office in various ways. Structural indicators cover the extent to which a country has integrated laws and mechanisms that cover human rights. Process indicators are the next grouping and cover the steps a country needs to take to adopt the right into society. Finally, the outcome indicators measure the performance of the State in implementing the rights. Similar indicator frameworks have been established in other UN departments, such as the Millennium Development Goals (MDGs) and their replacement, the Sustainable Development Goals (SDGs).

The ethics of condensing human rights attributes into a set of indicators has been debated and challenged since its curation, where some argue the framework can be 'reductionist' [13] and question the usefulness of indicators to improving human rights [13], and how investigators could better or more appropriately use EO data to aid their work. However, under the right conditions, indicators can act as a way to make 'seemingly vague obligations more concrete' [14]. Furthermore, the indicators can assist in measuring the relevance of technologies that can influence investigations and they have been used for that purpose in this paper. We hope that this approach is of interest to forensic scientists and investigators keen to learn more about how EO data can be used to aid the investigation, prosecution and defence of legal infractions on a large scale.

2. Methodology

2.1. Literature review

The foundation of the taxonomy is to link as many OHCHR indicators as possible to satellite imagery applications. This was achieved by conducting a comprehensive literature review to ensure a wide range of applications were covered. The literature review was based on a systematic search process, with the primary databases used being *Google*

Scholar and *Web of Science*. For each indicator, a database search was performed using relevant keywords derived from the indicator's description. For example, OHCHR 6.2.5, "Ratio of land consumption rate to population growth rate [11.3.1]," was associated with keywords such as **land consumption** and **population growth**. Synonyms, including **land use**, **urbanization**, and **population expansion**, were also employed to broaden the search.

Some indicators, such as OHCHR 2.9.1, "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])," cover a wide range of diseases, not all of which can be mapped using satellite imagery. For these broader indicators, the search strategy involved reviewing literature on the specific topic, followed by a more targeted database search using keywords identified from these review articles. Additionally, the database search incorporated the type of satellite payload (e.g., multispectral, hyperspectral) to refine the taxonomy by both payload and general application. The payloads used in this taxonomy were multispectral (visible), multispectral (infrared), multispectral (microwave), hyperspectral, synthetic aperture radar (SAR) and meteorological datasets.

The taxonomy relies solely on academic journal articles and peer-reviewed conference proceedings to outline the applications, excluding review articles. However, exceptions were made for certain indicators where substantive research exists outside of the academic field. For example, OHCHR 3.2.1, "Actual prison occupancy as a proportion of prison capacity in accordance with relevant United Nations instruments on prison conditions," has garnered more attention from NGOs, journalists, and charities, with information already used in human rights investigations but not typically published in academic journals. In these cases, newspaper articles and investigative reports were utilized to inform the taxonomy.

A similar review was conducted to find international court cases that have used satellite imagery as evidence in some form. Databases that were used for this form of the research were the ICC Legal Tool Database, along with the specific international court databases for the International Court of Justice (ICJ) and the Inter-American Court of Human Rights (IACHR) and the ECtHR. Journal articles were drawn from national and international legal and academic databases including Westlaw Google Scholar, and news reports from national and international outlets were also used to initiate further research into the relevant courts and their decisions.

2.2. Cataloguing indicators

The OHCHR categorised indicators across the 16 human rights, but the cataloguing is not numbered, which limits the capacity to reference specific indicators. Therefore, the first aspect in this research is to number and catalogue each indicator, to ease referencing through the subsequent research. This is a similar approach to the UN's Sustainable Development Goals, where each goal is numbered, but the 'targets' are separated by a decimal.507 unique indicators spanning all these rights were identified and catalogued in this process (refer to Table S1 in Supplementary Material'). However, these indicators are not evenly distributed among the rights, and specific indicators are duplicated across multiple rights. For instance, the indicator 'Life expectancy at birth or age 1' applies 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 organisation, each duplicated indicator is assigned to the right with which it shares a closer correlation. However, we acknowledge the relevance of all rights when assessing the impact of EO data on each right individually.

2.3. Relevance of EO in OHCHR framework

The premise of this aspect of the research is to demonstrate how satellite imagery can be used for human rights investigations, using the OHCHR framework as the backbone of this comparison. Similar work has been conducted with other international frameworks, such as the UN's Sustainable Development Goals (SDG) [15–17] and the Sendai Framework for Disaster Risk Reduction [18]. The SDG framework is similar in structure to the OHCHR, and some indicators overlap [19]. Furthermore, there has been considerable literature dedicated to mapping the SDGs to satellite analysis applications, with the premise of highlighting future possibilities [15–17]. The European Space Agency (ESA) provided a comprehensive report that drew on the expertise of several UN departments to qualitatively measure the extent EO data can be adopted for the SDGs. Each category is systemically reviewed with a 'traffic light' system - colouring red, amber, and green - to flag the relevance. Each criterion is coloured and thus finally condensed to measure the relevance of EO data for each indicator [17]. Andries et al. also reviewed the SDGs similarly by qualitatively measuring the extent to which EO can support the framework using a traffic light system [20]. 'Green' references EO data that can make a direct contribution, 'yellow' indicates partial contribution and 'red' indicates weak contribution. A combination of these approaches is applied to the following research using a traffic light system to demonstrate the extent to which each OHCHR indicator can be supported with satellite imagery. The traffic light system is used to measure the level that EO data can support each indicator. It categorises indicators based on the number of references used in the literature review so the volume of literature on the particular study exists already. Indicators with less than six references are marked red, those with 6–12 references are marked yellow, and those with over 12 references are marked green. The results of this scheme are outlined in Table 1. Table 1 displays the whole scheme of indicators, with colour coordination to indicators that can be backed by satellite imagery. This schema is intended to assist the scientific and legal communities in recognising where satellite data is already being used for legal purposes, and identifying where there is the most potential to use additional kinds of EO data in the future.

3. OHCHR framework

3.1. Full vs. Partial applications

This research has drawn a similar structure to the research of ESA [17] and Andries. et al. [20], where a systematic assessment is undertaken to establish the value of EO to each indicator in their respective frameworks. The positive results of Table 1 (indicated by green, yellow and red) are extracted and further analysed to assess the best forms of satellite imagery that can meet the needs of the selected indicators and to what capacity. The selected EO types for taxonomy are as follows: multispectral (visible), multispectral (infrared), passive microwave (MW), hyperspectral, synthetic aperture radar (SAR), and meteorological data. Table 2 outlines this analysis by highlighting imagery products that meet the indicator's needs and of the 16 human rights outlined by the OHCHR, 12 have the potential to utilise satellite imagery for human rights investigations, albeit to varying degrees. Although EO imagery is useful concerning 75% of the OHCHR rights, our analysis demonstrates that 50 specific indicators can be monitored with satellite imagery, weighted mainly to indicators featured in the right to adequate food, right to the enjoyment of the highest attainable standard of physical and mental health (will henceforth be referred 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 that they have a spatial determinant, which is an attribute associated with satellite imagery. Since the imagery collects electromagnetic (EM) information over large swathes of land, it is vital to monitor the surrounding environment, which may directly or indirectly impact nearby communities. The

Table 1
OHCHR indicators by number of corresponding EO case studies and relevant references. This table offers a condensed overview of OHCHR indicators, organised by the total number of EO case studies associated with each indicator(colour and symbol categorisation), along with relevant study references. For the comprehensive table, please refer to Table S2 in the Supplementary Material. [21–168].

Right to adequate food	··· 1.4.2 [21][22][23]	··· 1.4.5 [24][25][26]	··· 1.4.8 [27][28][29] [30]	··· 1.4.10 [31][32][33]	··· 1.4.11 [34][35][36] [37]	·· 1.5.6 [38][39][40]	··· 1.9.3 [31][41][42] [43]	··· 12.9.1* See 'Right to non-discrimination and equality'	··· 13.4.1* See 'Right to Life'					
Right to Adequate Health	·· 2.2.11 [44][45][46]	··· 2.3.2 [47][48][49] [50]	··· 2.3.9 [51][52][53]	· 2.5.9 [54][55][56]	··· 2.8.2 [57][58][59] [60]	··· 2.9.1 [61][62][63] [64]	··· 6.6.3* See 'Right to adequate housing'	··· 6.6.4* See 'Right to adequate housing'	··· 8.9.1* See 'Right to social security'	··· 13.4.1* See 'Right to life'	·· 13.4.5* See 'Right to life'			
Right not to be subjected to torture	· 3.2.1 [65][66][67]	· 3.2.2 [65][66][67] [68]	·· 3.5.2 [69][70][71] [72]	·· 3.8.3 [71][73][74]	··· 2.9.1* See 'Right to adequate health'									
Right to education	· 5.8.1 [75][76][77]	··· 6.7.2* See 'Right to adequate housing'	··· 13.4.1* See 'Right to life'	·· 13.4.5* See 'Right to life'										
Right to adequate housing	··· 6.2.1 [78][79][80] [81]	··· 6.2.3 [82][83][84] [85]	··· 6.2.5 [86][87][88]	··· 6.2.6 [89][90][91] [92]	· 6.6.1 [93][94]	··· 6.6.3 [82][95][96] [97]	··· 6.6.4 [7][96][98][99] [100]	··· 6.7.1 [101][102] [103][104]	··· 6.7.2 [105][106] [107]	·· 6.7.4 [108][109] [110][111]	··· 6.9.1 [112][113] [114][115]	·· 1.5.6* See 'Right to adequate food'	··· 13.4.1* See 'Right to life'	·· 13.4.5* See 'Right to life'
Right to work	··· 7.5.1 [116][117] [118][119]	·· 7.5.2 [120][121] [122][123]	· 7.6.4 [116][123] [124]	··· 7.9.3 [125][126] [127][128]	··· 7.9.4 [116][117] [121][126]									
Right to social security	··· 8.5.4 [42][129] [130][131]	··· 8.9.1 [132][133] [134][135]	· 2.5.9* See 'Right to adequate health'	·· 3.8.3* See 'Right not to be subjected to torture'										
Violence against women	··· 7.5.1* See 'Right to work'													
Right to non-discrimination and equality	· 12.3.5 [136][137]	· 12.6.1 [138][139] [140]	··· 12.6.2 [69][71][138] [141]	··· 12.9.1 [142][143] [144][145]	· 12.11.1 [139][140] [146]	··· 6.7.2* See 'Right to adequate housing'	··· 13.4.1* See 'Right to life'	·· 13.4.5* See 'Right to life'						
Right to Life	··· 13.4.1 [147][148] [149][150]	·· 13.4.5 [151][152] [153]	··· 13.6.2 [69][71][134] [138]	··· 13.9.2 [69][71][134] [138]	·· 13.10.2 [134][154] [155][156]	· 2.5.9* See 'Right to adequate health'								
Right to adequate water	··· 14.1.2 [157][158] [159][160]	··· 14.3.3 [161][162] [163][164]	··· 14.3.4 [165][166] [167][168]	· 3.2.2* See 'Right not to be subjected to torture'	··· 13.4.1* See 'Right to life'	·· 13.4.5* See 'Right to life'								
Right to freedom of peaceful assembly and association	·· 3.8.3* See 'Right not to be subjected to torture'													

LEGEND

·	: <6 References
··	: 6 - 12 References
···	: > 12 References

environment could include a natural landscape, such as water bodies or forests, or built-up settlements, such as cities.

A colour-coordinated scheme, similar to Table 1, is applied to differentiate between full and partial indicators, but only distinguish across two colours, green to indicate 'full' contribution and yellow to indicate 'partial' contribution. Thus, each indicator has been assessed to determine whether its primary objectives can be fully or partially met with EO. For example, the aim of OHCHR 1.4.5 is 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 of agricultural land and determine whether the farming practices ensure healthy and resilient crops.

Multispectral imagery is instrumental here (as seen in Table 2), as it allows for the inspection of both of the indicator's objectives by being able to detect and classify agricultural land. Land use and land cover (LULC) classification is the method of determining the type of landscape in an image, where it traditionally started with visual interpretation techniques [169], but machine learning algorithms have become common mode of classification due to its automisation and ease of compiling and interpreting large volumes of complex data [27]. This methodology lends itself well to indicator 1.4.5 because it can classify land types based on its spectral signature by separating agricultural land from other landcover types [170] and even separating agricultural land based upon the type of crop grown [25,171].

SAR is another vital data source 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 clouds. This form of data is typically integrated with multispectral imagery because it is not able to differentiate classes of land or crop on its own [171,172]. In this way, it is possible to see how combining different methods of EO can assist investigations by providing a complementary and comprehensive set of information on an area of interest.

The second aspect of indicator 1.4.5 is identifying and quantifying land used for sustainable agriculture. 'Sustainable agriculture' can have many interpretations, so various methodologies can be applied to quantify it. Multispectral imagery can be used in several ways to meet this purpose, such as by quantifying productivity [173], and susceptibility to drought [174,175]. Other forms of imagery can also play a role in monitoring the health and productivity of crops, whether in the form of sole data sources, such as hyperspectral imagery [176–178] and SAR [179] imagery, or in combination with other assimilated data such as meteorological data [174].

Thus, in the example of 1.4.5, the evaluation of the objectives of the indicator has been combined with consideration of all possible EO data types that could meet these objectives, leading to each imagery type being labelled as either fully or partially suitable under the taxonomy used in Table 2.

Since multispectral imagery (VIR) can be used to measure the area of land and determine if the land is being used sustainably, thus achieving all the requirements of indicator 1.4.5, this imagery type has been labelled as fully applicable (in green). The other imagery types have been labelled as only partially applicable (in yellow) because they can be used to observe only one or both of the requirements of the indicator but to a limited degree.

Table 2
Applicable OHCHR indicators compared against satellite data types: Multispectral (visible), multispectral (infrared), passive microwave, hyperspectral, SAR and meteorological datasets. The extent that the payload can support each OHCHR indicator was categorised into partial or full coverage. The number of international court proceedings that support each indicator are listed. [180–222].

		Multispectral (visible)	Multispectral (IR)	Passive Microwave	Hyperspectral	SAR	Meteorological data	Featured in cases	
	1.4.2	··	·	·		·		4	[180][181][182][183]
	1.4.5	··	·	·	·	·	·	4	[180][181][182][183]
	1.4.8	··	·		·			4	[180][181][182][183][184]
Right to adequate food	1.4.10	·	·	·	·	·			
	1.4.11	·	·	·	·	·			
	1.5.6	··	·			·		2	[185][186]
	1.9.3	·	·	·	·	·	·		
	2.2.11	·	·						
	2.3.2	·	·		·				
Right to adequate health	2.3.9	·	·		·				
	2.5.9	·							
	2.8.2	·	·		·				
	2.9.1	·	·	·		·	·		
	3.2.1	·	·						
Right not to be subjected to torture or to cruel, inhuman or degrading treatment or punishment	3.2.2	·	·			·			
	3.5.2	·	·			·		5	[187][188][189][190][191][192][193]
	3.8.3	·	·		·			3	[190][194][195]
Right to education	5.8.1	·							
	6.2.1	·	·		·	·			
	6.2.3	·	·	·	·	·			
	6.2.5	·	·			·		3	[180][181][182]
	6.2.6	·	·						
	6.6.1	·							
Right to adequate housing	6.6.3	·	·	·	·	·	·	22	[185][187][189][190][191][192][193][196][197][198][199][200][201][202][203][204][205][206][207][208][209][210][211][212][213]
	6.6.4	·	·		·	·			
	6.7.1	·	·			·		6	[190][191][195][208][210][214]
	6.7.2	·	·	·		·			
	6.7.4	·	·			·			
	6.9.1	·	·	·		·		17	[191][193][196][197][198][199][200][201][203][204][205][207][208][209][212][213][214]
	7.5.1	·	·					1	[210]
	7.5.2	·	·			·			
Right to work	7.6.4	·	·					1	[208]
	7.9.3	·	·			·		1	[208]
	7.9.4	·	·			·		1	[208]
	8.5.4	··	·		·	·	·		
Right to social security	8.9.1	·	·	·	·	·	·	24	[187][189][190][191][192][193][194][195][196][198][200][202][203][204][205][207][208][209][212][213][214][215][217][218]
	12.3.5	·	·					3	[187][210][214]
Right to non-discrimination and equality	12.6.1	·	·			·		25	[187][189][190][191][192][193][194][195][196][198][200][202][203][204][205][207][208][209][212][213][214][215][216][217][218]
	12.6.2	·	·	·		·		4	[189][190][192][195]
	12.9.1	·	·	·	·	·	·		
	12.11.1	·	·			·		8	[200][201][203][204][209][212][213][216][217]
	13.4.1	·	·	·	·	·	·	3	[185][186][206][211][218][219][220][221]
	13.4.5	·	·		·	·	·	3	[185][186][206][211][218][219][220][221]
Right to life	13.6.2	·	·			·		1	[190]
	13.9.2	·	·			·		3	[189][190][193]
	13.10.2	·	·			·		5	[189][190][192][194][195][222]
	14.1.2	·	·	·					
Right to adequate water	14.3.3	··	·	·	·	·		3	[185][186][206][211][218][219][220][221]
	14.3.4	·	·			·		1	[211]

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· : Partial coverage of EO data
·· : Full coverage of EO data

3.1.1. Broad indicator requirements

The taxonomy presented in Table 2 demonstrates the variety of applications that satellite imagery may have in documenting potential human rights violations. However, a clear aspect from the table is that satellite imagery only provides partial information for most indicators. Some indicators listed cover many broad features, such as OHCHR 13.8.4, which outlines the '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 diseases that need to be mapped, but this is not an exhaustive list of all 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 [223,224], cholera [62], tuberculosis [225] and meningitis [64]. The prevalence of these diseases can be predicted by satellites as they depend on their surrounding environment. For example, malaria 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 [226], which in turn will improve the measurements of particulate matter monitoring in cardiac and respiratory research [227]. However, in many instances, diseases are not traceable if the disease incubation, prevalence and trajectory are independent of the environment.

3.1.2. Combination with other data sources

One of the aims of this paper is to alert scientists and investigators to the potential for EO data to be used in combination with the methods and data sources with which they are already familiar. Some indicators provide good examples of how this can work. For instance, Indicator 13.8.4 has a broad range of requirements that rely on integrating other data sources with satellite technology for a meaningful result. Still, it also demonstrates the general limitation of satellite technology in this field because it relies on integrating other data sources for a meaningful result. The specific indicator requires a range of different data sources, including health records [62,64,224] and survey data [225] to substantiate the hypothesis. Other indicators also adopt different forms of data to train models [228] or refine models with expert knowledge [89] with forms of data that include in situ measurements, official statistics or eyewitness accounts. However, this is a limitation common to all forms of data, and indeed, in legal proceedings, all cases are built on as many relevant sources of evidence as possible. Some jurisdictions (e.g. Scotland) even specify that two sources of reliable and credible evidence must corroborate that an offence was committed; otherwise, the prosecution must fail [229]. The think-tank 'Betterplace Labs' states that human rights research requires 'both quantitative and qualitative research methods', so there will always be a need to collect information from many resources to conduct a thorough investigation [230].

The advantage of satellite imagery, in addition to being another data source, is that it can assist in delivering insights that are otherwise not always 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 of slavery studies but can provide information 'in remote areas which may have previously been inaccessible, or even unknown' [231]. 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, meaning that accounts of brutality, extremism, illegal imprisonments and killings arise but are unofficial and difficult to validate. Satellite imagery presents a unique vantage point from which to validate these testimonies. Son (2020) explores the work done by the NGO 'The Mapping Project', which aims to report on the alleged atrocities the North Korean Government has perpetrated against its people. The work uncovers the location of burial sites of victims of state-sponsored killings. They describe satellite imagery as improving the quality of the interviews because the images can 'contextualise the testimony' [70,232,233]. Thus, it is clear that mixed methods analysis has a vital role in these areas, including helping to identify common patterns of offending [234]. This is a useful addition to the portfolio of tools that can be used by investigators, prosecutors and defence council, to contextualise and illuminate other sources of evidence.

3.1.3. Spatial resolution requirements

The OHCHR indicators cover various spatial scales, from discerning individual buildings to aggregating nationally. Therefore, the satellite mission spatial resolution must match the detail required in the investigation. With some commercial satellite missions achieving resolution down to 20 cm, this broadens the possibility of incorporating EO data in human rights research, investigation, and prosecution. This level of resolution is greatly needed for indicators that require fine details. OHCHR 13.6.2, 13.9.2 and 13.10.2 all relate to determining the number 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 [70,71,132,134].

Lavers (2009) emphasises the preference for high-resolution satellite imagery in human rights research whenever feasible [235]. There is a variety of options in multispectral VIR imagery from commercial missions that reach resolutions <1 m. Still, there are options to use open-source imagery that can achieve resolution at approximately 10 m, such as ESA's Copernicus programme or NASA's Landsat programme. Both options are explored and referenced throughout the taxonomy, 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 [236], or a combination of both [237], with open-source imagery sometimes offering suitable resolutions, albeit contingent on the size of the monitored land. In contrast to multispectral VIR imagery, SAR imagery, although relatively newer in comparison, can also achieve very high spatial resolutions.

An ideal project specification would be to use the highest resolution satellite imagery is optimal because it can provide the most detail in an image, so more detailed and accurate results can be generated [238]. However, attaining such a resolution may prove unfeasible in many circumstances because storage and budgetary restrictions will always limit the user. These limitations are prominent in many public and charity areas, which are also where these investigations take place. For reference, the cost of commercial satellite imagery that can reach equal or better than 1 m spatial resolution is, on average, \$22.5/km^2 [239], which becomes expensive if generating a time-series analysis across a large area. This type of imagery may still be necessary for studies that require this level of detail. However, many open-source data options, including the Sentinel-2, Sentinel-3 (ESA), Landsat, Terra and Aqua (NASA) missions, can provide high spatial and spectral resolution sufficient for a variety of applications. Furthermore, non-commercial research can also obtain VHR imagery, which is free if applying for specialised grants.

Not all imagery forms have as many options as multispectral VIR and SAR, including passive microwave satellites that are limited in variety and abundance. Table 2 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, as emphasised in its abundance of appropriate 'right to adequate water' indicators which occurs over large scales with gradual variations so very high-resolution imagery is not required. Nevertheless, studies are limited to AOIs that can be resolved within the current standards of satellites. 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 Field-Of-View (FOV) to areas that can be resolved at this resolution. Studies on air pollution and weather also bear this problem, where the resolution of data limits them. Monitoring capabilities of Green–House Gases (GHG) are expanding due to the demand of industries to meet net-zero targets. GHGSat, a commercial satellite data provider, offers data down to 50 m at a cost. Unlike multispectral imagery, there is a large gap in capabilities between commercial and open-source data, as ESA's Sentinel-5 provides resolution at approximately 5.5 × 3.5 km.

Ultimately, spatial resolution requirements and the ability of the EO imagery to meet them vary depending on the indicator and the imagery available for a range of technical and pragmatic reasons (e.g. cost), but with continuing improvements being seen in many areas to meet the necessary demands. Thus while publicly-funded investigations and legal proceedings may at present find some EO methods infeasible due to cost, technology and usage will likely improve over time.

3.1.4. Temporal Resolution requirements

Temporal resolution is another key factor that makes satellite imagery highly valuable for human rights studies. Unlike other types of imagery, satellite data provides long-term, repetitive observations across vast areas. Drones and reconnaissance tools, on the other hand, only capture images when specifically deployed and permitted, and CCTV systems have a limited field of view despite their continuous monitoring. Satellite missions, however, can consistently observe an area of interest (AOI) at regular intervals, though they are influenced by factors such as weather conditions and the restrictive path of the satellite.

Most satellite missions are designed for extended durations, often determined by the life expectancy of the satellite's batteries and other components. Additionally, some missions deploy staggered satellite launches to extend their operational lifespan. For instance, NASA's Landsat program, despite the failed launch of Landsat 6, has maintained a continuous mission from 1972 to the present through the deployment of nine satellites. Although not all satellite programs have the same longevity as Landsat, they typically build up a comprehensive image repository over their operational lifetime, allowing researchers to access historical imagery, and ensuring they are not limited to real-time data acquisition.

However, despite the clear advantages of Earth observation (EO) satellites' temporal cycles, factors like weather conditions or system malfunctions can disrupt the frequency of data collection, potentially leading to missed observations on critical days. Even under optimal conditions, a satellite can only observe the AOI once per cycle, which can vary from daily to monthly intervals. Consequently, key information might be missed if the satellite's pass occurs just minutes before or after a significant event, particularly in dynamic scenarios involving human or vehicle activity. This limitation is especially relevant in cases involving criminal activity or conflict monitoring. For example, while satellite imagery is crucial for tracking attacks on communities and conducting spatial analysis, it is rare for a satellite to capture the precise moment of an event. The increasing number of EO satellites in orbit is helping to address this issue, enabling researchers to combine data from multiple satellites to gather as much information as possible. but such limitations will remain present even in future projects.

4. Earth Observation in International Law

So far, the research has demonstrated the vital role that EO data plays in human rights investigations to observe, measure and validate allegations and findings of human rights abuses. These observations can then be used by governments, police, NGOs, and other organisation in several accountability mechanisms, including advocacy, media coverage, and national and international legislation. Still, they can ultimately lead to legal prosecution if the case is sufficiently strong. In this next section, the relevance of EO data is assessed in the context of international human rights courts.

4.1. Subject of imagery

Another factor determining the type of evidence used in court proceedings is the subject of the cases and what artefacts of the alleged atrocity can prove or disprove the event. In the case of satellite imagery, clearly the subject of the analysis needs to be visible to satellites. In such cases, work has already begun to establish a standardised forensic approach to analysing satellite imagery. For instance, Raymond et al. (2014) derived a robust Mass Atrocity Remote Sensing (MARS) framework to effectively monitor and validate mass atrocities. Their research outlines MARS observables related to the conflict in the Darfur, Sudan region in 2011 [69]. Table 3 utilises a similar approach to Raymond (2014) but with a more extensive scope to include all of the legal cases analysed as part of this research paper. Therefore, added subjects include geophysical features and population identifiers. Like Raymond's paper (2014), this list is not exhaustive, however, it is a method through which to catalogue the observables used in the highlighted court cases.

Different sensors emphasise different features on Earth, and the most common sensor found on EO satellites is the multispectral sensor. It is also the simplest to universally understand because it operates similarly to the naked eye: red, green, and blue wavelengths (RGB), otherwise known as 'visible', are detected at the sensor. This means that objects visible to the naked eye can be detected. Most of the subjects listed in Table 3 only require RGB wavelengths for identification, and the array of satellite missions used in the reporting are listed in Table 4.

There are instances where non-visible artefacts are analysed for court proceedings, including in the International Court of Justice (ICJ). The ICJ case of *Pulp Mills on the River Uruguay (Argentina v. Uruguay)* tested the limits of moving away from traditional RGB imagery to more sophisticated data processing methods by creating a 'false-colour image' to detect algae blooms [206,218]. However, there was opposition to using this image from the defence, who stated that the image was 'digitally-enhanced' and had no precedence [219]. The imagery was admitted into evidence, but interestingly it showed high nutrient concentration both before and after the mill began operating, and so the prosecution ultimately did not succeed [220]. Nevertheless, in the judgment, Judge Vinuesa noted that the scientific evidence in the case, including the satellite imagery and the data used to validate the images, had provided 'clear evidence that the mill effluents contributed' to the algal bloom [221]. These proceedings are therefore a useful addition to the growing body of cases demonstrating the potential scope for EO technology in legal disputes.

Another way in which satellite imagery is emerging in legal proceedings relates to large fire investigations. Active fire detection is a type of processed data from infrared satellite imagery that detects instances of both natural fires (e.g. wild fires) and man-made fires (e.g. gas glaring and burning infrastructure). NASA's MODIS mission was the first to be used in this data product and has been used since 2000 for several monitoring purposes. These applications extend into human rights investigations for prosecution as seen in Table 4, where they have been used in several International Criminal Court (ICC) and ICJ proceedings. This product has been primarily used within court cases to demonstrate the intentional burning of residential buildings [196,197,203,204] and vegetation [198,199].

In terms of the subject of the EO imagery, Table 4 further emphasizes the importance of using high-resolution imagery in investigations where possible. This builds on the content of Table 3 which highlighted the various observables required in human rights investigations, which come in different scales ranging from a couple of meters (e.g. for

Table 3
Subject of EO surveillance in court cases.

Subject	Specific detail	Cases
Geophysical features	Water • River morphology • Ocean turbidity • Algae blooms • Sedimentation build-up • Erosion • Chlorophyll	*Prosecutor v. Mahamat Said Abdel Kani* (ICC), *Costa Rica v. Nicaragua (Construction of a Road in Costa Rica along the San Jun River)* (ICJ), *Costa Rica v. Nicaragua (Costa Rica vs Nicaragua - Certain Activities Carried Out by Nicaragua in Border Area)* (ICJ), *Argentina v. Uruguay* (ICJ), *European Commission v. United Kingdom (Portgual Intervening)* (ECJ)
	Vegetation • Vegetation • Forests • Agricultural land	*Sargsyan v. Azerbaijan* (ECtHR), *Prosecutor v. William Samoei Ruto and Joshua Arap Sang* (ICC), *Costa Rica v. Nicaragua (Costa Rica vs Nicaragua - Certain Activities Carried Out by Nicaragua in Border Area)* (ICJ), *Democratic Republic of the Congo v. Uganda* (ICJ), *Armed Activities on the Territory of the Congo (Democratic Republic of the Congo v. Uganda)*, *The Punta Piedra Garifuna community and its members v. Honduras* (IACHR), *Saramaka People v. Suriname* (IACHR), *Sawhoyamaxa Indigenous Community v. Paraguay* (IACHR), *The Indigenous Communities Of The Lhaka Honhat (Our Land) Association V. Argentina* (IACHR)
Infrastructure	Civilian infrastructure • Residential buildings • Mausoleums • Cemeteries • Sites of faith • Stadiums and theatres	*Prosecutor v. Bosco Ntaganda* (ICC), *Prosecutor v. Al Hassan Ag Abdoul Aziz Ag Mohamed Ag Mahmoud* (ICC), *Prosecutor v. William Samoei Ruto and Joshua Arap Sang* (ICC), *Prosecutor v. Germain Katanga and Mathieu Ngudjolo Chui* (ICC), *Prosecutor v. Bahar Idriss Abu Garda* (ICC), *Situation in Georgia* (ICC), *Prosecutor v. Ahmad Al Faqi Al Mahdi* (ICC), *Prosecutor v. Francis Kirimi Muthaura and Uhuru Mugai Kenyatta* (ICC), *Prosecutor v. Ali Muhammah Ali Abd-Al-Rahman ("Ali Kushayb")* (ICC), *Prosecutor v. Alfred Yekatom and Patrice-Edouard Ngaïssona* (ICC), *Situation in the People's Republic of Bangladesh/ Republic of the Union of Myanmar* (ICC), *Prosecutor v. Maxime Jeoffroy Eli Mokom Gawaka* (ICC), *Prosecutor v. Théoneste Bagosora, Gratien Kabiligi, Aloys Ntabakuze, Anatole Nsengiyumva* (ICTR), *Georgia v. Russian Federation* (ICJ), *Bosnia and Herzegovina v. Serbia and Montenegro* (ICJ), *Ukraine v. Russian Federation: 32 States Intervening* (ICJ), *South Africa v. Israel* (ICJ), *Sargsyan v. Azerbaijan* (EHCR), *Eritrea-Ethiopia* (PCA), *The Kichwa Indigenous People of Sarayaku v. Ecuador* (IACHR), *The Punta Piedra Garifuna community and its members v. Honduras* (IACHR), *Mohammed Abdullah Saleh Al-Asad v. the Republic of Djibouti* (ACHPR), *Prosecutor v. Kaing Guek Eav alias Duch* (ECCC)
	Temporary sites • Internal-displaced accommodation • refugee accommodation • Military stations	*Prosecutor v. Bahar Idriss Abu Garda* (ICC), *Prosecutor v. Abdallah Banda Abakaer Nourain*, *Prosecutor v. Francis Kirimi Muthaura and Uhuru Mugai Kenyatta* (ICC), *Prosecutor v. Ali Muhammad Ali Abd-Al-Rahman ("Ali Kushayb")* (ICC), *Prosecutor v. Alfred Yekatom and Patrice-Edouard Ngaïssona* (ICC), *Bosnia and Herzegovina v. Serbia and Montenegro* (ICJ), *Sufi and Elmi v. the United Kingdom* (ECHR), *Chowdury and Others v. Greece* (ECtHR)
	Humanitarian • Internally-displaced people (IDP)/refugee accommodation, e.g. tents, temporary buildings • Peacekeeping sites	*Prosecutor v. Francis Kirimi Muthaura and Uhuru Mugai Kenyatta*(ICC), *Prosecutor v. Bahar Idriss Abu Garda* (ICC), *Prosecutor v. Abdallah Banda Abakaer Nourain*, *Prosecutor v. Alfred Yekatom and Patrice-Edouard Ngaïssona* (ICC), *Bosnia and Herzegovina v. Serbia and Montenegro* (ICJ), *Sufi and Elmi v. the United Kingdom* (ECtHR)
	Military • Trenches • Revetments • Military buildings • Prisons	*Prosecutor v. Ali Muhammad Ali Abd-Al-Rahman ("Ali Kushayb")* (ICC), *Prosecutor v. Abdallah Banda Abakaer Nourain* (ICC), *Prosecutor v. William Samoei Ruto and Joshua Arap Sang*, *Prosecutor v. Alfred Yekatom and Patrice-Edouard Ngaïssona* (ICC), *Sargsyan v Azerbaijan* (ECtHR), *MH17 Plane Crash* (NPPS), *Prosecutor v. Kaing Guek Eav alias Duch* (ECCC)
	Transportation • Roads • Vehicles • Roadblocks • Bridge • Crossings	*Prosecutor v. Francis Kirimi Muthaura and Uhuru Mugai Kenyatta* (ICC), *Prosecutor v. William Samoei Ruto and Joshua Arap Sang* (ICC), *Prosecutor v. Alfred Yekatom and Patrice-Edouard Ngaïssona* (ICC), *Prosecutor v. Théoneste Bagosora, Gratien Kabiligi, Aloys Ntabakuze, Anatole Nsengiyumva* (ICTR), *Sargsyan v Azerbaijan* (ECHR), *Costa Rica v. Nicaragua (Construction of a road)* (ICJ), *Prosecutor v. Charles Ghankay Taylor* (SCSL), *South Africa v. Israel* (ICJ)
Artillery	Launch location	
	Evidence of attack • Craters • Shelling	*Georgia v. Russian Federation* (ICJ), *Prosecutor v. Kaing Guek Eav alias Duch* (ECCC)
Population	Movement	*Prosecutor v. Francis Kirimi Muthaura and Uhuru Mugai Kenyatta* (ICC), *Prosecutor v. Ali Muhammad Ali Abd-Al-Rahman ("Ali Kushayb")* (ICC), *Prosecutor v. Thomas Lubanga Dyilo* (ICC), *Sufi and Elmi v the United Kingdom* (ECtHR)
	Evidence of killing • Killing location • Burial sites • Mass graves • Bodies	*Prosecutor v. Ali Muhammad Ali Abd-Al-Rahman ("Ali Kushayb")* (ICC), *Prosecutor v. Mahamat Said Abdel Kani* (ICC), *Prosecutor v. Ali Muhammad Ali Abd-Al-Rahman ("Ali Kushayb")* (ICC), *Ukraine v. Russian Federation* (ICJ), *Prosecutor v. Kaing Guek Eav alias Duch* (ECCC)

vehicles, roadblocks, and burial sites) to kilometres of space (e.g. for forests and agricultural land), and ultimately influences the necessary resolution requirements. This also follows the work in Section 3.1.3, which noted that spatial resolution is a crucial factor in identifying observables that will be useful for human rights research, investigations and prosecutions.

It is worth noting that Table 3 does not list all of the missions used in the selected court cases because some cases do not publicly state which mission was used. However, even in cases where specific satellite missions are not identified, they still refer to the importance of "high-resolution" imagery.

There is a notable emphasis across international courts on monitoring infrastructure, especially residential housing. The majority of cases are associated with OHCHR indicators 6.6.3, 6.9.1, 8.9.1, and 12.6.1, all of which revolve around ensuring the safety and security of households. These indicators address threats such as hazardous conditions, hate crimes, and forced evictions directly tied to the fundamental right to adequate housing, as highlighted in Table 2. Earth Observation (EO) data is well-suited for monitoring changes in these indicators as it provides large-scale coverage and high-resolution imagery capable of discerning individual buildings. This makes EO technology a valuable tool for capturing damage and destruction of the urban environment, particularly in areas where ground or aerial surveys are unavailable or inadequate.

Table 4
List of satellite missions used in court cases, with spatial resolution and status of mission.

Type of data	Satellite mission	Resolution	Status of mission	Cases
Multispectral (VIR) imagery	CBERS-2B	20 m	Inactive	*Argentina v. Uruguay* (ICJ)
	Formosat-2	8 m	Inactive	*Situation in Georgia* (ICC)
	GeoEye-1	1.64 m	Active	*Prosecutor v. Alfred Yekatom and Patrice-Edouard Ngaïssona* (ICC), *Bosnia and Herzegovina v. Serbia and Montenegro* (ICJ)
	IKONOS	3.3 m	Inactive	*Prosecutor v. Bosco Ntaganda* (ICC), *Eritrea and Ethiopia* (PCA)
	Landsat (1–5)	80 m	Inactive	*Prosecutor v. Kaing Guek Eav alias Duch* (ECCC)
	Pleiades	2.8 m	Active	*Costa Rica v. Nicaragua* (ICJ)
	Quickbird	2.4 m	Inactive	*Prosecutor v. Bosco Ntaganda* (ICC), *Prosecutor v. Alfred Yekatom and Patrice-Edouard Ngaïssona* (ICC)
	RapidEye	5 m	Inactive	*Costa Rica v. Nicaragua* (ICJ)
	WorldView-1	0.5 m	Inactive	*Situation in Georgia* (ICC), *Georgia v. Russian Federation* (ICJ), *Bosnia and Herzegovina v. Serbia and Montenegro* (ICJ)
	WorldView-2	1.84 m	Inactive	*Prosecutor v. Al Hassan Ag Abdoul Aziz Ag Mohamed Ag Mahmoud* (ICC), *Prosecutor v. Ahmad Al Faqi Al Mahdi* (ICC), *Prosecutor v. Alfred Yekatom and Patrice-Edouard Ngaïssona* (ICC), *South Africa v. Israel* (ICJ)
	WorldView-3	1.84 m	Active	*South Africa v. Israel* (ICJ)
Active Fire detection	MODIS	1 km	Active	*Prosecutor v. Bosco Ntaganda* (ICC), *Prosecutor v. William Samoei Ruto and Joshua Arap Sang* (ICC), *Situation in Georgia* (ICC), *Georgia v. Russian Federation* (ICJ)

4.2. Analysis Methods

Different processing methodologies can be deployed with EO data to gain relevant information for investigations and legal proceedings. Raymond. et al. (2014) successfully categorises three methods that can be deployed, particularly for mass atrocity studies [69], which consist of *multi-temporal change detection*, *multispectral analysis* and *non-imagery data cross-referencing.* All serve as important methods for analysing activity and patterns on the ground, and we have utilised this approach to categorise the analysis methods reported in the court proceedings in this paper. This is an appropriate approach because expert witnesses in court proceedings routinely use multiple analysis techniques, reminiscent of the various observables in the MARS framework. Furthermore, there are a few instances where multiple EO processing methodologies have been deployed in a technical report for court proceedings, demonstrating the multitude of ways that the imagery can be processed and presented, even if for one study.

4.2.1. Multi-temporal change detection

Multi-temporal change detection is one such method described as ’the process of identifying differences in the state of an object or phenomenon by observing it at different times’ [240], including visualising the changes across each image, as seen in Fig. 1. The images show that the Mausolee Sidi Al Bekkai mausoleum (indicated with the white arrow) was destroyed on 22nd-25th December 2012. This acts as a powerful tool for analysts because it is straightforward to be validated by eyewitness accounts and is a strong form of visual evidence for the judging body to understand.

Satellite imagery can act as a very important visual aid demonstrating the objective of the analysis, to see if any change has occurred over a specific area, but it is challenging to gain quantitative insight, especially if there are many changes to the area of interest. We can see this if an alleged violation has occurred across a large area of land or in several regions. Therefore, a further analytic level is required to integrate all changes. Quantification calculation is a key form of analysis used in many court reports because variety of the observables or changes to observables in Table 3 are discrete. Therefore, the changes in the landscape can be summed across the area of interest. There have been many times this process has been used, including *Georgia v. Russian Federation* in the International Court of Justice. The trial covered the alleged atrocities of racial discrimination across South Ossetia and Abkhaz, and some of the atrocities include the destruction of properties. Fig. 2 is one of several figures that was presented in Georgia’s memorial, displaying a time series analysis of destroyed and severely damaged buildings across the Nuli region. The figure acts as a visual aid, but it is also a tool to help quantify the number of buildings destroyed/damaged. The analysis concluded that 94 buildings were likely destroyed and 25 severely damaged in this region [204]. This analysis was extrapolated across the entire Kurta Municipality, and the results determined that 479 buildings were destroyed and 148 were likely severely damaged [204]. The cause of destruction can sometimes be determined using active fire products. This process was applied in *Georgia v. Russian Federation* to compute the total number of destroyed/damaged buildings.

Buildings/accommodations were the most commonly observable for this analysis because they are detectable with satellite imagery and are an important factor in many human rights investigations. This is iterated in Table 2 where the ’right to adequate housing’ is the most populated OHCHR right to which EO can contribute. However, destruction was not the only observable change but also expansion. This is very important for quantifying the expansion of accommodation, particularly temporary structures. *Sufi and Elmi v the United Kingdom* was a case heard in the ECtHR that centred on the dangers of sending asylum seekers back to Somalia. A UNHCR report stated that satellite imagery shows there was rapid urbanisation in the Afgooye corridor, making living conditions unsafe [208].

Change detection can also be quantified with observables, even if the object may not be discrete. Instead, spatially-referenced calculations can be carried out across an area of land. In the case *Construction of a Road in Costa Rica along the San Jun River (Costa Rica v. Nicaragua)* heard at the ICJ, spatially referenced calculations were computed to measure 2D and 3D geometries, including estimating the distance of the road to the river [185] and volume of sediment removed from the gullies [186]. In the instance of 3D calculations, aerial photography was combined with satellite imagery to measure the depth of the gully [186].

These change detection methodologies are a widely adopted process for technical reports in legal proceeding, where the process has not been called into question and the evidence has been rejected only in instances where the actual observables are called into question. We postulate that judges and legal parties tend to accept evidence based on change detection methodologies because it is easy to understand and does not require any specialist technical knowledge in order to do so. Even when calculations are processed, such as in *Construction of a Road in Costa Rica along the San Jun River (Costa Rica v. Nicaragua)*, they are validated against several methods, including aerial imagery and in-person data collection. Furthermore, the critical aspect of this form of evidence is to demonstrate the difference in the landscape before and during the relevant event (here, the construction of a road), which is clear from the images, without needing to calculate the approximate values. Overall then, multi-temporal change detection can be recommended as a method that requires very little scientific literacy from courts and

Fig. 1. Very-high resolution imagery Mausolee Sidi Al Bekkai taken on the 22nd and 25th December 2012. Analysis and report composed by UNOSAT for *Prosecutor v. Ahmad Al Faqi Al Mahdi* (ICC) (with modified notation) [241].

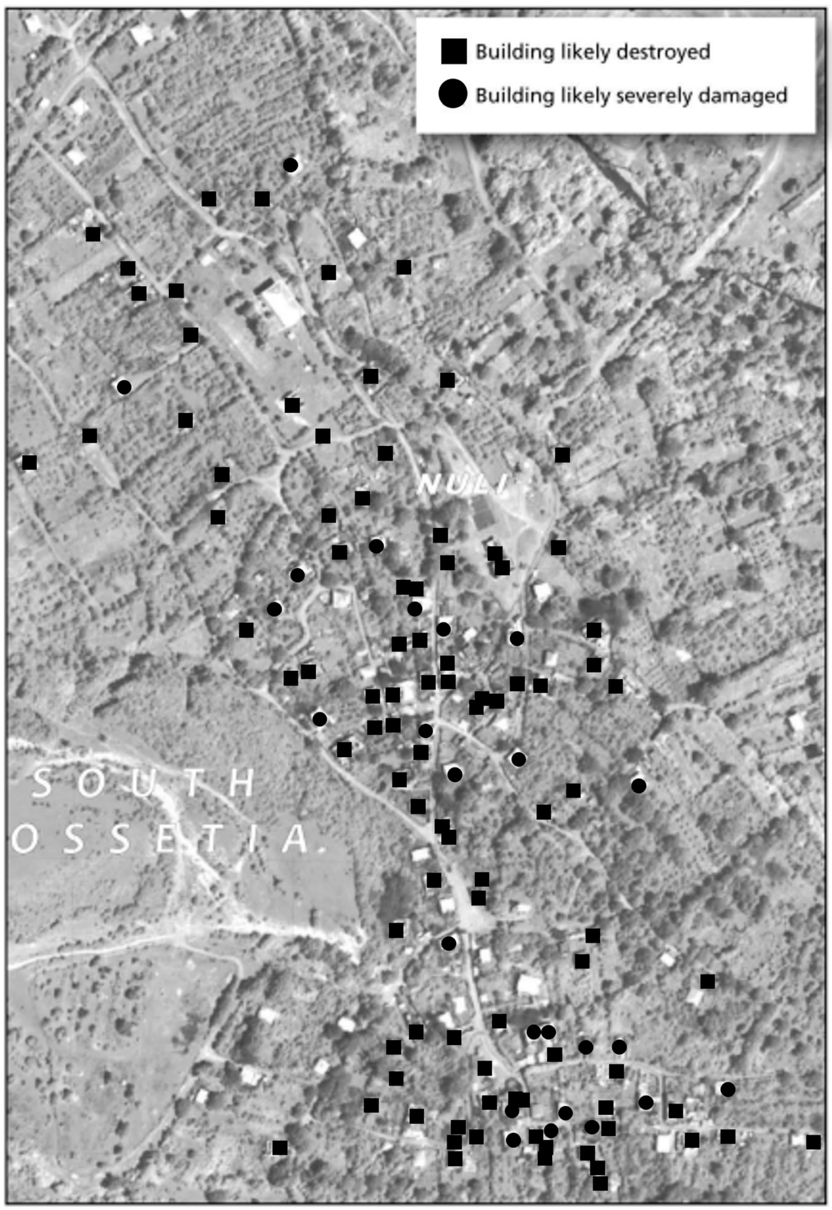

Fig. 2. Destruction of buildings in Nuli region, South Ossetia. Analysis and report composed by UNOSAT for *Georgia v. Russian Federation* (ICJ) (with modified notation) [204].

parties, whilst providing a powerful form of visual evidence that can be used in corroboration with other evidence types.

4.2.2. Multispectral analysis

Multispectral analysis is a scientific way of processing multispectral data collected from EO satellites by transforming the information from each spectral band into one digestible parameter. The simplest form of this analysis is using the visual bands to interpret the AOI based on features that could be seen with the naked eye. For many of the cases, the primary use of RGB imagery was for validating other forms of evidence, particularly witness statements or photographs/videos from the scene [189,190]. Corroborating the statements made by witnesses with satellite imagery can be made by determining the geophysical or structural features that they remember and this can be backed by identifying the features in the satellite image. In the ICC *Prosecutor v. Ali Muhammad Ali Abd-Al-Rahman ("Ali Kushayb")* case, satellite imagery was used to identify the police station and school, where civilians were captured and killed [242], and was based on the testimony of eyewitnesses. The evidence also must be related to the details of the case, otherwise known as 'relevance'. This is demonstrated in *Prosecutor v. Ali Muhammad Ali Abd-Al-Rahman ("Ali Kushayb")* where non-annotated versions of the evidence were presented, but untimately not deemed acceptable [243]. Other techniques can be used with visual interpretation, particularly counting of objects by hand, whether it be the number of IDP tents [191,208] or burnt structures [196,197,203]. Georeferenced measuring can also be used to quantify geophysical features, such as deforestation [180,182–184] or river measurements [185,186].

Multispectral analysis can also use other spectral bands beyond just the red, green and blue (visual) bands. Such spectral bands include infrared and microwave bands, which are referred to in Table 2. Analysts use specialised algorithms and techniques to process the data into valuable insights, including index computation, land classification and calibrated algorithms. This can provide greater enhanced insights, even though it is harder to validate with eyewitness accounts or in-person data collection. In *Pulp Mills on the River Uruguay (Argentina v. Uruguay)*, heard by the ICJ, there was debate around the relevance of the imagery to prove the culpability of the Mill [220,221] (see Section 4.1 for the details of the case), but there was no objection to the sophisticated processing methodology, which applied the research of Ekstrand (1992) to measure algal bloom prominence [218,244].

Another demonstration of multispectral analysis is LULC, which combines many spectral EM wavelengths to classify land cover types. Specialists on behalf of Costa Rica presented land cover classifications for the case of *Construction of a Road in Costa Rica along the San Juan River (Nicaragua v. Costa Rica)* and RapidEye imagery was used in this process [245]. Generating a land classification map requires processing beyond the realm of manual verification of RGB imagery and so can be deemed an important tool in this methodology.

Index computation uses similar processes to LULC, where a couple of spectral bands are assimilated to generate an imagery product that emphasises a specific feature. The Government of Greece employed the use of remote sensing after a verdict from in ECtHR *Chowdury and Other v. Greece* that Greece did not fulfil its obligations to protect victims of human trafficking and conduct an effective investigation. The post-verdict methodology employed the use of the Normalised Difference Vegetation Index (NDVI) to distinguish between vegetated and non-vegetated land, because this can help identify areas that are occupied by informal settlements, an indicator of human trafficking (particularly near agricultural land) [246]. Although this was not used during the court proceedings, this still served as a valuable tool in the wider judicial proceedings in terms of monitoring compliance with the judgement of courts and gives precedent for adoption as evidence in future court cases.

Table 4 clarifies that the vast majority of data used in technical reports are from multispectral missions, where most of these cases use the imagery for RGB image generation and not a further processing methodology. There are exceptions to this, particularly in cases where geophysical variables are determined (see Table 3) or in the deployment of active fire products. Overall then, multispectral analysis should be flagged as an emerging tool where information beyond standard RGB data will be useful in the investigation, prosecution and defence of human rights breaches and other legal disputes.

4.2.3. Non-imagery data cross-referencing

Non-imagery data cross-referencing is the process of using other forms of data and evidence (e.g. eyewitness accounts, reports, survey and scientific data) to assist in identifying and verifying observables. The nature of court proceedings means that this sort of cross-referencing is fundamental to ensure the relevance of technical reports, where the experts are given spatial–temporal metadata to focus their analysis on.[1]

Raymond also suggests the use of other non-imagery sources that 'may be cross-referenced with imagery' [69], a technique that is strongly recommended across all human rights monitoring research [247]. Indeed, non-imagery data cross-referencing was evident in the court proceedings analysed for the present research, where a wide range of sources including eyewitness accounts and interviews, government reports and surveys and scientific data were utilised to cross-reference the EO data, processing and analysis. This proved critical for *Prosecutor v. Kaing Guek Eav alias Duch* at the Extraordinary Chambers in the Courts of Cambodia (ECCC), which used a curated database from the Yale University Genocide Studies Program. The Cambodia Geographic Database (CGEO) is a specialised, interactive map that combines a variety of government, military and public sources to plot bombing sites, prisons, memorials, and burial sites against an evolving set of satellite images from 1973 to 1990 [193]. In this situation, satellite imagery was not solely sufficient to display the distribution of the observables, but the imagery provided an additional source of evidence, and a valuable visual context to all of the other forms of data in these proceedings.

5. Future expectations

The research presented in the paper has identified potential opportunities and forecast trends in this field, with the aspiration that a broader range of Earth Observation (EO) applications and technologies will be employed in the investigation, prosecution, and defence of human rights breaches and other legal proceedings on a national and international scale, However, there remain challenges and opportunities ahead, as this type of evidence, along with other digital evidence, may face obstacles in future court settings.

Artificial intelligence (AI) is rapidly evolving and may significantly alter the structure and admissibility of evidence in courts. In the realm of satellite imagery, the most relevant AI techniques are machine learning (ML) and deep learning (DL) algorithms, which are capable of processing vast amounts of data and producing more easily interpretable results. These technologies have the potential to revolutionize the analysis of imagery, particularly in multispectral change detection. Currently, the process of identifying and quantifying changes in images, such as the destruction of buildings, is carried out manually, which is time-consuming and prone to errors, especially when multiple individuals are involved. ML and DL algorithms could mitigate these issues. Nonetheless, concerns and legal challenges remain, such as data storage, the opaque nature of AI decision-making, and inconsistent outcomes from repeated analyses. However, a realistic near-term application of AI could be its role in assisting with multispectral analysis. Discussions are

[1] Discussed in a meeting with a specialist in satellite imagery, who has acted as the technical specialist for several court proceedings. Annex B of *Prosecutor v. Francis Kirimi Muthaura and Uhuru Muigai Kenyatta* (ICC) outlines the spatio-temporal requirements that the trial has put to the satellite imagery expert, Mr. Bromley. The annex also outlines the observables they must report (ICC-01/09–02/11–646-AnxB-Red).

already underway about adopting these tools during the preliminary data-gathering phase at the ICC, which could significantly reduce the burden on legal teams tasked with processing images.[2]

AI is poised to play a significant role in shaping the future of courts, as advanced scientific and technological tools increasingly need to align with traditional legal standards. While this shift could have positive impacts, there is also understandable concern about the use of AI-based evidence. One particular risk is generative AI, or "deep fakes," which could be exploited in court proceedings if not properly regulated. Deep fake technology is already being tested with satellite imagery to create "fake geography," raising concerns about the reliability of this typically perceived neutral data source[248]. This issue came to the forefront during the *MH17 plane crash* case at the Netherlands Public Prosecution Service, where Russia attempted to introduce fake images of a military site as evidence. Although these faked images were quickly debunked by news organizations[249], this case serves as a precedent in legal circles to ensure that the rules and regulations of the courts remain up-to-date. Efforts are already underway within the academic community to develop methods for detecting fraudulent images[250,251], but the AI sector is fast-paced and legislation must operate at the same rate.

Another potential factor in future court proceedings concerns the ownership of satellite data. Currently, private satellite operators manage the tasking of very high-resolution (VHR) imagery, which is primarily driven by demand, price, and priority. The U.S. has historically been, and remains, the largest provider of commercial satellite imagery. However, the rise of non-U.S. commercial missions prompted policy changes in 1999 with the *Land Remote Sensing Policy Act (P.L. 102–555)* [252]. This legislation relaxed satellite imagery tasking restrictions in the U.S. to maintain its global leadership in this field[252].

A significant development occurred in 2020 when the Kyl-Bingaman Amendment of the 1997 *National Defense Authorization Act*, which had limited imagery resolution over Israel and the occupied territories to a minimum of 2 meters, was lifted. The restriction was lowered to a 0.4-meter ground sampling distance (GSD)[253]. In 2023, the National Oceanic and Atmospheric Administration (NOAA), which oversees U.S. commercial satellite imagery licensing, removed additional restrictions, including temporary X-band synthetic aperture radar (SAR) conditions and 38 other limitations [254]. However, NOAA still maintains control over certain imaging locations.

There is often no centralized or official mechanism regulating the tasking of satellite imagery. One notable exception is the International Charter Space and Major Disasters, which coordinates international agencies and Earth observation (EO) data providers to task all available satellite resources during natural disasters. Currently, this effort has access to 270 satellites. During politically sensitive periods, especially in conflict or threats to national security, the legal implications of task satellite imagery remains unclear.

Addressing these gaps should be a priority for future research. Developing transparent and equitable mechanisms to ensure fair access to VHR imagery, particularly during crises, could greatly enhance the utility of satellite data for humanitarian and environmental monitoring purposes. Advocating for greater collaboration and open access across sectors could help overcome existing limitations and ensure that this valuable data is more widely available for all, whilst also maintaining public safety.

At present we also note that a limitation of satellite imagery in human rights investigations lies in its ground resolution, which can impede the discernment of small details, ultimately limiting its potential application as evidence in legal proceedings. Nevertheless, there is anticipation within the space sector of rapid advancements as more entities invest in satellite missions. This progress is already evident in multispectral imagery, with some providers offering imagery at remarkably high resolutions [255]. Similar advancements are expected for other payloads, such as SAR, hyperspectral, and microwave imagery, along with enhanced sharpening tools to augment the original imagery. Furthermore, the increasing number of imagery providers and satellite missions/constellations will enhance data availability [256], thereby improving the volume of data and improving the likelihood that imagery can capture information relevant to the investigation, prosecution, and defence of legal breaches. Thermal imagery in particular is expected to be revolutionised over the next decade because of the high investment and research for this payload. Although thermal infrared imagery is not a new concept, these payloads are often low resolution and so missions like HotSpot-1 and Hydrosat will change the industry by providing thermal imaging data down to 3.5 m spatial resolution.

Although improvements in technology and science can diversify the range of EO applications for the field, the acceptance and utilisation of such applications lie in legal professionals' attitude to such data because they are the ones to implement the use of it in court proceedings. Whilst a lack of technical understanding can prohibit the uptake of technology by lawyers, it is through increasing this understanding and working together with scientists to ensure that fair standards are adopted, that the maximum value of EO technology will be obtained. This work has already begun, with a collaboration between the Asser Insitute, United Nations Satellite Centre (UNOSAT), and Geneva Science-Policy Interface aimed to improve the knowledge gap of professionals in the ICC so that they can be empowered to integrate advanced technology and satellite imagery into their proceedings [257]. We would reiterate the need for ongoing work to improve the interface between scientists and lawyers in this way.

6. Conclusion

This paper examines the increasing efforts to leverage satellite imagery in the detection, investigation, prosecution, and defense of human rights violations. While courts have begun incorporating satellite data, their use remains limited to basic forms of evidence compared to the broader, more sophisticated applications seen in human rights research. This research aims to bridge the gap between scientific advancements and their legal applications by providing a taxonomy to better understand and utilize EO technology within legal frameworks, particularly in relation to the OHCHR indicators. It also underscore the importance of employing diverse methodologies to fully harness the potential of satellite imagery across a wide range of humanitarian contexts. The goal is to promote wider adoption of EO technology within the legal, scientific, and human rights communities, ensuring its appropriate and effective use in court proceedings.

One of the main obstacles to adopting such technologies is a lack of awareness in the legal sector and insufficient resources to test and integrate new methods. Even in courts that are aware of these technologies, the process of evaluating and validating new evidence can be slow and resource-intensive and costly. Despite these challenges, satellite imagery has the potential to significantly improve the accessibility and applicability of evidence in legal cases, particularly those involving human rights violations. As courts become more familiar with these technologies, they can enhance the detection, investigation, prosecution, and defence of human rights breaches and other legal issues. Although there are potential limitations on investigations due to budget constraints and storage capacities, we note that the accessibility of open-access imagery is increasingly enabling more stakeholders to benefit from EO data and analysis without the heavy financial cost.

The analysis of this research shows that high-resolution multispectral imagery is likely to remain the predominant form of satellite imagery in court proceedings, and more widely in humanitarian studies, because it is extremely versatile in all of the established applications and can be used in both simple and complex methodologies. Furthermore, visual multispectral imagery is useful for visual verification against witness testimony or other imagery collections (e.g. on-ground photo/video) in a number of the cases discussed in this paper. It will continue to be vital

[2] Discussed in meeting with former GIS officer at the ICC.

in the future. However, there is now an opportunity for other payloads such as microwave, SAR, hyperspectral and meteorological data, to feature more heavily in human rights proceedings, as it already has in scientific research around the same topic. Adopting satellite technologies allows courts to better tackle complex human rights cases, delivering more accurate, fair, and comprehensive outcomes—ultimately advancing the pursuit of justice.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.scijus.2024.09.006.

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