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Sensing human health from Space: An assessment of applications and big data platforms

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ABSTRACT

The integration of Earth Observation (EO) into human health research has expanded significantly, particularly since 2009, highlighting its potential for disease modelling, environmental exposure assessment, and public health decision-making. This review explores the evolving role of EO in health applications through a bibliometric analysis of 1751 research documents retrieved from the Web of Science (WoS) database. These documents were selected using targeted keywords and after excluding non-primary literature such as reviews, editorials, and meeting abstracts. Findings revealed a substantial increase in EO-health research outputs, growing from 2 publications in 1991 to 266 in 2024, with a notable surge beginning in 2009. More than 65 % of the selected studies contributed to Sustainable Development Goal (SDG) 13 on Climate Action, followed by SDG 3 on Good Health and Wellbeing ($n = 994$) and SDG 11 on Sustainable Cities and Communities ($n = 980$), illustrating EO's cross-cutting relevance. Despite this growth, the field remains fragmented due to inconsistent data formats, limited accessibility, and weak interdisciplinary collaboration. A key challenge is the persistent divide between EO data producers and health practitioners, which hampers the effective translation of EO insights into practice. This review highlights the importance of co-production approaches that bring together researchers, policymakers, and communities to address these barriers. By promoting standardisation, enhancing data interoperability, and fostering interdisciplinary collaboration, EO can be more effectively leveraged to support disease surveillance, environmental health monitoring, and evidence-based policy interventions aligned with global health and sustainability goals.

1. Introduction

Earth Observation (EO) serves as an important resource in the global effort to address environmental and public health challenges. EO data refers to information collected about the Earth's surface, atmosphere, and oceans using remote sensing technologies. These observations, typically gathered from satellites, but also from aircrafts, drones, and ground-based sensors, play a crucial role in the monitoring of, and understanding changes in, the environment, climate, and weather, and in monitoring of natural disasters and

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human activities. Given these characteristics, it is only natural that it also be applied to the public health domain. EO data enables comprehensive monitoring and analyses of atmosphere, biosphere, cryosphere and ocean ecosystems (McCabe et al., 2017; Rast and Painter, 2019; Avtar et al., 2020). This wealth of information is instrumental in understanding the intricate dynamics between environmental factors and human health, providing insight into the prevalence and spread of diseases, the impact of natural disasters, and the effectiveness of public health interventions (Jetz et al., 2022; Persello et al., 2022). A mounting body of evidence underscores the efficacy of satellite data in deciphering patterns of disease outbreaks in relation with environmental conditions (Barteit et al., 2023; Farooq, 2024; Wang et al., 2024).

The interaction between environment and human health underscores the urgency of addressing global problems associated with environment-related diseases and illnesses (McIntyre et al., 2017). For example, the prevalence of vector-borne diseases such as malaria (Wimberly et al., 2021) and dengue (Parselia et al., 2019) are amplified by climate change (Rocque et al., 2021; Alcayna et al., 2022), while increasing air pollution exacerbates respiratory ailments in major cities around the world (Tran et al., 2023). Water contamination and flooding lead to the spread of waterborne diseases (Racault et al., 2019; Sathyendranath et al., 2020) and deforestation heightens the risk of zoonotic outbreaks (Tajudeen et al., 2022). Chemical and biochemical pollutants contribute to chronic conditions, impacting neurological health and fostering antimicrobial resistance. As the occurrence of extreme weather events increases, the nexus of injuries, infectious diseases, and associated mental health challenges expands. Additionally, non-communicable diseases (NCDs) such as heat-related illnesses and cardiovascular complications are becoming more prevalent due to rising global temperatures and prolonged heatwaves (Jia et al., 2019; Sogno et al., 2020). A holistic approach involving sustainable environmental management and robust public health initiatives is imperative for mitigating these complex global health threats.

Climate change and anthropogenic activities pose multifaceted threats to human health through various mechanisms. Moreover, sea level rise acts as a potential driver of mass migrations and the resulting health issues. Alterations in environmental conditions, driven by global temperature anomalies, can exacerbate existing health challenges. Increasing temperatures contribute to the shift of the geographical range of disease vectors, such as mosquitoes carrying malaria and dengue, thereby modifying the risk of these diseases in new regions (Sutherst, 2004). Additionally, the frequency and intensity of extreme weather events, including hurricanes, floods and heatwaves, are on the rise (Garrabou et al., 2022; Salini, 2024). These events can result in direct injuries and death, displacement, disruption of healthcare infrastructure and affect mental health, amplifying vulnerability (Lee et al., 2020). Changing climate patterns also influence the occurrence and distribution of infectious diseases (Patz, 1996). Waterborne diseases, such as acute diarrheal disease and cholera, typically rise during periods with high precipitation and flooding, which can lead to contamination of drinking water sources (Levy et al., 2016; Abdulaziz et al., 2023; Abdulaziz et al., 2021). Moreover, a warming climate facilitates the emergence of novel diseases, as seen in the expanding geographical range of certain pathogens and the potential for previously unknown infectious agents at higher latitudes. This evolving landscape demands adaptive public health strategies, including early warning systems, resilient healthcare infrastructure, and research to understand the dynamics of emerging diseases. A recent study has also highlighted the cumulative impact of climate change and health on mental well-being, as well as ways to improve its condition (Lee et al., 2020). Mitigating the health risks associated with climate change necessitates a comprehensive approach, integrating environmental management, public health planning, and international collaboration to address the intricate challenges posed by the evolving climate-health nexus. An additional problem in addressing the role of environmental drivers in the spread of disease at various spatial scales is the availability of health data that can be integrated with EO data. Although availability of open-access data portals would address this problem, to date, such platforms remain scarce.

Health research using EO at local, regional, and global scales has gained growing recognition, and substantial advances have been made in the past decades, with a rapid increase in the number of peer-reviewed publications (particularly since 2009). While there is a growing body of evidence of the role of the environment in public health, there are only a handful of reviews that have synthesised the current understanding of how remote sensing observations of the environment can be used to improve public health. Moreover, these reviews typically focus on either broader elements of a Health-EO nexus (e.g.,Weng et al., 2014) or specific applications, such as disaster recovery (Shah et al., 2023), non-communicable diseases (Jia et al., 2019) or waterborne diseases, or summarise individual applications in editorial editions, such as Brazeau and Ogden (2022). Currently, there is no study which evaluates the overall trends and patterns in the application of EO in the public health domain along with information on both EO and health data available for broad use via open-access data platforms. Therefore, the aim of this review paper is to fil this gap by showcasing the general course of the EO-health discipline by a rigorous systematic literature review. First, we evaluate various EO applications and approaches in studies of human health by analysing peer-reviewed publication records from the Web of Science since 1970. However, data were only available from 1991 (see Section 2). Second, we catalogue and compare existing open-access data platforms for monitoring and forecasting risk to human health from the local to global scale and, in doing so, we highlight the challenges and opportunities of EO for human health resilience. This study offers a novel, data-driven synthesis of three decades of EO-health research, uniquely linking publication trends to Sustainable Development Goals while identifying structural gaps that hinder effective integration into public health practice.

We achieve our aim through the following objectives.

1. To develop an extensive literature database on EO and health (Section 2);
2. To identify trends in the characteristics of global EO-health research (Section 3);
3. To synthesise the key findings on topic hotspots, country collaboration, and annual trends;
4. To collate information on existing EO big data platforms for user-ready and open-access data (Section 4); and perform a Strengths, Weaknesses, Opportunities, and Threats (SWOT) along with Political, Economic, Social, Technological, Legal, and Environmental (PESTLE) analysis regarding its usage; and

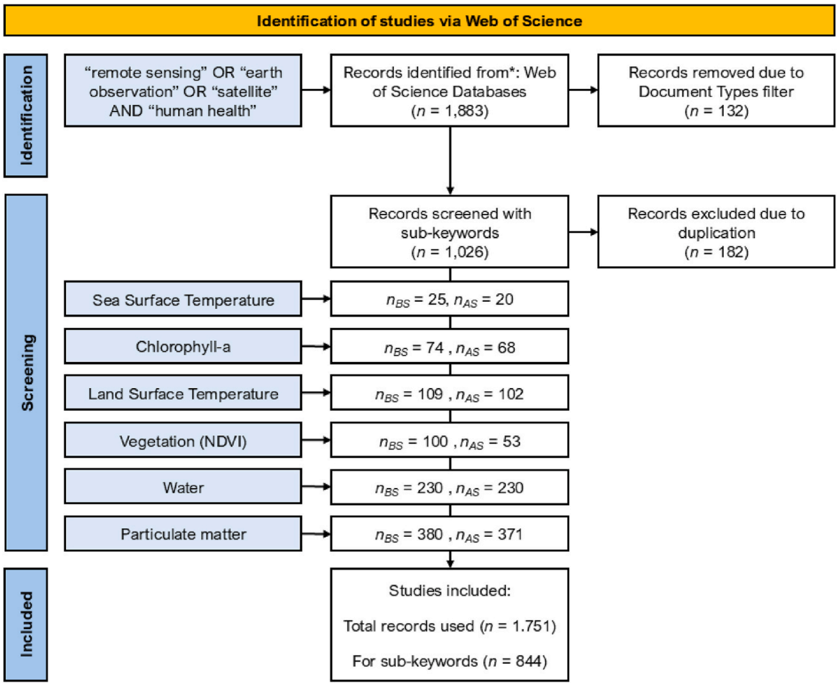

Fig. 1. Flow chart of keywords used in this study to extract publications from Web of Science (method adapted from Page et al., 2021b). Abbreviations: n_{BS} = number of publications before screening for duplication, n_{AS} = number of publications after screening for duplication. Python code used to filter duplicate publication can be found in code availability section.

Table 1
Definitions of the six EO-derived variables used in the study.

Parameter	Definition
Sea Surface Temperature (SST)	The temperature of the ocean's surface, measured using satellites, buoys, and ships. SST is crucial for understanding climate change, weather patterns, and marine ecosystems.
Land Surface Temperature (LST)	The temperature of the Earth's land surface, as measured by satellites. LST is essential for studying urban heat islands, droughts, and environmental changes impacting human health.
Chlorophyll-a	A pigment found in phytoplankton that is central to photosynthesis and is an indicator of biomass. Measuring chlorophyll-a levels in water bodies helps monitor algal blooms, ocean productivity, and water quality.
Normalised Difference Vegetation Index (NDVI)	A widely used numerical indicator for measuring and monitoring vegetation health and density. It works by comparing the difference between near-infrared and visible red light reflected by vegetation. This index is not only crucial for assessing ecological conditions, but is also increasingly recognised as a valuable indicator for monitoring the impact of vegetation on human health.
Water quality/Extent	Refers to the chemical, physical, and biological characteristics of water, including pollutants, dissolved oxygen, extent and turbidity. Monitoring water quality is vital for ecosystem health and human well-being.
Particulate Matter (PM)	Tiny solid or liquid particles suspended in the atmosphere, including dust, smoke, and pollutants. PM is a major air quality indicator and is linked to respiratory and cardiovascular health issues.

5. To provide priorities for directions of future research, drawing upon the findings of a user forum organised by the European Space Agency (ESA) in the context of their EO4 Health Resilience project (https://eo4society.esa.int/resources/esa-eo4health-user-forum-2024/) (Section 5).

2. Methods

2.1. Literature review

Our key objective is to perform a systematic mapping of English-language scientific literature on the application of EO to investigate human health. We used the PRISMA Statement 2020 flow diagram format, which is a standardised set of guidelines aimed at promoting transparent and comprehensive reporting of systematic reviews (Page et al., 2021a). In this section, we describe how the literature search was carried out, and how results were compiled. We then review and discuss the contents. A combination of

Table 2
Description of screening process used in developing the list of EO and health digital platforms.

Description	Keywords Used	Screening Process
Established criteria for platform relevance based on data accessibility, geographic coverage, thematic focus, and interoperability.	N/A	Reviewed key parameters for inclusion.
Conducted broad searches to identify relevant platforms.	"Earth Observation health data platforms", "climate-health data services", and "remote sensing health monitoring tools".	Initial screening based on search result relevance and platform descriptions.
Examined EO and health organisations' websites for endorsed platforms.	N/A	Selected platforms hosted or endorsed by ESA, NASA, WHO, and similar institutions.
Verified each platform's relevance and recorded attributes like data type, coverage, accessibility, and integration.	N/A	Detailed examination of platform features and usability.

systematic review and content analysis was used to collect scientific literature and filter for publications relevant to the scope and themes of this review. Published journal articles, academic theses, conference proceedings, and scientific reports from 1991 (where available) to December 2024 were sourced using the Web of Science (WoS; accessed on the December 18, 2024) search engine (Birkle et al., 2020; Pranckutė, 2021). Publications were filtered by topic, title, abstract, and full text (when possible) entering different grouped combinations of key search terms. Final key search terms used were “remote sensing” OR “earth observation” OR “satellite” AND “human health” (Fig. 1). Publications were manually checked to ensure that both human health and EO were addressed. Furthermore, we selected six key satellite-derived environmental variables to showcase their applications in the human health domain: Sea Surface Temperature (SST), Land Surface Temperature (LST), chlorophyll-a, Normalised Difference Vegetation Index (NDVI), water extend or quality and particulate matter (PM) in the atmosphere (Table 1). Data and Python codes used in this study are available via shared repository on Zenono and a link to this repository is available in the supplementary material.

To illustrate patterns in the literature, we used the Visualisation of Similarities (VOS) software, an advanced computational approach to literature review analysis, particularly beneficial in interdisciplinary domains (Van Eck and Waltman, 2007). Leveraging sophisticated algorithms such as co-citation, co-occurrence, and bibliographic coupling, VOS can be used to elucidate intricate connections within extensive bibliographic databases (Eck and Waltman, 2009; Waltman et al., 2010). Here, VOS software (https://www.vosviewer.com) was used to plot relationships between environmental variables derived from satellite data and health outcomes. These visual representations aid the identification of potential causal pathways and areas warranting further investigation.

2.2. Review of digital platforms for EO and health

To identify and compile a comprehensive list of digital platforms offering both EO and health-related data, we undertook a systematic examination of 30 web portals, hereafter referred to as digital platforms (Table 2). These platforms were evaluated based on their data coverage and relevance to the intersection of EO and health domains. The evaluation process involved the following steps.

1) **Defining Selection Criteria**: We identify relevant platforms, focusing on those that provide datasets, tools, or services integrating EO and health-related information. The criteria included data accessibility, geographic coverage, thematic focus (e.g., climate-health interactions, disease monitoring), and interoperability with other datasets or platforms;
2) **Comprehensive Web Search**: We conducted extensive searches in Google using the following search terms: "Earth Observation health data platforms", "climate-health data services", and "Remote sensing health monitoring tools". This ensured a broad scope of potential platforms;
3) **Review of Institutional Sources**: Websites of leading EO and health organisations, such as those from the European Space Agency (ESA), the National Aeronautics and Space Administration (NASA), and the World Health Organisation (WHO), were reviewed to identify platforms they host or endorse; and
4) **Manual Screening and Evaluation**: Each identified platform was manually examined to verify its relevance. Key attributes of the platforms, including the type of data offered, geographic and temporal coverage, user accessibility, and integration features, were recorded.

This study also incorporates insights from the EO4Health User Forum (https://eo4society.esa.int/resources/esa-eo4health-user-forum-2024/), held at the ESA ESRIN facilities in Frascati, Italy, in January 2024. During this forum, experts from academia, industry, and policy sectors discussed the role of Earth Observation in monitoring environmental health risks. Key discussions, particularly on remote sensing applications for assessing waterborne disease risk, helped refine our methodological approach. Using the Nominal Group Technique (Harvey and Holmes, 2012), feedback from experts were summarised for topics related to data selection, model parameterisation, and validation strategies, ensuring that our approach aligns with current scientific and operational needs.

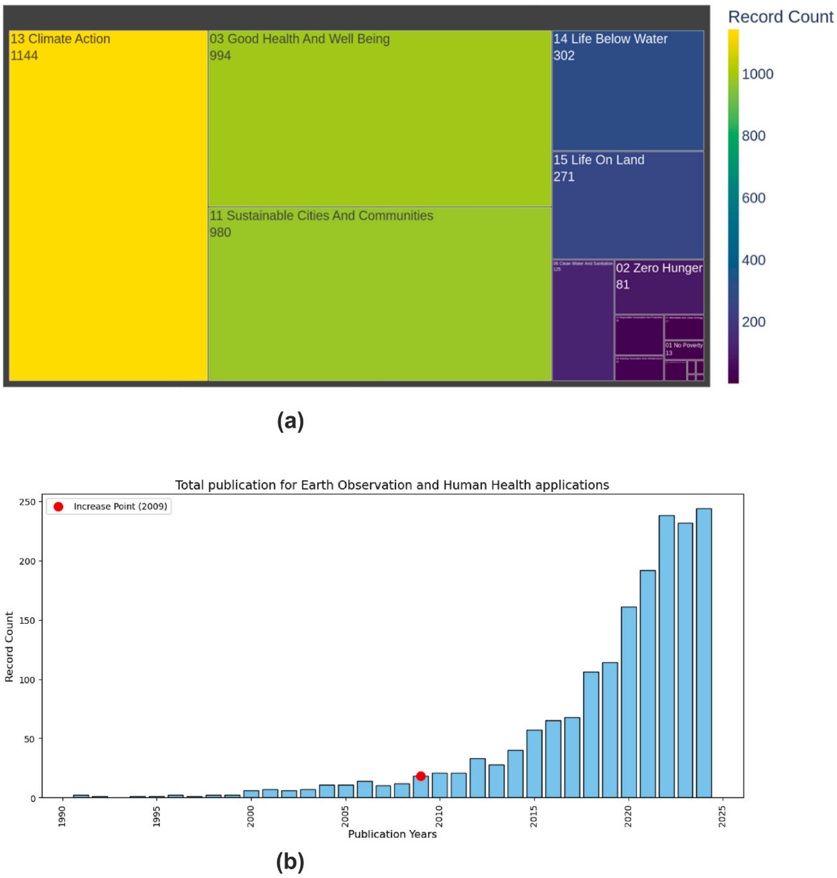

Fig. 2. a) Tree chart showing publications tagged as contributing towards different Sustainable Development Goals (note that 97 record(s) (5.5 %) do not contain information on SDGs). b) Bar chart showing number of publications under the domain of Earth Observation and human health from 1990 to 2024. The publication count started increasing significantly in 2009 with 18 records. (Data source: Web of Science).

3. Results

3.1. *Trends in the literature*

With the keywords described in Fig. 1, some 1883 research documents emerged from the WoS portal. Out of these, news items, book chapters, meeting abstracts, corrections, book reviews, letters, notes, retracted publications, bibliographies, and review papers were excluded from the study. This reduced the number of available research documents to 1,751, which were selected to analyse trends and patterns in research documents on the combined domain of EO and human health. Data derived from WoS further showcased contributions of authors towards Sustainable Development Goals (SDGs) (Fig. 2a). More than 1000 publications out of 1,751, or 65 %, addressed Goal 13 on Climate Action, followed by Goal 03 on Good Health and Wellbeing ($n = 994$) and Goal 11 on Sustainable Cities and Communities ($n = 980$). The number of publications over time on topics related to EO and human health rose from 2 publications per year in 1991 to 266 in 2024. A significant increase in research outputs was observed post-2009, using a threshold of a minimum of 5 publications per year (Fig. 2b).

All scientific publication records between 1990 and November 2024 that passed the search term filter “remote sensing” OR “earth observation” OR “satellite” AND “human health” extracted from WoS were subjected to a VOS cluster analysis with the maximum number of occurrences of a keyword per document limited to 10. Note that keywords such as “remote sensing” and “human health” are not accounted for in this analysis as they were used in the search. The results reveal frequently-used tools and common areas of applications of EO data in health research (Fig. 3). Four distinct clusters are apparent, each representing a concentrated area of research within the EO-human-health intersection: 1) Air quality; 2) Impact; 3) Water quality; and 4) Exposure; and the interactions between these four major research topics. It is noteworthy that measuring air quality from space emerges as one of the prominent applications of EO and human health. The analysis not only highlights the core areas of EO application in human health research, but also identifies inter-cluster relationships, pointing to interdisciplinary approaches that have been employed frequently.

The number of scientific publications related to EO and human health between 1991 and 2024 varies significantly across countries, with notable disparities in research output (Fig. 4). China (579 publications) and the United States (512 documents) lead the field by a

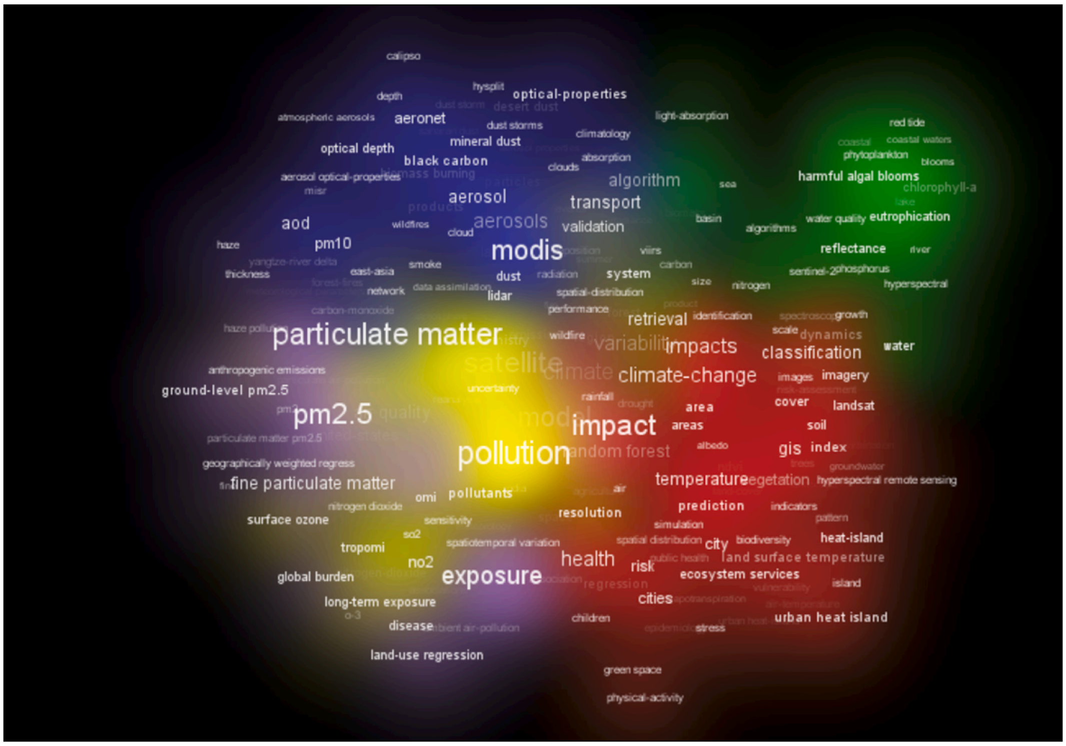

Fig. 3. shows results of the VOS cluster analysis with density of keywords patterns comprising four distinctive clusters: Air quality in blue, Impact in red, Water quality in green and Exposure in yellow.

substantial margin, reflecting their strong research infrastructure and investment in EO applications. India (113 documents) follows as the third-largest contributor, highlighting its growing role in this domain. Other high-output countries include England (88), Germany (84), and Italy (77), indicating strong European engagement. Mid-range contributors such as Australia (60), Iran (60), and South Korea (60) also play a role, while several other countries, including Argentina (15), Turkey (15), and Vietnam (14), have a lower, yet notable, number of contributions.

In terms of citations, the United States (18,338 citations) and China (13,389 citations) again dominate (Fig. 4). Publications from countries such as Germany (2,904), England (2,932), and India (2,313) have also accumulated significant citations between 1991 and 2024. Interestingly, while China has the highest document count, the United States has received more citations per paper, suggesting a potentially higher research impact, possibly driven by international collaborations or greater visibility of specific studies. Countries such as Belgium (1,174), South Korea (1,195), and Australia (1,300), despite having fewer publications, exhibit relatively high citation counts, suggesting strong research quality and relevance. The data highlight both the volume and impact of EO and health research worldwide, emphasising the leading roles of a few key nations, while showcasing the growing contributions of emerging players.

3.2. Earth observation for human health: analysing six key EO variables for Global Health insights

The growing body of studies illustrates the increasing use of EO data for human health research by scientists from around the world. A total of 1026 out of 1751 publications used six EO terms as key variables selected in our review (i.e., sea surface temperature, chlorophyll, land surface temperature, vegetation, water and particulate matter; see section 2). By utilising these keywords, we further investigated the trends of available publications since 1991 to showcase the growing application of EO derived data in mapping, monitoring and predicting disease outbreaks along with the impact of extreme environmental conditions on human health.

In recent years, EO data have been particularly used to measure air quality over time and space. Cities like Delhi, Shanghai (Guo, He and Wang, 2023b), and Hanoi frequently experience high levels of particulate matter (PM 2.5). This has led to increased cases of asthma, chronic obstructive pulmonary disease (COPD), and heart attacks among their populations. The proportion of scientific publications utilising Earth Observation (EO) data to assess and predict the impact of particulate matter in the atmosphere on human health increased from 2.1 % in 2015 to 14.9 % in 2024, representing a growing focus within the field. This trend accounts for a total of 371 publications identified within our search criteria (Fig. 5a). Furthermore, with a total of 109 publications, application of EO-derived land surface temperature (LST) data in the human health domain has doubled from 6.42 % ($n = 7$) in 2017 to 17.43 % ($n = 19$) by the end of 2024 (Fig. 5b). Additionally, LST is often combined with other EO datasets, such as rainfall, humidity and vegetation indices, to predict the outbreak of dengue fever (McIntyre et al., 2017b) or malaria (Wimberly et al., 2021). Since 2004, more than 50 scientific publications have applied NDVI in conjunction with human health and its application has increased with 4 publications in

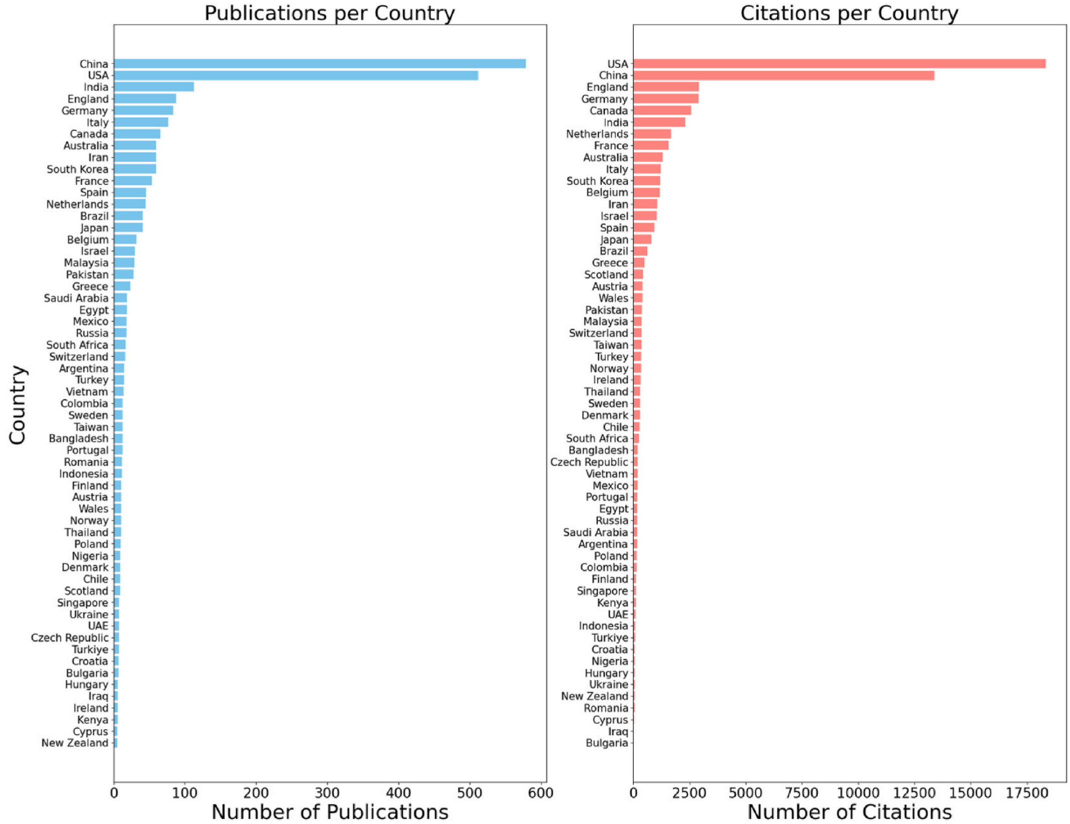

Fig. 4. shows the total number of publications (left) and citations (right) by country between 1991 and 2024 with keywords "remote sensing" OR "earth observation" OR "satellite" AND "human health". (Full list available in Supplementary Material).

2020 to 9 in 2023 (Fig. 5c).

Over 65 publications have used ocean-colour observations for mapping of chlorophyll-a in aquatic environments as a key indicator for understanding spatial patterns of waterborne diseases, such as cholera. It must be noted that 50 % of these documents were published post 2020, which shows recent interest in using ocean-colour remote sensing to monitor water quality and human health. The scientific publication record using EO for mapping of the chlorophyll concentration in relation to human health rose from just 2 in 2014 to 12 in 2024 (Fig. 5d). Our literature analysis also showed that 20 publications used EO data to measure Sea Surface Temperatures (SST) and predict risk from bacteria such as *non-Cholera Vibrio* (Fig. 5e). Publications employing remote sensing of water quality or extent of open water for human health applications have seen significant growth rising from 4 publications per year in 2014 to 40 publications per year in 2024 (Fig. 5f)

The link between outbreaks or occurrences of disease and the environment have been well documented in the scientific literature, but application of remote sensing technologies to investigate such environmental influence on human health has been underexplored. If we take cholera as an example of a disease that is caused by a climate-sensitive pathogen, a search on WoS on "cholera" results in 24,321 publications during the same time interval as our study period (1990–2024). In addition, a search on "west nile virus" yields 10,182 publications and "leptospirosis" yields 6647 publications. It is well recognised that environmental factors, such as water or land temperature, salinity, rainfall and floods, influence the occurrences of these diseases. However, of the more than 24,000 publications on cholera, only 36 mention remote sensing, even though the keyword "environment" appears in more than a 1000 of these publications and "temperature" appears in 600 publications. Similarly, 56 publications (out of 10,182) on West Nile virus mention remote sensing and publications on leptospirosis mention remote sensing in just 12 out of a total of over 6000 publications. This disparity reveals that remote sensing and satellite data are under-utilised in public health research, despite their huge promise, and highlights the need for greater integration of this source of data into health research. A potential cause for this under-utilisation could be a lack of access to user-friendly data and highlights the importance of recent efforts to bring EO and human health data together through digital platforms. In the next section, we explore some of the key platforms providing EO and human health data and discuss some of the major challenges that remain.

3.3. *Data access via EO digital platforms*

Here we define EO big data platforms as comprehensive systems designed to manage, process, analyse, and disseminate vast

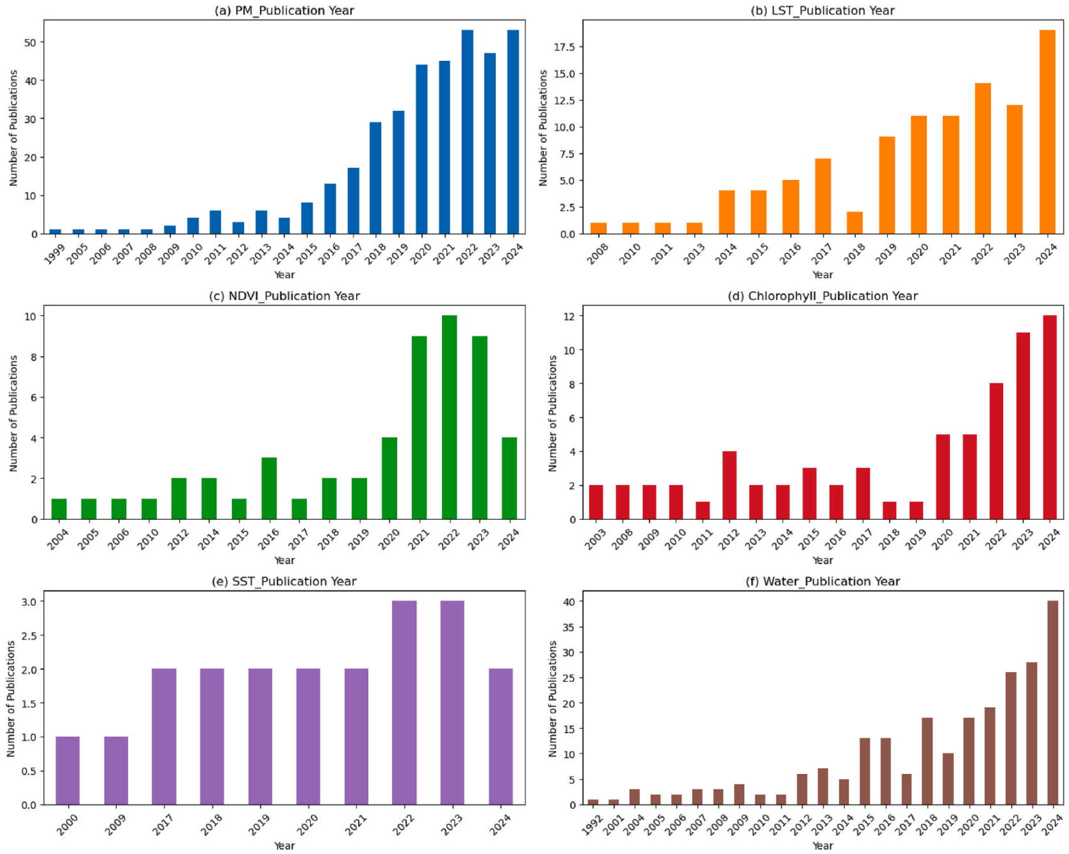

Fig. 5. a) Time series of the number of publications for the selected key EO variables: a) Particulate Matter (PM) in the atmosphere, b) Land Surface Temperature (LST), c) Normalised Difference Vegetation Index (NDVI), d) Chlorophyll, e) Sea Surface Temperature (SST), and f) Water, that were screened from the results obtained using the keywords “remote sensing” OR “earth observation” OR “satellite” AND “human health”. Availability of data varies between each keyword in the WoS portal.

amounts of data collected from EO sources, primarily satellites, but also including airborne sensors, drones, and ground-based instruments. We have identified 22 platforms that report EO and/or health data, as shown in Table 3.

The identified big data platforms have diverse yet interconnected roles in global health, environmental monitoring, and disease prevention, each offering unique capabilities and data types. Many of these platforms, such as the Food and Agriculture Organisation (FAO) Emergency Prevention System (EMPRES), the Global Early Warning System (GLEWS/GLEWS+), and the World Organisation for Animal Health (WOAH) World Animal Health Information System (WAHIS), focus on animal health and zoonotic disease surveillance, emphasising the importance of early detection and response to prevent outbreaks that could impact both animals and humans (Table 3). These platforms typically provide global coverage, allowing for a comprehensive view of health risks and trends across different regions. Another group of platforms, such as the European Climate and Health Observatory and the Copernicus Climate Data Store, concentrate on the intersection of climate and health. They offer EO data, which are crucial for understanding how climate change and environmental factors influence health outcomes. These platforms are particularly important in the context of rising global temperatures and changing ecosystems, which can alter the distribution of diseases and increase the frequency of extreme weather events that pose health risks. Platforms such as the Malaria Atlas Project (MAP) and HealthMap are more specialised, focusing on specific diseases or health conditions. MAP provides detailed information on malaria, including spatial data that helps track the disease distribution and guide interventions. HealthMap, on the other hand, aggregates data on various infectious diseases, offering a real-time view of emerging health threats worldwide. While most platforms offer global coverage, some are region-specific. For example, BEYOND Early Warning System for Mosquito Borne Diseases (EYWA) focuses on mosquito-borne diseases in Europe, reflecting regional health concerns and environmental conditions. Similarly, platforms like Colab + Atlantic and ARBOCARTO cater to specific geographical areas or issues, such as coastal health and arboviral diseases, respectively.

Additionally, the integration of EO platforms with planetary-scale human health presents both opportunities and challenges, as outlined in the SWOT and PESTLE analysis conducted among the authors of this study (Table 4). The strengths of EO platforms lie in their ability to provide open-source, global-scale data, which support evidence-based decision-making and improved spatial and temporal coverage. However, these platforms face challenges such as skill gaps, data privacy concerns, and a lack of political recognition. Economically, EO data offer cost-effective global insights, yet funding remains a hurdle. Socially, public health awareness

Table 3
List of big data platforms related to EO and human health with their spatial coverage. Abbreviations: Food and Agriculture Organisation (FAO), World Organisation for Animal Health (WOAH), United Nations Office for Outer Space Affairs (UNOOSA), European Food Safety Agency (EFSA), European Centre for Disease Prevention and Control (ECDC), Centre for Environment Fisheries and Aquaculture Science (CEFAS), and European Forest Institute (EFI).

Number	Name of the platform	Human and Animal data	EO data	Spatial coverage	Weblink
1	FAO Emergency Prevention System (EMPRES)	✓		Global	https://empres-i.apps.fao.org/diseases
2	FAO Agro-informatics platform	✓	✓	Global	https://data.apps.fao.org/?lang=en
3	Global Early Warning System (GLEWS/GLEWS+)	✓		Global	http://www.glews.net/
4	WOAH World Animal Health Information System (WAHIS)	✓		Global	https://www.woah.org/en/what-we-do/animal-health-and-welfare/disease-data-collection/world-animal-health-information-system/
5	UNOOSA Space and Global Health (SGH)	✓		Global	https://gdhub.unige.ch/implementome/
6	BEYOND Early Warning System for Mosquito Borne Diseases (EYWA)	✓	✓	Europe	http://beyond-eocenter.eu/index.php/web-services/eywa
7	Open Network for Water-Related Diseases (ONWARD)		✓		https://onwardnetwork.net/
8	European Climate and Health Observatory	✓	✓		https://climate-adapt.eea.europa.eu/en/observatory
9	Copernicus Health Hub		✓		https://hds.hub.copernicus.eu/datasets
10	Copernicus Climate Data Store		✓		https://atlas.climate.copernicus.eu/atlas
11	Urban Green Infrastructure (2018 only)		✓		https://www.eea.europa.eu/data-and-maps/dashboards/urban-green-infrastructure-2018
12	Defining Ecoregions and Prototyping on EO-based Vector-borne Disease Surveillance System for North Africa (PROVNA)	✓	✓		https://www.izs.it/IZS/Staff_9/OIE_project_to_support_Vector-Borne_Diseases_Surveillance_in_North_Africa_Rift_Valley_Fever_as_first_application
13	EFSA Living One Health Risk Assessment (L'ORA)	✓			https://etendering.ted.europa.eu/cft/cft-display.html?cftId=11651
14	ECDC/EFSA VectorNet	✓			https://www.ecdc.europa.eu/en/about-us/partnerships-and-networks/disease-and-laboratory-networks/vector-net
15	CEFAS data portal	✓	✓		https://data.cefas.co.uk/
16	EFI data portal		✓		https://efi.int/
17	Colab + Atlantic		✓		http://coastsense.colabatlantic.com/
18	ARBOCARTO	✓	✓		https://www.arbocarto.fr/en
19	Malaria Atlas Project (MAP)	✓	✓		https://malariaatlas.org/about-map/

(*continued on next page*)

Table 3 (*continued*)

Number	Name of the platform	Human and Animal data	EO data	Spatial coverage	Weblink
20	World Pop	✓	✓	Global	https://www.worldpop.org/datacatalog/
21	HealthMap	✓		Global	https://healthmap.org/en/
22	Copernicus Marine Data Service		✓	Global	https://marine.copernicus.eu/
23	VectorMap	✓		Global	https://experience.arcgis.com/experience/5f95c3edfbea4634b8347fec0bd1dcd6/
24	VectorBase	✓		Global	https://vectorbase.org/vectorbase/app
25	MOnitoring Outbreaks for Disease surveillance in a data science context (MOOD)	✓	✓	Global	https://mood-h2020.eu/
26	Global Biodiversity Information Facility	✓		Global	https://www.gbif.org/dataset/search?q=
27	Awesome Google Earth Engine Community dataset	✓	✓	Global	https://gee-community-catalog.org/
28	Google Earth Engine				https://developers.google.com/earth-engine/datasets
29	NASA Earth Data				https://www.earthdata.nasa.gov/
30	Computational Epidemiology Lab	✓			https://compepi.org/about/

can be raised by transparency and accessibility of data, but cultural and technological differences pose barriers. Technologically, advancements such as Synthetic Aperture Radar (SAR) and high-resolution imaging offer novel opportunities for disease forecasting and environmental monitoring, but gaps in data quality and resolution persist. Legally, EO data support advocacy and global non-governmental organisations (NGOs), yet it is not universally recognised as a valid source of evidence. Environmentally, EO platforms enhance the analysis of climate trends and disease outbreaks, but raise concerns about carbon emissions and space debris. Addressing these factors holistically is crucial for leveraging EO data platforms in the health sector.

4. Way forward – drawing suggestions from a user consultation forum

The analyses presented above highlights the important role that Earth Observation can play in managing outbreaks or occurrences of diseases that have an environmental connection. It has also revealed many challenges, and missed opportunities. In this section, we draw upon a user consultation forum organised by ESA. Feedback from experts helped shape data selection criteria, model parameterisation, and validation strategies, ensuring alignment with current scientific and operational needs. In this section we encapsulate the recommendations that emerged from the forum, with respect to the directions of future activities.

When discussing satellite-based methods for identification of distribution patterns of human pathogens and their change over time, it is important to state at the outset that satellites rarely observe pathogens directly. Satellite-based methods therefore rely mostly on establishing proxies for the pathogens that are observable from space, and then using satellite data to study the dynamics of the pathogen. This approach requires access to *in situ* observations matched in space and time with satellite observations, to establish reliable proxies. Similarly, predictions of potential outbreaks of diseases rely on establishing empirical relationships between environmental variability and disease outbreak, as the basis for satellite-based tools for prediction of outbreaks. Since empirical relationships are not often sufficient to establish causality, satellite-based investigations must be complemented by controlled experiments in the laboratory and the field to understand the mechanisms that underpin the correlations observed in the environmental data. Establishment of environment-disease relationships requires access to concurrent observations of environmental conditions, pathogens in the environment and reported cases of diseases. Ideally, such matched observations would be available from a variety of environmental conditions and over long time scales. One of the challenges in this field of research is to have access to such datasets. Use of statistical tools such as machine learning works best when the datasets are large, and cover all possible combinations of the input and output variables. We explore two distinctive data types critical for EO and Health domain.

(a) Epidemiological data

Epidemiological data refers to information related to the occurrence and distribution of diseases or health-related events, being the

Table 4
Strengths-Weaknesses-Opportunities-Threats (SWOT) and Political, Economic-Sociological-Technological-Legal-Environmental (PESTLE) analysis for usage of Earth Observation big data platforms and planetary scale human health.

	S - Strength	W - Weaknesses	O - Opportunities	T - Threats
P - Political	1 Public health policy 2 International initiatives for adaptation to climate change 3 Improved decision making	1 Data sharing among different departments	1 To merge space policy with health services 2 Raise political awareness of added value of EO data	1 Trust and data breach 2 Poor risk maps will lead to inadequate planning 3 EO not politically recognised as valuable 4 Access to health data now under threat due major changes in governance.
E – Economic	1 Open source EO data from space agencies 2 EO is likely the only way to have global data in an economically viable way	1 Funding acquisition	1 Business growth around EO and public health partnerships	1 International political crisis and wars
S - Social	1 Transparency and accessibility of data	1 Skill gap 2 Different cultures (health and technologically involved)	1 New creative jobs 2 Public health awareness	1 Data protection and privacy 2 Trust in EO data
T - Technological	1 Improved spatial and temporal coverage 2 Emergence of Synthetic Aperture Radar in the commercial space industry	1 Data standardisation 2 Availability of health data 3 Data management 4 Need for higher spatial and temporal resolution	1 Disease forecasting over space and time 2 Exploring high resolution satellite images 3 Time series health analysis 4 Identifying novel opportunities	1 Gaps in data 2 Quality of EO data 3 Not easily accessible in useable format
L - Legal	1 Supporting evidence-based advocacy 2 Open source EO data supporting NGOs globally	3 EO not recognised as legally valid source of evidence	1 Novel ways to generate evidence and improve decision making	1 Low granularity/resolution of EO data preventing valid evidence 2 Awareness of legal binding around EO
E Environmental	1 Better communication on environmental change 2 Data accessibility 3 Time series analysis for environmental trends	1 Carbon footprint of servers that manage terabytes of data	1 Data fusion for better forecasting of disease outbreaks 2 Trend analysis for early decision making	1 Carbon emissions from satellite development and launches 2 Space debris

branch of public health that focuses on studying the patterns, causes, and effects of health and disease conditions in populations, and are an essential component of data needed for understanding the dynamics of diseases, identifying risk factors, and informing public health interventions.

In a practical way, and from the perspective of development of projects related to EO data for health and resilience building, epidemiological data are essential for training disease projection models, especially in the context of public health, enhancing predictive analytics, early detection of outbreaks, and decision support for healthcare professionals. Among the several ways that epidemiological data can contribute, one can refer to 1) Disease prediction and forecasting, 2) Risk factor identification, 3) Spatial analysis of distribution or spread, 4) Early detection of outbreaks, or 5) Behavioural analysis.

Epidemiological data are often difficult to obtain, and this was highlighted in the discussions that took place during the user forum organised in the context of the ESA EO4Health project. There are a number of contributing factors for this.

- **The need for data anonymity and data protection** – Data anonymity and data protection are key aspects of data on diseases that can hinder sharing of data. Respecting confidentiality and safeguarding patient and healthcare are paramount when establishing protocols for sharing data for any broad application which go beyond the initial purpose for which the data were collected. For this, robust protocols for elimination of personal information and encryption mechanisms are essential to uphold confidentiality, and foster trust in the integration of disease and EO data. There are strategies that can contribute to overcome these difficulties, such as aggregating data over larger geographical regions rather than providing exact positions of any given occurrence (geocoding is a key factor to consider here). In fact, the higher the granularity of the data considered, the higher is the difficulty to get access to the data.
- **The types of diseases** – The type of disease is also a factor that greatly influences the capability of accessing data. In this regard, for obvious reasons, data from rare diseases are even harder to obtain.
- **Different health systems have different data sharing policies** – The variety in data sharing policies among health organisations is another factor that was clearly mentioned during the EO4Health user forum, with the US and EU health care systems as examples of being very restrictive in terms of data access.

However, there are strategies that can be put in place to overcome some of these limitations. Among these, we highlight.

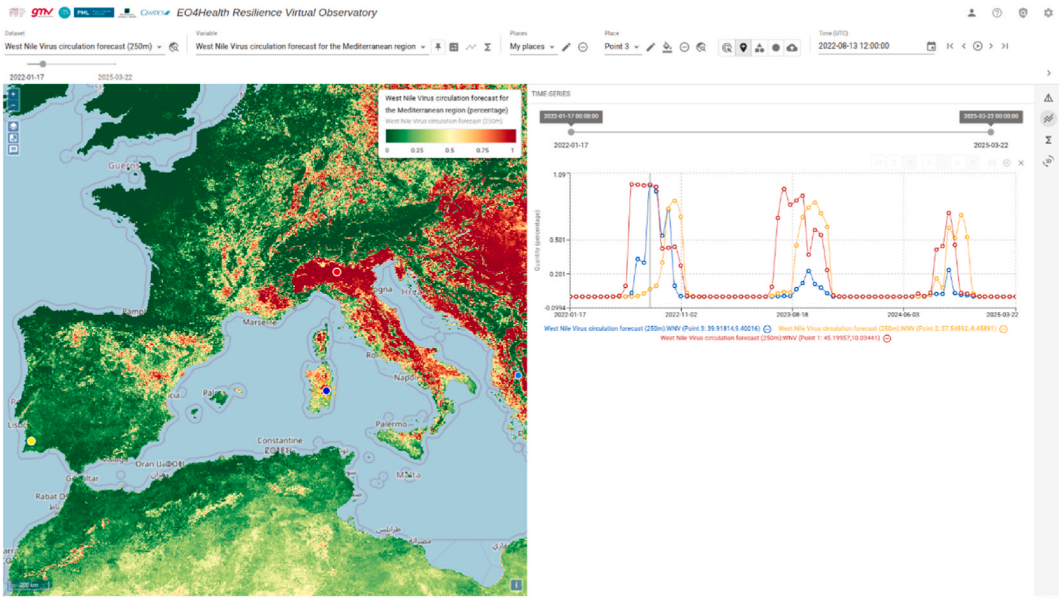

Fig. 6. Screenshot of the virtual Earth Observatory under development in the EO4Health Resilience project funded by the European Space Agency (ESA). Map shows Probability of Occurrence of West Nile Virus (Candeloro et al., 2020) in Europe along with the time series graph for a given location.

- Integrate professionals from the health sector in projects and initiatives who have easier access to epidemiological data. In this respect, emergency services data could be interesting to explore, since they have geolocation information typically associated with health data.
- Explore the possibility of using animal health data as proxies. These data should be easier to obtain in general and can also provide high added value, since humans and animals are affected by several similar diseases.
- To make access to anonymised disease data more acceptable to health professionals—similar to how COVID-19 and dengue data were more freely shared during emergencies—it is essential to establish clear guidelines and trust in data-sharing practices.

(b) Earth Observation data

EO data are especially valuable due to the global coverage, including over remote areas, and the frequent revisit times. There are, however, aspects that should be considered for full exploitation of EO data by the health community, which we have identified.

- EO data are complex for non-experts due to their large volumes, specialised data formats, and the need for advanced processing techniques. Additionally, interpreting the data requires expertise in remote sensing, geospatial analysis, and domain-specific knowledge. As a result, it is not always obvious how the data could be used for health-related topics. To overcome these types of problems, a centralised platform with examples of successful projects, case studies and stories would likely help. Ideally, non-expert users would have access to a series of graphical examples and documentation explaining the way EO data was used and what the positive impact was. For example, ESA has an EO4Society (https://eo4society.esa.int/) webpage, showcasing such examples. However, it was commonly agreed during theEO4Health user forum that more could be done in this regard.
- EO data are often large and require substantial processing capabilities, which can limit their full exploitation. Addressing this challenge involves two key aspects. First, the role of industry is crucial, as it provides expertise and processing power that may not otherwise be accessible. EO data experts typically handle pre-processing efficiently, ensuring the creation of ready-to-use datasets. Second, cloud-based processing helps overcome existing computational limitations. While commercial solutions such as Google Earth Engine are widely used, projects like EO4Health Resilience benefit also from ESA's Network of Resources (NoR), which offers advanced support for EO data processing and analyses.
- From a more general perspective, EO data still present limitations that can hinder their usage for health-related activities. These limitations include data latency which limit the viability of using this type of data in real-time scenarios. While freely available satellite images, such as those of Sentinel-2 have suitably high spatial resolution (up to 10 m), there are cases where a higher granularity is required, for instance for mapping trees for the study of non-communicable diseases. For passive sensors, such as multispectral imagers, there are also data gaps due to cloud cover, that can limit the availability of satellite data.

Once the datasets are assembled, the key next step is data integration. Due attention must be paid at this stage to the different spatial and temporal scales at which the various pieces of data are acquired. For example, satellite data tend to be collected at large spatial scales with high repeat frequency. Field samples are often point measurements with long gaps in time and space between individual measurements. Often, health and disease data are available after they have been integrated at national levels and on annual time scales. These are typically of too coarse resolutions to be able to link the information with transient events. One of the challenges in the integration of health and EO data is learning to deal with spatio-temporal differences in the data and representation errors. Standardisation is a critical aspect to account for when connecting different users and communities. By fostering common grounds for communication and interaction in several aspects, standardisation provides means to reduce errors and misinterpretations. In the connection between EO and health communities, both data and language should be standardised. One of the main needs is to have actionable data available. This refers to information that can be readily used to make informed decisions or take specific actions. This is achieved by the provision of data that is relevant, timely, and presented in a format that enables users to derive insights and implement changes based on it. In this regard, standardisation becomes a critical point to address. We propose the following.

- Standardising data packages and user communication is crucial in today's digital landscape. This ensures seamless interoperability, reducing compatibility issues and errors. Standardisation enhances data accuracy and system reliability while providing users with consistent input for EO-based models and algorithms and EO data to support decision making;
- Defining metadata contents for data to be self-explanatory;
- Standardising a range of EO-based predictors;
- Paying attention to existing and developing data platforms;
- Making sure that communication between platforms is made in a seamless manner; and
- Ensure that different initiatives can "work together", sharing knowledge, rather than duplicating efforts.

In addition to data standardisation, language standardisation is a topic that needs to be properly addressed when connecting diverse communities that speak "different languages". Questions such as "what is a hot day?" or "what is a heat wave?" may have different meanings for people working in distinct communities and, when striving to connect them, it is important to establish a common language for exchange of ideas. While it may be hard to anticipate which words, concepts or ideas should be addressed in this regard at this stage, it is a topic that should also be a focus of attention.

While public health and EO communities are very distant from each other in their scientific knowledge, they have been getting closer in recent times, facilitated by several activities and projects that connected both sectors. Several recent initiatives, such as the ESA EO for Health programme (https://eo4health.esa.int/), the Space and Global Health Hackathon (https://space-and-global-health-hackathon.sparkboard.com/) and the Space and Global Health network (https://sgh.network/), have connected remotely sensed data to health-related problem-solving activities. Even if there is clear progress in communication there are additional aspects of collaboration between different actors that should be improved to establish an organic and supportive path forward, incorporating the best from all options available, and creating a positive working environment. For this to happen, a paradigm shift is needed in the development of activities and projects, such as ESA's EO4Health Resilience, involving several partners with different backgrounds in all the development processes, to build a virtual Earth Observatory for human health applications (Fig. 6).

The way forward will be one where stakeholders start thinking of co-production rather than treating the community as producers versus users. This can be achieved by strengthening partnerships and bringing together diverse stakeholders and end-users. It also involves engaging specialists from disciplines that may not initially seem obvious, but are crucial in selecting EO data, modelling the problem, and interpreting the results. In the end, health related matters should be regarded as a perfectly horizontal topic, affecting everyone living in society, from decision makers to citizens, passing by specialists from various distinct backgrounds.

5. Conclusion

This study highlights the growing role of Earth Observation (EO) in public health research while underscoring the persistent challenges that hinder its full potential. Despite a surge in scientific publications demonstrating EO's applications in health, the field continues to grapple with issues of data accessibility, standardisation, and interdisciplinary collaboration. Difficulty of access to health data remains a big challenge to scientists outside the health domain, even when the data have been suitably anonymised. Addressing these challenges requires a shift toward co-production, where researchers, policymakers, and communities work together to bridge the producer-user divide. Standardisation efforts are essential to ensure clarity, enhance interoperability, and enable broader adoption of EO technologies.

While this review provides a broad overview of trends, thematic areas, and structural challenges in EO-health research, a key limitation is the lack of detailed analysis of individual studies. This may result in the omission of nuanced methodological approaches, specific case study insights, and variations in the practical application of EO across different health contexts. Future research should complement this macro-level synthesis with qualitative or systematic reviews that delve into the design, outcomes, and real-world implications of EO applications in public health.

Future research should also focus on developing shared frameworks for data governance, creating open-access platforms that integrate EO and health data, and piloting co-designed projects that demonstrate real-world impact. Greater emphasis on evaluating the effectiveness of EO-based interventions in diverse socio-ecological contexts will also be critical (Guo, He and Wang, 2023a). By fostering interdisciplinary collaboration and improving data integration, EO can be fully leveraged for disease surveillance, risk assessment, and public health decision-making.

6. Code and data availability

All data and code to generate the plots are shared via Zenodo, available at https://zenodo.org/records/15124452?token=eyJhbGciOiJIUzUxMiJ9.eyJpZCI6ImZkN2Q2NzAwLWY2N2YtNGZmNC05MTI1LWI5ZTQ0MzI1NTI2MCIsImRhdGEiOnt9LCJyYW5kb20iOiIxOTNmMDM0YjhkYWY3N2M4M2RjNmQwZTIxMGVkMzE0YSJ9.XqOx4EvtFhgVlyqVg3MUn7P0N_qPPLeSX-tC8-cGuSUbMob5bK6kruD-bxTYCrtYsjoioTHFmEkvy4lKTyorRw and codes to reproduce the plots made in this study are available at https://github.com/dhritirajsen/EO4-Health-Review.

CRediT authorship contribution statement

Dhritiraj Sengupta: Writing – original draft, Project administration, Formal analysis, Data curation, Conceptualization. **Filipe Girbal Brandão:** Writing – review & editing, Project administration, Funding acquisition, Formal analysis. **Shubha Sathyendranath:** Writing – review & editing, Investigation, Funding acquisition, Conceptualization. **Gemma Kulk:** Writing – review & editing, Visualization, Supervision, Project administration, Data curation. **Annamaria Conte:** Writing – review & editing, Visualization, Methodology, Investigation. **Carla Ippoliti:** Writing – review & editing, Visualization, Data curation. **Luca Candeloro:** Writing – review & editing, Formal analysis, Conceptualization. **Monica Bucciarelli:** Visualization, Software. **David Moffat:** Writing – review & editing, Validation, Formal analysis. **William Wint:** Writing – review & editing, Supervision, Conceptualization. **Marcello Maranesi:** Writing – review & editing, Project administration, Formal analysis. **Raffaele Scarano:** Software, Methodology, Formal analysis. **Joao Vitorino:** Writing – review & editing, Project administration, Methodology, Investigation. **Gunnar Brandt:** Writing – review & editing, Software, Resources. **Tejas Morbagal Harish:** Writing – review & editing, Visualization, Methodology, Conceptualization.

Ethical Statement for Solid state ionics

1) This material is the authors' own original work, which has not been previously published elsewhere.
2) The paper is not currently being considered for publication elsewhere.
3) The paper reflects the authors' own research and analysis in a truthful and complete manner.
4) The paper properly credits the meaningful contributions of co-authors and co-researchers.
5) The results are appropriately placed in the context of prior and existing research.
6) All sources used are properly disclosed (correct citation). Literally copying of text must be indicated as such by using quotation marks and giving proper reference.
7) All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

The violation of the Ethical Statement rules may result in severe consequences.

To verify originality, your article may be checked by the originality detection software iThenticate. See also http://www.elsevier.com/editors/plagdetect.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Shubha Sathyendranath reports financial support was provided by European Space Agency. If there are other authors, they 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 data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rsase.2025.101701.

Data availability

We have shared a link to private Zenodo repo, which will be made available publicly once accepted. All codes are also available in the lead author's Github

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