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A taxonomy of earth observation data for sustainable finance

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ABSTRACT

Corporate Environmental, Social and Governance (ESG) reporting has been subject to heightened attention and demand within the financial sector, with the objective of efficiently directing capital towards firms engaging in sustainable practices. Effective ESG monitoring is challenging, given the prevalence of self-disclosed internal data and managerial signalling incentives, presenting a need for comprehensive and diverse external data sources to augment existing ESG-related disclosure. Earth Observation (EO) technologies – particularly satellite data – play a crucial role in collecting spatial data on land, water, and atmosphere, making them highly useful for facilitating transition in the sector. This paper aims to outline the various ways in which EO data can be applied for the purposes of (i) future academic research in the subject area of sustainable finance and (ii) detailed ESG reporting and monitoring by practitioners. Using the ESG Key Performance Indicator (KPI) framework established by the European Commission and EFFAS, we present a framework listing all applicable KPIs against the types of satellite imagery that can be utilised in each case. Additionally, for ESG KPIs that EO data cannot directly address, we compile an ancillary list to explore potential indirect applications. To underscore the wealth of available EO data sources that can be used for sustainable finance research, we present a comprehensive catalogue of all open-access and relevant private satellite missions. Listed missions are categorised based on their spatial resolution, temporal resolution, and mission duration, facilitating research with specific requirements for these parameters.

1. Introduction

The pressing need to address our current and anticipated climate challenges has intensified the call for strategies that maximise economic growth while safeguarding the long-term ecological sustainability of our planet (Gilchrist et al., 2021). As a result, corporate managers now face a variety of internal and external pressures. While external shifts in public awareness, investor preferences, and environmental legislation have left firms facing societal pressure to achieve more sustainable business models (Kagan et al., 2003; Kordsachia et al., 2022), managers must also consider the expected internal impacts of climate change on existing business practices and future revenue streams.

Accordingly, reliable environmental reporting is paramount for corporate managers wishing to better understand their operating environment and effectively communicate ecological credentials. Environmental signalling is especially important, given that environmental performance is difficult to reliably capture for resource-constrained investors, presenting an asymmetry of information between a firm's management and its shareholders. Company disclosures have been shown to reduce information asymmetry in both a financial (Korajczyk et al., 1991; Van Buskirk, 2012a) and a non-financial context (Cormier et al., 2011). Therefore, accurate reporting of environmental, social and governance (ESG) factors will allow investors to evaluate risk and growth opportunities more effectively. ESG reporting remains voluntary in large economies such as the United States (US). Still, the European Union (EU) and the United Kingdom (UK) have become first movers in enforcing regulations to make disclosure mandatory.

Adequate disclosure of ESG metrics relies on developing versatile techniques to monitor and record performance accurately. Currently, firms can utilise various data sources for ESG reporting, namely internal datasets, government surveys, and ground-based data. Similarly, resource-constrained investors base their investment decisions on ESG ratings developed by third-party agencies. However, evidence highlights considerable inconsistencies between ratings awarded by different providers (Berg et al., 2022a), with a weak association between ESG ratings and corporate outcomes believed to be indicative of ESG quality (Larcker et al., 2022a). In this respect, Earth Observation (EO) represents a new and underused data source in finance that has the potential

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to offer transparency and consistency in ESG performance monitoring. This accessible data source can somewhat alleviate the existing asymmetries encountered in environmental performance measurement. Indeed, important early work by Caldecott et al. (2022) identifies spatial finance – the integration of geospatial data into financial theory and practice – as having a potentially transformative effect on the availability of information within finance.

The potential benefits of adopting satellite data and imagery in ESG reporting – and ESG research – are clearly articulated by Chen et al. (2021). Namely, (i) the wide availability of data, (ii) the high degree of spatial resolution in comparison to traditional data, (iii) the broad geographic coverage offered by a source that is not restricted by political, climate and geographical boundaries; (iv) the ability to trace historical changes using high-temporal satellite data; and (v) the potential to combine satellite data with artificial intelligence, to expand its applicability and value. Despite these advantages, the practical application of EO data within the finance domain remains relatively limited, which is perhaps a result of insufficient literature clearly outlining channels through which satellite data can assist in the provision of transparent corporate environmental reporting and the development of academic studies occurring within the burgeoning research area of sustainable finance.

To this end, we present a taxonomy that clearly articulates the potential applications of EO data for corporate environmental performance monitoring. To provide structure and practical relevance to our taxonomy, we map current and future EO capabilities to the European Commission's (EC's) *Key Performance Indicators (KPIs) for Environmental, Social and Governance (ESG) issues* (European Federation of Financial Analysis Societies, 2009). This framework provides recommendations for corporate and investment professionals.on using the KPIs within the framework of existing performance communication. As EO data are spatial data, our focus is primarily on Environmental KPIs. However, we also highlight some relevant Social and Governance KPIs that can benefit directly or indirectly from spatial analysis.

As a first stage, we identify EO payloads[1] – for example, Hyperspectral cameras, Light Detection and Ranging (LiDAR), and Synthetic Aperture Radar (SAR) – that can be useful in measuring ESG variables. We also highlight the appropriate EO satellite missions that can provide such measuring capabilities and report an overview of each mission's historical and future lifespan. Finally, we identify the primary application of each task, categorised by payload. Combined, we provide the reader with a comprehensive overview of specific payloads and missions that could be used for effective measurement of ESG variables identified in an internationally established framework, such as greenhouse gas emissions and renewable energy production, for inclusion in future finance research and practice.

The remainder of this paper is structured as follows. Section 2 provides financial context to our discussion by presenting an overview of research areas in academic finance where EO data has been applied, as well as future research areas that the authors believe could benefit from incorporating EO data. Section 3 presents an overview of the parameters a researcher should consider when selecting specific payloads and missions for EO applications. Section 4 outlines our taxonomy of EO payloads and mission use cases mapped to the European Commission's KPI framework. Section 5 concludes.

2. Relevant literature

The spectrum of physical and transition risks associated with climate change has become a critical consideration for corporate managers, asset managers, investors, lenders, and insurers in recent years (Cox et al., 2022), with an estimated $24.2 trillion of global assets at risk due to climate change events (Dietz et al., 2016). Furthermore, a move to sustainable practices may be utility-enhancing, with ESG assets estimated to be worth approximately $50 trillion by 2025 (Bloomberg, 2021). Despite the economic implications of climate risk, the increasing availability of EO data, and the monitoring improvements that satellite applications can offer, EO data for sustainable finance - and finance research more broadly - remains in its relative infancy, with only a handful of published studies. This is somewhat surprising given that remotely sensed data has been used for economic analysis since the 1930s (Donaldson & Storeygard, 2016).

Early finance studies using spatial and geographic information system (GIS) data focus primarily on geographic considerations within retail banking and real estate. For example, Birkin & Clarke (1998) demonstrate a positive potential role for spatial modelling, GIS and geodemographics in supporting corporate decision-making within UK financial services, such as bank relocations and closures. Can (1998) contributes a spatial analytical framework for the inclusion of GIS in housing and mortgage research, highlighting the ability of GIS to facilitate more effective visual examinations, error identification, and analysis. This builds on earlier work by Se Can & Megbolugbe (1997) suggesting that the inclusion of locational effects in statistical models has the potential to improve predictive power.

Satellite imagery and other forms of EO data have emerged in more traditional areas of financial markets and economics, albeit on a minimal scale. For example, using satellite imagery to count the number of cars in retail parking lots, Gerken & Painter (2022) provide evidence suggesting that financial analysts incorporate local information into their forecasts, mainly when firm-wide information is scarce. Furthermore, Dakhlia et al. (2021) use satellite luminosity data to construct an effective proxy measure of economic activity across Nigeria and Senegal, identifying a strong link between the degree of financial inclusion and levels of economic activity. These results advance previous findings that light density at night is a valuable economic activity measure (Elvidge et al., 1997).

The specific research area of sustainable finance presents exciting opportunities for EO implementation despite a current lack of application in this area. Caldecott et al. (2022) make a compelling case for the use of satellite imagery and -"spatial finance" for climate and environmental assessments given that "many environmental and climate risks are inherently spatial", while Black et al. (2016) highlight the potential use of satellite data for weather index insurance pricing, which may benefit farmers operating in regions susceptible to weather shocks. EO data for sustainable finance is particularly pertinent given that environmental performance is difficult to reliably measure when companies are characterised by complex supply chains, presenting potential information asymmetries (Hervani et al., 2005).

Such asymmetries within financial markets have previously given rise to signalling and pecking order capital structure theories within the traditional finance literature (Miller & Rock, 1985; Myers & Majluf, 1984). In a sustainable finance context, the presence of information asymmetry has the potential to lead to -"greenwashing", a possible new "miss-selling scandal" (Fletcher & Oliver, 2022), which risks undermining the credibility of the sustainable finance market. Though evidence suggests that more detailed company disclosures reduce information asymmetry (Cormier et al., 2011; Van Buskirk, 2012a), the static nature of self-disclosed corporate disclosures should also be considered. Fu et al. (2012) report that a higher reporting frequency reduces information asymmetry levels, though evidence suggests that this finding does not universally hold (Van Buskirk, 2012b). Environmental disclosures are often published annually; thus, information available to investors may not indicate current performance. To this end, using accurate and highly temporal EO data may lead to more timely, and thus reliable, reporting that could reduce existing frictions between managers and investors, with implications for the chosen method and associated cost of financing.

[1] By "payloads", we refer to those elements of the spacecraft dedicated explicitly to producing mission data and then relaying that data back to Earth (ESA, 2023).

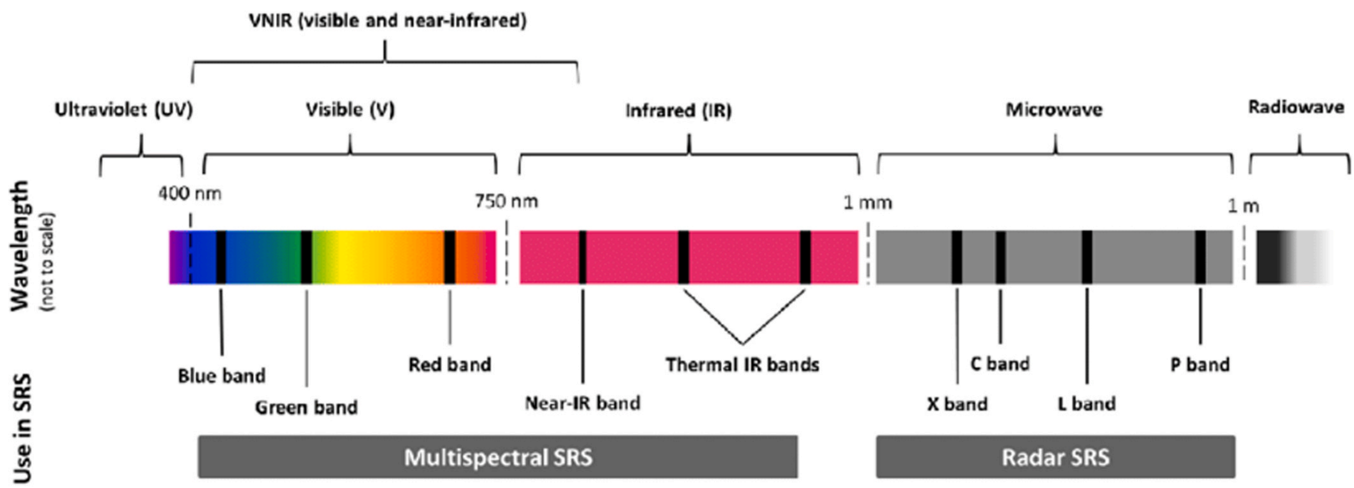

Fig. 1. The spectrum of electromagnetic radiation (not to scale). VNIR bands for satellite remote sensing defined (Pettorelli et al., 2018).

Table 1
Presentation of various forms of SAR bands with associated applications.

Band	Frequency	Application
X	8-12 GHz	Urban monitoring; ice and snow.
C	4-8 GHz	Change detection; areas with low/moderate penetration
S	2-4 GHz	Agriculture monitoring
L	1-2 GHz	Geophysical monitoring; biomass and vegetation mapping
P	0.3-1 GHz	Biomass and vegetation mapping and assessment

Given the established lack of timely and reliable data, resource-constrained investors rely, to some extent, on environmental ratings offered by third-party agencies, for which a growing literature suggests several issues. For example, ratings have been found to differ substantially between different providers (Berg et al., 2022b) and possess only a weak association with corporate outcomes that are considered indicative of ESG quality (Larcker et al., 2022b). Furthermore, third-party ratings are characterised by a lack of transparency regarding the data sources, weightings and methodologies used. As a result, it becomes challenging to ensure that a company's actual environmental performance is accounted for when making investment decisions (Abhayawansa & Tyagi, 2021; Kotsantonis & Serafeim, 2019).

There has been little academic investigation into the effectiveness of EO techniques for addressing existing topics and research questions within sustainable finance. Paravano et al. (2023) identify that several factors, including a lack of literacy and a scarcity of specialised knowledge, negatively impact the perceived value of satellite data by finance practitioners. The lack of academic enquiry suggests that this knowledge gap extends to the academic community, presenting the need for a clear and concise taxonomy of earth observation parameters and applications through the lens of existing ESG reporting guidelines.

3. Satellite imagery parameters

Many parameters need to be considered when selecting suitable mission(s) for a given project or task, primarily (i) satellite imagery type, (ii) spatial resolution, and (iii) accessibility. In this section, we provide the reader with some necessary context to these three core parameters, which may aid in identifying suitable missions through which relevant earth observation data can be accessed and used for finance research.

3.1. Imagery types

Satellite imagery is available in various forms depending on the type of sensing required and the payload carried by the satellite. Earth observation (EO) satellites have payloads designed to capture information across specific spectral bands to generate digital images of the observed scene. These missions can be classified as "passive" or "active" or may incorporate payloads capable of employing both methods.

Passive remote sensing focuses solely on collecting electromagnetic (EM) emissions from Earth. These emissions can originate from sunlight reflected off the Earth's surface or locally generated. Regardless of the source, the light is detected by sensors on the satellite, which then process the collected data to form an image. The most common type of EO satellite imagery, which is also passive, is sensing across the visual and near-infrared spectrum (VNIR) whereby the red, green, blue and near-infrared spectral bands are used to form composite images by changing the band combinations for an image. A natural colour image will use red, green and blue bands, but a color infrared (or false color) image will use red, green and near-infrared bands, which are used to highlight vegetation. Another possible way to manipulate an image with the various bands in multispectral imaging is by spectral index computation. Like band combinations, the index computation is derived from an algebraic formula involving a subset of the spectral bands. Spectral indices are used for various applications, including vegetation health, water quality, and destruction from natural disasters.

Fig. 1 displays a portion of the EM spectrum, emphasising the location of VNIR bands. This type of imagery is called 'multispectral' because it collects over multiple spectral bands. However, passive multiband imagery also expands across EM bands, including thermal bands (from mid-infrared, far-infrared and thermal infrared) and Microwave.

Another form of passive imagery is hyperspectral, which has a similar process to multispectral imaging but over many finer spectral bands. This is a valuable data source as it can detect more specific signals and display specific spectral signature plots of a target when stacked across all bands. In particular, this is a valuable type of imagery for detecting specific material in soil or water, such as contaminants or metals. Hyperspectral instruments will capture spectral features across >60 spectral bands in the order of 10's or 100's. Alternatively, hyperspectral data may only focus on a couple of spectral bands, but across many frequency channels in that spectral band. The different number of spectral bands or channels a satellite can capture is referred to as spectral resolution. Hyperspectral instruments are also vital for providing GHG and trace gas inventories on a local, national and global scale (Gao, 2022; Jervis et al., 2021) because they can distinguish the unique spectral signature (particularly across infrared) of specific gases in the atmosphere. Different instruments are adopted for this research, including grating spectrometers seen on the OCO missions and Tansat series, or interferometric instruments on the Gaofen-5 and Metop series. However, the same principles include detecting and quantifying specific

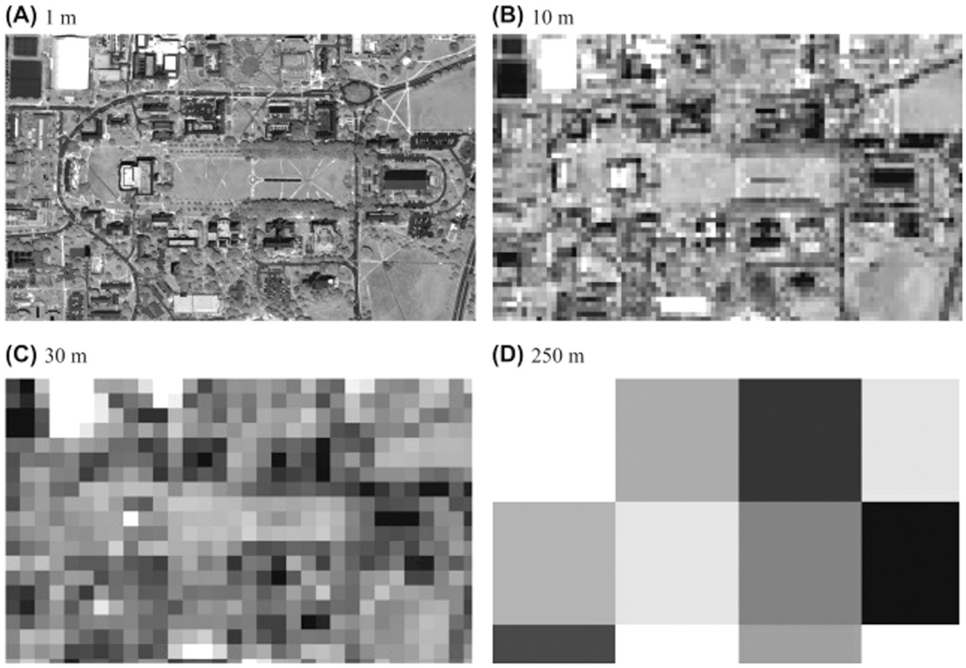

Fig. 2. Campus of the University of Maryland at four different Spatial resolutions, (A) 1 m, (B) 10 m, (C) 30 m, (D) 250 m (Liang & Wang, 2020).

atmosphere gases.

Active sensors operate differently because an instrument on the satellite emits a signal towards the Earth's surface. The sensor then detects the reciprocal signal reflected or modified by interactions occurring on the Earth's surface. Synthetic Aperture Radar (SAR) is a known active sensor, a form of radar that operates across the radio and microwave frequencies. Each transmitting band refers to a specific frequency produced by the satellite transmitter, and the particular frequency gives rise to different uses for each band, as seen in Table 1. Each SAR band has different resolutions and penetration levels, making them useful for specific applications. The main advantage of SAR instruments is that they can operate in cloudy conditions, as the emitted radiation can penetrate through clouds. Indeed, some bands can penetrate through forest canopies and soil, making SAR key in delivering insights into forestry health and deforestation.

LiDAR represents another form of active imagery, emitting pulsed laser signals to Earth from which a receiver detects the reflected light. It operates mainly in the near-infrared part of the electromagnetic spectrum. Similar to SAR imagery, it can penetrate canopy cover, so it is a promising data source for forestry and biodiversity research, and digital elevation models (DEM). LiDAR is an upcoming technology in remote sensing, particularly for atmosphere studies, as it can measure GHG emissions at finer precision and vertical resolution (Gao, 2022). There are currently no operational LiDAR satellites for CO_2 monitoring; however, there are many planned missions soon to meet this goal.

3.2. Spatial resolution

Spatial resolution represents an essential parameter for choosing a satellite mission for a specific application. It refers to the ground area covered per pixel over an instantaneous field of view. The current highest spatial resolution achieved by publicly accessible missions (not including any military surveillance satellites) is 30 cm without any further processing. Still, there are goals in the near future to reach 10 cm. However, sophisticated algorithms allow artificially generated images to reach higher spatial resolution than their native image. The necessary details to be observed in an image depend on the goals of the analysis and the technical limitations of the available payloads. For example, if the goal is to image a building or campus, as seen in Fig. 2, then a high spectral resolution is required to capture the details of the buildings, parks, and roads. One metre (1 m) is the best resolution for this purpose. However, ten metres (10 m) is also sufficient to retrieve the outline of the prominent buildings if that is sufficient for the goal of the analysis.

Lower spatial resolutions are sufficient to cover large areas, particularly at a national and global scale, with lower levels of detail. The imagery is more granular; however, it is easier to store and process. Furthermore, the mission may have a longer legacy compared to (very) high spatial resolution missions.

3.3. Accessibility

Satellite imagery was primarily developed for military surveillance and reconnaissance, limiting its accessibility to specific personnel. NASA soon developed its own Earth Observation (EO) satellite, and this imagery later became freely available to the public in the 2000 s. Other national and international agencies, such as ESA, JAXA, and NOAA, also offer open-access EO imagery, expanding the range of data sources for EO in the 2010 s. Over the past 15 years, private space missions have gained significant prominence, encompassing various space ventures like space tourism, exploration, launch services, and vehicles. Private companies have also entered the field of EO services, increasing the availability and diversity of imagery. However, these services come at a financial cost unless the study falls within a research area that can benefit from government or private investments. Consequently, in addition to data requirements, administrative restrictions may apply to a study. The high pricing of satellite imagery can discourage users, particularly if they do not fully comprehend the value of such data.

Another concern for interested parties is the shortage of personnel in the sector. Professionals in the field have indicated that teams interested in utilising spatial data may lack the necessary expertise (Paravano et al., 2023[2]) or be unsure of whom to consult to process this data effectively. Numerous satellite analyst providers are developing

[2] We were able to access insights into practitioners' attitudes towards EO data through consultation with various professionals in finance. Anonymised interview outcomes are available upon request.

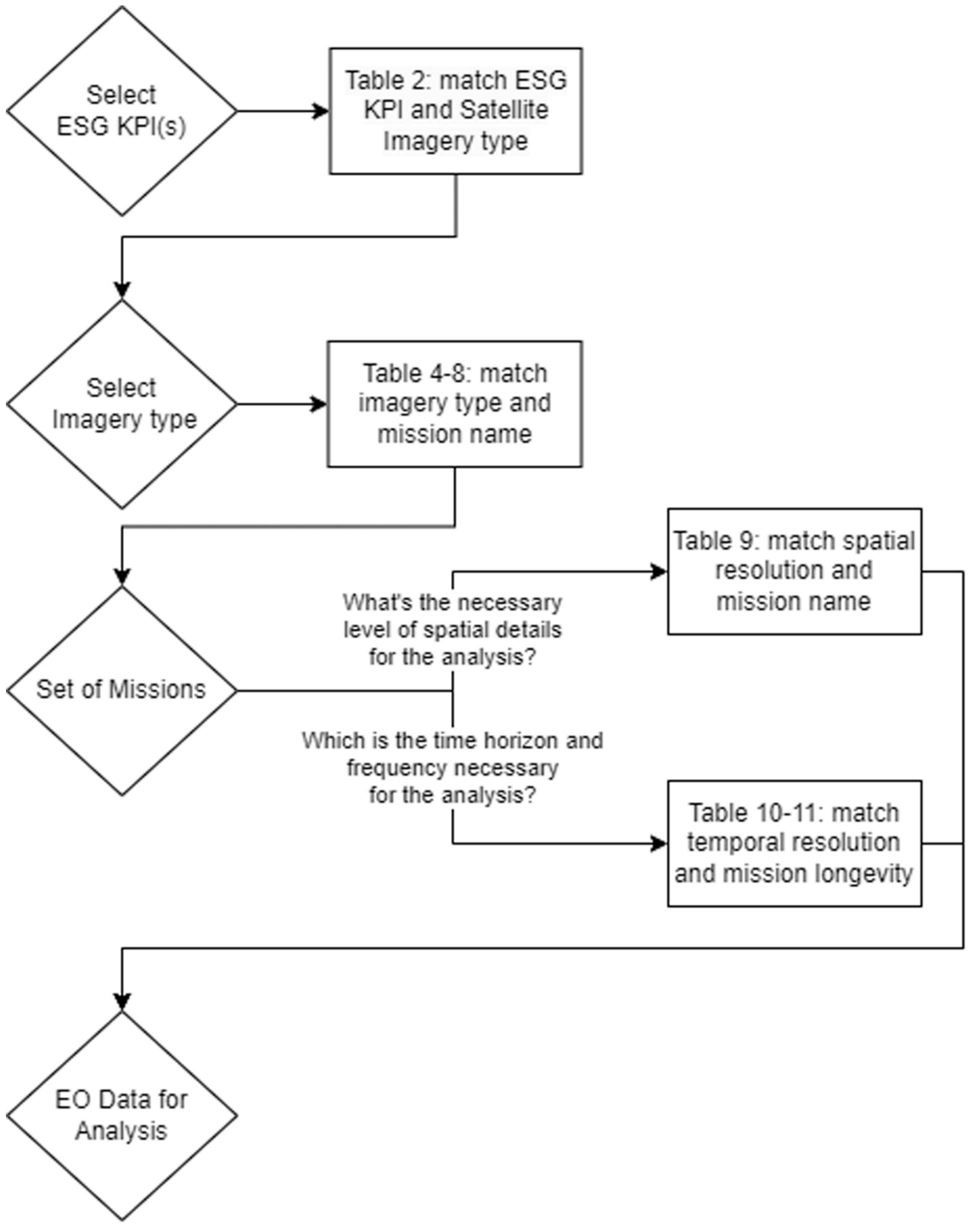

Fig. 3. Flowchart of the taxonomy's function, offering a process that enables interested parties to choose appropriate satellite mission(s) for their ESG reporting application.

products that utilise EO data to meet the demands of clients in various fields, including ESG providers and financial companies.

4. ESG taxonomy

The primary objective of this taxonomy is to create a unified structure for effectively integrating satellite imagery into ESG reporting and sustainable finance research. Section 3 outlines satellite imagery characteristics and emphasises the importance of carefully selecting the relevant parameters to ensure successful sustainability reporting and monitoring. Selecting appropriate key performance indicators (KPIs) is crucial in ESG reporting, as it determines how ESG-specific insights are generated. Each ESG rating provider has its unique KPIs framework, which is not always publicly accessible. However, the European Commission, in collaboration with the European Federation of Financial Analysis Societies (EFFAS), have publicly released suggested ESG KPIs that any company can adopt, and this is a popular foundation for private ESG providers (European Federation of Financial Analysis Societies, 2009). Specifically, the European Commission has established a list of 29 key performance indicators (KPIs) and their corresponding sub-indicators to facilitate reporting on various parameters such as Environmental, Social, Governance, and Long-term Viability.

The applicability of Earth Observation (EO) data for monitoring the extent of ESG KPIs varies but is extensive, which can make adoption confusing. This paper aims to resolve this confusion by establishing a framework for choosing appropriate satellite imagery that interested parties can adopt. Fig. 3 presents the recommended process for applying the framework to ESG KPI reporting and monitoring. The first step is to determine the type of imagery that can map or monitor the selected ESG KPI, for which a taxonomy of possible imagery types can be found in Table 2. Next, the framework involves choosing the satellite mission(s) that align with the study's application, as listed in Tables 4 and 8. This section of the framework provides a comprehensive list of appropriate satellite missions for this field, differentiated by data type.

To simplify our taxonomy, only active missions are included. Furthermore, only open-access satellite missions are listed, as these

Table 2
Taxonomy of ESG KPIs, developed by the European Commission, alongside satellite imagery types that can be used to monitor each variable.

A TAXONOMY OF EARTH OBSERVATION DATA FOR SUSTAINABLE FINANCE

European Commission KPIs (v2.1)	**Variables**						
	Hyperspectral	LiDAR	Multispectral optical	Multispectral (other)	Passive radar/ microwave	SAR	References
Environmental							
ESG 1-1 Energy consumption total							(Streltsov et al. 2020)
ESG 1-5 Heat consumption total							(Zhao & Wentz 2016)(Mullerova & Williams 2019)
ESG 2-1 GHG emissions, total							(Nassar et al. 2017) (de Gouw et al. 2020) (Varon et al. 2020) (Sadavarte et al. 2021) (Mohite et al. 2022) (Elvidge et al. 2009) (Elvidge et al. 2016) (Pierangelo et al. n.d.) (Gao n.d.)
ESG 2-2 GHG emissions, specific; Options: per unit of revenue, per employee, per unit of production volume (tons of steel, for example)							(Nassar et al. 2017) (de Gouw et al. 2020) (Varon et al. 2020) (Sadavarte et al. 2021) (Mohite et al. 2022) (Pierangelo et al. n.d.) (Gao n.d.)
ESG 10-1 Percentage of energy in kWh from renewable energy sources as a proportion of total energy consumed							(Streltsov et al. 2020) (Tapiador 2009) (Median-Lopez et al. 2021) (Edwards et al. 2022) (Ahamed et al. 2011) (Kumar et al. 2015) (Cuong et al. 2021)
ESG 11-1 NO, SO Emissions total							(Georgoulias et al. 2020) (Shen et al. 2021) (Mohite et al. 2022)
ESG 11-2 NO, SO Emission by generation portfolio coalfired							(Georgoulias et al. 2020) (Shen et al. 2021) (Mohite et al. 2022)
ESG 11-8 NO, SO Emissions total production sites							(Georgoulias et al. 2020) (Shen et al. 2021) (Mohite et al. 2022)
ESG 12-1 Waste by unit produced							(Silvestri & Omri 2008) (Alexakis et al. 2016) (Agapiou et al. 2016) (Papel et al. 2023)
ESG 13-3 Percentage of renewable energy produced as a proportion of total energy produced							(Tapiador 2009) (Median-Lopez et al. 2021) (Edwards et al. 2022) (Ahamed et al. 2011) (Kumar et al. 2015) (Cuong et al. 2021)
ESG 13-4 Total renewable energy produced from biomass							(Tapiador 2009)(Ahamed et al. 2011)(Kumar et al. 2015)(Cuong et al. 2021)
ESG 13-5 Total renewable energy produced from wind							(Tapiador 2009)(Median-Lopez et al. 2021)(Edwards et al. 2022) (Hasager 2014)
ESG 13-6 Total renewable energy produced from hydro							(Tapiador 2009)(KULKARNI et al. 2002)(Dorber et al. 2018)(Corbari et al. 2022)

Imagery can fully monitor the KPI

Imagery can partially monitor the KPI

missions are accessible by researchers and practitioners regardless of budgetary constraints. There are a few exceptional cases where private satellite missions are included, as they have been referenced as the primary data source in the cited papers within our taxonomy (see Table 2). The suitability of chosen satellite missions can be further verified through the framework by ensuring that the spatial and temporal resolution is sufficient to meet the demands of the selected application. This information can be found in Tables 9, 10, and 11. Additionally, Tables 10 and 11 provide the mission length, another factor in determining the acceptability of a mission, particularly when a study is conducted over a large time horizon.

4.1. Direct KPIs

Each measurable KPI is associated with relevant types of satellite imagery, for which findings are presented in Table 2. The usefulness of Earth Observation (EO) data depends on its specific application, and therefore, the level of potential utilisation is color-coded to indicate the ease of integration. Any KPI that can be fully monitored with satellite imagery is referenced in green, implying that satellite imagery can provide enough data to meet all the indicator requirements. Any indicator that can only be partially monitored with satellite imagery is labelled in yellow. There are several reasons why EO data may be limited, including limited availability of asset and supply chain information of a company, spatial and spectral resolution of satellite imagery and physical characteristics of the indicator for which EO data has a restricted view.

Among the 29 ESG indicators, six can be monitored to different extents using satellite imagery, as illustrated in Table 2. All six ESG KPIs are classified as Environmental, which is to be expected, as satellite imagery captures physical information of an environment, with particular benefits for measuring the impact of the surrounding vegetation, water, and atmosphere; all aspects of environmental monitoring.

ESG 1–5, which aims to measure total heat consumption, is the first notable KPI that can be linked with EO data, particularly with multispectral imagery, but only to a limited degree as the total consumption cannot be quantified directly from satellite. However, the thermal inefficiency of a building may give an indicator of thermal activity and heat consumption, so this principle is applied to studies on this KPI. Although thermal infrared measurements are available, all current openly available datasets have a coarse spatial resolution. Therefore, only large-scale thermal interactions can be monitored for this application, which plays a significant role in affecting the urban environments and can be influenced by construction and building companies. This phenomenon can be observed by assimilating low-resolution satellite imagery that can view larger areas with in-situ measurements (Zhao & Wentz, 2016) or airborne imagery. This research will advance substantially with the arrival of higher resolution thermal and mid-wave IR satellite imagery, such as Satellite Vu's 3.5 m resolution imagery, launched in 2023.

For more general applications, optical satellite imagery can also define small-scale energy consumption predictions by applying machine learning algorithms with the imagery and other energy consumption and/or footprint data to derive energy consumption estimations (Streltsov et al., 2020). Therefore, this can also assist in delivering insights into ESG 1–1, although not wholly monitoring it.

Notably, emissions monitoring, including greenhouse gases (GHG) and trace gases (NO_x and SO_x), can be fully monitored using EO imagery. The inherent characteristics of gas emissions, such as their difficulty to be concealed, allow for direct quantification when the appropriate technology and analysis techniques are applied. Measuring atmospheric chemistry and point source emissions requires data collected by EO explicitly designed for this purpose, typically hyperspectral data as the fine spectral bands can be calibrated to match the specific spectral characteristics of the chosen gas (de Gouw et al., 2020; Mohite et al., 2022; Nassar et al., 2017; Sadavarte et al., 2021; Varon et al., 2020). LiDAR is also a possible source of GHG retrievals as a number of planned missions are dedicated to atmospheric monitoring, including AEMS (CNSA mission) and MERLIN (CNES and DLR). However, these missions are not operational yet and cannot fully meet the KPI (and are thus indicated as partial). A limitation to emission inventories, emphasised in Table 2, arises when the emission inventory is based on further asset information, such as per revenue/employee/unit of production, as seen in ESG 2–2, 11–2, 11–8, and 12–1. Accessing this information is typically closed to the public, restricting any analysis to fine detail. Existing research estimates the production level or yield of products across various sectors such as mining (Prakash & Gupta, 1998), agriculture (Doraiswamy et al., 2003) and oil and gas (Elvidge et al., 2009), but these studies are typically specific to certain industries and provides only an approximation, which may not be sufficient to be included in indicators such as ESG 2–2, 11–2 and 12–1.

EO has a significant role in monitoring waste generation (see ESG 12–1) because it can be observed using nearly all, except two, of the sensing types. However, it can only provide partial insights into this KPI because it is limited by the type of industry and waste, and the location of the disposal site, as many landfill and waste sites may be covered or waste may be sent to a general landfill site. However, for industries with large-scale waste generation, where it may be too large to store the waste inside their premises, EO can play a vital role in monitoring its accumulation over time. Hyperspectral and multispectral imagery are valuable remote sensing types for this application as they can be applied to not only monitor the growth or reduction in waste sites, but can also assist in measuring the impact of the surrounding landscape through NDVI and other vegetation indices (Agapiou et al., 2016; Alexakis et al., 2016; Papel et al., 2023; Silvestri & Omri, 2008). SAR measurements can also be combined or solely to observe landfill sites because SAR interferometry can accurately measure volume changes over a time series (Agapiou et al., 2016; Papel et al., 2023).

Measuring energy usage, particularly from renewable energy generation, is an essential aspect of ESG reporting encompassing estimation of net-zero targets (ESG 13–1 and 13–5 in the European Commission's framework). Satellite imagery's role in measuring energy generation is limited, providing only partial monitoring capabilities, yet it remains valuable for reporting purposes. The primary sources of renewable energy production include photovoltaic (solar), wind, hydropower, biomass, and geothermal. Wind energy (ESG 13–5) depends on the wind speed at the site, which can be quantified using various satellite instruments such as scatterometers, microwave polarimetry, altimeters, or SAR imagery. While scatterometers and microwave radiometers have traditionally been instrumental in wind speed retrievals, SAR offers unique advantages in coastal areas and provides higher spatial resolution for site-specific analysis and wind farm wake details (Hasager, 2014). However, this capability is limited to offshore wind farm sites since it assesses wind speed based on wave information, which is not applicable onshore.

Hydroelectric energy is a form of renewable energy that not only meets the needs of ESG 13–3 but also has a separate KPI that monitors the source specifically (ESG 13–6). This energy source harnesses the power of flowing water, typically resulting from precipitation events like snow melting or rain runoff. These events can be observed and measured using meteorological satellite imagery, enabling the estimation of potential hydroelectric generation. To predict output accurately, it is crucial to quantify the volume of fluid used for hydropower generation. This can be achieved by measuring the water entering a hydroelectric reservoir from snow melt-off or rain runoff. Snow volume can be assessed by observing snow depth using optical and infrared imagery, which can also help measure snow-covered areas and albedo. Measuring snow depth is possible with either passive or active microwave (MW) imagery, with passive MW providing better revisiting time, but active MW (SAR) offering higher resolutions (Corbari et al., 2022; Li et al., 2017; Tanniru & Ramsankaran, 2023). LiDAR also shows promise for measuring snow parameters (Hu et al., 2022).

Table 3
ESG KPIs that have a link to EO research, but that cannot be monitored directly.

European Commission KPI (v2.1)	EO Application (s)
ESG 1-7% of R&D expenses on increasing energy efficiency as of total R&D expenses	Heat efficiency of buildings
ESG 6-4 Health rate	Vector-borne disease forecasting Water-borne disease forecasting Particulate matter Unsafe workplace (see 'ESG 21 Health & safety aspects of products')
ESG 10-3 Investments in Renewable Energy Generation as a proportion of total investments	Monitoring development of renewable sites
ESG 12 Waste	Water pollution indicators Land pollution indicators (not solid)
ESG 14-1% of material recovered for reusage and at end of life-cycle	Imagery of large material storage
ESG 21 Health & safety aspects of products	Flood (natural disaster) mapping Forest fire (natural disaster) mapping Earthquake (natural disaster) mapping Infrastructure fragility (human-induced/natural disaster)

Table 4
Hyperspectral Imagery Satellites. Missions in bold reference private missions; Missions not in bold reference public missions.

Mission	Organisation	Main application of mission
Aura	NASA	Measurements of trace gases in the atmosphere, including HCHO, NO_2 and SO_2 column densities
EnMap	DLR	Monitoring land and vegetation health
GHGSat	GHGSat	High resolution GHG (CO_2 and CH_4) retrievals
HySIS	ISRO	Geostationary mission used for land cover, vegetation and soil type assessments across India
NuSat	Satellogic	High resolution hyperspectral imagery used for agriculture, oil and gas industry, urban planning, climate monitoring, resource management, disaster response and infrastructure monitoring
Metop series	EUMETSAT, ESA	Climate monitoring and atmospheric trace gas measurements, including BrO, CH3Br, ClO, H2O, HCHO (Total Column), NO, NO2 (Total Column), O3 (Total Column), SO2 (Total Column)
OCO-2/3	NASA[3]	Monitoring CO_2 in atmosphere
PRISMA	ASI	Applications implemented for land, vegetation inner waters and coastal zone monitoring
Sentinel-5 P	ESA	Measuring atmospheric chemistry, HCHO, NO_2 and SO_2 column densities

[3]CSA, DLR, ESA, JAXA, Roscosmos

Table 5
LiDAR imagery satellites. All listed missions are provided by public organisations and are open-source.

Mission	Organisation	Main application of mission
GEDI	NASA[2]	Monitoring biomass, ecosystem and ice changes
ICESat-2	NASA	Dedicated to polar ice observation but also contributes to aerosol profiling, vegetation canopy and land topography

Similarly, rainfall predictions can be made using various remote sensing methods, such as visible/infrared as well as passive and active microwave measurements (Prigent, 2010; De Vera et al., 2021). Enhanced precipitation forecasting improves the estimation of current energy production and enables weeks-ahead energy production forecasts, aided by machine learning and regression modelling algorithms (Barzola-Monteses et al., 2022; Corbari et al., 2022; Tucci, 2023). Although data availability can help assess a hydroelectric plant's potential energy generation capacity, it cannot determine the final generated power without additional proprietary data only accessible to employees. Therefore, it is suitable for only a partial assessment.

Table 6
Multispectral sensing satellites. Missions in bold reference private missions; Missions not in bold reference public missions.

Mission	Organisation	Main application of mission
Aqua	NASA	Multidisciplinary mission to study Earth's surface. MODIS (one of its main payloads) provides multispectral imaging dedicated to collecting data on biological and physical processes on land and in water. This payload is also aboard the Terra satellite, improving the temporal resolution of the instrument. AMSR-E (a microwave radiometer) is another instrument aboard that is vital for monitoring the water cycle
Aura	NASA	See 'Hyperspectral imaging'
CBERS-4/4a	CAST[4]	Utilised across a range of applications including urban studies, water and land management and forestry monitoring
ECOSTRESS	NASA[2]	Thermal radiometer onboard to measure plant and soil health
Gaofen	CNSA	VSIR radiometer and optical imager
GCOM-C	JAXA	Designed to conduct surface and atmospheric measurements in order to gain a better understanding of carbon cycles
GeoEYE	MAXAR	High-resolution imagery for many VNIR imagery applications, including disaster and risk management, agriculture and other industries. Used to provide various band-combination imagery or spectral indices
GOES	USSF, NOAA	Geostationary imaging radiometer that provides information across Northern America regions
Landsat	NASA	Legacy mission that has lasted over 50 years. High resolution for many VNIR imagery applications, including disaster and risk management, agriculture and other industries. Used to provide various band-combination imagery or spectral indices
NuSat	Satellogic	See 'Hyperspectral imaging'
PlanetScope	Planet	High-resolution imagery for many VNIR imagery applications, including disaster and risk management, agriculture and other industries. Used to provide various band-combination imagery or spectral indices.
Pleiades Neo	Airbus	High-resolution imagery for many VNIR imagery applications, including disaster and risk management, agriculture and other industries. Used to provide various band-combination imagery or spectral indices
Sentinel-2	ESA	High resolution for many VNIR imagery applications, including disaster and risk management, agriculture and other industries. Used to provide various band-combination imagery or spectral indices
Sentinel-3	ESA	Multispectral radiometers onboard to provide ocean and land colour imaging, as well as sea and land surface temperature. Also, surface topography instruments are used to obtain surface and wave heights
SkySat	Planet	High resolution for many VNIR imagery applications, including disaster and risk management, agriculture and other industries. Used to provide various band-combination imagery or spectral indices
Spot		
Terra	NASA	Multidisciplinary mission to study Earth's surface. MODIS (one of its main payloads) provides multispectral imaging dedicated to collecting data on biological and physical processes on land and in water. This payload is also aboard the Aqua satellite, improving the temporal resolution of the instrument. ASTER is another instrument aboard Terra, providing multispectral imaging at a higher resolution
WorldView series	MAXAR, DigitalGlobe	High resolution for many VNIR imagery applications, including disaster and risk

(continued on next page)

Table 6 (*continued*)

Mission	Organisation	Main application of mission
		management, agriculture and other industries. Used to provide various band-combination imagery or spectral indices
VIIRS (instrument)	NOAA, NASA	Global observations on land, oceans, atmosphere and cryosphere. Nighttime light imagery is beneficial for observing artificial lights and hotspots. On-board Suomi NPP and NOAA-20/21 satellites

[4]INPE, CRESDA, AEB

Table 7
Satellites with passive microwave sensing capabilities. All of the listed missions are funded and operated by public organisations and are open-source.

Mission	Organisation	Main application of mission
GCOM-W	JAXA	Dedicated to mapping surface soil moisture and other land surface parameters
GPM Observatory	NASA/ JAXA	Provides global precipitation measurements
SMAP	NASA	Observes in active and passive l-band (radio waves). Monitors soil moisture and sea surface salinity
SMOS	ESA[5]	Microwave imaging that collects information on soil moisture and ocean salinity

[5]CDTI, CNES

Table 8
Synthetic Aperture Radar (SAR) satellites. Missions in bold reference private missions; Missions not in bold reference public missions.

Mission SAR	Organisation	Main application of mission
ALOS	JAXA	L-band SAR used for disaster risk management and biomass mapping
COSMO-SkyMed (CSK)	ASI	X-band SAR used for urban and agriculture monitoring. Free access is limited to scientific research and development
COSMO-SkyMed Next Gen (CSG)	ASI	X-band SAR used for urban and agriculture monitoring. Free access is limited to scientific research and development
ICEYE	ICEYE, ESA	X-band SAR with a range of applications for insights in many industries, including insurance, mining and energy
RADARSAT	CSA	C-band SAR used primarily for oil spill and sea-ice coverage.
Sentinel-1	ESA	C-band SAR
SMAP	NASA	See 'Passive microwave/radio' above
NOVASAR-S	Space-Eyes[6]	S-band SAR with applications in flood monitoring, crop assessment and biomass monitoring
SWOT	NASA, CNES	Provide water body topography measurements, such as measuring coastal sea level and wave height
TerraSAR	DLR	TerraSAR-x and TanDEM-X in series. X-band SAR with applications in hydrology, geology, climatology, oceanography, environmental and disaster monitoring, and cartography

[6]DOST-ASTI, CSIRO, UKSA, ISRO

Nevertheless, estimating precipitation levels from satellite data is crucial as it eases reliance on in-situ data collection, which is usually limited in capabilities and cannot cover a large spatial area or information in hard-to-reach areas.

EO data can also assist in delivering renewable energy insights by monitoring specific aspects of biomass production. The actual process of generating energy from biomass is not visible to EO data because many sophisticated chemical processes turn the feedstock into a suitable chemical that produces energy. However, EO may be vital in monitoring feedstock quality and quantity, so it can partially monitor ESG 13–4. Forestry biomass is a common source of energy production, which uses large areas of land. The large spatial swaths and regular temporal resolution ensure higher quality monitoring capacity than in-situ data collection or aerial imagery. Biomass quality and yield can be derived from multispectral imaging, using indices to estimate foliage and biomass (Ahamed et al., 2011; Kumar & Sinha, 2015). SAR and LiDAR are another significant EO source for biomass analysis because, unlike multispectral imaging, they can penetrate the canopy, allowing for studies below the canopy to be developed (Kumar & Sinha, 2015). SAR imagery has even been used to calculate the potential energy in rice straw for power generation, which is essential for deriving insights for ESG 13–4 (Cuong et al., 2021).

Solar energy generated through photovoltaic instruments is becoming an increasingly popular choice for companies looking to reduce their environmental impact. While it may not be included in a company's ESG KPI, it can be accounted for under ESG 13–3, which considers all forms of renewable energy utilised by the company. The photovoltaic cells are generally distributed over large areas and are visible to collect the greatest allowable solar energy, making them suitable for satellite monitoring. Understanding solar isolation forecasting is vital. Very high-resolution optical imagery is beneficial for identifying and segmenting solar arrays, and this can be done manually or with machine-learning algorithms (Sampath et al., 2019). Wide variations in meteorological conditions heavily influence the Global Horizontal Irradiance (GHI) and, thus, the power output. Sophisticated modelling of these fluctuations requires up-to-date meteorological data, particularly the vectors of clouds, which is easily obtained with satellite imagery (Ayet & Tandeo, 2018; Jang & Park, 2016). Geostationary missions are necessary to get an adequate estimate for GHI at the solar array, as they continuously observe above the chosen area.

With all of these KPIs in mind, ESG 10–1 is therefore listed as a KPI that can also be partially monitored with EO data because it can combine the insights of ESG 13–5 and ESG 13–6, which both quantify renewable energy varieties, and also ESG 1–1, which assists in quantifying the overall energy consumption Table 3.

4.2. Indirect KPIs

In the previous section we presented relevant EO research demonstrating the European Commission (EC) ESG KPIs that can be fully or partially monitored from space-based platforms. In this section, we present additional instances where EO research can be indirectly linked to these KPIs. It is important to note that ESG KPIs are not standardised, and different reporting providers may adopt distinct frameworks. Overlapping may occur, and specific requirements may differ, especially as financial and governmental regulations intensify to promote greater transparency in corporate reporting. Therefore, in this section we consider all KPIs and the potential indirect links to EO technology, while more generally remaining mindful of the suitability for EO data to be used for reporting and monitoring of KPIs outside of the EC/EFFAS framework.

Several ESG KPIs listed in the adopted EC/EFFAS framework pertain to revenue and expenses, which cannot be directly monitored using satellite imagery. Only a few indirect monitoring capabilities have been presented for this scope, such as inferring GDP from nightlight imagery. ESG 1–7 focuses on the percentage of R&D expenses, particularly energy efficiency. Although not all cases of improving energy efficiency can be resolved by EO data, one significant factor in this indicator is commercial building energy efficiency, especially thermal insulation. Satellites equipped with thermal and mid-wave infrared imaging capabilities can observe and provide valuable spatial data to enhance monitoring in this area.

Another aspect of EO research with indirect links to ESG KPIs is the forecasting of disease outbreaks relevant to ESG 6–4. Although this information may not differentiate the number of affected employees, it can

Table 9
A matrix of satellite imagery types against spatial resolution groups, from very high (< 5 m) to low (> 1*km*) spatial resolution. Selected satellite missions are plotted in the matrix. Missions in bold represent **private missions**, and international/governmental agencies govern all others.

Spatial Resolution	Hyperspectral	LiDAR	Multispectral optical	Multiband (other)	Passive microwave	SAR/Active radar
Very high spatial resolution (< 5 m)			**GeoEye series**	**GeoEye series**		Sentinel-1
			WorldView series	**WorldView series**		ALOS-2/4
			SkySat	**SkySat**		**CSK**
			NuSat	**NuSat**		**TerraSAR**
			PlanetScope	**PlanetScope**		**CSG**
						ICEYE
High spatial resolution (5–30)	PRISMA	GEDI	Landsat-7/8/9	Landsat-7/8/9		Sentinel-1
	EnMAP		Sentinel-2	Sentinel-2	SWOT	ALOS-2/4
	GHGSat		ASTER instrument (Terra)	ASTER instrument (Terra)		**RadarSat-1/2**
	NuSat		CBERS-4/4a	CBERS-4/4a		**CSK**
	HySIS					**CSG**
						TerraSAR
						ICEYE
Medium spatial resolution (30 m-1 km)	Sentinel-5 P		VIIRS instrument (SNPP, NOAA-20/21)	VIIRS instrument (SNPP, NOAA-20/21)		Sentinel-1
	GHGSat		MODIS instrument (Aqua and Terra)	MODIS instrument (Aqua and Terra)		ALOS-2/4
			ASTER instrument (Terra)	ASTER instrument (Terra)		**RadarSat-1/2**
			Sentinel-3	Sentinel-3		SWOT-2/4
			CBERS-4/4a	ECOSTRESS		
				CBERS-4/4a		
				NuSat		
Low spatial resolution (> 1 km)	Aura	GEDI	GCOM-C	GCOM-C	SMAP	SMAP
	OCO-2/3	ICESat-1/2	Metop series	Aura	SMOS	Sentinel-1
	Metop series			Metop series	GPM	SWOT
	Sentinel-5 P				GCOM-W	
					AMSR-E instrument (Aqua)	

be instrumental in preventing outbreaks from reaching employees. EO data can predict vector-borne diseases, such as malaria and lime disease, using multispectral imagery and meteorological data that measures rainfall and temperature, essential metrics for identifying possible outbreak locations. Satellite imagery can also predict water-borne diseases like cholera, cryptosporidiosis, and algal blooms. Multispectral and high-resolution radiometer capabilities can observe key indicators for water-borne disease tracking, such as water temperature and nutrient concentration.

Particulate matter - that is, tiny particles produced from combustion that can have significant health and environmental impacts - can also be measured with satellite imagery, particularly multispectral payloads. Aerosol Optical Depth (AOD) helps determine the proportion of solid and liquid particles in the atmosphere, making it applicable for measuring particulate matter.

Regarding health and safety reporting, EO can also monitor aspects not listed in the EC/EFFAS framework. One such factor is detecting building and infrastructure instabilities, which can prevent large collapses and protect personnel health and assets. Interferometric SAR (InSAR) is a process that uses active sensors to detect anomalous movements on the Earth's surface, providing insights into potential risks for various industries, including mining, dikes and dams, railway infrastructure, and residential areas. Satellite imagery is crucial in monitoring natural disasters, which are vital aspects of health and safety reporting and fall under ESG reporting. Flooding, forest fires, and earthquakes often encompass vast areas and can be effectively monitored using satellite imagery. Multispectral optical imagery is particularly valuable for this type of research, as various indices can highlight key features in natural disaster events, such as flooded or burnt areas (Cocke et al., 2005; Jesudasan et al., 2020; Quintano et al., 2018).

SAR (Synthetic Aperture Radar) is also critical in natural disaster mapping, especially for predicting and assessing damage caused by earthquakes and landslides. Interferometry (InSAR) enables the detection of rapid changes in surface movements (Barhnart et al., 2019; Necula et al., 2021; Ohki et al., 2020; Tolomei et al., 2021). Additionally, Persistent Scatterer Interferometry (PSI), a specific InSAR technique, can be leveraged for this research; it is capable of measuring very slow ground displacements down to sub-centimetre levels over an extended time series (Bardi et al., 2014; Righini et al., 2011). SAR's sensitivity to water also makes it highly useful for detecting and measuring flooding events (Notti et al., 2018).

Satellite imagery is highly valuable for renewable energy generation forecasting (ESG 13–3, 13–5, 13–6). Additionally, EO imagery can provide insights into renewable energy investments by detecting and quantifying the expansion of renewable energy assets. Machine learning algorithms are beneficial for this purpose, as they can detect changes in solar farms, wind farms, and hydroelectric dams using very high optical imagery or SAR when objects are difficult to discern.

ESG 12 describes the generation and removal of waste, which can be monitored with EO data partially as described in Table 2. However, other aspects of industrial activities don't generate solid waste but do release pollution into the surrounding environment, which can be considered as waste to some degree. Various industries can cause pollution through - for example - mine tailing, oil or gas leaks, and sewage. The quantity of pollution may not be able to be measured, but the area and destruction caused can be. Water and soil quality indices, derived from multispectral imagery, are one way of measuring the health of the surrounding environment. Hyperspectral imagery can also be essential as it can identify subtle spectral differences between healthy and polluted land. Instances of water pollution can also be tracked with passive microwave imagery and SAR, especially for oil spills.

ESG 14–1 is another KPI that has links to waste, but is unique as it emphasises material recovery. Satellite imagery can play a small role in providing insights in this regard, but it is limited to materials kept outside and exposed. However, this should still be considered, as many industries generate vast waste volumes and must store their material

Table 10
Temporal plot of selected satellite missions between 2000–2015. Missions in bold represent **private missions**, and all others are governed by **international/governmental agencies**. Cells with specific years indicate the year the mission extends back to.

A TAXONOMY OF EARTH OBSERVATION DATA FOR SUSTAINABLE FINANCE

Mission	Revisit time	Year 2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
ALOS	14d																
AURA	16d																
AQUA	2d																
CBERS	26d	1999															
ECOSTRESS	3d																
EnMAP	4d																
Gao Fen series	2d																
GCOM-C	2-3d																
GEDI	N/A[7]																
HySIS																	
ICESat series	91d																
Landsat series	8d	1972															
Metop series																	
OCO-2/3	16d/3d																
PRISMA	7d																
Terra	1-2d	1999															
SMAP	2-3d																
SWOT	11d																
Sentinel-1	6d																
Sentinel-2	5d																
Sentinel-3	27d																
Sentinel-5P	$\leq 1d$																
SMOS	3d																
VIIRS (instrument)	16d																
GHGSat series	14d																
ICEYE	1-22d																
RadarSat series	24d	1995															
CSK/CSG	16d																
TerraSAR	11d																
WorldView	1d																
NuSAT series	1.2h																
GeoEye series	3d	1999															
SkySat	1d																
PlanetScope	1d																

Missions in action

Future duration of current missions

Table 11
Temporal plot of selected missions between 2018–2040. Missions in bold represent **private missions**, and all others are governed by **international/governmental agencies.**Cells with specific years indicate the year the full timeline of the mission.

A TAXONOMY OF EARTH OBSERVATION DATA FOR SUSTAINABLE FINANCE

Mission	Revisit time	Year 2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
ALOS	14d															
AURA	16d															
AQUA	2d															
CBERS	5-26d															
ECOSTRESS	3d															
EnMAP	4d															
Gaofen series	2d															
GCOM-C	2-3d															
GEDI	N/A[8]															
HySIS																
ICESAT series	91d															
Landsat	8d															
Metop series series																
OCO-2/3	16d/3d															
PRISMA	7d															
Terra	1-2d															
SMAP	2-3d															
SWOT	11d															
Sentinel-1	6d															2031
Sentinel-2	5d															2032
Sentinel-3	27d															2035
Sentinel-5P	$\leq 1d$															
SMOS	3d															
VIIRS (instrument)	16d															2039
GHGSat	14d															
ICEYE	1-22d															2040
RADARSat series	24d															
COSMO-SkyMed series	16d															2034
TerraSAR (X-band series)	11d															
WorldView series	1d															
NuSAT series	1.2h															2040
GeoEye Series	3d															
SkySat	1d															
PlanetScope	1d															2039

Missions in action   Future duration of current missions outside, including redundant aircraft, derelict buildings, commercial sites and metals from legacy mining waste.

4.3. Satellite characteristics

Every satellite is uniquely designed with specific characteristics in mind, such as those discussed in Section 3. Data selection is dependent upon the application, as seen in Table 2, but choosing a suitable data source is also driven by other characteristics of the satellite mission. For example, spatial resolution is a crucial characteristic that assists in selecting an appropriate data source. In this respect, Table 9 can assist in choosing the most relevant mission. Tables 4, 56 to 7 display an extensive selection of satellite missions that are currently operating, grouped by type of imagery and spatial resolution. Multispectral and SAR are the best attainable forms of satellite imagery because there are a variety of providers and resolutions available. Multispectral imaging has been available for a very long period, since TIROS-1 in the 1960 s, which monitored the reflectance across five spectral bands within the visible to infrared portion of the spectrum. This has enabled the technology to advance and reach better resolutions, and the private space sector has dramatically grown this progression through the delivery of multispectral imagery at a highly granular level (30 cm). SAR imagery can also attain very high spatial resolution because the pulsed signal is focused into a 'synthetic aperture' and so is not limited by the resolution of a real antenna Table 8.

Hyperspectral imaging can achieve high resolution across several missions, as seen in Table 9. The difference across this group concerns the instrument that collects the information, such as an imager or sounder. A hyperspectral imager collects solar energy that is radiant or reflected from Earth's surface and atmosphere. PRISMA, EnMAP, NuSat and HySIS fall under this category as they generate a horizontal picture of the environment based on the spectral bands and channels it views across. Sounders are different because they sense the vertical and derive vertical profiles of atmospheric temperature, moisture and gas traces. This type of instrument is crucial for meteorological studies, as well as monitoring GHG and trace gas emissions, but typically only achieves medium to low spatial resolution. This is problematic for scenarios that require the ability to monitor a point source or over a minimal area, such as corporate reporting. *GHGSat* is a pioneering satellite manufacturer that is offering high-resolution CO_2 and CH_4 mapping, achieving a spatial resolution of 25 m at the surface, and many other private companies are following in its steps to provide high-resolution data for gas emissions.

Another critical characteristic for mission selection is the mission duration, documented in Tables 10 and 11. The selected missions from Table 9 have been plotted against the mission's duration, using the expected end-of-life reported date, with a colour separation to indicate that the mission life spans beyond the current year (2023). A selection of other redundant satellite missions is included in the list as the result of reference to these missions when connecting satellite imagery types to ESG KPIs (Table 2). The mission's duration assists in dictating how long that single mission can view the scene under observation. Although a combination of different missions can be used for one project, caution is advised here as specific characteristics of various tasks, such as the spectral, spatial and temporal resolutions, may not be aligned. This emphasises the importance of legacy missions such as the Landsat series, which has lasted since 1972 and has had nine satellites in orbit at overlapping intervals through time, optimised to ensure consistent image analysis across each newly launched satellite.

There is a balance to be struck when selecting the correct mission, where the priorities of the application must be identified to match the case to the specific data source. The provided tables have been created to assist in this task.

5. Conclusion

Caldecott et al. (2022) suggest that spatial finance – the integration of geospatial data into financial theory and practice – will become a key competency for financial analysis, with profound effects on information markets, risk assessment, valuation methods, and the discovery of investment opportunities. Despite this, there has been limited academic enquiry in the area thus far, and effective application by practitioners has been hindered by a lack of literacy regarding EO, amongst other factors. This paper highlights the potential applications of earth observation (EO) data for sustainable finance research. To do so effectively, we construct a taxonomy through the lens of the European Commission's Key Performance Indicators for Environmental, Social, and Governance (ESG) issues.

Our taxonomy indicates that EO data, while highly valuable, does not necessarily represent a panacea for sustainable finance research. There are ESG monitoring and reporting areas that EO data does not adequately address, especially within the social and governance categories. However, our taxonomy highlights key areas – specifically concerning environmental performance – in which EO data can further our knowledge of existing finance problems and address knowledge gaps. In particular, effective incorporation of EO data in ESG performance monitoring and reporting can address existing information asymmetries within sustainable finance reporting, thus contributing to a more efficient flow of capital towards sustainable business models and more transparent price-discovery within financial markets.

To add depth to our taxonomy, we discuss the parameters to consider when selecting the most relevant EO data for monitoring and reporting purposes and the characteristics of existing satellite missions. This information will inform the reader's decision-making when choosing appropriate missions and data sources. Ultimately, we believe that this paper presents a fundamental stepping stone that will allow researchers to explore and evaluate the effectiveness of EO data for sustainable finance analysis from both an academic and practical perspective.

There are clear extensions of this work. For example, the Taskforce on Nature-related Financial Disclosure (2023) has recently published its final recommendations – including recommended disclosures – that may assist in ensuring the efficient flow of capital to nature-positive outcomes. In this respect, EO data could potentially be used to monitor and report a firm's alignment with TNFD guidelines in a highly-temporal fashion. Future research could evaluate the limitations of EO data in light of new regulations and policies and apply this novel data source to address existing knowledge gaps in finance research.

CRediT authorship contribution statement

Rapach Seonaid: Investigation, Methodology, Writing – original draft, Data curation, Writing – review & editing. **Riccardi Annalisa:** Investigation, Methodology, Resources, Supervision, Writing – review & editing. **Liu Bin:** Conceptualization, Supervision, Validation. **Bowden James:** Methodology, Supervision, Writing – original draft, Writing – review & editing.

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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