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REVIEW ARTICLE

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Geospatial data and workflows for environmental and sustainability compliance reporting: including the private sector

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ABSTRACT

Geospatial data and workflows are rapidly becoming central to environmental and sustainability compliance reporting, but the relationship between evolving EU regulation and available Earth Observation (EO) and GIS technologies remains poorly systematized. Focusing on the European Union and including the private sector, we review binding and soft-law instruments such as the CSRD and ESRS, the EU Taxonomy, the SFDR and the EUDR, and analyse which provisions require which type of spatial information for which business activities. Building on a structured scoping review of scientific and grey literature, we synthesise state-of-the-art EO and geospatial approaches that can operationalise these legal requirements, with a particular emphasis on deforestation-related supply-chain regulations. We propose a conceptual framework that distinguishes three families of geospatial workflows—risk screening, attribution and verification—and maps them to typical corporate reporting processes. Across the reviewed legislation and applications, we identify recurring gaps between legal definitions and EO-derived classifications, significant uncertainties in global land use/land cover products, and challenges in integrating geospatial data quality metadata into auditable reporting processes. At the same time, we highlight emerging opportunities from open EO archives, global benchmark products and AI-enabled processing platforms that can support scalable, transparent and repeatable geospatial workflows for sustainability reporting. The paper concludes by outlining a research and innovation agenda for standardised reference datasets, benchmarking protocols and interoperable platforms that jointly involve regulators, data providers and corporate users to ensure that geospatial workflows are fit for purpose in environmental and sustainability compliance reporting.

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1. Introduction

1.1. Legislation that strongly influences the economic structure

As the global focus on environmental sustainability grows, businesses and organisations are increasingly required to comply with emerging sustainability regulations. Often, Environmental, Social and Governance (ESG) is used as an umbrella term. Since this term is heavily discussed politically and has already been extensively (re)interpreted by supporters and opponents in the public debate, this article relies on the broader and less emotionally discussed term "sustainability compliance". Sustainability reporting for companies, especially within the European Union (EU), has gained prominence as stakeholders increasingly demand transparency regarding how businesses manage their ecological and social footprints.

The European Union has established a comprehensive regulatory framework that imposes various environmental monitoring and reporting obligations on companies operating within its jurisdiction. These obligations span from legally binding directives to voluntary ESG frameworks, creating a complex landscape that companies must navigate to ensure compliance and demonstrate their commitment to environmental sustainability. This report examines how these environmental monitoring duties can be categorized into distinct but interconnected frameworks, specifically analysing legally binding obligations, ESG ratings requirements, non-financial disclosure mandates, and taxonomy-related obligations. Companies face increasing pressure to not only comply with these requirements but also to integrate them into their strategic decision-making processes, making a clear understanding of these categories essential for effective environmental governance.

1.2. Legally binding environmental monitoring obligations

The foundation of companies' environmental monitoring duties within the European Union rests on legally binding obligations established through various directives and regulations. According to the Scottish Environmental Protection Agency (SEPA), environmental monitoring work supports several regulatory functions including European statutory monitoring, assessment of environmental conditions, compliance verification, and pollution event tracking[1]. This statutory framework establishes the baseline requirements that companies must fulfil, irrespective of their voluntary commitments to environmental protection. The implementation of these requirements often involves specialized expertise in environmental modelling and data assessment, as evidenced by SEPA's Environmental Assessment Unit, which handles national reporting of data for statutory returns to government and the EU (DNV, n.d.).

A significant recent development in this category is the Corporate Sustainability Due Diligence Directive (CSDDD), which introduces specific monitoring obligations for large companies. This directive requires companies to "conduct appropriate human rights and environmental due diligence with respect to their operations," creating a legally binding duty to identify and address adverse environmental impacts such as pollution (Pingen, 2022). This extends beyond a company's direct operations to include their subsidiaries and their entire "chain of activities," representing a significant expansion of environmental monitoring responsibilities (Pingen, 2022). The CSDDD applies to large EU limited liability companies and partnerships with at least 1000 employees and EUR 450 million in turnover worldwide (approximately 6000 companies), as well as large non-EU companies with EUR 450 million turnover in the EU (about 900 companies) (Pingen, 2022).

Enforcement of these legally binding obligations is carried out through administrative supervision by designated national authorities, which are empowered to issue injunctive orders and impose "effective, proportionate and dissuasive penalties" including fines (Pingen, 2022). This creates a strong incentive for companies to implement robust environmental monitoring systems to ensure compliance and avoid penalties. The European Commission has further strengthened this enforcement mechanism by establishing a European Network of Supervisory Authorities to coordinate approaches across member states (Pingen, 2022). Additionally, the directive reinforces access to justice for individuals affected by introducing a five-year period for bringing claims, potentially increasing companies' exposure to litigation if they fail to properly monitor and mitigate environmental impacts (Pingen, 2022).

1.3. Relevant legislative frameworks

The NFRD (2018) requires large EU firms to disclose environmental, social, and governance data, forming the foundation for the CSRD and EU Taxonomy updates. The timeline for implementing these reporting requirements began in January 2022, when companies started providing eligibility-related disclosures for their economic activities (Thoms et al., 2024). Even companies with no taxonomy-eligible activities must report on their non-eligible activities, ensuring comprehensive coverage of all business operations regardless of their environmental characteristics (Thoms et al., 2024). The detailed reporting requirements create indirect monitoring obligations, as companies must track and assess their activities against specific environmental criteria to determine eligibility and alignment with the taxonomy. These disclosure requirements continue to evolve as the EU refines its sustainable finance framework, requiring companies to regularly update their monitoring systems to capture new metrics and apply new assessment methodologies.

The EU Taxonomy Regulation establishes a classification system for environmentally sustainable economic activities, thereby defining a distinct category of monitoring obligations for companies. This framework requires companies to assess and monitor their activities against specific environmental criteria to determine taxonomy alignment, which serves as the basis for sustainability-related disclosures. Under Article 8 of the Taxonomy Regulation, companies subject to non-financial reporting requirements must disclose information about the environmental sustainability of their activities according to taxonomy criteria (Thoms et al., 2024). This creates specific monitoring obligations focused on assessing activities against technical screening criteria for environmental objectives.

The Disclosures Delegated Act specifies detailed requirements for reporting taxonomy-related information, including definitions of Capital Expenditure (CapEx) and Operating Expenditure (OpEx) key performance indicators (Thoms et al., 2024). These definitions establish specific methodologies for calculating environmental metrics, creating detailed monitoring requirements for companies to track financial investments and expenditures related to environmental sustainability. The precision required in these calculations necessitates sophisticated monitoring systems that can attribute financial flows to specific environmental objectives and activities. Companies must monitor not only whether activities contribute to environmental objectives but also whether they comply with "do no significant harm" criteria for other objectives, requiring multi-dimensional environmental assessment. Companies must report on both taxonomy-eligible and taxonomy non-eligible activities, with "taxonomy non-eligible" defined as "any economic activity that is not described in the delegated acts" adopted pursuant to the Taxonomy Regulation (Thoms et al., 2024). This comprehensive reporting scope means companies must monitor all their economic activities to determine their relationship to the taxonomy framework. The evolving nature of the taxonomy, with new environmental objectives and technical screening criteria being developed over time, requires companies to continuously update their monitoring systems to capture new environmental metrics and apply new assessment methodologies (Thoms et al., 2024). This creates a dynamic monitoring obligation that expands as the taxonomy framework develops to cover more economic activities and environmental objectives.

CSRD (2026) expands sustainability reporting with ESRS standards but was simplified in 2025 to fewer companies and fewer data points.

Sustainable Finance Disclosure Regulation (SFDR): The SFDR mandates financial market participants and financial advisors to disclose how sustainability risks are integrated into their investment decision-making processes. It aims to mitigate greenwashing by ensuring that sustainability-related claims are backed by credible data.

Double materiality links financial impacts with social and environmental effects, guiding CSRD-compliant reporting. De Cristofaro and Gulluscio (2023) argue that the notion of double materiality has led to a relatively wide variety in both double-materiality assessments and adoption disclosures, as well as related criticalities. Describing how an organisation affects people, the planet and society while creating profits is at the core of sustainability reporting. This is defined as having an impact. The ESRS states that when describing the process to identify material impacts, risks and opportunities, a company should disclose all relevant criteria used in the process.

This paper focuses on EU-centric laws (CSDDD, CSRD) and highlights supply-chain relevance without covering all global frameworks. This narrow view of the European Union and a small number of laws and standards is a simplification of the extremely complex situation in which the interconnected global economy finds itself. Of course, there are numerous international regulations and standards from various organizations and professional associations. For instance, the proposed International Standard on Sustainability Assurance (ISSA) 5000, General Requirements for Sustainability Assurance Engagements, will serve as a comprehensive, standalone standard suitable for any sustainability assurance engagements.

In today's globally oriented economy, companies rarely operate in isolation. They typically work in complex global value chains and ecosystems and interact with many other organizations and individuals along supply chains as suppliers or buyers. Therefore, they are increasingly being held accountable for the environmental impacts and social and ethical actions of their partners along a supply chain. Therefore, in connection with the core themes of this article—sustainability from an ecological, economic and social perspective—the inclusion of supply relationships is necessary.

In the ESRS reporting standards, assessing an organisation's material impacts, risks and opportunities must be validated by a due diligence process to cover the relevant parts of that organisation's value chain. For example, the impact of GHG emissions needs to be categorised according to Scopes 1, 2 and 3 (Ducoulombier, 2021). Therefore, this article will include supply chain aspects where explicitly necessitated by the discussed legislations but will not comprehensively discuss the supply chain-specific legislations such as the "Directive on corporate sustainability due diligence" (CSDDD), approved by the Council of the European Union on 24 May 2024, thereby completing the adoption process. The aim of this Directive is to foster sustainable and responsible corporate behaviour in companies' operations and across their global value chains. The new rules will ensure that companies in scope identify and address adverse human rights and environmental impacts of their actions inside and outside Europe. The following sections on spatial aspects, workflows and tools only address the supply chain issue selectively—where required by other legislation.

1.4. Reporting obligations and geospatial aspects of selected legislations

The push for detailed sustainability reporting aims to create a transparent, accountable business environment, driving investments towards sustainable practices and enhancing corporate responsibility. Companies are increasingly integrating sustainability into their core strategies, aligning with the EU's broader environmental and social goals. To understand how these evolving obligations translate into geospatial information requirements, we carried out a structured narrative review that combined (i) a systematic screening of EU legal texts and guidance (CSRD, ESRS, EU Taxonomy, SFDR, EUDR and related sectoral directives) and (ii) a scoping review of the scientific and grey literature on EO- and GIS-based compliance monitoring. The literature search covered the period 2000–2025 and used combinations of terms such as "geospatial", "Earth observation", "corporate sustainability reporting", "CSRD", "EUDR", "deforestation-free", and "compliance" in major bibliographic databases and Google Scholar. We retained studies that explicitly link geospatial data to regulatory or certification schemes, sustainable finance or environmental compliance. For each document, we qualitatively coded (a) the type of legal or voluntary framework addressed, (b) the kind of spatial information required (e.g., asset locations, land use/land cover, supply-chain traceability) and (c) the role of geospatial workflows (screening, attribution, verification). This analytical lens informs the structure of the following sections, where we first synthesise the state of the art in geospatial technologies and then relate it to specific EU legislation. In this context, our review provides a structured overview of how EU sustainability and environmental regulations translate into concrete geospatial information demands and Earth observation/GIS workflows for corporate compliance reporting. By linking legal provisions to specific spatial data types and workflow functions, we offer a management-oriented perspective on how compliance obligations cascade into data capture, monitoring and interpretation tasks throughout corporate value chains (see Figure 1).

Earth Observation (EO), and geospatial technology have become critical tools for supporting large-scale analysis of visually assessable environmental condition. The term "Earth Observation" is preferred by entities such as the European Commission, as a comprehensive term encompassing satellite, airborne and in situ data. EO data are indispensable for collecting spatial information on land, water, and atmosphere environment, making them essential for sustainability compliance reporting such as in the context of CSRD or European Union Deforestation Regulation (EUDR). Rapach et al. (2024) report in detail on the possibilities and limitations of using EO in ESG reporting. They highlight the potential applications of EO data for sustainable finance research and construct a taxonomy aligned with the European

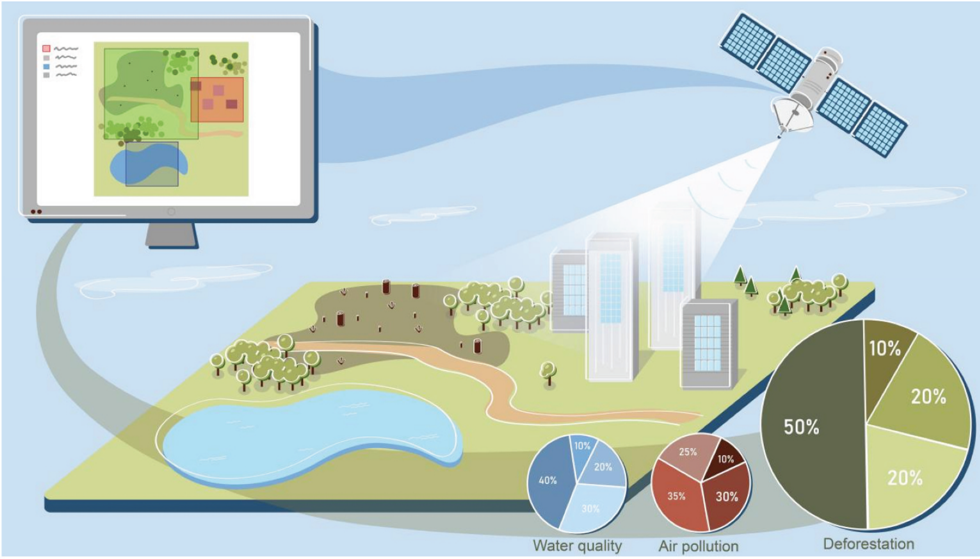

Figure 1. Conceptual framework illustrating the integration of geospatial workflows into sustainability compliance reporting. Numbers indicate the relative share of legislative provisions in our sample that contain explicit geospatial data requirements, and stylised percentages along the arrows summarise how frequently each type of geospatial workflow (screening, attribution, verification) is mentioned across the reviewed frameworks. These values are intended to be illustrative and to support the conceptual discussion rather than to represent exact statistics.

Commission's Key Performance Indicators for ESG issues. In the following section, we will build upon this general framework and will particularly address CSRD and EUDR issues while also evaluating the limitations of EO data considering these relatively new regulations and policies.

2. State of the art in geospatial technologies for environmental and sustainability compliance

2.1. Earth Observation

EO has increasingly become indispensable in environmental compliance monitoring, especially within the EU, driven by comprehensive legislations like the EUDR, CSRD, and SFDR. EO technologies, particularly satellite-based remote sensing, offer global, timely, and objective insights, addressing significant gaps left by traditional, ground-based monitoring techniques which are often resource-intensive and impractical for large-scale compliance verification (Lein, 2009; Purdy, 2006; Reid & Castka, 2023; Taylor & Lindenmayer, 2022).

Historically, EO first demonstrated its value in environmental policy compliance notably with the Kyoto Protocol (1997), providing critical capabilities such as carbon stock assessment, biomass tracking, and anthropogenic emissions monitoring (Rosenqvist et al., 2003). Within the EU context, EO's role expanded significantly, enabling agricultural subsidy verification (CAP; Purdy, 2006), detection of illegal constructions in protected forests (Karathanassi et al., 2003), and compliance monitoring for the Programme for the Endorsement of Forest Certification (PEFC) (Lopatin et al., 2016; Reid & Castka, 2023).

EO data availability has significantly evolved due to free and open data policies, greatly enhancing their utility for compliance assessments. Widely utilized satellite missions include MODIS (250–1000 m resolution), Landsat (30 m resolution), and especially the Sentinel-1 (S-1) and Sentinel-2 (S-2) missions from the EU's Copernicus program (10–20 m resolution). These missions provide consistent global coverage with frequent revisit intervals, essential for detailed and timely environmental monitoring necessary for compliance.

The EUDR exemplifies how EO currently supports environmental and sustainability compliance. EUDR requires that products such as coffee, cocoa, oil palm, soybean, cattle, rubber, and derived commodities entering EU markets must not be associated with deforestation or forest degradation after December 2020 (Regulation on Deforestation-Free Products-European Commission, n.d.). EO technologies offer substantial potential to meet EUDR requirements by providing spatially explicit evidence of land-use and land-cover changes, essential for tracing deforestation patterns within complex supply chains. Recent work by Berger et al. (2025) synthesises the ways in which existing and planned EO missions, global forest maps and near-real-time alert systems can act as an operational backbone for EUDR implementation, while emphasising the need for harmonised forest definitions, minimum mapping units and pan-tropical reference baselines. At the same time, large-scale mapping efforts such as the wall-to-wall tropical tree cover maps of Brandt et al. (2023) illustrate how Sentinel-1/2 time series and deep learning can provide the type of spatially explicit evidence required for risk screening under the EUDR when combined with national forest inventories and supply-chain information. Publicly accessible benchmark datasets significantly aid compliance monitoring at scale and can serve as baselines aligned with the EUDR's cut-off date of 31 December 2020 (Table 1, Figure 2).

Recent methodological advancements further enhance EO's capabilities for compliance monitoring. Techniques such as Random Forest (RF), Spectral Mixture Analysis (SMA), Object-Based Image Analysis (OBIA), and Deep Learning (DL) methods—including Convolutional Neural Networks (CNNs) and U-Net architectures—demonstrate notable improvements in classification accuracy. Specifically, integrating these advanced methods with Sentinel imagery has significantly enhanced the accuracy of land-use mapping, particularly for easily identifiable crops like oil palm (Descals et al., 2021, 2024) and soybean (Song et al., 2021), known for their distinct spectral signatures and extensive cultivation patterns.

In contrast, accurately mapping agroforestry systems, such as often used for coffee and cocoa production, remains problematic. Their complex canopy structures and spectral similarities with natural forests limit the ability of EO systems to distinguish them reliably using standard remote sensing techniques RF (Condro et al., 2020; Cordero-Sancho & Sader, 2007; Gaertner, 2017; Mosomtai et al., 2020). These classification limitations have significant implications for deforestation monitoring under the EUDR. They can lead to commission errors (false positives), where compliant agroforestry systems are mistakenly classified as deforested, and omission errors (false negatives), where actual deforestation goes undetected (see example in Figures 3, 4). Commission errors may result in producers, particularly smallholders, being unfairly excluded from EU markets, while omission errors can expose

Table 1. Benchmark EO-based land use/land cover (LULC) products.

Product name	Spatial resolution	Temporal coverage	Classification methodologies	Details	Data source
Landsat-based Global Forest Change (GFC) (Hansen et al., 2013)	30 m	2000–2024 (keep updating)	Decision Tree, Supervised Classification, Time-series analysis of spectral signature (NDVI and spectral reflectance)	Global tree cover extent, loss, and gain annually	Manually interpreted Landsat
ESA WorldCover (Zanaga et al., 2022)	10 m	2020, 2021	Gradient Boosting Decision Trees	Nature forest, Plantations (e.g., oil palm, eucalyptus, etc.), Afforestation/reforestation areas, Seasonally/permanently flooded forests (excluding mangroves) Consistent with FAO LCCS definitions	S-2 L2A (bands and indices), S-1 GRD (VV, VH backscatter + speckle filtering), Copernicus 30 m DEM, positional data (lat/lon, biome, realm), and meteorological data (from TerraClimate)
Google and WRI Dynamic World (Brown et al., 2022)	10 m	2015–2024	Deep Learning (Fully CNN)	~9 LULC	S-2 L1C for modeling and L2A for manual training annotation, all bands except B1, B8A, B9, B10 (upsampled to 10 m)
ESRI LULC (Karra et al., 2021)	10 m	2017–2022	Deep Learning segmentation model based on U-Net	~10 LC Classes	S-2 L2A (R, G, B, NIR, SWIR1, SWIR2)
JRC Tropical Moist Forest (TMF) (Vancutsem et al., 2021)	10–30 m	1990–2024	Decision Trees, Multi-temporal Anlysis		
JRC Global Forest Cover 2020 (GFC)	10 m	2020	Random Forest	Forest, Non-forest, Change	Annual S-2 (2018–2021)
JRC Global Forest Type 2020 (GFT) (Bourgoin et al., 2024)	10 m	2020	Random Forest	~10 major forest types	S-2 (bands and indices), JAXA ALOS PALSAR-2, Topography from SRTM, Climate variables (temperature, rainfall)

Figure 2. Benchmark datasets supporting EU deforestation-free regulation (EUDR) compliance.

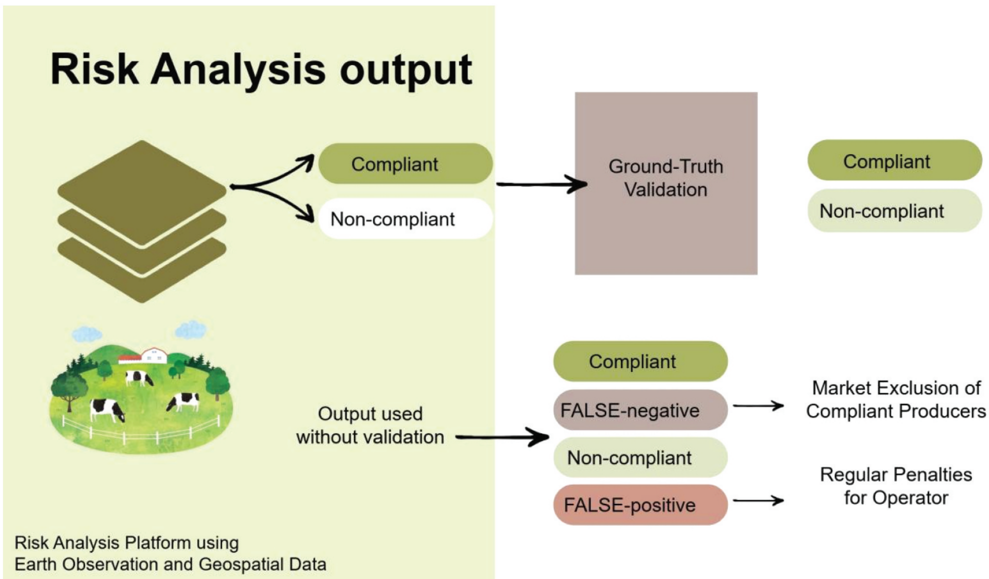

Figure 3. Example of the EUDR risk analysis output and possible implications for producers and operators.

traders and operators to regulatory penalties for failing to detect deforestation within their supply chains.

To address these challenges, methods such as RF (Condro et al., 2020; Mosomtai et al., 2020), SMA (Cordero-Sancho & Sader, 2007), OBIA (Gaertner, 2017), and high-resolution commercial satellite platfroms like WorldView and QuickBird (Chemura & Mutanga, 2016) have been explored. These approaches improve the discrimination accuracy of agroforestry systems, although limitations related to resolution, spectral confusion, and computational intensity persist. Continuous methodological refinement and innovation are essential for delivering more reliable monitoring.

Despite these technological advancements, EO integration into compliance verification continues to face significant barriers, notably legislative-technical gaps. These gaps occur when legal definitions and EO-derived classifications are misaligned,

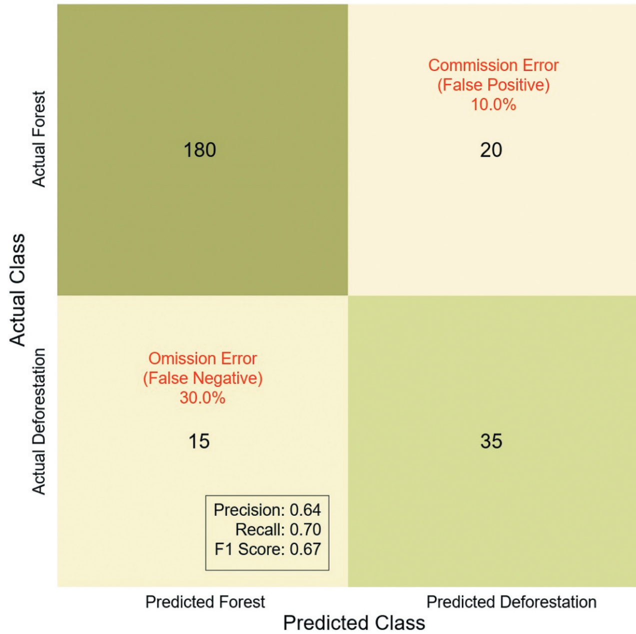

Figure 4. Example of confusion matrix of an analysed data sample with ground-truth data in a benchmarking framework.

complicating verification processes. Ensuring the legal robustness and acceptance of EO-derived monitoring results highlights the urgent need for standardized validation protocols and benchmarking frameworks. Such frameworks must be grounded in field-validated reference data and incorporate local producer knowledge to enhance detection accuracy across diverse agroecological contexts. Transparent benchmarking protocols will be increasingly vital for establishing trustworthy, comparable, and legally defensible EO-supported deforestation assessments, particularly in complex landscapes where agroforestry and forest regeneration coexist. Synthesising the reviewed applications, EO-based compliance use cases can broadly be grouped into three functional categories: (i) risk screening and prioritisation, (ii) attribution of impacts to specific assets or value-chain segments, and (iii) independent verification of self-reported information. Most existing work still concentrates on coarse-scale risk screening, whereas asset-level attribution and verification remain comparatively underdeveloped, especially for smallholders and heterogeneous land-use mosaics. These imbalances directly motivate the geospatial workflow typology that we discuss in the Results and Discussion sections.

2.1.1. Future directions

Future developments in EO technologies promise significant advancements in monitoring capabilities essential for environmental compliance reporting in EU. With the launch of ESA's Biomass satellite in April 2025, forest monitoring capabilities will be further enhanced by employing P-band SAR technology. Using radar technology, Biomass will measure not only the towering forest canopy but also the trunks, branches, and even leaves, capturing the full scope of a forest's carbon potential. The aim is to improve our understanding of forest dynamics and contribute insights into the global carbon cycle (The European Space Agency [ESA], n.d.). However, it has limited spatial resolution (~200 m) and restricted global coverage due to international frequency constraints. Sentinel-1 Next Generation might compensate for these limitations as it will provide higher resolution and frequent revisits, especially in cloudy tropical regions, to support land cover mapping, crop types, forest type and forest cover and so on (ESA-Star Publication, n.d.). Except for SAR missions, ESA also plans to launch the Copernicus Hyperspectral Imaging Mission for the Environment (CHIME) mission in December 2029. CHIME will enhance spectral data to support the policies in EU related to natural resources (Nieke et al., 2023). Therefore, it has potential to aid classification of complex agroforestry systems like coffee and cocoa.

Additionally, integrating AI-driven EO data processing methods on platforms like Google Earth Engine (GEE) will streamline workflows and increase accuracy in compliance monitoring. Recently, Google introduced AlphaEarth Foundations, an AI model that integrates vast amounts of EO data into unified, compact embeddings, enabling the creation of detailed and consistent global maps on demand. Users can conduct their analysis on this embedding dataset on GEE without downloading any data. This innovation means that instead of depending on a single satellite pass, scientists can now monitor crop health, track deforestation, or detect new construction with far greater precision (Brown et al., 2025; DeepMind, Google, 2025), providing a transformative new foundation for geospatial data and compliance reporting. Strategic utilization of these technologies will significantly bolster environmental compliance under EUDR and CSRD.

2.2. Turning data into information: geospatial data quality

The reliability of geospatial data is fundamental to credible sustainability reporting (Rossi et al., 2024). Due to the impossibility of perfectly capturing the full complexity and detail of the real world, geospatial data inevitably provides only an approximate reflection, which means their quality and reliability are inherently limited (Couclelis, 2003; Goodchild, 1995; Li et al., 2016). Therefore, it is critical to convey the quality of geospatial data consistently, clearly, and in standardized forms. This communication is fundamental for accurate environmental and sustainability compliance reporting at various scales. For example, if a mining company bases its reporting on indigenous lands using unreliable geospatial information, the resulting indigenous land boundaries may distort actual boundaries, causing misstatements regarding the company's adherence to regulatory standards. As another example, a study by Reiersen et al. (2021) that analysed tropical reforestation projects found that carbon estimates derived from satellite imagery can overstate actual forest biomass by as much as tenfold. Such oversights can damage trust and result in regulatory or strategic errors in sustainability initiatives.

To mitigate these risks, organizations need robust methods to assess and report geospatial data quality. Commonly accepted criteria for assessing this data quality include data source, lineage, completeness, logical consistency, positional accuracy, temporal accuracy, and thematic (attribute) accuracy (Devillers et al., 2007; Lush et al., 2012). Clear documentation about the source and lineage (the dataset's origin and any transformations it underwent) is critical because it allows auditors of sustainability reports to verify the credibility of the data production process. Completeness (whether portions of the data are absent or not spatially comprehensive) and logical consistency (the adherence of the data to logical relationships and rules) are additional quality dimensions that enable thorough sustainability audits. Positional accuracy involves evaluating how closely geographic coordinates (such as those for monitoring stations or protected regions) match their real-world positions. Meanwhile, thematic accuracy addresses the correctness of the classifications or attributes (e.g., verifying that land cover classes are correctly specified), and temporal accuracy pertains to the accuracy and validity of timestamps or periods associated with the data. Furthermore, explicitly communicating confidence levels (e.g., specifying that land-cover classification data has a 90% confidence rating) helps regulators and other stakeholders interpret data appropriately. Figure 5 presents a conceptual and summarized example of geospatial data quality indicators suitable for inclusion in compliance reporting for deforestation monitoring. These criteria collectively articulate data quality from the producer's viewpoint, but consumers ultimately must interpret and adapt this information according to their specific requirements, or "fitness-for-use" (Li et al., 2016).

However, user-specific requirements often extend beyond these standard quality measures. They may involve aspects such as spatial or spectral resolution, or more complex considerations like data continuity, factors that are less easily quantified. Because these user-driven requirements are subjective and context-dependent, researching fitness-for-use tends to be more complex than addressing straightforward, quantifiable aspects of geospatial data quality (Lush et al., 2012). Consequently, users frequently determine fitness-for-use by translating simplified quality indicators into their specific contexts (Duckham, 2002). While definitive user-oriented quality metrics specifically designed to assist fitness-for-use evaluations in environmental and sustainability

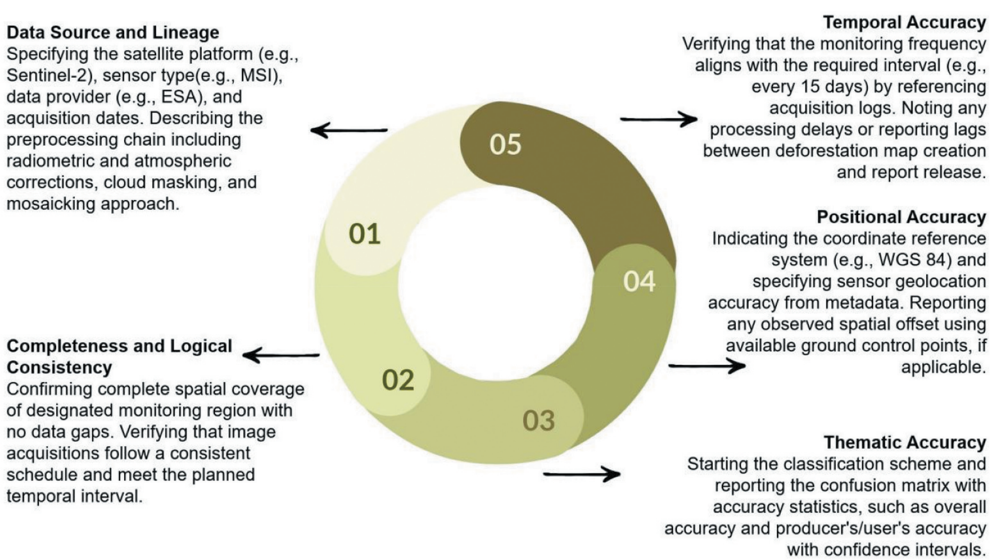

Figure 5. Example of geospatial data quality metrics in a hypothetical case of deforestation compliance reporting using satellite imagery. The metrics provide a structured basis for evaluating geospatial data reliability and fitness-for-purpose.

reporting have not yet been properly established, numerous existing metadata elements can potentially fulfil this role if provided consistently. Users can then interpret these metadata in alignment with their priorities and requirements. The prevailing framework for reporting geospatial data quality employs standardized metadata formats, notably ISO 19115, to document quality transparently and consistently (Fischer et al., 2023; Yang et al., 2013). The ISO suite specifically includes essential elements like lineage, completeness, logical consistency, positional, temporal, and thematic accuracy (Yang et al., 2013), serving as the basic set of information that must be included in the metadata of geospatial data for documenting data quality.

2.3. Environmental monitoring systems and platforms

The European Union has established various monitoring systems and platforms to facilitate environmental data collection, management, and sharing, creating a supportive infrastructure for companies' monitoring duties. A prime example is IPCHEM (the Information Platform for Chemical Monitoring), which serves as "the European Commission's reference access point for searching, accessing and retrieving chemical occurrence data collected and managed in Europe" (European Broadcasting Union [EBU], 2024). This platform helps address knowledge gaps on chemical exposure and its impacts on health and the environment, providing companies with valuable reference data for their own monitoring activities. IPCHEM is structured into four modules covering environmental monitoring, human biomonitoring, food and feed, and indoor air, offering a comprehensive approach to chemical monitoring across different media (EBU, 2024).

IPCHEM integrates various data collections, including those from targeted research projects and regulatory monitoring programs throughout Europe. For example, it includes data from the BIOSOIL, FATE, LUCAS, and WATCHLIST projects, creating a rich repository of environmental monitoring information that companies can leverage for benchmarking and context-setting (EBU, 2024). The platform recently incorporated Germany's Federal Environment Agency database on "Pharmaceuticals in the environment," demonstrating the ongoing expansion of available monitoring data across environmental media and chemical categories (EBU, 2024). This growing ecosystem of shared environmental data helps companies contextualize their own monitoring results and identify emerging environmental concerns that may require additional attention.

Beyond chemical monitoring, the EU has developed several other frameworks for monitoring and benchmarking, such as the Social Protection Performance Monitor (SPPM) and Joint Assessment Framework (JAF) (Lindqvist et al., 2024). While these frameworks primarily address social and employment issues, they illustrate the EU's approach to establishing comprehensive monitoring systems that identify trends, challenges, and outcomes across member states. The methodological approaches developed for these frameworks, including quantitative assessment based on indicators followed by qualitative assessment and prioritization of challenges, provide models that companies can adapt for their own environmental monitoring programs (Lindqvist et al., 2024). These EU monitoring frameworks demonstrate the importance of systematic data collection and analysis in supporting evidence-based policy making, an approach that companies are increasingly expected to adopt for their environmental management systems.

The CSRD requires companies to similarly assess the materiality of matters from an impact perspective, which considers the severity and likelihood of a company's impacts on society and the environment. This impact-materiality exercise includes analysing the scale, scope, irremediability, and likelihood of the company's global impacts (both positive and negative) on each issue. Once all ESG matters have been scored and mapped against each other, there needs to be a cut-off of what is and is not a material issue. Once such thresholds are set, any mapped ESG matter that scores higher than the impact threshold should be considered material from an impact perspective; and any matter that scores higher than the financial threshold should be considered material from a financial perspective.

However, there is no consensus on how to implement materiality, with its practical application as ambiguous (Reimsbach et al., 2020). In general, it is recommended in the standards that the company applies the principle of materiality and explains the stepstaken (Puroila & Mäkelä, 2019).

3. Analysis: geospatial data and workflows for the CSRD and the EUDR

3.1. Global availability of geospatial datasets and their accuracy

Over the past decade, there has been a significant increase in the availability of land use and land cover (LULC) products, at both global and regional scales. This expansion is mainly due to the open-sharing policy of key satellite data (e.g., Landsat and Sentinel), advancements in remote sensing and Earth observation technologies, the emergence of cloud computing platforms, and enhancements in classification algorithms (Hermosilla et al., 2022; Naboureh et al., 2021; Xu et al., 2024). According to Wang et al. (2023), there are currently over 100 large-scale LULC products (at national, continental, and global levels) derived from satellite data, with more than half of them covering the entire globe. These datasets are increasingly used in environmental monitoring, natural hazard assessments, and sustainability compliance (Anderson et al., 2017; Estoque, 2020; Zhao & Yu, 2025).

A variety of LULC products are now publicly available to users, ranging from global-scale datasets such as Globeland30 (Chen et al., 2015), Dynamic World (Brown et al., 2022), and MODIS (Friedl et al., 2010), to regional and national datasets, such as European CORINE Land Cover (CLC) (Büttner et al., 2004), and China land cover data set (CLCD) (Yang & Huang, 2021). Each product has its own characteristics in terms of classification system, spatial resolution, update frequency, and geographical coverage. This variety offers flexibility for users to select products that best match their specific objectives and supports authorities, environmental organizations, and researchers in comprehending land utilization, temporal changes, and the alignment of current land management methods with environmental regulations or SDGs (Guo et al., 2022). For example, Yang et al. (2022) combined GLC_FCS30 (Zhang et al., 2021) and Globeland30 products to track human expansions in Asian highlands. Similarly, Sasmito et al. (2023) employed the forest change product (Hansen et al., 2013) combined with some other datasets to monitor restoration of Indonesia's mangroves and progress toward SDGs 1, 3, 6, 13 and 14.

Despite these advances, the variety of available LULC products may introduce challenges, especially when used in sustainability and SDG reporting frameworks that demand high levels of consistency and accuracy. One major concern is the accuracy of

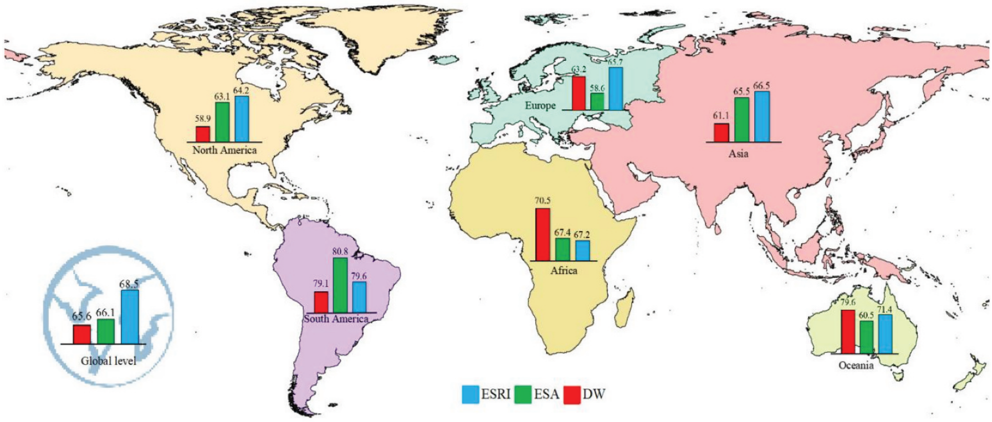

Figure 6. Accuracy assessment of ESRI, ESA, and Dynamic World land cover products over global and continental mountain areas (Naboureh et al., 2025).

existing global land cover products, especially in complex landscapes such as mountainous regions. As shown in Figure 6, Naboureh et al. (2025) evaluated the accuracy of three widely used 10-meter global LULC datasets across global mountains and found that none exceeded 69% overall accuracy. The study also reported notable regional discrepancies at both continental and major mountain range levels. Similarly, Pan et al. (2024) and Aryal et al. (2023) reported low to moderate accuracy of LULC products over mountainous regions. These miss-classifications are not just scientific issues; they directly impact the credibility of compliance reports. An area incorrectly identified as "natural vegetation" might be excluded from reforestation efforts, while a miss-classified "urban area" could result in unnecessary restrictions or miss-allocation of funds.

Limitations in temporal and spatial resolution further complicate the use of LULC data in sustainability reporting. Some products update annually (e.g., MODIS), others every few years (e.g., CORINE), and some only once a decade (e.g., GlobeLand30). Although MODIS offers valuable long time series, its resolution is too coarse for detecting small-scale changes, such as illegal land clearing on a farm plot or construction in a protected area. On the other hand, higher-resolution LULC products like Dynamic World provide finer spatial detail (10 meter) but are only available for recent years. These limitations highlight the need for caution when selecting LULC products for SDG monitoring and compliance purposes. Relying on low-resolution or outdated datasets can lead to underestimation or overestimation, ultimately affecting the credibility and effectiveness of sustainability measures.

Beyond technical challenges, another persistent issue is the lack of transparency around uncertainty. Most compliance reports require high confidence in reported findings, yet some LULC products provide limited or no information about their accuracy, especially at local scales. For example, the accuracy of the Globland30 product for the year 2000 is unknown. Without clear accuracy metrics or validation data, decision-makers may be hesitant to rely on these products, or worse, may unknowingly base policies on flawed information. Despite these challenges, LULC products remain essential tools for environmental compliance. The key lies in choosing the right product for the task, understanding its limitations, and, where necessary, adapting it to local needs. Harmonizing classification schemes, increasing temporal resolution, integrating multi-source data, and investing in better accuracy assessments are all steps in the right direction.

It is widely believed that remote sensing data offer global coverage, easy access, and availability in various spatial and spectral resolutions. In practice, many problems arise regarding data availability and applicability. The High-Resolution Global Maps of 21st-Century Forest Cover Change (GFC) is produced by the Group on Land Analysis and Discovery (GLAD) at the University of Maryland (Hansen et al., 2013). GFC harmonizes all available spectral data from the Landsat mission to derive descriptive annual and semi-annual statistics (median, maximum, minimum, and quantiles) for each spectral band that constitutes data inputs to produce annual forest loss estimates through the application of a supervised decision tree classifier. The final GFC product is constituted by two main datasets. Pixel values for the first one represent the percentage canopy cover in the first year of analysis (2000). The second layer assigns a value representing the year of forest cover loss to all pixels that were mapped with a tree cover higher than 30% in the reference year (2000). This layer enables users to define forest extent in terms of a minimum percent tree cover threshold. This threshold can be used to produce a mask of forest cover for the initial year with a tree cover above the user-specified threshold. This mask can then be applied to the layer on forest loss year to remove pixels labelled as loss that are under the defined tree cover threshold (Hansen et al., 2013).

3.2. Automating geospatial workflows

Rossi et al. (2024) showed that open-access global data can be used as the primary data sources. Using available open access data allows the exploitation of available resources and provides full transparency. This data is freely available and will allow us to produce science-based results at a high temporal frequency, applicable to any assets worldwide. Rossi et al. (2024) argue that this data provides valuable insights into various aspects of biodiversity and ecosystem health critical for corporate sustainability reporting. For forest applications, global "wall to wall" representation of forest cover and forest cover change at the Landsat (30 m) resolution became available 5 years after the opening of the Landsat Archive in 2008 (Hansen et al., 2013). Since then, more than 70 global products mapping forest cover and change have been developed. The availability of global assessments of forest cover and change has greatly facilitated a better understanding of the impacts of deforestation on the ongoing climate and biodiversity crises (Clerici et al., 2020; Harris et al., 2021; Millard et al., 2021).

Geospatial data and analyses offer several advantages for ESG assessments, including consistency, the potential for enhanced accuracy, and the ability to identify and assess environmental impacts at a detailed physical asset level (Rossi et al., 2024)—in addition to evaluating the broader spatial context. By incorporating geospatial information (obtained through manually processing remotely sensed data, or by using existing products) rating methodologies can be improved, and disparities can be addressed more effectively.

Earth observation data based on Copernicus imagery (Sentinel-1 and 2 satellites plus "third-party mission") will be utilized, along with various complementary datasets that evaluate remote, environmental, characteristics. Some of these include, but are not limited to datasets mentioned within the ESRS framework, such as Natura 2000 network of protected areas, World Database of Protected Areas (WDPA), IUCN Red List of Species, The Ocean Data Viewer, Global Forest Watch, The Living Planet Database, The International Waterbird Census Database, Key Biodiversity Areas etc.

To standardize and summarise this data, geospatial workflows are proposed by Rossi et al. (2024). These authors outline a methodology to combine open access data that reflects localized effects of an asset on biodiversity, and delocalized effects of an asset on global drivers of biodiversity loss (e.g., climate change). These scores are calculated through combining data on land use, soils, hydrology, biodiversity state, and emissions. These are all combined and weighted according to expert opinion and scientific literature to produce a single environmental (E) score, which is intuitively understandable.

The key question is whether geospatial workflows can (semi-)automatically process the data in a manner that is scientifically robust yet practical for corporate application. A survey of scientific literature reveals that EO and GIS technologies are transforming corporate sustainability practices and reporting.

EO and GIS technologies have already begun to play an important role in improving the accuracy and transparency of sustainability reporting. Recent advancements in EO technology have significantly improved the ability to monitor and assess environmental health and condition in a scalable manner. Remote sensing has already been implemented as standard practice to assess compliance in several regulations and standards.

The US Environmental Protection Agency Clean Water Act regulates water pollution of all surface water in the USA. To comply with this regulation, adherents have employed GIS and remote sensing to monitor water quality and manage water resources (Ramadas & Samantaray, 2018). This includes the use of satellite imagery to detect changes in water bodies, track pollutants, and thus ensure compliance with the Clean Water Act. The EPA also uses GIS to support the implementation of the Total Maximum Daily Loads (TMDLs) program, which identifies and restores impaired waters by calculating the maximum amount of a pollutant that a water body can receive while still meeting water quality standards (U.S. Environmental Protection Agency [EPA], 2011). Additionally, for the Clean Water Act, wetland protection is ensured through the use of GIS tools. This includes delineating wetland boundaries, classifying wetland types, and monitoring hydrological changes. This is crucial for regulatory compliance and conservation efforts.

The Forest Stewardship Council (FSC) also encourages organisations to utilise GIS technology to achieve FSC certification and ensure compliance with its standards (FSC, 2021). For this certification, GIS and EO is particularly important for collecting and analysing spatial data on forest resources. It enables high temporal analysis of deforestation and illegal logging and can highlight any unusual or unexpected changes in a forest area that could require further in situ investigation. It provides the FSC with a reliable way to document and report forest management activities (FSC, 2021). The FSC has even incorporated EO data into its own GIS portal to improve transparency and monitoring capabilities (FSC, 2021).

The integration of EO and GIS technologies offers several advantages for corporate sustainability reporting. These technologies provide high-resolution data with a high temporal frequency, they improve data and methodological transparency by enabling independent verification of corporate sustainability claims (Reid & Castka, 2023), and they support compliance with regulatory requirements by providing detailed documentation and quantitative values of environmental impacts (Rapach et al., 2024; Rossi et al., 2024). As these technologies continue to evolve, their incorporation into corporate sustainability strategies will likely become even more critical and widespread, driving further advancements in sustainable business practices.

4. Results

4.1. Geospatial data and workflows

Geospatial workflows—integrating spatial data, analysis, and visualization tools—play a pivotal role in supporting EU sustainability reporting requirements, especially under frameworks like the CSRD and the EU Taxonomy Regulation. Both frameworks necessitate detailed, verifiable data about environmental impacts and resource usage, areas where geospatial technologies provide distinct advantages.

The CSRD mandates large EU companies to disclose extensive ESG data in line with the European Sustainability Reporting Standards (ESRS). The directive emphasizes transparency on issues like greenhouse gas (GHG) emissions, water use, and biodiversity impacts, aligning with the EU Green Deal. Geospatial workflows, such as Geographic Information Systems (GIS) and satellite monitoring, assist in precisely mapping and monitoring environmental footprints, providing data critical for compliance. For instance, satellite imagery and remote sensing can measure carbon sequestration in forested areas, helping companies quantify and report on GHG emissions and land use changes. Additionally, GIS tools allow businesses to model and track pollution sources, facilitating accurate disclosures about air and water quality impacts in specific regions.

The EU Taxonomy Regulation defines criteria to determine whether economic activities are environmentally sustainable, guiding companies in disclosing how they meet climate change mitigation, adaptation, and other sustainability objectives. Geospatial workflows support taxonomy compliance by enabling spatial analysis of biodiversity and natural habitats, essential for assessing ecosystem impacts. For instance, GIS layers can be used to map habitat areas to ensure companies comply with biodiversity preservation requirements. Such workflows enable real-time data collection, helping firms assess if their operations avoid causing harm to protected areas or significantly contribute to climate resilience.

Many EU directives also push for transparency across supply chains and encourage circular economy practices. Geospatial workflows provide an end-to-end view of supply chain impacts by tracking raw material extraction, transport, and manufacturing locations. This spatial visibility supports compliance by allowing companies to quantify impacts, avoid ecologically sensitive regions, and minimize resource footprints.

Overall, geospatial workflows facilitate compliance with EU sustainability directives by providing accurate, spatially referenced data essential for reporting and managing environmental impacts. They enhance transparency, enabling more detailed and responsive sustainability assessments that align with regulatory demands.

4.2. Discussion

Our synthesis highlights that geospatial data and workflows are shifting from being optional "supporting evidence" toward becoming a core component of regulated sustainability reporting and due-diligence processes. Across EU frameworks such as CSRD/ESRS, the EU Taxonomy, SFDR and the EUDR, geospatial information is repeatedly required to (i) locate assets and supply-chain nodes, (ii) characterise environmental conditions and changes (e.g., land use/land cover, forest loss, ecosystem status), and (iii) document traceability and verification steps in ways that are internally controllable and externally auditable. This shift has direct implications for corporate data governance: geospatial layers need to be treated as regulated reporting inputs (with documented provenance, uncertainty and versioning), not merely as maps. In other words, our analysis makes explicit the chain from sustainability objectives and environmental conditions, via EO/GIS data, monitoring and reporting, and geospatial workflows, to the ways in which corporates and organisations are evaluated within their respective jurisdictional contexts.

A key contribution of this review is the explicit link between regulatory requirements and operational geospatial workflows. Rather than presenting EO/GIS capabilities as a technology catalogue, we propose and apply a workflow lens that distinguishes (1) risk screening workflows (prioritising geographies, suppliers or assets for attention), (2) attribution workflows (connecting impacts or risks to specific assets, operators or value-chain segments), and (3) verification workflows (independent checks of self-reported information). This typology helps explain why much of the current evidence base clusters around scalable screening products, while the more demanding attribution and verification tasks remain underdeveloped—especially in heterogeneous smallholder landscapes. The workflow lens also clarifies where technical improvements alone will not solve compliance challenges: definitional alignment, governance, and auditability are equally limiting.

Positioning against existing work, our review complements and extends recent contributions in two important ways. Rapach et al. (2024) highlight the growing relevance of geospatial data in the context of sustainable finance and taxonomy-aligned decision-making, but do not provide a cross-legislation mapping from specific EU legal provisions to the concrete geospatial information types and workflow steps needed inside corporate reporting processes. Berger et al. (2025) provide a timely and valuable perspective on EO as an enabling infrastructure for implementing the EUDR, yet their focus is necessarily centred on deforestation-free products. We broaden the scope by systematically relating EO/GIS workflows not only to EUDR-style supply-chain due diligence, but also to the wider CSRD/ESRS reporting architecture (including double materiality), EU Taxonomy disclosures and SFDR-related data demands. This broader linkage is essential for the private sector, where compliance workflows typically need to serve multiple overlapping reporting obligations with shared data pipelines.

The discussion also surfaces recurring technical—legal gaps. First, legal definitions (e.g., "forest", "deforestation", "degradation", or activity boundaries) rarely map cleanly onto EO-derived classification schemes, minimum mapping units, or time-series change definitions. Second, global land cover and forest products differ substantially in classes, legends, and uncertainty properties; without transparent benchmarking and reference data, companies risk "false confidence" when using a single product as evidence. Third, the auditability of geospatial evidence is still weakly standardised: many workflows do not preserve full processing lineage, training data provenance, or uncertainty statements in ways that can be evaluated by auditors or regulators. Embedding data-quality metadata (e.g., ISO 19115-style documentation) and reproducible processing pipelines is therefore not a peripheral technical detail but a prerequisite for defensible reporting.

Taken together, these findings suggest a practical agenda for both research and implementation. For companies, a "minimum viable evidence" approach can be operationalised by adopting modular workflows (screening → targeted attribution → verification), explicitly recording data versions, threshold choices and uncertainty, and integrating geospatial outputs with enterprise systems used for reporting. For regulators and standard setters, clearer guidance on acceptable reference layers, minimum documentation requirements and benchmarking protocols would reduce interpretive variability and support comparability. For the research community, priorities include open benchmark datasets tailored to legal definitions, systematic inter-comparisons of global products under compliance-relevant conditions, and reference implementations of auditable workflows that can be independently reproduced and scrutinised. These governance and business-oriented insights are intended to support corporate managers, lawmakers, supervisory authorities and spatial data experts in designing robust sustainability compliance architectures in an increasingly GeoAI-enabled reporting landscape.

4.3. Conclusions and outlook

Notwithstanding the massive trends in AI and machine learning that currently change our society so called GeoAI has recently transgressed from prototypical status to operational solutions and have manifested themselves widely. Several companies have launched AI-based ESG compliance packages to help organizations fulfil mobility requirements under CSRD regulations. This creates a huge market but opens the door to unsubstantiated commercial claims. AI image detection can be integrated within GIS workflows to increase the level of automation possible and identify environmental changes or issues that would have previously required human investigation (She et al., 2020). From a review perspective, these developments mark a clear shift from exploratory GeoAI prototypes towards operational compliance services that build on shared EO data infrastructures. At the same time, many emerging commercial "ESG analytics" offerings remain weakly documented in the scientific literature and rarely disclose details on training data, benchmarking protocols or data quality. This lack of transparency limits their suitability for use in regulated reporting contexts and underscores the need for open, peer-reviewed geospatial workflows and reference implementations.

Recent and future developments using cutting edge technology include:

- Advancements of multispectral and hyperspectral imaging technologies allow for detailed analysis of vegetation health, soil composition, and water quality. These technologies provide critical data for assessing the environmental impact of corporate activities (Goetz et al., 2009; Guo et al., 2022).
- Multispectral imaging, which captures data across multiple wavelengths, is widely used in monitoring land use and cover changes. Hyperspectral imaging, which captures a broader spectrum of light, offers more detailed information about the physical and chemical properties of the landscape and what is in it. These technologies offer great potential in improving the accuracy and reliability of monitoring deforestation, urbanization, and agricultural practices (Clark et al., 2005).
- The use of SAR technology has enabled the monitoring of land surface changes at increased resolution regardless of weather conditions, being able to pass through clouds and provide its own illumination, removing the impact of time of day.
- SAR data is particularly useful for tracking changes in forest cover, soil moisture, and surface deformation (Barrett et al., 2013; Besoya et al., 2021).
- The use of SAR in combination with optical and thermal imaging technologies provides a holistic view of environmental conditions, enhancing the reliability of ESG assessments.

Disclosure statement

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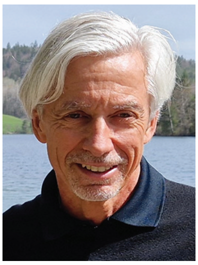

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Data availability statement

The authors confirm that no new data were generated in this study.

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