



## Research article

## Breaking the ESG rating divergence: An open geospatial framework for environmental scores

Cristian Rossi<sup>a,b,c,\*</sup>, Justin GD. Byrne<sup>c</sup>, Christophe Christiaen<sup>a,b</sup><sup>a</sup> UK Centre for Greening Finance and Investment (CGFI), Oxford, UK<sup>b</sup> University of Oxford, Oxford, UK<sup>c</sup> Satellite Applications Catapult, Harwell Campus, UK

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## ABSTRACT

Information about a company's environmental, social and governance (ESG) performance has become increasingly important in the decision-making process of financial institutions. The financial implications of environmental challenges (e.g. water stress), negative social impacts (e.g. health impacts in local communities) or poor corporate governance (e.g. breaching legislation) all continue to increase. Accordingly, there is a need for financial institutions to incorporate information on ESG risks, opportunities and impacts in decisions that relate to risk management, investments, credit, strategy, and reporting. ESG information is typically disseminated through ESG ratings, which combine the three constituents into a single rating, or ascribe them separate scores. The compilation of ESG ratings and the identification of appropriate data sources is an inherently complex process; as such, there is no single standard for data collection or reporting. This has led to a divergence in the underlying data sources used by different rating providers, as well as in the determination of factors that are deemed worthy of measurement in the first place. For example, when assessing a company's environmental impact, one rating provider may rely on company-provided data, while another may incorporate independent third-party assessments. Unfortunately, there is currently no clear mechanism for effectively resolving such disagreements to establish a standardised approach to ESG rating assessments. However, geospatial data and analyses offer several key 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, 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. This would enable a more comprehensive understanding of the environmental considerations of ESG assessments, promoting a more informed and precise decision-making process. Within this context, a few institutions (e.g. the University of Oxford, the WWF, and a few others) are pioneering thought leadership around spatial finance, including the assessment of ESG issues utilising geospatial intelligence, but there are no consistent frameworks for incorporating geospatial data into ESG ratings and analysis. This paper explores the opportunity for such a geospatial environmental scoring framework, defining a variety of methods in which open data with broad geographic coverage could be incorporated into ESG analysis, generalisable to a range of assets and sectors. The proposed framework is organised into two categories: localised effects, which directly impact the immediate vicinity of an asset, and delocalised effects, which contribute to global climate change and atmospheric pollution. Sub-scores are defined within these categories, which capture both the localised effects on land use, biodiversity, soils, and hydrology, and the global impacts resulting from atmospheric emissions. The approaches for handling geospatial data to generate both these sub-scores and the final *E-score* are presented, including a test case, and the complete methodology is made available in open repositories.

\* Corresponding author. UK Centre for Greening Finance and Investment (CGFI), Oxford, UK.

E-mail address: [cristian.rossi@gmail.com](mailto:cristian.rossi@gmail.com) (C. Rossi).<https://doi.org/10.1016/j.jenvman.2023.119477>

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## 1. Introduction

Environmental, Social, and Governance (ESG) scoring metrics are well established in the investment industry (Gibson et al., 2019). These scores combine and weight data to inform an overall E, S, or G score. Frameworks establish inputs, processes, and outputs to turn, typically company self-reported, data into scorecards. Different frameworks will vary in how they weight E, S, and G issues and their aggregated scores depending on the aspects to corporate governance that the framework aims to highlight. They also vary in how they handle missing data. ESG ratings guide financial decision making, from individual societally conscious pensions to national sovereign credit ratings (Halbritter and Dorfleitner, 2015). ESG ratings are dominated by several established organisations (such as MSCI, Sustainalytics, Refinitiv, S&P Global) and they all face significant challenges combining nuanced information regarding complex subjects into a single or multiple scores (Dorfleitner et al., 2015). Decisions are made about how to obtain, manipulate, and reduce the dimensionality of data bias in ESG scores (Kotsantonis and Serafeim, 2019). Methodological differences contribute to the disagreements in ESG scoring that occur when they are applied to the same company or when the distribution of scores from different agencies are compared (Berg et al., 2019).

The widespread disagreement in ESG scoring has raised concerns in academic literature as it may indicate that methods are failing to provide an objective measure – or even reach a loose consensus – on the efficacy of companies' governance (Gibson et al., 2019b). Different perspectives may exist within the industry. Companies may contend that their metric is differentiating itself from its competition due to improved methods, nuanced perspective, or in tailoring their score to a specific aspect of ESG. Agreement of metrics may even be undesirable because it removes a perceived competitive advantage in methodology that a company may have over others (Edmans, 2020). These are fundamental challenges to ESG metrics in a competitive commercial market and are separate from applied or practical challenges to generating scores.

Berg et al. (2019) indicate that discrepancies in ratings largely relate to practical challenges and methodological differences that differentiate the approaches of agencies when collecting data. These challenges include missing data, selecting relevant variables (scope), and determining which raw data feeds are selected to assess success for those variables (measurement). This leads to different frameworks forming divergent or even opposite conclusions on the performance of a company in a specific aspect of ESG, and it may combine with a strong “halo effect” where companies rated highly in one aspect will tend to score higher in other aspects by the same rater. Structural challenges are also key to understanding rating divergence, including a lack of industry verification, transparency, data standards, data sharing, or regulation (Kotsantonis and Serafeim, 2019).

Issues facing ESG ratings may be alleviated by analysing ESG issues at the physical asset level, introducing geospatial data to provide new metrics, a standard of comparison, a method to fill missing data, or an approach for verification (Caldecott et al., 2022). Geospatial data may help resolve some of the more abstract challenges of ESG ratings by providing a reference point to converge existing methods around. This work focuses on the environmental elements of ESG where its capacity to provide value is most evident.

Many geospatial datasets are open-source, removing challenges of data-sharing and creating a level playing field. Many datasets have global coverage, removing challenges of data availability. However, there are sometimes trade-offs between breadth of coverage and precision. Some products may be updated weekly, far more rapidly than information volunteered from companies; for others, the periods covered, and update schedule can be minimal.

To maximise accessibility, this work focuses on datasets that are open access and have global coverage. However, for some research areas, especially around risk modelling and biodiversity datasets, high-quality data for commercial use exist, such as the Integrated Biodiversity

Assessment Tool (IBAT) datasets (IBAT, 2020), that substantially improve over datasets that are free for commercial use. Because of this, rating bodies could consider their budget for geospatial assets and adapt their approach in line with that. The work also focuses on analysis at the asset-scale, assuming that geospatial asset data (such as spatial points or polygons defining the boundaries of a farm, mine, or facility) are available. Obtaining asset data is not without challenges, but open-source asset datasets such as power plants, cement plants or soy processing facility mapping are becoming increasingly available<sup>1</sup> for specific use cases (Rossi, et al., 2022).

This work describes an approach that can be scaled in accordance with the scope and budgets of rating agencies across multiple sectors. Section 2 lays out the main components of the framework that will be weighted and combined to form the final environmental impacts score (*E-score*); these are biodiversity and soil scores that are modified by a land use change score, along with a score for hydrology and contributions to global pollution. This section outlines why components have been selected, i.e. due to both the contributions each component makes to a healthy environment and the amenability of the component to geospatial analysis. Description of how geospatial data is combined with asset data to produce each sub-score are presented. Section 3 describes the practical implementation of the score with an example. Section 4 discusses how the framework highlights opportunities to incorporate geospatial data into new or existing metrics more generally. The section indicates how ESG agencies may move beyond free, global coverage datasets as required, and how sector specific data can be incorporated into a geospatial framework. Finally, Section 5 traces the study conclusions.

## 2. Framework characterisation

The *E-score* is created by combining several sub-scores. The score includes key environmental components that may already be part of traditional frameworks but provides new ways to assess the performance of an asset in this area with a transparent, impartial measure. The framework is divided between localised effects that directly impact the area around an asset and delocalised effects that contribute to global climate change via emissions of climate forcing gasses.

Localised effects include land and water impacts that are fundamental to food and water security, as well as impacting carbon sequestration and biodiversity (Senadheera, et al., 2021). When soils and hydrological systems are disturbed through activity or land-use change, biodiversity, food production capacity, water availability, and carbon storage around assets can be negatively impacted in the long-term. Finally, biodiversity declines are reported in widespread areas with huge numbers of species endangered or facing extinction due to anthropogenic pressures (Leclère, et al., 2020). In addition to the ethical issues associated with contributing to the mass-extinction of species, biodiversity loss is likely to have implications for human wellbeing and the global economy (Hanley and Perrings, 2019).

The construction of the localised impact scores follows a pattern of identifying the potential for harm – represented by the soil and biodiversity scores and the water-stress and protected area components of the hydrology score – and combining this with observable impacts, including land cover change, water extraction, and water pollution. Because of this, the framework modifies the impact of land-cover change by the scores for that area's biodiversity and soils values. Assets that are not associated with land use change may skip the soil and biodiversity section of this work as any score in those categories will be modified to 0 when the land use score is combined with them. Other soil and biodiversity impacts not associated with land use change should be considered, but are not easy to measure using remote sensing

<sup>1</sup> <https://globaleenergymonitor.org/>; <https://www.cgfi.ac.uk/spatial-finance-initiative/geoasset-project/geoasset-databases/>.

approaches.

Delocalised asset emission data, which are ubiquitously recognised as a core component of ESG frameworks, are also included due to the crucial need to tackle global climate change.

After generating individual scores for each component, they may be weighted and combined into an *E-score* (Fig. 1). The default weighting assigns equal importance to all components of the local impact score and treats both the local and global impact scores as equally significant. However, implementers may decide to weight scores differently at these stages.

The datasets used in the framework, selected to be free sources with broad geographic coverage, are listed in Table 1 (Appendix A) by score component. The framework incorporates multiple *hyperparameters* that represent intermediary weightings or manipulations. The *hyperparameters*, scoring, and weightings are defined in Table 2 (Appendix A).

Framework methods, rating agency policies, and sector-specific factors will shape the monitoring period over which environmental impacts are assessed. However, datasets that update frequently, vary seasonally, or concern infrequent events with a short window of detection should be monitored over a sufficiently extended period that is suitable for the variable in question.

## 2.1. Localised impacts

(ESG) analysts may wish to separate out effects that directly impact the area surrounding an asset from delocalised impacts from e.g. greenhouse gas emissions. The framework separates localised environmental effects into those impacting hydrology, soils, and biodiversity; with soil and biodiversity impacts modulated by the degree to which an asset contributes to land use change. In this context, the calculation can be likened to assessing risks, where the potential for hazardous impact is evaluated based on the soil and biodiversity components, while the land use component represents the likelihood of the asset triggering those impacts. The hydrology component, on the other hand, examines both the potential for impact and the evidence of impact within a single component.

### 2.1.1. Land cover change (natural class conversion)

Environmental impacts to soil and biodiversity in potentially vulnerable environments happen when habitats are degraded or converted. Remote sensing can detect land conversion, disturbance, and degradation by comparing differences in land cover over time, such as the conversion of forest to cropland or vice versa. However, high

precision land degradation or disturbance data may be challenging to source from free datasets or datasets with global coverage. Free to use land cover datasets are now available with high resolution (~10m) and refresh rates (~weekly). These land cover change datasets, including those available through Dynamic World (Brown, et al., 2022) or Global Forest Watch (Pickens et al., 2020), allow analysts to detect changes in land cover that may be caused by the conversion of natural habitats to crops, infrastructure, or built-up areas.

In the framework shown in Fig. 1, the potential risk to soil, habitats, and biodiversity – the soil and biodiversity scores – are weighted by the land cover change score. The derivation of this score is shown in Fig. 2. First, across the monitoring period ( $t_1$  to  $t_2$ ), the land cover is compared within the asset boundary. Second, the proportion of the area of the asset that is converted from natural cover classes to built-up area, cropland, or bare ground, is computed. This proportion represents the *E Land Cover Change Score*. This score can be weighted by a measure of company size such as production volume to scale across assets of different size or across sectors. The practical implementation of the score and an associated test case are presented in Section 3.

### 2.1.2. Biodiversity impacts

Ecosystems are highly complex and this structural complexity, part of which is biodiversity, varies geographically and has strong relationships to precipitation and temperature trends globally (Gaston, 2000). Absolute species richness or species abundance relates more to geography than ecosystem health – a healthy tundra forest may have fewer species and less biomass than a highly degraded tropical rainforest. This means that global spatial products that only map biodiversity or species richness are less informative than datasets that focus on ecosystem properties related to their healthy functioning or conservation value.

Informative products might involve mapping the preservation of historical land cover of high biodiversity value – such as primary forest intactness (Hansen, et al., 2013), historic grasslands (Scholtz and Twidwell, 2022), or peatland preservation (UNEP, 2022). Also of use are datasets developed to measure the conservation value of different landscapes, such as the STAR dataset (Mair, et al., 2021), Key Biodiversity Areas delimitations (GÜVEN, et al., 2004), or IUCN maps of endangered species distribution (IUCN, 2022); all of which are not available free for commercial use. Additional work, beyond the scope of this paper, is needed to describe how to integrate them into a geospatial framework.

Biodiversity datasets typically encompass collections of geographic areas that are deemed significant for species conservation. Examples

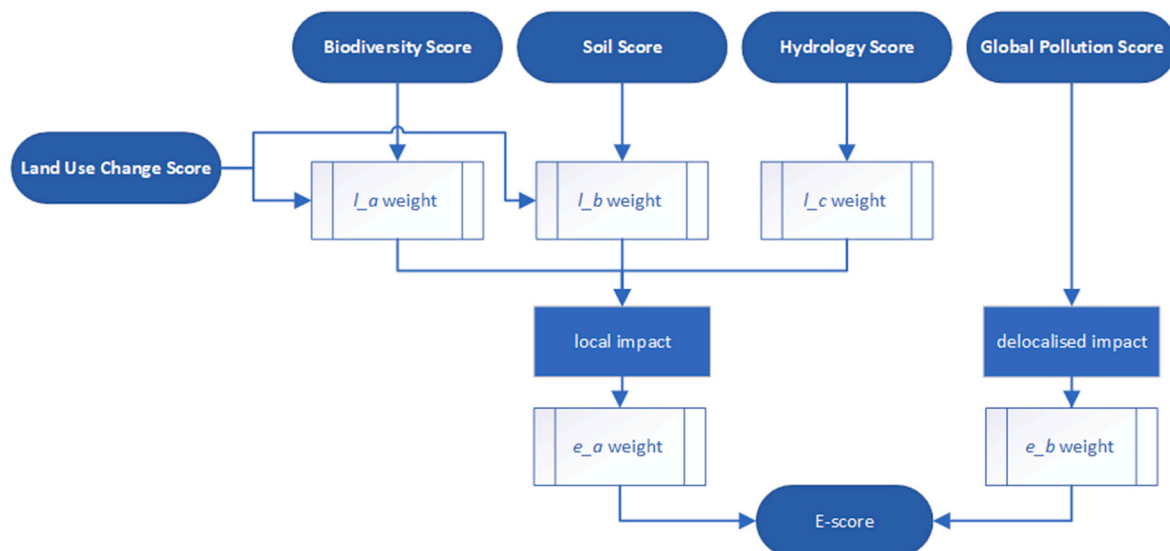
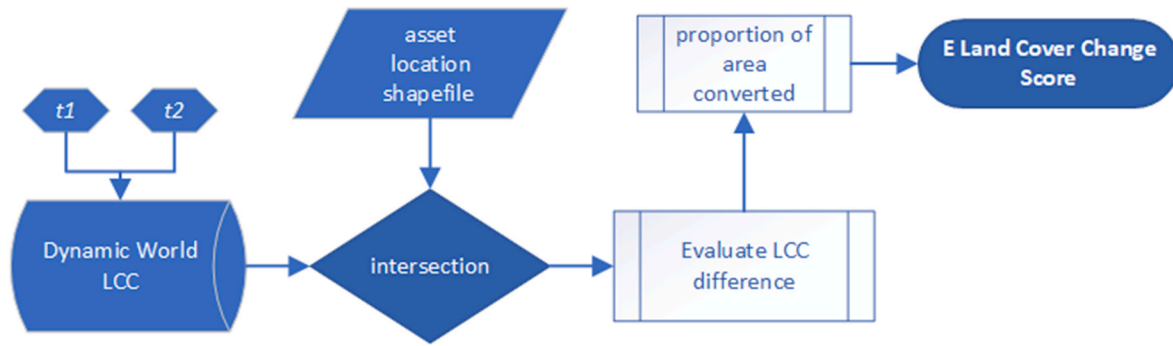


Fig. 1. The higher structure of the geospatial *E-score* framework.



**Fig. 2.** Flowchart of the *E Land Cover Change Score*. Dynamic World Land Cover Classification (LCC) maps and the asset boundary are the inputs for its derivation.

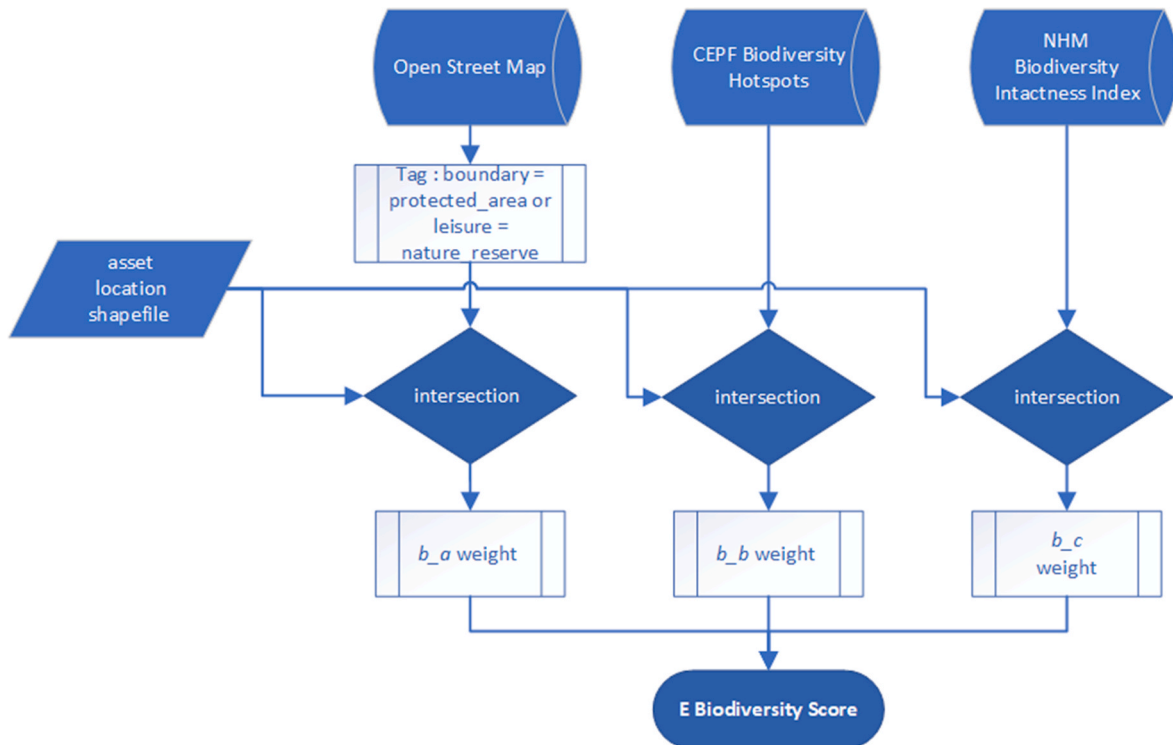
include the Biodiversity Hotspots dataset (Marchese, 2015), which identifies regions of high conservation value, or models that incorporate biodiversity information derived from observational datasets linked to specific spatial locations, such as the IUCN spatial distribution datasets (IUCN, 2022). Critically needed, high resolution light pollution data may soon become available providing a measure of an asset's contribution to light emissions that impact animal behaviour (Barentine et al., 2021).

The work focuses on freely available global datasets:

1. Protected areas and nature reserves are designated areas specifically set aside for biodiversity. Land conversion within them may be illegal, depending on local laws; is at increased likelihood of impacting biodiversity; and may undermine the purpose of the protected area.
2. Biodiversity Hotspots are threatened areas with high biodiversity and with high numbers of endemic species that are found nowhere else in the world (Marchese, 2015). Development in these areas is particularly likely to contribute to species extinction.

3. Biodiversity Intactness, which measures the proportion of the remaining natural biodiversity of an area at 1 km resolution (Newbold, et al., 2016). Areas with low intactness may represent areas that are especially vulnerable to further degradation, and development in these areas is placing further pressure on already weakened systems. However, areas with high intactness may represent areas that need to be conserved for species that require relatively pristine ecosystems to survive. Areas with values towards the extremes should be conserved for different reasons.

This framework, described in Fig. 3, compares asset locations to OpenStreetMap data to determine if assets are located in or adjacent to protected areas by using the *boundary: protected\_area* or *leisure: nature\_reserve* polygon labels. Assets located in high biodiversity areas are determined using the Critical Ecosystems Partnership Fund dataset for biodiversity hotspots which provide hotspot polygons. Finally, a measure of the intactness of biodiversity within the site's area is extracted from the Biodiversity Intactness Index dataset (Newbold, et al., 2016), which is available in raster format. These datasets can highlight the potential for land-use change to result in impacts to biodiversity. The



**Fig. 3.** Flowchart of the *E Biodiversity Score*, to assess the potential for negative biodiversity impacts from asset activity. Assets located in protected areas, biodiversity hotspots, or ecosystems with high intactness may be at greater risk of negative biodiversity impacts following from human activity.



scores are averaged to generate the *E Biodiversity Score*. Hyperparameter weightings are outlined in Table 2, and its practical implementation is described in Section 3.

Previous reviews, including those of the WWF (WWF-UK, Geospatial ESG, 2022) (WWF-UK, *The Biodiversity Data Puzzle*, 2022a,b) identified a wide range of remotely sensed or geospatial datasets that relate to ecosystem properties. In specific use cases, ESG analysts may identify a need to include additional biodiversity or habitats data and may find these resources useful.

#### 2.1.4. Soil impacts

Healthy soils underpin food security and water security, they sequester huge amounts of carbon, and they support high biodiversity terrestrial ecosystems. The disturbance of soils through human activity can negatively impact the ability of soils to provide for human and natural systems. The framework focuses on:

1. Soil Organic Carbon (SOC), the less stable form of carbon in soils (as opposed to soil inorganic carbon – i.e. mineral carbon such as calcium carbonate which is highly stable). It is formed from decomposed animal and plant matter, but can be sequestered long-term in suitable cold, wet soils. Much more carbon is stored in soils than in aboveground vegetation. But, if soils are disturbed, dried, or warmed through human activity, the organic matter is readily converted to atmospheric carbon by microbes. Therefore, converting land with high SOC to cropland, built-up areas, or bare ground is likely to result in carbon emissions.
2. The fertility of soils as measured by their Cation Exchange Capacity (CEC). CEC is a chemical measure of a soil's ability to hold on to positively charged ions – also called cations. CEC is a good measure of soil fertility because many of the essential nutrients that plants need are these cations and high CEC soils prevent nutrients from washing away with rainwater, so that they are available for plants to access. CEC is strongly impacted by soil acidity, but is also correlated with SOC. Organic matter is great at increasing soil CEC. Soils with a high CEC will also hold onto pollutant cations, such as some heavy metals, and so are also vulnerable to pollution. Fertile land is needed for food security, as well as materials industries that rely of plant growth, e.g. forestry or natural textiles. Converting fertile land to built-up areas or bare ground takes away land for plant growth and can negatively impact soil fertility in the future.

In addition to these variables, physical characteristics, such as texture, soil depth, depth of soil horizons, or soil type; and chemical characteristics, such as pH, nitrates, phosphates, or heavy metals; have the potential to be modelled at scale if extremely large datasets were available. However, producing spatial maps of global extent for large numbers of soil characteristics is unlikely to simplify the challenges ESG analysts face. Instead, simplified datasets of fertility and productivity that incorporate these data are needed for non-experts to utilise. Remote sensing has more limitations when applied to the analysis of an asset's effects on soils, as key soil properties vary with depth (Hartemink and Minasny, 2016). The qualities of deeper soil horizons may not be inferable from remotely sensed data but may be crucial to accurately estimating soil carbon stocks or fertility. It may still be possible to spatially model properties, such as soil texture, with sufficiently large training datasets (Liao et al., 2013).

In the framework, described in Fig. 4, the values for SOC (tonnes ha<sup>-1</sup>) are extracted from the GLOSIS – GSOCmap, v1.5.0, and nutrient availability data from the FAO's Harmonized Soil Database v2.0 for the top 20 cm of the soil (CEC<sub>SOIL</sub> variable at Depth Layer 1 D1), which can be found using the Harmonized Soil Database viewer downloaded from the ISRIC Data Hub page for the project. The scores are averaged to generate the *E Soil Score*. The weightings of the hyperparameters are outlined in Table 2.

If an asset boundary spans multiple polygons, the value for the pixel

in which most of the asset lies should be used to determine SOC or CEC values, or an average can be taken if the asset lies equally across multiple pixels. However, as SOC and CEC models at this resolution are likely to be strongly spatially autocorrelated and the nature of the framework's scoring system groups together soils with similar values, adjacent pixels are less likely to differ to such an extent that it will impact scoring.

#### 2.1.5. Hydrological impacts

Water is essential for life on earth. The biodiversity of freshwater, river, and wetland ecosystems are especially vulnerable to impacts such as sediment, fertiliser, or contaminant pollution (Vörösmarty, et al., 2010). The drivers and impacts of hydrological processes occur at large spatial scales and some lend themselves to spatial analysis. Geospatial ESG frameworks should include the potential for disturbance of downstream wetlands or protected areas, measure water pollution downstream of an asset, and consider the water consumption in relation to the degree of water stress locally.

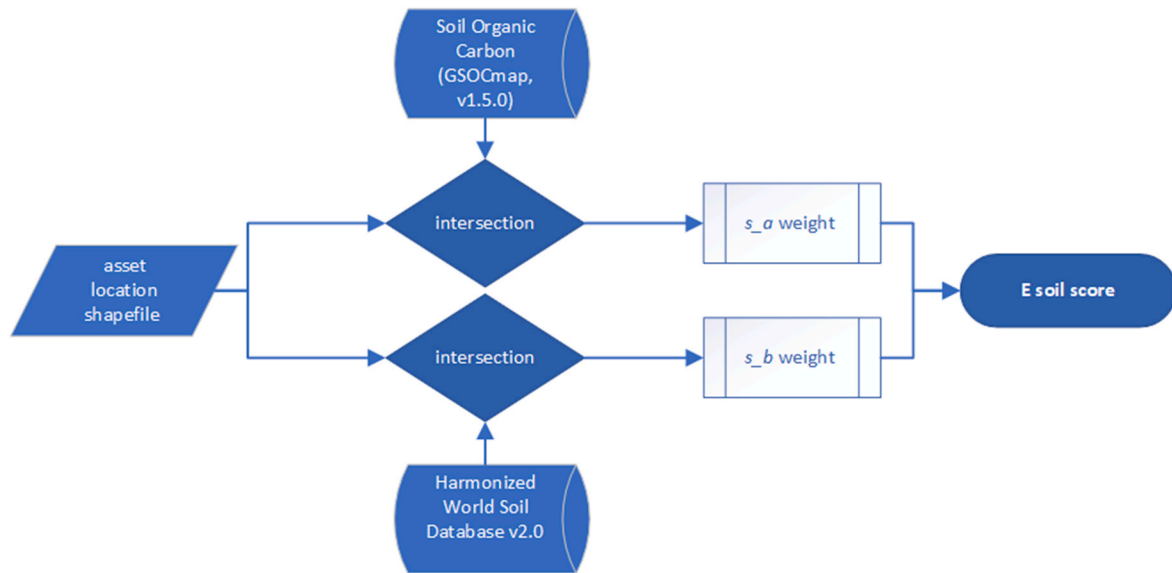
A wide range of freshwater quality variables can be monitored using satellite imagery and geospatial data. Remote sensing can indicate algal blooms; sedimentation; and dissolved organic carbon, phosphorus, and ammonia (Gholizadeh et al., 2016). For example, the impacts of fertiliser on freshwater systems is detectable using Sentinel-2 images (Rodríguez-Benito, Navarro and Caballero, 2020).

The proposed framework is shown in Fig. 5 and focuses on two hydrological impacts:

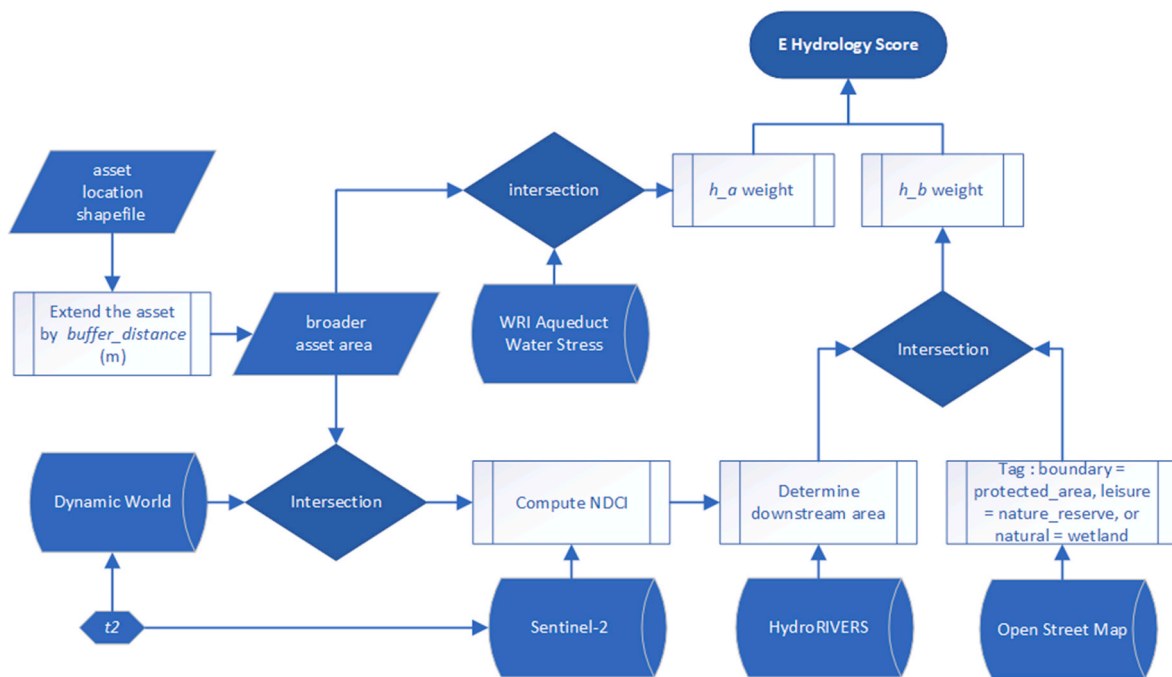
1. Algal blooms, which can indicate eutrophication, are caused by high levels of nutrients being carried into freshwater systems through surface runoff or groundwater infiltration, particularly from excessive fertiliser use. The elevated nutrient levels facilitate rapid algal and plant growth, blocking light from penetrating the surface of the water and interrupting natural water cycles. When these blooms consume the nutrients and die off, their decomposition results in rapid deoxygenation of the water, killing freshwater life.
2. Water extraction in water stressed areas which can lead to environmental and social impacts. Water stress compares total water withdrawals to surface and groundwater supplies, and high stress areas will struggle to balance the needs of water users and nature.

Starting with the disclosed asset boundary, such as the property boundary of a farm or manufacturing facility, an analyst creates a buffer around this asset location that describes the areas surrounding the asset within a certain threshold. A default buffer value (*buffer\_distance*) of 1 km is recommended, but this could be adjusted depending on the type of asset, especially when the asset produces or uses chemicals known to be hazardous to the environment. The Dynamic World dataset shows all large areas of water amenable to satellite analysis in the buffer area. The Normalized Difference Chlorophyll Index (NDCI) – generated from Sentinel-2 data (*band 4* and *5*) – of the water in the buffer zone is monitored to determine if there have been any pollution or sedimentation events. The NDCI can be linked to water pollution because it is a spectral index that measures the amount of chlorophyll-a in water bodies (Mishra and Mishra, 2012). Chlorophyll-a is a pigment found in algae and other aquatic plants, and its concentration is often used as an indicator of water quality. When water bodies become polluted, they can experience an increase in nutrient levels, which can lead to an overgrowth of algae and other aquatic plants. This can cause a spike in the concentration of chlorophyll-a in the water, which can be detected by appropriately thresholding the NDCI. A threshold level of 0.1 is used to detect water pollution. NDCI is tested over the downstream areas of rivers intersecting the asset, for the extended buffer distance. The downstream information is derived with the HydroSHED drainage direction product (Gong et al., 2011). If the area downstream of a site intersects with protected areas, reserves, or wetlands, then the impact of pollution events should be upweighted (described in Table 2).

In parallel, at the asset location, the value for Aqueduct Baseline



**Fig. 4.** Framework to derive the *E Soil Score*. Inputs values for soil organic carbon stocks are extracted from GSOcmap, and Cation Exchange Capacity from the Harmonized Soil Database v2.0.



**Fig. 5.** Framework to derive the *E Hydrology Score*, for assessing the potential for hazards to impact hydrological systems, including water provisioning and wetlands.

Water Stress is extracted and weighted (Table 2). The two scores are averaged to generate the *E Hydrology Score*.

## 2.2. Delocalised effects

Greenhouse gas emissions (GHG) traditionally form a major component of ESG scoring and geospatial approaches offer a method for verifying or supplementing reported data. This framework makes use of open access Sentinel-5P data, providing daily measurements of various atmospheric pollutants such as nitrogen dioxide (NO<sub>2</sub>), carbon monoxide (CO), sulfur dioxide (SO<sub>2</sub>) and methane (CH<sub>4</sub>) at a spatial resolution of 3.5 km × 5.5 km (NO<sub>2</sub>, SO<sub>2</sub>) and 5.5 km × 7 km (CO, CH<sub>4</sub>) (Veeffkind, et al., 2012). Currently, the spatial resolution of these datasets may limit

the precision of results, but the Earth observation market is seeing an increase in the planning of higher resolution sensors, and a few commercial providers are already selling data at a much higher-resolution (~25m) for methane emissions (Varon et al., 2020).

NO<sub>2</sub>, SO<sub>2</sub>, CO and CH<sub>4</sub> are harmful air pollutants that can have serious health and environmental impacts. They are often emitted from industrial assets and their monitoring and reduction is important for the public health and the environment. Specifically.

- 1) NO<sub>2</sub> is a greenhouse gas, which means that it contributes to the warming of the Earth's atmosphere. While it is not as potent as carbon dioxide, CO<sub>2</sub>, it has a much shorter atmospheric lifetime, which means it can have a more immediate impact on climate

- change. It has a serious impact on public health since it contributes to the formation of other air pollutants such as ground-level ozone and particulate matter.
- 2) CO is another GHG, with similar effects on public health to the ones described for NO<sub>2</sub> but with much smaller impact on climate change when compared to CO<sub>2</sub> and CH<sub>4</sub>.
  - 3) CH<sub>4</sub> is a potent GHG that has a significant impact on climate change. While less abundant than CO<sub>2</sub> in the atmosphere, methane is about 28 times more effective at trapping heat than CO<sub>2</sub> over a 100-year time frame, and its atmospheric concentration has been increased rapidly in recent decades (Varon et al., 2020). CH<sub>4</sub> is emitted into the atmosphere by a variety of natural and anthropogenic sources, including agricultural fields, livestock farming, coal mining and waste disposal. Reducing methane emissions is a major part of efforts to mitigate climate change.
  - 4) SO<sub>2</sub> is not a significant GHG and it is produced by burning fossil fuels such as coal and oil, as well as by some natural sources such as volcanic eruptions. It does not directly contribute to global warming, but it has similar public health impacts to NO<sub>2</sub> and CO. Moreover, when sulfur dioxide is released in the atmosphere, it can react with water vapour to form sulphuric acid, which can contribute to the formation of acid rain, having a significative negative impact on ecosystems and infrastructures.

Given the current available resolution for open-access products, rather than monitoring the emissions of a single point in time, the framework monitors the temporal average of atmospheric pollutants over the broader area surrounding the asset and builds a sub-score, *E Global Pollution Score*, where high pollution levels will be penalised, according to Table 2. It is important to carefully select the monitoring period to be temporally relevant, e.g. while the asset is operating, and is suggested to be lasting one month – ideally around the *t2* hyperparameter already employed in the previous sub-scores. The monthly average is extracted from Sentinel-5P data products, as shown in Fig. 6.

### 3. Framework application

The *E-score* overall framework is demonstrated with a practical example in this section. Section 3.1 outlines the practical implementation of the framework, with a description of the software and data used to derive all the sub-scores, while Section 3.2 presents an application over a coal mine in Russia.

#### 3.1. Practical implementation of the framework

As outlined in the introduction, the *E-score* makes use of open-access only datasets (Table 1). The principal motivation behind this choice is the provision of methodology that can be applied by anyone. Similarly, the processing tools chosen are also all open to researchers. Specifically, Google Earth Engine (GEE) (Gorelick, et al., 2017) and QGIS (Rosa-Chavoya et al., 2022) are the two main tools employed for this study. While GEE is an accessible geospatial platform that allows for cloud processing, i.e. remote sensing data do not need to be retrieved prior to their processing, QGIS is a platform that needs geospatial data to be locally downloaded and ingested but that then allows for powerful data management operations and visualisation. The only user input to the *E-score* framework is the area of interest, in form of a geospatial shapefile. This can be retrieved from available open datasets from selected industries (Caldecott et al., 2022; Rossi et al., 2022), or can be simply manually traced and produced in QGIS or other open geospatial tools. The sub-scores implementation is briefly described in the following list.

- a. *E Land Use Change Score*. Dynamic World is fully embedded in GEE, so GEE is the only tool employed for this sub-score.

- b. *E Biodiversity Score*. This sub-score makes use of OpenStreetMap to check specific tags. Open platforms such as Overpass (<https://overpass-turbo.eu/>) can be employed. Biodiversity Hotspots and Biodiversity Intactness Index (BII) are inspected in QGIS. Note that the average value of a product, e.g. BII, over the area of interest can be easily computed in QGIS with the *Zonal Statistics* function.
- c. *E Soil Score*. Both the GSOCmap and the Harmonized Soil World Database are inspected in QGIS.
- d. *E Hydrology Score*. Water presence, direction and pollution are computed in GEE. Water stress values are derived with an online tool (<https://www.wri.org/applications/aqueduct/water-risk-atlas>).
- e. *E Global Pollution Score*. All atmospheric gases are derived with Sentinel-5P data in GEE.

To further ease applicability, the developed Google Earth Engine scripts are made available.<sup>2</sup> A PyQGIS script to automatically perform geospatial operations is also provided.

#### 3.2. Exemplary application: coal mining, Kemerovo Oblast, Russia

To illustrate the *E-score* derivation, a coal mining area in Kemerovo Oblast, Russia, is chosen (Fig. 7). While in this case the area of interest (AoI) has been manually traced just to demonstrate the framework, without any defined industrial boundary or particular environmental relevance, the *E-score* analyst can choose to input a specific asset boundary or even a broad area to evaluate large-scale environmental impacts. On the practical side, while the first case requires the definition of two shapefiles, i.e. the *asset location shapefile* and the *broadier asset area* to evaluate global impacts, the second case do not typically require the extended shapefile given the already extensive coverage. This second case is chosen within this exemplary application. For reference, all datasets are presented in Table 1 and all hyperparameters in Table 2 (Appendix A).

The first sub-score is the *E Land Use Change Score*. As described in Section 2.1.1, a large temporal span is suggested to evaluate changes. In this case, a 2-year span is chosen. Specifically, the hyperparameters *t1* and *t2* are set to August 2020 and August 2022, respectively. The two land cover products are shown in Fig. 8. Most of the area is covered by trees and the mining operations are shown as bare soil. The changes from natural covers to non-natural ones are shown in Fig. 9. Most of the changes are represented by the mining operation expansion, i.e. land cover class 'trees' to 'bare', and account for 0.97% of the overall area of interest. *E Land Use Change Score* is therefore 0.097.

The second sub-score is the *E Biodiversity Score* (Section 2.1.2). The analysis of OpenStreetMap reveals that the AoI is not located in a protected area, thus the *b\_a* weight is 0 (Table 2). Similarly, the analysis of the CEPF Biodiversity Hotspots shows that the closest hotspot is the 'Mountain of Central Asia', which is located about 1000 km far away, thus the *b\_b* weight is 0 (Table 2). Finally, the intersection of the Biodiversity Intactness Index map with the AoI yields an average value of 0.91, indicating that the AoI is located in an area where biodiversity is heavily impacted. According to Table 2, the *b\_c* weight is 0.91. The potential for local biodiversity impacts, *E Biodiversity Score*, is the average of the three weights, i.e. 0.3.

The third sub-score is the potential for local soil impacts, *E Soil Score* (Section 2.1.3). Soil Organic Carbon is averaged over the AoI by intersecting it with the GSOCmap, as shown in Fig. 10, yielding an average SOC of 65.9 [t/ha]. The potential for land disturbance to release soil carbon, represented by the hyperparameter *s\_a* weight, is within the medium level, thus setting this weight to 0.4. The analysis of the Harmonized World Soil Database shows an average Cation Exchange Capacity of 18 [cmolc/kg]. According to Table 2, the potential for land disturbance to degrade soil fertility is medium, and the *s\_b* weight is 0.6.

<sup>2</sup> <https://github.com/montemisma/EScore>.



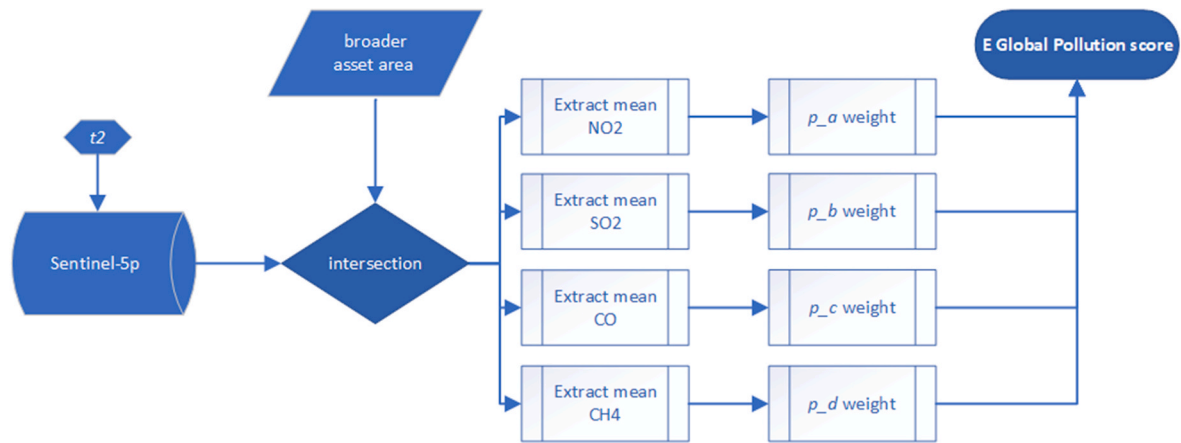


Fig. 6. Framework to derive the *E Global Pollution Score*.

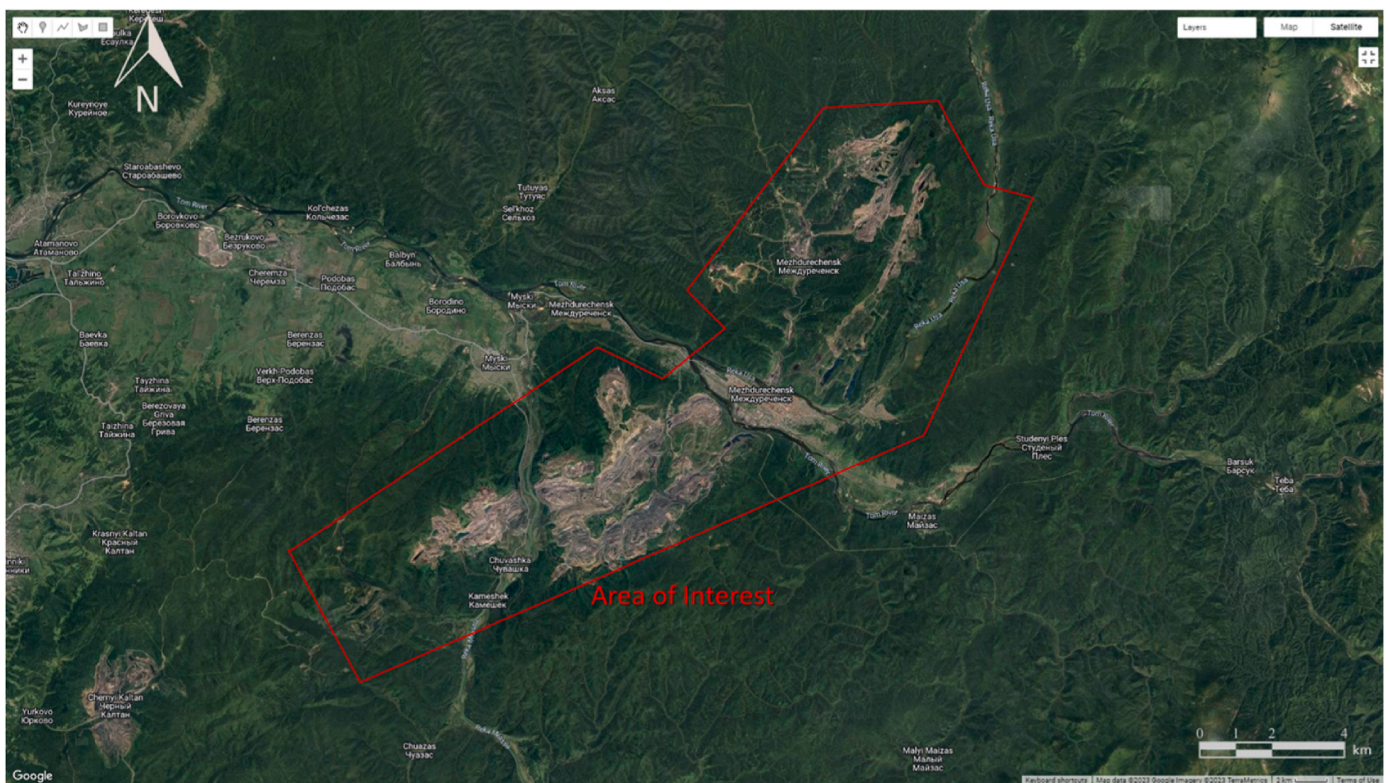


Fig. 7. Area of interest for the framework demonstration (red boundary). The area is around the city of Mezhdurechensk in Siberia (Russia) and it is composed of two mining areas at the north and south-west of the city, embedded in a forested area. The basemap is from Google Earth. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

*E Soil Score* is the average of the two hyperparameters, resulting in 0.5.

The last sub-score within the localised impacts is the *E Hydrology Score* (Section 2.1.4). First, water bodies are extracted from the land cover map shown in Fig. 8, for  $t_2$ . Second, NDCI is computed with Sentinel-2 and water pollution events are tagged for NDCI values larger than 0.1. Third, drainage direction is extracted from HydroSHEDS. The case under study is shown in Fig. 11. The drainage directions of the rivers intersecting the mining areas at the north and south-west of Mezhdurechensk are south-west and north, respectively, shown with yellow arrows in Fig. 11. Pollution events should be marked for locations from the asset under study to the broader asset area border according to the drainage direction. Interestingly, while no pollution events have been detected for  $t_2$  (August 2022), several pollution events have been

detected for  $t_1$  (August 2020), e.g. the one marked in yellow in Fig. 11, therefore revealing an enhancement in environmental practices in this region. According to Table 2, the  $h_b$  weight is 0. Finally, the impact of asset water consumption is evaluated by intersecting the AoI with the WRI Aqueduct Water Stress map. This operation shows that the asset is located in a highly water stressed area, i.e. the ratio of total water withdrawals to available renewable surface and groundwater supplies is high, and the  $h_a$  weight is set to 0.6 (Table 2). *E Hydrology Score* is the average of the two hyperparameters, resulting in 0.3.

The last sub-score is the *E Global Pollution Score* (Section 2.2). Emissions are computed with Sentinel-5P data and averaged over the area. Their impact is classified as low, medium, or high according to Table 2. In the study area, average nitrogen dioxide emissions at  $t_2$  are



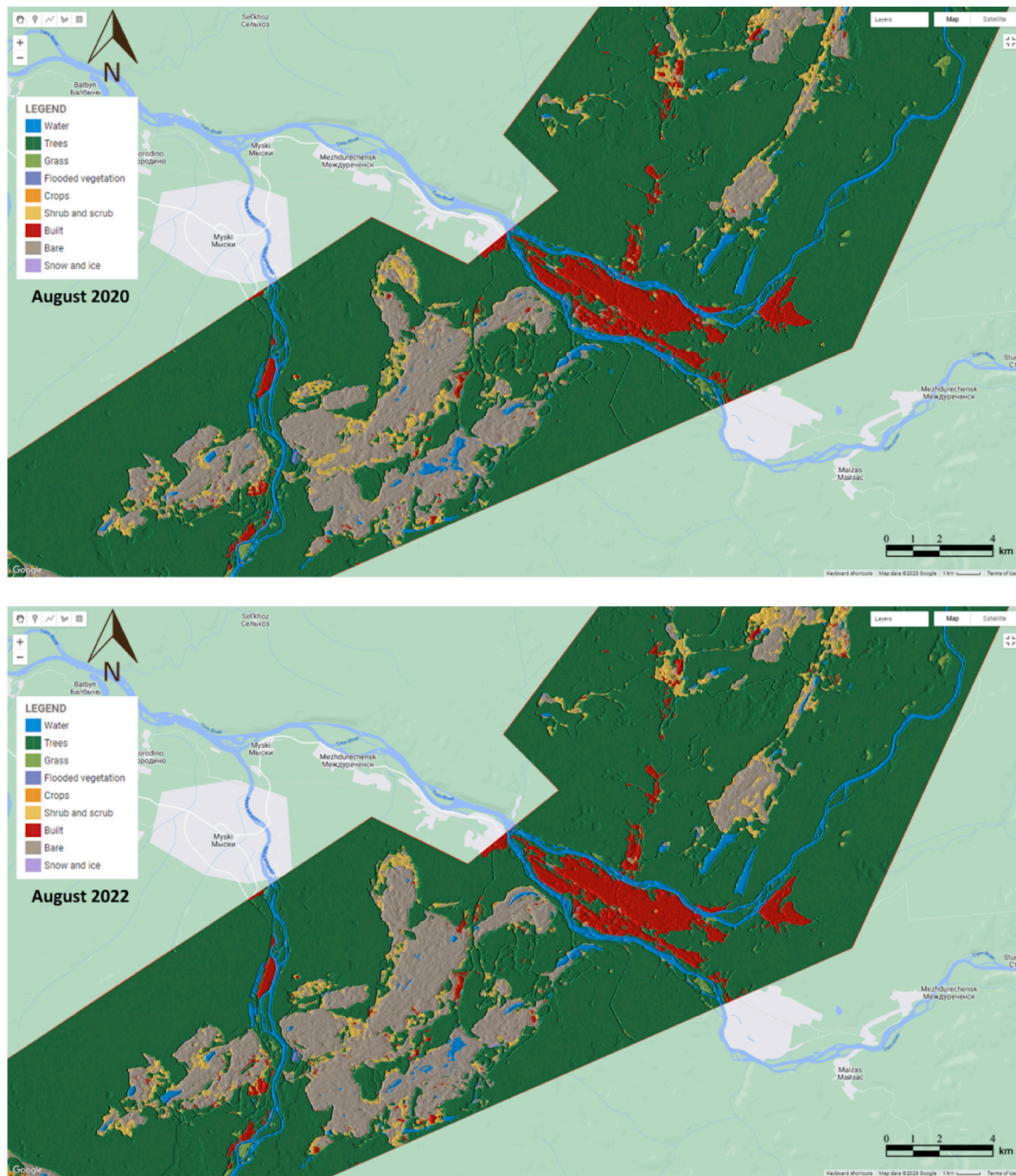


Fig. 8. Dynamic World land cover representation for August 2020 and August 2022, as outputted in Google Earth Engine.

0.0006 [ $\text{mol}/\text{m}^2$ ] (low,  $p_a$  weight = 0), shown in Fig. 12; average sulfur dioxide emissions are 0.0046 [ $\text{mol}/\text{m}^2$ ] (low,  $p_b$  weight = 0); average carbon monoxide emissions are 0.28 [ $\text{mol}/\text{m}^2$ ] (medium,  $p_c$  weight = 0.5); average methane emissions are 1949 [ppb] (medium,  $p_d$  weight = 0.5). *E Global Pollution Score* is the average of the four hypermeters, i.e. 0.25.

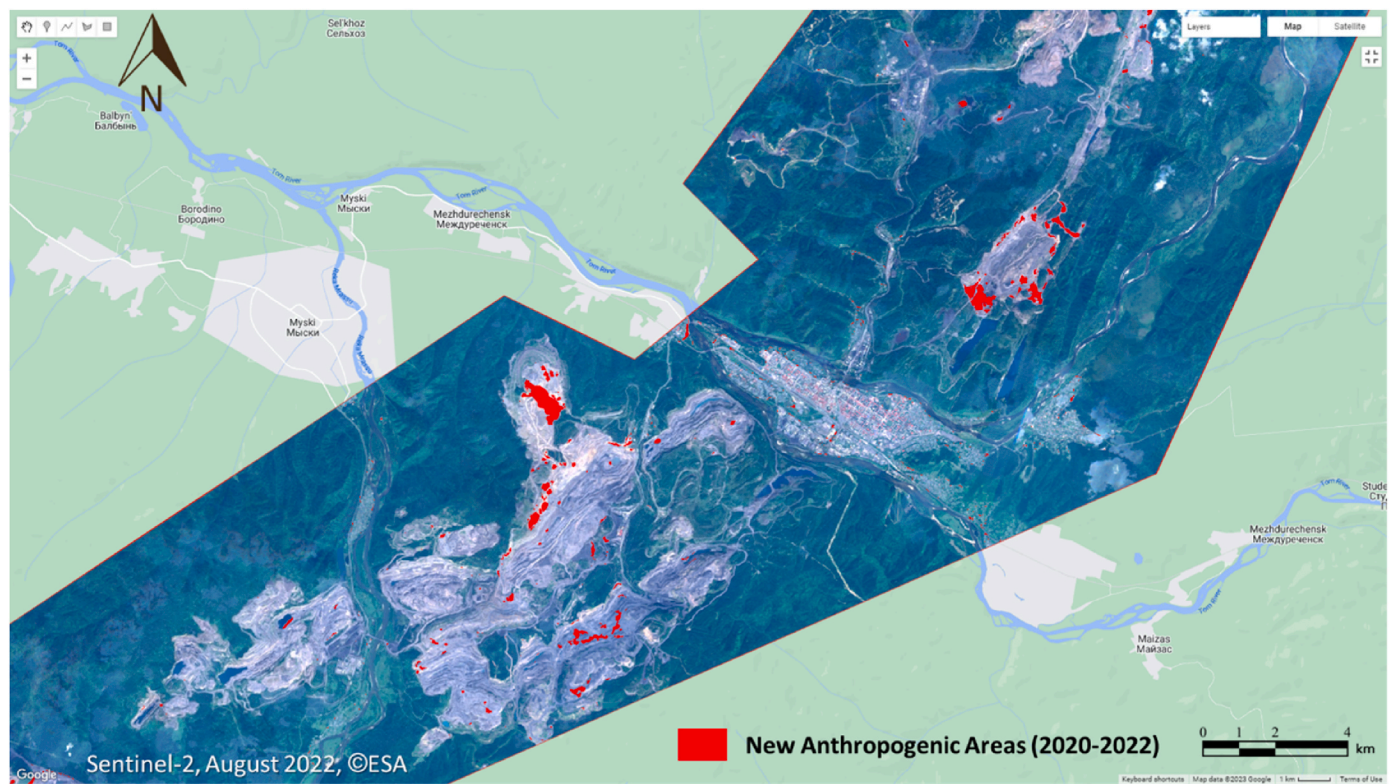
The final *E Score* is a composition of all the sub-scores, as described in Table 2. The localised impact of land cover change on biodiversity is the multiplication of *E Land Use Change Score* with *E Biodiversity Score*, with the  $l_a$  weight resulting in 0.003. The localised impact of land cover change on soils is the multiplication of *E Land Use Change Score* with *E Soil Score*, with the  $l_b$  weight resulting in 0.005. The total localised environmental impact of the area under study is the average of  $l_a$ ,  $l_b$  and the *E Hydrology Score*, with the  $e_a$  weight resulting in 0.01. To be

noted, this is particularly low and driven only by the *E Hydrology Score* since the chosen area is large and the land change from natural to non-natural covers only about 1% of the total area. The *E Global Pollution Score* is passed in full to the  $e_b$  weight and the overall *E Score* is an average of  $e_a$  and  $e_b$ , resulting in 0.18. The score is classified in five categories (Table 2), from very low impact to very high impact. The AoI is classified having a low environmental impact.

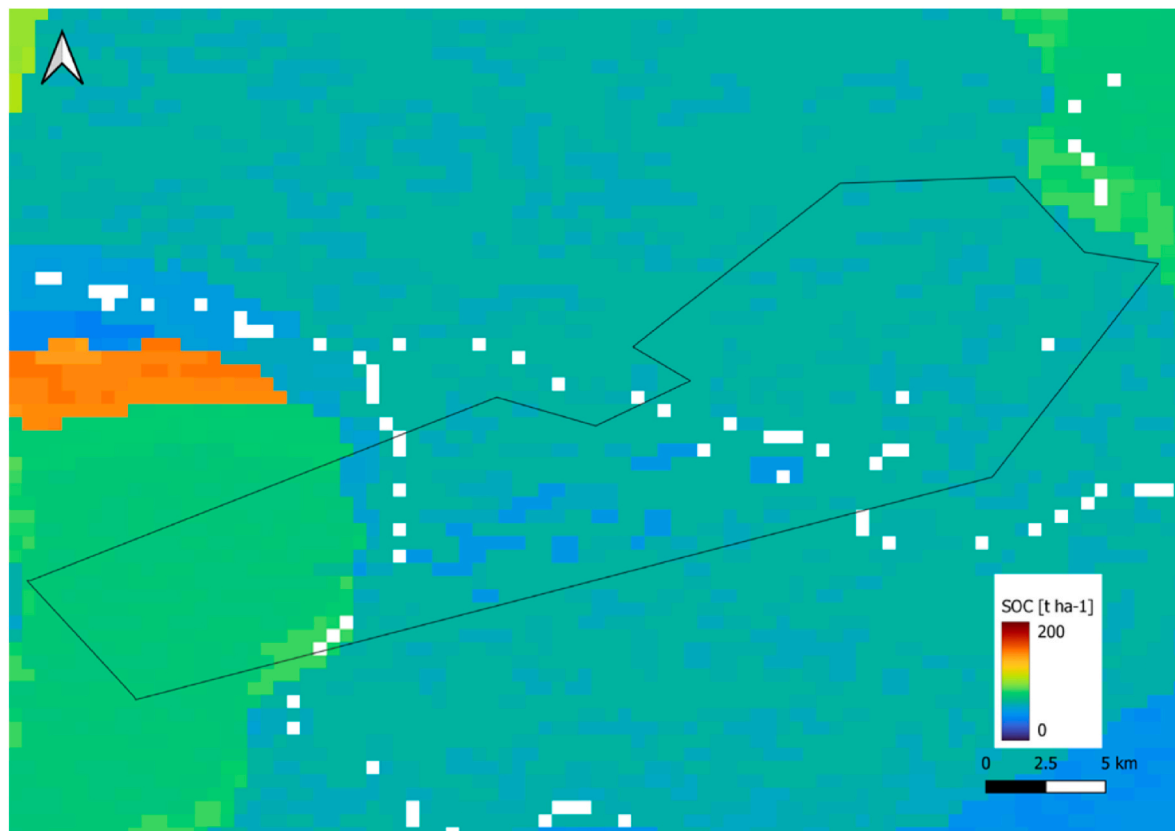
#### 4. Discussion

Incorporating geospatial and remote sensing approaches into ESG assessments is increasingly advocated for in the literature, especially in efforts to address the combined global, environmental crises of climate change, food security, and mass species extinction. New technologies

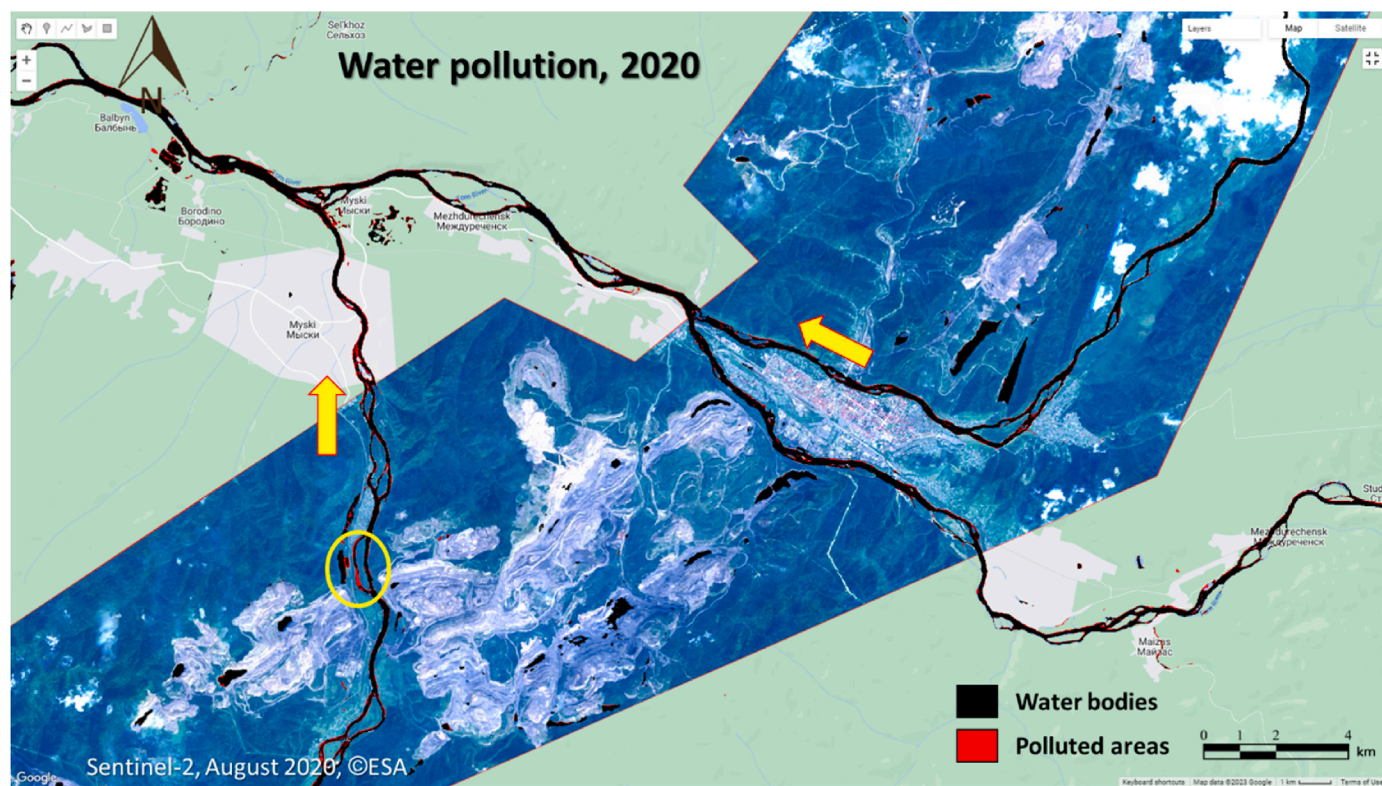




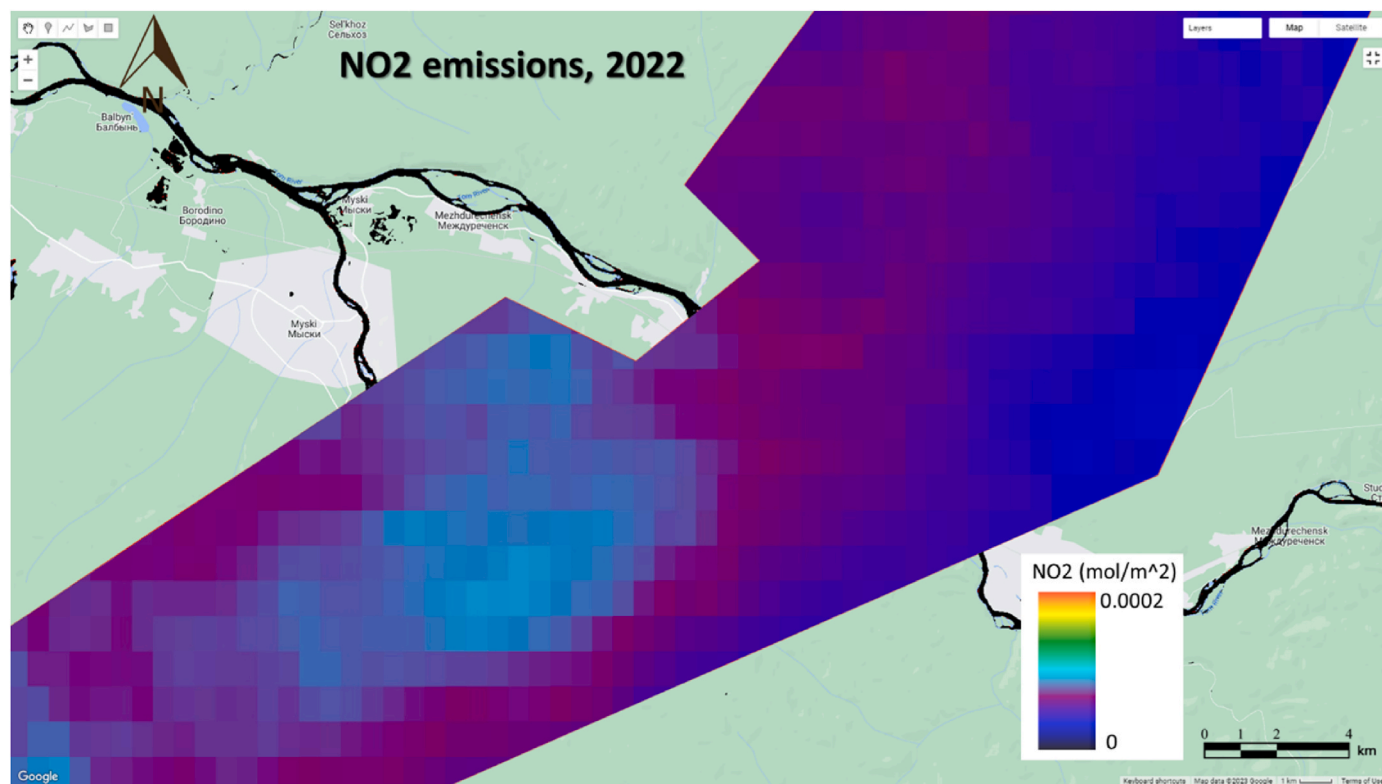
**Fig. 9.** Land cover changes from natural covers to non-natural ones, in red. Most of the changes are expansions of the mining area. The basemap is the Sentinel-2 acquisition of August 2022. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)



**Fig. 10.** Soil Organic Carbon map from the GLOSIS-GSOCmap v1.5.0 intersected with the AoI, traced in black.



**Fig. 11.** Water bodies (black) and pollution events (red) over the study area. A significant pollution event is marked with a yellow circle. The drainage direction is shown with yellow arrows. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)



**Fig. 12.** Nitrogen dioxide emissions over the study area, as outputted in Google Earth Engine.



and methods have the potential to revolutionise the way that environmental data is incorporated into decision making, including the high-throughput analysis of environmental DNA, automated drone data collection, and increasingly precise and timely satellite produced Earth observation data. The described framework seeks to enable ESG analysts to examine the impacts of economic assets on land use, freshwater systems, soils, and biodiversity using satellite data.

More nuanced analyses or pipelines for assessing the impact of land use change are also achievable, particularly for indirect environmental impacts in an asset's supply chain. Biodiversity impacts especially can be measured with a lot of depth. For example, when assessing land conversion impacts, habitat degradation that falls short of land degradation may be determinable through remote sensing methods depending on the site conditions at the start and end of the monitoring period. Additional datasets could be brought in at this stage to determine environmental hazards. For example, company policies that attempt to mitigate the impacts of land conversion with restoration or planting work might be taken into account in weighting the score. Environmental variables such as the connectivity of alternative wildlife corridors for species movement, or the distance of forested habitat to water sources are among the metrics that can be brought in to modify how land cover change is assessed to be creating local impacts. By considering the variations in carbon stocks among different habitat types, it becomes possible to differentiate and distinguish various conversions occurring between different natural cover classes. While the *E Score* provides us with a comprehensive methodology to assess environmental impacts with remotely sensed data, the complexity and missing availability of open access data prevents the adoption of the aforementioned modifications to the framework.

#### 4.1. Incorporating geospatial data into ESG analytics

Geospatial data offers opportunities to verify or supplement existing reported data as well as to enable ESG ratings to include data on variables that are not often measured. Geospatial data is not meant to replace company disclosures or replace high-quality on-site measurements, recording, and reporting. However, as the quality of reported data may vary, remotely sensed products allow ESG analysts to verify whether reported data are likely to be accurate by comparing expected and reported values. If no data is reported, or the quality of data is highly suspect, then geospatial data can supplement analysis. Missing data may be available directly from geospatial data layers, but statistical methods or interpolation applied to the spatial data may enable the estimation of the missing value.

In other cases, geospatial methods allow ESG analysts to explore ESG issues from both a bottom-up and a top-down, impartial perspective. For example, it's possible to request information regarding the safe handling and disposal of hazardous chemicals from a manufacturer but exploring the impacts of improper procedures or work on the downstream freshwater system allows a different source of information.

As ESG rating agencies begin to incorporate geospatial tools into their ratings, environmental issues relating to soil, water, biodiversity, land conversion, and emissions should be among the first to be explored for innovations in data sources and rating methods. This work sets out many freely accessible datasets with widespread coverage that can be used to supplement existing datasets and methodologies. Keeping abreast of new datasets that become available will remain an obstacle to innovation. ESG rating agencies should also work with academic and NGO groups to produce accessible geospatial datasets with global coverage and regular update schedules.

#### 4.2. Paid for datasets, local datasets, sector specific data

This work focuses on freely available datasets with global coverage that provide data that is relevant to many sectors. Paid for datasets exist that provide significant utility, especially in biodiversity assessment.

These include useful datasets describing Key Biodiversity Areas, protected areas, Red List species, Species Threat-Abatement and Restoration Metric (STAR), and rarity-weighted species richness; available from IBAT. Additional hydrological modelling, soil mapping, and asset data may be available from commercial sources and tailored to the needs of a specific ESG analysis method. National datasets may provide a much greater variety of information on specific variables at higher resolution than global datasets. These data may also be updated more frequently than datasets with global coverage. Included above is an EU-specific soil productivity dataset as an example. National datasets, such as soil classifications, habitat mapping, or asset ownership can be essential for capturing the impact of a company for specific use cases, but these are not available for all industries or all countries. ESG analysts should consider which sector-specific datasets might enable them to assess the impact of assets on the environment and build frameworks to account for them.

#### 4.3. Data gaps and opportunities in free, global data

This framework utilises datasets that are free to use and have widespread geographic coverage. High quality datasets that meet these criteria are not available for certain variables that would contribute to an understanding of assets' environmental effects. Protected area datasets for commercial use, along with advanced conservation importance metrics are available from IBAT. Regional databases can open up new avenues of analysis that can provide valuable information including productivity mapping for cropland, pasture, and forest soils in the EU (Tóth, et al., 2013); or tropical forest fragmentation data (Hansen, et al., 2013; Potapov et al., 2017). National governments often possess the highest quality maps of their country's soils and geology. As highlighted in previous reviews, there is a serious need across many types of ESG analyses for global extent, high-resolution datasets to be created with regular update schedules to serve various areas of environmental monitoring (WWF-UK, *Geospatial ESG*, 2022a,b) (WWF-UK, *The Biodiversity Data Puzzle*, 2022a,b). Stakeholders in the ESG data and ratings sector should consider the need to facilitate the creation and upkeep of these data products, in addition to maintaining those that currently exist.

Bespoke drone-collected datasets commissioned for key assets or asset portfolios would also enable high resolution emissions data to be collected, as has been shown for methane emissions (Hollenbeck et al., 2021). Asset characteristics can be measured using drone-mounted technology; for example, energy efficiency is assessable using infrared temperature sensors (Zheng et al., 2020) and light pollution via multi-spectrometers (Fiorentin et al., 2019).

## 5. Conclusions

Geospatial datasets are the natural inputs for the next generation of environmental impact assessments, and ESG impact analysis will benefit hugely from the incorporation of these datasets into their assessment frameworks. These geospatial datasets offer ESG analysts and rating agencies the ability to verify claims of company reported data, to fill in gaps where none is otherwise reported or available, or to provide new types of data that companies would not be able to provide themselves. Free to use geospatial datasets that have broad geographic coverage exist, and some are updated over time. Incorporating these datasets into existing methodologies would be cost-effective, enabling analysts and agencies to develop a geospatial offering rapidly. This paper has proposed a novel framework to address the aforementioned opportunity, by providing a comprehensive description of how a single descriptor to assess the environmental impacts of a study area can be generated with open access data. This framework aims to mitigate the reported divergence in ESG scores by using consistent and trusted geospatial data for environmental impact analysis at the physical asset level.

### Credit author statement

CR: conceptualisation, methodology, software, investigation, writing – original draft. JB: conceptualisation, methodology, writing – original draft CC: writing – review and 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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## Appendix A. Framework tables

**Table 1**

Framework variable descriptions.

Variable	Dataset	Tag/Band	Description	Spatial Resolution	Revisit time
<b>Hydrology Score</b>					
Water presence	Dynamic World	Water = 1	Determines where water is present	10m	2–5 days
Rivers	HydroSHEDS	Drainage Direction, 3 Arc-Seconds, product	Identify downstream river segments within 1 km	90m	NA
Protected areas	OpenStreetMap	boundary = protected_area, leisure = nature_reserve, natural = wetland, landuse = reservoir_watershed, Compute NDCI	To intersect with downstream river of site, highlighting potential for negative site impacts	Vectors	NA
Water pollution	Sentinel-2		Measures the amount of chlorophyll-a in water bodies as an indicator of water quality	10m	5–10 days
Water stress	WRI Aqueduct	Physical Risk/Water Stress	Measures the ratio of total water withdrawals to available renewable surface and groundwater supplies	1 km	NA
<b>Soil Score</b>					
Soil Organic Carbon	GLOSIS - GSOCmap	Band 1 = VALUE	The estimated SOC	1 km	NA
Cation Exchange Capacity	Harmonized World Soil Database	CEC <sub>SOIL</sub> , Depth Layer 1 D1	Cation Exchange Capacity is a measure of soil fertility	1 km	NA
<b>Biodiversity Score</b>					
Protected areas	OpenStreetMap	boundary = protected_area, leisure = nature_reserve, Polygon boundaries	To intersect with asset area	Vectors	Intermittent
Biodiversity Hotspots	Biodiversity Hotspots		Is the area within one of the hotspot boundaries?	Vectors	NA
Biodiversity Intactness Index	Biodiversity Intactness Index	Intactness (%)	Is the site within an area of high intactness that could be disturbed by activity, or in a highly vulnerable area?	~1 km	2016 data
<b>Land Cover Change Score</b>					
Land Cover	Dynamic World	LC at T1 != "Built-up Area", "Bare Ground", or "Crops" LC at T2 = "Built-up Area", "Bare Ground", or "Crops"	Does land cover change from a natural to a non-natural cover category?	10m	2–5 days
<b>Global Pollution Score</b>					
Atmospheric pollution	Sentinel-5P	Sentinel-5P OFFL CH4/ CH4_column_volume_mixing_ratio_dry_air_bias_corrected Sentinel-5P OFFL NO2/ tropospheric_NO2_column_number_density Sentinel-5P OFFL CO/CO_column_number_density Sentinel-5P OFFL SO2/SO2_column_number_density	Measures a range of atmospheric gases and pollutants that affect air quality and climate	1 km (resampled)	1 day

**Table 2**

Framework hyperparameter descriptions.

Variable	Description	Scoring
E Hydrology Score	The asset's hydrological impacts	Average (or weighted average if preferred) of h_a weight and h_b weight
h_a weight	The impact of asset water consumption	10% - Low: 0 10–20% Low-medium: 0.2 20–40% Medium-high: 0.4 40–80% High: 0.6 >80% Extremely high: 0.8 Arid and low water use: 1
h_b weight	The impact of asset water pollution	No pollution event (NDCI<0.1): 0 Pollution event/s (NDCI>0.1): 1 Pollution event/s with the potential to impact a protected area: 2
buffer_distance	The distance from the site to search for hydrological impacts	Default 1000m

(continued on next page)

Table 2 (continued)

Variable	Description	Scoring
t1 and t2	The monitoring period. A sufficiently long monitoring period is needed to detect events.	NA
E Soil Score	The potential for local soil impacts	Average (or weighted average if preferred) of s_a weight and s_b weight
s_a weight	The potential for land disturbance to release soil carbon	Low <50 t ha <sup>-1</sup> : 0.2 Medium – 50–100 t ha <sup>-1</sup> : 0.4 High - 100–200 t ha <sup>-1</sup> : 0.6 Very High >200 t ha <sup>-1</sup> : 1
s_b weight	The potential for land disturbance to degrade soil fertility	Very Low <5 : 0 Low – 5–10: 0.4 Medium - 10–25: 0.6 High >25: 1
E Biodiversity Score	The potential for local biodiversity impacts	Average (or weighted average if preferred) of b_a weight, b_b weight, and b_c weight.
b_a weight	Is the asset located in or adjacent to a protected area?	Not near protected area: 0 Within 1 km of a protected area: 0.5
b_b weight	Is the asset located in a CEPF Biodiversity Hotspots?	Inside a protected area: 1 Outside of a hotspot: 0 Inside a hotspot: 1
b_c weight	Is the asset located in an area already where biodiversity is already heavily impacted?	Moderately disturbed 70–80%: 0.25 Lowly Disturbed: 0.5 Highly Disturbed: 50–80%: 0.5 Very Highly Disturbed <50%: 0.8 Near Pristine: 1
E Land Cover Change Score	The proportion of the area of an asset that is converted from natural land cover to “Built-up Area”, “Bare Ground”, or “Crops”	Total asset area/area of land converted, or an estimation of the proportion of land converted is site boundaries are missing.
E Pollution Score	The asset's atmospheric impacts	Average (or weighted average if preferred) of p_a, p_b, p_c, p_d weights
p_a weight	The impact of nitrogen dioxide emissions	0–0.0002 mol/m <sup>2</sup> - Low: 0 0.0002–0.0005 mol/m <sup>2</sup> - Medium: 0.5 >0.0005 mol/m <sup>2</sup> - High: 1
p_b weight	The impact of sulfur dioxide emissions	<0.001 mol/m <sup>2</sup> - Low: 0 0.001–0.01 mol/m <sup>2</sup> - Medium: 0.5 >0.01 mol/m <sup>2</sup> - High: 1
p_c weight	The impact of carbon monoxide emissions	0–0.01 mol/m <sup>2</sup> - Low: 0 0.01–0.05 mol/m <sup>2</sup> - Medium: 0.5 >0.05 mol/m <sup>2</sup> - High: 1
p_d weight	The impact of methane emissions	<1800 ppb - Low: 0 1800–2000 ppb - Medium: 0.5 >2000 ppb - High: 1
l_a weight	The localised impact of land cover change on biodiversity	(E Biodiversity Score) x (E Land Cover Change Score)
l_b weight	The localised impact of land cover change on soils	(E Soil Score) x (E Land Cover Change Score)
e_a weight	The total localised environmental impact of the asset	Average (or weighted average if preferred) of l_a weight, l_b weight, and E Hydrology Score
e_b weight	The total delocalised environmental impact of the asset, consisting of the combined contributions of climate forcing emissions	E Global Pollution Score
E Score	The total localised and delocalised impacts of the asset	Average (or weighted average if preferred) of e_a weight and e_b weight <b>0–0.1 – Very low impact</b> <b>0.1–0.3 – Low impact</b> <b>0.3–0.5 – Medium impact</b> <b>0.5–0.8 – High impact</b> <b>0.8–1 – Very high impact</b>

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